Fuzzy Techniques in Visual Performance and Illumination Applications

التقنيات الضبابية في أداء الرؤية وتطبيقات الإضاءة

by

ISSAH M. ALHAMAD

A thesis submitted in fulfilment

of the requirements for the degree of

DOCTOR OF PHILOSOPHY IN ARCHITECTURE AND SUSTAINABLE BUILT ENVIRONMENT

at

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Fuzzy Techniques in Visual Performance and Illumination Applications

Abstract

The lighting design calculation has many variables that do not realistically have crisp values and therefore can be considered fuzzy. By fuzzy we mean that a particular variable does not have an exact value. The vagueness of such variables will certainly lead to imprecise outcomes. In fact, many visual performance and luminous variables and metrics are- either by nature or by virtue of their inherent complexity- not precise. To come up with an exact output from input that is, by its very nature, uncertain and imprecise is virtually impossible. We believe that the uncertainty that is inherent in many lighting design variables leads to imprecise lighting design outcomes. Hence, Fuzzy logic technique is suitable for implementation in visual performance and illumination applications. Moreover, Fuzzy logic can solve the problem of complex mathematical formulas and a large number of correction factors currently used in visibility models. This work is exploring the possibility of applying the fuzzy techniques in both indoor lighting and road lighting by demonstrating how lighting variables can be represented in fuzzy sets rather than crisp sets.

The first part of this study is related to indoor illuminance selection, three variables (Age, Task characteristics, and task importance) have been considered as an input for the fuzzy model with the target Illuminance as the output. This model allows for the lighting designer to select the precise target illuminance based on the actual conditions and avoid underlit or overlit situations. Moreover, a digital tool has been developed based on the membership functions established in this study that allows the lighting designer to check the state of the uniformity

and compare the target illuminance (based on his choice or based on the application) with the achieved illuminance from lighting calculations.

The second part of this study (road lighting) models the visual performance based on fuzzy techniques. This allows the proposed visual performance model to include more input variables compared to the current visibility models. The input variables are luminance contrast (positive and negative), age, visual size, retinal illuminance, eccentricity, background complexity, and disability glare, while the output variable is the Fuzzy relative visual performance (FRVP). The results of these models have been compared to the current visual performance model and it was found to be in good conformance. Moreover, the term ‘critical contrast’ is introduced, defined as the minimum contrast required to produce a change in the rating of the visual performance for a particular values of visual age, visual size, retinal illuminance, eccentricity, and background complexity. A digital tool has been developed to calculate the fuzzy relative performance and is available to be used.

التقنيات الضبابية في أداء الرؤية وتطبيقات الإضاءة

الملخّص

تحتوي حسابات تصاميم الإضاءة على العديد من المتغيرات التي ليس لها قيم واضحة بصورة واقعية، لذا يمكن اعتبارها ضبابية. يقصد بالضبابية هنا أن المتغير ليس له قيمة دقيقة؛ وبالتالي سيؤدي غموض هذه المتغيرات بالتأكيد إلى نتائج غير دقيقة. في الواقع، تعد العديد من المقاييس ومتغيرات الأداء البصري والإضاءة غير دقيقة، إما بطبيعتها أو بحكم تعقيدها المتأصل؛ ولذلك فإنه من المستحيل عمليا الوصول لنتائج دقيقة من المدخلات التي تعتبر بطبيعتها غير مؤكده وغير دقيقة. يعتقد بأن الغموض المتأصل في العديد من متغيرات تصاميم الإضاءة يؤدي إلى نتائج غير دقيقة لهذه التصاميم، ومن هنا فإن تقنية المنطق الضبابي مناسبة للتنفيذ في تطبيقات الأداء البصري والإضاءة. علاوة على ذلك، يمكن للمنطق الضبابي أن يحل مشكلة المعادلات الحسابية المعقدة وعدد كبير من عوامل التصحيح المستخدمة حاليًا في نماذج الرؤية. تستكشف هذه الدراسة إمكانية تطبيق التقنيات الضبابية في كل من الإضاءة الداخلية وإضاءة الطرق، من خلال توضيح كيفية عرض متغيرات الإضاءة في أوضاع ضبابية بدلاً من الأوضاع الواضحة.

يتعلق الجزء الأول من هذه الدراسة بالإضاءة الداخلية، وقد تم اعتبار ثلاث متغيرات (العمر وخصائص المهمة وأهمية المهمة) كمدخلات للنموذج الضبابي مع اتخاذ الإضاءة المستهدفة كمخرجات. يتيح هذا النموذج لمصمم الإضاءة اختيار الإضاءة المستهدفة الدقيقة بناءً على الظروف الفعلية وتجنب الأوضاع الأقل أو أكثر إضاءة. علاوة على ذلك، تم تطوير برنامج حسابات بناءً على المحددات المستخدمة في هذه الدراسة والتي تتيح لمصمم الإضاءة التحقق من مقدار و تجانس الاضاءة الداخلية، ومقارنة الإضاءة المستهدفة (بناءً على اختياره أو بناءً على التطبيق) بالإضاءة المحققة من حسابات الإضاءة.

يرتبط الجزء الثاني من هذه الدراسة بإنارة الطرق، ويناقش الأداء البصري بالاعتماد على التقنيات الضبابية. يسمح هذا لنموذج الرؤية المقترح بتضمين المزيد من المتغيرات المدخلة مقارنة بنماذج الرؤية الحالية؛ والمتغيرات المدخلة هي تباين الإضاءة ,عمر الرائي ,حجم الهدف, مقدار الإضاءة الواقعة على شبكية العين, الانحراف عن خط النظر بالاضافة الى درجة تعقيد منظر القيادة، في حين أن المتغيرات المخرجة هي الأداء البصري النسبي الضبابي. وقد تم مقارنة نتائج هذه النماذج بنموذج الأداء البصري الحالي، ووجد أنه متطابق بشكل جيد. بالإضافة إلى ذلك، قدّم في هذه الدراسة مصطلح "التباين الحرج"، والذي تم تعريفه على أنه الحد الأدنى من التباين المطلوب لإحداث تغيير في تقييم الأداء البصري، كما تم تطوير برنامج حسابي لايجاد الأداء النسبي الضبابي وهي متاحة للاستخدام.

Dedication

To my great father, the one who inspired me, believed in Me, and above all, loved me

To my wife Nirmeen, who struggled to gather my scattered papers and pieces of my life

To my son Adam, who always motivated me to do more

To my daughter Layla, who waited hours on my study-room door to show me her new drawings

To all the people who supported me, inspired me and encouraged me

I dedicate this work

Acknowledgments

I still remember the phone call that started it all, Dr. Riad Saraiji was on the line, he told me I have the right research topic for you; Visibility of targets, although it is something new to you but I know you can do it considering your background as a mechanical engineer, and most importantly, I know you can take difficult things seriously.

To be honest, I didn’t have a clue about the topic, besides, I didn’t know anything about Fuzzy logic. I was then in my first year at the Ph.D. Program and I still didn’t develop my own research path. I didn’t even know that I can continue my studies, so I kept stalling with Dr. Riad. I was even about to apologize to him. But I liked the idea that I was approached by someone who has faith in me and knows that I can do something worthy.

Three years have passed while working with Dr. Riad, and now I am submitting my thesis in the field of lighting and fuzzy logic. The efforts of Dr. Riad have successfully transformed me from someone who knows nothing about lighting, to someone who knows little about lighting, but can find his path in the darkness. The constant support and encouragement that Dr. Riad offered me cannot be described by words. Indeed. Every time I was feeling lazy or getting fed up from work, I would get in touch with him, so I can get a new dose of fresh enthusiasm to fuel me up for some time, and to let me find my way back to production. He was always there for me, generous with his time and great ideas, and he tolerated my long questions and discussions. I truly believe that without his dedication and devotion, this work might never have seen the light.

I also extend my sincere thanks for my second supervisor, Professor Bassam Abu-Hejleh, Dean of the Faculty of Engineering at BUiD, and to my dearest sister, Dr. Hanan Taleb, who taught me few courses during my Ph.D. journey. Yet, her contribution to building many of my views changed the way I look into things, and the joy and fun she brought into her student lives cannot be forgotten. And finally, I would like to acknowledge the insights of my greatest mentor, where words cannot do him justice, Professor Halim Boussabaine, Dean of Faculty of Business and Law at BUiD.

Finally, I would like to acknowledge the support I got from my colleagues at both BUiD and UAEU. Thank you so much for your motivation and encouragement throughout the most difficult times in my journey.

Thank you all,

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Abbreviation	Definition
L_A	Adaptation Luminance
$a(\alpha, L)$	Adrian Exposure Time Correction Function
AASHTO	American Association Of State Highway And Transportation Officials
ADAS	Advanced Driving Assistance System
AF	Adrian Age Correction Factor
AI	Artificial Intelligence
ANN	Artificial Neural Networks
A_p	Pupil Area
C	Contrast
CAD	Computer-Aided Design
C_{ch}	Critical High Contrast
cd/m^2	Candela Per Square Meter
C_{eff}	Glare Effective Contrast
CIE	Commission Internationale de l'Eclairage
Covid-19	Corona Virus Disease-2019
CSF	Contrast Sensitivity Function
C_{th}	Threshold Contrast
D	Distance Between The Target And Observer
DC	Dominant Contrast
ΔL_{th}	Luminance Difference Threshold
E_{eye}	Illuminance On The Eye
FIIL	Fuzzy Indoor Illuminance
FRVP	Fuzzy Relative Visual Performance
GUI	Graphical User Interface
IES	Illuminating Engineering Society
IESNA	Illuminating Engineering Society Of North America
L_b	Background Luminance
LED	Light-Emitting Diode
L_t	Target Luminance
L_{veil}	Veiling Luminance
MVL	Multi-Valued Logic
P	Age Correction Factor For Retinal Illuminance
r	Pupil Radius
RGB	Red, Green, Blue
RR	Rule Rank

RVP	Relative Visual Performance
STV	Small Target Visibility
SXGA	Super Extended Graphics Array
VL	Visibility Level
w	Solid Angle
$\boldsymbol{\alpha}$	Angular Angle
$\boldsymbol{\tau}$	Ocular Transmittance
$\mathbf{I_R}$	Retinal Illuminance
$\boldsymbol{\mu}(\mathbf{x})$	Membership Function
$\boldsymbol{\mu}_{\mathbf{C}}(\mathbf{x})$	Luminance Contrast Membership Function
$\boldsymbol{\mu}_{\mathbf{C}}^{+}(\mathbf{x})$	Positive Luminance Contrast Membership Function
$\boldsymbol{\mu}_{\mathbf{C}}^{-}(\mathbf{x})$	Negative Luminance Contrast Membership Function
$\boldsymbol{\mu}_{\mathbf{A}}(\mathbf{x})$	Visual Age Membership Function
$\boldsymbol{\mu}_{\mathbf{S}}(\mathbf{x})$	Visual Size Membership Function
$\boldsymbol{\mu}_{\mathbf{R}}(\mathbf{x})$	Retinal Illuminance Membership Function
$\boldsymbol{\mu}_{\mathbf{E}}(\mathbf{x})$	Eccentricity Membership Function
$\boldsymbol{\mu}_{\mathbf{B}}(\mathbf{x})$	Background Complexity Membership Function
$\boldsymbol{\mu}_{\mathbf{F}}(\mathbf{x})$	FRVP Membership Function
$\boldsymbol{\mu}_{\mathbf{TD}}(\mathbf{x})$	Task Difficulty Membership Function
$\boldsymbol{\mu}_{\mathbf{TI}}(\mathbf{x})$	Task Importance Membership Function
$\boldsymbol{\mu}_{\mathbf{U}}(\mathbf{x})$	Uniformity Membership Function
$\boldsymbol{\mu}_{\mathbf{FIIL}}(\mathbf{x})$	FIIL Membership Function

"As we work to create light for others, we naturally light our own way"

Mary Anne Radmacher

1 Chapter One: Introduction

1.1 Overview

Imagine yourself young again, healthy, sober, and completely alert. Safely driving your car at a well-lit street in a clear summer night while listening to a non-distracting music on your favourite radio channel. Completely able to see targets ahead of you such as pedestrians, traffic tie-ups, and other road users, regardless of their size, contrast, and their location with respect to your line of sight. At the same time, you are capable of viewing elements on the streetscape, reading traffic signs and road lines as well as your vehicle instruments and gauges. This situation means that your visual system is working its best not only to detect obstacles and stimuli ahead of you, but also to identify and avoid them safely and promptly. This shortly describes the concept of visual performance, and judging by this situation, most probably you will get home safe due to the virtue of high visibility, and live another day to appreciate the blessing of sight.

Now imagine someone old (above 80 years) sitting in the passenger seat. He is also healthy enough for his age, sober, completely alert, and sharing you the joy of the non-distracting music on your mutual favourite radio channel. But for many reasons, compared to you, his visual system is unable to get the same amount of information from his surroundings. These reasons are obviously related to the deterioration of vision with age, which may include the lower elasticity of his pupil lens which prevents correct light adaptation, as well as the yellowing of his eye lens, which makes less light goes into his retina and many other reasons. Therefore, his ability to detect and identify any stimulus on the road is almost certainly less than yours, in other words, his visual performance (as a visibility metric) is apparently lower than yours as a younger driver.

Although age is an important factor in defining visibility, it is not the only one. Since targets differ in characteristics such as contrast, size, shape, pattern, movement....etc., visibility of different targets will vary for the same driver/observer regardless of his age and mental conditions. Moreover, the location of the target from the line of sight (eccentricity) plays a major role in the detection process. Which adds more complexity to the visibility definition. And finally, the surrounding conditions such as lighting conditions and/or background complexity also has a significant effect on the visual performance of night-time drivers. In fact, the visibility of targets can be so complex in a way that it can be considered as a complete process. This means that it involves a source; which is the characteristics of the target or stimulus such as size and contrast, a receiver; which includes factors involving the observer himself such as age and mental conditions, and finally, a process path; which includes many variables such as the distance between the target and the observer, the location of the target from the line of sight and the presence of glare. As a result, visibility is a multi-discipline study that involves many different fields of science such as physics and light, medical factors, human factors…etc.

Despite many visibility models exist (Adrian 1989), Rea and Ouellette (1988, 1991), STV (IESNA 2000), utilizing different variables and parameters, they take a deterministic approach to model visibility. This is generally noticed as in current models, variables with exact values form the input parameters eventually result in a specific value of visibility, although many variables used in calculation do not realistically have crisp values and therefore can be considered as vague or fuzzy. Fuzzy means that a particular variable does not have an exact value. The vagueness of such variables will certainly lead to imprecise outcomes. In fact, many visual performance and luminous variables and metrics are, either by nature or by virtue of their inherent complexity, not precise. Examples of such imprecise variables that are commonly used in lighting is the reflectance of room surfaces, age of occupants or drivers, visual capability of the observers, etc. To come up with an exact output from input that is, by its very nature, uncertain and imprecise is virtually impossible. It is believed that the uncertainty that is inherent in many lighting design variables leads to imprecise lighting design outcomes.

Furthermore, besides some limitations with the current visibility models involving testing subjects with certain age groups, then providing correction factors to the rest of age ranges (Adrian 1989) or utilizing complex mathematical relations (Rea and Ouellette 1988, 1991) or employing limited range for some variables such as the target size in STV model (IESNA 2000). Visibility itself, as a metric, is hard to measure, and if measured, is imprecise. As an example, we often assume an age of occupant when we are designing for internal lighting, or an age of drivers when we design for roadway lighting. The age of the person can take the form of an exact number which all of the outcomes are based on. The outcomes that are based on imprecise assumptions are intrinsically imprecise. One could represent the age of the occupant in linguistic terms, for example; very young, young, old, and very old.

The age compatibility with “young”, or “old” is a matter of degrees and depends on our understanding of what the word means within the context that we are studying (Nguyen et al. 2000). For example, when studying sports lighting, as opposed to office lighting, or roadway lighting, in the context of those three different cases, someone might be classified as young or old differently. Two different people of different age, may both be considered young, but may have different degrees of being young.

To demonstrate the above, refer back to the example related to driving at night and consider someone who is older than you and younger than your old passenger is sitting on the rear seat.

This simply means that his visibility (as a metric) may be lower than you as a young observer and higher than your old passenger sitting beside you. However, as age groups (young, old, very old), in the context of vision, can include certain ranges of age in which people share similar visual characteristics, the value of the visibility (as a metric) is hard to calculate as an exact number since it does not really depend on the exact value of age as an exact number rather than the classification of which age group the observer may belong to (young, old, very old). Alternatively, the visibility in such a situation can be approximated based on the observer's age, or represented by a certain range of visibility values, or can be described in linguistic terms such as (high, medium, and low) and/or (sufficient and insufficient). This linguistic representation best describes the principle of fuzzy techniques as they are essentially approximations to model a certain variable, phenomenon, or decision for which mathematical precision is impractical or impossible (Boussabine and El Hag 1999).

Hence, with so many different factors from different fields contributing to the definition of visibility. Add to that the complexity of the current mathematical relations represented by the current models and the limited ranges of variables utilized, this study is exploring the possibility of applying Fuzzy logic techniques in modelling both indoor illuminance and target visibility as a suitable alternative to the current models/methods. Fuzzy logic is a useful technique due to its elasticity in including as many variables as needed without restriction on any range or order. Moreover, fuzzy models have a favourable advantage in which it can be easily revised to include more variables in the future. This saves the complex mathematical relations involved in modelling a certain phenomenon as well as the correction factors needed to include a certain variable or variable range in the future.

Fuzzy set theory (Zadeh 1965) allows dealing with the vagueness of the variables used in visual performance and illumination design. It is believed that the approach to lighting design in general and more specifically visual performance has a fuzzy rather than precise nature. In fact, many of the metrics and/or variables in lighting and visual performance can be described in linguistic terms rather than precise values. They also provide a solution to variables and metrics which do not have crisp boundaries and/or units. Furthermore, fuzzy techniques provide a convenient bridge between design and control, whereby, the control of a lighting system can be geared towards fulfilling design objectives using fuzzy logic.

It is believed that a more efficient and more realistic approach is to have fuzzy values whereby the targets are no longer either visible or non-visible, but rather have degrees of visibility, and indoor illuminance can have degrees in high, medium and low subsets. This is a novel approach that will impact the process and the design targets of the external and internal design of the visual environment.

1.2 Study Objective

The objectives of this work can be summarized as follows:

1. To investigate the applicability of fuzzy theory and techniques on lighting applications
2. To develop a new visual performance model that encompass wider range of variables through the use of fuzzy techniques
3. To simplify the illuminance selection procedure through the use of fuzzy techniques

Fuzzy Logic is a convenient and efficient way of modelling visual performance given the imprecision of the variables that contribute to night-time visibility. For example, an object can have the following degrees of visibility: completely visible, completely invisible, and partially visible. The expected outcome is a new visibility model (FRVP) and illumination design method (FIIL) based on Fuzzy Logic that would replace the current models/methods. The new proposed visibility model is based on Fuzzy logic techniques and will be called "Fuzzibility" which combines the two words (Fuzzy and visibility). "Fuzzibility" is expected to give better results in terms of road lighting as well as indoor lighting. In these models, variables with exact values form the input parameters ultimately result in a specific value of visibility.

1.3 Research questions

The research questions that this work is trying to answer are as follows:

1. Is fuzzy logic a suitable method to model visual performance and indoor illumination?: The proposed approach is using the concept of Fuzzy logic in modelling indoor illuminance and visibility where illuminance and visibility are no longer a rigid term (visible or non-visible target), but rather a term that involves many degrees of illuminance and supra-threshold visibility, such as high, medium and low illuminance, or completely visible target, partially visible, highly visible, completely invisible and partially invisible. This is a novel approach that has not been used before to model indoor illuminance and target visibility. This work is trying to experiment with the benefits, limitations, and applications of using this approach in modelling visual performance and indoor illumination.
2. Can fuzzy logic give better illuminance selection methods as well as a visibility model comparing to current methods/models? Current visibility models are limited to the variables that were used to develop them while ignoring many other factors. Moreover, some models are limited to the range of values considered in building that model.

Hence; the results of this approach will be compared to the current model results to check for similarities, advantages, disadvantages, and finally, decide on its worthiness.

1.4 Study Aims

The main aim of this study is to explore the possibilities to improve or enhance the method used in indoor illuminance selection as well as current visibility models using fuzzy logic techniques. Under the umbrella of this main objective relies on four specific aims as follows:

1. Review exciting variables used in indoor illuminance and modelling visibility
2. Study factors that can be used to expand the visibility models
3. Application of fuzzy logic technique in modelling indoor illuminance and visibility
4. Synthesis of knowledge by validating the proposed method/model results against current models and evaluating any enhancement that gives better insights about practical applications such as car headlights design, roadway lighting design, self-driving cars, and many others. Figure 1.1 shows the main aim and specific objectives of this study in details and Table 1.1 shows the study objectives and how to achieve each one of them.

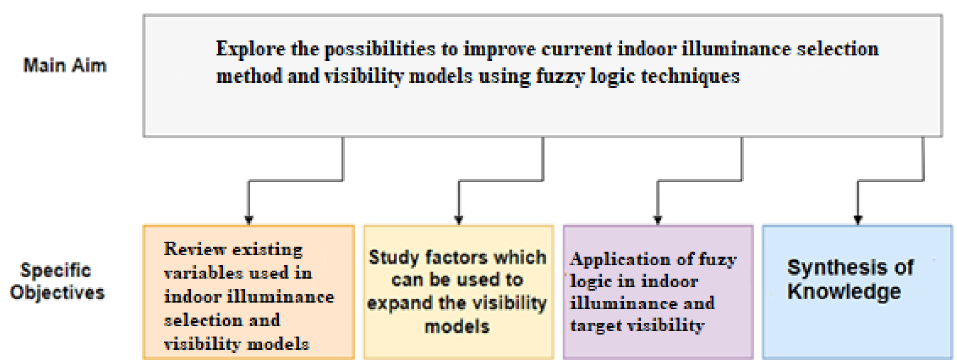


Figure 1.1: Main aim and specific objectives of the current study

Table 1.1: Objectives of this study and how to address each one of them

Sr.	objective	Stage	Criteria
1	Review existing variables used in indoor illuminance selection and visibility models	Literature review Methodology	• Current indoor illuminance methods will be studied • Variables involved in indoor illuminance selection will be identified • Current visibility models will be studied carefully • Current visibility variable shall be identified • Weight and effect of each variable shall be recognized • Classification of which visibility variables into categories based on their effect on the results • Choosing which variables shall be included in this study • Justification of the omitted variables
2	Study factors which can be used to expand the visibility models	Literature review Methodology	• Current visibility models will be studied carefully • Literature review shall identify the gaps in current visibility models • Identifying the visibility variables that were overlooked or used with limitations in current models
3	Application of Fuzzy logic in modelling indoor illuminance selection method and target visibility	Problem formulation Methodology	Using Matlab Fuzzy logic toolbox, the process is described in the research methodology section
4	Synthesis of knowledge	Results and discussion	• Results and discussion of the two models • Validation of FRVP with Rea and Ouellette RVP model (Rea and Ouellette 1988, 1991) • Validation of FIIL with respect to IES lighting handbook recommended illuminances (DiLaura et al. 2011) • Sensitivity analysis for FRVP model • Advantages/ limitation of the two models • Future research work

1.5 Significance of work

The need to develop an approach that responds to the shortcomings of the current illuminance selection methods and target visibility models is of great importance. This work is expected to generate a new method for indoor illuminance selection method based on fuzzy logic approach, this approach is more suitable as it allows for the calculation of the exact design values of the indoor illuminance based on the actual situations rather than a single inflexible value provided by the current standards. These actual values of indoor illuminance can have a great effect in avoiding underlit and overlit situations.

In other words, this work defines a new model for indoor illuminance requirements and target visibility in order to deliver enhancements to the design guidance of indoor lighting as well as road lighting. This enhancement can be adopted by users/designers based on their own characteristics and not based on a common standard values. For example; the proposed models allow a city with certain weather conditions, or a city with a high number of elderly drivers, or a city with numerous number of cyclists or pedestrians to adopt a certain type of street lighting to match its needs. Moreover, due to the nature of fuzzy logic techniques which endorses elasticity and diversity, the new models, in both visual performance and indoor illumination design, can provide insights to lighting fixtures designers of internal, external as well as vehicle headlamps in order to provide the required fittings, gear and controls to match a certain need such as an elderly driver, observer/worker, or to match a certain task such as CAD drawing or manufacturing, or to match a certain situation, such as busy roadways with complex driving scenes.

Such an effort of providing a specific model for a specific geographic location, community groups, and/or operating conditions is not a new concept. In a unique study, Joulan (2015) proposed an analytical age-dependent model of contrast sensitivity functions for an aging society (Joulan et al. 2015). This approach is widely used in applications involving heating and air-conditioning, in which the design procedure includes many variables of the space itself, the geographic location, occupant's age groups, type of operations or tasks involved, and many others. Hence, fuzzy logic is also widely used in heating and air-conditioning systems control and design (Dash et al 2012), (Kumari et al. 2012).

1.6 Structure of the thesis

This work is enclosed in six chapters. The first one was the previous introduction which provided a brief description of visibility and its variables as well as some concepts in illumination applications. It also provided the research aims, research questions, and the significance of this work.

The second chapter is the literature review. It begins with an overview of the indoor illuminance determination method, then it gives an overview of visibility definitions including Threshold and Supra-threshold visibility concepts as well as a brief history of some early studies in the field. Then an extensive description of the current visibility models was provided in which they were assessed and compared to each other. A review of the advantages, disadvantages, and limitations of each one allowed for the identification of the gap in which this work was designed to fill.

The third chapter is the Methodology of this work. A large chunk of this chapter is related to the fuzzy logic model proposed in this study, its advantages/disadvantages, limitations, and how does it compare to other models such as mathematical models and artificial intelligence (AI) and neural networks. Moreover, this chapter spots the lights on the methodology and procedure followed in this work such as the fuzzification of input variables, fuzzy inference systems, and rules as well as the defuzzification process.

Chapter fours is where the results are, for both the FRVP and FIIL models, the effect of each input variable on the visual performance and indoor illuminance has been presented in details with 2D and 3D graphs and surfaces. Moreover, conditions for high and low visibility have been presented and some new concepts such as the critical contrast and have been demonstrated. The chapter also includes a description and results of the newly proposed software packages

Chapter five includes the discussion of the result presented in the results chapter. It contains an extensive discussion for both the FRVP and FIIL models in terms of description, advantages, and limitations. Moreover, validation for both the FRVP model and FIIL model with respect to current models/methods is presented. For the FRVP model, sensitivity analysis was done and presented in this chapter.

Chapter six will demonstrate the conclusions of this work, as well as the outcomes of this study in terms of main findings. Furthermore, this chapter assessed both FRVP and FIIL models in terms of their ability to answer the research questions presented at the early stages of this study as well as the future works that can follow this study.

References and appendices will follow.

2 Chapter Two: Literature Review

2.1 Indoor target illuminance

Work-plane illuminance is one of the most widely used lighting metrics in the industry. The popularity of this metric is owed to its simplicity and measurability using simple equipment. Most lighting designs require the calculation of the illuminance on the work-plane. Design targets are based on the function of the space. The design targets often specify average work-plane horizontal or vertical illuminance.

Attempts to establish illuminance recommendations date back to 1920 -1950. The Illuminating Engineering Society (IES) has a prolonged record of producing illuminance recommendations used in lighting design. The first illuminance recommendations were proposed by IES as “lighting codes” (IES 1924). These codes provided illuminance values recommended for many applications such as offices, schools, and industry. In 1947, lighting recommendations were provided as a vital part of the 1st lighting handbook (IES 1947) and all the following editions.

Mathew Luckiesh (1934, 1944) and Richard Blackwell (1955) attempted to establish a basis for illuminance recommendations. These efforts resulted in the illuminance recommendations that appeared in the 4th and 5th editions of the lighting handbook (1966, 1972), whereby each task had a single and precise illuminance target. In 1980, the IES abandoned attempts to base recommended illuminance levels on the results of visual performance experimental data and adopted a consensus procedure (IES1980). This involved ranges of illuminance defined by three values. A range of illuminance was assigned by consensus to a task or area. The target was recommended by a consideration of the age of the observer, the reflectance of the task background, and task importance.

This process formed the basis for the recommendations in the 6th, 7th, and 8th editions of the Lighting Handbook (DiLaura et al. 2011). Figure 2.1 shows a sample of these illuminance values based on age, task characteristics for some visual performance categories (Dilaura et al. 2011).

Peter Boyce (1996) discussed that every task is unique in terms of the balance between visual, cognitive, and motor components. He argues that it is this uniqueness that makes the existence of a formula that quantifies the precise relationship between lighting conditions and task performance for a wide range of tasks impossible. In his view, the illuminance recommendations are based on either technological or financial or emotional factors and not on visual performance factors, hence, illuminance based on visual performance represents visual needs, and that based on expectations, represents visual wants. He suggested to develop lighting recommendations based on consensus data obtained from the field, and publish the illuminance recommendations based on this consensus (Boyce 1996).

DiLaura (2008 editorial leukos) argues that the single value that is in the 9th edition of the IES handbook is inflexible and recommended to use a range system. In that edition, the handbook states that "it is often difficult or impossible to know the age, retinal health, and optical refraction of the worker. . . Therefore, a precise calculation method for visual performance cannot be justified for typical areas or activities" (Rea 2000). "Missing a single-value illuminance target by more than a few percentage points may be considered a serious issue by a client and/or a code authority and/or a court of law" (Steffy 2006). A look at the history of illuminance recommendations in Table 2.1 shows how those recommendations significantly changed over the years.

Category		Recommended Illuminance Targets (lux) — Visual Ages of Observers (years) where **at least half** are: <25	25 to 65	>65	Some Typical Application and Task Characteristics	Visual Performance Description
interior and exterior applications	A	0.5	1	2	• Dark adapted situations • Basic convenience situations • Very-low-activity situations	**Orientation, relatively large-scale, physical (less-cognitive) tasks** Visual performance is typically not work-related, but related to dark sedentary social situations, senses of safety and security, and casual circulation based on landscape, hardscape, architecture, and people as visual tasks.
	B	1	2	4		
	C	2	4	8	• Slow-paced situations • Low-density situations	
	D	3	6	12	• Slow-to-moderate-paced situations • Moderate-to-high-density situations	
	E	4	8	16		
	F	5	10	20	• Moderate-to-fast-paced situations • High-density situations • Some indoor very subdued circulaton situations • Some indoor social situations	
	G	7.5	15	30		
	H	10	20	40		
interior and exterior	I	15	30	60	• Congested and significant outdoor intersections, important decision-points, gathering places, and key points of interest • Some indoor social situations • Some indoor commerce situations	
interior and exterior applications	J	20	40	80	• Some outdoor commerce situations • Some indoor social situations • Some indoor commerce situations	**Common social activity and large and/or high-contrast tasks** Visual performance involves higher-level assessment of landscape, hardscape, architecture, and people and can be work related.
	K	25	50	100		
	L	37.5	75	150		
	M	50	100	200		
	N	75	150	300		
	O	100	200	400		
	P	150	300	600	• Some indoor social situations • Some indoor education situations • Some indoor commerce situations • Some indoor sports situations	**Common, relatively small-scale, more cognitive or fast-performance visual tasks** Visual performance is typically daily life- and work- related, including much reading and writing of hardcopies and electronic media consecutively and/or simultaneously.
	Q	200	400	800	• Some indoor education situations • Some indoor commerce situations • Some indoor sports situations • Some indoor industrial situations	
	R	250	500	1000		
	S	375	750	1500		
	T	500	1000	2000	• Some sports situations • Some indoor commerce situations • Some indoor industrial situations	**Small-scale, cognitive visual tasks** Visual performance is work- or sports-related, close and distant fine inspection, very small detail, high-speed assessment and reaction.
	U	750	1500	3000		
	V	1000	2000	4000		
	W	1500	3000	6000	• Some sports situations • Some indoor industrial situations • Some health care procedural situations	**Unusual, extremely minute and/or life-sustaining cognitive tasks** Visual performance is of the highest order in respective fields of health care, industrial, and sports.
interior applications	X	2500	5000	10000	• Some health care procedural situations	
	Y	5000	10000	20000		

Figure 2.1: Fundamental ranges of values in the illuminance determination system (DiLaura et al. 2011)

Table 2.1: Illuminance recommendations in Foot-candles for office spaces (adapted from DiLaura et al. 2011)

Year	Task Difficulty		
	Easy	Medium	Difficult
1912*	2	4	6
1925*	4	6	12
1947	10	30	50
1952	10	30	50
1959	30	70	150
1966	30	70	150
1972	30	70	200
1981	10/15/20	50/75/100	100/150/200
1984	10/15/20	50/75/100	100/150/200
1993	10/15/20	50/75/100	100/150/200
2000	5	30	100

What is worth noting is that the current recommended illuminance targets shown in the IESNA Lighting Handbook (DiLaura et.al. 2011) are exact values (i.e. instead of being a range of acceptable values). Furthermore, the visual age of the observers has precise boundaries. The recommended illuminance suddenly doubles once the observer age is changed from one group to another. DiLaura et.al. (2011) justified that by assuming that the "legacy values of recommended illuminances were considered to apply to a population age of between 25 and 65 years. If it is known that at least half of the observers are at least 65 years old, then the legacy recommended illuminance (if one exists) is doubled". For example, the recommended average maintained horizontal illuminance for reading and writing tasks using a black ballpoint pen is 150, 300, 600 lux for visual age of observers of less than 25 years, 25-65, and greater than 65 respectively.

It is believed that neither the observer age nor the target illuminance has crisp and exact boundaries and therefore they are fuzzy for all practical purposes. Hence, the objective of this work is to develop an illuminance selection procedure based on fuzzy techniques to enhance the current illuminance selection guidelines.

2.2 Visibility of targets

Visibility is defined as the ability of the visual system to detect and identify a stimulus. For example, a night-time driver needs to detect and identify objects on his way, these objects can be static such as obstacles and traffic-tie ups and dynamic such as pedestrians and other road users. Moreover, the driving task for any motorist includes viewing elements on the streetscape, reading signs and road lines, reading the vehicle instruments, and many other visual tasks needed to a safe journey from a place to another. Hence, seeing or detecting targets on the road is not enough for safe driving, the ability to identify these objects is what makes it crucial for any motorist to react in time and avoid accidents.

Accordingly, target visibility can be described as either threshold visibility or supra-threshold visibility. The point at which a stimulus just becomes detectable is called the detection threshold. Under this paradigm, the term "visibility level" (VL) first described by Blackwell (CIE report 19.2, 1981) provided a metric for task visibility. VL can be defined as:

$$VL = \frac{Equivalent\ luminance\ contrast\ of\ the\ target}{Threshold\ luminance\ contrast} \qquad 2.1)$$

This definition means that VL indicated how much the target luminance is above its threshold value. Further development for the VL approach was done by Adrian (1989) were he incorporated the effect of viewing time, observer's age, and disability glare into visibility level. However, the VL model showed some problems as that equal visibility levels do not correspond to equal levels of task performance. Moreover, as more experiments were conducted and data sets were analyzed, the number of new correction factors proposed to make the model suitable was increased, this complicated the VL analytical approach to such an extent that the model lost its trustworthiness. Adrian model was later incorporated into small target visibility computation STV (IESNA 2000) in road lighting design.

Supra-threshold visibility, on the other hand, describes the speed and accuracy of processing visual information. Relative Visual Performance (RVP) model (Rea 1986), is an attempt to quantify supra-threshold visibility. The origins of this model rely on the results of Rea's first experiments (Rea 1981) to check the effect of luminance contrast on the performance of numerical verification tasks whereby the time and accuracy were recorded as a function of the luminance contrast. Further development to the model was done by Rea an Ouellette (1988, 1991) were they used reaction time to the onset of a square stimulus as a measure of visual performance. In both experiments, the visual performance was measured by the increase in reaction time following the reduction in visual size, luminance contrast, or the amount of light entering the eyes.

2.3 Early work

The revolution in the vehicle industry and transportation infrastructure in the 1930s called the scientific community for better research in vision science (Wood 1936). A concrete visibility model was needed to build a solid road lighting standard as well as reliable automotive headlamps. Although several attempts to conduct experiments to measure the visibility during night time driving, which resulted in proposing a road lighting standard in the UK (Weston 1943), the main contribution was done by H. Richard Blackwell who conducted extensive laboratory studies on the detection of targets under various experimental conditions (Blackwell, 1946). In the following years, under his supervision, CIE reports 19 (CIE 1972) and 19.2 (CIE 1981) proposed a general framework for various visibility models developed by different researchers with adaptation to particular problems. However, Blackwell focused on uniform targets on a uniform background, and the need for further developments for his work was serious.

Early attempts of solving problems related to visual and task performance were studied by Weston (Weston 1943, 1945). Such problems included the sufficient text size and contrast required for a typist to successfully do his work. Or, more generally, the amount of illumination, contrast, and visual size satisfactory to achieve the visual performance. However, Weston's experiments and techniques were poorly defined and performed (Rea 1986) to such an extent where he couldn't even replicate his results under the same testing conditions. On the other hand, Rea extended the work of Weston keeping the same philosophy but with incorporating tighter experimental controls and better analytical and statistical procedures (Rea and Ouellette 1988, 1991).

2.4 Threshold visibility

Threshold visibility refers to the visibility of objects to be just detectable. Or "just visible". An early attempt to quantify the threshold visibility was through the concept of revealing power (Waldram 1938). The revealing power measures the percentage of objects detectable on each point on the road where the diffuse reflection factor of these objects follows the statistical distribution of pedestrian winter clothes. Waldram used a set of 24-inch square targets located on a grid pattern on the roadway and calculated the visibility for each target to determine when the target becomes dangerous for night-time drivers at 30 mph. The data for the statistical distribution of pedestrian's winter clothing reflection factors used by Waldram was developed by Smith (Smith 1938). The revealing power concept was further developed and expanded by numerous researchers (Harris and Christie 1951) while many of them tried to adopt it as a metric for the analysis of road lighting installation (Hentschel 1971), Van Bommel and Boer (1980) but could not succeed as the practical application of their studies are still limited (Narisada and Schreuder 2004).

The visibility level (VL) approach was further advanced by Adrian (Adrian 1989) based on Blackwell data (Blackwell 1946) where he proposed the visibility level model (VL) and discussed the visibility threshold based on a 50% probability of target detection. Though, the model was still considering uniform objects on a uniform background. This is since VL calculation is based on two luminance measurements only, the target reference luminance (L_t) and its near background luminance (L_b), while at actual driving conditions, the luminance of road surface is not homogeneous (Güler and Onaygil 2003) (Brémond et al., 2010) and targets can be far away from uniform (Brémond and Mayeur 2011). Adrian model will be discussed in detail in the following sections.

The small target visibility model (STV) is an extension to Adrian's visibility model (Adrian,1989) adopted by the Illuminating Engineering Society of North America (IESNA 2000) as a metric for good quality road lighting installations. STV incorporates the calculation of visibility levels (VL) under specific conditions defined by IES. The value of STV is then calculated as the weighted average from these visibility level values at different grid points. STV model will be discussed in detail in the following sections.

As a quality criterion for road lighting, Narisada et al. (2007) introduced the notion "area ratio", which is defined as the percentage of road area in which the revealing power can be 90%

or more. It was considered that an area ratio of 70 % can provide acceptable road lighting visibility levels for important roads (Narasida and Karasawa 2001, 2003). However, the revealing power concept was still dealing with threshold visibility, which means that objects on the roadway are only detectable or “just visible”, while, from the traffic-safety point of view, this is not adequate as the driver should be able to detect and identify objects on his path as quickly as possible and with minimum effort to react in time and avoid it. Hence, the visibility at the threshold is not sufficient for night-time driving and supra-threshold visibility conditions are required.

An important theory that raised to the surface in the 1960s suggests that sinusoidal wave gratings are more adequate to describe the performance of the visual system than surface bodies (Campbell and Robson 1968). This allowed for the concept of contrast sensitivity function (CSF) to be developed and argued that it can fully describe the visual performance regardless of the stimuli properties (Van Nes and Bouman 1967). Contrast sensitivity function (CSF) is defined in terms of sine-wave gratings based on different spatial frequencies, the observer is then tested against these gratings with the ability to adjust the luminance contrast for each grating to the threshold value. Then the image can be described as the collection of Fourier components and the response of the visual system is the sum of these component responses. If the latter reaches some threshold value, then the object can be said to be visible (Barten 1999). A wide variety of practical applications can make use of the CSF model such as image-processing techniques and road visibility estimation (Joulan et al. 2011, 2012), road signs design (Bommel 2015), visibility in fog (Tarel et al. 2015).

2.5 Supra-threshold visibility

The visual performance concept was adopted as a measure for supra-threshold visibility. The visual performance is defined as the speed and accuracy of performing a visual task (Levy 1982). While task performance is a more complex term as it is a measure of productivity, or simply, the ability to complete a certain task. The philosophy embraced by researchers who adopted the concept of visual performance (Weston 1935), (Boyce 1973), (Rea 1986) was unique in a way that instead of measuring the absolute limits of visibility “threshold values” and extrapolating to supra-threshold visibility zone, they investigated the supra-threshold visual performance directly by designing special experiments to measure the speed and accuracy of completing certain visual tasks.

To assess the relative performance using a simulated realistic task, the numerical verification task was first used by Smith and Rea (Smith and Rea 1980) and later by many others (Rea 1981), (Slater et al. 1983). Yet, task performance measured by simulated realistic task included more factors other than visual performance, such as motor skills, motivation, and intelligence, so it was difficult to extract the visual performance results from task performance using this method and complex experimental and analytical procedures were required for this purpose (Rea 1981, 1986). The alternative for this complex method was to use reaction times instead of simulated realistic tasks (Boyce and Rea 1987) in measuring and quantifying the visual performance.

The relative visual performance model (RVP) was first developed by Smith and Rea (1982) for indoor lighting applications. Later experiments for reaction times and speed (Rea and Ouellette 1988, 1991) extended the use of the RVP model for roadway lighting. The RVP model was validated by the results of two independent experiments (Rea and Ouellette 1988, 1991) under a variety of luminance conditions. RVP values are typically located between zero and one. The value of zero RVP indicates the visibility at the threshold, while a value of one represents a reference condition of a target with high luminance contrast and large size is seen by a young adult against a high background luminance (Rea et al. 2010). RVP model will be discussed in detail in the following sections.

2.6 Visibility model

The above literature indicated that there are currently three visibility models that are wide-spread and most commonly used to quantify and assess visibility, these models are: the visibility level (Adrian 1989), STV model (IESNA RP 8-00, 2000) and RVP model (Rea and Ouellette 1988, 1991). The following sections will discuss each model in detail.

2.6.1 Adrian visibility model

Adrian visibility calculation model was introduced in 1989 and was based on laboratory work done by Blackwell (1946) and Aulhorn (1964). The model was an extension to Adrian work on 1969 which allowed the luminance differences to be calculated. Another modification to the 1969's model came in 1982 where the effects of the target's observation time were incorporated. In 1989 Adrian extended his older models to allow the calculation of the luminance difference threshold (ΔL_{th}) for negative contrast targets (targets darker than surrounding). Moreover, the model incorporated the effects of the target's observation time, contrast polarity, and observer's age into the visibility level (VL) calculation.

Based on Adrian model (1989), the luminance difference threshold is defined as the minimal luminance difference between the target and the background to perceive the target with a certain probability of 99.93%. The threshold value presented by Adrian was found to be mainly dependent on the target's contrast and target size. However Adrian introduced correction factors to account for observation time, observer's age and contrast polarity to be accounted in the calculation of the luminance difference threshold (ΔL_{th})

The observation time correction factor has a value of unity for a target's observation time of 2 seconds or more while for lower than 2 seconds the correction factor has values exceeding unity. This means that for shorter observation times, a higher threshold difference is needed in order to perceive the target. The same applies for an observer's age of more than 23 years of old except that, based on Adrian's model, the observer's age can be extended to 75 years of old and is divided into two groups; from 23 to 64 years of old and from 64 to 75 years of old with different correction factors formulas. The basis for this are the studies done by Blackwell and Blackwell (1980) and Weale (1961) to find the effects of age on visual performance by measuring the ocular transmittance where they found that it decreases with age. Consequently, higher values of ΔL_{th} is needed to perceive the target for elderly observers as shown in Figure 2.2.

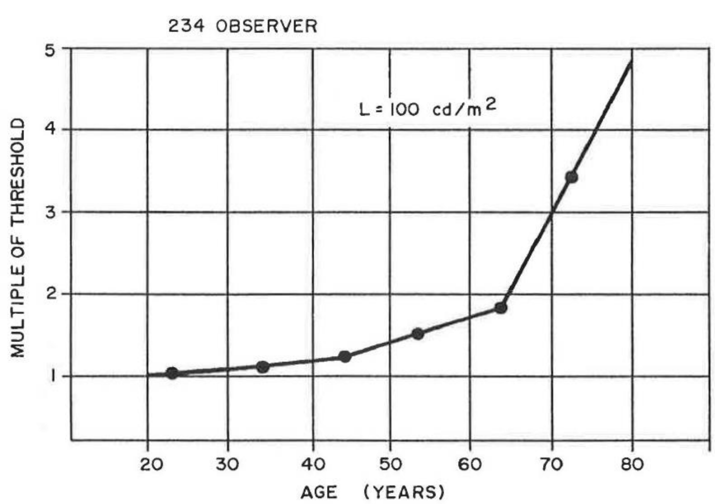


Figure 2.2: Multiple of the threshold contrast required for an observer of higher age in relation to the base group with an average of 23 years. (Adrian 1989)

The luminance contrast is the ratio between the target-background luminance difference and the background luminance. Since the target can be darker or lighter than the background, the luminance contrast can be positive (a black dot on a white background) or negative (a white dot on a black background). Aulhorn (1969) showed that for the same luminance difference (ΔL), negative contrast targets can be better perceived by human observers than positive contrast targets. Hence, negative contrast targets have lower ΔL_{th} than positive contrast objects. Adrian introduced a contrast polarity correction factor to account for the lower ΔL_{th} for negative contrast targets. The correction factor is based on the data presented by Aulhorn (1969) and has a value between zero and one.

Adrian (1989) highlighted the effect of disability glare as well in his visibility model. He reported that disability glare impairs targets due to the high illuminance of stray light in the cornea crystalline lens and the retinal layers. As a result, the stray light superimposes on the retinal image making the image layers to be reduced. Hence, higher ΔL is required in order to clearly perceive targets by a human eye. The effect of glare sources was taken into account by introducing a glare related luminance that is equivalent to the glare effect on the target visibility (L_{seq}). This glare luminance affects the target contrast as it will be added to the background luminance (L_b) and is a function of the illumination of the glare source at the eye, the age of the observer and the glare angle between the fixation line and the centre of glare source (between 1.5^o to 30^o).

The visibility level (VL) introduced by Adrian (1989) expresses how much the target is above the threshold perception. It is defined as the ratio between luminance difference (ΔL) and luminance threshold difference (ΔL_{th}). This visibility definition can be used to evaluate visibility in lighting installations and the quality of road lighting. The conclusion of Adrian's

(1989) work shows that in order to increase the visibility level (VL), either the contrast of the target or the target size should be increased. In other words, for a given target contrast, the distance between the observer and the target should be lowered in order to clearly see it.

In order to Test Adrian's visibility model under night-time driving conditions, Ising (2008) used an experimental approach to measure the response distance for spotting a certain target by drivers on a roadway. The targets were of rectangular shapes and were different in contrast levels and sizes. The observers were drivers with age groups ranging from 35-65 years old with an eye pigmentation factor of 0.5 (typical for brown eyes). A glare source was mounted on the front of the test automobile which imitates an approaching vehicle at 61 meters away from the test vehicle. The driver's eyes height was set at 1.11 m and was assumed to be 2.5 m away from the automobile bumper. The drivers were asked to drive the test vehicle on the designated roadway and give an indication once spotting a target ahead of them, the data for distances between the driver's eyes and target were then measured and used in the following analysis. The calculation used an expectation correction factor of 0.51 to account for unexpected drivers (Roper and Howard 1937), while an exposure time was fixed at be 0.2 seconds based on Adrian's work (1989). Moreover, the study incorporated the CIE General Disability Glare Equation (CIE-146 2002) which extended the glare angle range from between 1.5° and 30° to between 0.1° and 100°. It was found that older drivers required higher-visibility levels at target detection to spot the target than younger drivers. Moreover, it was also found that higher headlight beams required higher-visibility levels at target detection than lower headlight beams. There was also a correlation, even though weak, between the target's reflectivity and visibility levels at target detection. Furthermore, the study revealed that observer's age, target reflectivity, and headlight beam patterns have a significant effect on visibility levels at target detection of alerted drivers, while target size and position did not have a significant effect.

On the other hand, Lecocq (1999) addressed the gap of using a plane target in developing Adrian’s model (1989) by introducing a calculation method to calculate the luminance distribution around a solid spherical target. Hence, determining its visibility levels. Lecocq method (1999) was experimentally verified by Bacelar et al. (2000). The study used an experimental method to measure the target visibility at different positions by 23 observers with ages from 18-55 years old. Observers were placed 83 away and in line with the target. Observation time was controlled between 200-500 milliseconds and observers were asked to rate the target visibility based on five appraisal ratings: target not visible, weakly visible, passably visible, and satisfactory visible and finally; a target with good visibility. Experiments were conducted at the Rouen CETE track in France which consists of 7 m-wide roadway with R2 type coating. The targets were 20-cm balls with a surface reflection factor of 0.2. Bacelar study (1999) confirmed the reliability of the calculation method developed by Lecocq for hemispherical targets and no significant difference was found between experiments employing plane targets and hemispherical targets which suggests that either Adrian’s (1989) or Lecocq (1999) models can be used to describe road lighting geometries.

A study by Bre´mond et al. (2012) was also related to the target used to develop Adrian’s model (1989) which was a small grey plane square. The study tackled night-time target visibility in dynamic conditions by introducing more common targets to the night-time driver such as a roadway sign, a pedestrian, and a car. An experimental method using a driving simulator under controlled conditions was conducted on 27 subjects including males and females with an average age of 35 years. All subjects were selected to be licensed drivers with normal or optically corrected vision. The drivers were randomly exposed to several targets including a grey square, a roadway sign, a pedestrian, and a car at different locations and randomly ordered to eliminate the bias of anticipation of a certain target. Moreover, the successive time between each target and the other was also random to serve the same purpose. The driving simulator consists of a steering, a gearbox, and a pedal with a stationary driver's seat. The simulator software was graphically rendered to reflect a night-time virtual environment with Super Extended Graphics Array (SXGA) resolution. Drivers were asked to push a button on the driving simulator steering to indicate that he has spotted a target on the roadway. The reaction time for each driver was measured at different luminance values and the visibility levels (VL) were then calculated using an exposure time of 0.2 seconds based on Adrian's model. Bre´mond study (2011) results confirmed that Adrian's visibility level (VL) provides a reasonable description of the visual performance that is related to a safety index described by the target detection distance. Moreover, the study showed that there is a quantitative relation between the target detection performance using Adrian's square target and more natural targets such as a road sign, a pedestrian and a car. Thus, confirming that VL is of great importance in assessing visual performance under night-time conditions.

Hence, Adrian's visibility model (1989) is a useful tool for measuring the visibility of targets at night-time driving conditions. However, the model was established under laboratory conditions which are far different from actual environments in a way that many other driving components that are related to the visual performance are missing. These components may include driver's alertness and distraction, the actual feel of driving, sound and speed of the automobile, and most importantly, the complexity of the roadway that includes glare sources from other cars, background complexity, billboards distraction, and target's chromatic contrast.

These important driving components cannot be addressed in laboratory conditions (Adrian 1989) or by using a driving simulator with a stationary seat (Bre´mond et al. 2011) in comparison to an actual night-time driving experiment utilizing an actual automobile and actual roadway.

Moreover, Adrian model limits the glare source angle between 1.5^o to 30^o which does not reflect a real case situation for night-time driving. Another problem with Adrian VLs is that equal visibility levels do not correspond to equal levels of task performance. Furthermore, the supra-threshold performance of tasks with different visual and non-visual components occurring on and off-axis cannot be predicted from the on-axis threshold measurement (Boyce 2003).

2.6.2 Small Target Visibility (STV)

The small target visibility model (STV) was developed by IESNA (2000) and is based on Adrian's model (1989), the model largely simplifies the calculation of visibility level (VL) creating a visibility metric to calculate the visibility of an array of targets on the roadway. The early history of STV studies was done by Gallagher et al. (1976) who showed the relation between a cone target ahead on the roadway and the distance at which unwarned driver can avoid it. Janoff (1990) showed that there is a strong correlation between the visibility of a target and the distance that it could be observed and identified. Another study by Janoff (1992) found a direct link between the small target visibility level and the subjective rating of their visibility.

STV incorporates the effect of the target luminance, immediate background luminance, adaptation level of the adjacent surrounding, and disability glare in the step-by-step model calculation. The target object used in developing the model was a square with 180 mm side length and a reflectance of 20%. The object is located ahead of the observer at a distance to subtend 10 minutes of arc visual angle which corresponds to 83 m ahead of the observer with the observer to target size parallel to the centreline of the road. The observer is a 63 years old driver with an observation time of 0.2 seconds. STV was calculated by finding the visibility levels (VL) of an array of these square targets, then a single metric value (STV value) is created based on a weighting function depending on all visibility levels as seen in Figure 2.3. In the year 2000, Small target visibility (STV) approach was added to the IESNA R-P-800 standard (IESNA 2000), the standard provided three design approaches: Luminance, Illuminance, and STV.

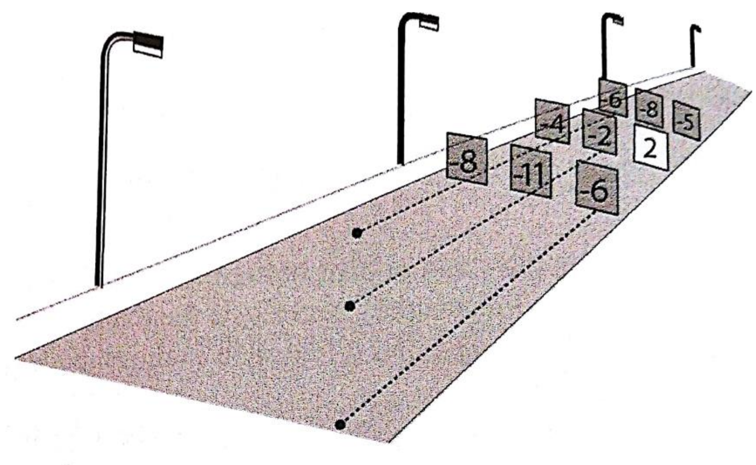


Figure 2.3: visibility level values (VL) for objects with the same reflectance factor. Negative values correspond to objects seen in negative contrast (silhouette). Black dots indicate the lengthwise observer positions for the different rows of grid points. (Bommel 2015)

The problem with STV is that while visual performance is a multi-faceted task, STV is limited to one facet which is the ability to detect small objects while targets can differ in sizes and contrast at the same time and targets can be even more complex such as multi contrasted targets. Indeed, the fact that the model is based on a single reflectance factor (50 % at first then changed by IES to 20% later) may lead to some misleading calculations and conclusions. Furthermore, STV allows observers to detect targets located ahead of them but ignores the need to spot targets at the boundaries of their visual field using peripheral vision.

An assessment study of a pedestrian crossing using a small target visibility model (STV) was performed by Tomczuk (2012). The study utilized a computer simulation for a pedestrian crossing using Dialux 4.9 software based on a small target visibility model (STV) which is built-in as one of three roadway lighting design methods in the software and recommended by IESNA RP-8-00. The simulation was done for a double-sided roadway with a single lane each with luminaire poles on one side only with one of them directly located next to the crossing. STV and visibility levels (VL) values were found at different locations at the roadway based on the fact that the pedestrians can cross from any side of the road and can be at any location at the crossing at any time. Results showed that visibility levels can provide fair to very good visibility levels at locations while not being able to achieve very poor levels at other locations and/or at different luminaire poles positions. This allows for the background luminance to reduce visibility levels to values that cannot ensure proper observation by the driver which may result in not detecting the pedestrian at the crossing. The results of this work meet the recommendation of IESNA RP-8-00 in that the STV model is not recommended as a roadway lighting design criteria. However, it can be useful as a verification method for roadway lighting designs including pedestrian crossing.

2.6.3 Relative visual performance (RVP)

The relative visual performance (RVP) model was developed by Mark Rea (1986) in an attempt to quantify supra-threshold visual performance levels under different lighting conditions. The model is based on the psycho-physics of lighting philosophy which were first developed by Weston (1945). Rea highlighted that visibility does not depend on illuminance levels only as illuminance does not reflect how the observer can see targets. More factors should be considered when designing for a lighting installation for better visibility such as reflectance of the target and any object in the visual field, luminous contrast of the target, chromatic characteristics of the target (target colour), size of the target, any glare source wither reflected or directed into the observer's perception and the observer visual characteristics (such as age).

Supra-threshold visibility does not only involve perceiving targets, but it is also related to how fast and accurate visual information can be processed. Hence, Rea based his model on experimental data of speed and accuracy of numerical verification tasks using two different experiments. The first one (1986), young adult subjects with healthy vision compared two columns of five-digits numbers, the first column on the left (reference list) was printed in one of two types on ink on a matt white paper with different illuminances, lighting geometries and ink types. This variation in conditions provided 64 different stimulus conditions. The other column on the right (response list) was printed with black ink of matt white paper with high contrast ($C \approx 0.6$ - 0.8) and background luminance (L_b) approximately matching the reference list. Rea marked the total time taken by the subjects to compare the two columns and the errors of both omission and commission were also obtained for each trial. The time results were used to obtain values of visual performance (VP) measured in reciprocal of time used to read the reference sheet. A three-dimensional model involving the log of luminance of the background

(cd/m^2), log on the contrast (C), and reciprocal of time (VP) was created defining the basis of the relative visual performance model (RVP) as shown in Figure 2.4.

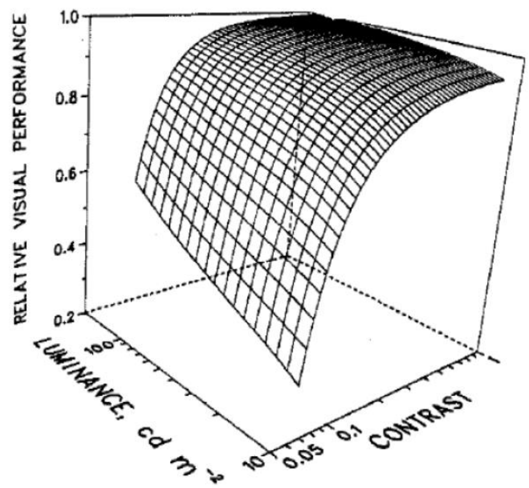


Figure 2.4: Three-dimensional representation of the visual performance model. Relative visual performance (RVP), scaled linearly, is plotted as a function of contrast (C) and luminance LB, both scaled logarithmically. (Rea, 1986)

The second experiment was conducted by Rea and Ouellette (1988) to measure the reaction times for targets that are darker than the background (decrements) and targets brighter than the background (increments). In both experiments (decrement and increment), subjects were examined to be having normal or above normal visual acuity in their left eye using Keystone Ophthalmic Teiebinocular as their right eye will be covered with an opaque patch and they will be using their left eye to view the stimulus display (square target with different sizes) on a video screen at a distance of 1.68 m away using a 2 mm artificial pupil with the help of neutral density filter and/or luminous veil, depending on the experimental conditions. Once the target is displayed on the screen, subjects have 3 seconds, before the target is removed, to press a button confirming their ability to detect the target before a computer randomly generates a new target on the screen. The experimental setup is shown in Figure 2.5

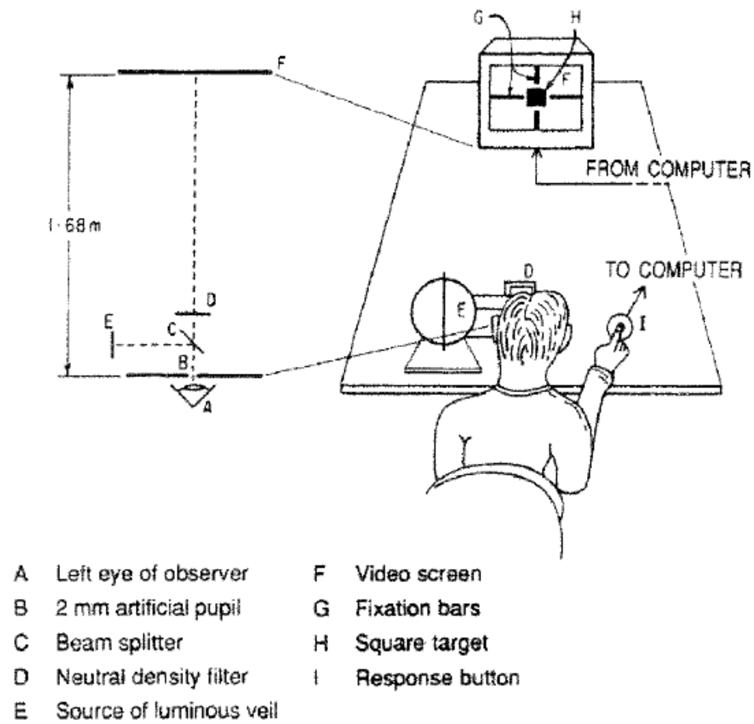


Figure 2.5: Schematic diagram of reaction time apparatus. (Rea and Ouellette, 1988)

The time between target display on screen and response was recorded for each experimental trial. For each trial, different combinations of luminance, contrasts, and target sizes were displayed to the subjects. Both experiments done by Rea and Ouellette (1988) came to show that the percent detection probability (RVP) increases with increasing the luminous contrast, target size (in Steradians), and the retinal luminance (in Trolands).

Figure 2.6 and 2.7 show the results of Rea and Ouellette increment and decrement experiments respectively (1991).

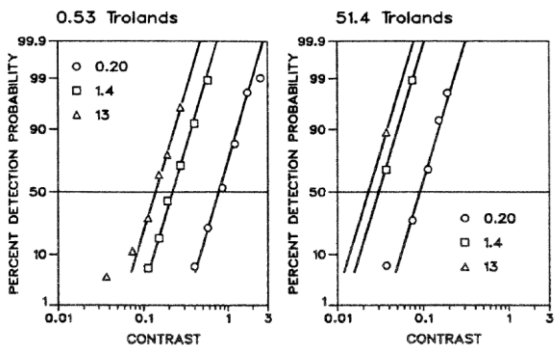


Figure 2.6: Mean percentage probability-of-detection data for three contrast increment target areas (0.20, 1.4, and 13 Microsteradians) plotted as a function of log the Contrast when presented at retinal illuminances of 0.53 and 51.4 Trolands. (Rea and Ouellette,1991)

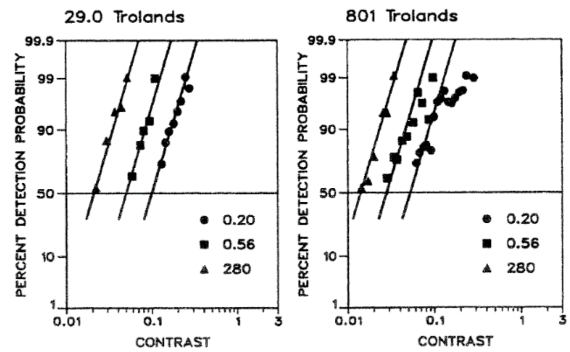


Figure 2.7: Mean percentage probability-of-detection data for three contrast decrement target areas (0.20, 0.56, and 280 Microsteradians) plotted as a function of log the Contrast when presented at retinal illuminances of 29.0 and 801 Trolands. (Rea and Ouellette,1991)

RVP model got a lot of praise and criticism at the same time. The model was referenced by the IESNA Lighting Handbook (2000) as one of the methods used for assessing the impact of light levels for different lighting applications. The benefit of the RVP model is that it can quantify the visual performance much better than the visibility level (VL) since VL was considered as a crude predictor of visual performance (Ross 1978). RVP can also predict the visual performance based on two independent experiments that were well documented and can be easily verified.

Similar experiments performed by Bailey (1993) and Eklund (2001) showed a strong correlation between their results and RVP model values which gives more credibility to the model. In one of these studies, Bailey (1993) measured an individual's ability to read a certain text consisting of an array of different words with an average of seven letters in length. The luminance contrast and text size were randomly varied through the experiment and the background luminance values ranged between 10 to 5500 cd/m^2. The data resulted from the calculation of the number of words that can be read per second were found to be strongly correlated with the estimates of response times using the RVP model. On the other hand, Eklund (2001) implemented an experimental approach in which subjects were tested to identify different sizes of alphanumeric codes printed with different luminance contrasts ranging between 0.1 to 0.93. The performance obtained from Eklund's results strongly conformed to the calculated RVP values.

Another study by Goodspeed and Rea (1999) measured luminance contrast effects on the capability of individuals to correctly identify the opening direction of a Landolt 'C' ring. The luminance contrast values were varied between 0.2 to 0.8 while the background luminance value was fixed at 7 cd/m^2 with surrounding luminances ranging between 0.01 to 0.1 cd/m^2. The data obtained from the experimental results were compared to predictions of response times using the RVP model and were found to be in good conformance that enables the RVP model to provide significant predictions of visual response at supra-threshold levels in a variety of situations.

To create a visibility calculation method that reduces the complexity of roadway lighting photometric data into a better suitable form that is easily used for decision making. Rea (2010) combined RVP calculation with a photometrically accurate lighting software in a unique approach that can provide more practical insights about the role of different driving and lighting characteristics such as illuminance, spatial extent, vehicle speed, roadway characteristics, driver's age, and many others. These insights can lead to more cost-effective, safe, and low hazard roadway lighting designs. In this approach, Rea used a lighting software tool (AGi32, Lighting Analysts). A virtual four-leg, right angle (cross) intersection has been created involving a total of three cars located at three legs of the intersection, two of them are stationary and facing each other and the third is approaching the intersection from the perpendicular side. The simulation considered each vehicle headlights to be always on under four different roadway lighting levels, representing a range of ambient lighting from highly urbanized areas to rural locations. Different scenarios have been created by the software utilizing the change in lighting conditions, lighting poles arrangements, hazard and observer's location and car speed, and most importantly, observer's age. RVP was used to evaluate the chosen variety of intersection lighting scenarios generated by the software. Based on these RVP values, the study confirmed that both low speed and high-speed intersection should be illuminated. This creates better visibility due to the high illumination levels and enhances the observer's visibility enabling him to identify potential hazards and reduce roadway crashes. It was also confirmed that age has a significant effect on the target's visibility as RVP values decrease with older drives. Thus, intersection illumination can be of great benefit for this group of drivers. Furthermore, the study stressed that lighting from other sources than roadway fixed illumination such as observers and other vehicle headlamps, buildings lighting, and any other lighting source that provides illumination on the roadway, are of great importance for night-time driving.

However, the RVP model has some limitations that rest its sole adaptation for lighting design (Boyce 2003). First of all; RVP predicts the visual performance and not the task performance. Second; RVP does not predict tasks that require peripheral vision. Third; the model incorporates luminance contrast, background luminance, and target size as factors affecting visibility and neglects other factors such as disability glare, contrast polarity, chromatic contrast (target colour), and eccentricity of the target. Moreover; the model is limited to the range values (Size, contrast, and luminance) that were used to develop it. Boyce (2003) states that the existence of a plateau in the three-dimensional representation of the RVP model

(Figure 2.4) may imply that for a wide range of visual conditions, visual performance changes slightly with the change of lighting conditions.

2.7 Road lighting design standards

Night-time visual activities such as driving is a continuous decision-making process. It is mainly based on the data that reaches our senses. As a result, a good road lighting is very important to maintain the visual performance at a good minimum level during low visibility periods. Moreover, drivers need to feel comfortable within the road environment to keep the fatigue levels as low as possible and keep the drivers alert.

Road lighting design is a standardized process, the most commonly used standards are ANSI/IESNA R-P- 800 (IESNA 2014), CIE Publication 115 (1995) which was replaced by CIE 115-b (2010), CIE 140 (2000) which was also replaced by CIE 140-b (2019). The American National Standard Practice for Roadway Lighting (ANSI/IESNA) adopted design criteria called the "Illuminance method" from 1932 to 1983 where the design was based on the amount of light that falls upon the street surface measured in foot-candles or lux. In 1983 a new approach "Pavement luminance method" was added to the standard (IESNA 1983). Luminance indicates how much luminous power the human eye can perceive and measured in candela per square meter (cd/m^2). The luminance of any point at the road is a function of illuminance and the reflection of the pavement material. Consequently, knowledge of road surface properties, geometry describing both the locations of the observer and the target is important to use this method. Pavement luminance was preferred as it related road lighting to visibility concept where it depends on the observer himself and how much light reaches into his eyes. However, in a conflict area where multiple directions of view are existing and little information is provided for geometry describing the target and observer, the illuminance method is preferred.

In the year 2000, Small target visibility (STV) approach was added to the IESNA R-P-800 standard (IESNA 2000), the standard provided three design approaches: Luminance, Illuminance, and STV. Small target visibility (STV) approach was developed by IESNA (IESNA 2000) based on Adrian's model (1989) and is built on the detection of small objects on the roadway. The STV is based on the following conditions:

- The target is flat with diffusive reflectance factor of 0.5 (changed to 0.2 by IESNA,2000)
- Target is square with 180x180 mm area located at a distance of 83 m ahead of the observer (visual angle 7.45 minutes of arc)
- Observer to target sightline is parallel to the road axis line
- Observer's age 63 years
- Observation time 0.2 seconds
- Observation height is 1.45 m with a downward viewing angle of 1^o
- Background luminance is average of the point luminance at the bottom of the target and the top of the object
- Regular calculation grid starting at 83 m from the observer between a span of luminaires.

The problem with STV method is that it is not field verified (cannot be measured) while the illuminance method can be field verified. Moreover, STV ignores the need of drivers to spot movement at the boundaries of the road using peripheral vision, to keep the vehicle between lane lines, to evaluate relative speeds and moving directions of vehicles since the driving conditions are created by a combination of road lighting and vehicle forward lights. Hence, STV approach received extensive discussion and review as well as critique, and finally, IESNA decided to withdraw STV as a design metric in 2006, and to retain luminance approach as the only design criteria, illuminance approach for field verification and STV as a selection criterion between designs (fine design tuning).

On the other hand, CIE, which is the French abbreviation for Commission Internationale de l'Eclairage, or the international commission on illumination published several recommendations of roadway lighting. In the previous CIE reports (CIE 1965, 1977), the recommendations used the illuminance and luminance thresholds for roadway lighting design. The visibility level (VL) concept first appeared in CIE report 115 (CIE 1995b) where Adrian's model (1989) was discussed along with STV methodology. However, the report did not recommend using STV as a figure of merit due to the lack of consensus of the target and the concept of STV itself. In the next version of the CIE 115 report (2010), the visibility concept almost disappeared from the report and was no longer part of the recommendations

To sum up, road lighting standard should consider how the human visual system detects objects and try to develop an approach that responds to these elements to improve visibility for drivers. The human visual system is usually affected by luminous contrast, chromatic contrast, and adaptation luminance, size of the object relative to the sight distance, and position of the object.

2.8 Road lighting and visibility

Driving is a continuous decision-making process. It is mainly based on the data that reaches our senses. An average driver gets almost 80% of this data from his visual resource (Boyce

2009). As a result, good road lighting is very important to maintain visual performance at a decent minimum level during low visibility periods. Moreover, drivers need to feel comfortable within the road environment to keep the fatigue levels as low as possible and keep the drivers alert. Numerous night-time accidents involve sleepy drivers or even asleep during driving.

Night-time driving can be very challenging due to the reduction of visibility levels. Hence, driving at night requires the driver to perform additional tasks than the day-time driver. These tasks include more concentration, better eye-adaptation, and most important; the ability to identify obstacles in order to avoid road accidents. A new NHTSA (National Highway Traffic Safety Administration) report showed that most of the pedestrian fatalities and injuries occur during the night-time (NHTSA 2014), and the most important factor affecting these numbers is the reduced visibility levels during the night. Many studies showed that road lighting can reduce the number of night-time accidents by almost 30-40 % (Elvik 1995, Wanvik 2009). A study based on New Zealand streets showed that the ratio between night to day road accidents can be lowered with increasing road luminance (Figure 2.8) and a reduction of almost 35% of road fatal accidents can be achieved by improving road lighting in some streets (Jackett and Frith 2013). Another study based on a fatal accident database in the USA showed that accidents involving pedestrians in urban and rural roads increase under low visibility levels (Sullivan and Flannagan 2007). Hence, road lighting is essential in lowering the possibility of accidents and help keep drivers and pedestrians safe. Figure 2.9 shows how road lighting can affect the visibility of any potential hazard in dark. The two cars in comparison are with headlamps working but it is clear that the one surrounded with enough street lighting is more visible and simply represents a less potential hazard for drivers (Bullough et al.2009).

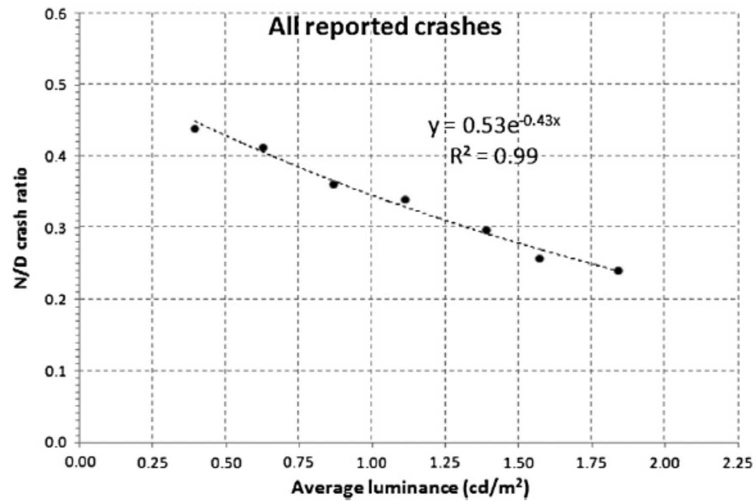


Figure 2.8: The relationship between average luminance and the night to day crash ratio for all reported crashes at New Zealand streets (Jackett and Frith 2013).

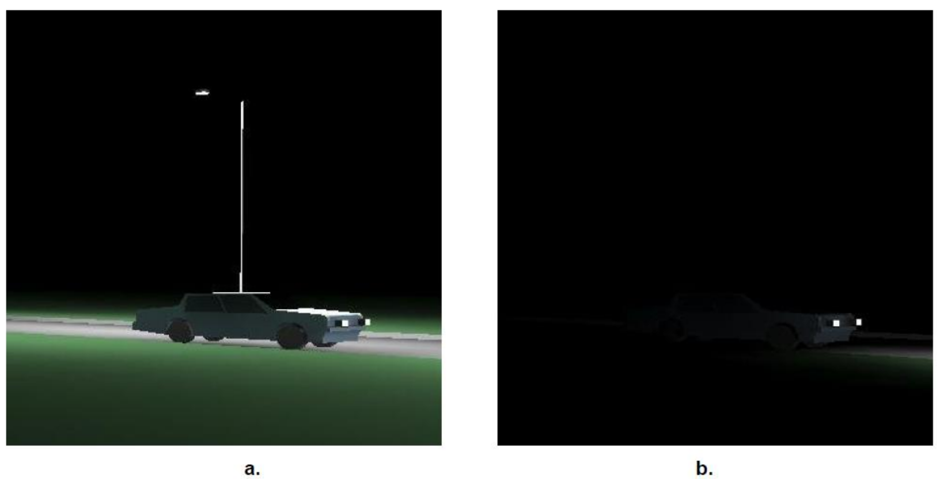


Figure 2.9: A computer simulation comparison between a potential hazard (car) surrounded by a road lighting pole (a) and without road lighting (b) (Bullough et al. 2009)

Many studies came to find out the proportion of road accidents that are related to poor visibility (Sabey and Staughton, 1975, Hills 1980). The studies were based on road accident numbers and causes in Britain. The Reported Road Causality Annual Report (UK Department for Transport, 2015) clearly stated that "Failed to look properly" was the most reported factor of road accidents between 2005-2014 which is directly related to poor visibility (Figure 2.10). In terms of the severity of road accidents. Figure 2.11 shows the percentage of accidents with contributory factors in each segment. The contributory factors related to poor visibility are: “Impairment or distraction”, “behaviour or inexperience” and “vision affected by external factors”. Combined, these three contributory factors make the highest percentage of fatal, serious, and slight road accidents.

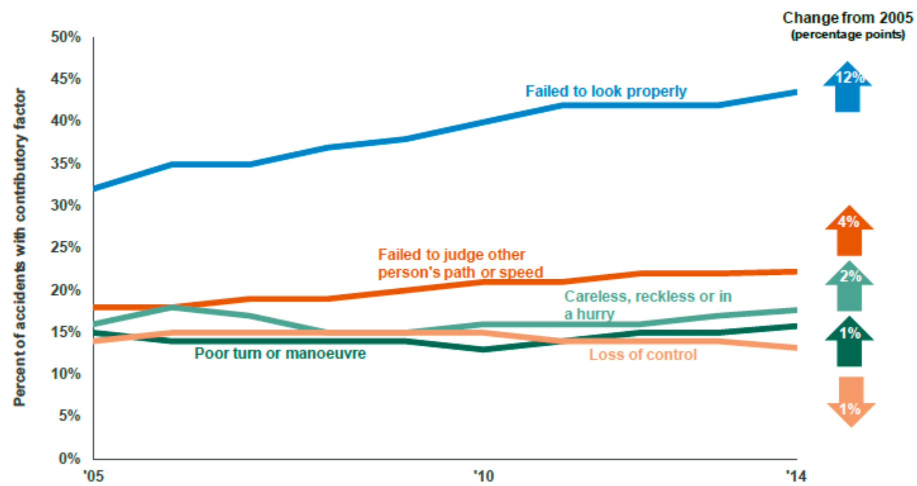


Figure 2.10: Top five contributory factors in reported road accidents, GB: 2005 to 2014 (UK Department of Transport, 2015)

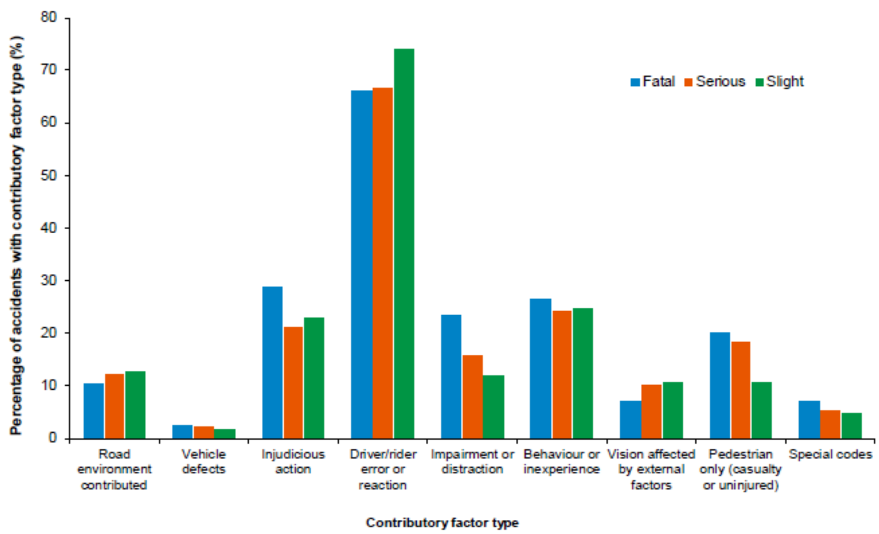


Figure 2.11: Contributory factor type, Reported accidents by severity, GB2014 (UK Department for Transport, 2015)

Another importance of proper road lightings that enhances night-time visibility is the security of urban areas. The link between lighting and crime has been identified since the fifteenth century (Painter and Farrington, 1999). In 1415, owners of expensive property in London were ordered to hang out lanterns or Candlemas when the moonlight was not sufficient to light the neighbourhoods. Paris followed a similar approach but altered the location of the lanterns to be covering the streets as well. In 1667, France suspended lanterns on cables over the street centre to create a public lighting system under police control. In the mid-19th century, gas street lighting spread widely to most European major cities. In London alone, 39,000 gas lamps were used to provide 215 miles of roads (Chandler and Lacey 1949). The first exterior electric lighting installation was installed in New York in 1850 and it was believed that they have a major role in fighting the crime that was spreading during that era (O'Dea 1958).

The idea of fighting crime with lighting surfaced in the USA in the 1960s along with an intense increase in crime rates. In 1979, Tien et al. (1979) published a review report for the effects of lighting on crime. He concluded that although there was no evidence that improved street lighting decreases the level of crimes, there was some indication that improved street lighting decreases the fear of crime.

In 1988, Painter conducted a field experiment in an outer city area in London (Painter 1988). He targeted a much-localized area to find the effect of street lighting on particular crimes. He collected his data using a survey carried out beyond dark. People were asked about their experience of crime in that area, fear of crime, any precautions they take, and any crime they observed. The study was able to conduct 207 interview responses before the lighting was changed and 153 responses after the lighting have changed. The results are shown in Figure 2.12

Type of Crime	Number of Respondents Experiencing Before Lighting Change (n = 207)	Number of Respondents Experiencing After Lighting Change (n = 153)
Robbery	2	0
Sexual assault	1	0
Physical assault	2	1
Threats	4	0
Stolen automobile	4	1
Stolen motorcycle	4	0
Stolen bicycle	1	0
Automobile damage	2	1
Motorcycle damage	2	0
Total	22	3

Figure 2.12: Crime experienced on the street by respondents over six week periods before and after the change in lighting (Painter 1988)

It can be clearly seen that there is a strong link between road lighting and crime. However, how lighting affects crime was not well understood. A study by Fisher and Nasar (1992) inspected the fear of crime on a college campus. They showed that fear of crime was highest in areas where criminals can hide in the dark, and good visibility can limit these places allowing more people to use the streets at night. The consequences of this idea are that with more people in the streets at night, informal surveillance is higher which makes a certain degree of risk for the criminals to continue their activities.

Hence, it can be concluded that street lighting with proper visibility has no direct effect on crime levels. However, it affects crime in two indirect ways; the first one is the “fear of crime” where people start having more confidence to use streets at night, hence increasing informal surveillance and decreasing the risk on criminal activities, the second one is the authority and community surveillance that allows identifying criminals trough face detection, which compromises their criminal activities and lowers crime rates due to risk factors.

2.9 Road lighting practices in the lighting of current visibility models

The history of paved roads is not new. They have been existing in Europe since the Roman Empire. Moreover, paved roads in South America have been there since the Inca Empire. However, road lighting is rather new practice. Lit roads started to exist at the beginning of the 1930s (Boyce 2009) as the revolution in vehicle transport called the scientific community for better research in vision science (Wood 1936). The evolution of road lighting was driven by three important factors: the first one was the technology advancements in electric distribution networks accompanied by the availability of suitable lamps and luminaires. The second was the establishment of official systems and governmental bodies concerned with controlling and regulating vehicles and traffic, and the third factor is the dramatic increase in the number of vehicles on the roads, as well as the higher speeds in which these vehicles could put up with.

This resulted in a large number of research produced in the area of lighting and visibility. Early attempts of Weston (1943) to measure the night time visibility resulted in proposing the first road lighting design standard in the UK. Followed by Blackwell (1946) who measured the detection of targets under various conditions allowed for the CIE (1972, 1981) to propose a general framework for various visibility models developed by different researchers with adaptation to particular problems. These advancements in research in the area of lighting and visibility were recognized by the most well-known and established lighting standards official bodies, such as IESNA and CIE. Many lighting standards and recommended practices are heavily relying on current visibility models.

In order to promote his VL model as a design metric for street lighting, Adrian (1993) tried to analyze his model under different experiments related to night-time driving. Adrian concluded that his VL model can be used as a measure of target perception at night and hence, suitable to be used as a lighting design metric. Fortunately, it seems that Adrian extraordinary work, as well as the large attention from the lighting scientific community, which was drawn into his VL model, was able to convince IESNA to incorporate his VL model (1989) in the IESNA R-P-800 standard (IESNA 2000) in the form of STV (small target visibility) as a visibility metric for road lighting, then it was proposed as a selection criterion between designs for fine-tuning (IESNA 2006). Moreover, the VL concept first appeared in CIE report 115 (CIE 1995b) where Adrian's model (1989) was discussed in detail along with STV methodology.

On the other hand, the relative visual performance model-RVP (Rea and Ouellette 1988, 1991) RVP model got a lot of praise and criticism at the same time. To create a visibility calculation method that reduces the complexity of roadway lighting photometric data into a better suitable form that is easily used for decision making. Rea (2010) combined RVP calculation with a photometrically accurate lighting software in a unique approach that can provide more practical insights about the role of different driving and lighting characteristics such as illuminance, spatial extent, vehicle speed, roadway characteristics, driver's age, and many others. The study confirmed that both low-speed and high-speed intersection should be illuminated. This can create better visibility due to the high illumination levels and enhances the observer's visibility enabling him to identify potential hazards and reduce roadway crashes. It was also confirmed that age has a significant effect on the target's visibility as RVP values decrease with older drives. Thus, intersection illumination can be of great benefit for this group of drivers. Furthermore, the study stressed that lighting from other sources than roadway fixed illumination such as observers and other vehicle headlamps, buildings lighting, and any other lighting source that provides illumination on the roadway, is of great importance for night-time driving.

Hence, the RVP model (Rea and Ouellette 1988, 1991) was referenced by the IESNA Lighting Handbook (2000) as one of the methods used for assessing the impact of light levels for different lighting applications. The benefit of the RVP model is that it can quantify the visual performance much better than Adrian's visibility level (VL) since VL was considered as a crude predictor of visual performance (Ross 1978). RVP can also predict visual performance based on two independent experiments that were well documented and easily verified. Moreover, the benefits of RVP on road lighting were analyzed by Bullough et al. (2009). The study used the relative visual performance model as a metric for visibility under various road lighting conditions including illumination and glare from vehicle headlamps. It was found that RVP can provide a proper assessment tool for road lighting especially in conflict areas such as intersections and interchange merge/diverge areas. A rather new study by AbouElhamd and Saraiji (2018) also provided successful criteria for street lighting based on the RVP model.

2.10 Limitation of the current visibility models

In earlier sections, three visibility models have been extensively discussed as well as the literature related to these models. Each of these models can describe visibility in a certain way, for instance, Adrain's model (1989) introduced visibility levels (VL) which is based on the ability of the observers to spot a certain target (small grey plane square). While RVP model (Rea and Ouellette 1988, 1991) was developed based on experiments measuring the response time for identifying numerical tasks. Both models are based on experiments under laboratory conditions that lack the actual characteristics of visual performance at night time driving. STV model (IESNA 2000) is based on Adrian's model (1989) which means that some limitations related to not considering the target's eccentricity and retinal luminance are common for both models.

Apart from that, the Adrian model (1989) was based on testing subjects of 23 years old, then extending the effects of age as per a correction factor. This factor is based on studies performed by Blackwell and Blackwell (1980) and Weale (1961) to find the effects of age on visual performance through measuring the change of ocular transmittance for older people. This indicates that Adrian (1989) did not really generate reliable data for the effects of age on VL apart from his tested subjects, since he did not design his experiments to accommodate older people.

Another limitation for the visibility model (Adrian 1989) is the use of planner uniform target, while in real-life scenarios, targets are usually 3D shaped and differ in size and geometry (Brémond 2020). This is again a problem with the STV model (IESNA 2000), which is an extension to Adrian's model (1989) where the target used is also a small planner square of 18 cm size. The use of this target size, shape, and contrast means that both Adrian's model (1989) and STV model (IESNA 2000) cannot be generalized to include three-dimensional targets, and/or targets that are complex in shape, or even multi-contrasted targets.

Furthermore, Adrian (1989) did not include the effects of the eccentricity of the target on VL, which is defined as the position of the target with respect to the observer's lines of sight. As a result, Brémond (2020) classified the VL model as a central vision model that only considers targets located at the observer's line of sight, and ignores task that requires peripheral vision. This is also valid for the STV and RVP models since both of them did not consider the eccentricity in the development of the models. Moreover, although the RVP model (Rea and

Ouellette 1988, 1991) did not consider the effects of glare, Adrian's model (1989) and STV (IESNA 2000) considered the effects of glare, however, the glare angle between the fixation line and the centre of glare source was limited to 1.5^{o} to 30^{o}, while in actual situations, glare angles can reach higher values of more than 60^{o}.

On the other hand, while each model has its supporters and critics. STV model succeeded in being adopted by IESNA (IESNA 2000) to be one of three design methods: luminance, illuminance, and STV. This may indicate how concerned lighting standards in providing a single metric to represent visibility rather than visibility levels at different locations in the design field. However, that did not work as STV had many misleading results and calculations. Table 2.2 shows the three models, variables used in developing each one of them, and their known limitations.

Table 2.2: Visibility models and variables and their most known limitations

Model	Variables	Limitations
Adrian Model **[Adrian,1989]**	▪ Target contrast ▪ Contrast polarity ▪ Observer's age ▪ Exposure time ▪ Disability glare ▪ Target size	Employs complex mathematical relations Too many correction factors Based on experimental results developed by testing young observers Does not consider certain Visibility variables such as (Eccentricity, retinal illuminance, background complexity)
RVP **[Rea, 1986]** **[Rea and Ouellette 1988, 1991]**	▪ Target contrast ▪ Visual age ▪ Retinal illuminance ▪ Target size ▪ Background luminance	Does not consider tasks that require peripheral vision Does not consider certain visibility variables such as (background complexity, eccentricity, disability glare)
STV **[IESNA,2000]**	▪ Target luminance ▪ Visual age ▪ Immediate background luminance	Does not consider tasks that require peripheral vision Limited to the ability to detect small objects

	▪ Disability glare ▪ Adaptation level of the adjacent surrounding	Limited by the range of values of variables used to develop it Does not consider certain Visibility variables such as (Eccentricity, retinal illuminance, background complexity)

In general, the current models either employ mathematical relations that may not be suitable, or at least, not good enough to represent and describe visibility in a clear way, or have limited range of variables, where some variables are partially considered or fully neglected. The other approaches employ experimental models that are also limited in describing visibility as most of the experiments used in developing the models were done on a young participant's age with good vision (Adrian model) or only consider small targets (STV) and cannot be extended to represent the visibility of larger targets.

A very recent study by Brémond (2020) provided a historical perspective for the visibility models. The study also provided a very important critique for the advantages and limitations of Adrian's VL model (1989), Rea and Ouellette RVP model (1988, 1991), and STV model (IESNA 2000). The study highlighted that the VL model developed by Adrian (1989) ignored the eccentricity of the target, which is defined as the position of the target with respect to the observer's lines of sight. As a result, Brémond (2020) classified the VL model as a central vision model that only considers targets located at the observer's line of sight. Moreover, Brémond emphasized that all visibility models considered a target against a uniform background while in actual road conditions, luminance background is not homogeneous. Moreover, Brémond emphasized that all visibility models considered a target against a uniform background while in actual road conditions, luminance background is not homogeneous.

For the STV model (IESNA 2000), Brémond pointed out that it usually shows a good correlation with computed visibility levels (VL). However, since it was a mean value, it allowed for the development of contrast inversion on the road surface, which allowed for bad lighting and/or almost invisible targets to be rated as good STV. Hence, it should not be adopted alone as a visibility metric without the concept of VL uniformity.

So, although each model has its own limitations for missing some visibility variables, or for being developed under laboratory conditions, or being limited to the range of variables used to develop it, these models are well known for being effective and useful in the design practice and assessment of visibility at night-time driving conditions. In other words, for each visibility model, there are some advantages and disadvantages based on the understanding of that model and the appreciation of the method in which that model was developed. For example; Adrain's model (1989) and RVP model (Rea and Ouellette 1988, 1991) can be used in the design of roadway lighting at roadway crossings and junctions and that was validated by Ising (2008) and Rea (2010). While STV model can be used as a selection criterion between designs or for fine design tuning (IESNA 2006).

Hence, it cannot be argued that a certain model is better than the other. All three models have been assessed and verified in many ways including experimental methods utilizing subjects performing visual tasks in both laboratory and actual roadways, driving simulators, as well as computer modelling. Moreover, many studies done by Adrian (1993) and Rea (2010) tried to assess and validate their models in a variety of different ways.

2.11 Fuzzy Logic

Fuzzy logic is a multi-valued logic (MVL) which enables intermediate values to be defined between conventional values such as true/false or high/low based on the degree of membership of that conventional value (Hellman 2001). In other words, intermediate values such as very low, fairly low can be used to describe a certain truth where this value relies on between the crisp values of high and low, in contrast to Boolean logic or classical mathematics which deals with only crisp values and only absolute truths are considered. Fuzzy logic is considered a soft-computing method that enables the calculation tolerance for sub-optimality and impreciseness (vagueness) and giving quick, simple, and sufficiently good solutions.

The early history of Fuzzy logic origins can be related back to Greek philosophers, especially Plato (428-347 B.C.) who indicated that there is a third region beyond truth and false where these opposites "tumbled out". Also, early Chinese and Indian civilizations were pioneers in considering that there are varying degrees of truth and falsehood as they early realized that things need not be of a certain form or type and there is a stopover in between.

In the early 20th century, Lukasiewicz (1920) suggested accepting three truth logic values (called trivalent) which deal with the value of intermediate truth in addition to true and false making a grade of membership of 0.5. Several years later, the German philosopher Max Black (1937) analyzed the problem of modelling "Vagueness". He suggested that classical logic can be a useful tool to represent vagueness at an appropriate level. He also provided some profiles and curves that he used to represent a certain analysis of the ambiguity of a word or symbol that are very consistent with today's membership functions of type-1 fuzzy sets.

The real father of Fuzzy logic is Professor Lotfi A. Zadeh (born in 1921) who published his first work “Fuzzy Sets” in 1965 at the journal “information and control”. In this work; Zadeh described linguistic variables as a means to modelling human tolerance for imprecision. This can be done by encoding certain fuzzy sets to describe decision-relevant information. Zadeh extended his work in 1971 publishing the article “Quantitative Fuzzy Semantics” at the journal “Information Sciences” where he showed the formal elements that led to the Fuzzy logic theory and its applications as we know it today. In 1973 Zadeh proposed his basic theory of Fuzzy controllers which opened the door for researchers from around the world to use his theories in various engineering applications such as mechanical and industrial processes and applications. During his life (1921-2017), Zadeh published over 200 single-authored papers related to Fuzzy logic theory and fuzzy controllers with more than 90,000 citations for his 1965’s paper alone.

Application of Fuzzy logic theory are numerous, the first fuzzy logic controller for a steam engine was developed by Mamdani (1980) to control a cement plant in Denmark. Hitachi (1987) used a fuzzy controller to control the Sendai train in Japan. It was not until 1987 where the Japanese company Omron designed its first commercially fuzzy controller (Fullér 1987), the same year was considered the “Fuzzy boom” due to the applications of this controller in many fields. In 1993, the Japanese company Fuji applied Fuzzy logic to control the chemical injection for water treatment plants for the first time in Japan (Garrido 2012).

With the development that was added to the Fuzzy logic theory and its applications by Japanese scientists, applications of fuzzy logic theory expanded to include many aspects of science and technology such as computing and electronics, aerospace and automotive industries, industry and manufacturing, defence and security sectors. Furthermore, Fuzzy logic applications extended to include business and decision-making models, phycology, and human behaviour such as behaviour reasoning and criminal investigations.

Of the many recent applications of Fuzzy logic in system control, the work done by Dash (2012) to design an intelligent air conditioning system using Fuzzy logic technique was noteworthy. The proposed system provided the required air conditioning for the building while utilizing efficient energy usage. The considered air conditioning input variables were: Thermostat temperature, Temperature difference between outside and inside, Dew point temperature, occupancy of the building, and time of the day. While the output variables were the fan speed, compressor speed, system mode of operation, and fin direction. The proposed system showed to be able to solve many complex air conditioning problems encountered in any building during the day without getting involved in sophisticated relationships within the physical variables. This is because an intuitive knowledge about the input and output variables and their relations to each other was enough to design a system that works efficiently.

An example of using Fuzzy logic techniques in business models is the work done by Boussabaine and Elhag (1999) where they applied fuzzy logic techniques to cash flow analysis. The model input data was based on 100% completed construction projects that were carried out under the Institute of Civil Engineers Standard Conditions of Contract. The results of the study demonstrated the successful implementation of Fuzzy logic techniques in business-related analysis compared to the traditional method. Table 2.3 shows some industrial applications of fuzzy logic.

Table 2.3: Some applications of fuzzy logic in industry (guru99.com)

Product	***Company***	***Fuzzy Logic***
Anti-lock brakes	Nissan	Controlling brakes based on car speed, acceleration, wheel speed, and acceleration
Auto transmission	NOK/Nissan	Controlling fuel injection and ignition based on throttle setting, cooling water temperature, RPM, etc.
Auto engine	Honda, Nissan	Selecting gear ratio based on engine load, driving style, and road conditions.
Copy machine	Canon	Adjusting drum voltage based on picture density, humidity, and temperature.
Cruise control	Nissan, Isuzu, Mitsubishi	Adjusting the throttle setting to set car speed and acceleration
Dishwasher	Matsushita	Controlling the cleaning cycle, rinse and wash cycles based on the number of dishes and the dirtiness of dishes
Elevator control	Fujitec, Mitsubishi Electric, Toshiba	Reducing waiting time for time-based on passenger traffic
Kiln control	Nippon Steel	Cement mixing
Microwave oven	Mitsubishi Chemical	Adjusting power and cooking periods
Palmtop computer	Hitachi, Sharp, Sanyo, Toshiba	Recognizing handwritten Kanji characters
Fitness management	Omron	Employees fitness check

2.12 State of the art

In the last decade, the visibility of targets has gained great attention from researches due to its importance in many fields. Such fields include, but not limited to, indoor lighting, street lighting, urban design, vehicle manufacturing, special lighting such as museums and stages, surveillance applications, and many others. Review and validation studies in the field of street installations and visibility in both threshold and supra-threshold levels have gained a large chunk of this research. An experimental validation for the photometric measurements in visibility level calculations was done by Brémond et al. (2010), under night time driving conditions, 34 adults with a driving license of at least 5 years old and no prior information about the goal of the study were tested against detecting a target in a closed-circuit road. The experimental data suggested that cautions should be taken when using visibility levels for the prediction of target detection performance. Furthermore, in another study, Brémond (2011) reviewed the visibility level (VL) as an index of visual performance while driving. He conducted a series of three experiments and concluded that the detection performance is lowered by the background complexity and apparent motion while target eccentricity is an important factor that should not be overlooked or underestimated. Zalesińska (2012) evaluated the practical means of implementing theoretical visibility models in road lighting design, she concluded that target visibility should be evaluated in three different levels: position, situational, and navigational level.

Furthermore, multiple studies tried to develop new concepts in target visibility to be used as a metric for street lighting design. One valuable perception related to night-time visibility and road lighting standards was developed by Keck (2001) where he/she introduced the STV-H concept. This concept is based on the small target visibility (STV) model but takes into account both vehicular headlights and street fixed lighting system rather than the latter alone. Keck (2001) wrote a computer program to calculate the weighted average target visibility (STV-H) in order to study the changing visibility as the vehicle approaches the target and he recommended that the IESNA should look into his concept and adopt it for as a design method to replace the current three design methods of street lighting. Likewise, Saraiji and Oommen (2014) developed the dominant contrast (DC) concept, which is defined as the contrast of any part of a pedestrian which provides the highest visibility levels. The concept was developed by theoretical analysis and Dialux simulation and was believed to be a useful metric for modelling visibility and the authors recommended that future researchers should focus on this concept to be transformed into a valuable metric for roadway design.

A computational image-processing model based on the contrast sensitivity function (CSF) of the human eye was proposed by Joulan (Joulan et al. 2011). The computation model was able to address any target (uniformity, shape) and any background with a luminance image as an input. The model was tested in many applications such as visibility in fog (Tarel 2015), Advanced Driving Assistance System (ADAS), (Halmaoui et al. 2015). Moreover, the computational model was extended to be used in the design of real-time age-dependent image coding and display applications (Joulan et al. 2015).

More recently, Saraiji et al. (2016) experimentally measured the pedestrian visibility at night under the effect of solid-state street lights. The experiment utilized measuring the detection distances as an indication for visibility level in the presence/absence of oncoming vehicle headlights. The target used in the experiment was a pedestrian who randomly changed his clothes colour. The street lighting used was either metal halide, high-pressure sodium, or LED luminaires. Results showed that, in the case of the unlit street, the detection distance was

52% shorter in the presence of oncoming vehicle headlamps compared to the absence of headlamps. Moreover, a pedestrian wearing black clothes was harder to detect with a mean detection distance 60% less than when the driver was not stunned by the oncoming vehicle headlights. Regarding the type of luminaire used, results showed that the mean detection distance for metal-halide and LED lamps were statistically similar, both of which better than that for a high-pressure sodium lamps.

In a very recent study, Yang and Wei (2020) investigated the possibility of improving the visual performance at night-time driving using light sources with a larger gamut area. They used an experimental approach in which the observers detection rate of off-axis targets with different luminance levels, hue, and chroma with a uniform background of 1.5 cd/m^2. Results showed that the detection rates, where much lower at zero luminance contrast (target and contrast at the same luminance level). However, improving the colour contrast by increasing the target chroma was found to enhance the visual performance. Hence, they proposed enhancing the colour contrast for targets perceived at night-time situations by using light sources with larger colour gamut size, which results in better colour rendering.

Another recent study by Cao et al. (2020) tried to assess the effect of driving speed on target visibility under mesopic conditions using a driving simulator. Moreover, the effect of target contrast, position, and initial distance were evaluated. Results showed that besides the effect of low target luminance contrast in reducing the detection rate and distance, the detection rate for negative contrast targets were better than positive contrast. Furthermore, it was also found that increasing driving speed has a significant effect in lowering target detection rate as well as the detection distance, and consequently, lowering the target visibility.

Regarding the future of road lighting, a very recent study by Brémond (2020) expects that new technologies such as image processing and artificial intelligence will soon be employed in lighting measurements and assessment. He also expects that virtual reality techniques have the capability of bridging the gap between visual performance in the lab and on real roads. Brémond (2020) argued that Artificial intelligence (AI) techniques are almost in every branch of science, yet, engineering standards, in general, are still developed in the classical methods. The adoption of Artificial intelligence "machine learning" techniques and "big data" could provide an alternative option to shape new lighting standards. These standards could involve many variables that are still not incorporated in the current standards such as weather, country, demographic variables, traffic conditions, luminaires model, road surface photometry, and the nature of the road markings…etc.

2.13 Problem statement

An extensive literature review has been done to understand the currently available method of indoor illuminance selection as well as visibility models, and as mentioned before, three models were found to be the most famous and commonly used to represent visibility, these models were described in the literature review section as Adrian model (1989), Relative visual performance-RVP which was first developed by Rea (Rea 1986) and then modified by Rea and Ouellette (1988, 1991), and lastly, Small target visibility model (IESNA 2000) which is largely dependent on Adrian's model (1989). These models were studied extensively and thoroughly to find the weakness and strength of each model, then to find out which model is using which parameters and which model is neglecting any parameters. The range of the parameters used in each model was studied as well to find which model is not enough in describing visibility and which model is focusing on a certain range of parameter values and neglecting the rest of the range.

This initial study showed that the best model to base the Fuzzy-logic proposed model was the RVP model as it is based on two different experiments that gave almost the same results (Rea 1986 and Rea and Ouellette 1988), these two independent experiments were well documented and easily verified. Moreover, RVP quantified the visual performance much better than Adrian's visibility level (VL) since VL was considered as a crude predictor of visual performance (Ross 1978). This gave a high credibility to this method to be adopted by the IESNA lighting handbook (2000) as one of the methods used for assessing the impact of light levels for different lighting applications. Nevertheless, RVP was successfully used in establishing a successful street lighting design criteria (Saraiji and Ragab 2015).

Therefore, the proposed Fuzzy-logic based model adopted the RVP model as a base model. Although the RVP model has some limitations such as measuring the visual performance and not the task performance and neglecting the tasks that require peripheral vision. It also neglects the contrast polarity, target eccentricity from the observer's line of sight, and disability glare. However, all these weaknesses in the RVP model shall be considered in the new fuzzy-logic based model which adopted the name for "Fuzzibility" which is a combination between the two words: Fuzzy and Visibility. The output of this model adopted the name of FRVP which means: Fuzzy Relative Visual Performance. This name indicates that the new model is based on Fuzzy logic and represents an extension or innovation to the RVP model as well.

This work defines indoor illuminance and target visibility in a new method. Based on Fuzzy logic techniques, it is expected that this model will give better results in terms of indoor and outdoor lighting. The argument behind this assumption is that the advantages of this model over the current model lie in the method of which illuminance and visibility is obtained, which suits the phenomena itself that is not exact.

Another advantage of this model is that it can include many variables that are missing in developing the current models. For example, Table 2.2 shows that all current visibility models missed to include the effect of eccentricity and background complexity in the modelling of visibility. Although it has been shown that a target located at 20 degrees relative to the fixation line of sight will have less than 15% chance of detection whereas targets within 6 degrees of the visual axis will have more than 60% chance of detection (Inditsky et al. 1982). Moreover, the suggested model has the ability to extend the ranges used in the current models. An example of this case is the STV model which incorporates the ability to detect small targets, while targets differ in sizes and shapes. The new proposed model is based on Fuzzy logic techniques. It is expected to give better results in terms of road lighting as well as indoor lighting.

3 Chapter Three: Methodology

3.1 Introduction

As seen in the literature review section, current visibility models either employ mathematical relations that may not be good enough to represent and describe visibility in a clear way, or have a limited range of variables, where some variables are not even considered in the model or partially considered. The other approaches employ experimental models that are also limited in describing visibility as most of these experiments were done on a young participant's age with good vision (Adrian 1989) or only consider small targets and cannot be extended to represent the visibility of larger targets.

Furthermore, the nature of visibility variables are subject to be easily fuzzified, and this is due to being vague enough for this process, for example; many people identify age groups as young, old and very old and this classification is not new, the same applies to lighting levels where people are used to consider describing a room or roadway lighting as high, sufficient or low. Moreover, many visibility models are considering ranges for visibility variables such as Adrian's model (1989) when considering the same age correction factor for individuals between 23 to 64 years of old, and another age correction factor for age groups between 65 to 75 years of old. This implies that Adrian (1989) considered the first age group as "young" and the second as "old". The same applies to how Adrian (1989) dealt with exposure times where he considered an exposure time of 2 seconds or more as sufficient and he added a correction factor for lower exposure times. This again implies that the exposure time of two seconds can be considered as sufficient, while higher and lower values can be considered as "high" and "low" respectively.

3.2 Advantages of Fuzzy logic approach

Fuzzy logic approach can be a better choice to model visual performance and indoor illuminance for the following reasons:

1. Easy to use and can save the complexity and density of mathematical models and long equations
2. Not limited to a single variable or range and can be applied to any number of input and output variables.
3. Where mathematical or experimental models fail, or cannot describe a certain phenomenon, Fuzzy logic approach is the better choice as it mimics how the human brain works and not how math work as there are values in between the true and false which can be considered as partially true or highly true or partially false.
4. Can be modified easily to account for new changes or to implement new factors
5. It can be easily extended in the future to include more factors, in contrast to mathematical models that may need high work capacities or multiple correction factors to extend a certain model or approach.
6. Can be easily integrated with available software and programming languages especially in controlling devices and machinery
7. Once the model is completed, a graphical user interface (GUI) and a separate application or software can be produced easily to describe the model

3.3 Fuzzy logic vs. Mathematical modelling

This study is based on scientific modelling, which is defined as an activity to make a phenomenon easy to understand, quantify, define, visualize, and simulate. Any scientific model must have input and output variables. For example, mathematical modelling is based on mathematical concepts, mathematical language, governing equations, assumptions, initial, and boundary conditions. However, the mathematical model needs input parameters that follow a certain sequence of calculations governed by mathematical operations in order to produce the output. And consequently, changing the input will change the output. Unless the model is not enough to represent the whole phenomena or works for a certain range of input or output parameters. In this case, the mathematical model is not the optimum technique to describe this phenomenon. Fuzzy logic modelling is no exception from any other scientific model. It needs inputs to produce outputs. However, the input and output parameters have to be vague or "Fuzzy" enough to be considered. In other words, Fuzzy parameters must be able to include the false and truth, and all the range between them in a clear way. This process is called Fuzzification which is trying to generalize the parameters from characteristic functions (math) to membership functions (Fuzzy). The basic steps for any fuzzy logic approach are (Zadeh 1965):

1. Fuzzification: which means converting parameters from a crisp value into a vague or fuzzy value called membership function. This membership function is based on linguistic terms describing the associated degree of truth or Fuzziness of that parameter. For example, in visibility modelling, visual age can be a crisp value of 21 years. However, fuzzification of visual age can give all values from 18-40 a linguistic term of young with a certain membership degree, and age values from 30-60 a linguistic term of old with another membership function. This will make the values of the visual age of 35 years for example as partially young and partially old. This is the essence of Fuzzy logic that deals with partial truths rather than full truths.

2. Fuzzy inference process: which combines the membership functions with the fuzzy rules to produce the fuzzy output. This is fundamentally the set of rules that communicate the input to the output. This resembles the set of equations and assumptions that govern the relationship between the input and output of the mathematical model.

3. Defuzzification: it is the opposite of the fuzzification process where the fuzzy output is converted into a crisp value based on the membership function of the output itself. This process is important in terms that it quantifies the value of the output to be used in decision making or controlling a certain process or system.

3.4 Fuzzy logic vs. artificial neural networks

Fuzzy logic is considered as a subset of Artificial intelligence. The advantage of selecting Fuzzy logic technique over other methods such as Artificial intelligence (AI) machine learning techniques or Artificial Neural networks (ANN) is that fuzzy logic mimics how the human brain works in terms of accepting intermediate values that may correspond to something with in-between characteristics such as grey, which relies between white (0) and black (1). However, AI machine learning and ANN mimics how humans react and work, and most importantly, how humans learn from things to recognize/deal with new things and situations. So, modelling visibility involves specified input and output parameters that are based on the programmer choice, and does not really need any new learning process that can be obtained from the input parameters. For example; machine learning and ANN are very useful tools for tasks involving speech recognition that requires adding new knowledge for the machine as it continuously works to recognize/identify more speech in the future or if the situations were changed. Table 3.1 shows a comparison between Artificial Neural Networks (ANN) and Fuzzy logic modelling.

Table 3.1: Comparison between ANN and Fuzzy logic models. (Kruse 2008)

ANN models	*Fuzzy logic model*
No mathematical model necessary	No mathematical model necessary
Learning from scratch	Apriori knowledge essential
Several learning algorithms	Not capable to learn
Black-box behavior	Simple interpretation and implementation

On the other hand, Fuzzy logic can be integrated within artificial intelligence machine learning and big data models. Fuzzy neural network, or sometimes called, Neuro-Fuzzy systems employs a learning machine based on fuzzy parameters by combining the human-like fuzzy reasoning with the connectionist structure of the neural network. This hybrid-like method of modelling has many applications in medicine (Chen 1995), transportation management (Levchenko et al. 2018), real-time control applications (Kayacan et al. 2015), and many other engineering applications.

3.5 Research approach

Based on the study aim and objectives described in previous chapters, the research approach of this study can be summarized in the following steps:

1. A comprehensive study of the literature to determine the variables involved in the current indoor illuminance selection method and the visibility of targets
2. Grouping visibility parameters into 3 categories; independent, dependent, and out of the scope of this study. Independent variables affect visibility directly, dependent variables affect visibility indirectly through their dependence on one or more

independent variables. And finally, variables that are out of the scope of this study will not be considered for reasons that will be correctly justified.

3. Fuzzification of input variables: Generating membership functions for fuzzy variables based on the current literature.
4. Fuzzification of output variable: Generating a membership function for the illuminance and visual performance based on the current literature
5. Generating fuzzy rules that relate input of the model to its output (Fuzzy inference system)
6. Defuzzification: Using Fuzzy logic approach to simulate the indoor illuminance and visibility based on the input/output membership functions and the set of rules to get the crisp values of illuminance and visibility (opposite to fuzzification process)
7. Generating the results output of simulation in the form of 2-D graphs, 3-D graphs and tables
8. Sensitivity analysis to check the stability of the visibility model and to test any changes in results associated with changing the input/output membership functions
9. Generating a computer application (*.exe) to help users/designers make proper calculations of indoor illuminance and degree of visibility
10. Validating the results by comparing the output of the new model with existing models/methods
11. Finding suitable practical applications for the new indoor illuminance and visibility model

The methodology of this work is designed to follow the steps mentioned in the research approach. Therefore each step was studied individually to build an efficient model. Figure 3.1

below shows a flow chart for the research methodology used in developing the FRVP model in details while the following show some insights about the methodology steps used in this study:

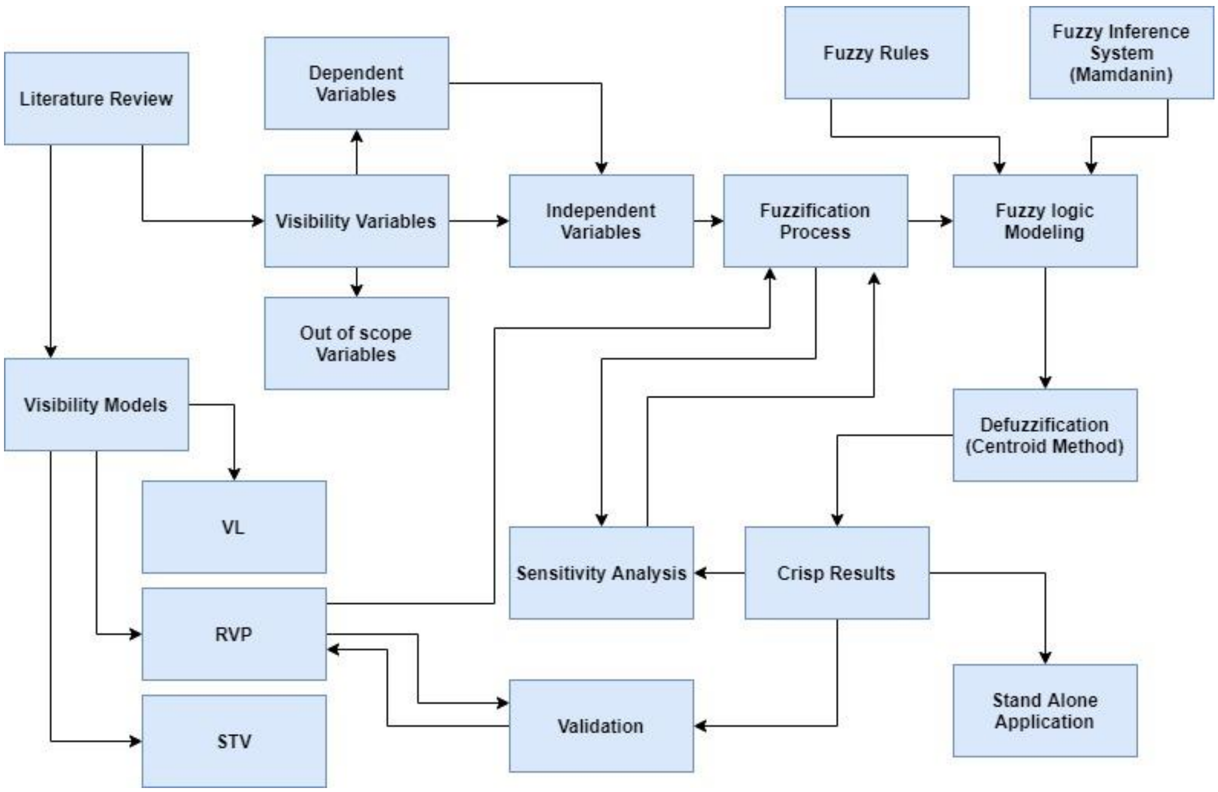


Figure 3.1: Research Methodology flow chart for FRVP model

3.6 Visibility variables

Visibility variables included in the current visibility models were studied. New parameters were discussed as well based on the current literature that has never been adopted by any previous visibility model. The range of each parameter was also studied. The following table shows the visibility variable divided into three groups; group-1 which are the independent visibility variables, group-2 which are the dependent visibility variables and group-3 which are the visibility variables that will be out of the scope of this work

Table 3.2: Visibility variables divided into 3 groups: (1) Independent variables, (2) Dependent variables, (3) out of the scope of this work

Group-1 Independent visibility variables	*Group-2 Dependent visibility variables*	*Group-3 Visibility variables out of the scope of this work*
Visual age	*Disability glare*	*Exposure time*
Luminance contrast		*Driver alertness*
Retinal illuminance (Trolands)		*Driver expectation*
Target size		*Target movement*
Eccentricity		*Chromatic contrast*
Background complexity		*Transient adaptation*

3.6.1 Independent variables

Independent variables are those incorporated explicitly in the fuzzy model. Independent variables are the most important visibility variables that are available in the literature. Luminance contrast has been mainly included in all visibility models (Adrian, RVP, STV). Age, visual size and retinal illuminance have been included in different ways in other models. However, other variables such as eccentricity and/or background complexity have been either neglected or not properly approached in other models. Moreover, the STV model incorporates small target sizes only. FRVP proposed model will be including these variables directly as input to the fuzzy logic model as seen in Figure 3.2.

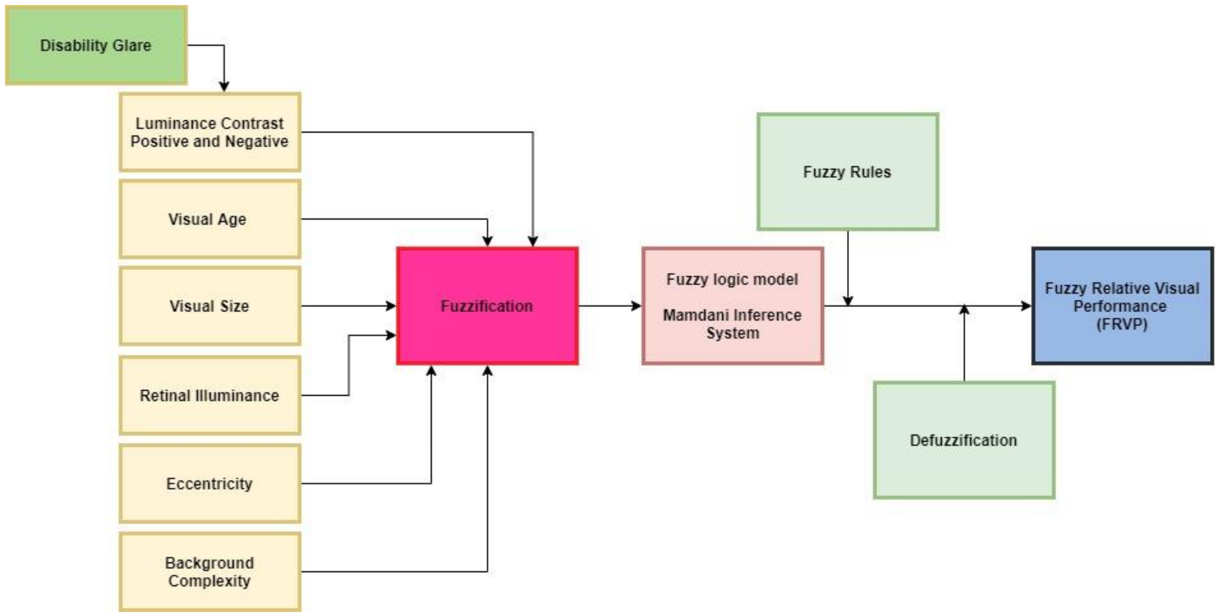


Figure 3.2: Fuzzy Logic Model with direct input variables

Independent variables used in the FRVP model are as follows:

3.6.1.1 Luminance contrast

Luminance contrast has been by far the most important factor in modelling visibility. It has been incorporated in early experimental studies of Blackwell (1946) which later became the basis for Adrian VL model (Adrian 1989) and many road marking computation models (CIE 1988), (COST 331 1999). The luminance contrast is defined as the difference between the luminance of the target and its background divided by the luminance of the background. Equation (3.1) shows the mathematical presentation of the luminance contrast

$$C_t = \frac{L_t - L_b}{L_b} = \frac{\Delta L_{actual}}{L_b} \tag{3.1}$$

Whereby, L_t and L_b are the luminance of the target and the luminance of the background respectively.

As the human visual system responds strongly to temporal changes in stimulus power (luminance), it also adapts quickly to the continued application of that power. Therefore, the luminance alone is not enough to fully characterize the nature of the stimulus with respect to the human visual system since it describes the stimulus power rather than changes in power. This allowed the concept of contrast to come into the surface as it defines the stimulus ability to excite the differential mechanism of the human visual system rather than the stimulus power alone. In other words, the luminance contrast necessary for an object to be visible does not depend on the object luminance itself but also depends on the background luminance, or more precisely, the luminance surrounding that object since they characterize the adaptation conditions of the human eye. This value of contrast that makes the objects as just visible is called the threshold contrast and can be given in the Equation (3.2)

$$C_{threshold} = \frac{\Delta L_{threshold}}{L_b} \tag{3.2}$$

Where $\Delta L_{threshold}$ is the luminance difference between the target and the background after applying the correction factors for object size, age, exposure time, contrast polarity, and glare.

Figure 3.3 shows threshold contrast values based on Adrian model at different visual angles (measured in minutes of arc). The figure clearly shows that increasing the background luminance or the visual angle decreases the contrast values needed to make the target as just visible (C_{th}). This change in the threshold contrast can be very sensitive at a lower value of background luminance and visual angles such as the case of 4 min. visual angle where the slope of the curve is very steep at the beginning. However, further increase in background luminance and visual angle can be less effective in changing the threshold contrast values as the slope of the 9 min curve is almost constant above background luminance value of 1 cd/m^2.

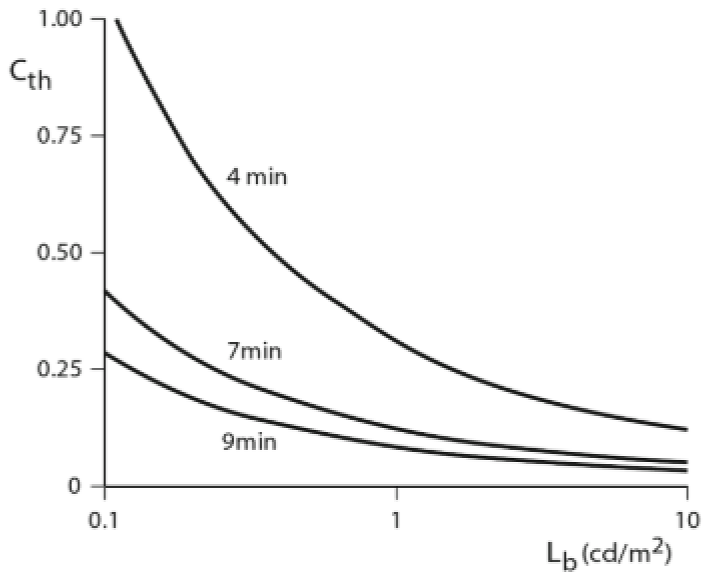


Figure 3.3: Decrease in threshold contrast C_{th} with increasing the background luminance (Lb) at observation time of 0.2 seconds and observers age of 30 years (Adrian 1989)

However, the concept of threshold contrast is not helpful in this work since it was defined based on threshold visibility where objects are either visible or not visible at different lighting and observer situations, or simply based on the breakpoint between seeing and not seeing the target by observers. Consequently, based on the threshold visibility concept by Adrian (1989), the contrast can be classified as a crisp parameter that takes a certain threshold value when the object is just visible. Further increase in contrast values above threshold values does not indicate that the object is more “just visible” but somehow indicates how much the object contrast should be above the threshold value to be seen under certain lighting and observer conditions.

Hence, it is better to look at the luminance contrast from the supra-threshold visibility point of view, or simply, luminance contrast in visual performance context. Rea and Ouellette (1991) defined luminance contrast based on relative visual performance as follows:

$$C_v = \left|\frac{L_B - L_T}{L_b}\right| \tag{3.3}$$

Whereby, L_T and L_B are the luminance of the target and the luminance of the background respectively. The threshold contrast (C_t) was also defined by Rea and Ouellette (1988) as the contrast associated with 50% probability of detection of a square target with a given size for each adaptation luminance and is given by:

$$log_{10} C_t = -1.36 - 0.179A - 0.813L + 0.226A^2 - 0.0772L^2 + 0.169AL \tag{3.4 }$$

Where;

$$A = log_{10}(20\ 000\omega) \tag{3.5 }$$

ω is the area of the target, in steradians, from 0.2 to 280x10^{-5} and L is given by

$$L = log_{10}\left(log_{10}\left(\frac{10I_R}{\pi}\right)\right) \tag{3.6}$$

Where I_R is the retinal illuminance, in Trolands and is given by

$$I_R = L_a \pi r^2 \tag{3.7}$$

Where L_a is the adaptation luminance in cd/m^2, from 0.17 to 255, and r is the pupil radius in mm.

The effect of contrast on visual performance can be seen in Figure 3.4. The constant performance lines from the RVP model represented by RVP contours show that for each RVP can remain high, medium, or low for a wide range of background luminance and luminance contrasts. For example, RVP can remain high (above 0.92) at a luminance contrast value of 0.6 if the background luminance values are more than 10 cd/m^2. However, the constant performance line of 0.92 RVP shows that RVP can still be high (above 0.92) at a luminance contrast value of 0.3 with a background luminance of 20 cd/m^2 and more. Only at low values of luminance contrast and background luminance, the RVP will drop considerably.

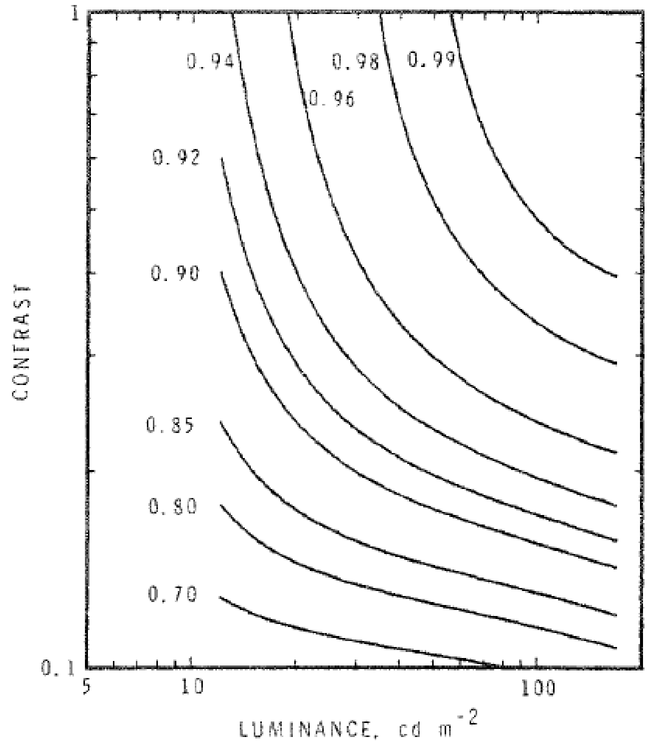


Figure 3.4: constant RVP contours in a log background luminance versus log contrast space. (Rea,1986)

Based on Adrian (1989) definition of the luminance contrast (Eqn. (3.1)), contrast values can take positive values if the target luminance is larger than the background luminance, such cases include bright letters on dark background. Alternatively, contrast can be negative if the target luminance is less than the background luminance such as dark letters on bright background). However, Rea (1986) defined the contrast by taking the absolute value for the luminance difference (Eqn. (3.3)). This does not mean that Rea did not include the contrast polarity in his RVP model, as Rea and Ouellette (1988) conducted experiments involving Targets darker than the background (decrement targets) and targets brighter than the background (increment targets). In all cases, this still means that targets can have different contrast polarities whatever definitions were chosen and/or different methods were used.

To account for contrast polarity, Adrian (1989) proposed a correction factor (F_{CP}), based on Aulhorn's data (1964), to be multiplied by the positive threshold contrast (ΔL_{pos}) as follows:

$$\Delta L_{neg} = \Delta L_{pos\,.}\ F_{CP} \qquad (3.8)$$

Where F_{CP} is a function of the background luminance and target size.

3.6.1.2 Visual age

Visual age is one of the major factors affecting the visibility of targets. The effect of visual age is related to the amount of light reaching the human retina which depends on two factors; pupil size and the spectral absorption of the human eye components. The area of pupil changes depending on the amount of light reaching the eye. This mechanics is called eye adaptation where the pupil increases in area to allow for more light at dark and decreases in area at high light levels. This eye adaptation mechanism is affected as the person gets older as the ratio between the maximum to minimum pupil diameter decreases causing the elderly not able to adapt for low light levels than young people. Figure 3.5 shows the effect of age on the minimum and maximum pupil diameters (Weale 1982)

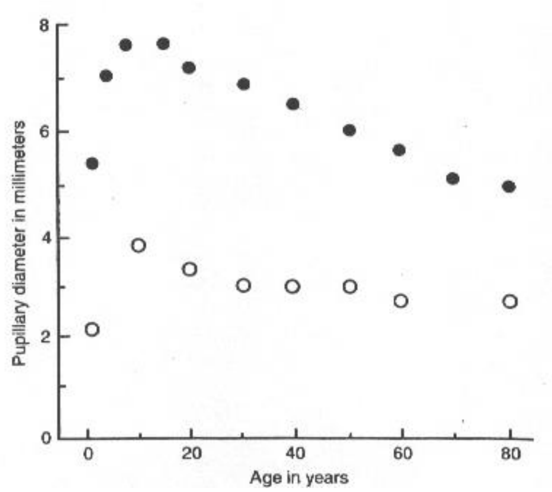


Figure 3.5: Maximum and minimum pupil diameters as a function of age (Weale, 1982)

The other factor that affects the amount of light reaching the human eye is the spectral absorbance of the eye which mostly occurs through the eye lens (Murata 1987). The absorbance of the human lens increases exponentially from birth (Weale, 1992). Figure 3.6 shows the spectral absorbance of the human lens as a function of wavelength for different ages (Weale 1988). The figure shows that the lens absorbance of short wavelengths increases radically with age which can explain the lower colour vision of older people. Consequently, since the amount of absorbed light in the short wave region increase with age, this lowers the amount of light transmitted through the lens which means less light is reaching the human eye. Moreover, the amount of scattered light through the human eye increases with age. This scattered light lowers the retinal image by reducing the luminance as well as the colour difference at the edges of the image.

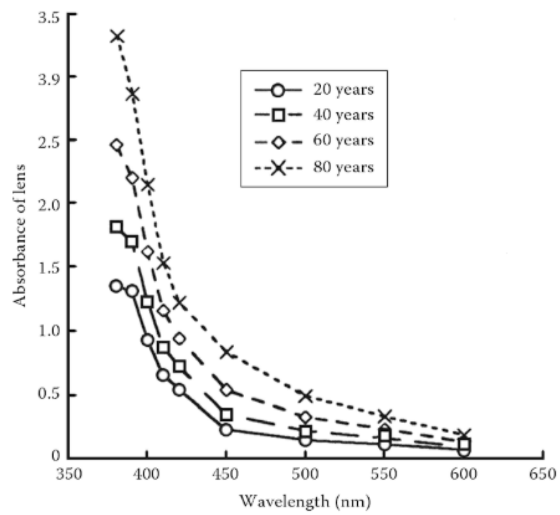


Figure 3.6: Spectral absorbance of the lens as a function of the wavelength for different ages (Weale, 1988)

Visual age has been considered in most visibility models. However, most of the models considered the age as a fixed value such as the RVP model where the model is based on experiments of the visual performance of young adults with perfect vision. A correction formula was introduced to correct for higher values of observer's age based on the decrease in retinal illuminance and retinal contrast due to the reduction of pupil's diameter, increased light absorbance and scatter through the eye and most importantly, reduced light transmitted into the human eye. This correction formula is given by:

$$I_r = PL_A\pi r^2 \quad (3.9)$$

$$P = 1 - 0.017(age - 20) \quad (3.10)$$

Where: I_r is the retinal illuminance (in Trolands), L_A is the phototopic adaptation luminance (in candela/m^2), r is the pupil radius and P is the correction factor representing the retinal illuminance reductions which has a value of 1 for the age of 20 years. This correction formula is valid for any observer's age between 20 to 65 years.

STV model included the effect of age based on the worst-case scenario by considering an observer's age of 63 years old and did not include any other age group in developing the model. However, Adrian's visibility model (1989) considered the age of 23 years in developing his model and provided a correction factor for older ages based on Blackwell and Blackwell (1980). To develop the correction factor (AF), Adrian tested 234 subjects with ages between 20 to 80 years old divided into age groups of 10 years. Adrian findings were enough to develop an age-dependent multiplier to account for threshold increase with older age. The data was obtained for positive contrast and Adrian suggested that is also valid for negative contrast. Figure 3.7 shows the multiple of Threshold of ΔL as a function of age based on Adrian visibility model (1989). The Age correction factor developed by Adrian has a value of unity for an observer at 23 years old and is given by the following equations:

$$\Delta L_{age} = \Delta L_{23}.AF \tag{3.11}$$

For 23<age<64

$$AF = \frac{(Age-19)^2}{2160} + 0.99 \tag{3.12}$$

For 64<age<75

$$AF = \frac{(Age-56.6)^2}{116.3} + 1.43 \tag{3.13}$$

Where ΔL_{age} is the threshold contrast for older subjects, ΔL_{23} is the same threshold contrast ΔL used in developing the model and AF is the age correction factor.

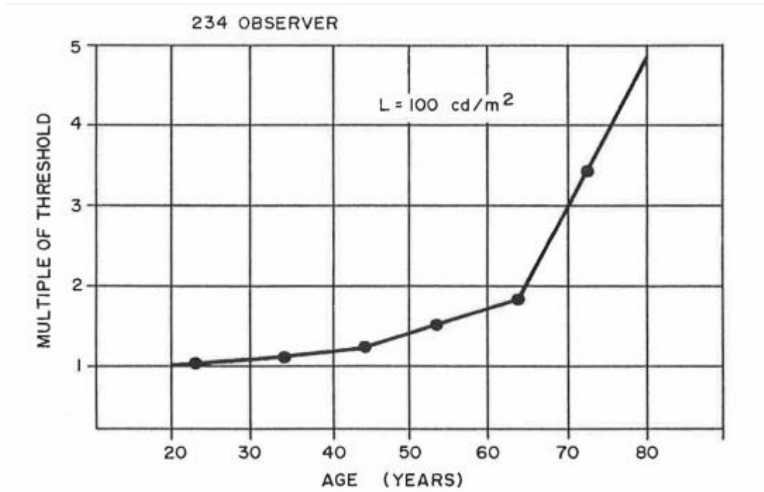


Figure 3.7: Multiple of the threshold contrast required for an observer of higher age in relation to the base group with an average of 23 years [adopted from the work of Mortenson-Blackwell and Blackwell]. (Adrian, 1989).

3.6.1.3 Visual size

There are several methods to define the size of an object presented to the visual system. However, it should be noted that the actual size of the object is different than the visual size where the latter is related to how the visual system perceives the image of the stimulus in the retina. Hence, three common factors define the visual size. The first one is the actual size or area of the stimulus. The second one is the distance between the observer and the object and the third is the size constancy which is related to the relative movement of the observer or the stimulus with respect to each other.

Therefore, the above factors (which define the visual size) are usually characterized by the angle in which the stimulus subtends at the observer eye. This angle can be represented either by the angular angle (α) measured in minutes of arc in a two-dimensional plane, or the solid angle (ω), measured in Steradians in a three-dimensional plane. The difference between the angular angle and the solid angle is that the first is calculated based on the target height and the distance between the observer and the target while the solid angle is based on the target area and the square of the distance between the observer and the target. Angular angle and solid angle are represented in Figure 3.8 and equations:

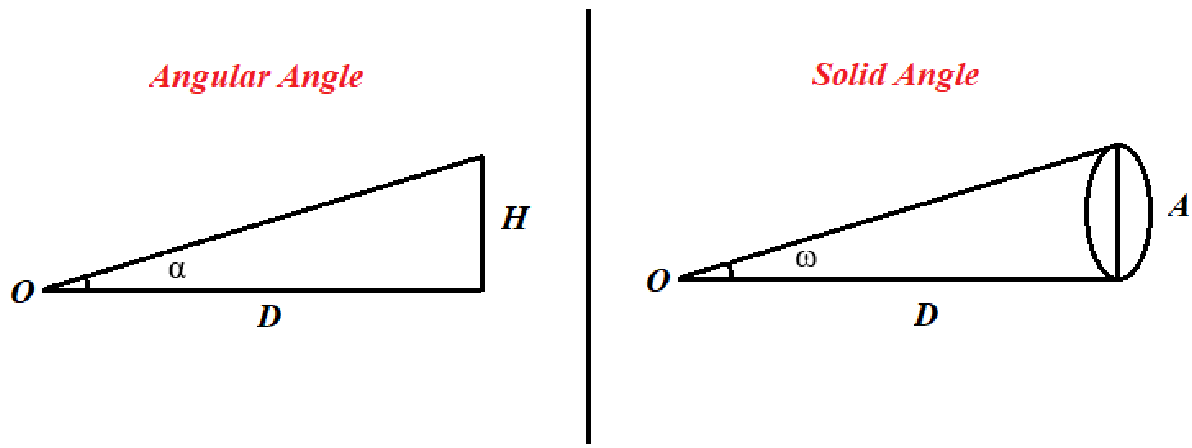


Figure 3.8: Comparison between angular angle and solid angle

$$\alpha = \tan^{-1}\left(\frac{H}{2D}\right) \tag{3.14}$$

Where α is the angular angle in Degrees, radians or min arc

H is the height of the target and D is the distance between the target and observer

$$\omega = \frac{A}{D^2} \tag{3.15}$$

Where ω is the solid angle in steradians

A is the area of the target and D is the distance between the target and observer

The effect of the visual size was included in the Adrian visibility model (Eqn. (3.14)) in terms of angular angle (α). Figure 3.9 shows the effect of the angular angle on the threshold luminance difference (ΔL). The figure shows that for small targets, ΔL drops exponentially with increasing the angular angle (α). However, for the large objects, ΔL starts to be independent of the size. This allowed Adrian (1989) to conclude that, at larger targets, the threshold luminance difference is independent of the angular angle (α) and only dependent on the background luminance.

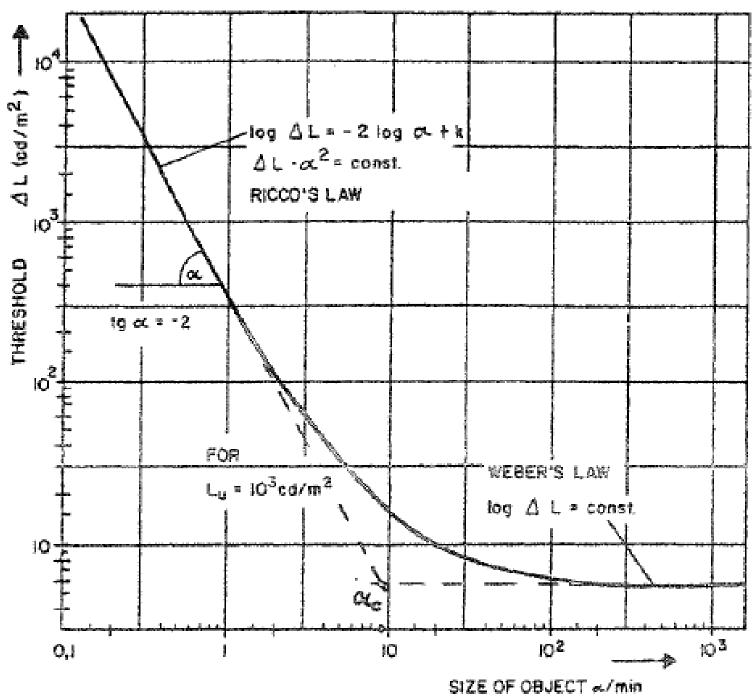


Figure 3.9: ΔL threshold as a function of angular angle at a constant background luminance of 1000 cd/m². Adrian (1989)

The small target visibility model (IESNA RP-8-00 2000), which is an extension to the Adrian VL model (1989), was developed based on a square target with 180 mm side length. The target is located at 83 m ahead of the observer with the observer to target size parallel to the centreline of the road. The size and location of the target corresponds to an angular angle of 10 min arc. This constant target size is based on the ability of observers to detect small targets based on Adrian's conclusion that visibility of larger objects is independent of size, and size only matters for small objects.

The RVP model (Rea and Ouellette 1988,1991), on the other hand, incorporated the effect of the visual size by manipulating the solid angle (ω) in the reaction time experiment. The argument for replacing the traditional angular angle with solid angle is based on the hypothesis that the visual area of the target can provide a robust method for describing the target visual size under both, threshold and supra-threshold visibility conditions while target shapes (square, disc, triangles…etc.) did not affect the detection threshold (Kristofferson 1957) and target details (corners, edges, lines..etc.) are less effective in producing a visual response (Campbell and Robson 1968). Moreover, it was more convenient to measure the solid angle of the targets using the CapCalc video photometer (Rea and Jeffrey 1990) where each pixel in the video image can be calibrated based on its area and distance from the observer. Hence, it was easier to identify the solid angle subtended by each digit in the numerical verification task experiment and compare the results with that of the reaction times experiment.

Figure 3.10 is a log scale representation of threshold contrast (C_t) plotted as a function of the target area, in Steradians, for the increment (open symbol) and decrement (closed symbol) experiments at different values of retinal illuminance values, from 0.5 to 801 Trolands (Rea and Ouellette 1988). The figure clearly shows that the threshold contrast decreases with increasing the visual area of the target until reaching a value of approximately $20\text{x}10^{-6}$ Steradians where the threshold contrast starts to become independent of the visual size for most of the retinal illuminance values. These results are in agreement with Adrian's results and conclusion shown in Figure 3.9 (above), where the threshold contrast becomes independent of the angular angle (α) for larger targets.

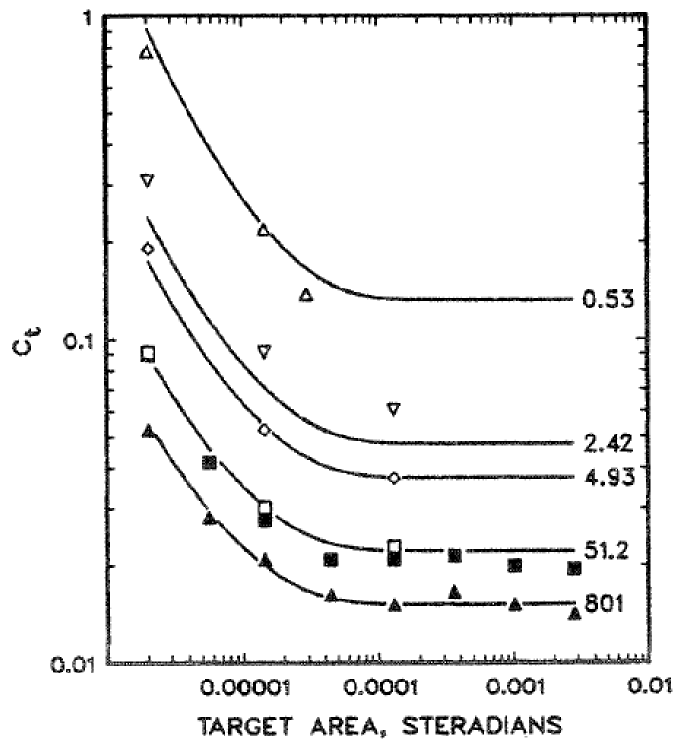


Figure 3.10: A log scale figure of Threshold contrast plotted as a function of the target area, in steradians, for the increment (open symbol) and decrement (closed symbol) experiments at different values of retinal illuminance values, from 0.5 to 801 Trolands (Rea and Oulette 1988)

The solid angle approach in representing the target area was found to be suitable to be considered as a basis for the fuzzification of the visual size parameter which will be explained in detail in the following sections of this work.

3.6.1.4 Retinal illuminance

Information can be processed by the human visual system over a wide range of luminance values. However, this process is not done at once. The human visual system constantly adapts based on the lighting conditions available. This allows for higher sensitivity at low lighting conditions, such as night conditions, and low sensitivity at high lighting conditions, such as daylight conditions. Moreover, when the visual system is adapted to a certain luminance, higher luminance values appear as bright while lower luminance values appear as black shadows. An example of this process is the change of appearance of vehicle headlights at day and night conditions although the headlight luminance is the same at both conditions, however, they appear bright at night as the visual system is adapted to much lower luminance values than the headlight luminance. In these cases, where lighting conditions are relatively normal under constant retinal illumination, the adaptation luminance can be considered as constant over a certain period of time. Yet, in some cases, where the visual system is not completely adapted to the surroundings, the adaptation luminance is changing dynamically over certain periods, this describes the case of transient adaptation. An example of this kind of adaptation is cases where there is a sudden change in retinal illumination such as entering a tunnel while day driving or an event of power failure inside a building without daylight.

The retinal illuminance can be defined as the amount of luminous power per area on the retina and is measured in Trolands It is more convenient to use the retinal illuminance instead of adaptation luminance in considering threshold or supra-threshold visibility models (Saraiji and Alhamad 2018). Since the eye is in a constant state of adaptation, the adaptation luminance is hardly constant over any period. This means that the pupil diameter changes continually to account for the lighting conditions available while the eyes are moving around from the visual fixation line. Moreover, targets can be moving as well allowing for the observer to have many fixation points. A good crude estimate for the adaptation luminance in real-life scenarios is a time average for all luminance of the whole scene, or more precisely, the pattern of fixation points. This is hard enough as the time between one fixation point and another can be very small, or the fixation points can be too many to be counted. Hence, it is impractical to use the adaptation luminance in a visibility model and the retinal illuminance can provide a better alternative for adaptation luminance

As the amount of light transmitted through the pupil is proportional to its area, the pupil diameter continually changes to allow for higher or lower light to be transmitted to the visual system. Hence, the retinal illuminance, which is defined as the amount of light entering the human eye, not only depends on the adaptation luminance, but also depends on the diameter of the pupil as well as the transmittance of the sensory eye structures which is called the ocular transmittance. The retinal luminance (E_r) is given by the following equation (DiLaura et al. 2011):

$$E_r = \frac{L_A A_p \tau \cos\theta}{15^2} \tag{3.16}$$

Where:

L_A is the adaptation luminance
A_p is the pupil area in mm^2
τ is the ocular transmittance
(θ) is the angular displacement of the object relative to the line of sight

The retinal illuminance unit of measurements is the Trolands. One Troland is defined as the illuminance at the retina when a human eye with a 1 mm^2 pupil is observing a target with luminous power of 1 cd/m^2 (Burns and Webb 1994). Hence the Troland can have a value of

$$1\ Troland = 0.0035\ lumens/m^2 \tag{3.17}$$

Yet, this value of Troland is based on a standard eye with no transmission loss in the ocular media. This means that two different observers with different-size eyes, different-size pupil, and different ocular-media transmission loss, viewing the same target will have different retinal illuminance. To solve this, Wyszecki and Stiles (2000) suggested the term "Troland value" to differentiate between the computed Trolands for a standard eye and the actual Trolands for an actual eye.

The transmittance of the ocular media is the percentage of light that passes through the eye sensory structures combined, namely; the cornea, pupil, lens, and the humors (aqueous and vitreous) of the eye. These structures remain transparent for a very long time, however, the transmittance of these structures depends on the light wavelength (spectral transmittance) and deteriorates as humans get older. Figure 3.11 shows the spectral transmittance of the eye sensory structures and Figure 3.12 shows the ocular transmittance of the human eye for different ages.

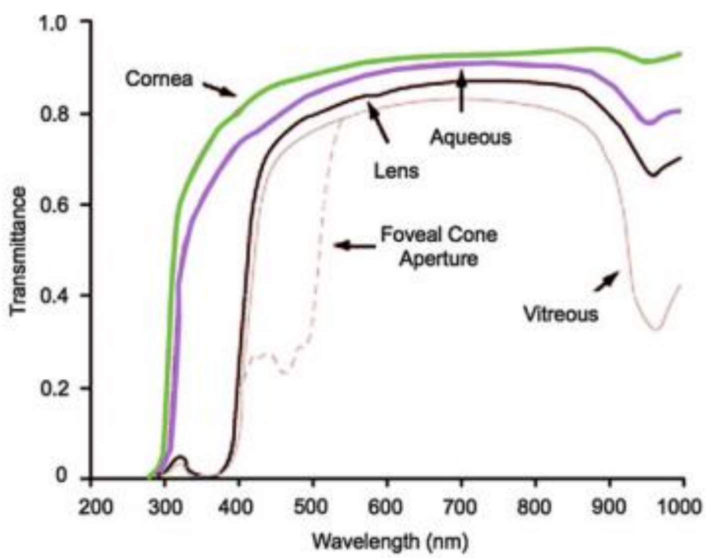


Figure 3.11: The transmittance of the ocular media based on measurements on freshly enucleated eyes (Ramamurthy and Lakshminarayanan, 2015)

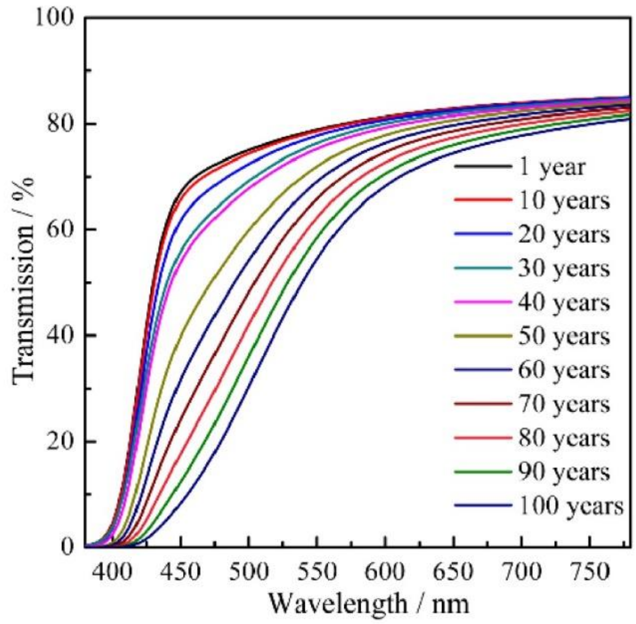


Figure 3.12: The spectral transmittances of different ages of the human eye. After Chaopu et al. 2018

The retinal illuminance was incorporated in Rea and Ouellette numerical verification task experiment (1991), as the background luminance was changing, the pupil diameter of subjects was constantly changing to adapt for different light levels. Hence, Rea and Ouellette (1991) used the equation of De Groot and Gebhard (1952) to calculate the pupil diameter but with a minor modification to avoid the pupil diameter to become zero at high adaptation luminance values. The corrected equation for pupil diameter developed by Rea and Ouellette (1991) was as follows:

$$D = 4.77 - [2.44 \tanh(0.3 log_{10} L_A)] \tag{3.18}$$

Figure 3.13 represents a three-dimensional view of relative visual performance (RVP) plotted as a function of retinal illuminance (Trolands) and contrast by Rea and Ouellette (1991).

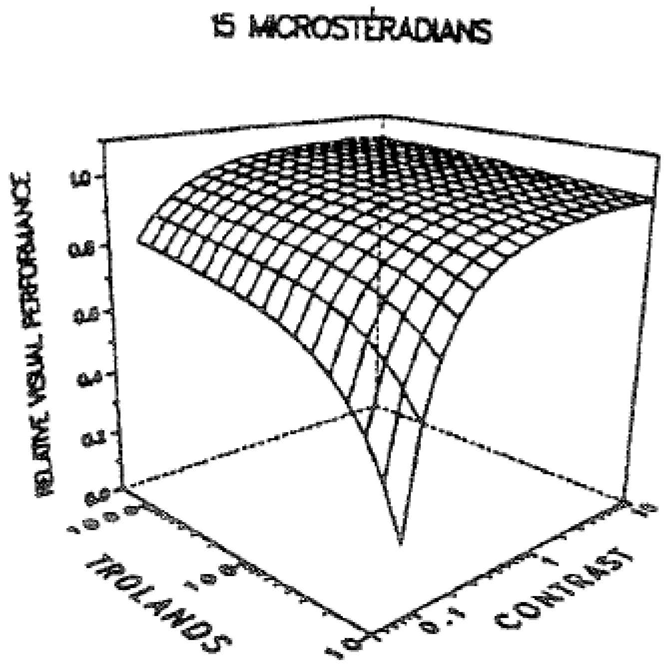


Figure 3.13: Three-dimensional views of relative visual performance (RVP) plotted as a function of retinal illuminance (Trolands) and contrast. (Rea and Ouellette 1991)

3.6.1.5 Eccentricity

Driving is mainly a visually-controlled task. It involves many activities that the driver learns by experience and practice. Some other tasks depend on the spontaneous behaviour of the person sitting behind the wheel, which comes naturally with a healthy person. For example, Human eyes subconsciously move away from the fixation line of sight towards different fixation points on the view. This action is very necessary for driving as drivers should not only be able to identify targets on the road, but also traffic signs, pedestrians, shops….etc. on the side of the road. Moreover, these eye movements play a major role in activities involving undertaking and approaching intersections or roundabouts.

The human retina contains millions of photoreceptors cells called cones and rods. Cones are responsible for vision at high light level (photopic vision) while rods are responsible for vision at low light levels (scotopic vision). Cones are concentrated on the fovea, which is part of the retina on which a sharp image is formed of the view and enclosed on 2º cone adjusted around the line of vision. This means that for detecting targets that are in the direction of view (on-line or foveal vision), only cones are used. On the other hand, rods are concentrated on the outer area of the retina with a maximum concentration at 15º from the direction of view. Thus, rods are important for off-line vision, also called, peripheral vision. Figure 3.14 shows the density of cones and rods in the human eye.

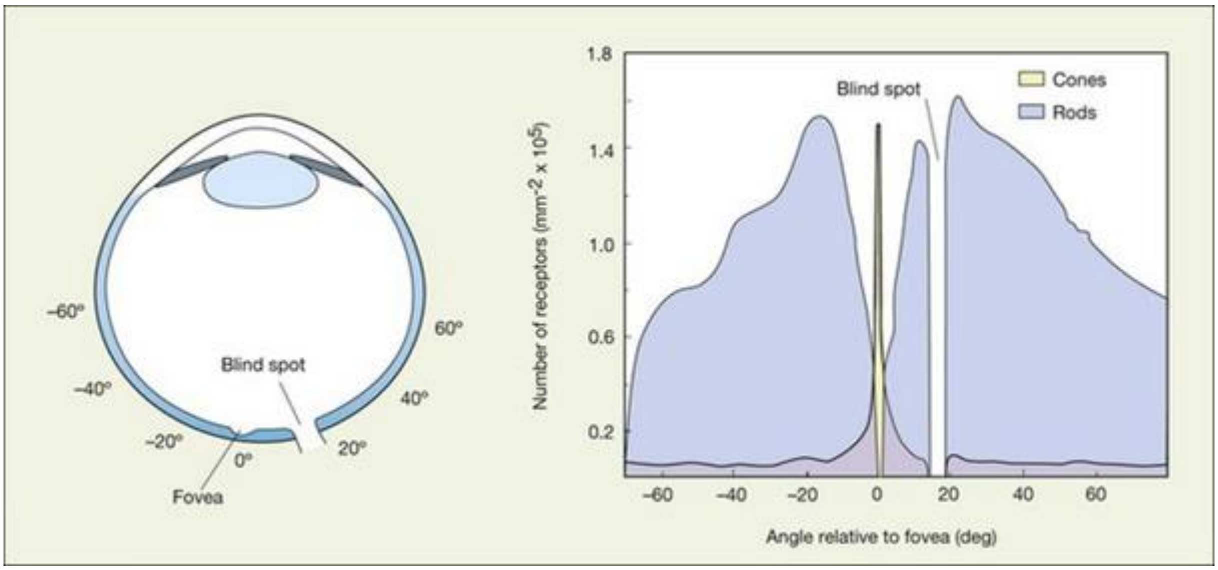


Figure 3.14: Angular Distribution of Rods and Cones on the Retina (Wandell BA. Foundations of vision, 1995)

Eccentricity is defined as the position of the target with respect to the fixation line of sight. One way to describe eccentricity is based on the probability of detection of the target while located at different angles on the scene (Inditsky et al. 1982). Figure 3.15 shows the probability of detecting a target based on eccentricity. The figure shows that the probability of detection of the target at any fixed angle depends on its contrast and visual size. However, for the same visual size and/or contrast, the probability of detection of the target decreases with higher values of eccentricity.

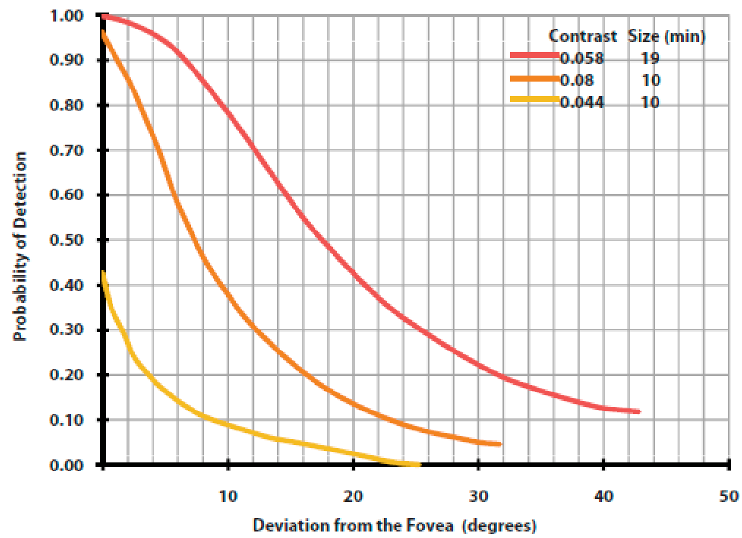


Figure 3.15: Probability of detecting a target as a function of the angle from the fixation visual axis (Inditsky et al.. 1982)

The following sections show the fuzzification process for the eccentricity membership function used in the FRVP model.

3.6.1.6 Background complexity

Background complexity, in the context of this study, is defined as the degree to which the background, as a complex scene, interferes with the observer's ability to detect and recognize a target at the forefront of that background. Under this definition, the background complexity is a function of the clutter and the variety of objects that are present in the background. An example of a complicated driving scene can include a typical night-time driving situation in a busy city with high traffic flow, static and billboard lighting, building internal and floodlighting, sidewalk users, mid-lane and sideways street trees, and shadows of objects. Such complicated scenes have the effect of distracting the visual performance of the driver/observer while viewing the same scene.

The complexity of the target background and the clutter of the scene certainly affects visual performance. It is believed that this is not a critical issue in indoor visual tasks. But in outdoor visual tasks, background complexity affects visibility. This subject is rarely studied in the roadway lighting literature. However, some studies were done with reference to computer vision and computer graphics (Langer and Mannan 2012). Visibility depends on the properties of the clutter, namely the size and density of *occluders* (objects that occlude the target) and the space between the *occluders* (Langer and Mannan 2012). Bravo and Farid (2006) tested the effect of clutter and image manipulation on object recognition. They showed that the larger the number of objects that are in the background the higher the error of recognition and the longer the reaction time. They also found that blur and edge manipulations of the image produce a modest decrement in performance with a sparse arrangement but a severe decrement in performance with a clutter arrangement. Davoudian (2011) showed that the background lighting complexity is influential in the saliency of urban objects at night

An example of complex driving scene is the presence of digital billboards which not only have a distracting effect for drivers (Edquist et al. 2011), but also increase the complication of the driving scene, and hence, it can be considered as a prime factor in raising the degree of complexity of the background. Many studies tried to measure the effect of the digital billboard as a stimulus of disturbance for the visual task of a night time driver. Edquist (2011) measured the effect of digital billboards during simulated driving for several drivers including older and inexperienced drivers. The study established a clear connection between the presence of billboards and the change of the driver's visual attention patterns and consequently, the driver's mistakes. Marciano and Setter (2017) used a statistical approach to check the relation between digital billboards and night-time driving, they created a billboard pool which includes 161 different real billboard photos and ranked them based on the density of information they contain. The results showed that labelled billboards significantly deteriorated the driver performance on the tracking task, while graphical billboards deteriorated the performance on colour change identification task. On the other hand, many other studies failed to establish a significant connection between the presence of digital billboards and the visual task of the night-time driver such as Lee (2004, 2007). Yet, Lee studies were criticized by researchers for some methodological and analytical flaws (Wachtel 2007).

While digital billboards are not the only elements that contribute to the complexity of a driving sight. It is believed that a more complex driving scenes will not only deteriorate the driver's visual task, it will also affect his visual performance negatively. A method for measuring the amount of information that a scene may include is by calculating the image entropy (Shannon 1948). This method is generally used in video gaming and image processing applications. The information entropy concept was firstly introduced by Shannon (1948) and can be understood as the level of information, surprise, or uncertainty in the variable's possible outcomes. Nevertheless, image entropy can be defined as corresponding states of intensity level in which individual pixels can adapt. This means that entropy simply describes the level of information content stored in the image (measured in bits). A low entropy image describes an image with low information content. i.e. a homogenous image. While higher image entropy defines a more detailed image with higher information content.

Image entropy can be calculated by considering a certain image as a bag of pixels that has a defined number of colour intensity levels (k). Then the image entropy (H) can be calculated as (Shanon 1948):

$$H = -\sum_{k} p_k log_2(p_k) \tag{3.19}$$

Where p_k is the probability associated with a certain colour intensity level (k)

This definition works for greyscale images as they have one band of colours only (grey). However, for coloured images, it works for one band of colours only. This means that the image entropy (H) can be calculated separately for each colour within a certain image. Hence, it more convenient to think of the combined image entropy of the primary colours within an image as a representation of the whole information content stored within the colour spectrum of that image. This method of colour representation is known as RGB (red, green, blue) colour scheme, where any image can be treated as a composition of different degrees of RGB colours, and it is widely associated with electronic displays such as cathode-ray tube (CRT) screens and liquid crystal display (LCD) monitors.

Image entropy has been widely used in image processing to evaluate the image quality (Tsai et al. 2008), face recognition applications (Aljanabi et al. 2018), authentication of art paintings (Sigaki et al. 2018), image compression (Li et al. 2020) and weather applications such as daytime fog detection (Craffa and Tarel 2014)

It is believed that image entropy measurements are directly related to the complexity of a driving scene. Once a driving scene is dense with objects, lights, cars, billboards, and other objects, it is expected to have higher entropy than a homogeneous scene. Hence the image entropy was used as an assessment method for background complexity. A typical driving scene has an average entropy values of 6.5 – 7.5 bits. Figure 3.16 shows a normal driving scene with average complexity at Al Ain City-Abu Dhabi, UAE compared to a complex driving scene in New York City, USA.

(a)

A driving scene in Al Ain city-UAE with an average entropy value of 7.26 bits. Photo credits: author (2020)

(b)

A driving scene in New York City with an average entropy value of 7.83 bits. Photo credits: Tripsavvy.com)

Figure 3.16: comparison between image entropy for different driving scenes

3.6.2 Dependent variables

Dependent variables are the variables that will be included in the model indirectly. Those variables depend on other variables that are included in the model. These variables include only one parameter which is the disability glare. The following summarizes how the effect of this variable was incorporated in the FRVP model.

3.6.2.1 Glare

Glare is a common problem in street lighting applications. The glare generated from street lamps and vehicle headlights is scattered across the observer eye, causing extra light to be falling on the retina at locations surrounding the area directly illuminated by the glare source. This light adds more luminance to the observer visual field called the veiling luminance and has an effect of reducing the luminance contrast of the target. The luminance contrast is given by:

$$C_t = \frac{L_t - L_b}{L_b} \tag{3.20}$$

Whereby, L_t and L_b are the luminance of the target and the luminance of the background respectively. Disability glare negatively influences the visual performance due to the light scatter acting at the observer's eye. It acts as a bright veil taking place at the field of vision with an equivalent veiling luminance of (L_{veil}) which is given by the following empirical formula (Holladay 1926):

$$L_{veil} = 9.86 * \frac{E_{eye}}{\theta^2}\left\{1 + \left(\frac{A}{6.44}\right)^2\right\} \tag{3.21}$$

Where, E_{eye} is the illuminance on the eye, θ is the angle between the direction of the glare source light incidence and the viewing field (from 1.5°-60°), and A is the observer's age. This veiling luminance acting due to a glare source modifies the luminance contrast and change it from target contrast (C_t) to the effective contrast (C_{eff}), where:

$$C_{eff} = \frac{|(L_t + L_{veil}) - (L_b + L_{veil})|}{(L_b + L_{veil})} = C_t \left(\frac{L_b}{L_b + L_{veil}}\right) \tag{3.22}$$

Hence, disability glare affects the contrast negatively in a decreasing manner due to the increase in effective background luminance from L_b to$(L_b + L_{veil})$. This effect is increased for older drivers as they tend to have problems coping with disability glare (Davoudian et al. 2013). Yet, to get more insights about the values of the effective contrast in the presence of a glare source, a typical driving scene encountered in urban driving (Aslam et al. 2007) was used to calculate the effective contrast at different luminance contrast values based on equation (3.22). In this driving scene, the coming car headlamps were used as a glare source (Figure 3.17).

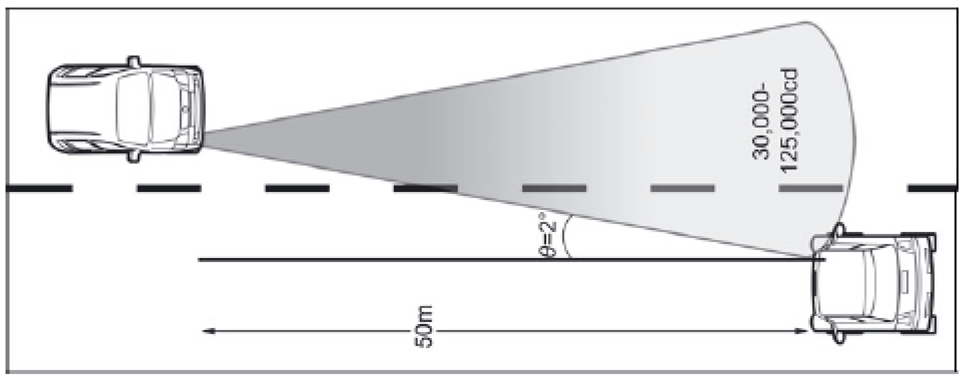


Figure 3.17: Typical state of vehicle headlights encountered in urban driving. (Aslam et al. 2007)

Based on this, the effective contrast has been calculated based on average background luminance of 1 cd/m^2, which corresponds to the average recommended value by IESNA for expressway roadway with high pedestrian conflict area (IESNA RP-8-00, 2000). Figure 3.18 shows the relation between the effective contrast and the target contrast at different veiling luminance values and Figure 3.19 shows the relation between the effective contrast and the veiling luminance at different target contrast values and an average background luminance of 1 cd/m^2. Values of veiling luminance in both graphs were chosen to be similar to those encountered in urban driving and based on typical vehicle headlamp intensities of between 30,000 to 125,000 cd and a viewing distance of 50 meters (Aslam et al. 2007).

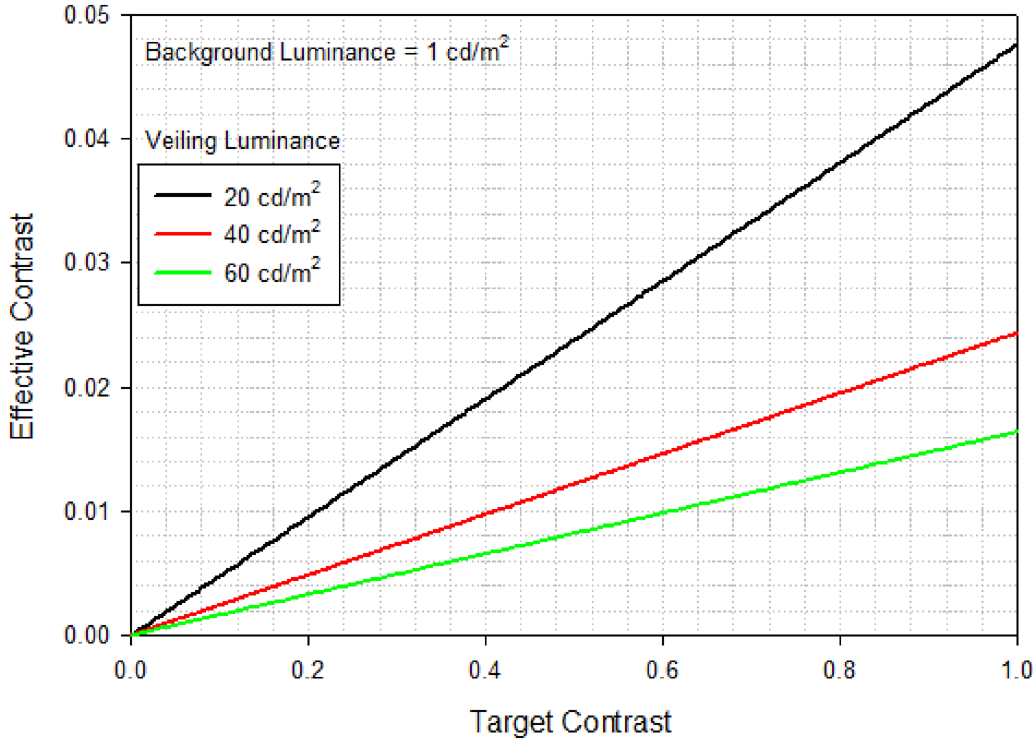


Figure 3.18: Relation between the effective contrast and the target contrast at different veiling luminance values and an average background luminance of 1 cd/m²

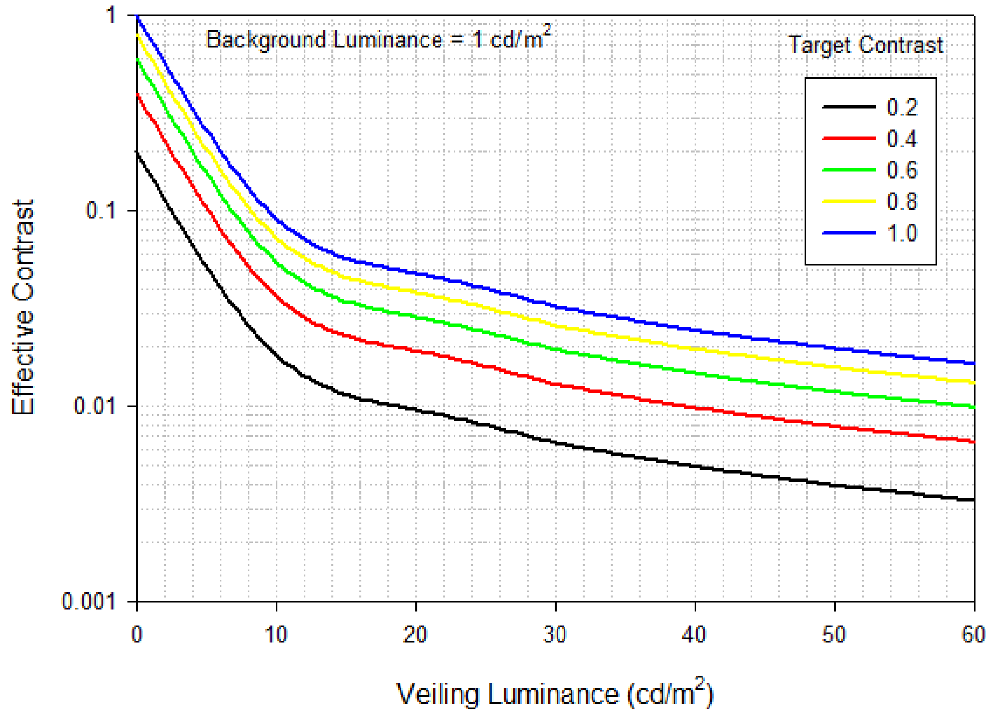


Figure 3.19: Relation between the effective contrast and the veiling luminance at different target contrast values and an average background luminance of 1 cd/m²

The above figures clearly show that the presence of veiling luminance has a lowering effect on the target luminance contrast. Hence, instead of using disability glare as a single input variable, it was coupled with the luminance contrast, where lowering the luminance contrast in the proposed model to values that are similar to the effective contrast may correspond to situations where the disability glare is present. Hence, the figures above were generated due to its importance in mapping the target luminance contrast to the effective contrast is studying the effect of glare in the proposed model.

3.6.3 Out of scope variables

These variables are not considered either directly or indirectly in the model. That is due to many reasons such as having no effect, or the effect is small enough not to be considered such as the case of exposure time. Other reasons may be related to the fact that some of these variables are omitted based on the worst-case scenario such as the case of target movement. These variables can be summarized by the following:

3.6.3.1 Exposure time

Exposure time is simply the time available to see the target. Adrian (1989) established his visibility model on an exposure time of 2 seconds or unlimited exposure time. For situations where the target exposure time is less than 2 seconds, Adrian introduced a correction function to be multiplied by the threshold contrast ($\Delta L_{t=2S}$). This correction function is given by (Adrian,1989):

$$\Delta L_t = \Delta L_{t=2s} \frac{a(\alpha, L) + t}{t} \tag{3.23}$$

Where a is a function of the target size, luminance level L_b and t is the exposure time. In other words, at shorter exposure times, the threshold contrast (ΔL) should be increased to properly perceive the target.

To mathematically check the effect of shorter exposure times on the luminance threshold (ΔL), the correction function $a(\alpha, L)$ has been calculated at different object sizes, luminance values, and exposure times. The results are shown in Figure 3.20 below.

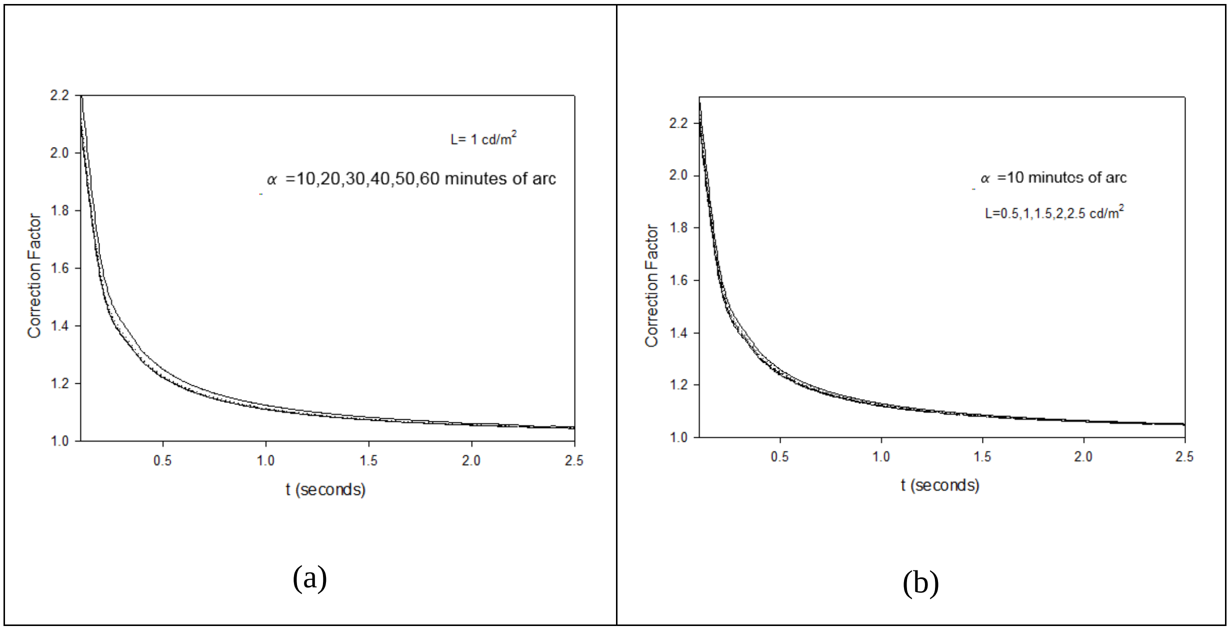


Figure 3.20 Correction factor to the threshold contrast for different exposure times (a) different object sizes α and (b) difference Luminance levels. (by author based on Adrian 1989) Note that the effect of α and L is minimal compared to the effect of t.

The figures clearly show that for exposure times between 0.5 second to 2.5 seconds, there is no significant difference in the value of the correction function a(α, L), which means that, for shorter exposure times up to 0.5 seconds, the reduction in the target's visibility is too small to be considered. Hence, exposure time will be assumed to be as 2 seconds, based on Adrian's work, and the effect of shorter exposure times will not be considered as they are too small to have a measurable effect.

3.6.3.2 Driver alertness

Driver alertness refers to the situation where the driver is fully attentive and focused on the driving process. While driver distraction is the act where the driver is engaged with other activities during driving. Such activities include the use of cell phones, even in hands-free mode, handling car equipment such as radio and GPS, talking to another person, eating and/or drinking, looking at roadway advertising and billboards, and many more. Lee (2009) defined driver distraction as ‘the diversion of attention away from activities critical for safe driving toward a competing activity’.

A great part of scientific research has been assigned to driver alertness and distraction, especially in the field of road safety and accident prevention. To start with, driver distraction has been classified into four types (Lee et al. 2009): 1) Manual distraction caused by the use of vehicle equipment and instruments, 2) Visual distraction where the driver is looking at an equipment or an outside scene. 3) Cognitive distraction when the driver is engaged in a conversation, or listening to distracting music and 4) Auditory distraction caused by a sudden ringtone or music which diverts the attention from the driving task.

Muttart (2007) investigated the performance of simulated driving during a hands-free cell phone operation. They strongly suggested that driver awareness is reduced by the use of a hands-free cell phone. Moreover, they concluded that hands-free cell phone operation while driving is responsible for two major accident type, rear-end collision, and sideswipe accidents. Furthermore, a review by Stelling and Hagenzieker (2012) discussed the effects of talking and listening (including cell phone and another passenger) on the driving task, they suggested that the driving behaviour can have significant patterns of change while engaging in conversations. Of these patterns they mentioned, reduction of driving speed, longer reaction times, reduced visual focus, and missing targets. Also, digital billboards effect on the driving performance has been studied by numerous researchers (Edquist et al. 2011, Marciano and Setter 2017) where they established a measurable relation between digital billboards, especially those with animation, and the degree of distraction of drivers (see Background complexity P. 95).

A very recent study by Robbins and Fotios (2020) tried to establish the critical types of driving distractions that can be simulated by lighting research. Two methods of collecting information were used. The first one was interviewing drivers after the collision and the second was monitoring drivers in real roads. Gathered data suggested that auditory distractions such as a conversation with passengers or listening to radio are prevalent distractions, and they are prominent to be incorporated in further lighting and hazard detection research.

Although driver alertness and distraction may affect the visual performance of drivers/ observers, there is no enough data in lighting literature to quantify this effect. In other words, many experiments confirmed the effect of driver distraction on driving performance and collisions. However, measuring this effect in the context of visual performance was hard. Hence, drivers/observers, in the context of this study, will be assumed to be fully alert without any distraction at the time being, while further research in lighting and hazard detection, as suggested by Robbins and Fotios (2020) may allow for this work to include them in the future.

3.6.3.3 Driver expectations

Driver expectation describes the state in which the driver can expect and respond to the road environment. This includes the road layout, road-related patterns such as lighting and traffic signs, and most importantly, targets ahead of him. Driving expectation is very important in the driving task as drivers rely on their expectation at many driving situations, a most common scenario is speedy driving at highways where the time needed to process visual information is very short, as a result, drivers have a certain anticipation for the dynamics of the road environment that allows them to rely on their expectancy more than the visual information they get and process (Smiley 2015). Another example is pedestrian/animals congested areas where drivers reduce their speed due to their expectation that a pedestrian/animal may be present at any time.

To check the effect of driver expectation on the driving task. A unique study has been done by Roper and Howard (1938). Subjects were asked to drive a vehicle at night to assess its headlamps, then they were told to head back to the laboratory since the study has been ended. However, the real test was on the way back where they were confronted by an unexpected pedestrian. They were then told to reverse back and approach the same pedestrian at the same speed. This time, drivers were able to spot the pedestrian at almost twice the distance before approaching the target compared to the first time when it was unexpected. Roper and Howard (1938) reasoned this by the ability of drivers on the second time to expect the target by knowing which pattern they should look for, and they suggested a 2:1 constant ratio between expecting and non-expecting drivers.

Although Roper and Howard (1938) did not mention the amount of information that was given to the driver, such as the location of the pedestrian, colour clothing, pedestrian movement and the environment in which they did the test, their work is still significant as they were the first to establish a connection between driver expectation and driving performance. However, there has been a huge debate between researchers for the solidity of their findings. Hyzer (2004) reported conforming results in his work to assess the 2:1 expectancy rule of Roper and Howard (1938) in night-time motor. While Muttart (2016) suggested that a “one size fits all” claim is not properly supported. They also reported that their experiments showed that the average detection distance for drivers who did not know the target was present is almost 12 times less than those who knew, dispelling the perception of 2:1 driver expectancy ratio. Furthermore, Moretimer (1996) wrote: “No support was found for the 2:1 constant ratio between ‘expected’ and ‘unexpected’ driver visibility in night driving.”

In all cases, the relation between driver expectancy and driving performance is clear and cannot be denied. Yet, to measure the degree of expectation and to check if there is a common response on driving tasks due to this is very hard. Hence, this work will adopt normal driving conditions where the driver is assumed to be fully experienced in the road environment and no unexpected targets are present. While this assumption may seem bland and hard to achieve, Muttart (2016) provided a well-established research with convincing results, therefore, for the time being, their ratio of 12:1 for driver expectancy can be used to correct the results of this work for unexpected drivers, if needed. Further future research related to this field can provide more insights on how to include driver expectations in the proposed FRVP model.

3.6.3.4 Target movement

Targets in real life can be moving or stationary. For example, a pedestrian before crossing can be considered as stationary, but once he is crossing the road, he is moving. Movement can be parallel, perpendicular, or in any direction with respect to the road axis. Yet, drivers respond more quickly to moving objects compared to stationary objects if they are wearing retroreflective or light clothing (Kledus et al. 2010), (Balk et al. 2008) and. However, when pedestrians were dresses in black, there was no significant difference in the response of drivers with respect to target movement (Muttart 2013).

Moreover, target movement affects the threshold contrast needed to perceive the target. Figure 3.21 shows the effect of the movement on the threshold contrast needed to perceive a 5^{o} bar pattern target moving at 24^{o}/s (filled square) or stationary (empty circle) under a background luminance of 9.8 cd/m^2 and different eccentricity values. The figure shows that at the eccentricity value of zero (the target is located on the driver visual axis), the threshold contrast needed to perceive the target is almost the same value for both a moving and stationary target. However, when the eccentricity increases, the threshold contrast for the moving target remains approximately constant at low threshold values, but the stationary target threshold increases dramatically with increasing the eccentricity angle. Moreover, the threshold contrast for a stationary target is always higher than that for a moving target regardless of the eccentricity value.

Based on this, and considering the worst-case scenario of a stationary target, which is harder to detect, targets in this work will be assumed stationary. Moving targets can be considered in future work.

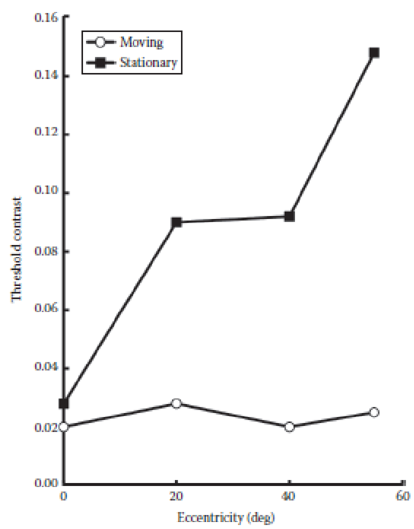


Figure 3.21: Threshold contrast plotted against eccentricity for stationary and moving bar pattern targets. (After Rogers, 1972.)

3.6.3.5 Chromatic contrast

Chromatic contrast refers to the contrast of colours, and colours are determined by the wavelengths emitted from the target. While luminance contrast depends on the total amount of light emitted from a stimulus and ignores the wavelengths, chromatic contrast depends on the colours of the stimulus and its background. Chromatic contrast is very important for the visibility of coloured objects with the presence of a coloured background. In fact, it is possible to detect a certain target with zero luminance contrast if there is a colour difference between the object and its background (Boyce 2003). Furthermore, at low luminance contrast values (less than 0.1 or 0.2), colour contrast is the prime factor that makes targets visible (Guth and Eastman 1970), (O'Donell and Colombo 2008).

While Adrian (1989) mentioned that colour differences between the target and its background can make the object visible, even if they have the same luminance. He neglected the effect of the chromatic contrast since road lighting visibility is mainly associated with brightness difference perception. In other words, Adrian (1989) suggests that at roadway lighting, there should be a luminance difference between the target and the background in order to perceive it. On the other hand, Raynham (2004) suggests that despite the shrinking of colour vision at low levels of lighting, colour contrast is still an important factor in vision and its importance becomes higher with the increase of traffic density on the road.

Although chromatic contrast is an important variable in defining the visibility of targets, it will not be considered in this study, due to its effect that is only measurable at low luminance contrast values. However, since it is an advantage for fuzzy models to be easily modified and revised, the possibility of including the effect of chromatic contrast in the proposed model can make good developments in future research.

3.6.3.6 Transient adaptation

When the visual system is not completely adapted to the surroundings, the adaptation luminance is changing dynamically over certain periods of time, this describes the case of transient adaptation. An example of this kind of adaptation is cases where there is a sudden change in retinal illumination such as entering a tunnel while day driving, or an event of power failure inside a building without daylight. Transient adaptation is usually unnoticeable indoors at normal conditions. Yet, it is substantial in a situation where the retinal illuminance gets sudden changes from high to low (Boynton and Miller 1963).

Adrian (1989) mentioned that changes in luminances perceived by the human eye will results in transient adaptation, where the threshold contrast (ΔL) will be higher than its normal values (steady-state value). However, when the difference in luminances does not overstep a certain value (± 2 log units), the transient adaptation will likely happen quickly and the threshold contrast will return to its steady-state value in almost 0.2 seconds.

Hence, it will be assumed that the transient adaptation problem is not significant enough to be considered in this model. This is based on Adrian's justification (1989) of the exclusion of transient adaptation in his model, and based on the assumption that this study is adopting normal driving conditions where the transient adaptation is unnoticeable (Boynton and Miller 1963). Future research can include incorporating the transient adaption in the propped model.

3.7 Fuzzification of visibility variables

Fuzzification is a process in which a certain crisp variable is converted into fuzzy. This is primarily possible if one can establish that the variable under consideration is not deterministic and carries a considerable amount of uncertainty due to imprecision, ambiguity, or vagueness (Ross 2017). Then, the variable can be represented using an appropriately designed membership function which can characterize the vagueness, or most accurately, the fuzziness of the variable. Membership function was first introduced by Zadeh (1965) in his first research paper "Fuzzy Sets".

The output of the fuzzy model is based on the fuzzification of the input/output parameters presented in the membership function. A membership function represents the degree of truth involved in a vaguely defined subset that is limited by the range from 0 to 1, where 0 defines a non-existent association with the variable subset and 1 defines full association. Consequently, values between 0 and 1 represents a partial association in the variable subset. This can be clearly understood by considering the temperature representation example shown in Figure 3.22. The figure on the left (a) shows a classical set for the temperature variable where the subsets "low", "medium" and "high" are bounded in a certain crisp (sharp) range of temperatures. Moreover, and temperature value will have a degree of truth of either 0 or 1 only in a certain subset. In other words, based on the classical set representation, temperatures can only be low, medium, or high, and when belonging to a certain subset, it has a full association with it and no association with the other subsets.

However, the fuzzy set allows for partial association with more than one subset, for example, the second graph (b) shows that temperatures between 30 ^{o}F and 70 ^{o}F can have partial association with the subset of low and medium at the same time, or the subset of medium and high depending on its value. In other words, the crisp boundaries in the classical set representation were changed into vague or smooth boundaries in the fuzzy set allowing the variable values to belong to one, two, or even three subset simultaneously.

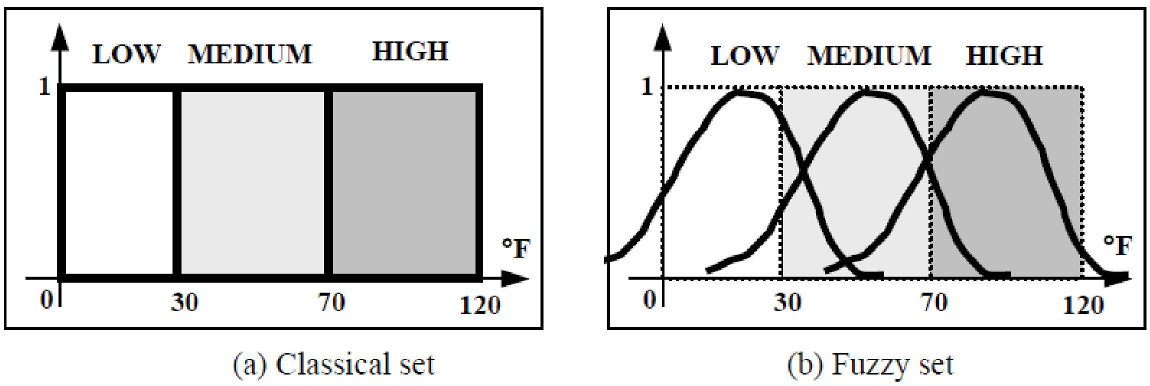


Figure 3.22: Representations of classical and fuzzy sets (Bai and Wang, 2006)

Hence, a fuzzy set allows a certain element to have a partial degree of membership in a certain subset and this value can be mapped to a universe of membership values. Assuming a fuzzy set A with element $\boldsymbol{x}$ as a member of this fuzzy set. This mapping can be donated mathematically as:

$$\mu_A(x) \in [0,1]$$
$$A = (x, \mu_A(x) \,|x \in X) \tag{3.24}$$

This means that a subset A with element x has a membership function of $\mu_A(x)$ in the universe of disclosure (X). If this unit of disclosure (X) is discrete and finite (as opposed to continuous and infinite), this mapping can be expressed as:

$$A = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots = \sum_i \frac{\mu_A(x_i)}{x_i} \tag{3.25}$$

An example of how this mapping works for a discrete universe of disclosure (X) is shown in Figure 3.23 where members x_1, x_2, and x_3 have a full membership in the subset (B) while members x_4 and x_5 have partial membership (0.7 and 0.3 respectively.). The mathematical expression associated with this mapping is as follows:

$$\mu_B(x) = \frac{1}{x_1} + \frac{1}{x_2} + \frac{1}{x_3} + \frac{0.7}{x_4} + \frac{0.3}{x_5} \tag{3.26}$$

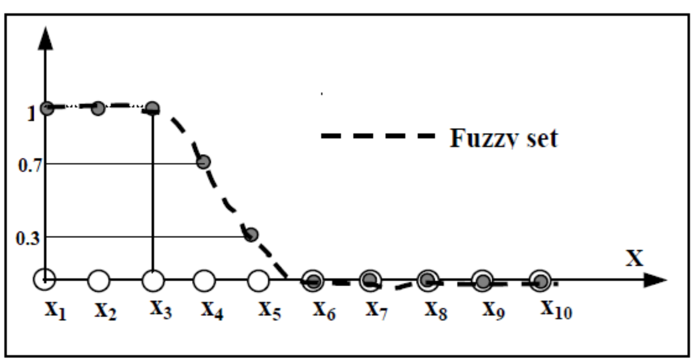


Figure 3.23: The comparison between classical and fuzzy sets. (Bai and Wang,2006)

Membership functions can take any shape or form as long as it describes the fuzziness incorporated within the variables under consideration and varies from 0 to 1. The most common membership function forms are triangular, trapezoidal, Gaussian, and Bell-shaped (Figure 3.24). However, despite the membership function from is very important for the outcome of the fuzzy logic system results, the number of membership functions involved in the representation of the variable, the total range of the variable, and the interval of each subset is also very important. For example, consider the representation of age as the variable under consideration, once can classify age subsets as {young, old, very old} where the total range is $[0 \rightarrow 100]$ years and intervals of {0, 50,100}. However, others can classify the same variable as {very young, young, old, very old} with a total range of $[18 \rightarrow 80]$ and intervals of {18, 45, 60, 80}.

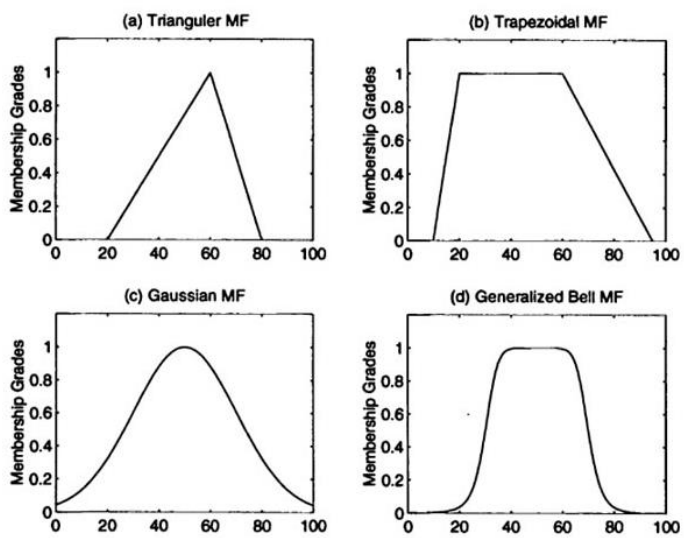


Figure 3.24: Examples of four classes of parameterized MFs: (a) triangle (x; 20, 60, 80); (b) trapezoid (x; 10, 20, 60, 95); (c) Gaussian (x; 50, 20); (d) bell (x; 20, 4, 50). (Researchhubs.com, 2015)

While there is no exact way or procedure to choose the membership function form, total range, and subset interval, the process is not merely arbitrary. Many studies tried to propose directions to select the appropriate membership function depending on the field of study (Wu, 2012), (Rutkowska 2016). However, these directions can be used for insights and recommendations. Simply because the actual design of the membership function depends on the nature of the problem such as its type and size, and more importantly, it depends on how one believes a certain variable can be represented in linguistic terms. The trial and error method is usually used for beginners. Yet, experience in fuzzy systems as well as the proper understanding of the nature of the variable plays the biggest part (Sadollah 2018).

Fuzzification of visibility parameters means changing the selected parameters from crisp values into fuzzy values. This process includes two major aspects; the first one is to find the best membership function that describes the variable based on the current literature and the second aspect is to represent this membership function with the proper linguistic terms. Fuzzification can be one of the most challenging processes in this work as visibility variables are included differently in the current models of visibility. Moreover, the effect of these variables on the visibility of targets has been studied by a large number of researchers. So adopting a certain method of representing the variables may conform to a single study and may not be in accordance with another study. Hence, the selection of the best method of fuzzification of any variable can be quite difficult as it includes studying a wide range of the available literature, especially the most recent, to have the most suitable membership function representation.

The membership function type (triangular, trapezoidal, Gaussian…etc.) as well as the range of the fuzzy variable has a great impact on the model results as well. The most basic membership functions are the triangular and trapezoidal types so they will be considered in this study for simplicity. The range of the fuzzy variable is decided based on the current literature as well as the suitable conditions affecting the night time visibility of targets. For example, for the variable of age, the selected range was from 18 to 80 years old which corresponds to the age of licensed vehicle drivers in most countries. While for the variable of retinal illuminance, the literature has been studied to determine the typical driving conditions at night, and calculations were made to determine the minimum and maximum values needed to define the range. However, some variables range has been extended to include more information such as visual size since the current models are limited to a certain visual size value such as the STV model (IESNA 2000), which is only considering targets with small visual size.

The following shows the method of Fuzzification for all independent visibility variables that were included in this model as well as FRVP itself, which is the output of the Fuzzy model based on relative visual performance.

3.7.1 Luminance contrast

The luminance contrast input parameter was fuzzified based on the RVP model developed by Rea (1986) Rea and Ouellette (1988 and 1991). It is believed that what defines the luminance contrast to be high or low is the way it affects the visual performance. This means that the luminance contrast can be considered as high if it yields to high RVP at relatively low values of background luminance (L_B) and vice versa. Figure 3.25 shows that luminance contrast value of 0.6 and above can provide and High RVP (above 0.92) at background luminance values around 15 cd/m^2, while a luminance contrast values of 0.2 and less are generally producing lower RVP values cannot provide high RVP unless the background luminance is almost doubled (around 30 cd/m^2). This shows that luminance contrast of 0.2 and 0.6 can provide appropriate boundaries that define the low and high contrast values respectively. In other words, a luminance contrast of 0.2 and below can be considered as low, and a luminance contrast of 0.6 and above can be considered as high. Consequently, the range between 0.2-0.6 can be considered as medium. The luminance contrast membership function is shown in Figure 3.26. The figure shows that the low luminance contrast has a 100% degree of membership in “low” when the values are between 0-0.2. Further increase in the luminance contrast (up to 0.4) means that the degree of membership in “low” is decreasing until it reaches 0% at 0.4, which defines the peak of the medium membership function subset (100 % degree of membership in medium). The range of between 0.2 to 0.4 marks a combination of low and medium contrasts with varying degrees of membership in both (partially low and medium). For example at a luminance contrast of 0.3, the degree of membership in “low” and “medium” contrast is 50%. The same applies to the range between 0.4 to 0.6 where the luminance contrast is having a partial membership degree in medium and high respectively. Luminance contrast values of 0.6 and above defines the “high” luminance contrast subset with a membership degree of 100% in “high”.

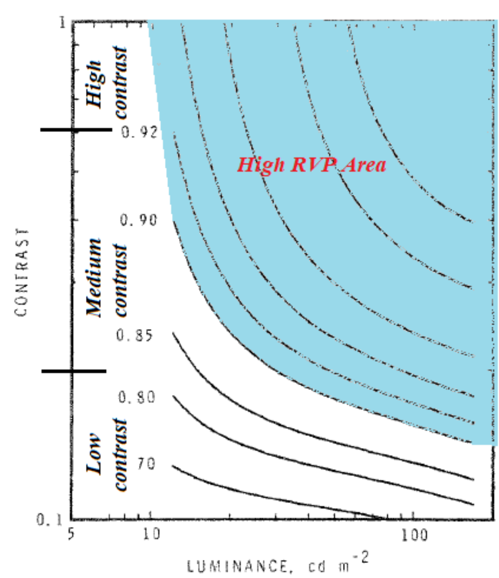


Figure 3.25: Luminance contrast fuzzy sets. (Rea and Ouellette 1991)

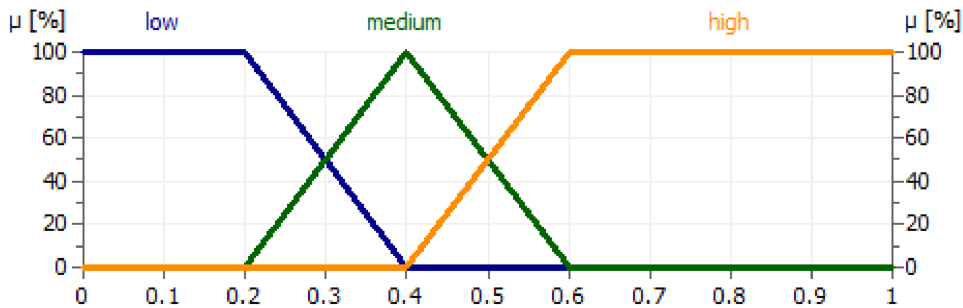


Figure 3.26: Luminance contrast membership function

The mathematical representation of the luminance contrast membership function is shown in the below equations

$$Luminance\ Contrast = \mu_C(x)$$

$$\textit{Where } 0 \leq x \leq 1 \textit{ and } \mu_C(x) \in [0 \rightarrow 1] \tag{3.27}$$

$$\mu_{C,low}(x) = \begin{cases} 1\,, & x < 0.2 \\ \dfrac{0.4 - x}{0.4 - 0.2}\,, & 0.2 \leq x \leq 0.4 \end{cases} \tag{3.28}$$

$$\mu_{C,medium}(x) = \begin{cases} \dfrac{x - 0.2}{0.4 - 0.2}\,, & 0.2 \leq x \leq 0.4 \\ \dfrac{0.6 - x}{0.6 - 0.4}\,, & 0.4 < x \leq 0.6 \end{cases} \tag{3.29}$$

$$\mu_{C,high}(x) = \begin{cases} \dfrac{x - 0.4}{0.6 - 0.4}\,, & 0.4 \leq x \leq 0.6 \\ 1\,, & x > 0.6 \end{cases} \tag{3.30}$$

The above membership function for representing the luminance contrast as an input variable for the FRVP model can be used if the contrast polarity is not considered. Indeed, it was used in the FRVP model before deciding to consider the contrast polarity. But with the presence of contrast polarity, the above membership function cannot be used unless considered as positive contrast then multiplied by the contrast polarity correction factor (F_{CP}) provided by Adrian (1989) as expressed in Eqn. (3.8). This method can be adopted as a shortcut expect that it does not really express the real case of negative contrast situations as positive contrast is only fuzzified, and negative contrast critical values, that should be explicitly included in the membership function, may not be accurate. Alternatively, it was decided to design two membership functions for both positive and negative contrast.

When it comes to seeing targets in outdoor driving conditions, pedestrians are seen under positive contrast until the distance between the driver and the pedestrian becomes short as shown in Figure 3.27 (Meyer and Gibbons 2001), where the luminance contrast values to the left of the intersection point between the target luminance line and the background luminance line represent negative contrast, and value to the right of the intersection point represents the positive contrast. This was justified by Meyer and Gibbons (2001) as when the distance between the observer and pedestrian is large, the background is more composed by the dark night sky behind the pedestrian, making the background darker than the target (positive contrast). Whereas, as the observer approaches closer to the pedestrian, the background becomes more composed of the road surface behind the pedestrian, which makes the background brighter than the target (negative contrast).

Some studies show that targets under negative contrast have longer recognition distance than those under positive contrast (Janoff 1994). Pedestrian contrast measured using an imaging photometer in lit streets showed contrast ranging from -0.55 to 6.56 (Tomczuk 2012). Pedestrian contrast can be very complex as the driver could see one part of the pedestrian and not the other part. This has led to the concept of dominant contrast (Saraiji and Oommen 2015). It is believed that a single and unique membership function for the luminance contrast cannot be developed. The membership function for the luminance contrast is a function of the context of the study and whether the visual task is outdoors or indoors.

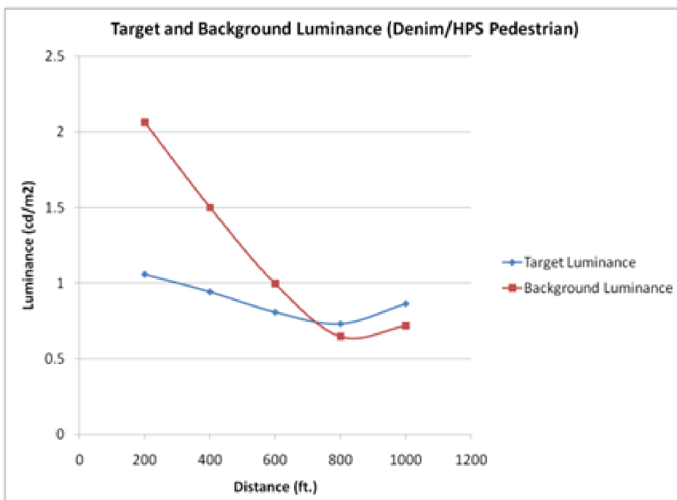
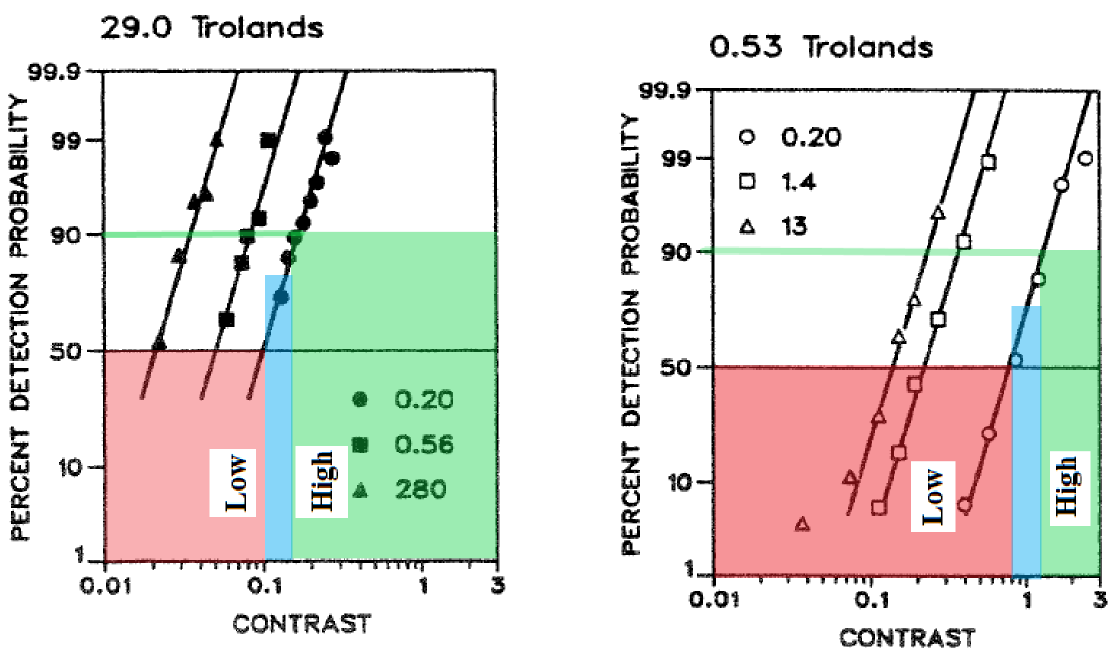


Figure 3.27: Comparison between target and background luminance as a function of distance. (Meyers and Gibbons 2011)

As a result, two membership functions have been developed to account for positive and negative contrasts based on the contrast sign convention proposed by Adrian (1989), which defines the target contrast as positive if the target is brighter than the background and vice versa. Figure 3.28 shows the Mean percentage probability of detection as a function of contrast for both decrement experiment (a) and increment experiment (b) developed by Rea and Ouellette (1988). For both cases, high contrast can be defined as the contrast that results in over 90% probability of detection for a small target seen at low retinal illuminance and small visual size while low contrast results in a 50% probability of detection under the same conditions. It should be noted that the range for retinal illuminances for the decrements and increments were different in Rea's experiment. Rea justified this as the data for increment experiment did not reach an apparent level of saturation under small targets and low retinal illuminances.

Hence, for decrement targets, the figure shows that 90% probability of detection can be achieved under a contrast of almost 1.2, and a probability of detection of 50% can be achieved at a contrast of almost 0.8. Similarly, for increment targets, high can be achieved under a contrast of almost 0.17 (say 0.2) while low contrast can be achieved at 0.1.



(a) *(b)*

Targets darker than the background (decrement targets) *Targets brighter than the background (increment targets)*

Figure 3.28: Mean percentage probability of detection as a function of contrast. (After Rea and Ouellette 1988)

Based on the above, the positive contrast membership function can be represented as shown in Figure 3.29

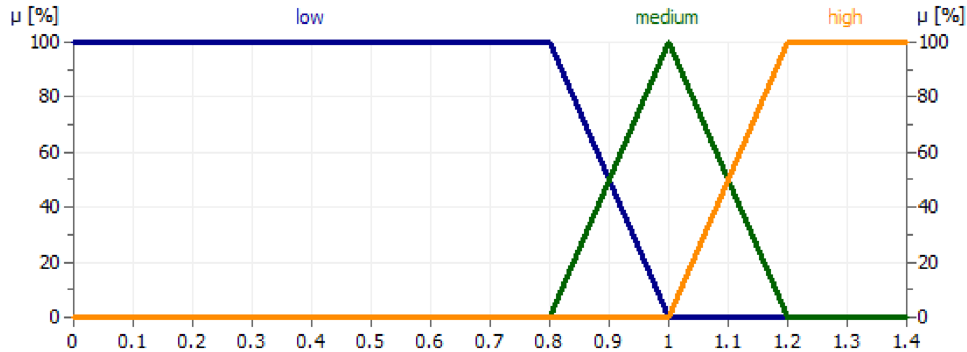


Figure 3.29: Positive contrast membership function

The mathematical representation for the positive contrast membership function can have the following form

$$Positive\ Contrast = \mu_C^+(x)$$

$$Where\ 0 \le x \le 1.4\ and\ \ \mu_C^+(x) \in [0 \to 1] \tag{3.31}$$

$$\mu_{C,low}^+(x) = \begin{cases} 1\,, & x < 0.8 \\ \dfrac{1-x}{1-0.8}\,, & 0.8 \le x \le 1.0 \end{cases} \tag{3.32}$$

$$\mu_{C,medium}^+(x) = \begin{cases} \dfrac{x-0.8}{1-0.8}\,, & 0.8 \le x \le 1.0 \\ \dfrac{1.2-x}{1.2-1}\,, & 1.0 < x \le 1.2 \end{cases} \tag{3.33}$$

$$\mu^{+}_{C,high}(x) = \begin{cases} \dfrac{x-1}{1.2-1}, & 1.0 \le x \le 1.2 \\ 1, & x > 1.2 \end{cases} \tag{3.34}$$

On the other hand, the negative contrast can be represented as per the membership function shown in Figure 3.30.

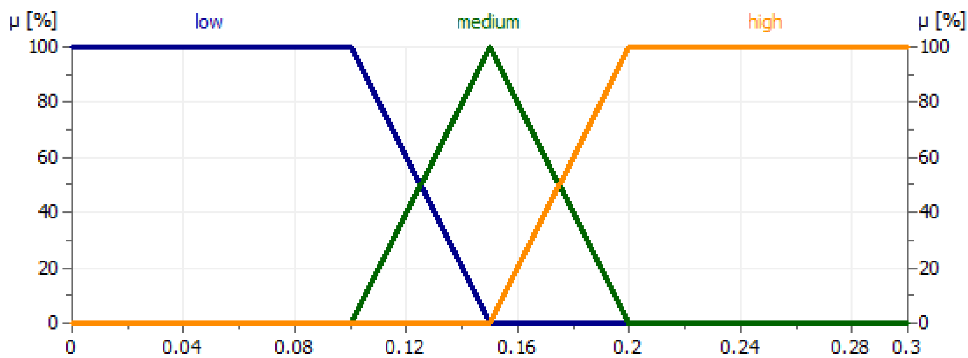


Figure 3.30: Negative contrast membership function

The mathematical representation for the negative contrast membership function can have the following form

$$Negative\ Contrast = \mu^{-}_{C}(x)$$

$$Where\ 0 \le x \le 0.3\ and\ \ \mu^{-}_{C}(x) \in [0 \rightarrow 1] \tag{3.35}$$

$$\mu^{-}_{C,low}(x) = \begin{cases} 1, & x < 0.1 \\ \dfrac{0.1-x}{0.15-0.1}, & 0.1 \le x \le 0.15 \end{cases} \tag{3.36}$$

$$\mu_{\bar{C},medium}(x) = \begin{cases} \dfrac{x - 0.1}{0.15 - 0.1}\,, & 0.1 \leq x \leq 0.15 \\[2ex] \dfrac{0.2 - x}{0.2 - 015}\,, & 0.15 < x \leq 0.2 \end{cases} \qquad (3.37)$$

$$\mu_{\bar{C},high}(x) = \begin{cases} \dfrac{x - 0.15}{0.2 - 0.15}\,, & 0.15 \leq x \leq 0.2 \\[2ex] 1\,, & x > 0.2 \end{cases} \qquad (3.38)$$

With the presence of two membership functions to describe the luminance contrast, the FRVP model will incorporate each one individually. This means that with the same model, positive contrast can be replaced with negative contrast depending on the conditions of the problem under consideration.

3.7.2 Visual age

The fuzzy nature of the age parameter can be attributed to the following factors: a) the impracticality of assuming a single age to a variety of observers, drivers and/or building occupants, b) the lack of reliable estimates of age-dependent light scatter in the crystalline lens (Rea and Ouellette 1991) and, c) the impact of light scatter on visual performance being dependent on the characteristics of the target.

Whereas the RVP model has a mathematical formula that accounts for the effect of age on retinal illuminance and therefore on visual performance, Rea and Ouellette (1991) point out that these equations should be considered “highly tentative”. Furthermore, the current RVP model is limited to the age group of 20-65 years and was based on experimental data that were obtained from young adults.

In the crisp membership function, the membership in the set of young age is either 1 or 0. On the other hand, using the characteristic function of a fuzzy set, the membership is 1 for age less than 20 and there are varying degrees of membership till the age of 40. The age 20 and 40 are dependent on the context of the study and could vary accordingly.

In the context of visual performance, one could give the term visual age to the fuzzy membership function. The experiments that were done to develop the RVP model were based on young subjects with a mean age of 21 years. To correct for the effect of age Rea (1991) used an age factor to reduce the retinal illuminance(I_r), measured in Trolands. The argument here is that the age reduces(I_r). The RVP will be the same for two situations with the same(I_r). For example, for an observer who is 60 years for age, the *Ir* can be corrected using:

$$I_r = PL_A\pi r^2 \tag{3.39}$$

$$P = 1 - 0.017(age - 20) \tag{3.40}$$

Whereby L_A is the photopic adaptation luminance in cd/m^2 and r is the pupil radius in mm. The reduction in Trolands will result in a reduction in retinal contrast. Rea and Ouellette (1991) cautioned that those equations should be considered tentative because the impact of light scatter within the eye is affected by the spatial characteristics and the size of the target. The notion that the spatial characteristics of the target does not affect visual performance is true only for the same age group. As the eye ages, the spatial characteristics of the target start to influence visual performance.

As shown in the previous sections. Age is one of the most important factors in defining the visibility of targets. Indeed, age is also a significant factor in lighting applications in general. The multiple of threshold contrast required for an observer of higher age relative to younger age observers Figure 3.31 developed by Blackwell and Blackwell (1980) was found to be suitable to define the membership function of visual age in the current model.

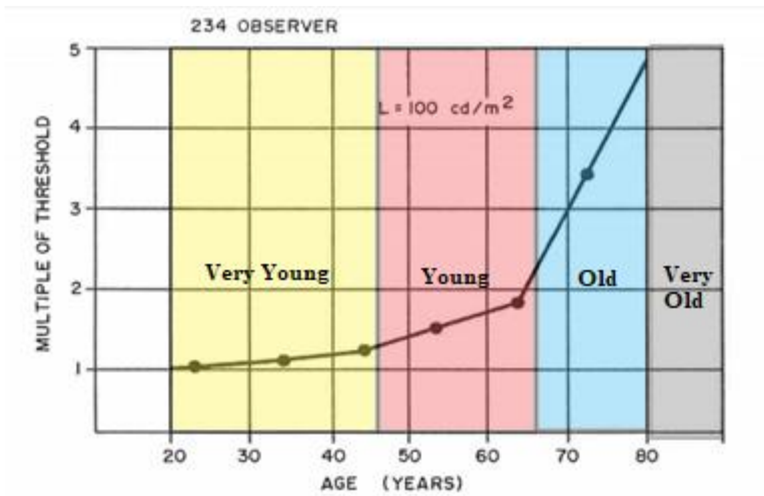


Figure 3.31: Visual age fuzzy sets based on multiple of the threshold contrast required for higher age observers (after Adrian, 1989).

The figure shows that there is no significant difference in the multiple of threshold value for ages between 20 to almost 42.5 years old, this means that this age group has the same characteristics with respect to visibility even though the age varies. Hence, this age group can be considered as the "very young" age group. The figure also shows that there is a significant difference in the multiple of threshold contrast between the age groups from 42.5 years to almost 67.5 years and from 67.5 years to 80 years. This suggests that ages above 42.5 can be considered as young while ages between 67.5 to just below 80 can be considered as old. However, despite the range of the ages presented in the graph ends at 80 years, the slope of the curve for the old age group (67.5-80) is very steep. This suggests that if the curve was continued, it will show a significant difference between age groups below and above 80 years of old.

Hence, it was decided to add an extra age group of "Very old" for observers above 80 years. The disadvantage in having more subsets is that it will increase the complexity of the fuzzy rules used as well as the time needed in the process of fuzzification and de-fuzzification

Based on this, the membership function of the age was developed and shown in Figure 3.32

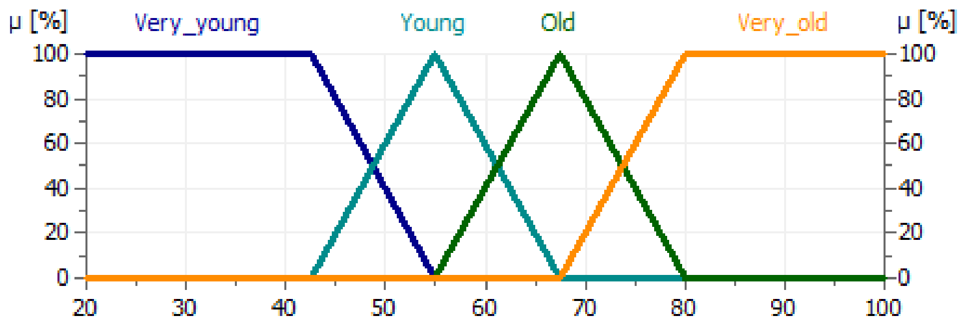


Figure 3.32: Visual age membership function

The mathematical representations of the visual age membership function is shown in the below equations

$$Visual\ Age = \mu_A(x)$$

$$Where\ 20 \leq x \leq 100\ and\ \mu_A(x) \in [0 \rightarrow 1] \tag{3.41}$$

$$\mu_{A,very\_young}(x) = \begin{cases} 1\,, & x < 42.5 \\ \dfrac{55 - x}{55 - 42.5}\,, & 42.5 \leq x \leq 55 \end{cases} \tag{3.42}$$

$$\mu_{A,young}(x) = \begin{cases} \dfrac{x-55}{55-42.5}, & 42.5 \leq x \leq 55 \\ \dfrac{67.5-x}{67.5-55}, & 55 < x \leq 67.5 \end{cases} \tag{3.43}$$

$$\mu_{A,old}(x) = \begin{cases} \dfrac{x-67.5}{67.5-55}, & 55 \leq x \leq 67.5 \\ \dfrac{80-x}{80-67.5}, & 67.5 < x \leq 80 \end{cases} \tag{3.44}$$

$$\mu_{A,very\_old}(x) = \begin{cases} \dfrac{x-67.5}{80-67.5}, & 67.5 \leq x \leq 80 \\ 1, & x > 80 \end{cases} \tag{3.45}$$

3.7.3 Visual size

The size of the target is an important independent variable that determines visual performance. In this context, the visual size of the target is measured in a solid angle unit of (Steradians) which takes into account the dimensions of the target, inclination relative to the visual axis, and how far the target is from the eye.

What determines a size to be small or large is our visual performance in seeing (or not seeing for that matter) the target within the context of particular luminous conditions.

The solid angle w can be approximated by using the following equation

$$w = \frac{A\cos\theta}{D^2} \tag{3.46}$$

Whereby A is the area of the target, D is the distance between the eye and the target, and θ is the inclination angle.

The membership function can be determined by finding the relative visual performance value (Rea and Ouellette 1991) of various visual sizes. For example, the visual size of 130 Microsteradians will make most of the RVP values greater than 0.8 which is the Plateau region of RVP, and would, therefore, be classified as a large size. On the other hand, a visual size of 1.9 Microsteradians, will need high contrast and high retinal illuminance to get the RVP into the plateau region and would, therefore, be classified as small.

Different visual sizes were calculated based on common stopping distance for a vehicle traveling at 100km/hr (AASHTO 2011) and common obstacles that could be found in roadways and they are shown in Table 3.3 and Figure 3.33. The importance of this step was to get an idea of how to characterize the size in terms of small and large from a practical point of view. The stopping distance of (AASHTO 2011) was used in a driving task as a way to give an idea of the visual sizes that could be encountered.

Hence, a small size target can be defined as the target that results in high threshold contrast given a high retinal illuminance (0.53 Trolands). From Figure 3.34, we find this to be 3 Microsteradians which is equivalent to a cat seen from a 185-meter distance as per Table 3.3. On the other hand, a target of large size is the one that results in low threshold contrast given a low retinal illuminance, which gives us a value of 20 Microsteradians this is equivalent to a 165 cm tall pedestrian seen from 185 meters. A square box of 20x20 cm, which is the size of the target used in the STV model (IESNA 2000), seen from 185 m distance results in a visual size of 1 Microsteradian. The proposed fuzzy set of target size is shown in Figure 3.34 and the visual size membership function is shown in Figure 3.35.

Table 3.3: solid angle for some obstacles that could be encountered in a driving task.

Speed 100 km/hr. Stopping distance = 185 m			
Target	Height x Width (cm x cm)	Area (m^2)	Visual Size (Microsteradians)
Square box	20x20	0.04	1
Human	165x40	0.66	19
Cat	25x45	0.11	3
Still car	145x185	2.66	78
Child	100 x 40	0.40	12

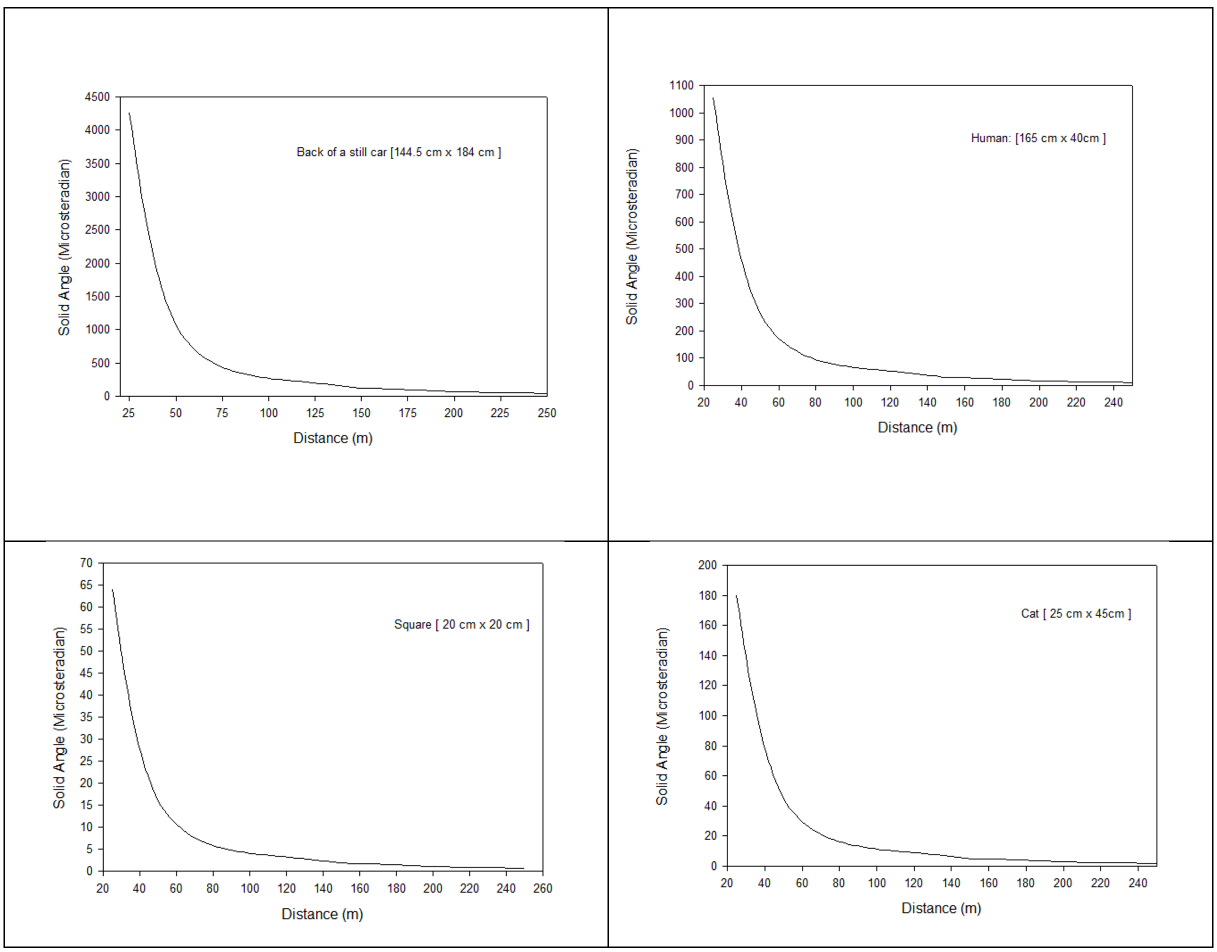


Figure 3.33 Solid angle subtended by a still car, Human, 20x20 cm square and a cat located at the fixation line of sight as a function of the distance between the observer and the standing vehicle.

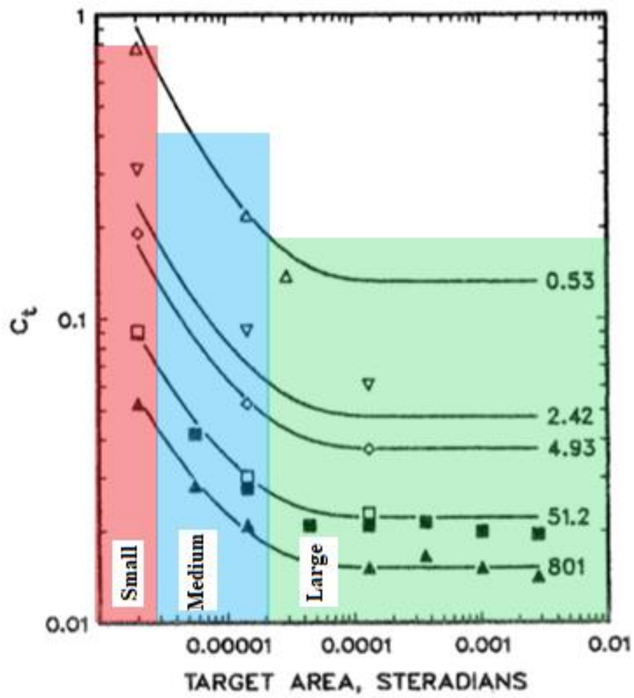


Figure 3.34 Visual size fuzzy sets based on threshold contrast as a function of target size (steradians) for positive and negative contrast and different retinal illuminances.(after Rea and Ouellette 1988)

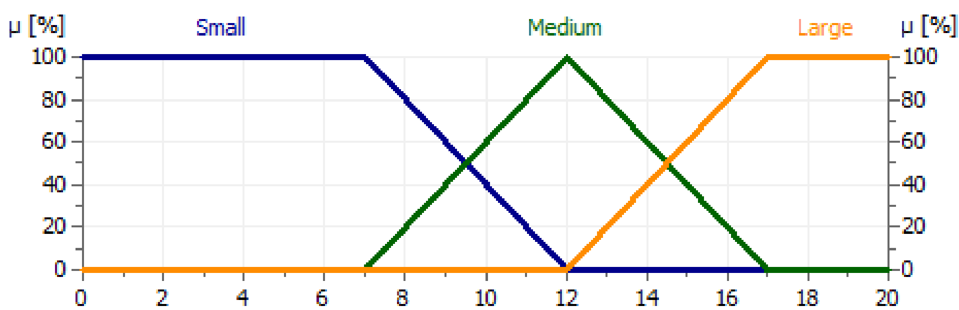


Figure 3.35: Visual size membership function

The mathematical representation of the visual size membership function is shown in the below equations:

$$Visual\ Size = \mu_S(x)$$

$$Where\ 0 \leq x \leq 20\ and\ \mu_S(x) \in [0 \rightarrow 1] \tag{3.47}$$

$$\mu_{S,small}(x) = \begin{cases} 1\,, & x < 7 \\ \dfrac{12 - x}{12 - 7}\,, & 7 \leq x \leq 12 \end{cases} \tag{3.48}$$

$$\mu_{S,medium}(x) = \begin{cases} \dfrac{x - 7}{12 - 7}\,, & 7 \leq x \leq 12 \\ \dfrac{17 - x}{17 - 12}\,, & 12 < x \leq 17 \end{cases} \tag{3.49}$$

$$\mu_{S,large}(x) = \begin{cases} \dfrac{x - 12}{17 - 12}\,, & 12 \leq x \leq 17 \\ 1\,, & x > 17 \end{cases} \tag{3.50}$$

3.7.4 Retinal illuminance

To use an exact value for adaptation luminance in a visibility model is impractical. This is because the eye is in a constant state of adaptation. In a day-lit office, for example, the eye could adapt to the luminance of the sky, then to the luminance of the computer screen, then to the luminance of the desk, etc.

In real-life scenarios, pupil size is rarely constant and the pupil is in constant adaptation. The eccentricity is also not fixed especially in driving situations whereby the car is in motion and the target could be standing still or moving. The fuzziness of these variables renders the adaptation luminance to be fuzzy. Hence, the retinal illuminance can be used as a measure of adaptation luminance. The amount of light entering the eye is often referred to as retinal illumination and is measured in Trolands.

To have an idea about the retinal luminance in practice, practical values of adaptation luminance (cd/m^2) were collected from different resources and represented in Figure 3.36. This step was necessary to select the range of adaptation luminance values encountered in typical night-time driving situation. The figure (in log scale) shows that 100,000 cd/m^2 can be used as a good approximation for high adaptation luminances. Then, Figure 3.12 was studied in order to find the average ocular transmittance for different age groups at wavelengths corresponding to the visible light. The results are shown in Table 3.4.

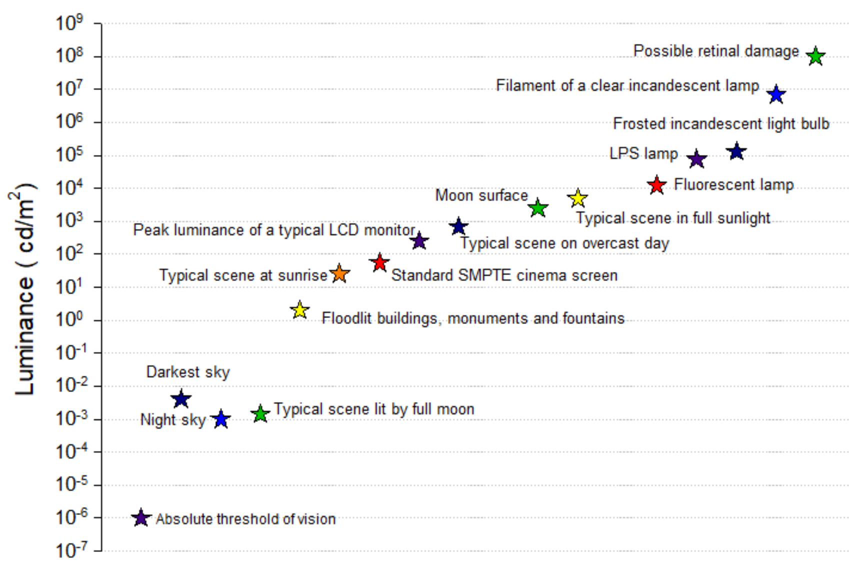


Figure 3.36: Example of luminances for different targets and scenes

Table 3.4: ocular transmittance for different age groups

Age (years)	τ (%)
20	75
40	70
60	61
80	54
90	51

Finally, the retinal illuminance was calculated using equation (3.16) considering a range between 0 and 100,000 for the adaptation luminance. The results are shown in Figure 3.37, the figure shows the relation between the retinal illuminance and the adaptation luminance (in log scale) and based on ocular transmittance data obtained from (Chaopu et al. 2018). Hence, a range of retinal illuminance from 0 to 100 was selected. Values of 0 retinal illuminance corresponds to situations lower than the threshold of vision. While retinal illuminance value of 100 corresponds to an adaptation luminance of almost 5,000 (Figure 3.37), which is almost to the same as the typical scene in full sunlight (Figure 3.36).

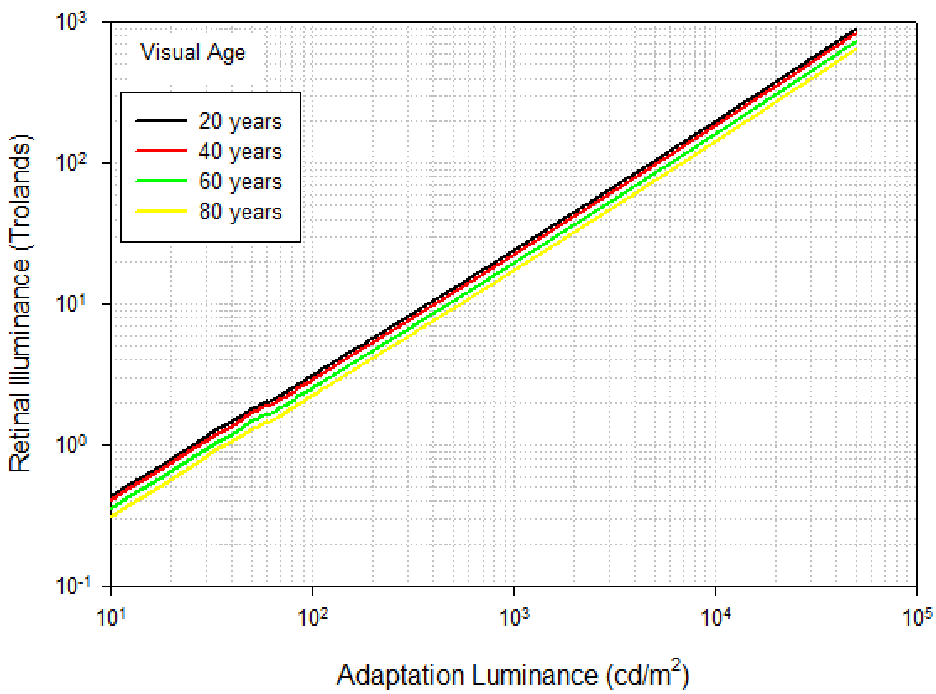


Figure 3.37: relation between retinal illuminance and the adaptation luminance (in log scale)

A high retinal illuminance can be defined as the one that results in a threshold contrast of less than 0.1 for the smallest visual size target (0.2 Microsteradians), based on the work of Rea and

Ouellette (1988) and shown in Figure 3.38. This makes a retinal illuminance of 30 Trolands or more to be high. A low retinal illuminance can be defined as the one that results in a threshold contrast greater than 0.6 which leads to a value of 0.8 Trolands or less. The membership function of the retinal illuminance fuzzy set is shown in Figure 3.39.

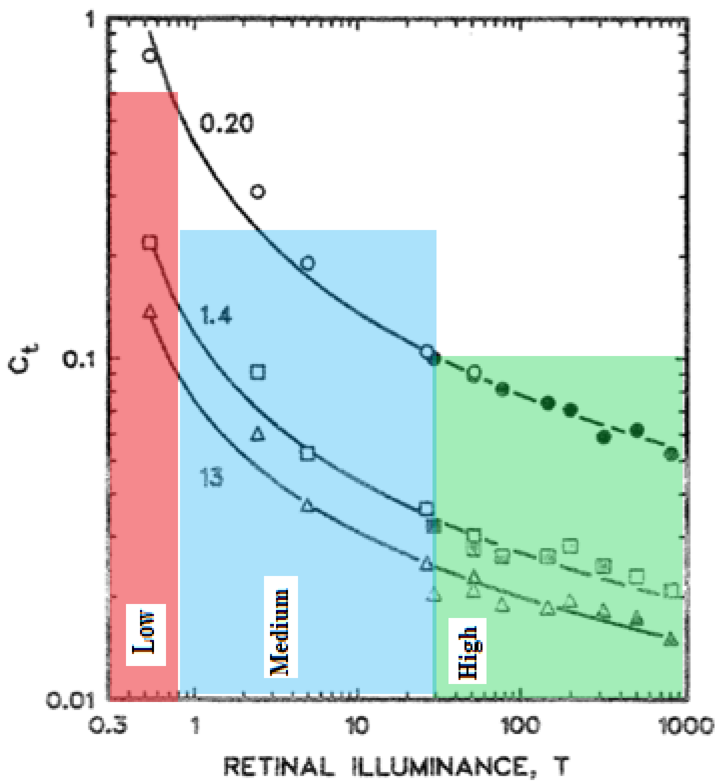


Figure 3.38 Retinal illuminance fuzzy sets based on threshold contrast as a function of retinal illuminance. (After Rea and Ouellette 1988)

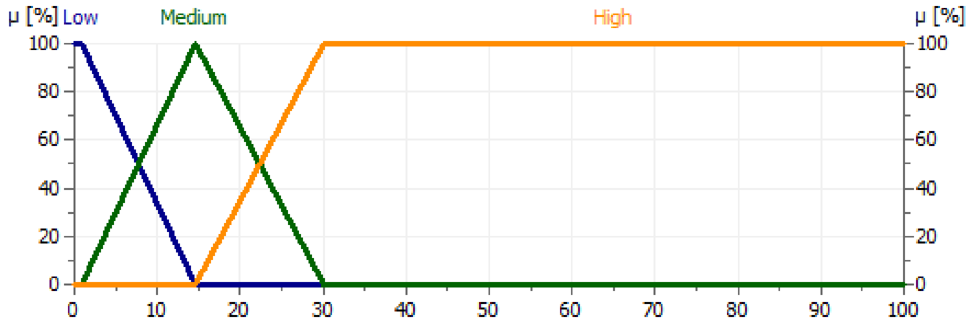


Figure 3.39: Retinal illuminance membership function

The mathematical representation of the retinal illuminance is shown in the below set of equations

$$Retinal\ illuminance = \mu_R(x)$$

$$Where\ 0 \le x \le 100\ and\ \mu_R(x) \in [0 \to 1] \tag{3.51}$$

$$\mu_{R,low}(x) = \begin{cases} 1\,, & x < 0.8 \\ \dfrac{14.6 - x}{14.6 - 0.8}\,, & 0.8 \le x \le 14.6 \end{cases} \tag{3.52}$$

$$\mu_{R,medium}(x) = \begin{cases} \dfrac{x - 0.8}{14.6 - 0.8}\,, & 0.8 \le x \le 14.6 \\ \dfrac{30 - x}{30 - 14.6}\,, & 14.6 < x \le 30 \end{cases} \tag{3.53}$$

$$\mu_{R,high}(x) = \begin{cases} \dfrac{x - 14.6}{30 - 14.6}\,, & 14.6 \le x \le 30 \\ 1\,, & x > 30 \end{cases} \tag{3.54}$$

3.7.5 Eccentricity

The position of the target relative to the fixation line of sight is termed eccentricity. The eccentricity of the target can have a membership function with linguistic terms as: a) within the visual axis, b) away from the visual axis, c) far from the visual axis.

One can define the eccentricity based on the probability of detecting a target (Inditsky et al. 1982). Figure 3.40 shows the probability of detecting a target based on eccentricity. In this work, a target contrast of 0.08 and a size of 10 min of arc will be used to define the membership function of eccentricity. As can be deduced from Figure 3.40, a target with $\theta >$ 20 degrees will have less than 15% chance of detection whereas targets within 6 degrees of the visual axis will have more than 60% chance of detection. The membership function of the eccentricity fuzzy set is shown in Figure 3.41.

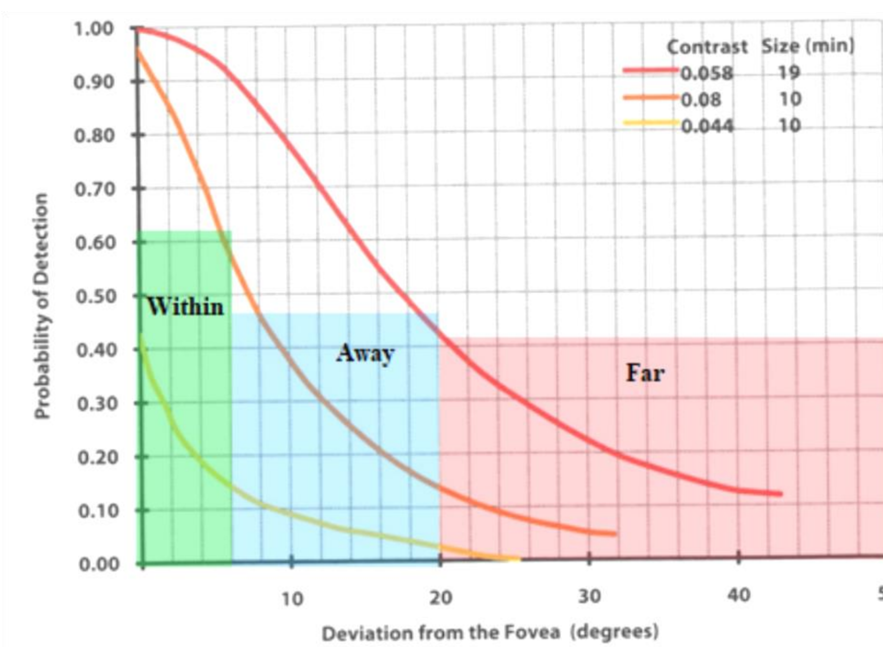


Figure 3.40: Eccentricity fuzzy sets based on the probability of detecting a target as a function of the angle from the fixation visual axis. (Inditsky et al.. 1982)

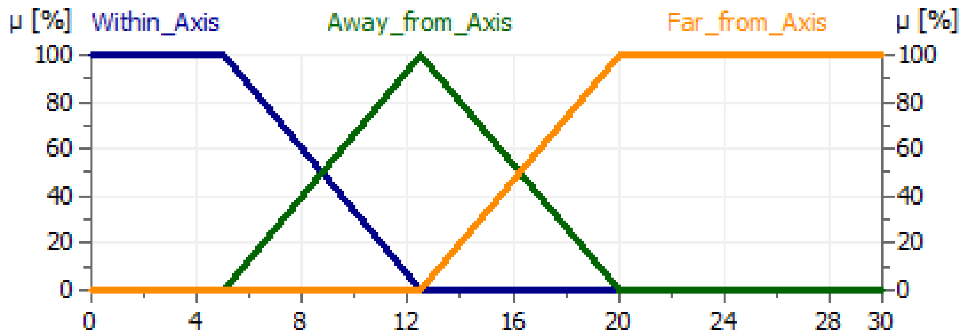


Figure 3.41: Eccentricity membership function

The eccentricity membership function is represented mathematically by the following set of equations:

$$Eccentricity = \mu_E(x)$$
$$Where\ 0 \leq x \leq 30\ and\ \mu_E(x) \in [0 \rightarrow 1] \tag{3.55}$$

$$\mu_{E,within\_axis}(x) = \begin{cases} 1\,, & x < 5 \\ \dfrac{12.5 - x}{12.5 - 5}\,, & 5 \leq x \leq 12.5 \end{cases} \tag{3.56}$$

$$\mu_{E,Away\_from\_axis}(x) = \begin{cases} \dfrac{x - 5}{12.5 - 0.5}\,, & 5 \leq x \leq 12.5 \\ \dfrac{20 - x}{20 - 12.5}\,, & 12.5 < x \leq 20 \end{cases} \tag{3.57}$$

$$\mu_{E,far\_from\_axis}(x) = \begin{cases} \dfrac{x - 12.5}{20 - 12.5}\,, & 12.5 \leq x \leq 20 \\ 1\,, & x > 20 \end{cases} \tag{3.58}$$

3.7.6 Background Complexity

As seen in the previous chapter, background complexity can be represented using the entropy of the driving scene image. With the use of image processing techniques, image entropy (measured in bits) measures the level of information content enclosed with a certain driving scene image. A low image entropy defines a low complexity driving scene and a high image entropy defines a high complexity driving scene. A typical driving scene can have an image entropy value of 6.5-7.5 bits (measured).

To measure entropies of different driving scenes, the Matlab image processing toolbox has been used, then a code has been written (by the author of this work) to measure the entropy of RGB images (Red, Green, Blue). The first step of the calculation is to split the image into 3 channels corresponding to RGB scheme. This allows Matlab to generate a colour map that includes the primary RGB colours as well as their degrees in any colour component included within the image. Then the colour value distribution showing the frequency of occurrence for each colour level value with respect to the colour intensity levels is plotted. This plot is called the image histogram and is shown in Figure 3.42 andFigure 3.43.

An image histogram is generated by defining equally spaced data values corresponding to the RGB colour intensities called bins, then calculating the number of RGB colour pixels included in each bin range. By defaults, Matlab uses 256 bins for grey-scale and RGB colours histogram generation (Figure 3.43). The next step is to calculate the probability associated with a certain colour intensity level (p_k) by converting the histogram data counts into three vectors corresponding to the RGB colours. This means that for each RGB channel and its components, a vector of 256 entries will be generated to represent the data enclosed within the image histogram.

As this study is related to night-time driving, where the background is dark enough to be considered as black, it is important to get rid of zero entries enclosed in each RGB colour histogram for two reasons; the first one is related to the entropy of the black colour (H=0), which makes it mathematically impossible to continue with the calculation (the dominator in the next equations will be zero). The second reason is related to the ability of such extremely dark colours to dominate the value of entropy by lowering its values, and since all night-time driving scenes have the common dark (almost black) background, it is better to neglect its effect.

Figure 3.42: Colorful houses and boats in Burano Island, Italy (Shutterstock 2018)

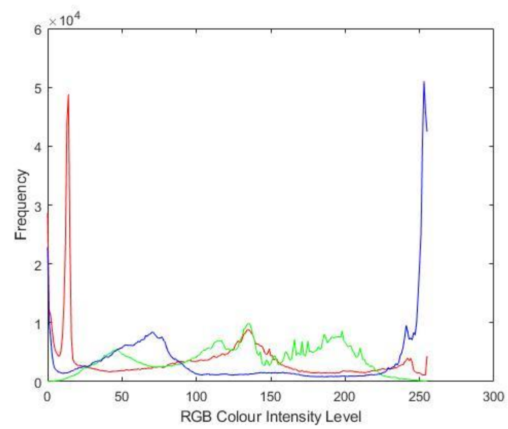


Figure 3.43: RGB image histogram for Figure 3.24 (by author)

As images differ in size and resolution, it is very important to consider the dimension of the image. Hence, the data obtained from the image histogram are normalized with respect to the total number of pixels. This is usually done by dividing the RGB channel data by the total number of pixels in the image in order to ensure that the sum of all entries of each RGB vector will be equal to 1.

The next step is to calculate the image entropy (H) for each RGB colour channel using the below equation (Shanon 1948):

$$H = -\sum_{k} p_k log_2(p_k) \tag{3.59}$$

However, the result will be three image entropies for each RGB channel. The average can be taken as a metric of information content stored within the image (Laskar and Hemachandran 2012). However, average calculations are usually sensitive to extreme values, which means that if there is an eccentric value associated with any colour frequency at a certain pixel, it will shift the average entropy value towards itself resulting in either underestimating or overestimating the value of the image entropy. In other words, this means that the calculated image entropy in such a case will be largely affected by the dominating colour, and loosely associated with the distracting items within the night driving environment (billboards, building lights, and traffic lights….etc.)

Hence, another method of obtaining the combined image entropy of the driving scene was used. This method involves converting (vectorizing) the RGB channel data into a vector with a number of entries equal to the total number of entries for the three individual vectors together. In other words, the resulting vector will be having a total number of 768 entries, which is the summation of three entries of 256 each. This method is inspired by the need to measure the background complexity by defining a metric for the non-homogeneous distribution of colours due to the distractions enclosed within a driving scene. Hence, even if the values of the combined image entropy is based on a higher number of entries (768 instead of 256), it is considerably more accurate than using a largely shifted average image entropy value that is affected by any dominating colour within the night-driving scene

Then the combined image entropy (H) can be calculated for the image using equation ((3.59). This value of entropy reflects the actual relations between the RGB colours and is more accurate than using the average entropy for three individual RGB colours. To make things easier, a Matlab-based computer software has been generated to calculate the entropy of different driving scene images. The software allows the user to browse into the selected image, then gives the value of the entropy. Table 3.5 shows the entropy of different images calculated using the RGB entropy software.

Table 3.5: Image entropy for different driving scenes

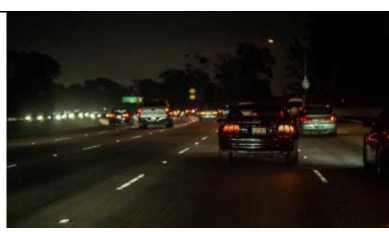
Image	RGB Entropy	Classification
	1.99 bits	Low complexity
	2.561 bits	Low complexity
	5.928 bits	Low Complexity

Image	RGB Entropy	Classification
	6.464 bits	Medium Complexity
	7.498 bits	High Complexity
	7.834 bits	High Complexity

However, since the concept of image entropy is not so familiar outside the computer and image processing community, it was decided not to use the scale of entropy as an input for the model. Instead, a new scale has been created to map background complexity to image entropy. The scale ranges from 1 to 3 where 1 corresponds to the lowest complexity, 2 for medium, and 3 for the highest complexity. The reason for not using a larger scale is that the scale itself can be considered as fuzzy. This means that the user can choose any value between 1 and 3, including non-integer values. While other scales are crisp, which enables the user to select crisp values only such as 1, 2, or 3. This gives more convenience to lighting professionals to decide on the degree of complexity of the background. At the same time, the FRVP software enables the user to either use the proposed scale and select any value between 1 and 3 based on his judgment, or browse for a certain driving scene image in which the entropy will be calculated and mapped to the background complexity scale, then used as an input for the FRVP model. The proposed scale is shown in Table 3.6.

Table 3.6: Background complexity mapping to image entropy of the driving scene

Background complexity scale	Image entropy range (bits)
1 (Low)	0.0-6.4
2 (Medium)	6.5 – 7.4
3 (High)	≥ 7.5

Hence, the membership function for the background complexity can be presented in Figure 3.44

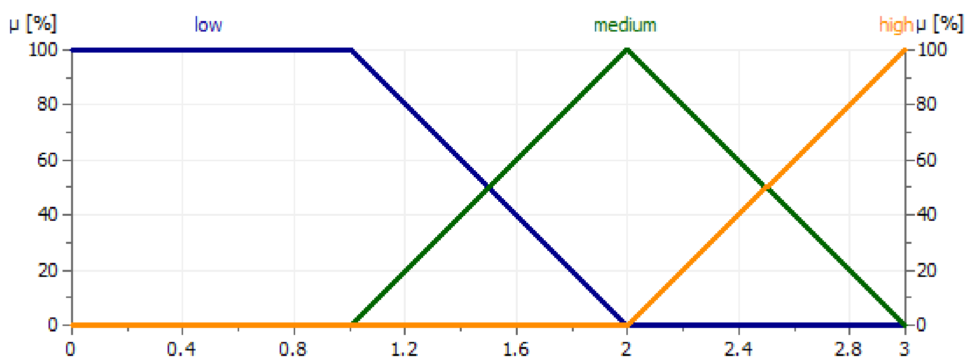


Figure 3.44: Background complexity membership function:

The Background complexity membership function is represented mathematically by the following set of equations

$$Background\ complexity = \mu_B(x)$$

$$Where\ 0 \leq x \leq 3\ and\ \mu_B(x) \in [0 \rightarrow 1] \tag{3.60}$$

$$\mu_{B,low}(x) = \begin{cases} 1\,, & x < 1 \\ \dfrac{2-x}{2-1}\,, & 1 \leq x \leq 2 \end{cases} \tag{3.61}$$

$$\mu_{B,medium}(x) = \begin{cases} \dfrac{x-1}{12-1}\,, & 1 \leq x \leq 2 \\ \dfrac{3-x}{3-2}\,, & 2 < x \leq 3 \end{cases} \tag{3.62}$$

$$\mu_{B,high}(x) = \begin{cases} \dfrac{x-2}{3-2}\,, & 2 \leq x < 3 \\ 1 \quad . & x = 3 \end{cases} \tag{3.63}$$

3.7.7 Visual performance

FRVP stands for Fuzzy Relative Visual Performance and it is the output of the visibility fuzzy logic model under consideration. RVP model (Rea and Ouellette 1988, 1991) is the base considered while developing the membership function of FRVP. Figure 3.45 shows a 3D representation of RVP as a function of luminance (candela/m^2) and contrast. The figure shows that there is a certain value of RVP that are located at the upper plateau region and considered as high RVP, the plateau approximately includes all values of RVP from 0.9 to 1.0. The figure also shows that at the RVP value of 0.8 and below the curve stars decreasing dramatically until it reaches the lowest value of 0.2. The curve shows that at a contrast values of 0.1 for example, increasing the luminance values to the maximum does not have any significant effect in increasing RVP. The same applies to low values of luminance where increasing the contrast does not help in increasing RVP values.

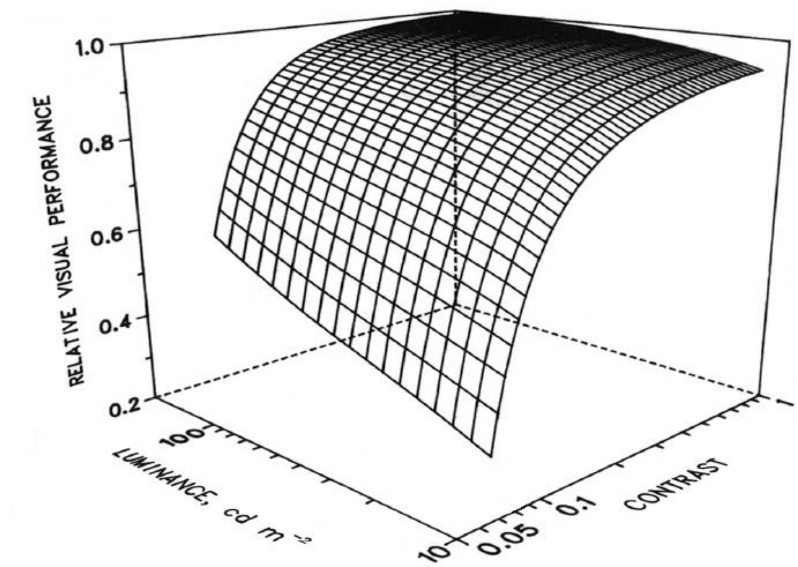


Figure 3.45: RVP model 3D presentation (Rea and Ouellete 1991)

Hence, the same approach was considered for developing FRVP membership function where any value above 0.9 is considered high and has a membership value of unity, in other words, it has a degree of membership of 1 in high FRVP. The lower limit of FRVP was selected to be 0.5 as it is the average of FRVP values which has a range from 0 to 1. This means that all FRVP values of 0.5 and below are considered low FRVP and has a degree of membership of 1 in low FRVP. Consequently, FRVP values of between 0.5 to 0.9 are not low and not high either, they are something in between having a certain degree in membership in both low and high. Figure 3.46 shows the membership function of FRVP based on the above criteria.

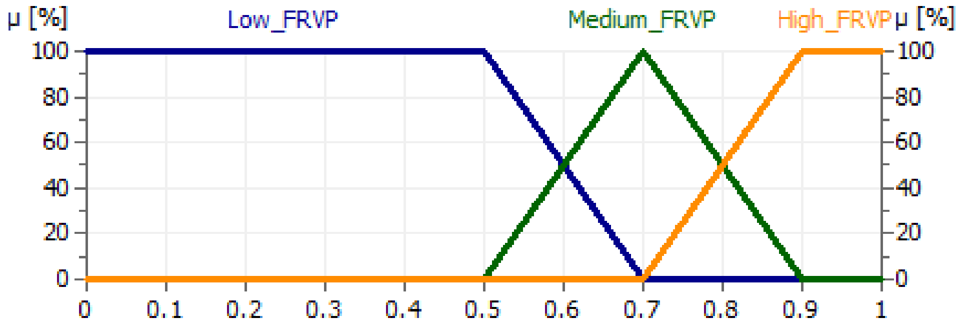


Figure 3.46: Fuzzy relative visual performance (FRVP) membership function

The mathematical representation of the FRVP membership function is shown in the below set of equations

$$Fuzzy\ Relative\ Visual\ Performance = FRVP = \mu_F(x) \tag{3.64}$$

$$\textit{Where } 0 \leq x \leq 1 \textit{ and } \mu_F(x) \in [0 \rightarrow 1]$$

$$\mu_{F,low\_FRVP}(x) = \begin{cases} 1, & x < 0.5 \\ \dfrac{0.7 - x}{0.7 - 0.5}, & 0.5 \leq x \leq 0.7 \end{cases} \tag{3.65}$$

$$\mu_{F,medium\_FRVP}(x) = \begin{cases} \dfrac{x - 0.5}{0.7 - 0.5}, & 0.5 \leq x \leq 0.7 \\ \dfrac{0.9 - x}{0.9 - 0.7}, & 0.7 < x \leq 0.9 \end{cases} \tag{3.66}$$

$$\mu_{F,high\_FRVP}(x) = \begin{cases} \dfrac{x - 0.7}{0.9 - 0.7}, & 0.7 \leq x \leq 0.9 \\ 1, & x > 0.9 \end{cases} \tag{3.67}$$

3.8 Indoor illuminance variables

The fuzzy indoor illuminance model (FIIL) employs three input variables and one output. The input variables are the visual age, task difficulty, and task characteristics. The output of the model is the fuzzy illuminance in lux. Figure 3.47 shows the FIIL model input and output variables. Although uniformity was not considered in the FIIL model development, horizontal illuminance is often specified with illuminance uniformity as a design criterion for indoor lighting. Hence, a membership function was designed for illuminance uniformity (average/minimum) and was used in the FIIL software only to check the illuminance uniformity based on the user calculated uniformity.

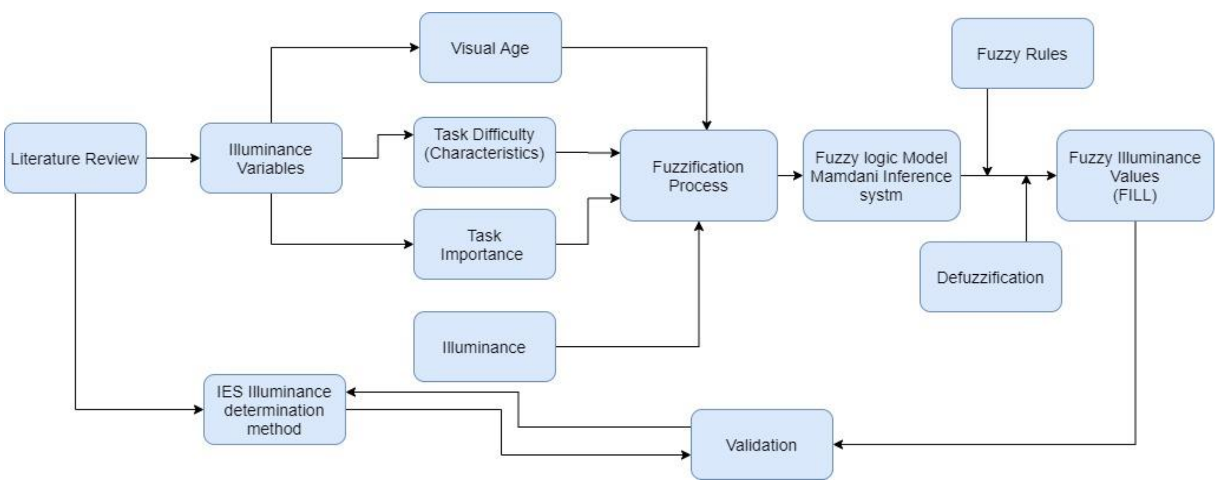


Figure 3.47: Indoor illuminance selection method (FIIL) flow chart

3.8.1 Visual age

The effect of visual age on vision has been studied in previous sections (see page 80). The main effect of age was found related to reducing the amount of light entering the human retina. This is mainly due to the decreasing in the transmittance of the human ocular media

(Figure 3.12), which allows for less amount for light to enter the human eye. Moreover, older persons are less able to adapt to low light levels compared to young people (Weale 1982). This is due to the decrease in the capability of the pupil to increase/decrease its area based on the amount of light level reaching the eye (Figure 3.5).

The illuminance determination procedure established by the IES lighting handbook (DiLaura et al. 2011) provided illuminance recommendations based on visual age groups. Observer visual age was categorized into three categories, below 25 years, between 25 to 65 years and above 65 years old. However, to use these recommendations, it is necessary to make sure that 50% or more of observers occupying the space under consideration belong to a certain age group.

The membership function for visual age used in the FRVP model (Figure 3.32) was developed in earlier sections (see page 126) where four visual age subsets were introduced {very young, young, old, very old} based on critical values obtained from the multiple of the threshold contrast required for higher age observers (Figure 3.31- after Adrian 1989). The utilizing of four visual age subset for the FRVP model was done as the FRVP model was studied in road lighting context, where the degree of hazard resulted from collisions and accidents is much higher than indoor lighting.

So, for the indoor illuminance model, it is believed that there is no need to include four visual age subsets, and three visual age subset {young, old, very old} were found enough to describe the visual age. The visual age in the FIIL model was fuzzified based on the subtended line widths of letters that can just be read by 50% of observers in distant and uncorrected vision. (Figure 3.48- after the US Department of Health, Education, and Welfare, 1964). It was found that age groups below 40 years share the same ability to read line widths of less than 1 min arc, after 40 years of old, the letters line width should be increased to more than double to be read by observers at 65 years of old. For observers of 80 years and above, the line widths needed to read the letters is almost triple that for young observers.

Based on this, the visual age membership function for the FIIL model was developed (Figure 3.49). The graphical representation of the membership function shows that observers below 40 years are considered young with a membership degree of 100%. After 40 years. The “old” subset starts and peaks at almost 52 years of old, which marks the age that has a 100% membership degree in the subset. The “very old” subset starts increasing from observer age of 65 years (end of medium subset) and above, until reaching the age of 80 years, where beyond this age, observers are considered to be having a membership degree of 100 % in the “very old” subset.

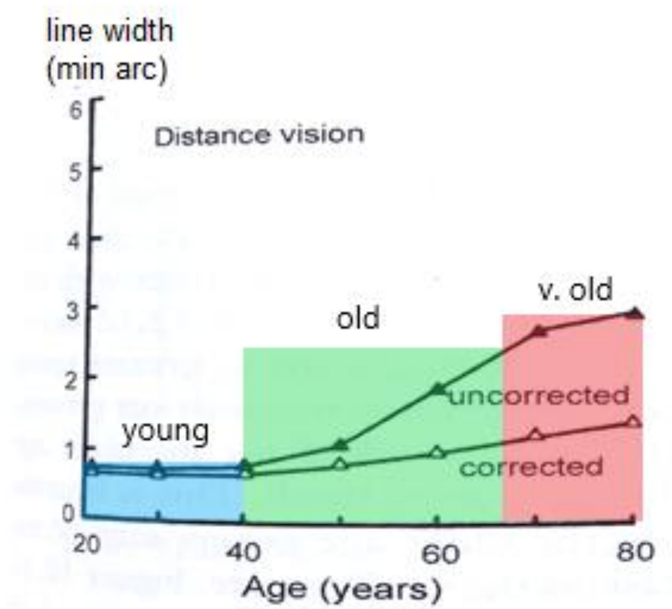


Figure 3.48: Subtended line widths of letters that can just be read by 50% of observers in distant vision. (After US Department of Health, Education, and Welfare, 1964)

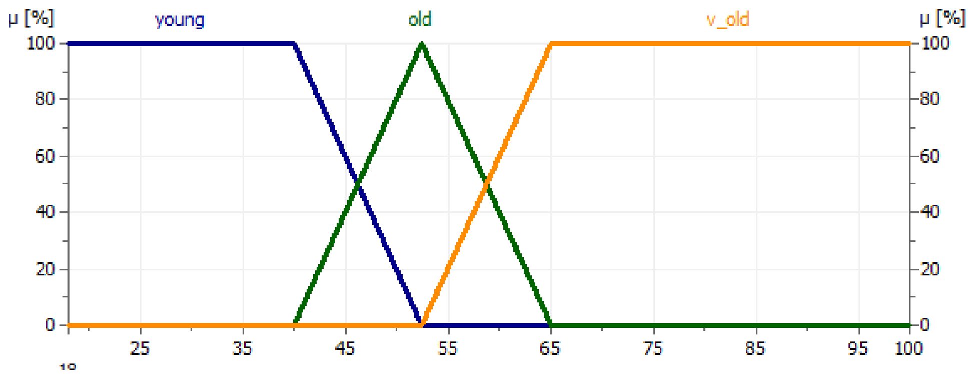


Figure 3.49: Observer/worker age membership function

The mathematical representation of the visual age membership function is shown in the below set of equations:

$$Age = \mu_A(x) \tag{3.68}$$

$$Where\ 18 \leq x \leq 100\ and\ \mu_A(x) \in [0 \to 1]$$

$$\mu_{A,young}(x) = \begin{cases} 1\,, & x < 40 \\ \dfrac{52.5 - x}{52.5 - 40}\,, & 40 \leq x \leq 52.5 \end{cases} \tag{3.69}$$

$$\mu_{A,old}(x) = \begin{cases} \dfrac{x - 40}{52.5 - 40}\,, & 40 \leq x \leq 52.5 \\ \dfrac{65 - x}{65 - 52.5}\,, & 52.5 < x \leq 65 \end{cases} \tag{3.70}$$

$$\mu_{A,very\_old}(x) = \begin{cases} \dfrac{x - 65}{80 - 65}\,, & 65 \leq x \leq 80 \\ 1\,, & x > 80 \end{cases} \tag{3.71}$$

3.8.2 Task difficulty (task characteristics)

Visually difficult tasks can be defined as tasks that have visual stimuli close to visual threshold (stimuli just to be seen), in which visual information is difficult to be extracted (Boyce 2014). The visual system extracts visual information from the visual environment in a way that is described as a "signal-to-noise" notion (Rea 2000), where the desired information is the signal, and the remaining information in the visual field is the noise. When the visual task has certain characteristics that make the "signal-to-noise" ratio low, it can be considered a difficult task.

Studies conducted by Weston (1935, 1945) suggest that visual tasks with characteristics involving small visual size, and/or low luminance contrasts, can be considered as difficult tasks. Figure 3.50 shows the Mean performance scores for Landolt ring charts of different critical size and contrast, plotted against illuminance (Weston 1945). The figure shows that as the visual size (min arc) of the Landolt ring critical detail (gap) decreases, along with the luminance contrast, the speed and accuracy needed to identify the Landolt ring gap decrease (mean performance score). Moreover, the figure also shows that Landolt ring gaps perceived under low illuminance values can add to the difficulty of the task. However, increasing the illuminance follows a law of diminishing outcomes, in which further equal increases in the illuminance result in smaller and smaller changes in the mean performance score (visual performance) until it reaches a value in which any increase in the illuminance will have no effect in changing the visual performance (saturation). Hence, Boyce and Raynham (2009) suggested that larger improvements in visual performance can be done by changing the task rather than increasing the illuminance. They also concluded that increasing the illuminance over any range, will not make the visual performance of a difficult task to be the same as an easy task.

However, Rea (1988) suggests that the illuminance can be roughly predictive of the visual performance. Since illuminance is related to the adaptation level of the visual system, higher illuminances mean higher levels of adaptation, and consequently, higher visual performance. Rea (1988) provided an example to show this by considering how difficult it would be to read a newspaper under an illuminance of 10 lux, compared to reading the same paper under 100 lux.

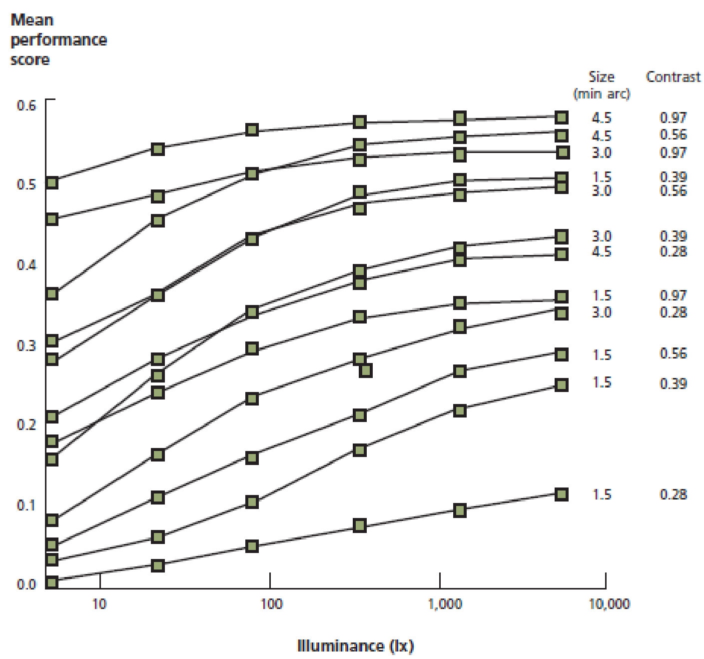


Figure 3.50: Mean performance scores for Landolt ring charts of different critical size and contrast, plotted against illuminance. (After Weston 1945)

IES older version of the lighting handbook (IES 1912-2000) classified visual tasks as easy, medium, and difficult (Table 2.1). This classification is based on the task visual size, luminance contrast, and task reflectance, which is defined as the ratio of the reflected luminous flux to the incident luminous flux. Based on this classification, as easy visual task can be defined as having a large visual size, high luminance contrast, and high target reflectance, while the difficult visual task is the opposite. Older versions of the IES lighting handbook provided nine levels of task difficulty (reduced to seven in 2000) and left the assessment to the designer to select the most appropriate based on his own preferences. Yet, the latest IES handbook (DiLaura et al. 2011) provided 25 levels of task characteristics (from A to Y) along with typical examples of these tasks. The levels start with tasks including dark-adapted situation (A) and ends by some healthcare procedural situations (X and Y).

Alternatively, visual tasks can also be classified as having: {low difficulty, medium difficulty, and high difficulty}, which is the classification adopted in developing the task difficulty membership function. While IES handbooks provided several categories of task difficulty/characteristics, it was difficult to quantify the task difficulty in a certain range of values that correspond to {low, medium, high} difficulty/characteristics, especially that the IES categories change the illuminance within a large scale of values (from 0.5 to 20,000 lux). Hence, the best solution was to employ an imaginary scale for the task difficulty membership function and divide it into three regions (subsets) of {low, medium, high} with the medium peak at 50%.

After several trials, and considering the large number of task characteristics category in IES handbook, the low subset was considered below 10% of the task difficulty scale, while the high subset was considered above 90%. Values between 10% and 90% are considered in the medium subset but with different degrees of membership. The membership function of the task difficulty is shown in Figure 3.51.

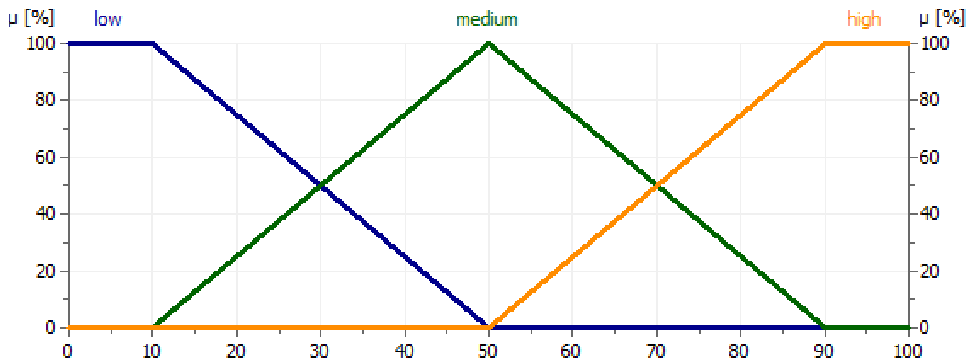


Figure 3.51: Task difficulty membership function

The mathematical representation of the task difficulty membership function is shown in the below set of equations:

$$Task\ Difficulty = \mu_{TD}(x) \tag{3.72}$$

$$Where\ 0 \leq x \leq 100\ and\ \mu_{TD}(x) \in [0 \rightarrow 1]$$

$$\mu_{TD,Low}(x) = \begin{cases} 1\,, & x < 10 \\ \dfrac{50 - x}{50 - 10}\,, & 10 \leq x \leq 50 \end{cases} \tag{3.73}$$

$$\mu_{TD,Medium}(x) = \begin{cases} \dfrac{x - 10}{50 - 10}\,, & 10 \leq x \leq 50 \\ \dfrac{90 - x}{90 - 50}\,, & 50 < x \leq 90 \end{cases} \tag{3.74}$$

$$\mu_{TD,High}(x) = \begin{cases} \dfrac{x - 50}{90 - 50}\,, & 50 \leq x \leq 90 \\ 1\,, & x > 90 \end{cases} \tag{3.75}$$

3.8.3 Task importance

Task importance describes the significance of the consequences related to performing a certain task. For example, some tasks require only detection and/or recognition such as reading a newspaper or watching television. These tasks may not include any significance in their task performance consequences, and thus, can be considered as low importance tasks. However, some other tasks such as medical surgeries, night-time driving, and working with heavy/sharp equipment, have high significance of consequences, hence, the importance of speed and accuracy is high and health and wellbeing may be at risk. Hence, they can be considered as high importance tasks.

The Illuminance determination system proposed by IES lighting handbook (DiLaura et al. 2011) provided five levels of task importance (Figure 2.1), in which the level of importance is described in terms of different types of visual performance. The scale of task importance starts with tasks that are less-cognitive such as orientation and physical tasks, and ends with tasks that are unusual, extremely minute, and/or life-sustaining cognitive tasks such as healthcare, industrial, and sports.

As with task difficulty, the same problem of quantifying the task importance was also encountered during the design of the membership function. Although many levels of task importance were provided by IES (DiLaura et al. 2011), it was difficult to map each one of these levels to a certain value that can be used to define the critical values for the membership function, especially with the large difference in illuminance values with respect to changing the task importance level. Hence, the same imaginary scale that was used earlier in defining the task difficulty membership function, was again used to define the task importance membership function. However, the low subset was considered to be below

20% of the scale, and the high subset was considered at values above 80%. Values between 20% and 80% are considered as medium with various membership degrees and a peak at 50%. The task importance membership function is shown in Figure 3.52

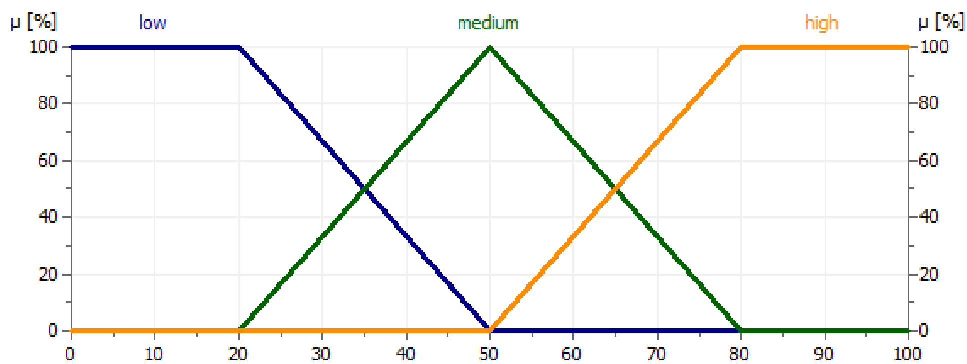


Figure 3.52: Task importance membership function

The mathematical representation of the task importance membership function is shown in the below set of equations:

$$Task\ Importance = \mu_{TI}(x) \tag{3.76}$$

$$Where\ 0 \leq x \leq 100\ and\ \mu_{TI}(x) \in [0 \rightarrow 1]$$

$$\mu_{TI,Low}(x) = \begin{cases} 1\,, & x < 20 \\ \dfrac{50 - x}{50 - 20}\,, & 20 \leq x \leq 50 \end{cases} \tag{3.77}$$

$$\mu_{TI,Medium}(x) = \begin{cases} \dfrac{x - 20}{50 - 20}\,, & 20 \leq x \leq 50 \\ \dfrac{80 - x}{80 - 50}\,, & 50 < x \leq 80 \end{cases} \tag{3.78}$$

$$\mu_{TI,High}(x) = \begin{cases} \dfrac{x-50}{80-50}, & 50 \leq x \leq 80 \\ 1, & x > 80 \end{cases} \quad (3.79)$$

3.8.4 Illuminance Uniformity

The illuminance uniformity is a measure of the variation of illuminance at different points. The latest IES lighting handbook (DiLaura et al. 2011) indicated that illuminance uniformity usually is usually calculated as a ratio between:

- average/minimum: in situations where illuminance too far below average conditions is noticeable and detrimental to task performance or inconsistent with normal expectations
- maximum/minimum: in situations where too much variation in illuminance is considered undesirable and untenable from a performance or safety perspective
- average/maximum: in situations sensitive to even a relatively small degree of overlighting.

However, the handbook highlighted that using the maximum and minimum values should be done with caution, as a single extreme low and/or high illuminance value might distort the ratio and misrepresent the outcome in a certain space. The illuminance uniformity membership function (average/minimum) was developed based on the values provided by the IES lighting handbook (DiLaura et al. 2011), where uniformity values below 2 were considered as low, medium starts above 2 and ends just below 4 with a peak at 3, while high illuminance uniformity corresponds to values above 4. The illuminance uniformity membership function is shown in Figure 3.53

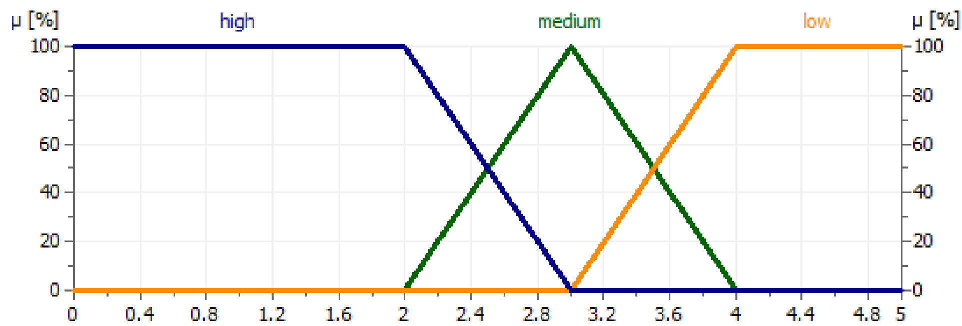


Figure 3.53: Uniformity membership function

The mathematical representation of the task importance membership function is shown in the below set of equations:

$$Uniformity = \mu_U(x) \tag{3.80}$$

$$\textit{Where } 0 \leq x \leq 5 \textit{ and } \mu_U(x) \in [0 \rightarrow 1]$$

$$\mu_{U,High}(x) = \begin{cases} 1\,, & x < 2 \\ \dfrac{3-x}{3-2}\,, & 2 \leq x \leq 3 \end{cases} \tag{3.81}$$

$$\mu_{U,Medium}(x) = \begin{cases} \dfrac{x-2}{3-2}\,, & 2 \leq x \leq 3 \\ \dfrac{4-x}{4-3}\,, & 3 < x \leq 4 \end{cases} \tag{3.82}$$

$$\mu_{TD,Low}(x) = \begin{cases} \dfrac{x-3}{4-3}\,, & 3 \leq x \leq 4 \\ 1\,, & x > 4 \end{cases} \tag{3.83}$$

The illuminance uniformity was not used in the FIIL model. It was only used in the FIIL software to allow for the user to check and assess the uniformity of his space lighting design.

Software users can select the uniformity value and the software will calculate the degree of membership in the subsets of {low, medium, high} associated with his input value.

3.8.5 Illuminance

Illuminance is defined as the luminous flux incident on a surface per unit area. Illuminance is measured in lumens/m^2 which equals to 1 lux. Work-plane illuminance is one of the most widely used lighting metrics in the industry. The popularity of this metric is owed to its simplicity and measurability using simple equipment. Most lighting designs require the calculation of the illuminance on the work-plane. Design targets are based on the function of the space. The design targets often specify average work-plane horizontal or vertical illuminance.

One can define the horizontal illuminance in four subsets; Low, Medium, High, and Very high as shown in Figure 3.54. The borderlines between any of the aforementioned subsets are fuzzy and not crisp. As the illuminance is increased, it will have different degrees of membership in its respective fuzzy set. A design target should not have an exact value, but rather a membership in a fuzzy set. For example, if the target horizontal illuminance is 500 lux, then the figure shows that this belongs to the Medium Illuminance subset and a maintained average illuminance of 450-550 lux will be on target (100% membership degree in medium subset). Values of 400 lux or 600 lux are still part of the on-target Medium illuminance subset, but have a lower degree of membership of that subset. As the illuminance decreases, its degree of membership of the Medium Illuminance subset decreases. Design targets can specify which illuminance fuzzy sub-set will give a range of acceptable illuminance values. For example, the design target for an office building could follow the "medium illuminance" fuzzy subset shown in Figure 3.54 and acceptable membership of that subset of 0.85 or more. This allows average illuminance values that slightly deviate from the exact targets to be considered as ‘on target’.

High values of illuminance are considered in the range of 850 to 950. These values have a 100% membership degree in “high illuminance subset”. Illuminance values slightly less or more than these values are still considered as high illuminance but with marginally different membership degrees. For example, illuminance values of 800 lux will have a membership degree of 0.83 in the “high illuminance subset” and a membership degree of 0.17 in the “medium illuminance subset”. Very high illuminance starts from above 950 lux with increasing membership degrees until it reaches 1300 lux, which marks the values in which illuminance starts to have a 100% membership degree in the “very high illuminance subset”. The range of illuminance is limited by 3000 lux with also has a 100% membership degree in the highest subset.

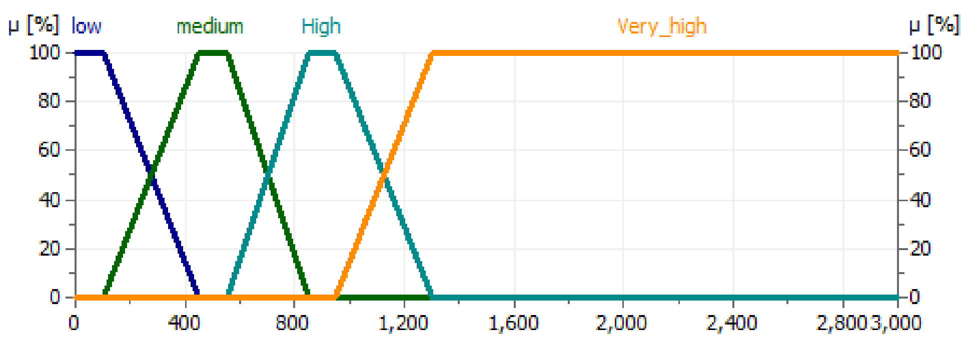


Figure 3.54: Indoor illuminance membership function

The mathematical representation of the Fuzzy illuminance membership function is shown in the below set of equations:

$$Fuzzy\ indoor\ illuminance = FIIL = \mu_{FIIL}(x) \tag{3.84}$$

$$\text{Where } 0 \leq x \leq 3000 \text{ and } \mu_{FIIL}(x) \in [0 \rightarrow 1]$$

$$\mu_{FIIL,Low}(x) = \begin{cases} 1\,, & x < 100 \\ \dfrac{450 - x}{450 - 100}\,, & 100 \leq x \leq 450 \end{cases} \tag{3.85}$$

$$\mu_{FIIL,Medium}(x) = \begin{cases} \dfrac{x - 100}{450 - 100}\,, & 100 \leq x \leq 450 \\ 1\,, & 450 < x \leq 550 \\ \dfrac{850 - x}{850 - 550}\,, & 550 < x \leq 850 \end{cases} \tag{3.86}$$

$$\mu_{FIIL,High}(x) = \begin{cases} \dfrac{x - 550}{850 - 550}\,, & 550 \leq x \leq 850 \\ 1\,, & 850 < x \leq 950 \\ \dfrac{1300 - x}{1300 - 950}\,, & 950 < x \leq 1300 \end{cases} \tag{3.87}$$

$$\mu_{FIIL,Very\ High}(x) = \begin{cases} \dfrac{x - 950}{1300 - 950}\,, & 950 \leq x \leq 1300 \\ 1\,, & x > 1300 \end{cases} \tag{3.88}$$

3.9 Fuzzy inference system

Fuzzy inference system is a process in which the input conditions of the fuzzy logic system is interpreted, based on the fuzzy rules, and then a value for the output conditions is assigned (Kalogirou 2014) In other words, the input conditions are mapped to the output values based on the fuzzy rules. Fuzzy inference system involves all the pieces of the fuzzy logic model, including the membership functions, fuzzy rules, and fuzzy logic operators to defuzzify the output variable. The defuzzification of the output variable simply means converting it into a crisp one. There are two mostly-used types of fuzzy inference systems that can be used. Mamdani-type (1977) and Sugeno-type (1985). While both systems can give close outputs under certain conditions, the method of defuzzification for each system is different.

Mamdani inference system assumes the output variables to be fuzzy. This means that there is a membership function with certain fuzzy sets for each output variable that has been already designed by the user, and the crisp values of the results are obtained by the defuzzification of rules consequent. This makes Mamdani system more intuitive and well-suited for human input applications as well as having more interpretable fuzzy rules. Hence, it has a more widespread acceptance for fuzzy models involving the user experience and knowledge such as decision making and medical applications. A typical rules for Mamdani fuzzy inference system can have the following form:

$$IF\ \mu_A\ is\ \mu_{A1}\ AND\ \mu_B\ is\ \mu_{B1}\ then\ \mu_{C\ is}\ \mu_{C1} \tag{3.89}$$

However, despite Sugeno system is similar to Mamdai in having a membership function for input variables as well as fuzzy rules, Sugeno expects the output to be linear or constant. This means that there is not membership function for the output variables and it is calculated based on mathematical analysis. As a result, Sugeno system is more computationally efficient and works well with linear techniques such as PID controllers as well as optimization and adaptive systems (Mathworks 2020). A typical rule for Sugeno inference system can take the following form

$$IF\ \mu_A\ is\ \mu_{A1}\ AND\ \mu_B\ is\ \mu_{B1}\ then\ C = f(x, y) \tag{3.90}$$

Mamdani fuzzy inference system was used in this work for its ease of use and widespread acceptance. Indeed, it is the default system in Matlab fuzzy logic toolbox. The visual performance output has been fuzzified to allow the use of this system and the rules were designed to include the most accurate subset of the output.

3.10 Fuzzy rules

Fuzzy rules can be considered as the main tool for communicating the parts of knowledge for a fuzzy logic system. Fuzzy rules are conditional statements used to infer the output of a fuzzy system based on its input variables. By employing connectors such as {if, then, and, or, not}, fuzzy rules can connect between different subsets of membership functions. This allows for the fuzzy logic model, based on the fuzzy rules, to conclude which action or output should be taken considering the currently observed information algorithm. A fuzzy “IF-THEN” rule maps a subset of the membership functions to a certain conclusion in linguistic forms, the “IF” part captures the knowledge from the input and the "THEN" part gives the conclusion. The fuzzy "IF-THEN" is widely used in fuzzy logic models to calculate the degree in which the input information matches the degree of the rule.

A typical fuzzy "IF-THEN" rule can be written in the following form:

$$IF\ \mu_A\ is/is\ NOT\ \ \mu_{A1}\ AND/OR\ \ \mu_B\ \ is/is\ NOT\ \mu_{B1}\ then\ \mu_C\ \ is/is\ NOT\ \ \mu_{C1} \tag{3.91}$$

Where A_1, B_1, C_1 are subsets of the membership functions A, B, and C respectively, while {AND, OR, NOT} are the fuzzy operators. Fuzzy operator are used to join fuzzy expressions together to generate a fuzzy logic relation between input and output. "AND" operator represents intersection, "OR" represent union and "NOT" represents complement or negation. Based on Zadeh notation (1965), these operators can be represented by Zadeh operators as follows:

Intersection (AND)

$$\mu_{A\cup B}(x) = max(\mu_A(x), \mu_B(x)) \tag{3.92}$$

Union (OR)

$$\mu_{A\cap B}(x) = min(\mu_A(x), \mu_B(x)) \tag{3.93}$$

Complement (NOT)

$$\mu_{A^c}(x) = 1 - \mu_A(x) \tag{3.94}$$

Where $\mu_A(x)$ and $\mu_B(x)$ are membership functions that define the variables A and B respectively on the universe X. Figure 3.55 shows a graphical representation of Zadeh logic operators.

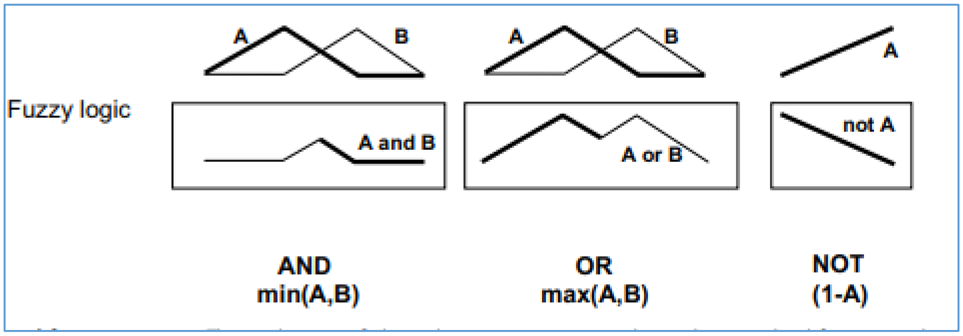


Figure 3.55: Fuzzy logic (Zadeh) operators explained (D'Negri and Vito 2010)

Although fuzzy rules are the key tool for mapping input to output, there is no specific method for generating or extracting fuzzy rules. This step mainly depends on the experience and knowledge of the person setting up the fuzzy logic model (Bai and Wang 2006). However, for a complex system like FRVP, where the number of rules exceeds 900 logic statements, a calculation method utilizing a rank for each rule has been used to set the fuzzy rules depending on the rule ranking (RR) concept.

The proposed visibility Fuzzy system has five input variables with three fuzzy subsets (Contrast, size, retinal illuminance, eccentricity, and background complexity) and one input variable (age) with four fuzzy subsets. Therefore, the required number of rules equals to the number of probable incidents that can occur based on the input membership functions subset arrangement. Hence the total number of rules can be calculated as follows:

$$No.of\ Rules = 3^5 x\ 4 = 972\ Rule \tag{3.95}$$

A weight of 3 has been given to each membership function of the input variable. Then each input variable was studied and a rank was given to each fuzzy set (subset) based on its contribution to visual performance. For example, a rank of 1 was assigned to the subset "Low" of the luminance contrast fuzzy set and 2 and 3 for the subset "Medium" and "High" respectively. This ranking came from our prior knowledge as well as literature insights, that increasing the luminance contrast increases the visual performance. For the age membership function, which has 4 subsets, a rank of 3 was assigned to the subset "Very Young" and 2.25, 1.5, and 0.75 to subsets "Young", "Old", "Very Old", respectively. The same has been applied to the rest of the membership functions. Table 3.7 shows the rank of each subset of the membership functions input variables included in the fuzzy model.

Table 3.7: fuzzy sets rank of membership functions variables involved in the FRVP model

Membership function	Subset-1	Subset-2	Subset-3	Subset-4
Luminance contrast	Low	Medium	High	-
	1	2	3	-
Age	Very young	Young	Old	Very old
	3	2.25	1.5	0.75
Visual size	Small	Medium	Large	-
	1	2	3	-
Retinal illuminance	Low	Medium	High	-
	1	2	3	-
Eccentricity	Within axis	Away from axis	Far from axis	-

Membership function	Subset-1	Subset-2	Subset-3	Subset-4
	3	2	1	-
Background complexity	Low	Medium	High	-
	3	2	1	-

Since all rules used are incorporating intersection operators (and only), the maximum possible weight for the combination of the input variables subsets can be found from the logic rule where input variables are joining the highest rank subsets of the membership function, i.e., the subsets which contribute the most to the highest value of FRVP. This logic rule is as follows:

IF luminance contrast is high (W_1=3) AND Age is very young (W_2=3) AND visual size is large (W_3=3) AND retinal illuminance is high (W_4=3) AND eccentricity is within-axis (W_5=3) AND Background Complexity is Low (W_6=3) THEN FRVP is high.

Where the numbers between brackets represent the assigned rank for each fuzzy subset.

The total weight for this rule equals 18 which represents the maximum total weight value. The Rule Rank (RR) can then be calculated as follows:

$$RR = \frac{The\ total\ weight\ for\ the\ ith\ rule}{The\ total\ weight\ for\ the\ maximum\ case} \tag{3.96}$$

$$RR = \frac{\sum_i W_i}{18} \tag{3.97}$$

Hence, the rule ranking for the previous rule equals to 1.0. The higher RR is the higher the visual performance.

Similarly, the rule that results in the least FRVP is as follows:

IF Luminance contrast is low (W_{1}=1) AND age is very old (W_2=0.75) AND visual size is small (W_3=1) AND retinal illuminance is low (W_4=1) AND eccentricity is far from axis (W_5=1) AND Background Complexity is high (W_6=1) THEN FRVP is low

The rule ranking for this rules equals to:

$$RR = \frac{5.75}{18} = 0.319 \tag{3.98}$$

This means that $0.319 < RR \leq 1.0$. The rest of the rules were developed based on their RR values. A low FRVP was assigned for RR values below 0.6, medium for values between 0.6 to 0.8, and high FRVP for RR values above 0.8. Table 3.8 shows the first four fuzzy rules for the proposed fuzzy model and a table of all rules will be provided in the appendix.

Table 3.8: An example of the first four rules of the proposed FRVP model

Rule No.	[Input] Luminance Contrast	[Input] Age	[Input] Visual size	[Input] Retinal Illuminance	[Input] Eccentricity	[Input] Background complexity	RR	[Output] FRVP
1	Low	Very old	Small	Low	Far from axis	High	0.32	Low
2	Low	old	Small	Low	Far from axis	High	0.36	Low
3	Low	young	Small	Low	Far from axis	High	0.40	Low
4	Low	Very young	Small	Low	Far from axis	High	0.44	Low

For the FIIL mode, things are much easier since the number of required rules is much less. As the model employs 3 input variables with 3 subsets each, the number of rules was calculated to be 27 only. The same method of rule ranking was employed to determine the outcome of each rule. If the rule ranking (RR) was found to be equal or less than 0.5, the FIIL was fixed at low, medium FIIL between 0.5 to 0.7, high FIIL between 0.7 to 0.8, and very high FIIL for RR above 0.8. Table 3.9 shows an example of the first three rules of the proposed FIIL mode. The rest of the rules are provided in the appendix.

Table 3.9: An example of the first three rules of the proposed FIIL model

Rule No.	[Input] Visual age	[Input] Task importance	[Input] Task difficulty	RR	[Output] FIIL
1	Young	Low	Low	0.33	Low
2	Old	Low	Low	0.44	Low
3	Very old	Low	Low	0.55	medium

3.11 Defuzzification

The defuzzification process is the opposite of the fuzzification process. It is the process in which a crisp value of the output is produced out of the aggregated fuzzy sets (Masoum and Fuchs 2015). In other words, it is the process where fuzzy sets are transformed into crisp sets based on the fuzzy inference system and rules algorithm. There are several methods used for defuzzification in the Mamdani inference system, but the most commonly used are the centre of gravity (COG) or sometimes referred to as the centroid method (most popular), bisector method, mean of maximum (MOM) and the centre average methods.

The centre of gravity (COG) or centroid method is usually good enough for most of the applications. However, the user can try other methods to check if he can get better output. The centroid method returns the centroid of the area along the x-axis by dividing the total area into smaller sub-areas, then the centroid of each sub-area is calculated, the centroid of the total area is then calculated using the following formula

$$\bar{x} = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)} \tag{3.99}$$

Where $\bar{x}$ is the centroid of the area, $\mu(x_i)$ *and* x_i denotes the area and the centroid of the ith portion of the membership function$\mu(x)$. Figure 3.56 shows the effect of different fuzzification methods on the crisp output of a Mamdani fuzzy system.

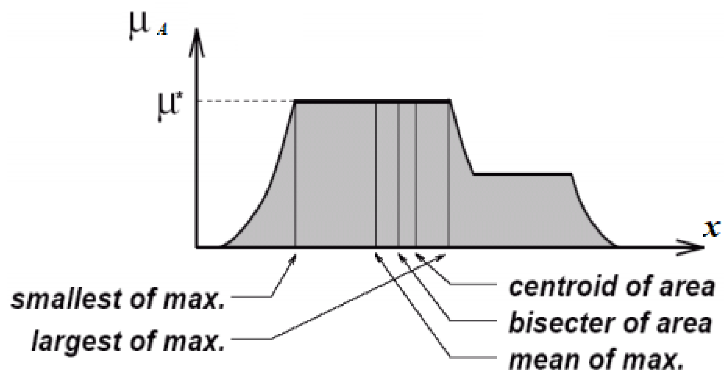


Figure 3.56: Results using different defuzzification methods for a particular function (Naz et al. 2011)

On the other hand, the Sugeno inference system is usually defuzzified using the weighted average method proposed by Yager (1988). This method usually produces results that are very close to the centroid method but with different calculation methods. Each membership function is weighted based on its maximum membership function value and then the crisp output is calculated using the below formula

$$x^* = \frac{\sum_i \mu(x_i)x}{\sum_i \mu(x_i)} \tag{3.100}$$

Where x denotes the maximum value for the membership function in the domain universe of X.

As the inference system used in this work is the Mamdani system, the centroid method is used for the defuzzification process for its ease of use and widespread. The centroid method is the default method for the defuzzification of Mamdani systems in Matlab.

3.12 Matlab Fuzzy logic toolbox

Matlab is a multi-computational numerical computing environment and programming language software. It was developed by Mathworks in 1984. Matlab allows the user to manipulate matrices, implementing algorithms, plotting data as well as functions, and most importantly, writing codes and programs. The software has huge acceptance around the world in the fields of engineering, science, medicine, and economics.

Moreover, Mathworks has successfully developed certain toolboxes that are specialized in a certain field such as Simulink, which provides simulation and modelling to dynamic and control systems, Image processing, and Fuzzy logic…etc. these toolboxes increased the popularity of Matlab worldwide and increasing the global number of its user to 4 million worldwide (Mathworks 2020).

The fuzzy logic toolbox is an add-on to the Matlab software. It provides functions, applications, and simulation of fuzzy logic design activity in a graphical user interface (GUI). Although there are many software available for fuzzy logic design and modelling. Matlab fuzzy logic toolbox is amongst the highest most used due to its reliability and ease of use. Moreover, it is widespread can be related to the popularity of the Matlab software itself as a computing and programming environment. Figure 3.57 shows a snapshot of the Matlab fuzzy logic toolbox.

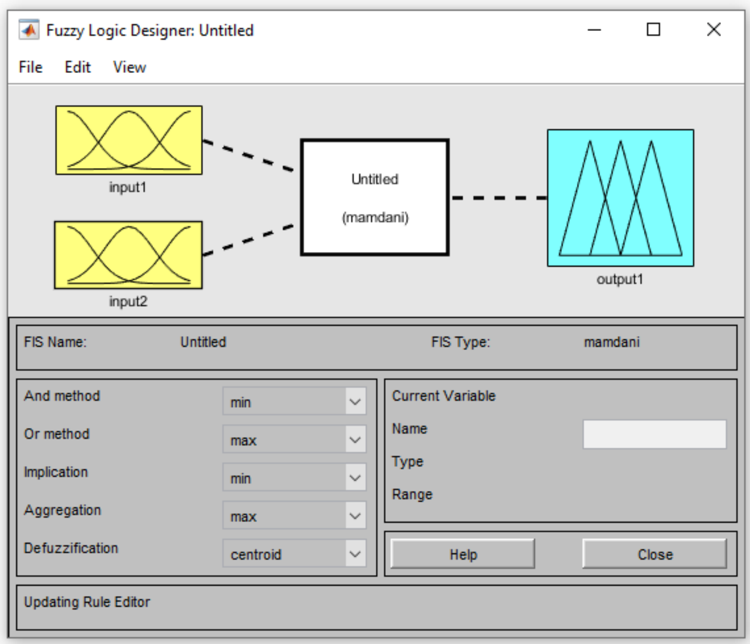


Figure 3.57: Snapshot of Matlab Fuzzy logic toolbox (Matlab 2020)

There are two built-in fuzzy inference systems in Matlab fuzzy logic toolbox. Mamdani and Sugeno. Although Mamdani is the default system, users can select Sugeno at the beginning of modelling the system, or can switch to Sugeno once the model has finished. Moreover, all fuzzy logic operators {AND, OR, NOT} are available in the toolbox, allowing the users to express the rules simply and efficiently, at the same time, rules in the form of matrix or vector can be also provided for more expert users. Figure 3.58 shows a typical rule editor in Matlab fuzzy logic toolbox.

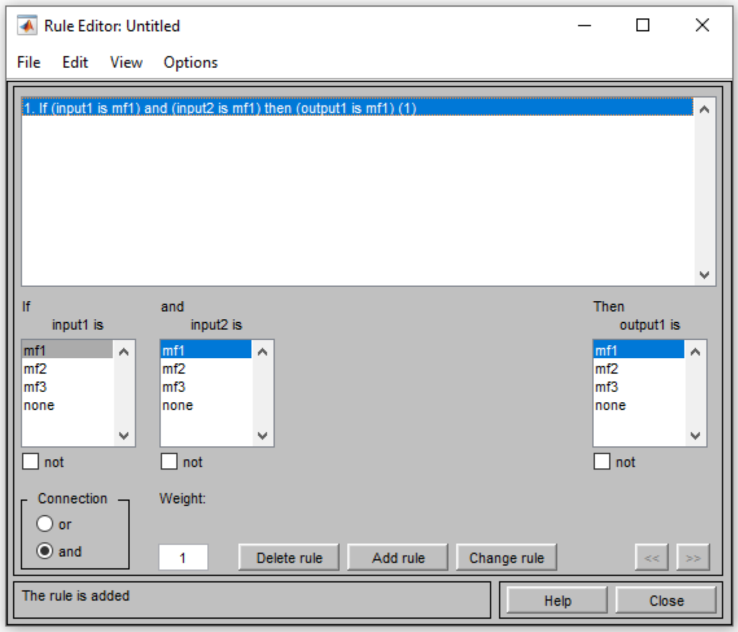


Figure 3.58; Rule editor in Matlab fuzzy logic toolbox (Matlab 2020)

For Mamdani fuzzy inference system, Matlab fuzzy logic toolbox has 5 built-in defuzzification methods including the centroid method, bisector method, middle of maximum, smallest of maximum and largest of maximum. The default method of fuzzification in the Mamdani inference system is the centroid method, but the program allows the user to define his defuzzification process based on his knowledge and experience.

Finally, another important feature for the Matlab fuzzy logic toolbox is the ability to simulate and graph the output as a 3D surface, and to change the variables of the input directly at the graph screen. Figure 3.59 shows a typical 3D surface generated by Matlab fuzzy logic toolbox.

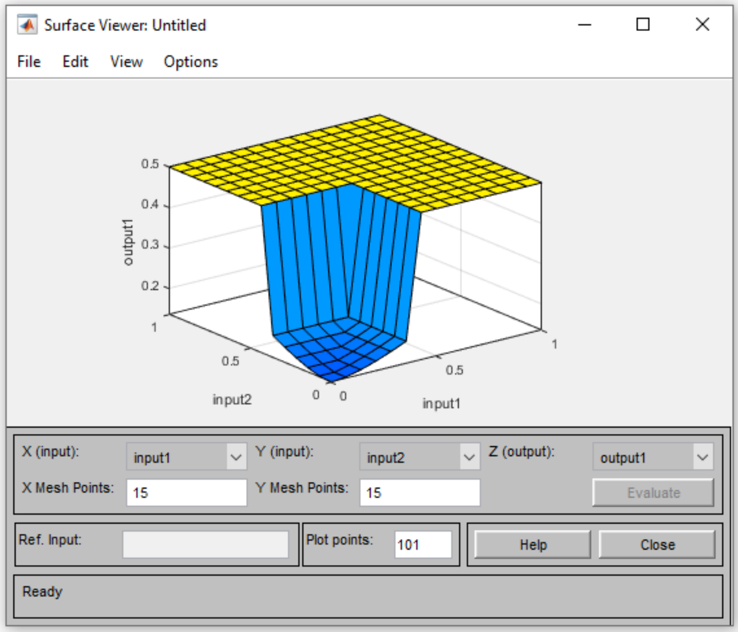


Figure 3.59: Surface viewer in Matlab fuzzy logic toolbox (Matlab 2020)

The downsides for Matlab fuzzy logic toolbox, in which we faced in this work, can be summarized by two points:

1. Data for a certain simulation cannot be exported from the software to another software such as MS excel of word.
2. The axis range in the 3D surface viewer is automatic, this is good sometimes but in the cases where graphs are compared without having the same scale or range, it creates confusion.

Hence, the fuzzy logic model was designed using the Matlab fuzzy logic toolbox including all components such as membership functions and fuzzy rules as well as fuzzification, then another software called “Fuzzylite” was used to review the results and export the data to a graphing software called “Sigmaplot”.

3.13 Software packages

Matlab software provides a powerful tool to convert programs into stand-alone applications, moreover, these applications can be exported to Matlab server to allow other users (within the same organization) to use and test the application. Older versions of Matlab (up to 2015) provided a graphical user interface (GUI) called "guide" to design the application, then a compiler application can be used to deploy the program into a stand-alone application. Though, newer versions of Matlab used a more developed tool called "Appdesigner".

Since this work started in 2017, the version of Matlab used then was Matlab R2015a. Matlab "guide" application was used to develop the first version of the stand-alone application. However, due to the *Covid-19 pandemic* (2019-2020), where students lost the ability to visit the university campus, Matlab thankfully provided academic users with a free full license for Matlab R2020a to be used at their homes. Moreover, they provided another tool to migrate programs developed in "guide" to "Appdesigner". Hence, Matlab "Appdesigner" was adopted to create the applications in this work and to export them into Matlab sever.

3.14 Validation

The proposed FRVP model will be validated against the RVP model (Rea and Ouellette 1988, 1991). The comparison will be based on the similarities and differences between FRVP and RVP under different conditions, it is expected that FRVP will show good similarities with RVP under high visibility conditions whereas, differences are expected to be present under low visibility conditions. The FRVP model is expected to define a similar plateau to the RVP 3D-presentation shown in Figure 14. However, as the FRVP model incorporates more variables than the RVP model (eccentricity, background complexity), these values will be fixed at be at the highest subset of the membership function, with respect to their contribution to FRVP. In other words, the eccentricity will be fixed at “within axis” and background complexity will be fixed at “low” during the comparison.

For the FIIL model, it will be validated with respect to the current IES recommended illuminance for various applications, which are provided in the latest edition of the IES lighting handbook (DiLaura et al. 2011).

3.15 Sensitivity analysis

Sensitivity analysis, or sometimes referred to as “What-if” analysis, is a method to check the effects of fluctuations in the input variables of a mathematical model or system on the output and/or performance of the system/model (Balaman 2018). One or more input parameters can be either slightly or significantly changed and the effect on the output can be measured. A sensitive model means that the solution of this model will have great changes considering a slight change in the input, while an insensitive model has a solution that marginally change (or remains the same) with significant changes in the input.

In this work, one membership function of an input variable for the FRVP model will be modified at a time and the effect of this new memberships function on the output FRVP will be noticed and compared to the original values.

3.16 Assumptions and scope of work

This work is an attempt to apply fuzzy logic on visual performance and illumination applications. A model for both illuminance selection and visual performance has been developed. The output for the illuminance model is the value of illuminance based on three input variables: age, task difficulty, and task characteristics.

The output for the FRVP model is the value of relative visual performance based on six independent variables and 1 dependent variable. The variables FRVP are as follows:

1. Contrast, both positive and negative. The range of the positive contrast is from zero to 1.4, while the range for negative contrast is from zero to 0.3
2. The age of the observer/driver, with a range from 20 to 100, which corresponds to the age of licensed drivers in most countries
3. Visual size, which is the area of the target divided by the square distance between the target and the observer, in Microsteradians, and considering the observer at the visual axis of the observer (θ=0), the range of the visual size is from zero to 30 Microsteradians
4. Retinal illuminance, which is the amount of light entering the eye of the observer, in Trolands. The range for retinal illuminance is from zero to 100 Trolands, which corresponds to the adaptation luminance values that can be encountered during night-time driving conditions.
5. Eccentricity, in degrees, which the angle between the observer's fixation line of sight and the target, the range of eccentricity is from zero to 30^{o}
6. Background complexity, which is a measure of how homogeneous the driving scene. Background complexity is mapped with the image entropy of the driving scene and has a scale from 1 to 3.
7. Disability glare: which has a measurable effect at low luminance contrast situations

For FRVP model, the following assumptions have been made:

1. The driver/observer is assumed to be healthy, both physically, mentally and visually.
2. The driver /observer assumed to be sober and/or intoxicated.
3. The driver is assumed to be fully alert while driving
4. The driving task is assumed to be without distractions
5. The target is assumed to be stationary and has no movement in any direction
6. The target exposure time is assumed to be 2 seconds or for an unlimited time.
7. Target exposure times less than 2 seconds are neglected
8. Chromatic contrast is neglected
9. Transient adaptation is neglected

3.17 Ethical considerations

This research is mainly analytical simulation using computer simulation software. MATLAB has been selected for its ease of use and global widespread, and its ability to be easily integrated into other programming languages as well as the capacity to produce a stand-alone application describing the studied model. For results presentation, Sigmaplot and Excel software packages have been used.

All the used software is licensed and has been acquired legally. All resources and references used in this work are also acquired legally and will be cited properly. There are no surveys or interviews involved in this research. Moreover, there will be no usage of any confidential data from any kind or source. A small fieldwork involving taking some pictures of different driving scenes at different locations will be done to serve a certain purpose in some parts of this research. Yet, it will not create any threat to the life and/or safety of any human and/or animal.

4 Chapter Four: Results

This work has set a new method for indoor illuminance selection based on fuzzy logic techniques. Moreover, fuzzy logic was also used to define and model the visibility of targets. The previous chapters showed an overview of the topic, literature review, and the methodology used to approach the indoor illuminance as well as the relative visual performance in terms of parameters, fuzzification of input and output variables, fuzzy rules…. etc.

This chapter shows the outcome of all the previous efforts described above. Figures describing the new criteria of indoor illuminance selection as well as fuzzy relative visual performance will be presented in this chapter. Yet, due to the different nature between the two topics, different presentation styles for the figures will be adopted. The fuzzy relative visual performance (FRVP) results will be presented at the beginning, then the fuzzy indoor illuminance selection (FIIL) will follow.

4.1 Fuzzy relative visual performance (RRVP)

Relative visual performance was first defined by Levy (1982) as the speed and accuracy of performing a visual task. It was adopted by Rea (1981, 1986) and Rea and Ouellette (1988, 1991) in developing the RVP model. The previous chapters showed the limitations of the current RVP model in terms of using complex mathematical relations, or using results for a certain age group of observers, or neglecting some variables such as eccentricity and background complexity. Moreover, the previous sections of this study successfully established an important conclusion related to the ability of using fuzzy logic on the relative visual performance, this is due to the nature of the visibility parameters, which is usually vague, or inherently complex and imprecise, and the possibility of getting exact outcomes of such imprecise parameters, using the traditional methods, is unlikely. The fuzzy logic approach is a good replacement for classical math in modelling a complex phenomenon.

The following sections will show the effect of each input variable alone on the fuzzy relative visual performance (FRVP). Since there are six input variables for the proposed model (luminance contrast, visual age, visual size, retinal illuminance, eccentricity, background complexity), the results will be presented using a 3D surface for FRVP as a function of two input variables only. The rest of the variables, called the *other influence variables* will be constant for the same scenario. Hence, multiple scenarios will be presented where the influence variables will be changed to see the effect of the main variables under consideration on FRVP under different situations. These scenarios were selected carefully to show the effect of each input variable under low, medium, and high visibility situations.

For luminance contrast, polarity will be considered by presenting separate results for positive and negative contrasts. Moreover, results for the critical contrast, which is defined as the minimum contrast that gives high FRVP, will be presented at the end of this chapter.

Although disability glare was not considered in the model as an independent input variable, a direct connection was established between the disability glare effect on the luminance contrast (see Glare page 99). Results for the effect of disability glare will be shown also at the end of this chapter.

4.1.1 Luminance contrast effect

Luminance contrast can be considered as the most important visibility parameter. It has been included in all current visibility models (Adrian 1989), Rea and Ouellette (1988, 1991) and STV (IESNA 2000). This model is no different than the current models in the way that contrast affects the degree of visibility. In other words, higher contrast values will result in better visibility. Luminance contrast effect is a combination effect for both the target luminance (L_t) and background luminances (L_b), see equation (3.1)

To see the effect of any input variable on the output (FRVP), a 3D surface graphs were generated for FRVP as a function of two variables while the rest of variables are constant Results of positive contrast effect on the Fuzzy relative visual performance (FRVP) are shown in Figure 4.1 through Figure 4.10, while results for negative contrast effect on FRVP are shown in Figure 4.11 through Figure 4.20. This was done since both positive and negative contrast have unique membership functions with different scales and critical limits. FRVP as a function of positive and negative contrast 3D graphs have been generated at different values of other influence input variables. These variables (age, size, retinal illuminance, eccentricity, background complexity) values have been selected in a way that reflects the effect of luminance contrast on FRVP at low, medium, and high visibility scenarios. A combination of low visibility can be defined (in the context of this work) as a situation where contrast is low, visual age is very old, visual size is small, retinal illuminance is low, eccentricity is away from the axis, and background complexity is high. The same methodology applies to medium and high visibility situations.

Figure 4.1 and Figure 4.2 show FRVP as a function of positive contrast and visual age at different values of other influence variables. The first part of the figure (4.1-1A) shows that at low visibility situations, FRVP values lie on a lower plateau of almost 0.3. Any further increase in luminance contrast or decrease in visual age, or both, cannot contribute to increasing the values of FRVP. This was noticed in all situations where input variables are fixed to the subset that contributes the least on FRVP.

The second part of the figure (4.1-1B) shows how increasing one variable (retinal illuminance) creates v a second medium plateau at FRVP values of almost 0.5. This plateau corresponds to high contrast values and low visual age values. Yet, this medium plateau is still small in size and most of FRVP values are still at the lower plateau. A further increase in retinal illuminance, visual size, and decrease in eccentricity and background complexity (figures 4.1-2A and 2B) adds another dome-shape at FRVP values of almost 0.7. This dome-shape is the base for the third (highest) plateau that is more visible by a further change in the other influence variables (Figure 4.2 1A and 1B).

The effect of luminance contrast and visual age at high visibility situations are shown in Figure 4.2. The figure shows that FRVP values create either two or three plateaus depending on the input values. However, if the input parameters were finxed to the maximum values that contribute to the visibility (figure 4.2-2B), FRVP can have only two plateaus of high and medium at almost 0.9 and 0.6 respectively. The higher plateau corresponds to positive contrast values of 1.0 and above and visual age values of 50 years and below, while the medium plateau forms the rest FRVP values. It was also noticed that the transition between the two plateaus corresponds to the critical values used to design the membership functions of both positive contrast and visual age.

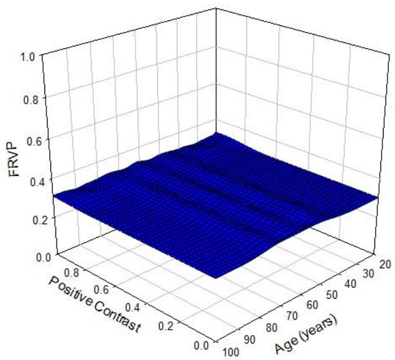
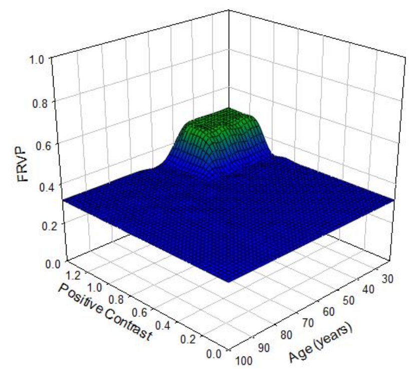
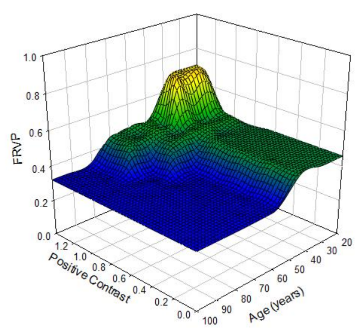
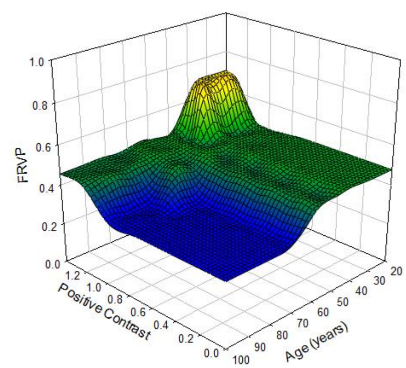
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>5</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>10</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.1: FRVP as a function of positive contrast and visual age (1/2)

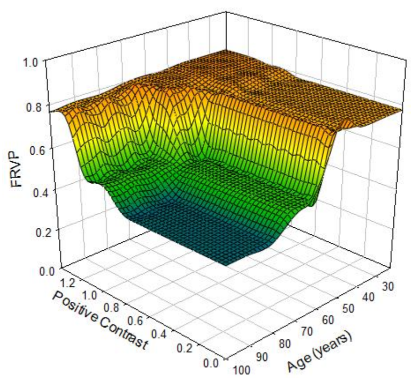
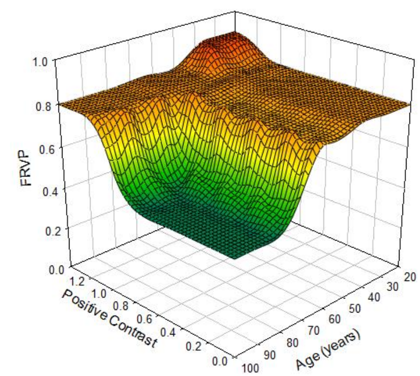
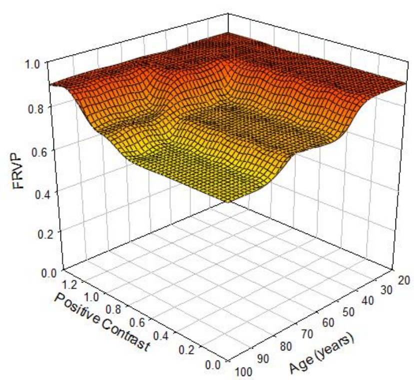
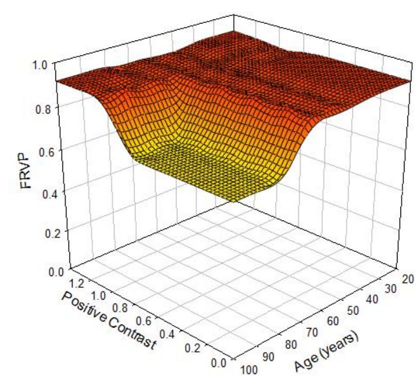
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>15</td><td>10</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>20</td><td>5</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.2:FRVP as a function of positive contrast and visual age (2/2)

FRVP as a function of positive contrast and visual size is shown in Figure 4.3 and Figure 4.4. Both figures show the increase of FRVP values from the lower plateau, passing through the medium then the high plateau. Figure 4.3(1A and 1B) show that there is no effect on either the positive contrast or the visual size in increasing FRVP values when the other influence variables are fixed at the subset that contributes the least to FRVP.

However, a further decrease in the visual age and retinal illuminance, and a decrease in eccentricity and background complexity creates the medium plateau. This plateau corresponds to high values of positive contrast and visual size. Figure 4.4 (2A) corresponds to FRVP values where the other influence variables are fixed to high (but not maximum) values, the figure shows that FRVP are located at three plateaus of almost 0.6, 0.7 and 0.9. However, the medium plateau (at 0.7) is temporary and disappears once all other influence variables are fixed to the maximum values contributing to FRVP (figure 4.4-2B). In this case, the higher plateau (at 0.9) increases in area and corresponds to positive contrast values above 1.0 and visual size values above 15 Microsteradians.

The same figure (4.4-2B) shows that the transition between the higher and medium plateaus corresponds to the critical values used to design the membership functions of both positive contrast and visual size. This is noticed in most of the figures, especially when the input parameters are fixed to the maximum values which contribute to FRVP.

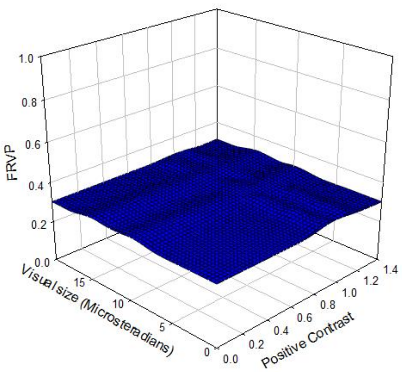
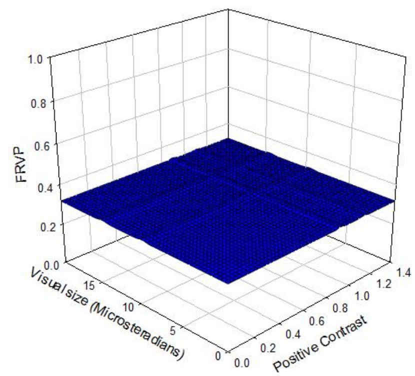
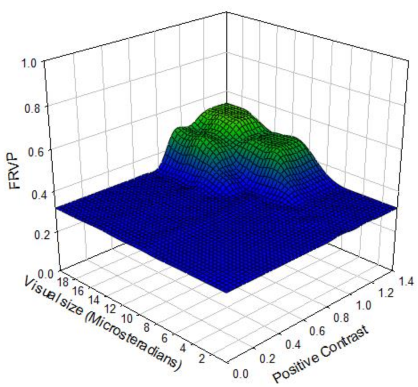
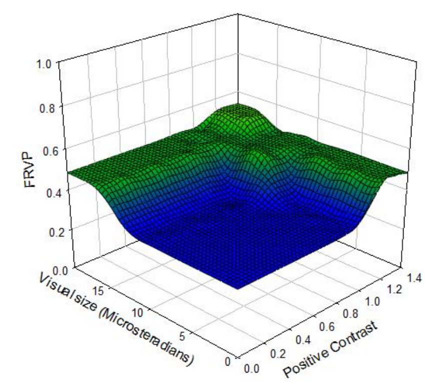
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Eccentricity	Background Complexity
	0.5	10			
1			80	20 °	3
2			70	15 °	2
	A	B	Fig. No.		

Figure 4.3: FRVP as a function of positive contrast and visual size (1/2)

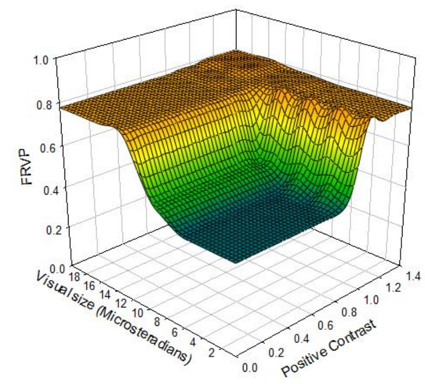
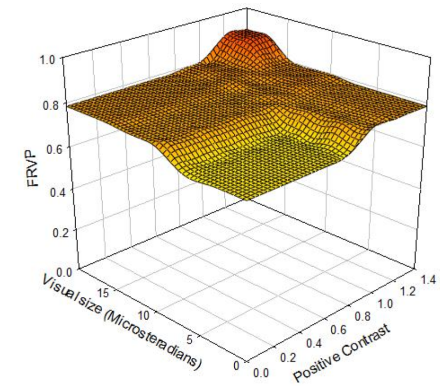
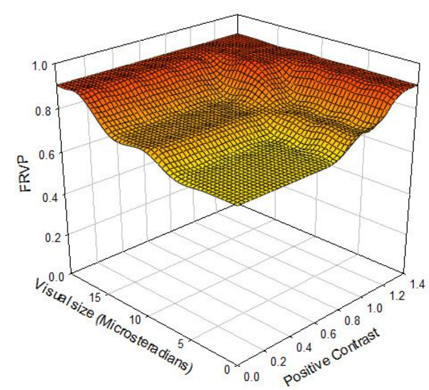
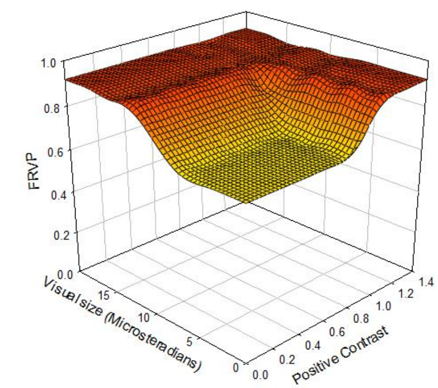
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Eccentricity	Background Complexity
	20	40			
1			50	10	1.5
2			20	5	1
	A	B	Fig. No.		

Figure 4.4:FRVP as a function of positive contrast and visual size (2/2)

Figure 4.5 and Figure 4.6 show FRVP as a function of positive contrast and retinal illuminance. Again the same trend is noticed concerning the growth of FRVP values depending on the rest of the variables. There is no effect for changing the contrast or retinal illuminance, or both at input variables fixed to the least values with respect to its contribution to FRVP (Figure 4.5-1A and 1B). A further increase in the input variables (Figure 4.5-2A and 2B) shows a formation of the medium plateau. Which corresponds to high positive contrast values (above 1.0) and most of the retinal illuminance values. The reason why this plateau lies for most retinal illuminance values is related to the design of the retinal illuminance membership function (Figure 3.39) where the low subset is defined at below 0.8 Trolands, and by considering the large range of the retinal illuminance (up to 100 Trolands), the medium plateau seems to be covering all its range. Yet, a close look at figure 4.5 (2B) shows that there is still a lower plateau at very low retinal illuminance (below 10 Trolands) and positive contrast (below 1.0) values.

The development of the high FRVP plateau is shown in Figure 4.6. The four parts of the figure show how the increase in the other influence variables (age, size, eccentricity, background complexity) affects the way in which both contrast and retinal illuminance contribute to FRVP. Figure 4.6 (2B) corresponds to the other influence variables fixed to the maximum values. The figure shows a large plateau for high FRVP corresponding to luminance contrast values above 1.0 and retinal illuminance values above 10 Trolands. The figure shows that luminance contrast affects FRVP at low retinal illuminance values only, while at high retinal illuminances, FRVP is located at the higher plateau and any change in positive contrast does not affect its values.

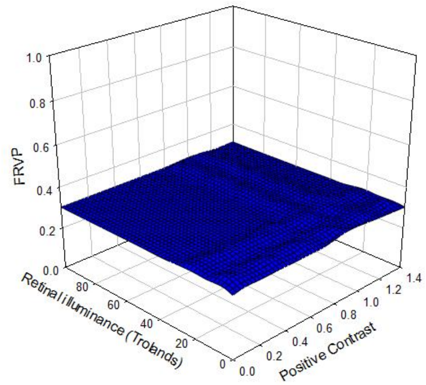
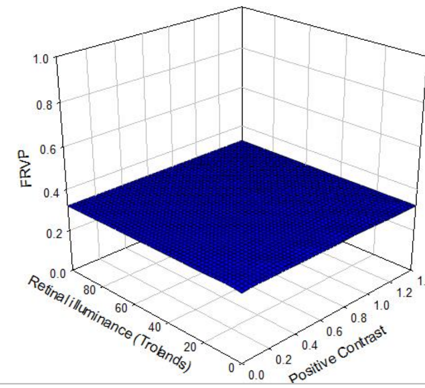
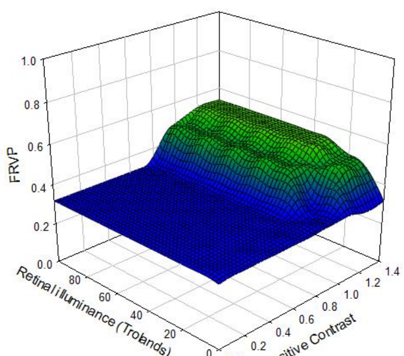
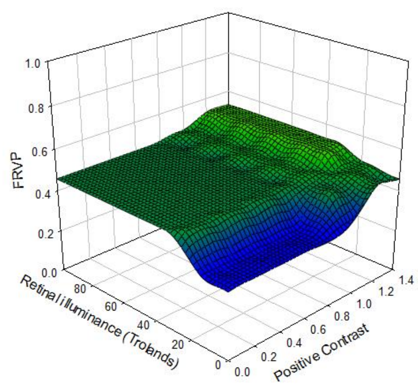
Fig. No.	Visual size (Microsteradians)		Age (years)	Eccentricity	Background Complexity
	5	10			
1			80	20 °	3
2			70	15 °	2
	A	B	Fig. No.		

Figure 4.5: FRVP as a function of positive contrast and Retinal illuminance (1/2)

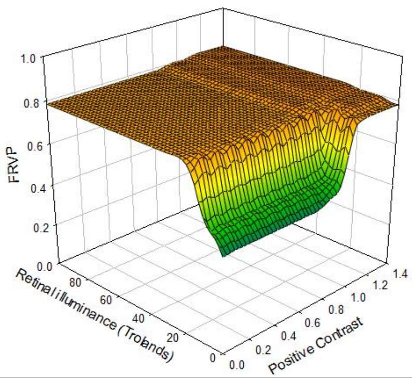
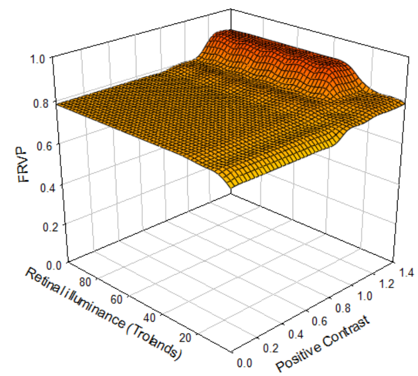
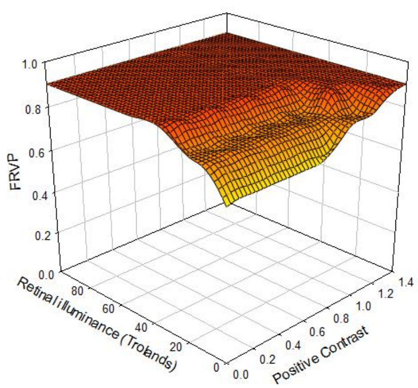
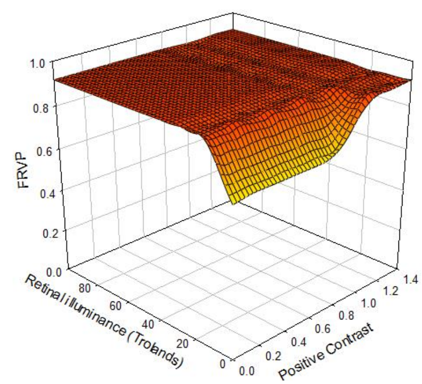
Fig. No.	Visual size (Microsteradians)		Age (years)	Eccentricity	Background Complexity
	15	20			
1			50	10	1.5
2			20	5	1
	A	B	Fig. No.		

Figure 4.6:FRVP as a function of positive contrast and Retinal illuminance (2/2)

Figure 4.7 and Figure 4.8 show FRVP as a function of positive contrast and eccentricity. It was noticed that the same trend exists in these figures as well. Once the values of the other influence variables are fixed to the lowest subset, there is no effect for changing the positive contrast or eccentricity, or both, on the FRVP values (Figure 4.7-1A and 1B). A further change in the other influence variables (age, size, retinal illuminance, background complexity) is shown in Figure 4.7 (2A and 2B). It is noticed that the medium plateau starts to rise at high values of positive contrast (above 1.0) and low values of eccentricity (below 10^o-20^o).

As the other influence variables are increasing, this medium plateau rises above and expands in size (Figure 4.8-1A, 1B, and 2A), until it reaches the highest values when the other influence variables are fixed to the highest subset contributing to FRVP (Figure 4.8-2B). In this situation, a higher plateau exists at almost 0.9 FRVP and a medium plateau at almost 0.6 FRVP. The higher plateaus correspond to high positive contrast values (above 1.0) and low eccentricity values (below 10^o). This means that positive contrast effects FRVP at low contrast values (below 1.0) and high eccentricity values only (above 10^o), the rest of FRVP values are located at either the high of medium plateaus.

The transition between the high and medium plateaus in figure 4.8 (2B) corresponds to the critical values used in designing the membership functions of both the luminance contrast and eccentricity variables.

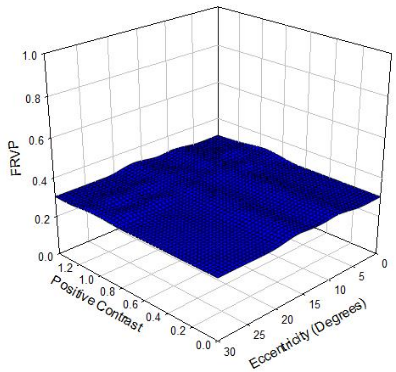
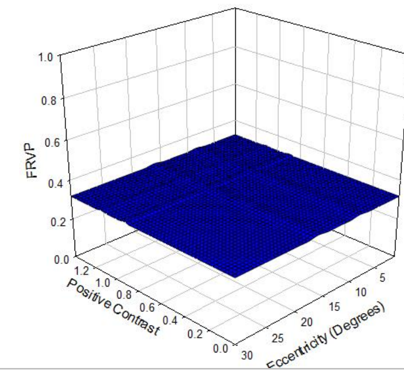
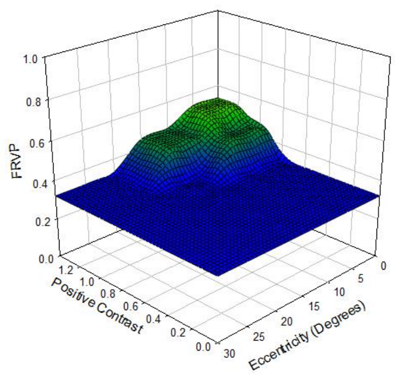
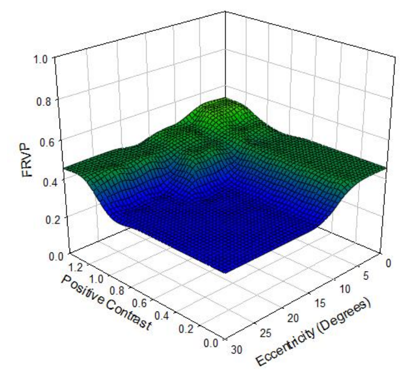
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Size (µstr)	Background Complexity
	0.5	10			
1			80	5	3
2			70	10	2
	A	B	Fig. No.		

Figure 4.7: FRVP as a function of positive contrast and eccentricity (1/2)

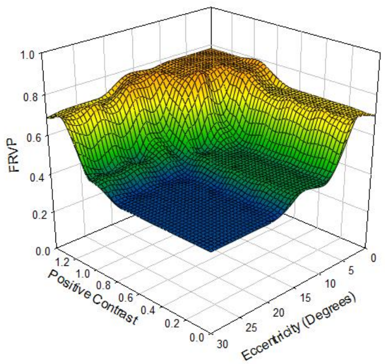
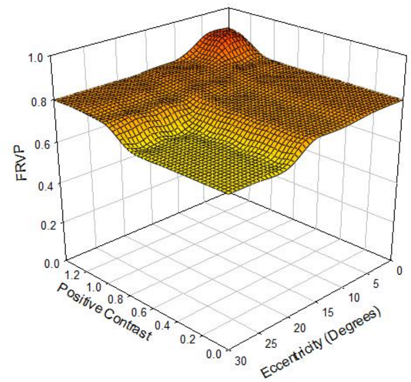
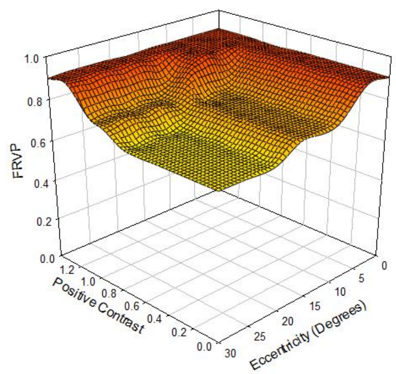
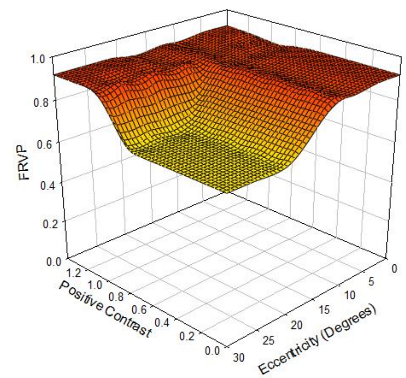
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Size (µstr)	Background Complexity
	20	40			
1			50	15	1.5
2			20	20	1
	A	B	Fig. No.		

Figure 4.8:FRVP as a function of positive contrast and eccentricity (2/2)

FRVP as a function of positive contrast and background complexity is shown in Figure 4.9 and Figure 4.10. The same trend of FRVP development from the lower, passing through the medium, and ending at the higher plateaus is noticed in these figures as well. Figure 4.9(1A and 1B) shows that there is no effect for the positive contrast, or background complexity, or both on FRVP when the visual age is fixed at 80 years, the visual size is fixed at 5 Microsteradians, the retinal illuminance is fixed at 0.5 Trolands, and the eccentricity is fixed at 20^o. In other words, once all other influence variables are fixed at the least subset that contributes to FRVP, there is no effect for any individual variable on FRVP. In this case, the values of FRVP are determined based on the majority of variables. , and no individual variable can change it with help for the other influence variables.

Figure 4.10 (2A and 2B) shows how the high plateau starts as a dome-shape (Figure 4.10-2A) with a small area corresponding to high contrast values (above 1.0) and low background complexity values (below 1.5). However, a further increase in the other influence variables flattens the high plateau surface and increases its area (Figure 4.10-2B). In this case, positive contrast effects FRVP at low contrast values (below 1.0) and high background complexity values (above 1.5). The rest of FRVP values are mostly located at the higher plateau, in which any change in contrast or background complexity will not affect the value of FRVP. The transition from the medium to high plateaus corresponds to the critical values used in the design of membership functions of both positive contrast and background complexity.

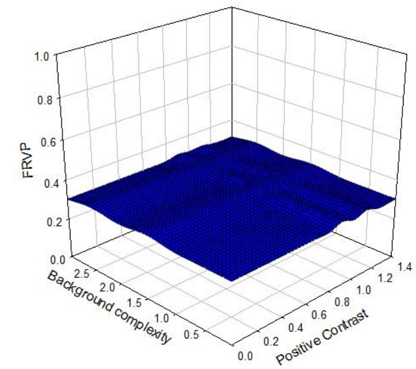
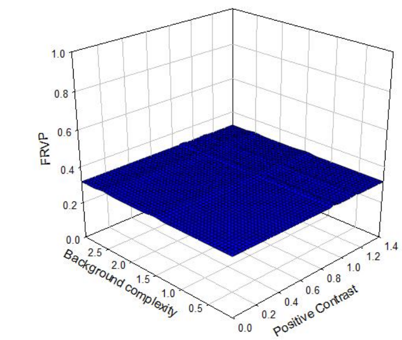
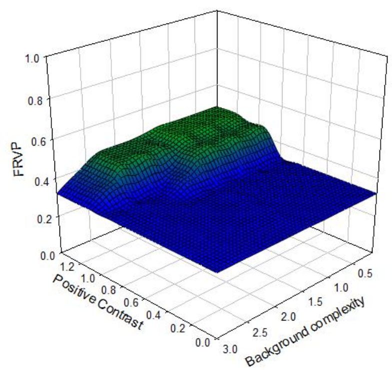
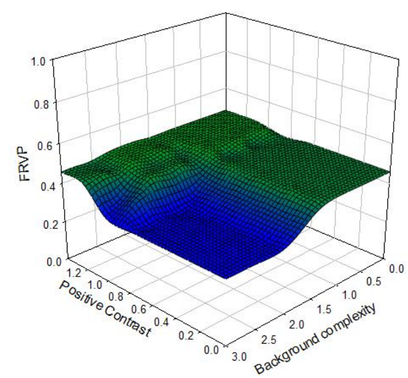
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">Age (years)</th><th rowspan="2">Size (µstr)</th><th rowspan="2">Eccentricity</th></tr>
<tr><th>0.5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>80</td><td>5</td><td>20</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>70</td><td>10</td><td>15</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.9: FRVP as a function of positive contrast and background complexity (1/2)

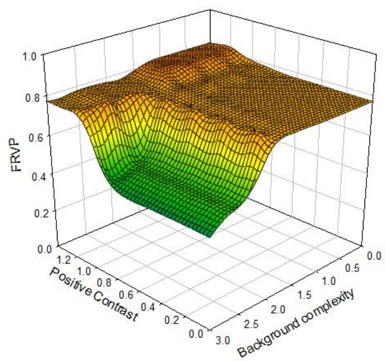
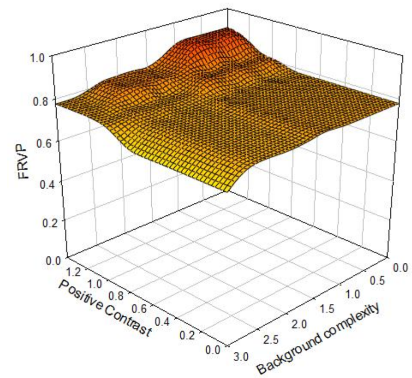
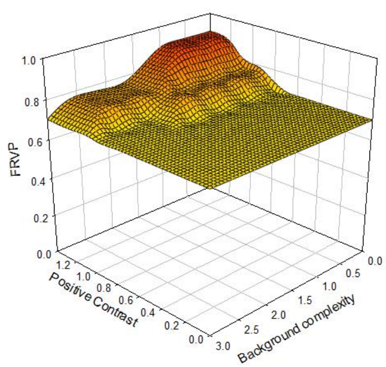
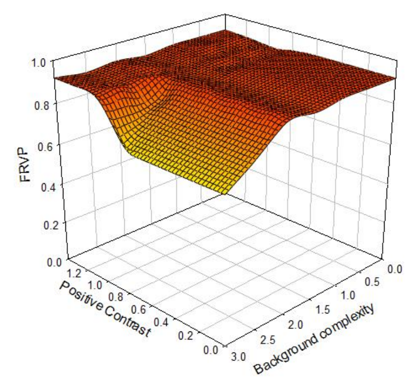
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Age (years)</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>50</td><td>15</td><td>10</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>20</td><td>20</td><td>5</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.10:FRVP as a function of positive contrast and background complexity (2/2)

Figure 4.11 through Figure 4.20 shows the effect of negative contrast on FRVP. The same trend is noticed regarding the development of FRVP plateaus from low to medium to high. However, the range of the negative contrast is from 0 to 0.3, which is different than that for the positive contrast. Hence, the negative values in which FRVP changes from low to medium, or form medium to high plateaus are 0.15 and 0.25 respectively. These values correspond to the critical values used in the design of the negative contrast membership function (Figure 3.30).

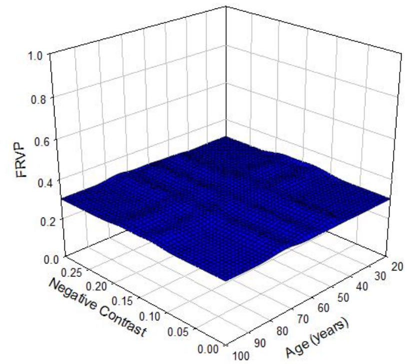
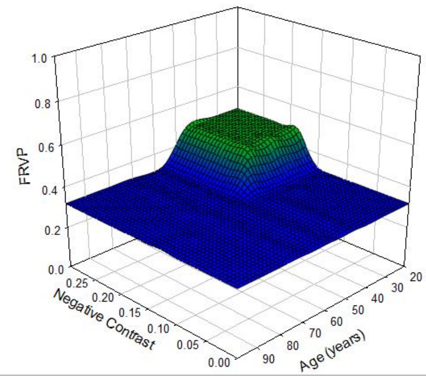
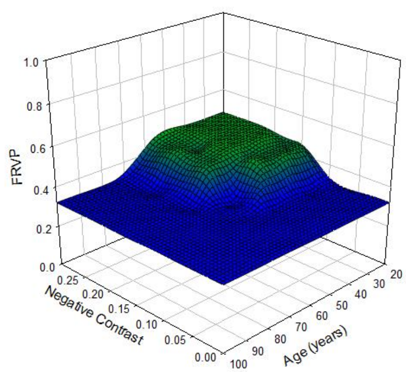
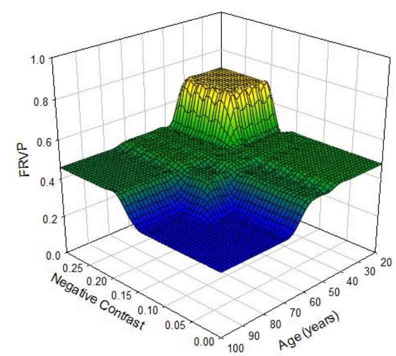
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>5</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>10</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.11: FRVP as a function of negative contrast and visual age (1/2)

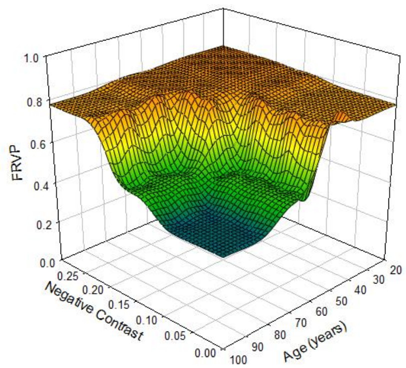
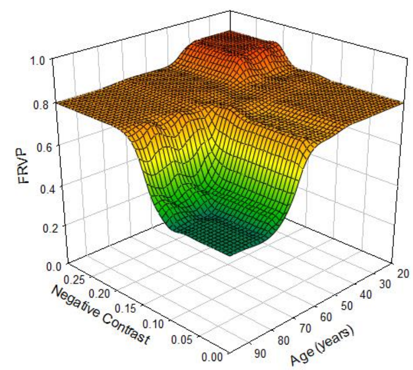
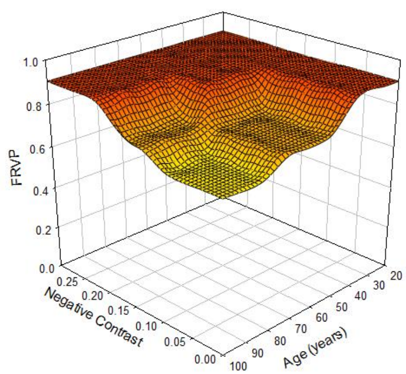
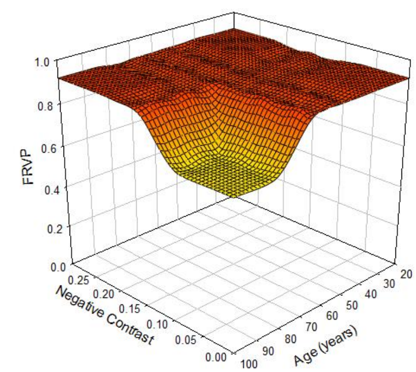
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Size (μstr)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>15</td><td>10</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>20</td><td>5</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.12:FRVP as a function of negative contrast and visual age (2/2)

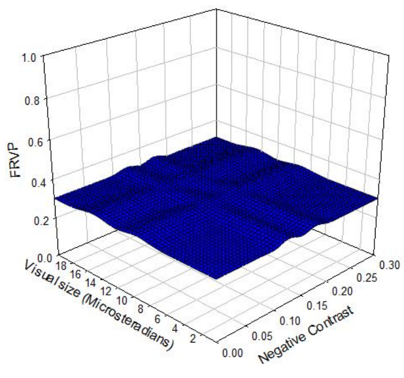
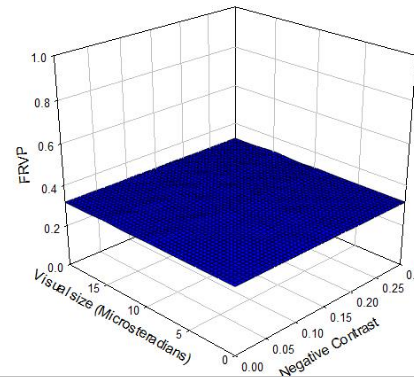
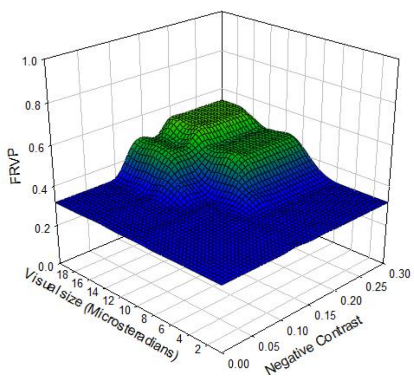
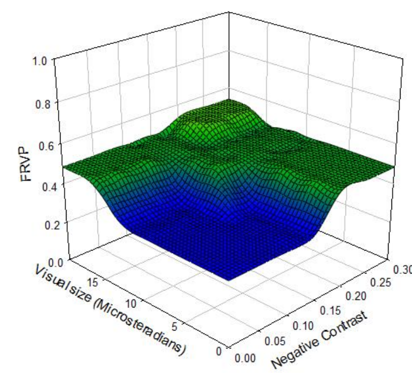
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Age (years)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>80</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>70</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.13: FRVP as a function of negative contrast and visual size (1/2)

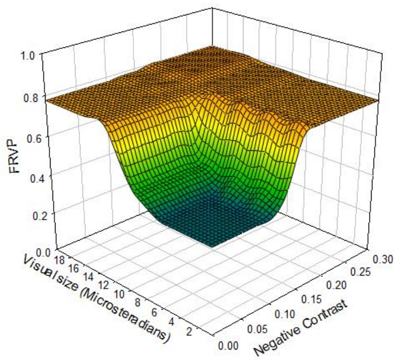
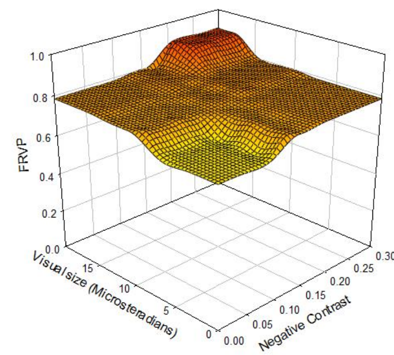
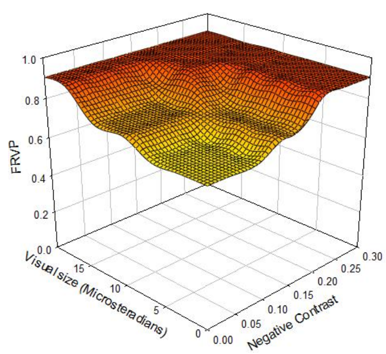
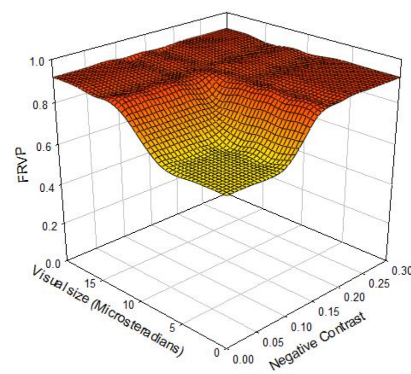
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Age (years)</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>50</td><td>10</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>20</td><td>5</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.14:FRVP as a function of negative contrast and visual size (2/2)

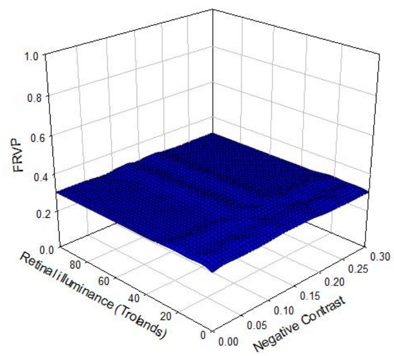
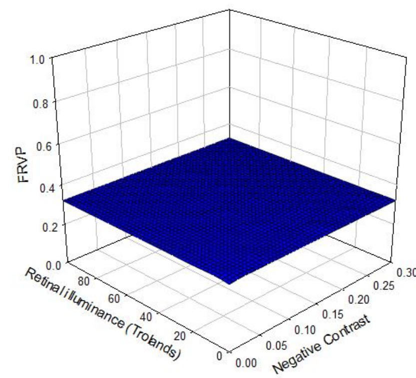
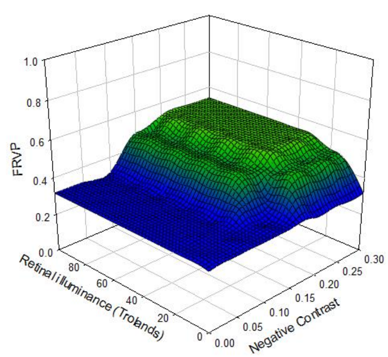
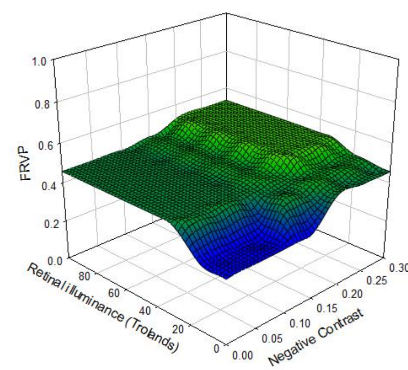
Fig. No.	Visual size (Microsteradians)		Age (years)	Eccentricity	Background Complexity
	5	10			
1			80	20 °	3
2			70	15 °	2
	A	B	Fig. No.		

Figure 4.15: FRVP as a function of negative contrast and Retinal illuminance (1/2)

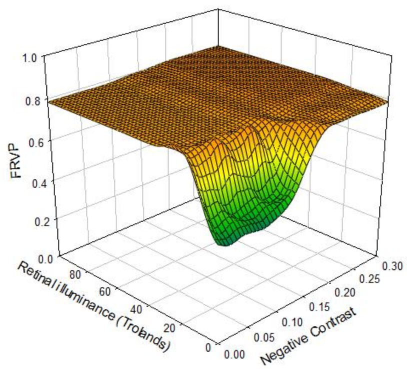
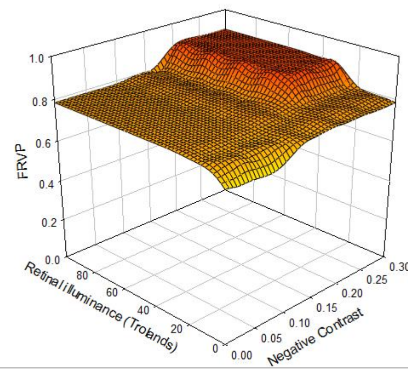
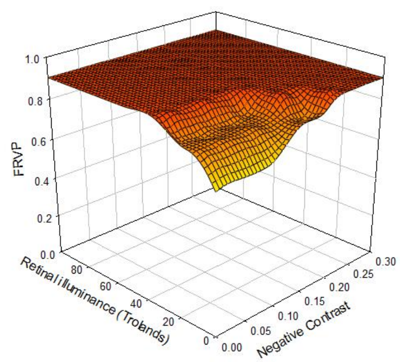
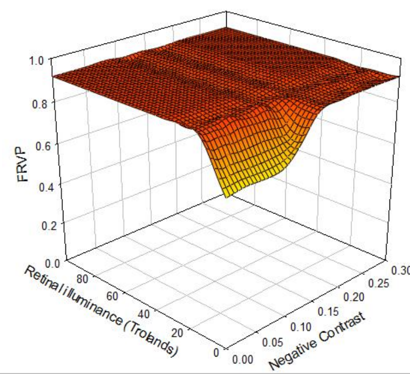
Fig. No.	Visual size (Microsteradians)		Age (years)	Eccentricity	Background Complexity
	15	20			
1			50	10	1.5
2			20	5	1
	A	B	Fig. No.		

Figure 4.16:FRVP as a function of negative contrast and Retinal illuminance (2/2)

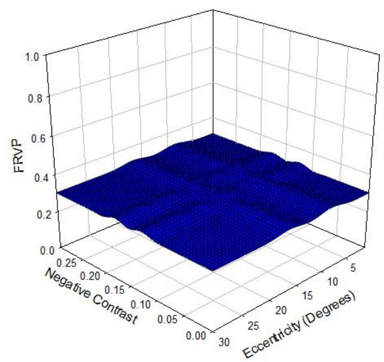
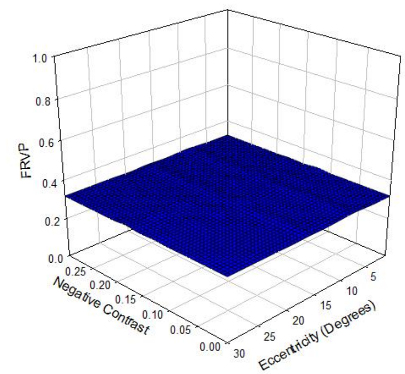
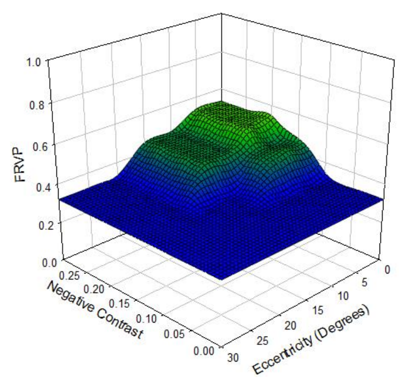
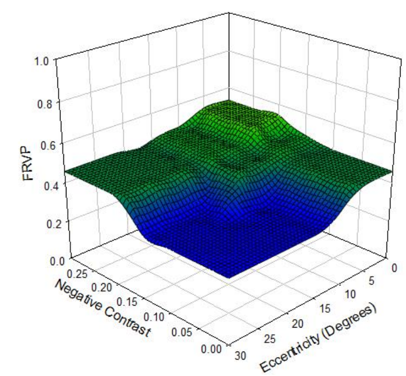
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">Age (years)</th><th rowspan="2">Size (µstr)</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>0.5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>80</td><td>5</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>70</td><td>10</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.17: FRVP as a function of negative contrast and eccentricity (1/2)

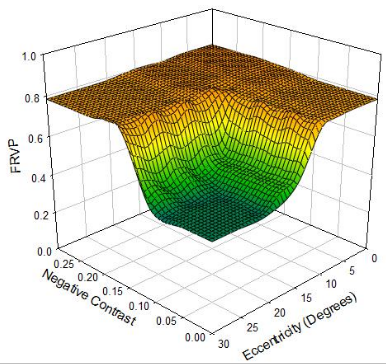
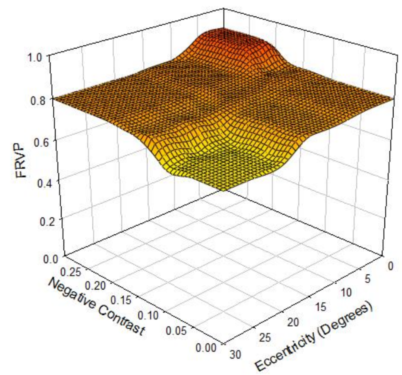
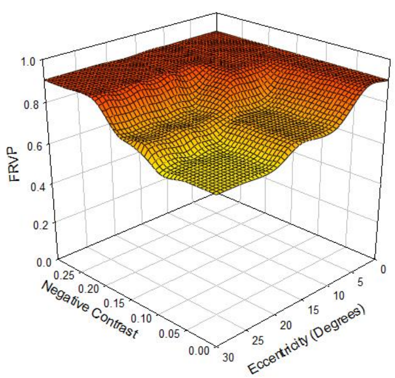
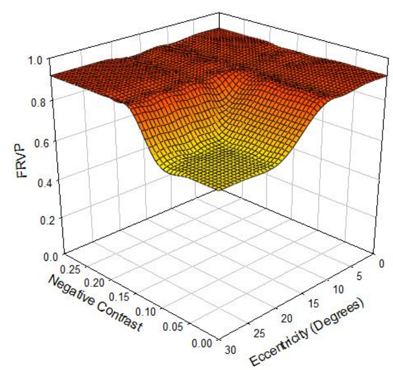
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Size (µstr)	Background Complexity
	20	40			
1			50	15	1.5
2			20	20	1
	A	B	Fig. No.		

Figure 4.18:FRVP as a function of negative contrast and eccentricity (2/2)

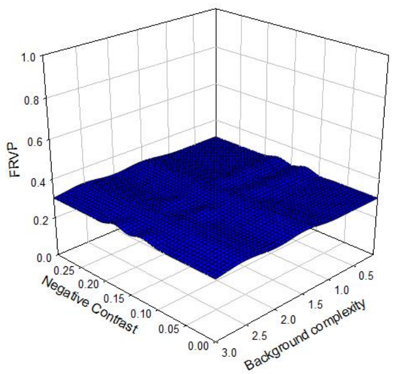
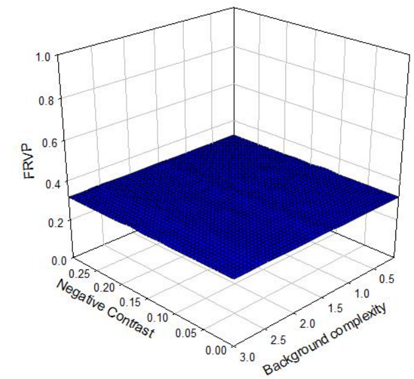
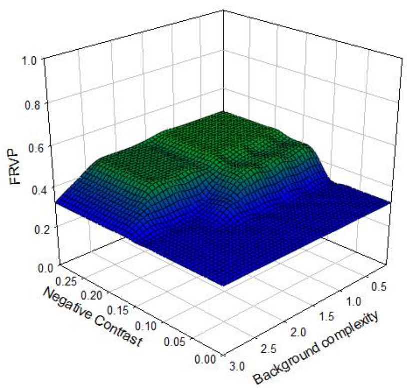
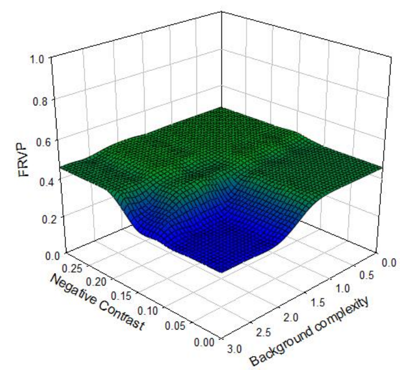
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">Age (years)</th><th rowspan="2">Size (µstr)</th><th rowspan="2">Eccentricity</th></tr>
<tr><th>0.5</th><th>10</th></tr>
<tr><td>1</td><td></td><td></td><td>80</td><td>5</td><td>20</td></tr>
<tr><td>2</td><td></td><td></td><td>70</td><td>10</td><td>15</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.19: FRVP as a function of negative contrast and background complexity (1/2)

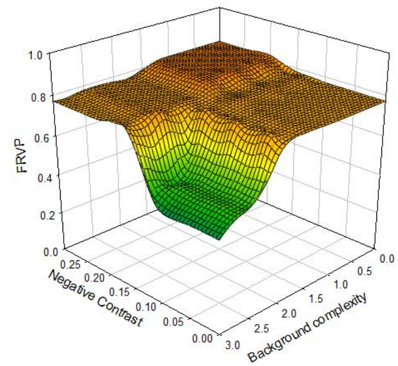
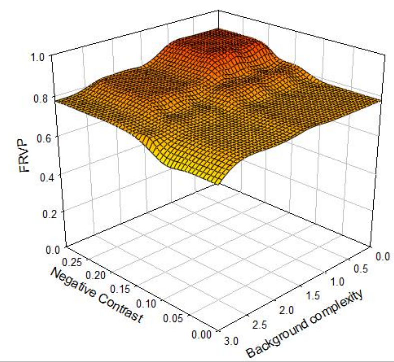
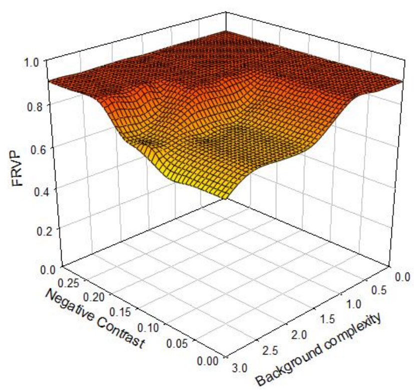
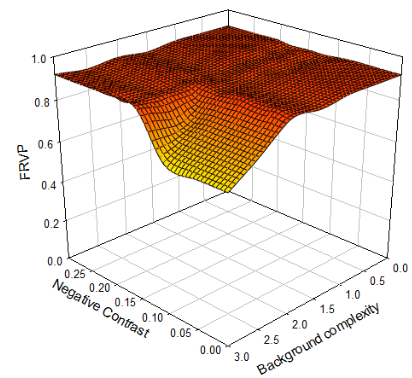
Fig. No.	Retinal Illuminance (Trolands)		Age (years)	Size (µstr)	Eccentricity
	20	40			
1			50	15	10
2			20	20	5
	A	B	Fig. No.		

Figure 4.20:FRVP as a function of negative contrast and background complexity (2/2)

4.1.2 Visual age effect

The current visibility models were based on experiments involving healthy subjects and considered the effect of age by developing correction factors (Adrian 1989), or involving complex mathematical relations to account for older observers (Rea and Ouellette 1988, 1991). However, this model considers age as an independent input variable that has its characteristics and uniqueness. The attention given to age in this design of this model was enough to get a measurable effect for this variable.

FRVP as a function of visual age and luminance contrast can be seen in Figure 4.1 and Figure 4.2 for positive contrast and Figure 4.11 and Figure 4.12 for negative contrast, so these figures will not be repeated in this section. The remaining figures (from Figure 4.21 to Figure 4.28) show FRVP as a function of age and visual size, retinal illuminance, eccentricity, and background complexity, respectively.

The general trend in all these figures shows that once FRVP is having values at a plateau (low, medium, or high), nothing can be done to change its value. In other words, there is no effect for any single variable alone on FRVP. The only effect can be seen in the transition area (between plateaus) which correspond to the critical values used to develop the visual age membership function. Moreover, the effect of the visual age is more noticeable when the other influence variables (not included in the graph) are fixed to medium or high values corresponding to its effect on FRVP (figure 4.22-2A and 2B). The same situation shows that FRVP high plateau can be noticed at ages almost below 55 years of old, and medium plateau at ages above 65 years old.

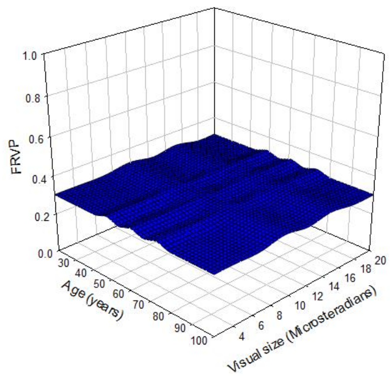
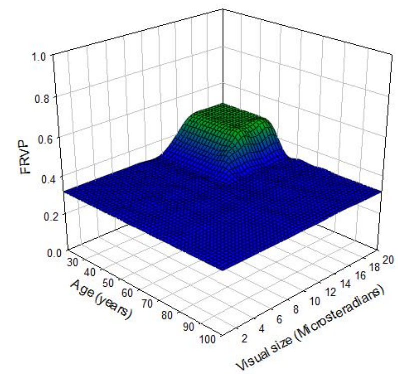
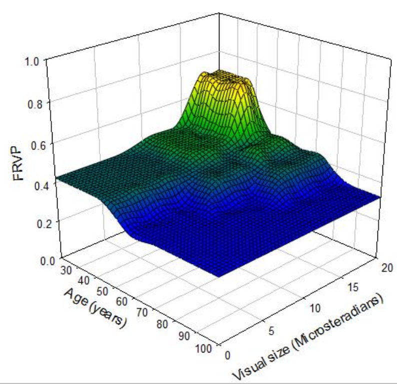
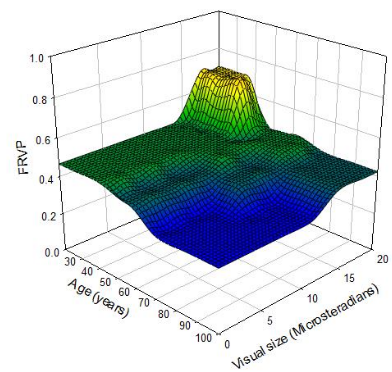
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Contrast</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.21: FRVP as a function of visual age and visual size (1/2)

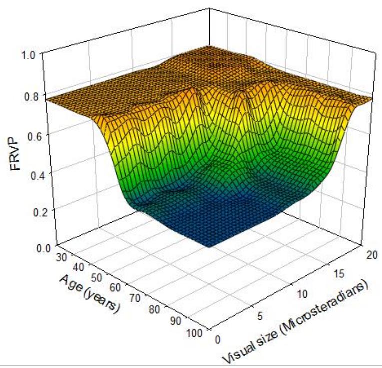
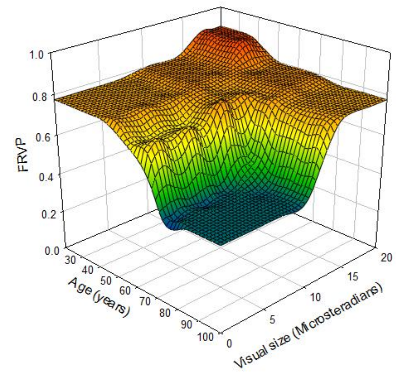
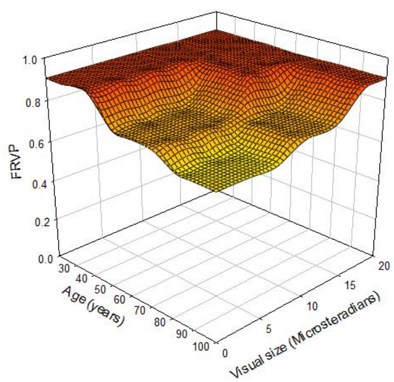
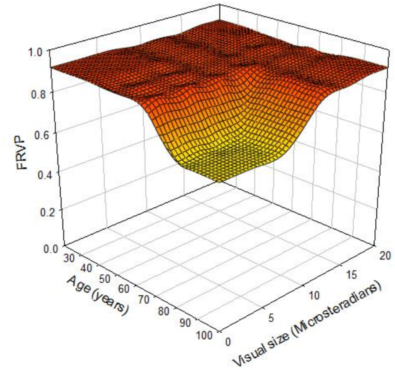
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">contrast</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>1.0</td><td>10</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>1.2</td><td>5</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.22:FRVP as a function of visual age and visual size (2/2)

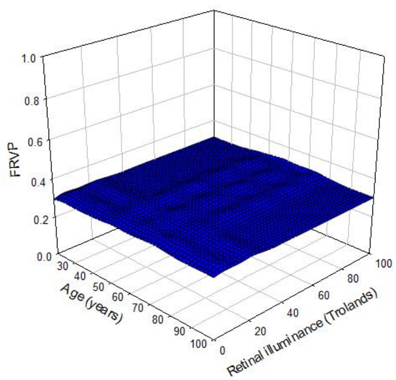
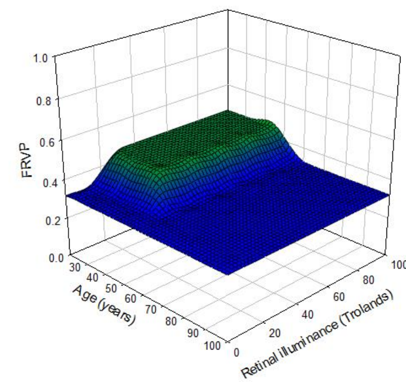
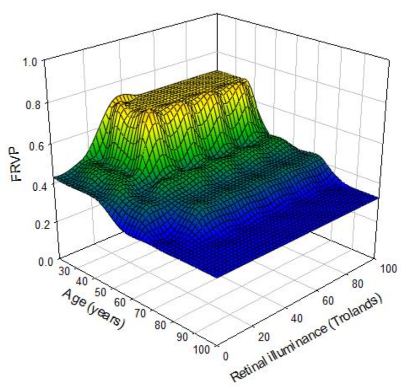
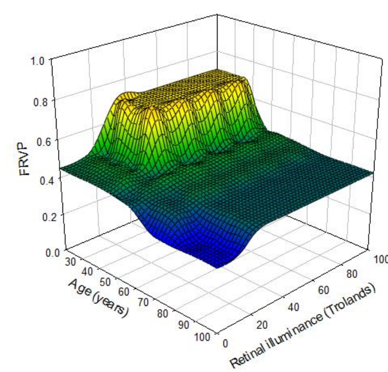
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Visual size (Microsteradians)</th><th rowspan="2">Contrast</th><th rowspan="2">Eccentricity</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.23: FRVP as a function of visual age and Retinal illuminance (1/2)

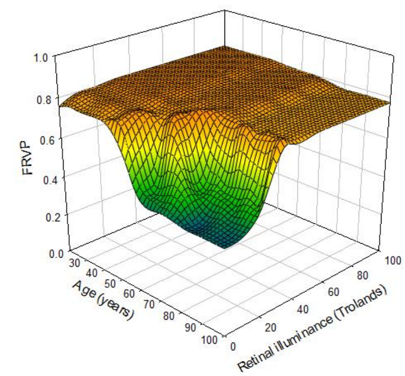
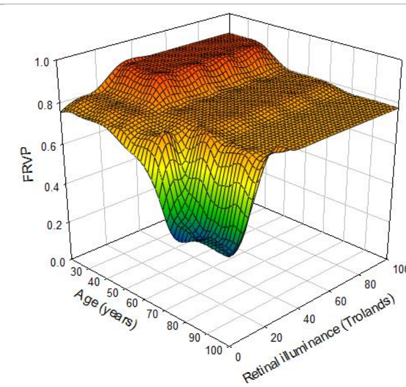
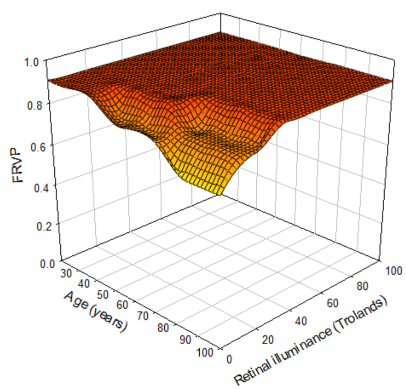
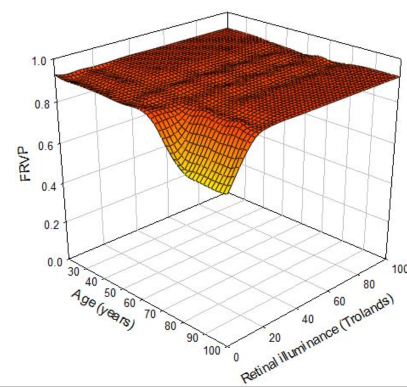
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Visual size (Microsteradians)</td><td rowspan="2">Contrast</td><td rowspan="2">Eccentricity</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>15</td><td>20</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>1.0</td><td>10</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>1.2</td><td>5</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.24:FRVP as a function of visual age and Retinal illuminance (2/2)

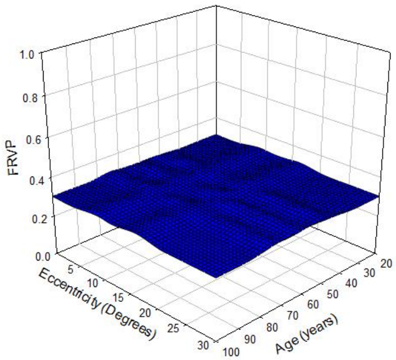
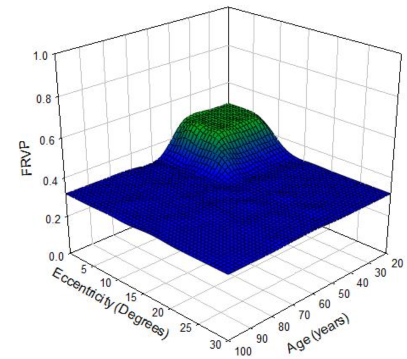
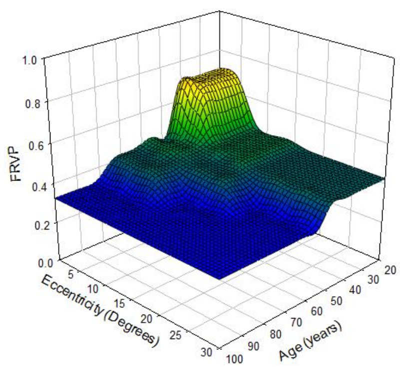
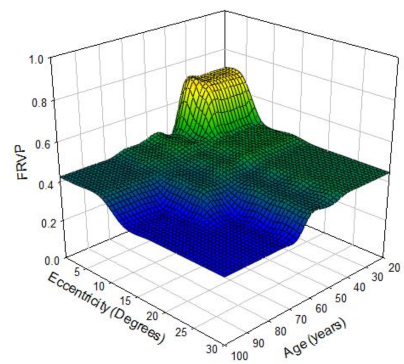
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Contrast</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td></td><td></td><td>0.3</td><td>5</td><td>3</td></tr>
<tr><td>2</td><td></td><td></td><td>0.9</td><td>10</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.25: FRVP as a function of visual age and eccentricity (1/2)

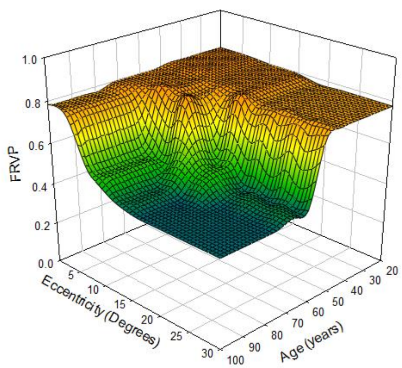
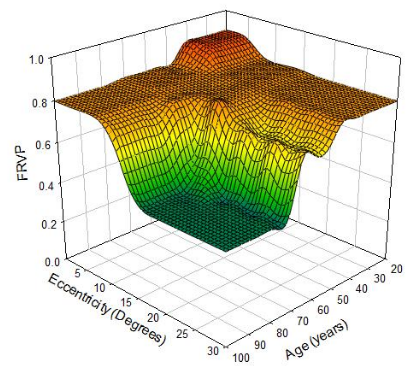
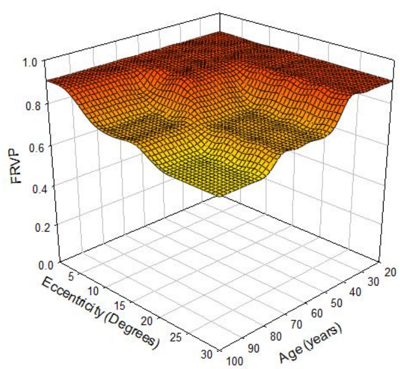
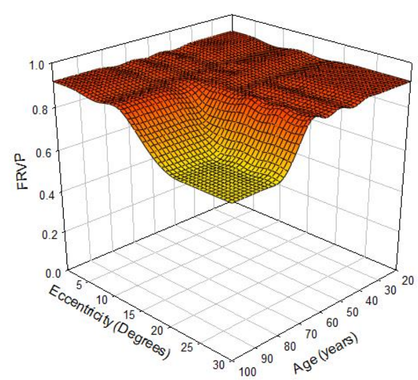
Fig. No.	Retinal Illuminance (Trolands)		Contrast	Size (µstr)	Background Complexity
	20	40			
1			1.0	15	1.5
2			1.2	20	1
	A	B	Fig. No.		

Figure 4.26:FRVP as a function of visual age and eccentricity (2/2)

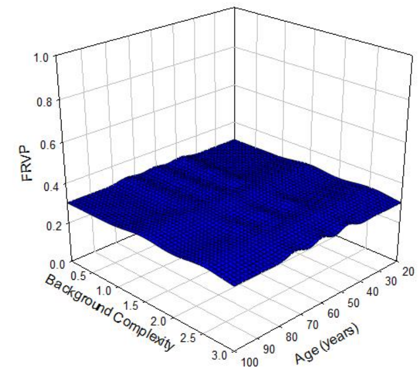
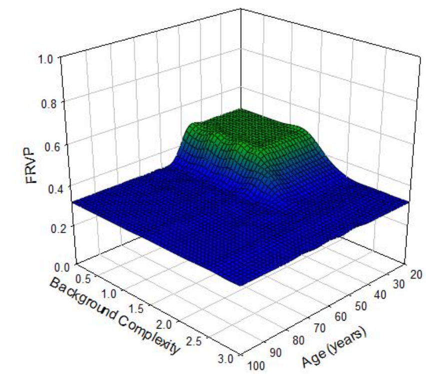
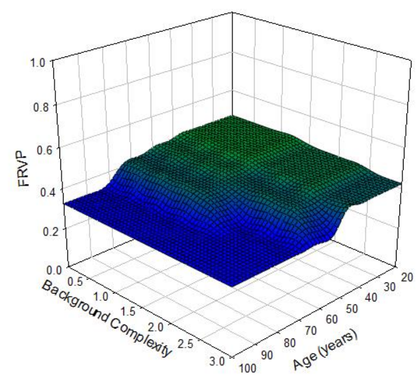
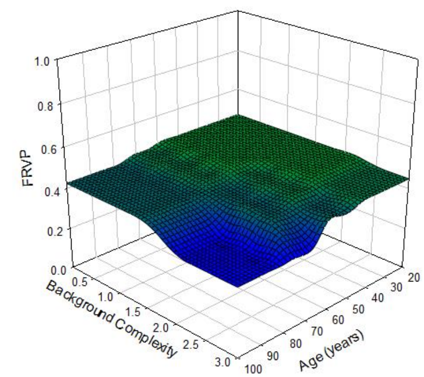
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">contrast</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>5</td><td>20</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>10</td><td>15</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.27: FRVP as a function of visual age and background complexity (1/2)

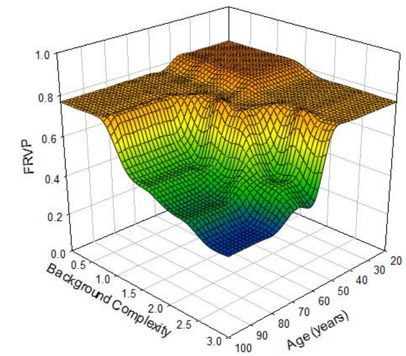
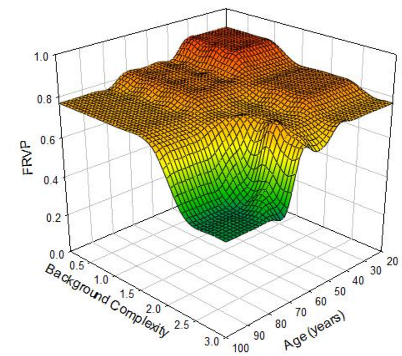
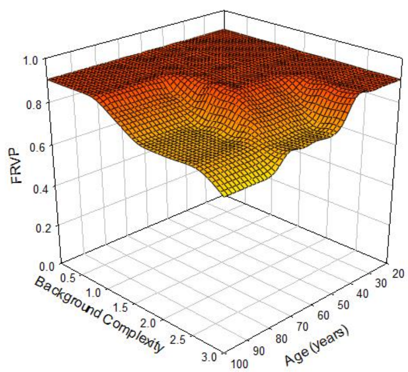
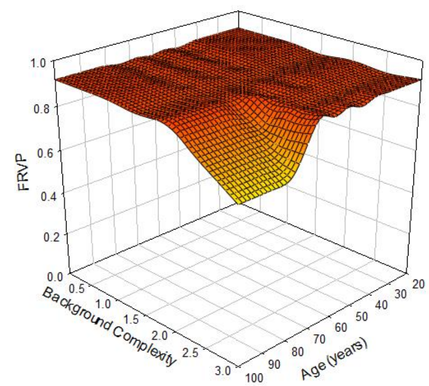
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Contrast</td><td rowspan="2">Size (µstr)</td><td rowspan="2">Eccentricity</td></tr>
<tr><td>20</td><td>40</td></tr>
<tr><td>1</td><td></td><td></td><td>1.0</td><td>15</td><td>10</td></tr>
<tr><td>2</td><td></td><td></td><td>1.2</td><td>20</td><td>5</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.28:FRVP as a function of visual age and background complexity (2/2)

4.1.3 Visual size effect

The visual size is also one of the most important visibility factors, it was incorporated in Adrian's visibility level (1989) as the target size (measured in minutes of arc). It was also incorporated in the RVP model (Rea and Ouellette 1988, 1991) as per the definition of the solid angle (measured in Steradians). STV model (IESNA 2000) incorporated the effect of small targets only. In this work, the visual size has been included as an independent variable, based on the definition of the solid area (As per Rea and Ouellette 1988, 1991), with a range that includes small, medium and large sizes (up to 20 Microsteradians).

FRVP as a function of visual size and luminance contrast graphs as shown in Figure 4.3 and Figure 4.4 (for positive contrast) and Figure 4.13Figure 4.14 (for negative contrast). Moreover, FRVP as a function of visual size and visual age is shown in Figure 4.21 and Figure 4.22. Hence, there is no need to repeat them in this section. The remaining graphs of FRVP as a function of visual size and retinal illuminance, eccentricity, and background complexity are shown in Figure 4.29 through Figure 4.34.

Visual size figures show that FRVP values are located at either lower, medium, or upper plateaus. These plateaus area and size depend on the combination of the other influence variables (not included in the graph) that contribute, either positively or negatively on the degree of visibility. The lowest plateau can be seen in figure 4.29 (1A and 1B) at a value of almost 0.3 FRVP. Any change in the values of visual size in this situation will not affect the value of FRVP. Once the other influence values (not included in the graph) start to increase, another medium plateau starts to exist. A further increase in the other influence variables creates the third plateau (higher plateau) and reduce the size of the medium plateau. It was noticed that plateaus boundaries correspond to the critical values used to design the membership function of the visual size. For example, Figure 4.29 (2A) shows that a medium plateau exists at visual size values above 5 Microsteradians. Also, Figure 4.30(1A) shows that there is a high plateau at visual size values above almost 15 Microsteradians. These values correspond to the critical values used to design the membership function of the visual size (see Figure 3.35).

Any change in the values of the visual size while FRVP is located at any plateau will not affect FRVP values. This is seen in all figures as the combined effect of the other influence variables are too large to be changed by only one variable or even two variables alone. This can be seen in figure 4.31 (1A and 1B) as FRVP is located at the lowest plateau and there is no effect for either visual size or eccentricity on its value. However, once all other influence variables are fixed at the maximum with respect to its contribution to FRVP (figure 4.32-2B) there is a small effect of visual age outside the higher and medium plateaus (in the transition region between the high and medium plateaus).

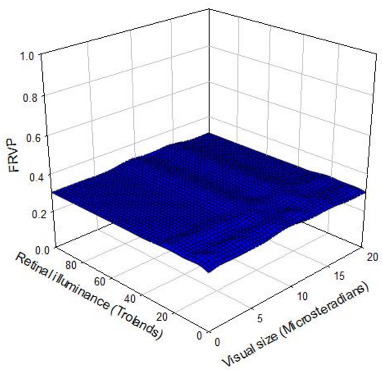
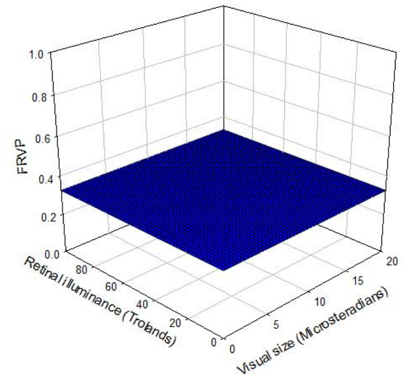
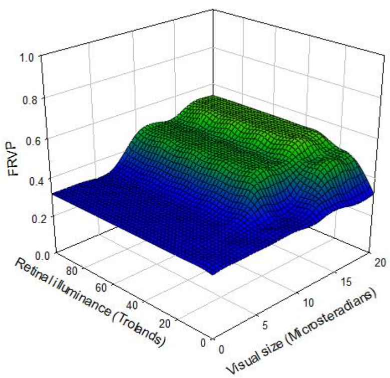
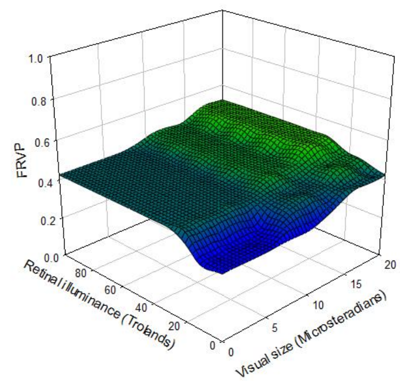
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Eccentricity</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>0.3</th><th>0.9</th></tr>
<tr><td>1</td><td></td><td></td><td>80</td><td>20 °</td><td>3</td></tr>
<tr><td>2</td><td></td><td></td><td>70</td><td>15 °</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.29: FRVP as a function of visual size and Retinal illuminance (1/2)

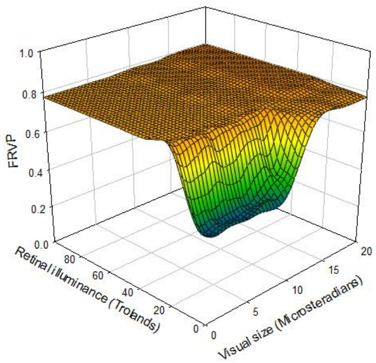
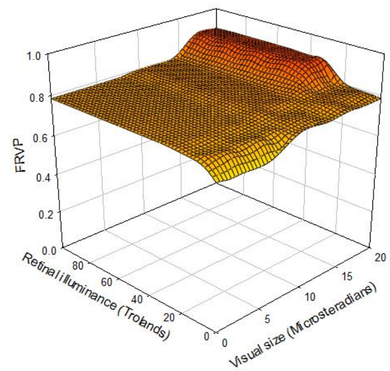
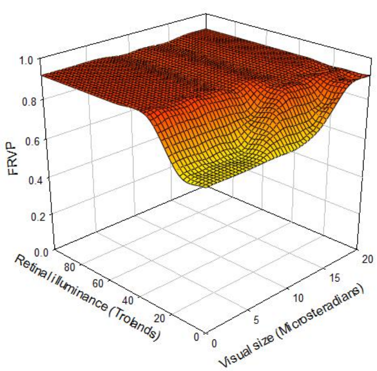
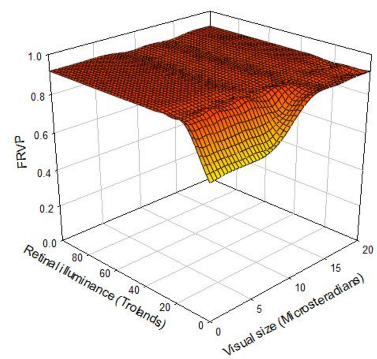
Fig. No.	Contrast		Age (years)	Eccentricity	Background Complexity
	1.0	1.2			
1			50	10	1.5
2			20	5	1
	A	B	Fig. No.		

Figure 4.30:FRVP as a function of visual size and Retinal illuminance (2/2)

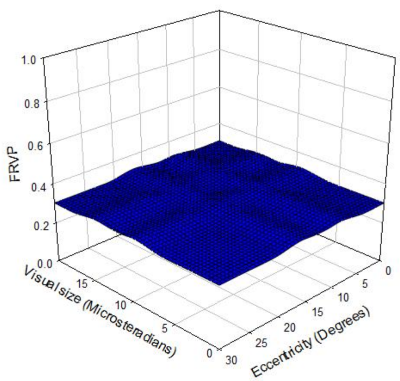
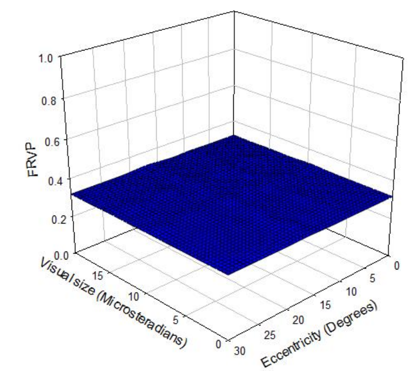
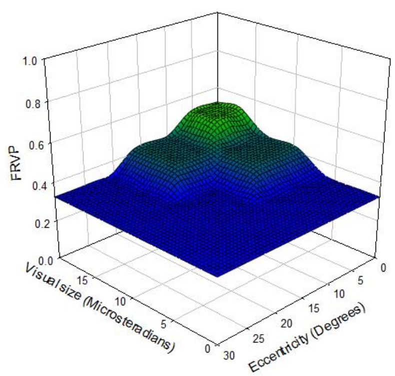
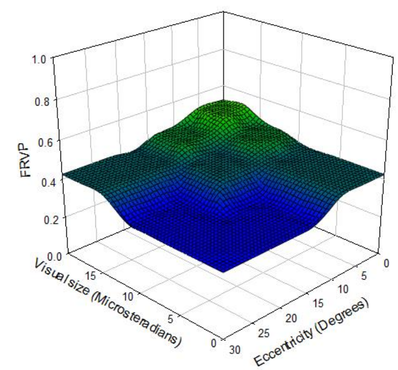
<table>
<tr><td rowspan="2">Fig. No.</td><td colspan="2">Retinal Illuminance (Trolands)</td><td rowspan="2">Contrast</td><td rowspan="2">Age (years)</td><td rowspan="2">Background Complexity</td></tr>
<tr><td>0.5</td><td>10</td></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>80</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>70</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.31: FRVP as a function of visual size and eccentricity (1/2)

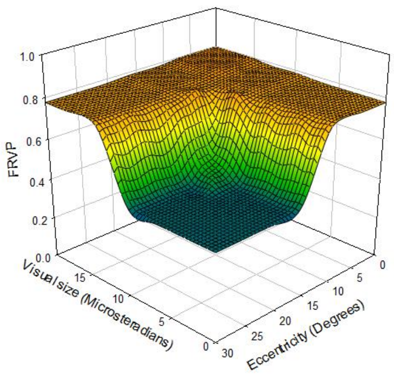
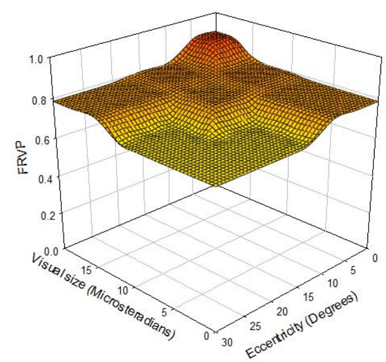
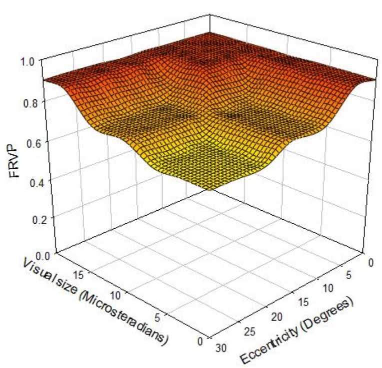
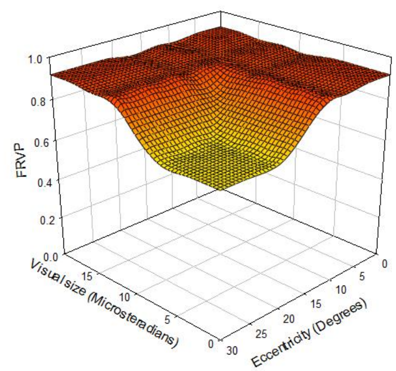
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>20</th><th>40</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>1.0</td><td>50</td><td>1.5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>1.2</td><td>20</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.32:FRVP as a function of visual size and eccentricity (2/2)

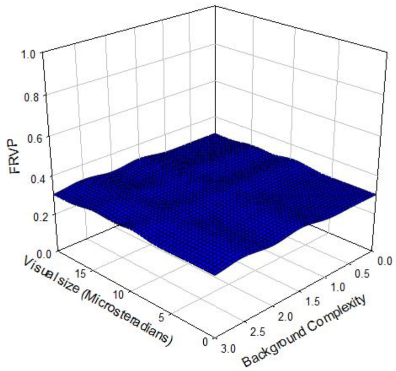
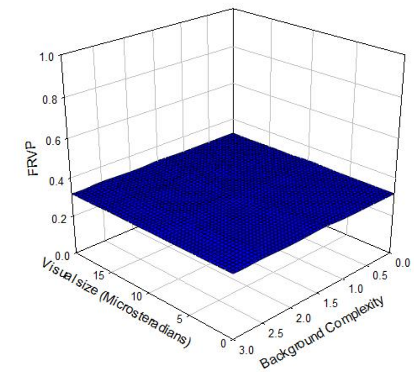
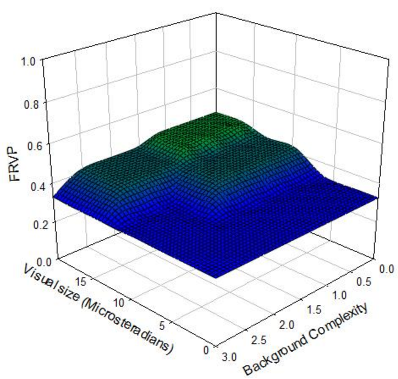
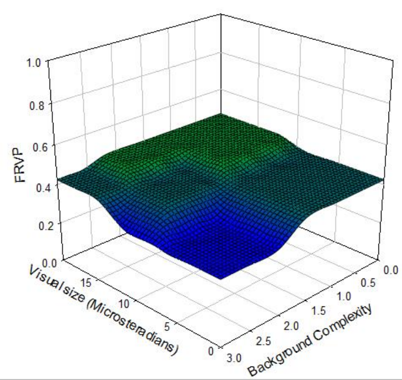
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Eccentricity</th></tr>
<tr><th>0.5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>80</td><td>20</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>70</td><td>15</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.33: FRVP as a function of visual size and background complexity (1/2)

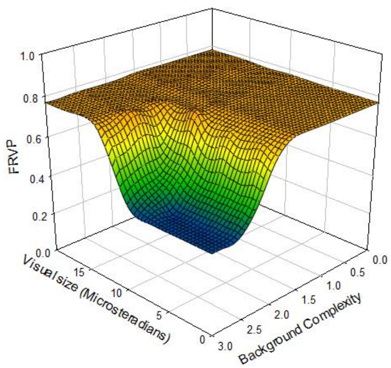
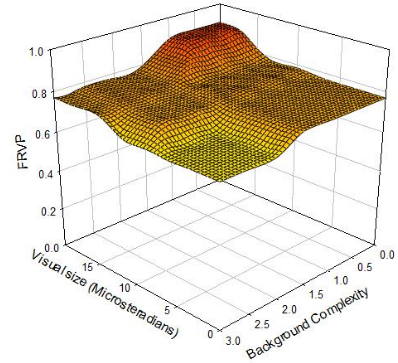
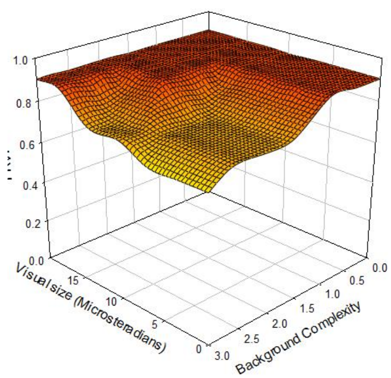
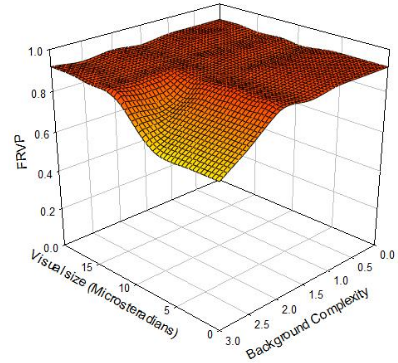
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Eccentricity</th></tr>
<tr><th>20</th><th>40</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>1.0</td><td>50</td><td>10</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>1.2</td><td>20</td><td>5</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.34:FRVP as a function of visual size and background complexity (2/2)

4.1.4 Retinal illuminance effect

The retinal illuminance can be defined as the amount of luminous power per area perceived by the human retina and is measured in Trolands It is more convenient to use the retinal illuminance instead of adaptation luminance in considering threshold or supra-threshold visibility models (Saraiji and Alhamad 2018). The range of retinal illuminance adopted in this study is from almost zero to 100 Trolands, which includes low, medium, and high values of Trolands which correspond to actual night-driving typical scenarios (Figure 3.38 and Figure 3.39).

Results for FRVP as a function of retinal illuminance and luminance contrast are shown in Figure 4.5 and Figure 4.6 for positive contrast and Figure 4.15 and Figure 4.16 for negative contrast. FRVP as a function of retinal illuminance and visual age is shown in Figure 4.23 and Figure 4.24. FRVP as a function of retinal illuminance and visual size in Figure 4.29 and Figure 4.30, so there is no need to repeat them in this section. The remaining figures for FRVP as a function of retinal luminance are shown in Figure 4.35 and Figure 4.36 (with eccentricity) and Figure 4.37 Figure 4.38 (with background complexity).

It is clear from the retinal illuminance figures that the same trend of plateaus growth from low to medium to high. However, retinal illuminance figures have a certain feature in which the medium plateau and high plateaus are usually larger than any other variables figures (figure 4.35 2A and 2B). This is related to the unique design of the retinal illuminance membership function (Figure 3.39) which is denser at the beginning with critical Trolands low and medium values, while the high Troland values extend on a wider range (from 30 to 100 Trolands). This is more clearly noticed in Figure 4.36 and Figure 4.40 when the other influence variables are fixed at medium and/or high, with respect to their contribution to FRVP.

When the influence variables are fixed at the maximum, with respect to their contribution to FRVP, it is noticed that there is no effect for retinal illuminance above almost 30 Trolands, as the values of FRVP are located at the higher plateau. However, at below 30 Trolands, there is a clear effect for increasing the retinal illuminance in changing FRVP values from almost 0.7 to 0.9. it is also clear that the critical values used to design the retinal illuminance membership function play an important role in determining the shape of the 3D surface and plateaus.

The same can be said when the influence variables are fixed at the minimum values, with respect to their contribution to FRVP (figure 4.35 1A and 2A), where there is no effect for the retinal illuminance at these situations. This has been noticed in most of the figures and related to the combined effect of the influence variables which makes FRVP low regardless of the values than any other single variable can take.

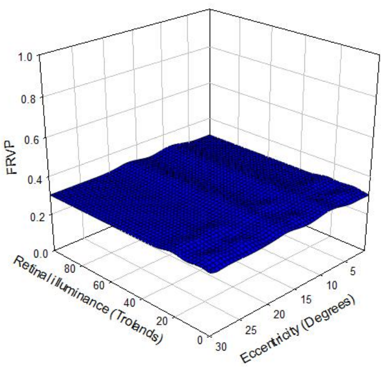
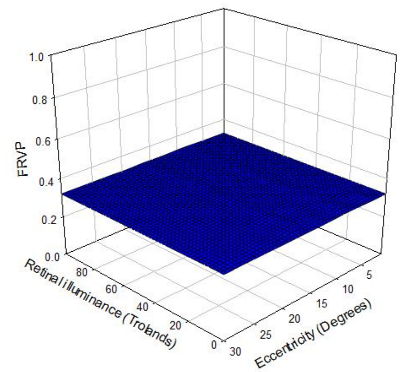
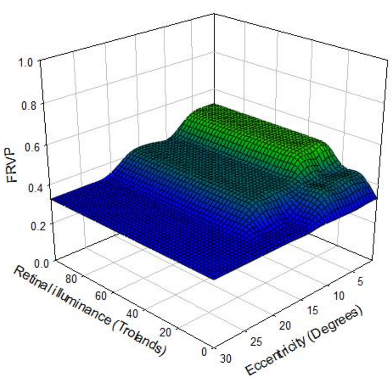
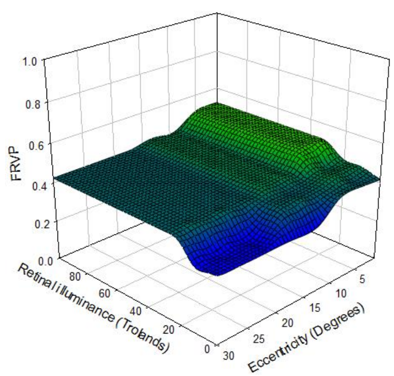
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Visual Size (Microsteradians)</th><th rowspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>80</td><td>3</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>70</td><td>2</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.35: FRVP as a function of Retinal illuminance and eccentricity (1/2)

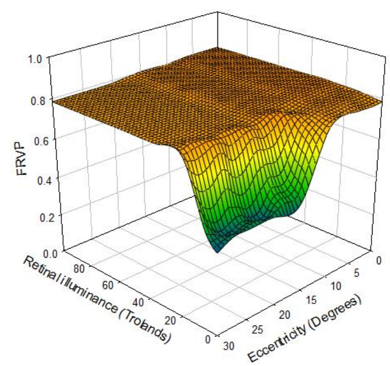
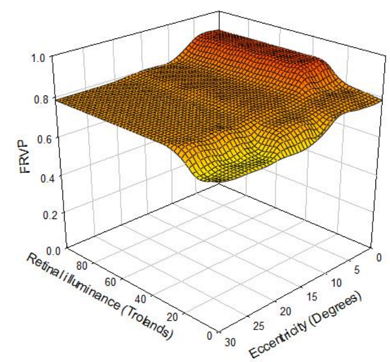
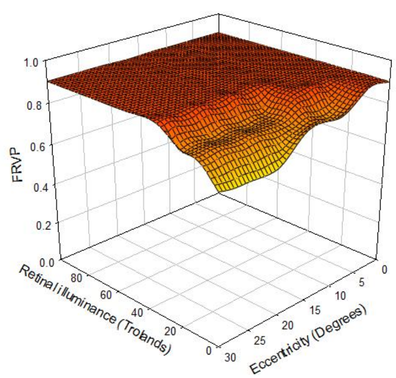
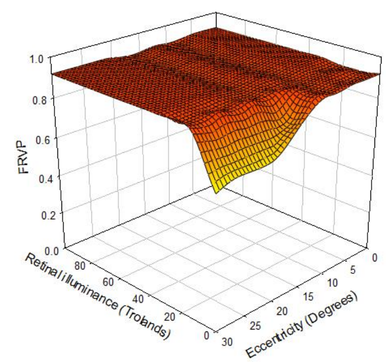
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Visual Size (Microsteradians)</th><th rowspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Background Complexity</th></tr>
<tr><th>15</th><th>20</th></tr>
<tr><td>1</td><td></td><td></td><td>1.0</td><td>50</td><td>1.5</td></tr>
<tr><td>2</td><td></td><td></td><td>1.2</td><td>20</td><td>1</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.36:FRVP as a function of Retinal illuminance and eccentricity (2/2)

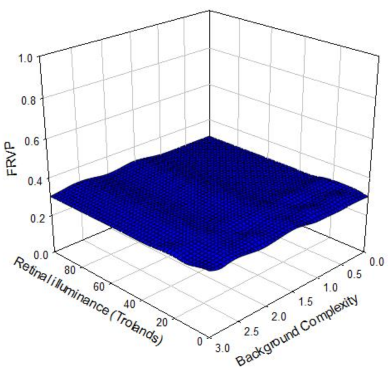
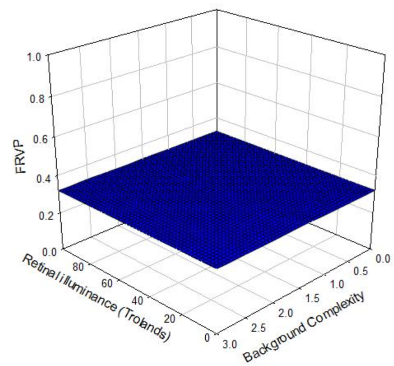
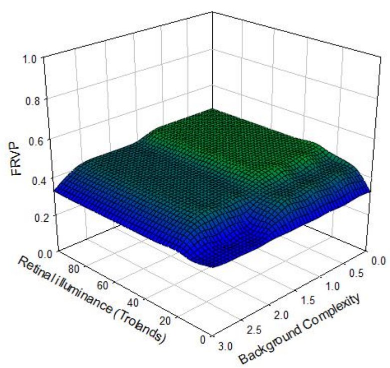
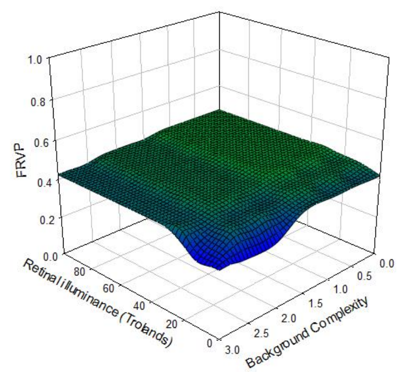
Fig. No.	Visual Size (Microsteradians)		contrast	Age (years)	Eccentricity
	5	10			
1			0.3	80	20
2			0.9	70	15
	A	B	Fig. No.		

Figure 4.37: FRVP as a function of Retinal illuminance and background complexity (1/2)

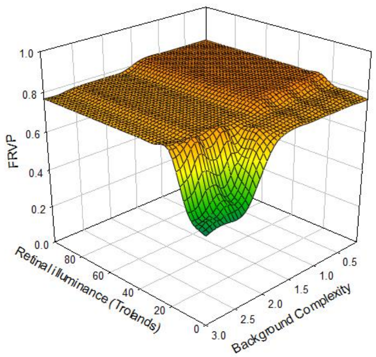
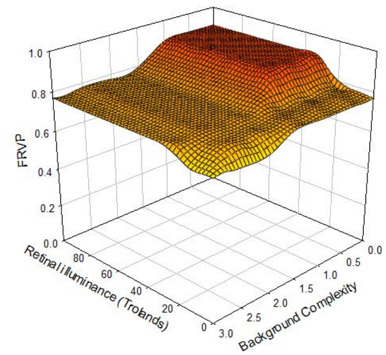
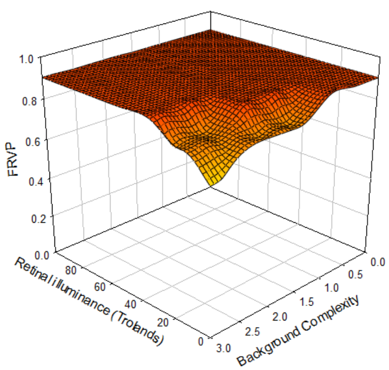
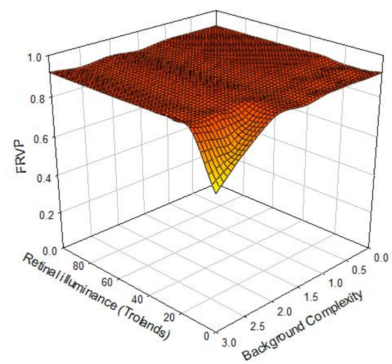
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Visual Size (Microsteradians)</th><th rowspan="2">Contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Eccentricity</th></tr>
<tr><th>15</th><th>20</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>1.0</td><td>50</td><td>10</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>1.2</td><td>20</td><td>5</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.38:FRVP as a function of Retinal illuminance and background complexity (2/2)

4.1.5 Eccentricity effect

Eccentricity can be defined as the deviation of the target from the observer's line of sight (measured in degrees). These important variables were neglected in the development and Adrian's' visibility model (1989) as well as the RVP model (Rea and Ouellette 1988, 1991). However, the proposed FRVP model includes the eccentricity as an individual independent parameter that has the same weight of the rest of any other input variable involved in the FRVP model. Eccentricity was defined based on the probability of detection of targets (Inditsky et al. 1982. and has a unique membership function that incorporates a range of angles from zero (target within the axis of the line of sight) to 30^o (target far away from axis).

FRVP as a function of eccentricity and luminance contrast can be seen in Figure 4.7 and Figure 4.8 (for positive contrast) and Figure 4.17 and Figure 4.18 for negative contrast. FRVP as a function of eccentricity and visual size can be seen in Figure 4.25 and Figure 4.26. FRVP as a function of eccentricity and visual size in Figure 4.31 and Figure 4.32. FRVP as a function of eccentricity and retinal illuminance in Figure 4.35 and Figure 4.36.

FRVP as a function of eccentricity and background complexity in Figure 4.39 and Figure 4.40. It is noticed from the eccentricity figures that once FRVP is located at a certain plateau (low, medium, or high), there is no effect for changing the eccentricity. The only effect is measurable at transition areas between and upper and lower plateaus. Moreover, the critical values of eccentricity used to develop the eccentricity membership function (Figure 3.41) plays an important role in determining the shape of the 3D surface and the areas of the plateaus. When all influence variables are fixed at the maximum values, with respect to its contribution to FRVP, eccentricity has no effect below the value of 5^o such as the case in Figure 4.40 (2B), while for above than this values, eccentricity has a clear effect of FRVP until it reaches a value of 20^o. Here, eccentricity affects FRVP only at high values of background complexity.

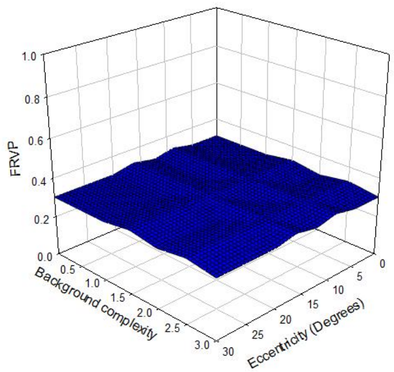
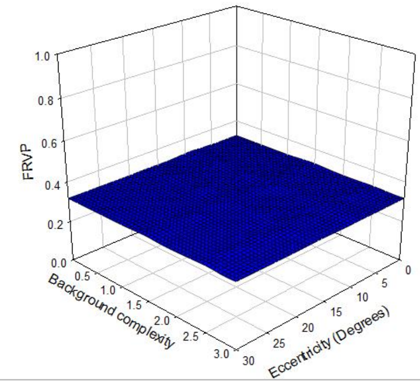
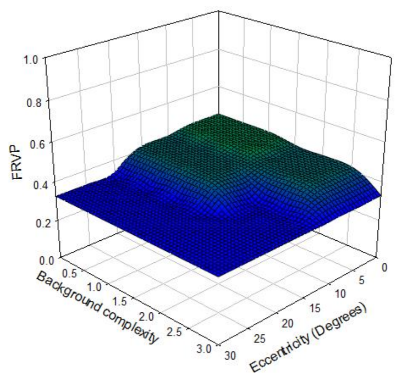
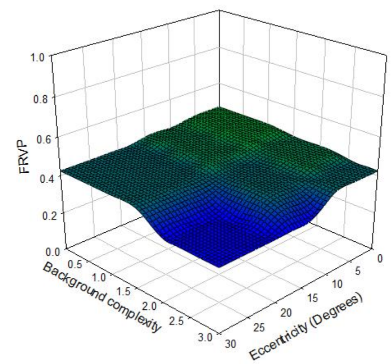
<table>
<tr><th rowspan="2">Fig. No.</th><th colspan="2">Retinal Illuminance (Trolands)</th><th rowspan="2">contrast</th><th rowspan="2">Age (years)</th><th rowspan="2">Size (µstr)</th></tr>
<tr><th>0.5</th><th>10</th></tr>
<tr><td>1</td><td>
</td><td>
</td><td>0.3</td><td>80</td><td>5</td></tr>
<tr><td>2</td><td>
</td><td>
</td><td>0.9</td><td>70</td><td>10</td></tr>
<tr><td></td><td>A</td><td>B</td><td colspan="3">Fig. No.</td></tr>
</table>

Figure 4.39: FRVP as a function of Eccentricity and background complexity (1/2)

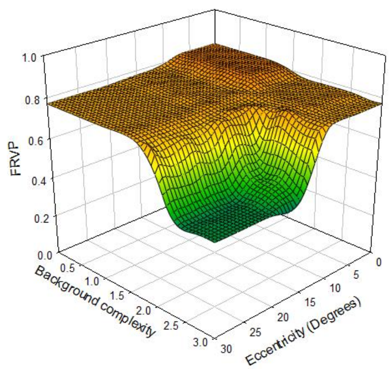
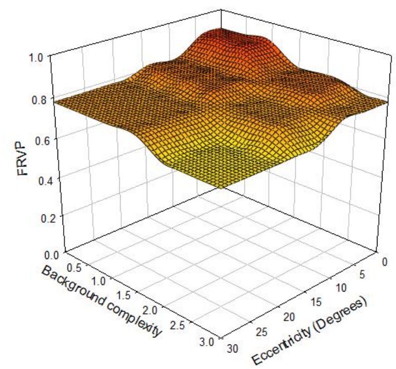
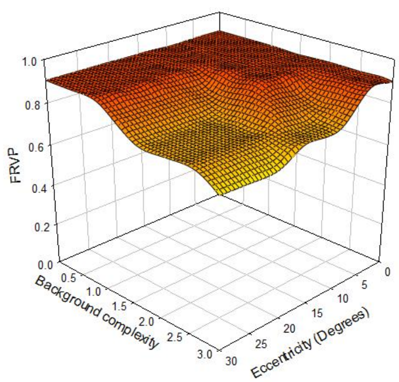
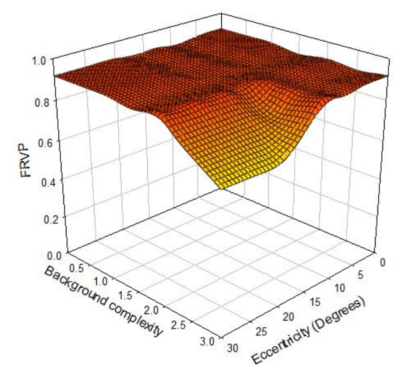
Fig. No.	Retinal Illuminance (Trolands)		Contrast	Age (years)	Size (μstr)
	20	40			
1			1.0	50	15
2			1.2	20	20
	A	B	Fig. No.		

Figure 4.40:FRVP as a function of Eccentricity and background complexity (2/2)

4.1.6 Background complexity effect

Background complexity can be defined as the degree of complication that a night-time driver/observer may experience in his viewing scene which affects his visual performance, or at least, visually disturb his concentration. An example of a complicated driving scene can include a typical night-time driving situation in a busy city with high traffic flow, static and billboard lighting, building internal and floodlighting, sidewalk users, mid-lane and sideways street trees and shadows of objects. Such complicated scenes have the effect of distracting the visual performance of the driver/observer while viewing the same scene. Background complexity was neglected in both Adrian's model (1989) and RVP model (Rea and Ouellette 1988, 1991)

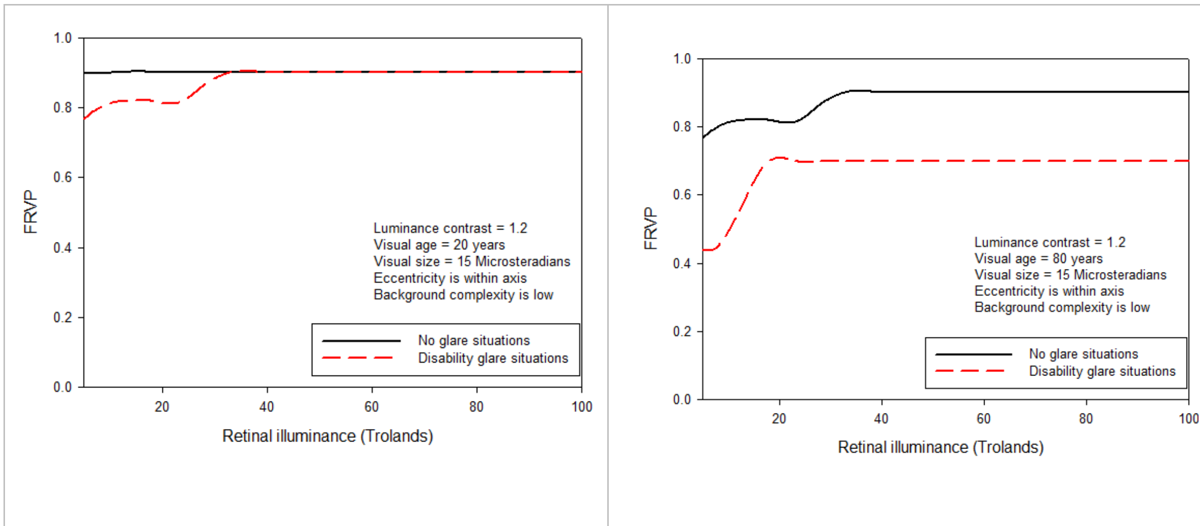
FRVP as a function background complexity and luminance contrast can be seen in Figure 4.9Figure 4.10 (for positive contrast) and Figure 4.19 and Figure 4.20 (for negative contrast). FRVP as a function of background complexity and visual age in Figure 4.27 and Figure 4.28. FRVP as a function of background complexity and visual size in Figure 4.33 and Figure 4.34. FRVP as a function of background complexity and retinal illuminance in Figure 4.37 and Figure 4.38. And finally, FRVP as a function of background complexity and eccentricity in Figure 4.39 and Figure 4.40.

4.1.7 Glare effect

As shown in chapter 3, the disability glare was not incorporated directly in the FRVP model. However, it was disability glare creates a veiling luminance that changes the luminance contrast into the effective contrast (equation). Figure 3.18 was developed to show the effect of disability glare on the luminance contrast for three different veiling luminances (20, 40, 60 cd/m^2). These veiling luminance values correspond to normal night time driving conditions. The graph clearly shows that whatever the value and/or the polarity of the luminance contrast, the veiling luminances of 20,40 or 60 cd/m^2 will decrease the value of the luminance contrast to a value that is less than 0.05.

Based on the luminance contrast (both positive and negative) definition (Figure 3.29 and Figure 3.30), a value of 0.05 luminance contrast corresponds to the “low” contrast subset (under the three values of veiling luminance). This means that whatever the value of the veiling luminance in a range of 20-60 cd/m^2 or even the value of the luminance contrast between 0.05 to 1.4, the effect of the disability glare is lowering the luminance contrast to “low” in the FRVP model. For example, consider a situation where the positive luminance contrast is fixed at 1.2, the visual age is 20 years, the visual size is 15 Microsteradians, the retinal illuminance is 15 Trolands, the eccentricity is within axis and the background complexity is low. The corresponding FRVP value is 0.903. However, if disability glare was encountered during this driving situation, the effective contrast will be less than 0.05, consequently, the corresponding value of FRVP at this luminance contrast value will drop to 0.82.

To demonstrate the effect of the disability glare graphically for veiling luminances up to 60 cd/m^2, graphs for FRVP as a function of retinal illuminance were generated for two situations, a very young observer (a) and a very old observer (b) under the influence of veiling luminance values less than 60 cd/m^2. The results are shown in Figure 4.41. A drop in the FRVP values are noticed in the presence of glare situations. However, this drop is more vibrant at medium to low retinal illuminance values (below 30 Trolands) for very young observers (20-40 years old). For very old age groups (above 80 years), the effect of disability glare can be seen at all retinal illuminance values.



(a) (b)

Figure 4.41: The effect of glare on FRVP for two situations: (a) very young observer (b) very old observer at veiling luminances less than 60 cd/m^2

Moreover, the driving situation denoted by Figure 4.41 can be represented by a 3D surfaces as shown in Figure 4.42. The figure shows FRVP as a function of retinal illuminance and visual size for two visual age values, 20 and 80 years respectively, and under two situations: (a) no glare and (b) with the presence of disability glare. The figure shows that in the case of a very young observer/driver (20-40 years old), the presence of disability glare will lower FRVP by decreasing the area of the high plateau (FRVP = 0.9) and creating another plateau at medium FRVP at almost 0.7. Moreover, at younger ages, the effect of glare can only be detected at low size targets (below 7 Microsteradians) and medium to low retinal illuminance values (below 30 Trolands). Whereas, for very old age groups, the effect of disability glare can be seen at most values of visual size and retinal illuminance values.

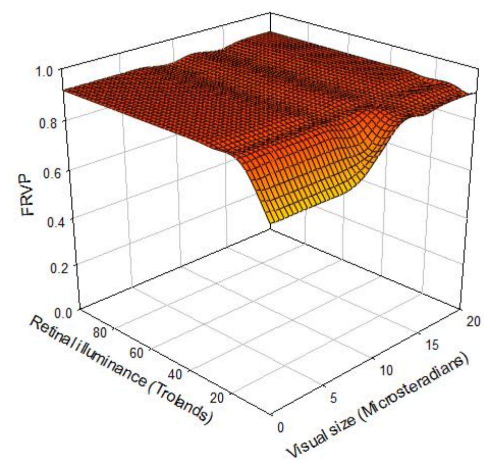
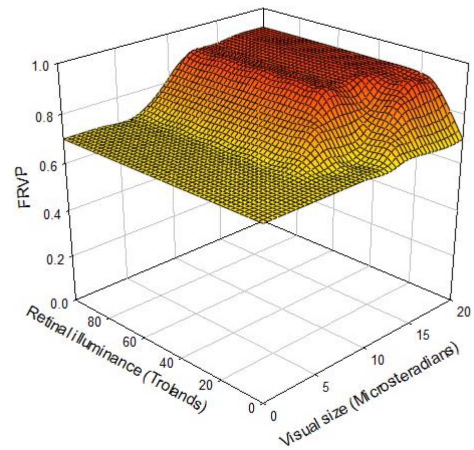
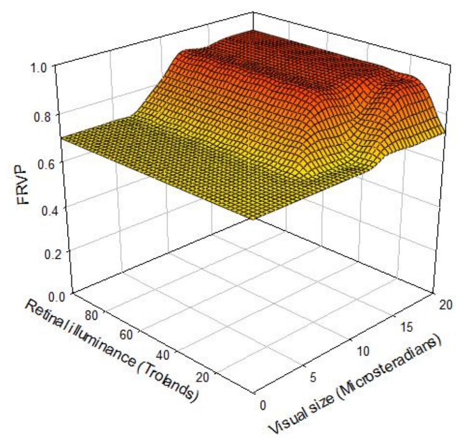
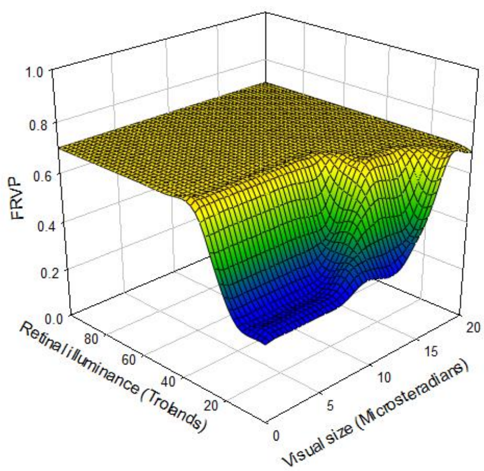
<table>
<tr><th>Visual age</th><th>(A) No glare situations</th><th>(B) Glare situations</th></tr>
<tr><td>20 years</td><td>
</td><td>
</td></tr>
<tr><td>80 years</td><td>
</td><td>
</td></tr>
</table>

Figure 4.42: FRVP as a function of Retinal illuminance and visual size for two situations: (a) without glare and (b) with glare

4.1.8 Critical contrast

The luminance difference threshold was defined by Adrain (1989) as the minimal luminance difference between the target and the background to perceive the target with a certain probability of 99.93%. Moreover, Adrian (1989) provided correction factors for the luminance difference (ΔL) to account for factors that vary from the conditions used in developing his model such as object size, observer age, exposure time, contrast polarity, and glare. Rea and Ouellette (1988, 1991) defined the threshold contrast using two approaches based on two experiments of readability and detection. For example, the threshold contrast based on the readability of the numerical verification task digits experiment (Smith and Rea 1981) was defined as the contrast at which the digits were "just readable". While the definition of threshold contrast based on the detection experiment (Rea and Ouellette 1988) was based on a 50% probability of detection of a certain target by observers. In both experiments, contrast values were directly determined from reaction times. However, it is just not practical to compare the threshold expectations obtained from the two experiments together as each experiment subjects used a different threshold criteria, and in general, the threshold values obtained from the detection experiment was always lower than the values obtained from the readability experiment for the same object size and retinal illuminance.

This work defines the *Critical high contrast* (C_{ch}) as the minimum contrast that will cause the FRVP to become high. The value is critical because it causes the FRVP to change from one category to another. Obviously, the value of the critical contrast is a function of age, visual size, and retinal illuminance. The concept of critical contrast is important because it has the potential to become a design target in some lighting calculations where the fuzzy relative visual performance can be said to be high (FRVP>0.85) for a particular visual size and age group. For the rest of the influence variables (retinal illuminance, eccentricity, and background complexity), it is assumed to be not affecting the values of the critical contrast. Hence, they will be fixed at the maximum subset with respect to their contribution to FRVP (high retinal illuminance, within axis eccentricity, low background complexity).

Figure 4.43 shows the critical high contrast (C_{ch}) as a function of visual size at different visual ages and a fixed retinal illuminance of 30 Trolands. The figure shows that as the visual size values increase, the critical contrast decreases for all age groups. However, for old observers (above 50 years old), a higher critical contrast is needed to get a high FRVP. At visual sizes below almost 7 Microsteradians, a critical contrast of 0.95 is needed for age groups between 20-40 years to get high FRVP, and a critical contrast of almost 1.1 is needed for age groups between 50-70 years. Yet, for age groups of 80 years and above, increasing the contrast will not help in obtaining a high FRVP at low visual size values (below 7 Microsteradians). This means that this age group is expected to always have a problem with the visibility of small targets.

A further increase in the visual size will lower the critical contrast needed to perceive the target with high FRVP to almost 0.1 for age groups below 70 years old, and almost 0.95 for age groups of 80 years old and above. Moreover, once the visual size is larger than almost 12 Microsteradians, which corresponds to the medium and large targets as per the visual size membership function (Figure 3.35), there is a sharp drop in the critical contrast. This sharp drop means that visual tasks involving above medium (in size) targets are expected to be easily performed with higher speed and accuracy.

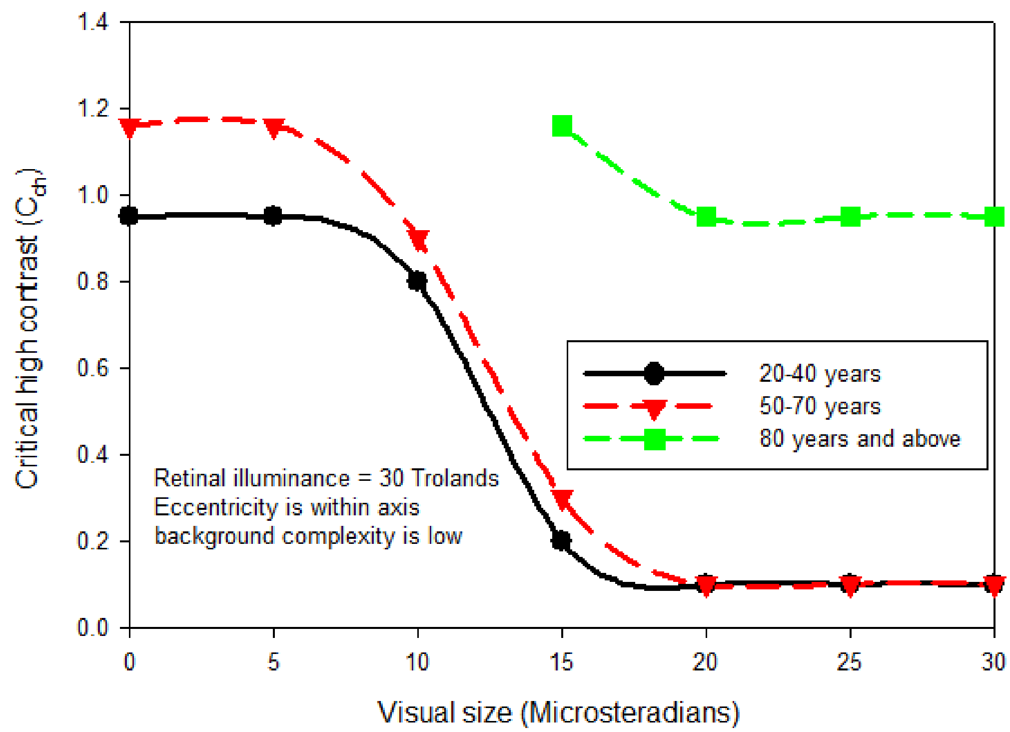


Figure 4.43: Critical high contrast as a function of visual size at different visual ages and retinal illuminance of 30 Trolands

At medium retinal illuminance values (Figure 4.44), it is noticed that the critical contrast increases for all age groups. Moreover, the figure shows that age groups between 50 to 70 years will not be able to get high RVP below a visual size of almost 15 Microsteradians. The same applies to age groups above 80 years but at visual size values above 20 Microsteradians. However, for this age group (above 80 years), they need a constant high contrast to perform. In other words, this age group (above 80 years) need high contrast as well as visual size to perform at medium retinal illuminance values. This is a very important result as it gives great insights into the area of lighting for the elderly.

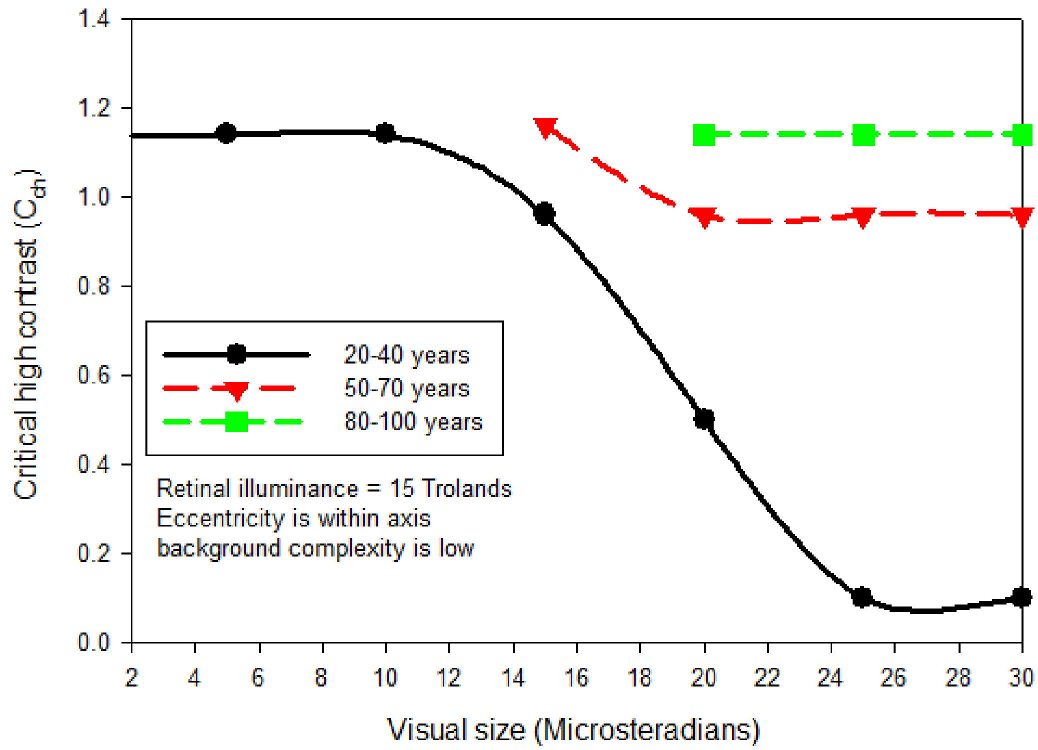


Figure 4.44: Critical high contrast as a function of visual size at different visual ages and retinal illuminance of 15 Trolands

At low retinal illuminance values (Figure 4.45), the age group above 80 years old is missing. This means that this age group will not be able to have high FRVP at low Trolands. This adds another constraint to this particular age group (80 years and above) in which beside low visual size situations, low retinal illuminance situations deny them from getting high FRVP. Even for very young age groups (20-40 years), the same figure shows that they are unable to get high FRVP at low retinal illuminance and visual sizes below medium (less than 10 Microsteradians). While for age groups between 50 to 70 years, they will only perform at targets with large visual sizes (above 20 Microsteradians) at low retinal illuminance situations.

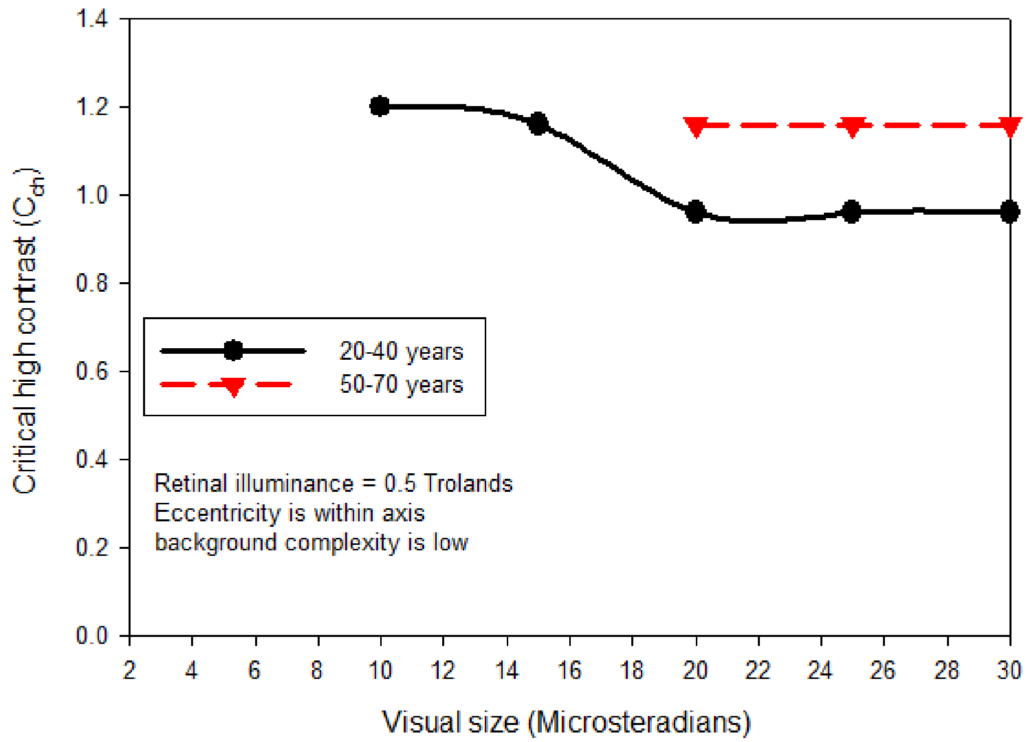


Figure 4.45: Critical high contrast as a function of visual size at different visual ages and retinal illuminance of 0.5 Trolands

Critical contrast results are prominent to become an important visibility measure especially for situations involving small targets or low retinal illuminance or old observers. However, when all these situations are combined, critical contrast can give very useful insights about the visual performance at extreme conditions involving worst-case scenarios.

4.2 Fuzzy illuminance selection (FIIL)

This work defined a new method for target illuminance selection based on fuzzy logic. The input variables for the model are visual age, task importance, and task difficulty. The output of the model is the fuzzy illuminance (lux) to do a certain task. The results of this model were presented in 2-D contours. This presentation style was found to be more suitable than normal 2D presentation and 3D surfaces (as in FRVP).

Results for target illuminance as a function of task importance and task difficulty are shown in Figure 4.46 (A) for young observer/worker, Figure 4.46 (B) for old observer/worker, and Figure 4.46 (C) for very old observer/worker. The figure clearly shows that as an observer/worker's age, task importance, and task difficulty increase, the required target illuminance becomes higher. This expected rational result is nothing but a common-sense interpretation of the importance of these three factors in determining the target illuminance required to do a certain task.

However, at young ages (below 45 years), the target illuminance required to perform a certain task decreases (Figure 4.46-A), even at situations of high target importance and difficulty (less than1000 Lux). A further decrease in the task importance and/or difficulty will lower the target illuminance to less than 100 Lux in the best cases (low task importance and difficulty). Yet, a medium importance and difficulty task may require around 500 Lux while a highly important and difficult task needs around 900 Lux to be performed by a young observer/worker.

As the observer/worker age increases from young to old (45-65 years), the target illuminance needed to perform a high importance and difficulty task increases to around 2000

Lux (Figure 4.46-B), while for low difficulty and importance tasks, it is less than 100 Lux. A medium importance and difficulty task needs around 900 Lux to be performed by an old individual. Very old observers/workers need more illumination. A very old observer requires around 500 Lux to perform a low difficulty and importance task, around 900 Lux for medium and around 2000 Lux for high (Figure 4.46-C).

Target illuminance as a function of age and task difficulty are shown in Figure 4.47 for three different task importance categories, low (Figure 4.47-A), medium (Figure 4.47-B), and high (Figure 4.47-C). Moreover, Figure 4.48 shows the target illuminance as a function of age and task importance for three target difficulty sets, low (Figure 4.48-A), medium (Figure 4.48-B) and high (Figure 4.48-C). Both figures have the same trend as the previous figure (Figure 4.46) in terms of the required target illuminance values to perform certain tasks by different age groups.

As tasks may differ in their importance and difficulty, a certain task may have a certain importance with different difficulties, based on the method adopted to perform this task. In these cases, target illuminance figures (Figure 4.46, Figure 4.47, Figure 4.48) are very useful in obtaining the required illuminance based on the observer/worker age. For example, a high importance task with low difficulty needs around 500 Lux if performed by a young observer/worker and around 900 Lux if performed by an old or very old observer/worker. The same values of illuminance are also valid for a high difficulty task with low importance.

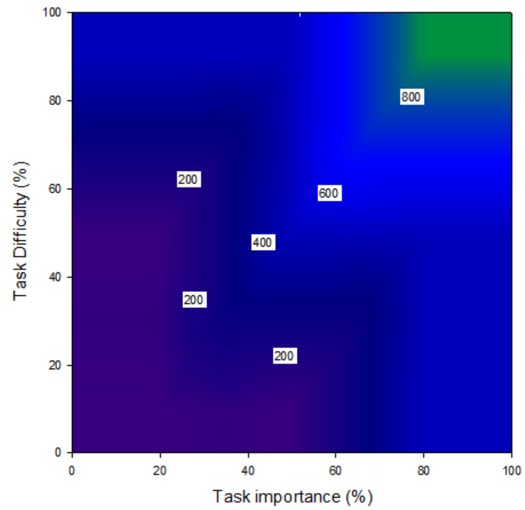
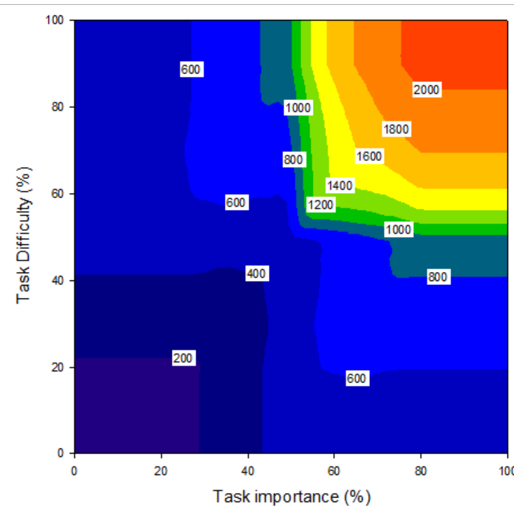
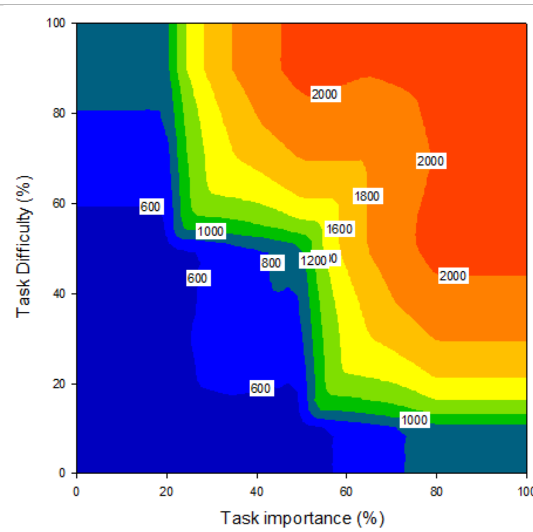
<table>
<tr><th>Col.</th><th>Age</th><th>Contour graph</th></tr>
<tr><td>A</td><td>Young</td><td>
</td></tr>
<tr><td>B</td><td>Old</td><td>
</td></tr>
<tr><td>C</td><td>Very old</td><td>
</td></tr>
</table>

Figure 4.46: Target illuminance as a function of task importance and task difficulty

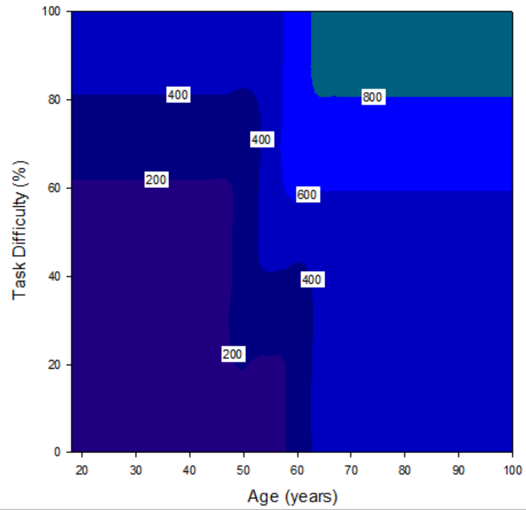
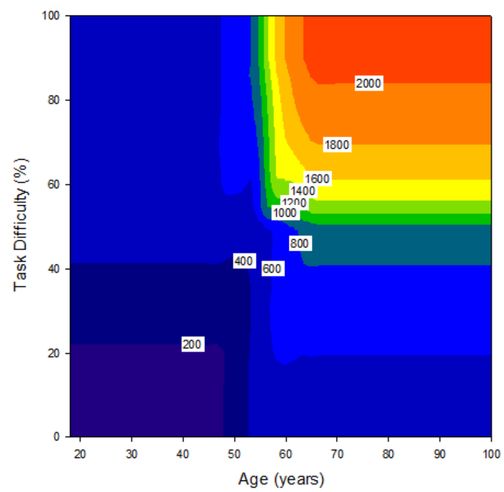
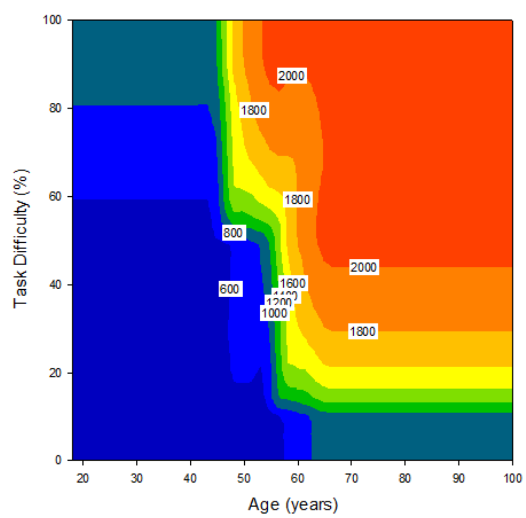
Col.	Task Importance	Contour graph
A	Low	
B	Medium	
C	High	

Figure 4.47: Target illuminance as a function of age and task difficulty

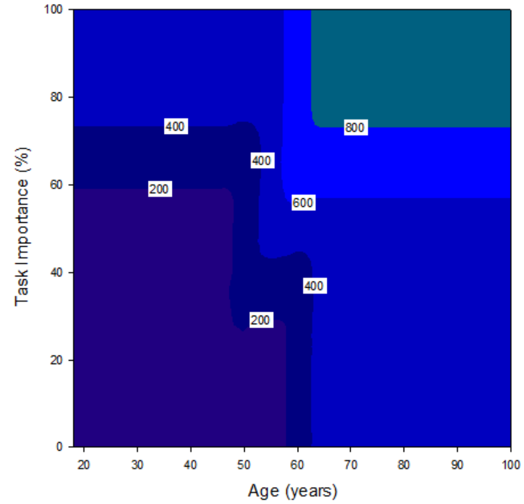
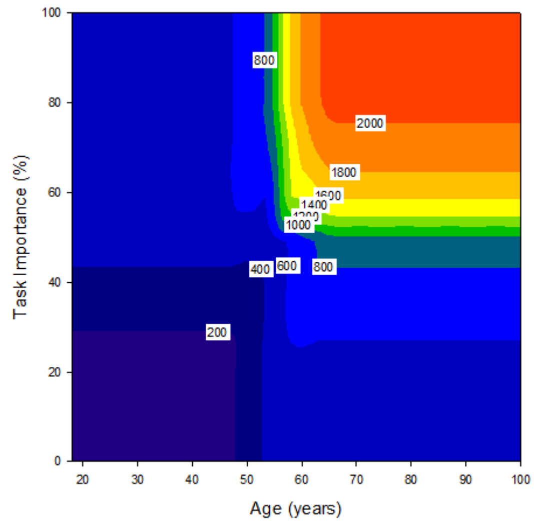
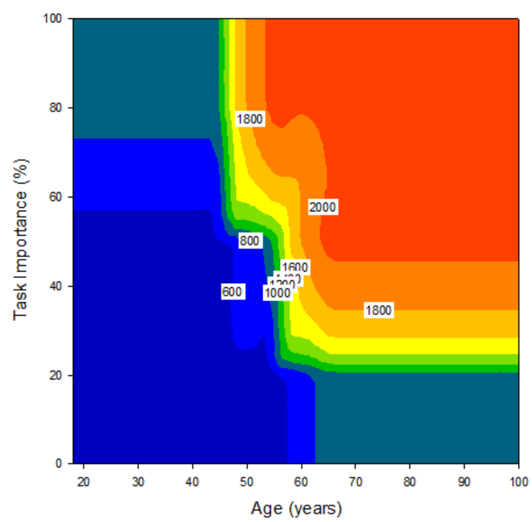
<table>
<tr><th>Col.</th><th>Task Difficulty</th><th>Contour graph</th></tr>
<tr><td>A</td><td>Low</td><td>
</td></tr>
<tr><td>B</td><td>Medium</td><td>
</td></tr>
<tr><td>C</td><td>High</td><td>
</td></tr>
</table>

Figure 4.48: Target illuminance as a function of age and task importance

To get more insights about the proposed fuzzy illuminance selection method, values of the input variables (age, task difficulty, and task importance) has been generated for achieving a certain illuminance value. This data was then tabulated and presented in Table 4.1

Table 4.1: Target illuminance values with respect to a variety of input variables

Illuminance (Lux)	**Age (years)**	**Task importance (100%)**	**Task difficulty (100%)**
50	20	20	10
100	56	20	10
200	55	30	10
300	55	35	20
400	50	40	30
500	55	50	50
700	60	50	50
1000	46	65	90
1500	62	60	50
2000	75	75	50

4.3 Software package results

Four stand-alone applications were designed during this work, the first one is called "RVP calculator" where all equations developed by (Rea and Ouellette 1991) were programmed into a Matlab code. This was done to make it easier to calculate the values of relative visual performance (RVP) values and compare it to the fuzzy logic model results of FRVP in the validation part. Figure 4.49 shows a snapshot of this application.

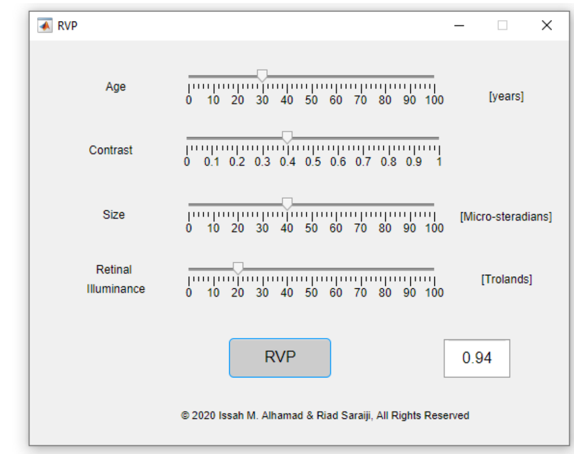


Figure 4.49: RVP calculator application

The second application developed during this work is the RGB entropy calculator. This application allows the user to browse for a certain image and select it. Then the application calculates the image entropy of that image. This was done in the phase of background complexity membership function design. Figure 4.50 shows a snapshot from the RGB entropy application.

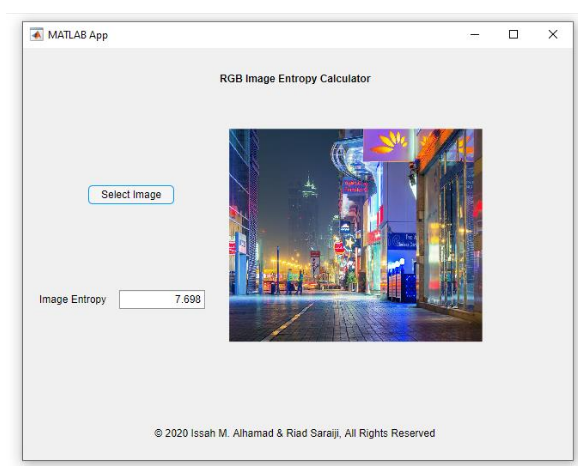


Figure 4.50: RGB entropy calculation application

The third software is the indoor Illuminance selection software. This application allows for the lighting designer to select the precise target illuminance based on the actual conditions to avoid underlit or overlit situations. Moreover, the user can check the state of the uniformity and compare the target illuminance (based on his choice or based on the application) with the achieved illuminance from lighting calculations. Figure 4.51 shows a snapshot from the Illuminance selection software.

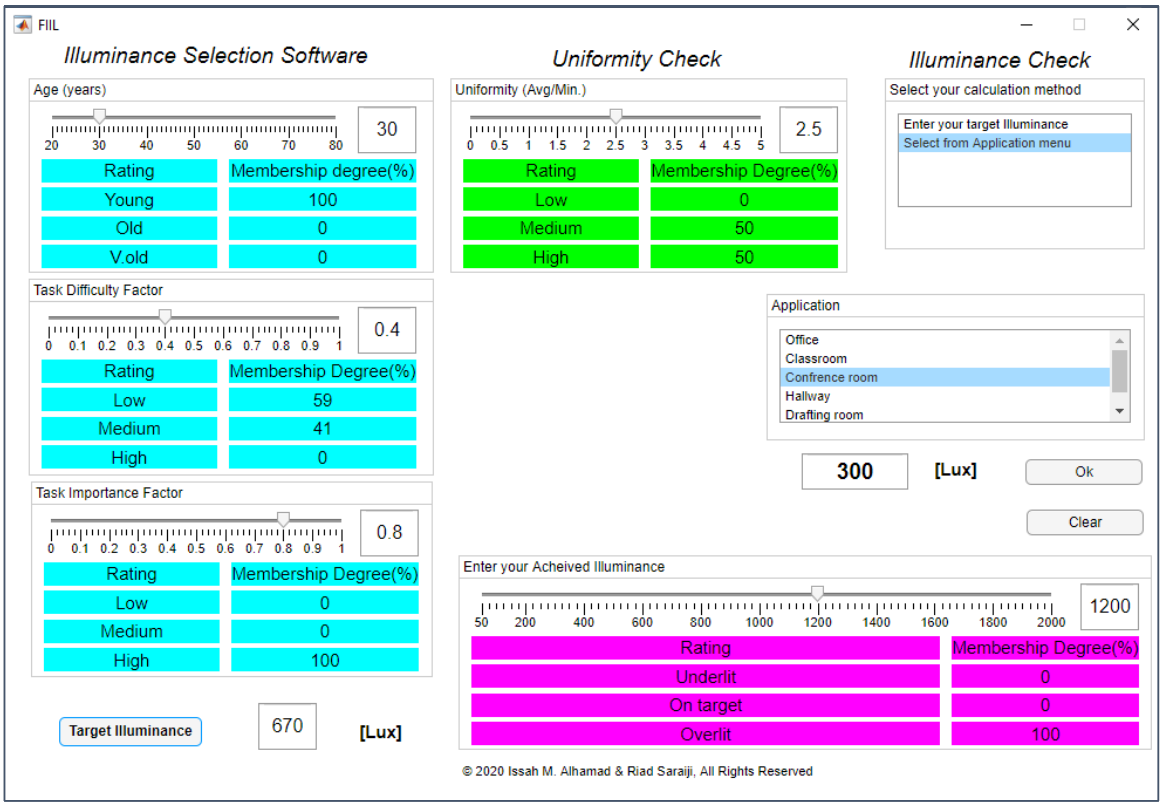


Figure 4.51: Illuminance selection software based on Fuzzy Illuminance model

The fourth application is the FRVP software. This software can calculate the relative visual performance (RVP) based on Rea and Ouellette (1988, 1991) and the FRVP based on fuzzy techniques proposed in this work. The software allows the user to select the contrast polarity and value, as well as values for age, visual size, retinal illuminance, and eccentricity. The background complexity can be either entered manually, or an image for the driving scene under consideration can be selected and the background complexity can be calculated automatically based on the image entropy techniques. The software provides the values of RVP, FRVP, and the membership degree of FRVP in the subsets {Low, Medium, High}. Figure 4.52 shows a snapshot of the FRVP software.

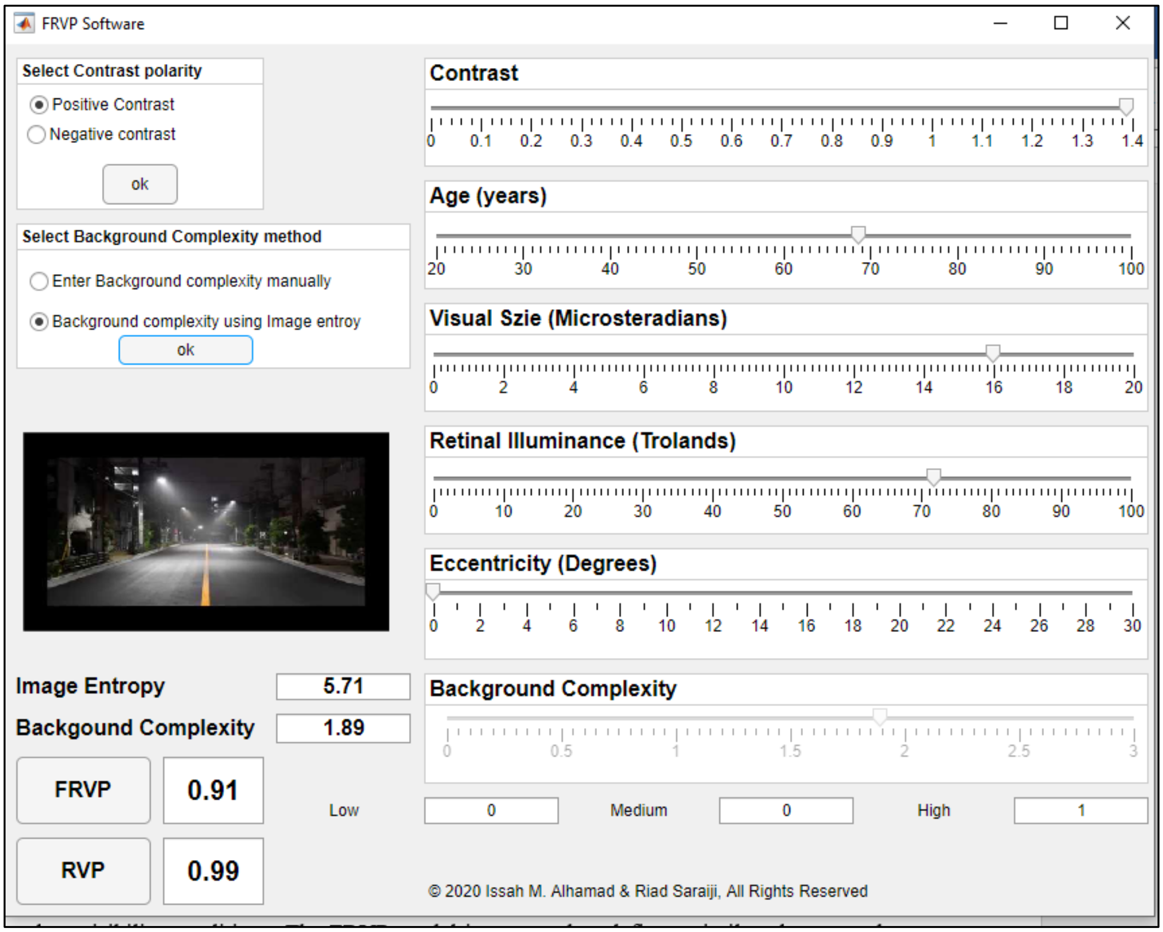


Figure 4.52: A snapshot from the FRVP software

5 Chapter Five: Discussion

The previous chapter showed the results of both the fuzzy relative visual performance model (FRVP) and the fuzzy indoor illuminance selection model (FIIL). The effect of each variable involved in the development of the fuzzy models was discussed in detail. Moreover, the effect of visibility dependent variable (disability glare) was also discussed. The contrast polarity was included in the model by designing two unique membership functions for the luminance contrast, one for positive contrast and one for negative contrast, the results for both contrast were showed as well. The concept of critical contrast was introduced where it is the minimum contrast required to achieve high FRVP. Critical contrast values at different scenarios were also discussed.

This chapter will be discussing the impactions of both FRVP and FIIL model results. It will also show the major trends of results for both models. The chapter will also discuss the advantages and limitations of the newly proposed models. Moreover, the FRVP model will be compared to the RVP model at the validation section, while the FIIL model will be compared to the IES illuminance selection method. Furthermore, the chapter will also show the results for sensitivity analysis of the FRVP model based on changing the independent variables membership functions in order to see the effect of different fuzzification methods on the output of the model.

5.1 Discussion of the FRVP model results

The fuzzy relative visual performance model (FRVP) is a unique attempt to model target visibility in a new and improved method. An attempt that considers new variables and enlarge the ranges for some existing variables. The method used is very suitable to the nature of variables used in lighting, in general, as these variables are not precise by nature. Moreover, it reduced the complexity of the equations used in current models. In fact, the FRVP model was developed without the use of any equation involving the input or output variables (except for the equations already built-in in the fuzzy logic modelling software), yet it can give reasonable outputs, and in many occasions, very close to the current RVP model.

The FRVP model involved six independent variables and one dependent variable. The independent variables are; luminance contrast, visual age, visual size, retinal illuminance, eccentricity, and background complexity, while the dependent variable is the disability glare. The dependent variable (disability glare) was not considered directly in the model, but its effect was associated with low luminance contrast situations. The effect of eccentricity and background complexity was not included in any of the current visibility models (VL, RVP, STV), so this adds to the value of this model. In fact, the use of image entropy as a measure of background complexity is a clear utilization of image processing techniques in modelling visibility.

It was assumed when developing the membership functions and fuzzy rules that the weight of each individual variable is equal. A weight of 3 has been given for each variable as most membership functions for the input variables are composed of 3 subsets. However, since the visual age membership function has 4 subsets {very young, young, old, very old}, each subset was given a weighs of 0.75 instead of 1. Then, each membership function subset was ranked based on its contribution to FRVP. For example the ranking of luminance contrast subsets was {1, 2, 3} with respect to {low, medium, high} while the ranking for the background complexity was {3, 2, 1} for {low, medium, high}. This simply means that when the luminance contrast is increased from low to high, it contributes to increasing FRVP, while the increasing of background complexity from 1 to 3 lowers FRVP.

Moreover, the dependencies between any two independent variables were ignored to avoid any redundancy resulted from taking the effect of the same variable more than once. For example, although the visual age affects the retinal illuminance values (Eqn. (3.16)), the membership function of the retinal illuminance was developed without considering age effects. All age effects were assumed to be included in the visual age membership function. The same was also applied in developing the visual size membership function, where it was assumed that the target is located at the observer's line of sight and no eccentricity effects were involved in the visual size calculations. This allows for the eccentricity membership function to include all effects related to eccentricity.

The results for the FRVP model was represented by 3D surfaces in the previous chapter where two variables were plotted in the x and z axes and FRVP was plotted on the y-axis. The effect for each input variable on FRVP was shown using the 3D surfaces when plotted against all other variables respectively. This means for the effect of luminance contrast, as an example, FRVP was 3D plotted as a function of luminance contrast and visual age at 8 scenarios in which the influence variables are taking low, medium, and high values with respect to their contribution to FRVP. Then another 8 scenarios were generated for FRVP as a function of luminance contrast and visual size, retinal illuminance, eccentricity, and finally, background complexity. This makes a total of 40 surfaces were generated to describe the effect of each independent variable on the FRVP.

The general trend that was noticed in most figures that FRVP is either located at a plateau or in between plateaus. For influence variables fixed at the least values with respect to their contribution to FRVP, all figures showed that FRVP is located at a low plateau of almost 0.3, which donates the lowest value for the FRVP model (such as the case described in Figure 4.1-

1A). In this situation, the combined effect of the influence variables is very strong in which it controls the value of FRVP. This means that increasing the values of the variables involved in the graph will not affect the FRVP value. These results are very important in which it gives insights about the at target visibility at extreme low visual performance situations. An example of this situation may be a case where very old observers are trying to perceive a target with small visual size and low contrast under high background complexity situations, or when the target is located far from the visual axis of the observers.

Figure 5.1 shows FRVP as a function of luminance contrast for different age groups {very young, young, old, very old} under three different situations: (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed at high with respect to their contribution to FRVP. The first situation (Figure 5.1-A) represents the extreme low visual performance situation described above. It is clear how increasing the luminance contrast and/or age will not change the FRVP value. In other words, at this situation, the visual performance of a very young observer perceiving a high contrast target will be the same as the visual performance of a very old observer perceiving a low contrast target.

This can give a serious alert to road lighting designers to generate new methods capable of enhancing the visual performance, or at least, take precautionary measures to avoid such situations. For example, better luminaire types can be used based on Saraiji et al. (2016) where he showed that the mean detection distance for metal-halide and LED lamps was better than that for a high-pressure sodium lamps. Another proposed solution is to use luminaires with a larger gamut area which enhances the colour rendering of the target based on Yang and Wei

(2020). Moreover, advanced driving assistance systems (ADAS) and image processing techniques can be used to solve major problems related to visual performance. An example of the precautionary measures that can be taken at low visual performance situations is reducing the driving speed based on the study of Cao et al. (2020) in which confirmed that increasing driving speed has a significant effect in lowering target detection rate as well as the detection distance.

At medium values of influence variables (Figure 5.1-B), FRVP results showed that an additional plateau at medium FRVP values (almost 0.7) has been generated where FRVP values are located at this plateau or the lower plateau, or in between. At the same time, the difference between age groups is best noticed at medium situations. The luminance contrast points in which the FRVP change from a state to another corresponds to the critical points used to define the positive contrast membership function (Figure 3.29). For example, a positive contrast value of 0.8 represents the value in which the "low" positive contrast subset ends while a value of 1.2 represents the starting point of the "high" positive contrast.

When the influence variables are fixed at the highest value with respect to their contribution to FRVP (Figure 5.1-C), it is noticed that age groups {very young, young, and old} behave the same with respect to their visual performance. While the "very old" age group is struggling at low luminance contrasts (below 0.8), this also raises a red flag concerning the visual performance of people who are above 80 years when they perceive low contrast targets. The figure also shows that above a luminance contrast of 0.8, the relative visual performance of this group starts to climb until it reaches high FRVP at a luminance contrast of almost 1. This is similar to the effect of the age correction factor (AF) proposed by Adrian (1989) in which a higher threshold contrast difference (ΔL_{age}) is required to perceive targets for older age groups (Eqns. (3.11) to (3.13)).

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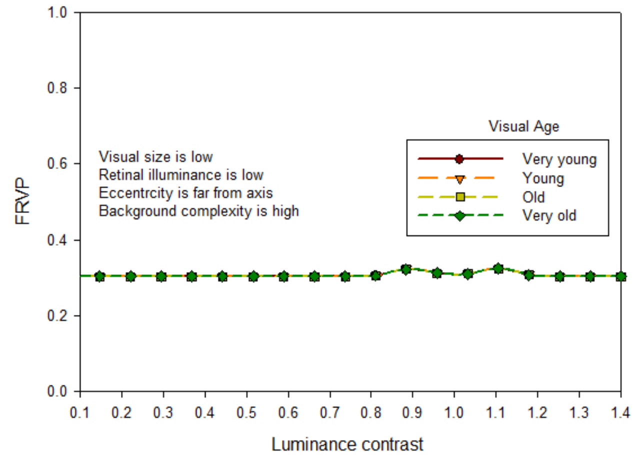
<tr><td>A</td><td>
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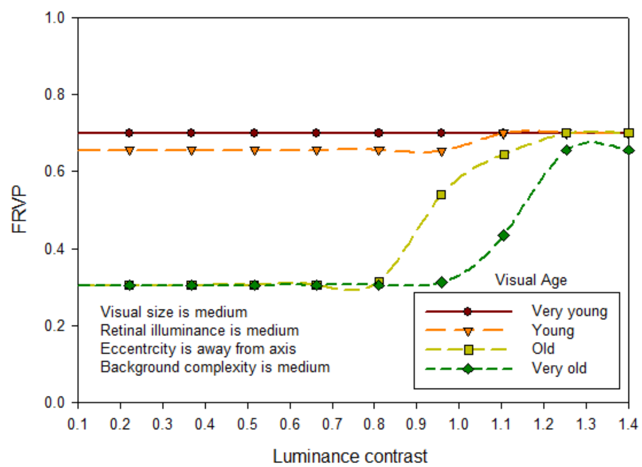
<tr><td>B</td><td>
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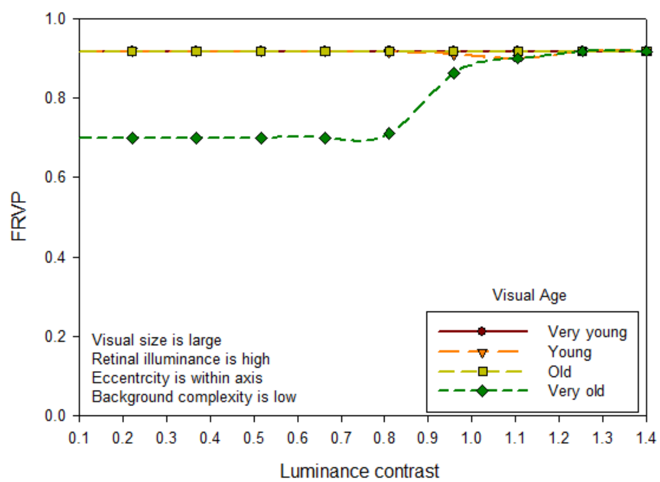
<tr><td>C</td><td>
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Figure 5.1: FRVP as a function of luminance contrast for different age groups

Figure 5.2 shows FRVP as a function of visual age for different positive contrast groups {low, medium, high} under three different situations: (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed at high with respect to their contribution to FRVP. Again, the figure shows that when the influence variables are fixed at low (Figure 5.2-A), they tend to control the FRVP so any change in the visual age and/or contrast will not change the FRVP values. A further increase in the influence variables to medium (Figure 5.2-B) shows a difference between different contrast values with respect to changing FRVP. This FRVP change occurs at the critical points (42.5, 67.5, and 80 years) used to design the visual age membership function (Figure 3.32).

When the influence variables are fixed at high, with respect to their contribution to FRVP (Figure 5.2-C), the combined effect of the influence variables is strong enough to make both the medium and high contrast targets at high FRVP regardless the observer's age. However, for low contrast targets, it can have high FRVP as long as the observer age is younger than almost 67 years, where above this age, the FRVP will deteriorate until it reaches a value of 0.7 at visual age values above 80 years old.

It is also noticed that the difference in luminance contrast groups {low, medium, high} is best observed when the influence variables are fixed at medium (Figure 5.2-B). This can be related to the neutral effect of the influence variables when fixed at medium. In other words, at this situation, the influence variables are not low, nor high, so their effect of FRVP can be considered as neutral. Hence, their combined effect can also be considered as neutral in which different luminance contrast groups may be distinguished from each other.

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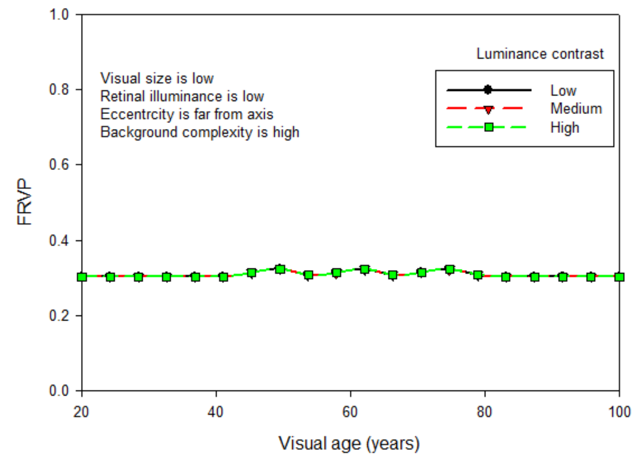

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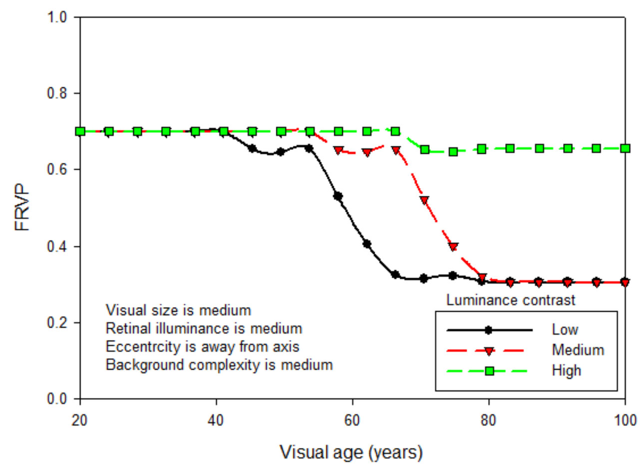

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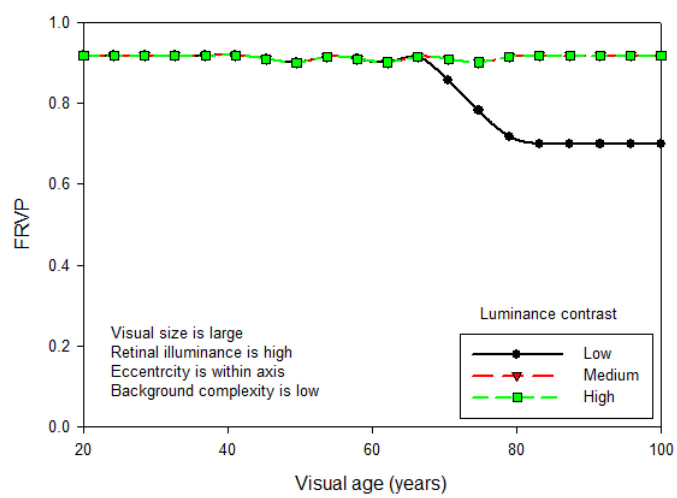

Figure 5.2: FRVP as a function of visual age for different luminance groups

Figure 5.3 shows FRVP as a function of visual size for different retinal illuminance groups {low, medium, high} under three different situations: (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed at high with respect to their contribution to FRVP. Again, the figure shows that when the influence variables are fixed at low (Figure 5.3-A), they tend to control the FRVP so any change in the visual size and/or the retinal illuminance will not change the FRVP values. A further increase in the influence variables to medium (Figure 5.3-B) shows a difference between different retinal illuminance values with respect to changing FRVP. This FRVP change occurs at the critical points (7, 12.5, and 17 Microsteradians) used to design the visual size membership function (Figure 3.35).

When the influence variables are fixed at high, with respect to their contribution to FRVP (Figure 5.3-C), the combined effect of the influence variables is strong enough to make both the medium and high retinal illuminance groups at high FRVP regardless the visual size. However, for low retinal illuminance situations, it can have high FRVP as long as the target size is larger than almost 12.5 Microsteradians (which defines the medium target as per the visual size membership function-Figure 3.35), where below this size, the FRVP will deteriorate until it reaches a value of 0.7 at the visual size of 7 Microsteradians and lower (low visual size).

It is also noticed that the difference in retinal illuminance groups {low, medium, high} is best observed when the influence variables are fixed at medium (Figure 5.3-B). At this situation, the influence variables are not low, nor high, so their effect of FRVP can be considered as neutral. Hence, their combined effect can also be considered as neutral in which different retinal illuminance groups may be distinguished from each other.

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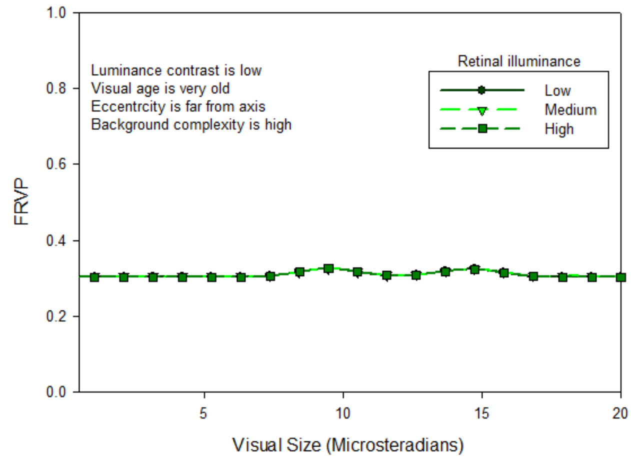
<tr><td>A</td><td>
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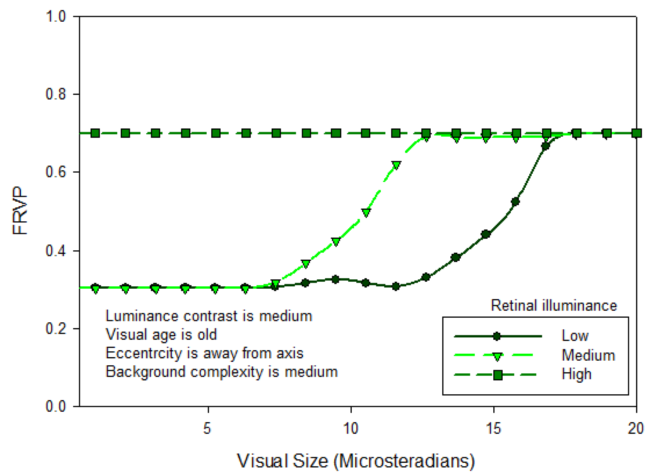
<tr><td>B</td><td>
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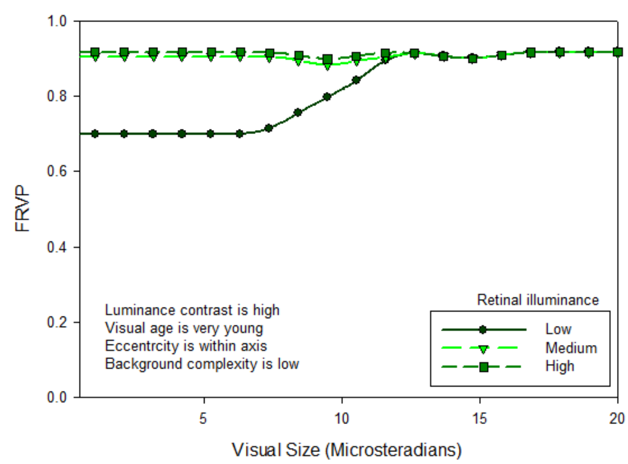
<tr><td>C</td><td>
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Figure 5.3: FRVP as a function of Visual size for different retinal illuminance groups

Figure 5.4 shows FRVP as a function of retinal illuminance for different visual size groups {small, medium, large} under three different situations: (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed at high with respect to their contribution to FRVP.

The figure shows that when the influence variables are fixed at low (Figure 5.4-A), they tend to control the FRVP so any change in the visual size and/or the retinal illuminance will not change the FRVP values. A further increase in the influence variables to medium (Figure 5.4-B) shows a difference between different visual size groups with respect to changing FRVP. This FRVP change occurs at the critical points (14.5, 20 and 40 Trolands) used to design the retinal illuminance membership function (Figure 3.39).

When the influence variables are fixed at high, with respect to their contribution to FRVP (Figure 5.4-C), the combined effect of the influence variables is strong enough to make both targets with medium and large visual sizes at high FRVP regardless the retinal illuminance values. However, for smaller targets (below 7 Microsteradians), high FRVP can be achieved as long as the retinal illuminance is larger than almost 14.5 Microsteradians (which defines the medium target as per the retinal illuminance membership function-Figure 3.39).

It is also noticed that the difference in visual size groups {small, medium, large} is best observed when the influence variables are fixed at medium (Figure 5.4-B). At this situation, the influence variables are not low, nor high, so their effect of FRVP can be considered as neutral. Hence, their combined effect can also be considered as neutral in which different visual size groups may be distinguished from each other.

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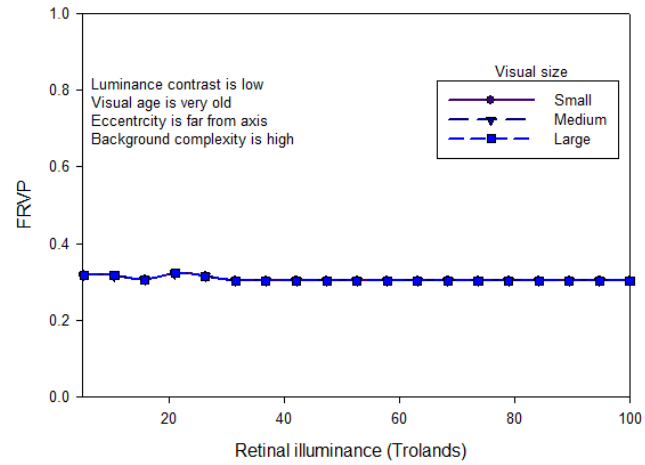
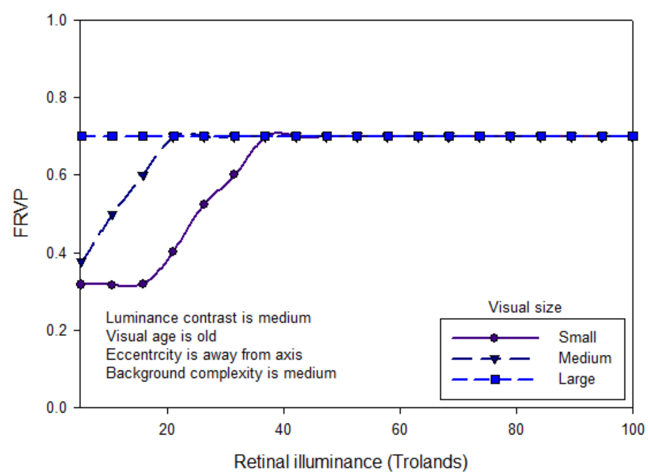
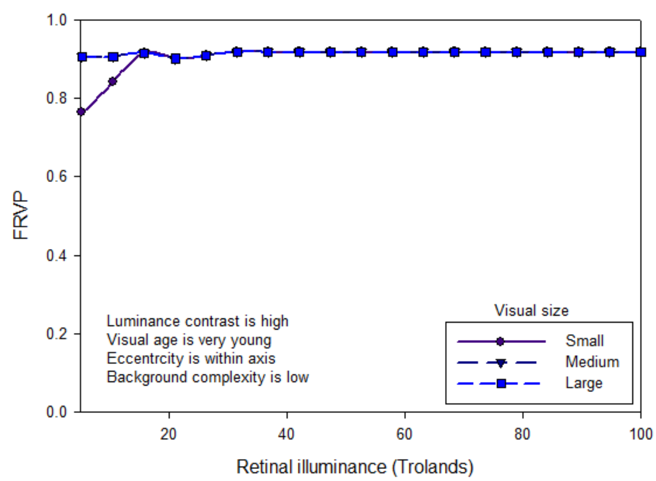
A	
B	
C	

Figure 5.4: FRVP as a function of retinal illuminance for different visual size groups

Eccentricity and background complexity adds a great value for the FRVP model as they have not been included in earlier visibility models as unique input variables. Eccentricity defines the location of the target with respect to the observer visual line of sight, while background complexity is a measure of the homogeneity of the driving scene. Eccentricity was defined based on the probability of detecting a target (Inditsky et al. 1982), while an imaginary scale from 1 to 3 was developed to indicate the degree of background complexity based on the user choice. Furthermore, image entropy of the driving scene can be used to define the degree of background complexity. This method was only used in the FRVP software developed based on the FRVP model, where the user is given a choice to enter the background complexity as a value from 1 to 3, or the browse for a certain driving scene, then the software will calculate the image entropy and select the corresponding background complexity automatically. This method, by itself, is an innovative technique based on image processing and can enhance a variety of applications including Advanced Driving Assistance System (ADAS) and Autonomous Vehicles (AV) technology.

Figure 5.5 shows FRVP as a function of eccentricity for different background complexity degrees {low, medium, high} under three different situations: (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed At high with respect to their contribution to FRVP. While Figure 5.6 shows FRVP as a function of background complexity for different eccentricity degrees {target is within axis, away from axis, far from axis} under the same conditions described above. Both figures show the same general trends described in the previous FRVP figures such as the development of the low plateau when the influence variables are fixed at low (Figure 5.5-A and

Figure 5.6-A), as well as the critical values of eccentricity (5 ^{o}, 12.5 ^{o}, 20^{o}) and background complexity (1, 2,3) that change the FRVP values from low to medium, or from medium to high. These critical values are in correspondence to the values used to develop the membership function of eccentricity (Figure 3.41) and background complexity (Figure 3.44).

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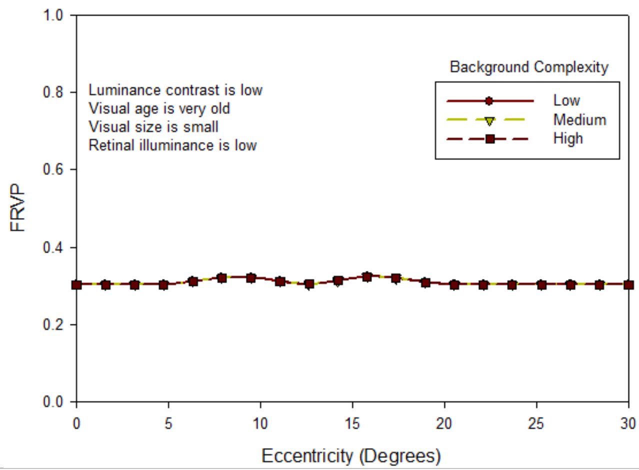

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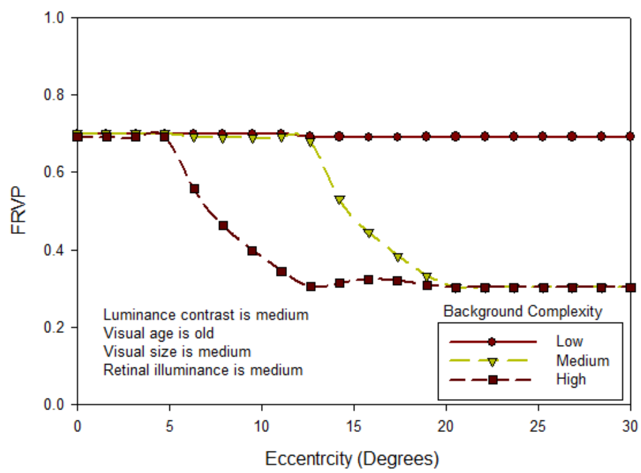

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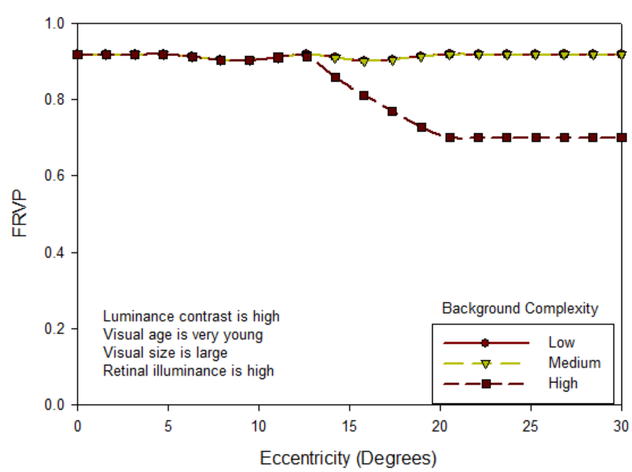

Figure 5.5: FRVP as a function of eccentricity for different background complexity groups

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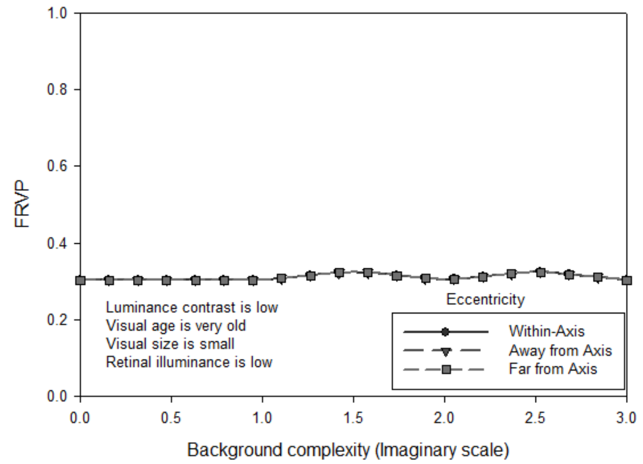
<tr><td>A</td><td>
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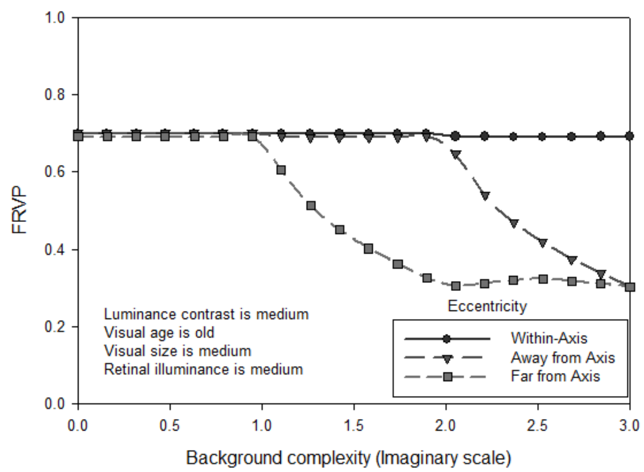
<tr><td>B</td><td>
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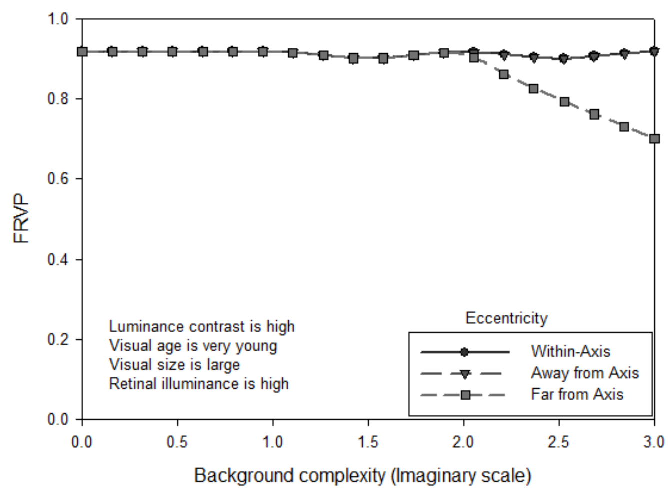
<tr><td>C</td><td>
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Figure 5.6: FRVP as a function of background complexity for different eccentricity groups

At the beginning of this study, and for simplicity reasons, it was assumed that the contrast polarity will be neglected, and only targets with positive contrast shall be included. This assumption allowed for this work to define the luminance contrast based on the way in which it affects visual performance (Figure 3.25), this means that a critical values of 0.2, 0.4 and 0.6 were adopted to design the luminance contrast membership function, where 0.2 and below corresponds to low contrast, medium contrast is between 0.2 to 0.6, where 0.4 represent 100 % medium, and luminance contrast values above 0.6 were considered as high. As a result, a luminance contrast membership function was generated as shown in Figure 3.26.

However, the literature review part of this study showed that the contrast polarity is a vital parameter in road lighting that cannot be ignored. For example, some studies showed that targets under negative contrast have longer recognition distance than those under positive contrast (Janoff 1994). While Meyer and Gibbons (2001) confirmed that in outdoor driving conditions, the background luminance gets brighter as the observer/driver approaches the target, hence, pedestrians are seen under positive contrast until the distance between the driver and the pedestrian becomes short enough to make the background luminance larger than the target luminance, at this point and beyond, pedestrians start to be seen under negative contrast.

As a result, there was a need to include to contrast polarity in the FRVP model. The first idea that came to mind is to use the contrast polarity function developed by Adrian (1989) and expressed as seen in Eqn. (3.8) to account for negative contrast situations. However, this method was found to be very complicated and may not produce accurate outputs in negative contrast situations. Moreover, it is believed that this method contradicts with the essence of this study, which uses fuzzy logic modelling to avoid complex math and lessen the need for correction factors/functions.

Hence, the only option left was to design two separate membership functions for the luminance contrast, one for positive contrast based on the Rea and Ouellette (1988, 1991) percent detection probability of increment targets, and the other for negative contrast based on the Rea and Ouellette (1988) percent detection probability of decrement targets (Figure 3.28). The positive contrast membership function is shown in Figure 3.29, while the negative contrast membership function is shown in Figure 3.30. However, the FRVP model cannot accept two membership functions for the same variable, so it was necessary to develop two FRVP models, one for positive contrast and the other for negative contrast. The Two FRVP models share the same rules, inference system and defuzzification method, only the contrast membership functions are different.

It worth mentioning that in the FRVP software (Figure 4.52), users can select the contrast polarity at the beginning, then the program automatically locates the FRVP model (positive or negative contrast) based on the user selection. 3D results for FRVP as a function of luminance contrast (positive and negative) have been shown in chapter four. However, to get a better understanding of how equal values of contrast with different polarities affect FRVP, 2D graphs have been generated to compare FRVP with respect to the effect of positive and negative contrasts.

Figure 5.7 shows a comparison between positive and negative contrasts with respect to their effect on FRVP for three situations; (A) when the influence variables are fixed at low with respect to their contribution to FRVP, (B) when the influence variables are fixed at medium with respect to their contribution to FRVP, and (C) when the influence variables are fixed at high with respect to their contribution to FRVP. The figure shows that when the influence variables are fixed at low or high with respect to their contribution to FRVP (Figure 5.7-A & C respectively), contrast polarity has no effect on FRVP. This simply means that targets perceived under positive and negative contrast will have the same FRVP. However, when the influence variables are fixed at medium, with respect to their contribution to FRVP (Figure 5.7-B) targets perceived under negative contrast have higher FRVP in the range of 0.1 to 1. This agrees with Rea and Ouellette (1988) percent detection probability of decrement and increment targets (Figure 3.28), where the figure clearly shows that in order to get a percent detection probability of 90%, decrements need lower contrast values than increments.

To conclude, it can be confirmed that targets received under negative contrast tend to change the state of FRVP from low to medium, or from medium to high earlier than positive contrast targets. This is clear in Figure 5.7-B, where negative contrast targets above 0.3 are having and FRVP value of almost 0.7, yet, positive contrast targets will have the same FRVP at contrast values above 1.0. This conforms to the findings of Janoff (1994) in which targets under negative contrast have longer recognition distance than those under positive contrast, which means that negative contrast targets (decrements) are likely to have higher visual performance than increments.

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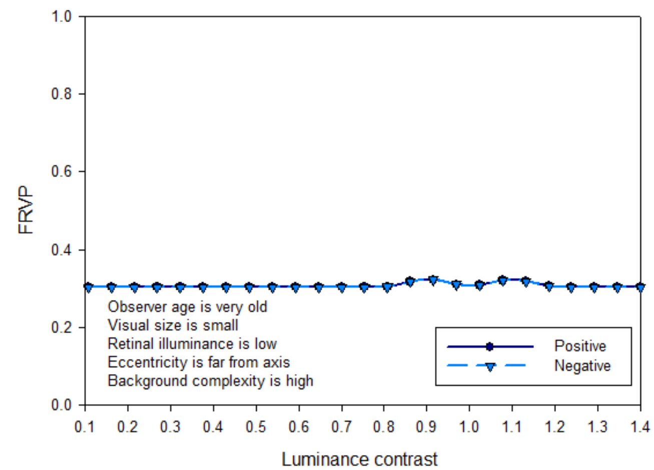
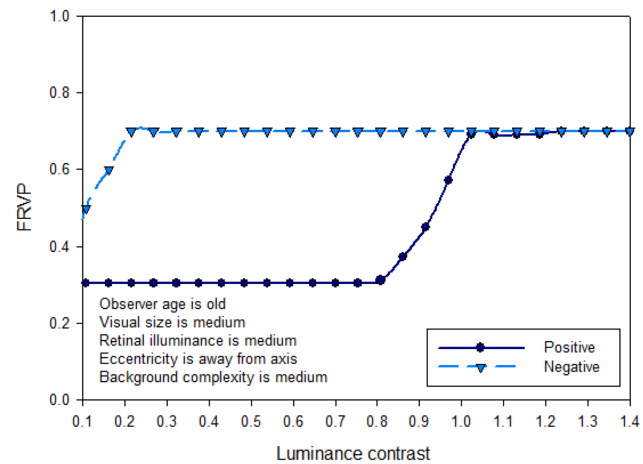
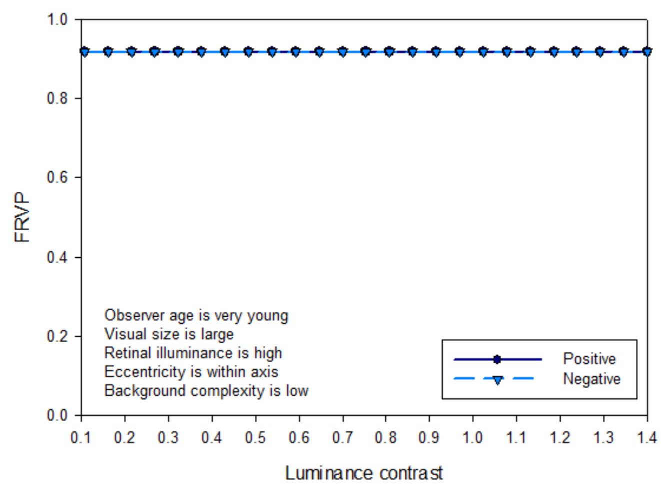
A	
B	
C	

Figure 5.7: A comparison between positive and negative contrasts with respect to their effect on FRVP

5.2 Validation of the FRVP model

Validation of the FRVP model will be done with respect to the relative visual performance model (RVP) by Rea (1986) and Rea and Ouellette (1988, 1991). FRVP and RVP values will be calculated under the same values of luminance contrast, age, visual size and retinal illuminance, then they will be compared together at the same graph, under the same situation (influence variables). It worth mentioning that since target eccentricity and background complexity were not included in the RVP model, they will be always fixed at the lowest subset of the membership function (eccentricity is within axis, background complexity is low) to avoid any effect for them in the FRVP results.

As the RVP model is structurally a mathematical model, and FRVP is based on fuzzy logic, it is not expected for the FRVP model to give smooth lines such as the RVP model. This is related to the nature of the fuzzy logic which depends on the design of the membership function and the fuzzy rules, and since the rule number for the FRVP model are high (972 rules), too successive points in the FRVP domain may be calculated based on more than one rule, this makes the FRVP lines to be winding in shape. Moreover, it was expected, since the beginning of this study, there will be a good agreement between RVP and FRVP at situations incorporating high visual performance, such as young observers, high contrast, large size, and high Trolands. While at low visual performance situations, it was expected that there will be mild-to-significant differences depending on the situation.

Figure 5.8 shows a comparison between RVP and FRVP models based on luminance contrast (x-axis). The first notable observation is that RVP is very responsive to luminance contrast changes below 0.3, especially at low values of visual size and retinal illuminance.

Moreover, the figure shows that as the luminance contrast values increase, the difference between RVP and FRVP decrease. This is a general trend in all graphs included in Figure 5.8. However, at low contrast values, the difference between FRVP and RVP is measurable, especially at old ages (Figure 5.8-3B and 4A), small target size (Figure 5.8-2A and 2B), and low retinal illuminance (Figure 5.8-1A and 1B). Yet, when all other influence variables are fixed at the maximum, with respect to their contribution to FRVP (very young age, large size and high retinal illuminance) which is shown in (Figure 5.8-3A), there is a good agreement between FRVP and RVP values when the luminance contrast exceeds 0.2.

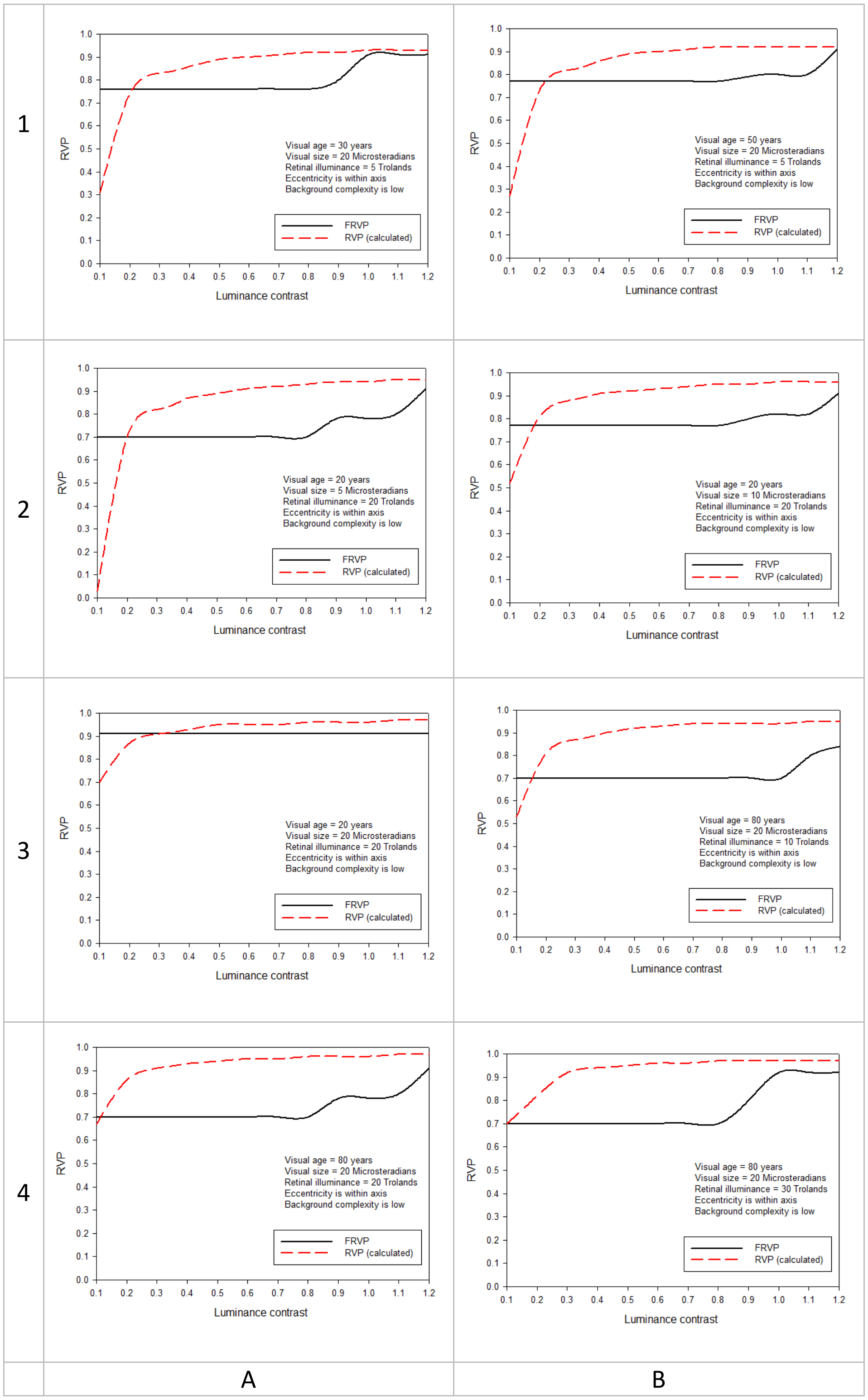


Figure 5.8: Comparison between RVP and FRVP based on luminance contrast

A clear effect for the visual age on the difference between FRVP and RVP values can be seen when comparing Figure 5.8-3A and Figure 5.8-4A. Both figures are the same except that the visual age in the first one is 20 years and the second one is 80 years. This effect can also be noticed in Figure 5.9, which shows a comparison between FRVP and RVP based on visual age. In these figures, the RVP model seems to be unresponsive to any changes in the visual age values as RVP values are constant in all graphs. However, there is a clear effect for the visual age, especially at low luminance contrast (Figure 5.9-1A) and small visual size (Figure 5.9-1B) and low retinal illuminance (Figure 5.9-3A).

A good agreement between FRVP and RVP values is clear once the luminance contrast is fixed at high, the visual size is large and the retinal illuminance is high (Figure 5.9-4B). This means that the influence variables (not included in the graph) has a major effect in increasing the values of FRVP (at any age) to be close to RVP values. In this figure, both RVP and FRVP values are above 0.9, which corresponds to a high relative visual performance. A slight decrease in luminance contrast values from high (1.2) to medium (0.9), the visual age effect starts to be more visible (Figure 5.9-4A). This effect takes place at visual ages above 40 years old. However, below these values, there is a good agreement in the two models.

It is believed that the decrease of FRVP values with higher ages is an advantage for the proposed FRVP model since RVP values are constant for all age groups, regardless of the value of the influence variables. This means that the proposed FRVP model is taking the effect of the visual age in a more suitable technique than that used in the RVP model.

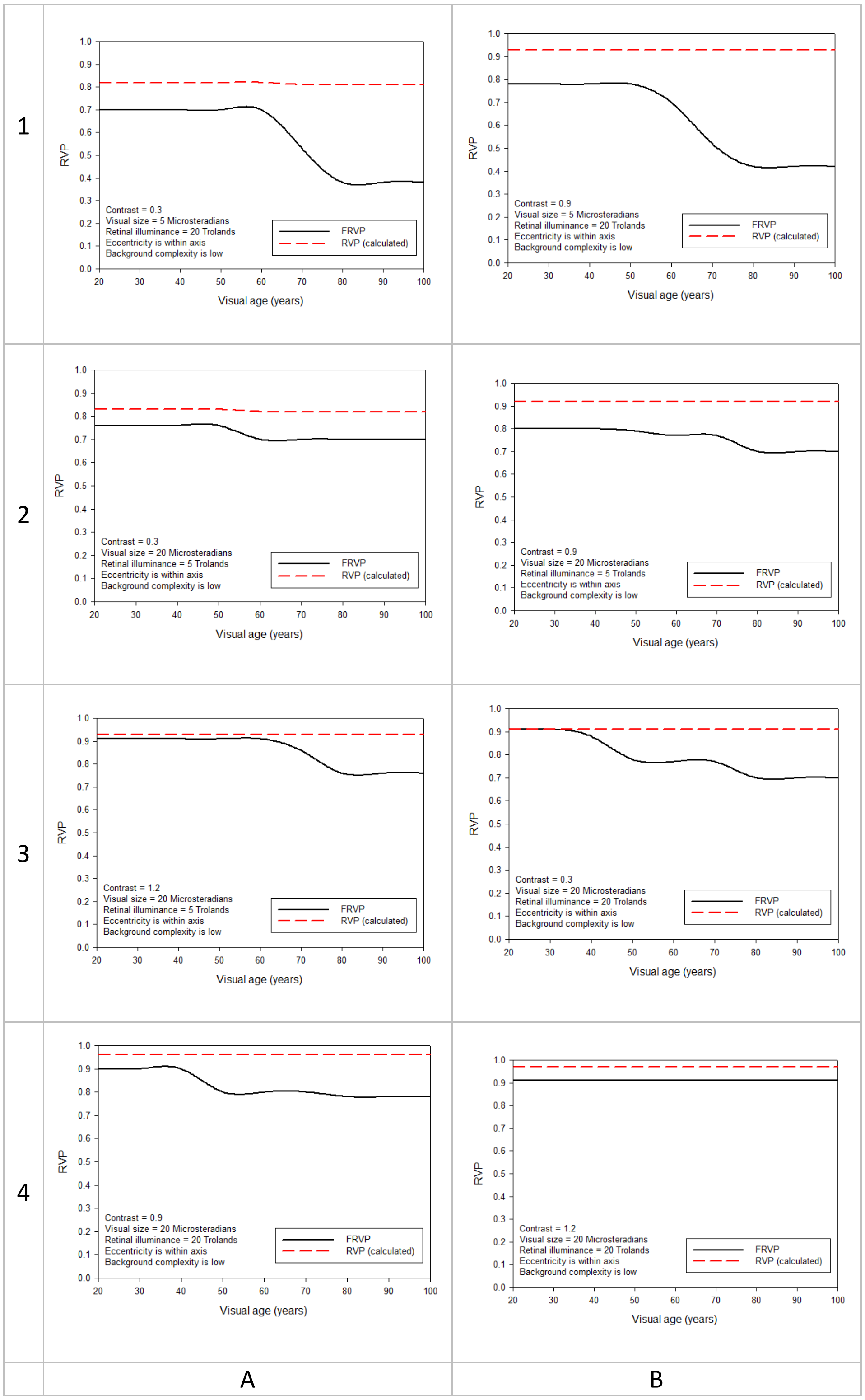


Figure 5.9: Comparison between RVP and FRVP based on visual age

The comparison between RVP and FRVP based on the visual size (on the x-axis) is shown in Figure 5.10. a general trend of almost constant RVP values with respect to changing the visual size is noticed except when the luminance contrast and retinal illuminance is low (Figure 5.10-1A). Despite that the visual size is used as an input variable in the RVP model, it seems that its mathematical weight is low with respect to changing RVP values, unless the influence variables (luminance contrast and retinal illuminance) is low.

Another very good agreement can be seen between FRVP and RVP after a visual size value of 12 Microsteradians (medium visual size), even when the retinal illuminance is low (Figure 5.10-2A) or the visual age is old (Figure 5.10-4A). Yet, a combination of low luminance contrast and retinal illuminance (Figure 5.10-1A) will shift this agreement to be occurring at large visual size values (almost 15 Microsteradian).

Once luminance contrast and retinal illuminance is high (Figure 5.10-4B), a very good agreement between FRVP and RVP is noticed, even when the visual age is old (50 years). In this case, both FRVP and RVP values are above 0.9, which corresponds to a high relative visual performance.

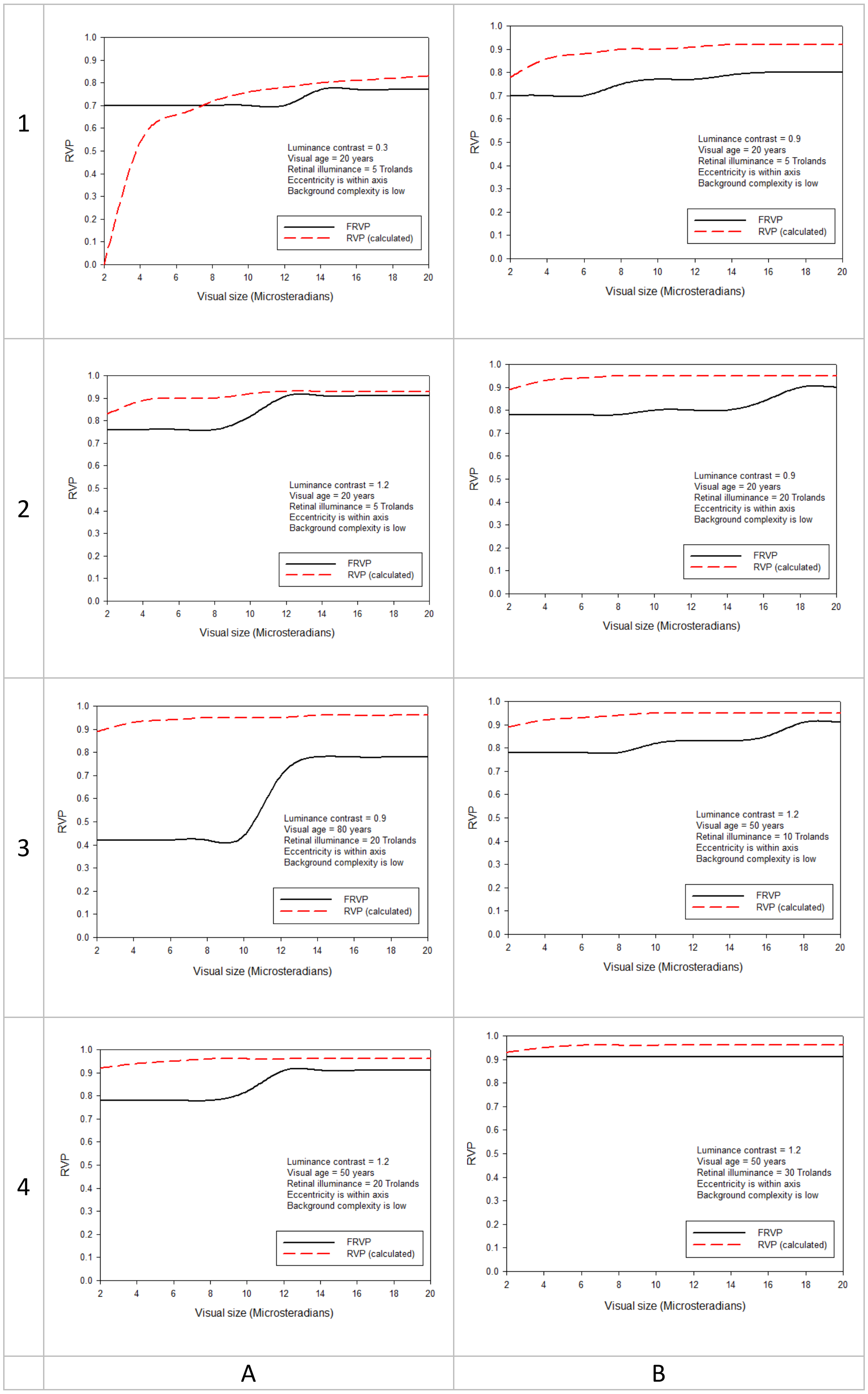


Figure 5.10: Comparison between RVP and FRVP based on visual size

Results for the comparison between RVP and FRVP based on retinal illuminance are shown in Figure 5.11. It seems that the RVP model is more responsive to retinal illuminance than visual size and visual age, especially at low luminance contrast (Figure 5.11-1A). The figure also shows that as the retinal illuminance values increase, FRVP values increase as well to be closer to RVP and reduce the difference between the two models. However, at low retinal illuminance values, there is a measurable difference between the values of RVP and FRVP, especially at old visual age values (Figure 5.11-3B).

A good agreement between the two models is noticed at high luminance contrast and low visual age values, even if the visual size is medium (Figure 5.11-4A and 4B) and high (Figure 5.11-2A). Nevertheless, a combination of older ages and below medium luminance contrast (Figure 5.11-3A and 3B) will increase the difference between the two models. The best agreement was noticed at high visibility situations, where the influence variables are fixed at the maximum, with respect to their contribution to both RVP and FRVP. This is shown in Figure 5.11 (2A). In this case, both RVP and FRVP are taking values above 0.9, which corresponds to high relative visual performance.

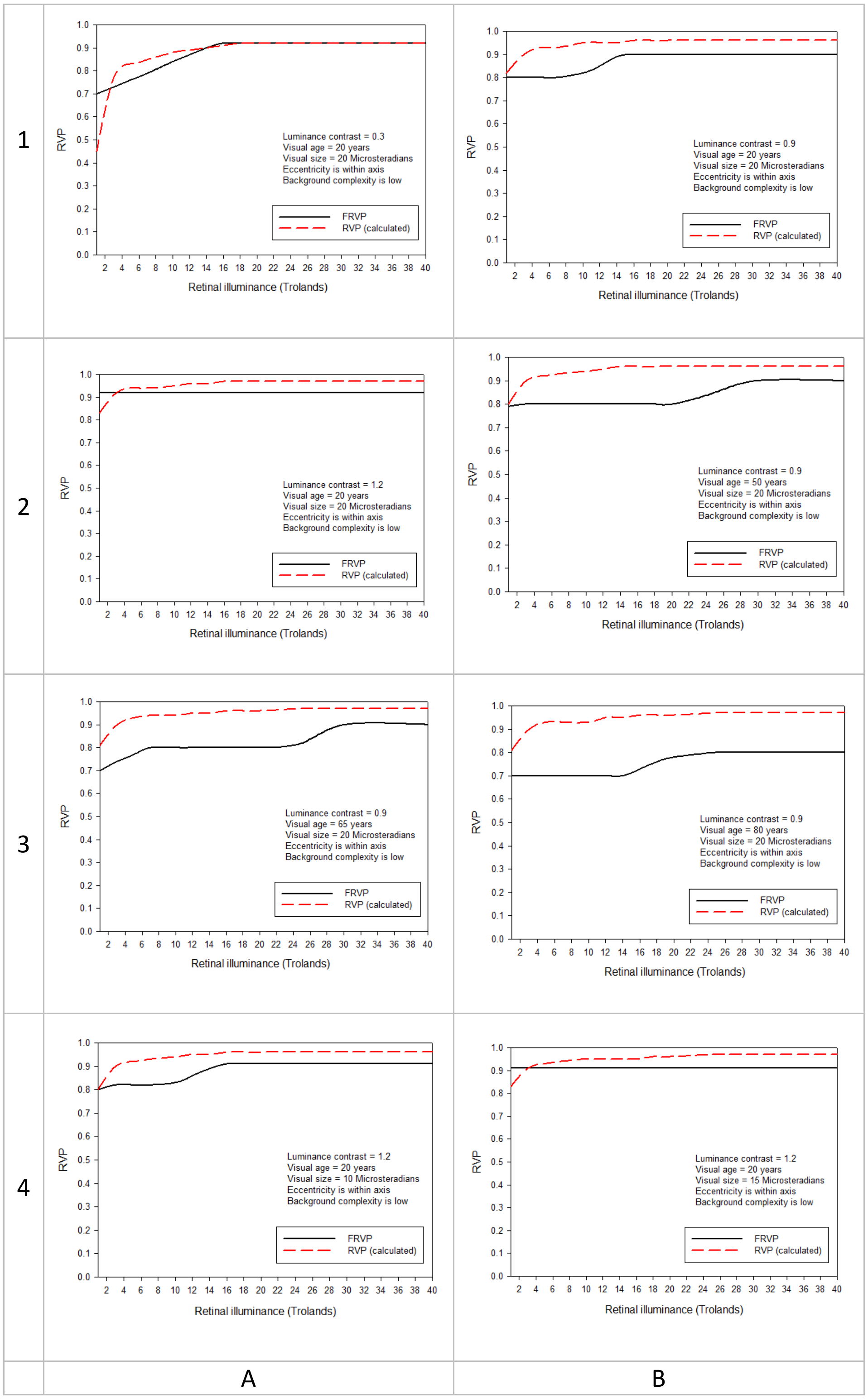


Figure 5.11: Comparison between RVP and FRVP based on Retinal illuminance

5.3 Sensitivity analysis of FRVP model

Sensitivity analysis provides important information to the designer/decision-maker. Of this information is the identification of the input variables that have the most significant effect on the output, this allows for the designer/decision-maker to carefully observe this variable with cautious and more focus. Moreover, sensitivity analysis is important to explore the unexpected, or at least, the unknown relationships between input and output variables that may not be noticed in the original model (Kang et al. 2011). Despite nothing wrong with the solution being sensitive, close monitoring for the model or process is very important to keep the system running flawlessly (Eiselt and Sandblom 2012).

In the context of this work, one membership function will be modified at a time and the effect of this new memberships function on the output FRVP will be noticed and compared to the original values. Though, due to the nature of the fuzzy logic modelling, it is expected that some input variables will result in large output sensitivities at certain values only. These values are very likely to be those enclosed within the intersection of membership function subsets. 2D graphs shall be used to present the comparison between the original membership function effect and the newly designed membership functions for the use of sensitivity analysis.

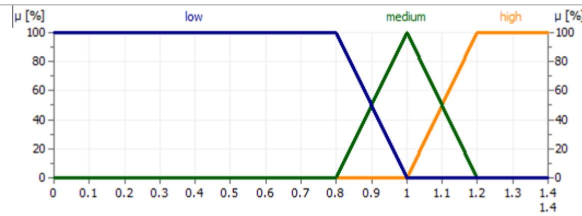
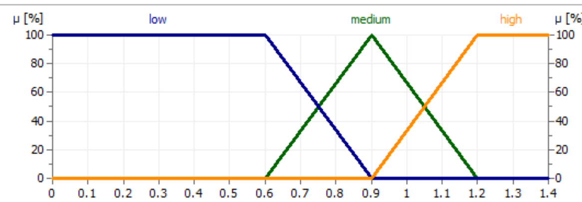
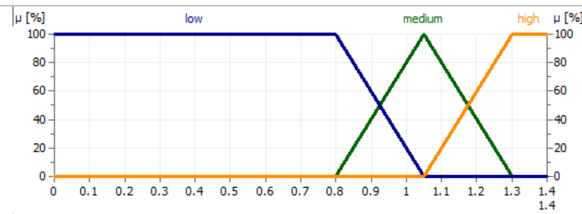
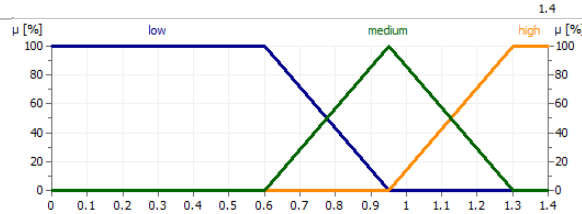
Regarding background complexity. Unlike other variables, there will be no need for sensitivity analysis. The reason behind this is that the scale of background complexity is rather imaginary than real. This means that the sensitivity analysis for background complexity will add to benefit to the FRVP model because there is no meaning in measuring the sensitivity with respect to an imaginary scale variable.

In this work, sensitivity analysis will be depending on the membership functions for the input variables. This means that new membership functions will be designed which hold a certain change in the low, medium, or high subset, with respect to its contribution to FRVP. Four membership function will be used for each variable, the first one is the original one, the second is based on a modification in the low subset, the third is based on a modification in the high subset and the fourth is based on a modification in both high and low subsets. The medium subset (s) will follow the modification in the low and high subset automatically to keep the degree of truth (y-axis of the membership function) of 1.0 at with respect to any variable value within its range.

A 2D graphical representation between FRVP and the same variable under consideration will be used to measure the sensitivity of changing the input membership functions. The influence variables (not included in the graph) will be selected to give three scenarios of low, medium, and high FRVP respectively. However, eccentricity and background complexity will always be set at “within axis” and “low” respectively. This was done to avoid the situation where FRVP is located at a certain plateau where there is no effect for any single variable alone (see FRVP results page 183).

For the positive luminance contrast, the newly designed membership functions are shown in Table 5.1 and the sensitivity results are shown in Figure 5.12 (A, B, C). The original membership function (MFC-1) is the same that was used to develop the FRVP model based on the available literature (Figure 3.29). The results show that when the influence variables are fixed at low (Figure 5.12-A), there is no change in FRVP below 0.8. Yet, after this value, there is a clear change in FRVP with respect to different membership functions, this change occurs at the critical values of the newly designed membership functions. Once the influence variables are fixed at medium (Figure 5.12-B), the change in FRVP value is rather small and Though, once the influence variables are fixed at high (Figure 5.12-C), there is no change in FRVP values what so ever with respect to changing the membership functions of the variables under consideration. It is also noticed that changing the membership function does not affect the lower and upper values of FRVP since all lines start and end at the same point.

Table 5.1: Positive contrast membership functions used in sensitivity analysis

Membership function	Graphical representation	Description
MFC-1		Original
MFC-2		Lower limit modified
MFC-3		Upper limit modified
MFC-4		Lower-upper limits modified

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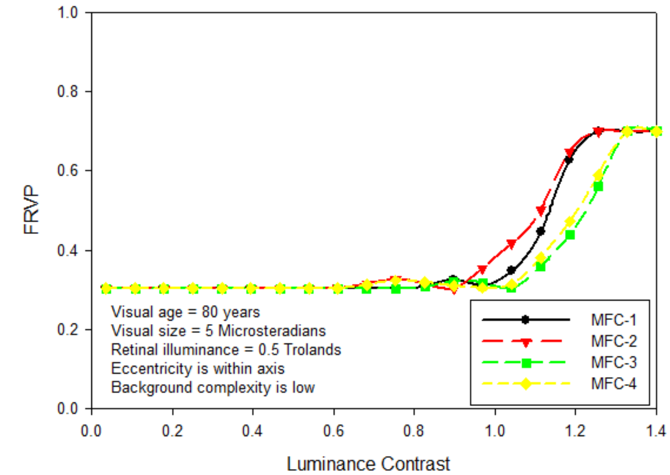
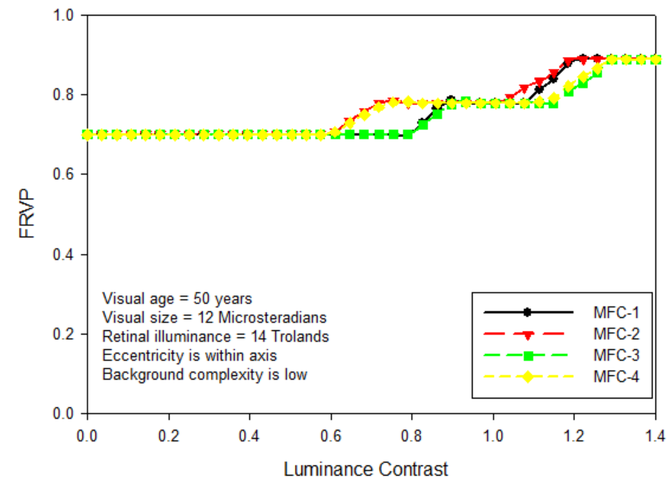
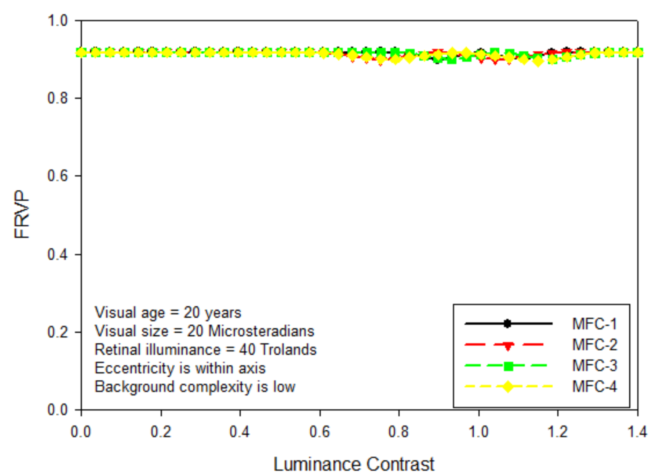
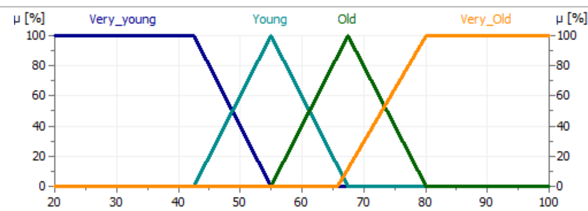
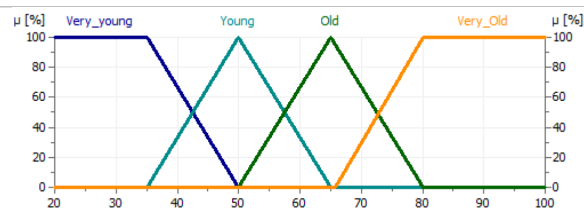
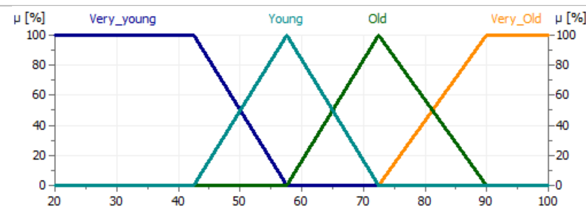
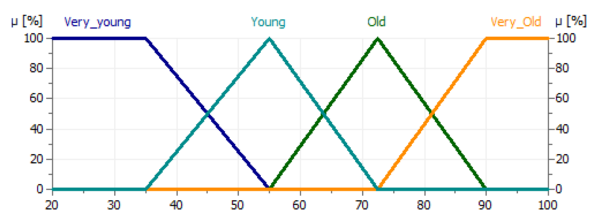
A	
B	
C	

Figure 5.12: Sensitivity analysis based on changing positive contrast membership function

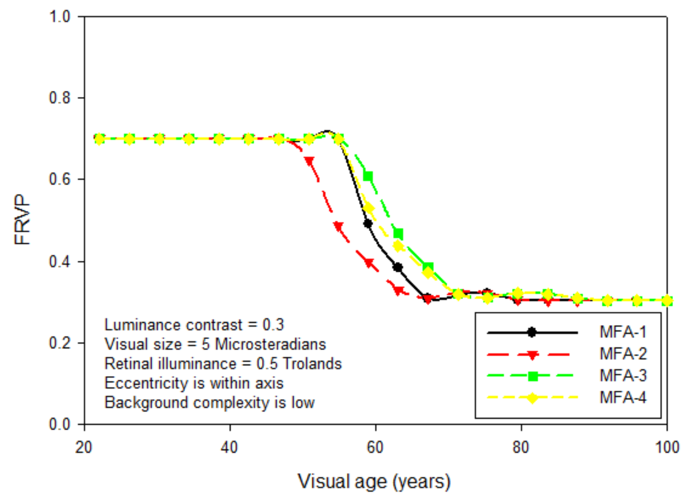
For the visual age, the proposed membership functions used in sensitivity analysis are shown in Table 5.2 and the sensitivity results are shown in Figure 5.13 (A, B, C). The results clearly show that there is a clear effect for changing the membership functions when the influence variables are fixed at low (Figure 5.13-A), this effect starts to decrease in the medium range of influence variables (Figure 5.13-B) until it is demolished when the influence variables are fixed at high (Figure 5.13-C). However, the limits for FRVP are independent of changing membership functions as all lines start and end at the same point.

Table 5.2: Visual age membership functions used in sensitivity analysis

Membership function	Graphical representation	Description
MFA-1		Original
MFA-2		Lower limit modified
MFA-3		Upper limit modified
MFA-4		Lower-upper limits modified

Col.

A



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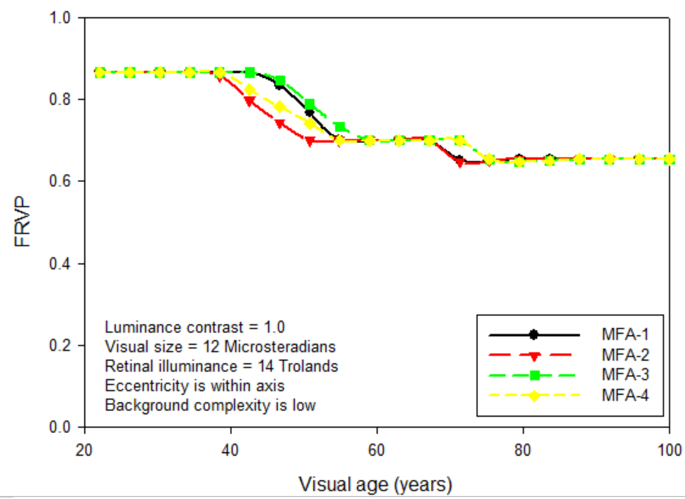


C

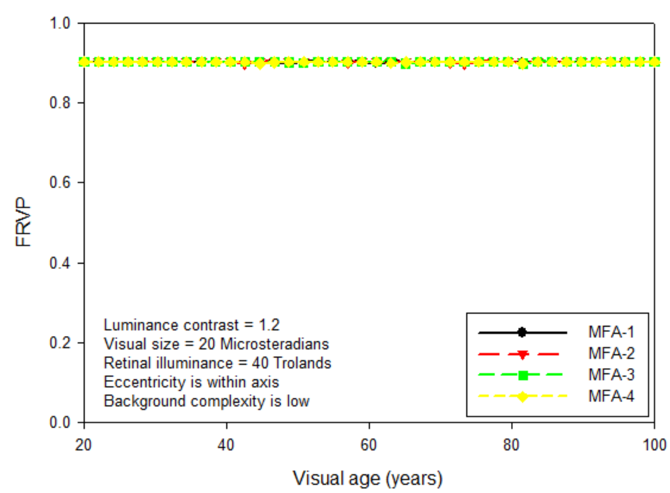
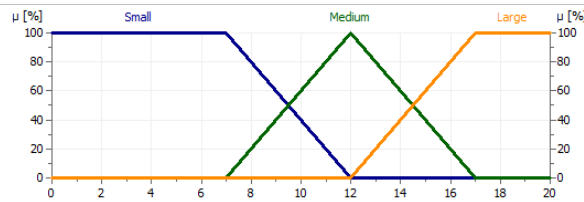
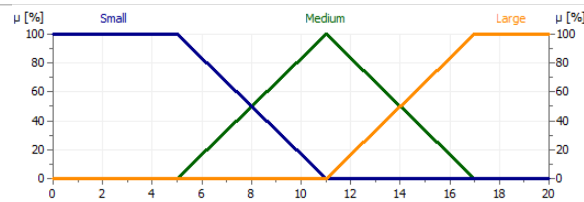
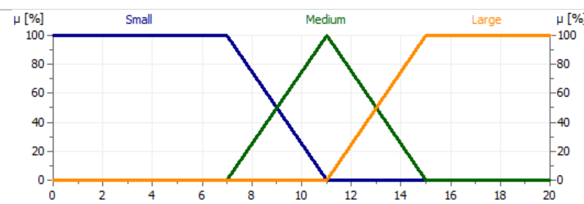
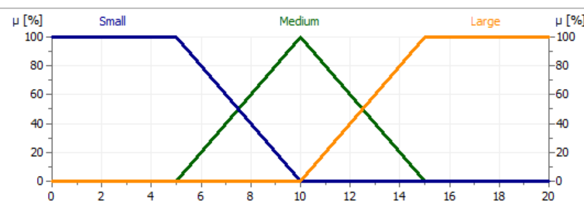


Figure 5.13: Sensitivity analysis based on changing visual age membership function

Regarding visual age, the proposed membership functions used in sensitivity analysis are shown in Table 5.3 and the sensitivity results are shown in Figure 5.14 (A, B, C). The same trend of FRVP sensitivity to membership function changing is noticed in the figures. This change is clear when the influence variables are fixed at low (Figure 5.14-A), decreases at low (Figure 5.14-b), and disappears at high (Figure 5.14-C).

Table 5.3: Visual size membership functions used in sensitivity analysis

Membership function	Graphical representation	Description
MFS-1		Original
MFS-2		Lower limit modified
MFS-3		Upper limit modified
MFS-4		Lower-upper limits modified

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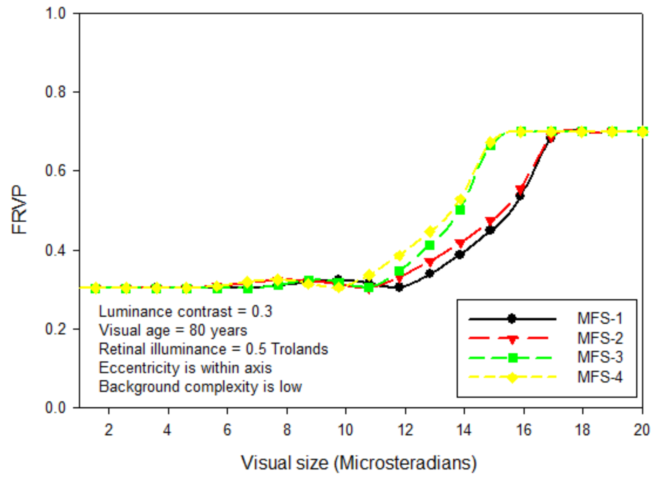

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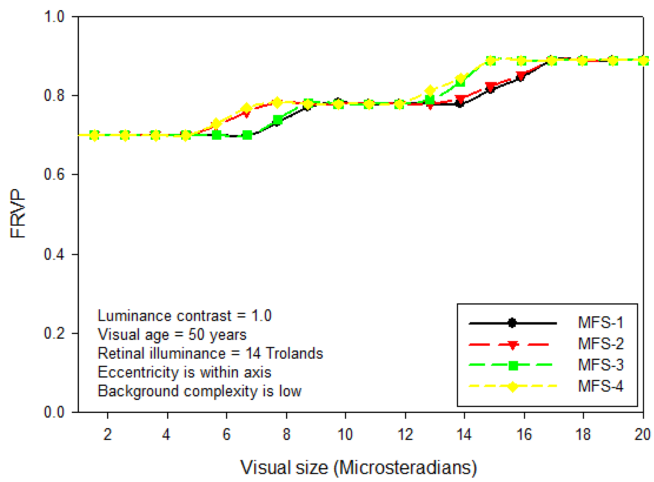

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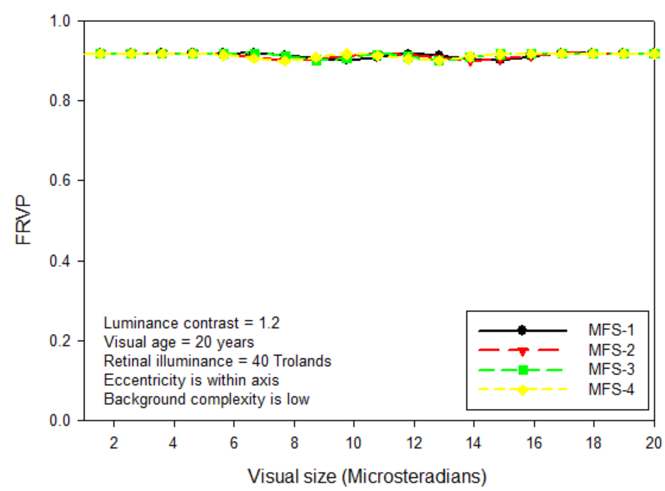

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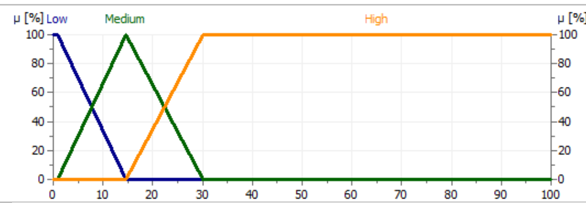
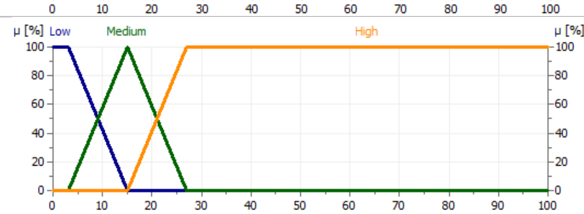
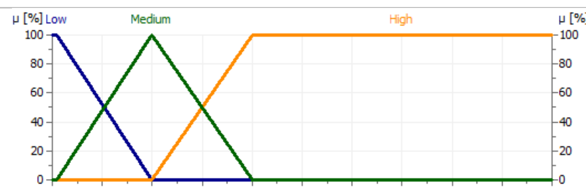
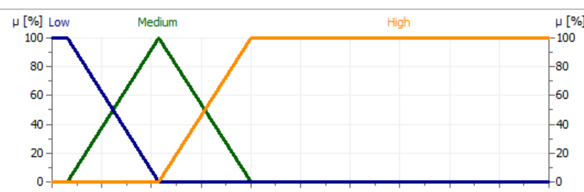
Figure 5.14: Sensitivity analysis based on changing visual size membership function

Retinal illuminance proposed membership functions for sensitivity analysis are shown in Table 5.4 and sensitivity results are shown in Figure 5.15 (A, B, C). In all figures, it is noticed that the model is insensitive to retinal illuminance values above 40 Trolands. However, there is a clear sensitivity below this value, especially at low influence variables (Figure 5.15-A). It also noticed that in all figures, FRVP starts and ends at the same point regardless of the design of the membership function.

Table 5.4: Retinal illuminance membership functions used in sensitivity analysis

Membership function	Graphical representation	Description
MFR-1		Original
MFR-2		Lower limit modified
MFR-3		Upper limit modified
MFR-4		Lower-upper limits modified

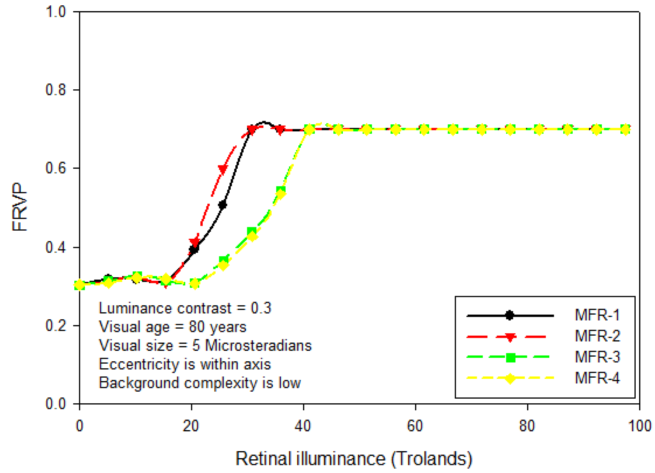
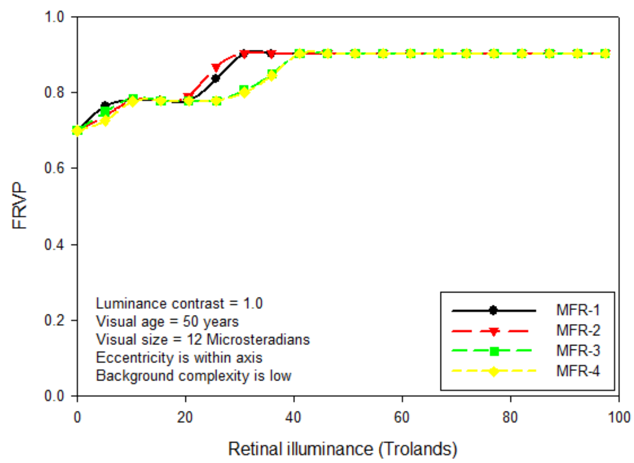
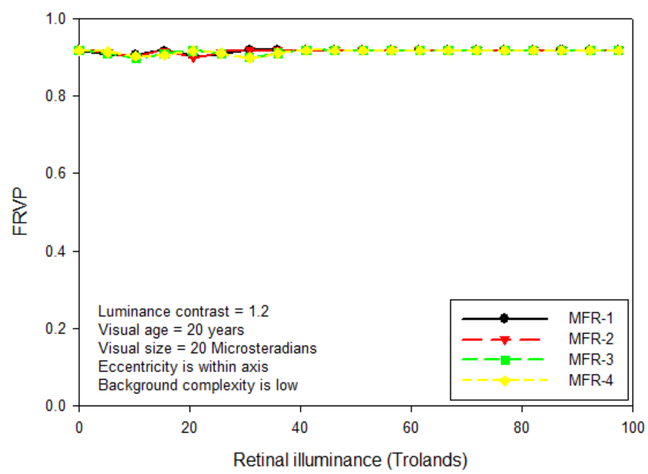
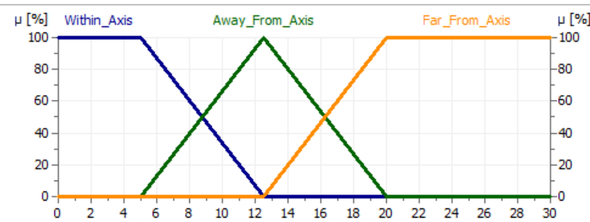
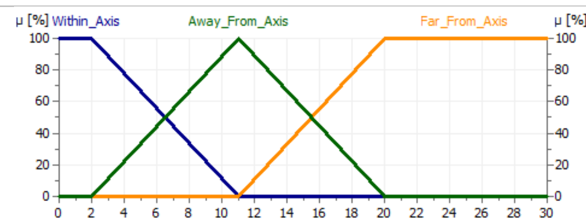
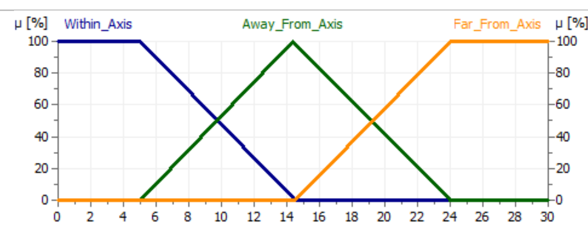
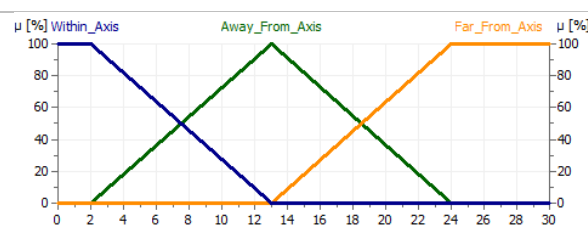
Col.	
A	
B	
C	

Figure 5.15: Sensitivity analysis based on changing Retinal illuminance membership function

Eccentricity membership function used in the sensitivity analysis can be seen in Table 5.5 and sensitivity results are shown in Figure 5.16 (A, B, C). the figures show that different eccentricity membership functions can change FRVP in case the influence variables are fixed at low, with respect to their contribution to FRVP (Figure 5.16-A). A further increase in the influence variables (Figure 5.16-B) decreases the sensitivity of the FRVP model it becomes insensitive once the influence variables are fixed at high Figure 5.16-C).

Table 5.5: Eccentricity membership functions used in sensitivity analysis

Membership function	Graphical representation	Description
MFE-1		Original
MFE-2		Lower limit modified
MFE-3		Upper limit modified
MFE-4		Lower-upper limits modified

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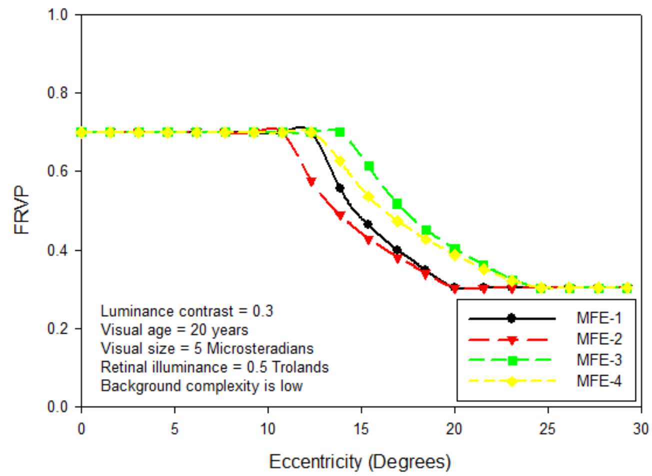

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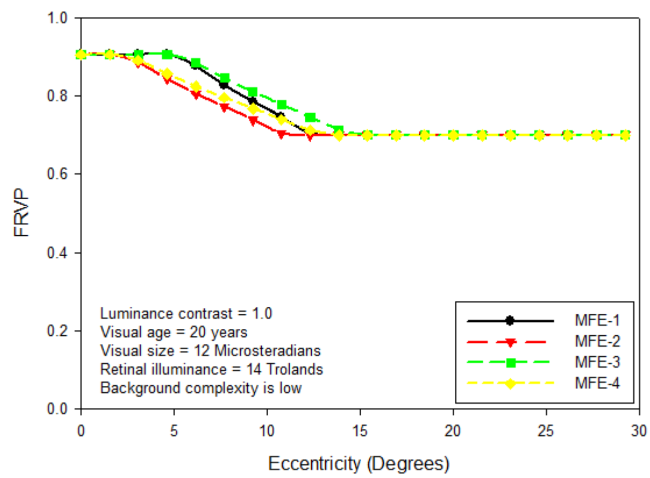

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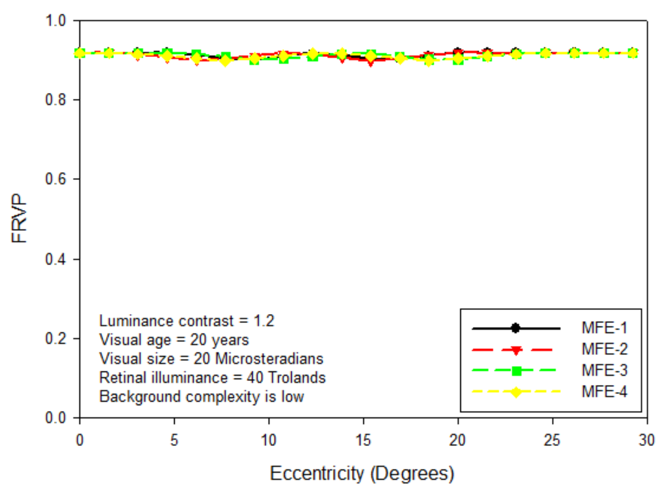

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Figure 5.16: Sensitivity analysis based on changing Eccentricity membership function

The results of the sensitivity analysis proved that the FRVP model can be sensitive, moderately-sensitive, and insensitive depending on the value of the other influence variables, or more accurately, at locations outside the flat plateaus shown in the previous chapter. Moreover, sensitivity analysis showed that changing the member function of any variables changes how FRVP increase/decrease, but does not affect the limits in which FRVP is bounded for that situation.

5.4 Advantages of the FRVP model

The FRVP model was designed to address the limitations of the current visibility models. Such limitations include ignoring some important visibility parameters, and limiting the model to a certain range of variables. Limitations of the current visibility models are presented in the literature review section (Table 2.2). Some advantages of the FRVP model were predicted since the starting of this work. For example, it was predicted from the start that the proposed model will address the problem of complex math involved in the current models. However, some advantages cam to surface once the model was developed and tested. An example of these advantages is the capability of the FRVP model to respond to different age groups, unlike the current RVP model, where it was shown in the validation section that it is insensitive to older age groups. Table 5.6 shows some advantages of the FRVP model when compared to classical mathematical models, as well as current visibility models.

Table 5.6: Advantages of the FRVP proposed model

Advantages of FRVP model	Compared to
• Can be easily corrected and modified for any mistakes and/or errors • Based on Artificial intelligence (AI) • Employs image processing techniques • Can be easily integrated with new AI technologies such as ADAS and AV • No complex mathematical relations • Close to the human way of thinking with respect to analysing and accepting partial degrees of truth • More appropriate for modelling lighting parameters since they are non-exact and can be considered as fuzzy	**Mathematical models**
• Employs more input variables such as eccentricity, retinal illuminance and background complexity • No complex mathematical relations • No correction factors	**VL model (Adrian 1989)**
• Employs more input variables such as eccentricity, disability glare, and background complexity • No complex mathematical relations • The effect of old observer on visual performance is measurable unlike RVP model which is insensitive to older ages • Values are not limited to a high plateau, medium and low plateaus can be seen as well • Can give valuable insights for the visual performance at extreme low situations	**RVP model (Rea and Ouellette 1988, 1991)**
• Employs more input variables such as eccentricity, retinal illuminance and background complexity • No complex mathematical relations • Can include a variety of target sizes and not limited to small targets only	**STV model (IESNA 2000)**

5.5 Limitation of the FRVP model

Such as any model, FRVP model has limitations. These limitations are related to either the fuzzy technique itself, or to the assumptions made in developing the fuzzy model. However, fuzzy-based models, unlike classical mathematical models, can be easily modified to address any serious limitations and/or disadvantages that may come to the surface after testing the model. The following shows some limitations for the FRVP model:

1. The FRVP model did not take the effect of chromatic contrast into consideration. It was assumed that there should be a difference between the target luminance and the background luminance in order for the target to be seen, based on Adrian (1989). However, a study by Raynham (2004) suggests that despite the shrinking of colour vision at low levels of lighting, colour contrast is still an important factor in vision and its importance becomes higher with the increase of traffic density on the road.

2. The FRVP model ignored the effect of transient adaptation. This assumption was based on Adrian (1989) justification where the transient adaptation will likely happen quickly and the threshold contrast will return to its steady-state value in almost 0.2 seconds. However, in real-life night-driving situations, substantial changes of the retinal illuminance can occur, making the effect of transient adaptation to be measurable.

3. With respect to the driver's expectations, the FRVP model adopted normal driving conditions where the driver is assumed to be fully experienced in the road environment and no unexpected targets are present, for the time being. While the effect of driver's expectations on the driving task is clear (Muttart 2016), further future research related to the effect of this variable on driving/visual performance can provide better insights on how to include it in the FRVP model

4. Although driver alertness and distraction may affect the visual performance of drivers/ observers, there is no enough data in lighting literature to quantify this effect. In other

words, many experiments confirmed the effect of driver distraction on driving performance and collisions. However, measuring this effect in the context of visual performance was hard. Hence, drivers/observers, in the context of this study, was assumed to be fully alert without any distraction at the time being, while further research in lighting and hazard detection, as suggested by Robbins and Fotios (2020) may allow for this work to include them in the future

5. Fuzzy logic models show problems of accuracy when the number of rules is not enough to cover the complete range of possible input arrangements. For example, the proposed FRVP model employs 972 rules, which is equal to the total number of probable incidents that can occur based on the input membership functions subset arrangement. These rules cover the whole range of the model operation involving different subsets from different membership functions of the input variables. Yet, the model can work if the number of rules is less but the results will not be as accurate as it should be. Hence, extra care should be taken when developing such complicated models and accuracy checks should be always done to limit faulty outputs.

6. As the membership function of the input variable has multiple subsets, the number of fuzzy rules increases. Moreover, as more variables are included, the number of rules also increase dramatically. For example, the proposed FRVP model employs 972 (See Appendix). However, if another input variables with a membership function of 3 subsets to be included in the model, the number of rules will be multiplied by 3, resulting in 2916 rule. This may increase the time and effort needed to enter the rules. Moreover, it can increase the possibility of getting data entry mistakes. While this may seem a huge

problem to beginners, Matlab software accepts fuzzy rules in a form of vectors instead of manual rule entering. For example, a fuzzy system with input variables A, B, and output variable C can have a rule in the form of { IF A is low and B is low then C is low}, this rule can be manually entered in Matlab fuzzy logic toolbox as it is, or it can be entered in the fuzzy model programming environment as

$$a_1 = [1\ 1\ 1\ 1\ 1] \tag{5.1}$$

Where a_1 is the rule number, the first number between brackets indicates the subset in membership function of variable A, the second indicates the subset in membership function B, the third indicates the subset in the membership function of the output C, the fourth indicates the weight of the rule, and the fifth indicates the connection of AND (1) or OR (2) between the inputs. Hence, complicated fuzzy models such as the FRVP model need plenty of experience, practice, and most importantly, patience, in order to be correctly developed.

5.6 Discussion of the FIIL model results

The fuzzy indoor illuminance selection method (FIIL) was designed to enhance the current illuminance selection guidelines. The input variables used in the fuzzy model is the visual age, task difficulty (characteristics), and task importance. The output of the fuzzy model is the Fuzzy indoor illuminance (lux). Fuzzification of the input and output parameters was discussed in the methodology chapter, while the results for the FIIL model was presented in the previous chapter. Moreover, a software was designed based on the FIIL model to help users/designers in selecting the appropriate value of indoor illuminance based on input values that correspond to the type of the visual performance. The software can also check and assess the uniformity and target illuminance based on few applications (office, classroom, conference room, hallway).

To get more insights about the proposed illuminance selection method, 2-D graphs have been generated for the FIIL as a function of each variable, while the other variables are constant. FIIL (lux) as a function of visual age at different task importance groups is shown in Figure 5.17 for 3 task difficulty categories: low (A), medium (B), and high (C). The figure shows that when the task difficulty is low (Figure 5.17-A), the required illuminance ranges between 50-500 lux for ages below 55 years old. However, as the visual age increases above 55 years, the minimum required illuminance increases to almost 500 lux for low and medium importance tasks, and almost 950 lux for high importance tasks.

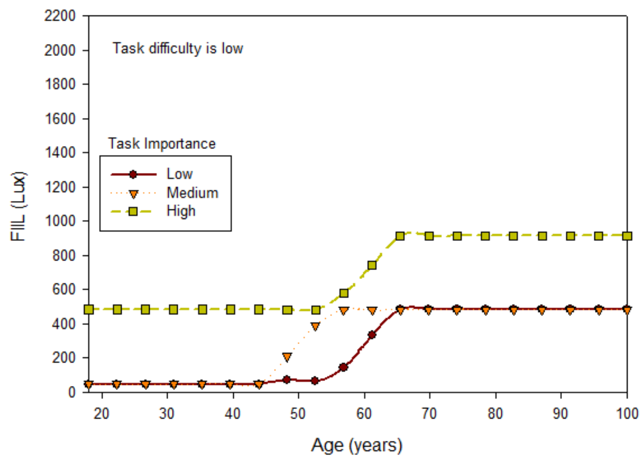
For medium task difficulty situations (Figure 5.17-B), the illuminance values start to be ore distinguishable based on the task importance groups. This can be seen at visual age above 55 years old, where the minimum required illuminance is having values of 450, 950, 2000 lux for low, medium, and high importance tasks respectively. Moreover, it is noticed that there is a large jump in illuminance values for high importance tasks after the age of 55 years old. Once the task difficulty is fixed at high (Figure 5.17-C), it is noticed that the minimum required illuminance increases for all task importance groups and visual ages. Moreover, medium importance tasks start to require high illuminance values after the age of 40 years, which corresponds to the end of the young age subset.

Figure 5.18 shows the FIIL (lux) as a function of task importance for different age groups and 3 task difficulty levels: low (A), medium (B), and high (C). The figure shows that low difficulty tasks (Figure 5.18-A) require less than 50 lux when performed by young people at task importance values below 50%. While for very old people, the same task requires almost 500 lux. As the task importance exceeds 50%, almost 400 lux is needed for young people to perform a low importance task, while almost 900 lux is needed for very old people. For the old age group (40-65 years), the required illuminance is closer to the young age group but they start to need higher illuminance values of almost 500 lux at task importance values above 20%, which is much earlier than the young age groups (80%).

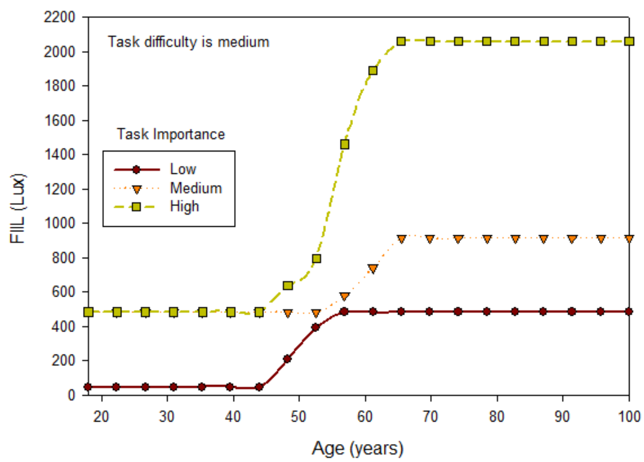
Furthermore, a large jump in illuminance values from almost 500 to 2000 lux is also noticed at medium task difficulty tasks (Figure 5.18-B) for the very old age groups after task importance values of 50%, which marks the peak of the medium task importance (100% membership degree in medium subset). This jump is also noticed for high difficulty tasks (Figure 5.18-C) but for both old and very old age groups. However, the required illuminance for very old age groups starts to increase after task importance values above 20%, while it starts to increase after task importance values of 50% for old age groups. Both groups require almost 2000 lux to perform at high task importance and task difficulty situations.

Col.

A



B



C

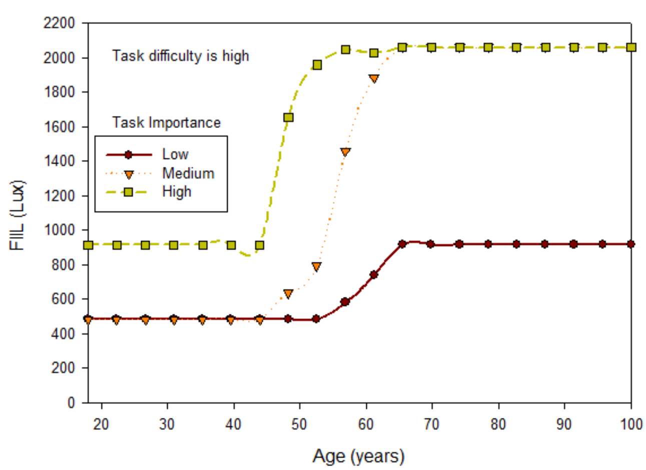


Figure 5.17: FIIL as a function of age at different task importance groups

<table>
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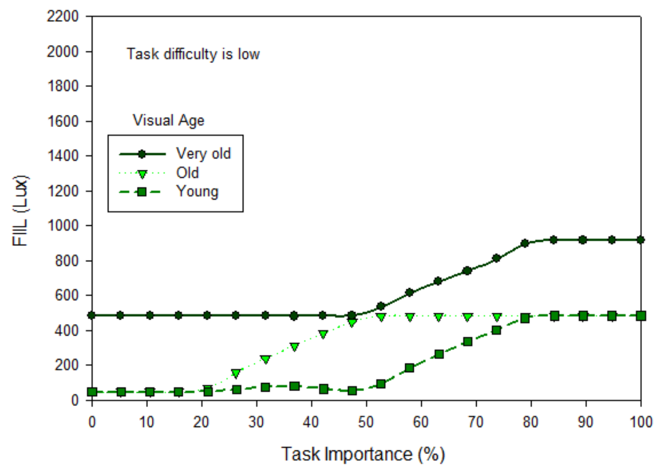
<tr><td>A</td><td>
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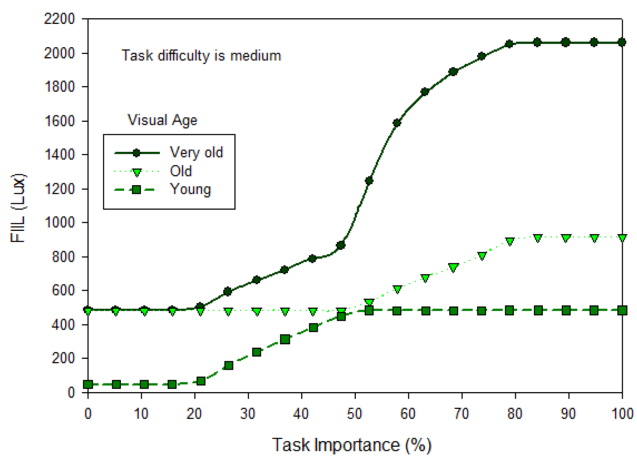
<tr><td>B</td><td>
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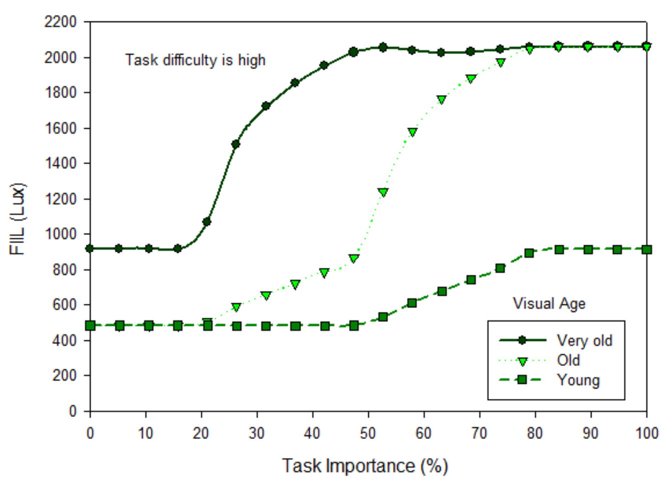
<tr><td>C</td><td>
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Figure 5.18: FIIL as a function of task importance at different age groups

Results for FIIL (lux) as a function of task difficulty at different visual age groups are very similar to those for FIIL as a function of task importance, except that the increase in illuminance values occurs at a slightly earlier percentage of task difficulty. This is related to the design of the task difficulty membership function which considers values less than 10% to be included in the lower subset, and values above 90% to be in the highest subset, while medium subset corresponds to values in between. Figure 5.19 shows FIIL as a function of task difficulty at different visual age groups for 3 task importance levels: low (A), medium (B), and high (C).

The figure shows that situations involving low task importance (Figure 5.19-A), task difficulty of 50% marks the inflection point in which age groups start to require more illuminance. However, once the task difficulty is increased to medium, the very old age group start to increase from almost 500 lux to almost 950 lux between task difficulty values of between 10%- 50%. Then a further sharp increase in illuminance is noticed between task difficulty values between 50% to 90% which takes the illuminance values to almost 2000 lux. Yet, the required illuminance for the old age group is almost constant at 500 lux below task difficulty of 50%, then it increases to almost 800 lux at 90% task difficulty. On the other hand, the required illuminance for young age groups is low at almost 50 lux at task difficulty below 10%, then it starts to increase up to almost 450 lux after 50% task difficulty values.

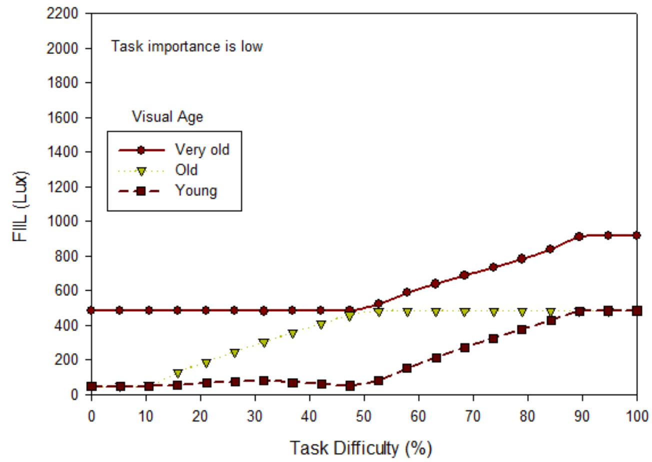
Once the task importance is fixed at high, all age groups start to require higher illuminances at task difficulty above 10%, which marks the end of the lowest subset. However, the increase in the illuminance for the very old age group is sharp from almost 950 lux to 2000 lux at task difficulty of almost 60%. Whereas, the required illuminance for old age group increases in two stages, the first stage is moderate and between task difficulty values of 20% to 50% where the illuminance increases from almost 450 to 800 lux, while the second stage is sharp and occurs between task difficulty values after 50% until 90%. In this stage, the required illuminance for old age groups increases from almost 800 to 2000 lux.

The required illuminance for the young age group also increases at situations involving high task importance and high task difficulty. However, the increase is moderate and values of illuminance are almost constant at 500 lux below task difficulty of 50%, then the illuminance starts to increase moderately until it reaches less than 800 lux at 90% task importance.

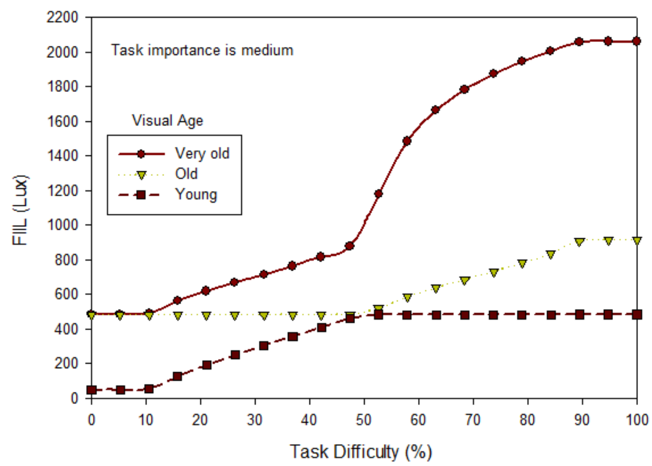
The FIIL model, it is still an early attempt to model indoor illuminance. Yet, it has plenty of potential in the future to be developed in a more convenient way. The problem with determining the illuminance for different applications and tasks is very complex, especially for tasks that are close to each other in terms of task characteristics and importance. The IES illuminance recommendations overcame this problem by providing a large range of task characteristics and importance categories (Figure 2.1) that starts from very low cognitive tasks requiring very low illuminance values (0.5 – 60 lux) such as dark adapted situations, and ends by unusual extremely minute tasks that require very high illuminance values (1500-20,000 lux) such as medical procedures. However, these task characteristics and importance categories cannot be mapped into a simple 3 subset membership function, such as the one provided in the FIIL model. Moreover, the large range of illuminance values provided in the IES recommendations cannot be easily integrated into the output illuminance membership function scale without a large increase in the number of subset used. As a result, the FIIL method can give reasonable results in a certain range of task applications and characteristics that require illuminance values between 50-2000 lux only.

Col.	

A



B



C

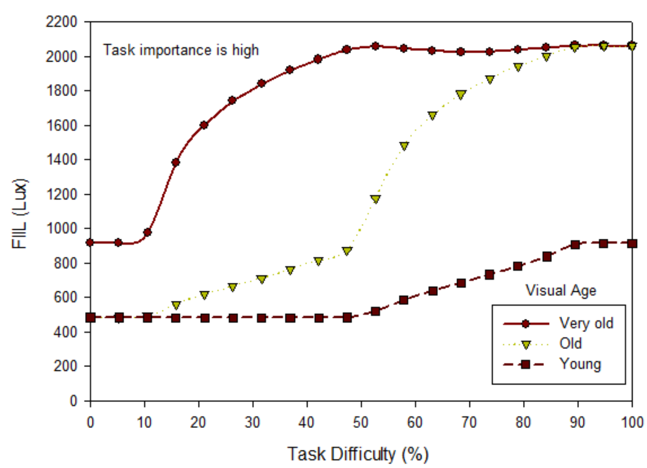


Figure 5.19: FIIL as a function of task difficulty at different visual age groups

5.7 Advantages of the FIIL model

The Fuzzy indoor illuminance selection model (FIIL) was developed to enhance the illuminance determination method provided by the latest edition of the IES lighting handbook (DiLaura et al. 2011). FIIL method provided the required illuminance based on three factors: visual age, task difficulty (characteristics), and task importance. These factors are the same used by the IES illuminance determination method. FIIL method is based on fuzzy logic, which is a part of artificial intelligence. Hence, it can be integrated easily into different software, machine learning, artificial neural networks, and big data applications.

The main advantage of the FIIL model is that it gives the closest estimate for the required illuminance based on the input variables, this illuminance value can be used by users/designers to avoid underlint or overlit situations. Moreover, FIIL method saves time and effort required to go through different lighting selection tables and categories. It also has the capability to increase the accuracy of the lighting design, and in most situations, FIIL values are less than the current IES illuminance determination method, hence, it has some potential in lowering energy consumption.

As for the advantages of the fuzzy logic modeling itself, many of them were discussed earlier while demonstrating the FRVP advantages. However, the main advantage of fuzzy logic modeling in lighting applications is the ability to modify the model easily. This can be very useful if a new variable is to be included in the model, or in upgrading the model to include other applications such as unusual, extremely minute and life-sustaining tasks.

5.8 Limitations of the FIIL model

FIIL model has the potential of becoming a successful lighting design software. For that purpose, FIIL software needs to include a database for various tasks and visual performance types. This database is already included in standards and references such as the IES lighting handbook (DiLaura et al. 2011) illuminance recommendations tables. However, software mapping with this database should be done by an expert as it needs plenty of experience and accuracy. Moreover, FIIL model is still limited to IES illuminance categories below category "W", where the maximum illuminance out from the model is 2000 lux. Hence, further development of the model can extend the range of the output illuminance to reach values up to 20,000 lux (categories X and Y).

The imaginary scale used to develop the task difficulty (characteristics) and task importance can represent the categories described in the IES lighting handbook (DiLaura et al. 2011) in a basic way. However, it can be upgraded to include more subsets, or at least, provide a closer mapping to IES categories. This can also increase the sensitivity of the model with respect to visual tasks applications that are close in description but have different task importance and/or characteristics. An example of these tasks are some indoor education situations where occupants can be either at a classroom or laboratory, or some indoor education situations taking place at different laboratories where the instrument/equipment hazard may significantly vary between one and another. This is already done in the IES illuminance recommendation tables by involving 25 categories. Yet, in FIIL model, it is up to the user/designer to approximate the visual task difficulty and importance based on his own experience.

5.9 Validation of the FIIL model

FIIL model results are compared with the recommended illuminance values provided by the latest edition of the IES lighting handbook (DiLaura et al. 2011) for various applications and tasks. The comparison gave worthy results for FIIL model in most of the situations. The applications chosen for comparison include lighting for education, manufacturing, library, offices, and miscellaneous applications. In general illuminance values obtained from the FIIL model is lower than that obtained from the IES method. Table 5.7 shows a comparison between illuminance values obtained from the FIIL model and those obtained from IES tables for different applications.

Table 5.7: Comparison between illuminance values obtained from FIIL model and those obtained from IES tables for different applications

Sr.	Space	Task	Method	Visual age (years)	Task difficulty (characteristics)	Task importance	Illuminance (lux)
1	Education Auditoria	Study	IES method	25-65	IES category P		300
			FIIL method	45	Level (%) 50	Level (%) 30	216
2	Education Auditoria	Study	IES method	> 65	IES category P		600
			FIIL method	70	Level (%) 50	Level (%) 30	640
3	Education Classroom	Blue line blueprint	IES method	25-65	IES category R		500
			FIIL method	45	Level (%) 60	Level (%) 40	365
4	Library	Book processing	IES method	25-65	IES category M		100
			FIIL method	45	Level (%) 10	Level (%) 20	48

Sr.	Space	Task	Method	Visual age (years)	Task difficulty (characteristics)	Task importance	Illuminance (lux)
5	Manufacturing Machining	Fine grinding	IES method	< 25	IES category W		1500
			FIIL method	20	Level (%) 90	Level (%) 80	916
6	Manufacturing Sheet metal works	Medium benchwork	IES method	25-65	IES category S		750
			FIIL method	45	Level (%) 60	Level (%) 60	614
7	Miscellaneous Applications Toilet/locker room	General	IES method	< 25	IES category K		50
			FIIL method	20	Level (%) 10	Level (%) 10	48
8	Offices Meeting	Discourse	IES method	25-65	IES category P		300
			FIIL method	45	Level (%) 50	Level (%) 30	216
9	Offices Reading and writing	Analog	IES method	25-65	IES category R		500
			FIIL method	45	Level (%) 60	Level (%) 50	483

6 Chapter Six: Conclusions

6.1 Summary

This study aimed to model visual performance and indoor illuminance using fuzzy techniques. Current visibility models and illuminance selection method were studied extensively. The variables involved in visibility modeling and indoor illuminance selection were identified. Then visibility variables were classified into three categories: independent (a), dependent (b), and out of scope (c). While for illuminance selection, the same variables used in the IES illuminance determination method were used. Two new models have been developed based on the fuzzy logic approach. The first one is the Fuzzy Relative Visual Performance model. (FRVP) and the second is the Fuzzy Indoor Illuminance selection model (FIIL). The FRVP model involves the luminance contrast (both positive and negative), visual age, visual size, retinal illuminance, eccentricity, background complexity, and glare as input variables, while the output of the model is the value of FRVP. The FIIL model considers the visual age, task difficulty (characteristics), and task importance as input variables, and the output is the FIIL values in lux. Stand-alone applications were also developed based on the two models.

6.2 Main findings

This work had three main objectives, the first one was to investigate the applicability of fuzzy techniques in lighting applications. The second objective was to develop a new visual performance model that encompass wider range of variables based on fuzzy techniques, and the third was to simplify the illuminance selection procedure using fuzzy techniques. To address the first objective, visibility and illuminance selection models/methods were extensively studied in order to establish that their variables and outcomes comprehend a certain degree of "vagueness" or "fuzziness". Once this was successfully done, these variables/outcomes were ready to be fuzzified. A membership function was designed based on the current literature for each of these variables/outcomes. This membership function defines the values of these variables in linguistic terms called subsets, which can take the form of {low, medium, high} for variables such as luminance contrast, or {young, old, very old} for variables such as the visual age.

The proposed fuzzy relative visual performance model (FRVP), and fuzzy indoor illuminance selection model (FIIL) were then developed by combining the membership function with the set of rules in the fuzzy inference system. The output for both models was a crisp value of visual performance and illuminance (lux) respectively through a process called defuzzification, which incorporates transforming the fuzzy sets into crisp sets.

The results of the two models were presented and discussed in this work. Moreover, the FRVP model was validated with respect to the RVP model (Rea and Ouellette 1988, 1991) and showed a good conformance, while the FIIL model was validated against the current illuminance determination method, which is provided in the latest edition of the IES Lighting Handbook (DiLaura et al 2011). A sensitivity analysis for the FRVP model was done to check the stability and readability of the model. Then the advantages and limitations of each model were discussed.

Both the FRVP model and the FIIL model provided many insights with respect to indoor and road lighting. The FRVP model was developed while taking the limitations of the current visibility models into consideration, while the FIIL model was developed to simplify the current methods of illuminance determination.

One of the most useful advantages of both model is the elasticity of the models to include and/or modify variables without any restriction on the number of variables involved, or the range of values in which these variables can utilize. This allowed for the FRVP model to include six input variables (luminance contrast, visual age, visual size, retinal illuminance, eccentricity, background complexity), as well as to address the contrast polarity and glare effects. This also means that the story of the FRVP and FIIL models has not finished yet, as the models have the capacity of including more variables in the future, or to be modified based on insights coming from future research.

To show the results of the FRVP model, 3D surfaces were provided in the results chapter representing the FRVP as a function of two input variables. These variables were called "variables under consideration" since the graph shows the effect of these variables on the FRVP value. However, other variables which are constant and not included in the graph were called "influence variables". The influence variables can be considered as a description of the lighting condition at any state. For example, at many occasions, the influence variables were fixed at low, medium, and high, with respect to their contribution to FRVP, this means that each influence variable was fixed at the subset that makes FRVP low, medium, and high respectively. This was necessary as FRVP increases with the increase of some variables (luminance contrast, visual size) and decreases with the increase of other variables (visual age, eccentricity). Hence, it was important to show the effect of the "variables under consideration" with respect to the worst case scenario of lighting conditions (influence variables fixed at low subset with respect to their contribution to FRVP), as well as the finest lighting condition scenario (influence variables set to high). At medium influence variables, the effect of the variables under considerations was more measurable compared to the other lighting conditions since it resembles a situation where the lighting conditions are in the medium stage (neutral), and no combined effect of low or high is present.

Moreover, the state of lighting conditions defined by the influence variables showed that the effect of the “variables under considerations” are not absolute, but rather depend on the lighting conditions. This means that the visual performance depends on all the input variables at once, which is more like a combined effect for these variables. As the combined effect of the lighting conditions (influence variables) increases, the effect of the “variables under considerations” becomes very small. This was very clear when the influence variables were fixed at the lowest subset, with respect to their contribution to FRVP, where the effect of a single variables, and sometime two variables is less than the combined effect of the influence variables, allowing the FRVP model to be independent with respect to any changes in the “variables under considerations” (lower FRVP plateau). This can give valuable insights for the visual performance at extremely low lighting conditions, which was not provided by the RVP model.

The results of the FRVP model were good enough to be in conformance with the RVP model (Rea and Ouellette 1988, 1991) at many situations. In fact, it was expected from the beginning of this work that this conformance will be most noticed at high visual performance situations. However, this conformance started to fade out at higher visual age values, where the FRVP model starts to drop, while the RVP model remains almost constant. It is believed that this divergence in values between FRVP and RVP at older ages is an advantage to the FRVP model, as the RVP model was found to be insensitive to higher values of visual age, although the visual age was considered while developing the mathematical relations describing the RVP model.

Unlike the RVP model (Rea and Ouellette 1988, 1991), were a single RVP plateau was capable of defining a large range of lighting conditions, the FRVP model incorporates three plateaus {low, medium and high}, these three plateaus can be present to describe FRVP at the same time, two at a time, or only one at a time, depending on the values of the input variables. This means that the FRVP model has the ability to define the visual performance in a wide range of lighting conditions compared to RVP, where the existence of a plateau in the three-dimensional representation of the RVP model may imply that for a wide range of visual conditions, visual performance changes slightly with the change of lighting conditions (Boyce 2003).

However, It worth mentioning that the FRVP model was developed as an extension to the RVP model (Rea and Ouellette 1988,1991). This extension either widens the range of the variables used in the RVP model, or incorporates additional variables compared to the RVP model. Hence the validation of the FRVP model with respect to the RVP model was limited to the shared variables and their ranges, while the effect of the new variables (eccentricity, background complexity, disability glare) on vision will be left to be tested by future research. For example, Adrian's experiments (1989) and Rea and Ouellette (1988, 1991) work could be repeated using a three-dimensional object that is located at a certain angle from the observer's line of sight in order to test the effect of eccentricity on vision. Moreover, a non-homogeneous complex background could be added to the experiments to check the effect of background complexity. Older subjects can be also used for the visual age effect.

This does not decrease the credibility of the FRVP model in any way as it is still a new model, and a closer look into the literature shows that Adrian's VL model was first proposed in 1969. Then, the model was verified, tested, and criticized by many researchers, which allowed for Adrian to extend and upgrade his model again in 1988. The same applies to the RVP model, which was first proposed by Rea in 1981, then was proposed again in 1988 and 1991 by Rea and Ouellette.

On the other hand, the FIIL model showed decent conformance with the current illuminance determinations method, provided by the latest edition of the IES lighting handbook (DiLaura 2011). In fact, the Fuzzy indoor illuminance (FIIL) figures shown previously in the results and discussion chapters provide a great alternative to complex tables and charts provided in lighting standards and recommendations, where they can be directly used to obtain the required illuminance values based on the input variables adopted in this work.

Two stand-alone applications (software) were developed based on the FRVP and FIIL models. These applications are ready to use once installed on the user computer. The FRVP software allows the user to enter the input variables, select the contrast polarity, and select the method used to describe the background complexity based on two choices: directly by entering a value for the background complexity, or indirectly by uploading a picture for the driving scene, then the software calculates the entropy and defines the background complexity accordingly. Then the software calculates FRVP based on the input variables and map this calculated values with the membership function to define the membership degree of FRVP in each subset (low, medium, high).

The FIIL software, on the other hand, allows the user to enter the task difficulty, task importance and visual age, then it calculates the needed illuminance based on these variables. Moreover, for each input/output variables, the FIIL software calculates the membership degree with respect to any subset based on the membership function for that variable. Another advantage for the FIIL software is that it can check the calculated uniformity for a lighting design and define its membership degree in each subset based on the illuminance uniformity membership function.

6.3 Future work

Science is a cumulative process. Facts are injected within other facts, and new observations can falsify or prove current theories. Hence, knowledge has an infinite end, where scientists stand on the shoulders of giants, building discoveries based on theories developed by the early scholars, and then passing their legacy to the new generation of scientists. This simply describes how knowledge gradually grows through generations to illuminate the nature of creativity.

The proposed future work for this study is based on the limitations of the FRVP and FIIL model. This can involve including more parameters, altering the method used to design some membership functions, and suggesting alternative modelling techniques. For FRVP model, the following can be done to enhance the model in the future:

1. The effect of eccentricity and background complexity on human vision could be experimentally validated and compared to the results obtained from the FRVP model. Adrian's experiment (1989) as well as Rea and Ouellette (1988,1991) work could be repeated while considering three dimensional targets. To check the eccentricity effect, the target can be shifted from the observer's line of sight. Moreover, a non-homogeneous background could be used to study the effect of background complexity.

2. Driving speed can be included in the FRVP model as an independent input variable. A study by Cao et al. (2020) confirmed that driving speed affects the driver's visual

performance. However, future research may give more insights on how to quantify its effects on visual performance

3. Driver's expectations, chromatic contrast, and transient adaptation can also be included in the FRVP model. This allows for the FRVP model to be more accepted and appreciated in the future

4. More research related to utilizing image entropy in visibility models can open the door for image processing techniques to develop better visibility models that are based on real-life scenarios. In fact, images from a live-feed camera can be processed in real-time to give valuable information related to the driving scene

5. While the FRVP and FIIL models are based on fuzzy logic techniques. It can be upgraded to be based on Fuzzy-Neural Network, which is a hybrid between the method of human reasoning of the fuzzy logic and machine learning of the neural networks. This can make a major enhancement to the FRVP and FIIL model

6. Studies on the methods of integrating the FRVP model in real-life applications such as the involvement in Advanced Driving Assistance System (ADAS) and Autonomous Vehicles (AV) can make a huge benefit for these systems. Especially that fuzzy logic models can be easily integrated within artificial intelligence systems

7. FIIL model can make a wide base for multiple studies involving upgrading the model to include different indoor tasks, or to include the light colour as an additional output for the model. In fact, the FIIL model as it is now, can be integrated into a fuzzy controller for dimmable lighting fixtures to give the amount of lighting needed based on task importance and task characteristics.

8. Methods of incorporating the daylight into the FIIL system can provide valuable outcomes related to energy-saving and sustainable environments.

6.4 Final words

The above shows that the study aims were successfully achieved for both the FRVP model and the FIIL model. Yet, this study was developed to answer two important research questions. The first one is related to how suitable fuzzy logic is in modeling visual performance and indoor illuminance, and the second one is related to how better the results of the models based on fuzzy logic compared to the current models/methods.

After an extensive study of the literature to check the advantages and limitations of the current models/methods. Followed by the development and testing of both models. Comparisons were made between the proposed FRVP and FIIL models with current models/methods. This allowed for this study to develop some limitations related to the newly proposed model/method. However, these limitations can be addressed and/or improved in future research as fuzzy logic models have the ability to be easily modified and corrected.

So, with respect to the first research question, the experience gained in developing the fuzzy logic models proposed in this study, as well as the extensive study for the current models/methods allowed for this study to have confidence in answering the first research question positively. This study confirms that Fuzzy logic modeling is a suitable method in modeling many lighting applications, including visual performance and indoor illuminance. This is not only based on the reasons provided in the beginning of this study (complexity of current models and inherent vagueness of lighting parameters), but also based on the results of this study, that came to support the evidence of fuzzy logic modeling suitability in lighting applications. What is also remarkable is that despite no mathematical equations were involved in developing both FRVP and FIIL models, in many situations, very close agreements were noticed between the current RVP model and FRVP model, as well as the IES illuminance values and FIIL values. This indicates how powerful fuzzy modeling can be, if done correctly, in terms of producing suitable results based on human reasoning methods only, that mimics how the human brain works.

One the other hand, to answer the second research question, which is related to the possibility of giving better results compared to the current models/methods. A closer look into the advantage and limitations of these models compared to the newly proposed model is needed. The FRVP model involved more input variables compared to current models (eccentricity, background complexity, and glare), enlarged the range of some variables (visual size), and gave weight to some other variables (visual age) although it was included in other models but did not make a huge difference. Moreover, the FRVP model is based on fuzzy logic techniques which can be easily integrated into artificial intelligence machine learning and fuzzy-neural network, it can be also integrated into big data applications involving huge database for geographic locations, different climates, and multiple applications. As a result, the confidence in the FRVP model allows this study to confirm that the FRVP model can be as good as any other visibility model. Yet, it can give better results on many occasions.

With respect to the FIIL model, it has the potential to become a very good lighting software. However, it needs an expansion to include all task difficulty and task importance categories (from A to Y), which are already defined by the latest edition of the IES lighting handbook (DiLaura et al. 2011). Moreover, it can be expanded to incorporate illuminance values up to 20,000 lux in the future by introducing more subsets to the fuzzy illuminance membership function.

Finally, we believe this work will open the door to explore new models/methods in lighting and visual performance applications. Artificial intelligence and machine learning have already invaded all aspects of our lives, and the need to employ them in lighting applications is critically urgent at this time. Moreover, machine learning makes it easier to include new task applications/characteristics and/or visual performance requirements in the future. Furthermore, as the FRVP model employed a simple image processing technique (image entropy), that is already used in video-gaming applications, the results of this work are expected to point some of the lighting research into this area.

7 References

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8 Appendix

FRVP model rules

No.	Rule statement
1	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
2	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
3	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
4	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
5	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
6	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
7	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
8	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
9	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
10	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
11	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
12	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
13	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
14	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
15	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
16	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
17	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
18	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
19	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
20	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
21	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
22	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
23	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
24	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is High then FRVP is MED
25	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
26	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
27	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
28	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
29	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
30	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
31	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
32	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is MED
33	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
34	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is LOW
35	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is MED
36	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is High then FRVP is MED
37	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
38	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
39	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
40	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
41	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
42	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
43	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
44	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
45	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
46	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
47	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
48	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
49	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
50	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
51	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
52	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
53	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
54	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
55	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
56	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
57	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
58	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
59	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED

No.	Rule statement
60	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
61	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
62	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
63	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
64	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
65	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
66	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
67	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
68	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
69	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is LOW
70	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
71	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
72	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is High then FRVP is MED
73	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
74	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
75	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
76	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
77	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
78	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
79	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
80	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
81	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
82	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
83	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
84	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
85	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
86	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
87	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
88	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
89	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
90	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
91	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
92	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
93	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
94	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
95	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
96	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
97	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
98	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
99	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
100	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
101	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is LOW
102	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
103	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
104	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
105	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
106	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
107	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
108	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is High then FRVP is MED
109	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
110	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
111	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
112	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
113	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
114	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
115	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
116	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
117	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
118	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
119	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
120	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
121	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
122	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
123	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
124	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
125	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW

No.	Rule statement
126	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
127	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
128	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
129	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
130	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
131	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
132	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
133	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
134	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
135	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
136	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
137	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
138	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
139	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
140	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
141	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is LOW
142	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
143	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
144	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is High then FRVP is MED
145	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
146	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
147	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
148	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
149	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
150	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
151	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
152	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
153	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
154	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
155	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
156	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
157	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
158	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
159	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
160	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
161	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
162	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
163	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
164	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
165	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
166	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
167	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
168	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
169	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
170	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
171	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
172	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
173	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is LOW
174	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
175	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
176	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
177	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
178	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
179	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
180	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is High then FRVP is MED
181	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
182	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
183	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
184	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
185	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
186	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
187	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
188	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
189	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
190	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
191	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED

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192	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
193	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
194	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
195	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
196	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
197	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
198	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
199	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
200	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
201	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
202	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
203	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
204	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
205	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is LOW
206	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
207	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
208	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
209	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
210	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
211	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
212	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
213	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
214	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
215	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is MED
216	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is High then FRVP is HIGH
217	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
218	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
219	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
220	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
221	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
222	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
223	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
224	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is MED
225	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
226	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
227	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is MED
228	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is High then FRVP is MED
229	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
230	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
231	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
232	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
233	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
234	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
235	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
236	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
237	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
238	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
239	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
240	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is High then FRVP is MED
241	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
242	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
243	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
244	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
245	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is LOW
246	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
247	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
248	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
249	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
250	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
251	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
252	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is High then FRVP is MED
253	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
254	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
255	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
256	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
257	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW

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258	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
259	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
260	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
261	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
262	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
263	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
264	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
265	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
266	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
267	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
268	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
269	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
270	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
271	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
272	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
273	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
274	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
275	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
276	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
277	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is LOW
278	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
279	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
280	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
281	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
282	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
283	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
284	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
285	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
286	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
287	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is MED
288	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is High then FRVP is HIGH
289	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is LOW
290	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is LOW
291	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
292	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
293	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is LOW
294	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
295	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
296	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
297	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
298	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
299	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
300	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is High then FRVP is MED
301	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is LOW
302	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
303	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
304	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
305	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
306	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
307	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
308	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
309	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
310	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
311	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is MED
312	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is High then FRVP is HIGH
313	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
314	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
315	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
316	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
317	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
318	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
319	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
320	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is HIGH
321	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is MED
322	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is HIGH
323	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is HIGH

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324	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is High then FRVP is HIGH
325	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
326	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
327	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
328	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
329	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
330	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
331	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
332	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
333	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
334	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
335	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
336	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
337	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
338	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
339	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
340	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
341	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
342	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
343	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
344	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
345	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
346	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
347	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
348	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
349	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
350	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
351	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
352	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
353	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
354	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
355	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
356	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
357	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is LOW
358	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
359	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
360	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Moderate then FRVP is MED
361	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
362	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
363	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
364	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
365	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
366	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
367	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
368	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
369	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
370	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
371	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
372	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
373	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
374	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
375	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
376	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
377	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
378	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
379	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
380	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
381	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW

No.	Rule statement
382	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
383	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
384	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
385	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
386	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
387	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
388	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
389	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is LOW
390	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
391	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
392	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
393	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
394	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
395	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
396	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Moderate then FRVP is MED
397	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
398	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
399	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
400	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
401	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
402	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
403	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
404	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
405	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
406	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
407	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
408	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
409	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
410	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
411	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
412	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
413	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
414	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
415	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
416	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
417	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
418	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
419	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
420	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
421	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is LOW
422	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
423	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
424	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
425	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
426	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
427	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
428	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
429	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
430	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
431	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is MED
432	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Moderate then FRVP is HIGH
433	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
434	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
435	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
436	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
437	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
438	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW

No.	Rule statement
439	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
440	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
441	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
442	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
443	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
444	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
445	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
446	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
447	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
448	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
449	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
450	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
451	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
452	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
453	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
454	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
455	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
456	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
457	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
458	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
459	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
460	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
461	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is LOW
462	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
463	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
464	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
465	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
466	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
467	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
468	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Moderate then FRVP is MED
469	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
470	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
471	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
472	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
473	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
474	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
475	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
476	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
477	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
478	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
479	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
480	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
481	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
482	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
483	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
484	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
485	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
486	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
487	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
488	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
489	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
490	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
491	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
492	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED

No.	Rule statement
493	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is LOW
494	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
495	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
496	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
497	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
498	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
499	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
500	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
501	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
502	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
503	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is MED
504	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Moderate then FRVP is HIGH
505	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is LOW
506	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is LOW
507	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
508	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
509	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is LOW
510	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
511	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
512	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
513	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
514	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
515	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
516	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
517	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is LOW
518	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
519	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
520	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
521	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
522	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
523	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
524	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
525	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
526	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
527	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
528	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is HIGH
529	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
530	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
531	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
532	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
533	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
534	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
535	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
536	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is HIGH
537	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is MED
538	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is HIGH
539	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is HIGH
540	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Moderate then FRVP is HIGH
541	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
542	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
543	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
544	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
545	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
546	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW

No.	Rule statement
547	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
548	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
549	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
550	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
551	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
552	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
553	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
554	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
555	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
556	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
557	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
558	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
559	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
560	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
561	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
562	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
563	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
564	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
565	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is LOW
566	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
567	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
568	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
569	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
570	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
571	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
572	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
573	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
574	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
575	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is MED
576	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Moderate then FRVP is HIGH
577	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is LOW
578	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is LOW
579	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
580	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
581	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is LOW
582	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
583	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
584	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
585	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
586	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
587	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
588	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
589	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is LOW
590	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
591	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
592	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
593	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
594	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
595	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
596	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
597	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
598	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
599	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
600	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is HIGH
601	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
602	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
603	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED

No.	Rule statement
604	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
605	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
606	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
607	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
608	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is HIGH
609	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is MED
610	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is HIGH
611	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is HIGH
612	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Moderate then FRVP is HIGH
613	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is LOW
614	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
615	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
616	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
617	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
618	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
619	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
620	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
621	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
622	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
623	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
624	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
625	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
626	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
627	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
628	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
629	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
630	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
631	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
632	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
633	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
634	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
635	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
636	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
637	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
638	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
639	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
640	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
641	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is MED
642	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
643	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
644	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
645	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
646	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
647	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
648	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Moderate then FRVP is HIGH
649	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
650	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
651	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
652	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
653	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
654	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
655	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
656	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
657	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
658	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
659	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
660	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
661	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW

No.	Rule statement
662	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
663	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
664	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
665	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
666	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
667	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
668	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
669	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
670	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
671	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
672	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
673	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
674	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
675	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
676	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
677	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is LOW
678	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
679	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
680	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
681	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
682	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
683	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
684	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is FFA and B_Compl is Low then FRVP is MED
685	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
686	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
687	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
688	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
689	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
690	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
691	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
692	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
693	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
694	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
695	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
696	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
697	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
698	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
699	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
700	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
701	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
702	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
703	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
704	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
705	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
706	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
707	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
708	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
709	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is LOW
710	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
711	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
712	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
713	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
714	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
715	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
716	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
717	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
718	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
719	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is MED
720	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is FFA and B_Compl is Low then FRVP is HIGH
721	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is LOW
722	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is LOW
723	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
724	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
725	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is LOW
726	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
727	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED

No.	Rule statement
728	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
729	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
730	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
731	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
732	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
733	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is LOW
734	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
735	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
736	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
737	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
738	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
739	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
740	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
741	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
742	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
743	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
744	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is FFA and B_Compl is Low then FRVP is HIGH
745	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
746	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
747	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
748	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
749	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
750	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
751	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
752	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is HIGH
753	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is MED
754	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is HIGH
755	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is HIGH
756	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is FFA and B_Compl is Low then FRVP is HIGH
757	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
758	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
759	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
760	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
761	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
762	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
763	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
764	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
765	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
766	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
767	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
768	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
769	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
770	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
771	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
772	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
773	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
774	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
775	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
776	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
777	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
778	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
779	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
780	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
781	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is LOW
782	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
783	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
784	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
785	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
786	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
787	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
788	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
789	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
790	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
791	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is MED
792	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is AFA and B_Compl is Low then FRVP is HIGH
793	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is LOW

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794	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is LOW
795	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
796	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
797	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is LOW
798	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
799	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
800	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
801	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
802	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
803	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
804	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
805	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is LOW
806	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
807	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
808	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
809	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
810	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
811	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
812	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
813	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
814	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
815	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
816	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is AFA and B_Compl is Low then FRVP is HIGH
817	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
818	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
819	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
820	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
821	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
822	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
823	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
824	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is HIGH
825	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is MED
826	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is HIGH
827	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is HIGH
828	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is AFA and B_Compl is Low then FRVP is HIGH
829	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is LOW
830	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
831	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
832	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
833	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
834	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
835	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
836	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
837	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
838	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
839	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
840	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
841	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
842	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
843	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
844	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
845	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
846	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
847	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
848	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
849	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
850	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
851	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
852	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
853	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
854	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
855	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
856	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
857	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is MED
858	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
859	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH

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860	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
861	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
862	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
863	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
864	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is AFA and B_Compl is Low then FRVP is HIGH
865	if Contrast_P is low and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is LOW
866	if Contrast_P is low and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is LOW
867	if Contrast_P is low and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
868	if Contrast_P is low and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
869	if Contrast_P is MED and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is LOW
870	if Contrast_P is MED and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
871	if Contrast_P is MED and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
872	if Contrast_P is MED and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
873	if Contrast_P is high and Age is v.old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
874	if Contrast_P is high and Age is Old and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
875	if Contrast_P is high and Age is Young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
876	if Contrast_P is high and Age is V.young and Size is small and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
877	if Contrast_P is low and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is LOW
878	if Contrast_P is low and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
879	if Contrast_P is low and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
880	if Contrast_P is low and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
881	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
882	if Contrast_P is MED and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
883	if Contrast_P is MED and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
884	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
885	if Contrast_P is high and Age is v.old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
886	if Contrast_P is high and Age is Old and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
887	if Contrast_P is high and Age is Young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
888	if Contrast_P is high and Age is V.young and Size is MED and Trolands is low and E is WA and B_Compl is Low then FRVP is HIGH
889	if Contrast_P is low and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
890	if Contrast_P is low and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
891	if Contrast_P is low and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
892	if Contrast_P is low and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
893	if Contrast_P is MED and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
894	if Contrast_P is MED and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
895	if Contrast_P is MED and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
896	if Contrast_P is MED and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is HIGH
897	if Contrast_P is high and Age is v.old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is MED
898	if Contrast_P is high and Age is Old and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is HIGH
899	if Contrast_P is high and Age is Young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is HIGH
900	if Contrast_P is high and Age is V.young and Size is large and Trolands is low and E is WA and B_Compl is Low then FRVP is HIGH
901	if Contrast_P is low and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is LOW
902	if Contrast_P is low and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
903	if Contrast_P is low and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
904	if Contrast_P is low and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
905	if Contrast_P is MED and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
906	if Contrast_P is MED and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
907	if Contrast_P is MED and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
908	if Contrast_P is MED and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
909	if Contrast_P is high and Age is v.old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
910	if Contrast_P is high and Age is Old and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
911	if Contrast_P is high and Age is Young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
912	if Contrast_P is high and Age is V.young and Size is small and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
913	if Contrast_P is low and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
914	if Contrast_P is low and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
915	if Contrast_P is low and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
916	if Contrast_P is low and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
917	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
918	if Contrast_P is MED and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
919	if Contrast_P is MED and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
920	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
921	if Contrast_P is high and Age is v.old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
922	if Contrast_P is high and Age is Old and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
923	if Contrast_P is high and Age is Young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
924	if Contrast_P is high and Age is V.young and Size is MED and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
925	if Contrast_P is low and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED

No.	Rule statement
926	if Contrast_P is low and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
927	if Contrast_P is low and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
928	if Contrast_P is low and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
929	if Contrast_P is MED and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is MED
930	if Contrast_P is MED and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
931	if Contrast_P is MED and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
932	if Contrast_P is MED and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
933	if Contrast_P is high and Age is v.old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
934	if Contrast_P is high and Age is Old and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
935	if Contrast_P is high and Age is Young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
936	if Contrast_P is high and Age is V.young and Size is large and Trolands is MED and E is WA and B_Compl is Low then FRVP is HIGH
937	if Contrast_P is low and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
938	if Contrast_P is low and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
939	if Contrast_P is low and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
940	if Contrast_P is low and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
941	if Contrast_P is MED and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
942	if Contrast_P is MED and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
943	if Contrast_P is MED and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
944	if Contrast_P is MED and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
945	if Contrast_P is high and Age is v.old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
946	if Contrast_P is high and Age is Old and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
947	if Contrast_P is high and Age is Young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
948	if Contrast_P is high and Age is V.young and Size is small and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
949	if Contrast_P is low and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
950	if Contrast_P is low and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
951	if Contrast_P is low and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
952	if Contrast_P is low and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
953	if Contrast_P is MED and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
954	if Contrast_P is MED and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
955	if Contrast_P is MED and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
956	if Contrast_P is MED and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
957	if Contrast_P is high and Age is v.old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
958	if Contrast_P is high and Age is Old and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
959	if Contrast_P is high and Age is Young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
960	if Contrast_P is high and Age is V.young and Size is MED and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
961	if Contrast_P is low and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is MED
962	if Contrast_P is low and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
963	if Contrast_P is low and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
964	if Contrast_P is low and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
965	if Contrast_P is MED and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
966	if Contrast_P is MED and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
967	if Contrast_P is MED and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
968	if Contrast_P is MED and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
969	if Contrast_P is high and Age is v.old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
970	if Contrast_P is high and Age is Old and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
971	if Contrast_P is high and Age is Young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH
972	if Contrast_P is high and Age is V.young and Size is large and Trolands is high and E is WA and B_Compl is Low then FRVP is HIGH

FIIL Model Rules

No.	Rule Statement
1	if Age is Young and Taskimportance is Low and TaskDifficulty is Low then FIIL is Low
2	if Age is Old and Taskimportance is Low and TaskDifficulty is Low then FIIL is Low
3	if Age is Very old and Taskimportance is Low and TaskDifficulty is Low then FIIL is MED
4	if Age is Young and Taskimportance is MED and TaskDifficulty is Low then FIIL is Low
5	if Age is Old and Taskimportance is MED and TaskDifficulty is Low then FIIL is MED
6	if Age is Veryold and Taskimportance is MED and TaskDifficulty is Low then FIIL is High
7	if Age is Young and Taskimportance is High and TaskDifficulty is Low then FIIL is MED
8	if Age is Old and Taskimportance is High and TaskDifficulty is Low then FIIL is High
9	if Age is Veryold and Taskimportance is High and TaskDifficulty is Low then FIIL is High
10	if Age is Young and Taskimportance is Low and TaskDifficulty is MED then FIIL is Low
11	if Age is Old and Taskimportance is Low and TaskDifficulty is MED then FIIL is MED
12	if Age is Veryold and Taskimportance is Low and TaskDifficulty is MED then FIIL is High
13	if Age is Young and Taskimportance is MED and TaskDifficulty is MED then FIIL is MED
14	if Age is Old and Taskimportance is MED and TaskDifficulty is MED then FIIL is High
15	if Age is Veryold and Taskimportance is MED and TaskDifficulty is MED then FIIL is High
16	if Age is Young and Taskimportance is High and TaskDifficulty is MED then FIIL is High
17	if Age is Old and Taskimportance is High and TaskDifficulty is MED then FIIL is High
18	if Age is Veryold and Taskimportance is High and TaskDifficulty is MED then FIIL is VeryHigh
19	if Age is Young and Taskimportance is Low and TaskDifficulty is High then FIIL is MED
20	if Age is Old and Taskimportance is Low and TaskDifficulty is High then FIIL is High
21	if Age is Veryold and Taskimportance is Low and TaskDifficulty is High then FIIL is High
22	if Age is Young and Taskimportance is MED and TaskDifficulty is High then FIIL is High
23	if Age is Old and Taskimportance is MED and TaskDifficulty is High then FIIL is High
24	if Age is Veryold and Taskimportance is MED and TaskDifficulty is High then FIIL is VeryHigh
25	if Age is Young and Taskimportance is High and TaskDifficulty is High then FIIL is High
26	if Age is Old and Taskimportance is High and TaskDifficulty is High then FIIL is VeryHigh
27	if Age is Veryold and Taskimportance is High and TaskDifficulty is High then FIIL is VeryHigh