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Driver Monitoring System Based On Eye Tracking

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"The true sign of intelligence is not knowledge but imagination."

Albert Einstein

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Abstract

Recent statistics indicate that driver drowsiness is one of the major causes of road accidents and deaths behind the wheel. This reveals the need of reliable systems capable of predict when drivers are in this state and warn them in order to avoid crashes with other vehicles or stationary objects.

Therefore, the purpose of this dissertation is to develop a driver's monitoring system based on eye tracking that will be able to detect driver's drowsiness level and actuate accordingly. The alert to the driver may vary from a message on the cluster to a vibration on the seat.

The proposed algorithm to estimate driver's state only requires one variable: eyelid opening. Through this variable the algorithm computes several eye parameters used to decide if the driver is drowsy or not, namely: PERCLOS, blink frequency and blink duration. Eyelid opening is obtained over a software and hardware platform called SmartEye Pro. This eye tracking system uses infrared cameras and computer vision software to gather eye's state information.

Additionally, since this dissertation is part of the project "INNOVATIVE CAR HMI", from Bosch and University of Minho partnership, the driver monitoring system will be integrated in the Bosch DSM (Driver Simulator Mockup).

Resumo

Estatísticas recentes indicam que a sonolência do condutor é uma das principais causas de acidentes e mortes nas estradas. Isto revela a necessidade de sistemas fiáveis capazes de prever quando um condutor está sonolento e avisá-lo, de modo a evitar colisões com outros veículos ou objetos estacionários.

Portanto, o propósito desta dissertação é desenvolver um sistema de monitorização do condutor baseado em *eye tracking* que será capaz de detetar o nível de sonolência do condutor e atuar em conformidade. O alerta para o condutor pode variar entre uma mensagem no painel de instrumentos ou uma vibração no assento.

O algoritmo proposto para estimar o estado do condutor apenas requer a aquisição de uma variável: abertura da pálpebra. Através desta variável, o algoritmo computa alguns parâmetros utilizados para verificar se o condutor está sonolento ou não, nomeadamente: PERCLOS, frequência do pestanejar e duração do pestanejar. A abertura da pálpebra é obtida através de uma plataforma de *hardware* e *software* chamada SmartEye Pro. Esta plataforma de *eye tracking* utiliza câmaras infravermelho e software de visão por computador para obter informação sobre o estado dos olhos.

Adicionalmente, uma vez que esta dissertação está inserida projeto: "INNOVATIVE CAR HMI", da parceria entre a Bosch e a Universidade do Minho, o sistema desenvolvido será futuramente integrado no Bosch DSM (*Driver Simulator Mockup*).

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List of Acronyms

API	Application Programming Interface
BD	Blink Duration
BR	Blink Rate
DSM	Driver Simulator Mockup
ECG	Electrocardiogram
EEG	Electroencephalogram
HMI	Human Machine Interface
IDE	Integrated Development Environment
IR	Infrared
KSS	Karolinska Sleepiness Scale
LED	Light Emitting Diode
PERCLOS	Percentage of Closure
SDLP	Standard Deviation of Lane Position
SWM	Steering Wheel Movement

Chapter 1

Introduction

It is common knowledge within the automotive industry and, increasingly, among the general public, that drowsy drivers contribute to a significant number of road crashes. Driving under sleep deprivation or during long-distances decreases the driver's consciousness and increases the probability of traffic accident. According to a study published by AAAFoundation in 2014 regarding drowsy driving [1], 6 per cent of all motor crashes and 21 percent of all fatal crashes between 2009 and 2013 in the United States have involved a drowsy driver. It also suggests that an average of 109,000 crashes result in injuries and 6,400 people are killed annually due to this cause.

These numbers reveal the need of reliable systems capable to predict when a driver is drowsy and warn him efficiently in order to avoid crashes with other vehicles or stationary objects. Therefore, the purpose of this dissertation is to develop a driver's monitoring system based on eye tracking that will be able to detect driver's drowsiness level and actuate accordingly.

Additionally, since this dissertation is integrated with the Bosch & UMinho's INNOVATIVE CAR HMI project, this system's development assumes other relevance because Bosch is investing on the driver's monitoring and do not have any product with eye tracking technology. Furthermore, it is rare to find car brands with drowsiness detection systems on the market, especially recurring to driver's facial monitoring. Moreover, at this partnership project, more three dissertations concerning drowsiness detection will be developed, one of them using eye tracking as well.

1.1 Defining Drowsiness

Drowsiness or sleepiness, used as synonymous in this dissertation, can be defined by "the urge to fall asleep" [2] and results of lacking of sleep or fatigue. It is the state of transition between awake state and sleep during which the abilities to observe and analyze are strongly compromised. Therefore, drowsiness severely reduces driver´s consciousness leading to dangerous situations while driving.

Drowsiness also increases the likelihood of microsleeping. Micro-sleep consists in a short sleep episode, or loss of consciousness, ranging from a fraction of a second up to thirty seconds. It is possible that an individual experiences a microsleep without realizing it.

1.2 Objectives and Research Question

The main objective of this dissertation is the development of a reliable drowsiness detection system recurring to an eye tracking platform. However, the developed system can be integrated in automotive HMI in future, therefore, the complexity of the drowsiness detection algorithm should be taken into account, in order to keep low processing power requirements. Moreover, another objective of this dissertation is that the drowsiness detection algorithm requires the minimum input possible from the eye tracking platform with the purpose of, hereafter, have the eye tracking platform reduced in complexity, processing power demand, size and cost, meeting the automotive industry requirements.

Another dissertation developed for the same project is pursuing a similar main objective, but following an opposite approach: more complex algorithm that uses a greater number of inputs from the eye tracker, without concerns of processing power requirements. At the end, it is intended to compare the advantages and disadvantages of each implementation.

These objectives define the research question of this dissertation: Is it possible to develop a reliable drowsiness detection system based on eyelid opening parameters only?

1.3 Dissertation Structure

The structure of the dissertation should broadly follow this outline.

- In the chapter two are presented the most common methods and processes found in the literature about drowsiness detection, including a review on drowsiness detection methods, drowsiness behavioral clues and data fusion algorithms. And a representative number of products on the market regarding driver's drowsiness detection.
- The chapter three describes the followed methodology to develop and validate the proposed system.
- The fourth chapter details the development of the drowsiness detection system, including the system analysis and specification.
- In chapter five the experimental results are presented and discussed. Firstly, each eye tracking parameter performance is evaluated, and then, the final system performance as a whole.
- The chapter six unveils the conclusions that were obtained during the development of this dissertation. This chapter also includes a section that suggests the future work.

Chapter 2

State of the Art

In recent years, car manufactures and independent companies are investing a significant amount of resources to develop systems aiming to detect driver drowsiness. Moreover, many research with innovating methods are being carried out in order to help solving this problem.

In this chapter will be presented the most common methods and processes found in literature and a representative number of products on the market regarding driver's drowsiness detection.

2.1 Literature Review

This section intends to summarize the methods found in literature to detect drowsiness and review in detail the most studied drowsiness behavioral indicators. A brief survey about data fusion algorithms follows.

2.1.1 Drowsiness Detection Methods

There are several different methods to detect drowsiness. Currently, they are normally classified into five categories: subjective, vehicle-based, physiological, behavioral, and hybrid. The method used in this dissertation is classified as a behavioral method. However, for better comprehension, this section provides a brief survey of driver's drowsiness detection methods in each of the five categories.

Subjective Methods

Subjective methods are based in questionnaires answered by the drivers to evaluate their drowsiness level. They are considered subjective because they depend on the proper interpretation and comprehension of the questions by the subject. Regarding the nature of these methods, they are only suitable for simulated environments, where they are widely used to validate other methods [3][4][5].

Table 2.1: Karolinska Sleepiness Scale (KSS).

Rating	Verbal descriptions
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert, fighting sleep

The most commonly used drowsiness scale is the Karolinska Sleepiness Scale (KSS), a nine-point scale that has verbal anchors for each degree, as shown in Table 2.1. Researchers concluded that the KSS is closely related to EEG and behavioral variables, indicating a high validity in measuring drowsiness [6][5].

Other well-known scales are the Epworth Sleepiness Scale (ESS) and the Stanford Sleepiness Scale (SSS).

Vehicle-Based Methods

Nowadays, vehicle-based methods are the most popular among car manufactures. These methods rely on a theory that a drowsy driver creates specific driving patterns that can be measured [7].

The two most commonly used vehicle-based measures for driver drowsiness detection are: (1) SWM and (2) SDLP.

1. **Steering wheel movement**. This method uses an angle sensor mounted on the steering column which allows the detection of micro-corrections on

the steering wheel. The number of micro-corrections is lower when a driver is drowsy providing an approach to detect drowsiness. However, there are certain factors that affect this system's reliability:

- Driver's driving characteristics;
- Geometric characteristics of the road;
- Kinetic characteristics of the vehicle.

2. **Standard deviation of lane position**. SLDP systems rely on cameras to monitor the car relative position within its lane. A typical drowsy driver´s behavior is leave a designated lane and crossing into an opposite traffic lane or going off road. This method intends to detect this behavior although it is highly dependent of several external factors:
   - Road marking conditions;
   - Weather and lighting conditions;

Physiological Methods

This type of methods aim to detect drowsiness by measuring the subject's physiological signals. As these signals begin to change during the first stages of drowsiness, physiological methods have potential to detect drowsiness before the others [7]. Nowadays however, these methods are highly invasive regarding the nature of the physiological signals acquisition. Therefore, physiological methods are not used in real situations yet.

The most studied physiological methods are: (1) ECG and (2) EEG.

1. **Electrocardiogram**. The methods based on ECG analyze the heart's activity. By this analysis it is possible to determine when a driver is leaning towards a drowsy state. The most common approach to acquire the signals is through electrodes applied in certain body places. This limitation might be overcome in the near future with the development of wireless sensors that can be placed on the seat.
2. **Electroencephalogram**. The EEG records electrical activity from the brain. The brain's signals are complex, however, its waves can be analyzed aiming the drowsiness detection. Typically, the electrical signals are

obtained from electrodes placed around the subject's head.

Behavioral Methods

Behavioral methods are the focus of this master thesis. The discussed method, based on eye tracking, is grouped in this category.

These methods are based upon non-invasive observation of the driver behavior, in particular, of his facial expressions. Typically, the systems based on this method use one video camera (or more) pointed at the driver's face for image acquisition, and rely on computer vision software to detect specific behavioral clues exhibited by a drowsy person.

Eye state, head pose and yawning are the most studied parameters found in the literature. Later in this chapter, these parameters will be explained in detail.

Hybrid Methods

Hybrid Methods are a fusion of two or more methods mentioned above with the purpose of improving the reliability and accuracy on drowsiness detection.

In fact, several research studies have proven that combined methods obtain better results than one method as stand-alone [8]. The disadvantages for this approach are only the increasing complexity and cost of the detection systems.

2.1.2 Drowsiness Behavioral Indicators

The eye state is the major resource for drowsiness detection based on behavioral methods. However, others parameter as head pose and yawning are also studied, despite of being frequently implemented along with the eye state.

Eye State

The key point to establish the eye state is to distinguish if the eye is widely open, partly open or closed. That done, percentage of eye closure, blink frequency,

blink duration, eyelid opening and eye closing speed are some of the most commonly analyzed parameters.

1. **PERCLOS** has been found to be a reliable measure to predict drowsiness and it is widely used [9]. This method calculates the percentage of time that eyes are at least 80 percent closed in a certain period. If this percentage of time is greater than a determined value, then the driver is considered drowsy.

2. **Eyelid Opening** is the aperture between superior eyelid and inferior eyelid. Typically, when a person is sleepy, this opening becomes narrower.

3. **Blink Frequency** represents the number of blinks over a period of time. The human being blinks more often when experiencing early stages of drowsiness [10], therefore, blink frequency is a possible measure of drowsiness.

4. **Blink Duration** is defined by the difference of time between the point when the eyelid opening has reached half of the closing amplitude and the point when the eyelid opening has reached half of the opening amplitude. The blink duration increases as a person gets sleepier [10].

5. **Eye Closing Speed** represents the eyelid movement speed when the eye is closing. It relies on the fact that a drowsy person closes his eyes more slowly than normal [10] for determining if a driver is drowsy or not.

The Figure 2.1 explain how these five parameters can be measured.

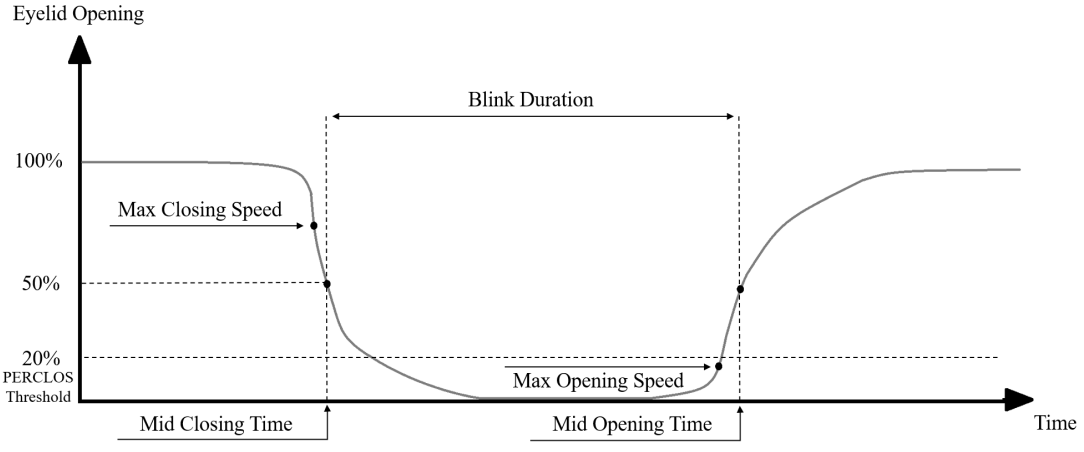

Figure 2.1: Blink Characteristics.

Gaze fixation and saccades are others parameters that can be obtained from the eye. Gaze fixation is measured by the time that a person is staring to the same point. Drowsiness increases the number and duration of gaze fixations. Saccades

define rapid movements of both eyes that abruptly change the point of fixation. Saccades occur naturally when reading for example, and become less frequent when a person is drowsy.

Head Pose

The driver's head pose can provide significant information regarding it's state [11]. When a driver is affected with drowsiness, some of the muscles in the body begin to relax, leading to nodding. This nodding behavior can be detected indicating a drowsy state.

Yawning

It is common knowledge that frequent yawning is an indicator of drowsiness. Based on the frequency of yawning, this method can determine whether a driver is drowsy. However, since yawning does not always occur before the driver goes into a drowsy state, this method cannot be used as stand-alone [12].

Multiple Facial Actions

With less frequency, multiple facial actions are also studied aiming drowsiness detection [13]. Usually combined with one of the previous methods, the analyzed parameters can be the state and position of the eyebrow or lip and jaw dropping.

2.1.3 Data Fusion Algorithms

Using more than one drowsiness behavioral indicator leads to a problem. How to merge multiple source of data in order to classify a data set as drowsy or not drowsy?

In the literature many algorithms for data fusion can be found. At this section, K-Nearest Neighbor Classifiers, Artificial Neural Networks and Fuzzy Logic Classifiers are the data fusion algorithms that will be briefly described.

These algorithms are widely used in different applications, for instance, computer vision, wireless sensor networks and business performance management.

K-Nearest Neighbor Classifier

K-Nearest neighbors algorithm (k-NN) is a classification method which outputs a class membership. This is achieved in two phase: first the algorithm locates the k-number of points that are closest to the unclassified data sample, then, assigns it a class, calculated by a majority vote of its k-nearest neighbor, where k is the number of votes (or closest data points) needed for class attribution. There are several ways to measure the distance between data points, such as Euclidean, Mahalanobis and Minkowski distance. This algorithm is best motivated through examples.

The Figure 2.2 shows an example of k-NN classification. The sample to be classified (circle) should be classified either in one class, the class of squares or the class of triangles. If k = 3 (large circumference), the sample is assigned to the class of squares because there are two squares and only one triangle in the three nearest neighbors.

The k-NN algorithm is considered among the simplest of all machine learning algorithms.

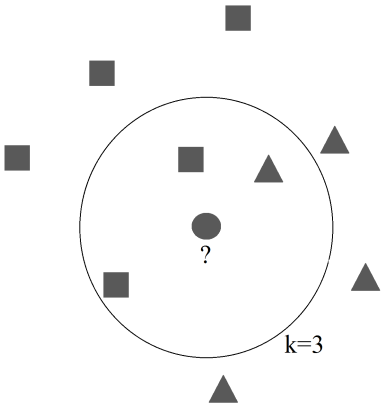

Figure 2.2: K-Nearest Neighbor Classification Example.

Artificial Neural Network

Beyond the data fusion and classification, artificial neural networks (ANNs) also have the potential to predict data patterns. They have been designed to create artificial intelligence, like human intelligence and are used in a wide variety of fields, including computer vision and speech recognition.

The ANNs architecture is inspired by the human brain architecture, which consists of neurons and connections among neurons. ANNs have many processing units (nodes), like neurons, and connections between processing units. These connections have adaptive weights, tuned through training, making ANNs capable of learning.

Briefly, a node receives many input signals, each one multiplied by the respective connection weight, and then applies a mathematical function that computes the node output, called activation. The activation of each node is passed to other nodes, through connections, until an output node is reached. The higher a weight of connection is, the stronger the node input will be.

The Figure 2.3 introduce a simple artificial neural network where each circle represents a node and an arrow represents a connection from the output of one node to the input of another.

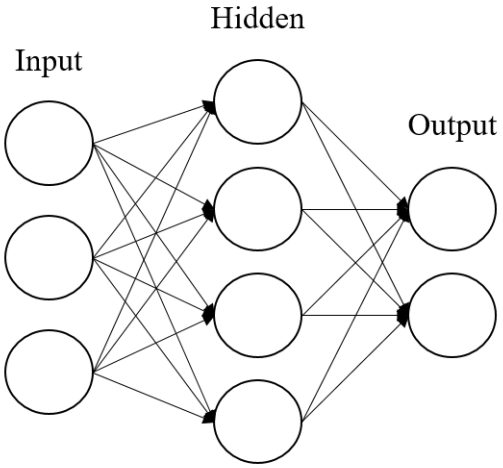

Figure 2.3: Artificial Neural Network Example.

Fuzzy Logic Classifier

Fuzzy Logic is a method of reasoning that resembles human reasoning. The approach of fuzzy logic mimics the way of decision making in humans that involves all intermediate possibilities between digital values true and false. For instance, the statement "today is sunny", might be 100 percent true if there are no clouds, 80 percent true if there are only a few clouds, 40 percent true if it is hazy and 0 percent true if it rains all day. By contrast, in Boolean logic, the statement may only be true or false, these are called crisp values.

In brief, a fuzzy logic classifier starts by transforming the inputs into fuzzy variables. These variables have a value between 0 and 1 that represents the membership degree to a class. For example, the class drowsiness. Next, all the fuzzy variables are combined in one fuzzy set which ultimately leads to a crisp output, following the previous example, drowsy or not drowsy.

The fuzzy variables are commonly combined through linguistic rules (if condition, then conclusion) [14]. However, another method is suggested in [15], where the fuzzy variables are combined through a equation that can be a simple median.

2.2 State of the Market

Far from being a standard in vehicles marketed nowadays, drowsiness detection systems are increasing popularity within the automotive industry. Therefore, car manufactures and aftermarket companies are creating solutions for detecting drowsiness. Furthermore, companies specialized in eye tracking are developing technology for automotive purposes.

2.2.1 Car Manufactures

Several car manufactures have already drowsiness detection systems in its portfolio, others are at the developing phase. Ford, Mercedes, Toyota and Volvo systems presented below are just examples of what we can expect in the automotive market today and in the near future.

Ford: "Driver Alert System"

Ford's Drive Alert System was introduced in 2010 [16]. It is packed with a forward-facing camera mounted behind the rear view mirror that tracks the lane lines and estimates the driver's alertness level based upon his capabilities to maintain the car within its lane. Thus, this system is considered a SDLP vehicle-based method.

If the driver is appearing to be drowsy, an alert arises on the instrument cluster with a massage along with a coffee cup icon. Depending on the drowsiness level, also an audible alert is emitted.

Mercedes-Benz: "Attention Assist"

This drowsiness detection system was rolled out by Mercedes on its 2010 E-Class model. Attention Assist measures the steering wheel movements and creates a driver profile of driving in order to detect when a pause should be suggested [17]. This system falls under the SWM vehicle-based category of driver drowsiness detection methods.

The warning method is definitely similar to Ford's and an example is presented in the Figure 2.4.

Figure 2.4: Attention Assist alert [18].

Toyota/Lexus: "Driver Monitoring System"

The first version of the Driver Monitoring System was launched in 2006 and equipped some high-end Lexus models [19]. This version tracks the orientation of the driver's face and sounds a warning if it detects a sustained period of inattention. However, in 2008 Toyota updated this system to detect driver's drowsiness. The system relies on a driver-monitoring camera and image-processing software, which determine the position of the driver's upper and lower eyelids to perceive the state of the eye.

As illustrated in Figure 2.5, the Driver Monitoring System includes a camera and six infrared LED projectors placed on the steering column. The infrared LEDs illuminate the driver's face in order to ensure the same lightning conditions at day and night.

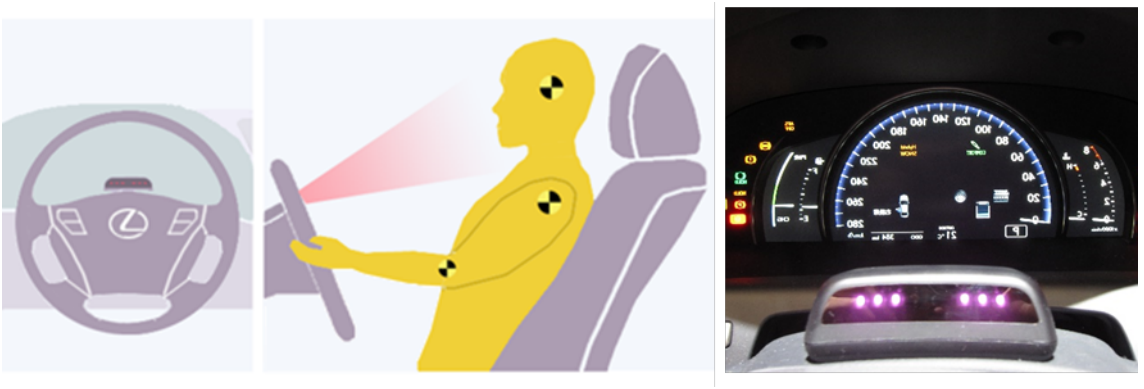

Figure 2.5: Toyota/Lexus Driver Monitoring System [20].

Volvo: "Driver State Estimation"

Volvo's Driver State Estimation is a technology at developing phase, however, it is already installed in test vehicles. This system monitors driver's gaze direction, eyelid opening and head position aiming to detect drowsiness and distractions [21].

It uses the same approach of Toyota's Driver Monitoring System, camera and infrared LEDs mounted on the steering wheel column, Figure 2.6.

Figure 2.6: Volvo's Driver State Estimation [21].

2.2.2 Aftermarket Products

Eagle Portable, Vigo and HealthyRoad are three of the several products in the market assessing drowsiness while driving. In particular, Eagle Portable and

Vigo are wearable gadgets that operate with smartphone integration. Also using a smartphone, HealthyRoad is a mobile application that aims to detect driver's drowsiness and distractions.

Eagle Portable

Eagle Portable is from Optalert company which has as target the businesses with a mobile workforce, including console operators, courier drivers or employees with long commutes.

The system is composed by Optalert´s wireless glasses, Figure 2.7, paired with a smartphone where it is shown the driver's drowsiness score, alerting the users to their risk of falling asleep. Optalert technology uses a system of infrared reflectance oculography housed in a pair of glasses that can monitor the eyelid movements. More specifically, a infrared LED built into the frame of the glasses measures the velocity of the operator's eyelid 500 times per second, allowing the identification of several ocular variables that can be combined to quantify drowsiness.

Figure 2.7: Optalert Glasses [22].

Vigo

Vigo is a smart Bluetooth headset, Figure 2.8, that tracks driver's drowsiness and stimulates him when needed. When paired with a smartphone, Vigo is also a Bluetooth headset for hands-free calling or music streaming.

This headset uses an infrared sensor, accelerometer, and its own algorithm to track patterns in blinks and head movements to gauge the alertness level in real-time. The user can choose from several alerts, including a gentle vibration,

a blinking LED or a song that is played through the headpiece from a paired smartphone.

Figure 2.8: Vigo Headset [23].

HealthyRoad

HealthyRoad is a mobile application, developed by a Portuguese company with the same name, that aims to detect driver's drowsiness and distractions, using eye tracking. The smartphone running the app must be placed on the vehicle windscreen with the screen facing the driver. A correct smartphone positioning is essential because the frontal camera has to capture the driver´s face in order to enable the app measure the driver's behavior.

The drowsiness detection is based on eye blinking analysis and microsleeps are detected when the driver closes both eyes during a travelled distance of twenty five meters. The distractions detection module only relies on the angle between the driver's face and the smartphone, ignoring the gaze direction. Which leads to a problem, the driver may be looking off the road and the face still be facing forward, not being detected any distraction. The detection systems are only performed when the vehicle speed is superior to thirty kilometers per hour. The velocity is calculated trough the smartphone GPS.

In case of drowsiness, a warning is displayed on the smartphone screen, figure 2.9. If microsleep or distraction is detected, an alert sound is reproduced.

Due to the use of a normal smartphone frontal camera, without infrared or any type of artificial illumination, the app performance is very poor at night or under low light conditions. For the same reason, sunglasses also compromise the eye tracking.

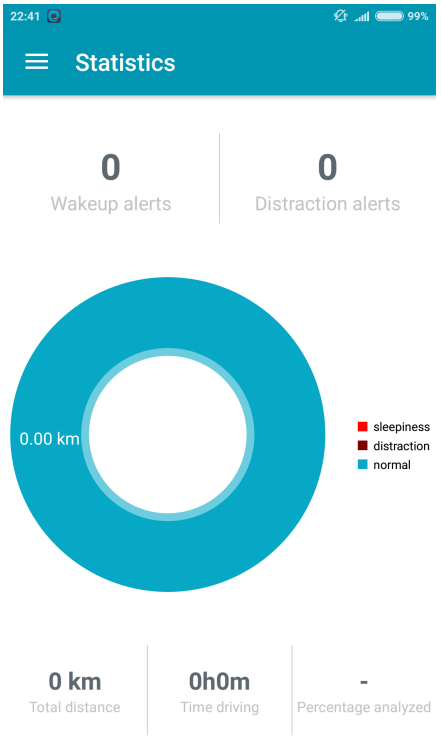

Figure 2.9: HealthyRoad.

HealthyRoad also promises vehicle personalization (using facial recognition), health tracking (based on heart rate, stress and emotions detection) and smart dashboard (by analyzing the face to improve the interface between Human and Machine). However, at the moment this dissertation is being written, this features are not implemented yet.

The app is currently available for free on the Google Play Store, only for android operating system.

2.2.3 Eye Tracking Technology

Independent companies are developing eye tracking technology for drowsiness detection purposes expecting to have their systems integrated by car manufacturers. One of these technologies, SmartEye Pro, is adopted in this dissertation. Seeing Machines and Tobii are other eye tracking systems that will also be addressed in this section.

SmartEye Pro

SmartEye Pro system, from Swedish company Smart Eye, is a software and hardware platform for eye tracking research proposes. Smart Eye has several well-known clients within the automotive industry, for instance, Audi, BMW, Jaguar and Volvo. This platform is used at this dissertation to acquire information from driver's face that might be useful to detect drowsiness. It is a requirement from Bosch.

SmartEye Pro uses cameras, infrared projectors and computer vision proprietary software to obtain eyes and head features. The infrared light emitted by the projectors reflects on the eyes and skin of the subject and the camera captures this light. Since an infrared pass-through filter is used, the captured image is mostly composed by infrared light from the projectors. Therefore, the system is robust for different ambient, light conditions or skin color.

The SmartEye software provides several variables, the ones regarding drowsiness can all be grouped into four: eyelid opening, gaze direction, head pose and pupil diameter. Additionally, each variable is accompanied by the corresponding confidence value, that is based on the estimated quality of the measurements. A list of all variables is provided in appendix B. These variables can be provided in real time over TCP or UDP communication or through a graphical output as illustrated in Figure 2.10. Moreover, the eye tracking variables can be saved in a log file or a video file recorded for further analysis.

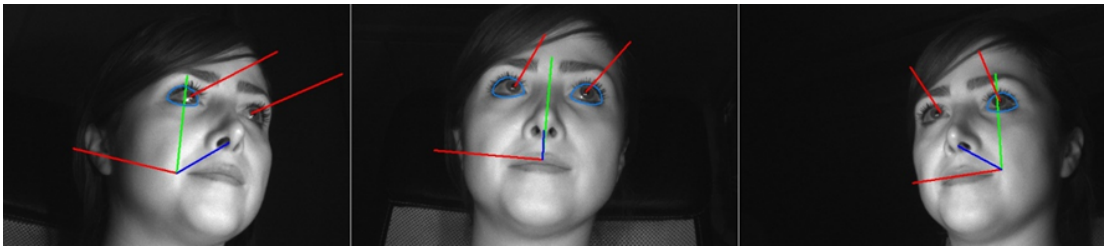

Figure 2.10: SmartEye Pro graphical output [24].

The hardware of SmartEye Pro includes a desktop PC, camera and infrared projectors controller, cameras (one to eight) and infrared projectors. The hardware architecture is represented in Figure 2.11. The desktop PC, responsible for executing the Smart Eye software, runs Windows® 7 and it is powered by an Intel® Core™i7 quadcore processor, 8 gigabytes of RAM and a solid state drive of 256 gigabytes, to handle large bandwidth of video recordings. This PC has a passive

refrigeration system, which in combination with the solid state drive makes it with no moving parts, meaning that is suitable for using in real vehicles.

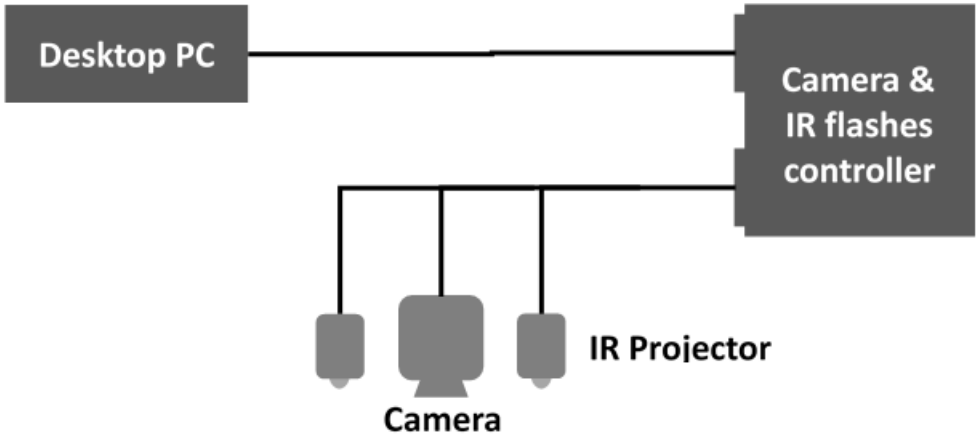

Figure 2.11: SmartEye Pro hardware architecture.

The hardware configuration of SmartEye Pro makes this system more suitable for use in laboratory or simulation environment. However, Smart Eye also provides an embedded solution specially designed to meet the automotive industry requirements. This solution, called Blackbird, is much more compact and easy to integrate in cabin, Figure 2.12. Blackbird follows the same principle of operation of SmartEye Pro, which integrates one infrared camera at the center and two infrared light projectors, one at each side.

Since Blackbird measures driver head pose, gaze direction and eyelid closure it also has potential to be a reliable source for drowsiness detection. However, at the moment this dissertation is being written, it was not possible to determine whether this product is ready to hit the market.

Figure 2.12: SmartEye Blackbird [25].

Seeing Machines

FaceLAB is a Seeing Machines product which tracks head and eyes for research purposes. FaceLAB is based on the same approach as SmartEye Pro, using cameras and infrared illuminators in order to overcome the light changing conditions of the environment. However, the basic system operates with two cameras (stereo) as shown in figure 2.13, but even more cameras can be added for extending the field of view.

FaceLAB delivers the following output data: head position and rotation, eye position and rotation, eye gaze, eyelid opening, pupil diameter, saccade events, blink events, blink frequency and blink duration. Furthermore, FaceLAB delivers PERCLOS fatigue metric.

Figure 2.13: FaceLAB [26].

Tobii

Tobii is a company dedicated to eye tracking solutions. The most popular product, Tobii Eyex in Figure 2.14, is a device to be used as a PC peripheral that aims to revolutionize the way of interacting with computers. Tobii Eyex provides the control of basic mouse functions recurring to user's gaze direction. It also has applications when playing games. Furthermore, Tobii has other eye tracking solutions in its portfolio, perhaps the most important to this dissertation is the one for automotive integration. This solution is developed meeting the requirements of each client.

The principle of operation of Tobii's eye tracking systems is very similar to SmartEye systems. The core of the system is composed by infrared projectors to create patterns in the eyes and infrared cameras to acquiring the data. The

number of cameras and infrared projectors may vary depending on the product.

Figure 2.14: Tobii [27].

2.2.4 Market Review

The table 2.2 summarizes the systems addressed above.

Table 2.2: Market Review

Product	Method	Status
Driver Alert System (Ford)	Steering wheel movement	Commercialized
Attention Assist (Mercedes-Benz)	Standard deviation of lane position	Commercialized
Driver Monitoring System (Toyota)	Driver facing camera and infrared lights	Commercialized
Driver State Estimation (Volvo)	Driver facing camera and infrared lights	Under development
Eagle Portable (Optalert)	Infrared reflectance oculography	Commercialized
Vigo (Vigo)	Infrared reflectance oculography and head movements	Commercialized
HealthyRoad (HealthyRoad)	Driver facing smartphone	Commercialized
SmartEye Pro (Smart Eye)	Driver facing camera and infrared lights	Commercialized for lab
FaceLab (Seeing Machines)	Driver facing camera and infrared lights	Commercialized for lab
Tobii Eyex (Tobii)	Driver facing camera and infrared lights	Commercialized for lab

Chapter 3

Methodology

In this chapter is presented the followed methodology to develop and validate the proposed system.

3.1 Development Approach

This dissertation uses a custom engineering process approach with five distinct phases: analysis, design, implementation, test and validation, arranged as shown in figure 3.1. Design, implementation and test phases form a iterative cycle, where each of these cycles starts with a feature to be implemented and ends when this feature is functional and bugs free.

Analysis

The analysis phase includes gathering the system requirements and constraints, and formulate the system overview. Several requirements are imposed by Bosch, however, some space is left to define others by self-interest. The system overview is the early conception of a system to meet the requirements. This allows to understand if the requirements could be fulfilled and predict possible problems.

At the end of this phase it is expected to have a list of requirements and constraints, and a block diagram representing the system overview.

Design

At the design phase is established a plan to implement the system previously specified. In case of software, flowcharts define the algorithm to implement each system feature. If hardware, schematics detail components and their behaviors and interfaces.

Thus, as work product, design phase should release software flowcharts and hardware schematics.

Implementation

In the implementation phase the software and hardware are actually implemented and the system takes shape. The software will be written in C++ and developed in the well-known IDE from Microsoft, Visual Studio. This IDE was chosen due to the API and code samples from Smart Eye eye tracker software were prepared for this platform.

Software and hardware are the expected work products from the implementation phase.

Testing

The testing phase is important to test the system features and improve the product quality. In this dissertation, testing phase is closely connected with the design and implementation phases in order to fix problems more quickly and prevent that these escalate to other features. Mainly through on desk testing, this phase should ensure the proper operation of each feature and look for malfunctions.

If any bug is found, this phase should provide a bug report to the design or implementation phase.

Validation

In validation phase, the developed system is subjected to an extensive test and the results are compared against the requirements to verify if they were sat-

isfied. The methods that will be used on validation are explained in detail in the following section.

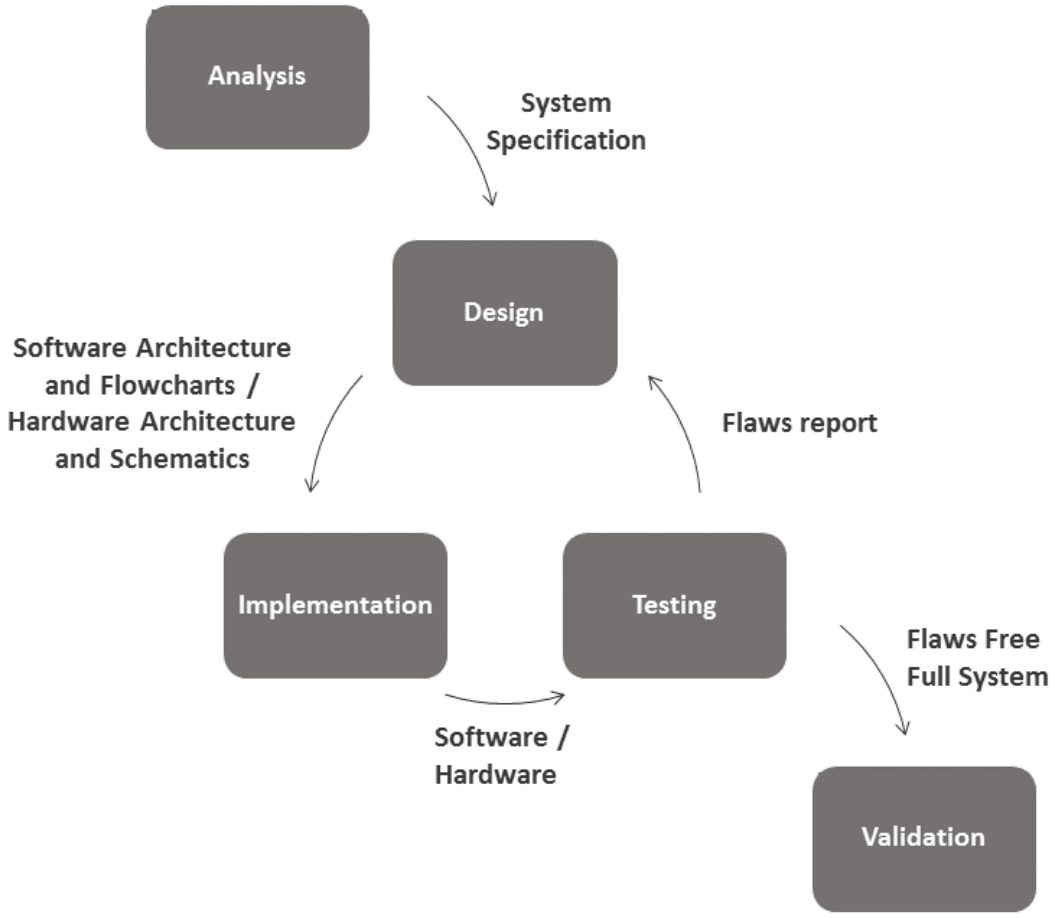

Figure 3.1: Development Methodology.

3.2 Validation Methods

Before starting the development phase, it is good practice to specify how the system will be validated, which are the methods and tools to measure the system overall performance.

Given the nature of the phenomenon that the system developed at this dissertation aims to measure, drowsiness, this is difficult or even impossible to simulate digitally. Therefore, the system will be subjected to the human behavior in a set of tests performed by individuals in the conditions that are specified in the following subsection.

Furthermore, the Karolinska Sleepiness Scale is the chosen method to perform concurrently during system tests. Thus, it is possible to compare results and benchmark the developed system. And, ultimately, lead to some conclusions.

3.2.1 Test Conditions

The experiments will be performed in Driver Simulator Mockup (DSM), figure 3.2. DSM delivers a very realistic sensation of driving and can simulate several different environments, as day or night and city or highway routes.

Figure 3.2: Driver Simulator Mockup.

Each user will drive under two different conditions of fatigue: one session without sleep deprivation during 30 minutes and another session with sleep deprivation during 1 hour. The users without sleep deprivation have a regular habit at bedtime, with a rest duration of 7 hours and a half with a difference of +/- 30 minutes between 00:00 am and 08:00 am; the test should be performed during the day and in the next 10 hours after the awaken. The sleep deprivation condition test should be realized during night and when the driver is awake for at least 15 hours, increasing the chances of drowsiness episodes during the test. Moreover, the driver will answer the KSS every five minutes during the tests [5].

The experiments will be performed by individuals that may comply to the following conditions:

- Non-professional drivers holding current license;
- Aged between 18 and 55 years;
- No history of epilepsy, sleep disorder or major medical illness;
- No recent surgery;

- No alcohol and caffeine in the previous 24 hours.

3.2.2 Karolinska Sleepiness Scale

According to the literature review, the Karolinska Sleepiness Scale (KSS) has proven to be a reliable and widely used method to validate drowsiness detection systems.

For simplicity, and to have a coherent output with the proposed system, the KSS was further divided into two broad classes 'Active' and 'Drowsy'. The table 3.1 shows the KSS and its two category classification according to [28], which states that this division marks the border when the driver's drowsiness begins to interfere with the driving task. Thus, from level 1 to 6 the driver is considered 'Active' and from 7 to 9 is considered 'Drowsy'.

Table 3.1: Two Classes KSS

Rating	Verbal descriptions	State
1	Extremely alert	Awake
2	Very alert	
3	Alert	
4	Fairly alert	
5	Neither alert nor sleepy	
6	Some signs of sleepiness	
7	Sleepy, but no effort to keep alert	Drowsy
8	Sleepy, some effort to keep alert	
9	Very sleepy, great effort to keep alert, fighting sleep	

Once the driver will have to respond the questionnaire every five minutes, this test could be a little intrusive and distracting, possibly adulterating the drowsiness results. To ease this side effect and facilitate the data analysis, at this dissertation an android application was developed so that the driver could answer with one single touch, instead of having to speak or use pen and paper.

The features of the Karolinska Sleepiness Scale android application are presented below.

KSS Android Application

The developed application has a main screen where the questionnaire is shown and a hidden menu that is revealed when a swipe from the left side occurs. This is illustrated by the figure 3.3 with two screenshots.

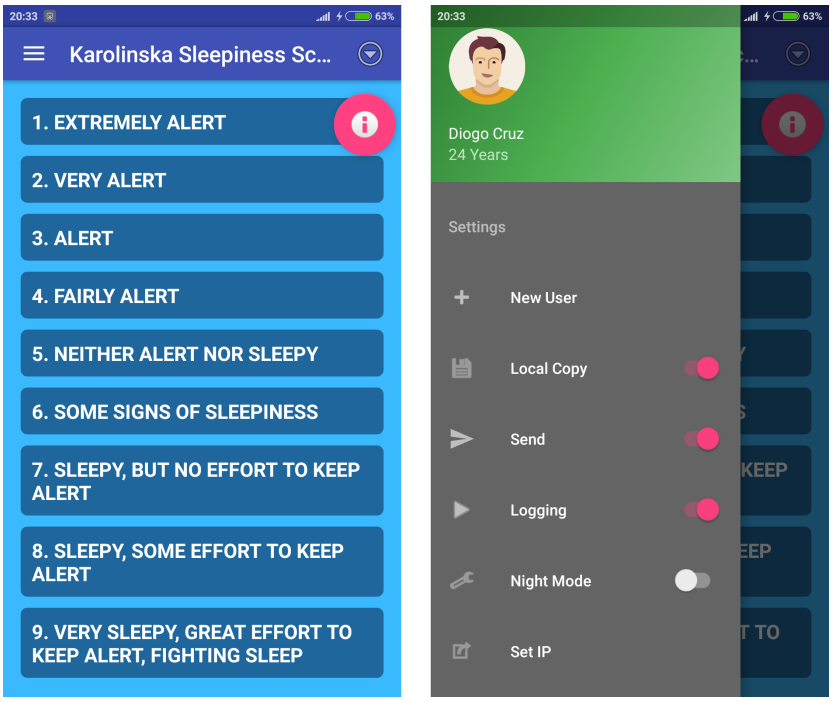

Figure 3.3: KSS Android Application.

The main screen is intended to the test subject. The layout is simple and the less distracting as possible, only with nine answer buttons and one to call assistance if needed. When the driver presses an answer button the screen turns off, and only turns on again if touched or if the questionnaire time interval is over and it is time to answer again. Thereby, the driver is minimally disturbed during the test.

In order to inform the driver that it is time to answer again, besides the screen turning on, a small beep is sounded.

The menu is designated to the test operator. Here it is possible to add a new driver and configure the application behavior. The operator can:

- Enable local copy: a log file named with the name, age and gender of the driver is generated saving locally the driver answers;

- Enable send: the answers are sent, in real time, over TCP/IP to the operator's PC;
- Start and stop the logging;
- Enable night mode: to do not disturb the driver under low light environments;
- Set the IP to which answers are sent if send is enabled;
- Set the question period, five minutes by defect;
- Change the language to Portuguese or English.

More screenshots illustrating this features can be found in the appendix A.

Chapter 4

System Development

Since the literature and market were already studied and development methodology defined, this chapter finally unveils the development of a system that should be capable of detect and issue warnings when the driver is becoming drowsy or when he experiences a microsleep.

Firstly, the system analysis is presented, which includes a system overview. And then, the specification of the proposed system is described in detail.

4.1 System Analysis

The system analysis starts with the requirements and constraints for the proposed system and next, it is presented a system overview. This section also details which components will be used, in this case, which are the chosen eye tracking variables and fusion algorithm and why.

4.1.1 Requirements and Constraints

The requirements for the drowsiness detection system to be developed are the following:

- Detect drowsiness;
- Detect eyes closed microsleeps;

- Require the minimum data possible from eye tracker;
- Reasonable processing power demand algorithm;
- Recover to data loss.

The constraints of the proposed system are presented below:

- Receive the eye tracking data from Smart Eye Pro: The eye tracking platform was chosen by Bosch;
- Implement in C++ language: The API provided by Smart Eye was written in this language;
- Send the warnings via TCP/IP: The automotive HMI in which the proposed can be integrated communicates with this protocol.

4.1.2 System Overview

The previous section states the system requirements and constraints. This section introduces an overview of a system concept aiming to fulfill these requirements. It is an early glimpse of the solution that allows to understand the expected behavior of the system as a whole and of each block, and predicts the amount of labor necessary to each task and potential glitches.

Figure 4.1 presents the system overview, with tasks divided in blocks. As shown, the system to be developed only requires one variable from the eye tracker, eyelid opening, and uses a fuzzy logic algorithm to estimate the driver state.

The first block, parameters calculation, receives the eyelid opening in millimeters and computes three different parameters: PERCLOS, blink duration and blink rate.

These three parameters are the input of a larger block, fuzzy logic algorithm, that is responsible for answering the question: is the driver drowsy or awake? The fuzzy logic algorithm is subdivided in three blocks, the first to estimate the fuzzy variables, the next is in charge of fusing the variables and the last, makes the decision.

The last block, warning generation, includes the strategy to warn the driver.

There are two different possible approaches: a preventive approach and an active approach. The preventive approach is activated when the driver is becoming drowsy and advises him to rest. The active approach occurs when the driver is experiencing a microsleep and tries to wake him up so that he can control the car.

In the following subsections is explained why the eyelid opening was the chosen variable from the eye tracker and why the fuzzy logic was the chosen algorithm to compute the driver state.

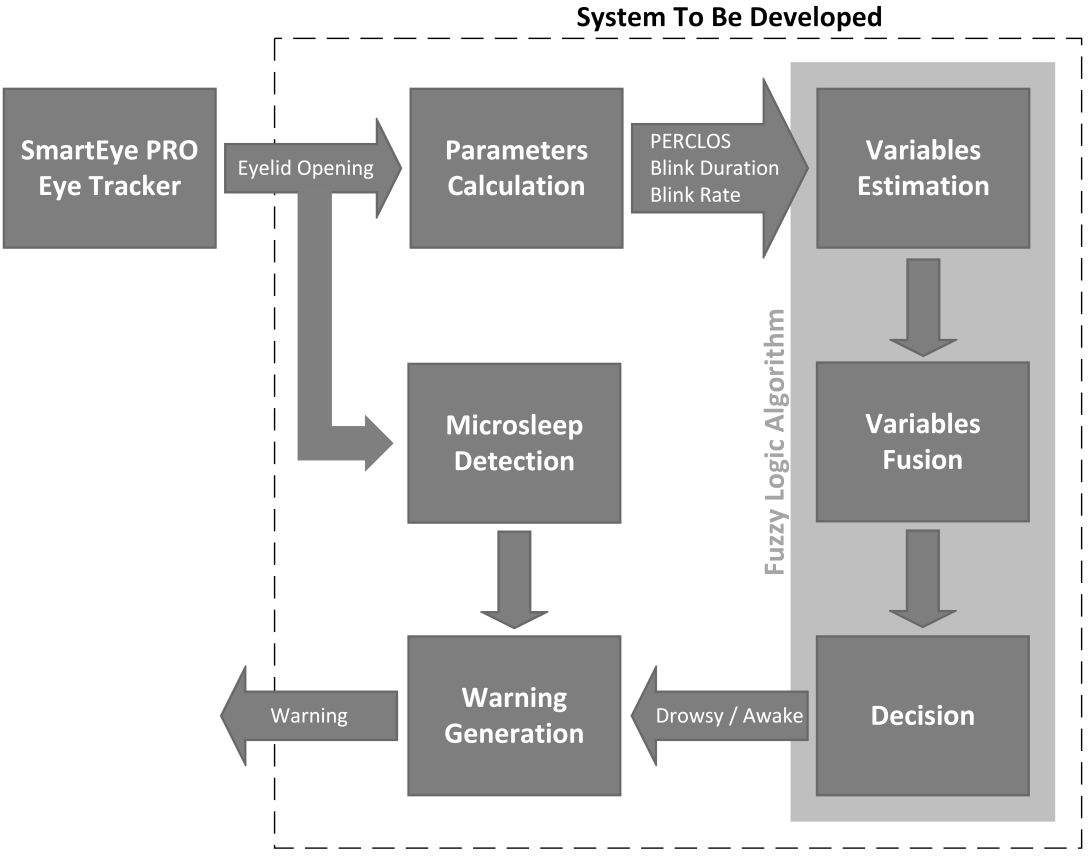

Figure 4.1: System Overview.

4.1.3 Why Eyelid Opening?

The SmartEye Pro provide an extensive list of eye tracking variables, shown in appendix B, however, they can all be grouped into four: eyelid opening, gaze direction, head pose and pupil diameter.

According to the literature review in chapter 2, it is possible to state that eyelid opening is, among the addressed variables, the one which could provide more

information about the driver drowsiness state. Since it is possible to calculate several parameters from the eyelid opening, certainly is, to use alone, the eye tracking variable with more potential to estimate the driver´s drowsiness level.

Additionally, eyelid opening can be considered one of the most basic variables that an eye tracker can acquire, meeting one of the project requirements - enable the complexity reduction of the eye tracker in future. Since it is based solely on measurement of the gap between the pupils, the computation of eyelid opening is less complex than gaze direction or pupil diameter for example.

4.1.4 Why PERCLOS, Blink Duration and Blink Rate?

Several parameters can be calculated from the chosen variable of the eye tracking platform, eyelid opening. For instance: PERCLOS, blink duration (BD), blink rate (BR), average eyelid opening, eye closing speed and eye opening speed.

Eye closing and opening speed could be good indicators of drowsiness, however, given the tiny time interval in which they have to be measured, these parameters require a very high frame rate system to be analyzed. The SmartEye Pro eye tracker runs typically at 60 frames per second, which is insufficient to measure eye closing and opening speed.

With eye closing and opening speed discarded by technical constraints, the choice is restricted to PERCLOS, BD, BR and average eyelid opening. A study carried out in [29] analyze these four parameters. The mean results of each parameter, assigned to one drowsiness class, are presented in figure 4.2.

As shown in figure 4.2, the values of PERCLOS, blink rate and blink duration reveal significant difference between drowsiness classes and linear growth, which makes them valid drowsiness measures. On the other hand, the average eyelid opening reveals inadequate difference between classes and a nonlinear growth, with the greater value in the middle drowsiness class. However, in a different study [30] is stated that blink rate is not suitable to detect drowsiness, due to the high variation caused by other factors, besides sleepiness. Other research studies [14][15] have proven that PERCLOS, blink duration and blink frequency obtain good results detecting drowsiness, with a little worse performance for blink frequency.

For the aforementioned reasons, PERCLOS, BD and BR are the chosen pa-

rameters for the proposed drowsiness detection system. However, blink rate will be under approval from the obtained results.

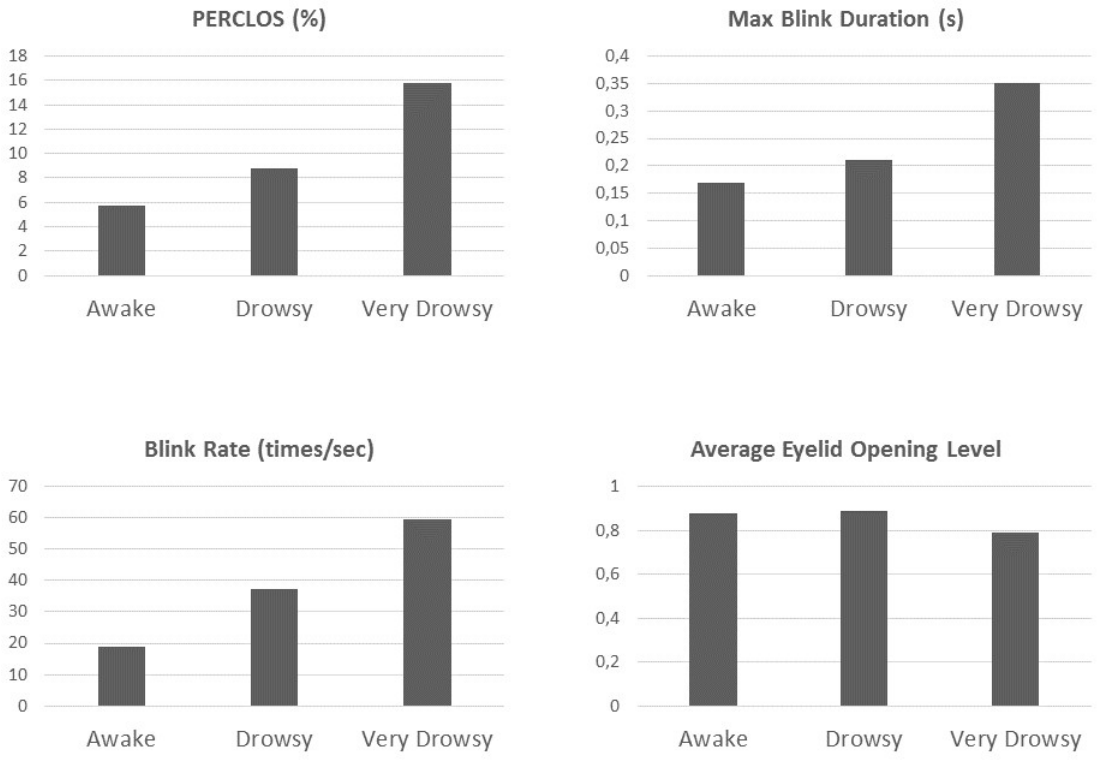

Figure 4.2: The statistical description of each parameter.

4.1.5 Why Fuzzy Logic?

From the data fusion algorithms addressed in literature review, K-Nearest Neighbor and Artificial Neural Networks are machine learning methods, and Fuzzy Logic Classifier is a straighter method.

Machine learning algorithms require a training phase, leading to an extended implementation time. Moreover, the training requires large data sets, which in the case of this dissertation translates to many hours and human resources at the Driver Simulator Mockup.

The Fuzzy Logic Classifier does not require a training phase, which greatly facilitates its implementation. Further, this algorithm reveals to be less complex comparing to the machine learning methods, potentially leading to less processing

power demand software, contributing to fulfill a project requirement.

Therefore, and also bearing in mind that another objective is to compare with the other dissertation that is being developed using machine learning, the fuzzy logic classifier was the chosen method to merge the different parameters and estimate the driver state.

4.1.6 Target Platform and Interfaces

The system will run in the same PC of the eye tracker, already specified in chapter 2. In this way the hardware structure is not increased, which facilitates the integration in the DSM.

The algorithm will receive the eye tracking data from the Smart Eye software through TCP/IP. In addition to the data received in real time from the eye tracker, the software to be developed should be capable of receiving the eye tracking data from a log file, which is generated by the SmartEye software, allowing an offline analysis of the data for testing purposes.Therefore, a software program to read the log files and send the data over TCP/IP to the algorithm will be developed and another interface to receive and parse this data will be added to the algorithm.

Moreover, the proposed system should be capable of issuing the generated warnings to the remaining HMI, that will perform an action on the driver. Since the internal communications of the HMI where the system can be integrated are via TCP/IP, another TCP/IP interface must be attached to the system.

Therefore, once the interfaces will be developed in separate modules of the algorithm, in case of changes in the eye tracker or even using a different eye tracker only the interface modules have to be updated, maintaining the algorithm intact.

To summarize, the algorithm should have three interfaces. One is responsible for receiving and parsing the online data form the eye tracker, other for receiving and parsing the offline data from the log files and other for emitting the warnings.

4.2 System Specification

This section introduces the specification of the drowsiness detection system, which includes software flowcharts, block diagrams and equations to explain the

behavior of each system component. The outline follows the system overview structure.

4.2.1 Software Flowchart

The figure 4.3 presents the flowchart of the software main part.

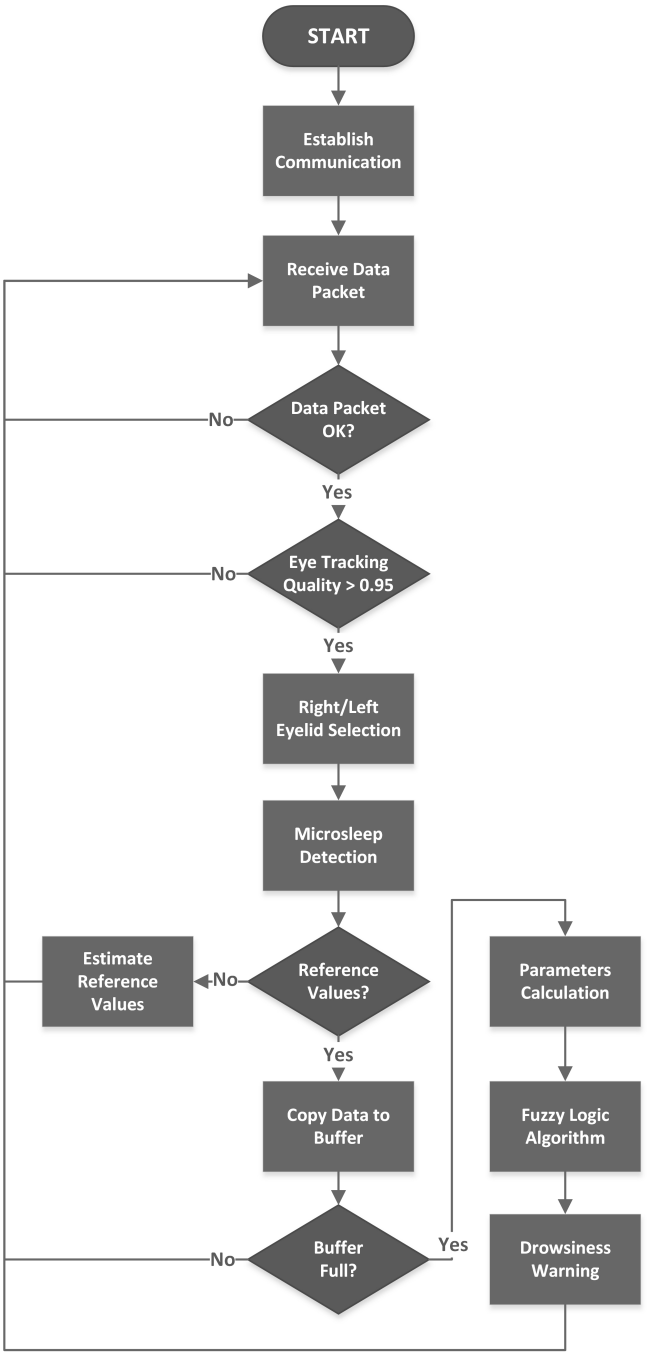

Figure 4.3: Main Flowchart.

The system starts by establishing the communication channel with the eye tracker, via TCP/IP. Then, begins to receive data packets and checks its integrity. If one packet is considered defective, it is discarded and the next is received.

Each data packet contains the acquired values of the right eyelid opening and left eyelid opening, in nanometers, and a variable of quality control, that indicates the eye tracking certainty degree. This variable ranges from 0 to 1. A time stamp, which represents the time passed, in milliseconds, since the eye tracker starts up, also comes in the packet.

If the received data packet is intact, the eye tracking quality of both eyes is verified. If the eye tracking quality of the right and left eyelids are below 0.95, the present data packet is discarded and the next is received. If at least one eyelid scores above 0.95, the eyelid with greater eye tracking quality is selected. The following subsection explains the advantages of using separate values of eyelid opening.

Afterward, the occurrence of a microsleep is checked and, if it has not already done, the reference values of the eyelid opening are calculated. Next, the right and left eyelid opening values are stored in buffers, as well as the value of the time stamp. This process is repeated until the buffer reaches its limit.

The buffer limit is 7500 values. Since the eye tracker runs at approximately 50 Hz, this corresponds to 2 and a half minutes to fill the buffer. Therefore, 2 minutes and a half is the interval in which the system produces a response regarding the driver drowsiness state.

When the buffer is full, the system calculates the parameters to estimate drowsiness and runs the fuzzy logic algorithm. If the driver is found drowsy, a warning is generated. Thereafter, the buffer is emptied and starts again receiving data until filled.

4.2.2 Right or Left Eyelid Selection

The eyelid opening, right or left, with best quality in the eye tracking, is considered from here as the default eyelid opening for the forthcoming operations. In case of one eye opened and the other closed, it is the opened eye that is taken in consideration. If both eyes are opened and with equal eye tracking quality, the right eye is chosen.

This feature allows the system to perform the drowsiness detection even when one eye is not being tracked correctly. A faulty eye tracking of one eye could mean several situations, for instance, when the driver is not looking straight in the camera direction, a shadow over one eye or when the head is making an angle different from normal with the camera. Thus, the chance of executing the drowsiness detection algorithm when one of these situations occurs is increased.

4.2.3 Microsleep Detection

As the figure 4.4 reveals, the system detects microsleeps only relying on the eyelid opening.

Figure 4.4: Microsleep Detection Diagram.

The Healthy Road app addressed in the study of the market, introduces an interesting concept to estimate the microsleep time threshold. It is based on the distance, 25 meters, that the driver travels with both eyes closed, hence, it depends on the vehicle velocity.

Since at this moment it is not possible, yet, to receive the velocity from the HMI implemented on the DSM, a default velocity of 70 km/h was established. At this velocity it takes 1286 milliseconds to travel 25 meters.

When the right and left eyelid opening are equal to 0, meaning that both eyes are closed, a flag is triggered and the time stamp saved. The time stamp of the next samples with both eyes closed is compared against the saved time stamp, if the difference is greater than 1286 milliseconds a microsleep warning is generated. If a sample with at least one eye opened is received, the previously activated flag is cleared. The flowchart that describes this operation is represented in the figure 4.5.

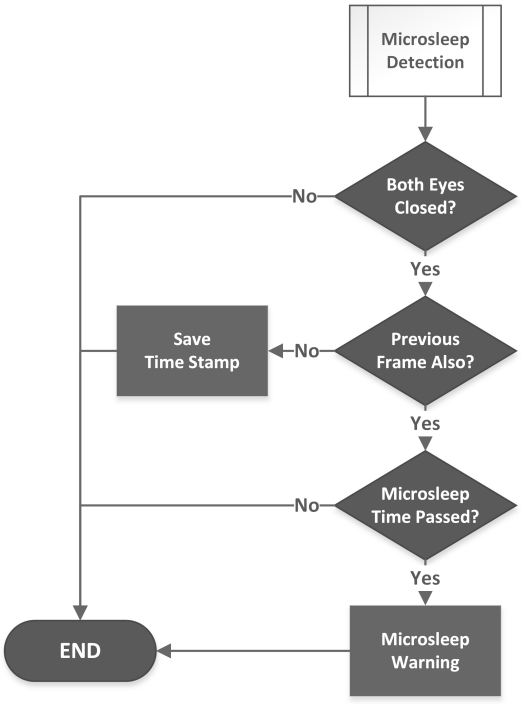

Figure 4.5: Microsleep Detection Flowchart.

4.2.4 Reference Values Estimation

To calculate the parameters for the drowsiness detection, reference values of the eyelid opening half and eyelid opening 80 percent are required. The system uses the eyelid opening half to calculate the blink rate and blink duration and the 80 percent of eyelid opening to calculate the PERCLOS.

The mode was the chosen method to estimate the reference eyelid opening values. Comparing to the median, the mode has the advantage of ignoring the samples with closed eyes, once the eye is open the overwhelming majority of the time. Thus, the mode provides the most common value in the buffer, which equals to a correct eyelid opening reference.

The figure 4.6 shows the flowchart that defines the reference values estimation. The eyelid opening values are copied to a buffer until it reaches 1000 samples. When the buffer is full, the mode is calculated over this eyelid opening values, and then, the mode result is multiplied by 50 percent and 80 percent. A flag is also turned on to indicate that the reference values have been generated, preventing this operation of being performed again.

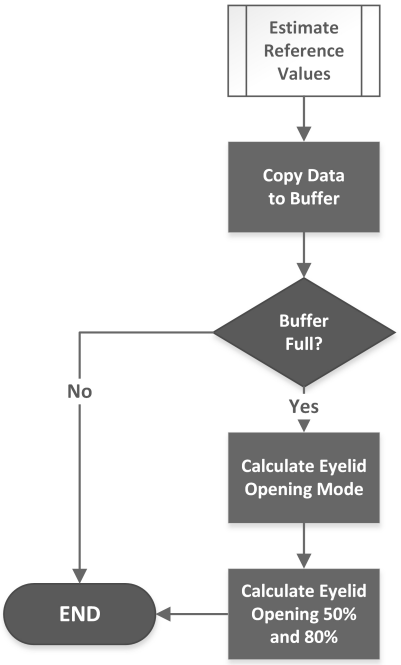

Figure 4.6: Reference Values Estimation Flowchart.

4.2.5 Parameters Calculation

The Parameters Calculation block is responsible for providing the fuzzy logic algorithm inputs. As shown in figure 4.7, three parameters are calculated: Perclos, Max Blink Duration and Blink Rate, only relying on the eyelid opening.

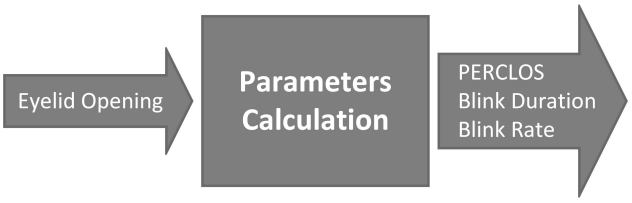

Figure 4.7: Parameters Calculation Diagram.

To obtain the Perclos, the number of samples where the eyelid opening is less than 80 percent of the eyelid opening reference value is divided by the total number of samples in the buffer. Then, the result of this operation is multiplied by 100.

The Max Blink Duration and Blink Rate require the detection of blinks among the buffer samples. As demonstrated in the state of the art, the duration of a blink is determined by the period that the eyelid opening is less than 50 percent of the reference value. Moreover, to be considered a valid blink, during that period

the eyelid opening must reach the value of 0 at some moment. Thus, the Blink Rate is defined by number of blinks per buffer and the Max Blink Duration is the result of the 8 longest blinks average, in milliseconds.

4.2.6 Fuzzy Logic Algorithm

The Fuzzy Logic Algorithm receives the previously calculated parameters and delivers an answer regarding the drowsiness state of the driver.

Figure 4.8: Fuzzy Logic Algorithm Diagram.

The algorithm, inspired by the study conducted in [15], can be divided into three tasks, the estimation of fuzzy variables, the fusion of these variables and the final decision. Following, the role of each task is described.

Variables Estimation

The previously calculated parameters have different units and scales. Therefore, this data should be normalized before the fusion. The equations 4.1, 4.2 and 4.3 demonstrate how the normalization is performed on the parameters. This operation results in one fuzzy variable to each parameter.

$$FuzzyVariable = \begin{cases} 0 & if \quad parameter < a \\ \frac{parameter - a}{b - a} & if \quad a \leq parameter \leq b \\ 1 & if \quad parameter > b \end{cases} \tag{4.1}$$

$$a = parameterThreshold - 0,25 \times parameterThreshold \tag{4.2}$$

$$b = parameterThreshold + 0,25 \times parameterThreshold \tag{4.3}$$

The equations 4.2 and 4.3 define the limits for the equation 4.1 through the threshold of each parameter. The thresholds will be determined in the following chapter.

As is evidenced in the equation 4.1, a fuzzy variable takes the value of 0 if the its parameter is less than 75 percent of the respective threshold. And takes the value of 1 if the parameter is greater than 125 percent of the respective threshold. If the parameter is between the two limits, the respective fuzzy variable assumes a value between 0 and 1, exclusively.

Therefore, a fuzzy variable ranges from 0 to 1, where 0 indicates the total absence of drowsiness, in the respective parameter, and 1 means the total presence of drowsiness.

Variables Fusion

Once more than one parameter are used to estimate drowsiness, it is mandatory to proceed to its fusion in order to obtain a single answer. This fusion is performed according to equation 4.4.

$$Fusion = \frac{previousFusion + \frac{fuzzyPerclos+fuzzyMBD+fuzzyBR}{3}}{2} \tag{4.4}$$

As it can be inferred from the equation, an average is applied to the three fuzzy variables. Furthermore, to smooth the output and prevent a faulty sample of generating a false-positive, and sustaining on the gradual drowsiness behavior, the previous fusion output has half the preponderance in the current output.

Moreover, the driver is considered drowsy when the fusion value is greater than 0,5.

Decision

The Decision block translates the output of the Variables Fusion block into a binary answer for the ultimate question: is the driver drowsy or not? If the Decision Output is 1, the answer is affirmative and a warning will be generated, if it is 0, the answer is negative.

As shown in the equation 4.5, the Decision output is 1 when the fusion is above 0,5 and it is 0 when the fusion is equal or below 0,5. Therefore, since the decision is only affirmative when the fusion is greater than 0,5 and not equal, one parameter alone can not trigger a drowsiness warning.

$$Decision = \begin{cases} 1 & if \quad Fusion > 0,5 \\ 0 & if \quad Fusion \leq 0,5 \end{cases} \tag{4.5}$$

4.2.7 Warnings

Since the drowsiness detection system is intended to be integrated in the DSM along with several HMI components that are being developed, the warnings generated by the present system will be sent over TCP/IP to another system responsible for managing and delivering all the HMI warnings to the driver. As the diagram in figure 4.9 suggests, the warning generation block receives the indication of detected drowsiness or microsleep and sends the respective warning via TCP/IP.

Figure 4.9: Warning Diagram.

Two types of warnings were established: the type one means drowsiness and the type two microsleep. The messages will be sent following the structure represented in the figure 4.10.

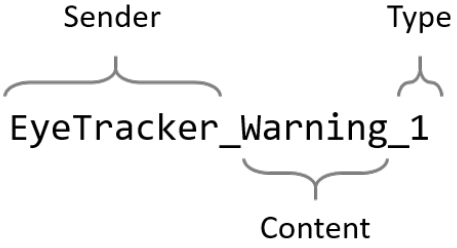

Figure 4.10: Warning Message.

Based upon the state of the art, it is possible to formulate a vision of how the warnings should be delivered to the driver. Therefore, two possible solutions to warn the driver are suggested next.

The figure 4.11 is inspired by the Attention Assist system from Mercedes Benz. This message could be displayed in the cluster when the driver is found drowsy. In case of a microsleep the warning can not be visual, hence, the action should be a vibration in the seat or steering wheel, eventually accompanied by an audible alarm.

Figure 4.11: Warning of Drowsiness.

Chapter 5

Experimental Results and Discussion

For the results presented in this chapter, two subjects, subject A and subject B, performed the driving experience under the conditions mentioned in chapter 3. Thus, four sets of results were obtained: subject A during day, subject A during night, subject B during day and subject B during night.

Following, the experimental results are presented and discussed. Firstly, each parameter performance is evaluated, to validate its presence in the final system. And then, the final system performance as a whole. In both cases, the system outputs are compared with the results of the Karolinska Sleepiness Scale.

Additionally, the results of two more experiences performed during day by different subjects are presented in the appendix C. In these experiments was never found drowsiness. Therefore, they are not discussed in detail at this chapter.

5.1 Parameters Performance

In this section, the parameters calculation block outputs will be evaluated. Perclos, Blink Max Duration and Blink Rate are compared against the KSS results in order to estimate the performance of each parameter.

If one parameter does not reveal any correlation with the KSS, or it is not possible to define one threshold value between the awake state and the drowsy

state, it will not be considered a valid measure for the proposed system.

Remembering, the KSS threshold defined in chapter 3 was the seventh point of the scale.

5.1.1 Perclos

Analyzing the Perclos results of subject A, showed in figures 5.1 and 5.2, and subject B, represented by the figures 5.3 and 5.4, it can be seen that the Perclos correlates with the KSS. Thus, it is a viable measure of drowsiness for the present system. Moreover, it was possible to outline a threshold of 10%, that based on these results and on testing experience suits all the four samples.

The Perclos experimental results of subject A and subject B will be construed in detail in the following subsections.

Subject A

As shown in figure 5.1, the KSS maximum value is 4. Therefore, since the previous defined KSS threshold to consider a person drowsy is 7, the subject A during the day test was always awake. Regarding the Perclos values, these vary approximately between 4% and 9%. It is also possible to observe that the Perclos curve follows the KSS curve.

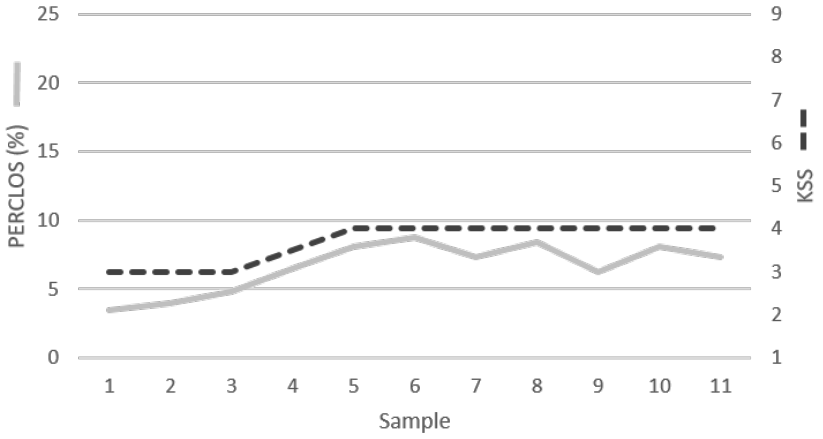

Figure 5.1: Perclos - Subject A during day.

During the night test, subject A went through periods of drowsiness. As it

can be seen in figure 5.2, the KSS values reached the top of the scale, the point 9, and the Perclos values range from 3% to 15%, a greater maximum value than during the day test. The graph also shows resemblances between the Perclos and KSS curves.

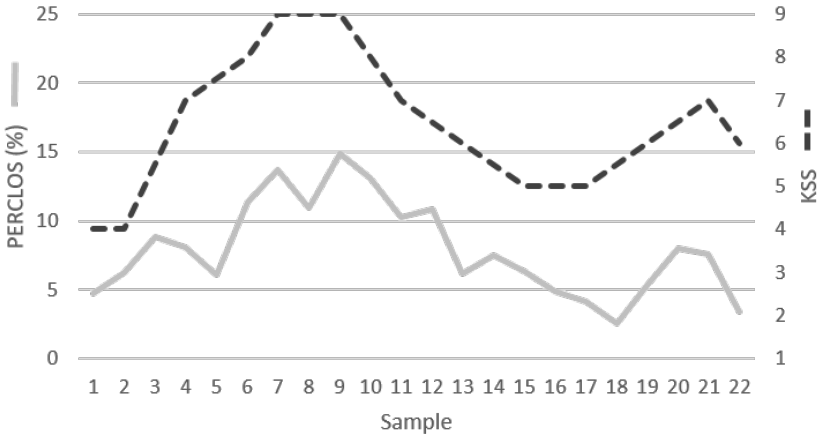

Figure 5.2: Perclos - Subject A during night.

Subject B

The subject B has reached the point 7 in the Karolinska Sleepiness Scale during the day test, the first that indicates drowsiness. As shown in figure 5.3, the Perclos hits a maximum of approximately 16% and a minimum of 6%.

Comparing the two curves, a slight lag between the maximum of the two curves can be noticed. This could be explained due to the difference between the frequencies that the system generate an output and the subject answer to the KSS.

As stated at the previous chapters, the system generate an output at every two minutes and a half, approximately, and the KSS at every five minutes. In this case, the KSS provided one answer at the sixth sample and the next only at the octave sample, Perclos reaches is maximum at the seventh sample. Which could mean that at the seventh sample the subject was already in a state equivalent to the point 7 on the Karolinska Sleepiness Scale.

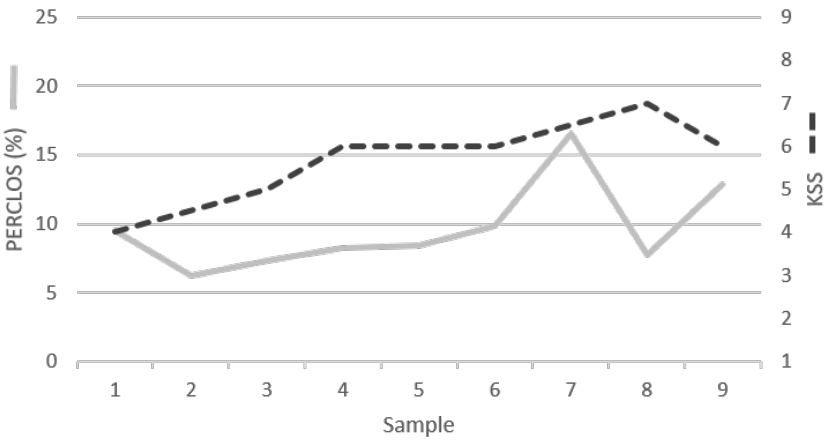

Figure 5.3: Perclos - Subject B during day.

As it might be seen in the figure 5.4, the subject B was predominantly very drowsy during the night test. Most of the time the driver considered itself at the point 9 of the Karolinska Sleepiness Scale, with a decrease at the end of the experience. The Perclos followed the KSS score and reached it's minimum at the same sample.

The Perclos varied approximately between 9% and 23%, a greater maximum value when compared with the diurnal test.

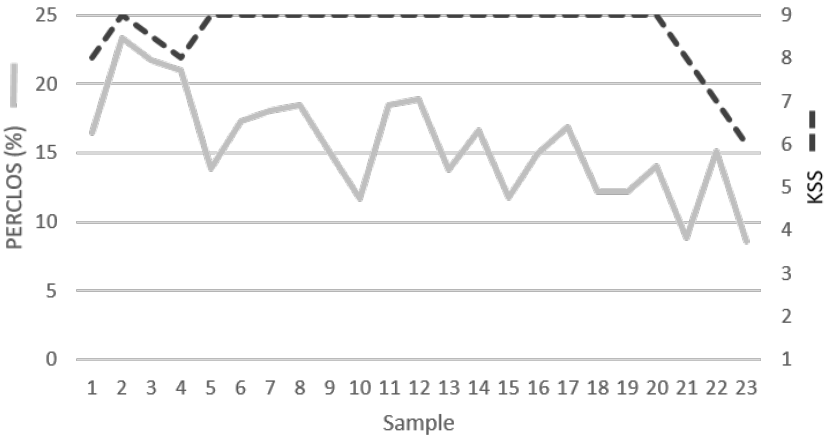

Figure 5.4: Perclos - Subject B during night.

5.1.2 Max Blink Duration

The Max Blink Duration results of subject A, presented in figures 5.5 and 5.6, and subject B, showed in figures 5.7 and 5.8, demonstrate significantly different average values between the samples classified as awake and drowsy by the KSS. Therefore, MBC is considered a viable measure of drowsiness for the present system. Moreover, it was possible to define a MBC threshold of 500ms, that based on these results and on testing experience suits all the four samples.

The Max Blink Duration experimental results of subject A and subject B will be analyzed in detail in the following subsections.

Subject A

During the day test, subject A stayed always awake. As evidenced by the figure 5.5, the Karolisnka Sleepiness Scale only reached the point 4, and the Max Blink Duration values range from 190ms to 370ms. The graph also shows resemblances between the Max Blink Duration and KSS curves.

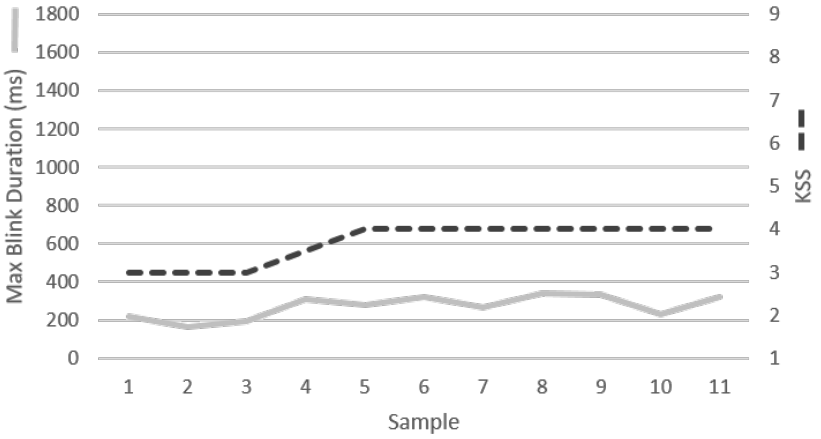

Figure 5.5: Max Blink Duration - Subject A during day.

As it is possible to infer from the figure 5.6, the subject A went through periods of drowsiness during the night test. The KSS reached the maximum point of 9 and the Max Blink Duration varied approximately between 410ms and 1600ms, greater values than during the day test. Moreover, it is possible to observe that the Perclos curve follows the KSS curve.

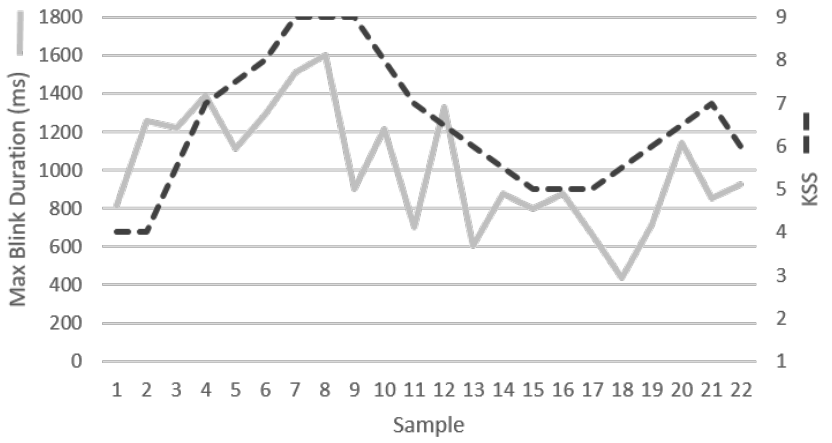

Figure 5.6: Max Blink Duration - Subject A during night.

Subject B

As shown in figure 5.7, the KSS maximum value is 7, indicating drowsiness. However, this value was only reached in one sample, meaning that the subject B stayed awake almost during the entire test. Regarding the Max Blink Duration values, these vary approximately between 200ms and 860ms.

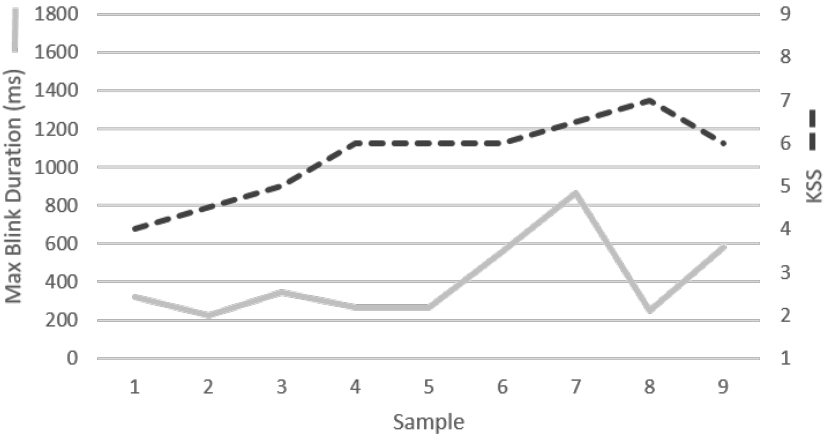

Figure 5.7: Max Blink Duration - Subject B during day.

The subject B has reached the point 9 of the Karolinska Sleepiness Scale during the night test, and remained at this maximum level the majority of the test. As it can be observed in the figure 5.8, the Max Blink Duration hits a minimum of 350ms and a maximum of 1200ms, superior values comparing with the ones registered at the diurnal test.

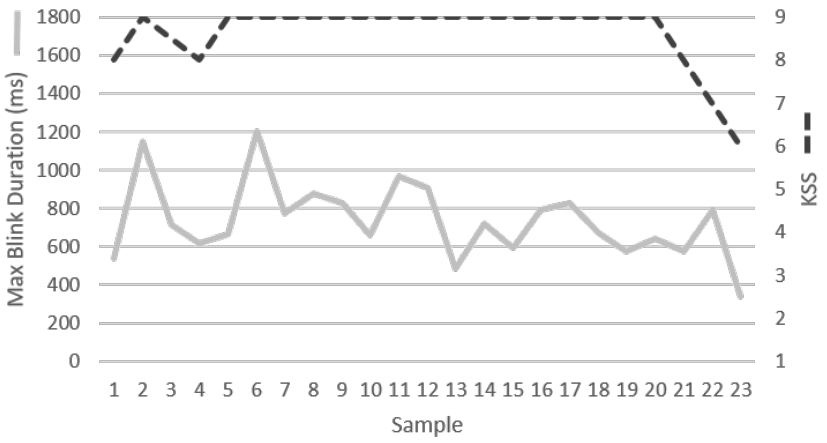

Figure 5.8: Max Blink Duration - Subject B during night.

In this case, it is more difficult to detect similarities between the two curves as the drowsiness level of the subject has remained approximately constant, however, it is possible to verify that the minimum of the two curves coincide in the same sample.

5.1.3 Blink Rate

After analysis of the subject A Blink Rate results, represented by the figures 5.9 and 5.10, and subject B, exposed in the figures 5.11 and 5.12, it was impossible to establish a threshold that distinguishes the awake and drowsy samples. Hence, Blink Rate is not considered a viable measure of drowsiness for the present system.

The Blink Rate experimental results of subject A and subject B will be construed in detail in the following subsections.

Subject A

As previously mentioned, during the day test the subject A stayed always awake and just reached the point 4 at the KSS. As it might be seen in the figure 5.9, the Blink Rate ranged from 55 to 140 blinks per sample.

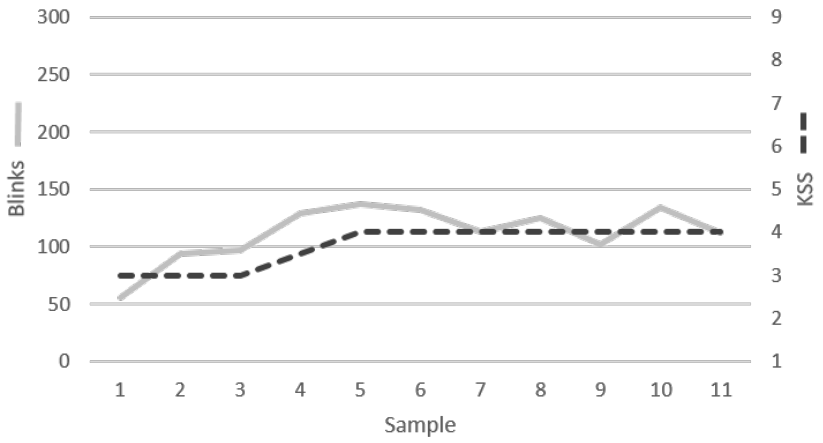

Figure 5.9: Blink Rate - Subject A during day.

At the night test, subject A reached the top of the Karolinska Sleepiness Scale, as shown in the figure 5.10. However, the Blink Rate maximum was just 135 blinks per sample, which is slightly smaller than the day test maximum.

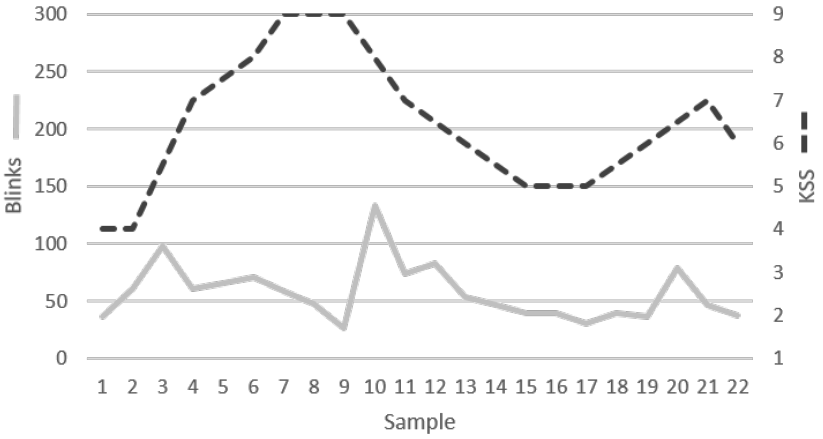

Figure 5.10: Blink Rate - Subject A during night.

Subject B

The subject B reached the point 7 in the Karolinska Sleepiness Scale during the day test. As shown in the figure 5.11, the Blink Rate hits a maximum of 250 blinks per sample and a minimum of 105 blinks per sample.

During the night test, subject B was very drowsy most of the time. As it can be seen in figure 5.12, the KSS values reached the top of the scale, the point

9, and the Blink Rate values range from 55 to 180 blinks per sample. These are values below the diurnal test results.

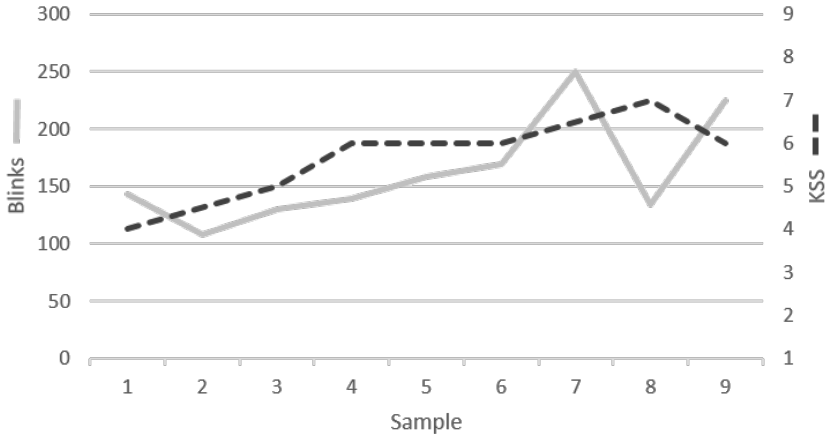

Figure 5.11: Blink Rate - Subject B during day.

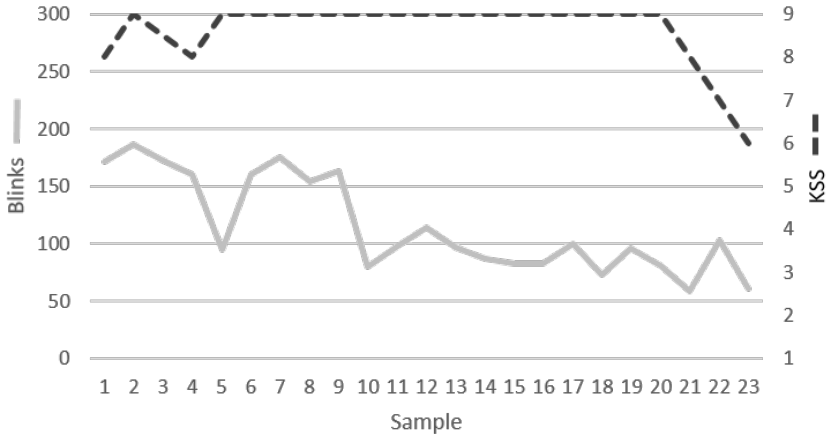

Figure 5.12: Blink Rate - Subject B during night.

5.1.4 Conclusions

The study of the parameters performance proved that not all of the implemented parameters are suitable for the desired system.

Perclos and Max Blink Duration revealed satisfactory performance and will be included in the final system, on the other hand, Blink Rate failed to prove viable and will be discarded.

Furthermore, the thresholds for Perclos and Max Blink Duration were established. 10% for Perclos and 500ms for Max Blink Duration.

5.2 Final System Overview

Since in the previous section was concluded that Blink Rate can not be considered a valid measure, it had to be removed from the system. Therefore, the figure 5.13 represents the final system overview.

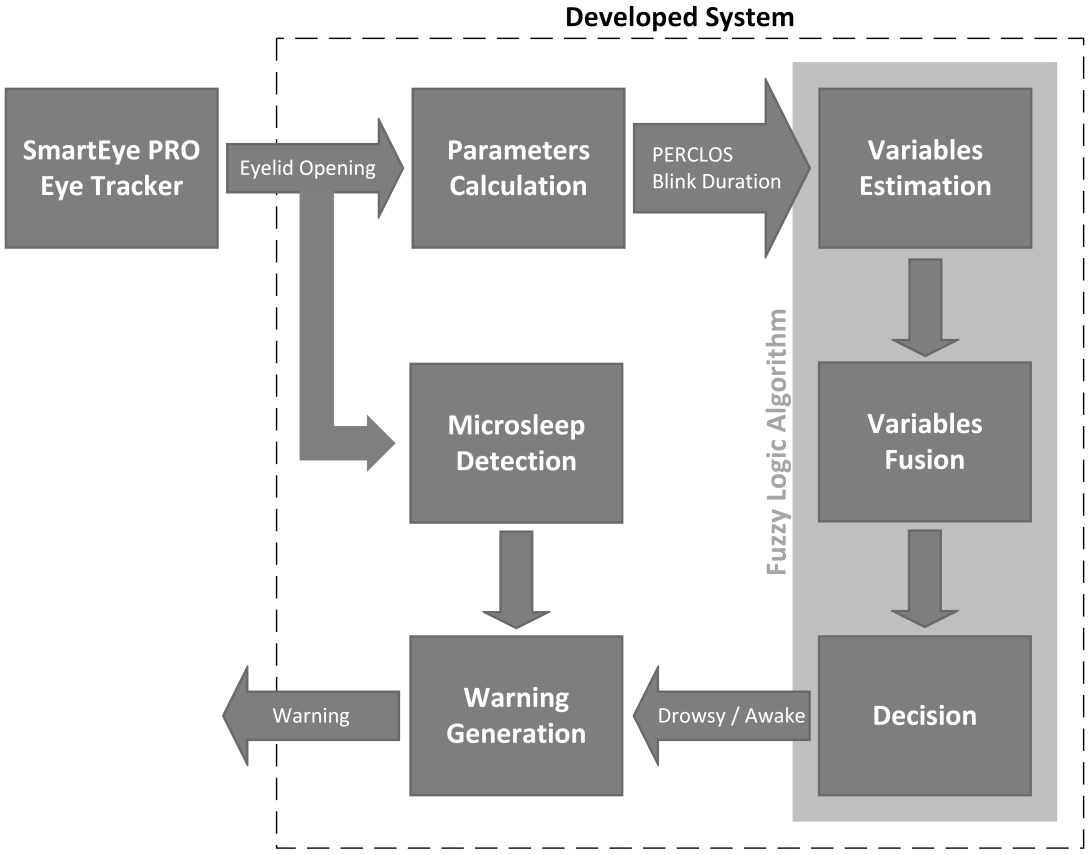

Figure 5.13: Overview of the Final System.

5.3 System Performance

At this section the performance of the system will be evaluated using the same previous experiments. Firstly, comparing the fuzzy fusion output with the KSS score, to understand the system closeness to the real subject drowsiness level. Secondly, comparing the system's ultimate output with the KSS threshold, in order to perceive the accuracy of the system when it decides if a driver is drowsy or not and eventually, triggers a warning.

5.3.1 Fuzzy Fusion Output

Fuzzy Fusion output is the result of the parameters merging. It ranges from 0 to 1, where 0 means the total absence of drowsiness signs and 1 means the total presence of drowsiness signs. As stipulated in chapter 4, the subject is considered drowsy when this score is greater than 0,5.

As it might be seen in the figure 5.14, the Fusion curve follows the KSS curve and reaches a maximum of 0,1, which is in accordance with the KSS maximum of 4, meaning that the subject remained always awake.

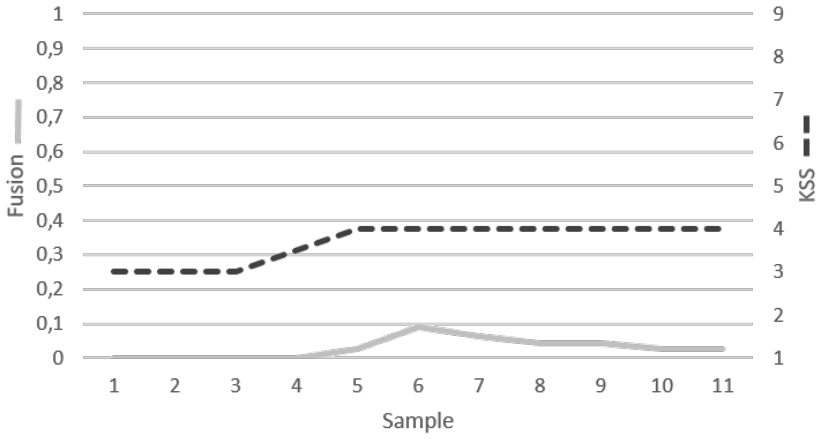

Figure 5.14: Fuzzy Fusion Output Against KSS - Subject A during day.

The figure 5.15 shows great similarity between the Fusion and KSS curves. Both reached the top of its scale, 1 for the Fusion and 9 for the KSS, and approximately in the same period of time.

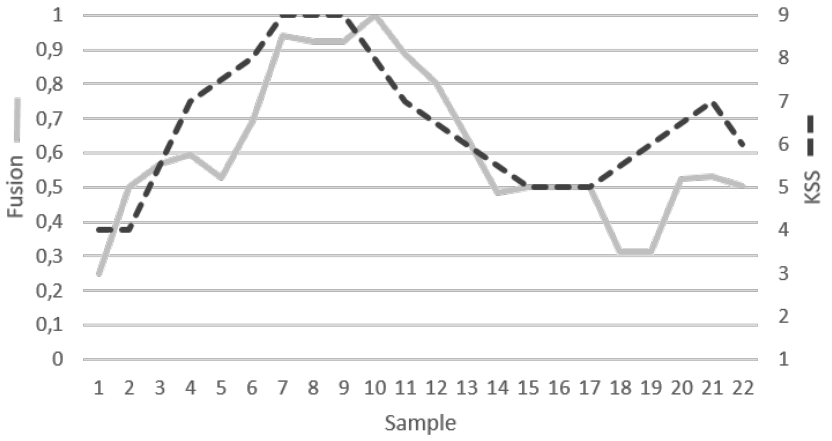

Figure 5.15: Fuzzy Fusion Output Against KSS - Subject A during night.

The experiment represented by the figure 5.16 reveals that the Fusion and KSS maximums were reached one sample apart, circumstance that was already explained before. However, the Fusion and KSS agree that the subject was drowsy during that period of time.

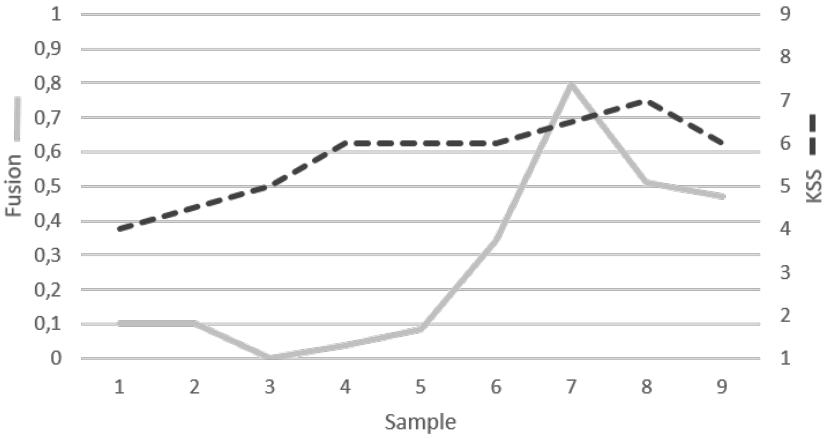

Figure 5.16: Fuzzy Fusion Output Against KSS - Subject B during day.

As evidenced in the figure 5.17, the Fusion and KSS curves show great resemblance. The two curves remained near the top for most of the experience, agreeing that the subject was very drowsy during this experiment. By the end of the test, the Fusion and KSS values drop to levels near its threshold.

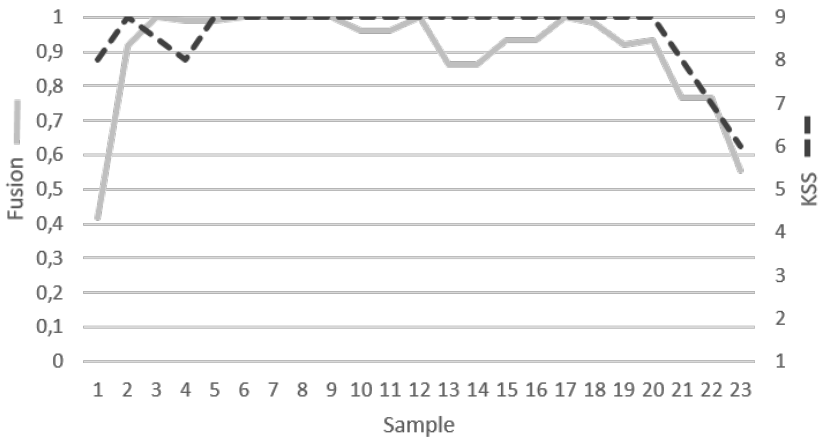

Figure 5.17: Fuzzy Fusion Output Against KSS - Subject B during night.

5.3.2 Decision Output

Decision output translates the results presented in the previous subsection into a binary answer for the ultimate question: is the driver drowsy or not? If the Decision output is 1, the answer is affirmative and a warning will be generated, if it is 0, the answer is negative.

Therefore, this section takes the most important role in the chapter of results. It introduces, in the figures 5.18, 5.19, 5.20, 5.21, the final results that will trigger a direct action on the driver, when he is drowsy. These results are compared against the KSS score to evaluate the overall system performance.

In accordance with the thresholds established in the chapter 3, for the KSS, and in the chapter 4, for the Decision, the KSS Threshold is 1 when the KSS is equal or above 7 and it is 0 when the KSS is below 7. The Decision output is 1 when the fuzzy fusion is above 0,5 and it is 0 when the fuzzy fusion is equal or below 0,5.

During the diurnal test, according to the KSS score shown in the figure 5.18, the subject A never experienced drowsiness. The system agrees with the Karolinska Sleepiness Scale as the Decision output was always 0, never detecting drowsiness.

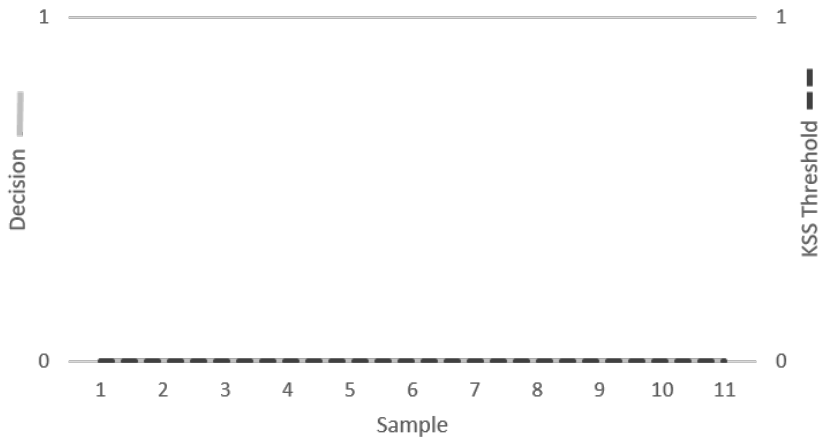

Figure 5.18: Decision Output Against KSS Threshold - Subject A during day.

Unlike the day test, the subject A experienced two periods of drowsiness, as it can be seen by the KSS score in the figure 5.19. The system also detected the same two periods of drowsiness, but with the advance of one sample. This circumstance might result from the different frequencies of operation between the system and the KSS, previously explained, or the delay of the subject to have consciousness that he is showing signs of drowsiness.

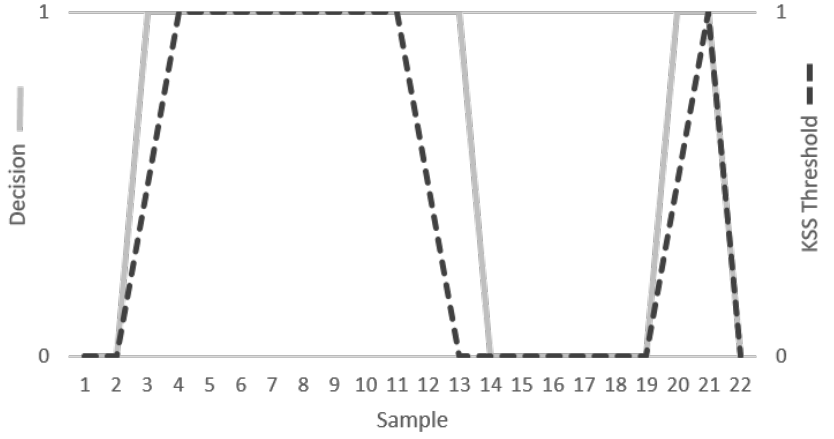

Figure 5.19: Decision Output Against KSS Threshold - Subject A during night.

The KSS results of subject B, in figure 5.20, demonstrate that he was drowsy for a short period of time. The system detected drowsiness at the same period, but again, one sample earlier. This could result from the different frequencies of operation between the system and the KSS or the subject's defective judgment.

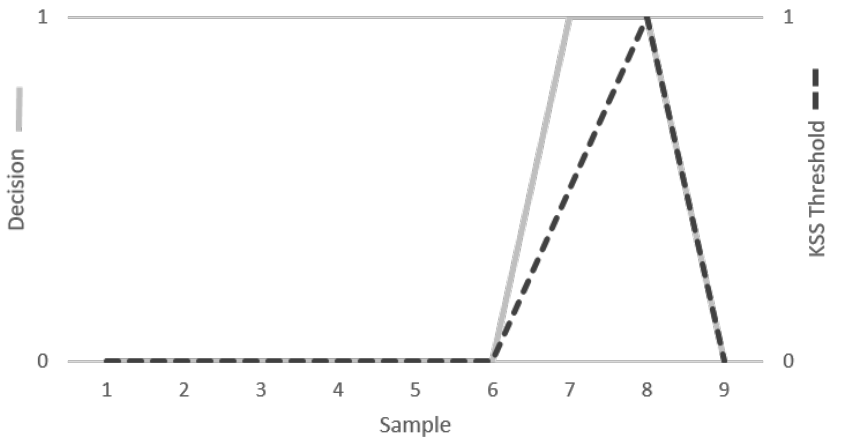

Figure 5.20: Decision Output Against KSS Threshold - Subject B during day.

According to the KSS Threshold score presented in the figure 5.21, the subject B was drowsy during almost all the night test. The Decision output obtains similar results, since it is 1 for most of the samples.

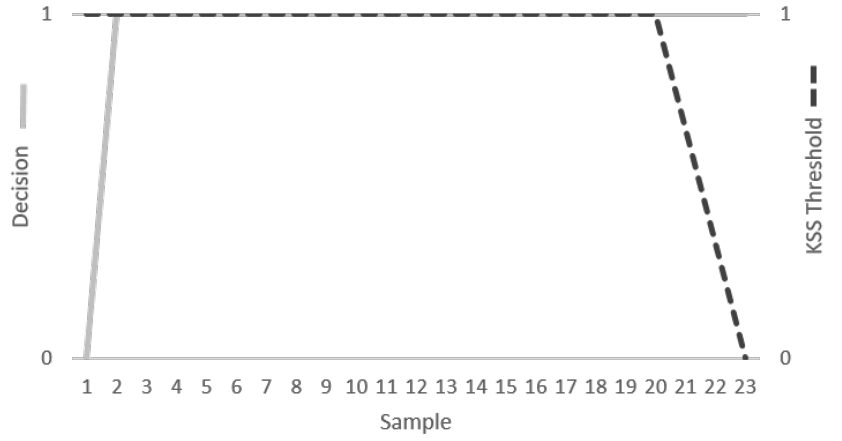

Figure 5.21: Decision Output Against KSS Threshold - Subject B during night.

At the first sample the KSS indicates already presence of drowsiness but the system does not. This occurs because the algorithm does not have any previous reference at the first sample, it is the cost of the solution found to avoid possible false positives in the first sample. However, as might be seen in the figure 5.17, the Fuzzy Fusion output is 0,41 in this sample, meaning that is very close to be considered drowsiness by the system.

By the end of the experience, the KSS points that the driver is awake, counteracting the Decision output. This could be a slight wrong judgment by the

subject of his own state. As shown in the figure 5.17, the subject answered with 6 in the KSS, just one point below the KSS threshold. At the same time, the Fuzzy Fusion output is approximately 0,54, very close to the Decision threshold. This could indicate that if the experience had continued, the system and the KSS would eventually be in accordance.

5.3.3 Conclusions

As demonstrated in this section, the system never failed to detected a period of drowsiness on the conducted experiments, despite the small set of subjects. It was also never found a false positive. The system revealed concordance with the KSS scores, however, it is important to remember that the KSS is a subjective method that relies on the subject interpretation.

5.4 Warnings

The warnings generated by the drowsiness detection system will be sent over TCP/IP to another system responsible for managing and delivering all the HMI warnings to the driver. Since this system is not yet implemented, a PC with a TCP/IP terminal was used to receive the warning messages.

An excerpt of the warnings sent during the experience of the subject A is shown in figure 5.22. Remembering, the warning type 1 stands for drowsiness and the warning type 2 indicates a microsleep.

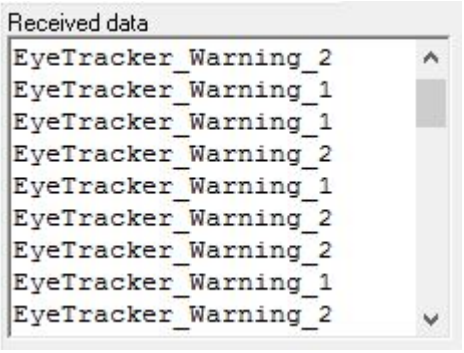

Figure 5.22: Warning Messages Terminal Print Screen.

During the diurnal test of subject A no warning was received, which is in

accordance with the graphic present in figure 5.18. In contrast, during the night experience of subject A were received several warnings for drowsiness and microsleeps. To be precise, 13 warnings of type 1 and 29 warnings of type 2. Analyzing the figure 5.19 it is possible to see that 13 samples have the decision value equal to 1, matching the number of drowsiness warnings.

Chapter 6

Conclusion

In this last chapter, are presented the conclusions that were obtained by the author during the development of this dissertation. Recognizing that the work can be improved and expanded, it is also presented a section that suggests the future work.

6.1 Accomplished Work

This dissertation proposed the development of a driver monitoring system based on eye tracking capable of detecting driver's drowsiness and actuate accordingly.

The SmartEye Pro was the chosen eye tracking platform to provide the selected parameter, eyelid opening. An algorithm retrieves the necessary information from this parameter to calculate two variables capable of indicating the driver's drowsiness level. A total of three variables were tested, of which two revealed great correlation with the drowsiness level, PERCLOS and Max Blink Duration. The other variable, Blink Rate, does not revealed satisfactory correlation with drowsiness.

The selected variables, PERCLOS and Max Blink Duration, go through a process of fuzzy logic that normalizes and indicates the certainty degree of each variable on the driver's drowsiness. Then, the variables are merged and it is provided a binary decision about the driver condition: drowsy or not drowsy. Moreover, the algorithm detects microsleeps; i.e., when the driver closes both eyes

for a certain period of time.

Since the present system was developed in view of its integration on a complex automotive HMI, when drowsiness or microsleeps are detected the system issues the corresponding warning via TCP/IP to another system responsible for managing and delivering all the warnings of the HMI.

Additionally, was developed an innovative android application, based on the Karolisnka Sleepiness Scale, to help on the drowsiness detection system test and validation. Currently, there are no similar applications in the mobile application markets.

It is also important to consider that the phenomenon addressed in this dissertation, drowsiness, led the author to new challenges related with the testing procedures, and, certainly, to new fields of study. For instance, the human behavior and the physiology behind the transition between the awake and the sleep state.

6.2 Future Work

It is possible to state that all the proposed objectives in this dissertation were achieved. However, there are still opportunities for further enhancements, especially, related with the system validation.

This dissertation addresses a total of six experiments performed by four different subjects, in which only two revealed drowsiness. Clearly, such amount of experiments is insufficient for considering the system validated. The high variability in human behavior demands more extensive validation. Therefore, it is strongly suggested that the system be tested with a larger set of individuals, in the conditions mentioned in the chapter three. The new tests will generate data sets that could be analyzed to slightly adjust the current thresholds values, this values can be easily changed on the developed software.

The study of the system performance relies only in the Karolinska Sleepiness Scale as term of comparison, which has proven its validity and it is widely used with this purpose, however, it is a subjective method. Thus, for more reliable results, it is suggested the introduction of other drowsiness detection methods, as already validated COTS products, in the experiments.

Furthermore, the experiments in the DSM were performed with a movable installation of the eye tracker, without proper calibration, especially, of the infrared illuminators. This circumstance can affect the eye tracking performance and lead to several eye tracking losses during the experiments. Thus, the last suggestion concerns with the use of the eye tracker properly calibrated by a qualified person.

As far as has been discussed, the project in which this dissertation is part has plans to extensively test and validate the developed system, by a specialized team, and to install a new eye tracker, properly calibrated, in the Driver Simulator Mockup.

Appendices

Appendix A

Karolinska Sleepiness Scale Android Application

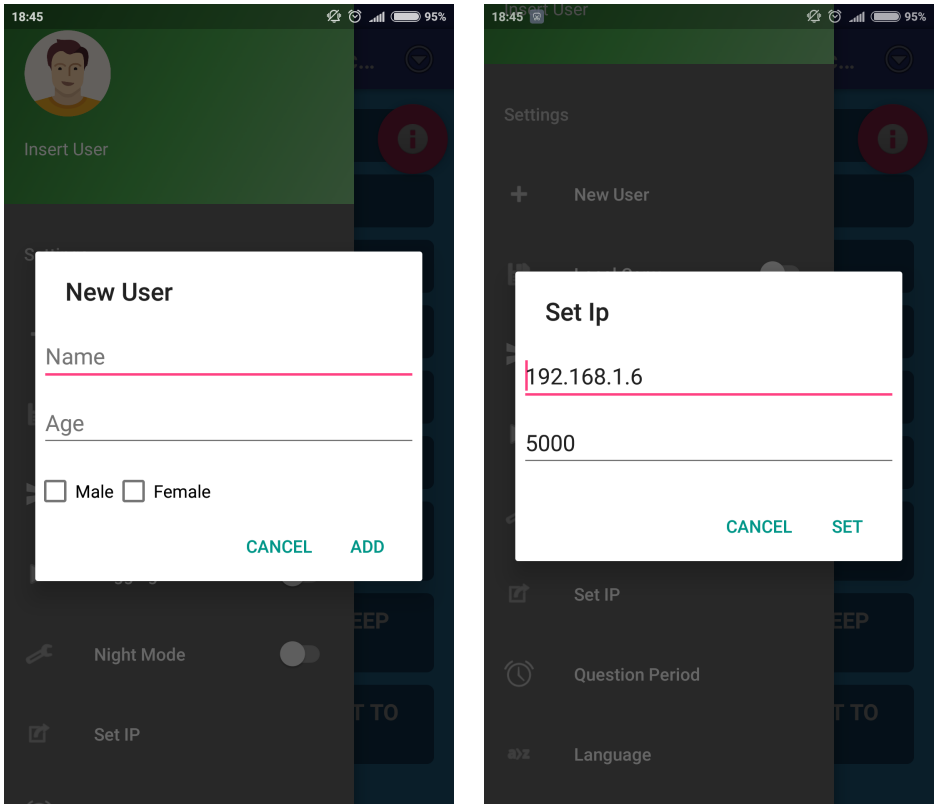

Figure A.1: New user and set ip dialogs.

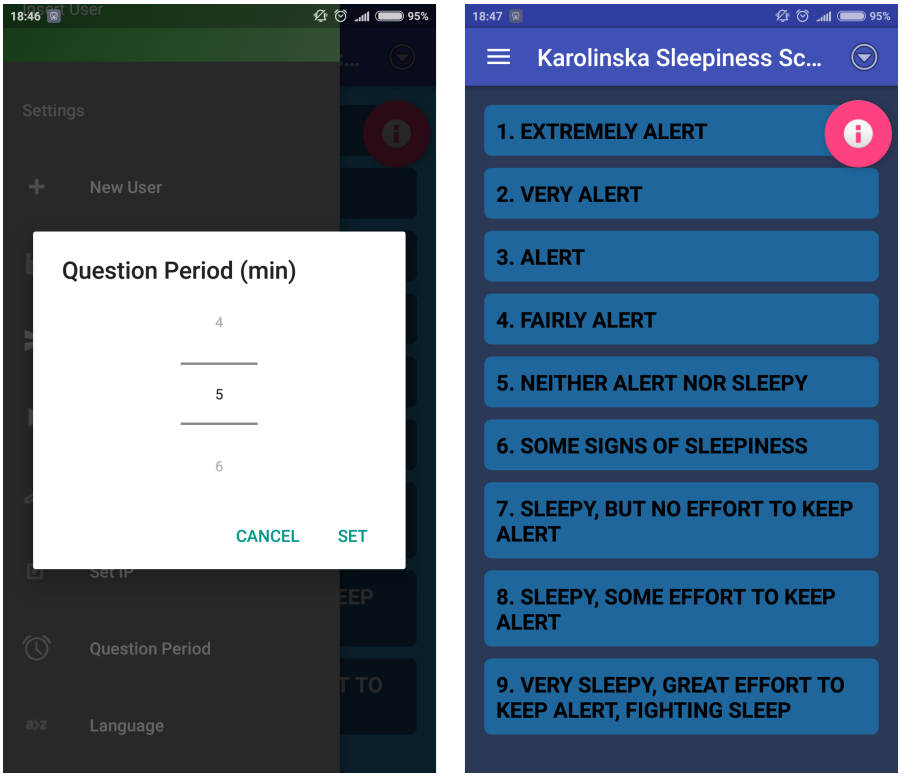

Figure A.2: Set question period dialog and night mode.

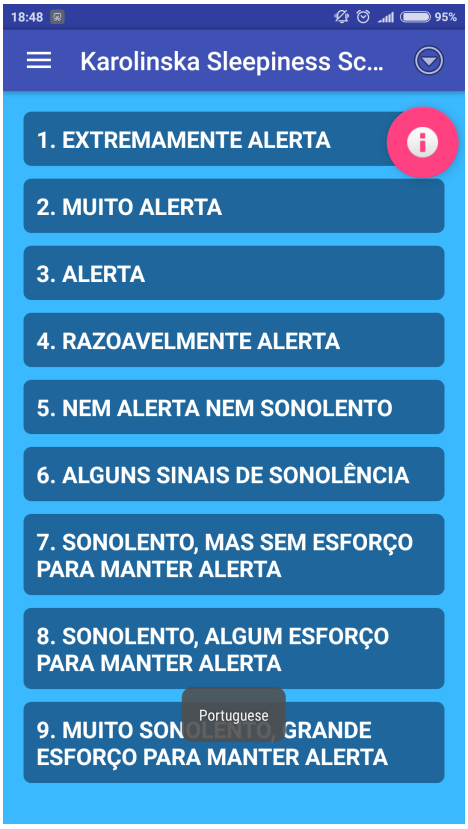

Figure A.3: Questions in portuguese language.

Appendix B

SmartEye Pro Outputs

Table B.1: SmartEye Pro Outputs.

Variable	Unit
FrameNumber	
EstimatedDelay	ms
TimeStamp	s
FrameRate	Hz
RealTimeClock	
HeadPosition	m
HeadPositionQ	
HeadRotation	
HeadNoseDirection	
HeadUpDirection	
HeadLeftEarDirection	
HeadHeading	rad
HeadPitch	rad
HeadRoll	rad
HeadRotationQ	
EyePosition	m
GazeOrigin	m
GazeDirection	
GazeDirectionQ	
GazeHeading	rad
GazePitch	rad
LeftEyePosition	m
LeftGazeOrigin	
LeftGazeDirection	
LeftGazeDirectionQ	

Table B.2: SmartEye Pro Outputs.

Variable	Unit
LeftGazeHeading	rad
LeftGazePitch	rad
RightEyePosition	m
RightGazeOrigin	
RightGazeDirection	
RightGazeDirectionQ	
RightGazeHeading	rad
RightGazePitch	rad
EyelidOpening	m
EyelidOpeningQ	
LeftEyelidOpening	m
LeftEyelidOpeningQ	
RightEyelidOpening	m
RightEyelidOpeningQ	
PupilDiameter	m
PupilDiameterQ	
LeftPupilDiameter	m
LeftPupilDiameterQ	
RightPupilDiameter	m
RightPupilDiameterQ	
Saccade	
Fixation	
Blink	
LeftBlinkClosingSpeed	m/s
RightBlinkClosingSpeed	m/s
LeftBlinkOpeningSpeed	m/s
RightBlinkOpeningSpeed	m/s
CameraRotation	
ClosesWorldIntersection	
HeadClosesWorldIntersection	
AllWorldIntersection	
HeadAllWorldIntersection	
NumericalClosesWorldIntersection	

Appendix C

Complementary Results

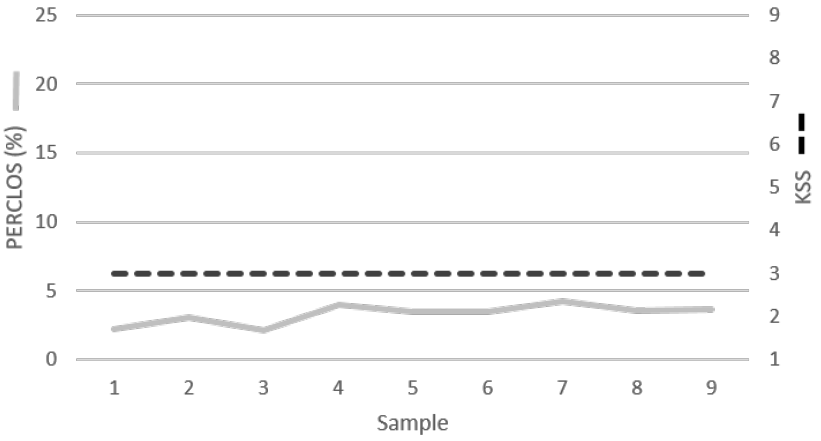

Figure C.1: Perclos - Subject C during day.

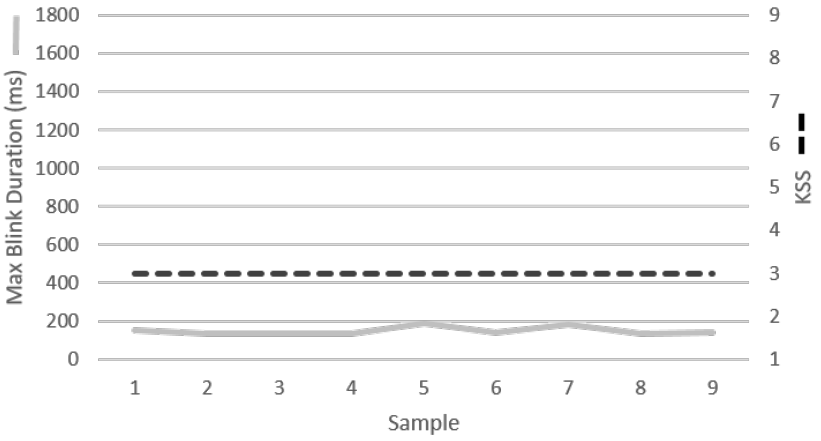

Figure C.2: Max Blink Duration - Subject C during day.

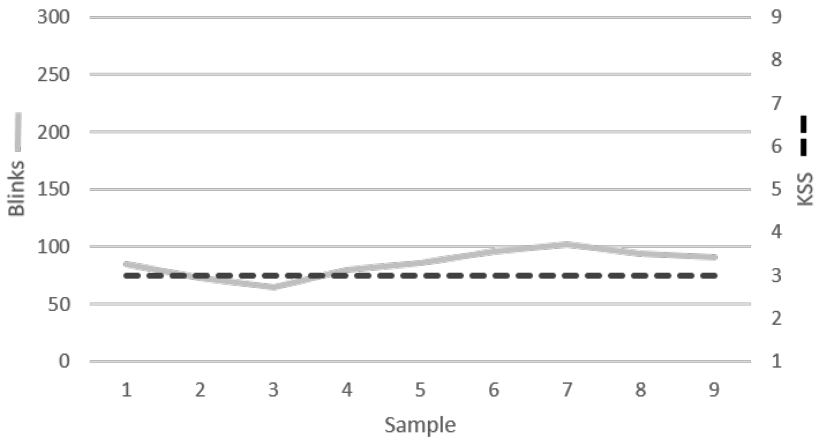

Figure C.3: Blink Rate - Subject C during day.

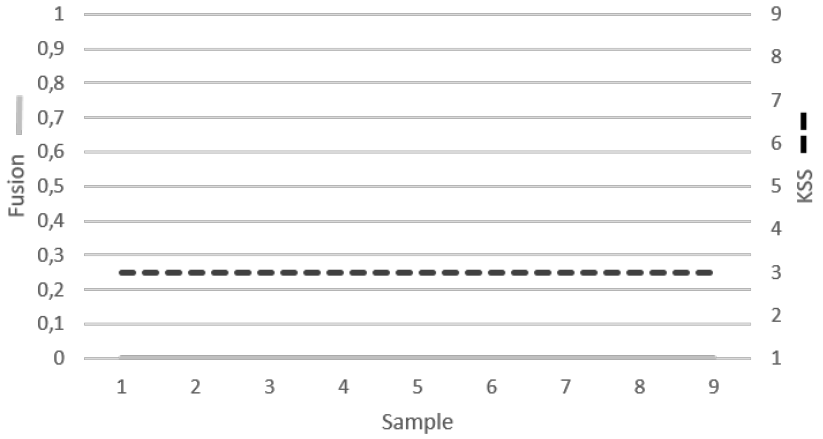

Figure C.4: Fuzzy Fusion Output Against KSS - Subject C during day.

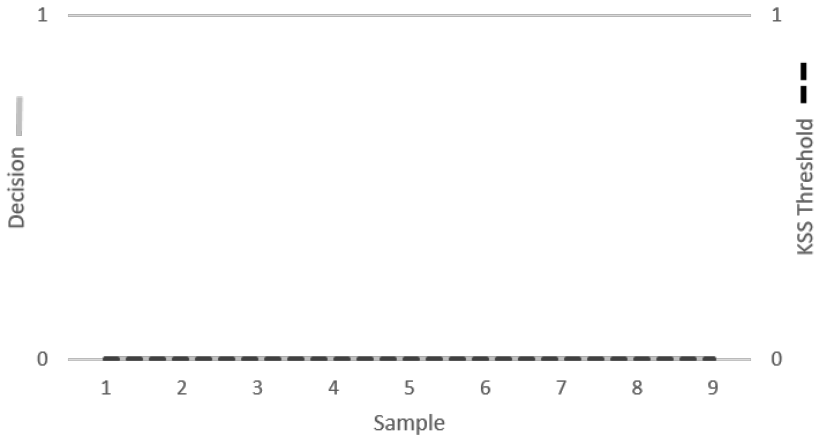

Figure C.5: Decision Output Against KSS Threshold - Subject C during day.

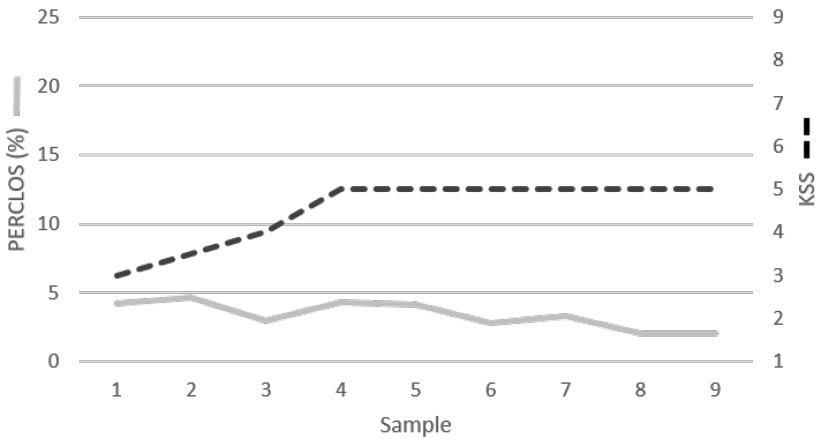

Figure C.6: Perclos - Subject D during day.

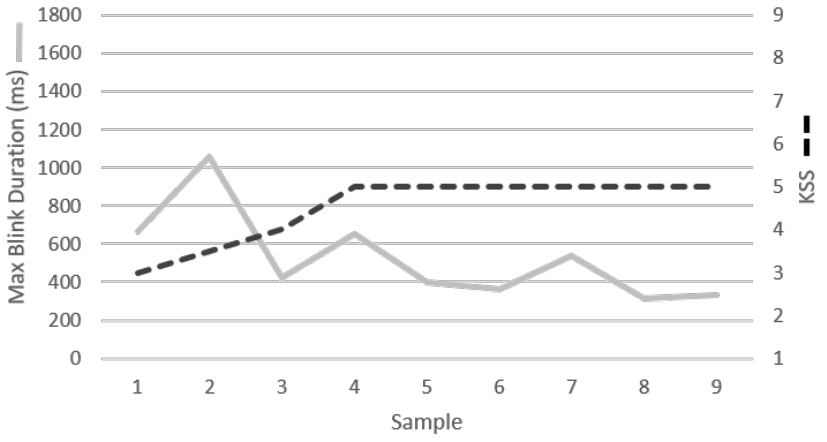

Figure C.7: Max Blink Duration - Subject D during day.

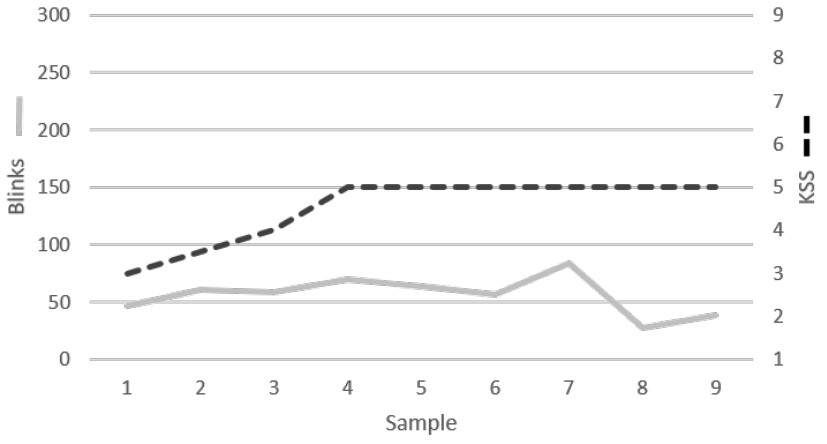

Figure C.8: Blink Rate - Subject D during day.

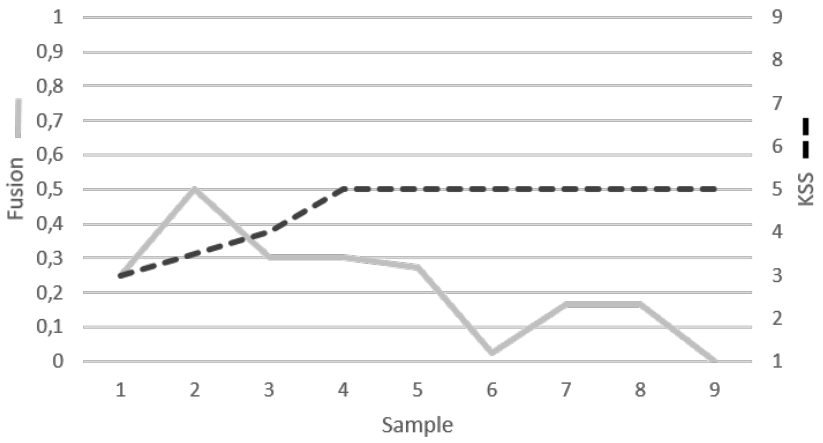

Figure C.9: Fuzzy Fusion Output Against KSS - Subject D during day.

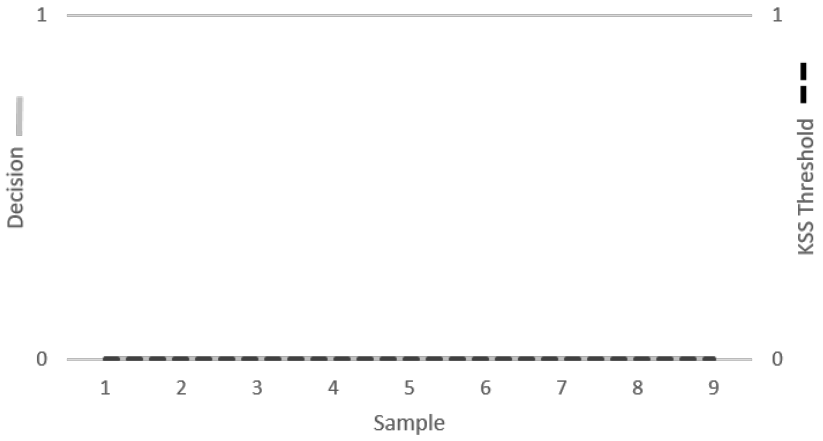

Figure C.10: Decision Output Against KSS Threshold - Subject D during day.

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