

**DRIVER DROWSINESS DETECTION**  
**BASED ON EYE BLINK**

A Thesis submitted for the degree of Doctor of Philosophy

By

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## **Abstract**

Accidents caused by drivers' drowsiness behind the steering wheel have a high fatality rate because of the discernible decline in the driver's abilities of perception, recognition, and vehicle control abilities while sleepy. Preventing such accidents caused by drowsiness is highly desirable but requires techniques for continuously detecting, estimating, and predicting the level of alertness of drivers and delivering effective feedback to maintain maximum performance.

The main objective of this research study is to develop a reliable metric and system for the detection of driver impairment due to drowsiness. More specifically, the goal of the research is to develop the best possible metric for detection of drowsiness, based on measures that can be detected during driving. This thesis describes the new studies that have been performed to develop, validate, and refine such a metric.

A computer vision system is used to monitor the driver's physiological eye blink behaviour. The novel application of green LED illumination overcame one of the major difficulties of the eye sclera segmentation problem due to illumination changes. Experimentation in a driving simulator revealed various visual cues, typically characterizing the level of alertness of the driver, and these cues were combined to infer the drowsiness level of the driver.

Analysis of the data revealed that eye blink duration and eye blink frequency were important parameters in detecting drowsiness. From these measured parameters, a continuous measure of drowsiness, the New Drowsiness Scale (NDS), is derived. The NDS ranges from one to ten, where a decrease in NDS corresponds to an increase in drowsiness. Based upon previous research into the effects of drowsiness on driving performance, measures relating to the lateral placement of the vehicle within the lane are of particular interest in this study. Standard deviations of average deviations were measured continuously throughout the study.

The NDS scale, based upon the gradient of the linear regression of standard deviation of average blink frequency and duration, is demonstrated as a reliable method for identifying the development of drowsiness in drivers. Deterioration of driver performance (reflected by increasingly severe lane deviation) is correlated with a decreasing NDS score. The final experimental results show the validity of the proposed model for driver drowsiness detection.

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## Author's declaration

This is to certify that the work submitted in my thesis is my own and has not been submitted for any other degree.

Attention is drawn to the fact that some of the preliminary results have been published. Chapter 5 ("Eye Blink Detection System") has been published as:

- **Detection and Tracking of Eye Blink to Identify Driver Fatigue and Napping**, *2<sup>nd</sup> International Road Safety Conference, 6-7 Nov 2006, Dubai UAE.*
- **Detection and Tracking of Eye Blink to Identify Driver Fatigue and Napping-stage -1**, *HCI 2006 Engage, The 20<sup>th</sup> BCS HCI Conference, 11-15 Sept 2006, Queen Mary University London.*
- **Detection and Tracking of Eye Blink using their Physiological Appearance and Dynamics with MATLAB Simulink**, *Quality Drivers Lean, IIE/ASQ Lean and Quality conference, 30-31 Oct 2006, Atlanta, USA.*
- **Detection and Tracking of Eye Blink to Identify Driver Fatigue**, *Research Poster Conference 2006, Brunel University, London.*

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## Abbreviations

<b>AC</b>	Alternative Current
<b>ADC</b>	Analog Digital Converter
<b>AVI</b>	Audio Video Interleave
<b>CCD</b>	Charge-Couple Device
<b>CDL</b>	Commercial Driving License
<b>CMOS</b>	Complementary Metal oxide Semiconductors
<b>CMV</b>	Commercial Motor Vehicle
<b>CDL</b>	Commercial Driving License
<b>DC</b>	Direct Current
<b>DDDS</b>	Drowsy Driver Detection System
<b>DSP</b>	Digital Signal Processor
<b>EEG</b>	Electroencephalogram
<b>EMG</b>	Electromyographic
<b>EOG</b>	Electrooculogram
<b>ESS</b>	Epworth Sleepiness Scale
<b>HSV</b>	Hue, Saturation values-a colour space model
<b>IR</b>	Infrared
<b>JDS</b>	Johns Drowsiness Scale
<b>JTV</b>	Johns' Test of Vigilance
<b>KSS</b>	Karolinska Sleepiness Scale
<b>LED</b>	Light Emitting Diode
<b>MC</b>	Microcontroller
<b>MWT</b>	Maintenance of Wakefulness Test
<b>NIR</b>	Near- Infrared
<b>OO</b>	Orbicular Oculi
<b>PERCLOS</b>	Percentage eye lid closure
<b>REM</b>	Rapid Eye Movements
<b>RGB</b>	Red, Green and Blue colour system
<b>RGB</b>	Primary Colours (Red, Green, Blue)
<b>SVM</b>	Support Vector Machine
<b>TOD</b>	Time-of-Day
<b>TOT</b>	Time-on-Task
<b>VAS</b>	Visual Analogue Scale
<b>VC</b>	Vision Chip

## **CHAPTER 1**

# **INTRODUCTION TO DRIVER DROWSINESS AND FATIGUE DETECTION SYSTEMS**

## **1.1. Motivation**

Loss of driver alertness is almost always preceded by psycho-physiological changes (Weirwille, 1994); these changes are the reason that it is possible to detect the onset of drowsiness associated with loss of alertness in driving.

The basic idea behind driver drowsiness detection systems is to monitor the driver unobtrusively by means of a reliable system that can detect when the driver is impaired by drowsiness. This system senses various driver-related variables (such as physiological measures) and driving-related variables (driving performance measures), computing measures from these variables on-line, and then using the measures separately or in a combined manner to detect when drowsiness is occurring, and more importantly to predict the onset of drowsiness. Measures are combined because no single unobtrusive operational measure appears adequate in reliably detecting drowsiness (Weirwille, 1994).

It is important to point out the distinction between prediction and detection of drowsiness. Clearly prediction is the main aim, since at the detection point, drowsy driving may already have led to a potentially hazardous situation or even an accident. Another aspect is the great inter-individual variability in driver and driving behaviour, which an eventual automated system must be able to handle.

### **1.1.1. Driver Drowsiness and Road Accidents**

Driver drowsiness represents an important risk on the roads, as it is one of the main factors leading to accidents or near-missed accidents (Weirwille, 1994). This has been proven by many studies that have established links between driver drowsiness

and road accidents. Reducing the number of accidents related to driver drowsiness would save society a significant amount of money and personal suffering.

According to data from The Royal Society for the Prevention of Accidents (RoSPA 2006), 20% of serious accidents in the UK are due to driver extreme tiredness or weariness resulting from physical or mental activity (Haworth & Rowden, 2006). Whitty, et al. (2000) identified drowsiness as one of the main areas of driver behaviour to be addressed to reduce the number of people killed or seriously injured in road accidents. In driving experiments concerning drowsiness, there is the repeatedly observed phenomenon called 'driving without awareness' (DWA), which occurs when drivers demonstrate low attention levels during driving without being drowsy. At a certain moment the driver 'awakes' and he or she cannot remember the foregoing drive period. This phenomenon has been labelled as 'Driving without awareness' and also as 'Highway hypnosis' or 'Driving without attention mode' (DWAM) (Brown 1997).

Driver state monitoring is an ongoing topic concerning the development of driver support systems to prevent car accidents resulting from sleep. There are several criteria to predict driver drowsiness. The most important are related to the eye blink behaviour of the driver, and prolonged eyelid closure. Observation of the eye blink phenomenon is an important factor to identify driver drowsiness. The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Owing to the hazard that drowsiness presents on the road, methods need to be developed for counteracting its effects.

### **1.1.2. The Mechanisms of Human Sleepiness**

A body of literature exists on the mechanisms of human sleep and sleepiness that affect driving risks. The sleep-wake cycle is governed by both homeostatic and circadian factors. Homeostasis relates to the neurobiological need to sleep; the longer the period of wakefulness, the more pressure builds for sleep and the more difficult it is to resist (Dinges et al., 1995). The circadian pacemaker is an internal body clock that completes a cycle approximately every 24 hours. Homeostatic factors govern circadian factors to regulate the timing of sleepiness and wakefulness.

### **1.1.3. Biology of Human Sleepiness and Fatigue**

‘Fatigue’ is generally used in everyday speech to describe a general set of feelings or sensations, including one or more of the following: tiredness, sleepiness, boredom, or physical weariness. However, the term is too imprecise to be useful in scientific research. For this type of research, it is necessary to describe fatigue in terms of an operational definition. There is a lack of an agreed definition of fatigue, even as to whether the term refers to a fact or a theoretical entity. ‘Sleepiness’ is also difficult to define. In this thesis, it is taken to be synonymous with ‘drowsiness’ and its definition, and distinction from ‘fatigue’, is discussed in section 1.2.1.

Fatigue has subjective, objective (performance) and physiological components which may occur in the short-term or as a continual state. Many theories of fatigue have been proposed, varying in their precision and the type of concepts they employ. Neural models are inspired by the structure of the brain and a neural network consists of a set of highly interconnected entities, called *nodes* or *units*. Each unit is designed to mimic its biological counterpart, the neuron. Each accepts a weighted set of inputs



and responds with an output (Anderson, 1995) but may be more suited to the explanation of muscular fatigue than to driver fatigue (Rong-ben, et al., 2003). Arousal theories can explain why fatigue develops in the low demand situation of highway driving, as it links the concepts of attention and fatigue and allows for psychological and physiological measures of fatigue. One disadvantage of these theories is that the physiological measures sometimes give inconsistent results (Eby & Kantowitz, 2006).

The study by Brown (1997) suggested that three main factors determine whether humans can continue performing work at an acceptable level in the long term: (1) the length of continuous work spells and daily duty periods; (2) the length of time away from work that are available for rest and for continuous sleep; and (3) the arrangement of duty, rest, and sleep periods within the 24-hour cycle of daylight and darkness, which normally determines individuals' circadian rhythms. For drivers who work shifts or irregular hours over extended periods, the effects of these three factors are not independent. Drowsiness can become irresistible; recognition is emerging that neurobiological based sleepiness contributes to human error in a variety of settings, and driving is no exception (Horne & Reyner, 1995).

The terms 'drowsiness' and 'inattention' are likely to be used with sleepiness; however, these terms have individual meanings (Brown, 1997). It is more appropriate to use the term 'drowsiness' as the consequence of a physical phenomenon or a long-lasting experience and it is defined as a disinclination to continue the task at hand (Brown, 1994). In regard to driving, a psychologically based conflict occurs between the disinclination to drive and the need to drive. One result can be a progressive withdrawal of attention to the tasks required for safe

driving. Inattention can result from drowsiness, but the crash literature also identifies other factors such as preoccupation and distractions inside the vehicle, as causes of inattention.

## **1.2. Evaluating Current Driver Drowsiness Detection Methods**

One of the major problems in dealing with crashes and road safety is the difficulty in detecting driver drowsiness. Drowsiness is different from other road safety problems that can emanate from changes in the driver's functional state, such as alcohol or drugs, which can be detected comparatively readily by measuring their content in the body. Drowsiness measurement is a significant problem as there are few direct measures, with most measures being of the outcomes of drowsiness rather than of drowsiness itself. However, it is probable that one very important aspect of fatigue, namely drowsiness, is related to some physiological measures such as eye blink behaviour, brain wave changes (EEG measures) and face muscle changes (Johns et al., 2003, Wierwille and Muto, 1981).

The characteristics of drowsiness measurement present a real problem for road safety. Over the last ten years, there has been an increasing interest in the development of drowsiness detection devices, with some motor vehicle manufacturers including devices in their vehicles that are marketed as 'drowsiness warning systems' (Fletcher et al., 2003; Lee et al., 2006). The problem of drowsiness detection is being researched using a range of approaches. Johns et al., (2003) argue that video camera methods have difficulty in capturing images reliably when the environmental light conditions are highly variable, as when driving in sunlight with shadows, or when prescription glasses or sunglasses are worn. The Johns Drowsiness Index or JDI (Johns & Tucker, 2005) is the most recent driver drowsiness detection

method and followed the PERCLOS (percentage of eye lid closer, Dinges & Grace, 1998) method. The JDI has been implemented in a commercial product called “Optalert” which detects eye blink open and close speed to predict driver drowsiness using IR (infrared) light.

There are standardized methods for monitoring sleep and wakefulness in patients with sleep disorders that have been used on experimental participants in sleep laboratories around the world. Those methods include monitoring the electroencephalogram (EEG), the electrooculogram (EOG), and the electromyogram (EMG). However, the need for electrodes to be attached to the participant makes these methods inappropriate for monitoring drivers regularly. Moreover, when such methods have been used for research in drivers, they did not detect drivers’ drowsiness well (Wierwille and Muto, 1981).

The video camera method used to detect the driver’s eye movements is more often used than EEG/EOG methods (Wylie et al., 1996). The video camera systems are particularly used for the PERCLOS (Dinges & Grace, 1998) method which measures the proportion of time that the pupils are at least 80% covered by the eyelids during periods of a few minutes. In this method, video cameras have to be fitted in front of the eyes to capture eyelid closure duration. If the camera is not fitted to a head mounted unit, advanced detection algorithms are required to track the eyes when head movements occur. The majority of research on driver fatigue detection has identified that eye blink and eye movements are the most consistent factors to predict driver drowsiness (Erwin et al., 1980; Johns et al., 2003).

### **1.2.1. Concepts and Theories of Fatigue and Drowsiness**

Muscio (1921) started researchers thinking about the necessity of defining drowsiness. He argued that without an acceptable definition and reliable measures, it was impossible to conduct drowsiness tests. The earliest definitions separate fatigue into three different types: subjective fatigue, the feeling of being tired; physiological fatigue, as determined from bodily changes; and objective fatigue, when performance on a task shows a progressive deterioration (Platt, 1964).

Cameron (1973) also looked at drowsiness, especially in relation to driving. He argues the importance of anxiety, and examines the link between drowsiness and sleep disturbances. Cameron suggests that drowsiness is a generalized response to stress over time.

The term “drowsiness” as used in this thesis refers to a state of reduced alertness (Wierwille et al., 1994), usually accompanied by physiological and performance changes that may result in impaired driving. The term “driver fatigue” is also widely used to describe this condition, especially on Police Accident Reports and in accident data files. However, Stern et al. (1994), Tepas & Paley (1992) and others have pointed out that drowsiness is distinct from physical fatigue. Fatigue and Drowsiness are two interrelated, but distinct phenomena; observed in a number of psychiatric (diagnosis and prevention of mental and emotional disorders), medical and primary sleep disorders. Despite their different implications in terms of diagnosis and treatment, these two terms are often used interchangeably (Sharon et al. 1996).

### **1.2.2. Review of Driver Drowsiness Detection Devices**

A review of commercial and experimental driver drowsiness detection systems presently available was undertaken. Since the majority of the devices were based on computer vision techniques, most of the investigation is related to these topics. The majority of systems used eye tracking and blink related methods. Most eye tracking devices are based on computer vision imaging systems, yet some are based on other means of detection. For instance, one technique is based on fixed items such as a tiny mirror engraved on a head mounted unit; the reflections of eye images from these mirrors serve as detectable points for a tracker CCD camera or even a single photo detector, (Beach et al., 1998). Other items such as induction coils have been embedded within contact lenses to give a signal when the user is exposed to a high electromagnetic field (Takemori et al., 1989). Another method detects the changes in the electrical potential of the skin around the eye (described in section 2.5.3), since an electrostatic field rotates along with the eye.

A common drawback of the above methods of detection lies in the difficulty of use for driver drowsiness detection. For example, the application of contact lenses or electrodes to one's eye is uncomfortable for the user. The more effective methods were found to be imaging systems that did not interfere with their participants. Such video devices are fixed on a vehicle dashboard to capture the driver's facial expressions and eye movements. These methods are commonly used to detect driver drowsiness but encounter difficulties of use requiring advanced detection algorithms to minimize the environmental light changes and vehicle vibrations. Many imaging techniques have been developed based on reflections of light from various portions of the eye. Some of these methods detect reflections off the surface of the eye, where

the changes in the intensity of reflected light beams are used to detect eye blink. These methods use Infrared (IR) light which is invisible and will not disturb the driver. The only disadvantage with IR systems is concern for the safety of the human eye.

The hazard potential of near-infrared (NIR) light should be considered from two perspectives: eye hazards and skin hazards.

The eye lens focuses the light on the retina. Focused light is stronger in terms of irradiance than non-focused light. Hence, injury potential increases with focusing. The majority of eye blinks detection systems that use IR light are focused light. There are some efforts by the International Commission on NonIonizing Radiation Protection (ICNIRP), the International Electrotechnical Commission (IEC) and American National Standards Institute (ANSI) to develop regulations about IR LED hazards. Most efforts have been concentrated on eye injury due to radiated energy (Bozkurt & Onaral, 2004).

The studies by Mori et al. (1999) found infrared radiation will increase eye temperature. A finite element model of the human eye is employed to calculate the temperature rises experienced by the intraocular (inside eyeball) media when exposed to infrared radiation. The model is used to calculate transient and steady-state temperature distributions for various exposure times and a range of incident irradiances. The effect of the eye's natural cooling mechanisms on the heating is investigated. Specific absorption rates in the infrared irradiated eye are presented. Results showed radiant energy by the iris and the lens combined with conduction of heat from the anterior regions is found to be responsible for increases in the lens temperature of 1-2 degrees C. Even if low power IR is used, long exposure to the naked eye will be harmful to eye cells and the retina.

The studies by Scott (1998) found temperature increase of the human skin caused by near infrared LEDs. Effects of the conducted and radiated heat in the temperature increase have been analysed separately. Research results show the skin temperature may be increased by up to 1°C. The effect of radiated heat due to NIR (Near Infrared) absorption is low – less than 0.5°C – since emitted light power is comparable to the NIR part of sunlight. The conducted heat due to semiconductor junction of the IR LED can cause temperature increases up to 9°C. Scott's study demonstrates that the major risk source of the LED in direct contact with skin is the conducted heat of the LED semiconductor junction, which may cause serious skin burns.

The only legal restrictions and medical advices available on the web were concerned with infrared emissions of heat lamps or in the welding process. This suggests that IR light as emitted by other IR devices will be harmful, even the low power emitted IR LEDs (ca. 300mW). However, the effect of infrared light projecting for a long time at the naked eye will have a high potential of damaging the eye biological cell structure.

### **1.3. Research Aim and Objectives**

The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its effects.

The aim of this research is to develop a prototype drowsiness detection system to detect driver drowsiness to warn the driver before driving is impaired. The focus will

be placed on designing a system that will accurately monitor the blink frequency and blink duration of the driver's eyes in a series of tests in a driving simulator. By monitoring the eyes, it is believed that the symptoms of driver drowsiness can be detected early enough to avoid a car accident. Detection of drowsiness involves a sequence of images of an eye, and the observation of eye blink patterns.

Associated with this research is the development of a method to record image changes to the side of the eye, and to determine the position of the eye sclera region. An image-processing system is developed to assess driver drowsiness by examining eye blink using vision techniques to work with reflections off the eye sclera region involving a detection method to monitor the changes in the eye sclera region. The detection of the white sclera area between the dark upper and lower eye lids is termed blink, and changes of area quantify the length of the blink.

To achieve the *aim*, this research has the following *objectives*:

- To investigate two other current methods related to driver drowsiness detection systems: PERCLOS (percentage of eye lid closure) and JTV (Johns' Test of Vigilance). Discussion of the reliability of these methods will be important for informing the implementation of the new method.
- To design a driving simulator and a driver reaction time measurement system. Driver alertness can be estimated by monitoring the steering wheel movement, brake patterns, vehicle speed or lateral acceleration, and lateral displacement. A basic driving simulator is designed to detect driver performance by monitoring the response of the driver.

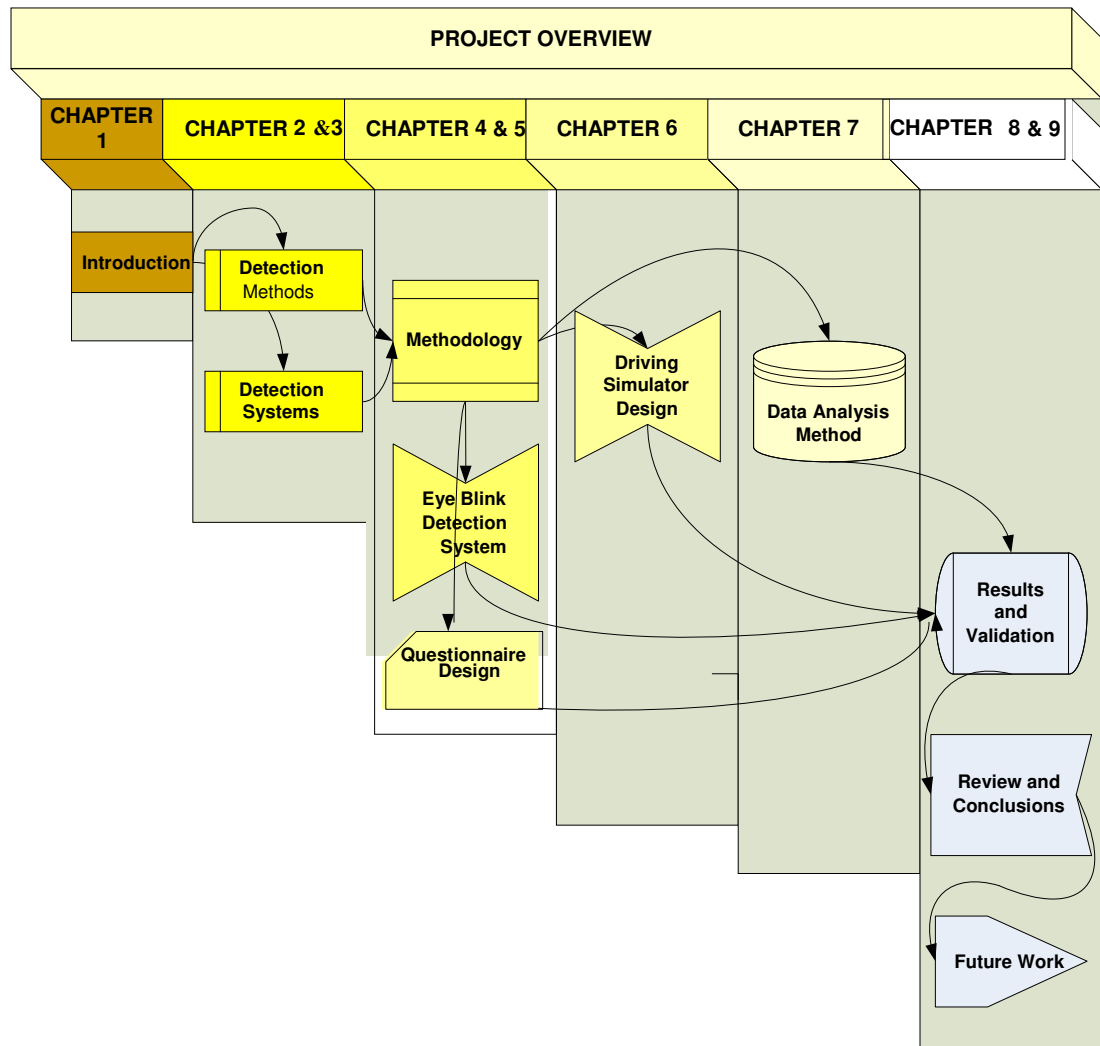


- To design a head mounted video camera with low intensity light to illuminate the sclera region of the eye and capture changes of this sclera area relating to blink to identify blink duration and frequency.
- To establish if eye blink frequency and duration are reliable factors to predict driver performance. By measuring the blink frequency and duration in participants in a driving simulator, it will be ascertained how these variables affect driver performance. The effects of sleep deprivation will be examined.
- To create a new operational measure of drowsiness based on eye blink durations and frequency of drowsy drivers, and to establish a driver drowsiness detection metric for future use in the development of drowsiness detection algorithms.

#### **1.4. Thesis Structure**

This thesis is organised in nine chapters, as follows:

**Chapter One:** This chapter contains a brief review of driver drowsiness as a cause of road accidents. Three main characteristics were considered in this chapter. The first was the mechanism of human sleepiness and its interrelation to driving risk; the second was the biology of human sleepiness and the third was driver drowsiness detection systems. The section 1.3 in this chapter states the research aim and objectives. Figure 1.1 shows the overview of project structure.



**Figure 1-1: Project Overview**

**Chapter Two:** Reviews the literature relating to driver drowsiness detection methods. This gives a detailed review of current driver drowsiness detection methods, including physiological measures and their effectiveness. It reviews the popular methods used such as eye blink, eye movements and facial expressions. Consideration is also given to other methods of human drowsiness detection and their effectiveness in comparison to eye blink analysis.

**Chapter Three:** Reviews the literature relating to existing driver drowsiness detection systems. This gives a detailed review of existing driver drowsiness detection systems and their effectiveness. This review focuses mainly ‘In-Vehicle’ systems.

**Chapter Four:** This chapter introduces the methodology for a new driver drowsiness detection system, which includes an eye blink detection system, a driving simulator and a subjective drowsiness measure questionnaire. In addition, this chapter briefly describes a new eye blink detection system and the main approach to the experimentation.

**Chapter Five:** Describes the development of the Eye Blink Detection System (EBDS). The system tracks eye blinks from the side of the eye. The reliable detection and tracking of eye blink is an important requirement for measurement of eye blink frequency and blink duration in the detecting of driver alertness. Image acquisition and image processing algorithms are used for blink detection. By using a spectacle mounted sensor, the problem of analysis of head movement is minimised. The three-step eye blink detection procedure of background estimation, template matching and tracking is used to analyse eye blink dynamics. Video and image acquisition tools, signal processing tools and data analysis tools in MATLAB Simulink software are used to design the eye blink detection system.

**Chapter Six:** Discusses the development of a driving simulator. There were two simulators used to measure driver performance. The first simulator measures driver reaction time and is designed using virtual reality tools in MATLAB Simulink. The second and main simulator measures five different parameters of driver performance.

**Chapter Seven:** Data Analysis Methodology. This chapter focuses on determining the variables and statistical procedures for data analysis. The physiological measures in this study have been identified as indicators of drowsiness in previous research studies. These measures included two eyelid-closure measures, the average blink duration (AVEBLDU) and average blink frequency (AVEBLFR).

The driving performance measures in this study were operational measures that would be obtainable in the driving simulator. The measures collected during this study included *driving-related* measures, and *secondary task* performance measures.

**Chapter Eight:** Final Data Analysis Results: Development of Driver-Drowsiness Detection Model. Regression analyses were initially used for data manipulation for all eighteen participants. Several correlation tests were performed with the data in different configurations, including: all participants/all data for one-minute intervals, ten-minute intervals, and five-minute intervals. Analyses were also undertaken after “selecting” participants performance data (this method consists of using data from each participant and categorizing that data into high performance decrement, medium performance decrement, and low performance decrement categories) using a moving average filter.

Correlation tests were performed between the collected physiological measures (standard deviation, SD, of average eye blink durations and frequency) and the collected performance measures (standard deviation, SD, of average deviations from centre line and reaction time for colour light changes). Linear regression analysis was used to develop drowsiness detection model.

**Chapter Nine:** Summarizes the research outcomes, draws conclusions; discusses further development to improve research results.

## **1.5. Summary**

The problems of extracting quantified information from physiological and performance indicators of the drowsiness level of a vehicle driver are addressed. An outline has been given of a new approach for processing the physiological and performance outputs from a driver drowsiness monitoring system. The performance indicators are collected from the driving simulator (e.g. lateral movements of a vehicle (deviations from centre line), average speed, and reaction time for traffic signal). New results show how the physiological and performance indicators can be used to detect drowsiness. The development of new system for detection of driver drowsiness linked to impairment of driving performance is discussed in the following chapters.

The next chapter reviews the literature relating to driver drowsiness and detection methods. This gives a detailed assessment of current driver drowsiness detection methods, including physiological measures and their effectiveness.

## **CHAPTER 2**

### **REVIEW OF THE LITERATURE ON THE PHYSIOLOGY OF DRIVER DROWSINESS**

## **2.1. Introduction**

This literature review provides background information regarding driver drowsiness analysis methods. Current countermeasures to minimize drowsiness in car driver drowsiness are reviewed. In order to develop a new concept, it is important that the principles of current driver warning systems be reviewed and understood. Research papers concerning driver drowsiness detection systems and their effectiveness are discussed. Furthermore, the methods relating to eye blink analysis for human drowsiness detection and their effectiveness are reviewed.

## **2.2. Driver Drowsiness**

Drowsiness represents a significant social and economic cost to the community in relation to road crashes, especially motorway crashes. Drowsiness-related crashes are often more severe than other crashes as drivers' reaction times are often delayed or drivers have not engaged any crash avoidance manoeuvres. Furthermore, it is difficult to quantify the level of driver drowsiness due to the difficulties in objectively measuring the degree of drowsiness following a crash. Lack of sleep reduces the alertness and concentration needed for safe driving. The quality of decision-making may also be affected (van den Berg et al., 2005).

## **2.3. Driver Drowsiness and Road Accidents**

There are difficulties in determining the level of sleep related accidents because there is no simple, reliable way for an investigation to determine whether drowsiness was a factor in the accident and, if it was, what level of drowsiness the driver was suffering. This result in varying estimates of the level of sleep related accidents and,

in particular, evidence based on accident reports usually produces lower estimated levels than research based on in-depth studies.

A British study by the Sleep Research Centre (Horne and Reyner, 2000) indicated that driver drowsiness causes up to 20% of accidents on motorways. This suggests that there are several thousand casualties each year in sleep related accidents. An earlier study (Horne and Reyner, 1995) on road accidents between 1987 and 1992 found that sleep related accidents comprised 16% of all road accidents, and 23% of accidents on motorways. Transport Research Laboratory (TRL) research (Maycock, 1995) found slightly lower proportions of sleep related accidents: 9% - 10% of accidents on all roads, and 15% of accidents on motorways involved driver sleepiness. In this study, 29% of drivers reported having felt close to falling asleep at the wheel at least once in the previous twelve months.

The National Highway Traffic Safety Administration (NHTSA) estimated that there are 56,000 sleep related road crashes annually in the USA, resulting in 40,000 injuries and 1,550 fatalities (NCSDR/NHSTA, 1998). Another study (Johnson, 1998) calculated that 17% (about 1 million) of road accidents are sleep related. Research by Wang (1996) suggested that 2.6% of accidents caused by driver inattention were due to drowsiness. Reissman, (1996) studied road accidents on two of America's busiest roads and found that 50% of fatal accidents on those roads were drowsiness related and 30% - 40% of accidents involving heavy trucks were caused by driver sleepiness. In summary, research in many countries around the world has shown that sleep related accidents constitute a significant proportion of road accidents.



## **2.4. Defining Drowsiness**

The phenomenon of drowsiness is a highly researched participant, but does not have a universally accepted definition. The term drowsiness is a condition characterized by a lessened capacity for work and reduced efficiency of accomplishment, usually accompanied by a feeling of weariness and tiredness (Engleman et al., 1997). Using this definition, the involvement of drowsiness in a road crash can range from falling asleep at the wheel to inattention (HORSCC, 2000).

The general consensus is that the four main determinants of driver drowsiness are:

- Lack of sleep
- Time of day
- Time spent performing a task (Hartley, et al., 2000; Williamson, et al., 2000).
- Type of driver

Individual factors such as age, physical fitness and medical condition also affect the incidence of drowsiness (HORSCC, 2000).

### **2.4.1. Lack of Sleep**

Human beings need to sleep. Sleep is essential for everyone. The longer someone remains awake, the more difficult it is to resist falling asleep. The need for sleep varies between individuals, but sleeping for 8 out of 24 hours is common, and 7 to 9 hours sleep is required to optimise performance (Reichman et al., 1996).

Humans are usually awake during daylight and asleep during darkness. Sleeping less than four hours per night impairs performance. Sleepiness reduces reaction time, which is a critical element of safe driving. Lack of sleep reduces the alertness and concentration needed for safe driving. The quality of decision-making may also be affected (van den Berg et al., 2005).

#### **2.4.2. The Time of Day**

Humans possess a neurobiological based sleep-wake cycle called a circadian rhythm or body clock (Folkard, 1997). Research has shown that there are two periods during the 24 hour circadian cycle where the level of sleepiness is high. The first period is during the night and early morning, and the second is in the afternoon (Hartley et al, 2000). During these periods of sleepiness, many functions (e.g., alertness, performance and subjective mood) are degraded (Rosekind, 1999).

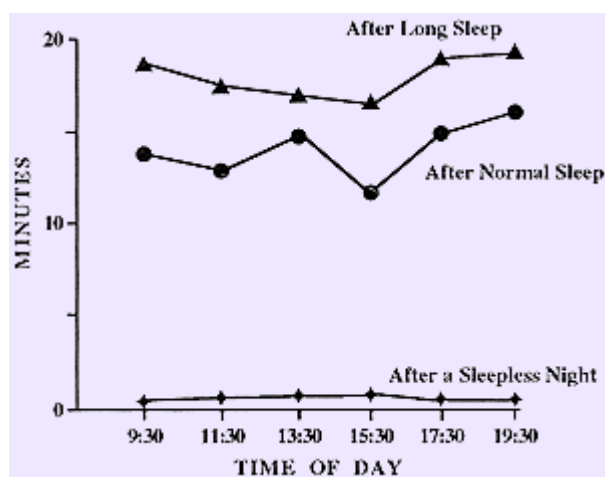
Sleep related accidents have peaks in the early hours of the morning, between 2.00 am and 6.00 am, and mid afternoon, between 3.00 pm and 4.00 pm. Drivers are 50 times more likely to fall asleep at the wheel at 2.00 am than at 10.00 am (Horne and Reyner, 1995). This risk is three times as great between 3.00 and 4.00 pm as at 10.00 am. Horne and Reyner's studies identified that young drivers are more likely to sleep at the wheel in the early hours in the morning and older drivers are more likely to fall asleep at the wheel during the afternoon sleep period.

The long sleep-wake cycles are the result of variable insensitivity to the sleep drive. In one study, randomly selected volunteers spent seventy-two hours without sleep and rated their drowsiness every three hours on a scale in comparison with their normal drowsiness (=100 percent) (BOSB, 1997). The feeling of drowsiness was

always highest in the early hours of the morning and lowest in the afternoon (Figure 2-1).



**Figure 2-1: Fatigue during seventy-two hours of sleep deprivation (BOSB, 1997)**



**Figure 2-2: Time required falling asleep (BOSB, 1997)**

Figure 2-2 shows the time required to fall asleep during the day, after long sleep, normal sleep, and a sleepless night. The participants lie down at two-hour intervals between 9:30 a.m. and 7:30 p.m. The amount of time required to fall asleep is used

as a measure of sleep propensity. After an extended sleep during the preceding night, the participants take a longer time to fall asleep; after a night without sleep, the time is greatly reduced.

### **2.4.3. Time on Task**

Prolonged physical activity without rest leads to muscular drowsiness. Similarly, a prolonged mental workload without rest will lead to reduced alertness and disinclination to continue the effort (Grandjean et al., 1988).

Research based on driving tasks has shown that the length of time on a task affects performance. As time spent on a task is increased, the level of drowsiness is increased, reaction time is slowed, vigilance and judgement is reduced and the probability of falling asleep during the task is increased (Engleman et al, 1997; HORSCC, 2000).

### **2.4.4. Type of Driver**

Several studies have identified young male drivers, aged less than 30 years, as one of the groups most at risk of being involved in sleep related road accidents (Maycock, 1995). In addition, company car drivers have a higher probability of falling asleep at the wheel as they tend to drive long distances on tight schedules (Hackett et al., 2003). In addition, shift workers and people with sleep problems are also in the risk group. The close environment of the inside of a car and loss of air flow and low oxygen rate also increase the tendency to sleep (Garder & Alexander 1994).

## **2.5. Physiological Measures Related to Driver Drowsiness**

### **Detection**

The purpose of this section is to discuss measures that may lead to detect driver drowsiness and their operational definition. In this thesis drowsiness and sleepiness are considered synonymous, but the term drowsiness will be used. Another concept commonly used is drowsiness, which is an extreme tiredness that results from physical or mental activity. Drowsiness can also be described by the grade of wakefulness or vigilance. Wakefulness is the same as alertness or state of sleep inability, whereas vigilance can be described as watchfulness or a state where one is prepared for something to happen (Leproult et al., 2003).

#### **2.5.1. Eyelid Closure**

Eyelid closure is a very reliable predictor of driver drowsiness (Erwin, et al., 1980; Dinges, et al., 1985). Erwin et al, examined various measures to determine if they were predictive of sleep onsets, including plethysmography (a device for measuring and recording changes in the volume of the body or of a body part or organ), respiration rate, Electroencephalography (EEG), skin electrical characteristics, Electromyography (EMG), heart rate variability, and eyelid closure. It was found that eyelid closure was the most reliable predictor of the onset of sleep among the measures examined.

Eyelid closure is indicative of sleep onset and undoubtedly the cause of poor performance in visual tasks, especially tracking tasks such as driving. It seems quite obvious that if a driver's eyelids are closed, the ability to operate a vehicle would be impaired. Skipper et al. (1984) examined the ability of sleep deprived drivers to

perform a one and one half hour driving task. Various disturbances were purposely input into the steering system of the driving simulator to mimic on-the-road conditions. It was found that performance measures such as lane deviation and steering velocity were highly correlated with eyelid closures. The apparatus used to capture eyelid closures in the studies by Skipper et al, (1984) was a low-light level camera. A linear potentiometer was used manually by an experimenter to track and record the eyelid movement of the participants.

### **2.5.2. Eye Movements**

There are two general methods used to record eye movements during sleep or before sleep. The first method is Rapid Eye Movements (REMs). The second is based on the onset of sleep in most participants being accompanied by slow, rolling eye movements (Carskadon, 1980). Slow, rolling eye movements may accompany the onset of sleep or are precursors of sleep onsets. This phenomenon also occurs with the transition to stage 1 sleep during the night. The characteristics of human eye movements change greatly with alertness level. Slow eye movements (SEMs) prove to be one of the most characteristic signs of the phase of transition between wakefulness and sleep (Planque et al., 1991). A completely awake individual can be observed as having quick eye movements. As participants become drowsy, their eyes move in a pendulum motion from left to right (Hiroshige and Niyata, 1990) and the number of quick, voluntary movements of the eyes begins to lessen. Several SEMs are detected during stage 1 sleep, but they also appear during the long period separating waking from sleep. Convergence of the eyes is also possible when a person becomes drowsy.

*Electrooculography* (EOG) Figure 2-3 (page 50) shows the measuring of eye movements via electrodes in contact with the skin surrounding the eyes. The process of measuring eye movements with EOG is quite simple due to the electrical nature of the human body. In the eyeball, there is a small electro-potential difference from the front to the back. The front (cornea) of the eye is positive with respect to the back (retina) of the eye. Before a certain point in a person's awake but drowsy state, SEMs do not exist. However, after a particular moment in the onset of sleep, slow, rolling, lateral, ocular movements create sinusoidal activity in the EOG (Lairy and Salzarulo, 1974). On the EOG signal, the SEMs are translated by slow deflections lasting more than a second. It is likely that amplitudes of at least 100 microvolts will be seen (Torsvall and Akerstedt, 1988). The EOG waves that are normally observed are moderate in amplitude initially, but increase with the degree of drowsiness (Planque et al., 1991). These researchers found that after several minutes of driving only blinking and glances at simulator instrumentation were recorded. Approximately 30 minutes into the study deterioration of deliberate eye movement was observed. Planque et al. (1991) argue that, by analyzing the EOG, it is possible to follow clearly the deterioration of alertness.

### **2.5.3. Muscle Activity**

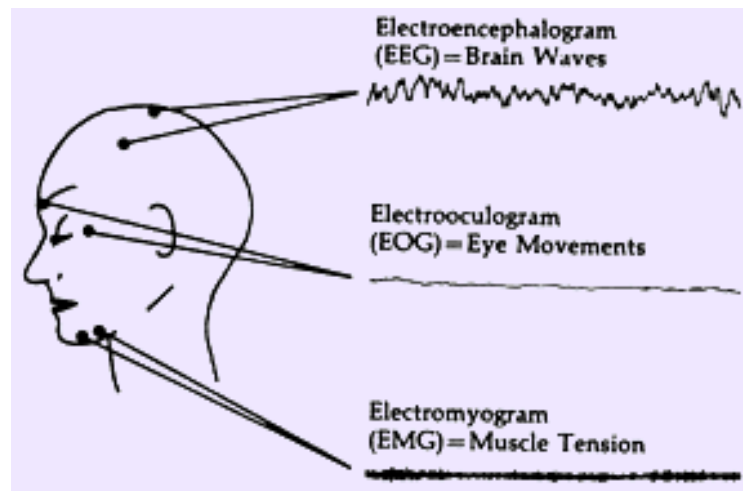
The Electromyogram (EMG), conventionally abbreviated as "EMG" is a record of the electrical activity which emanates from active muscles, especially in the facial muscles. It may also be recorded from electrodes on the skin surface overlying a muscle. In humans, the EMG is typically recorded from under the chin, since muscles in this area show very dramatic changes associated with the sleep stages (BOSB, 1997). Hauri (1982) demonstrates that EMG recorded on the chin steadily,

though not dramatically, decreases as a person nears sleep. Even when a person is totally relaxed, small muscle potentials will be seen. This is because every muscle is composed of many contractile fibres that are innervated by nerves. When a muscle fibre is activated through nerve innervations, a change in the electrical potential is seen. When the muscle is relaxed, fewer nerves discharge, thus a smaller EMG potential is recorded. EMG (figure 2-3) is used to predict drowsiness with electrical potential differences of facial muscle.

#### **2.5.4. Brain Wave Activity**

The *Electroencephalogram (EEG)* is conventionally abbreviated as "EEG" and is popularly known as "brain waves." The EEG was discovered in 1929 by Hans Berger, a Swiss psychiatrist. He found that small changes in voltage between two electrodes occurred when they were placed in contact with the scalp. Voltage changes are amplified and examined for variations in duration. The exact physiologic basis of the voltage variations are not entirely known, but it is believed that they originate largely from changes in voltage of the membranes of nerve cells. Erwin, et al. (1980) found that there is no reliable alteration in background brain activity prior to eyelid closure. Upon eyelid closure, the researchers found that a very rapid shift in brain wave patterns takes place. This shift is identifiable as the early stage of sleep. However, Planque et al. (1991) argue that sharp changes in the frequency content of brain wave activity are observed during the crossing from alertness to a stage of hypoalertness, then to drowsiness, and finally to sleep. A slowdown of the brain activity in general, an increase in the percentage of alpha waves and, in turn, a decrease in the percentage of beta waves, is observed at the same time that a decline in performance is seen.





**Figure 2-3: Positions of Physiological Measures**  
(BOSB, 1997)

### **2.5.5. Heart rate Variability**

Heart beats interval variability has been found to correlate with drivers' level of drowsiness (Wierwille and Muto, 1981). On the other hand, Volow and Erwin (1973) found no correlation between heart rate variability and sleep onset.

### **2.5.6. Pupil Aperture Size Variability**

Natural pupil movements in darkness in the normal awake individual have been described as reflecting "tiredness," "drowsiness," and "sleepiness". The changes in pupillary stability and extent of oscillations have been consistently shown to occur in normal "tired" participants. The pupillary behaviour in individuals suggests that the actions of the pupil do reflect autonomic events, and that it is consequently an indirect but accurate indicator of sleepiness or arousal level (Sharon et al, 1996).

	<u>Relaxed Waking</u>	<u>NREM Sleep</u>	<u>Tonic REM</u>	<u>Phasic REM</u>
Sympathetic	S	S	s	<b>S</b>
Parasympathetic	P	P	P	<b>P</b>
Heart Rate	70+	65+	60+	80+
Pupil Diameter	○	○	○	○

**Table 2-1: Autonomic Nervous System Activity during Sleep  
(BOSB, 1997)**

Table 2-1, shows how the pupil diameter changes during different stages of sleep.

Therefore, recognition of pupil diameter can help to measure drowsiness.

## **2.6. Evaluation of Drowsiness with Physiological Measures**

BOSB (1997) studies found that changes in psychological parameters such as EEG and EOG reflected changes in driver status and could predict driving impairment that might lead to a disastrous traffic accident. They showed that during a night drive a significant intra-individual correlation was observed between subjective sleepiness and the EEG alpha burst activity. End-of the-drive subjective sleepiness and the EEG alpha burst activity were significantly correlated with total work hours. As a result of a regression analysis, total work hours and total break time predicted about 66% of the variance of EEG alpha burst activity during the end of drive.

Many studies have used psychophysiological measures such as blink, EEG, eye movements, and heart rate to assess drowsiness (BOSB, 1997). Wierwille and Muto, (1981) suggested caution in interpreting eye movement velocity change as an index of drowsiness since most of the reduction in average eye movement velocity might be secondary to increase in blink frequency. No measures alone can be used reliably

to assess drowsiness, because each has advantages and disadvantages. The results of these studies must be integrated and effectively applied to the prevention of drowsy driving.

The example of the BOSB, (1997) studies discussed below, employs physiological measures such as EEG, EMG and EOG. Figures 2-4 and 2-5 show the test results for different age groups for three measures during wakefulness and the major sleep stages. There are two major patterns during EEG measurements. One is low voltage (about 10-30  $\mu$ V) fast (16-25 Hz) activity, often called an "activation". The other is a sinusoidal 8-12 Hz pattern (most often 8 or 12 Hz) of about 20-40  $\mu$ V which is called "alpha" activity. Typically, alpha activity is most abundant when the participant is relaxed and the eyes are closed. The activation pattern is most prominent when participants are alert with their eyes open, and they are scanning the visual environment. REMs (Rapid Eye Movement) may be abundant or scarce, depending on the amount of visual scanning, and the EMG may be high or moderate, depending on the degree of muscle tension. Measurements of alpha, theta and delta waves of the brain waves are shown in Figure 2-4. Voltage variations ( $\mu$ V) will facilitate the detecting of awake and sleep conditions. The two EOG measures in Figure 2-5 illustrate the voltage variations in the left and the right eyes individually. The stages of sleep are as follows:

### **STAGE-1**

Alpha activity decreases, activation is scarce, and the EEG consists mostly of low voltage, mixed frequency activity, with much of it at 3-7 Hz. REMs are absent, but slow rolling eye movements appear. The EMG is moderate to low.

### **STAGE-2**

Continuing background of low voltage, mixed frequency activity, bursts of

distinctive 12-14 Hz sinusoidal waves called "sleep spindles" appear in the EEG. (Sleep spindles are characterized by a burst of very regular oscillations at a frequency of 12 to 14 cycles per second). Eye movements are rare, and the EMG is low to moderate.

### **STAGE-3**

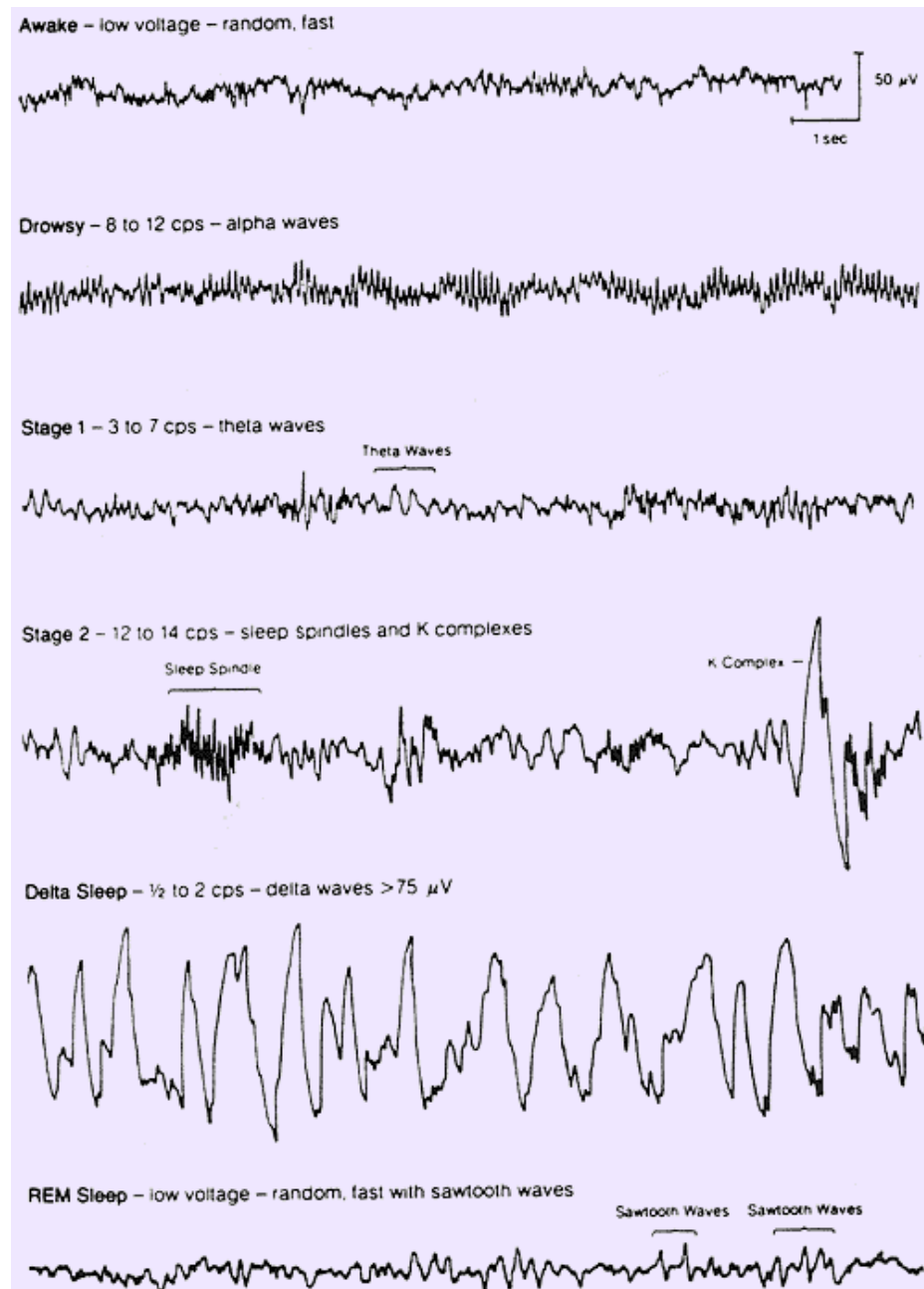
High amplitude (>75 mV), slow (0.5-2 Hz) waves called "delta waves" appear in the EEG, EOG and EMG.

### **STAGE-4**

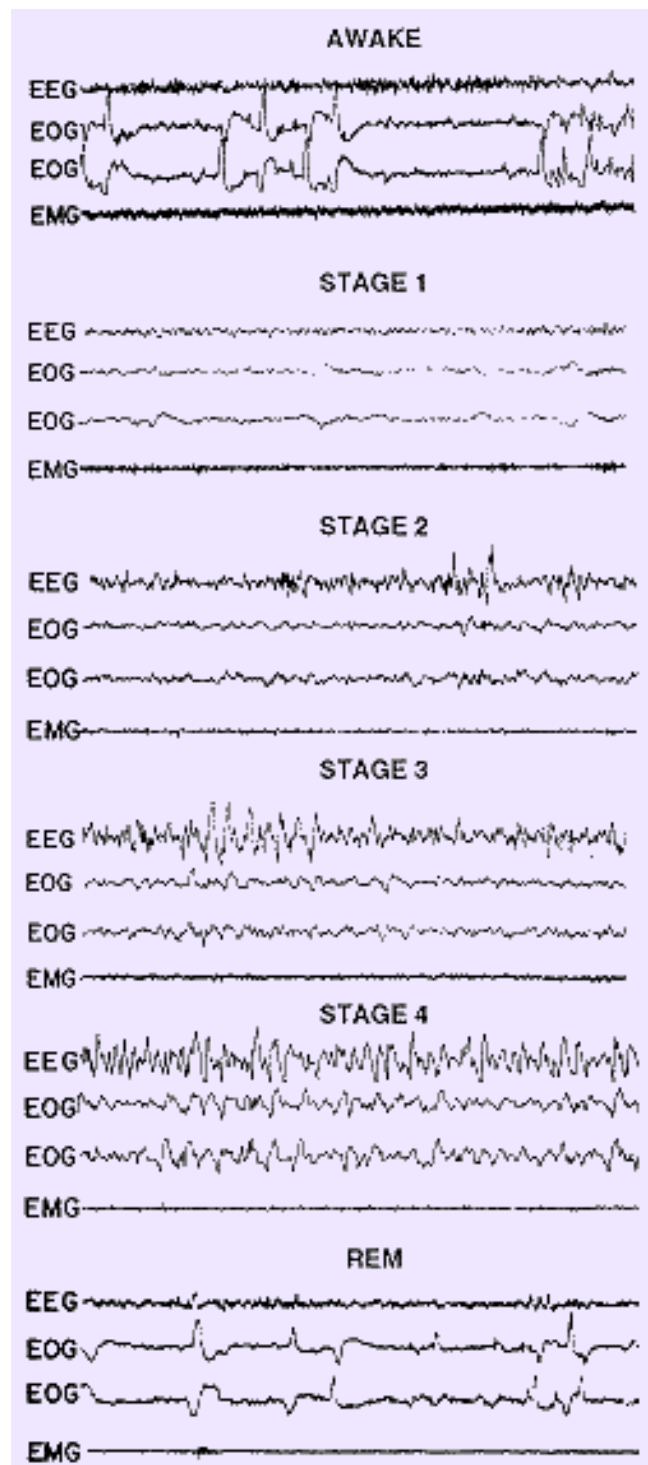
There is a quantitative increase in delta waves so that they come to dominate the EEG tracing.

### **REM (Rapid Eye Movements)**

The EEG reverts to a low voltage, mixed frequency pattern similar to that of Stage 1. Bursts of prominent rapid eye movements appear. The background EMG is virtually absent, but many small muscle twitches may occur against this low background (BOSB, 1997).



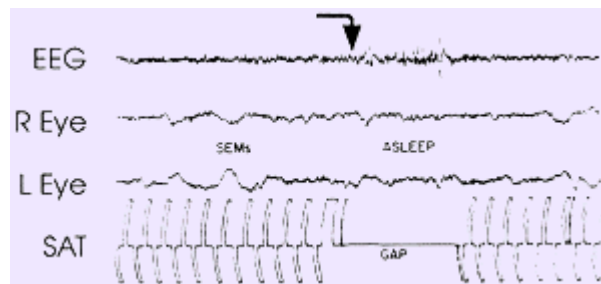
**Figure 2-4: Polygraphic recording in an alert young adult (BOSB, 1997)**



**Figure 2-5: EEG, EOG and EMG measures of waves of the brain nerves.**  
(BOSB, 1997)

The major differences between Stages 1, 2, 3, and 4 are in their EEG patterns. Although there are some exceptions, the general physiology of these stages is fairly similar. In contrast, the physiology of REM sleep is so dramatically different from the other four stages that sleep researchers have distinguished two major kinds of sleep, namely REM sleep and NREM (non REM) sleep, which is comprised of Stages 1, 2, 3, and 4 (BOSB, 1997).

BOSB (1997) suggests that sleep is a behavioural disengagement from the environment. The organism is far less responsive to sensory input during sleep than when awake. This relative insensitivity has been demonstrated in a number of sensory domains. For example, participants asked to respond to a flash of light in front of their eyes do so during wakefulness (BOSB, 1997). The failure to respond is not an inability to make a response, but a failure to see the stimulus, indicating that humans are functionally blind during sleep (Figure 2-6).



**Figure 2-6: Less Response to Sensory Input during Sleep  
(BOSB, 1997)**

Figure 2-6 shows the results of a volunteer who was asked to tap two switches alternately, shown as pen deflections of opposite polarity on the channel labelled SAT. When the EEG pattern changes to Stage 1 sleep (arrow), the behaviour stops

for the period indicated by the word "gap," returning when the EEG pattern reverts to wakefulness (SEMs=slow eye movement).

## **2.7. Other Methods of Drowsiness Detection**

### **2.7.1. Number of hours sleep**

The study by Peters et al. (1995) of the Effects of Partial and Total Sleep Deprivation on Driving Performance was conducted jointly by the Federal Highway Administration's (FHWA) Human Factors Laboratory and the Walter Reed Army Institute of Research's (WRAIR). It examined the effects of progressive sleep deprivation on simulated driving performance in the laboratory to assess the rate of accidents and changes in driving performance resulting from sleepiness or fewer number of hours sleep. The primary purpose of the study was to examine the effects of reduced sleep and progressive sleep deprivation on driver accident rates under controlled conditions. The results showed that the loss of one night's sleep can lead to extreme short-term sleepiness, while habitually restricting sleep by 1 or 2 hours a night can lead to chronic sleepiness. Sleeping is the most effective way to reduce sleepiness. Sleepiness causes auto crashes because it impairs performance and can ultimately lead to the inability to resist falling asleep at the wheel. Critical aspects of driving impairment associated with sleepiness or fewer hours sleep is deterioration in reaction time, vigilance, attention, and information processing (Weinger & Ancoli-Israel, 2002).



### **2.7.2. Epworth Sleepiness Scale (ESS)**

The Epworth Sleepiness Scale (ESS) was developed by researchers in Australia and has been widely used (Lundt, 2004). The ESS is a simple, self-administered questionnaire that provides a subjective assessment of the day-to-day effects of sleepiness. It is a more appropriate method for assessing ‘overall’ sleepiness than the current traditional methods (e.g., Karolinska Sleepiness Scale, KSS).

The concept of the ESS was derived from observations about the nature and occurrence of daytime sleepiness. Participants are asked to rate the likelihood of dozing off or falling asleep in eight different sedentary situations commonly encountered in daily life (e.g., watching television). For each situation, the participant rates the likelihood of dozing as never (=0), slight (=1), moderate (=2) or high (=3). The total (out of 24) is the ESS score. ESS scores can distinguish participants and diagnostic groups over the whole range of daytime sleepiness. A score of less than 11 on the ESS is considered to be within the normal range, whereas scores of 11 or over are indicative of Excessive Sleepiness (ES). An ESS score of 14 or higher are associated with high sleepiness. The ESS has been used in several driver drowsiness detection research studies and its major advantage, apart from ease of use, is that it directly reflects the impact that sleepiness is having in real life (something that a laboratory test cannot assess).

### **2.8. PERCLOS (percentage eye closer) measure**

‘PERCLOS’ is the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures (“droops”) rather than blinks (Dinges & Grace, 1998).

The PERCLOS drowsiness metric was established in a 1994 driving simulator study as the proportion of time in a minute that the eyes are at least 80 percent closed (Wierwille et al., 1994). Eyes wide open represented 0% and eyes closed represent 100%. Today there are three PERCLOS measures in use:

- P70, the proportion of time the eyes were closed at least 70%;
- P80, the proportion of time the eyes closed at least 80%; and
- EYEMEAS (EM), the mean square percentage of the eyelid closure rating.

It has to be noted that in the study by Wierwille et al. (1994), and the related technical brief from the Federal Highways Administration the face of the participant was monitored and recorded in order to detect eyelid closes, and then trained human scorers viewed the recordings and rated the degree to which the drivers' eyes were closed from moment to moment. The challenge related to the PERCLOS metrics is the automatic measurement of the eyelid position; however, successful attempts to measure eyelid position (and derive PERCLOS from it) are reported by Dinges & Grace, (1998), where a CCD camera monitors the face of the driver. The PERCLOS metrics are measured directly and estimated with non-parametric methods for detecting drowsiness in drivers. Dinges & Grace (1998) used connected-component and support vector machine to verify eye blinks. The driver performance data was correlated with PERCLOS measurement to judge whether the driver is drowsy.

The main weaknesses of the PERCLOS measure will now be discussed. Termed "PERCLOS", the device and detection technique relies on the percentage of slow-eyelid closures during a several-minute period. Fast eye blinks (about 100 ms duration) or micro blinks is an important measure for detecting micro sleep during

driving and the PERCLOS system was not capable of measuring micro sleep (Hargutt, 2003). The PERCLOS system needs to measure eye parameters from the front of the eye (Dinges & Grace, 1998). The study by Kithil et al.(2000) suggested that the PERCLOS detection rate was overstated because a percentage of the population is not conducive to eye-reflectance techniques, or because the PERCLOS technology is unable to work during bright daylight or for drivers with reflective dark glasses.

Another potential disadvantage of PERCLOS is that it is a slow eyelid closure system requiring a restricted field of view. Consequently, if the user is operationally required to move around frequently, the system cannot capture the user's eyes with the use of single camera array. Detection of drowsiness in an operational environment, in which the user's head moves requires an array of cameras or modified system that would be mounted to the head of the user, making it obtrusive and restricting the individual's overall field of view. An automated on-line drowsiness system that relies on slow eyelid closures as the input variable is not ideal in low humidity environments, where users are likely to close their eyes slowly ( and keep them closed over a period of time) in an attempt to moisten the eye (Kithil et al. 2000). An automated slow eyelid closure system, based on video images only, cannot differentiate between eyes closed due to drowsiness or eyes closed due to a rewetting (wet eye) of the eyes, which can potentially result in false positives.

## **2.9. Summary**

According to the literature, both EOG and EEG are valid indicators of drowsiness. Drowsiness is characterized by increased blink detection, decreased blink amplitude and increased blink frequency and EOG can be used to measure changes in these

parameters. Most of the drowsiness detection method literature has indicated eye blink and eye movement related measures are generally consistent for detection of drowsiness. According to Hargutt (2000), different eye blink parameters can be used for classifying different stages of drowsiness. Hargutt, (2000) suggested that analysis of eyelid movements is one of the most promising approaches to predict driver status. It is widely accepted that eye-lid parameters are valid in the case of extreme stages of drowsiness. Little is known about whether it is possible to discriminate between different driver states ranging from full wakefulness to sleepiness on the basis of the time course of these parameters.

A series of experiments conducted during Hargutt's studies conclude that time on task was varied, revealing that eyelid movements are physiologically controlled by at least two different processes. Therefore, closure time/speed and blinking frequency must be treated as two different parameters. Increased blink frequency indicates reduced vigilance, which is the first stage in the drowsiness process, and the blink duration and blink amplitude indicate increased drowsiness. Hargutt's method is able to identify a stage of vigilance decrements with only a slight decrease in performance as well as the final stage shortly before the driver falls asleep. The driver often does not notice that he is in the early stage in which there may be a high probability of inadequate reactions to sudden critical events. The differentiation between drowsiness and vigilance decrements are important when thinking about possible countermeasures.

Some of the findings of this study were similar to other studies in that the operational definition identified a higher number of male drowsiness d drivers/riders than female, and more drowsiness d drivers/riders less than 29 years of age compared with older age groups. Other studies also found that most early morning fatigued drivers/riders were less than 29 years of age, and fatigued drivers/riders over 50 years of age were involved in more afternoon crashes than in early morning crashes.

Drowsiness was in many cases not found in the EEG even though a change in the eye parameters was detected. It could thus be concluded that the eye parameters were better than EEG for an early detection of drowsiness. EEG signal interpretation is a very challenging task; such signals are complex and difficult to process.

The next chapter reviews some of the systems that have been developed, based on the physiological effects reported in this chapter.

## **CHAPTER 3**

### **REVIEW OF THE LITERATURE ON DRIVER DROWSINESS DETECTION SYSTEMS**

### 3.1. Introduction

A promising countermeasure designed to reduce the incidence of driver drowsiness related crashes is a system that can detect drowsiness and issue warnings accordingly. Many researchers and companies have designed and developed such systems to warn the driver. The most important factors are the efficiency and the reliability of these systems to warn the driver of the situation in good time. Some systems discussed in this chapter will warn the driver in their danger stage of sleepiness, when it is too late to avoid the accident.

Two of the greatest safety issues that drivers face today are the effects of drowsiness and in-vehicle distraction. Several methods have been used for monitoring sleep and wakefulness in volunteer participants in sleep laboratories. As discussed in chapter 2, those methods include monitoring the electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG). However, the need for electrode attachments makes these methods inappropriate for monitoring drivers routinely. In addition, when such methods have been used for research in drivers, they have not detected drowsiness accurately (Wylie, et al., 1996). In recent years, video-camera methods have not been used because of technical difficulties (e.g. environmental light changes disturb the capturing of face or eyes for detection of drowsiness). These difficulties particularly affect PERCLOS (Dinges et al., 1998) which gives an overall measure of eyelid closure, based on the proportion of time that the pupils are at least 80% covered by the eyelids over a few minutes.

Drowsiness measurement is a significant problem as there are few direct measures, with most measures being of the outcomes of drowsiness rather than of drowsiness itself. This chapter will investigate existing driver drowsiness detection systems.

### **3.2. In-Vehicle Technology**

Several studies have identified in-vehicle devices to detect drivers falling asleep and to provide warnings to alert them of the risk, or even to control the vehicle's movement, to prevent accidents (Boverie, 2004). Some systems detect changes in vehicle movement, such as drifting out-of-lane. However, there are concerns about the reliability of these devices. Also there are concerns that the driver may rely on them for warnings of when the situation becomes particularly dangerous rather than consider and plan when they should take rest breaks. An evaluation of three drowsiness monitors (an eye closure monitor, a head nodding monitor and a reaction time monitor) suggests that these devices showed an ability to detect drowsiness (Haworth & Vulcan, 1991).

In-vehicle driver drowsiness detection will provide the most direct evidence of driver alertness and its relationship with driving capacity (e.g., Heitmann et al., 2001). The European Union has adopted this approach in the 'AWAKE' project (System for Effective Assessment of Driver Vigilance and Warning According to Traffic Risk Estimation) (e.g., Boverie, 2004). The majority of research projects employed driver state measures including eyelid movement, changes in steering grips and driver behaviour including lane tracking, use of accelerator and brake and steering position. These measures were then combined and evaluated against an assessment of current drowsiness systems (e.g., PERCLOS, JTV, EEG, and EOG) obtained from research studies, anti-collision devices, driver gaze upon sensors and odometer readings. Many research studies have shown that, by monitoring the eyes from a sequence of images and the observation of eye movements and blink patterns the symptoms of driver drowsiness can be detected early enough to avoid many accidents (e.g. Yamamoto et al., 2002).



### **3.2.1. In -Vehicle Drowsiness Detection**

There is a large amount of research and development on driver assistance systems (e.g., Fletcher et al., 2003; Onken & Feraric, 1997). All of these systems focus on providing information to drivers that will facilitate their driving and warn them of threats to driving safety. In the main, the road safety problems for these systems are the same, relating mainly to when and how the information is conveyed to the driver. Work by a group of researchers at Carnegie Mellon University (Ayoob et al., 2003) has looked at the attitudes of experts and users (i.e., drivers) towards drowsiness detection devices and the type of information that would be most readily accepted by users. Interestingly, the findings suggest that warning devices should be able to be turned off or have their volume modified significantly, clearly reducing their effectiveness. Similarly, the AWAKE project concluded that drivers should be trained in appropriately responding to warning devices, especially if they occur occasionally as this may result in the problem of startle effects which can negatively or adversely affect driver safety.

Several devices have been developed to detect when drivers are falling asleep at the wheel and to provide warnings to alert them of the risk. Some are designed to monitor the driver and detect driver changes; others detect changes in vehicle movement, such as drifting out of the lane.

### **3.2.2. Generic Driver Assistance and Warning Devices**

As previously noted, there is a large amount of research and development on driver assistance systems but in this chapter we concentrate on the most important systems, as discussed below.

### **3.2.2.1. Optalert™ system**

This is a driver drowsiness detection system published by Johns et al., (2003). Their aim was to measure the amplitude/velocity ratio of blinks (AVRBs) in alert participants and to see how those ratios changed with drowsiness as a result of sleep deprivation. The practical significance of any such changes in AVRB, in terms of the participant's performance, was assessed by a new psychomotor vigilance test, the Johns test of vigilance (JTV), that also enabled eye and eyelid movements to be recorded.

The Optalert system consists of regular spectacle frames equipped with light emitters and sensors, which are used to measure eye and eyelid movements to detect drowsiness (Johns & Tucker, 2005). Eye and eyelid movements are recorded by a specially developed infrared (IR) reflectance method using 50-microsec pulses of IR light every 500 microsec from light-emitting diodes, one pointing at each eye, the reflected pulses being detected by adjacent phototransistors. The effect of environmental light measured just before each pulse is subtracted from the output. The pulse height (position) and the change in pulse height per 10 msec (velocity) are calculated each millisecond and displayed on a PC screen that also displays the occurrence of each visual stimulus and the participant's response. Changes in the output of the IR detection system were linearly related to the calibrated amplitude of eye movements. The main disadvantage of this system is that the users (drivers) have to wear spectacles and it uses IR light beam directly into the eyes.

### **3.2.2.2. “Co-pilot” system**

Grace (2001) designed a useful low-cost drowsy driver monitor, with driver interfaces. This system consists of a digital camera integrated with a low-cost digital signal processor (DSP). This monitoring system, called ‘Co-pilot’, has been used successfully in simulators and road vehicles (see Figure 3-1). The Co-pilot measures slow eyelid closures as represented by PERCLOS (Percentage Eyelid Closure). PERCLOS is defined as the proportion of time that a participant’s eyes are closed over a specified period.

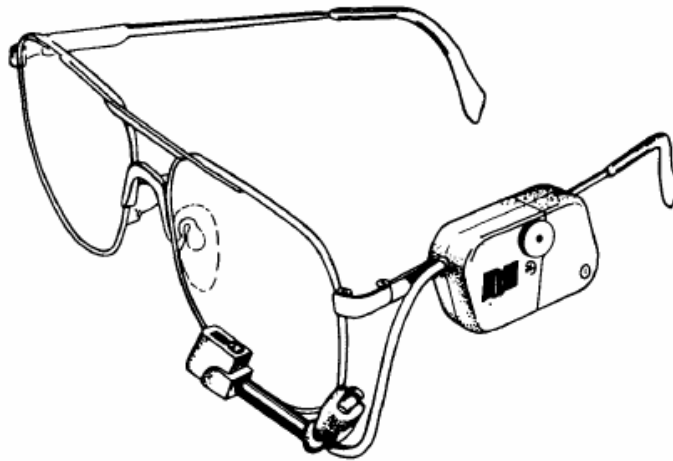
Grace’s current driver interface is based on recent experimental results on drowsiness feedback to the driver, and can reduce drowsiness and improve driver performance for sleep deprived truck drivers operating a truck simulator. A controlled experiment was undertaken with 16 Commercial Driving License (CDL) holders driving a high-fidelity truck simulator (TruckSim®) to establish the effects of drowsiness feedback on: driver alertness-drowsiness, driving performance and driver-initiated behaviours. The test simulated a four hours night drive without drowsiness feedback (control condition) and one simulated a four hours night drive with drowsiness feedback. Although there was significant variability between drivers in drowsiness and consequently in the number of drowsiness-based alarms and warning alerts, drowsiness feedback tended to have consistent effects on key classes of outcome variables, including reduced drowsiness levels, improved driver performance and self-alerting activities (driver movements). The warning triggers are associated with PERCLOS calculated over three minutes. Grace’s research still continues with an interface consisting of an audible tone that is associated with the readings of a visual gauge.



**Figure 3-1: The “Co-pilot” system**

#### **3.2.2.3. The ‘Onguard’ Eye Closure Monitor**

Onguard is an optical electronic eye monitor developed by Xanadu Ltd, an Israeli company. It is not currently available but the device consists of a small infra-red (IR) sensing unit which observes the eye, and an electronic processor which contains batteries, alarm buzzer, and switch (see Figure 3-2) (Haworth & Vulcan, 1991). The device is designed to be mounted on any standard eyeglass frame (similar to the Optalert system). The electronic sensing unit directs a beam of infrared light at the eye and measures the reflected light. Eye closures are detected as reductions in the amount of light reflected when the eyelid covers the surface of the eye. The electronic sensing unit emits an audible alarm when eye blink duration is longer than 0.5 seconds.



**Figure 3-2: The Onguard eye closure monitor (Haworth & Vulcan, 1991)**

The above system uses the eye blink method but does not use any physiological relation with eye blink and driver drowsiness to evaluate sleepiness or drowsiness to warn the driver. The average duration of human blink varies between 0.3 and 0.4 seconds (McWilliams, 1998; Stern et al., 1974) but, under some normal conditions, it may increase and be higher than the normal range. The main disadvantage of the system is its warning to the driver all the time when the eyes blink durations are longer than 0.5 seconds.

#### **3.2.2.4. The 'FaceLAB' system**

The FaceLAB system is a commercial product developed by Seeing Machines (Seeing Machines, 2005) for face and eye tracking and measurement. This system was developed after four years co-operative R&D between the Australian National University, and Volvo Technological Development (Victor, et al., 2001; Fletcher, et al., 2003).

Victor et al. (2001) designed a new visual behaviour measurement tool and automated analysis procedure that eliminates the video transcription process often

involved in data collection of visual behaviour. Results from a study aimed at validating this automated analysis with a standardised video transcription based method are presented. The comparison of measurement performance is applied to six in-vehicle tasks that were performed in a driving simulator. The car consisted of a Volvo S70 instrument panel set on a table with the instrument cluster removed to house the two FaceLab cameras (Figure 3-3). A conventional computer game steering wheel was used without pedals. A left car door with a rear view mirror, and a car seat were added. A camera and video recorder for collection of separate video images for transcription was installed.



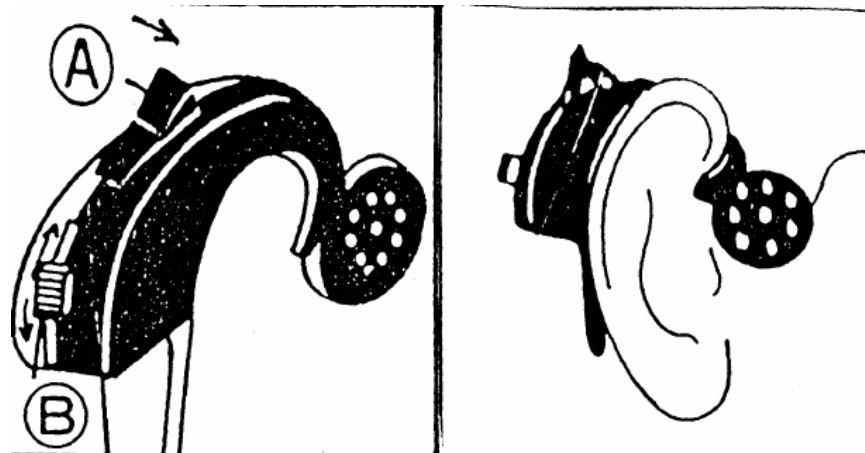
**Figure 3-3: The interior of the simulator used in the study FaceLab system (Victor et al., 2001).**

The results show that the automatic analysis of visual behaviour developed in the system correlates very highly with the manual video transcription based method across all measures. The study showed that differences in average glance duration would be more sensitive than the other measures to the loss of time precision in the video analysis method. This study compared the automatic analysis of eye movement data with a video transcription based method. The results successfully validated the automatic analysis method as being highly correlated with the video transcription method. Analysing facial expressions and eye blink is required for advanced detection methods. With the standard two camera FaceLab system, it cannot track either head movements or eye movements outside the head tracking range. By upgrading

FaceLab system with more cameras, it is expected to cover the whole driver's head range within the simulator. Victor et al. (2001) suggested that head-mounted systems could provide a much better tracking range, giving the participants more freedom of movement.

#### 3.2.2.5. Head Nodding Monitor – Dozer's Alarm

A number of companies have marketed simple devices to monitor head nodding by drivers (Haworth & Vulcan, 1991). The device consists of an ear piece which hooks over the ear and contains a battery; an alarm and angular detector (see Figure 3-4). When the driver's head nods forward beyond a predetermined angle, the device buzzes loudly.



**Figure 3-4: Dozer's Head nodding monitor (Haworth & Vulcan, 1991)**

This system warns the driver when the head nodding gets near to a certain angle. Considering human sleepiness behaviours, head nodding occurs after eyes are fully shut with micro sleep or deep sleep in 2-3 seconds. The operation of this device will

be too late to warn drivers of the onset of sleep and hence will not prevent potential accidents (Haworth & Vulcan, 1991).

#### **3.2.2.6. The “Head box” system**

Whitfield (2003) developed an in-vehicle eye tracking system using a vision system to take video of the eyes and analyze their movements to identify driver drowsiness. The hardware involves two infrared light sources and a small camera mounted on the instrument panel, and is focused on the driver’s head while they are driving. This system is named “Head box” and the software used in the system will move the camera to locate the eyes. This method requires sophisticated software algorithms. The system tracks drowsiness or lack of focus based on several eye movement criteria. The main disadvantages of this system are variation of vehicles inside temperature and vibration of cameras causing unreadable results (Misener et al., 2007). More sophisticated and new algorithms to track eye moments are currently being developed. Digital Signal Processors are becoming faster and less costly and camera technology continues to improve the system. Recent developers rely on expensive CCD (Charge-coupled device) imaging solutions for eye-tracking, but research has now shifted entirely to the use of low cost CMOS (Complementary metal oxide semiconductors) images, as used in modern cameras. The eye tracking R&D project by Whitfield (2003) indicates that the main inhibitors to system performance of eye tracking are fast head movements and bright sunlight. Using the CMOS high dynamic range sensors that limit the saturation effect of sunlight allows the camera to “see” the eyes more clearly. CMOS sensors have several advantages over CCDs. They use only 10-20% power of CCDs, making them a good choice for battery-powered cameras. CMOS sensors are made using the same techniques and



equipment as more familiar CMOS circuits formed in computers, so they cost less to produce than CCDs, which require specialized fabrication equipment. Like CCDs, CMOS sensors use an array of photodiodes to convert light into electronic signals. The weak electronic charge generated by the photodiode is stored in a small capacitor. The major difference between CCDs and CMOS sensors is in the way the stored charges are converted into a usable signal. A CCD sensor scans its pixels consecutively. Stored charges from each row are shifted down to the next row (thus the term "charge-coupled") and, at the bottom of the array, the charges in the final row are output in a serial stream. The voltage levels of each pixel in the serial stream are amplified by an on-chip amplifier prior to output, and sent to either an external or internal analog to digital converter (ADC) where the signals are converted into digital values which make up the image. Each pixel in a CMOS sensor has its own amplifier circuit, so signal amplification is performed before the image is scanned. The resulting signal is strong enough to be used without any further processing (Litwiller, 2001).

### 3.3. Summary of Drowsiness monitoring devices

#### 3.3.1. Drowsiness monitoring systems and technique

**Table 3-1: Summary of drowsiness monitoring devices**

Eye blink, Eye movements, facial expressions measures and In-Vehicle systems	
Approach/System	Technique
Tracking of gaze	Eye camera follows head movements by keeping pupil central, uses infrared light to produce corneal glints that are picked up by camera to detect pupil-glint vectors.
Eye closure and Eye Blink	Video cameras capture images of the driver's face and a number of cues including eye gaze direction are used to infer driver states such as drowsiness.
Blink behaviour and Face tracking	Measures the blink rate of a driver in real time via motion picture processing from which driver states are inferred.
	Automated detection of eye closure by using video imaging of the face then computation methods for locating the eyes and changes in intensity to determine whether eyes are open or closed. Responds as closed eye if eye is closed for five consecutive frames.
In- Vehicle systems	Uses Infra-red light to locate pupils and detect head motion then Kalman filtering to predict facial feature locations so tracking more than simply changes in the eye, uses predictive analysis to cope with facial occlusion problems.
Lane tracking	Uses two-dimensional radar sensing and extended Kalman filtering for fast detection and tracking of road curbs
	Attempts to overcome problems of previous lane tracking methodologies that use single cues relating to the edges of the lane such as centre lines or edge markings but which cannot cope with changes in road characteristics and lighting changes. This approach uses the Distillation Algorithm to combine a number of available visual cues (captured by video camera) which together provide robust estimates of the location on the vehicle in the lane, even when some of the main features are missing.
Vehicle lateral position and steering wheel input	Uses lateral position and steering wheel input to detect driver drowsiness.

### 3.4. Summary

The aim of driver drowsiness warning devices is to provide information to the driver that their alertness is below a level compatible with safe operation of a vehicle. There is evidence that such warnings are useful to drivers who may be aware that drowsiness is increasing, but not aware of the impact of the drowsiness on their driving capacity. Some of these devices have benefits for drivers, and summaries of these devices and systems in driver drowsiness detection systems, physiological measure systems, driver performance measure systems and companies are given in Appendix A1, A2 and A3. If the warning occurs early enough in the development of drowsiness, such devices could enhance driver alertness sufficient to avoid a collision, although many of the devices currently under development, especially the driver state measures, will be detecting later stage drowsiness which is unlikely to be overcome by a short period of stimulation such as a warning signal.

All of these systems focus on providing information to drivers that will facilitate their driving and warn them of threats to driving safety (Parkes, et al., 2006). These systems will also, therefore, function as devices that should respond to the effects of drowsy driving in the same way as the measures of driver performance designed specifically for driver drowsiness discussed in chapter 2. In the main, the road safety problems for these systems are the same, relating mainly to when and how the information is conveyed to the driver. The 'AWAKE' project concluded that drivers should be trained in appropriately responding to warning devices, especially if they occur infrequently as this may reduce the problem of startle effects which can negatively affect driver safety. Further research is needed on different approaches to

providing warning to drivers of increased safety risk. Other approaches to driver assistance and warning signals which have been evaluated, including vibration of the seat and force feedback through the steering wheel in response to lane deviations (Mohellebi et al., 2001). Seat vibration was a pilot study (Heitmann et al., 2001), however, and the method needs more validation under simulation and on-road conditions.

Through the experimental design and finished products of driver drowsiness systems, further understanding is expected about warning the driver before they get into dangerous levels of sleepiness or drowsiness. It is believed that drowsy impaired driving can be successfully mediated by simple reliable technology. Some of the problems with the drowsiness detection devices currently under development refer to the stage of drowsiness that is being detected. More research and development is needed before effective drowsiness monitoring devices can become standard features in on-road vehicles.

The next chapter shows a novel approach to sleep/ drowsiness detection using simple and safe technology. An explanation of the new driver drowsiness detection system, including eye blink detector and driving simulator is given. The development of a subjective drowsiness measure questionnaire is explained. Furthermore, the method of the main investigation is discussed.

## **CHAPTER 4**

### **METHODOLOGY**

## 4.1. Introduction

In this PhD thesis, drowsiness and sleepiness are considered as synonymous, but the term drowsiness is used. The term drowsiness describes the grade of wakefulness, tiredness or vigilance.

The PERCLOS system (Wierwille, 1999) introduces a possible indicator of drowsiness. It is based on the registration of lid closure being greater than eighty percent. It has been suggested (Knipling, 1998) that an increasing blink rate could indicate moderate drowsiness and increase of blink duration severe drowsiness. The Johns Drowsiness Scale (Johns et al., 2003), based on a combination of several weighted variables, including amplitude–velocity ratios of eye lid closure, was introduced and validated against different levels of impairment in driver performance. It is calculated as the change of position of the eyelids during a blink, from eyelids open to eyelids closed, in uncalibrated units (A), divided by the maximum change of position ( $\Delta A$ ) per 10 msec. These two variables are known to be highly correlated in alert participants (Evinger et al, 1994).

These are the two main methods currently in use for driver drowsiness detection. Both systems measure eye blink from the front of the eye using the eye pupil's size changes and Infrared (IR) reflection. One question for this warning system is how often it sets off a false alarm. Another question is how often a severe sleepiness is not detected (missed) as the driver sleeps with open eyes (Gillberg, et al., 1996). Use of IR reflection for blink detection is still questionable when considering health and safety issues (Llorente, et al., 2003).

In this PhD research, a new method is developed for monitoring the drowsiness of drivers continuously, based on the detection of eye blink from the side of the eye by

measuring eye sclera area changes to extract eye blink frequency and duration. PERCLOS and JDS (Johns drowsiness scale) systems cannot measure drowsiness by detecting or tracking the eye from the side.

An underlying general question is whether the individual process of falling asleep can be characterised by group means (measures of drowsiness for group of people) (Parkes et al., 2002) or is it necessary to individualize the diagnosis of drowsiness? This research examines closely individual changes from driver performance tests and reaction time measures as the drivers increasingly became drowsiness d. The new method focuses on eye blink duration and blink frequency correlation with driver performance for each individual driver.

## **4.2. Detailed Research Methodology**

There are many approaches to measuring eye movements and blink; most are more suitable for laboratory experiments than as an adjunct to normal vehicle use. The proposed system captures eye blink from sides of the eye and measures the eye blink durations and frequency to correlate with subjective performance data. It has been found that eye blink durations and frequencies are highly correlated when a driver becomes sleepy or inattentive to driving. Looking at the problems presented by current eye tracking products and research, the proposed system has many advantages. These advantages include the indirect vision of eye: this method will remove any health and safety problems which may result from eyes being subjected to projection of an IR beam to the eye. The other advantage is removal of head movement analysis. Complex and sophisticated algorithms are normally required to detect eye movements with head movements in video detectors placed in front of the drivers. Additionally, this system avoids complex adaptive background model

algorithms required to segment the foreground (eye blink) from the background image, due to lighting changes (Maragos, 1987). In the proposed system components are fitted to the headphone to illuminate the eyes and record eye sclera changes. Chapters Two and Three illustrate how drowsiness can be measured through physiological measures, performance measures, self report or ratings. Physiological measures have frequently been used for driver drowsiness detection as they can provide a direct and objective measure. Possible measures are eyelid closure, eye movements, blink duration, pupil size change measure, skin conductance and production of the hormone adrenaline, Electroencephalography (EEG) and heart rate.

Considering all physiological methods, eyelid closure (eye blink) has been found to be a very reliable predictor of the drowsiness (Erwin, 1980) and several studies on drowsiness detection found that eyelid closure, eye movements and pupil size changes were the most reliable predictors in driver drowsiness detection. Electroencephalography (EEG) results have also been shown to be a reliable indicator of drowsiness. The problems with both Electroencephalography (EEG) and Electrooculography (EOG), (see EEG and EOG methods in Chapter 2, section 2.5.4), are the requirements for obtrusive electrodes which make them unsuitable for use in cars, as cabling of drivers would not be practicable or acceptable. Cabling methods are simply not feasible for real-time drowsiness detection systems.

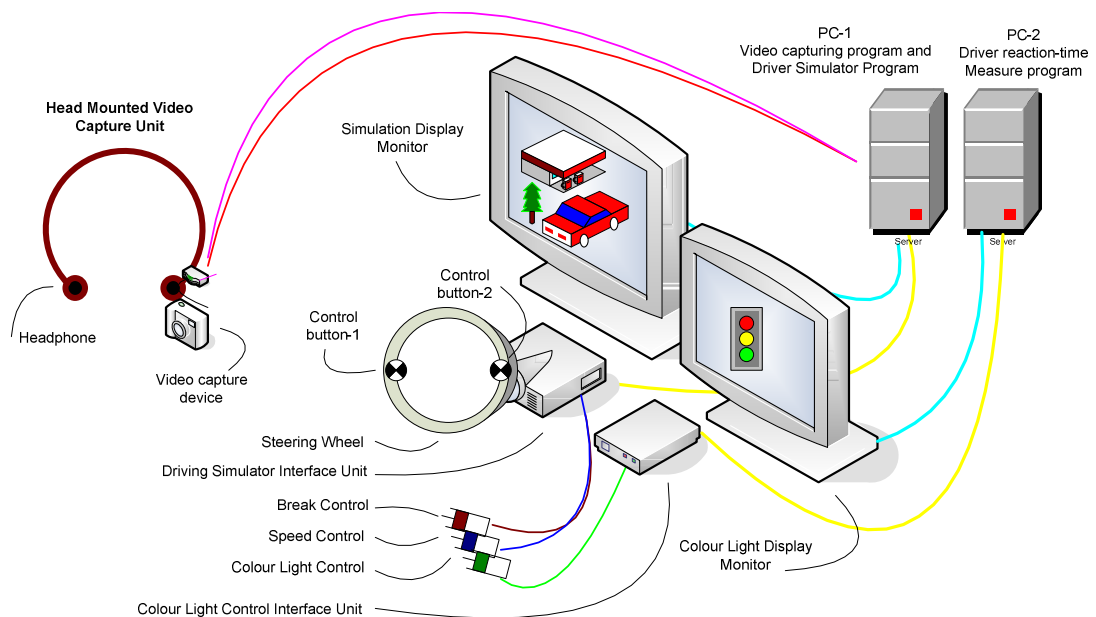
#### **4.2.1. Physiological Measures**

The proposed method for monitoring the eye blinks and blink duration is different from the most common method used by Johns et al., (2003). Johns' eye blink detection system is similar to the method described by Leder et al. (1996). It is different from the more widely used sclera reflection method of Torok et al. (1951).



Johns used pulses of invisible infrared light from an LED positioned below and in front of the eye, housed in a frame as would be used to hold prescription lenses. All other eye blink detection systems described in Chapter 3 use a similar method, as described by Johns and Tucker (2005).

The system which is described in this thesis to measure eye blink is new to driver drowsiness detection. It minimizes the disruption to the participant (driver) while detecting the eye blink. Considering the health and safety issues for the eye, it is very safe to use. Figure 4-1 shows the equipment arrangement. The key innovative idea is to shine the light from a low emitting green LED in to the side of the eye to illuminate the eye sclera region with a unique spectrum of light. By using a head mounted sensor, the problem of analysing head movement is minimized.



**Figure 4-1: Equipment Arrangement of Drowsiness Experiment**

### **4.2.2. Apparatus**

Figure 4-1 shows the equipment arrangement for the drowsiness experiment. Items of equipment are discussed separately in the following sections.

#### **4.2.2.1. Simulator**

The simulator used for this research was a computer-controlled, stationary automobile driving simulator (see Figure 4-2). The simulator remained static during the entire experiment. The participants viewed the simulator display in the large screen and traffic signal in the small screen. The steering wheel of the simulator had two push-buttons for the participants to use as emergency brakes and for speed control. Three paddles were used to control acceleration, braking and reaction time measurements (e.g. traffic signal control). The driving simulator environment is important for this research because it can affect the driver's performance.

This simulator was designed to measure driver reaction time, average deviation from centre lines, average speed and maximum speed. Driver performance data are stored every ten seconds and driver reaction time data is saved every one second for further analysis. A detailed description of the driving simulator is given in Chapter 6.



**Figure 4-2: Driving Simulator**

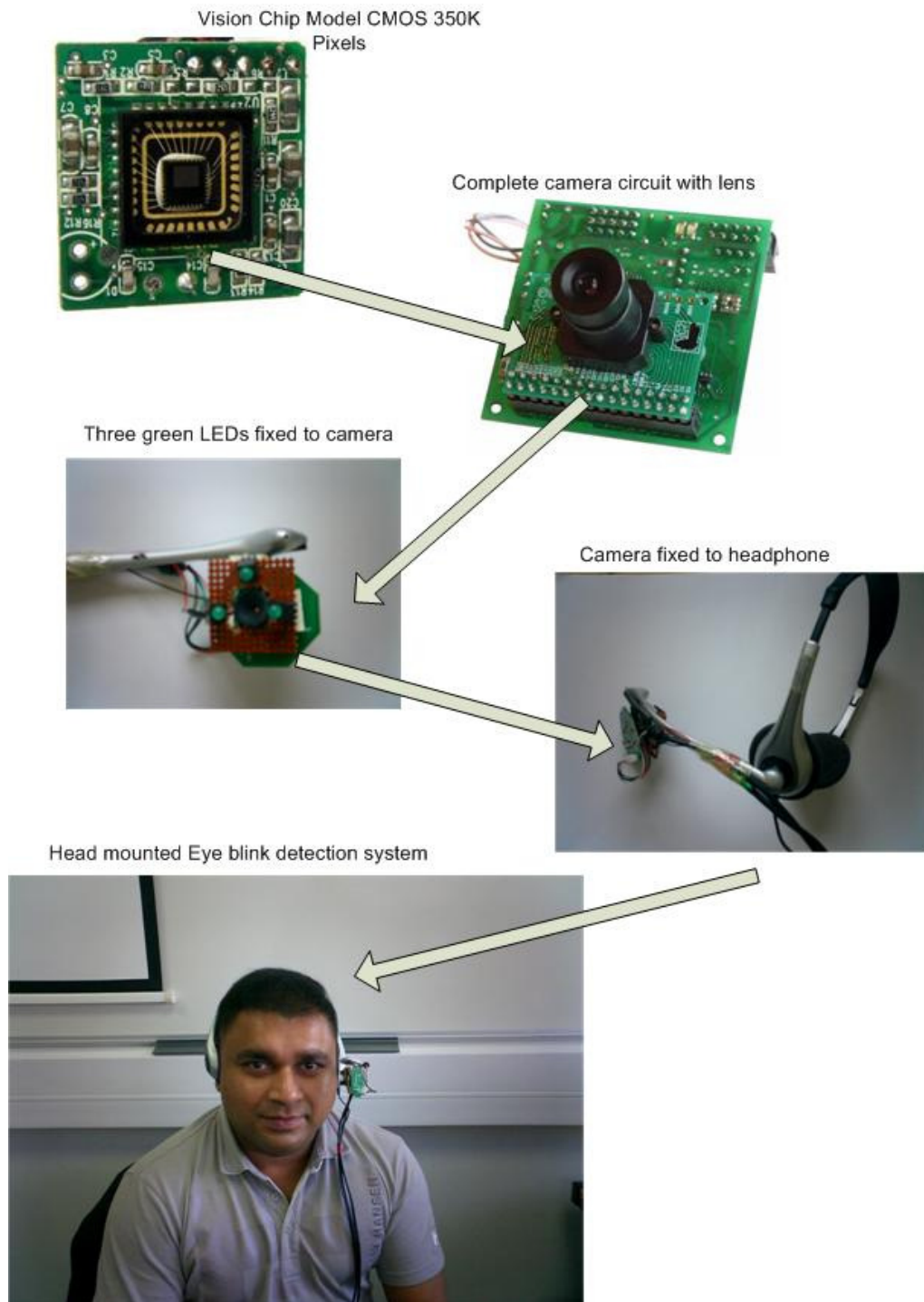
#### **4.2.2.2. Eye Blink Detection System**

The VC, (Vision Chip) (Komuro et al., 2003) is special purpose tracking hardware that enables the eye tracking system to track the movements of the eye with the required frame rate. Essentially, the VC is a camera system with integrated image processing capabilities. This section describes how the images of the eye are taken, how the tracking of a target is performed and how its position is calculated. In particular, the functionality that is used to perform image segmentation by binarization and region growing is addressed.

The system tracks eye blinks from the side of the eye. The reliable detection and tracking of eye blink are important requirements for measuring eye blink duration

and blink frequency in detecting driver alertness. Image acquisition and image processing algorithms are used for blink detection. By using a spectacle mounted sensor (Figure 4-3), the problem of analysis of head movement is much reduced.

There are three-steps to the eye blink detection procedure: background estimation, template matching and tracking. MatLab Simulink software is used to design a video capturing algorithm. Simulink software provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development (Matlab Simulink, Version 7.0.4, 2005). The system is initially designed to allow the data to be stored for off-line analysis.

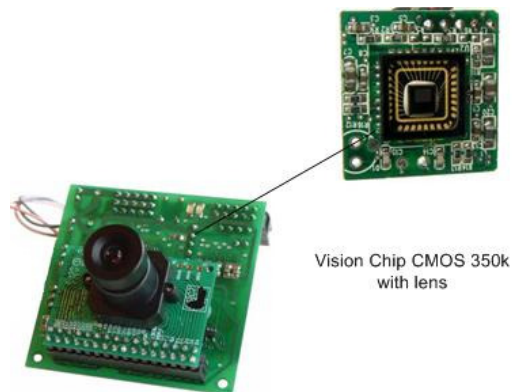


**Figure 4-3: Eye Blink Detection System.**

#### 4.2.2.3. Vision Chip

Figure 4-4 shows the main components of the CMOS 350K Vision Chip setup. The depicted circuit board integrates the Cypress CMOS 350K chip and the Vision Chip (VC) component. The CMOS 350K chip contains a CMOS compatible microcontroller and circuit necessary to connect to the chip via a USB connector. The USB interface is connected to the PC and controls its operation from Windows system32 architecture.

The connection to the tracking component is established using port pins. The MC (microcontroller) program uses regular port commands to control the VC via these connections.



**Figure 4-4: The CMOS 350K Vision Chip**

The Charge-Couple Device (CCD) digital vision chip captures eye blinks from the side of the eye. The CCD camera captures '144x176' pixels resolution video images at a capture speed of 30fps (frame per second) and saves in AVI format. The average time it takes for a complete human blink is about 300 to 400 milliseconds or 3/10ths to 4/10ths of a second (McWilliams, 1998). This is only an average and can differ

from person to person. Also, there are other factors that can affect blink speed, such as drowsiness, medications, diseases, and injury to the eye area (Planque, et al., 1991).

The VC lens is adjustable and has a focal length of 3.0 mm. The image is projected onto a sensor, with a pixel size of '144x176'. The Logitech Quickcam Pro 3000 was chosen for the following reasons:

- The VC component makes frame rates of up to 30 fps, which is ideal for rapid eye blink tracking.
- The sensitivity to infrared illumination is a requirement in respect to low light conditions.
- The low price is an important advantage in comparison to other high speed eye tracking systems.
- Due to its USB connection, the Logitech Quickcam Pro 3000 is easily integrated into a computer system.
- The small size makes it easy to fix on headphone and will not disturb the participant.

The relevant functions performed using the Vision chip are the following:

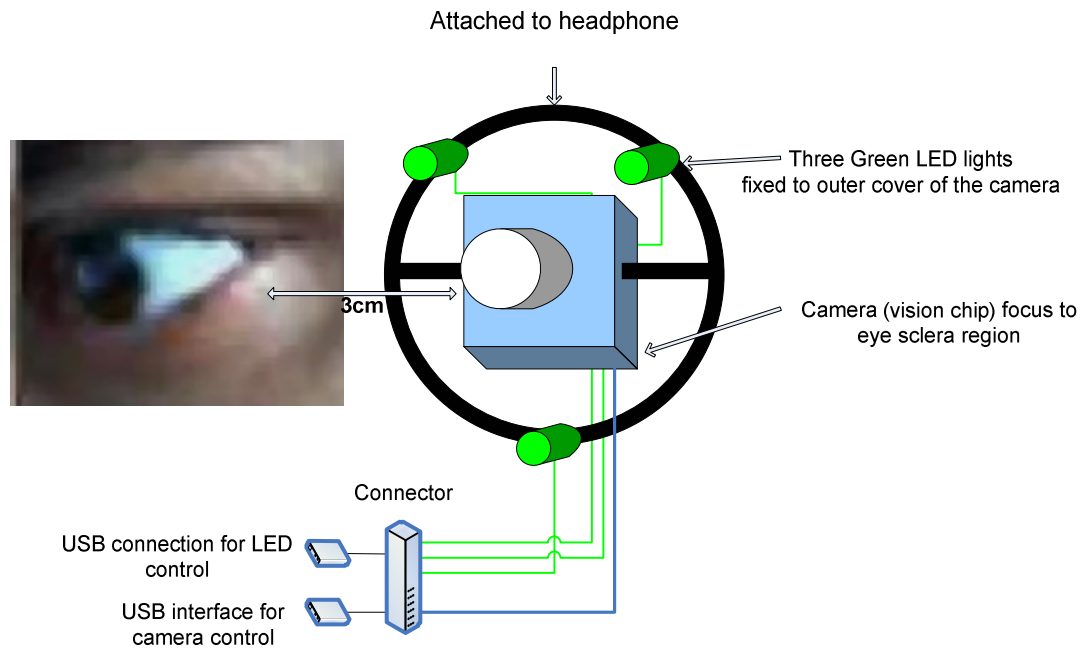
- Tracking of eye sclera region. The Logitech Quickcam Pro 3000 lens can be focused to a minimum of 1 cm distance.
- RGB/HSV colour adjusts to increase Green effect on images. The inherent problem is that colour-based methods are usually extremely sensitive to noise caused by changes in illumination. This was the foremost problem in video based detection systems used for eye blink detection. This PhD study has

found a solution to overcome this problem. The VC software allows changing the intensity of RED, BLUE and GREEN colours. Reducing the red and blue intensity and increasing the green intensity will minimize the effect of changes in illumination in captured images. Details of this new method will be discussed in the next section.

- Capture images in low intensity conditions. The IR sensitive feature in Logitech Quickcam Pro 3000 will increase the image quality in low light conditions (colour sensitivity will decrease but image quality will improve).
- Maintain steady frame rate of  $28 \approx 30$  fps, able to capture rapid eye blinks.

Captured RGB images convert to grey and binary images. The tracking and all calculations are based on the Grey and Binary image conversion using the Matlab program. The analog to digital conversion necessary for greyscale image conversion is performed by an ADC (Analog Digital Converter) built on the VC. Figure 4-5 shows the schematic of the hardware setup for the eye tracking device. The VC is placed 3 cm from the eye. This video device captures eye images every  $1/3$  of a second and this sampling rate is adequate to capture the fastest blink.





**Figure 4-5: Schematic of the hardware setup for the eye tracking device.**

#### 4.2.2.4. Noise reduction caused by illumination.

The choice for the illumination was influenced by the following factors:

- Segmentation
- Skin colour
- Disturbance caused by light source
- Disturbance caused by other light sources

All these factors have an impact on the image analysis to be performed, as discussed below.

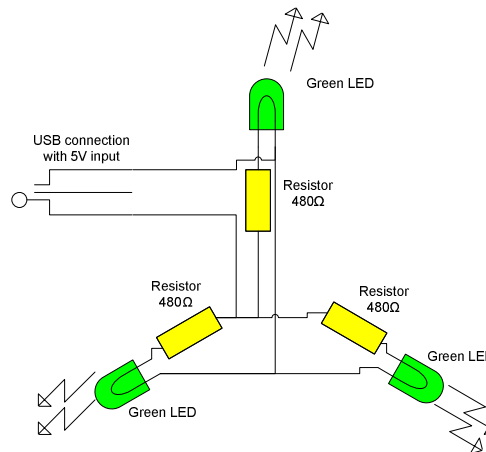
**Segmentation:** To be able to perform the binarization to separate the eye sclera region from the rest of the image, a threshold has to be found. The higher the contrast of the images is in general, the more reliably the threshold can be found, and the less sensitive the binarization is to other effects such as the distortion caused by the lens.

**Skin Colour:** Skin colour can affect the detection of the eye sclera region. Skin

regions that are bright (R, G, B approach 255) reflect light intensity similarly to reflection of light from the eye sclera region (white area). This affects the measurement of the eye sclera area. Reducing the intensity will cause dark images and it will also be difficult to measure the size of the sclera region.

**Disturbance caused by other light source:** Environmental light can be a major obstacle to successful image processing (Jahne, 2003). The other aspect is the degrading spectral sensitivity of the VC for wavelengths close to the infrared part of the spectrum. In low light conditions, the VC will pick the IR illuminations from other sources and this will affect the tracking. The use of a Green LED light source overcomes this problem. The green LED placed around the VC will project the low illumination green light source to eye regions. Reducing the red and blue intensity values and increasing the green intensity greatly reduces the problem of skin colour and other light source effects. The VC microcontroller has an RGB converter to Hue-Saturation-Value (HSV) colour space models. HSV contain 128 colours of each RGB colour. Reducing R-to-20, B-to-20 and increasing G-to-80; (R-red, B-blue and G-green) will illuminate an eye sclera region clearly from the skin around the eye. In addition, the reduction of Red and Blue colour on the VC will reduce the skin brightness during capture. Additionally, an increase in green light gives very low reflection from the human skin.

The LED sensitivity system is depicted in Figure 4-6 together with the specifications of three tested LEDs. The LEDs with a wide beam angle are more suitable and will minimize the disturbance to users. Experiments with narrow beam LEDs generate high illumination light spots and disturb the participant. Wide beam LEDs gives a more diffuse illumination to cover the eye sclera area more evenly.



**Figure 4-6: Specifications of the green LED setup**

### 4.3. Driving Performance Measures

A review of the previous literature identified driving performance measures that could be used in an experiment to identify an issue of concern. Previous studies have generally used sleep deprivation as the independent measure, and looked at average driving performance across different levels of sleep deprivation (Otmani et al., 2005). Participants attend several sessions in various stage of sleep deprivation, and driving performance is compared across sessions. In these studies, the driver performance was used to compare eye blink behaviour to measure drowsiness or sleepiness. However, it cannot simply be assumed that being sleep-deprived is equivalent to begin drowsy, or that being non-sleep-deprived is equivalent to being non-drowsy (Bittner et al., 2000). Drowsiness changes over time, and can occur when the participants are having a lack of sleep condition as well as normal condition (Suh et al., 2007). One advantage of this research, in comparison to other studies is the measuring of the effect of changing drowsiness over time, rather than simply measuring average driving performance across discrete levels of sleep deprivation.

One problem concerning driving performance measures, as indicators of drowsiness, is inter- and intra- individual differences in driving performance, which could be resolved by a combination of different measures. It has been suggested that the combination of performance measures with physiological measures (e.g. average eye blink durations and blink frequency) would give a sufficiently reliable detection method (Johns, 2003).

#### **4.3.1. Participants**

Eighteen participants were recruited to take part in the simulator test and four of them participated in two sessions, one of which was in a sleep deprived condition. The eighteen participants who attended at least one session comprised fourteen males and four females (age range 20 years to 70 years), with an average age of 35.6 years (SD=12 years). All participants filled out a questionnaire regarding subjective details and sleeping habits before the experiment was run. In addition, four participants who were in a sleep deprived condition (less than three hours during the last 24 hours) were also analysed. The selected participants are very diverse with respect to ethnicity, gender and age. Participants participated in different time sessions and different sleepiness conditions. There were two sessions: session one was in the morning (9-11:45am) and session two was in the afternoon (12-3pm). Each participant drove approximately 30-40 minutes. All the participants had a five to ten minutes training session to get used to the simulator. In order to examine the effects of driver state, the sleep deprived participants participated in the same driving session as the one in which they participated in the good sleep condition. Participants were instructed to drive at a speed of 0 to 60 km per hour, and the simulator speed was set to a maximum of 60kmph.

Several exclusion criteria were applied when recruiting participants. Shift workers and people with diagnosed sleeping disorders were excluded due to the possibility of having disrupted circadian rhythms, and the potential to respond with difficulty after a night of sleep deprivation. Sufferers of severe motion sickness or epilepsy were prevented from participating because of the potential for adverse reactions in the driving simulator. People who wear spectacles to drive also participated and the detection camera was mounted to the spectacles. People with narrow eyes were also included because their eye-sclera shape helped to calibrate the detection system. All the sleep deprived participants were volunteered are instructed not to have a morning sleep. All participants were advised not to take any drugs or alcohol before the simulation test. Finally, transport was arranged for the participants who volunteered in a sleep deprived condition.

#### **4.3.2. Driving Scenarios**

The simulation test consisted of a two-lane rural road, with centre lines and lateral edge lines. All participants were asked to take part in a driving simulator-based experimental trial in which they were required to drive along a scenario partitioned into a “rural” section, representing dual lane country roads with hills and bends, a “straight” section, representing a stretch of same road, fairly straight, open road, free of traffic. The participants were seated in the driving simulator at a distance of 1.5 metres from the screen. The simulation is intentionally designed to increase the sleepiness of the participants by inclusion of the above effects. The road edges and out-of-bounds were created as rough surfaces, which provided an audio feedback to participants (participants) if they ran off the road. It was considered that having the rough road edges was a more realistic option than having the experimenter verbally

advise the participant that they must return to the road. The driving scenario was a loop of approximately two to three minutes to continue one loop, with average speed of 60 km/h. Participants were free to drive at any speed between 0 to 60 km/h. An on-screen timer (clock) was available. The signed speed limit for most of the scenario was 60 km/h because at greater speeds it is difficult to control the vehicle on the centre line of the road. The single driving session for each participant tested lasted approximately 30-40 minutes.

#### **4.4. Variables Measured Throughout the Driving Simulator Test**

##### **4.4.1. Eye Blink Data**

Eye blink frequency and duration were measured continuously by the head-mounted video system (the video camera attached to audio headphone system). As a second measure of drowsiness, the percentage of time the eyelids were closed (PERCLOS) was measured throughout the driving sessions using the MATLAB program.

##### **4.4.2. Driving Performance Data**

Three driving performance measures were collected during the simulation. These consisted of: (1) steering error (deviations from centre), (2) Out of bounds and (3) Reaction time measure. Each of these measures is described below.

- 1) **Steering Error (deviations from centre line):** The lane deviation provides a valuable measure of driving task interference that has resulted in a measure of performance of concentration. The absolute value of the average deviations were collected every second (The absolute value of deviations is determined by ignoring the + or – sign and taking all values

as positive). The absolute value was then averaged over the 10 seconds. Greater deviations from the centre line suggest degrading driving performance or lack of concentration.

- 2) **Out-of-Bounds:** Large lateral accelerations provide insight into the degree to which a vehicle is off-track and, therefore, the magnitude of inattention. When the participant drives out of the road, it will record the time and count the number of times the vehicle went out-of-bounds.

#### 4.4.3. Reaction Time Data

Participants were required to push the break paddle as quickly and as accurately as possible based on the colour light change presented (e.g., Green-to-Red). This test provided a simple reaction time, reflecting the participant's awareness while driving; faster reaction time implies an improvement in situation awareness. Reaction time was calculated by subtracting the time when the button was pressed from the time when the colour change presented (Red-to-Green). In addition, a too-fast response (reaction time less than 100 ms) or a delayed response (reaction time longer than 20 s) was not included in the data analysis, and was regarded as an error.

#### 4.4.4. Speed related data

Average speed and maximum speed is measured during the simulator test.

- 1) **Average speed:** Vehicle speed can be considered a vehicle state that, at some level, has to be held constant in most circumstances. Therefore, accuracy and variations in speed were used to evaluate performance. Vehicle speed is a common indicator of driving performance, as driving

speed is affected by changes in attention and workload. Previous research (e.g., Wierwille et al., 1990) has shown that drivers adapt to the increased task demand by modifying their behaviour and driving more “vigilantly”. Monty (1984) found speed maintenance to be a sensitive measure of changes in the amount of attention demanded by secondary driving tasks. Drivers are required to make instant changes to throttle and braking to maintain a constant speed while driving. These are very difficult tasks and driver attention might veer away from maintaining constant speed. Mean and standard deviation of the speeds are then measured for each 10 second segment.

- 2) **Maximum Speed:** Rapid driving speed changes can also provide a sensitive measure of performance. For example, consider a driver driving a vehicle and performing a secondary, colour light change task that requires him/her to look away from the driving scene. At some point, the driver glances back to the driving scene and realizes that an unanticipated event is occurring (e.g., sharp bend ahead). The driver reacts to this event by quickly and firmly depressing the brake pedal. This reaction results in vehicle deceleration that is greater than would occur in normal braking situations. Then the driver has to accelerate the vehicle back to normal speedily. Since the maximum speed is a potentially important variable, the maximum speed (MAXSP) is measured during each 10 second segment.



## 4.5. Procedure

Participants (participants) who expressed interest in participating in the test were informed in detail about the nature and purpose of the research, and provided with an explanatory statement. Participants who volunteered to participate in both sessions had their sessions arranged on two different dates. (Four participants volunteered to participate in the sleep-deprived conditions.) Simulator test time was divided into four sessions, two in the morning and two in the afternoon.

All eighteen participants were asked not to consume any alcohol, caffeine or stimulants before the test. Questions in the general questionnaire covered the sleep behaviour in the night prior to the test. Participants were seated in the driving simulator, and drove through 5-10 minutes to become familiar with the controls and handling characteristics of the simulator. Upon arrival for their first experimental session, participants completed a questionnaire.

After the familiarisation drive (10 to 15 minutes), the eye blink detection system was set up to monitor the participant's eye blink and blink durations. Participants were informed of the possibility of simulator sickness and asked to report any symptoms if they occurred. Participants were instructed to drive on the centre line of the road. At the beginning of each driving simulation session, the data logging system for the driving simulator and eye blink detection system were initiated at the same time to ensure that the data could be matched for future analysis. Once all of this was completed, the participants began the test drive.

The simulator test is 30-40 minutes. The on screen clock helps the participants to see the simulation time. It is at the participants' discretion to leave the test at any time within the 30-40 minutes. After finishing the simulation test, participants filled in

the final two questions in the questionnaire describing the sleepiness or tiredness level after the simulation test.

Study limitations concerned design, biases, and in many cases, small sample sizes. The number of participants involved in this current research could be viewed as being relatively small for a statistical analysis perspective, and in comparing to other studies concerning driver drowsiness. For example: Johns et al. (2003) utilised 26 participants; Campagne et al. (2004) had 46 participants; Bittner et al. (2001) studies employed 600 participants. The simulator interface devices (e.g. steering wheel) were fixed to the moveable desk placed in front of the projector screen; so this not strictly realistic. The simulator tests were conducted under normal fluorescent light and the room lighting conditions were changeable because of daylight changes. The simulator setup room was situated near to the highway and the room temperature was maintained constant by a central air-conditioning circulation system. Whilst these extraneous factors, such as noise, light, humidity, were not controlled, they are assumed to have an insignificant impact upon driver performance.

#### **4.6. Ethics**

All participants were warned of 'potential driving sicknesses' during the test. They were required to fill in an informed consent form which stated that all results would be anonymized. Any questions concerning the instructions, the informed consent form, or the experiment in general were answered. Safety of the sleep deprived participants has been considered and transport was arranged before and after the test. These arrangements were approved by the relevant ethics committee at Buckinghamshire New University.

## 4.7. Summary

The eighteen participants participated in different time sessions in an alert condition, and four of them volunteered in a sleep deprived condition. The proposed method in this study is well within the capabilities of modern real-time embedded digital signal processing hardware to perform in real time using MATLAB Simulink<sup>®</sup> software. The proposed methods thus might be used to construct and test a portable embedded system for a real time alertness-monitoring system. Identification of physiological variables that correlate with driver performance measures may enable predictors of driver impairment to be developed. This will be discussed in chapter 8.

Most other research studies have used relatively large sample sizes and were concerned with just one or two measures from the participating individuals (e.g. Epworth Scale, reaction time, lane deviations). Considering the small sample size used in this current research, it was necessary to pay attention to a broader range of individual characteristics. Consequently, 12 different measures were collected from each participant; with seven of these being measured over time (e.g. blink durations and frequency were measured every second during the 40 minute test, corresponding to 2400 data points).

The next chapter explains the development of the Eye Blinks Detection System. The system tracks eye blinks from the side of the eye. Image acquisition and image processing algorithms are used for blink detection. This chapter explains the development of a headphone mounted sensor and the three-steps of the eye blink detection procedure: background estimation, template matching and tracking. Video

and image acquisition tools, signal processing tools and data analysis tools in MATLAB Simulink ® software are used to design eye blink detection systems.

## **CHAPTER 5**

### **INITIAL DROWSINESS DETECTION EXPERIMENT:**

### **THE DEVELOPMENT OF EYE BLINKS DETECTION SYSTEM**

## 5.1. Introduction

Most of the available measuring methodologies for driver drowsiness analysis are laboratory-oriented and their applicability under field conditions is limited; their validity and sensitivity are often a matter of controversy. Spontaneous eye blink is considered to be a suitable ocular indicator for drowsiness diagnostics (Caffier, et al., 2003). To evaluate eye blink parameters as a drowsiness indicator, most methods use a contact-free measurement of the spontaneous eye blinks using infrared (IR) sensors and video cameras to record eyelid movements continuously. Experimental results show that several parameters of the natural eye blink can be used as indicators in drowsiness diagnostics (Yano et al. 1999; Al-Qayedi and Clark, 2000; Caffier, et al., 2003). The parameters of blink duration and reopening time, in particular, change reliably with increasing drowsiness. Also, the proportion of long closure duration blinks proves to be an informative parameter. Some results demonstrate that the measurement of eye blink parameters provides reliable information about drowsiness/sleepiness, which may also be applied to the continuous monitoring of the tendency to fall asleep.

A few methods have been proposed for automatic blink detection. For example, Yano, et al., (1999) use frame differencing for eye blink detection. Frame differencing devices the subtract of two consecutive images to identify any minor pixel changes occurring in a sequence of images. Frame differencing allows quick determination of possible motion regions. If they are detected, optical flow is computed within these regions. The direction and magnitude of the flow field are then used to determine whether a blink has occurred. Al-Qayedi and Clark (2000) track features about the eyes and infer blinks through detection of changes in the eye shape. Smith et al. (2000) try to differentiate between occlusion of the eyes (due to

rotation of the head) and blinking. The participant's sclera (the white of the eye) is detected using intensity information to indicate whether the eyes are open or closed i.e., a blink is occurring. Black et al. (1998) detect blink using an optical flow algorithm but the system restricts motion of the participant and needs "near frontal" views in order to be effective. The reported 65% success rate in detecting blinks seems to be too low for driver drowsiness or sleepiness detection (Black et al. 1998). Generally, eyes are tracked and comparisons of scores between the 'open eye' and the corresponding 'closed-eye' template are used to detect blinks. Use of these methods makes it difficult to measure blink durations accurately. Another disadvantage of the system is that changing camera positions require the whole system to be retrained.

This chapter describes the development of an eye blink detection system to capture real-time eye images using prototype computer vision systems for monitoring driver vigilance. The main components of the system consist of a head mounted video camera, a specially designed system for real-time image acquisition for off-line analysis and for controlling the eye illuminator with specially designed luminosity control systems. Various computer vision algorithms have been developed for simultaneously monitoring various visual bio-behaviours of eye blink that typically characterize a driver's level of drowsiness (Caffier, et al., 2003). MATLAB Simulink is the software used to develop the eye blink detection algorithm. For details about MATLAB Simulink software, see Appendix –B2.

After this introduction to eye blink detection systems, section 5.2 describes the hardware used for capturing eye blinks. Section 5.3 discusses eye blink capture speed and properties of human blink. Section 5.4 describes the methodology for the

confident measurement of eye blink detection. Section 5.5 describes the proposed new system. Section 5.6 describes the method of displaying results.

## **5.2. Camera Hardware**

The primary item to be considered in image acquisition is the video camera. A review of several journal articles reveals that face and eye monitoring systems have used an infrared-sensitive camera to generate eye images (Eriksson and Papanikolopoulos 1997; Grace et al., 1998; Perez et al., 2001; Singh & Papanikolopoulos, 1999).

Instead of 'normal' light, most of the eye tracking systems uses IRLED (Infrared Light Emitting Diodes) to illuminate the eye. Using a light source that is invisible to the user has the advantage that the light does not affect the field of view, but exposure of the eye to an IR light beam for a long time will damage eye cells. This disadvantage is one of the greatest risks when using invisible IR light to detect eye blink. For this reason, the new system uses a green LED light source attached to the camera to illuminate the participant's eye. The camera used in this system is a CCD camera.

Figure 5-1 shows the prototype design of the video capture device setup. The CCD camera used is light sensitive. The ICNIRP (International Commission on Non-Ionizing Radiation Protection) guidelines chosen for this thesis are described by Sliney et al. (2005). These guidelines have been chosen as they provide a good safety measure while not making unreasonable worst-case assumptions that do not apply to the blink detection system, and low green light illumination levels is well within the safe range of visible wave length (for the visible light range, see Appendix B2) .



**Figure 5-1: Prototype system of Eye blink capture device**

### **5.3. Frame Resolution and Capture Speed**

The next stage of any image acquisition system is to convert the video signal into a format which can be processed by a computer. The camera captures 144x176 pixels resolution video images at 30 fps (frame per second) and in AVI format. The video capturing speed is fast enough to adequately capture the fastest human eye blinks.

#### **5.3.1. Human Eye Blink**

Eye blink activities have been assessed by different investigators over the last 75 years for development in human drowsiness analysis for different purposes (Doughty, 2001). Kircher et al. (2002) report that the spontaneous eye blink rate (SEBR) was consistently dependent on the activities of subjective behaviours (e.g.

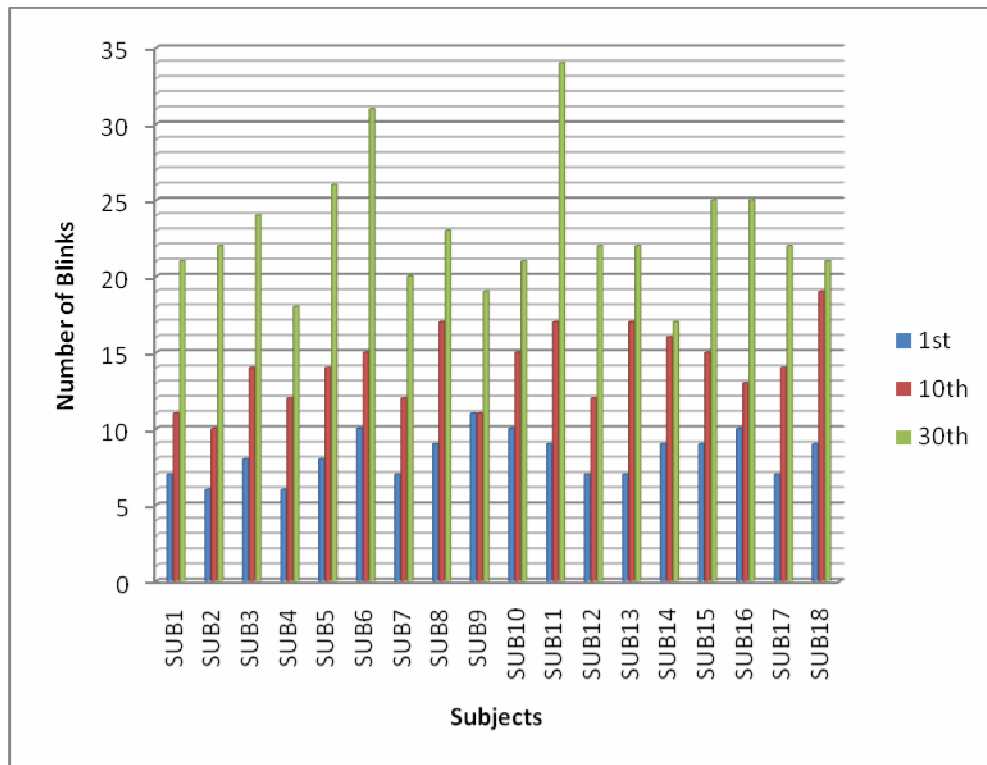


reaction time). The statistical analysis (with calculation of 95% confidence interval values) indicated that reading-SEBR is normally between 1.4 and 14.4 eye blinks/min, primary gaze-SEBR between 8.0 and 21.0 eye blinks/min and normal-SEBR between 10.5 and 32.5 eye blinks/min for normal adults. The average blink rate for a normal adult is almost 23 eye blinks/min. The average time taken for a complete human blink is about 300 to 400 milliseconds (McWilliams (1998); Stern et al., (1974)).

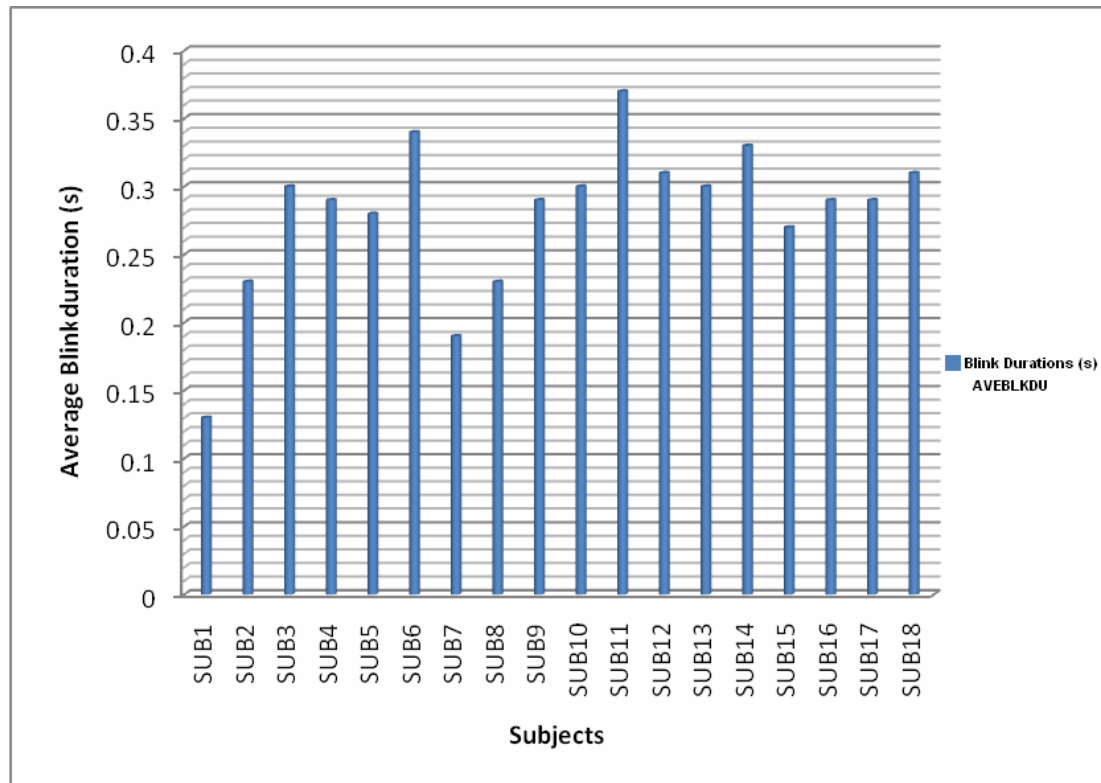
### 5.3.2. Accuracy of Eye Blinks Capture

Figure 5-2 (a) shows the captured total eye blinks for all 18 participants in their 1<sup>st</sup>, 10<sup>th</sup> and 30<sup>th</sup> minute in the simulator test. Generally all the participants had a low blink count in the 1<sup>st</sup> minute, with this gradually increasing though to the end of the test. The participants showed an average blink count of 22.94 at the 30<sup>th</sup> minute. Participants 6 and 11 showed a relatively high blink count at the 30<sup>th</sup> minute. The blink frequency increases gradually and settles to the normal average human blink rate (23 eye blinks/min) during the last 10 minutes of the test. Figure 5-2 (b) shows the average blink durations for all 18 participants at the 15<sup>th</sup> minute of the simulator test. The average blink duration at the 15<sup>th</sup> minute for all participants is 0.27 seconds. The alert participant's blink durations varies between 220 – 350 ms. Figure 5-2 (c) shows the frame by frame images of complete eye blink in RGB colour images and the converted grey images below with frame numbers. The capturing system is calibrated to start the capture of the eye sclera region when the eye lid shuts ½ way to close and reopen to ½ (see more details in section 5.5.3). The detection system captures a single frame about every 33 ms. In Figure 5-2 (c), the eye blink starts from frame 4 and ends in frame 12. In this example, the number of frames for the

complete blink is 9, and the total duration is  $33 \times 9 = 297$  milliseconds. Detection system measured value = 0.00288 (with the sampling time of 0.01 s)  $\approx 288$  milliseconds. The current system's eye blink capture accuracy is 97% (eye blink durations and frequency).



**Figure 5-2(a): Total eye blinks at 1<sup>st</sup>, 10<sup>th</sup> and 30<sup>th</sup> minute for all participants**



**Figure 5-2(b): Average blink durations at the 15th minute during the test for all participants**



**Figure 5-2(c): Frame by frame images of the complete eye blink**

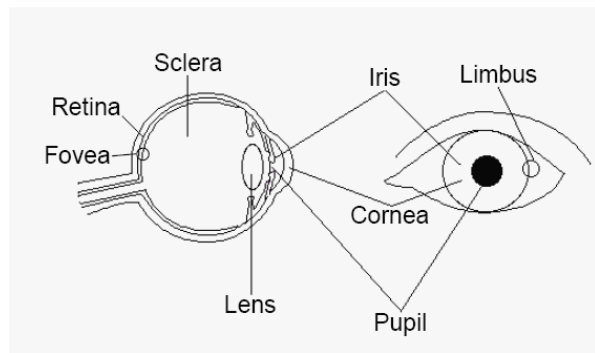
#### 5.4. Exploiting the confidence measure for eye blink detection

The feature of the eye that affects the task of tracking is the eye sclera region, the white area of the eye. In building a system for this task, it is necessary to simplify and use workable models of the eye. It is important to judge these simplifications and

the performance of a system for a given application, and regard every measured characteristic separately. In general, the purpose of an eye blink tracking system is, simply stated, to monitor eye blink durations and eye blink frequency as accurately as is necessary to characterize a driver's level of vigilance. It is envisaged that this off-line system will eventually be applied to a real-time system with the application of suitable changes to hardware and software.

#### 5.4.1. Eye Terminology

To discuss the eye, it is necessary to introduce some common terms to refer to different parts of eye anatomy (Mather, 2000). Figure 5-3 depicts a cross-section and a frontal view of the eye. The important area for detecting eye blinks described in this research is the eye sclera region. In the front view of eye, the area between the outer region of eye cornea and two ends of the eye covers the sclera region.



**Figure 5-3: Eye Anatomy (Werkmann, 2005)**

#### 5.5. Proposed System

The system proposed here reduces complexity by performing frame auto thresholds and template matching. The eye blink tracking system consists of three steps: Background estimation, Template matching and Eye sclera tracking (see

Figure 5-4(a)). Combination of these steps is used to analyse eye blink dynamics. The algorithm does not require any camera calibration and is applied for a range of environmental situations. Also it does not require users to do any pre- preparation prior to having their eyes detected. The advantage of using a head mounted camera is the removal of the need for head movement analysis. Figure 5-4 (a), shows a block diagram of the eye blink detection systems (EBDS). The template matching, background estimation and eye tracking steps will be discussed in this chapter. Figure 5-4(b) shows the complete eye blink detection system, using MATLAB Simulink. A full explanation is given in the next section.

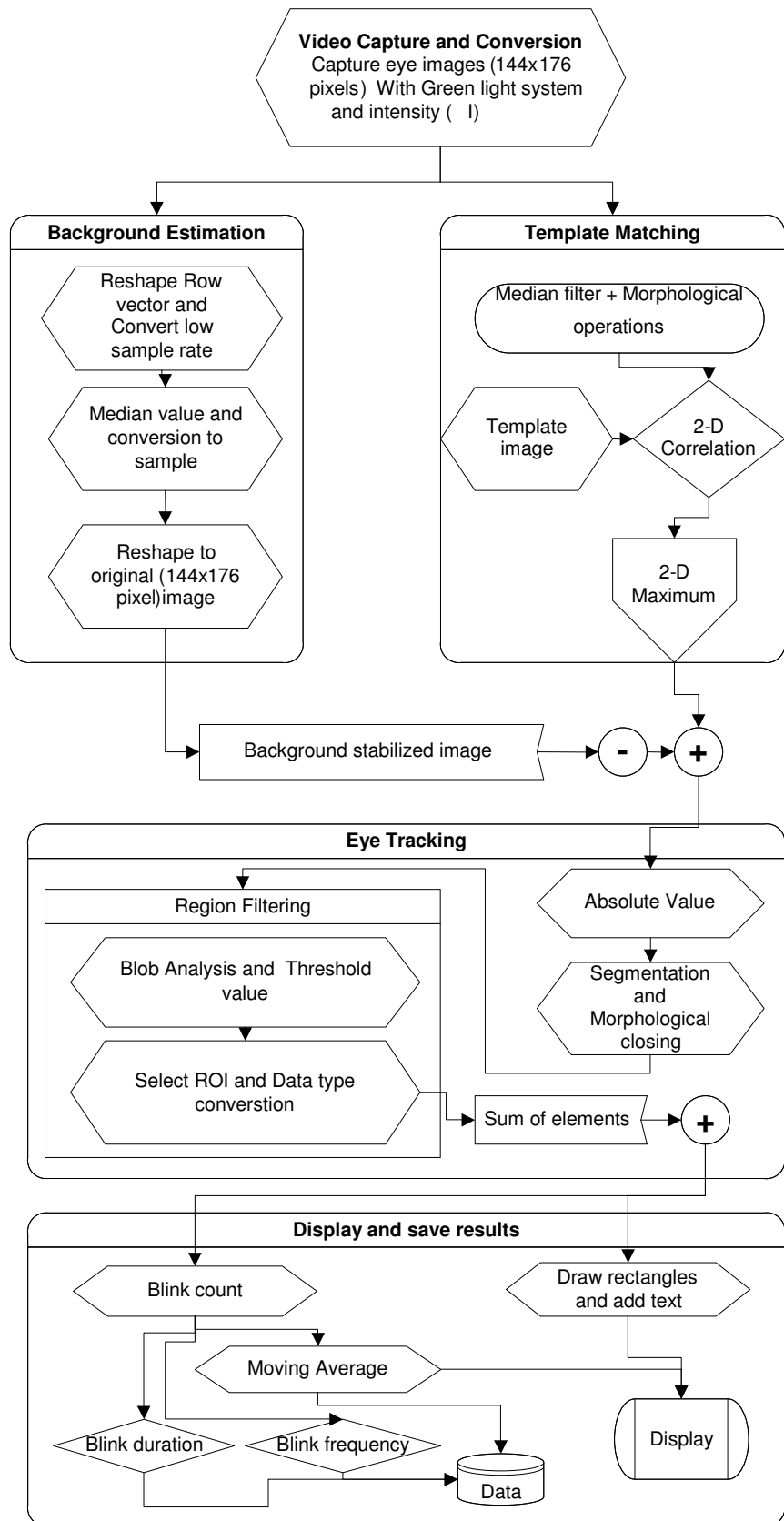


Figure 5-4 (a): Block diagram of Eye Blink Detection System



Sub Systems

Sub Sub Systems

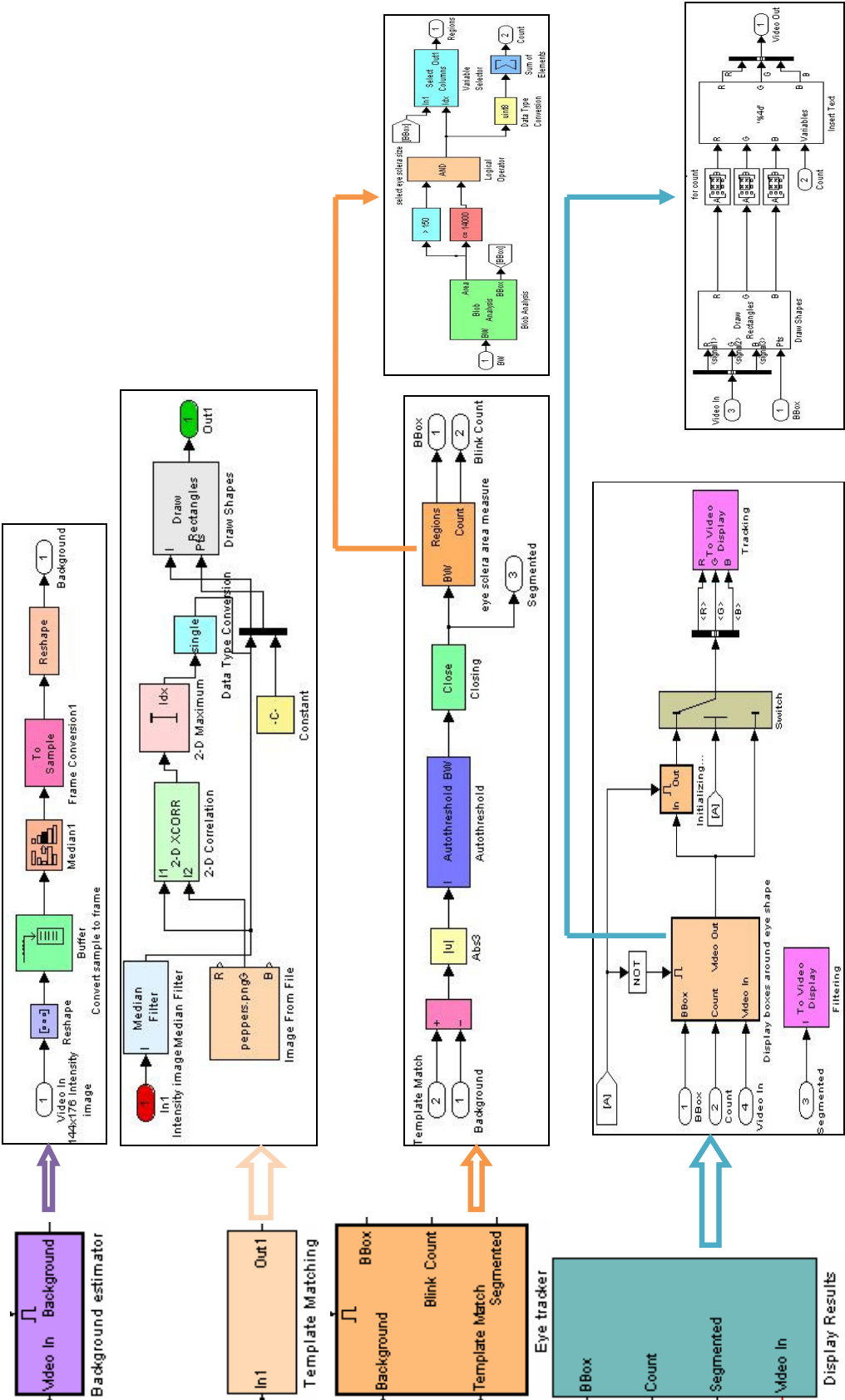


Figure 5-4 (b): Complete eye blink detection system, MATLAB Simulink



### **5.5.1. Video Capture and Conversion**

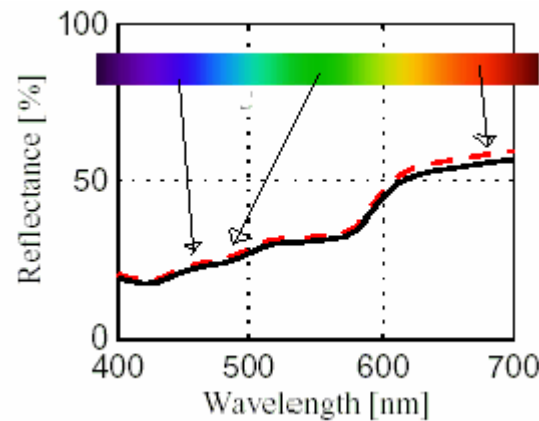
Large amounts of noise appear if the image of the eye is binarized with an inappropriate threshold. Together with the fact that the threshold varies for different areas around the eye, this comprises a serious obstacle to successfully tracking the eye sclera area. Image noise frequently occurs when the eye lids are closed. The ability to cope with a range of varying lighting condition is a challenge for segmentation. The background light will strongly affect the tracking of the eye sclera section (white area) from sides from the eye.

#### **5.5.1.1. Effect of changing illumination in detection**

Eye sclera area variations are used to detect blink and blink duration. The intensity change on the face is a crucial effect because it will increase the intensity on eye lashes. This links to segmentation of the eye outer area and sclera area and its effect on detection. Since this design is a prototype, a controlled lighting area was set up for testing. The proposed technique to overcome the problem of changes of illumination is the low light reflection method. Considering the lowest reflection colours from human skin helps to design this system (see Appendix B2, human skin properties). The green light is the lowest reflection colour from the skin (Brill & Finlayson, 2002), and controlled illumination conditions will help to overcome the skin reflections problem. Table 5-1 shows the spectral reflectance curves of skin and average and extreme skin spectra for different skin groups. The skin spectra between the groups are mainly separated by a bias. Therefore, assuming a reasonably linear camera, all skin chromaticities are very close to each other (Brill & Finlayson, 2002).

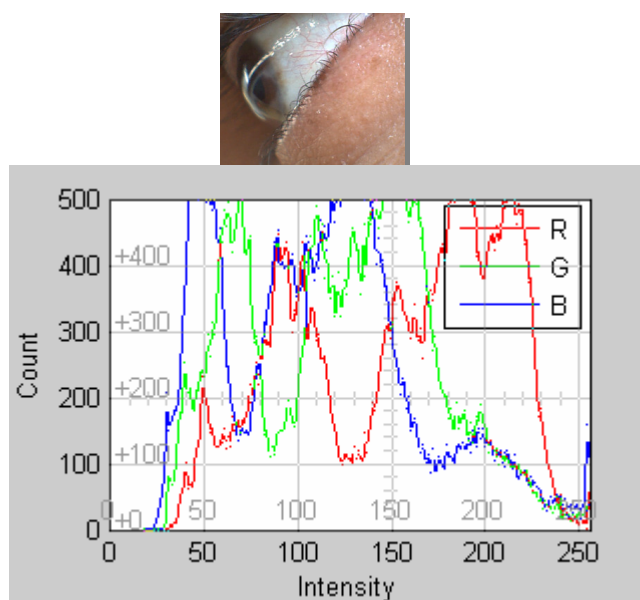
Use of low emitting green LED and increase of green value in RGB colour control in the camera will overcome this problem.

**Table 5-1: The spectral reflectance curves of skin (Wyszecki & Stiles, 1992).**

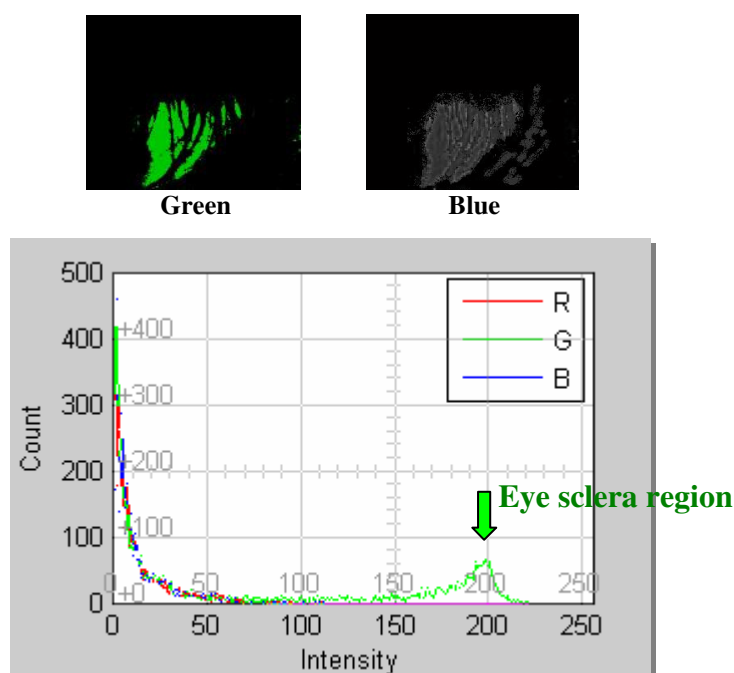


Low surrounding light (ambient light) is also important, since the only significant light illuminating the eye sclera area should come from the green LEDs. The background light change has a greater effect on RGB (colour) image analysis. To overcome this problem, the capture hardware properties were adjusted by reducing Red and Blue colour intensity and by increasing Green intensity to illuminate the eye sclera area (according to skin reflections). This setup is more effective and reduced the capturing of bright skin areas around the eye comparable to eye sclera. Figure 5-5 (a) and (b), illustrate the difference between colour RGB images and intensity increased green image conversion. The system was tested for blue light, which is lower than green reflection from the skin, but it did not show better results compared to green light. The blue light reduced the eye sclera intensity (see Figure 5-5(b) top right image, grey image of blue light condition). Figure 5-5 (a) shows the RGB Histogram for captured eye image in normal condition. The 'X' axis represents the intensity range from 0-255, where 0 represents RGB-dark intensity and 255 represents RGB-light intensity. The 'Y' axis represents the count of number of bins

(binary units) on each RGB colour intensity distribution all over the image. In colour image of the eye, the graph of intensity values spread through the range 0-255, where the difficult to separate eye sclera white area is in the 180-250 range.



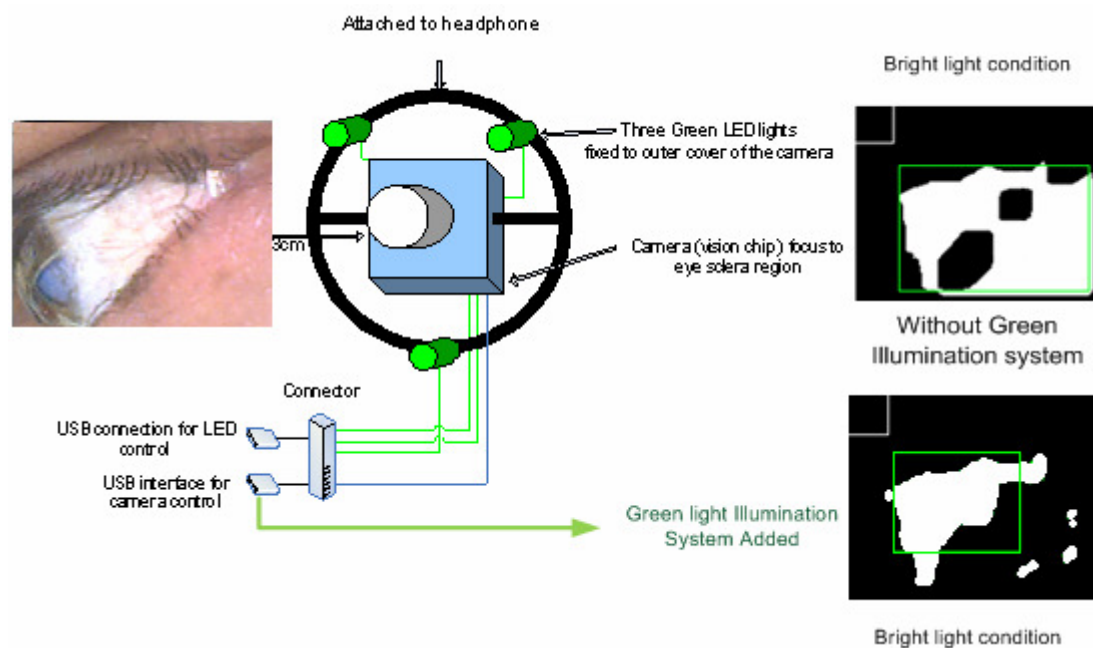
**Figure 5-5(a): RGB histogram of captured eye colour (RGB) image without the Green light system**



**Figure 5-5(b): Intensity increased and Green light system image (left), Blue light image (right) and RGB Histogram (bottom).**

Figure 5-5 (b) shows the increased green intensity and green LED systems applied to the same eye images. The captured image clearly shows the eye sclera area from other regions around the eye. Both images (colour and green intensity increased) were captured in the same background intensity conditions. In Figure 5.5 (b) the RGB Histogram graph shows the majority of the RGB intensity values ranged between 0-50 (black area in image), and green intensity bins peak at an intensity value of 200. This illustrates a clear separation of the eye sclera regions, making it easier to automatically set threshold levels for segmentation.

Figure 5-5 (c) shows the captured RGB image and green illumination system added images converted to binary image in the final sclera tracking stages for analysis. It clearly indicates that the green illumination system filters the skin reflections and enhances the sclera region for segmentation.



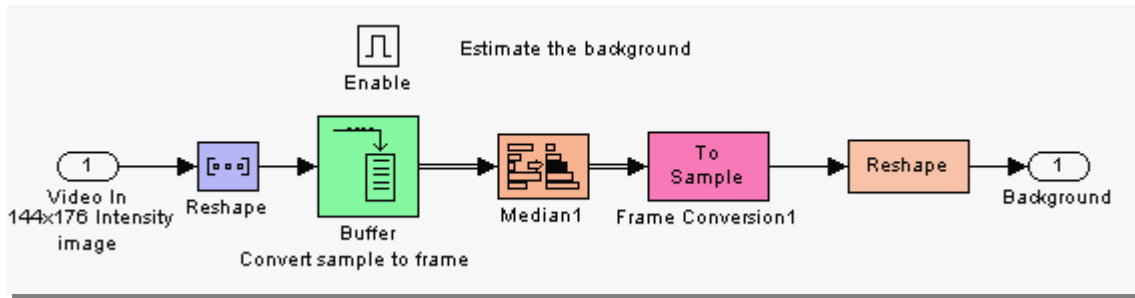
**Figure 5-5(c): Eye images with and without green illumination**

The primary RGB video block output in the blink detection system (Figure 5.4 (b)) is converting to an intensity (Grey) image. The irises of the eye appear as relatively darker objects than eye sclera and their respective surroundings (Brunelli and Poggio, 1993). Thus, we can use intensity valleys as the separation regions to detect eye sclera regions. The grey conversion is given with R' G' B' values in equation (5-1) using the standard parameters for conversion:

$$Intensity = [0.299 \quad 0.587 \quad 0.114] \begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} \quad (5-1)$$

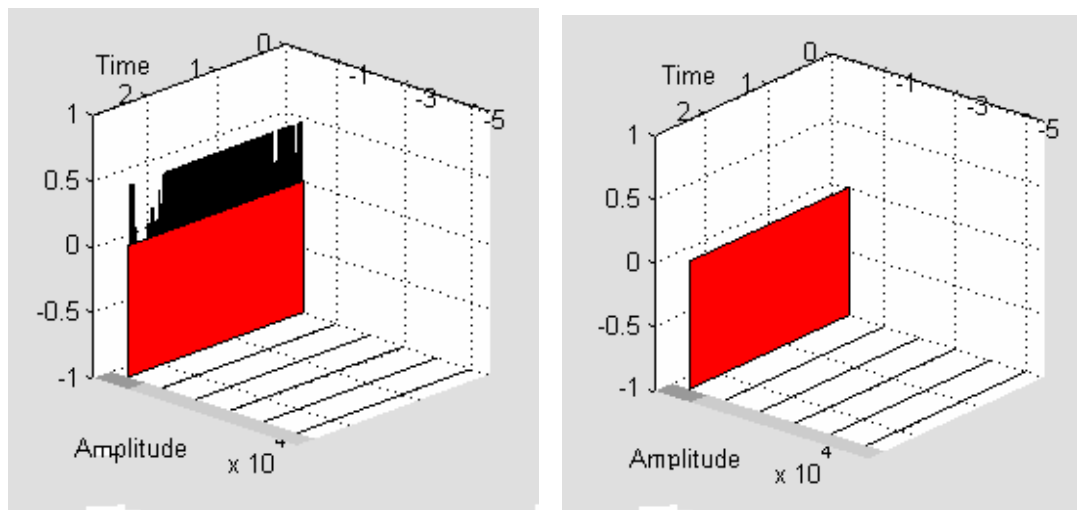
### 5.5.2. Background Estimation

To separate the foremost motion fragment (eye blink) from other small muscle movements around the eye it is important to measure eye blink precisely. A background estimation method is then imperative to revoke small muscle movements disquieting to eye sclera area measurement. The filtering of small amounts of movements around the eye will generate stable images. These small movements change the skin reflections. Figure 5-6 illustrates the modified version of the background estimation process for generating stable images. The modifications have been made to control the requirements to the background stabilization process in this research. Captured RGB video is converting to Grey image (intensity image) for foremost analysis, and the first few frames of the video stream are used to estimate the background image. It subtracts the background from each video frame to produce foreground images.



**Figure 5-6: The background estimation process, Simulink control diagram.**

The Eye lid moves vertically and the small muscles near the upper and lower lids move horizontally. In figure 5-6, the reshape block changes the dimensionality of the input signal of images by converting a matrix input signal (144x176) to a row matrix, i.e., a 1-by-N matrix where N is 176. The original frame size is then reduced to 1-by-176. Figure 5-7 illustrates the buffer process creation of slow frame output (stabilized image). This process removes the small movements around the eye to create stabilized output for stable eye blink detection.



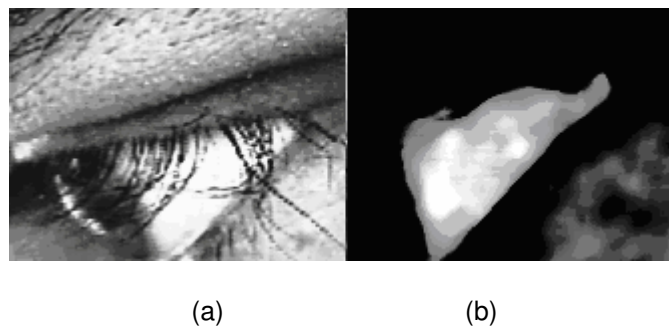
**Buffer input: black peaks shows the small movements**

**Buffer output: filtered output**

**Figure 5-7: Background motions slowing process (Matlab Help, 2005).**

### 5.5.3. Template Matching

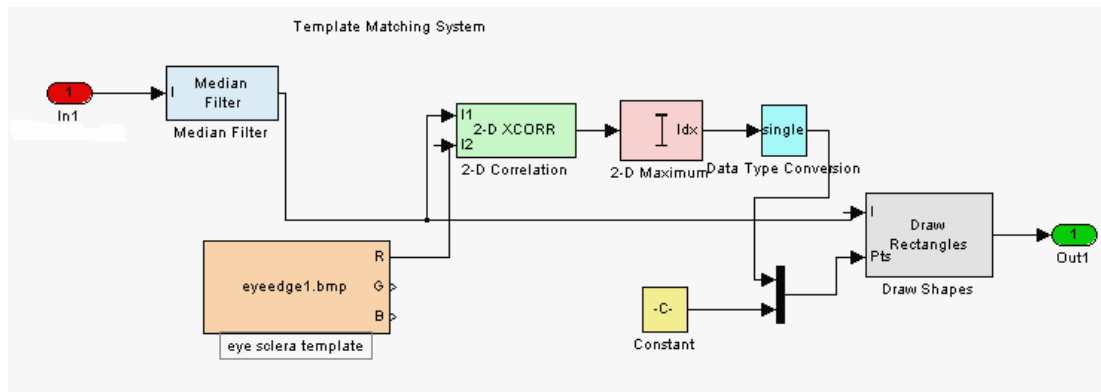
Another step performed before tracking is started is the template matching to identify the eye sclera area. Considering all the existing and ongoing research systems for eye tracking from the front of the eye (Eriksson & Papanikolopoulos, 1997; Gonzalez, and Woods, 2002; Grace, et al., 1998, Perez, et al., 2001; Singh & Papanikolopoulos, 1999; Ueno, et al., 1994; Weirwille, 1994), the foremost disadvantage in the detection of the eyes from the front, with systems using head mounted or spectacle mounted devices, is the disturbance to the participant. Especially, in driver drowsiness analysis, it will cover the driver's front view. Detecting blink from the side of the eye is then important, as it does not disturb the driver. Figure 5-8 shows the side view of eye, and sclera area (white area of eye) and the grey scale morphology with segmentation of sclera regions. This shape is common for all people but the area is different. For a confident tracking system it is then important to detect the clear eye sclera area.



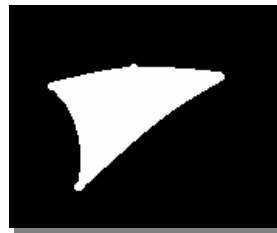
**Figure 5-8: (a) Side view of eye, (b) Grey scale morphology of captured eye sclera area.**

To locate the eye sclera area, a modified pattern matching system is to be used before the blink detection process. Figure 5-9 illustrates the template matching system, using a Simulink block diagram. Figure 5-10 shows the eye sclera template (binary

template for template matching). This process will track the eye sclera region with the use of cross-correlation for pattern matching and to help to clear the noise around the sclera region.



**Figure 5-9: Template matching Simulink block diagram.**

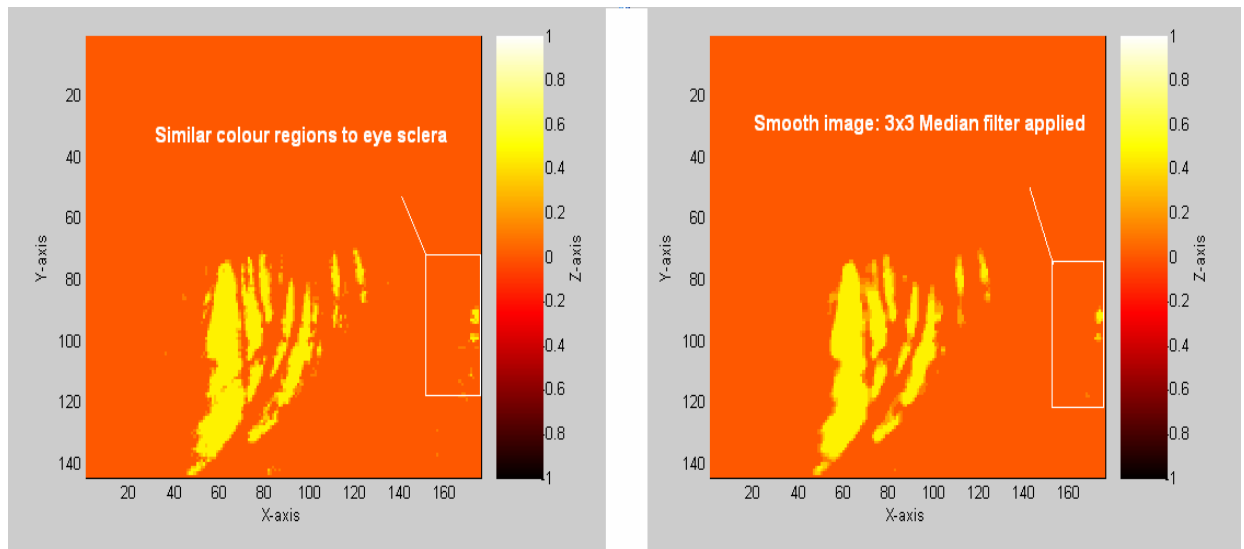


**Figure 5-10: Eye sclera template (binary image for template matching)**

Noise suppression or noise removal is an important task in capturing eye images. The median filter (3x3 windows) is applied to grey scale images in the template matching processes. The median filter is a nonlinear operator that arranges the pixels in a local window according to the size of their intensity values and replaces the value of the pixel in the result image by the middle value in this order. The problems occurring here are located to the similar colour regions. For example some bright images (intensity towards 255) give intensity regions around the eye similar to the eye sclera regions. Consider the following example: Figure 5-11 shows the grey image with similar colour regions to eye sclera area (Left) and 3x3 neighbourhood size median

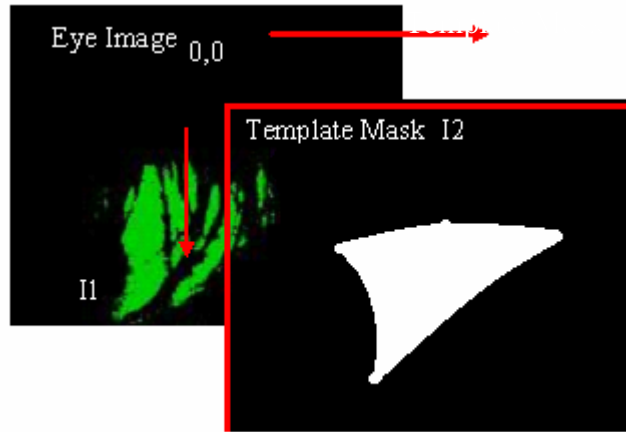


filter applied images (Right). A potential solution to reduce the size of similar coloured regions is to increase the neighbourhood matrix size but this solution creates another problem of image analysis speed. Also it reduces the eye sclera area and effect to the ‘natural’ triangular shape. The 3x3 neighbourhood size median filter was selected to overcome this speed problem.



**Figure 5-11: Left-Gray image matrix view with similar colour regions to eye sclera, and Right- 3x3 Median filter applied image (Image smoothing)**

Furthermore, median filtering generates smoother images by eliminating impulsive and high frequency noise. Then the template matching will protect the eye sclera region and remove the noise around the eye image. Consider the image below (Figure 5-12) when the eye images and the mask are shown in a red outline. The figure 5-12 shows the template mask, 144x176 pixel sizes and cross correlation calculated (see figure 5-9, cross correlation and template matching).



**Figure 5-12: Eye image and Template mask**

The peaks in this cross correlation ‘surface’ are the positions of the best matches in the image of the mask. The I1 (eye image), the first input matrix, has dimensions (144,176). I2 (template mask), the second input matrix, has dimensions (144,176). Then the 2D-XCORR (comparison of normalised correlation score, compare template mask with target image in pixel overlapping method) function returns the  $C_{full} = 287 \times 351$  dimension matrix, when the block uses the following equations (5-7) to determine the number of rows and columns of the output matrix.

$$C_{full} = I1_{rows} + I2_{rows} - 1 = 144 + 144 - 1 = 287$$

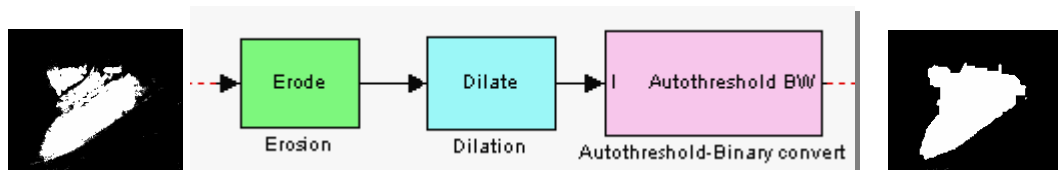
$$C_{full} = I1_{columns} + I2_{columns} - 1 = 176 + 176 - 1 = 351 \quad (5-7)$$

The calculation of cross correlation for the elements of the above matrix used cross correlation equation (see Appendix B1, cross-correlation). This cross correlation process is double the size of the input image when analysing. The output is converted back to 144x176 pixel images.

The following problems are evident:

- This process is very similar to 2D filtering except that the image is replaced by an appropriately scaled version of the correlation surface.
- Eye lashes in the input image will affect the triangular sclera shape (see Figure 5.11). This will affect the identification process, and the mask will not match with the target image.

In this template matching process, the eye lashes affect the sclera region. To resolve these issues, a morphological operation (Dilation and Erosion) technique is added to the median filtered images. By choosing the size and shape of the neighbourhood, the morphological operation is sufficiently sensitive to remove eye lashes in the input image. The 2D-Maxima block identifies the value and/or position of the largest element in each input matrix or in a sequence of inputs over a period of time. This process is used to verify the eye sclera output and includes additional filtering to clear the small vivid areas in backgrounds.

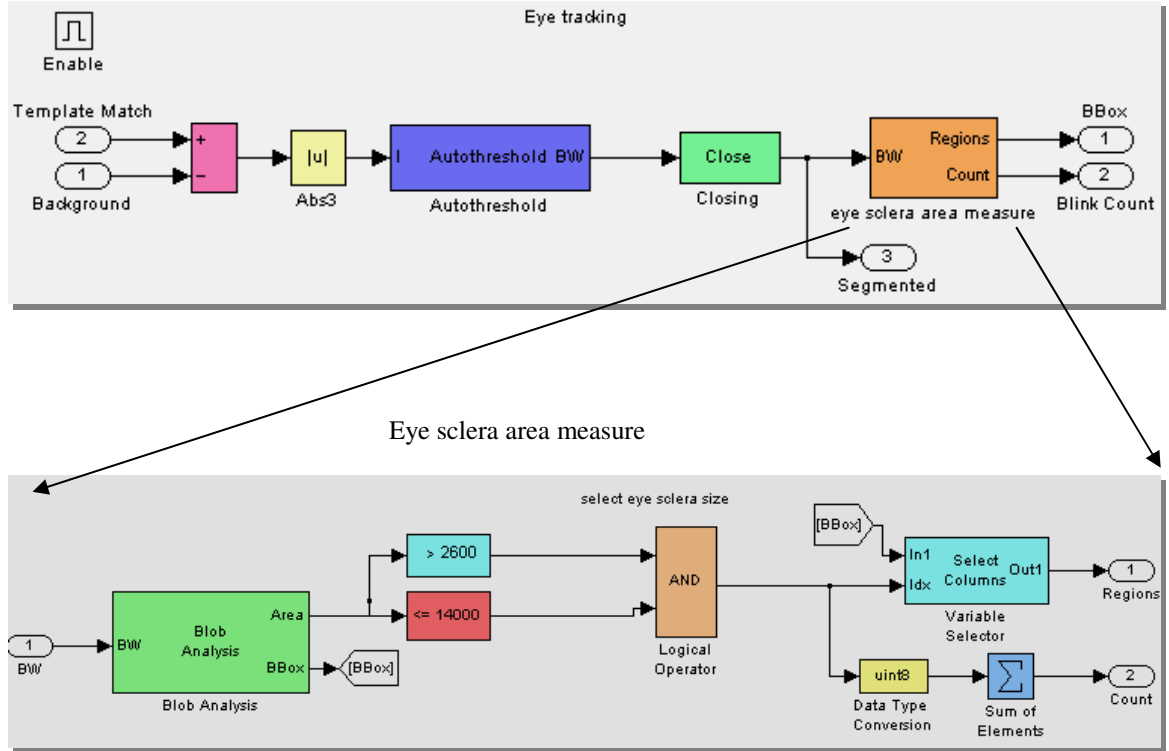


**Figure 5-13: Constructed morphological operation to remove eye lashes.**

Figure 5-13 illustrates the constructed morphological operation to remove eye lashes. The ‘Opening’ (Opening process performs an erosion operation followed by a dilation operation using a predefined neighbourhood or structuring element) morphological techniques are applied to the median filtered Grey images (Figure 5-13, Left) and the binary image conversion is used to enhanced the image quality

(Figure 5-13, Right) (for more details of Opening technique, see Appendix -C1).

Figure 5-14, shows the tracking process Simulink diagram.



**Figure 5-14: Eye blink tracking process (above), and eye sclera area measure process (below)**

Subtracting the background estimate output [1] from the template matching output [2] will give a stable image with large elements. The 'Erosion' process will remove the pixels from the edge of the object, and 'Dilation' will add pixels to the object. This process will remove the eye lashes and fill the gap with white pixels similar to the eye sclera region. Figure 5-15 (a) shows the erosion process and (b) shows the adding of dilation process. This will reshape and smooth the eye sclera region by filling the gaps in the sclera area.



**Figure 5-15: (a) Binary image before adding morphological Closing, (b) after morphological Closing**

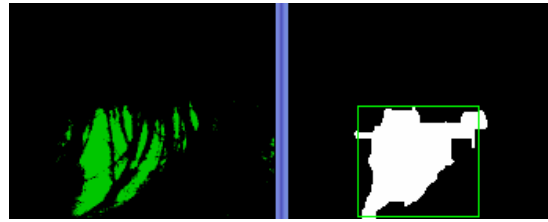
#### 5.5.3.1. Blob Analysis technique

The Blob Analysis method calculates statistics for labelled regions in the binary image and returns the area of each element. With ‘rough’ searching, the eye sclera area can be envisaged as connected blobs. While approximating a blob shape by use of an ellipse, the area was calculated (Horn, 1986) (see Appendix B1 for eye sclera area calculation equation). The Blob analysis technique in MATLAB has standard blocks for area calculation. The best match for eye sclera region detection is the ellipse shape.

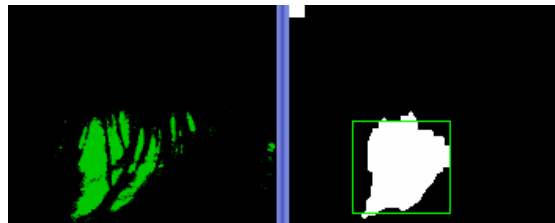
Parameters of the ellipse such as shape, aspect of short and long axes, and the size of area are used to decide the area of eye sclera section. The captured eye blink in three different stages is shown in Figure 5-16 (a), (b), (c).



**Figure 5-16 (a): Full opened eye sclera region, image from left- (i) captured eye sclera image using green illumination system, (ii) Blob analysis tracking image.**



**Figure 5-16 (b): half way closed eye, eye sclera area reduced in binary image**



**Figure 5-16 (c): captured 3/4 of closed eye**

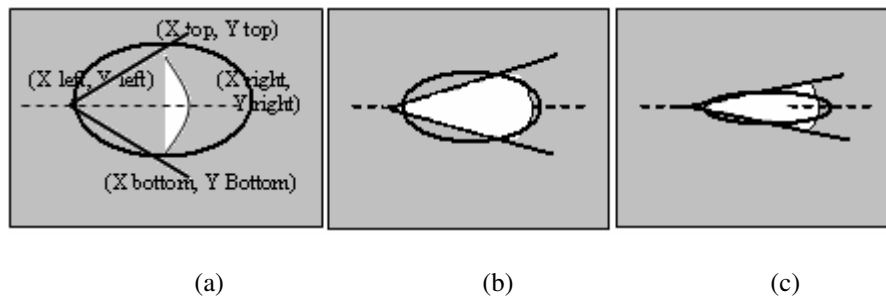
In the Blob analysis technique (the technique calculates statistics for labeled regions in a binary image) for tracking and measuring the eye sclera area, the major and minor axis lengths have been calculated to design a common threshold to detect blink for different people having different sizes of eye sclera region. The procedure is as follows:

- Estimate common threshold level for measuring the eye sclera area to detect blink duration.
- Threshold level needs to readjust for different participants with reference to their eye sclera area.

This PhD research considered the displacement and speed of blobs for behavioural state estimation. The eye region consists of the upper and lower eyelids and eyelashes (for blob detection, see Figure 5-17 (a)). In the detection process, the eye region has been divided into upper and lower portions. The intensity distribution is changing when the upper and lower portions of the eyelids close and open during blink. When the eye lids are closing the sclera area is reduced, and when the eye lids

are opening the area increases. This concept is used to calculate the eye blink duration. The blob analysis starts to measure blink duration when the eye lids shuts to half - to full close - to half open. This procedure is considered as a complete eye blink. The major and minor axis lengths of the ellipse change according to eye sclera region changes as illustrated in Figure 5-17 (a), (b) and (c).  $(X_{left}, Y_{left} - X_{right}, Y_{right})$  is the major axis coordinates and during the eye close this axis will reduce. The minor axis coordinates are  $(X_{top}, Y_{top} - X_{bottom}, Y_{bottom})$  and will reduce during the eye close. These lengths change within the range  $\{X_i, Y_i; i = \text{left, top, right, bottom}\}$  from the full eye open to full eye close, and the range of the axis changes is given in the following equation.

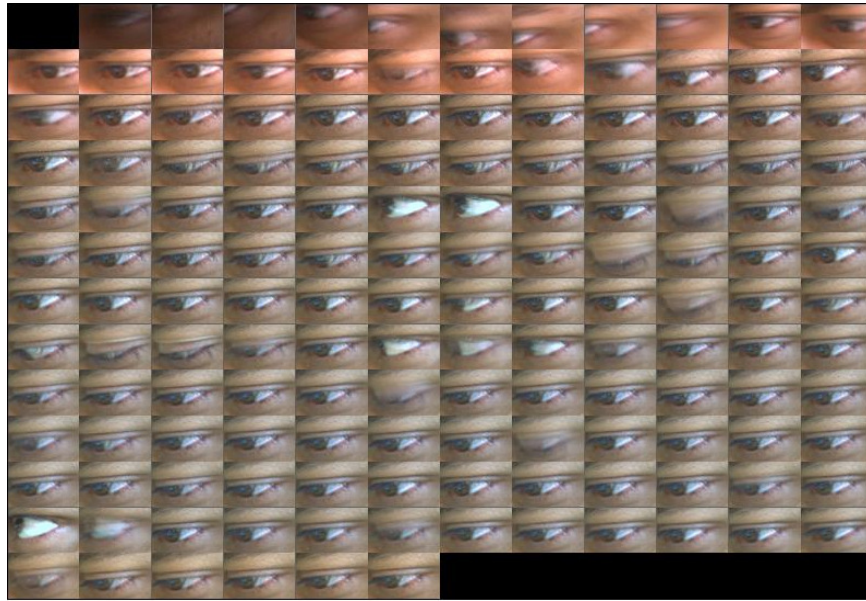
$$I(x, y) = \left\{ I(x, y) \mid x_{left} \leq x \leq x_{right}, y_{top} \leq y \leq y_{bottom} \right\} \quad (5-8)$$



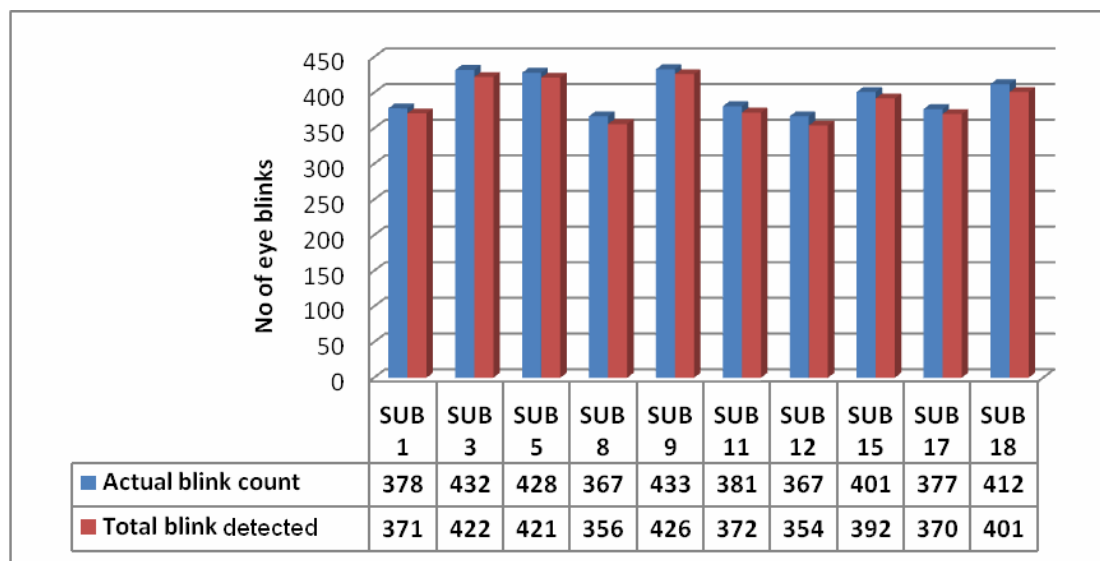
**Figure 5-17: (a) The Blob detection model of eye sclera region detect using ellipse method, (b) Half eye close position, (c) quarter of eye close position.**

Figure 5-17 (a), (b) and (c) illustrate the three positions of eye closure. The next position after (c) is full closed image and it appears as a blank image in detection. To measure the accuracy of the blink detection system, the total blinks during the 40 minute simulator test were manually counted for randomly selected ten participants and compared with the total blinks counted from the system. Figure 5-18 (a) shows

an example of captured video file conversion to frame by frame image file for manual blink count. Figure 5-18(b) shows the actual eye blink count and the eye blink count from the system. The average of the actual blink count for ten participants was 397.6 and the average eye blink count from the system is 388.3. The error was 2.3% and the accuracy of the detection system was 97.7%.



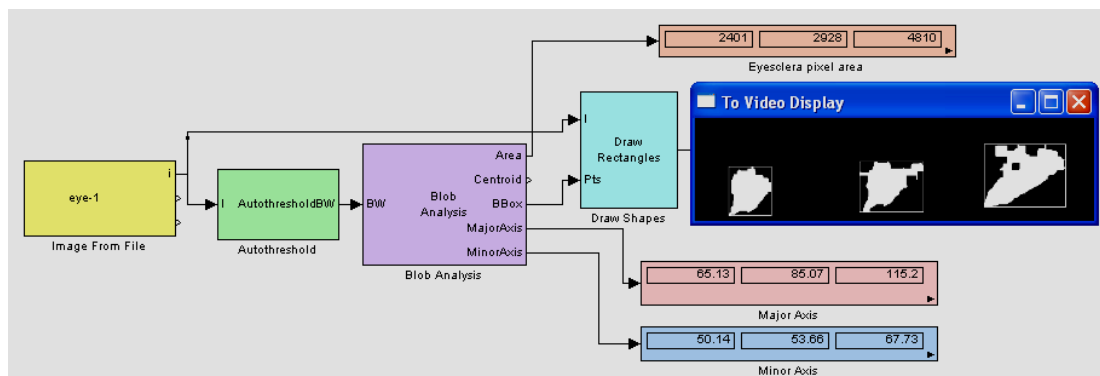
**Figure 5-18 (a): Frame by frame eye images used for the blink count.**



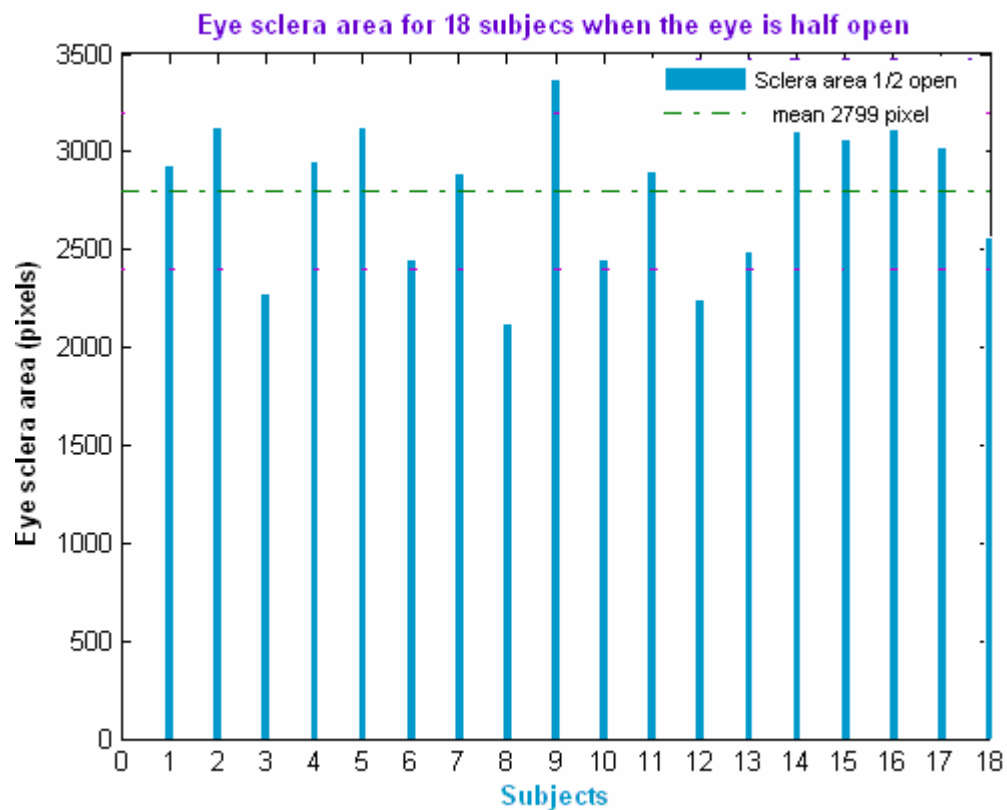
**Figure 5-18 (b): Frame by frame eye images used for the blink count.**



In the validation of a common threshold pixel value for the eye sclera region (full eye open), the Simulink model was designed to measure different eye sclera regions in the half eye open position for all participants. The average pixel area of the half eye open position was quantified to select the common threshold for all participants. The Figure 5-19 illustrates the Simulink model designed to measure the eye sclera area for different sizes of sclera regions (i.e., Figure 5-16 (a), (b) and (c) shows binary image sclera region selected to quantify the pixel area from quarter (1/4) eye open to full eye open. The pixel area change 5-16(a) 3410 pixels (full eye open), 5-16(b) 2928 pixels (half eye open) and figure 5-16 (c) 2401 pixels (quarter eye open). The Blob detection ellipse axis change, according to the above positions [(a), (b) and (c)], is [(67.73, 115.2), (53.66, 85.07), (50.14, 65.13)]. Figure 5-20 shows the calculated eye sclera area for eighteen participants when their eyes are half open. The mean eye sclera value for all participants = 2799 pixels and the SD of sclera area is for all participants = 394.3 pixels. The eye sclera area in full eye open position for all participants is averaged to make a common threshold value for eye blink detection. The common threshold value is 3000 pixels, and this value was calculated by adding the participants' mean sclera value to participants' SD of sclera area ( $2799 + 394 = 3193 \approx 3000$  pixels).



**Figure 5-19: The Simulink model designed to measure different size of eye sclera regions.**



**Figure 5-20: Eye sclera areas for eighteen participants for half eye open.**

## 5.6. Eye blinks duration and blink frequency calculation.

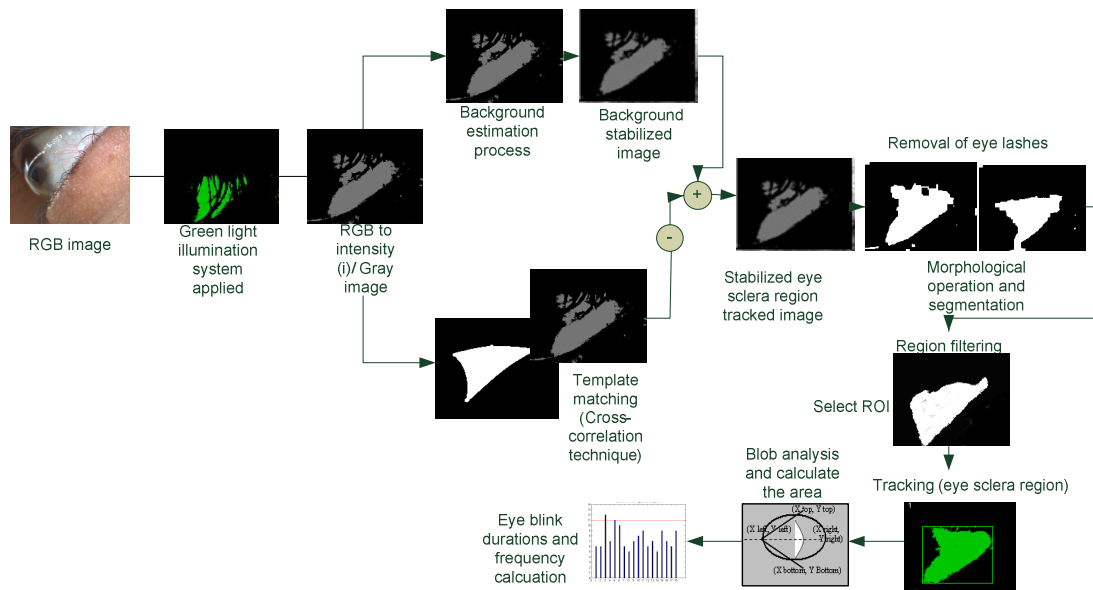
The eye blink duration and blink frequency calculation procedure shown in figure 5-4 (b) is the output from a 'Blink Count' test that employs a static lower bound function to filter any lopsided eye blink durations formed when participants touch their headphone camera system during the simulation. This filtered signal is used to calculate the eye blink duration, frequency and average eye closure. The 'Moving Average' block computes the average of a user-determined number of samples of the input signal, which are all evenly-spaced in time. The average is 'moving' in time, because at each sample time the oldest sample is replaced by a new sample,

according to the 'last in, first out' principle. All the data are displayed graphically and saved to MATLAB data file formats for further analysis.

## 5.7. Summary

Most of the eye blink detection algorithms previously reported use image normalization, eye tracking, and eyelid movement parameters computation, face pose discrimination, and gaze at estimation. However, such algorithms require the edge difference to measure the changed block of eye blink in the video stream. The eye blink detection system proposed in this research uses background estimation and template matching to measure eye blinks durations and frequency. The proposed system uses a combination of image processing techniques to measure eye blink that have not been used previously for eye blink detection. A particular innovation is that the eye sclera region changes are measured according to upper and lower eyelid closing and opening, as assessed by eye blink duration. This system does not depend simply on detecting long eyelid closures as the measure of drowsiness, as used with other drowsiness detection systems. Figure 5-21 illustrates the complete eye blink detection system. The step by step procedure is:

- Green light illumination system is applied in natural light condition.
- RGB (Green illumination) image conversion to grey image.
- Background estimate process to remove minor movements around the eye.
- Template matching process to filter background noise around the eye sclera region.
- Morphological operation for removal of eye lashes.
- Region filtering and Blob analyses to calculate the eye sclera region.
- Calculate eye blink duration and frequency.



**Figure 5-21: Complete eye blink detection process**

The green light illumination system proposed in this research has not been used previously in any video detection system. This method prevents the effect of changes of illumination in the detection environment and does not disturb the participant.

The system is highly reliable in measuring eye blink durations and frequency. This system has been used by eighteen participants for many hours per day, without inconvenience or interference with their driving in the simulator. It is easy to use and close to the eyes, and head movement does not affect the segmentation process.

The second most important factor in driver drowsiness detection is the measures of driver performance. The next chapter shows an attractive approach to measuring driver performance using a simple and safe driving simulator. This chapter will explain the driving simulator system and the reaction time measurement system.

## **CHAPTER 6**

### **INITIAL DROWSINESS EXPERIMENT:**

### **THE DEVELOPMENT OF A DRIVING SIMULATOR**

## **6.1. The Driving Simulator**

Driving Simulators are used for entertainment as well as for driver training and research purposes. This research monitors driver behaviour and performance, and measures attention. During the development of the driving simulator, two simulators were designed to measure the driver's performance and reaction time. The main simulator was used to measure driver performance and the second simulator was designed to measure reaction time.

Consideration was given to the equipment cost and the accessibility of these simulators. Designing a simple simulator is more reliable and less expensive. The design of a simple driving simulator to measure driver performance is important in driver drowsiness detection.

The most advanced driving simulator in the UK is at the Transport Research Laboratory (TRL) in Berkshire (Transport Research Laboratory simulator, UK). TRL's driving simulator has been designed based on a Honda Civic family hatchback car. An electro mechanical system fixed to the vehicle drives its engine and major mechanical parts and contributes towards creating real driving scenarios. All control interfaces have a realistic feel and the manual gearbox can be used in the normal manner. Surrounding the simulator vehicle are three large display screens connected to an oval shape to create a highly realistic surrounding effect for the driver. The level of environmental detail includes photo-realistic images of buildings, vehicles, signing, and markings, with terrain accurate to the camber and texture of the road surface (Parkes, et al., 2002). This simulator system helped in identifying the requirement for a virtual driving simulator to be developed for this research.

## **6.2. Experimental design**

### **6.2.1. Virtual-Reality-driving simulator**

The objective of designing the driving simulator for this research is to develop reproducible and flexible methods for studying the relationships between physiological driver states and performance in a realistic driving environment. Initial experiments were conducted with 18 healthy male and female participants aged 20 to 70 in carefully controlled conditions.

The virtual reality (VR) 3D interactive vehicle scenes were developed using the MATLAB Simulink software. The virtual reality tools were used to create models of various objects (such as cars, roads, and trees) for the scene and to set up the corresponding positions, altitudes, and other relative parameters between objects. Dynamic models were placed among these virtual objects and a complete road simulated scene was built with the aid of high-level C-based Simulink function (S-function) models. Figure 6-1 shows a typical VR-based road scene displayed on a colour XVGA 17 inch monitor. The road system is designed with a double lane separated by a middle stripe. The distance from the left-hand side to the right-hand side of the road is evenly divided into 256 parts (digitized into values 0-255) and measured in centimetres.



**Figure 6-1: VR- based simulator screen**

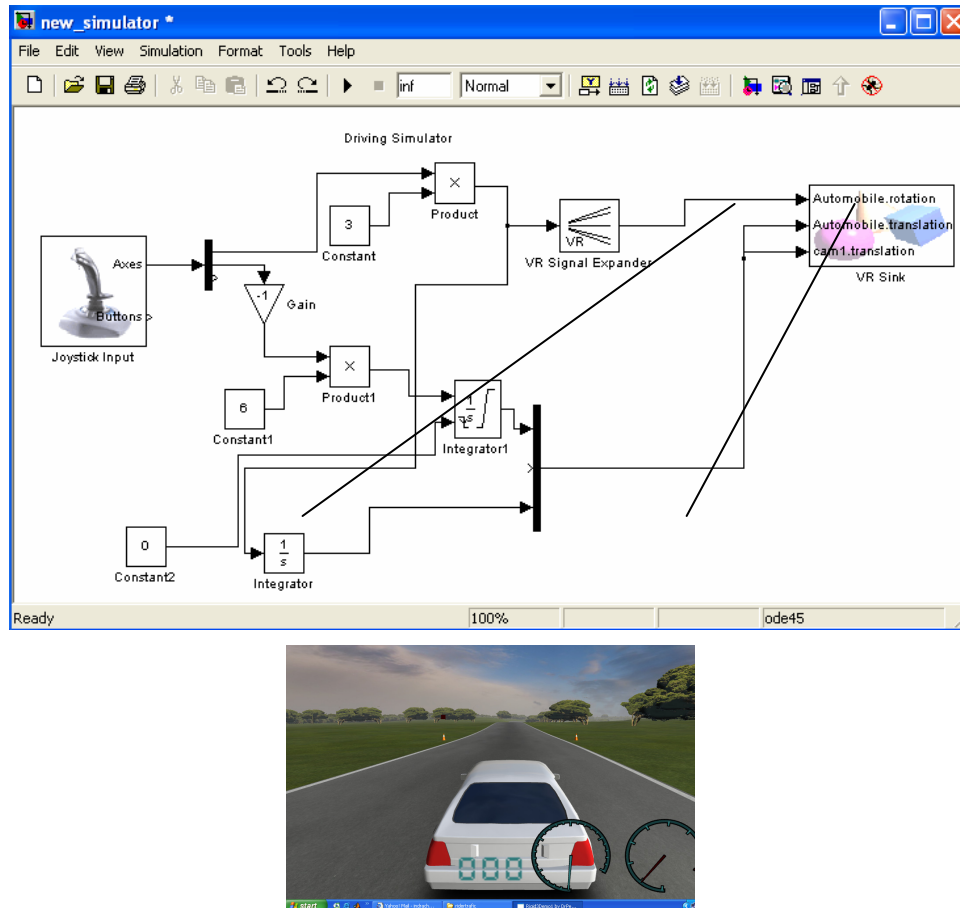
Figure 6-1 shows the main simulator screen. The simulation of vehicle movement, vehicle speed, revolutions per minute and time (driving time) is displayed on the screen and can be adjusted to user requirements. The simulation view can be adjusted with a simulated dashboard display as well as full road view or full vehicle view modes. These forms of vehicle intelligence influence the vehicle's motion through simulated commands to the accelerator, brake and steering wheel. The VR-simulator user interface provides facilities for visualizing and influencing the interactions with the virtual environment. The tactical-level focus in the VR-simulator directs a number of choices. The virtual environment changes the scenario randomly during



the drive. Additionally, colour light (traffic light) controls were displayed at the end of the loop (track) and the reaction to the light changes was monitored.

### 6.2.2. Architectural Design of the VR-Simulator

**Experiment Layout:** The overall architecture of the VR- simulator model was designed using MATLAB Virtual Reality tools. The VR- simulator measures car deviations from centre line, average speed, maximum speed, out of bounds and reaction time for traffic lights and records these parameters every 10 seconds. Figure 6-2 shows the V-Realm virtual reality tools used to interface hardware components and display. The hardware configuration being used was specified. Special attention was paid concerning the selection of the graphics card. The bottleneck in system operation was the scene rendering, which is directly related with the graphics card performance. Therefore, a high-end graphic display model (GeForce 6200 TurboCache, 256MB dual VGA out with Direct X 9), which is compatible with dual VGA display and high resolution, was selected. The configuration of the main simulator is more complex because of the control of the virtual reality tools in Simulink. At this level a second dedicated PC is used for reaction time measurements of the simulator. The automotive design features in the V-Realm database are composed of two types of objects: car interior (shift gear, steering wheel, pedals, and mirrors) and environment objects (streetlights, road signs, autonomous vehicles, and lamppost). Hidden surfaces have been removed and visible surfaces have been minimized in order to increase the graphic speed.



**Figure 6-2: Overall architecture of the driving simulator.**

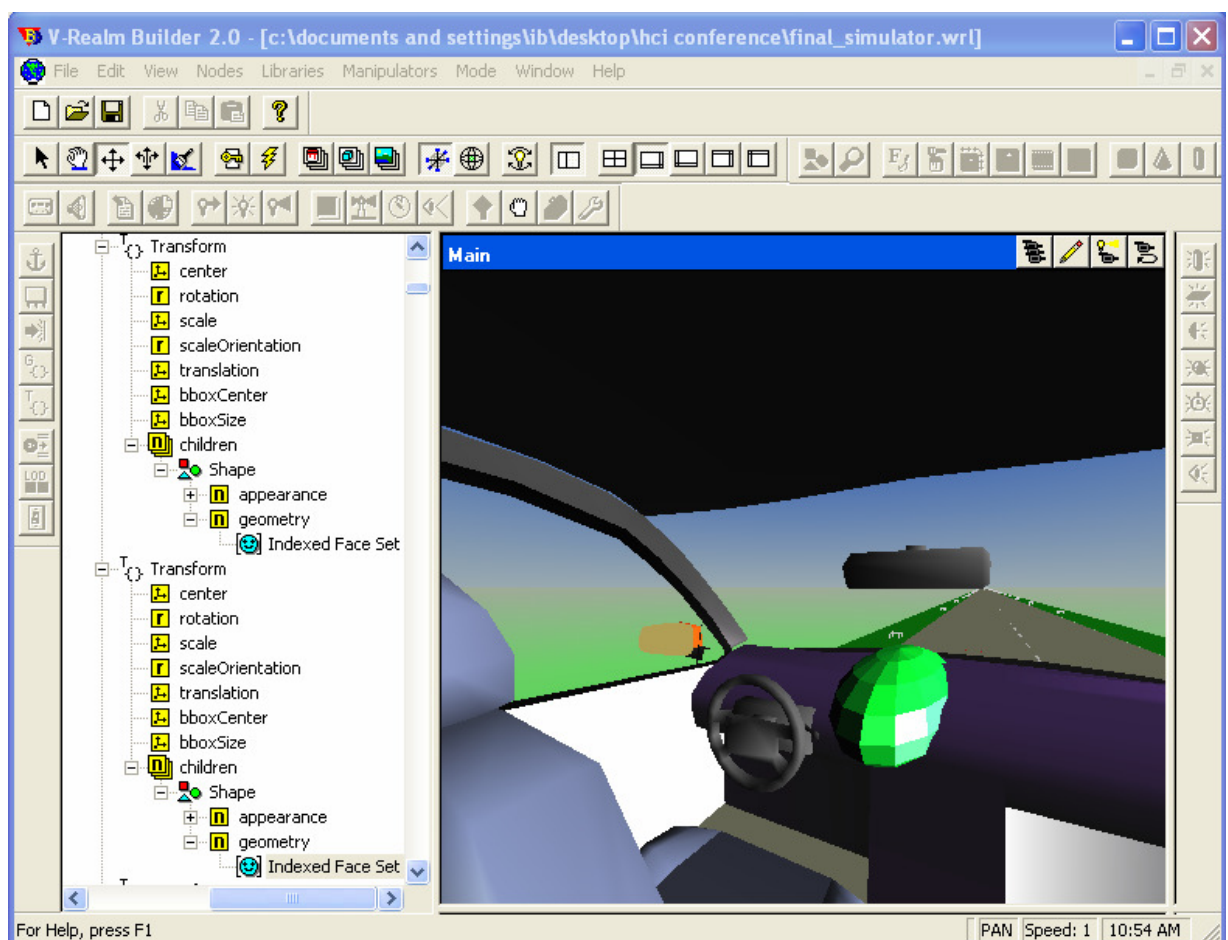
The V-Realm builder conceptual architecture, shown in Figure 6-3, presents the overall software architecture of the entire driving simulator in order to highlight the programming method with MATLAB Simulink. As illustrated in Figure 6-4, the link between hardware components (e.g. steering wheel, push buttons and paddles) and the rest of the interactive system interface is through the USB and virtual object control in VR Simulink software.

This database is composed of:

- Objects of the car interior: steering wheel, gearshift, and mirrors used by the FIAT model. These models correspond to a real car. The automatic gear system was designed to minimize the complexity of

the interface devices to control the simulation. Three main views can be selected according to the participant's performance.

- Outdoor objects (road, trees, buildings and traffic lights). Some of these objects have extended features to simulate environmental changes (clouds and light). The animation of the car and the outdoor objects are controlled by the behavioural module (section 6.2.3).



**Figure 6-3: V-Realm builder virtual reality interface**



**Figure 6-4: Hardware interface devices**

### 6.2.3. VR Behavioural Module

The VR-simulator provides users with several interactive scenario control features. It allows users to change basic parameters of the selected vehicle such as viewing angle, velocity and position. The design allows users to use “Pause” and “Play” options during the simulation. All the scenarios during the simulation are saved to disk and can be played back. The basic control of the loaded objects of the scene are already specified and implemented. This relates to the control of the vehicle’s motion (the user and the autonomous cars), the control of the user’s car devices (steering wheel, brakes, accelerator), and the control of other scene objects such as traffic lights, clouds and illumination.

### **6.2.3.1. Shapes**

Creating shapes with VRML is achieved by defining coordinates in space and connecting them in order to create surfaces. Some basic shapes are already implemented, and these shapes are used to create the driving environment. For example a box, a cone, a cylinder and a sphere are ready to use. Shapes can also be made by hand and inserted into the surfaces that form the shape together. This can be achieved in 'V-Realm Builder'.

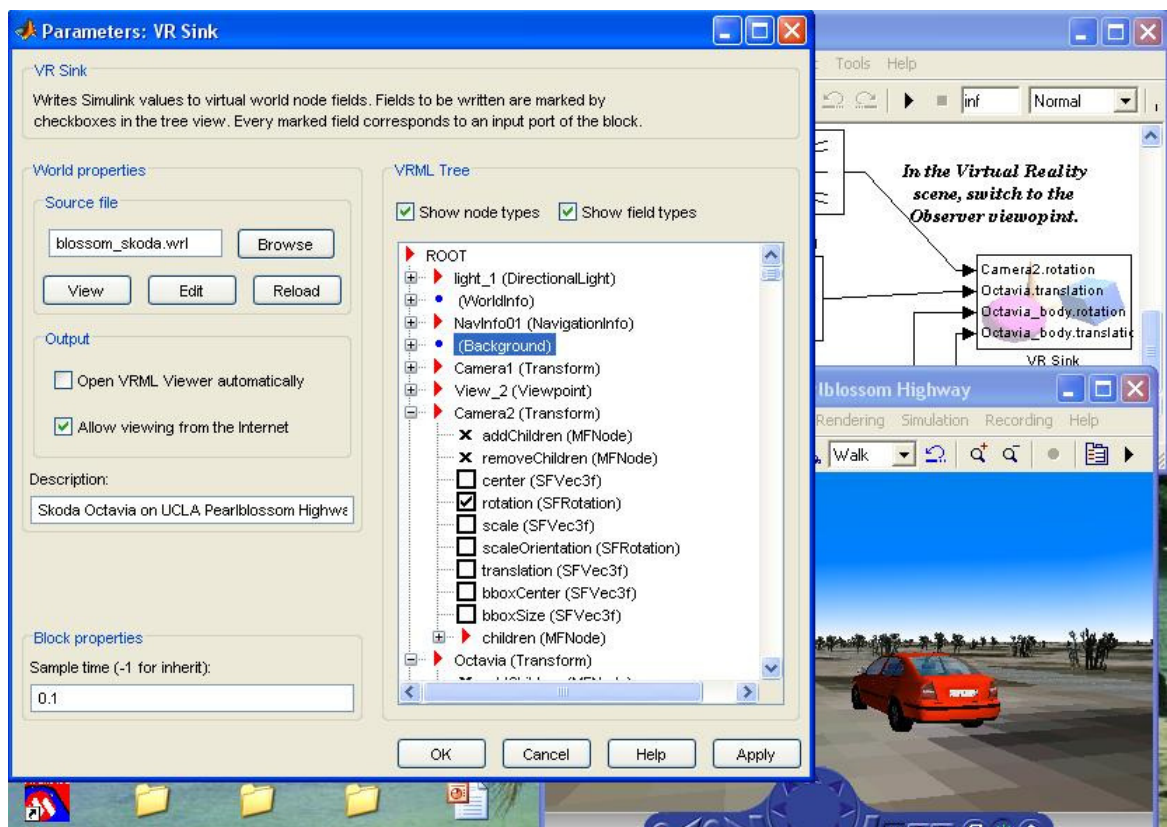
### **6.2.3.2. Appearance**

The appearance of an object can be adapted by changing its colour, or by inserting a texture. Different colours can be selected as well as a shining colour and the shininess. Many illumination models have been proposed to simulate surfaces properties. The specification of the surface colour appearance must include spectral and spatial distribution of the reflected light. The BRDF (Bidirectional Reflection Distribution Function) is the most general way to represent these distributions.

### **6.2.3.3. Car and circuit design**

The main idea of creating a car by hand is making in object oriented language one parent that defines all different parts as its children in order to be able to make the whole car move as one. Not all parts of the car are included in the design, simply because it takes a lot of time to make very detailed objects by hand. The car consists of four main parts, chassis, wheels, suspension, and the steering wheel. The direct instructions and flowchart model were given to Peter Thomas of Uppsala University Sweden, who designed the virtual objects and simulator track. The car and the

picture of the circuit was designed using Borland C++ and loaded into MATLAB and is converted to a line with a width of one pixel. In figure 6-5 one can get an impression of how the 'VR-Sink' works (The VR Sink block writes values from its ports to virtual world fields specified in the block parameter box). The size of the input signals from the interface devices are multi dimensional. Translation inputs consist of the X-, Y-, and Z-values in the virtual world. In Figure 6-5, a screenshot of a car is shown with a translation in the Z-direction together with the VR Sink control window for virtual objects. Figure 6-6 shows the out-of-bounds limits on the VR road system. Figure 6-7 shows a road layout and the centre line.



**Figure 6-5: Impression of the 'VR Sink' in Simulink**



**Figure 6-6: Out of Bounds on VR road system**



**Figure 6-7: Road layout and centre line**

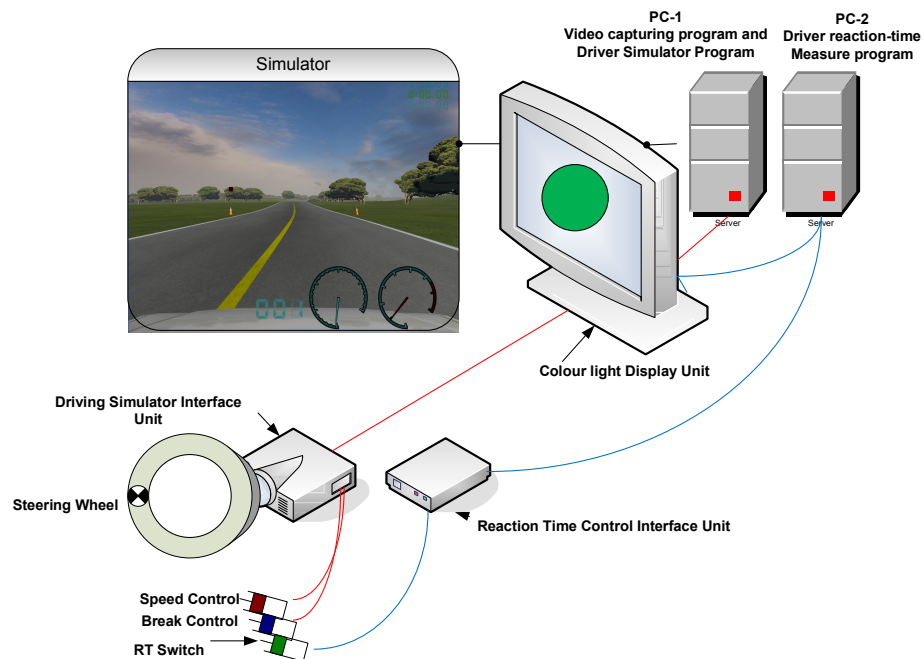
#### **6.2.4. Realistic feedback**

To get an even more realistic driving experience, realistic feedback has been implemented in the simulator. In this simulator, two kinds of realistic feedback are applied. The first feedback is a realistic vehicle movement display on the main screen. When this information is available, it is possible to see the wobbly movement as soon as the car leaves the track, to get a more realistic driving impression. The second feedback is sound. For a realistic driving experience, sound is a very important aspect. Two types of sound are implemented in the simulator. The first is engine sound, and the second is the sound of slipping wheels and brakes. The sound of the engine is especially important. If it is realistic enough this sound will help to control the speed. Since the frequency and volume of the sound should vary continuously, it is almost impossible to use recorded sound samples. The sound has to be generated online. The signal that will be sent to the sound card should be some sort of wave form. The basic frequency of this wave should be the same as the engine speed. To realize this, the accelerator variations are integrated to engine speed and sent through a sine function. This generates a sine wave having amplitude one and the same frequency as the engine. When the accelerator is completely floored, the sound is loudest. When the accelerator is not pushed at all, the volume of the sound is set to 20% of the maximum value.



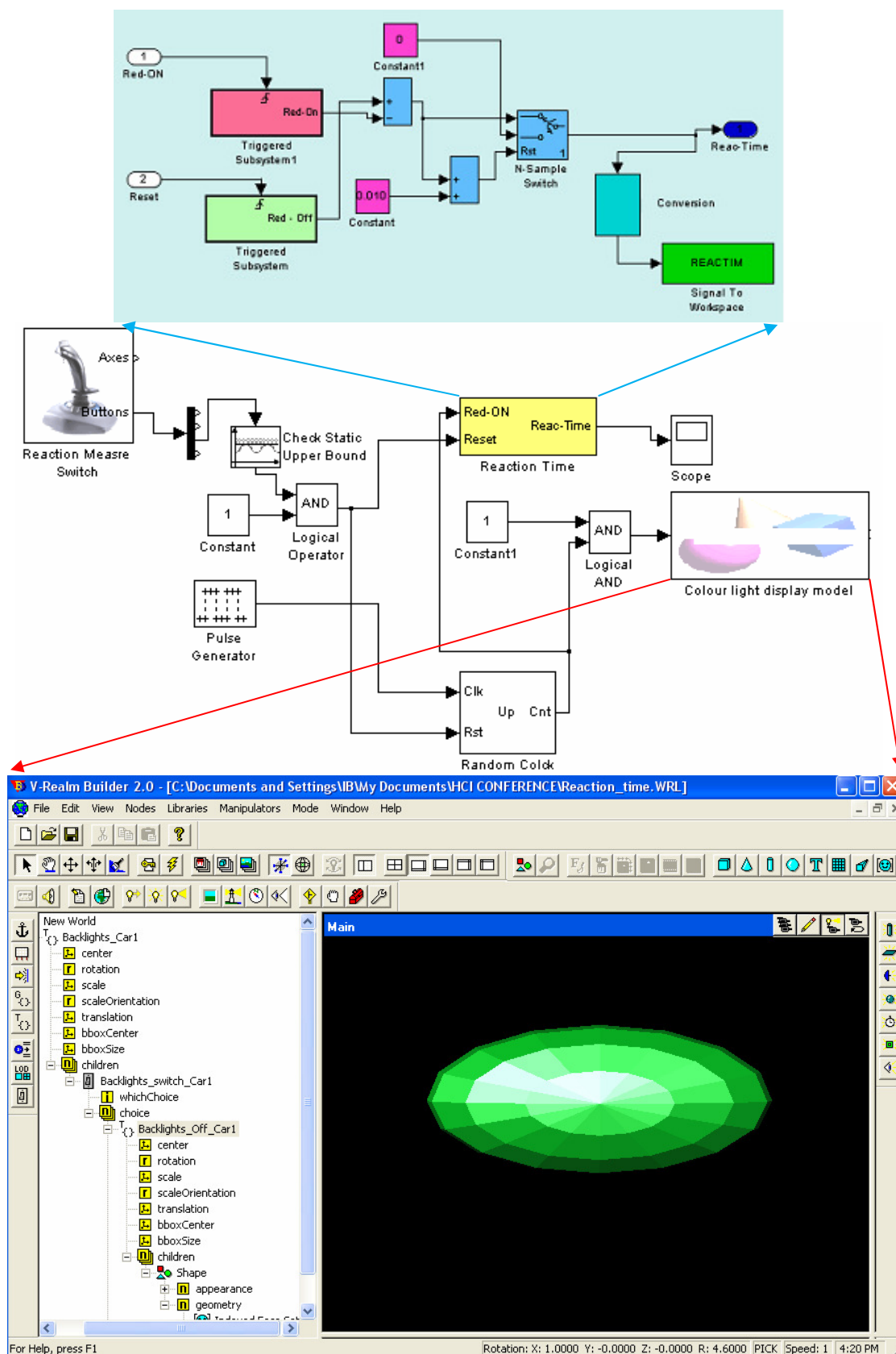
### 6.3. Reaction time measuring system

Reaction time is the ability to respond quickly to a stimulus. It is important in many driver alert research activities (e.g. Brooks & Green, 1998). Simple reaction time is the time taken between a stimulus and movement e.g., sprint start. Such simple reaction time depends on nerve connections and signal pathways that are 'hard wired' in the body and cannot be improved. Another type of reaction time, choice reaction time, is the time taken between stimulus and action which requires a choice. In this research choice reaction time is measured in the driving simulator. MATLAB Simulink virtual reality tools were used to design the reaction time measurement system. The reaction time measurement system was designed to measure the response time of the drivers (participants) to colour light changes during driving. MATLAB Simulink virtual reality tools were used to design the virtual colour light system and the computer interface device connections (switch fixed next to the footbrake paddle). This test was conducted parallel to the main simulator. Figure 6-8 shows the reaction time measure system setup.



**Figure 6-8: Reaction time measure setup**

The green light appears on the separate colour light display monitor and is placed next to the main simulator screen. The colour changes randomly (Green-Red). Participants have to press the reaction button (RT Switch) next to the brake paddle when the colour changes from Green to Red. After pressing the reaction button the red colour virtual bulb changes back to green. The time taken between colour change and the reaction (press the button) to change the colour back to green was measured. Figure 6-9 shows the MATLAB Simulink VR model designed for the reaction time measurement system. This reaction time measurement test is conducted parallel to the main simulator test. The time is measured in milliseconds and copied to text format for the analysis. The light changes are controlled from a random clock. The main objective of this measure was to calculate the participants' reaction times while driving.



**Figure 6-9: Matlab V-Realm colour light change model**

## 6.4. Summary

Driver behaviour and performance were measured across five different parameters (average deviations from centre line, maximum speed, average speed, out-of-bounds and reaction time to control colour light change). MATLAB Simulink virtual reality tools and automotive tools were used to develop the simulator design and controls. The simulation was projected to wide screen to create more realistic driving scenarios for the participants. The simulator speed was fixed to a maximum of 60 km/h. The driving simulator test is a realistic tool for driver drowsiness detection studies and the performance measures, discussed in subsequent chapters, seem to give promising results for drowsiness detection system development.

The MATLAB Simulink VR tools were used to design the reaction time measurement colour signal model. The reaction time system is attached to the main simulator and measures a driver's reactions to colour light changes. The colour light is displayed on a separate screen next to the main simulator display.

The next chapter presents the data analysis methodology, including all the driver drowsiness related measures to be used in this research.

## **CHAPTER 7**

### **DATA ANALYSIS METHODOLOGY**

## 7.1. Introduction

According to the American PERCLOS-system (Wierwille, 1999), which is based on the percentage of eye lid closure, if eyelid closure is greater than 80%, then at this value a signal should be made to warn the driver. This method introduced eye blink and its parameters as a possible means of drowsiness detection. It has been suggested that an increasing of eye lid closure duration could indicate moderate drowsiness (Hargutt, 2003). Thus this metric could be used to warn the driver of impending danger when the blink duration changes to prolonged durations (see detailed discussion on section 2.8).

These suggestions were derived from examining a sample of drivers in alert and drowsy conditions. The PERCLOS measure is based on tracking of the eye pupil (circular area) to measure blink. Two pivotal questions arise for future warning systems. First, how often the system sets off a false alarm, for example when the system cannot track the driver's pupils. Second, how often an episode of severe sleepiness is not detected (misses) as the driver sleeps with open eyes. In this PhD research, individual changes in the course of increasing drowsiness from a driving simulator experiment are examined.

Data analysis is focused on the development of an operational indicator of drowsiness based on a combination of slow eyelid closure and blink frequency measures. Slow eyelid closure is a very accurate operational indicator of drowsiness (Lal & Craig, 2002). However, the primary limitation of slow eyelid closure or long blink duration measures is that drivers may not exhibit this behaviour until they are severely drowsy and/or impaired. The slow eye closure measure is mainly associated with the PERCLOS measure and JDS. The problems with slow eyelid closure as a

measure are discussed in Chapter 2, section 2.8. Therefore, the purpose of this study is to determine if another blink behaviour measure (e.g., blink frequency), could be used to create an enhanced indicator of drowsiness. If such an indicator can predict performance under a variety of apparent drowsiness levels, then it could serve as an alternative detector of drowsiness.

## **7.2. Measures to Identify Drowsiness in Drivers**

**Experiment Management:** The virtual driving simulator and reaction time simulator were designed to measure four different parameters relating to driving and one reaction measure relating to visual changes. These measures are lane position variance, out- of- bounds, speed-related measures and reaction time measures. These measures are obviously important since drivers must maintain proper lane position and respond to colour light changes. The purpose of these measures is to evaluate effects of driver drowsiness while a participant is in a virtual automotive environment.

### **7.2.1. Driving Performance Measures**

**Lane deviations or lateral position:** Literature on driver drowsiness detection systems and methods has shown that sleep loss produces decrements in driving skills (e.g. Johns et al. 2003). Driving performance measures include lane-related measures and reaction time. The main task in the driving simulator is for participants to drive on the centre line on the road. Deviations to the right and left from the centre line are measured and average deviations are calculated. The lane position measure is directly related to lateral position measures and steering wheel movements' measures.

Several studies have found lateral control measures to be closely related to prolonged driving (Johns et al. 2003; Weirwille et al. 1994). These measures are obviously important since drivers must maintain proper lane position to avoid vehicles in nearby lanes and objects located on the side of the roadway. As reported by Wylie et al (1996), steering wheel variability is related to the amount of driver drowsiness (variability greater as drivers become drowsier). Research by Skipper et al. (1984) found that lane deviations were highly correlated with eye closure and were influenced by sleep deprivation. Skipper's studies found standard deviation (SD) of lane deviation is highly correlated with eye closure and is influenced by sleep deprivation and time on task. Furthermore, the global maximum lane deviation was found to be highly correlated with eye closure. Dinges et al. (1985) found the mean square of the lane deviation contains a significant amount of independent information and is an accurate and reliable measure for the detection of drowsiness.

Measures of the lateral position of the vehicle on the road or in its lane of travel have been found to be accurately and reliably related to driver drowsiness (Arnedt et al., 2001; Bittner et al., 2000; Philip et al., 2003). Research by Arnedt et al. (2001) found that, following lack of sleep, or one full night of sleep deprivation, drivers exhibited a safety-critical decline in lateral placement control. In particular, after sleep deprivation, drivers were more likely to drive towards the middle of the road, their lane position variability tended to increase and they departed from their correct lane and ran off the simulated road more frequently. This research also found that prolonged sleep deprivation produced a similar magnitude of driving impairment to a Blood Alcohol Concentration (BAC) of 0.08%.



In this task, participants have to concentrate to maintain the vehicle on the centre line. The distance from the left side to the right side of the road is evenly divided. The algorithm was designed to measure deviations (absolute value) 75 times per second and reports an average of that every 10 seconds (see data logging, Appendix B1). For each participant the average deviation position relative to the centre of the road has been calculated for both straight and curved road sections. The purpose of the average deviation (AVEDEV) measure is, primarily, to evaluate driver drowsiness while a participant is driving in a simulator (this simulator emulates an environment in which a participant is behind the wheel of an automobile). It is possible to derive a number of variables from lane deviations, which are linked in some way with drowsiness, such as average (absolute) deviations from centre line and standard deviation of lateral position. The studies by Dinges et al. (1985) and Kircher et al. (2002) found correlations between different indicators of driver impairment, such as lane measures, and eye closure measures. They found that two variables related to lane deviations had higher correlations with the PERCLOS measure than the other measures of eyelid closure (see Table 7-1),

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	.47	.54	.62
LANEDEVV	.50	.55	.60

**Table 7-1: Eye Measure vs. Lane Measure Correlations. (Dinges et al., 1985; Kircher et al., 2002)**

The variables in Table 7-1 were defined as follows:

EYEMEAN: mean eyelid closure (zero=wide open), EYEMEAS: mean-square percentage of the eyelid closure signal, PERCLOS: proportion of the time that the

eyes are 80% to 100% closed, LANEX: count of the number of samples taken when the simulated vehicle was out of the lane, LANDEVV: lane position variance.

In this PhD study, the standard deviation of average deviations (SD-AVEDEV) is measured as a driver performance measure. Standard deviations of average deviations gives clear variance in changes of deviations with time (see section 8.1.1 for more details). The SD-AVEDEV is a similar measure to SDLAT and LANDEVV. According to several prior investigations on drowsiness and vehicle control, there is a close relationship between drowsiness and standard deviation of lateral position (SDLAT) and LANDEVV (Klein et al., 1980; Dinges et al., 1985; Kircher et al., 2002).

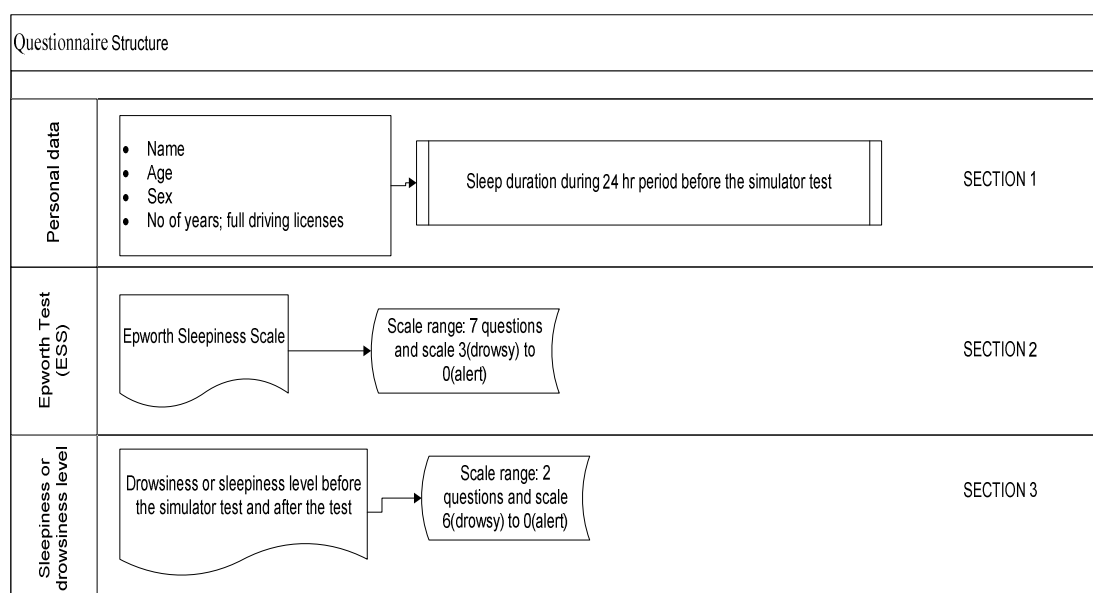
**Reaction time:** Philip et al., (1999) found that Reaction Time (RT) is highly correlated with driver drowsiness. Their research experiment consisted of filling out a questionnaire about the drive and previous sleep pattern, and to carry out a 10 min long, simple reaction time (RT) test. The level of performance is identified by the 10% slowest RTs. Multiple regression analysis, with the mean of the 10% Slowest RTs as the dependent variable, showed that age, duration of drive, and duration (shortness) of previous breaks were the main predictors. This study suggests that public awareness may need to be raised with respect to excessive length of driving, especially in young drivers. Reaction time is an important measure in driver drowsiness detection. In this research, the average reaction time (AVEREATM) measure test is designed to run parallel to the driver simulator (detailed explanation in Chapter 6) and to measure the participant's reaction time during driving. The study by Philip et al. (2003) shows SD of reaction times (RTs) and unstable driving performance significantly increased over time, indicating that excessive driving time

is a significant drowsiness factor and potential cause of drowsiness-related accidents. In this PhD study, standard deviation of average reaction time (SD-AVEREATM) was used for the final regression analysis. Standard deviations of average reaction time gives clear variations (see section 8.1.1 for more details).

**Out of Bounds:** Several studies have found increased lane deviations or out-of-bounds are an important measure for detecting driver drowsiness (Chi & Lin, 1998). The underlying causes of driver drowsiness appear to be associated with driving during the early morning period, working long shifts and driving after having worked a series of night shifts (Phillip et al. 2003). The research by Phillip et al examined driver drowsiness in employees who lived close to their workplace showed that average sleepiness and driving impairment of shift workers were greater at the end of day and in cases of night shift. Night shift was the most problematic, with 59% reporting being more sleepy than alert. About 3% of shift workers reported incidents as a result of falling asleep including lane drift and running off the road (out of bounds). The survey by Fell & Black (1997) investigated the features of driver drowsiness incidents (accidents, near accidents and unintentional drifting-out-of-lane events) which occurred in cities. The results show similar patterns to the study by Phillip et al., (2003), identifying prior sleep loss and late night driving featuring as factors. The Out-of-Bounds (OUTOFBON) measure included in this study is a similar measure to the drifting-out-of-lane measure (LANEX) employed by Dinges et al. (1985) and Kircher et al. (2002). OUTOFBON indicates the sum of times the vehicle is out of bounds in each one minute time interval during the simulation test.

### 7.2.2. Self reported measures

All self reported measures are included in the questionnaire. Each participant has to complete the questionnaire before the simulator test. The subjective information questionnaire is designed to measure the Epworth score and participants' sleepiness or drowsiness level before and after the simulation test, age, gender and number of hours sleep before the test during 24 hour period. Table 7-2 shows the structure of the questionnaire designed and (for more details, see Appendix C2).



**Table 7-2: Questionnaire Structure**

**Age, Gender and Time of the Day:** Age, gender and time of the day influence driver performance in different driving conditions. Research findings, discussed below, demonstrate age and gender dependent relative risk in a driving accident in which the driver was injured or killed. Akerstedt & Kecklund (2001) used accident register data and road traffic flow data to compute the age and gender-dependent

relative risk of being involved in a driving accident in which the driver was injured or killed. Alcohol-related accidents were excluded from the analysis. The results showed that the night-time risk, compared with that of the forenoon, was dramatically increased for younger drivers (18-24 years) and reduced for older (65+) drivers. In direct comparison, the younger drivers had 5-10 times higher risk of being involved in an accident during late night than during the forenoon, with the excess risk during the daytime being considerably lower. Women had a less pronounced night-time peak than men. In direct comparison, men had twice as high a risk as women during the late night hours.

The research by Deery (1999) indicates that young drivers underestimate the risk of an accident in a variety of hazardous situations. At the same time, they overestimate their own driving skill. Young drivers are also more willing to accept risk while driving than experienced drivers. Crash death rates for drivers under 25 at night are roughly double those of older drivers. Young men are particularly at risk, with death rates of up to three times those of young women. Age and time of the day (TODD) are included in this current study as self repeated measures. Gender was reported but not analysed further, because the simulator test was conducted during the daytime and the only evidence for a link between driving performance and gender was found in studies of day and night driving (Deery, 1999). Further studies are needed to investigate this gender effect in more detail.

**Number of Hours Sleep:**

In this PhD study, the number of hours sleep (NOHS) in the previous 24 hours has been considered and used to categorize the participants into the sleep deprived and alert groups.

**Epworth Sleepiness Scale:** The Epworth Sleepiness Scale (ESS) is a valuable tool to identify people who suffer from excessive sleepiness. The participant rates the likelihood of dozing, very low (=0), slight (=1), moderate (=2) or high (=3). The total (out of 24) is the ESS score. If the Epworth score is greater than or equal to 11, it indicates that a person is subjectively sleepy. More details are given in section 2.7.2. Several driver drowsiness detection studies have used the Epworth scale as a tool to assess driver sleepiness, as discussed below.

Maycock (1997) conducted a survey of 996 heavy goods vehicle (HGV) drivers and the relationship of accidents to daytime sleepiness (measured using the Epworth Sleepiness Scale). The drivers were sampled randomly at motorway service areas. The mean ESS score and the mean accident frequency (the average number of accidents in the 3-year recall period) were analyzed, and other relevant physical characteristics were investigated. The average age was 41.4 years (SD 10.5). They drove an average of 69 700 miles annually (SD 36 120), and their average score on the Epworth daytime sleepiness scale was 5.65 (SD 3.31). Maycock's results reported an average accident liability of 0.26 accidents in a 3-year recall period. Accident liability increased with increasing scores on the Epworth daytime sleepiness scale. These findings suggest that further investigation of the mechanisms behind the higher accident rates of some categories of HGV drivers would be

justified in the interests of road safety. ESS is a simple, self-administered questionnaire which is shown to provide a measurement of a participant's general level of daytime sleepiness. The purpose of including Epworth score in this PhD study is to investigate the relationship between the subjective ESS score and driver performance.

**Sleepiness Scale:** Ingre et al. (2006) aimed to provide subject-specific estimates of the relation between subjective sleepiness, as measured by the Karolinska Sleepiness Scale (KSS), with average blink duration (AVEBLKDU) and standard deviation of the lateral position (SDLAT) (KSS is a 9 point self rating scaling method of measuring subjective drowsiness (Kerstedt and Gillberg, 1994). Increased subjective sleepiness on the Karolinska Sleepiness Scale (KSS) has been related to increased amounts of slow eye movements (Karrer et al., 2004) and higher levels of sleepiness on a visual analogue scale (VAS) and related to longer eye blink durations (Caffier et al., 2003) (VAS is a measurement instrument that measures a characteristic or attitude that is believed to range across a continuum of values and cannot easily be directly measured). Lane drifting was calculated as the standard deviation of the lateral position (SDLAT) in a high-fidelity moving base driving simulator. Ingre et al. (2006) showed that SDLAT was significantly related to the KSS. Ingre et al. (2006) used a small sample of five male and five female shift workers who participated in a 2-hour drive (08:00–10:00 hours) after a normal night sleep and after working a night shift. To calculate average blink durations (AVEBLKDU), the EOG (Electrooculogram) method (see section 2.5.2) was used with a sampling rate of 128Hz with a band pass filter. The results suggest that there is a linear relationship of the KSS with SDLAT from the centre line. Average deviations increase by 0.032

m (Standard error,  $SE = 0.004$ ) for each level of the KSS. The estimate for AVEBLKDU showed a similar pattern as for SDLAT but with a large diversity in the subject-specific estimates between different levels of the KSS. The linear trend of the KSS for AVEBLKDU is an average increase of 0.0056 s ( $SE=0.0006$ ) for each level of the KSS. The final results estimate the direct association between the KSS and SDLAT/AVEBLKDU and information about individual differences. The results have implications for any application that needs prediction at the subject level (e.g. driver drowsiness warning systems) as well as for research design and the interpretation of group average data.

The purpose of including the Sleepiness Scale (SLEPSCAL) in this PhD study is to investigate subject-specific estimates of drowsiness, before and after the simulation test. The SLEPSCAL scale ranges from 1 = very alert to 7= very sleepy. This scale is very similar to the KSS but it slightly simpler as it uses a 7 point scale rather than a 9 point scale for self rating. Both measures are simpler to administer than the ESS, as participants are required to answer only one question instead of seven questions. This makes it easier to conduct a before and after comparison of self-reported sleepiness.

### **7.2.3. Speed Related Measures**

**Average speed and Maximum speed:** Two speed related measures included in this simulator were maximum speed and average speed. The ability of a driver to control the accelerator adequately so as to maintain a consistent driving speed is of obvious importance. A few studies have reported evidence questioning whether a linear relationship between speed and injury accidents is credible for all ranges of speed (Carsten et al., 1998).



The study by Campagne et al. (2004) focused on driver performance related to driver drowsiness and his studies were conducted for forty-six male drivers, divided into three age categories: 20–30, 40–50, and 60–70 years, performed a 350-km motorway driving session at night on a driving simulator. Driving errors were measured in terms of number of running-off-the-road incidents (RORI) (out-of-bounds) and large speed deviations (maximum speed). The evolution of physiological vigilance level was evaluated using electroencephalography (EEG) recording. The experiment results show that, for young and middle-aged drivers, the deterioration of the vigilance level is associated with driving errors (RORI and speed variations). Research by Lemke et al. (1982) found that driving under monotonous conditions decreases the vigilance of the human controller and his performance of the driving task. Vehicle related signals (speed) were measured. The investigations were performed on a driving simulator. The experiment results show that the average speed correlates with mean eye blink durations and indicates the driver's vigilance. This was explained by increased risk-acceptance at decreased performance or decreased vigilance.

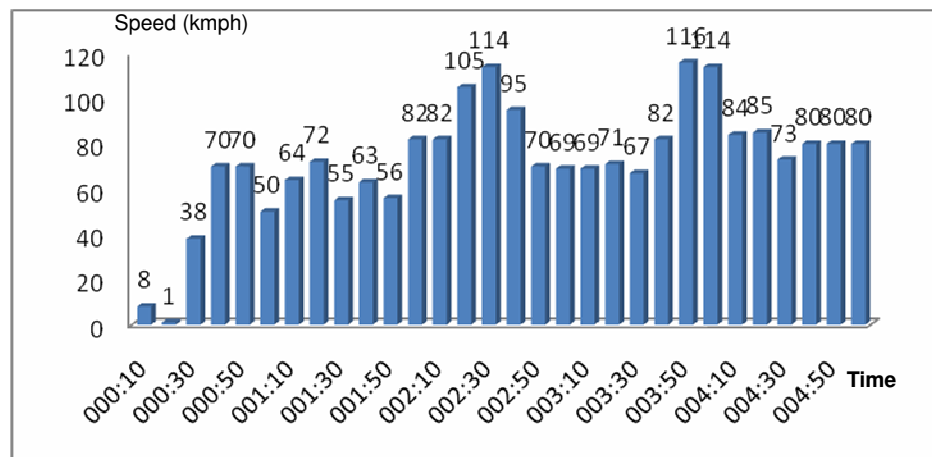
Research by Lemke et al., (1982) found that speed variability (average speed) has some correlation to driver drowsiness. Lemke et al.'s studies found average speed to increase gradually when the drivers become drowsy. In this current study, maximum speed (MAXSP) and average speed (AVESP) have been measured as indicators of speed. The system is designed to check the speed every second and log the data every ten seconds. The highest value in every ten seconds is recorded as the maximum speed (MAXSP). Figure 7-1 shows an example of recorded data for the maximum speed for participant 1 in the first five minutes of the simulator test. The

system records the average speed every ten seconds. The average is calculated by calculating the speed every second and averaging these values over a ten second period. Equation 7-1 gives the calculation for average speed. Figure 7-2 shows an example of recorded data for average speed for the participant 1 in the first five minutes of the simulator test.

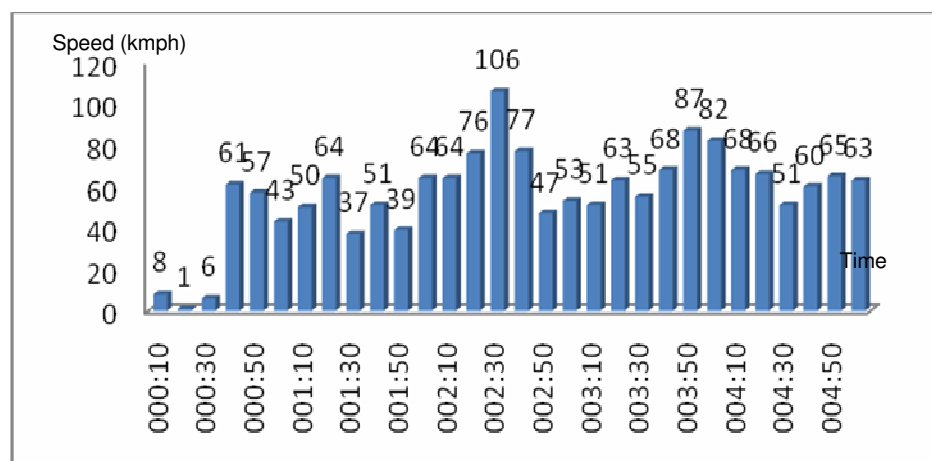
$$AVESP = \frac{1}{10} \sum_{i=1}^{10} a_i \quad (7-1)$$

Where  $i = 1, \dots, 10$  and  $a = \text{speed}(\text{every second})$

These measures are correlated with driver performance to investigate the effects of driver drowsiness.



**Figure 7-1: Maximum speed in first five minutes (Participant 1)**



**Figure 7-2: Average speed in first five minutes (Participant 1)**

#### 7.2.4. Physiological Measures

**Eye Blink Durations and Frequency:** Eyelid closure and related eye measures are, according to the literature, the most promising and reliable predictors of drowsiness and sleep onset (Du et al. 2008; Devi & Bajaj 2008; Johns et al. 2003). As a driver's drowsiness increases, the eye movements slow down, sometimes accompanied by characteristic rolling movements. Eye blinking is also slower and more frequent with increasing levels of drowsiness (blink frequency increases with drowsiness). The most published and accepted indicator of drowsiness is average blink duration (Kircher et al., 2002). Research by Hakkanen et al. (1999) focused on eye blink duration as a measure of sleepiness in on-road driving and on the driving performance of professional bus drivers. Ten bus drivers participated in the study. The Maintenance of Wakefulness Test (MWT) and a monotonous on-road driving task were completed. Eye blink duration and blink frequency and speed control were measured while driving. This study found eye blink duration correlated significantly with driving performance. However, no significant correlations were found between average blink frequency and driving performance. These results support the use of blink duration as an indicator of increased sleepiness and have important implications for those involved in the transport technological industry.

The study by Caffier et al. (2003) found that eye blink duration is considered to be a suitable ocular indicator for drowsiness. To evaluate eye blink parameters as drowsiness indicators, a contact-free method for the measurement of spontaneous eye blinks was developed. In a series of sessions with 60 healthy adult participants, the validity of spontaneous blink parameters was investigated. The subjective state was determined by means of questionnaires immediately before the recording of eye

blinks. The results show that several parameters of the spontaneous eye blink can be used as indicators in drowsiness diagnostics. The average blink duration and average reopening time, in particular, change reliably with increasing drowsiness. Furthermore, the proportion of long closure duration blinks proves to be an informative parameter. The results demonstrate that the measurement of eye blink parameters provides reliable information about drowsiness/sleepiness, which may also be applied to the continuous monitoring of the tendency to fall asleep.

The study by Akerstedt & Kecklund, (2001) found that driving in the early morning is associated with increased accident risk affecting not only professional drivers but also those who commute to work. Ten shift workers participated after a normal night shift and after a normal night sleep. The results showed that driving home from the night shift was associated with an increased number of incidents (decreased time to first accident), increased lateral deviation (AVEDEV), increased eye closure duration (average blink duration), and increased subjective sleepiness. The results indicate late night shift effects on sleepiness and driving performance. The study by Van den Berg et al., (2005) focused on eye activity measures used to model drowsiness related changes during a visual tracking task. Results suggest that information from multiple eye measures (eye blink duration and frequency) may be combined to produce accurate individualized real-time drowsiness detection.

Previous studies' results demonstrate that the measurement of eye blink parameters (blink frequency and blink duration) provides reliable information about drowsiness/sleepiness. In this PhD study, the standard deviation (SD) of the average blink duration (SD-AVEBLKDU) and the SD of the average blink frequency (SD-AVEBLKFR) were selected. Previous studies have suggested that average blink

duration may be the most sleepiness-sensitive continuous performance measure (Arnedt et al., 2001; Skipper, et al., 1984; Ingre, et.al., 2006; Caffier et al., 2003). Therefore, the average eye blink duration (AVEBLKDU) and average frequency (AVEBLKFR) were measured in the current PhD study to evaluate driver drowsiness. In addition, the standard deviation of average blink duration and frequency (SD-AVEBLKDU & SD-AVEBLKFR) were used in the linear correlation model with performance measures with the aim of producing a more accurate drowsiness detection model. The calculation of standard deviation (SD) for average blink duration and average blink frequency has not been discussed in any previous studies. The advantage of SD calculation will be discussed in section 8.1.1.

### **7.3. Experimental Design**

In order to determine the driving performance measures to be used in the present study, it was important to establish the driving performance measures that have previously been demonstrated to be related to drowsiness. Review of the previous literature related to driver performance measures have used advanced and simple driving simulators (Beach et al., 1998; Dinges et al., 1985; Fletcher et al., 2003; Rong-ben et al., 2003; Johns et al., 2003). Previous studies have used sleep deprivation as the predictor variables, and looked at average driving performance across different levels of deprivation. The simulator design used in the present study was a single track virtual reality design (for a detailed description, see section 6.1). The reasons for designing a simple simulator for this research were: i) flexibility of changing parameters according to research needs and ii) being able to conduct the research with a small fund (simulators available to hire for driver drowsiness detection are very expensive). Every volunteered participant has to drive for 30-40

minutes in the simulator. Before starting their test, they have a 5-10 minutes practice session. All the procedures are given to the participants prior to the simulator test. To complete one track with average speed of 60 km/ph will take approximately two minutes. During the 30-40 minute test, participants were exposed to different elevations on road structure. There were separate colour light signal sequences of tasks for all the participants to respond to simultaneously with driving. The simulation time was selected with reference to previous driver drowsiness detection research (Dinges, et al., 1985). The simulator test was conducted in two sessions: a morning session (9:00 am to 12:00 pm) and an afternoon session (12:00 pm to 3:00 pm). No self reporting measures were collected during the test because it may distract their driving. However sleepiness measures were conducted before and after a test.

### **7.3.1. Participant Procedure**

Each participant who finished the questionnaire was asked to read the general instructions for the experiment and to read and sign an informed consent form. Any questions concerning the instructions, the informed consent form, or the experiment in general were answered.

Each participant participated in 30-40 minutes driving session, either in the morning or in the afternoon. Participants are free to choose any session; there is no additional preparation before starting the test.

The reaction time measuring equipment was placed beside the simulator screens and the participants in the simulator could clearly see the colour light changing screen. The participant was then given a five to ten minutes practice session. Once the

practice session was completed, the physiological monitoring equipment was fitted to the participant, the lights were controlled constant, and the data collection began. The participants performed the tasks on the simulator for the entire duration of the experiment.

### **7.3.2. Experimental Task Procedures**

The experimental tasks that the participants were required to perform were to drive on the centre line of the road and to react to colour light changes. The road layout was designed with hills, slopes and bends; therefore extra concentration on controlling the speed is required. To complete a single track in simulation varied between 1 to 3 minutes with a maximum of 60 km/h. The reaction time measuring experiment was designed to assess reaction to colour light change. Participants have to concentrate on the display screen beside the simulator while driving when the 'Green' light turns to 'Red' randomly and need to press the brake paddle to reset the 'Red' light back to 'Green' (for reaction time experiment details, see chapter 6).

## **7.4. Data Analysis Overview**

### **7.4.1. Variables to be analysed**

As justified in the previous section, twelve variables were collected during the experiment as follows:

1. Eye blink durations (average eye blink duration)
2. Eye blink frequency (average eye blink frequency)
3. The absolute value of average deviations from road centre.
4. The average reaction time for colour light changes.

5. Number of out of bounds from road
6. Maximum speed every one minute period
7. Average speed every one minute period
8. EPWORTH sleepiness scale value
9. Number of hours sleep during the previous 24 hour period.
10. Age of participants
11. Time of day that the test was taken
12. Sleepiness scale before and after the simulation test (SLEPSCAL).

The following measures were used for data analysis:

### **Predictor Variables**

#### **Physiological measures**

- AVEBLKDU: The average eye blink duration (total blink duration is a length of closing - remaining closed - reopening time), averaged over a one minute period. More details are given in Table 7-3. Standard deviation of average blink duration was calculated for the final linear correlation (SD-AVEBLKDU).
- AVEBLKFR: The average blink frequency. A moving average filter was used on eye blink frequency signals to sample over a one minute interval. More details are given in Table 7-3. Standard deviation of average blink frequency was calculated for the final linear correlation (SD-AVEBLKFR).

#### **Speed related measures**



- **MAXSP:** The maximum speed. The simulator speed is set for a maximum of 60 km/h. The simulator checks every second during the test if the participants reach this set speed and this is recorded. A moving average filter was used for recorded data to sample over a one minute interval.
- **AVESP:** The average speed. The simulator records the average speed every second during the 40 minute test. A moving average filter was used to sample the AVESP data over a one minute interval.

### **Self reported measures**

- **EPWOSCL:** The Epworth sleepiness scale. The Epworth questionnaire gives a numerical value of subjective drowsiness. The maximum score is 24 (from eight questions). If the participant's total score is 11 or more will indicates that he/she is subjectively sleepy.
- **NOHS:** The number of hours sleeps during the last 24 hours.
- **SLEPSCAL** Sleepiness scale; all participants have to log their sleepiness level before and after the simulator test. Participants need to scale their sleepiness level from 1-7 (1=alert and 7=sleepy).
- **TODD:** The time of the day, when the participants starts the simulation test.
- **AGE:** Age is categorized according to two groups; younger drivers aged 20-29 years and older drivers aged 30-70 years.

### **Predicted Variables**

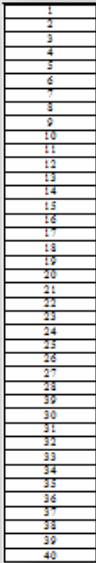
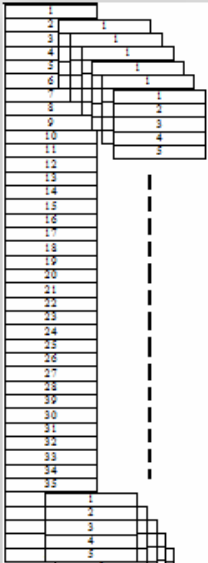
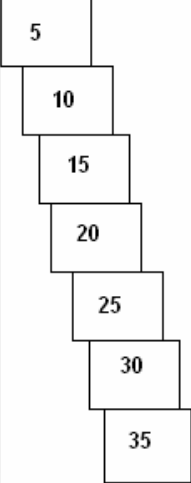
- **AVEDEV:** The average deviation from the centre (calculated as the vehicle deviation from centre line and by the average deviation every 1 second period). These values go through a five minute moving average filter. More details are given in Table 7-3. Standard deviation of average deviations was calculated for the final linear correlation (SD-AVEDEV).
- **AVEREATM:** The average reaction time. Every participant has to respond to random colour light change runs simultaneously with the simulation test. Total reaction times during the 30-40 minute simulation test go through a moving average filter to sample over a one minute interval. Standard deviation of average reaction time was calculated for the final linear correlation (SD-AVEREATM).
- **OUTOFBON:** The out of bounds. Each participant is required to drive on the centre line of the road. If they go out of the road limits, this records the time during which the participant has gone out of bounds. OUT-OF-BON indicates the sum of out of bounds in each one minute time interval during the simulation test.

All measures were first computed over one-minute intervals. Data manipulation procedures were then undertaken to prepare data for statistical analysis. Initially, the first five minutes from all measures were deleted as discussed above. This was done

so that the data to be analyzed did not include the time when participants were suspected of “settling in” to the driving task. Even though all participants were given a practice driving session it was thought that, in the first five minutes of driving some participants demonstrated inconsistencies concerning their driving behaviour reactions, and physiological measures.

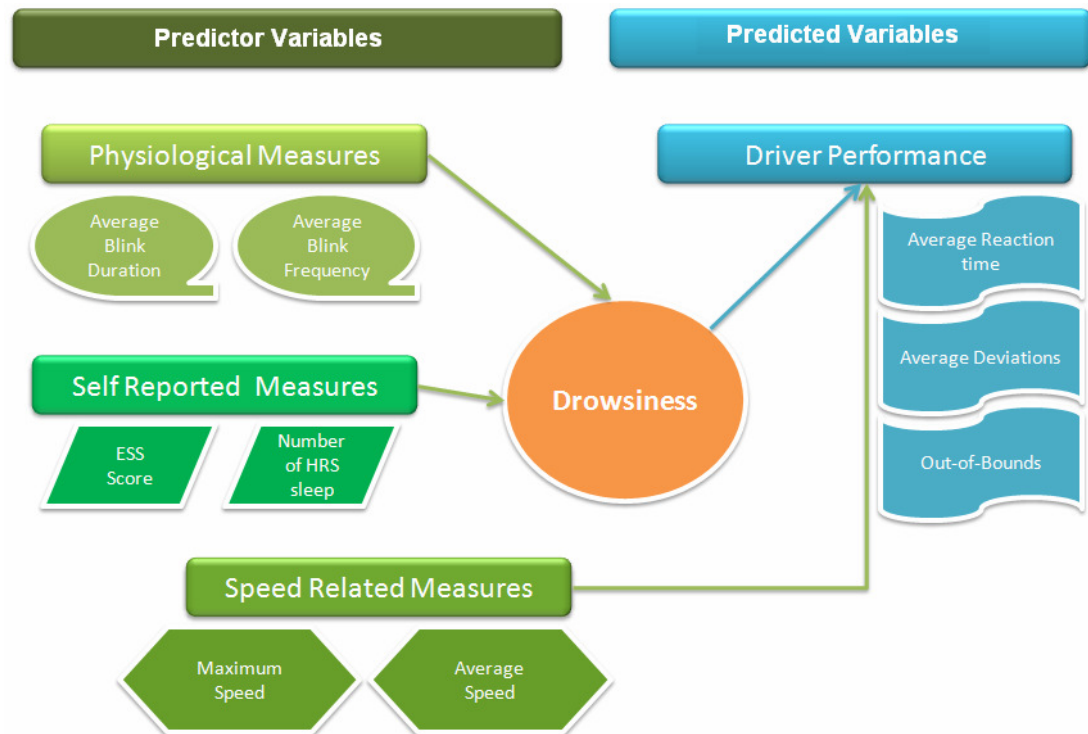
All measures collected through time were averaged in one minute blocks. Then mean and standard deviations were calculated for minutes 1 to 5, 2 to 6, 3 to 7, etc, giving a five minute moving average filter. The first five minutes of the data had been deleted.

After completion of the moving average procedure, all the data were arranged in five-minute intervals. Five or six-minute averages had been shown previously to have higher correlation values with driver performance measures than one-minute, two-minute, or four-minute averages (Wierwille, et al., 1994). As the results for five and six minute averages were close, the five minute filter was chosen, as being more convenient for data of 35 or 40 minutes duration. (See Table 7-3 for a pictorial overview of the data manipulation procedure.) The studies by Dinges et al. (1985) found that longer intervals were better in the detection and prediction of the danger state of drowsiness.

1 minute average	Five minute moving average filter for SD	Five minute blocks	Data manipulation
			5 minutes: The first 5 minutes are deleted from all data
			5 minutes: 5 minute average calculated
			5 minutes: 5 minute average calculated
			5 minutes: 5 minute average calculated
			5 minutes: 5 minute average calculated
			5 minutes: 5 minute average calculated
			5 minutes: 5 minute average calculated

**Table 7-3: Data manipulation procedure**

The data analysis for this research composed of two major parts. The first part of the analysis consisted of correlation analyses of all the data. The purpose of the analysis was to determine which of the variables could possibly predict impairment due to drowsiness. The second part of the analysis consisted of linear regression analyses. The purpose of the regression analysis was to find one or more variables that would best predict impairment resulting from drowsiness. Figure 7-3 shows the implicit model: variables change (predicted variables) because of drowsiness and variables exemplify drowsiness (predictor variables).

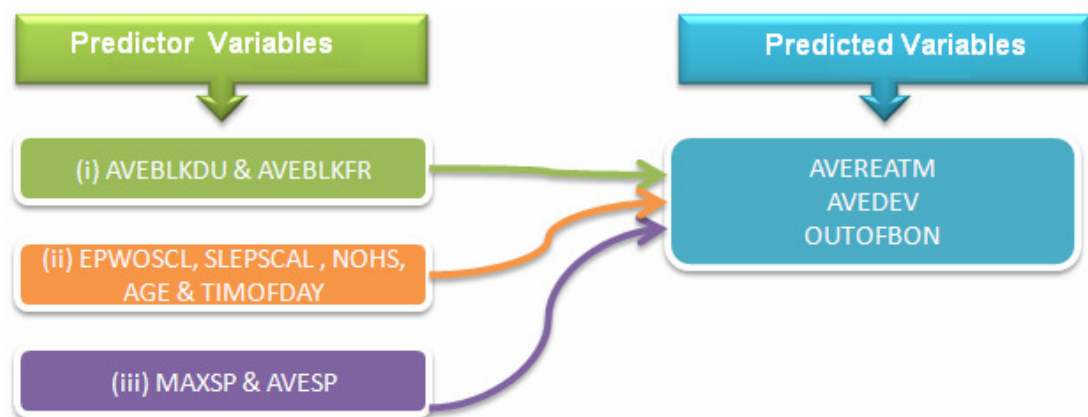


**Figure 7-3: Implicit Model, Predicted and Predictor variables for drowsiness detection**

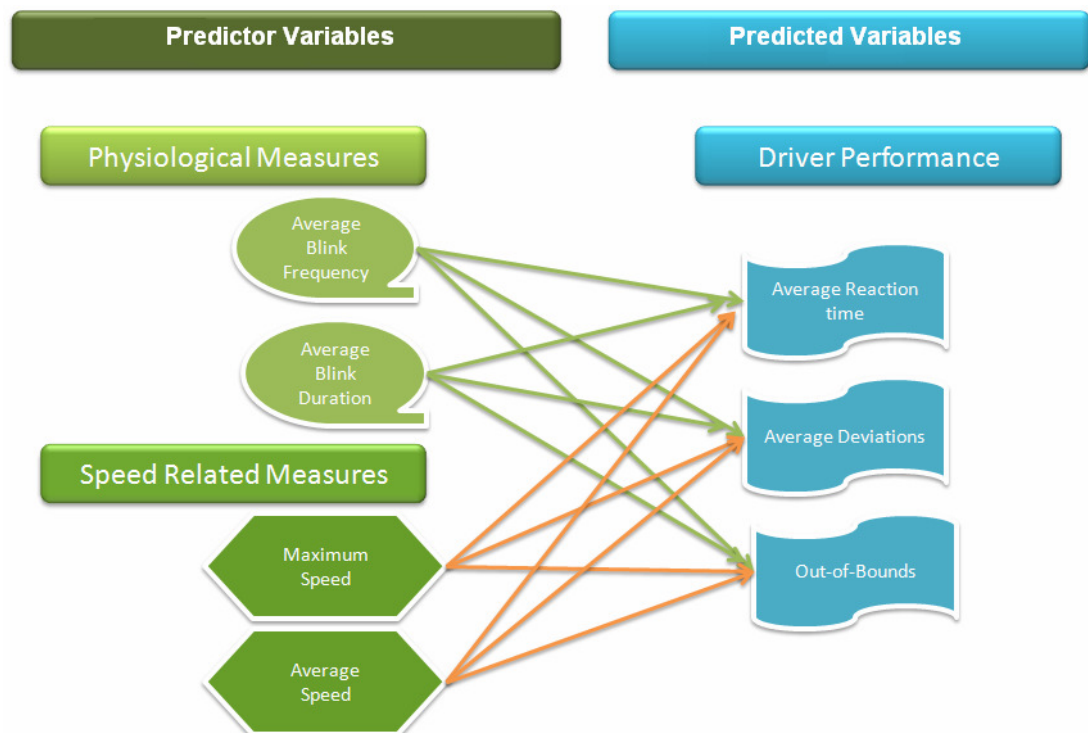
#### 7.4.2. Regression and Correlation Analysis

Regression and correlation analyses were performed on the collected physiological and speed related data with performance data to determine the best indicators of drowsiness. Correlations were performed between the collected physiological measures and the collected performance measures. For example, SD of average blink duration and SD of average blink frequency were analysed for correlation with each performance measure (i.e., the SD of average deviations, SD of average reaction time, etc). The main reason of speed related measures included under predictor variables and correlated with predicted variables was to see any influence to driver performance. The speed related measures do not directly associate with drowsiness

but it could influence to deprive driving performance (Peters, 2001). Figure 7-4 shows the predictor variables and predicted variables used for regression and correlation analysis. Figure 7-5 summarizes the correlation analysis. Regression analyses were performed between physiological and speed related measures and performance measures to determine the best predictor variables as indicators of drowsiness.



**Figure 7-4: Predictor and Predicted variables analysis**



**Figure 7-5: Stat model of correlation analysis**

In regression analysis, the term predictor variable refers to a predictor variable, and the term predicted variable refers to a variable that is being predicted. There are three classes of predictor variables: i) physiological variables AVEBLKDU (average blink duration), AVEBLKFR (average blink frequency), ii) sleepiness EPWOSCL (Epworth Sleepiness Scale), sleep scale SLEPSCAL (before and after the test) and NOHS (number of hours sleep during 24 hr period), Age, Time of the day TOD (simulator test), and iii) speed measures AVESP (average speed) MAXSP (maximum speed). The predicted variables are driver performance measures: AVEDEV (average deviations), AVERATM (average reaction time), and OUTOFBON (out of bounds). The regression analysis for physiological measures was calculated individually for all participants. In the same way the regression analysis for the speed related measures was calculated individually for all participants.

### **7.4.3. The t-test analysis**

The t-test assesses whether the difference in means of two groups is *statistically significant*. The t-test has been commonly used by many driver drowsiness detection studies (Johns et al. 2003; Arnedt et al., 2001; Skipper et al., 1984; Ingre et.al., 2006; Caffier et al., 2003).

In this study, the t-test was performed between driver performance measures for different groups of participants, according to their self-reported measures (see Figure 7-6). For example, number of hours sleep (NOHS) is categorized into two groups: i) 3 to 4 hours sleep and ii) 7 to 9 hours sleep. Then the driver performance measures were categorized to these two groups and the t-test was used to test the significance of differences in mean performance variables between the two groups. Box plots

were used to illustrate the variations of median values across all categories used for driver performance in the t-test analysis.

#### 7.4.4. Linkage between variables

All twelve variables have been considered for drowsiness detection and categorized for analysis in various forms. The self reported measures and performance measures across individuals are analyzed for drowsy and non-drowsy participants using a t-test (see Figure 7-6). Physiological and speed related measures were correlated with driver performance measures for each individual to identify the most reliable predictors (see Figure 7-6).

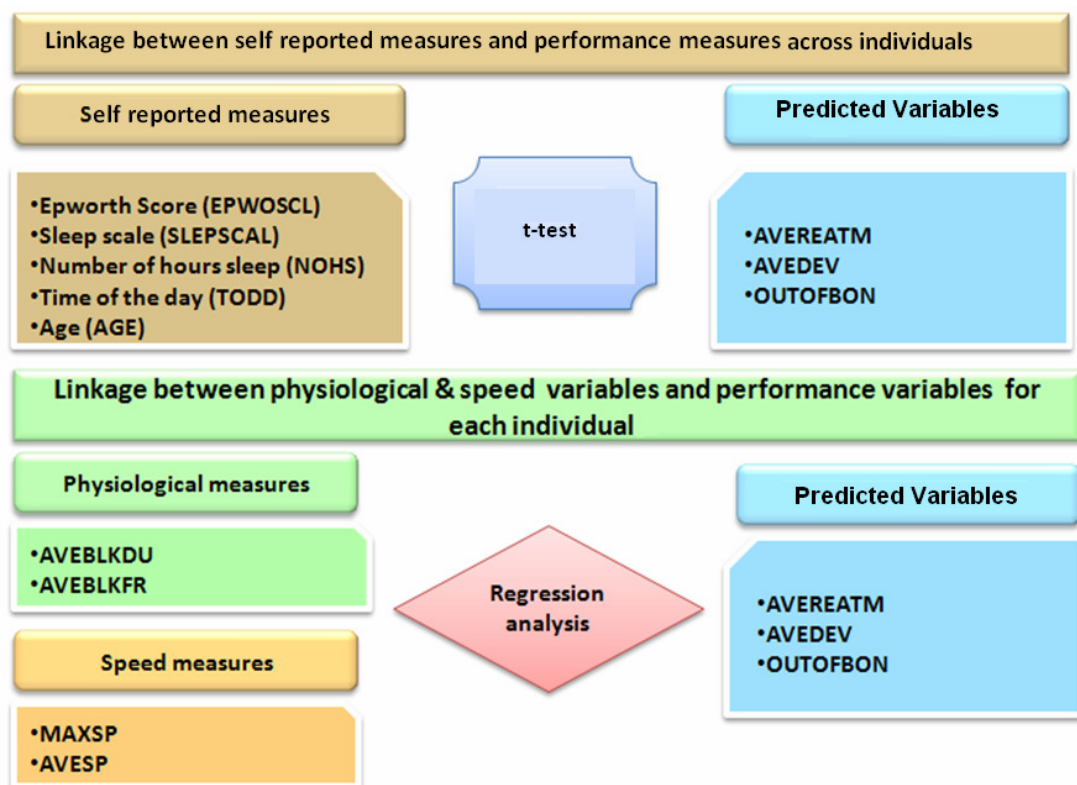


Figure 7-6: Linkage between collected drowsiness detection measures



EPWOSCL score, SLEPSCAL values and NOHS are compared with predicted variables to analyse their effect. TODD and AGE were considered to analyse any possible influence on driver performance. Regression analysis was used for the physiological and speed related measures with predicted variables to identify the best indicator of drowsiness.

## 7.5. Summary

The objective of this chapter was to investigate driver drowsiness detection methods and recommend reliable data analysis methods for detection of drowsiness and prediction of driver performance measure. The research literature helped to identify potentially sensitive indicators for drowsiness data analysis. The regression analyses performed in this study represent an attempt to relate physiological and speed related measures with driver performance measures.

**Driver performance measures:** three different measures used in this category were AVEDEV, AVEREATM and OUTOFBON. Each performance measure will be considered individually in the data analysis process with predictor variables.

**Self reported measures:** five different measures used in this category were EPWOSCL, SLEPSCAL, NOHS, AGE and TODD. The NOHS is the sleep duration before the simulation test and TODD is the time of the day when participants participated in the simulator test. The t-test analysis will be use for self reported measures and predicted variables to verify the relationship with drowsiness.

**Speed related measures:** two speed related measures used in this research were MAXSP and AVESP. Regression analysis will be use for both speed related measures with each predicted variables to identify the relationship of speed variations with driver performance.

**Physiological measures:** two physiological measures used in this research were AVEBLKDU and AVEBLKFR. Regression analysis will be use to verify the relationship of physiological measures with predicted variables.

The next chapter shows that there is a relation between the driver performance measures and eye blink related measures. The final model development is discussed in this chapter.

## **CHAPTER 8**

### **FINAL DATA ANALYSIS RESULTS: DEVELOPMENT OF DRIVER-DROWSINESS DETECTION MODEL**

## 8.1. Introduction

Eighteen participants who attended for at least one session, and had complete and analysable sets of data (i.e. two complete sessions for four participants and a single session for 14 participants) were available for driver drowsiness detection.

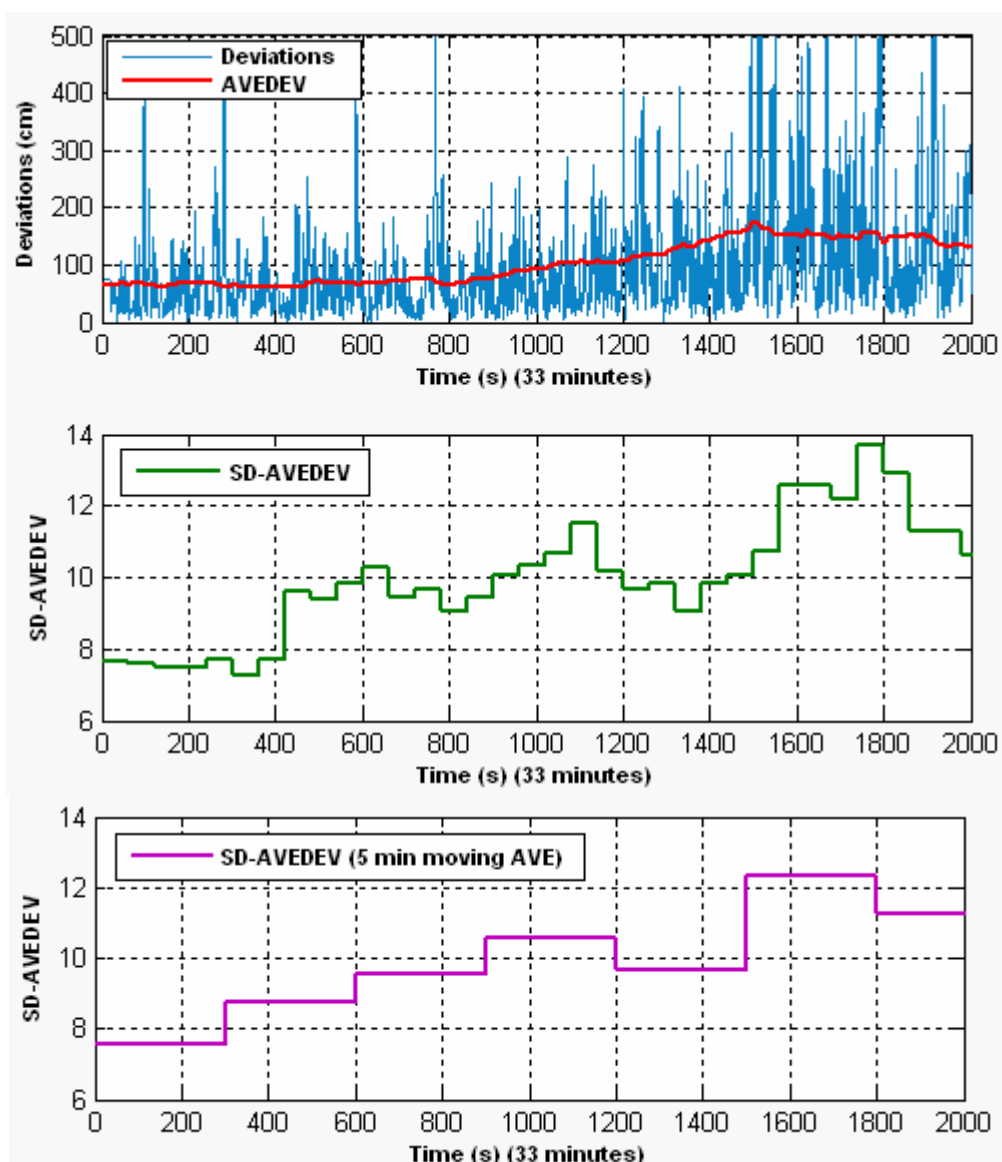
The four complete data sets comprised the following:

- Four participants provided complete driver performance data for the alert and drowsy conditions. The other fourteen participants completed the simulator test in a non-drowsy condition. From those fourteen participants, some of them showed lack of performance in the latter stage of the test.
- Captured eye blink durations, blink frequency and eye open percentage for all eighteen participants has been converted from video formats to numerical formats for analysis.
- Sleep condition (i.e. duration of sleep during the 24 hour period), age and time of the day were used to categorize the 18 participants for analysis.
- The EPWORTH sleepiness score was calculated before the simulator test. The final question is self rating of sleepiness or tiredness level after the simulator test. Each participant had to log their sleepiness or tiredness level (see Appendix C2, for the questionnaire).

### 8.1.1. Standard Deviation (SD) Calculation

Standard deviation (SD) was calculated for physiological measures and predicted variables. The correlation of SD of average values shows a slightly better correlation than the normal average values for all participants. Figure 8-1 shows, time plots of deviations, AVEDEV and SD-AVEDEV for participant number 1. The 5 minute moving average of SD values shows a clear difference in increase of deviations with time towards the end of the test. Comparing to the deviations and AVEDEV, the SD-AVEDEV is more appropriate for driver performance analysis. The SD-AVEREATM showed similar results when compared to the reaction time and AVEREATM.

Table 8-1 shows the correlation coefficient comparison of SD of AVEBLKDU & AVEBLKFR with AVERBLKDU & AVEBLKFR for all participants. The correlation values show a small increment for the SD values. The results of Table 8-1 show correlation coefficients are slightly higher for SD of averages than for the averages themselves. Therefore SD of average values was calculated for physiological measures and predicted variables.

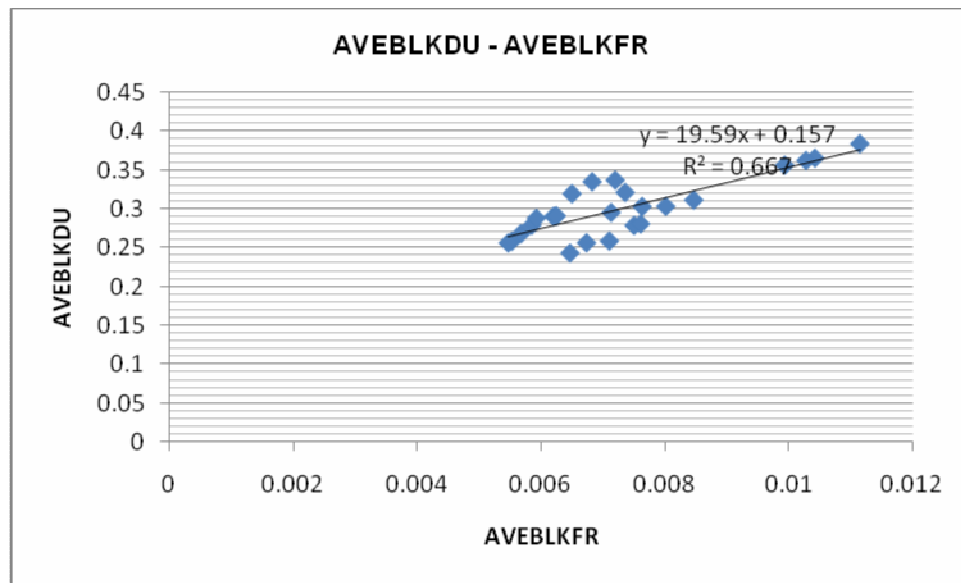


**Figure 8-1: Difference between deviations, AVDEV and SD-AVEDEV**

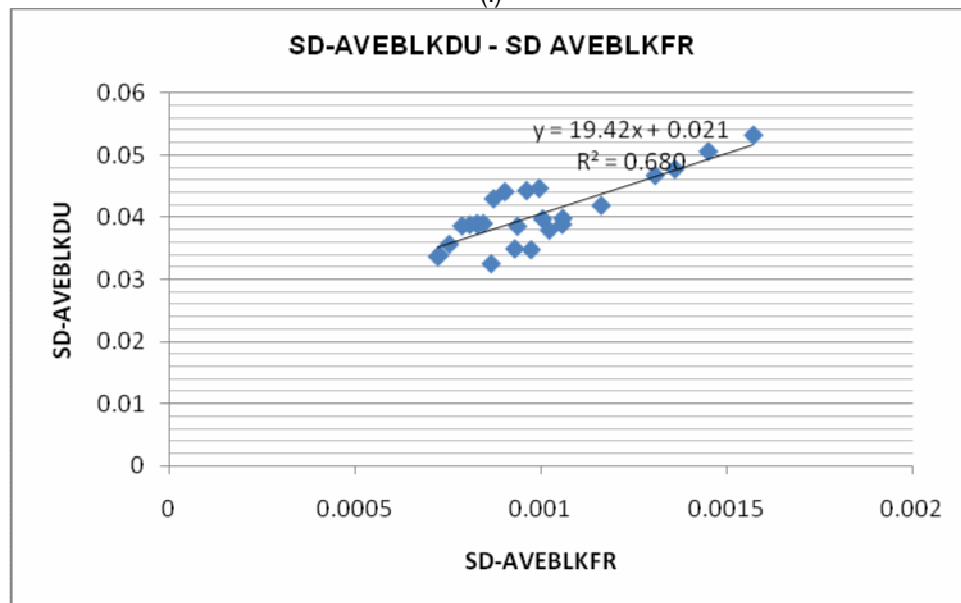
SUB No:	SUB1	SUB2	SUB3	SUB4	SUB5	SUB6	SUB7	SUB8	SUB9
SD of AVEBLKDU & AVEBLKFR	0.9691	0.992	0.89	0.96	0.809	0.794	0.964	0.918	0.96
AVEBLKDU & AVEBLKFR	0.967	0.99	0.884	0.957	0.806	0.731	0.959	0.915	0.956
SUB No:	SUB10	SUB11	SUB12	SUB13	SUB14	SUB15	SUB16	SUB17	SUB18
SD of AVEBLKDU & AVEBLKFR	0.84	0.806	0.89	0.680	0.968	0.911	0.915	0.797	0.975
AVEBLKDU & AVEBLKFR	0.837	0.801	0.884	0.667	0.964	0.907	0.909	0.791	0.971

**Table 8-1: Linear Correlation Comparison**

Figure 8-2 (a) shows an example of a randomly selected participant's linear correlation of SD-AVEBLKDU and SD-AVEBLKFR compared with linear correlation of AVDBLKDU and AVEBLKFR. Figure 8-2 (b) shows the linear correlation of SD- AVEBLKDU and SD-AVEDEV (average deviation) compared with correlation of AVEBLKDU and AVEDEV for a drowsy participant. Figure 8-2 (c) shows the linear correlation of AVEREATM (average reaction time).

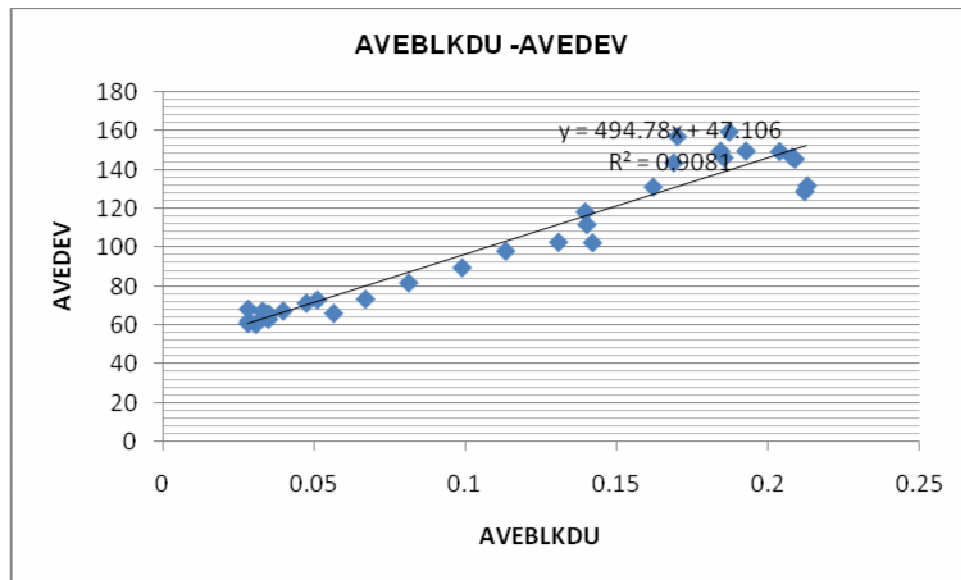


(i)

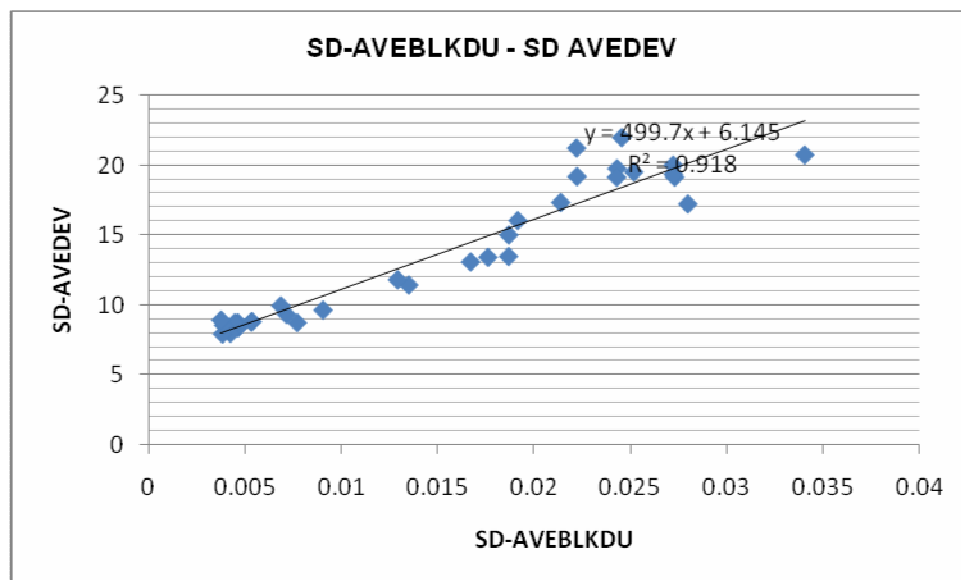


(ii)

**Figure 8-2(a): (i) Linear Correlation of AVEBLKDU and AVEBLKFR, (ii) Linear Correlation of SD-AVEBLKDU and SD-AVEBLKFR**



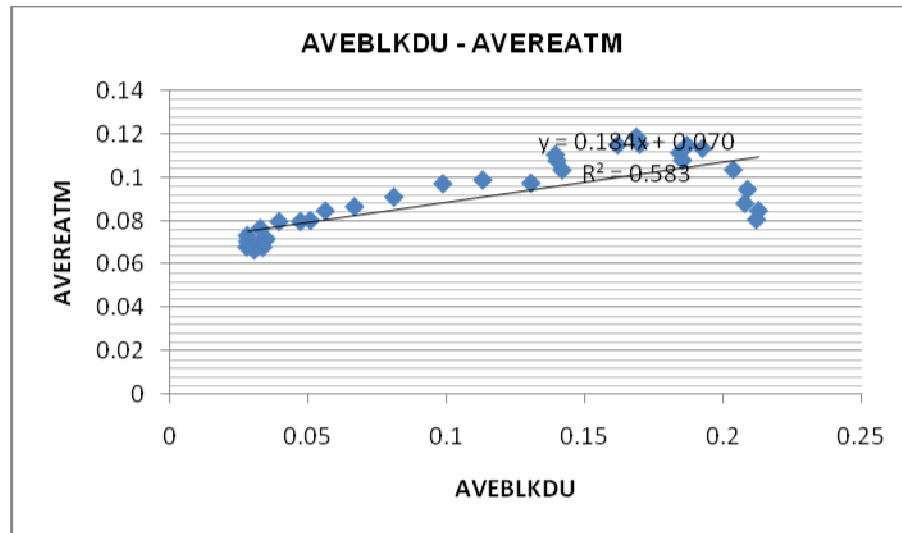
(i)



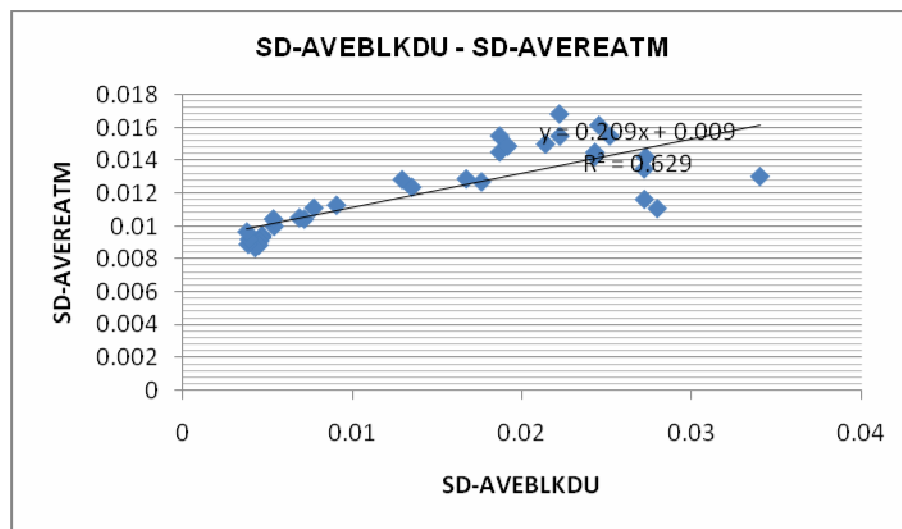
(ii)

**Figure 8-2(b): (i) Linear Correlation of AVEBLKDU and AVEDEV, (ii) Linear Correlation of SD-AVEBLKDU and SD-AVEDEV**





(i)



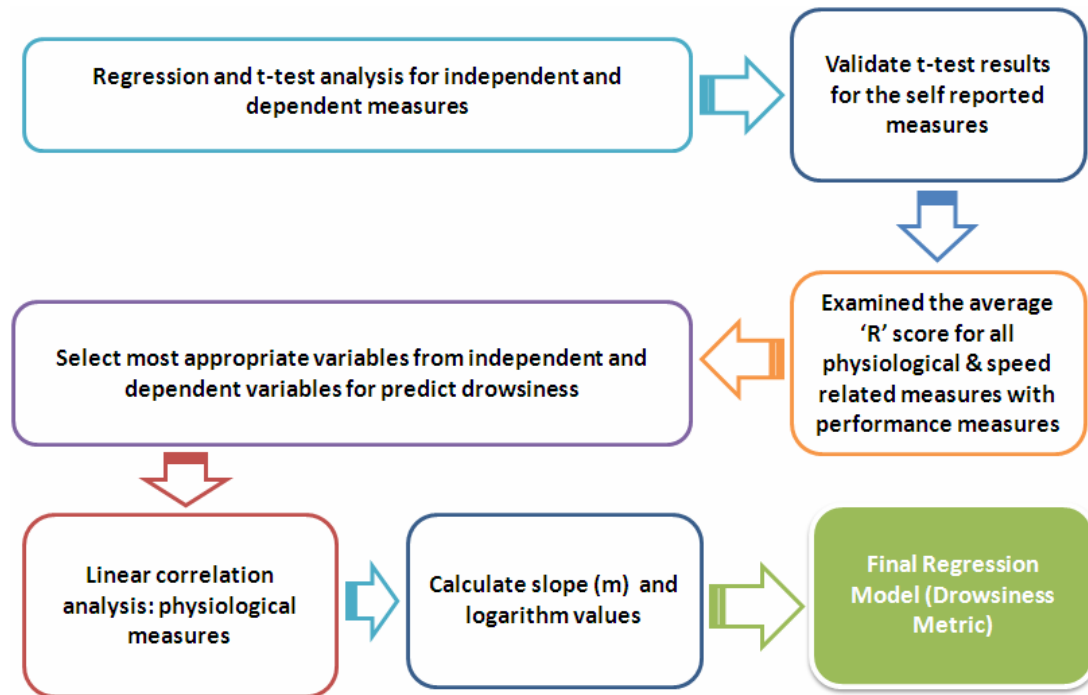
(ii)

**Figure 8-2(c): (i) Linear Correlation of AVEBLKDU and AVEREATM, (ii) Linear Correlation of SD-AVEBLKDU and SD-AVEREATM**

All the measures were averaged for one minute. After completion of the one minute average procedure, the five minute moving average was calculated. The five minute average is used to develop a new metric.

Regression analyses were used for several reasons. First, it was possible to analyse any portion of the data using regressions. Also, by using regressions, the experimenters were able to gain valuable insight into which measures contributed

consistently to the prediction of driver impairment and the detection of drowsiness. A block diagram of the procedure is shown in Figure 8-3. The steps of this procedure are explained in the subsequent sections.



**Figure 8-3: Block Diagram of the Main Steps in the Drowsiness Metric Development Procedure**

### 8.1.2. Participants

Eighteen participants volunteered to take part in the study and four participants volunteered for morning and afternoon sessions. The eighteen participants who attended at least one session comprised 14 males and 4 females, with average 35.6 years (SD 12 years). Three participants were aged over 60 and eleven participants were aged between 30–40 years. All others were aged between 20–29 years. Ten participants participated in the morning session (9:00am to 12:00pm) and the others participated in the afternoon session (12:00pm to 3:00pm). Fifteen participants drive

their own vehicle and the average length of time that participants had held their license was 15.30 years. Five participants travel on a motorway daily.

## 8.2. Self reported measures analysis

The t-test comparisons were used to identify relationships between five self reported measures and the performance measures. Four t-tests were performed for EPWOSCL, NOHS, TODD and AGE across all participants with performance measures and one paired t-test was performed for the SLEPSCAL.

### 8.2.1. EPWORTH Sleepiness Scale (EPWOSCL)

All participants filled in a questionnaire with the Epworth sleepiness scale. The EPWORTH scale is used to determine the level of daytime sleepiness (Lundt, 2004). A score of 11 or more is considered sleepy. A score of 18 or more is very sleepy (Lundt, 2004). This scale helps to obtain a general indication of participants' daytime sleepiness. Figure 8-4 shows the EPWORTH sleepiness scores for all eighteen participants.

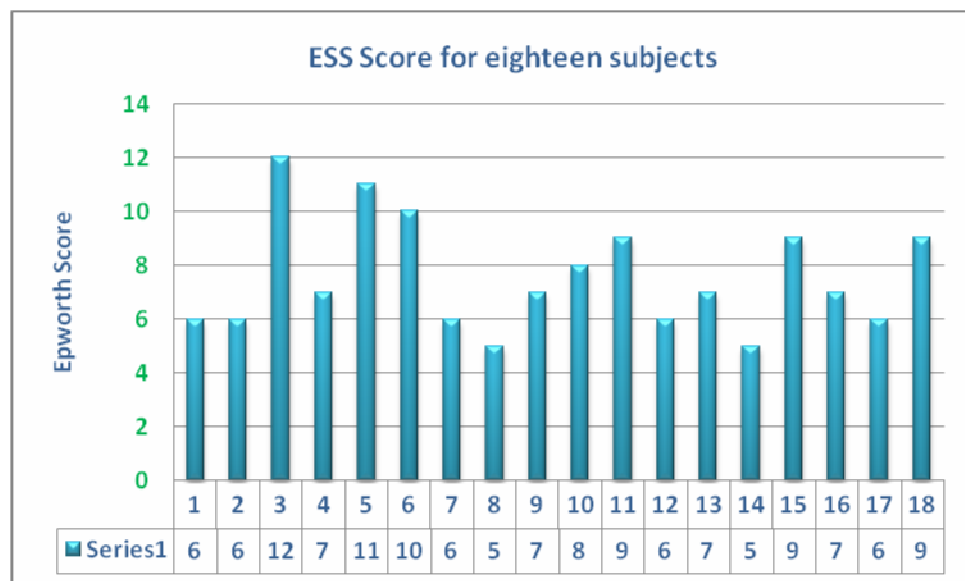
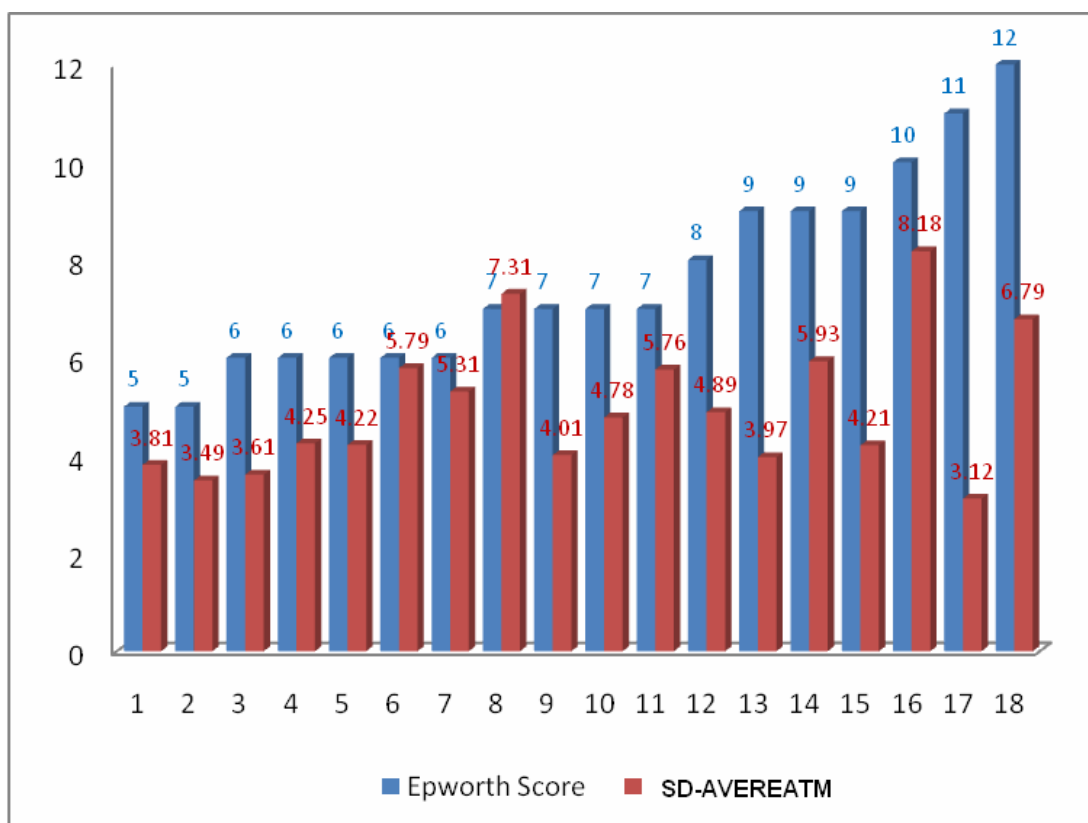
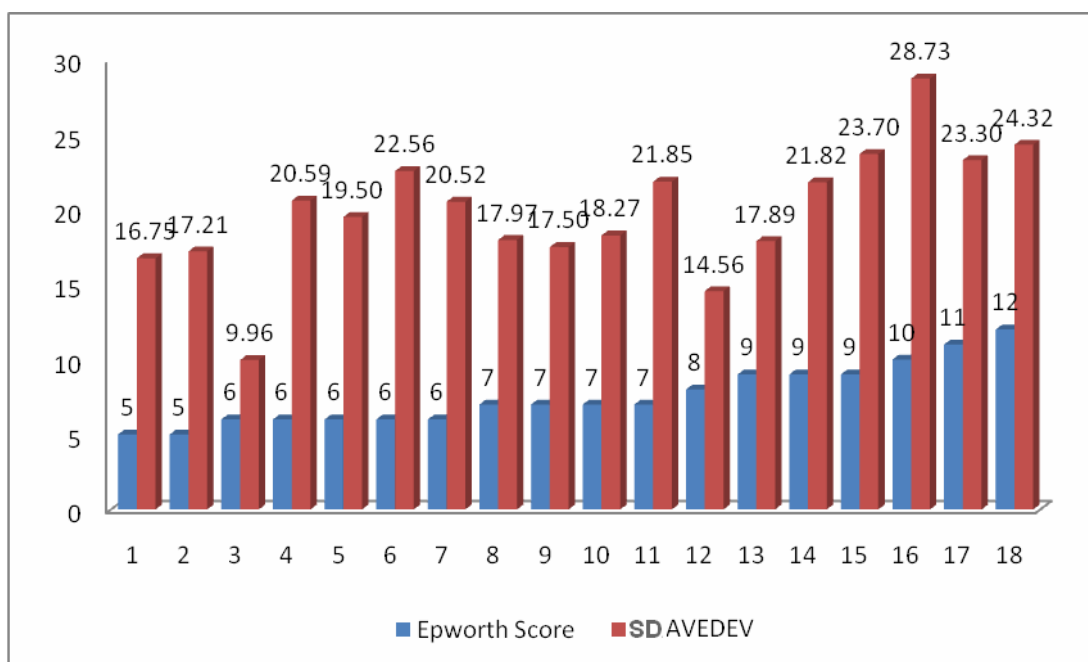


Figure 8-4: Epworth sleepiness score for each participant

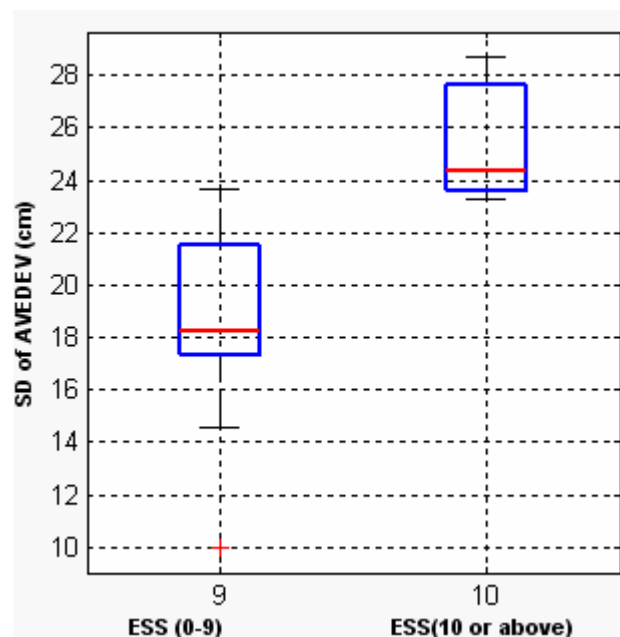
Only two participants showed a high Epworth sleepiness score ( $ESS \geq 11$ ). The mean ESS for all eighteen participants is 7.2 and the standard deviation (SD) is 2.16. ESS results showed that 89% of participants who participated in the driving simulator test did not report any sleep deprivation problems at the time of the test. The Epworth scale helped to categorize the participants, with their sleep deprivation problem and normal condition. In the analysis, participants with  $ESS \geq 10$  were considered as sleepy, because only two participants had high ESS across all 18 participants. In this study, the participants who had  $ESS \geq 11$  and the participant who had  $ESS = 10$  showed similar performance results. Therefore, the  $ESS \geq 10$  is considered as a high ESS value for further analysis.

Figure 8-5 shows the ESS score arranged from smallest to largest score with SD of AVEDEV and SD of AVEREATM (converted to seconds).



**Figure 8-5: SD of AVEDEV and SD of AVEREATM with ES score for all participants.**

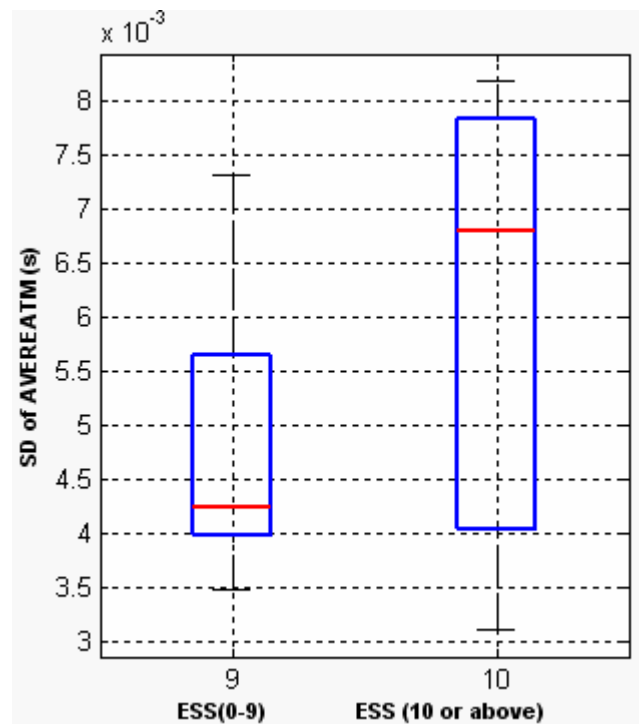
The Epworth sleepiness score is highly correlated with driver performance (Sallinen et al., 2004). Figure 8-6 shows the Boxplot of the ES scores and average deviations (AVEDEV) (categorized to two groups) for eighteen participants. It indicates that the three participants who have ES score greater than or equal to 10 have higher average deviations. The median value (see Figure 8-6, Boxplot) shows a clear difference of alert and subjectively sleepy participants' performance. The median values comparison is shown in Table 8-2.



**Figure 8-6: Boxplot of ES score and average deviations (AVEDEV).**

Figure 8-7 shows the Boxplot of the ES score and average reaction time (AVEREATM) for eighteen participants. It indicates that the three participants who have ES score greater than or equal to 10 have longer (slower) reaction times compared to participants who have ES scores less than or equal to 9. The AVEREATM is categorized by the Epworth score  $ESS \leq 9$  and  $ESS \geq 10$ . The t-test gives the value  $t=0.83$  ( $d.f=2$ ), which is not significant ( $p>0.20$ ), indicating that the differences in means between the two categories is not significantly different from

zero. The reasons for not detecting a significant difference between two categories were high variability of drowsy participants and the small sample. Further study is needed to clarify whether significant differences exist, with a large sample.



**Figure 8-7: Boxplot of ES Score and average reaction time (AVEREATM)**

Table 8-2 shows the ES Score and the median values of AVEDEV and AVEREATM for all participants. The ES Score is divided into two categories as before:  $ESS \leq 9$  (Alert) and  $ESS \geq 10$  (Drowsy).

	Epworth Score (EPWOSCL)	Median value of AVEDEV	Median value of AVEREATM	Number of participants
All participants	ESS≤9 (alert)	18.27	0.0043	15
All participants	ESS≥10 (Drowsy)	24.32	0.0068	3

**Table 8-2: Epworth score compare with AVEDEV and AVEREATM for all participants**

The Out-of-Bounds did not show any correlation with the ES score. There were only 3 drivers who went out-of-bounds, but the ESS score varied between 6 and 12 for

those three drivers. The correlation results across all participants for the OUTFBON measure will be discussed in section 8.4.

The AVEDEV is categorized by Epworth score  $ESS \leq 9$  (subjectively alert participants) and  $ESS \geq 10$  (subjectively sleepy). The difference in mean ESS score between the alert and subjectively sleepy categories is statistically significant ( $t(3) = -3.56$ ;  $p < 0.05$ ). Thus, the results substantiate an increase in average deviation for high ESS participants.

### 8.3. Effect of Sleep Duration on Driver Performance

The average amount of time spent by all the participants in the simulator was 34.1 minutes. Every participant had to log their sleep durations (number of hours sleep, NOHS) in the 24 hour period before the test. Figure 8-7 shows the Boxplot of sleep durations categorized to two groups, and SD of average deviations. It indicates a clear difference in median values between participants who had few hours sleep and those who had a good sleep during the 24 hour period before the test. The AVEDEV is categorized to two groups (3 to 4 hours sleep and 7 to 9 hours sleep) by the NOHS before the simulation test. The participants showed poorer driving performance if they had less sleep but the difference in AVEDEV between the two categories is not statistically significant  $t=1.05$  (d.f=3),  $p > 0.12$ . A possible reason for not detecting a significant difference was high variability in group one (3 to 4 hours sleep). Further research is needed, on large samples.

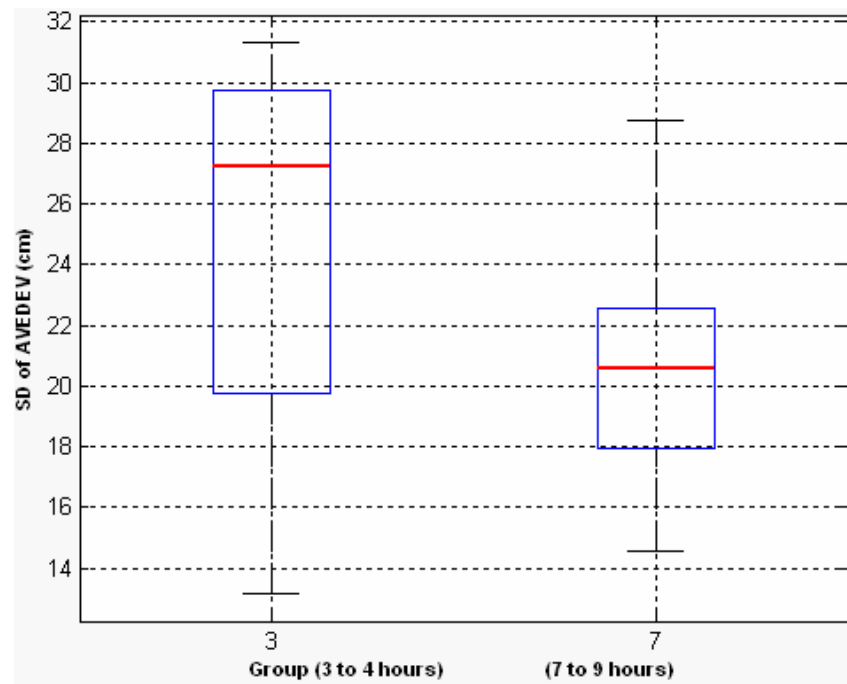
Figure 8-8 shows the Boxplot of sleep duration and SD of AVEREATM categorized to two groups (3 to 4 hours sleep and 7 to 9 hours sleep). The median values show a clear difference between two groups (see Table 8-3). The t-test results were not



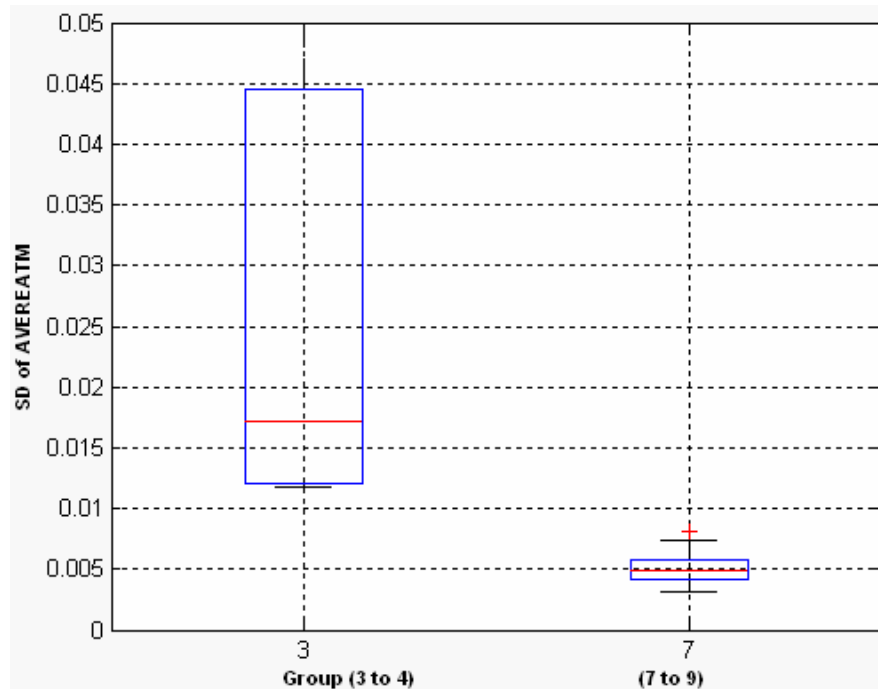
significant at 5%, but were significant at 10%,  $t=1.76$  (d.f=3),  $p<0.1$ . As discussed above, the difference in mean of AVEDEV is not statistically significant, but the difference in mean value of AVEREATM is significant for two categories. Considering the results for both AVEDEV and AVEREATM with sleep durations indicates that sleep duration is potentially an important indicator for driver impairment.

Sleep durations (during 24 hours before the test)	Median value of AVEDEV	Number of participants	Median value of AVEREATM	Number of participants
3 to 4	27.25	4	0.017	4
7 to 9	20.55	14	0.0048	14

**Table 8-3: Sleep durations and median values of average deviations for all participants.**



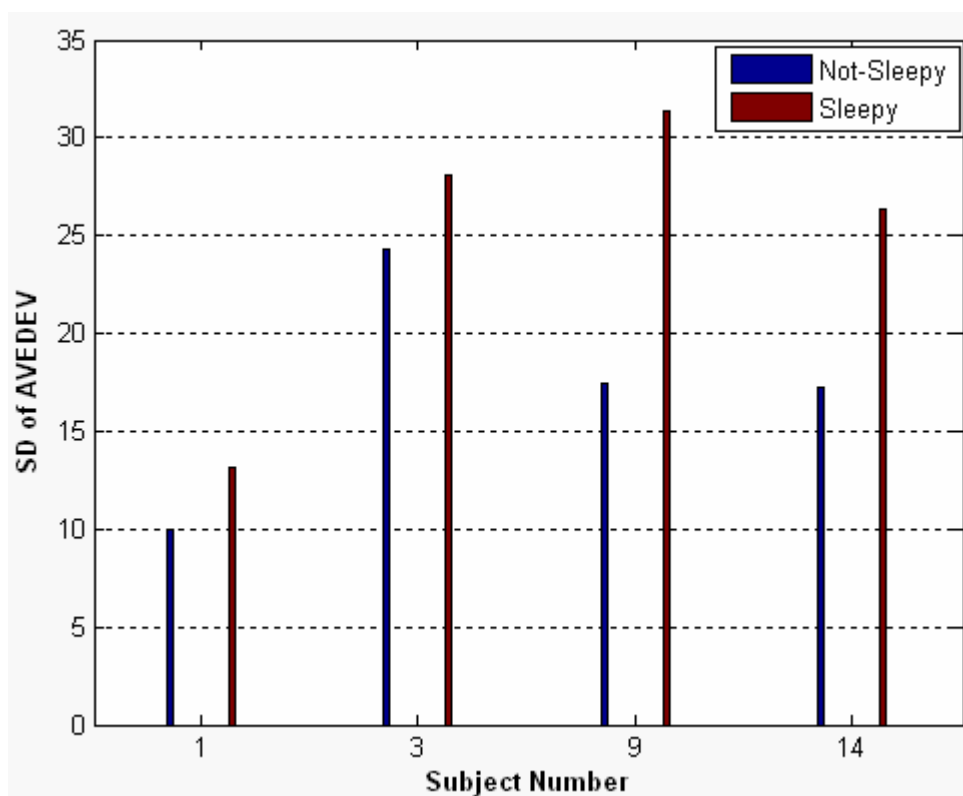
**Figure 8-7: Boxplot of sleep durations (two groups) and SD of AVEDEV**



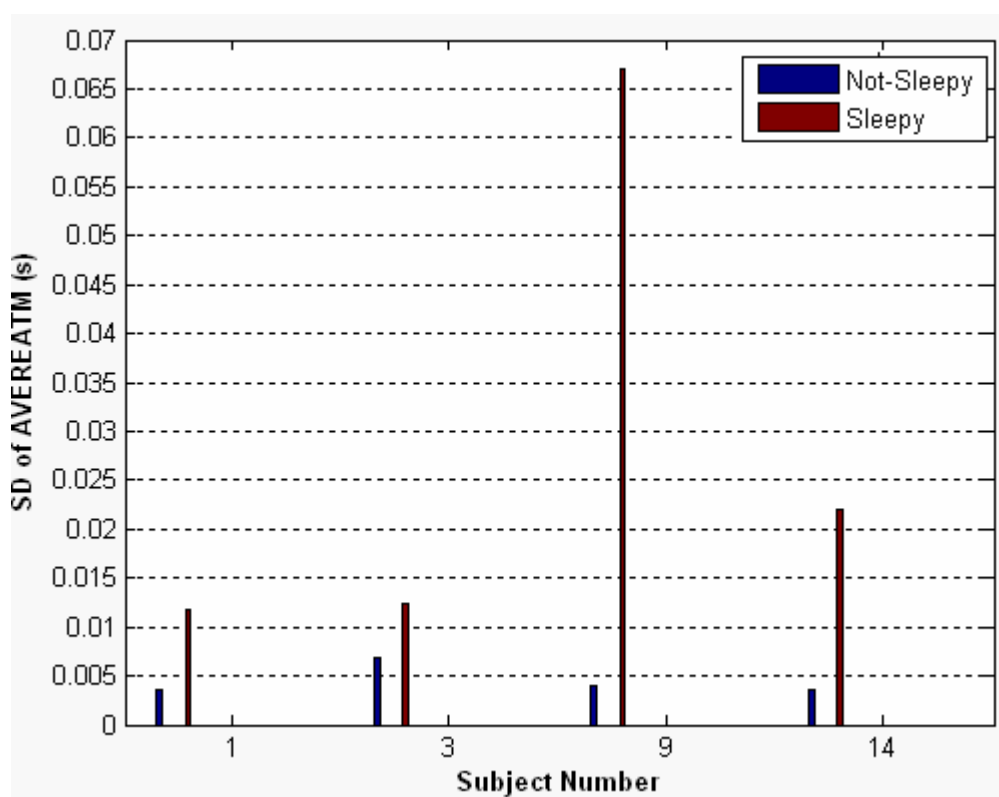
**Figure 8-8: Boxplot of sleep durations and AVEREATM (during 24 hour period)**

### 8.3.1. Participants Who Participated in Sleep Deprived Condition

In this section, we discuss the four participants who participated in a lack of sleep condition (sleep  $\leq 4$  hours during the 24 hour period) for the simulator test. Three participants had ES scores less than 10 and one participant had ESS = 12. Comparing their normal sleep condition results and lack of sleep condition results shows some large differences. Figures 8-9 (a) and (b) show a comparison of driving performance for participants in their alert condition and sleep deprivation condition (AVEDEV and AVEREATM). Results show that all four participants have higher average deviations (poor driving performance) in their sleep deprivation condition compared to their normal condition. This is particularly noticeable for the AVEREATM measure.



**Figure 8-9(a): Comparison of average deviations (AVEDEV) of participants with their normal conditions and sleep deprivation condition.**



**Figure 8-9(b): Comparison of average reaction time (AVEREATM) of participants with their normal conditions and sleep deprivation condition.**

An initial analysis of the individual participants' driving behaviour is important to develop new drowsiness scales (Lundt, 2004). A relationship between drowsiness and the standard deviation of average deviations SD-AVEDEV (steering error) can be detected for participants 1, 3, 9 and 14 (both from normal and sleepy conditions). These four participants are examples of drivers in their sleep deprivation condition that have higher amplitudes in the average deviation than other alert participants. The driver performance results show several participants have higher average deviations at the end of the simulator test, compared to their average deviations at the beginning of the test.

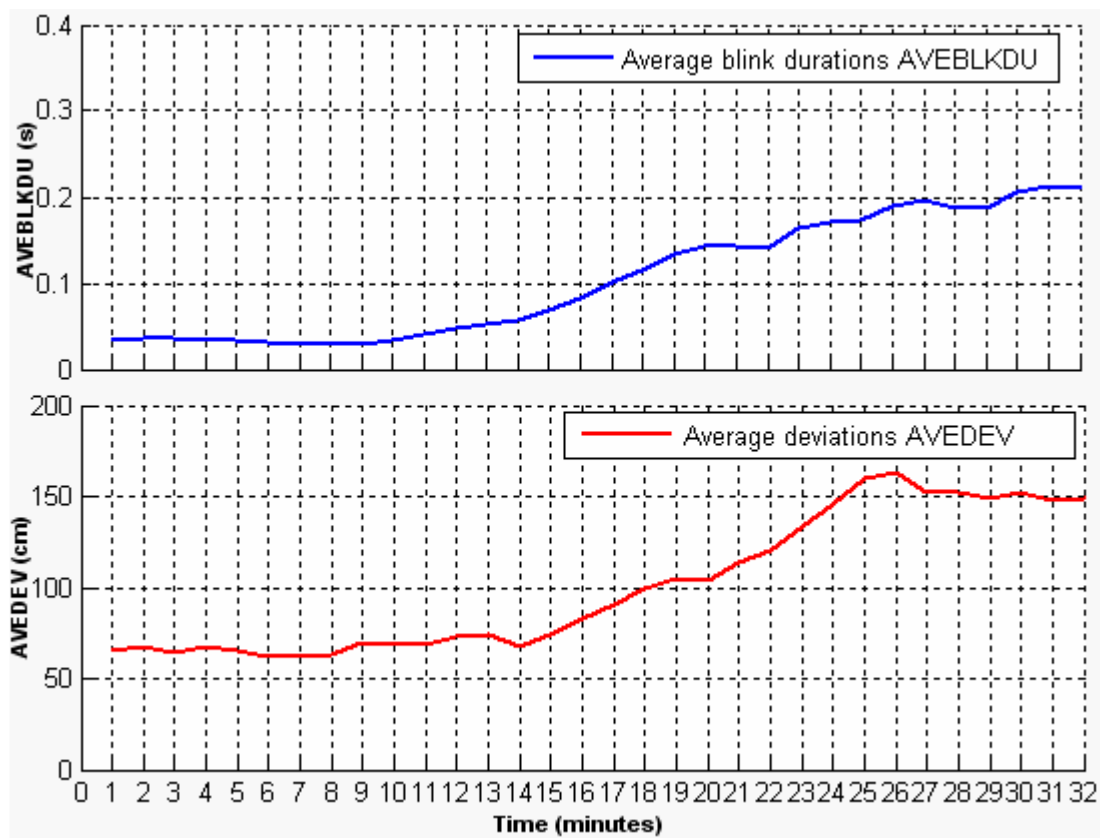
### **Participant number 1**

The participant number one participated in both sleepy and sleep-deprived conditions. This participant's results were selected of those people who participated in both conditions and are shown here for illustration purposes. Figures 8-10 (a) and (b) show driver performance (average deviations AVEDEV) and average blink durations (AVEBLKDU) changes for both sleepy and not-sleepy conditions. The data were averaged and logged at one minute intervals. During the 35 minutes of the simulator test, participant one shows clear variations in driver performance and increase of average blink durations compared to his not sleepy conditions. In the sleep deprivation condition, the participant's performance starts to decline after the 14th minute and AVEDEV shows a rapid increase up to 100 cm during three minutes and, at the same time AVEBLKDU increased gradually. In the not-sleepy condition, the participant's performance (AVEDEV) is stable during the first twenty-five minutes, with a slight increase in the last ten minutes. Table 8-4 shows the variation

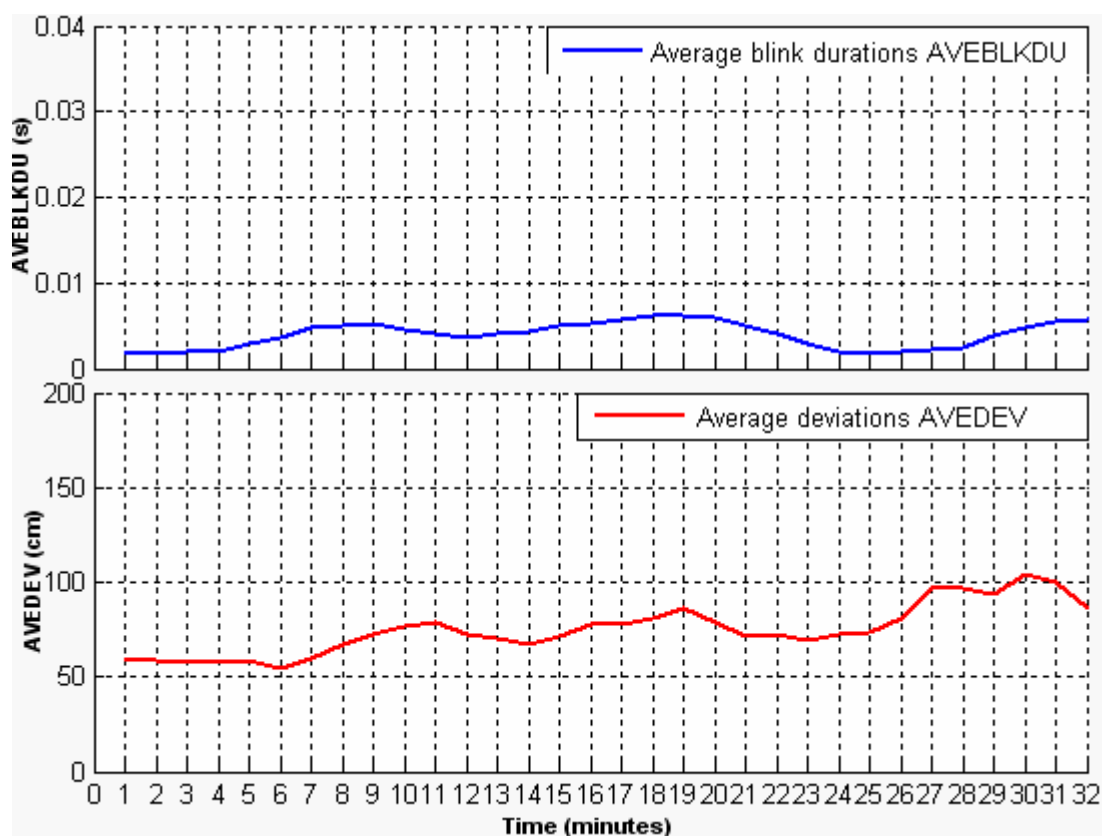
analysis results for sleepy and not-sleepy conditions during the 35 minutes of the simulator test. Variance for not-sleepy is 2.81 and for sleepy is 24.68.

	<i>SD of AVEDEV (Not Sleepy)</i>	<i>SD of AVEDEV (Sleepy)</i>
<b>Mean</b>	9.957	13.562
<b>Variance</b>	2.809	24.681
<b>Observations</b>	34	34
<b>P(T&lt;=t) one-tail</b>	$2.909 \times 10^{-6}$	
<b>t Critical one-tail</b>	1.692	
<b>P(T&lt;=t) two-tail</b>	$5.817 \times 10^{-6}$	
<b>t Critical two-tail</b>	2.0345	

**Table 8-4: Variation analysis for SD of AVEDEV for sleepy and not sleepy conditions**



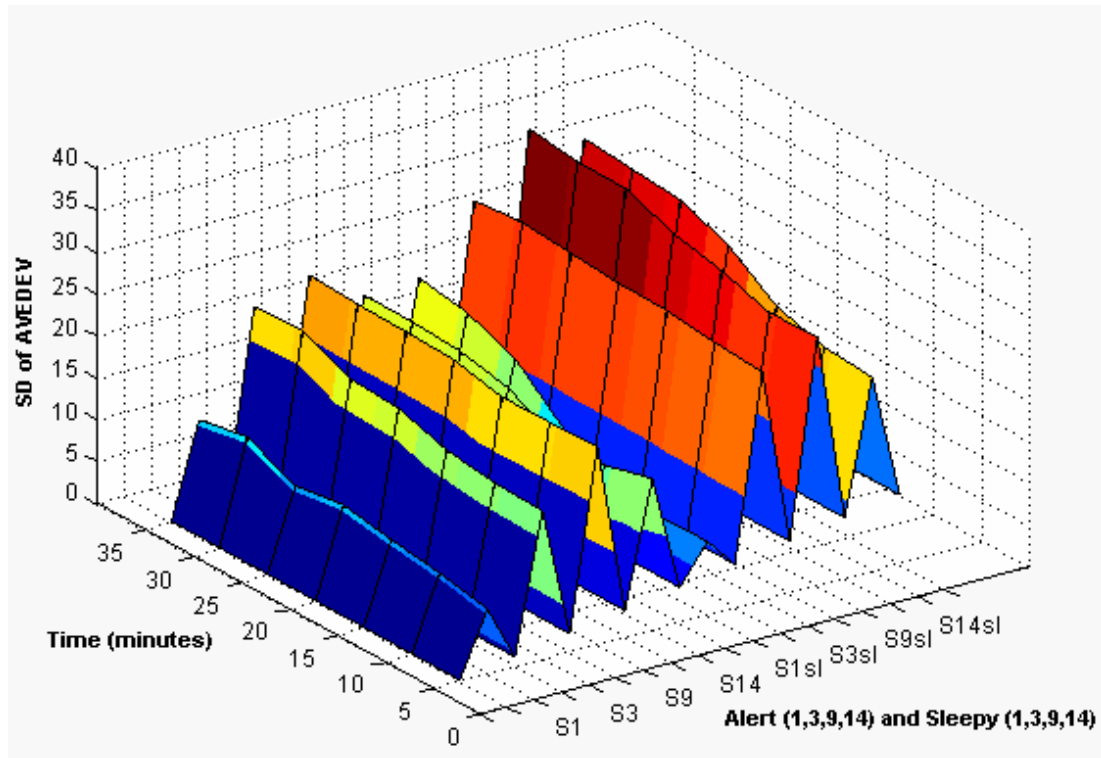
**Figure 8-10(a): Average deviations and average blink durations for participant 1: sleepy condition.**



**Figure 8-10(b): Average deviations and average blink durations for participant 1: not-sleepy condition.**

### Sleep Deprived Participants

Figure 8-11 shows how SD-AVEDEV is affected for every five- minute period for alert and sleepy participants. The figure demonstrates that the participants with sleep deprivation condition have large peaks on the SD of AVEDEV values.



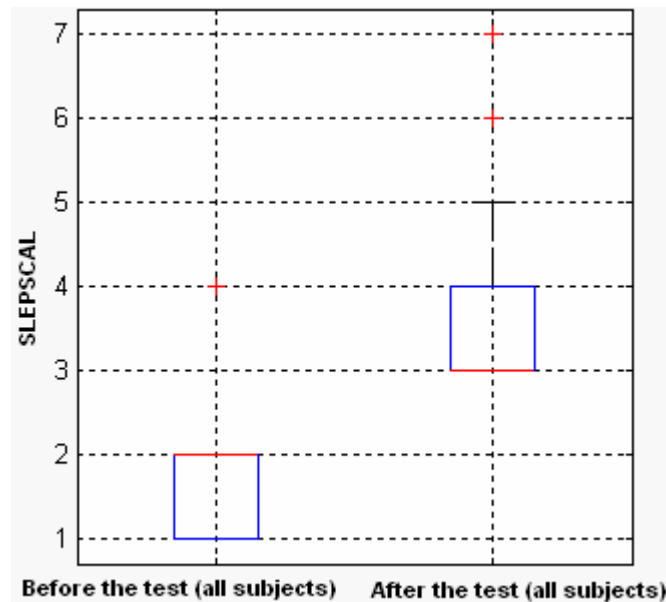
**Figure 8-11: Standard deviation of average deviations (SD-AVEDEV) for four participants under sleep (S1sl, S3sl, S9sl, S14sl) and not-sleep (S1, S3, S9, S14) condition.**

The above results indicate there is a strong relation between sleepiness and the average deviations from the centre line (steering error). Sleep deprivation participants show higher average deviations (30 cm or above). The participants who participated under normal conditions have average deviations (AVEDEV) varying between 5 and 25 cm. Even some of the participants in the normal condition showed an increase in AVEDEV in the last few minutes of their simulation test.

### 8.3.2. Sleepiness Scale (SLEPSCAL)

SLEPSCAL is included in the questionnaire and each participant has to answer before and after the test. Participants were asked to rate how sleepy they felt after the forty minutes using the driving simulator and before the simulator test. The question

is a rating scale from 1 (not-sleepy) to 7 (extremely sleepy, can't keep awake). This question was related to the Karolinska Sleepiness Scale (KSS), widely used in driver drowsiness detection research (Gillberg et al., 1994). As expected, participants reported feeling significantly sleepier at the end of the simulation test compared to the beginning of the test  $t = -15.93$  (d.f.=21),  $p < 0.05$ ) (see Figure 8-10). The mean values of the sleepiness rating before and after the test are 1.81 (Before) and 3.77 (After). Figure 8-12 shows the Boxplot of SLEPSCAL before and after the simulation test.



**Figure 8-12: Boxplot of SLEPSCAL score before and after the simulation test for all participants.**

The SLEPSCAL results also clearly indicates that participants showed some deprived driving condition at the end of the simulation test, because participants become tired or bored while driving for 30-40 minutes on a single track virtual driving simulation. The results indicate that the driver performance declines towards the end of the test.



### **8.3.3. Age (AGE) and Time of the day (TODD)**

The simulation test was conducted in the two sessions, the morning session (9:00am to 11:30am) and the afternoon session (12:30pm to 3:00pm). The study by Wylie et al. (1996) concluded that time of the day is a good predictor of decreased driving performance. Night driving is more associated with drowsiness related accidents than day driving (Akerstedt & Kecklund, 2001). Considering the participants' availability and other factors, the simulator test was conducted in the day time. In this PhD research, TODD and AGE is included under self reported measures in the main predictor variables category. These two measures were analyzed to identify any relationship with performance measures. Ten participants participated in the afternoon session and eight in the morning session. Sleep deprived participants are not included in this study, because their sleepiness conditions are independent of time of the day or age.

The study by Clarke et al. (2006) found young novice drivers (18-24 years old) have a crash rate that is more than four times higher than that of experienced drivers (30-59 years old). The rate of young males is even more than six times higher. The main causes are a lack of experience and the age itself. In the current research, age is categorized into two groups (20–29 years old and 30-70 years old) and analyzed for time of the day with performance measures. Figure 8-13 shows the two age groups who participated in morning and evening sessions and their median values of driving performance measures. It is clear that young drivers (20-29 years old) show poorer driving performance in the mid afternoon session compared to 30-70 years old drivers. The two age groups comparison of SD-AVEDEV is statistically significant,  $t=1.84(d.f=8)$ ,  $p<0.05$ . This compares with SD-AVEREATM which is not significant

at 5%, but it is significant at 10%,  $t=1.75(d.f=3)$ ,  $p=0.088$ . In the morning session, 30-70 years old drivers showed some poorer performance according to SD-AVEDEV and the difference is statistically significant  $t=-1.93(d.f=6)$ ,  $p<0.05$ . The difference with SD-AVEREATM is not significant for these two groups in the morning session.

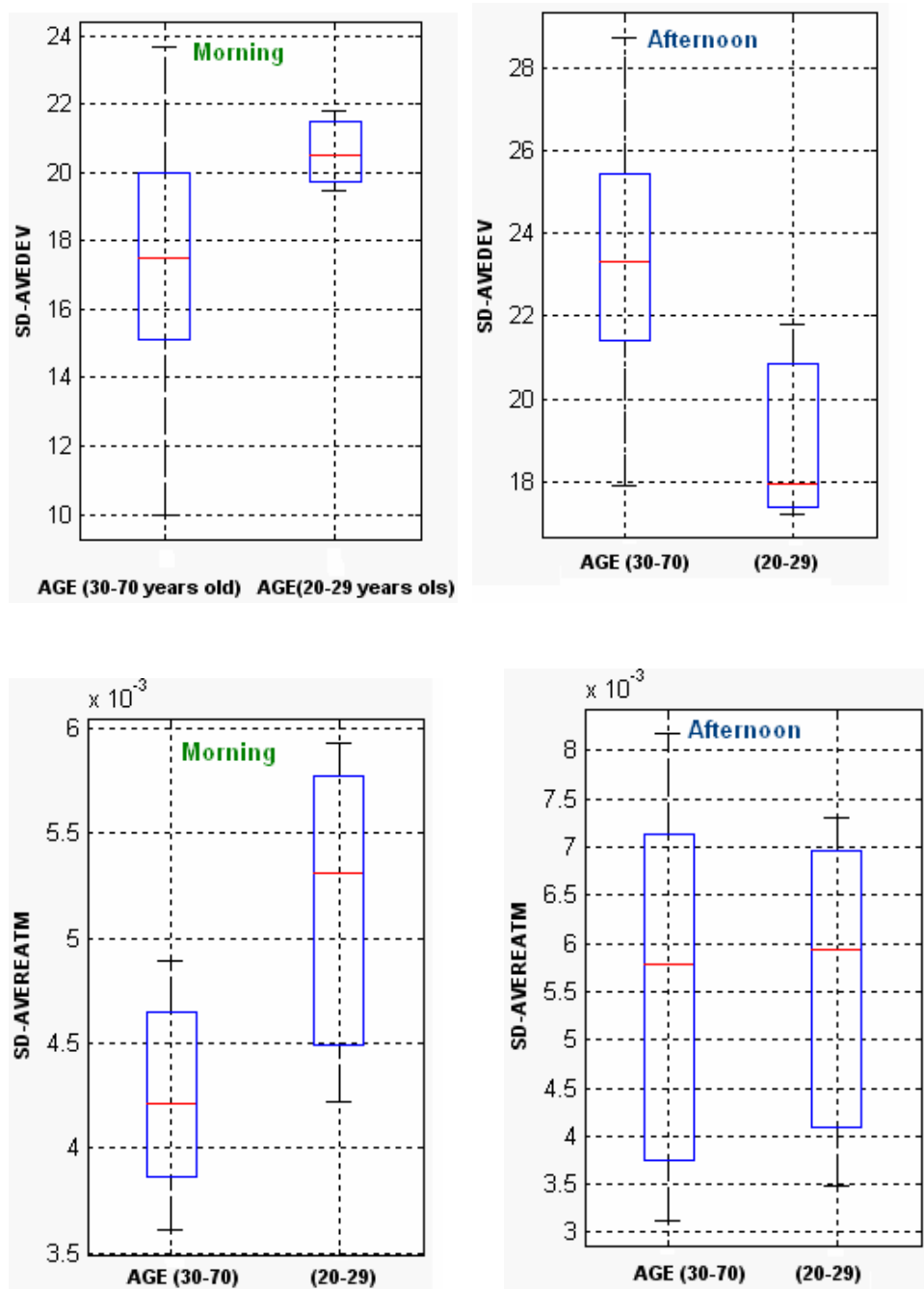


Figure 8-13: Boxplot of performance; participants participated in two sessions

### 8.3.4. Conclusions of the self reported measures

The results from this study indicate there is a good degree of consistency among the self reported measures and performance measures. The SLEPSCAL results showed most of the participants are feeling sleepy or tired after the test and the difference in sleepiness is statically significant. The analysis of Epworth score (EPWOSCL) and the number of hours sleep (NOHS) has shown a significant relationship with performance measures. The age and time of the day results showed young drivers feel sleepy in the mid afternoon session and the middle age drivers showed poor driving performance in the morning session. Table 8-5 summarizes the advantages and disadvantages of self reported measures.

Measure	Advantages	Disadvantages
<b>Epworth Score - EPWOSCL</b>	A measure that may be an indicator of drowsiness. Help to driver drowsiness detection.	Large test sample needed to clarify the significant differences of driver performance.
<b>Number of hours - NOHS</b>	A measure that may be directly associated with drowsiness.	Individual performance variability is high with same NOHS. Difficult to see significant differences between tired and alert with small test sample
<b>Sleep scale - SLEPSCAL</b>	A measure that is directly associated with drowsiness	
<b>Age- AGE</b>	A measure that shows some association with accidents (literature)	Difficult to relate to driver drowsiness with a small test sample
<b>Time of the day- TODD</b>	A measure that shows some association with drowsiness	Difficult to see significant differences between tired and alert with small test sample

**Table 8-5: The advantages and disadvantages of self reported measures**

#### 8.4. Correlation of physiological & speed related measures with performance measures

In this PhD research, physiological and speed related measures are important predictor variables to predict driver impairment. Table 8-6 shows the different sets of measures that were used in the regression analyses.

Predicted Variables	Predictor Variables			
	Average Blink Durations (AVEBLKDU)	Average Blink Frequency (AVEBLKFR)	The Maximum Speed (MAXSP)	The Average Speed (AVESP)
The Average Reaction Time (AVEREATM)				
The Average Deviations (AVEDEV)				
The Out-of-Bounds (OUTOFBON)				

**Table 8-6: Sets of measures used in Regression Analyses for each predicted variables.**

An examination of the average R scores across all sets of predictor variables for each of the three predicted variables gives an indication of the strength of the linear relationship. The results of the average R-score analysis seen below were obtained by averaging the R values for all eighteen participants and four participants with sleep deprivation condition (see Table 8-7).

**Alert participant (participant 1) R value**

Predicted Variables	Predictor Variables			
	Average Blink Durations (AVEBLKDU)	Average Blink Frequency (AVEBLKFR)	The Maximum Speed (MAXSP)	The Average Speed (AVESP)
The Average Reaction Time (AVEREATM)	0.955	0.954	0.213	0.232
The Average Deviations (AVEDEV)	0.904	0.896	0.216	0.223
The Out-of-Bounds (OUTOFBON)	0.383	0.372	0.181	0.187

**Drowsy Participant (participant 1) R value**

Predicted Variables	Predictor Variables			
	Average Blink Durations (AVEBLKDU)	Average Blink Frequency (AVEBLKFR)	The Maximum Speed (MAXSP)	The Average Speed (AVESP)
The Average Reaction Time (AVEREATM)	0.904	0.946	0.037	0.033
The Average Deviations (AVEDEV)	0.856	0.899	0.136	0.127
The Out-of-Bounds (OUTOFBON)	0.620	0.610	0.092	0.087

**Table 8-7: Table of Regression Analyses Results Showing R Values for single participant (Alert/Drowsy)**

An examination of the average R scores across all predicted variables, for each of the four predictor variables, gives a preliminary indication of the relative predictive strengths of the predictor variables. The results showed that two predictor variables

(AVEBLKDU & AVEBLKFR), for all participants and for just sleep-deprived participants, are strongly correlated to the predicted variables.

- AVEBLKDU: Average R = 0.9401 across 18 participants.
- AVEBLKFR: Average R = 0.9351 across 18 participants
- AVEBLKDU: Average R = 0.8646 across 4 sleep deprivation condition participants
- AVEBLKFR: Average R = 0.9139 across 4 sleep deprivation condition participants
- AVESP: Average R = 0.227 across 18 participants
- MAXSP: Average R = 0.238 across 18 participants
- AVESP: Average R = 0.087 across 4 sleep deprivation condition participants
- MAXSP: Average R = 0.138 across 4 sleep deprivation condition participants

The predicted variable 'OUTOFBON' did not show high correlation with predictor variables, but in drowsy participants it showed a clear difference. The OUTOFBON measure was very hard to predict, because only three people went out of bounds in the experiment. This was the main reason to drop OUTOFBON from further analyses. Average R-scores for 'OUTOFBON' for all eighteen participants and four drowsy participants are shown below.

- OUTOFBON: Average R = 0.3214 across 18 participants
- OUTOFBON: Average R = 0.4952 across 4 sleep deprivation condition participants.

### 8.4.1. Final regression model of predictor and predicted variables

Development of the final regression model considered all physiological, speed related and self rating measures with performance measures. The statistical methods have been used for selecting the final regression model variables. The average ‘R’ values discussed in the previous section show the most significant variables to be used for further analysis. Four measures have been selected for the final data analysis. The two variables from predictor variables and the two variables from predicted variables have been finalized. Figure 8-14 shows the final regression model.

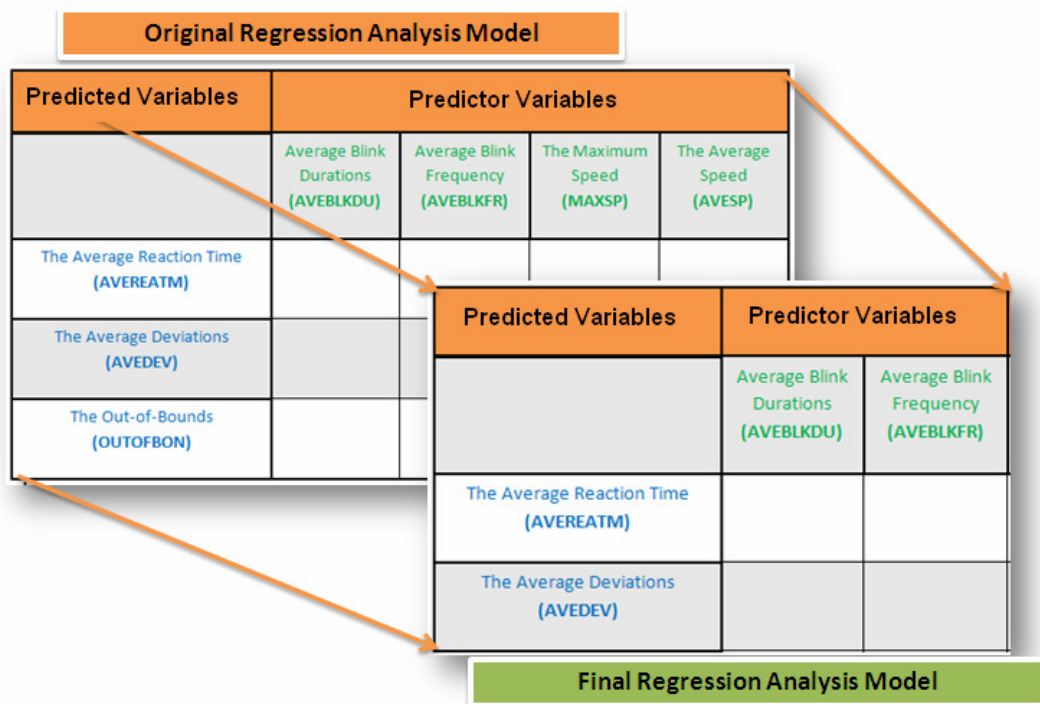
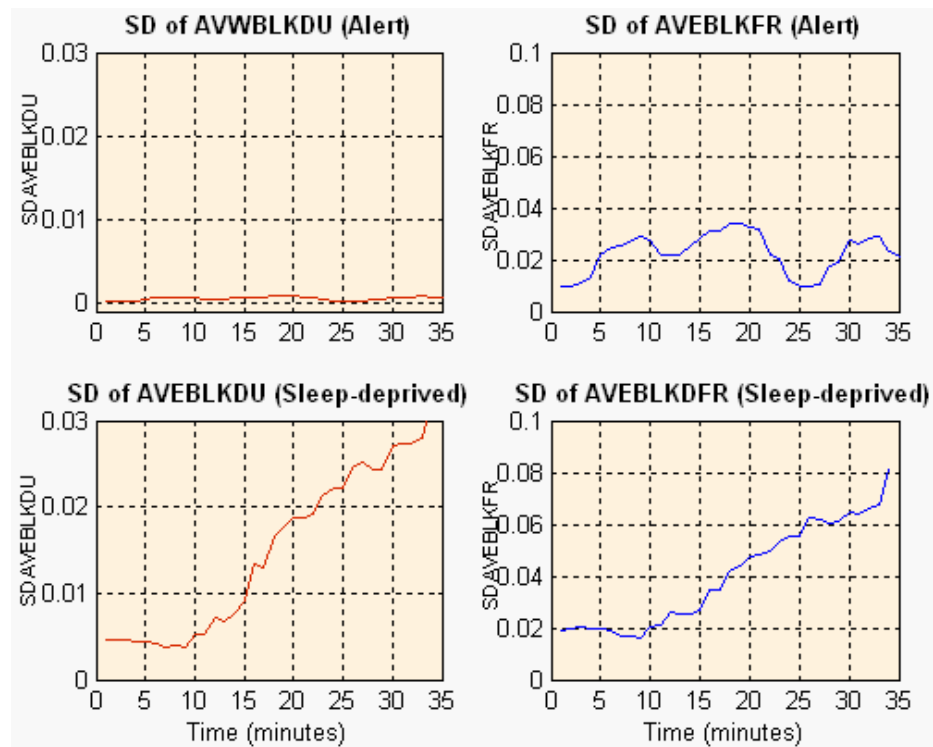


Figure 8-14: Final regression analysis model

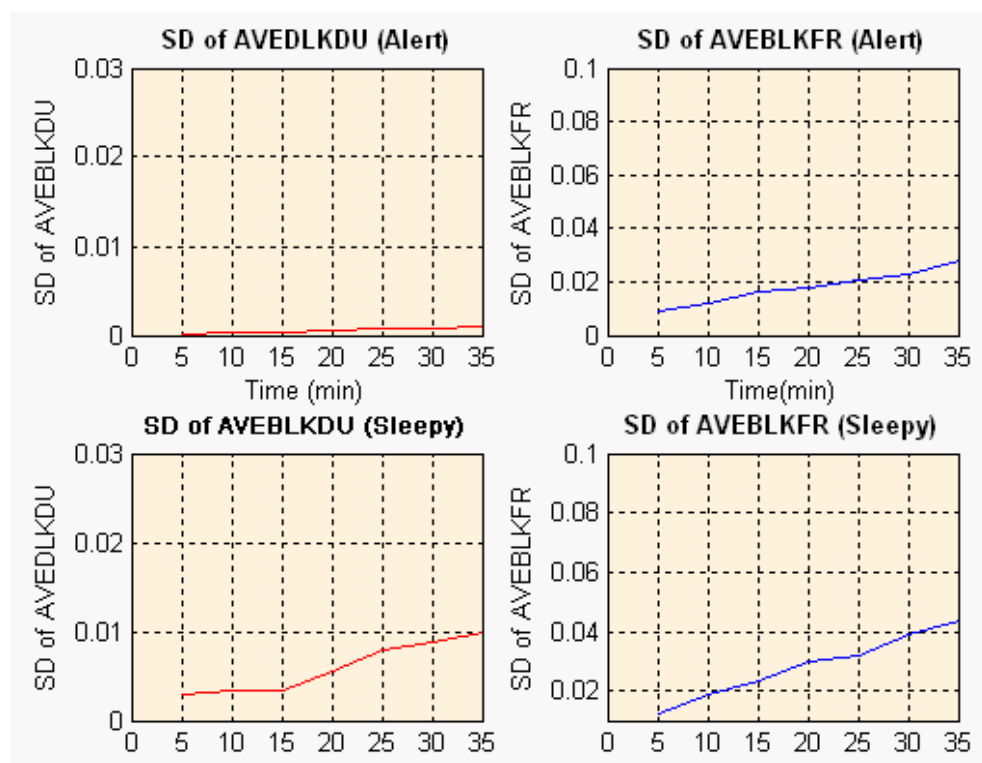
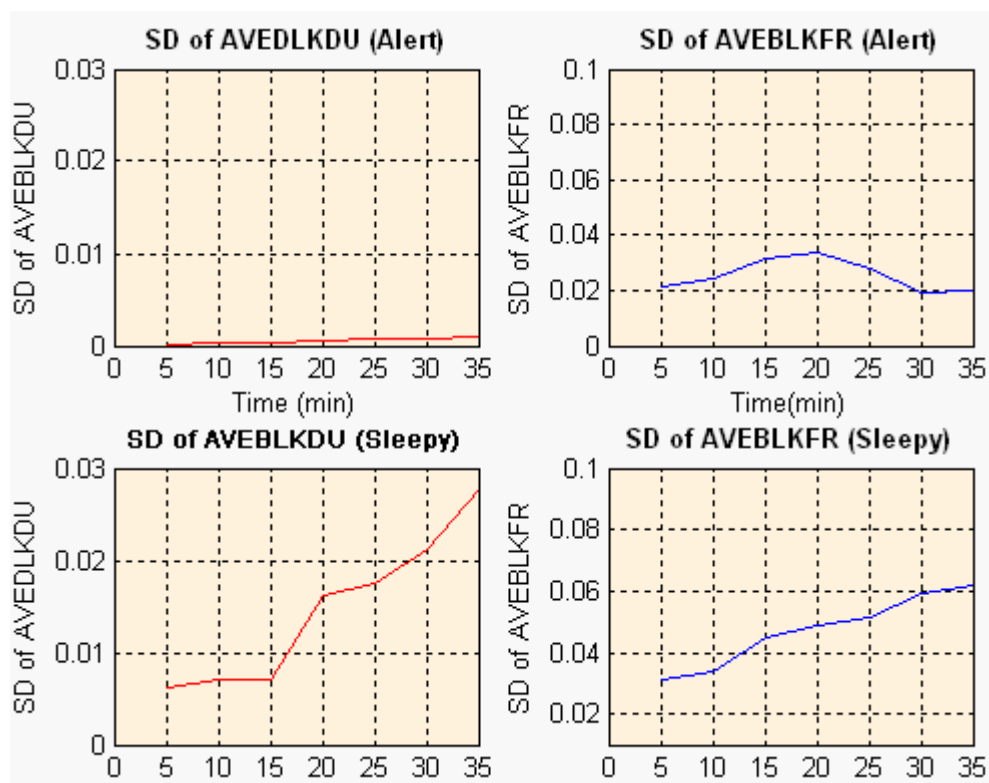
### 8.5. The duration of eye blinks and blink frequency changes with drowsiness

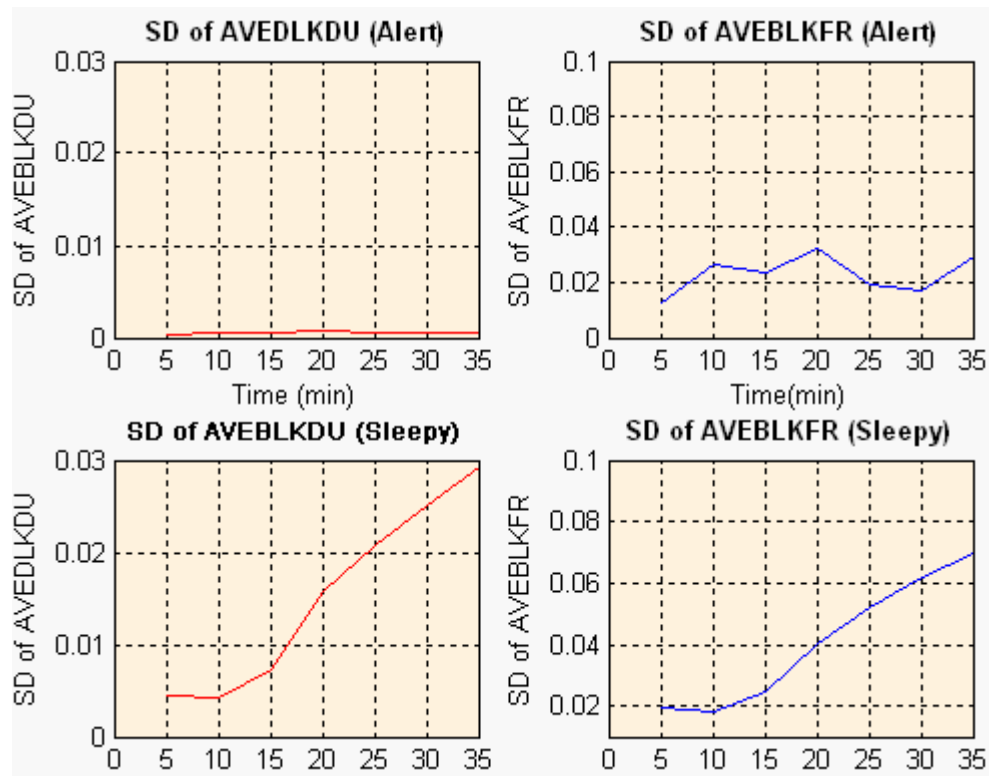
The increased duration of spontaneous blinks has been suggested as an early indicator of the drowsy state (Wijesuriya et al., 2007). Figure 8-15 shows the standard deviation of average blink durations and average blink frequency changes during the simulation test for participants 1, 3, 9, 14 in the alert and sleep deprived conditions. The Figure clearly illustrates the SD of AVEBLKDU and AVEBLKFR (standard deviation of average blink durations and frequency) in an alert condition are significantly lower ( $p < 0.001$ ) compared to the sleep deprived condition.



**Participant: 1**



**Participant: 3****Participant: 9**

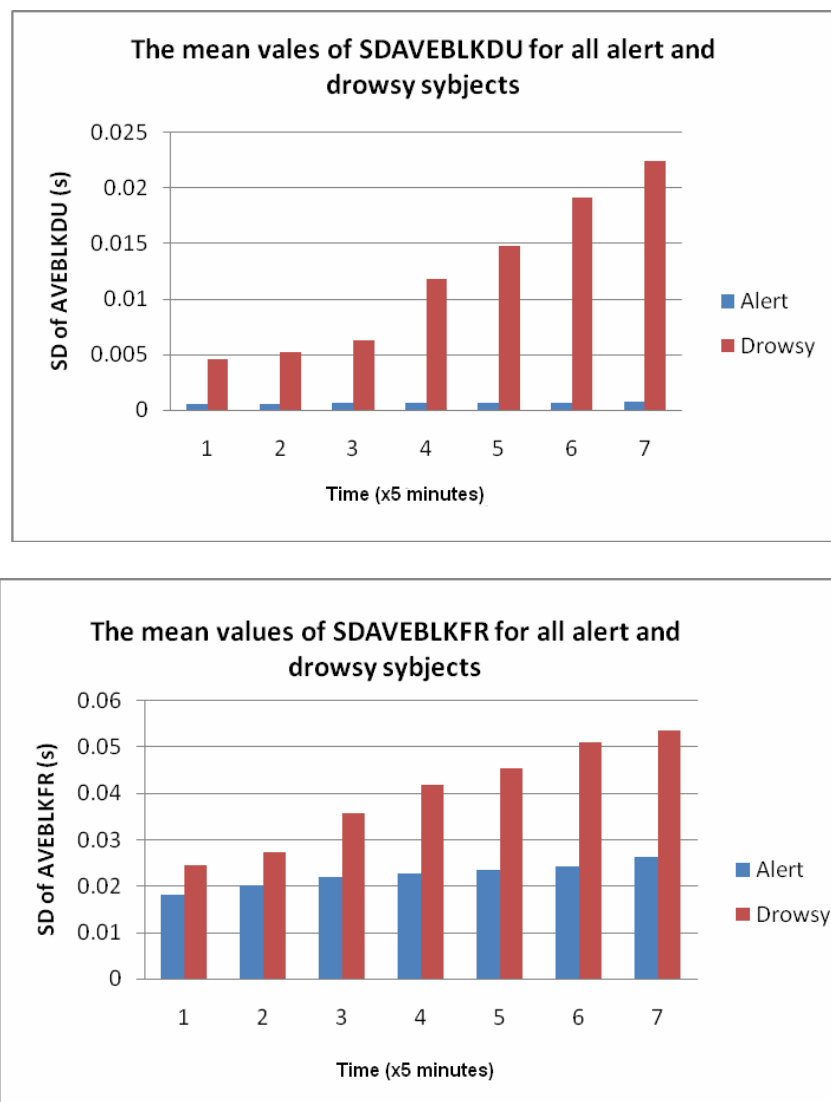


**Participant: 14**

**Figure 8-15: SD of AVEBLKDU and AVEBLKFR variations for participants 1, 3, 9 and 14 in alert and sleepy conditions**

Figure 8-16 shows the mean values of SDAVEBLKDU and SDAVEBLKFR for eighteen participants and the participants who participated in sleep deprivation conditions (see Appendix C2 for further details). Figure 8-16 illustrates the averages over every 5 minutes for all participants. All eighteen participants participated in their normal conditions but participant No 5 showed poor driving performance in the test (participant 5 had a high ESS score of 11). The participant No 5 was added to the sleep deprivation condition category, leaving seventeen participants in the alert category. The mean values of SD of AVEBLKDU for alert participants were significantly lower compared to sleep deprivation participants (average for alert participants = 0.00062 sec and drowsy participants = 0.012 sec) ( $p < 0.001$ ) (see Fig. 8-11). The SD of AVEBLKFR is significantly lower (average for alert participants =

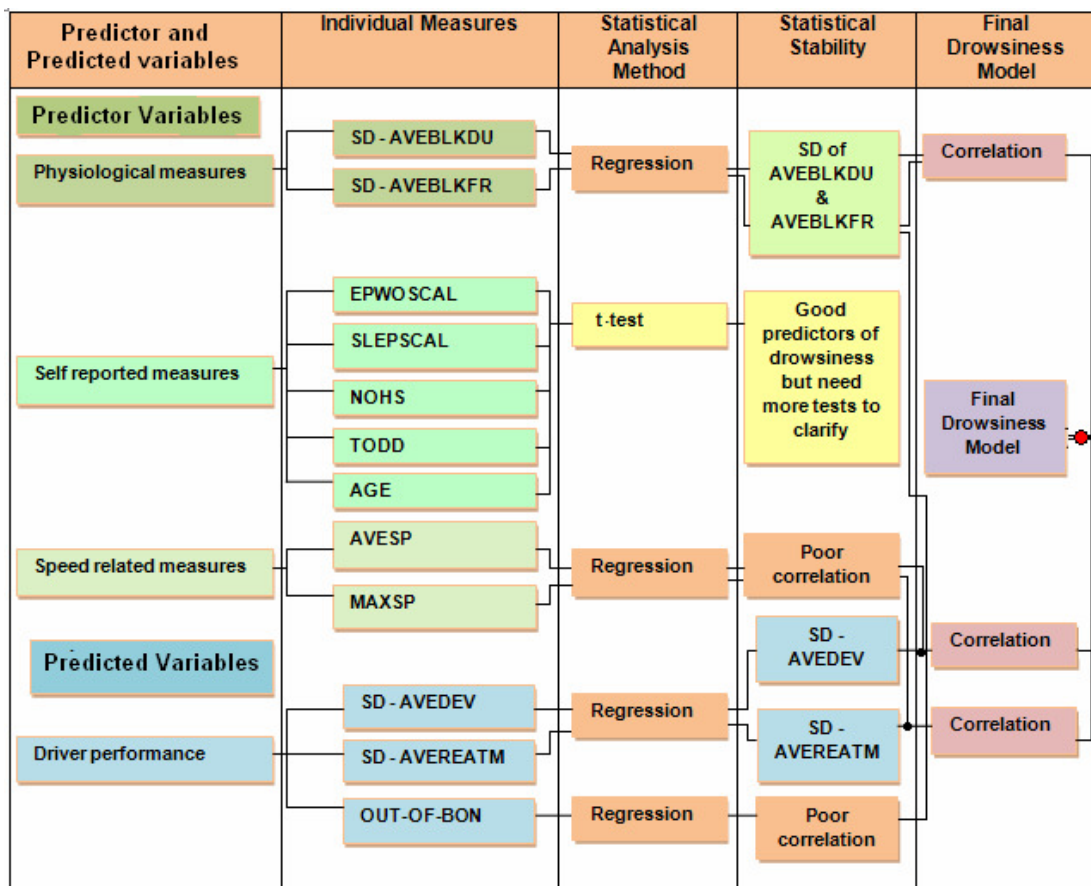
0.022 seconds and drowsy participants = 0.034 seconds) ( $p < 0.001$ ) for alert participants compared to sleep deprivation participants. In alert participants, the SD of average blink duration was very small (variation  $2 \times 10^{-3}$  sec), but this increased markedly to  $17.8 \times 10^{-3}$  sec variation and was highly variable in the drowsy state (see Appendix C2 for 5 minute average data for all participants). The SD of blink frequency in participants when alert (variation  $8.2 \times 10^{-3}$  sec) also increased significantly after sleep deprivation (variation  $29 \times 10^{-3}$  sec,  $p < 0.001$ ).



**Figure 8-16: The mean values of SDAVEBLKDU and SDAVEBLKFR for eighteen participants and the four participants participated in sleep deprivation conditions**

## 8.6. Final correlation analysis model

The final correlation model was designed having taken into account all twelve measures and having considered the statistical significances of these measures. The self rating measures have provided good background in predicting driver impairment according to the reported driver characteristics. Possible reasons for not seeing a relation of MAXSP and AVESP with driving performance is that the speed was limited to 60 km/h. Potential effects on driving performance beyond that speed have not been observed. Figure 8-17 shows the final drowsiness prediction model and the statistical stability of all measures.



**Figure 8-17: Final correlation analysis model and the drowsiness prediction model**

## 8.7. Correlation analysis for SD of average blink duration and average blink frequency.

Data were available for 720 minutes from 18 participants in an alert state and another 160 minutes from four drowsy participants. The test results illustrate that SD of average blink frequency and average blink duration increases significantly ( $p < 0.001$ ) for sleep deprivation participants. Correlation analysis was performed for standard deviation of eye blink (blink frequency and duration) and driver performance measures (deviations and reaction time). Table 8-8 shows the correlation coefficients for alert and sleep deprivation participants (Participant No: 1, 3, 9 and 14).

Standard deviation of average blink duration and frequency correlate with average deviation											
Alert			Alert			Alert			Alert		
SB-1	SD-DU	SD-FR	SB-3	SD-DU	SD-FR	SB-9	SD-DU	SD-FR	SB-14	SD-DU	SD-FR
SD-DE	0.3999	0.228	SD-DE	0.055	0.021	SD-DE	0.697	0.3372	SD-DE	0.0281	0.0903
Drowsy											
SB-1	SD-DU	SD-FR	SB-3	SD-DU	SD-FR	SB-9	SD-DU	SD-FR	SB-14	SD-DU	SD-FR
SD-DE	0.954	0.968	SD-DE	0.946	0.903	SD-DE	0.984	0.9902	SD-DE	0.7848	0.9265

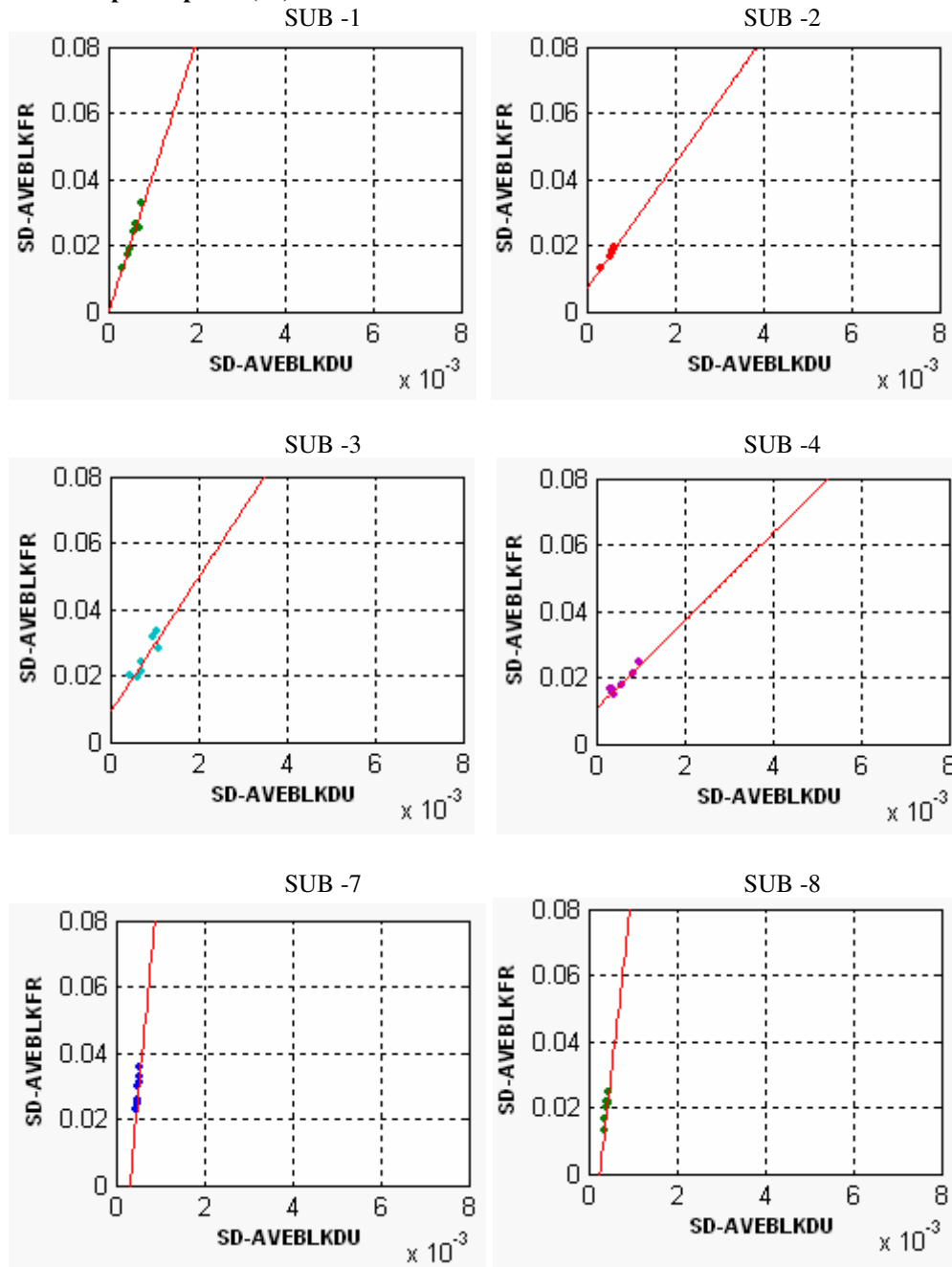
**Table 8-8: Correlation results for alert and drowsy participants**

Note: **SD-DU**; Standard deviation of average blink duration (**SD-AVEBLKDU**)  
**SD-FR**; Standard deviation of average blink frequency (**SD-AVEBLKFR**)  
**SD-DE**; Standard deviation of average deviations (**SD-AVEDEV**)  
**SD-RE**; Standard deviation of average reaction time (**SD-AVEREATM**)

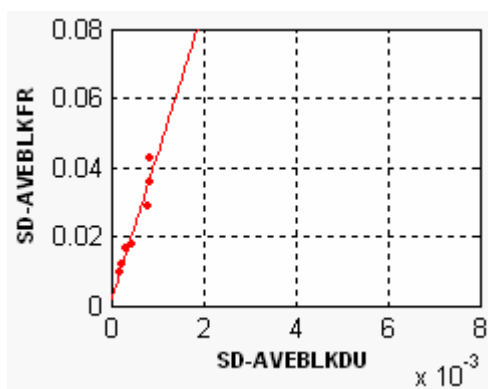
Standard deviation of average blink duration and frequency correlate with average reaction time											
Alert			Alert			Alert			Alert		
SB-1	SD-DU	SD-FR	SB-3	SD-DU	SD-FR	SB-9	SD-DU	SD-FR	SB-14	SD-DU	SD-FR
SD-RE	0.698	0.522	SD-RE	0.54	0.004	SD-RE	0.201	0.212	SD-RE	0.271	0.304
Drowsy											
SB-1	SD-DU	SD-FR	SB-3	SD-DU	SD-FR	SB-9	SD-DU	SD-FR	SB-14	SD-DU	SD-FR
SD-RE	0.954	0.718	SD-RE	0.961	0.914	SD-RE	0.89	0.993	SD-RE	0.916	0.904

Correlation results show that the SD of Average Deviations is highly correlated with SD of average blink duration and average blink frequency for drowsy conditions. The correlation coefficient for SD of average blink duration and frequency for alert participants are very low compared to drowsy participants.

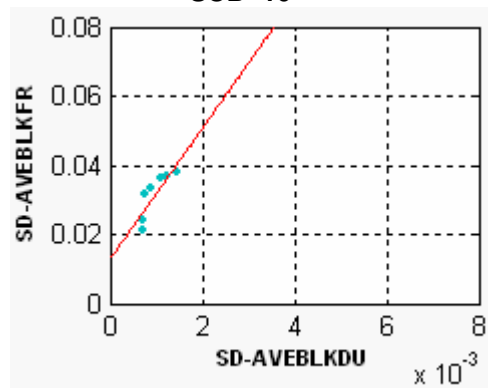
#### All Alert participants (18)



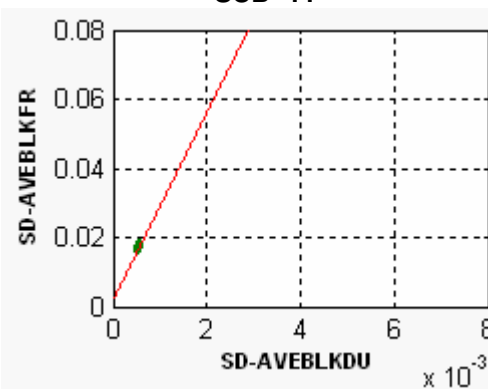
SUB -9



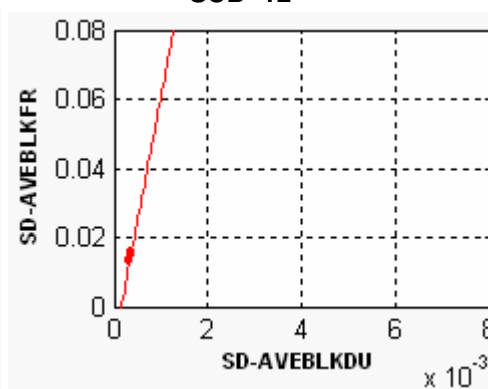
SUB -10



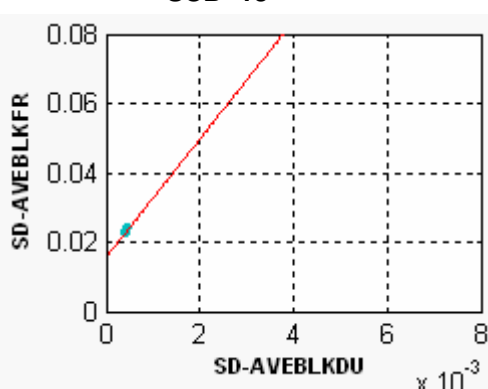
SUB -11



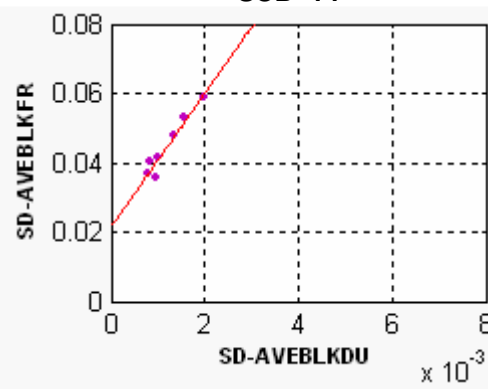
SUB -12



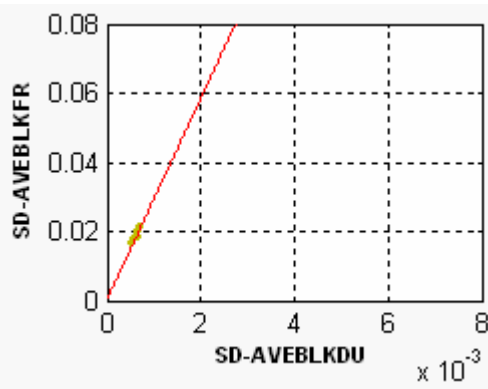
SUB -13



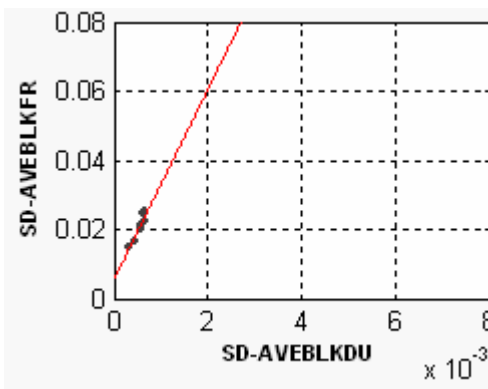
SUB -14

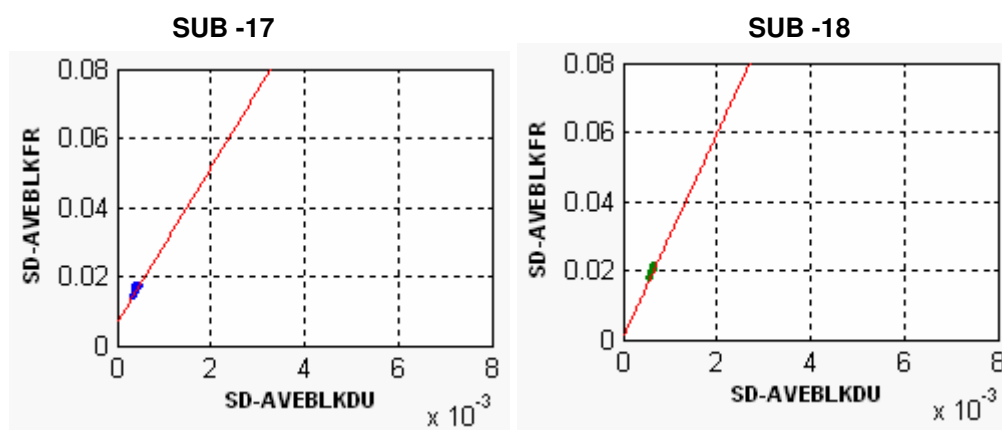


SUB -15

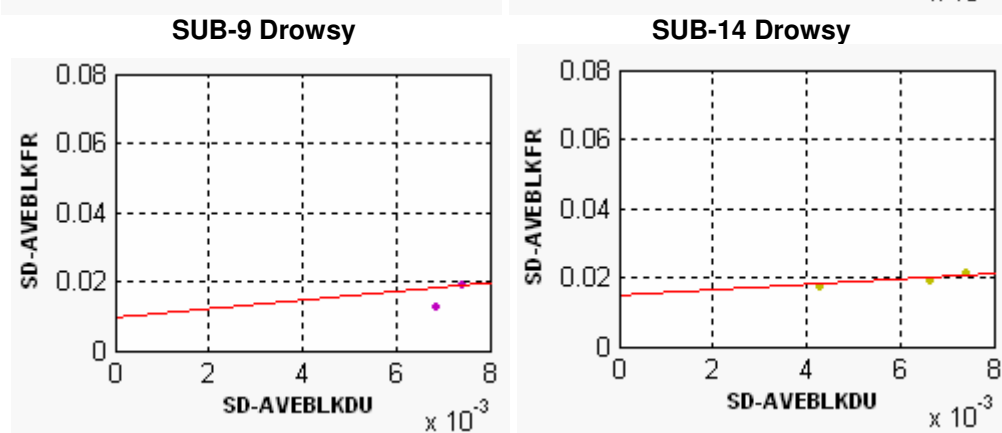
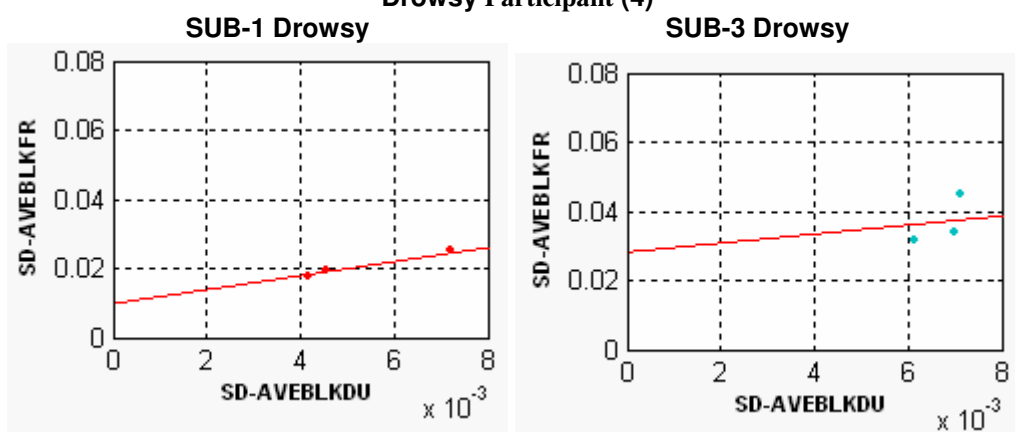


SUB -16





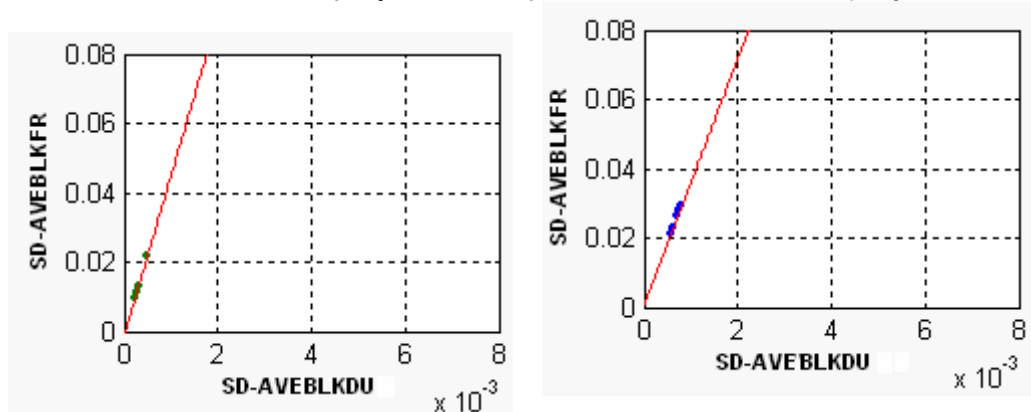
Drowsy Participant (4)



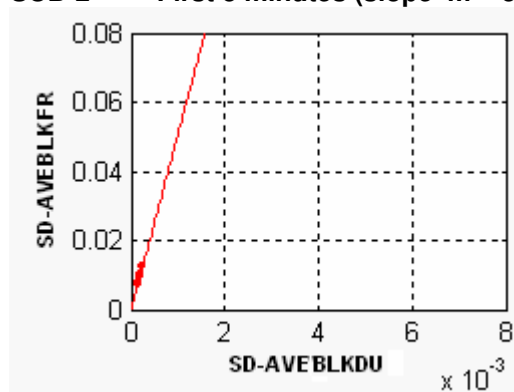
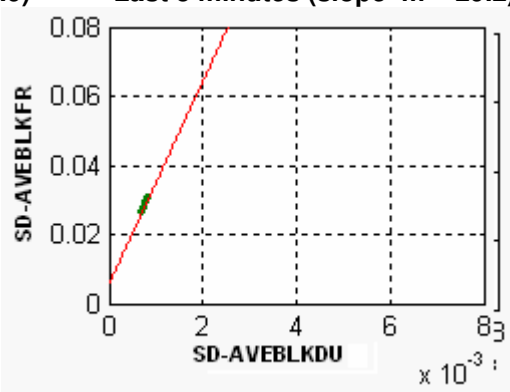
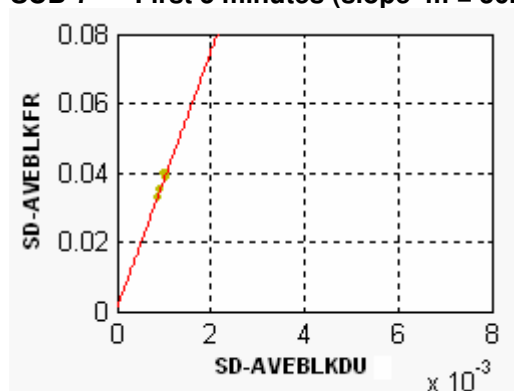
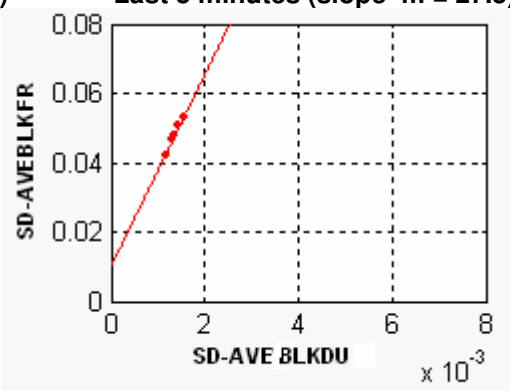
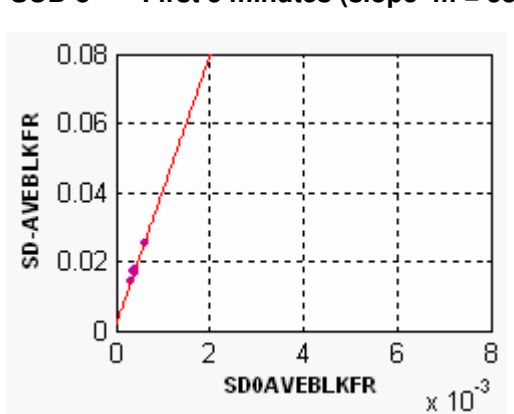
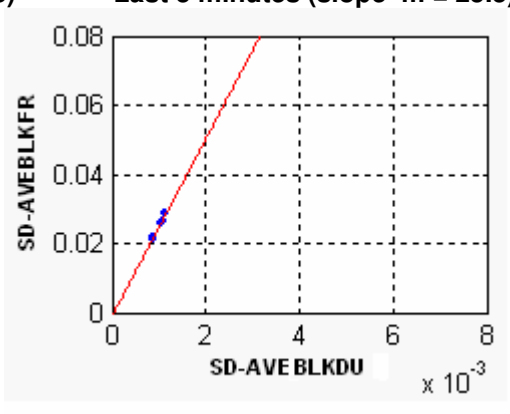
**Participants showed deprived driving performance at the end of the test**

**SUB-1 First 5 minutes (slope 'm' = 46.2)**

**Last 5 minutes (slope 'm' = 35.5)**

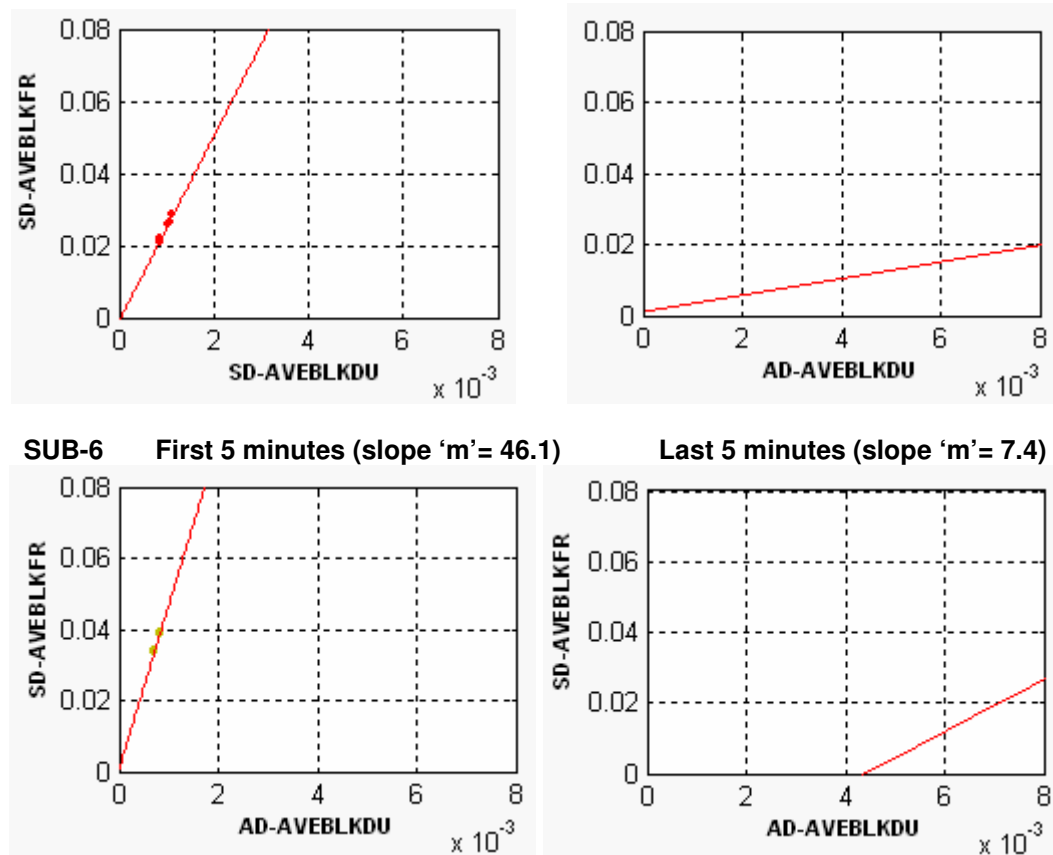




**SUB-2 First 5 minutes (slope 'm'= 50.9)****Last 5 minutes (slope 'm'= 29.2)****SUB-7 First 5 minutes (slope 'm'= 36.8)****Last 5 minutes (slope 'm'= 27.5)****SUB-8 First 5 minutes (slope 'm'= 38.8)****Last 5 minutes (slope 'm'= 25.5)**

**Participants got high ESS score**

**SUB-5 First 5 minutes (slope 'm'= 25.5)****Last 5 minutes (slope 'm'= 2.3)**



**Figure 8-18: Correlation analysis: measure of linear relationship strength between SDAVEBLKDU and SDAVEBLKFR for all alert and drowsy participants**

### 8.7.1. Alert participants

The correlation results of SD of average blink duration and average blink frequency in alert participants are shown in Figure 8-18 (Alert) (see Appendix C2 for all participants). Each point represents a five minute average of blink duration and frequency (each point equals 300 data points). These two variables are very highly correlated for both drowsy and alert participants (Pearson's  $r = 0.98$ ,  $n = 7$ ,  $p < 0.001$ ). Table 8-9 shows the correlation coefficients (Pearson's  $r$ ) for two variables for all alert and drowsy participants. The comparable correlation between SDAVEBLKDU and SDAVEBLKFR for the alert state (Fig. 8-18) was almost as high ( $r = 0.97$ ,  $n = 7$ ,  $p < 0.001$ ) but with a different regression slope.

**Table 8-9: Correlation coefficients of SDAVEBLKDU and SDAVEBLKFR for all alert and drowsy participants**

SUB No: (Alert)	1	2	3	4	5	6	7	8	9
	0.96	0.99	0.89	0.96	0.81	0.79	0.96	0.92	0.91
SUB No: (Drowsy)	1	3							9
	0.99	0.93							0.94
SUB No: (Alert)	10	11	12	13	14	15	16	17	18
	0.84	0.81	0.89	0.75	0.97	0.91	0.92	0.8	0.98
SUB No: (Drowsy)					14				
					0.99				

The slope of linear regression is higher in alert participants compared to sleep deprived participants or drowsy participants (slope range for alert participants,  $m = 18$  to 140). The statistical model used for linear regression is:  $y = mx + b$ .

In this particular equation, the constant ' $m$ ' determines the 'slope' or gradient of that line. Example below shows the slope for linear regression for participant 1 in alert and sleep deprivation condition.

**SB 1 Alert:**  $m = 41.10$   
 $b = -0.00053$

**SB 1 Drowsy:**  $m = 2.012$   
 $b = 0.0099$

### 8.7.2. Drowsy participants

The relationship between the SD of AVEBLKDU and SD of AVEBLKFR in the drowsy state is shown in Fig. 8-18 (Drowsy). There were very low slopes for drowsy participants,  $m = 0.05$  to 2.0, compared to slopes of  $m = 18$  to 140 for alert participants. i.e., the blink duration and frequency was high and more variable for most participants in the sleep deprivation state than in the alert state (see Appendix C2, SD of AVEBLKDU & FR change with AVEDEV and AVEREATM for alert and drowsy state).

## 8.8. A New Scale of Drowsiness Based on Multiple Characteristics of Blinks.

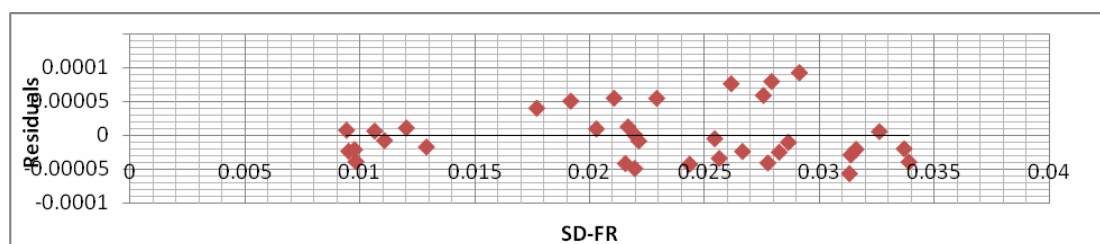
The above correlation results focused on the development of an operational definition of drowsiness based on a combination of SD of blink duration and SD of blink frequency. Although blink duration is a very accurate operational definition of drowsiness (Johns, 2003), no previous research has looked at the form of the relationship between the variables of eye blink duration and frequency as a possible predictor of drowsiness. This is examined in this section.

### 8.8.1. Evaluating the Goodness of Fit

The linear relationship between SD of blink duration and frequency was evaluated for its goodness of fit. The residual plots are used to test the goodness of fit. The residuals from a fitted model are defined as the differences between the response data and the fit to the response data at each predictor value.

$$\text{residual} = \text{data} - \text{fit}$$

Figure 8-19 shows the residual plot for participant 1 in an alert condition with predicted SD-AVEBLKDU. The results show the residuals appear randomly scattered around zero indicating that the model describes the data well.



**Figure 8-19: The residual plot for participant 1 in alert condition**

Most of the alert participants showed some increase in their blink duration and frequency in the last few minutes of the simulator test. The reason for this behaviour suggested that they were not fully concentrating on the driving, or were bored. The primary limitation of the slow eyelid closure measures (PERCLOS and Johns' drowsiness scale) is that drivers may not exhibit this behaviour until they are severely drowsy and/or impaired. The advantage of this eye blink correlation method is it can identify the drowsiness at the very early onset of drowsiness or drowsiness.

### **8.8.2. Calculating Slope (m) for all alert and drowsy participants**

All available eye blink data from alert participants (630 min from 18 participants), and all data (140 min from 4 participants) from sleep deprivation participants' SD of average blink duration and SD of average blink frequency were correlated and the linear regression coefficient and slope (m) recorded. Table 8-10 shows the slope 'm' (SD-AVEBLKDU vs SD-AVEBLKFR) for all participants and their performance data (alert and sleep deprived conditions).

Participant No:	Age	Epworth Score	Sleep time During 24hrs	AVGDEV	SD-AVEREAT M	Slope (m)
1	35	6	9	9.96	0.00361	41.096
2	36	6	8	20.59	0.00425	18.921
3	65	12	7	24.32	0.00679	20.352
4	27	7	7	17.97	0.00731	13.181
5	32	11	9	23.3	0.00312	13.906
6	30	10	7	28.73	0.00818	27.781
7	25	6	8	19.5	0.00422	140.41
8	31	5	7	16.75	0.00381	115.65
9	31	7	8	17.5	0.00401	42.052
10	60	8	9	14.56	0.00489	18.851
11	40	9	8	17.89	0.00397	27.033
12	38	6	9	22.56	0.00579	71.533
13	51	7	7	18.27	0.00478	17.034
14	22	5	8	17.21	0.00349	19.217
15	26	9	7	21.82	0.00593	29.029
16	30	7	8	21.85	0.00576	27.396
17	24	6	7	20.52	0.00531	22.335
18	38	9	7	23.7	0.00421	29.344

#### Participants participated in alert condition

Participant No:	Age	Epworth Score	Sleep time During 24hrs	AVGDEV	SD-AVEREAT M	Slope (m)
1	35	6	3	13.17	0.0117	2.0181
9	31	7	3	28.14	0.0124	1.3033
3	65	12	4	31.32	0.067	1.2336
14	22	5	3	26.37	0.022	0.78114

#### participants participated in sleep deprived condition

**Table 8-10: Participants' data with linear regression m (slope) values**

### 8.8.3. Logarithm of Slope (m) values and ranking

The correlation coefficient (r) was calculated for all 18 and 4 drowsy participants. The correlation coefficient (r) values do not exhibit a clear difference of value between the two states of alertness and drowsiness. The slope (m) values were converted to 'ln' (natural logarithm) transformation to produce a matrix for the detection method (see Table 8-11). Rank ordering the slope (m) and taking the logarithm of these values, showed clear partitioning in the values.

Participant No	Slope (m)	participant Rank	Descending	Ln	Categ	Range
1	41.096	5	140.41	4.944	10	Alert
2	18.921	14	115.65	4.750	10	Alert
3	20.352	12	71.533	4.270	9	Alert
4	13.181	18	42.052	3.738	8	Alert
5	13.906	17	41.096	3.716	8	Alert
6	27.781	8	29.344	3.379	7	Alert
7	140.41	1	29.029	3.368	7	Alert
8	115.65	2	27.781	3.324	7	Alert
9	42.052	4	27.396	3.310	7	Alert
10	18.851	15	27.033	3.297	7	Alert
11	27.033	10	22.335	3.106	7	Alert
12	71.533	3	20.352	3.013	6	Alert
13	17.034	16	19.217	2.955	6	Alert
14	19.217	13	18.921	2.940	6	Alert
15	29.029	7	18.851	2.936	6	Alert
16	27.396	9	17.034	2.835	6	Alert
17	22.335	11	13.906	2.632	5	2.57 Ques'ble
18	29.344	6	13.181	2.578	5	2.57 Ques'ble
1SLP-19	2.0181	19	2.0181	0.702	2	Drowsy
3SLP-20	1.3033	20	1.3033	0.264	1	Drowsy
9SLP-21	1.2336	21	1.2336	0.209	1	Drowsy
14SLP-22	0.78114	22	0.78114	-0.247	1	Drowsy

**Table 8-11: The slope (m) values, 'ln' (natural logarithm) values and rank order.**

The values ranged from 4.94 at the highest to around zero at the bottom end. The participants on ln range 4.94 to 2.57 were very alert. The next range (2.57 to 1.5) was the questionable range in this study, where it is difficult to detect whether the participant is drowsy or alert. Most of the participants in the questionable range showed some deprived driving performance in the last 5 to 10 minutes of the test. Dividing these values into partitions was then important to understand the range of alertness. The logarithm value range from 0 to 5 is easily divided into 10 divisions that can clearly identify this range.

#### 8.8.4. Categorization of New Scale

Table 8-11 shows the ‘logarithm’ transformation values of slope categorized to range 0-10 for quantifying subjective drowsy level. The range 0-10 (see Table 8-12) is a score based on linear correlation from standard deviation of blink duration and frequency on alert and drowsy conditions (coded 0 and 10) from the ocular variables, minute by minute. The natural logarithm values range from 4.9 to 0.2 (Alert - to - Drowsy). The rank ordering divides the slope (m) values into three categories. The sleep deprived participants showed this lower slope (m) values and the drowsy range categorized to 0.0 to 1.5. The values lower than 2.6 and above 1.5 are categorized as the questionable category. In the questionable category range, participants showed some poor driving performance in the last 10-15 minutes of their driving test. The values above the 2.6 are categorized as alert range. In this range (2.6 – 4.95) participants did not show any poor driving performance.

Category	10	9	8	7	6	5	4	3	2	1
logarithm values of slope(m)	4.6 - 5.0	4.1 - 4.5	3.6 - 4.0	3.1 - 3.5	2.6 - 3.0	2.1 - 2.5	1.6 - 2.0	1.1 - 1.5	0.6 - 1.0	0 - 0.5

**Table 8-12: Categorization of Drowsiness Scale**

#### 8.9. Validation of new drowsiness scale

The driving performance data collected during the simulation session were compared to the new drowsiness scale to investigate the relationship between drowsiness and driving performance, in terms of average deviation from centre line, and average reaction time. Because the raw data have already been summarised as per-minute measurements, the scatter plot is not a suitable way to illustrate this



relationship between drowsiness and the driving performance. Instead, the continuous slopes (m) were categorized to scale range from 1 to 10 (see Table 8-12).

### 8.9.1. Relationship between driving performance and new drowsiness scale (NDS)

The driving performance data collected during the simulation session were categorized to the new drowsiness scale to investigate the relationship between drowsiness and driving performance, in terms of SD of average deviations and average reaction time. Figure 8-20 shows the standard deviation (SD) of average deviation (AVEDEV) across categories of New Drowsiness Scale (NDS) for the entire alert and sleep deprived participants. The SD-AVEDEV is categorized by the new drowsiness scale NDS (1-5, Drowsy and Questionable) and NDS (6-10, Alert), the t-test gives the value  $t=5.95$ , which is significant ( $p<0.05$ ), indicating that the differences between two categories were greater than zero for drowsy participants.

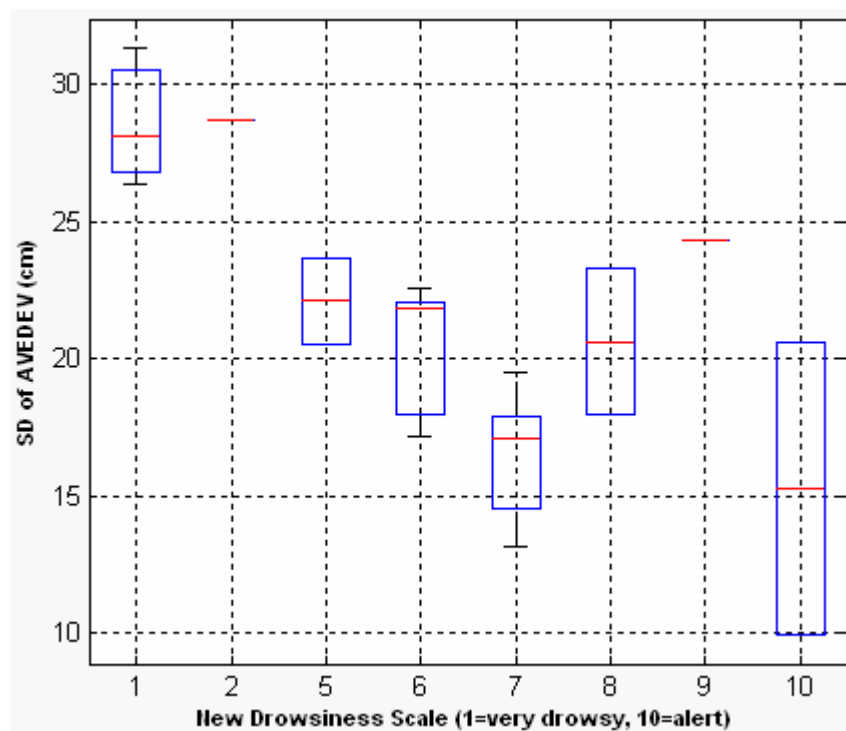


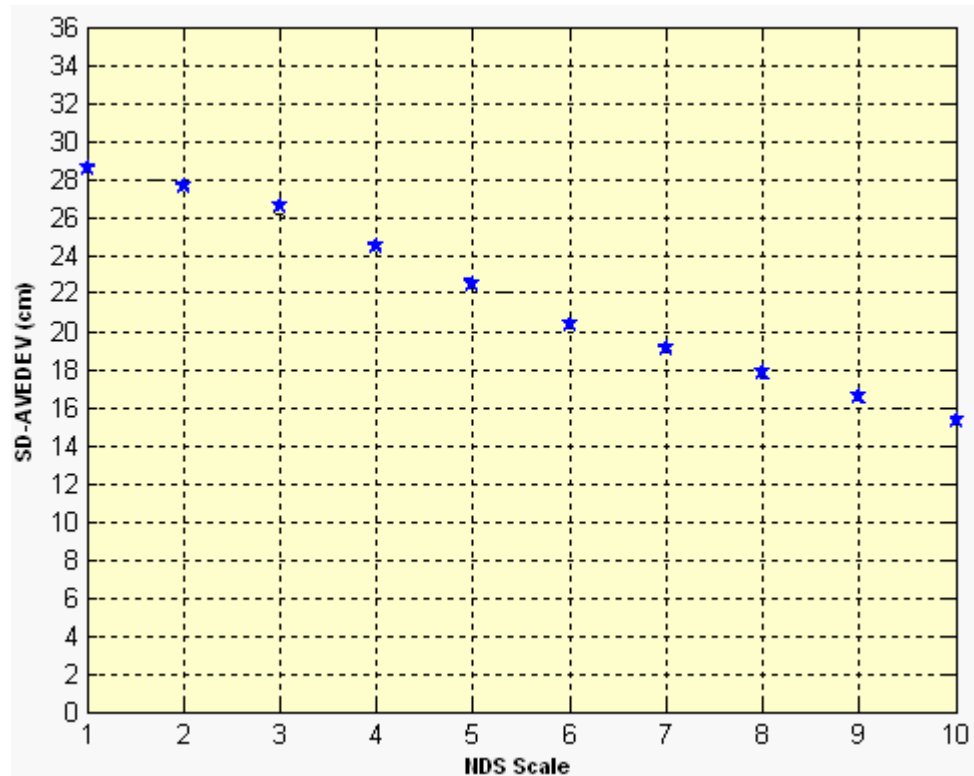
Figure 8-20: SD of AVEDEV across new drowsiness scale for all participants

### 8.9.2. Variability in lane position (SD-AVEDEV)

Figure 8-21 shows the average SD-AVEDEV value for the each NDS category for all alert and sleep-deprived participants (22 participants). As drowsiness increases, the SD-AVEDEV increases. This relationship appears to vary according to whether the driver is sleep-deprived or not; for NDS categories of 3 and below, there is a trend for the standard deviation of average deviations to be greater in the sleep-deprived sessions than the alert session for any given NDS (NDS category, 1=very drowsy and 10=very alert). Table 8-13 shows the SD-AVEDEV averaged to NDS categories and the logarithm values of slope (m) for all alert and sleep-deprived participants.

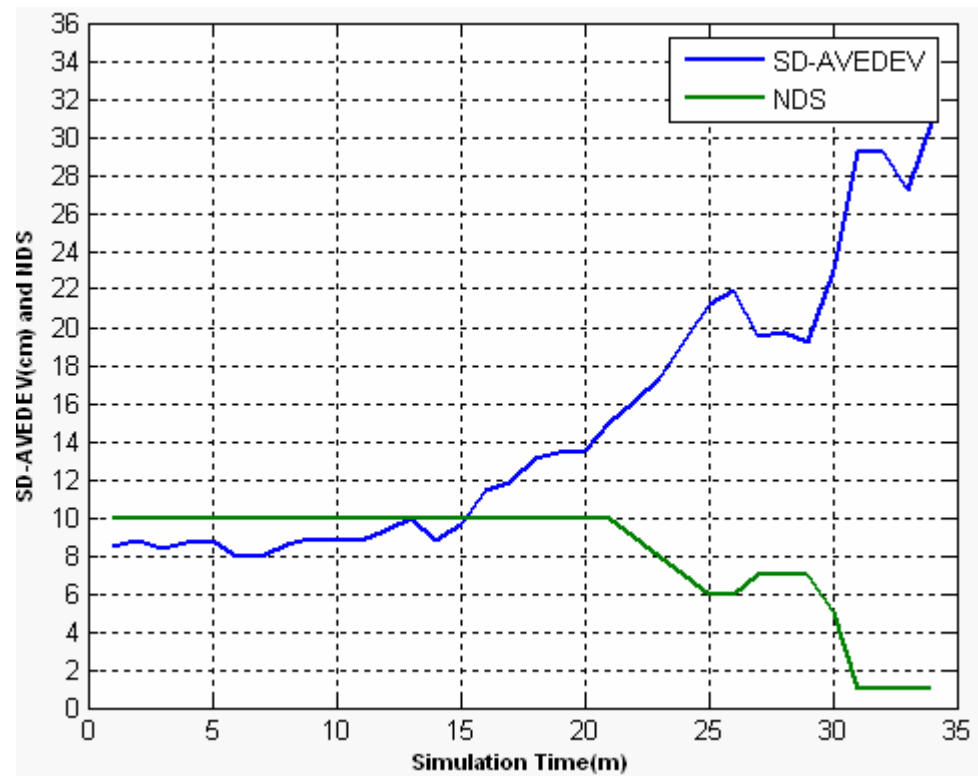
<i>ln of Slope(m)</i>	<i>NDS</i>	<i>SDAVEDEV(cm)</i>
<b>0 - 0.5</b>	<b>1</b>	28.61
<b>0.6 - 1.0</b>	<b>2</b>	27.58
<b>1.1 - 1.5</b>	<b>3</b>	26.55
<b>1.6 - 2.0</b>	<b>4</b>	24.50
<b>2.1 - 2.5</b>	<b>5</b>	22.43
<b>2.6 - 3.0</b>	<b>6</b>	20.37
<b>3.1 - 3.5</b>	<b>7</b>	19.09
<b>3.6 - 4.0</b>	<b>8</b>	17.82
<b>4.1 - 4.5</b>	<b>9</b>	16.55
<b>4.6 - 5.0</b>	<b>10</b>	15.28

**Table 8-13: SD-AVEDEV averaged to NDS categories and ln of slope (m)**

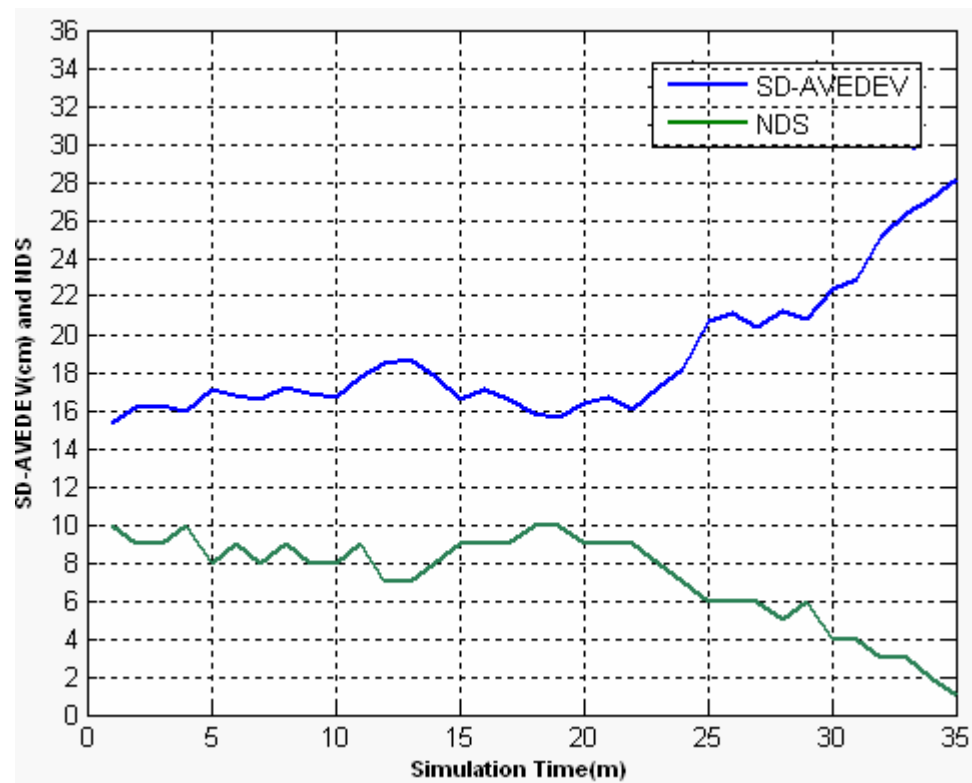


**Figure 8-21: SD-AVEDEV and NDS categories for all alert and sleep-deprived participants**

Figures 8-22 (a), (b), (c) and (d) show four sleep-deprived participants' SD-AVEDEV changes compared with NDS (1 to 10). Figure 8-22 (a) shows the participant 1's SD-AVEDEV changes and it clearly indicates that in the first 20 minutes, participant 1 showed an alert condition. For the 40 minute simulation, the poor driving performance started after 20 minutes of driving. The driver is thus becoming drowsy or inattentive to driving towards the end of the test. The NDS drops from 10 to 1 in the last 15 minutes of the test. All sleep deprived participants and some alert participants showed poor driving performance in the last 20 minutes of the test. The SD-AVEDEV is categorized by simulation time (first 20 minutes and last 20 minutes). The difference between first 20 minutes and the last 20 minutes of SD-AVEDEV is statistically significant,  $t=-8.73(d.f=15)$  and  $p<0.05$ .



**Figure 8-22(a): Participant 1's SD-AVEDEV changes during 35 minutes and NDS**



**Figure 8-22(b): Participant 9's SD-AVEDEV changes during 35 minutes and NDS**

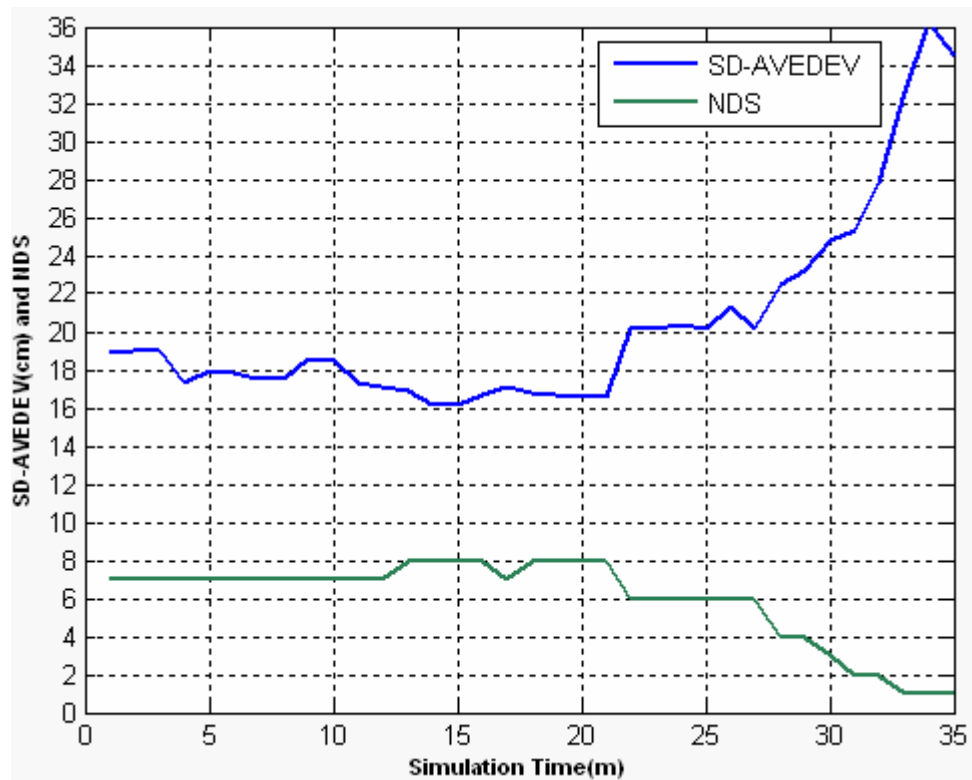


Figure 8-22(c): Participant 14's SD-AVEDEV changes during 35 minutes and NDS

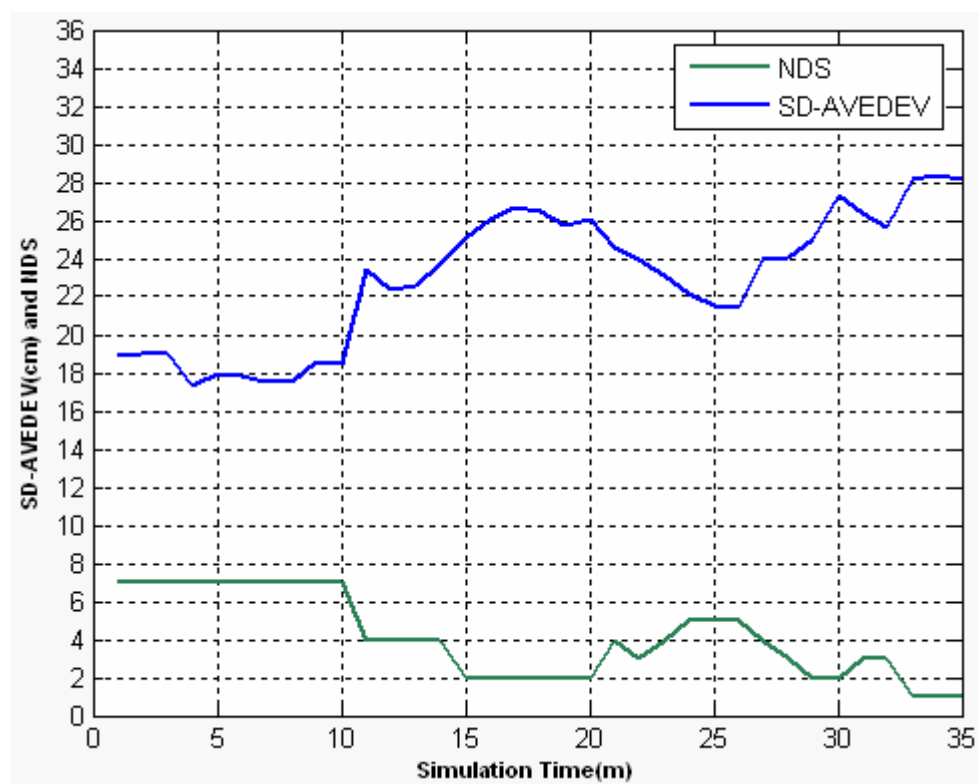
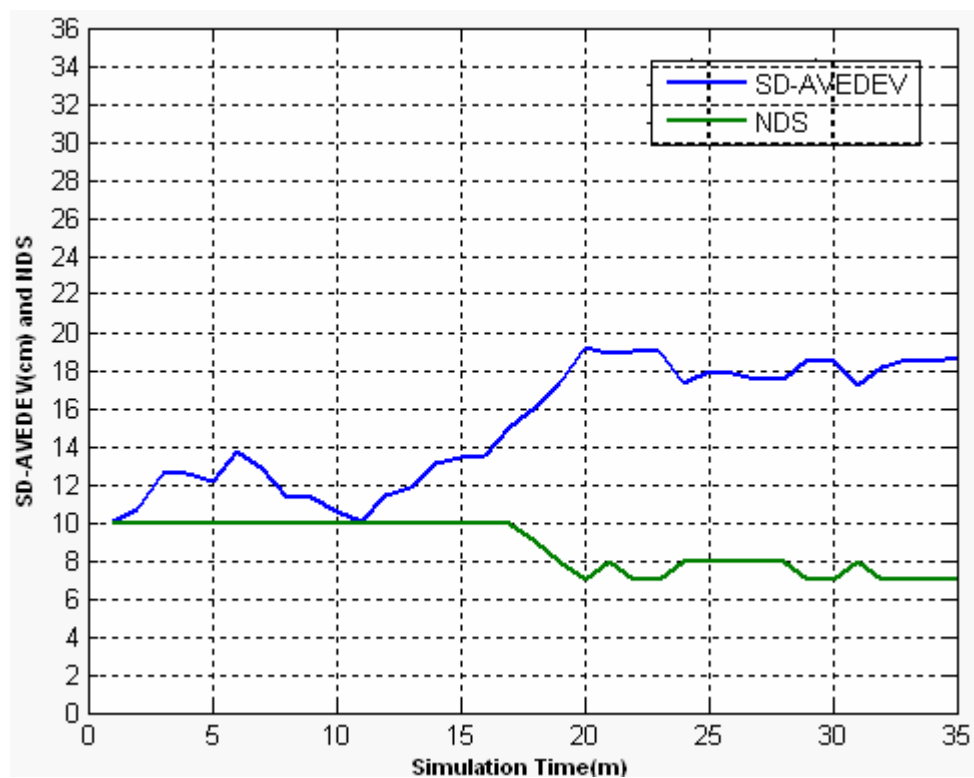
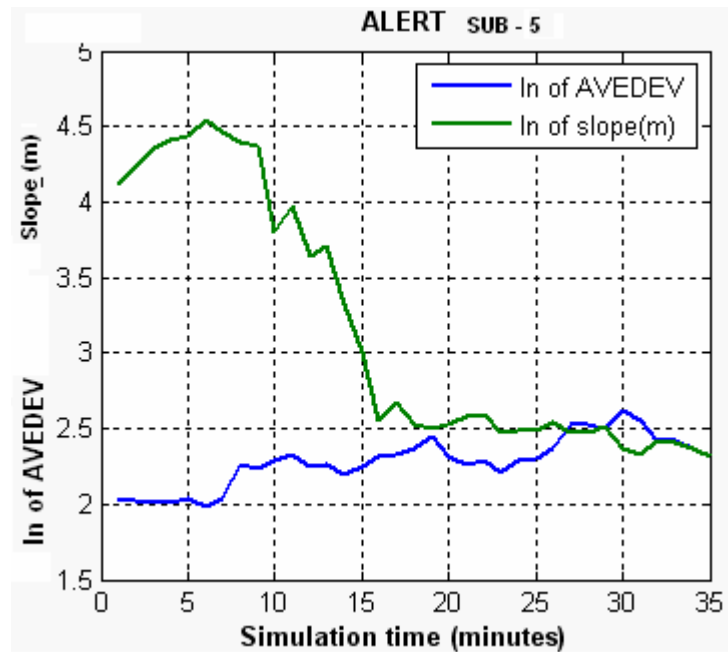


Figure 8-22(d): Participant 3's SD-AVEDEV changes during 35 minutes and NDS

Figure 8-23 shows the participant 9's SD-AVEDEV changes during the 35 minutes and NDS changes. The SD-AVEDEV is categorized by simulation time (first 15 minutes and last 20 minutes) for the participant 9's data on alert condition. The difference between first 20 minutes and the last 20 minutes of SD-AVEDEV is statistically significant,  $t=-9.26(d.f=23)$  and  $p<0.05$ .



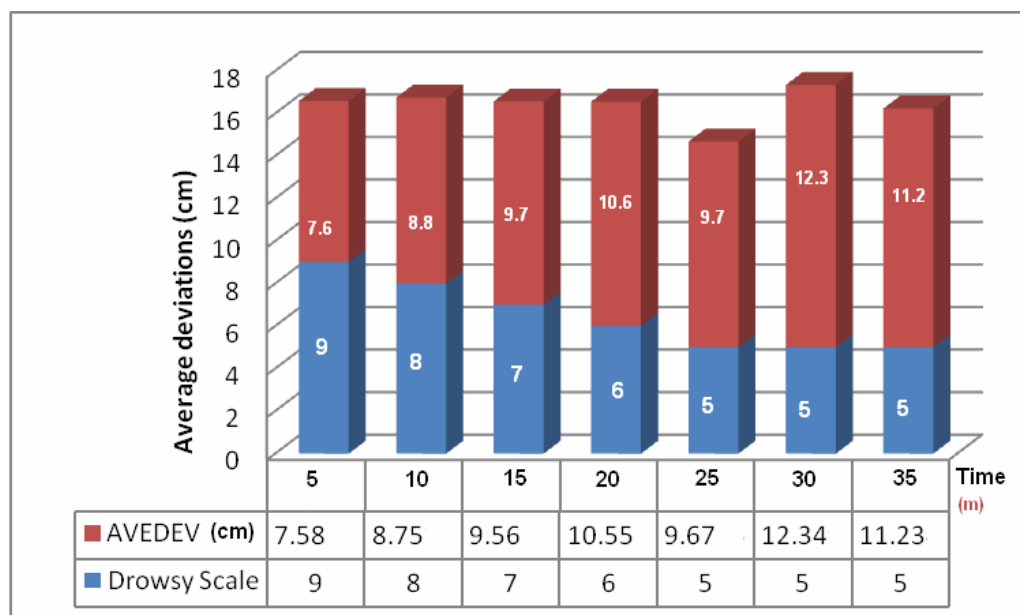
**Figure 8-23: Participant 9's SD-AVEDEV changes during 35 minutes and NDS (alert)**



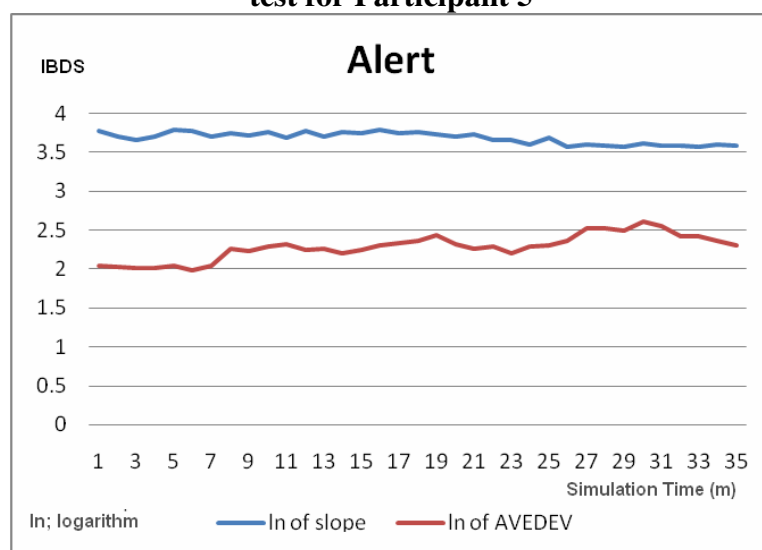
**Figure 8-24: NDS categories across SD-AVEDEV for the SUB -5 (high ESS).**

Figure 8-24 shows participant 5 (questionable condition) and how logarithm values of the new drowsiness scale and SD-AVEDEV change during the test. In this example, participant 5 showed some drowsy conditions after 15 minutes of simulator test. The 'ln' values of average deviations increase after 15 minutes and slope (m) values start decreasing from that point. In this situation, participant 5's slope (m) value decreases from 4 to 2.3. Reference to Table 8-13, the NDS categories according to slope (m) values for participant 5's varies from NDS 9 to 5. The NDS category 5 is in the questionable range and participant 5's driving performance decreases gradually with time. Figure 8-25 shows the bar graph of the participant -5 drowsiness scale variation. Figure 8-25 clearly indicates that the increase of average deviations during the 35 minutes of the simulator test is accompanied by a decrease in the drowsiness scales. Increase of average deviations illustrates the deprived driving performance caused by the lack of concentration or drowsiness. The

participant 5 had high ES (Epworth Score=11) and he was naturally drowsy when driving.

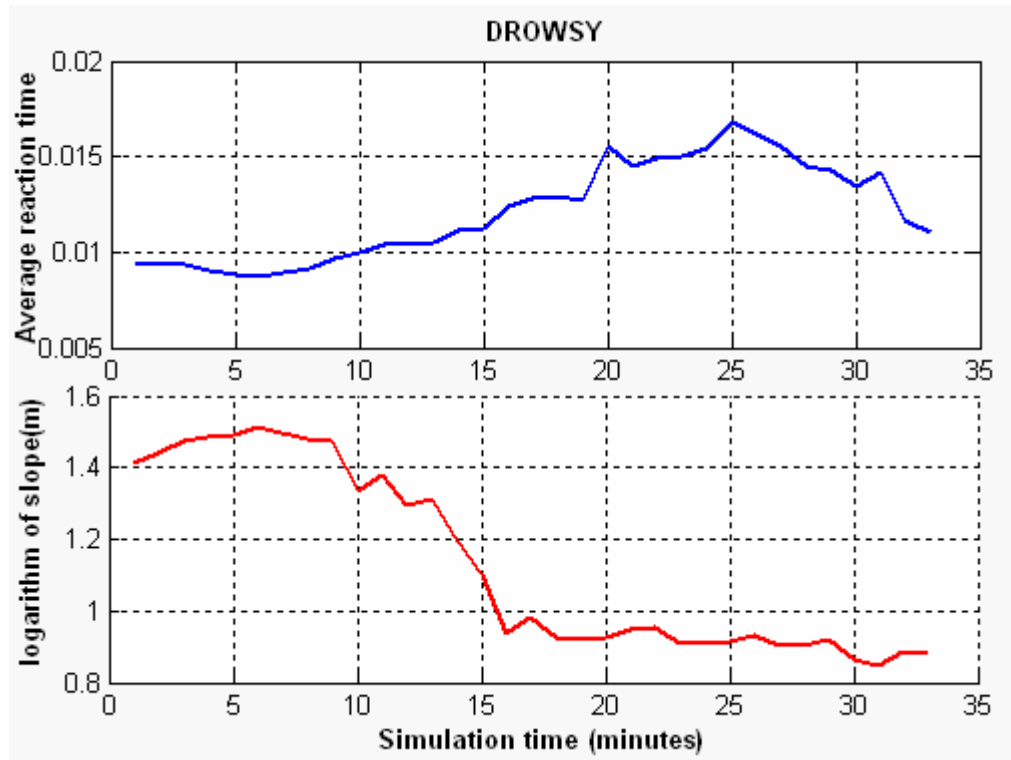


**Figure 8-25: Drowsiness scale and Average deviation during 35-minute simulator test for Participant 5**



**Figure 8-26: Drowsiness scale (ln of slope) variations of AVEDEV for alert participant -1**





**Figure 8-27: The average reaction time (AVEREATM) changes with drowsiness scale (logarithm values of slope (m)) participant 9**

Figure 8-27 shows the participant 9's SD-AVEDEV changes during the 35 minutes and NDS changes. The SD-AVEDEV is categorized by simulation time (first 15 minutes and last 20 minutes) for the participant 9's data in an alert condition. The difference between first 15 minutes and the last 20 minutes of SD-AVEDEV is statistically significant,  $t=-9.26$  and  $p<0.05$ .

## 8.10. Summary

The driving session data was divided into 5 minute periods in the analysis. Some of the alert participants showed some drowsiness in the last few minutes in the simulation test. This was clearly identified by the new drowsiness scale. In the alert participants, the SD of average blink durations and average blink frequency did not demonstrate any correlation with driving performance (average deviations, average

reaction time). However, the new drowsiness scale clearly indicates the driver performance variations are related to physiological properties of eye blink.

The correlations between eye blink frequency/duration and driver performance were quite low with alert participants. The blink duration was only moderately correlated with that driver performance in alert participants, and the correlation coefficient for all alert participants was  $r = 0.32$ , ( $p < 0.001$ ). In drowsy participants, the blink duration was highly correlated with the blink frequency, with a correlation coefficient for all participants (Pearson's  $r$  of 0.97, with  $p < 0.001$ ). The results indicate that the increases of drowsiness can be detected from the physiological properties of eye blink. Low values on the new scale indicate that participants are more likely to reach dangerous levels of drowsiness.

The questionable range (Drowsiness scale 4-5) in the drowsiness scale is the most difficult to segment to evaluate the drowsiness level. This range appears in the last 10 minutes in the simulator test for some participants. These participants showed deprived driving performance during that period, possibly because of lack of concentration or tiredness. Sleep deprived participants showed very low logarithm values of slope (Drowsiness scale 0.01-1.5).

The accuracy of capturing eye blink data was discussed in Chapter 5 and 3% of data was lost during the capturing process. In the driving simulator and performance measures, 2% of data were lost. The main task of this research was to determine if physiological measures, used in conjunction with SD of average blink durations and SD of average blink frequency, could be used to create an enhanced definition of drowsiness. The end results show that the logarithm of the slope of the linear

relationship between eye blink frequency and blink durations provides a clear identification of drowsiness.

## **CHAPTER 9**

### **DISCUSSION AND CONCLUSIONS**

## 9.1. Discussion

Driver drowsiness is a major, though elusive, cause of traffic crashes. Drowsy drivers cause about 30% of all highway crashes, and this may be even higher for heavy vehicles. Research has shown that drowsiness impairs a person's abilities and awareness of situations. This makes it difficult for drivers to assess their risk. Too often, a driver only recognises drowsiness in hindsight. It requires only a few seconds in a drowsy state to veer off the road and collide with a roadside object or another vehicle. Drowsy crashes are serious in their consequences because they often occur at full speed, with no evasive action being taken. "Think of it this way: Drivers often close their eyes for up to three seconds at a time as drowsiness approaches. At 70 miles an hour, that's like driving the length of a football field with your eyes closed" (Nerad, 2004).

Driver state monitoring is an ongoing research topic concerning the development of driver support systems to prevent car accidents resulting from sleep. There are several criteria to predict driver drowsiness; most of them are related to the eye blink behaviour of the driver that leads to prolonged eyelid closure.

Research and experimentation has shown that eye blink behaviour is an important factor in identifying driver sleepiness. The development of a reliable method for detecting drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its effects. Scientific support for the feasibility of this countermeasure concept is provided by research showing that:

- Drowsy drivers typically do not “drop off” instantaneously. Instead, there is a preceding period of measurable performance decrement with associated psycho physiological signs.
- Drowsiness can be detected with reasonable accuracy using driving performance measures such as lane deviation, steering error and reaction time.
- The use of direct, unobtrusive driver physiological monitoring (e.g., of eye blink) could potentially enhance drowsiness detection significantly.

This research study has focused on reliable detection of driver drowsiness. A number of investigations were carried out during the period of study. It should be remembered that all of the results obtained are for research conducted in a virtual reality simulator using ordinary people in a state of normal and sleep deprivation conditions. These results are believed to be indicative of actual driving under similar on-the-road conditions.

The aim of driver drowsiness warning devices is to provide information to the driver that their alertness is below a level compatible with safe operation of a vehicle. There is evidence that such warnings are useful to drivers who may be aware that drowsiness is increasing, but not aware of the impact of the drowsiness on their driving capacity. If the warning occurs early enough in the development of drowsiness, such devices could enhance driver alertness sufficiently to avoid a collision, although many of the devices currently under development, especially the driver state measures, will be detecting later stage drowsiness, which is unlikely to be overcome by a short period of stimulation such as a warning signal.

The present literature review served to explore possibilities to predict and detect drowsiness based on driver performance variables such as lateral position variability, as well as physiological variables such as eye blink. While physiological variables reveal the physical consequences of drowsiness, driving performance variables point to the effect of driving in a drowsy state, namely dangerous driving behaviour. It should be noted also that a useful and acceptable method has to be reliable and robust.

The literature survey clearly indicates that no single variable, besides possibly eye related measures, is sufficient for the established goal, even though various single variables show association to drowsiness. A combination of different measures is recommended for drowsiness prediction. Furthermore, it should be noted that so far there is no commercial system available that provides a sufficiently reliable method that detects drowsiness to overcome the serious problems with drowsiness related accidents. This clearly indicates the complexity of the problem of detecting or predicting drowsiness induced impaired driving behaviour.

According to the literature, both Electrooculogram (EOG) and Electroencephalography (EEG) are valid indicators of drowsiness. Drowsiness is characterized by increased blink detection, decreased blink amplitude and increased blink frequency and EOG can be used to measure changes in these parameters. The majority of drowsiness detection method literature indicated eye blink and movement related measures are generally consistent for detection of drowsiness. According to Hargutt (2000), different eye blink parameters can be used for classifying different stages of drowsiness and four different stages can be distinguished. Increased blink frequency indicates reduced vigilance, which is the first stage in the drowsiness

process, and the blink duration and blink amplitude indicate increased drowsiness. Drowsiness was in many cases not found in the EEG even though a change in the eye parameters was detected. It could thus be assumed that the eye parameters were better than EEG for an early detection of drowsiness.

All of these systems focus on providing information to drivers that will facilitate their driving and warn them of threats to driving safety (Parkes, et al., 2006). These systems will also, therefore, function as devices that should respond to the effects of drowsy driving in the same way as the measures of driver performance designed specifically for driver drowsiness discussed in chapter 2.

Some of the problems with the drowsiness detection devices currently under development include the stage of drowsiness that is being detected. A significant issue is the timing and nature of the warnings used. The following summarizes the main findings of the review related to current research.

### **9.1.1. Eyelid closure**

Eyelid closure and related eye measures are, according to the literature, the most promising and reliable predictors of drowsiness and sleep onset. The problem with these methods is the eye tracking and monitoring technology needed to record the eye parameters of the driver. Varying light conditions, diversity of drivers' facial features and usage of glasses constitute substantial difficulties that have to be overcome by the developers of unobtrusive eyelid sensors. PERCLOS (percentage of eyelid closure) and the JDS (John's drowsiness scale) are the current methods used to detect drowsiness from eyelid closure speed.



### **9.1.2. Driving performance measures**

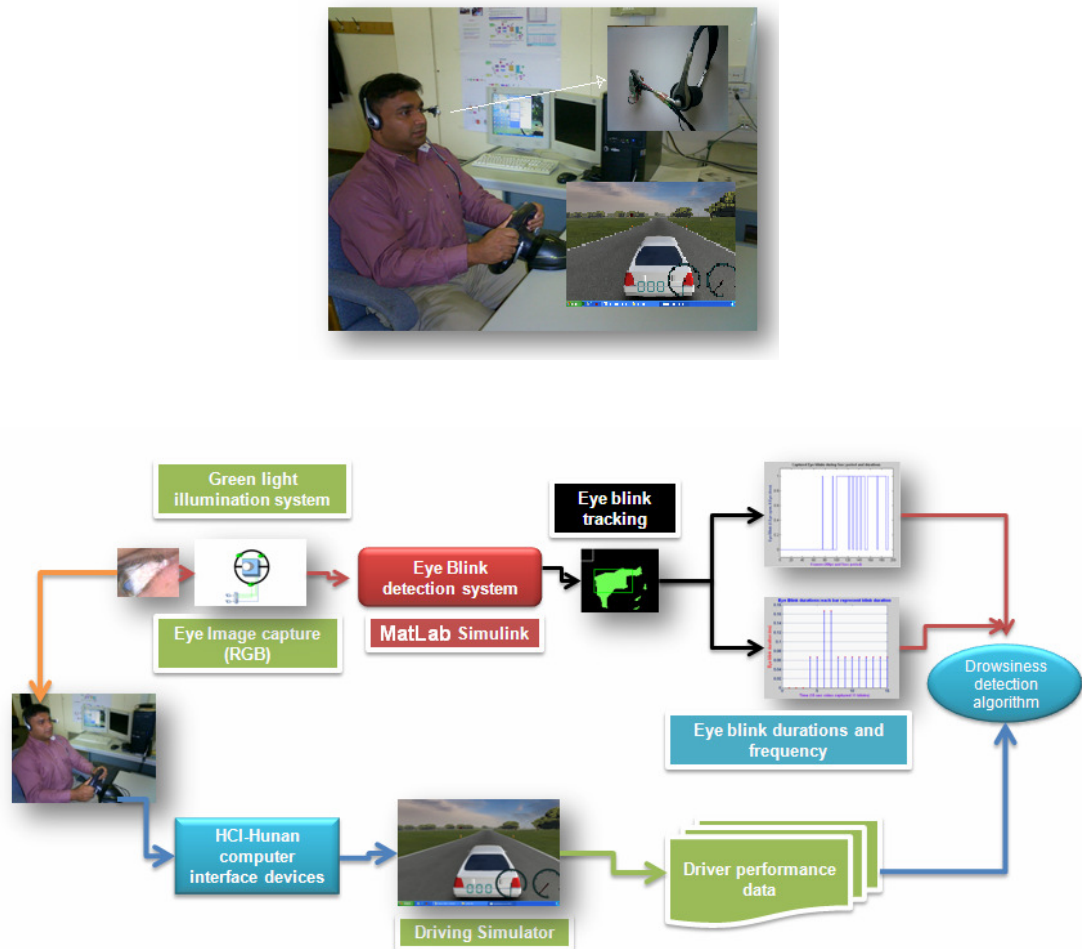
Driving performance measures, such as lane-position measures (lane deviation, standard deviation of the lane position, the mean square of lane deviation) and steering wheel related measures are treated as drowsiness indicators in the literature. A drowsy driver shows worse sensitivity to small movements and, as a result, the number of micro-wheel adjustments decreases and lane keeping becomes poorer with increasing drowsiness. This type of measure seems to be promising and should be further explored. It also has an advantage in that it is possible to use existing sensors in the vehicle. However, longitudinal velocity related measures, such as speed of vehicle, were not found capable of detecting drowsiness.

## **9.2. Research Conclusions**

### **9.2.1. The Methodology**

The method for monitoring eye blink duration and frequency is unique. The eye blink capturing system described in this thesis measures the eye blink duration and frequency. It is different from the more widely used infrared light (IR) reflection method of (Johns et al., 2003). The new head mounted capturing system uses low emitting light from green LEDs positioned to the side of the eye, housed in a frame such as would be used for headphones; Fig.9-1 shows the eye blink capturing device setup, driving simulator setup and the system development process. The 'headset' weighs only 150 gm, which is similar to the weight of normal spectacles. The video system is capable of capturing eye blink at a frequency of about 30 Hz. The total light reflected back from the eye sclera region is detected by a CCD camera sensor.

The level of environmental light changes are minimized using the green light reflection method, which removes the unwanted effect of environmental light, even in changing conditions. The proposed system captures eye blink from sides of the eye and measures the eye blink durations and frequency.



**Figure 9-1: Eye blink capturing device setup and system development process.**

Three specific goals were identified when developing the driving simulator;

Goal 1: Replicate real driver behaviour and performance.

Goal 2: Make driving simulator studies easy to conduct.

Goal 3. Do not harm participants.

The main objective of designing the driving simulator for this research is to develop reproducible and flexible methods for studying the relationships between physiological driver states and driver performance in a virtual driving environment. Health and safety issues were considered in the design of the laboratory based driving simulator. The Epworth Sleepiness Scale (ESS) and the subjective sleepiness condition were included in the questionnaire. This data helped categorize the participants' results from their sleep deprivation condition and quality of sleep before the simulator test. Initial experiments were conducted with 18 healthy male and female participants aged 20 to 70 in carefully controlled conditions. Five different performance measures were collected during a 40 minute simulator test. The reaction time measurements system is an additional feature that added to the driving simulator to improve the quality of performance measures.

### **9.3. Research Results**

The eye blink correlation classification matrices and corresponding linear regression values based on alert and drowsy data illustrates very clear classification of alert and drowsy conditions. The linear regression results indicated that the regression slopes were quite low for the sleep deprivation participants and high for alert participants. The driver performance data (deviation from centre line, reaction time, maximum and average speed) showed very high correlation with eye blink data when the participants were in sleep deprivation conditions.

### 9.3.1. Main Findings

#### 9.3.1.1. Drowsiness detection

1. A new metric has been identified and for validating driver drowsiness. This metric relates to the correlation of standard deviation of average blink duration and average blink frequency, consisting of the standardized values for detecting sleepiness for drivers when drowsy.
2. The new metric is based on the logarithm values of slope, in linear regression of standard deviation of average blink duration and blink frequency. The logarithm values are categorized 1 to 10 according to the driver performance measures related to subjective sleep conditions. Figure 9-2 shows the new metric categorization.

Category	Alert					Questionable		Drowsy		
Category	10	9	8	7	6	5	4	3	2	1
In values of linear (slope)	4.6 - 5.0	4.1 - 4.5	3.6 - 4.0	3.1 - 3.5	2.6 - 3.0	2.1 - 2.5	1.6 - 2.0	1.1 - 1.5	0.6 - 1.0	0 - 0.5

**Figure 9-2: Categorization of Drowsiness Scale**

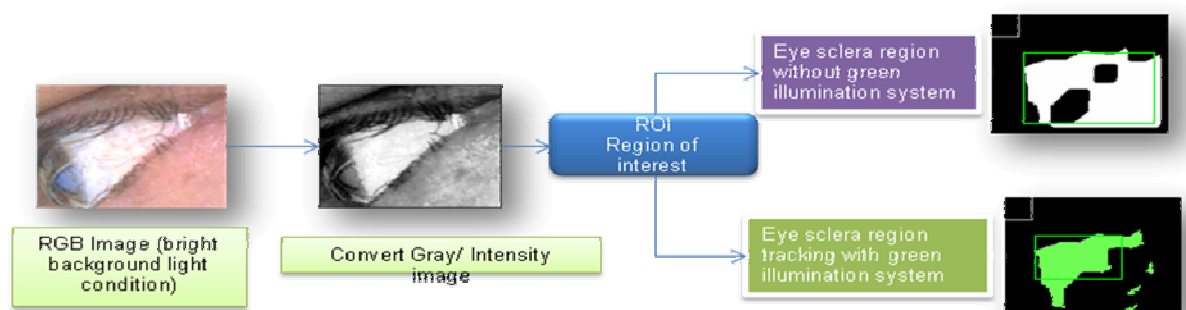
3. Drowsiness causes a loosening of the normally tight controls of blink durations and frequency, and the results of that loosening vary with time and differ between participants.
4. In the drowsy state or sleep deprived condition, the blink frequency increases noticeably with steady increase of duration. This variably is highly correlated with driver performance. During the forty minute simulation test, some

participants showed lack of concentration in the last quarter of the session and showed the same blink variations as in drowsy condition.

5. Linear correlation shows the best fit for the eye blink variables. The relative predictive strengths of the two definitional measures of drowsiness used in this study varied somewhat with four different predictor variables (AVEBLKDU, AVEBLKFR, MAXSP and AVESP) and three predicted variables (AVEDEV, AVEREATM and OUTBON). Epworth Sleepiness Scale (ESS), age (AGE) and the sleep duration (NOHS) were also considered. The regression analysis found the optimized correlation of variables that best predicted “drowsiness” during the driving sessions.

#### 9.3.1.2. Eye blink detection

1. Environmental light changes were the main obstruction in the video based detection methods. The second most important finding in this research is the green light illumination system. This system can be used in situations with varied illumination conditions. Figure 9-3 shows the green light illumination system.



**Figure 9-3: Green light illumination system**

2. Eye sclera region analysis for blink detection was new and does not disturb the participant. Averaging the eye sclera area for eighteen participants (different ethnic, different sex, different ages) indicates the very low variation in area of individual eye sclera regions. This assisted the determination of a common threshold level for eye sclera area calculation and blink duration detection.
3. Detecting eye blink from the side of the head using a head mounted detection system minimizes the complexity of detection algorithm. Furthermore the side detection is safer than front eye detection techniques.

#### **9.4. Recommendations**

Efforts are currently being undertaken to develop a reliable system for drowsy-driver detection. The first phase focuses on the effectiveness of wireless headphone mounted warning systems. The purpose of the warning system should be to alert the driver that he or she is becoming drowsy. The system would also be used as a means of arousing the driver. The other practical implications of this system are in the aviation industry (e.g. pilots), rail (e.g. rail drivers), nuclear industry (e.g. scientists and operator working in the nuclear reactors), mining industry and medical research (human sleep related research).

An effective warning must get the attention of a driver even if he or she is drowsy. However, warnings for a drowsy-driver detection device must not be so intrusive and jarring that they startle the driver. Another consideration pertaining to the intrusiveness of the warning is the degree of driver annoyance. However, the

warning must not be so conservative that it fails to result in the desired effect of alerting or arousing a driver.

Maximum speed did not contribute any major influence to be related to driver performance, and speed control displayed a complex relationship that was not investigated further. The out of bounds measure showed some relation when the drivers are in drowsy condition, but in the driver performance analysis not many drivers went out of bounds in the test.

One of the objectives of the further development of the research will be to determine the validity of detection algorithm to be used for the initial warning of drowsiness.

## **9.5. Limitations of the study and further research and analysis**

By assessing the state of the driver, their driving performance and their perceptions, this PhD study has contributed towards knowledge of how to design a video based eye blink detection system for drowsy drivers. However, more work needs to be done to investigate the issue of the questionable range in the NDS to warn the driver in good time before they get into the danger level of drowsiness. This study does not address the Out-of-Bound measure as a highly contributing factor to detect driver performance, but this measure showed some variation in alert and drowsy condition. Further research might find some relation to drowsiness.

Not all participants attended for both the alert and sleep-deprived sessions, and hence not all data sets were complete. In future studies, all experimental sessions could be extended until every driver experiences both drowsy and non-drowsy periods. However, this could lead to experimental sessions being quite prolonged, and different participants would need to drive for different lengths of time.

The results presented in the current research focused mainly on the comparison of driving performance and physiological measures (blink duration and frequency). The relationship between the NDS and driving performance, in terms of lane position and reaction time was only investigated descriptively within the study. Complex time series analysis and Fourier transformation methods could be used, however this would also need to be analyzed separately for each participant and each session. However a successful analysis of this type could lead to empirically derived NDS levels and correct time to warn the driver before they get into danger level of drowsiness could be validated in future research.



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Appendix - A1- Driver Drowsiness Detection Techniques

Eye blink, Eye movements and facial expressions measures		
Approach/System	Reference	Technique
	Perez, Cordoba,	Eye camera follows head movements by keeping pupil central, uses infrared light to produce corneal
	Garcia, Mendez &	glints that are picked up by camera to detect pupil-glint vectors.
	Munoz	
	(2003).	
Tracking of gaze	Zhu & Qiang (2004).	Video cameras capture images of the driver's face and a number of cues including eye gaze direction are used to infer driver states such as
		fatigue.

	Ito, Mita, Kozuka, Nakano & Yamamoto (2002).	Measures the blink rate of a driver in real time via motion picture processing from which driver states are inferred.
Eye closure and Blink	Parmar & Hiscocks (2002).	Automated detection of eye closure by using video imaging of the face then computation methods for locating the eyes and changes in intensity to determine whether eyes are open or closed. Responds as closed eye if eye is closed for five consecutive frames or more.
PERCLOS- Percentage	Wierwille et al., (1994), Dinges et al., (1998);	PERCLOS is a video-based method of measuring slow eye closure using trained observers to make judgments of eye closure from moment to moment. Evaluated against performance measures of lapses in attention using the Psychomotor Vigilance test (PVT). Showed reasonable correlations between eye closure and lapses.



of eye lid closure	Grace,et al., (1998).	
	Galley & Schleicher, (2002)	
Blink behavior and Face tracking	Svennson (2004).	Validation of Electrooculogram for fatigue detection using EEG and self reported drowsiness. Blink behavior hangs with increasing fatigue, but large individual differences.
	Gu, Hi & Zhu (2002).	Uses Infra-red light to locate pupils and detect head motion then Kalman filtering to predict facial feature locations so tracking more than simply changes in the eye, uses predictive analysis to cope with facial occlusion problems.

Appendix – A2, Driver Drowsiness Detection Systems

Physiological measures		
Approach/System	Reference	Technique
EEG, EOG and EMG measures	BOSB, (1997),	According to the literature, both EOG and EEG are valid indicators of drowsiness. Validation of these
	Lal, Craig, Boord,	measurements as a tool for assessing fatigue using a simulator task. Methodology needs to be evaluated on-
	Kirkup & Nguyan (2003).	road.
Driver performance measures		
Approach/System	Reference	Technique
	Wijesoma,	Uses two-dimensional radar sensing and extended Kalman filtering for fast detection and tracking of road

Lane tracking	Kodogoda & curbs Balasuriya (2004).	
	Apostoloff & Zelinsky (2003);	Attempts to overcome problems of previous lane tracking methodologies that use single cues relating to the edges of the lane such as centre lines or edge markings but which cannot cope with changes in road characteristics and lighting changes. This approach uses the Distillation Algorithm to combine a number of available visual cues (captured by video camera) which together provide robust estimates of the location on the vehicle in the lane, even when some of the main features are missing.
	Fletcher, Apostoloff, Chen & Zelinsky (2001).	
	Pilutti & Ulsov (1995);	Uses lateral position and steering wheel input to detect driver fatigue.
	Pilutti & Ulsov	
Vehicle lateral position and		

steering wheel input	(1998).	
	Ladstaetter	& Used a range of physiological measures including ECG, EEG, EOG Skin temperature and impedance, Pulse
	Mahler (2001);	and oxygen saturation in blood, respiration frequency and head movements, eye closure and lane tracking to
Predicting fatigue-related	Rimini, Manstetten, Altmueller,	predict crashes in simulations involving high stress driving (fog) and long driving stints. Showed that lane tracking predicted crashes. Further analysis is needed to evaluate relationships between other variables
crashes using lane tracking,	Ladstaetter &	
eye-closure and changes in physiological state	Mahler (2001).	

<b>AWAKE project</b>	<p data-bbox="406 176 438 2067">Boverie (2004).</p> <p data-bbox="438 176 646 2067">Uses multiple parameters to detect real time hypovigilance and drowsiness while driving. Parameters for driver hypovigilance include eyelid changes and steering grip change and for driver behavior include lane tracking, use of accelerator and brake and steering position. If all of this information signals risk, a driver warning system is activated. The system is currently being piloted.</p>
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Appendix – A3, Driver Drowsiness Detection Techniques

Leading driver fatigue detection systems design companies			
Approach/System	Company address	name/	Technique
Optalert™	Sleep Diagnostics Pty		By calculating Johns Drowsiness Scale JDS every minute, Optalert™ gives a measure of a driver's
	Ltd		drowsiness at any point in time and provides predictive warnings before the driver's drowsiness reaches a
	Suite 9, 150 Chestnut		critical and dangerous level. When the driver approaches a dangerous level of drowsiness, a first level
	Street		warning is triggered. When the driver reaches that critical level of drowsiness, at which point he or she is
	Richmond, Melbourne		no longer fit to drive, a second level warning is triggered.
	VIC 3121 Australia		

<b>DDS- Driver State Sensor</b>	<b>Seeing Machines</b>	Take Human Performance Measurement into the real world. More than just an eye-tracker, faceLAB 's
	Level 3, Innovations	flexible and mobile tracking solution enables analysis of completely naturalistic behavior—including head
	Building	pose, eyelid movement and gaze direction in real-time, under real-world conditions. PERCLOS system is
	Corner Garran and	used for analyses and model fatigue and drowsiness in real-time. The faceLAB <sup>TM</sup> collaborate with
	Eggleston Rd	seeing machine to develop this system.
Canberra ACT 2600		
AUSTRALIA		
<b>Eye-blink observation-S Class</b>	<b>Mercedes-Benz</b>	An infrared camera directed at the driver's head permanently monitors the eye-blink frequency, enabling
	<a href="#">Germany</a>	microsleep to be detected the instant the eyes stay closed for a certain period of time. A warning signal
		sounds in the car's cockpit in response.

Mirror-In-Motion, LaneFX	<p>LaneFX works with vehicle's existing power mirror system – its detect the lane position and warn the driver when the vehicle cuts the lane. LED indicators on mirror indicates the left and right lanes. System is only active when the driver wants to check the blind spot.</p>
Highway Safety	<p>The DD850 is designed to monitor drivers eye blink and used PERCLOS in real time to warn the driver.</p>
Eye Alert, Fatigue Warning System	<p>The system can mount on dashboard and plug into vehicle power system.</p>
Group	
PO Box 141	
Zephyr Cove, NV	
89448	



Co-pilot	<b>National Robotics Engineering Consortium</b> Ten 40th Street Pittsburgh, PA 15201	<p>This project is no longer active.</p> <p>The Copilot is the first device to accurately detect and track human drowsiness and provide a warning to the driver. The Copilot provides a continuous real time measurement of eye position and eyelid closure. A direct measurement of drowsiness is calculated from the analysis of slow eyelid closures. In particular the Copilot calculates PERCLOS or percent eye closure, simply defined as the proportion of time the eyes are closed over a specified time interval. The Copilot provides a visual gauge representing the driver's drowsiness level and an audible warning when a preset drowsiness threshold is reached.</p>
	<b>National Robotics Engineering Consortium</b> Ten 40th Street Pittsburgh, PA 15201	<p>OASYS provides a continuous real time measurement of eye position and eyelid closure. A direct measurement of drowsiness is calculated from the analysis of slow eyelid closures. In particular OASYS calculates the proportion of time the eyes are closed over a specified time interval and provides a visual gauge representing the driver's drowsiness level and an audible warning when a preset drowsiness threshold is reached.</p>
	<b>Operator Alertness System (OASYS)</b>	<p>This project is no longer active.</p>

## Appendix – B1, Driver Performance Data

The code measures deviation 75 times per second and reports a simple average of that every 10 seconds.

### Data logging

Example of all performance data collected from simulator

e.g. Maximum Speed (max speed, kph = km/h), Average Speed (avg speed, kph = km/h), Out of boun (Out of bounds), Average deviations (avg deviations)

Log started								
Time								
000:10	max speed	008 kph	avg speed	000 kph	0 out of boun	0 avg deviation	075 cm	
000:20	max speed	001 kph	avg speed	001 kph	0 out of boun	0 avg deviation	087 cm	
000:30	max speed	038 kph	avg speed	006 kph	0 out of boun	0 avg deviation	105 cm	
000:40	max speed	070 kph	avg speed	061 kph	0 out of boun	1 avg deviation	095 cm	
000:50	max speed	070 kph	avg speed	057 kph	0 out of boun	0 avg deviation	108 cm	
001:00	max speed	050 kph	avg speed	043 kph	0 out of boun	0 avg deviation	087 cm	
001:10	max speed	064 kph	avg speed	050 kph	0 out of boun	0 avg deviation	079 cm	
001:20	max speed	072 kph	avg speed	064 kph	0 out of boun	0 avg deviation	096 cm	
001:30	max speed	055 kph	avg speed	037 kph	0 out of boun	0 avg deviation	094 cm	
001:40	max speed	063 kph	avg speed	051 kph	0 out of boun	0 avg deviation	122 cm	
001:50	max speed	056 kph	avg speed	039 kph	0 out of boun	0 avg deviation	070 cm	
002:00	max speed	082 kph	avg speed	064 kph	0 out of boun	0 avg deviation	067 cm	
002:10	max speed	082 kph	avg speed	064 kph	0 out of boun	0 avg deviation	046 cm	
002:20	max speed	105 kph	avg speed	076 kph	0 out of boun	0 avg deviation	057 cm	
002:30	max speed	114 kph	avg speed	106 kph	0 out of boun	0 avg deviation	055 cm	
002:40	max speed	095 kph	avg speed	077 kph	0 out of boun	0 avg deviation	107 cm	
002:50	max speed	070 kph	avg speed	047 kph	0 out of boun	0 avg deviation	096 cm	
003:00	max speed	069 kph	avg speed	053 kph	0 out of boun	0 avg deviation	107 cm	
003:10	max speed	069 kph	avg speed	051 kph	0 out of boun	0 avg deviation	031 cm	
.....								
.....								
.....								
Summary stats:								
Out of bounds:		20						
Redlights:		6						
Top speed:		126.31 kph						
Distance travelled:		8.5 km						
Time elapsed:		43.5 min						

### Cross-correlation:

The calculation of two-dimensional cross-correlation of two input matrices equation. Assume that matrix A has dimensions (Ma, Na) and matrix B has dimensions (Mb,

Nb). When the block calculates the full output size, the equation for the two-dimensional discrete cross-correlation is

$$C(i, j) = \sum_{m=0}^{(Ma-1)} \sum_{n=0}^{(Na-1)} A(m, n) \cdot \text{conj}(B(m+i, n+j))$$

where  $0 \leq i < Ma + Mb - 1$  and  $0 \leq j < Na + Nb - 1$ .

### Calculating eye sclera area

In calculating the eye sclera area, the long-axis 'a' and short-axis 'b' of the ellipse with following equations (Horn, 1986).

$$a = \sqrt{6 \left( p + r + \sqrt{q^2 + (p-r)^2} \right)}$$

$$b = \sqrt{6 \left( p + r - \sqrt{q^2 + (p-r)^2} \right)}$$

Where

$$p = \frac{M_{20}}{M_{00}} - x_c^2 \quad q = 2 \left( \frac{M_{20}}{M_{00}} - x_c y_c \right) \quad r = \frac{M_{02}}{M_{00}} - y_c^2$$

Where  $M_{00}$ ,  $M_{20}$  and  $M_{02}$  are the second order moment, which is calculated from the image intensity  $I(x, y)$  as following.

$$M_{00} = \sum_x \sum_y I(x, y) \quad M_{10} = \sum_x \sum_y xI(x, y) \quad M_{01} = \sum_x \sum_y yI(x, y)$$

Likely, the second order moment is calculated by the following equations.

$$M_{20} = \sum_x \sum_y x^2 I(x, y) \quad M_{02} = \sum_x \sum_y y^2 I(x, y)$$

## Appendix – B2, Eye Sclera Region Calculation

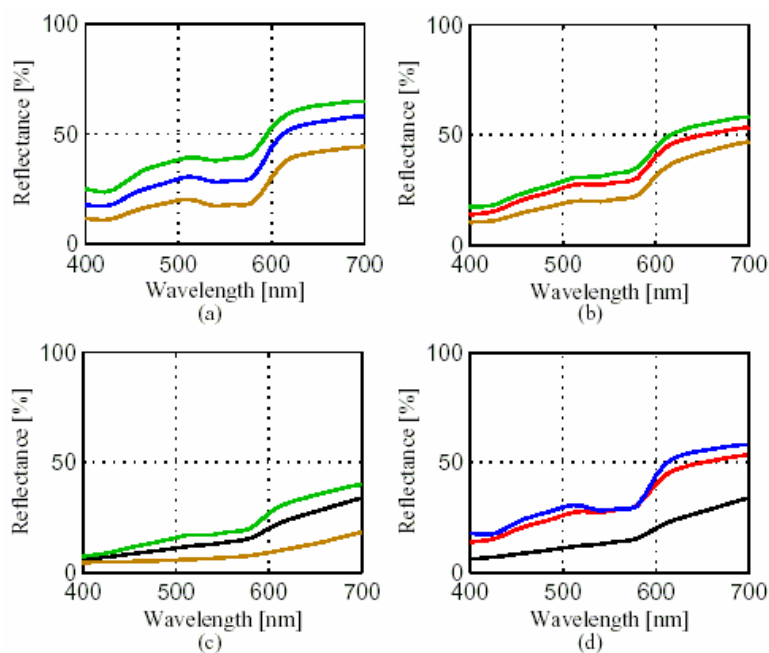
### Introduction to Matlab

**Software:** MATLAB is a high-performance, interactive numeric computation and visualization environment that combines the advantages of programmable and has the same logical, relational, conditional, and loop structures as other programming languages, such as Fortran, C, BASIC, and Pascal. Because the flexible MATLAB language is matrix-oriented, it is the natural language for technical problem solving, allowing customizing and extending MATLAB and adding new functions as needed. MATLAB handles numerical calculations and high-quality graphics, provides a convenient interface to built-in state-of-the-art subroutine libraries, and incorporates a high-level programming language (Matlab 2005).

Recently, high-level languages such as MATLAB have become popular in prototyping algorithms in domains such as video and image processing. The Eyelink toolbox supports the measurement of eye movements. The toolbox provides an interface between a high-level interpreted language (MATLAB), a visual display programming toolbox (Psychophysics Toolbox), and a video-based eye tracker (Eyelink). The eye blink detection algorithm proposed in this chapter used some tools from Eyelink toolbox.

## Light Reflections from Human Skin

Skin is composed of a thin surface layer, the ‘epidermis’, and the ‘dermis’, which is a thicker layer placed under the epidermis. Interface reflection of skin takes place at the epidermis surface (Storring, et al., 2000). It is approximately 5% of the incident light independent of its wavelength and the human race (Storring, et al., 2000). The rest of the incident light (95%) is entering the skin where it is absorbed and scattered within the two skin layers (body reflectance). The epidermis mainly absorbs light; it has the properties of an optical filter. The light is transmitted depending on its wavelength and the epidermis. Testing with camera properties, increase of RGB value for blue light (low reflective light from skin, Storring, et al., 2000) does not make any different to the skin region and the eye sclera region according to environmental light changes.



**Spectral reflectance curves (SCE): (a) Caucasian; (b) Asian; and (c) Negroid complexions; (d) average curves for each group (Wyzecki and Stiles, 2000).**

## Appendix – C1, Morphological Operations

### Opening technique;

In *erosion* process, structuring element over an image, finds the local minima (minimum value), and creates the output matrix from these minimum values. If the neighbourhood or structuring element has a centre element, the block places the minima in created neighbourhood window, if input matrix does not have centre element then the block has a bias toward the upper left corner and places the minima

there. For example; sets  $A$  and  $B$  in  $Z^2$  the erosion of  $A$  by  $B$ , denoted  $A \ominus B$ , is defined as

$$A \ominus B = \left\{ z \mid (B)_z \subseteq A \right\} \quad (\text{Gonzalez \& Woods, 2002})$$

$Z^2$  is called Cartesian product of image matrix on  $xy$  plane convert into grid, with the coordinates of the centre of each grid being a pair element from Cartesian product.  $Z$  is real integers (Gonzalez & Woods, 2002). The neighbourhood parameter is defined by entering a vector of ones and zeros and specifies a structuring element with the 'strel' function from the Image Processing Toolbox (Matlab Simulink).

'SE = strel (shape, parameters)', creates a structuring element, SE, of the type specified by shape. The function then modified to 'SE = strel('square',5)' creates a square structuring element whose width is 5 pixels. If the structuring element is decomposable into smaller elements, the block executes at higher speeds due to the use of a more efficient algorithm.

Matrix C-1; shows the structuring element.

SE = strel ('square', w)

$$\text{SE} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & [1] & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad w = 5 \text{ (5x5) and } [1] \text{ is the Origin}$$

**Matrix C-1: Modified structuring element for Erosion.**

For example; with A and B as sets in  $Z^2$ , the *dilation* of A by B, denoted  $A \oplus B$ , is defined as

$$A \oplus B = \left\{ z \mid \left( \hat{B} \right)_z \cap A \neq \emptyset \right\} \quad (\text{Gonzalez \& Woods, 2002})$$

Same shape is used to structural element, SE, of dilation and slightly bigger matrix used to parameter matrix. Dilation function; 'SE = strel('square', 7)' fills the eye lashes gap to create complete eye sclera shape.

The 'max' command computes the maximum value in each column of the 144-by-176 input matrix u,

$$[\text{val}, \text{idx}] = \text{max}(\text{u}) \quad \% \text{ Equivalent MATLAB code}$$

and outputs the sample-based 1-by-176 index vector, idx. Each value in idx is an integer in the range [1 144] indexing the maximum value in the corresponding column of u. The inputs to the 2D maxima block are double-precision values and the output index values also double-precision values. The blink detection process use 'single' data type, therefore data type conversion is used to convert double-precision to single-precision by;

$$\text{I} = \text{im2single}(\text{Idx}) \quad \% \text{ Equivalent MATLAB code}$$

The background estimation and template matching outputs are used for tracking process.

## Appendix – C2, Predictor and predicted Variables Data

Subject No, age, Epworth score (ESS), sleep duration during 24hrs before the simulator test, average value of centre line deviations (40 minutes simulation) and average value of reaction time (40 minutes simulation).

Subject No	Age	Epworth Score(ESS)	Sleep time (during 24hrs)	AVGDEV (cm)	SD-AVEREATM (s)
1	35	6	9	9.9604898	0.00361
2	36	6	8	20.59	0.00425
3	65	12	7	24.32	0.00679
4	27	7	7	17.97	0.00731
5	32	11	9	23.3	0.00312
6	30	10	7	28.73	0.00818
7	25	6	8	19.5	0.00422
8	31	5	7	16.75	0.00381
9	31	7	8	17.5	0.00401
10	60	8	9	14.56	0.00489
11	40	9	8	17.89	0.00397
12	38	6	9	22.56	0.00579
13	51	7	7	18.27	0.00478
14	22	5	8	17.21	0.00349
15	26	9	7	21.82	0.00593
16	30	7	8	21.85	0.00576
17	24	6	7	20.52	0.00531
18	38	9	7	23.7	0.00421

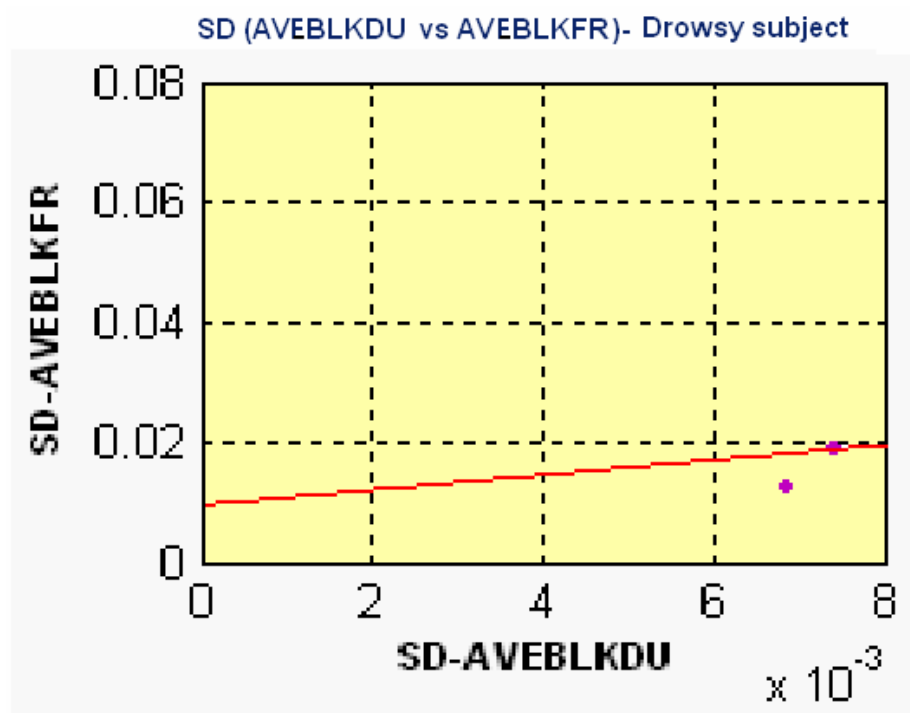
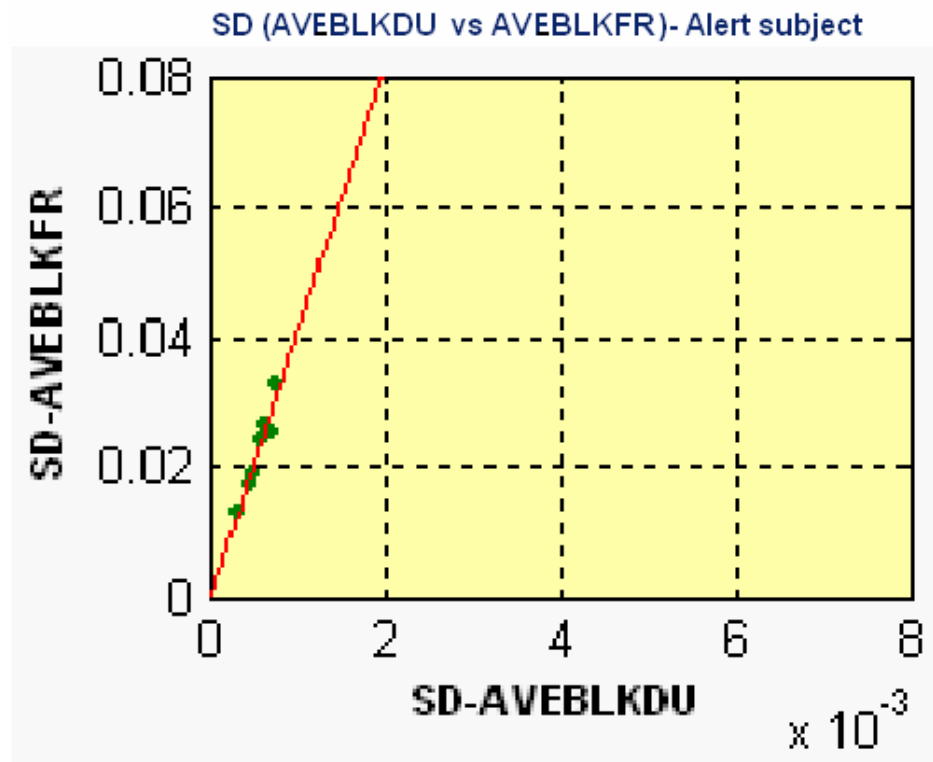
Subjects participated in sleep deprivation condition

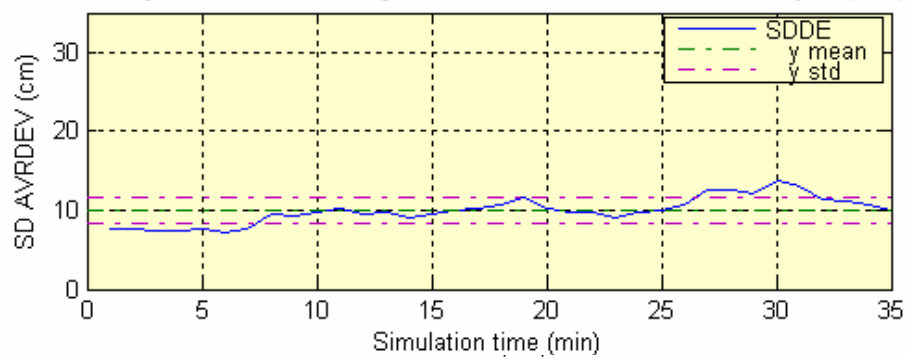
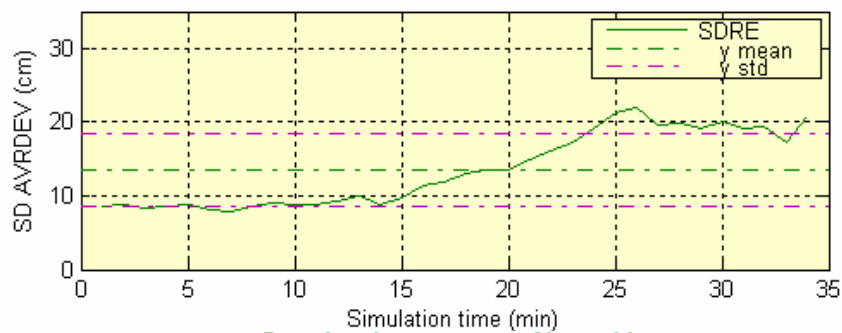
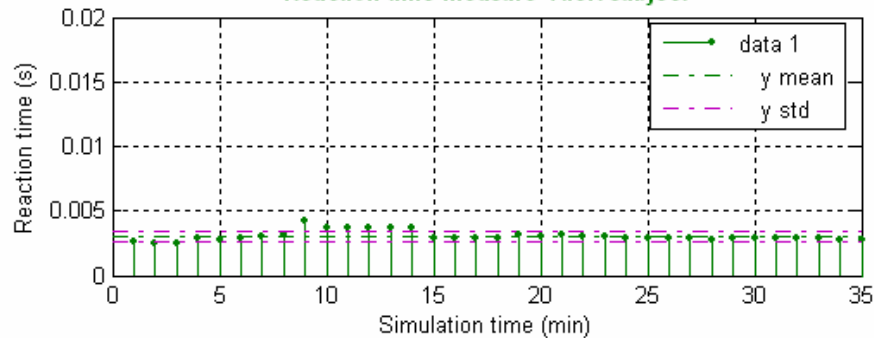
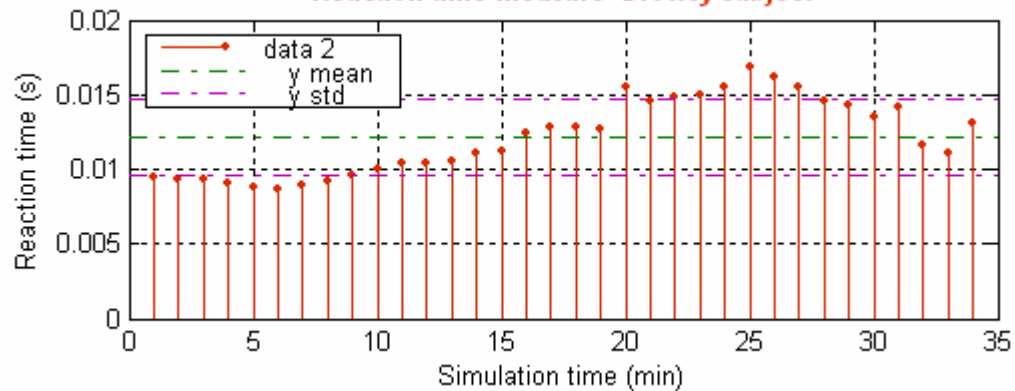
Subject No	Age	Epworth Score(ESS)	Sleep time (during 24hrs)	AVGDEV (cm)	SD-AVEREATM (s)
1	35	6	3	13.17	0.0117
9	31	7	3	28.14	0.0124
3	65	12	4	31.32	0.067
14	22	5	3	26.37	0.022



SD- AVEBLKDU: Standard deviation of average blink durations  
SD- AVEBLKFR: Standard deviation of average blinks frequency  
SD- AVEREATM: Standard deviation of average reaction time  
SD- AVEDEV: Standard deviation of average deviations  
Example of all predictor variables measured.

SUB-1	IB-Mor		AGE=35		EPWSCL=6		SLPDU=9		SLPSCAL Before &After =1,4	
	SD- AVEBLKDU	Mean- AVEBLKDU	SD- AVEBLKFR	Mean- AVEBLKFR	SD- AVEDEV	Mean- AVEDEV	SD- AVEREATM	Mean- AVEREATM		
0.000225		0.001722	0.00981	0.075056	7.671967	58.41694	0.002595	0.019933		
0.000233		0.001712	0.009494	0.072167	7.602645	59.10139	0.002449	0.019042		
0.000286		0.002002	0.011057	0.078333	7.511989	57.31683	0.002475	0.019321		
0.000319		0.002051	0.012881	0.081333	7.471469	58.085	0.002832	0.021554		
0.000498		0.002956	0.021958	0.121778	7.675211	58.50672	0.002816	0.021985		
0.00056		0.003697	0.024346	0.155722	7.247554	54.27944	0.002948	0.022958		
0.000624		0.004688	0.02544	0.195167	7.692455	59.95617	0.00303	0.02364		
0.000633		0.004919	0.026652	0.206222	9.601212	67.543	0.003116	0.024304		
0.000693		0.005266	0.02865	0.219	9.364242	72.23789	0.004176	0.029204		
0.000642		0.004526	0.027754	0.186056	9.85143	76.40039	0.00372	0.029029		
0.000548		0.004059	0.02196	0.162667	10.25678	78.42478	0.003673	0.028682		
0.000496		0.003681	0.02155	0.156389	9.441036	72.72494	0.003756	0.029302		
0.000543		0.004007	0.022133	0.169111	9.661969	69.97761	0.003756	0.029333		
0.000599		0.004292	0.025637	0.182167	9.040877	67.15322	0.003641	0.022882		
0.000669		0.004946	0.028248	0.2095	9.433837	71.10378	0.002901	0.022653		
0.000709		0.005285	0.03131	0.231611	10.06648	77.27756	0.002862	0.022347		
0.000738		0.005737	0.031371	0.243278	10.31617	78.07356	0.002947	0.022964		
0.000787		0.00609	0.033904	0.260111	10.68297	80.63978	0.002945	0.023		
0.000801		0.006239	0.033695	0.259444	11.51961	86.16861	0.00313	0.024267		
0.000802		0.005961	0.032611	0.242556	10.19466	79.33083	0.003076	0.024014		
0.000752		0.0051	0.031602	0.201333	9.638887	71.60406	0.003115	0.024319		
0.000553		0.003983	0.021665	0.155611	9.836221	72.68078	0.002978	0.023067		
0.000518		0.003025	0.020288	0.1155	9.063974	69.81617	0.003032	0.023633		
0.000327		0.002069	0.012009	0.082111	9.827293	71.98439	0.002893	0.0224		
0.000242		0.001862	0.009753	0.074056	10.02651	73.22478	0.002901	0.022653		
0.000262		0.001929	0.009403	0.072278	10.71056	80.65583	0.002862	0.022347		
0.00029		0.002226	0.01063	0.080611	12.58592	96.452	0.002946	0.022969		
0.000488		0.002506	0.017689	0.091	12.56189	97.33517	0.002804	0.021729		
0.000533		0.003749	0.019169	0.136833	12.19533	94.15639	0.002909	0.022618		
0.000738		0.004752	0.027558	0.173444	13.69226	103.983	0.002862	0.022347		
0.000722		0.005565	0.02616	0.201056	12.92262	100.2362	0.002901	0.022653		
0.000767		0.00582	0.027919	0.211611	11.2926	86.65261	0.002826	0.022031		
0.000808		0.005805	0.029129	0.212611	11.26886	86.87133	0.002903	0.022638		
0.000625		0.004763	0.022913	0.172889	10.61628	82.39556	0.002762	0.021396		
0.000582		0.004405	0.02106	0.157333	10.07338	77.86044	0.002818	0.021971		



**Driver performance- Average deviations from centre -Alert subject (min)****Driver performance- Average deviations from centre -Drowsy subject (min)****Reaction time measure- Alert subject****Reaction time measure- Drowsy subject**

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## Driver Fatigue Analysis

### 1. Driver's Details :

1.1 Age

1.2 What age group do you fall in?

- 18-25 ☐  
 26-35 ☐  
 35-45 ☐  
 Above 45 ☐

1.3 Sex: **Male** ☐ **Female** ☐

1.4 Date: 

DD	MM	YY
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1.5 Time of day of Driving: 

HH	MM
----	----

 24HRS

### 2. Daily sleep period:

2.1 Number of hours sleep: 

HH	MM
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2.2 Sleep period:

21:00	22:00	23:00	24:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00
9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00

