# Abstract.

The development of technologies for preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Preventing drowsiness during driving requires a method for accurately detecting a decline in driver alertness and a method for alerting and refreshing the driver. As a detection method, the authors have developed a system that uses image processing technology to analyse images of the road lane with a video camera integrated with steering wheel angle data collection from a car simulation system. The main contribution of this study is a novel algorithm for drowsiness detection and tracking, which is based on the incorporation of information from a road vision system and vehicle performance parameters. Refinement of the algorithm is more precisely detected the level of drowsiness by the implementation of a support vector machine classification for robust and accurate drowsiness warning system. The Support Vector Machine (SVM) classification technique diminished drowsiness level by using non intrusive systems, using standard equipment sensors, aim to reduce these road accidents caused by drowsiness drivers. This detection system provides a non-contact technique for judging various levels of driver alertness and facilitates early detection of a decline in alertness during driving. The presented results are based on a selection of drowsiness database, which covers almost 60 hours of driving data collection measurements. All the parameters extracted from vehicle parameter data are collected in a driving simulator. With all the features from a real vehicle, a SVM drowsiness detection model is constructed. After several improvements, the classification results showed a very good indication of drowsiness by using those systems.

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# Introduction

The following introduction provides a background to the PhD thesis dissertation which is the basis of the research interest. The motivation, research aims and objectives will be laid out to give the reader a glimpse of what is the inspiration for the work.

## 1.1 Background to driver drowsiness

Using transportation is an everyday practice, a characteristic of the modern world, but the human role is basically taken for granted. People are using different transportation modes such as cars, buses, trains, ships or aircrafts. From all these modes of transportation road traffic injuries is consistently one of the top three causes of death for people aged between 5 to 44 years old. More than 1.2 million people die on the world's roads every year, and as many as 50 million others are injured [4].

When people drive while they are tired, drowsy or sleepy, this is commonly referred to as "driver fatigue" or drowsy driving**.** Drowsiness in driving is believed to cause an increasing number of accidents on the roads. "Official" figures claim that driver drowsiness is estimated to cause 1-3 % of the traffic accidents, but an actual number is generally considered to be much higher. Drowsiness is the transition state between being awake and being asleep during which a decrease of vigilance is generally observed. This can be a serious problem for tasks that need sustained attention, such as driving.

Driver drowsiness is a significant factor in the increasing number of accidents on today's roads and has been extensively accepted [7]. This evidence has been confirmed by many researchers that have formed connections between drowsiness and road accidents. Even though it is hard to decide the accurate number of accidents due to drowsiness, it is likely to be underestimated because of the difficulty to distinguish from those caused by other factors like alcohol or drugs.

Research based in the UK shows that drowsiness is one of the greatest causes of road accidents, totalling up to 20% of serious accidents on motorways and rural roads in Great Britain [58]. The Government has identified driver drowsiness as one of the main areas of a driver behaviour that needs to be addressed. The above statement shows the significance of any research with the objective of reducing the dangers of accidents accredited to drowsiness.

So far, researchers have tried to model the behaviour by discovering relationships between drowsiness and certain indications that linked the vehicle with the driver behaviour [7], [8], [9]. We will explore this in more details to help clarify the problem.

Time is nowadays expressed in 24 hours operation, and more and more people are conducting vigilance-based activities at any time other than the traditional daytime working hours. Starting at the end of the last century, night-time has become an opportunity for production, and there is evidence that these tendencies will increase [10]. The numbers of accidents caused by drowsiness are increasing due to the tendency that sleep is being less prioritized; hence, more people are sleep deprived. Commercial drivers are no exception. Tight schedules and time pressure make drivers drive for longer hours and during night time to avoid traffic. Individual differences on how to handle sleepiness and to which extent it affects performance exists, but they are limited. There is no evidence that the need for sleep of “professionals” is different from what observed in other persons. Motivation, commitment and extra pay could only prevent sleepiness for transient periods of time. People in general tend to overestimate their own ability to handle their sleepiness. They often consider the risk of reduced performance less when it comes to their own driving, with the argument that precedent ensures an adequate safety margin (i.e. they have performed sleepy in the past and not had a catastrophe). The circadian rhythms are low in the early-morning hours as well as in the mid-afternoon.

Driving during these hours could affect performance in combination with other factors like sleep loss or driving for longer periods of time be the cause of sleepy driving, depends on the professionalism of the driver [11]. Hence, drivers are not always good judges of their own sleepiness. Even if they are aware of their sleepiness, they could be unaware of the risk of falling asleep [12].

Populations that have been known to be at higher risk for involvement in sleep-related crashes include young people, especially young males, persons with sleeping-disorders, those who have taken soporific medications and night-time or shift workers. Commercial vehicle operators are also at increased risk for sleep-related crashes due to factors like extended driving times; irregular work and sleep schedule, higher frequency of night-time driving and inadequate sleep [12]. This opinion is also shared by Sagberg [13] who had looked at several crash statistics from different references and come to the conclusion that the problem with fatigue-related crashes seems to be higher among truck drivers than drivers in general, probably since truck drivers mainly drive on large monotonous roads and often drive during night-time. The accidents associated with sleepy driving are therefore, more often fatal since the speeds are higher on highways, main roads and motorways combined with a delayed reaction time of the driver. Dinges, David F. [10] claims from the statistics which indicate that the sleepiness-related accidents are common on long stretches of the motorway, perhaps amounting to 40 % or more of the fatal crashes. According to him, National Transportation Safety Board (NTSB) (1990) has implicated that fatigue is the most frequent contributor to crashes in which a truck driver was fatally injured. Stutts, J.C. [12] made a population-based case-control study where drivers involved in accidents in North Carolina were interviewed over the telephone. They compared a group of drivers who had been reported (by the police) to be asleep or fatigued by the time of the crash with a control group where drivers had either been in a recent crash not related to fatiguing or not in a crash at all. Results showed that drivers in the sleep-related crashes were more likely working in multiple jobs, night shifts or other irregular work schedules, more likely to have used soporific medications, had been driving for longer time and had slept fewer hours the night before. They also reported poorer quality of sleep (and averaged less sleep per night), drove more often late at night, and had more prior instances of sleepy driving.

Dinges, David F [10] states that a low level of vigilance gives risk to a dangerous driving style in terms of steering wheel movements, lane keeping and speed variation. Other researchers [13], [14] have studied changes in steering wheel activity associated with decreased alertness. Their study showed that small magnitude steering wheel movements decreased in frequency when the driver was not sleepy. On the other hands when the driver was getting sleepier, large magnitude steering wheel movements will be increased in frequency.

This has also been identified in [11] as showing possible warning signs of a sleepy driver along with factors such as:

- No memory of the last few miles driven.
- Zigzag driving, lane drifting, hitting rumble strips, keeps jerking the vehicle back into the lane.
- Wandering or disconnected thoughts.
- Repeated yawns.
- Difficulty to keep eyes open.
- Driving too close to the vehicle in front.

Technology, particularly which monitors a driver behaviour and shares this information could play an important role in changing norms and the driving culture. A number of approaches to drowsiness detection mainly make pre-assumptions about the relevant driver behaviour, concentrate on blink rate, eye closure, and yawning [15], [16]. The automobile industry also has tried to develop various systems to predict driver drowsiness but there are only a few commercial products available today [17]. The systems do not look at driver performance and overlook driver ability and characteristics. Naturally, most people would agree that different people drive differently. Thus, it is proposed that the system that is developed must be able to accommodate to the changes of the different driver behaviour.

In-vehicle sleepiness detection measures variables from the vehicle itself. These systems are based on the idea that a driver goes through different stages as he/she is getting sleepier. Before the sleepy stage, there is usually a period of degraded driving, which can be detected by measuring different in-vehicle variables [18]. Such a system would gather signals in real-time that are then passed through an algorithm that is trained to detect sleepy driving behaviours. If the outcome from the formulas of the algorithm is higher than the set threshold, the system should produce a warning. It is important to notice the difference between detection and prediction. A system should preferably be able to predict driver sleepiness, although this is harder to achieve. Detection of driver sleepiness could be sufficient, but it could also mean that the system discovers the sleepy driving behaviours too late, and the accident cannot be avoided.

## 1.2 The models

The body of research that has been accumulated on driving behaviour presents a collection of findings and conclusions from which it is possible to make a coherent picture. That picture is our theory of driving behaviour. Once we have a theory, we can continue gathering additional ‘facts’ to fill the remaining gaps. The purpose of the models and theories of driver behaviour is to make sense of all the research results. A theory and a model are not synonyms. A theory is a conceptual organization of concepts, mechanisms and processes that are involved in the operation of a system. A model is less presumptive in the sense that it does not presume that these mechanisms and processes actually exist, but only that if we posit them, then we can explain human behaviour. Often, a model of human behaviour is developed and then a search is made to see if some of its mechanisms actually exist.

A model can often serve as a basis for a theory. In general, unless there is independent evidence for the existence of specific processes and mechanisms, it is safer to talk on models of driver behaviour than theories of driver behaviour [6].

## 1.3 Drawbacks of current developments

Numerous kinds of warning systems have been developed to prevent the driver from falling asleep while driving. Some of these systems are based on body signals from the driver:

- EEG.
- Eye movements.
- Blinking rate.

To be able to receive these signals, special sensor equipment like wiring or camera is needed and that could be an obstructive or disturbance for the driver. Using camera to read signals from either eye movement or blinking rate could, except being a quite expensive method, be difficult to use in a non-heterogeneous environment where different lighting and other factors like usage of glasses complicate the gathering of information.

A system that measures in-vehicle signals:

- Steering wheel variance.
- Lateral lane position drifting.

According to [19] there are existing in-vehicle systems meant to detect driver sleepiness in commercial and non-commercial driving but the evidence to judge its application and efficiency is insufficient. In a study made [20] where behavioural adaptation of drivers to Fatigue Warning Systems (FWS) was evaluated. They concluded that their findings suggested that FWS is currently conceived may not contribute to reduce fatigue induced collisions. This implies that systems famous to today do not live up to the expectations of FWS and that further studies are needed.

## 1.4 Research aim and objectives

The aim of this thesis is to contribute to the study of driver behaviour, through the development and evaluation of a driver drowsiness detection system. A non-intrusive system is chosen as a preferred approaches due to comfort to the drivers as it is done by monitoring the driver's activity through the various vehicle controls such as steering wheel, accelerator and brake and the measurements from the relationship between the vehicle and its environment. A further aim of the research is to produce systems that can be capable in detecting the drowsiness level at an early stage by giving warning to drivers about their lack of attention due to drowsiness or other factors. In other words, they can correct the behaviour or stop driving when they are in drowsiness state. This system needs to be robust against the interferences and comfort constraints and particularly not false indicators, which would cause a driver to distrust and ignore the system.

Our first objective is to develop an algorithm which relies on only in-vehicle variables, for which extensive experiments need to be done to collect adequate information from real situations. This means that quantitative tests have to be performed in a driving simulator. Through these tests, proper variables could be identified to show when a driver is sleepy. The best variables should be combined to create a formula that, if shown to be effective, might be implemented in future systems.

The second objective of this research is to identify the current drowsiness detection by investigating adaptable methods in studying the relationships between driver's manoeuvre performances whiles the vehicle on the move and the physiological driver drowsiness states.

The third objective is to study on pattern recognition methods in detecting drowsiness from the collected variables.

This thesis outlines the following task for the research design and development of a system that focuses on driver's drowsiness detection and prediction through the following methods:

- Initial research to characterise the measurements available from a vehicle such as steering angle, steering angle velocity, speed, acceleration, brake and accelerator inputs. Real measurements from vehicles have been obtained.
- Development of a research test-bed simulator consisting of driver controls connected to a computer running simulated road conditions.
- Validation of simulator results with real measurements for non-drowsy and drowsy behaviour.

The main focus of the research is the development of the drowsiness detection and prediction system algorithms using the following:-

- Monitoring the driver behaviour by observing the vehicle manoeuvre stability and performance.
- Validate and measure the progress by using a specific algorithm.
- Updating the current performance by comparing with the last action stored in the system database.
- Warning the drivers if the behaviour fall outside the standard thresholds that have been set.

To increase the accuracy of detection and its reliability of the prediction, the methods mentioned earlier have been used. Here, we will employ machine learning methods to classify the data of actual human behaviour during drowsiness.

This is done by studying and evaluating the learning phase identification of a driver's driving pattern by evaluating the parameters comprehensively. For achieving the best possible alert a control system mechanism that integrates human and machine classification using information from various sources has been used.

## 1.5 Research approach

The early stages of the research work were used to identify from a range of possibilities for the best approach to study the problem. Building and fitting instrumentation to a vehicle were considered and background research conducted, but such measurement systems are now being incorporated into new vehicles by manufacturers as part of the improved road holding and performance features and 'drive by wire' vehicle control systems. Any modification to a real vehicle could compromise vehicle safety and were not approved. After extensive research and evaluation, a method of study was developed and an experimental environment defined. Thus, the scope of the thesis is defined as follows:

- The evaluation of the algorithms will be restricted to the simulation environment only.
- There are no obstacles in the road lane, and thus there is no collision-avoidance aspect to manoeuvre.
- It is assumed that the vehicle will operate within a fixed velocity of 50km/h.

- Two main parameters were identified from the research as indicators for the system detection and these consist of distance to lane boundary and steering wheel angle.

## 1.6 Contributions

The contributions of the thesis research extend to several areas. The main contribution of this study is a novel algorithm for drowsiness detection and tracking, which is based on the incorporation of information from a road vision system and vehicle performance parameters. Refinement of the algorithm is more precisely detects the level of drowsiness by the implementation of a support vector machine classification for robust and accurate drowsiness warning system.

The adaptive system is deriving by combining data from the road vision and data logger to provide an efficient method in detecting drowsiness. It is designed to work with under several modes and with different road conditions. This is supported by experimentation using different drivers with various conditions in order to build the adaptive system. The system was further refined by the incorporation of a novel strategy which employed a fault diagnosis technique that integrates information from trained classifiers, which are used to improve the accuracy and reliability.

The postulation of a model that considers the driver as a component or part of the vehicle in a closed-loop system and the evaluation of a minimum subset of parameters that would characterise the closed loop sufficiently to allow system performance degradation to be detected.

## 1.7 Thesis outline

As an introduction, Chapter 1 will examine the role of fatigue and extreme sleepiness in automobile accidents, and the enormous costs (both monetary and human) associated with them. The objectives of the current study are outlined, and an overview of the thesis is presented.

Chapter 2 of this report consists of a comprehensive review of literature and existing systems for incorporating the relevant previous findings, eliminating duplication of efforts, and examining the earlier proposed detection and warning systems, with a particular emphasis on driving conditions. Factors that contribute to drowsiness, measures to counter driver fatigue/drowsiness, previous studies and surveys are discussed in details. We have attempted to provide a complete overview of existing systems and previous work.

Chapter 3 presents the first steps in order to obtain and validate certain inputs that can be used reliably toward the classification process. It describes the driving simulator laboratory setup, how the simulator was used to conduct the experiments for this project. Full details about the capabilities, working and activities performed during construction. During these experiments, drivers drove the simulator. Data was recorded for vehicle parameters related to driver driving activity. Data recorded in these experiments was used to develop and validate the detection algorithm.

Chapter 4 discusses on how distance to lane boundary data extraction technique was set and how the data being extracted. Matlab toolbox is used as a tool to extract the data from moving image and converted to meaningful data analysis.

Chapter 5 presents the support vector machine concept and implementation. The rationale and purpose of the study are reviewed, followed by a detailed description of the experimental methodology, including the data collection and analysis procedures and finally, the algorithm development and testing. It summarizes the results of this research and presents findings from the parametric study and presents the main results of this study. The results can be classified into three sections, each consisting of a description of the main findings, discussion and concluding remarks of the results.

Finally, the conclusion of the research and recommendation on future research are provided in Chapter 6, which presents the important conclusions from this study, the industrial significance of this work and provides recommendations for future work. The appendix contains a sample of the major experiment files used to perform the simulation.

# Chapter 2

# Literature Review

The first phase of this research is a study through review of the literature from past research projects, conferences and journals that relate to drowsiness detection systems. An extensive search was conducted, and the work of key researchers has been reviewed to identify key studies, reports and research initiatives addressing drowsiness towards driving issues. The study has investigated the available knowledge in the field and has characterized the most promising indicators of drowsiness in drivers. Most of these methodologies have only been developed in the laboratory or have had a limited application on-road.

Several tasks have been formed to meet this objective accomplishment:

- Search all the available or published research performed in the field of driver fatigue/drowsiness detection.
- Review the overall system that related to fatigue/drowsy detection systems regarding their advantages and disadvantages.
- Critically review any specific studies or data pertaining to driver drowsiness detection.
- Reviewing and recognizing the pattern of drowsiness driver's behaviour driving data.

The literature review is organized by the type of technology and methods used for detecting drowsiness. A more details description on the background of the problem of driver drowsiness is provided at the beginning. Statistics on the problem size and scope are provided. Various factors that affect driver alertness and causes of driver fatigue are reviewed.

Note: Much driver drowsiness research has been conducted in the USA and so reference may be made to highway, interstate, etc. We will assume these are synonymous with motorway and cross-country. Although differences will exist the general outcomes of the research apply.

## 2.1 Factors contributing to drowsiness related accidents

Researchers have identified many factors that can be attributed to the causes of drowsiness-related accidents. Factors that influence driver fatigue/drowsiness include greater daytime sleepiness, less sleep, more difficult schedules, more hours of work, a driver's age, driver experience, cumulative sleep debt, the presence of a sleep disorder and the time of day of the accident [23],[24].

### 2.1.1 Sleep deprivation

The most common cause of drowsiness is lack of sleep. The effect of sleep deprivation is cumulative and losing one or two hours of sleep a night can accumulate to cause serious sleep deprivation overtime [25]. Sleep disruptions or fragmented sleep causes a loss of sleep and will result in sleep deprivation [26]. Indeed, the loss of one night of sleep can result in extreme sleepiness.

The sleep deprivation understanding will be useful in order to strengthen our research technique, especially when we want to select specific data that will be collected during our training later.

Many studies have reported the adverse effect of sleep loss on driving. The findings of these studies include:

- Sleeping less than four hours per night severely impairs driving performance [27].
- Drivers with an average of less than five hours of sleep per night will increase the risk of being asleep while driving nearly, five times [28].

- Loss of sleep increases the tendency of falling asleep and reduces driving performance [29].
- A 1995 National Transportation Safety Board [NTSB] report identified the duration of the driver's last sleep period. The total sleep obtained during the 24 hours preceding a crash and fragmented sleep patterns was the most important contributing factor towards a drowsiness related, single vehicle and large truck crashes.
- According to [30], the two important contributing factors in differentiating between drowsiness and non-drowsiness interrelated accidents are the duration of the last sleep period and the amount of sleep in the last 24 hours. The duration of continuous wakefulness, acute sleep loss and the cumulative sleep debt contributed significantly to fatigue related accidents.

Sleep deprivation gave negative impact on the driver performance. In order to design a good system some data from the deprivation driver need to be considered.

### 2.1.2 Impact on work schedule

Many studies point to a driver's work schedule as having a significant impact on driver fatigue, particularly for commercial vehicle operators:

- Erwin, C. W. Researchers like [31] have reported that the total driving time greatly increased the crash risk.
- According to one experimental study, driving performance among truck drivers started declining after five hours of driving for drivers with irregular schedules as compared to eight hours for drivers with regular schedules [32].
- Harris, W. et al [33] found that the driver's risk of being involved in a crash increases after four hours of continuous driving.
- Truck drivers, who divide their eight hours of required off-duty time into two shifts, are at bigger risk of being implicated in a deadly crash [35].
- Lavie, P. [36] argues that truck drivers, who work on irregular night shifts and are compelled to sleep during the daytime, may not be getting the restorative quality of night time sleep.
- Factors associated with sleep-related crashes include working two or more jobs, working on night shifts and working more than 60 hours per week [37]. Work schedule also contribute to the driver performance, some indication show it relies back to the fatigue condition when the work schedule is not properly organized.

### 2.1.3 Sleep disorder/quality of sleep

Sleep disorders can also have a significant impact on driver performance:

- Individuals with sleep and other sleep disorders that cause excessive daytime sleepiness are at high risk for accidents [38], [39].
- Drivers involved in sleep crashes are more likely to report that they often or always had problems falling or staying asleep. They are also more likely to report that the overall quality of their sleep is poor [40].

### 2.1.4 Time of day

Sleep accidents are more likely to occur during the early-morning hours from 2 am to 6 am and to a lesser extent during the afternoon from 2 pm to 4 pm. Both [32], [33] found that a correlation exists between time of day and level of fatigue. Due to circadian rhythms, people feel sleepy during the afternoon and evening hours, even among people who are not slept deprived [26].

Driver schedules that interfere with natural circadian sleep patterns can disturb sleep. Truck drivers whom drive during night time are at higher risk of being involved in a crash [35], [40].

### 2.1.5 Repetitiveness of road impact driving condition

A situation is said to be repetitive when the stimuli remain unchanged or change in a predictable manner [41]. The repetitiveness of the roadway geometry and environment has been implicated as a cause of driver drowsiness by a number of studies:

- Due to the repetitiveness of highways (and motorways), highway night drivers are particularly exposed to sleep on related accidents [42].
- Sleep-related accidents may be more common on long stretches of interstate (cross-country) highways and may amount to 40% of fatal accidents [43].
- Driving performance degrades at a faster rate on straight road sections than on curves [44].
- 40% of sleep-related accidents occur on highways [45].
- According to one estimate, 30% of accidents on rural roads are due to driver drowsiness [46].
- In a self-reported driver fatigue/drowsiness study, the U.S. drivers were found to be more prone to drowsy driving as compared to Norwegian drivers [47]. Sagberg et al [13] argues that the cause may be the geometry and environment of the U.S. highways. He further argues that the risk of falling asleep is higher on straight, monotonous roads with low traffic, where boredom is more likely to occur.
- A simulator study suggested that fatigue is likely to occur much earlier when driving in a repetitive, low demanding road environment [48].

### 2.1.6 Characteristics of drowsiness related accidents

Thiffault and Bergeron [49] identified criteria by which sleep-related vehicle accidents could be identified. These criteria include vehicle running off the road, no sign of braking, no mechanical defect, good weather and elimination of speeding. National Transportation Safety Board (NTSA) reported that the following statistics on crashes indirectly related to the driver drowsiness.

- The highest number of crashes occurs during the period from midnight to early morning. More than 40% of crashes occur between 1 am and 7 am. The probability of falling asleep is very high during this time interval.
- About, 70% of crashes occur on rural highways with a 55 to 65 mph speed limit. This provides a monotonous and calm atmosphere, which is just right for falling asleep.
- As an overall of the accident, 64% collisions with fixed objects (trees, guardrail, highway sign, etc.), which is another characteristic of sleepy drivers. 17% are collisions with another moving vehicle, 7% are rollover and 6% are collisions with parked vehicles.

## 2.2 Driver alertness detection system

In our research, the techniques that implemented are capable in detecting the driver's drowsiness pattern at the earliest stage; we were considering looking into several researches that used various methods for detection and warning systems. Some of the devices that were available in the mid-1960s and early 1970s include the following [50]. Those gadgets are very useful in order to help drivers in preventing accidents.

- The electronic Transistor Safety Alarm was a lightweight plastic device that curled around the driver's ear and buzzed when the driver's head nodded.
- The Button Steering Wheel Alarm plugged into the car and was mounted on the steering wheel. An alarm will sound any time when the button was released. The device was deemed to be very impractical.
- The ALERTMASTER was a pedal positioned on the floor to the left of the clutch pedal. Anytime, the pedal pressure was released, the horn would sound.
- The Alert-O-Matic was based on the driver's response to a light signal presented every 60 seconds. If the driver's response (tapping on the horn) was not adequate, an alarm would be set off.

## 2.3 Overall picture of driver alertness detection system

As we have been observed driver alertness refers to an extensive physical and functional characteristics indicative of features such as distraction, drowsiness, attention capacity and mental workload. Alertness detection can be based upon both obvious and hidden measures, as indicated in Figure 2.1.

In the scientific literature, researchers have approached the problem of driver drowsiness detection by using different techniques. We have identified that these techniques can be broadly classified into two categories based on sensing of a driver physical and physiological phenomena and sensing performance output of the vehicle hardware. The diagram below, Figure 2.1, groups the major measures that have been considered in drowsiness detection into one image. Each of these techniques is detailed in this section.

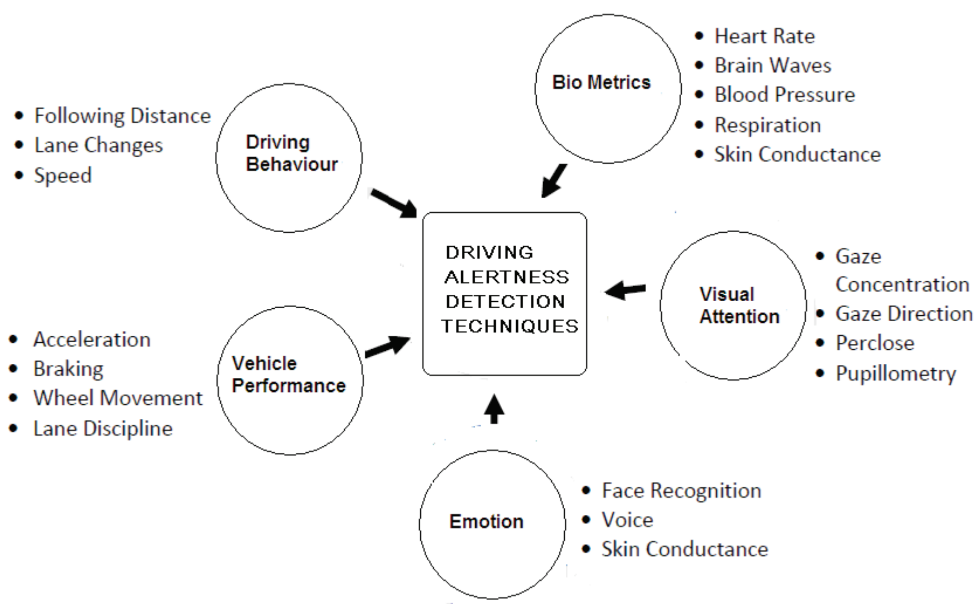


**Figure 2.1: Driver alertness detection techniques.**

A variety of techniques are used to sense the physical and physiological phenomena of driver's alertness. This method is illustrated in Figure 2.1:

- Vehicle performance.

  The performance of the vehicle can be classified into several areas such as acceleration, braking, wheel movement and lane discipline. Example of the system is being developed by Ford's motor that comprises a small forward-facing camera connected to an on-board computer. The camera is mounted on the back of the rear-view mirror and is trained to identify lane markings on both sides of the vehicle. When the vehicle is on the move, the computer looks at the road ahead and predicts where the car should be positioned relative to the road lane boundaries. It then measures where the vehicle actually is, and if the difference is significant the system issues a warning.

- Emotion.

  Emotion of the driver had been used widely as an indicator of alertness. It can be classified into three different areas such as face recognition, voice and skin conductance.

- Visual attention.

  Visual attention also gives a strong indicator for a researcher to investigate the alertness of the drivers through gaze upon concentration, gaze upon direction, percentage of eyes closure (PERCLOSE) and pupillometry.

- Bio metrics.

  Bio metrics also can be used as an indicator of the alertness level by monitoring the heart rate, brain waves, blood pressure, respiration and skin conductance. Most of the system used a specific sensor to read the data from the driver while driving.

- Driving behaviour.

  The driver behaviour also gives a strong indicator of the alertness level. It can be seen from the following distance behaviour, lanes changes and speed changes.

## 2.3.1 The details of techniques

- Eyelid Closure.

  Eyelid closure is one of the most obvious approaches in monitoring driver drowsiness. A number of different techniques are available for obtaining this measure.

  Erwin [51] studied various measures to determine whether they were predictive of sleep and reported eyelid closure as the most reliable predictor of the onset of sleep. Haider and Rohmert [52] evaluated blink rate, while subjects drove a truck simulator for four hours, and reported an increase in the blink rate between 80% to 100% during that time, and it seems quite obvious that if a driver's blink rate is increased, the ability to drive a vehicle will be greatly reduced.

  Skipper, Wierwille and Hardee [53] studied the performance of sleep deprived drivers, who performed a one and half hour driving task. The experimenters used a linear potentiometer to manually track the eyelid movements of the drivers. The researchers concluded that eyelid closures could be used as a measure for detecting drowsiness.

Ogawa and Shimotani [54] analysed data from a driving simulator experiment. They concluded that long duration blinks of half a second or more, corresponds to subjective evaluation of sleepiness. The authors define a degree of alertness ($\alpha$) as:

$$\alpha = \text{number of long duration blinks/total number of blinks.}$$

The driver was considered drowsy every time the value of $\alpha$ increased above a specified threshold value.

Different techniques have been used to track the eyelid closures. In the [55] studies, experimenters manually track the eyelid movements. By looking at the video image on a monitor, an experimenter used a linear potentiometer to track the position of the eyelids.

[56] used a method based on the Feret's diameter of the eye to track the eyelid closures. The system analyses the image of driver face taken by a video camera. After separating the eyes from the rest of the facial features, it defines a rectangular window around the eye based on the Feret's diameter of the eye. The maximum number of black pixels along the vertical axis of the window indicates the degree of eye openness and is used, as a basis for judging whether eyes are open or closed.

Electroculography (EOG) involves the measuring of eye movements through electrodes attached to the skin surrounding the eye. The detection of the eye movements is satisfactory only when the movements are visually unambiguously definable and isolated. Failure rate is very high for a typical eye movement.

[54] used the angle of inclination of eye corners to track the eyelid closures. This angle is steep when eyes are open and shallow when eyes are closed.

[57] developed a method that uses reflection from the retina (bright pupil) to determine whether the eyes are open or closed. In this method, a charge-coupled device (CCD) camera, using an infrared light to illuminate a driver's face, captures the driver's facial image, which is then converted into digital images. The pupil is identified based on their geometric features and relative positions using the binary image. The eyes are considered closed when there is no reflection from the retina.

- Electroencephalogram.

The Electroencephalogram (EEG) recorded from the human scalp is the most important physiological indicator of the central nervous system activation and alertness. Many researchers have used this physiological indicator to identify the period of drowsiness.

From a state of fully awake to a state of fully asleep, the EEG varies in frequency bands ranging from 0 to 20 hertz. These frequency bands are classified as follows:

i. Delta waves ranging from 0 – 4 hertz.

ii. Theta waves ranging from 4 – 8 hertz.

iii. Alpha waves ranging from 8 – 12 hertz.

iv. Beta waves ranging from 13 – 20 hertz.

> An alert mental state is accompanied by fast frequency beta activity, whereas a sleep state is accompanied by slower theta activity. Alpha activity is associated with relaxed experience during which attention is unfocused, showing drowsiness.

Researchers have proposed various methods to extract features from a segment of the raw EEG. In the time domain, average value, standard deviation and sum of squares of EEG amplitude are most commonly used. In frequency domain, energy content of each band (Beta (β), Alpha (α), Theta (θ), Delta (δ), means frequency, and centre of gravity of the EEG spectrum are commonly used. Other models, such as Auto Regressive Moving Average (ARMA) and power spectrum estimation, are also used by some researchers to extract EEG features.

Torsvall, L. et al [58] measured continuous EEG spectra for 11 train drivers. They reported that lapsed of attention were preceded by an increase in low frequency of the EEG activity. The researchers also showed that the driver vigilance tends to diminish rapidly after prolonged driving and can be measured by spectral analysis of the EEG.

The European PROMETHEUS project used EEG in conjunction with other variables to find the correlation between drowsiness and EEG. Akerstedt, T. et al [59], Huang, R. et al [60] used fluctuations in mean frequency of EEG to detect the state of alertness. Generally, EEG is considered suitable for making accurate and quantitative judgments of alertness levels.

- PERCLOS.

  PERCLOS (Percent Eye Closure) is a video-based method that measures eye closure. One of the strengths of PERCLOS is that attempts have been made to establish its validity as a fatigue detection device. Satisfactory relationships were obtained between eye closure and lapses in attention, providing some convergent evidence. When a measure correlates with other tests believed to measure the same and construct of the system's ability to detect the current state of the driver. Furthermore, PERCLOS showed the clearest relationship with performance on a driving simulator in comparison to a number of other potential drowsiness detection devices including two electroencephalographic (EEG) algorithms, a head tracker device, and two wearable eye-blink monitors among many drowsiness detection measures. According to a study performed by [81], drivers in an automobile simulator exhibit certain characteristics when drowsy, that can be easily observed in the eye and facial changes [81]. Alert drivers were reported to have a normal facial tone, and fast eyes blinks with short ordinary glances. Drowsy drivers were reported to have decreased facial tone and slower eyelid.

- Gaze Direction

  Other potential pleasant fatigue parameters include various parameters that characterize the pupil movement, which relates to the driver gaze and awareness of the happenings in surroundings area.

The movement of a person's pupil (gaze) may have the potential to indicate one's intention and mental condition. For example, for a driver, the nominal gaze is frontal.

Looking at other directions for an extended period of time may indicate fatigue or inattention. In addition, when people are drowsy, their visual awareness cannot cover a wide enough area, concentrating on one direction. Hence, gaze (deliberate fixation) and saccade eye movement may contain information about the one's level of alertness.

- Head position monitoring rotation.

The advantage of computer vision techniques is that they are non-invasive, and thus are more amenable to use by the general public. There are some significant previous studies about drowsiness detection using computer vision techniques. Most of the published research on computer vision approaches to detection of drowsiness has focused on the analysis of blinks and head movements. It has been studied that these drivers exhibit certain physiological patterns that are expected and detectible. The standard "head bobbing" movement, where the driver's head drops and then rapidly pulls back upward is one of the patterns that is frequently displayed when an individual is becoming drowsy while seated in an upright position.

Head movement like nodding or inclination is a good indicator of a driver's drowsiness or the onset of drowsiness [89]. It could also indicate driver attention. Head movement parameters such as head orientation, movement speed, frequency, etc. could potentially indicate the attention. Finally, facial expression may also provide information about the attention. For example, a typical facial expression that indicates the onset of drowsiness is yawning.

Head monitoring tracking is a significant process for many vision-driven interactive user interfaces. It is looking for the position of orientation for pose determination and recognition such as simple gestures including nodding and head movement. The stabilize image obtain by viewpoint de-warping of the facial image according to the acquired parameters is ideal for facial expression identification [90] or face identification applications.

Head monitoring system developed by Advanced Safety Concepts, Inc. is the non-contact Proximity Array Sensing System (PASS), is an apparatus designed to record the x, y and z coordinates of the head at electronic rates using three electromagnetic fields. Its development is based on research that indicates a relationship between micro-motion of the head and impairment or drowsiness. It is hypothesized by ASC that changes in the X, Y, Z coordinates of the head may be an indicator of drowsiness onset, and that PASS may detect micro-sleeps based on different head movement patterns. Advanced Safety Concepts, Inc. reports that in laboratory tests, the PASS system can detect changes in the head position as little as 0.0 l", while providing absolute XYZ resolution of head position to about 0.1."

## 2.4 Suitability of monitoring techniques for drowsiness detection

An EEG can provide very good detection accuracy, as it is a direct measure of the activity of the central nervous system. However, the problem with an EEG is that it requires the use of electrodes to be attached to the scalp, which makes it very impractical. Eye closure activity can also provide good detection accuracy but capturing eye images unobtrusively can be challenging under certain conditions. Changes in light conditions, correction glasses, angle of face and other conditions can seriously affect the performance of the image processing systems.

### 2.4.1 Vehicle performance measures

Other approaches for detecting driver drowsiness are based on monitoring driver inputs or vehicle output variables during driving. These methods have the advantage of being non-intrusive to the drivers. In this category, the focus of measurement is not on the condition of a driver but it is on the driver's response to the environment detected through measures of his input to vehicle controls or measures of the performance of the vehicle. The vehicle control systems that might be monitored to sense driving operation include the steering wheel, accelerator and brake pedal. The vehicle parameters that can be measured include the vehicle speed, acceleration, yaw rate and lateral displacement. Since these techniques allow non-contact detection of drowsiness, they do not give the driver any feeling of discomfort.

On the negative side, they are subject to numerous limitations depending on the vehicle type and driving conditions. Wierwille, Wreggit and Mitchell [62] discussed the performance measures as indicators of driver drowsiness in detaisl. A summary of these measures is presented in the following sections.

### 2.4.2 Vehicle Steering Activity

For many years, experiments have been carried out to determine the physical parameters characterizing driving, which could be correlated with EEG parameters that can predict the driver drowsiness. Vehicle steering activity has been cited by many of these studies.

Hulbert [50] found out that the sleep-deprived drivers have a lower frequency of steering reversals (every time the steering angle crosses zero degrees) than that of rested drivers. Dureman, E. et al [63] have found out that there is a deterioration of steering performance with drowsiness.

According to [64], effort and Steering Wheel Reversing Rate (SWRR) are linked. He showed that the SWRR decreases under the influence of substances such as alcohol, which reduces the driver activation level. Ryder, J, et al [65] found that the frequency of steering reversals decreases with time on a task.

[66] hypothesized that when a driver is drowsy or falling asleep, his or her steering behaviour becomes more erratic. Yabuta, K. et al [66] defined this erratic steering behaviour as “more frequent steering manoeuvres during wakeful periods, and no steering correction for a prolonged period of time followed by a jerky motion during drowsy periods.”

[55] found out that several steering related measures, such as steering velocity, steering wheel increment, and low velocity steering, can be used to predict drowsiness.

[67] provided a review of patterns of steering wheel movements and vehicle speed. They have affirmed the complexity of the analysis of these two variables and reported that the environmental factors could highly affect the steering precision.

A study conducted by [68] suggests that there exists some correlation between micro steering movements and drop in vigilance. During high vigilance (alert) periods, small amplitude steering wheel movements are frequent, but during fatigued periods, large amplitude movements are more visible.

[69] analyzed actual driving data from one hour of continuous driving by professional drivers. They reported that steering wheel reversals and standard deviation of steering wheel angle are two measures that show some potential as drowsiness indicators. They also reported that gap-size (i.e., the angle that the steering wheel must be reversed before being counted as a reversal) has a major influence on the reversal rate. Their gap-size function has a dead-band that disregards any extremely small reversals such as those due to road variations.

[70] developed a driver drowsiness detection system at the Toyota Motor Company. The authors used steering adjustment time to estimate drowsiness. Their method consists of the following:

- Steering adjustment intervals are calculated at different speeds for alert conditions (learning). These intervals vary with speed and individual behaviour, but it follows the same pattern. The steering adjustment intervals are normalized at 80 km/hr.

These intervals are constantly calculated. Whenever it reaches a threshold value, the driver is classified as drowsy. The value of drowsiness threshold is not constant, but it varies with speed. The driving threshold is calculated by taking the product of the mean value of learned steering adjustment intervals in the normal state and the mean value of most-recent steering adjustment intervals. The results show a good correlation with EEG.

[71] conducted an experiment based on the performance of 17 long haul truck drivers under alert and fatigue conditions on a closed circuit track. They presented a steering based set of weighing functions. These functions are based on steering angle and steering velocity. According to the researchers, these weighing functions are correlated with EEGs and subjective evaluations of drivers. According to their findings, phase plots of steering wheel angle versus steering wheel velocity can be used as an indicator of drowsiness.

[72] developed an algorithm, which is based on the ANN learning of driver steering. They trained an ANN model using data from a driving simulator, driven by human subjects under various levels of sleep deprivation. The model identified drowsiness and non-drowsiness steering behaviour, by calculating over fixed period of time, with good accuracy.

- **Steering wheel movements.**

Studies indicate that steering wheel movement increases with the amount of drowsiness [85]. The steering activities become larger and occur less often. While the lateral position variability increases as the driver gets drowsier and the minimum distance to any in front vehicle response decreases. The response time to any unexpected events also gets longer with increased drowsiness. Different studies have shown that there is a relationship between various steering related variables and drowsiness. The steering-related variables have the advantage that they are easy to measure since they require no camera or image processing. The drawback is that these variables are dependent upon the road curvature and are therefore, most reliable on highways [86].

Other researchers have studied drowsiness detection using steering angle rotation as an input to detect drowsiness by tracking steering angle by using a camera [87]. It tracks the steering wheel angle by using a single camera system put on inside the car. The approach is based on the modelling of the motion of the steering wheel, as it appears perceptively distorted by the point of view of the un-calibrated camera. The system has some disadvantages such as the steering image being blocked by the driver's head, light beams that confuse the feature detection algorithm and camera setup that is unsuitable for a portable application for steering angle analysis.

Another drowsiness detection algorithm is based on the steering wheel. This algorithm works with three kinds of functions [88]:

- Time based functions (weighting functions developed from the time variations of the angle and the angular velocity),
- Frequency based functions (weighting functions developed from the variations in the power spectrum)

- Phase based functions (weighting functions developed from the variations in the angle plotted against the angular velocity).

This algorithm is interesting because it proposed new detection ideas, such as the use of the phase diagram. The algorithm was tested on a special track with really drowsy drivers and it seemed to work pretty well. However, it has been created using data from drives on straight roads, so it may only work for straight roads, similar to motorways.

### 2.4.3 Vehicle speed

Generally, variability in speed has not shown any significant results that can be used to predict drowsiness. [73] reported no increase in speed variability during a 24 hours driving experiment.

[74] recorded vehicle speed during an eight hours night driving experiment. They reported an increase in the standard deviation of speed, calculated over 45-minute intervals, after the first three hours of driving.

[75] recorded speed in a six hours driving experiment, with 45-minute pause after three hours of driving. The researchers reported a regular increase in the standard deviation of speed from the third driving hour.

### 2.4.4 Vehicle lateral position

Several researchers such as [76] found out that the lane tracking ability decreases as the time on task increases. [53] found that measures related to vehicle lane position could be used to detect drowsiness. Variables such as the number of lane deviations, the standard deviation of lane position and the maximum lane deviation are found to be highly correlated with eye closures. According to [55], the mean square of lane deviation and mean square of high pass lateral position show good potential as drowsiness indicators.

[77] studied the effect of impairment on driving performance in truck drivers. Using data from a simulator experiment, Stein found out that the standard deviation of lane position increases remarkably after the driver got fatigued at 13 hours of driving. The standard deviation of the heading error also began to increase after 13 hours.

[78] performed experiments on the driving simulator at the Ford Research Laboratory for detecting driver fatigue. The results, reported by the authors, show that only the standard deviation of the lateral position show significant change and correspond well with the PERCLOS model.

- **Lane Departure Warning Systems (LDWS)**

  The Lane Departure Warning System (LDWS) is used to determine the position of the vehicle on the road. It is used either to warn the driver when the vehicle is on a white line or to predict when the driver is in danger of departing from the road. A vehicle lateral position or lane departure situation occurs when the vehicle runs off the road, either on the left or on the right side of the road. This kind of situation is also called Run-Off-Road (ROR) or Single Vehicle Roadway Departure (SVRD).

The simplest system is the rumble strip which alerts the driver when he is in a situation of lane departure in order to avoid ROR crashes. Rumble strips are areas of grooved pavement usually situated under the white lines of the road. When the vehicle drifts to the line, its tyre hits a rumble strip, which vibrates the vehicle and makes a loud noise, alerting the driver to take a corrective action. This simple system is efficient since it has been shown to reduce the number of run off road crashes by 70% [84] but requires infrastructure modification. Another approach is to use a system inside the vehicle, which detects when the driver is in danger of departing from the road and trigger an alarm in time for the driver to react.

### 2.4.5 Yaw/Brake/Acceleration activity

[55] found that the yaw deviation variance and the mean yaw deviation (calculated over a three-minute period) show some promise to be considered as drowsiness indicators.

However, several researchers found no relation between drowsiness and vehicle yaw, brake, or acceleration. [79] analysed data from a twenty-four hours driving experiment and reported that the accelerator pedal reversals are correlated with driving time; however, according to the research conducted by [55], there is little evidence of any relation between accelerator activity and time of drowsiness.

In addition, researchers such as [80] found out no evidence of any correlation between accelerator and drowsiness.

## 2.5 Summary of suitability

The main advantages and disadvantages associated with using performance outputs of the vehicle to measure driver drowsiness include:

- No electrodes and wires are to be attached to the body of the driver.
- No cameras, monitors, light sources or other devices are to be aimed at the driver.
- No dependence on the environmental and other road conditions.
- Less computational power is required for processing signals such as steering angle, which makes the online processing of data easily achievable.

The hardware requirement for capturing signal from vehicle components such as steering, throttle and gas paddle are much less than that required for an image processing or human body signals. These are often much cheaper and readily available. Because of the non-obtrusive nature of these methods, they are more likely to be acceptable to drivers.

Due to the variation in the dynamics of different types of vehicles, a universal system that will fit all vehicles is very difficult to achieve. These systems must be tuned for all type of vehicle in use. Accuracy may not be very high as compared to EEG monitors, since EEG monitors are constantly attached to the body and a signal is received even if the car is not in motion.

i. PERCLOS Disadvantages

Percent Eye Closure (PERCLOS) the technical definition is the percentage of time when a vehicle driver's eyes are closed. Sometimes a driver who is trying to stay awake can fall to sleep with his eyes open and this is the disadvantage of PERCLOS. Another problem with this system is that the curve for warning is extremely steep at the end, which means that no warning is given at an early stage and then the situation is very serious quickly.

ii. LDWS Disadvantages

Lane departure warning systems (LDWS) is a system that is currently being used to detect drowsiness. If the driver is drowsy, sooner or later the vehicle will drift to the side of the road and when it crosses the lane boundaries, a warning signal is given to alert the driver. The problem with this system is that the warning signal is given every time the driver crosses the line, it does not consider that the crossing could be intentional.

iii. TLC. Disadvantages.

A commonly used variable in the warning algorithm of the LDWS is the Time to Line Crossing (TLC). The Time-to-Line Crossing (TLC), is the estimated time taken by the vehicle to cross the line, which is based on a predicted path of the vehicle and the speed. The major problem with TLC is its computation in real time while driving on the road. Moreover, the computation is different on straight roads and on curved roads.

iv. EEG Disadvantages.

To measure this signal while driving causes annoyance to the driver, because multiple sensors have to be attached to the driver. This can affect the driver so much that it changes the driving behaviour, which is not good at all in traffic safety research.

v. Eye Detection Systems Disadvantages.

The eye detection systems are good but not perfect, when the driver is wearing glasses, there might be errors in the detection, which in some systems leads to false warnings. Sunglasses cause problems that almost none of the systems can deal with, which makes the inattention detection almost impossible when the driver is wearing sunglasses. Different ethnical people are another problem. The eyes of Asian people differ from European people, but most manufacturers claim that it should not be a problem.

# Chapter 3

# Drowsiness indicators

The major finding from our research review was that after 40 years of research involving vast sums of money there were no systems in regular use. The review has attempted to identify why. The solution lies in finding an effective non-invasive or non-intrusive method that is reliable. Furthermore the systems being developed should manage to predict drowsiness at an early stage and enhanced with the capability to classify the level of the drowsiness.

# 3.1 Experimental setup

The experiments were conducted using car driving game simulator, all the data was recorded and logged and then these data were used as inputs to Matlab programs which attempted to discriminate between normal and abnormal driving. After trying several algorithms we eventually used a Support Vector Machine (SVM). The basic block diagram for the Support Vector Machine classification system is illustrated in Figure 3.1. It shows the experimental method used to examine the driver drowsiness detection. There are two main components that were used during the classification process.

- Distance to lane boundary (m) - using Matlab vision technique.
- Steering angle (deg) - MOTEC data logger from GTR2 Car simulator.

The support vector system will analyze the data and then process it using the algorithm that has been set. The system will alert the driver if the system detects that the driver in the drowsiness state.

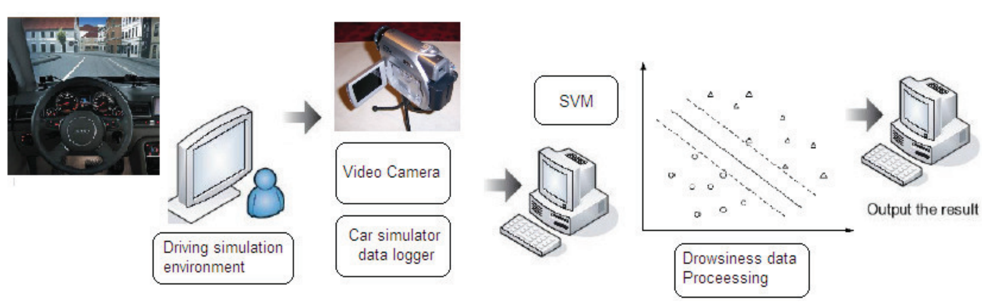


**Figure 3.1: Illustration of research test-bed system components.**

## 3.2 Overview of the simulator experiment

The simulator which we used for this experiment is fixed in one place, it is fully interactive and composed of the hardware interface to the system, including steering angle using the Matlab vision technique plus with acceleration pedal, brake pedal, and a force-feedback steering wheel illustrated in Figure 3.2. The software is equipped with a MOTEC i2 data logger system for capturing the driver responses.

MoTeC's i2 data analysis software has been developed over a number of years with valuable input from professional race teams worldwide. It delivers an extensive package of powerful analysis tools and innovative data-management features, whilst maintaining a simple and intuitive user interface.

A simulation based on a highway and track circuit driving environment that is part of the GTR 2. Car simulation game was used in our experiment to investigate the drivers' behaviour during driving. Video camera detection for the lane boundary has been set within the specific range in front of the driver and was projected on the screen in front of the driver's seat. The audio of the simulator was played through a speaker system. The room in which the participants used the simulator was darkened and relatively soundproof, simulating night time driving and thereby maximizing the probability of drowsiness.

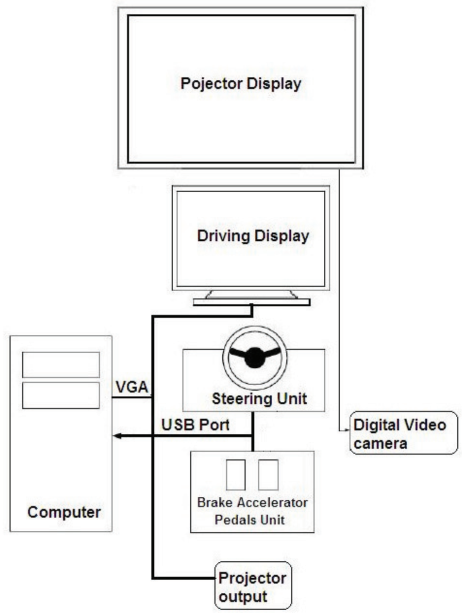


**Figure 3.2: Simulation environments illustration.**

## 3.2.1 Equipment listing on experiment setup

In the following table the equipment used in the project will be presented.

- **Hardware**

- Driving Force Steering Wheel comes with Accelerate, shift, and brake mounted pedals.
- Projector.
- PC, Dell (with Windows XP sp3)
- Digital recording camera (30fps)

- **Software**

- MATLAB Version 7.6.0.324 (2008a)
- Image Processing Toolbox Version 6.1
- Video and Image Processing Blockset Version 2.5
- Python 2.5
- GNUplot 4.4.0
- GTR 2 Game simulation
- Ms Dos (to run the execution program)

In order to monitor the driver and the road environment to detect drowsiness, it is necessary to integrate multiple parameters. As revealed in the introduction, the steering wheel characteristic system and distance to lane boundary system have been used as an input for this experimental system to detect the drowsiness driver. The output of the classification will be used later on for developing a specific detection algorithm.

The experiments were conducted at the laboratory and during this experiment part of the research; the drivers drove a car simulator under several levels of conditions such as wakeful and drowsiness conditions. Data was logged for parameters related to driver activity and vehicle driving performance. Details of the study population, equipment used in the experiment, driving scenario and experimental protocol are provided in the following sections.

## 3.3 Vehicle speed experiment validation

The university had a number of experimental vehicles which had been instrumented for research. We had access to previous work but protocol restrictions meant that it was not possible to use a real vehicle for drowsiness experiments. Time was spent investigating simulation and eventually it was decided to build a simulator. Experiments were conducted on the simulator using human volunteers to identify whether vehicle speed could be used as an indicator of drowsiness. Steering angle, vehicle velocity and distance to lane boundary were measured and the results analysed. During the experiments the subjects were monitored by the researcher for the well-established signs of drowsiness such as eye closure and head 'nodding'.

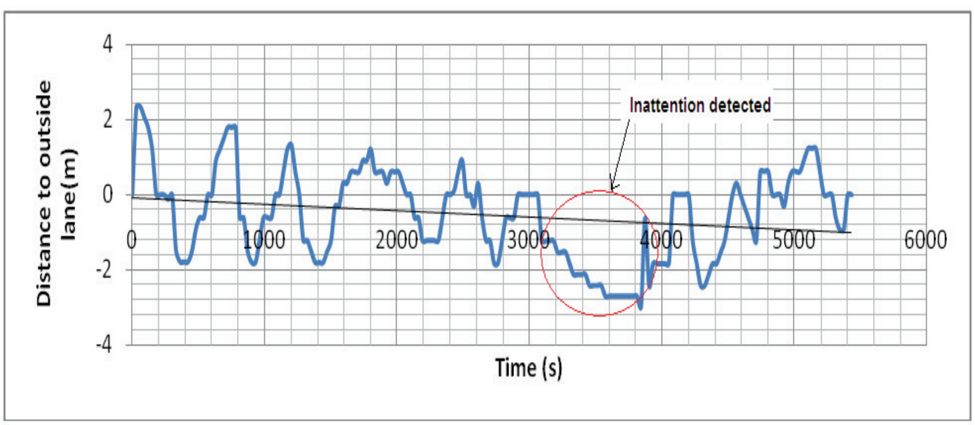


**Figure 3.3: Comparable analysis between distance to lane boundary and time.**

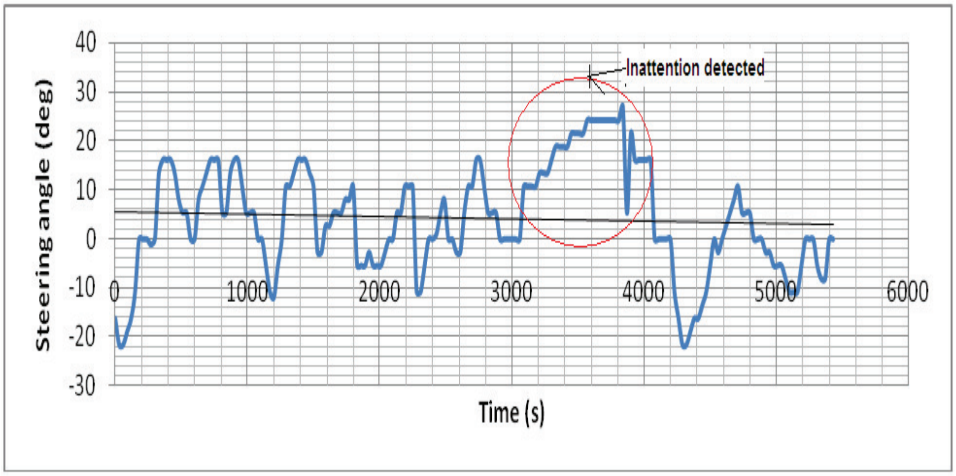


**Figure 3.4: Comparable analysis between steering angle and time.**

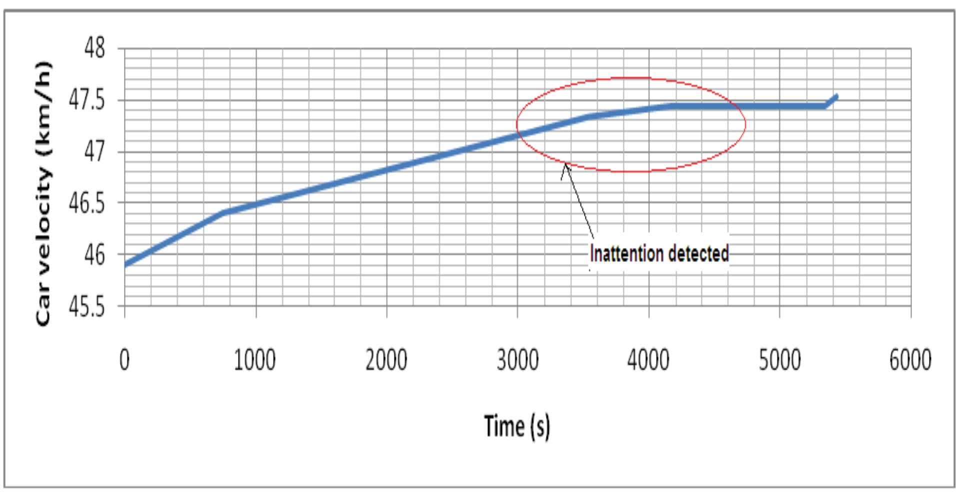


**Figure 3.5: Comparable analysis between car velocity and time.**

The results are plotted and described; Figure 3.3 shows the data collected from the car simulator experiment that has been processed using Matlab vision technique. Matlab vision technique is a method of integrating Matlab simulink toolbox with external video input of simulation environment.

From the graph shown, we spot that the distance to lane boundary of the car is changeable until at one point suddenly the car is drifting slowly towards the left of the road lane. This graph is very clear because it shows the car already crossing the road lane marker.

Figure 3.4 refers to the steering wheel angle activity. The angle is changeable as the wheel is rotated back and forth until at one point suddenly the angle movement continues with the same degree that affected the car to drift to the road lane marker for a while, and then a very high steering angle value when the driver discover and try to make a correction on its position.

Figure 3.5 shows the data collected from the car simulator experiment that has been processed using Motec software. The MoTec software is a fundamental way that monitors the car performance analysis by tapping its ECU data controls by using software concept.

From the data itself, we see that car velocity is increasing until at one point the car velocity is stagnant for a while. This situation rarely happens throughout the process of our data collection, but we are confident with the hypotheses, with the support of the distance to lane boundary and steering wheel angle as in the case above, we predict the driver's alertness is decreasing.

The velocity is not very suitable to be used as a data testing and training because not much data with this type occur regularly. After checking from all the dataset that we have, this is the only one that have good indicator because speed increasing at very low rate also will happen when the driver reaches a curving road. From the point of view of our research it is very useful data if we know the road route. It also has to be accompanied with other elements such as road view, view heading, road curvature and environment noise. This will be discussed in the further work section.

## 3.4 Eye closure and vehicle parameters validations

A simple experiment has been conducted to analyse the relationship between driving behaviour with the percentages of Eyelid Closure, which is based upon slow eye lid closure. This experiment is to get a basic idea which action occurs first. As mentioned earlier the objective of the thesis is to predict drowsiness at a very early stage. Most of the predictions from the biological signal normally happen at the very last stage, and it would be too late to give an alarm to the driver. We asked participants to drive the car simulation experiment and all the activity is recorded in order to observe the drivers behaviour and drivers reaction when they are in drowsiness mode. Figure 3.6 show how the eye's closure activity is graded. Several parameters have been outlined to be monitored during the experiment. Velocity has been set at a constant rate of 40 km/h. For each of the test drivers have been advised to control the steering angle at 0° as long as possible on straight road condition if possible. Eye closure has been characterised to 4 levels as mention in Figure 3.6. All eye reactions will be counted and will be recorded.

| |  |  |  |  |
|---|---|---|---|---|
| Percentage (%) of Eyelid Closure | 100% | 50% | 25% | 0% |
| Level | 1 | 2 | 3 | 4 |

**Figure 3.6: Eyes closures characteristic.**

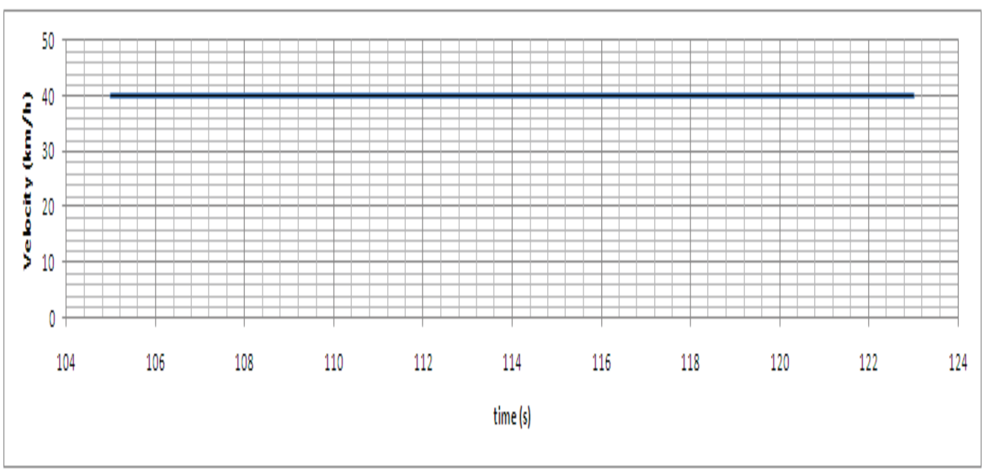


**Figure 3.7: Comparable analysis on velocity against time.**

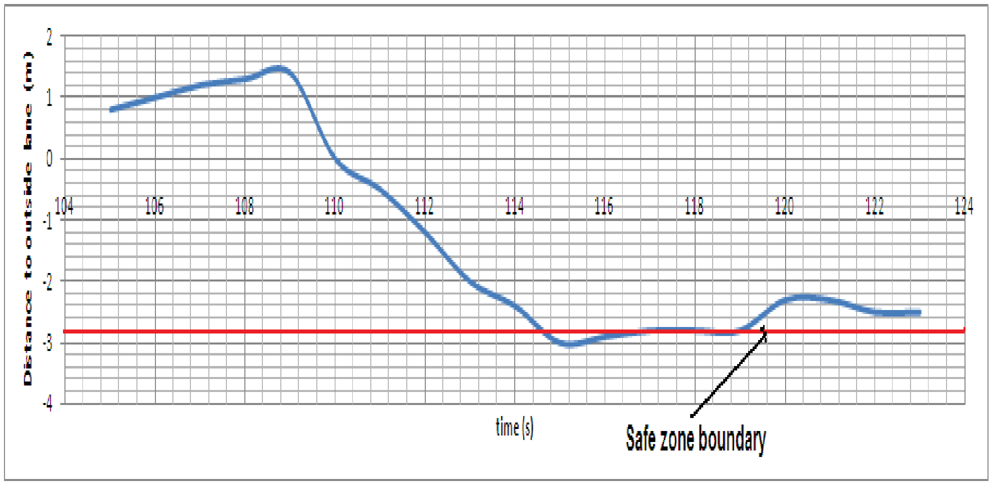


**Figure 3.8: Comparable analysis on distance to outside lane against time.**

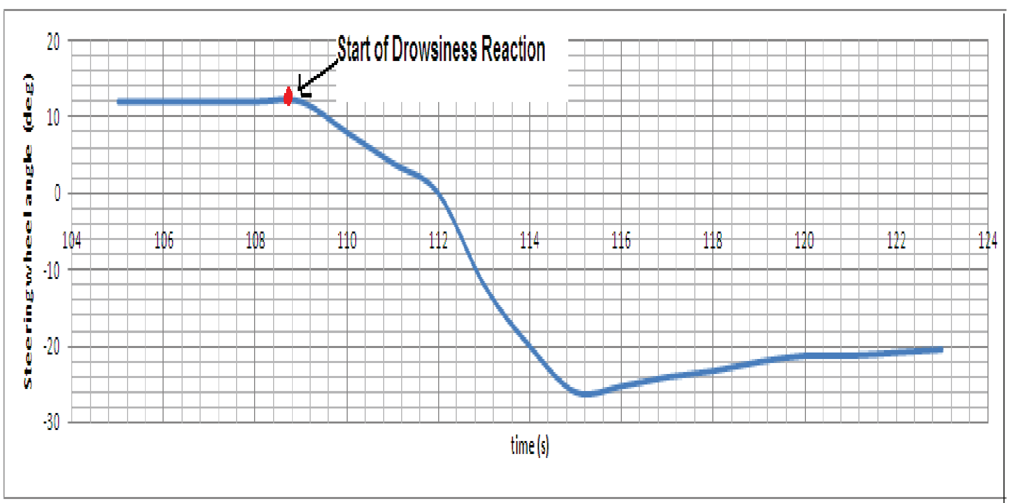


**Figure 3.9: Comparable analysis on steering wheel angle against time.**

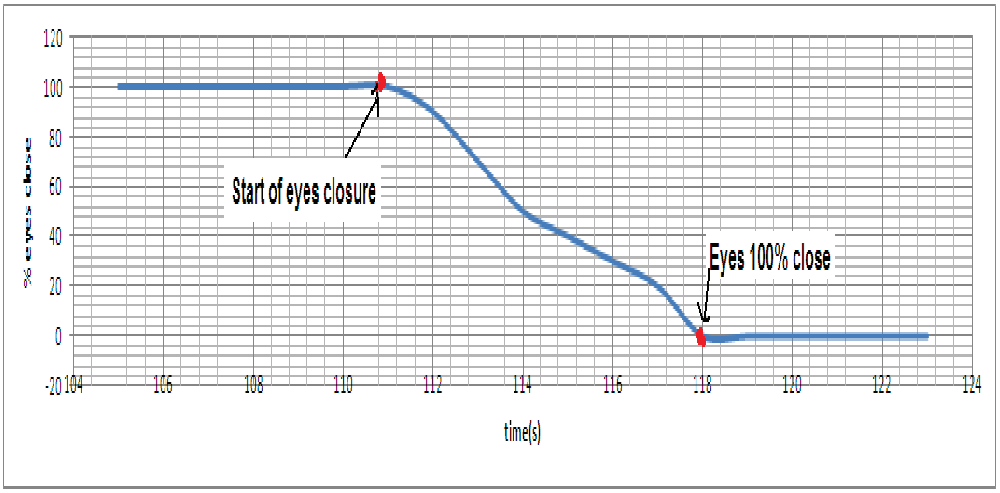


**Figure 3.10: Comparable analysis on percentage of eye closure against time.**

We asked the driver to drive the car simulation at a constant speed of 40km/h in order to have an easy control of the car movement. The alertness level starts to decrease at 109s, it can be observed from the graph in Figure 3.8 that shows the car starts to drift toward the left departure at 109s. It is due to the steering wheel angle slowly changing direction. At 111s, the eyes of the driver start to close at level 2. When the car reached at 114s, the car has already reached the border of distance of lane boundary, but the eyes have only reached three levels. It is apparent that the eyes closure activity and steering angle response are very close and it is only within a few second but distance to lane boundary give a good indicator when it started to drift. Again, a number of trials were conducted to establish a repeatable experimental technique, and the experiments were repeated with a number of subjects. The result presented is representative of the range of experiments. 90% of the statistics from this experiment result shows a good input as the outcome of this research programme suggests that steering angle and lane position may be reliable indicators of drowsiness. Whilst we can observe the effects by looking at the graph, we need to determine whether an automatic system can be devised to trigger an alarm with no observation of actual data or graphs.

## 3.5 Research approach

Several fundamentals have been taken into consideration when designing the drowsiness detection system. Some researchers have already followed this route with encouraging results. By using several hypotheses and finding transformations in vehicle and driver behaviour, three basic parameters will be tested for potential to predict the vehicle behaviour characteristic. In the investigation, the signal will be recorded for various drivers, and data recorded for each of the drivers will be analysed. It is important to notice from the data, that each driver has his own style of driving.

Proposed systems that focus on the drowsiness detection system by using the non-intrusive method where the vehicle driver drives the simulation system and all the activities while driving will be monitored.

The proposed non-intrusive drowsiness warning system uses information that would be obtained from a road information environment, and this is actually taken from the software simulator during the road simulation experiment. The systems will use steering angle activity and distance to boundary lane as inputs, and warn the driver when drowsiness is predicted. The system is composed of several main processes:

- Road information by calculating the distance to the lane boundaries from a vision input system.
- Extraction of the steering wheel angle data.

- Use of physical input data for training and testing of a suitable intelligent detector during the modelling process.
- Valid warning to the driver to eliminate a false alarm.

If the driver actions can be monitored, it is possible if we use an ‘intelligent’ detector to “personalize” the warning to adapt to different driving styles. In addition, it is also possible to track the changing driver parameters during a long drive. This would enable the system to provide warning as a function of changing driver state (e.g. drowsiness). For that reason, a method is looked for to detect changes in driving patterns so that an assessment of driver alertness/performance can be made. This assessment could then be used as one of the inputs to a drowsiness detecting system. The hypothesis is that the system identification techniques can be used to form a set of driver parameters that can be correlated with various levels of driving performance. Variations from this system will then permit the driver drowsiness states to be monitored by the system more comprehensively.

**i. Distance to lane boundary.**

As we have shown earlier the Lane Departure Warning System (LDWS) can determine the position of the vehicle on the road. This position can then be used either to warn the driver when the vehicle is on white line or to predict when the driver is in danger of departing from the road [9].

The technique that we plan to use is to measures the distance between the car position and the road lane border. This is believed to be a relevant suggestion because the LDWS is normally triggered when it reaches the lane border. This was found to be too late to warn the drivers.

### ii. Steering wheel angle.

Studies indicate that the steering wheel variability increases with the amount of drowsiness [1]. A variety of steering wheel techniques have been suggested to measure steering behaviour, from the standard deviation of steering wheel angle [91], steering wheel velocity [92], [93], steering wheel action rate [94], [95], to more advanced techniques such as a high-frequency component of steering wheel angle [96]. Drowsiness effects on steering behaviour could be summarized as follows: fewer small, smooth steering adjustments (micro-corrections), greater steering entropy (measure of steering randomness), larger changeable steering movements (indicating e.g. overcorrecting for unanticipated road changes), lateral drift outside the driver's comfort zone, larger and faster steering corrections [97].

The hypothetical relationship between driver's state of alertness and steering wheel position is that, under an alert state. The driver makes small amplitude movements of the steering wheel, corresponding to small adjustments in the vehicle trajectory, whereas, under a drowsy state. The movements become less precise and larger in amplitude, resulting in large changes in the trajectory [98].

Some have already followed this route with encouraging results. The researchers more significant works in this field are [99], [100], [101], [102]. According to their studies, in the normal condition of a guide, the driver maintains the right trajectory with very small and frequent corrections, sometimes imperceptible movements of the steering angle that are translated into small corrections of the vehicle trajectory. However, it has been demonstrated that there is a direct correlation between the corrections of the steering wheel and the driver state of attention.

Under the conditions of driver drowsiness, the following facts have been recorded:

- The micro corrections are effectuated with a lower frequency;
- The angular amplitude of such corrections tend to increase;
- The corrective movements are less precise.

However, there are some inconveniences that complicated the management and the reliability of the system:

- The average amplitude of the steering micro-corrections decreases with the vehicle speed.
- Under conditions of equal tiredness, the frequency and the amplitude of the micro corrections varies from one driver to another driver.

**iii. Changes of velocity.**

More recent research demonstrated that speed variability was higher for sleep-deprived drivers than for control drivers [2].

## 3.6 System design overview

Having identified the sorts of measures we wished to investigate, we could design our experimental testbed. This chapter principally documents our experimental simulator design; it includes additions to the simulator that were added later (chronologically) as the research progressed. The protocols followed, and the data collection techniques remained the same as those used initially and described below. The flow chart for the overall design of the non-intrusive drowsiness detection system is illustrated in Figure 3.11. The idea is to optimize the whole system for the detection of drowsiness by supplying the required parameters, such as steering wheel angle, angular velocity of steering wheel and distance to lane boundary. These complete systems use the Support Vector Machine as the learning system for identification of in-bound and out-bound values. The system will use classification technique; the idea is to differentiate the input level for each of them for Support Vector Machine (SVM) training in order to improve the output accuracy.

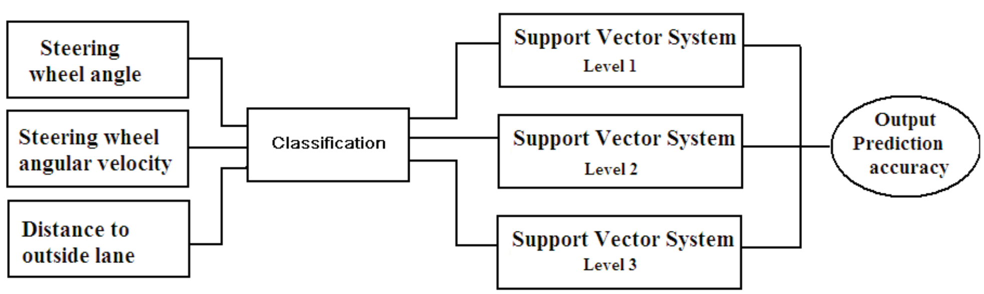


**Figure 3.11: A Flow Chart for drowsiness development system.**

The support vector system will be discussed in details in Chapter 4. This chapter focuses on the stage of the research which has made extensive use of the simulator and collection of data for the three chosen parameters.

## 3.7 Driving simulator

The ability of an individual to control and operate a motor vehicle depends upon a wide variety of cognitive skills. While the cognitive processes associated with driving emphasise contributions of planning, memory, psychomotor control and visual-spatial abilities, all depend on the central role of attention [103]. Therefore, the assessment of attention abilities may prove useful in the assessment of driving abilities.

One problem with the attention tests is that they cannot be used simultaneously with driving as they interfere with the underlying process and distort the fundamental task of driving, when used in the typical divided attention paradigm [104].

One method in introducing new technology in transportation research is to make use of simulations and simulators, which have several advantages to research. The benefits of simulators include safety, exposure to high-risk, low likelihood events and cost-effectiveness. The impact of simulator learning on performance in the real situation has been evaluated and is the standard practice in the aviation and space industries, for example.

Advances in computer technology have facilitated the development of interactive simulators. There are several reasons for using an off-road driving simulator rather than in-vehicle or on-road testing, not the least of which includes safety and cost. Moreover, off-road simulators allow a larger degree of experimental control and accuracy of performance measures without the interruption of other variables that may operate in various uncontrolled ways in the real world. However, the course and extent of driver drowsiness cannot be resolved based on results in driving simulators without validation in an operational environment; to date, this validation is rare.

Even the most sophisticated driving simulators do not provide all the visual, vestibular, and proprioceptive changes that happen when the steering wheel is turned and the vehicle changes course [105]. Furthermore, missing in the laboratory environment is the subject's knowledge that the consequences of driving control responses affect his or her own safety. Most of the driver performance measures and all the measures of a driver physiological state that has been used to assess driver fatigue can be gathered in either the simulator or in real driving environments [105]. However, the applications of simulators in driver training have not yet been established as ‘standard’ practice.

### 3.7.1 Study population

During the experiment, all scenes are moving according to the displacement of the car and the subject’s wheel handling. The driving speed is fixed at 50 km/h and the experiment is divided into two conditions (day and night). Day simulation is conducted at 11.00 am to 13.00 pm and night simulation is conducted at 1.00 am to 3.00 am. We asked the drivers to keep driving the car as long as possible. While the drivers are alert, his or her response time will be short and deviation of the car will be small; otherwise the subject’s response time and the car deviation will be slow and long. In the highway driving experiment, the virtual based freeway scene provides only one car driven on the road without any other event stimuli to simulate a monotonous and unexciting task that will make drivers fallen asleep.

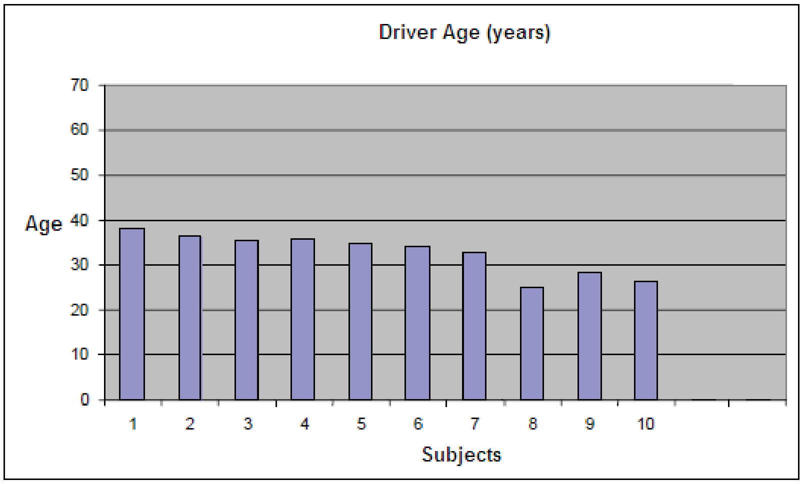


**Figure 3.12: Drivers age.**

A total of ten subjects (ages from 25 to 39 years old) participated in the simulation based driving experiments as illustrated in Figure 3.12.

### 3.7.2 Experiment protocol

The protocol consists of testing the driving performance of car's drivers under drowsiness and non-drowsiness conditions in a driving simulator. There were a total of three simulators driving sessions: a practice session, a morning session and a night session. To make the best use of the chance in order to get useful data for our study, all the experiments were conducted in the early afternoons. Statistical reports [106] showed that driver often get drowsy in less than one hour of a non-stop driving during these periods, indicated that drowsiness is not necessarily caused by long driving-hours.

### 3.7.3 Practice session

Drivers who responded and showed interest were contacted and briefly informed about the car simulator system and were briefed about the experiment and operation of the simulator; all the functions and driving controls were explained to them. Each subject was given details written instructions of what was required from her/him in the experiment. They were told to follow all the rules of the road and maintain the instructed speed limit and then started to keep the car at the centre of the cruising lane by manoeuvring the car with the steering wheel.

They then drove the simulator for two-hours length of the scenario and they were scheduled for the actual experimental session on the day of their availability. Each driver was required to complete two experimental driving sessions, a morning session and a night session. Table 3.1 shows the amount of sleep deprivation and time schedule for the two experimental sessions.

Subjects reported this amount of practice to be sufficient to train participants to asymptote on the task.

**Table 3.1: Amount of sleep deprivation.**

| | **Morning Session** | **Night Session** |
|---|---|---|
| Amount of continuous wakefulness | 5 – 6 hours | 18-19 hours |
| Time schedule | 11:0 am to 13:00 pm | 1:00 am to 3:00 am |

### 3.7.4 Morning session

Participants were advised to have at least eight hours of sleep the night before their scheduled testing date. In the morning session, participants drove the car simulator for an hour. During this session, participants were fresh and experienced no fatigue due to sleep deprivation. After completing the morning experimental driving session, they were allowed to carry on with their daily life activity.

### 3.7.5 Night session

For the night session, participants arrived at the laboratory 30 minutes before the start time of the experiment. The night experimental session started at 1:00 am and continued until 2:00 am or until the driver was too drowsy to continue driving. The same an hour driving scenario was continuously repeated. In this session, participants were sleep depressed and were weak to fall asleep while driving the simulator.

### 3.7.6 Data collection

Two types of data were collected during the experiments: data related to steering wheel angle parameters and video of the road lane images using Matlab vision technique that will be explained in the next chapter.

## 3.8 Design methodology

The core of this research is to develop an algorithm that can be used in a software system based on driver drowsiness system detection. The first aspect of the design is to choose the system architecture, the experimental method, the hardware, the software and the respective reasons for making those choices. Initial research considered whether a single measurement parameter could be used as cited in some of the previous research. We proposed that two independent parameters are used. Steering wheel angle and distance to lane boundary are the two components that are correlated in our design. Sometimes the high amplitude of steering angle is due to the curvature of the road. However, to make sure this parameter does not trigger driver intention and becomes a false alarm. We can check the current distance to lane boundary. In addition to the steering wheel angle, we are also able to log angular velocity, although angular velocity is not used as an input at this stage. An example of the relationship between steering angle and lane position is illustrated in Figure 3.13.

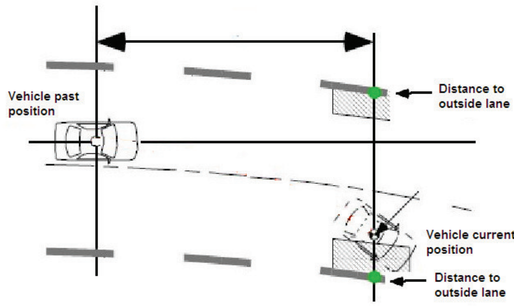


**Figure 3.13: Relationship between steering angle and vehicle lane position**

Figure 3.14 illustrates the relevant correlation between the steering angle and the distance from the centre line of the lane, showing that if both values are high there is a possibility of abnormal behaviour. A straight section of the road is shown for ease of illustration.

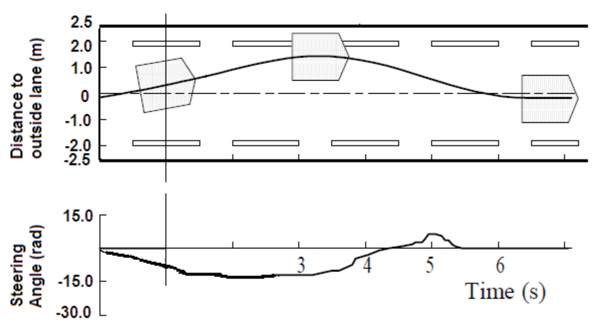


**Figure 3.14: Relationship between steering angle correlation and distance to lane boundary.**

In this research, we proposed to analyse the data from the steering wheel characteristic. This was because the system was not intrusive, secondly an electric steering system as found on newer cars, does not require any additional hardware.

We have shown that the steering wheel parameters are very interesting, especially the angle, since small steering corrections made by the driver decrease when the driver is drowsy. However, the steering movements are also highly dependent on the location of the vehicle on the highway or suburban road. So, the steering wheel angle should be corrected from route dependent effects to fully achieve its potential as a drowsiness indicator.

In this framework, an interesting problem is the detection of the steering wheel rotation angle. The possibility to compute this angle in real-time can be exploited to provide a feedback to the driver in terms of virtual or reality, or to support an automatic guidance system, or to analyse the style of the driving by observing how the steering wheel's angle changes along time.

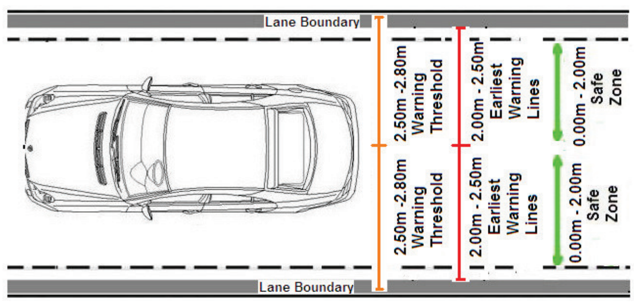


**Figure 3.15: Illustration on distance to lane boundary overview.**

Distance to lane boundary is one of the attributes that is used to observe the coordination of a vehicle within a lane and to use as an indicator to show if the vehicle is out of the road lane or is about to divert outside of the road lane. The actual measure is distanced from the lane centre line. The danger zone would vary with lane width, but for our experiments it has been set as shown above with a lane width of 5.6m.

Lane position is used as an input to our detection algorithm (later the SVM) to classify whether the driver has departed from a safe lane position when the vehicle is approximately near to a certain threshold. As shown in Figure 3.15, the distance to the lane boundary parameter has been decided in order to have a specific range to classify the driving behaviour.

The “earliest warning line” is outside of safest zone and the “warning threshold zone” is the area after the earliest warning lines. We plan to train the data as tabulated in Table 3.2; the idea is to detect the alertness level as early as possible.

**Table 3.2: Drowsiness possibility alertness level.**

| **Zone** | **Level** |
|---|---|
| Safest zone | Level 1 |
| Earliest warning | Level 2 |
| Warning thresholds | Level 3 |

Our original research explored the use of steering angle and steering angle velocity alone and was successful in providing a model for a system that could be used to detect driver drowsiness with a single non-intrusive measurement. It also showed that it is possible to design an adaptive system that constantly adjusts its boundary conditions to different drivers or different road conditions.

However, the experiments showed that there are situations where it is difficult to distinguish between safe and unsafe situations. Although the system is accurate in 90% of situations, a 1 in 10 false positive is not acceptable to drivers. The next chapters will consider the lane measurement issues and the algorithm design in greater details.

# Chapter 4

# Detection and calculation of distance to lane boundary

Distance to lane boundary is a significant feature of this application. The system also can be used to monitor the driver's state [107], predict driver intention [108], [109], warn the drivers if near to lane departures [110] and assist in the vehicle lane positioning [111], [112]. With such wide category of system objectives, it is foremost that we examine how distance the lane boundary is detected and performance with relevant metrics in a variety of environmental conditions.

Within the last few years, research in intelligent vehicles has expanded interests in applications of that work for human user. Human-factors research is merging with intelligent-vehicle technology to create a new generation of driver-assistance systems that go beyond automated control systems by trying to work at the same time with a human operator.

## 4.1 System design

In designing the system, we have observed that our system had a similarity with the current lane position detection technique. So we have distinguished the characteristics as the following:

i. Lane-Departure-Warning Systems:

   For a lane-departure warning system, it is important to accurately predict the trajectory of the vehicle with respect to the lane boundary [113], [114].

ii. Driver-Attention Monitoring Systems:

   For a driver attention monitoring system, it is important to monitor the driver's attention to the lane-keeping task. Measures such as the smoothness of the lane following are important for such monitoring tasks [107].

In designing the system, the role of lane position sensors and algorithms had to be considered in fulfilling the objective listed.

### 4.1.1 Lane detection system

Referring to the previous survey conducted by Joel C. McCall and Mohan M.Trived [130], most lane tracking system design literature from 1984 to 2006, followed a very similar method.

Firstly, a model for the road view and vehicle is being proposed. This model varies between a simple straight line, clothoid or spline. After the proposed decision, a selection for a special tool needs to be considered in order of gathering the environmental information used to extract features such as motion flow, edge, texture, etc. These extracted features in combination with the actual road model are used to estimate the lane's position. Finally, a model is required for the moving vehicle to refine these estimates.

Road Modelling is necessary for "eliminating the false positives via outlier removal". The applied model is determined based on the expected degree of sophistication e.g. a spline model is too many complexes for a system intended for only highways.

Road marking extraction seems to be the most important phase. Since the road and lane marking vary greatly, applying only a single feature extractor is challenging. Edge based techniques work properly with solid and segmented lines. On the contrary, if there are many extraneous lines, this approach is very likely to fail.

In order to improve the extracted features and estimates post processing is mandatory. There are various approaches towards post processing namely Hogh Transform [139], [140].

The last phase is tracking. There are two common tracking techniques namely Kalman filtering [131], [132] and particle filtering [142], [143]. There are combinatory structures with a more complex structure like [144] as well. In all these approaches feature extraction and position tracking are combined in a closed feedback loop.

## 4.2 Tools selection

Various tools have been studied to perform lane position detection. Examples of these include:

- Camera and vision sensors.
- Internal vehicle-state sensors.
- Line sensors.
- LASER radio detection and ranging (RADAR) sensors.
- Global positioning system (GPS) sensors.

While LASER RADAR sensors, line sensors and GPS sensors can perform extremely well in certain situations, vision sensors can be utilized to perform well in a wide variety of situations. LASER RADAR sensors are useful in rural areas in helping to resolve road boundaries [115], but fail on multilane roads without the aid of vision data. Line sensors, while accurate for current lateral position, have no look ahead and cannot be used well for trajectory forecasting, which is needed to compute metrics such as time to lane crossing (TLC) [113].

GPS, especially differential GPS (dGPS), can provide accurate position resolution, but this requires infrastructure improvements to achieve these accuracies, and to rely on map data that may be out dated and inaccurate [145]. Vision sensors can provide accurate position information without the need for external infrastructure or relying on previously collected map data. In the situations where vision sensors do not perform well (i.e. extreme weather conditions or off-road conditions), the vision data can be fused with other sensor modalities to provide better estimates.

This makes vision sensors a good base on which to build a robust lane position sensing system.

## 4.3 The system implementation

In our system the distance to lane boundary data was analysed using a Matlab lane detection technique that employed Hough Transform, Hough Lines and Kalman Filter blocks to create line detection and tracking algorithm. The system detects and tracks road lane markers in a video sequence.

The implementation of this technique steering angle is illustrated in Figure 4.1 and Figure 4.2 using the following steps:

- Detect lane markers in the current video frame.
- Match the current lane markers with those detected in the previous video frame.
- Find the left and right lane markers.
- Issue a warning message if the vehicle moves across left or right of the lane markers.
- Show the output on a graph.

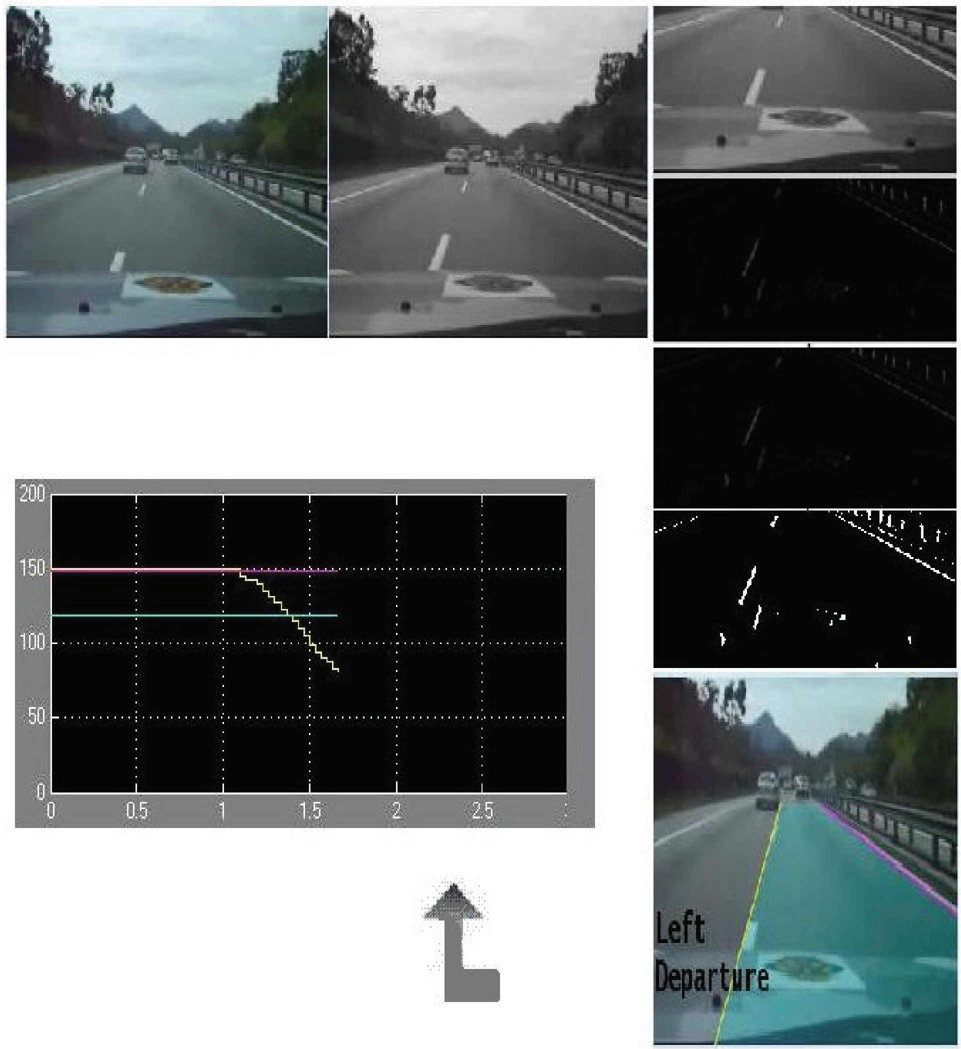


**Figure 4.1: Illustration of experiment output layout.**

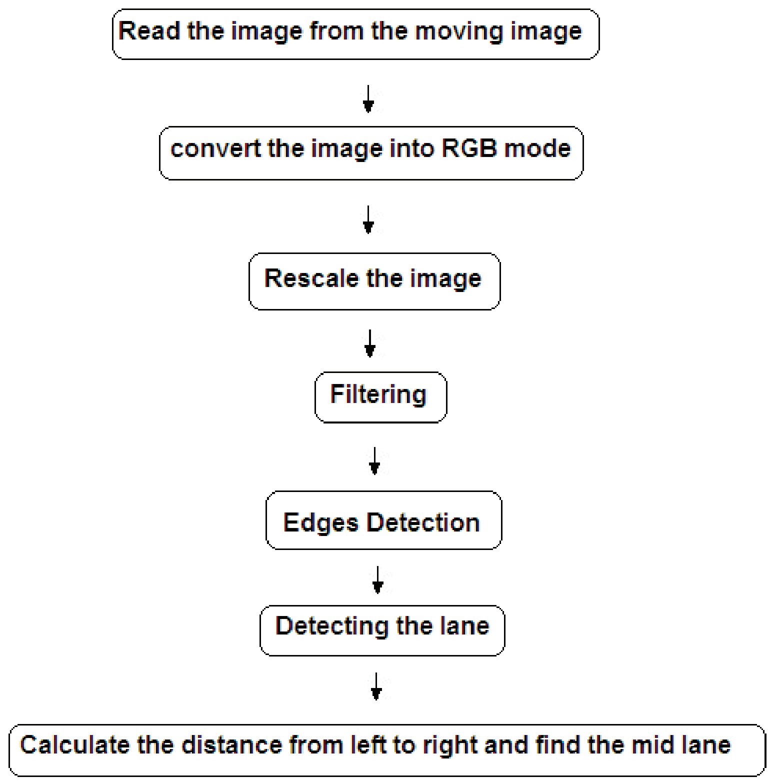


**Figure 4.2: Illustration of process flowchart.**

## 4.4 The vision system

The system is based on a video camera and works in the following way:

- The process starts with the image capturing stage using a video camera with a maximum frame rate of 25fps.
- Video camera is constantly filming the road in front of the vehicle.
- Image processing is applied to the recorded data to extract the lane markings from the road.
- The position of the car on the road is computed from the angle of the lane markings.

## 4.5 Matlab system implementation

To build a distance to a lane boundary system, we need to integrate Matlab simulink, the signal-processing blockset and video and image processing blockset. Initially, we develop a floating-point model of the road lane detection system. We configure the road lane as line segments. It is detected by using the Hough transform technique detecting the edges in a video frame. We input a video sequence to the simulation environment using the Multimedia File block from the Video and Image Processing Blockset. During simulation, the video data is processed in the Lane Marker Detection subsystem, which outputs the detection algorithm results to the Video Display block for computer visualization as illustrated in Figure 4.3.


**Figure 4.3: Illustration of system model.**

## 4.6 Lane detection and visualization

Figure 4.4 presents the main components of our Simulink model. The sequence of steps in the lane marker detection and tracking algorithm will be explained below.

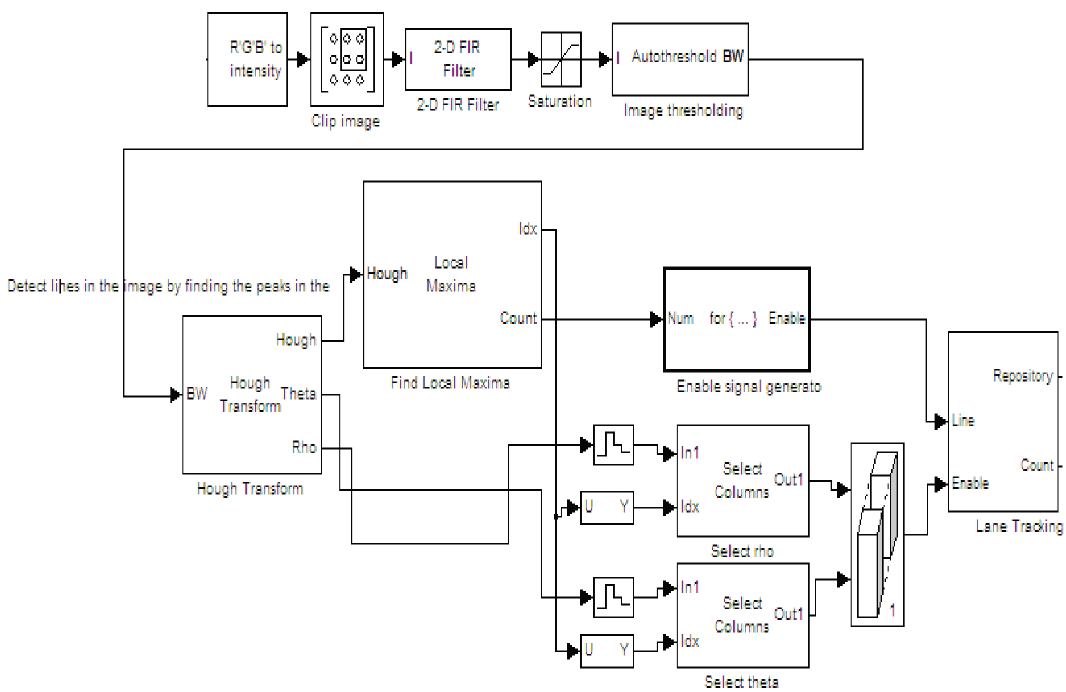


**Figure 4.4: Illustration of simulink model.**

We start with a pre-processing which defines the relevant field of view and filters the output of the operation in order to reduce the image noise. Then the edges of the image are determined by using the Edge Detection block in the Video and Image Processing block set. With this block, we can use the Sobel, Prewitt, Roberts or Canny methods to output a binary image or a matrix of Boolean values corresponding to edges.

Next, we detect the lines by using the Hough Transform block, which maps points in the Cartesian image space to curves in the Hough parameter space by using the following equation:

*rho = x * cos(theta) + y * sin(theta)*

The block output is a parameter space matrix whose rows and columns correspond to the *rho* and *theta* values, respectively. Peak values in this matrix represent potential lines in the input image.

The lane marker detection and tracking system uses a feedback loop to further improve the lane marker definitions. We post-process the Hough Transform output, using line segment rectification to deal with image boundary outliers, and then compute the Hough lines. The Hough lines block in the Video and Image Processing Blockset finds the Cartesian coordinates of line end-points by locating the intersections between the lines, characterized by the *theta* and *rho* parameters and the boundaries of the reference image.

### 4.6.1 Lane detection subsystem

This subsystem uses the 2-D FIR Filter and Autothreshold blocks to detect the left and right boundaries of the lane markers in the current video frame. The boundaries of the lane markers resemble straight lines and correspond to peak values in the Hough transform matrix. This subsystem uses the Find Local Maxima block to determine the Polar coordinate location of the lane markers.

### 4.6.2 Lane tracking subsystem

The system saves the previously-detected lanes in a repository and counts the number of times each lane is detected. This subsystem matches the lanes found in the current video frame with those in the repository. If a current lane is similar enough to another lane in the repository, the system updates the repository with the lane's current location. The Kalman Filter block predicts the location of each lane in the repository, which improves the accuracy of the lane tracking.

### 4.6.3 Lane departure warning system results

The Lane Distance Signals figure below shows the distance from the centre of the video bottom boundary to the left lane of departure (yellow) and to the right lane of departure (magenta), and the warning distance threshold (cyan) by referring to the Figure 4.5. The warning will trigger if the driver exceeded either at the right or at the left side and it also will calculate the distance of the departure.

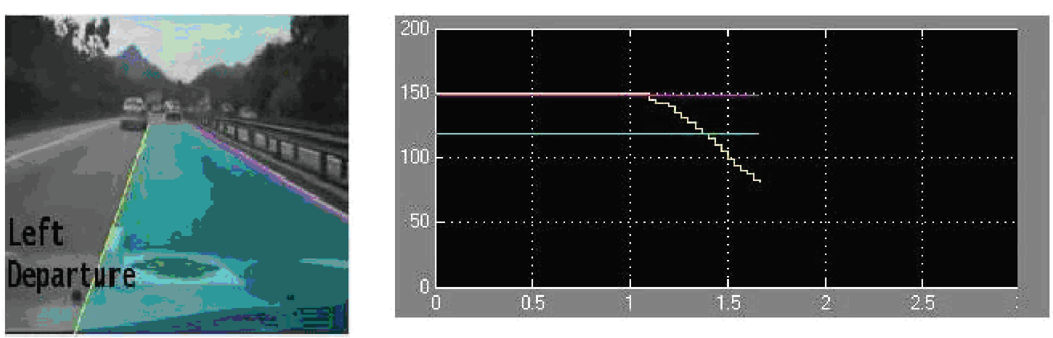


**Figure 4.5: Example road experiment result**

# Chapter 5

# Training and testing data by using Support Vector Machine

The aim of this aspect of the research is to reveal the fundamental functionality and to get an extensive understanding of how the model based fault detection works. The section also summaries what has to be considered when the system is applied, which fields of application exist and what the fields of researches nowadays are.

After consideration of a wide range of alternatives, this study uses an upcoming technique known as Support Vector Machines, or SVM, which is considered to be an effective and robust method for pattern classification and has received positive reviews in the signal-processing field, as a classification tool to process and interpret data for the detection of driver drowsiness.

We propose the SVM-based approach in this thesis because of its theoretical benefits over other learning algorithms. SVM has been applied in various pattern recognition fields, but there is very little prior work on the use of SVM in drowsiness detection. In this section, we first review the motivation and algorithm of SVM. Then we move on to introduce LibSVM, which are the tools used to perform supervised learning, and how they can be applied in the drowsiness detection system. LibSVM [120], which is a famous open-source SVM implementation, is renowned for its efficiency and accuracy in practical classification tasks.

## 5.1 SVM classification

A classification task usually involves training and testing data, which consists of some data instances. Each instance in the training set contains one “target value” (class labels) and several “attributes” (features). The goal of the SVM is to produce a model which predicts the target values of data instances in the testing set which are given only the attributes. This study aims to enable SVMs to not only distinguish data between alert and drowsy states accurately and reliably, but to also work as a fore-warning drowsiness detector for driving safety.

SVMs are learning machines that can perform binary classification (pattern recognition) and real valued function approximation (regression estimation) tasks [121]. The SVM learns from known labelled data, and performs classification on an unknown unlabelled data.

SVMs are generally competitive to (if not better than) Neural Networks or other statistical pattern recognition techniques for solving pattern recognition problems [122], [123], [124]. They are also handy for solving the regression problems, which is convenient for continuous tracking problems. More importantly, SVMs are showing high performance in practical applications in recent studies.

A remarkable property of SVM is its good generalization capacity independent of the input space dimension [121]. Similar to most machine learning systems, the application of SVM comprises three major steps: feature extraction, machine training and evaluation of machine performance.

## 5.2 General Principles of SVM

The general principles behind the computations involved in SVM are described as follows. Given a dataset *D* consisting of N samples in the form of $\{\mathbf{x}_j, y_j\}_{j=1}^{N}$ where $\mathbf{x}j$ ε $R^d$ is the $j^{\text{th}}$ sample and $yj$ ε {−1, 1} is the corresponding class label, the basic principle of SVM for the two-class classification problem is to build an optimal separating hyperplane with the largest margin between the two classes. If the data are not linearly separable in the input space $R^d$ (as most of the real-world problems), a nonlinear SVM is often used by mapping the feature vector $\mathbf{x} \in R^d$ into a high (possibly infinite) dimensional Euclidean space, *H*, using a nonlinear mapping functions $\Phi$: $R^d \rightarrow H$. This is motivated simply by the fact that data from two classes can always be separated by a hyperplane with an appropriate nonlinear mapping function $\Phi$ to a sufficiently high dimension [6].

In the case of nonlinear SVM, the decision boundary of the two-class problems takes the form of an optimal separating hyperplane, $w \cdot \Phi(x) + b = 0$, in *H*, obtained by solving the convex optimization problem [125] [123].

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i, \tag{5.1}$$

subjected to $y_i(w \cdot \Phi(x_i) + b) + \xi_i \geq 1$ and $\xi_i \geq 0$, for $i = 1, \cdots, N$, over $w \in H$, $b \in R$ and the non-negative slack variable $\xi \in R^{N.}$ $C > 0$ is a parameter that balances the size of $w$ and the sum of $\xi_i$. It is well known that the numerical computation of (5.1) is achieved through its dual formulation.

Suppose $\alpha i$ be the Lagrange multiplier corresponding to the $i^{th}$ inequality, and then the dual formulation of (5.1) can be shown to be

$$\min_{\alpha} \frac{1}{2} \sum_{i,j=1}^{N} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{i=1}^{N} \alpha_i, \tag{5.2}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} y_i \alpha_i = 0 \text{ and } 0 \le \alpha_i \le C, \text{ for } i = 1, \cdots, N,$$

Using the kernel function

$$K(x_i, x_j) \equiv \Phi(x_i)^T \Phi(x_j) \tag{5.3}$$

And
$$w = \sum_{i=1}^{N} \alpha_i y_i \Phi(x_i) \tag{5.4}$$

The expression of the hyperplane $w \cdot \Phi(x) + b = 0$ becomes

$$f(x) = \sum_{i=1}^{N} y_i \alpha_i K(x_i, x) + b \tag{5.5}$$

This serves as the decision function for all unseen samples of $x$ in that the predicted class is +1 if $f(x) > 0$ and −1 otherwise.

The procedure for running SVM has been recommended as follows [57]:

- Transform data to the format of an SVM software.
- Conduct simple scaling on the data.

- Select the RBF kernel $K(x, y) = \exp(-\gamma||x-y||2)$.
- Use cross-validation to find the best parameter *C* and $\gamma$.
- Use the best parameter *C* and $\gamma$ to train the whole training set.
- Test.

### 5.2.1 SVM classification example

This study follows the above procedures for carrying out SVM classification of data. Some of the above steps are briefly described below:

- Data transformation

  SVM requires that each data instance is represented as a vector of real numbers. Hence, if there are categorical attributes, we first have to convert them into numeric data. It is recommended that we use *m* numbers to represent a *m*-category attribute. Only one of the *m* numbers is one, and others are zero. For example, a three-category attribute such as {red, green, blue} can be represented as (0,0,1), (0,1,0) and (1,0,0). If the number of values in an attribute is not too many, this coding might be more stable than using a single number to represent a categorical attribute.

- Data scaling

  It is important to scale the data before applying SVM. The main advantage is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. Another advantage is to avoid numerical difficulties during the calculation. A linear scaling of each attribute to the range [-1, +1] or [0, 1] is recommended. The same scaling is adapted to testing data as well.

- Selection of RBF kernel

  For the reliable detection of drowsiness for this study, a nonlinear SVM was selected. This was a popular Gaussian kernel function known as the radial basis function (RBF):

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0 \qquad (5.6)$$

  where $\gamma$ is a kernel parameter. The RBF kernel nonlinearly maps samples into a higher dimensional space, so it can handle the case when the relation between class labels and attributes is nonlinear.

- Cross validation and grid search to find the best C and $\gamma$

  There are two parameters while using RBF kernel: $C$ and $\gamma$. It is not known beforehand which C and $\gamma$ are the best for one problem, i.e. some kind of model selection (parameter search) must be done. The goal is to identify good (C, $\gamma$) so that the classifier can accurately predict unknown data (i.e. testing data). Note that it may not be useful to achieve high training accuracy (i.e. classifiers accurately predicting training data whose class labels are pre-known). Therefore, a common way is to separate the training data to two parts of which one is considered unknown in training the classifier. Then the prediction accuracy on this set can more precisely reflect the performance on classifying unknown data. An improved version of this procedure is cross-validation.

In $v$-fold cross-validation, we first divide the training set into $v$ subsets of equal size. Sequentially one subset is tested using the classifier trained on the remaining ($v$-1) subsets. Thus, each instance of the whole training set is predicted once, so the cross-validation accuracy is the percentage of data which are correctly classified.

The cross-validation procedure can prevent the over-fitting problem. Figure 5.1, which is a binary classification problem (triangles and circles), are used to illustrate this issue. Filled circles and triangles are the training data while hollow circles and triangles are the testing data. The testing accuracy of the classifier in Figures 5.1(a) and 5.1(b) is not good since it over-fits the training data. If we think training and testing data in Figures 5.1(a) and 5.1(b) as the training and validation sets in cross-validation, the accuracy is not good. On the other hand, classifiers in Figures 5.1(c) and 5.1(d) without over-fitting training data gives better cross-validation as well as testing accuracy.

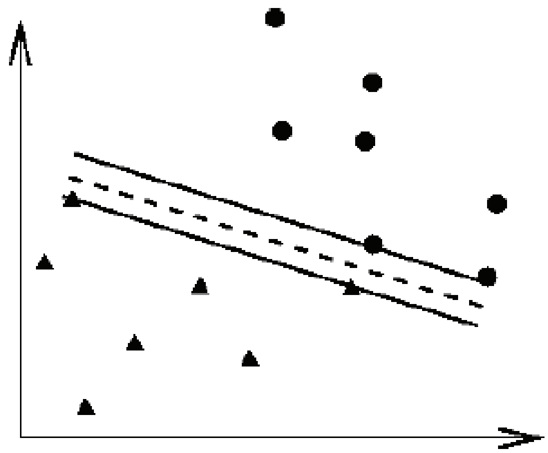

**Figure 5.1(a): Training data and an over-fitting classifier.**

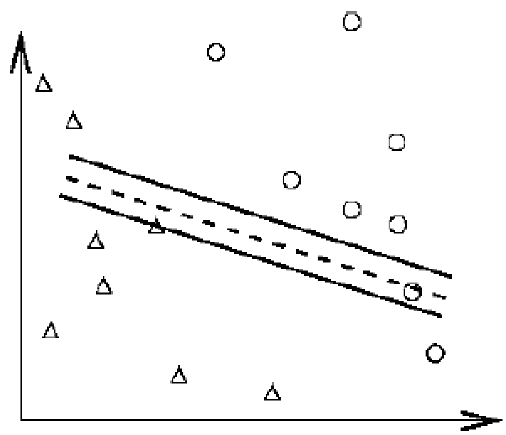

**Figure 5.1 (b): Applying an over-fitting classifier on testing data.**

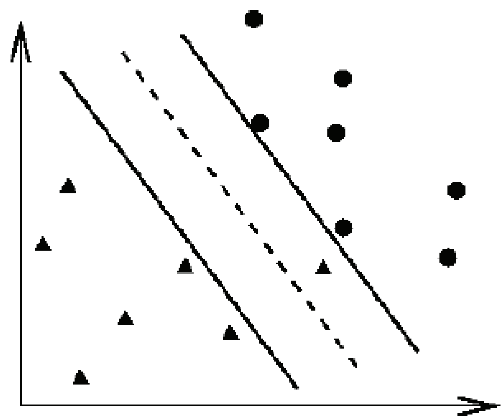

**Figure 5.1 (c): Training data and a better classifier.**

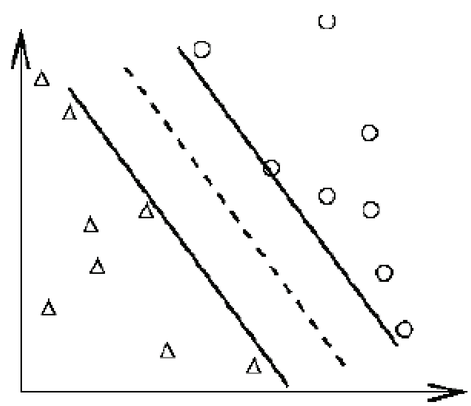

**Figure 5.1 (d): Applying a better classifier on testing data.**

Figure 5.1(a), (b), (c), (d): An over-fitting classifier and a better classifier (filled triangles and circles = training data; hollow triangles and circles = testing data) [120].

### 5.2.2 One-Class Support Vector Machine

A powerful extension of SVM to one-class problems is referred to as One-Class SVM (OC-SVM) [127]. The One-Class Support Vector Machine (OC-SVM) is a most popular method in anomaly detection. It is based on the kernel trick and standard SVM procedures. It uses a trade-off parameter that defines the ratio between the number of samples in data class and that of outlier class. The sensitivity of the trade-off parameter involved in the OC-SVM is investigated with respect to noisy mislabelled data, and some original modification of the method is proposed.

Binary classification Support Vector Machines (SVMs) have attracted much attention recently because of their excellent quality in various real-world applications [126]. Utilizing the kernel trick that is a method of converting a linear classification algorithm into a non-linear one by replacing a dot product in high dimensional feature space with kernels, SVM can find the maximum-margin hyperplane that separates two clouds of data points at equally located distances. SVM is reputed to achieve high performance, not suffering from the problem of dimensionality even when the number of training samples is small compared to the feature vector dimensionality. The great advantage of SVM is that the algorithm often does not suffer from over fitting and this enhances its generalization capability. In order to use kernels as dot product, note that the kernel function must be symmetric and positive semi-definite.

Using an appropriate kernel function, OC-SVM first maps the data points into a high dimensional feature space and then finds the hyperplane that separates, with maximum margin, the feature vectors from the origin of the transformed space.

Thus, the hyperplane (or linear decision boundary) corresponds to the classification rule:

$$f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b \tag{5.7}$$

Where w is the normal vector and is b a bias term. The OCSVM solves an optimization problem to find the rule *f* with maximal geometric margin. We can use this classification rule to assign a label to a test example

If $f$ (x) < 0 we label x as an anomaly, otherwise it is labelled normal. In practice there is a trade-off between maximizing the distance of the hyperplane from the origin and the number of training data points contained in the region separated from the origin by the hyperplane.

The kernel most commonly used in SVM and OC-SVM is the Gaussian radial basis function. The OC-SVM interprets the origin of the transformed feature space as the second class and feature vectors that are classified as belonging to the second class are regarded as outliers or anomalies. In risk management applications, OC-SVM is typically used for classification of anomalies and malfunctions occurring in nuclear components and systems from measured operational data [128].

In the quadratic programming formulation of OC-SVM, there is a parameter that controls a trade-off between maximizing the distance of the hyperplane from the origin, and containing most of the training samples in the domain created by the hyperplane.

Our research explores sensitivity investigations of this trade-off parameter involved in the OC-SVM against noisy mislabelled data since the parameter significantly influences the quality of classification. In addition, we propose some original modification of the method based on the sensitivity experiments.

## 5.3 Using LibSVM

LibSVM [120] is a well-known Support Vector Machine implementation. LibSVM is open source software implemented in C++, python and Java programming language. LibSVM is renowned with its execution efficiency and the precision of solving the SVM's optimization problem. LibSVM implements a sequential minimal optimization (SMO) algorithm [6] to solve the SVM's quadratic programming optimization problem. The SMO algorithm is an SVM scaling method for large scale data. The SVM's quadratic programming optimization problem requires $O(n2)$ memory space for $n$ instances of the training data. Hence solving the SVM problem by a normal quadratic programming solver is not applicable to large-scale data.

The SMO algorithm requires only a constant amount of memory which scales the SVM to large-scale data. Another advantage of the SMO is that the SMO solves an analytical problem rather than the numerical problems in traditional convex quadratic programming (QP) solvers.

Hence a numerical solver is not needed in SMO which prevents the potential precision problems. Solving the SVM problems by the SMO algorithm is usually more efficient than by QP solvers.

## 5.3.1 LIBSVM Commands

LibSVM is a command-line tool. In this section we describe the commands that were used in this research. Recall that in a typical machine learning experiment a file of labelled feature vectors is divided into two parts, a training set and a test set.

- Svm-scale

  C:\MATLABR2008a\softwrae\libsvm-2.9\tools>svm-scale

  Usage: svm-scale [options] data_filename

  options:

  -l lower : x scaling lower limit (default -1)

  -u upper : x scaling upper limit (default +1)

  -y y_lower y_upper : y scaling limits (default: no y scaling)

  -s save_filename : save scaling parameters to save_filename

  -r restore_filename : restore scaling parameters from restore_filename

  > svm-scale -s scaling_parameters train_data > scaled_train_data

  > svm-scale -r scaling_parameters test_data > scaled_test_data

- svm-train [options] trainingfile [model_file]

  C:\MATLABR2008a\softwrae\libsvm-2.9\tools>svm-train

  Usage: svm-train [options] training_set_file [model_file]

  options:

  -s svm_type : set type of SVM (default 0)

  0 -- C-SVC

  1 -- nu-SVC

  2 -- one-class SVM

3 -- epsilon-SVR

4 -- nu-SVR

-t kernel_type : set type of kernel function (default 2)

0 -- linear: u'*v

1 -- polynomial: (gamma*u'*v + coef0)^degree

2 -- radial basis function: exp(-gamma*|u-v|^2)

3 -- sigmoid: tanh(gamma*u'*v + coef0)

4 -- precomputed kernel (kernel values in training_set_file)

-d degree: set degree in kernel function (default 3)

-g gamma: set gamma in kernel function (default 1/num_features)

-r coef0: set coef0 in kernel function (default 0)

-c cost: set the parameter C of C-SVC, epsilon-SVR, and nu-SVR (default1)

-n nu: set the parameter nu of nu-SVC, one-class SVM, and nu-SVR (default 0.5)

-p epsilon: set the epsilon in loss function of epsilon-SVR (default 0.1)

-m cachesize: set cache memory size in MB (default 100)

-e epsilon: set tolerance of termination criterion (default 0.001)

-h shrinking: whether to use the shrinking heuristics, 0 or 1 (default 1)

-b probability estimates: whether to train a SVC or SVR model for probability estimates, 0 or 1 (default 0)

-wi weight: set the parameter C of class i to weight*C, for C-SVC (default1)

-v n: n-fold cross validation mode

-q: quiet mode (no outputs)

- svm-predict [options] test_file model_file output_file

  C:\MATLABR2008a\softwrae\libsvm-2.9\tools>svm-predict

  Usage: svm-predict [options] test_file model_file output_file

  options:

  -b probability_estimates: whether to predict probability estimates, 0 or 1 (default 0); for one-class SVM only 0 is supported

The above provided the research environment and tools for our study of use of SVM for the separate identification of normal and drowsy driver conditions.

## 5.4 Experimental result collection

One of the primary objectives of this project was to conduct driving simulator experiments in order to collect data on driver behaviour. This data is then used to develop detection models for driver drowsiness. This chapter describes the experiments conducted, data collected and statistical analysis of the data.

### 5.4.1 Data analysis

Before a drowsy driver detection system can be developed, the data from the experiments is analysed to identify the potential variables that are correlated with drowsiness. This section first reviews the characteristics of driver's drowsiness, the manner in which it could be identified, and how other factors such as fatigue can play a role in driving performance degradation. Data collected during experiments on drivers and their driving outcomes are then individually analysed.

The objective here is to identify variables correlated with driver drowsiness. Such variables can then be used either as input for a drowsy driver detection system or to detect drowsiness for the evaluation of the performance of such a system.

As shown in Figure 5.2, the model includes three phases. In the first phase it just classifies the driver as drowsy or not. In the second and third phase of the model, it also predicts the level of drowsiness.

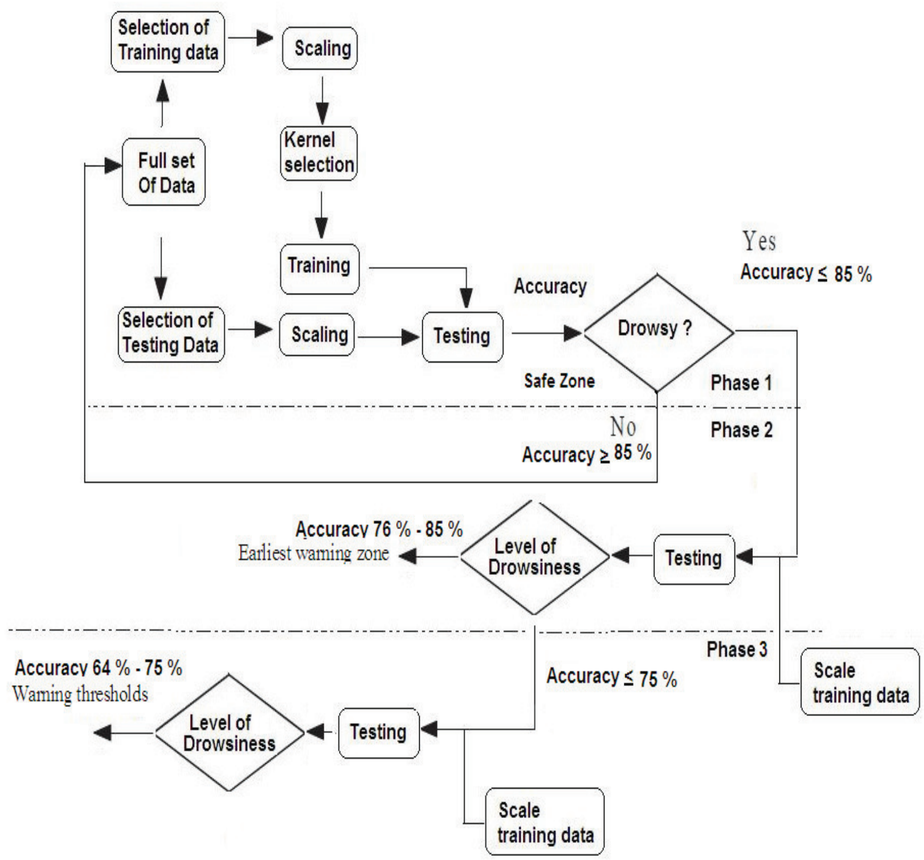


**Figure 5.2: A Flow Chart for One Class Support Vector Method.**

To demonstrate how all the attributes classify in the one class Support Vector Machine, we have carried out experiments on human behaviour driving using car simulation to collect several types of data such as distance to lane boundary (m), steering angle (deg) and car velocity (km/h). These datasets are compared with other researcher data to see if the collection has any similarity. All the datasets have been sampled and reviewed in order that only validate data is used as training and testing data.

This method combines the idea of reducing features as well as achieving high predictive accuracy.

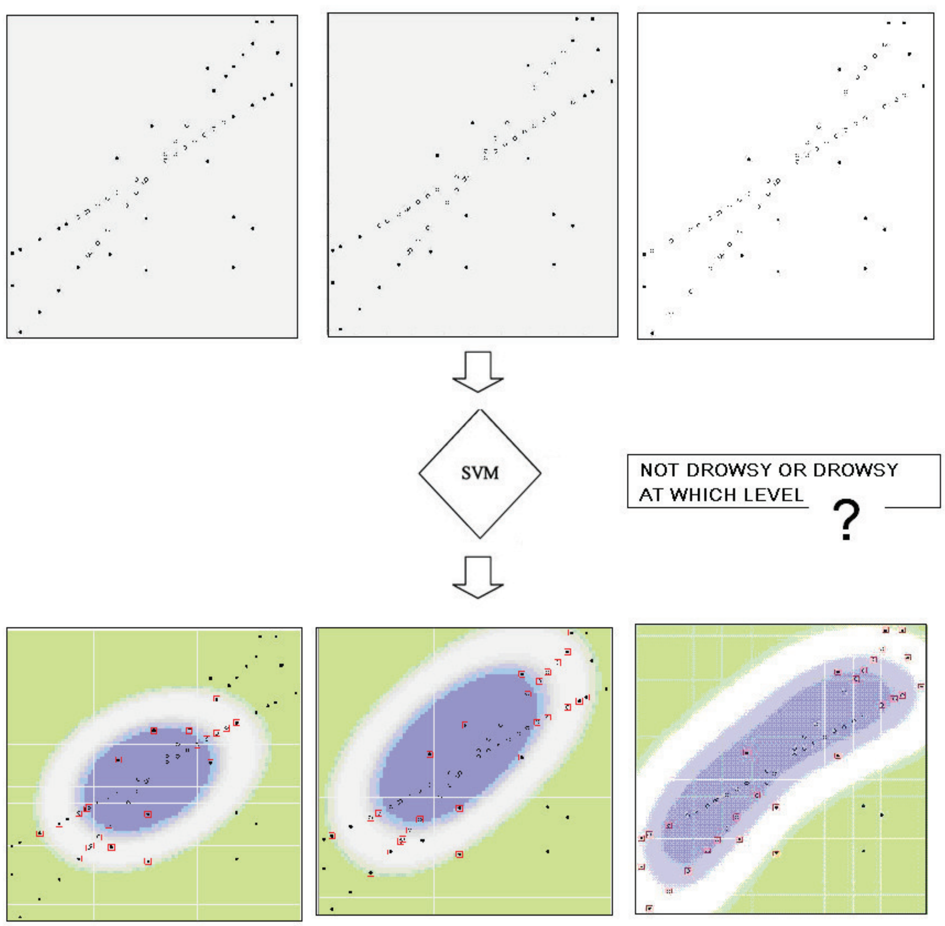


**Figure 5.3: The boundary expansion by employing SVM.**

By referring to the Figure 5.3, we can see how the process is implemented. As we know the standard SVM takes a set of input data and predicts, for each given input, which of two possible classes the input is a member of. We need to train the data in several trains in order to get the best fitting data for the training purposes. After we get the accurate training data we divide the training data to several levels that use to indicate the level of drowsiness.

In data classification training, the data that is collected from simulation experiment will be used as training and testing data set. We separated the source of data into 2 categories; day data and night data where the purpose is to investigate if the system has any different normal pattern and abnormal pattern.

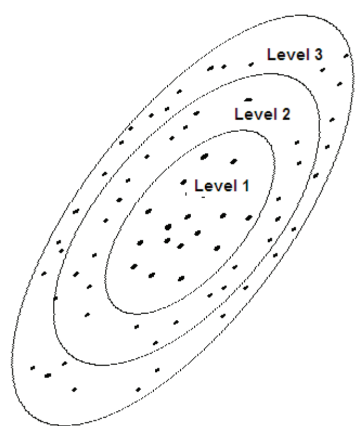


**Figure 5.4: The drowsiness level stage by implementing boundary control.**

The system will classify the level of drowsiness by employing boundary control. If the drowsiness level is increasing the boundary region will increase from say level 1 to level 2. We have set the level of drowsiness to 3 levels. The level will determine the drowsiness stage. This implementation is illustrated in Figure 5.4.

## 5.5 Data Feature

The dataset includes basic features of steering angle and distance to lane boundary. We train SVM by using a large number of data that contains this feature. We processed the source data and made them fit with the format of the SVM.

Randomly 60% of each data set was selected as test for training data. The other 40 % of data were training data. It shows good test results with very high average detection rates above 90%. Result of the accuracy of the training being calculated as mention in Figure 5.5, by taking correct position classification data divided by total data multiply with 100.

$$\text{Accuracy \%} = \frac{\text{Correctly Classified Data}}{\text{Total Data}} \times 100$$

**Figure 5.5: Accuracy calculation formula.**

## 5.6 Steering angle activity experiment results

These sections analyses the data that have been collected in order to classify the data to be used as criteria for training purposes. The steering angle activity experiment has been made to get an idea to differentiate the pattern of drowsiness and non-drowsiness driver.

### 5.6.1 Analysis on steering angle (deg) vs time (s)

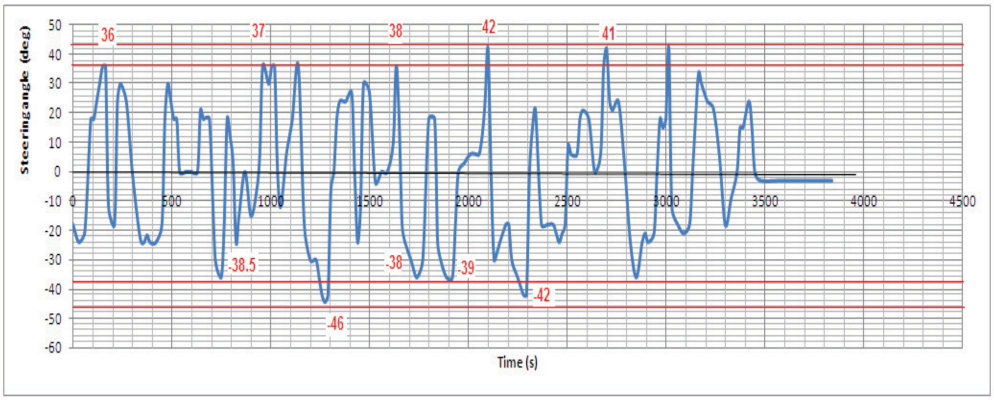


**Figure 5.6: Non-drowsiness data steering angle (deg) vs time (s)-driver 6.**

The result from Figure 5.6 is a sample taken from driver number 6, the graph shows the response at non-drowsiness time, steering angle (degree) versus time (s). Overall we can see that the maximum amplitude steering angle is around 36° to 42° and -38° to -46°. It was noticeable that the steering angle change is very active and represents regular correction of direction.

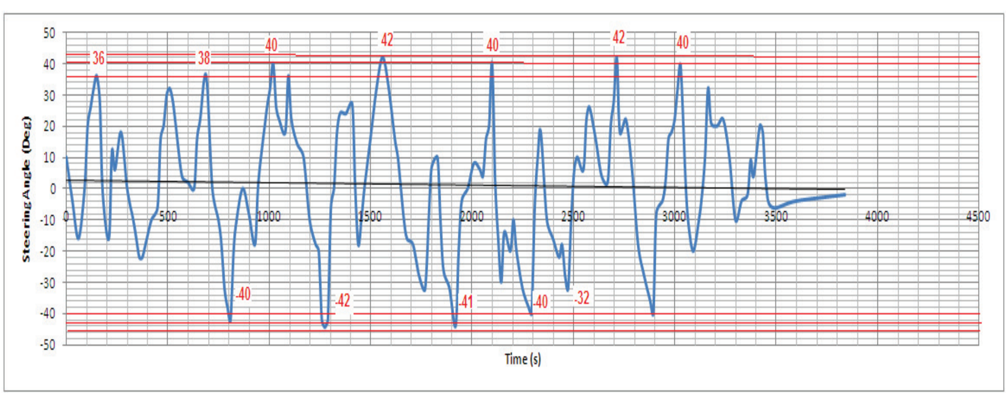


**Figure 5.7: Non-drowsiness data steering angle (deg) vs time (s)-driver 8.**

The result from Figure 5.7 is a sample taken from driver number 8, the graph shows the response at non-drowsiness time, steering angle (degree) versus time (s). Overall we can see that the maximum amplitude steering angle is around 36°

to 42° and -32° to -42°. It was noticeable that the steering angle change is very active and represents regular correction.

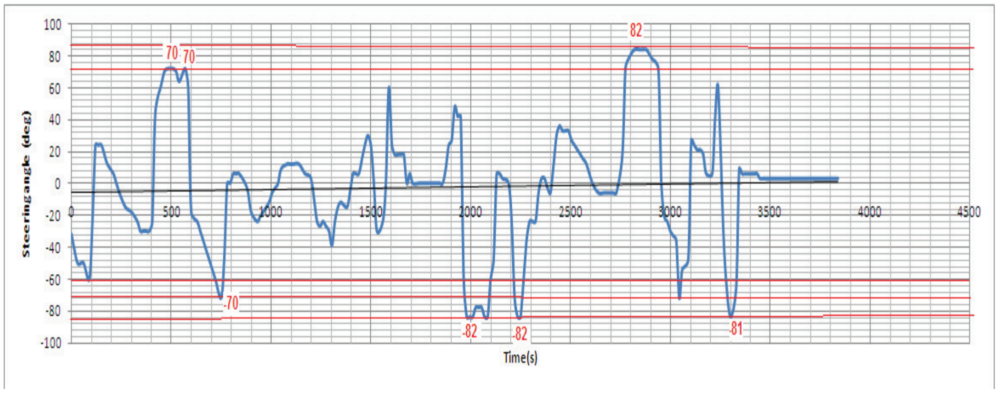


**Figure 5.8: Drowsiness data steering angle (deg) vs time (s)-driver 2.**

The result shown in Figure 5.8 is a sample taken from driver number 2, the graph shows the response at drowsiness time, steering angle (degree) versus time (s). Overall we can see that the maximum amplitude steering angle is around 70° to 82° and -70° to -82°. It was noticeable that the steering changes activity is very slowed and represented with high value of steering velocity frequently.

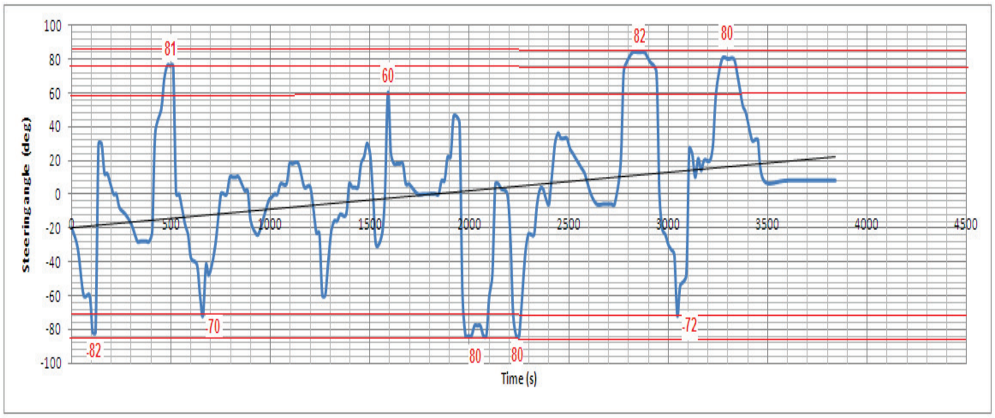


**Figure 5.9: Drowsiness data steering angle (deg) vs time (s)-driver 8.**

The result from Figure 5.9 is a sample taken from driver number 8, the graph shows the response at non-drowsiness time, steering angle in rad versus time. As overall we can see that the maximum amplitude steering angle is around 60° to 82° and -70° to -82°. It was noticeable that the steering activity is very slowed and replicated of very high steering velocity regularly.

After observing both results from the non-drowsiness and drowsiness graphs mentioned previously, we can see that the amplitude of the steering angle gave a significant indication of the current state of the driver condition. Most of the drowsiness data (amplitude) is larger than non-drowsiness time.

### 5.6.2 Analysis on steering angle and distance to lane boundary results

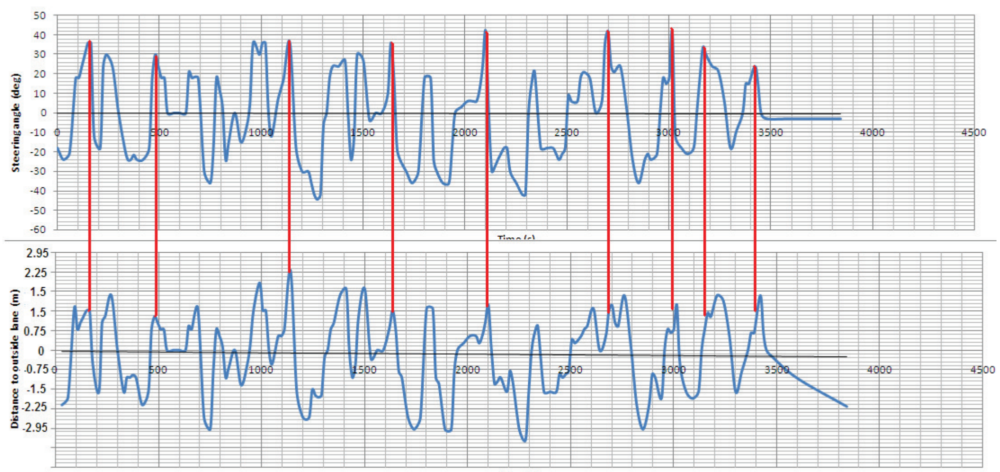


**Figure 5.10: Comparison between steering angles (deg) with distance to lane boundary (m).**

The data shown in Figure 5.10 are steering angle (deg) and distance to lane boundary (m), from the observation steering angle changes will influence the distance to lane boundary value proportionally. Generally, when the steering angle value is high, the distance to lane boundary will give a similar indication. We analyse the results plotted in Figure 5.6, Figure 5.7, Figure 5.8 and Figure 5.9. The steering angle movement is proportional to distance to lane boundary due to the constant speed of car movement. We can know if the car is drifting to the left or right and approaching the lane boundary for certain time period the level of driver alertness is also decreasing.

### 5.6.3 Analysis on steering angle activity experiment results

We have shown the results in the previous section as graphical plots against time. Whilst this allows us to see the dynamic nature of the changes it does not allow easy machine discrimination. If we plot steering angle versus distance to lane boundary we may be able to see a difference between drowsy and non-drowsy patterns.

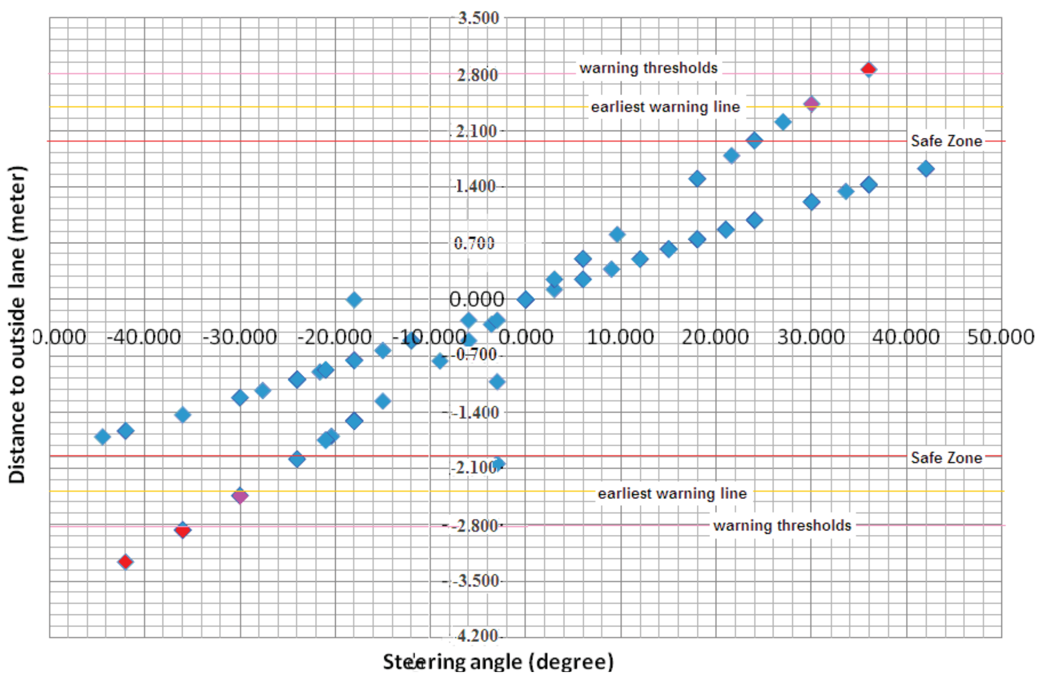


**Figure 5.11: Non-drowsiness steering angle (deg) vs distance to lane boundary(m) before scaling.**

The distance to lane boundary has been categorised with three levels as driving indicators which consists of safe zone, earliest warning zone and warning thresholds.

Observation from Figure 5.11, shows most of the data collected during non-drowsiness time is in a safe zone marked by the red line on the graph. The classification design will be based on these parameters in order to get a good prediction result.

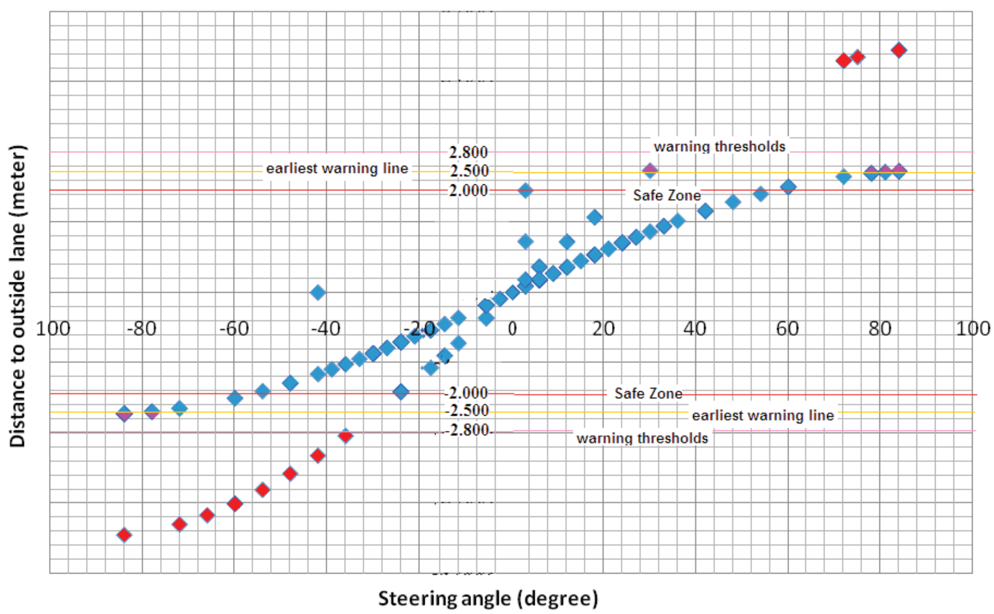


**Figure 5.12: Drowsiness steering angle (deg) vs distance to lane boundary(m) before scaling.**

Observation from Figure 5.12 shows most of the data collected during drowsiness time is out of the safe zone.

### 5.6.4 Analysis on steering angle versus distance to lane boundary results

We will now take the same sets of results and consider bounds for the steering angle which will be plotted on the graph.

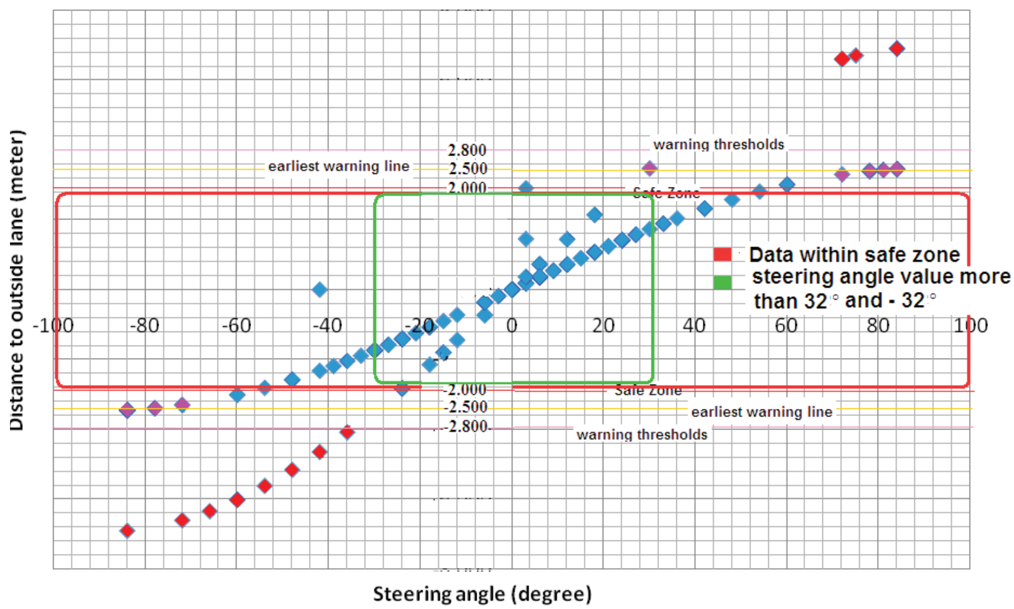


**Figure 5.13: Illustration the discriminate data more than 32° and -32°.**

It is postulated that a high value of steering angle will influence the value of the distance to lane boundary. From the observation, we will discriminate the data outside the safe zone as in Figure 5.13. Furthermore, the amplitude of the steering angle also has to be considered as an input to the drowsiness factor contribution. After consideration of the experiment data we consider to eliminate steering angle data that have a value more than 32° and -32°, due to the level 1 classification area.

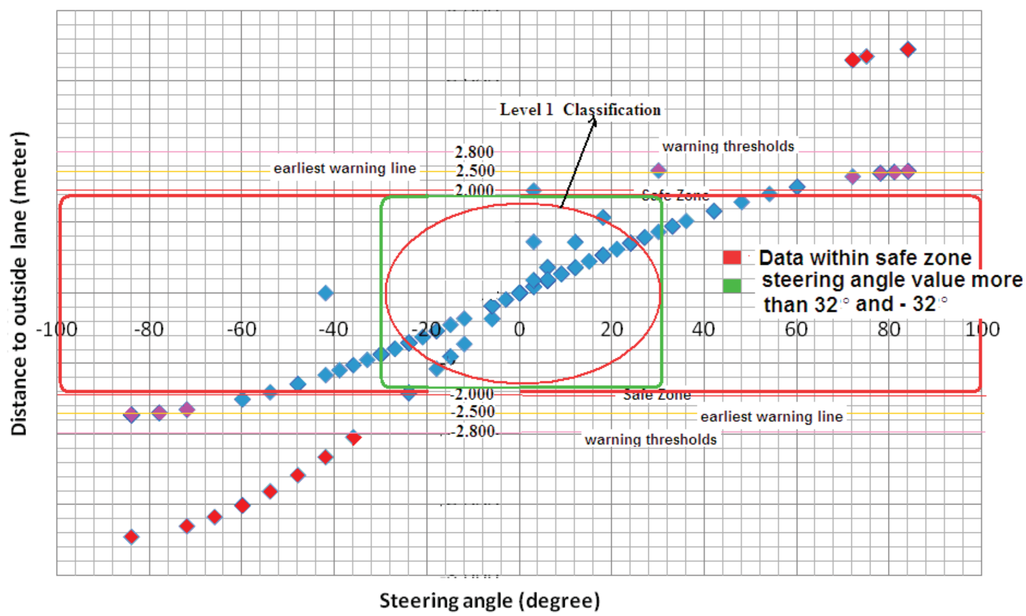


**Figure 5.14: Drowsiness stage on level 1.**

By using the radial basis function [RBF], we aim to model the output of the training data to classify the data that lies within the level 1 boundary in order to distinguish the alertness level of the driver. In this classification, we consider the distance to lane boundary that lies between 0.0 m - 2.0 m value (that being categorised as the safe zone). The idea was illustrated in Figure 5.14.

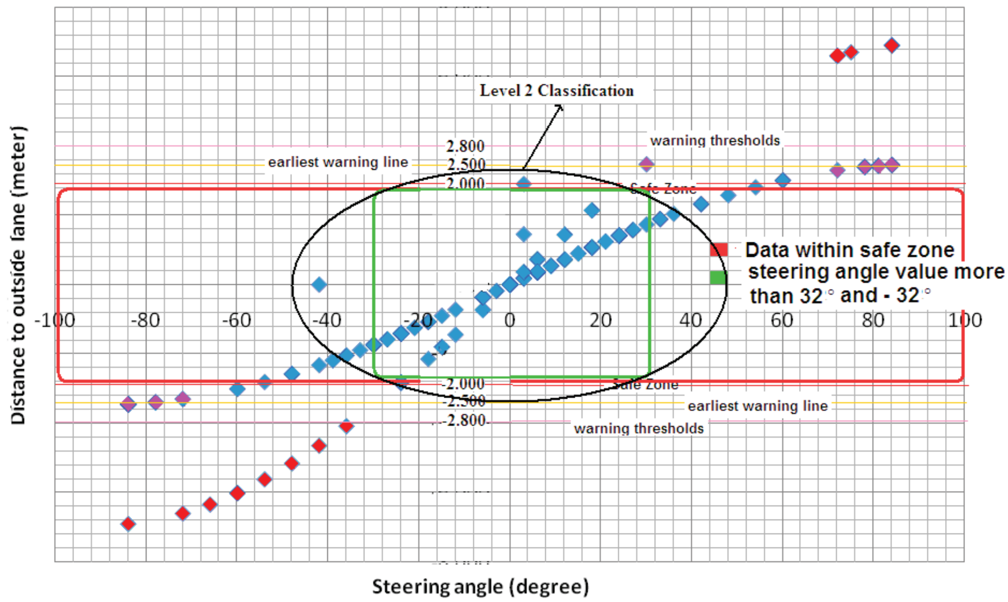


**Figure 5.15: Drowsiness stage on level 2.**

Using the RBF function we model the output of the training to classify the data within the level 2 boundary in order to distinguish the alertness level of the driver. In this classification we consider the distance to lane boundary that lies between 2.0 m to 2.5 m value (that being categories as earliest warning zone). The idea is illustrated in Figure 5.15.

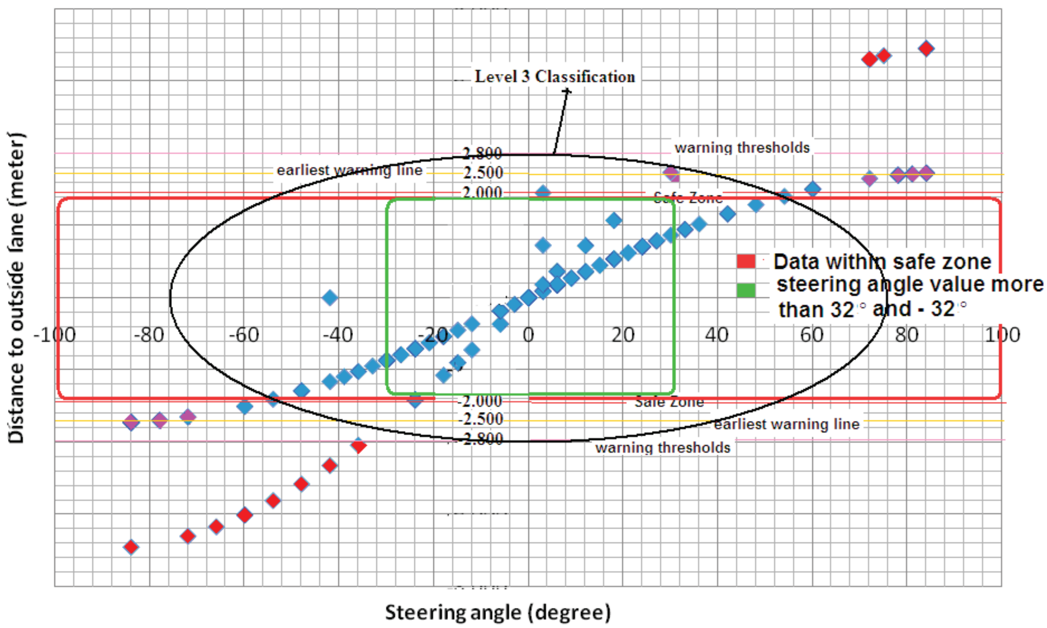


**Figure 5.16: Drowsiness stage on level 3.**

By using RBF function we model the output of the training to classify the data within the level 3 boundary in order to identify the alertness level of the driver. In this classification we consider the distance to lane boundary that lies between 2.5 m to 2.8 m value (that being categorised as warning thresholds). The idea is illustrated in Figure 5.16.

### 5.6.5 Analysis on steering angular velocity activity experiment results

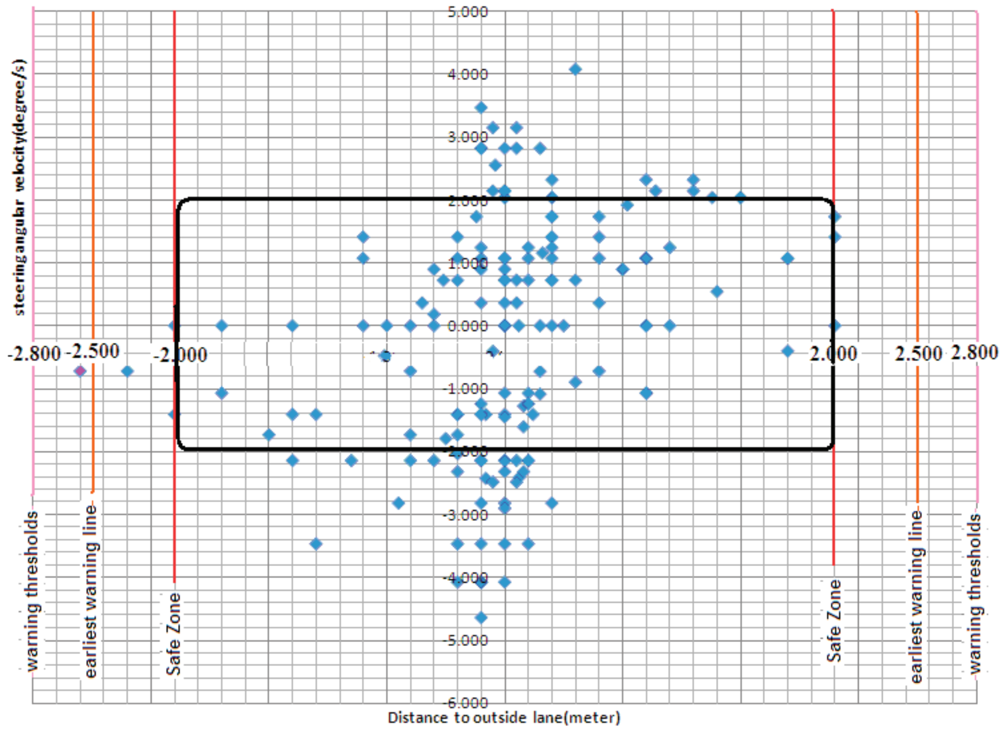


**Figure 5.17: Non-drowsiness steering angular velocity (deg/s) vs distance to lane boundary (meter)**

A very high value of steering angular velocity will reflect the movement of the vehicle if the vehicle is traveling at high velocity. Figure 5.17 shows that most of the data are located at region +2(deg/s) and -2(deg/s) during the non-drowsiness data collection period.

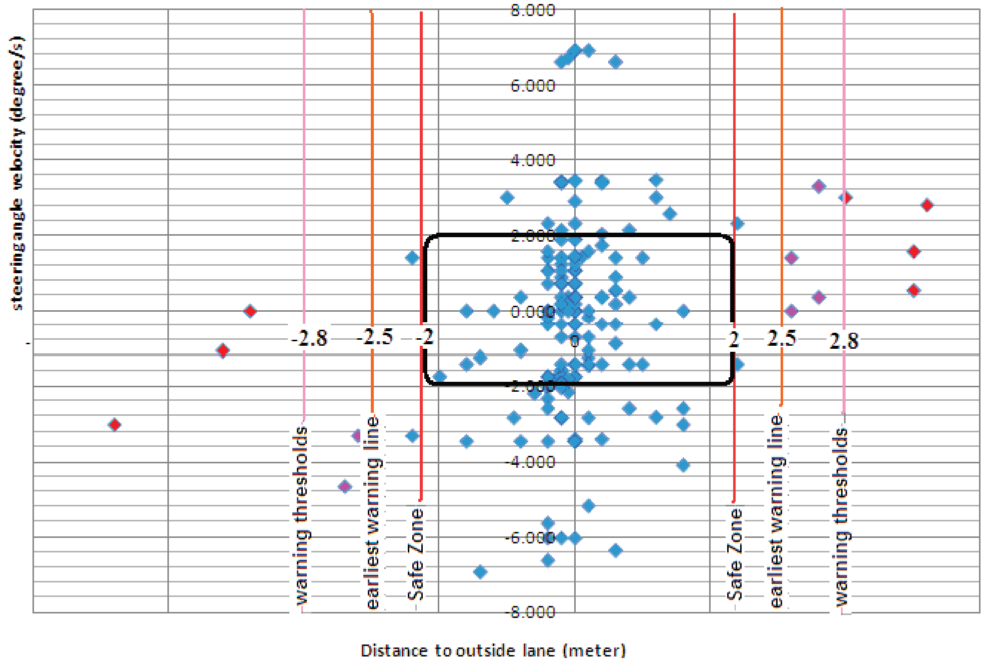


**Figure 5.18: Drowsiness steering angular velocity (deg/s) vs. distance to lane boundary (meter).**

Figure 5.18 shows the results for data collected during the drowsiness stage, the data is mainly located outside of the region of +2(deg/s) and -2(deg/s) for the steering angular velocity.

### 5.6.6 Analysis on steering angular velocity and distance to lane boundary results

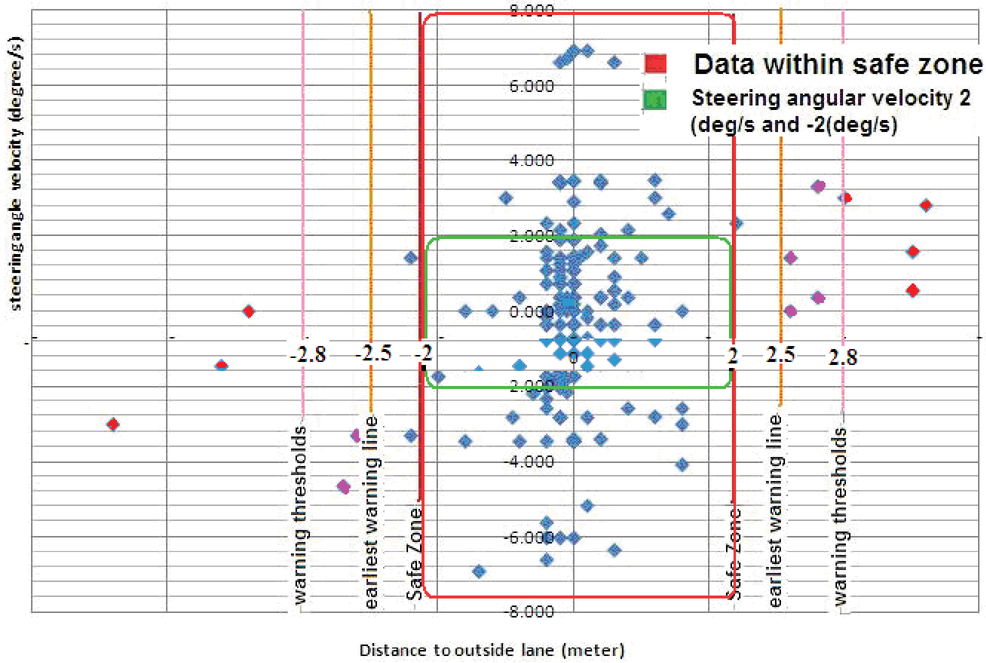


**Figure 5.19: Data discrimination for distance to lane boundary & steering angle velocity.**

After considering several results we were able to discriminate data beyond the safe zone due to the fact that the car is drifting near to the outside of the road lane. As discussed at previous section we decided to eliminate data beyond +2 (deg/s) and -2 (deg/s) as shown in Figure 5.19 due to the location of lane boundary safe zone.

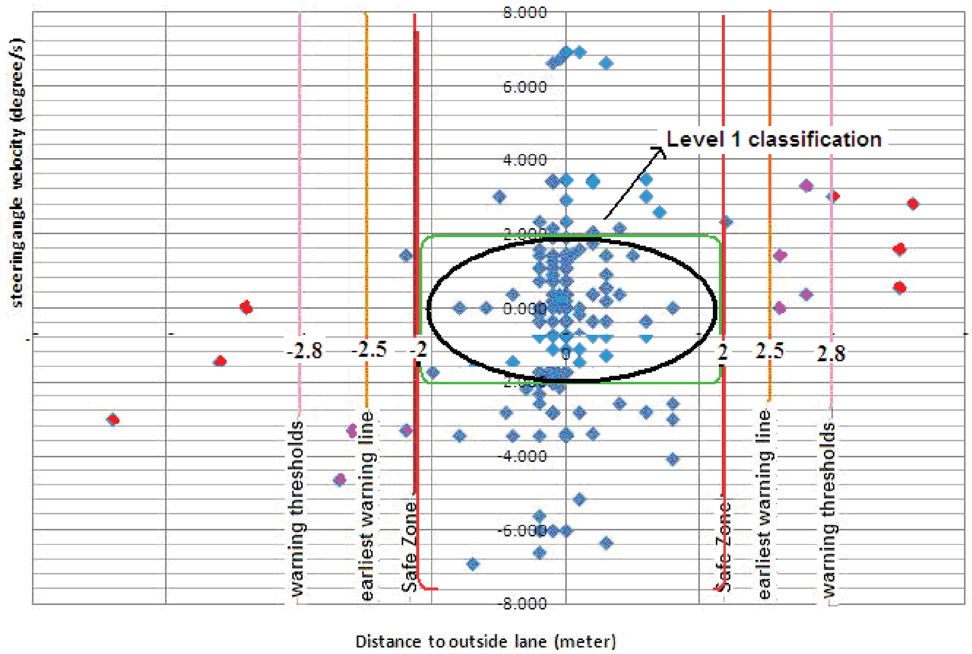


**Figure 5.20: Drowsiness stage on level 1.**

Level 1 classification concerns the data within the safe zone area. The idea is to classify the drowsiness state at safe zone operating mode. The idea illustrated in Figure 5.20.

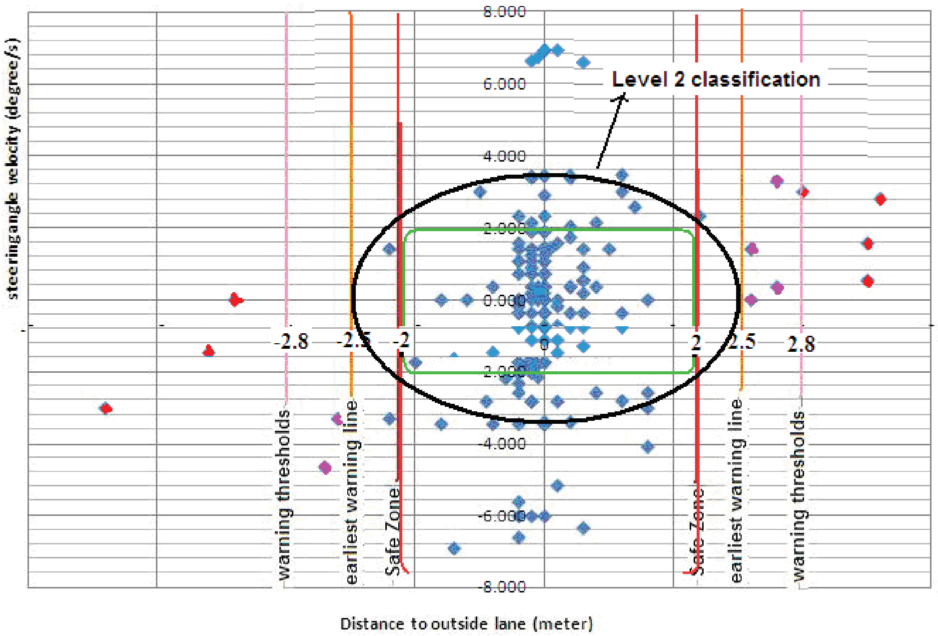


**Figure 5.21: Drowsiness stage on level 2.**

Level 2 classifications consider data within the earliest warning zone. The idea is to classify the area that represents the drowsiness state that is related to early detection mode. The idea is illustrated in Figure 5.21.

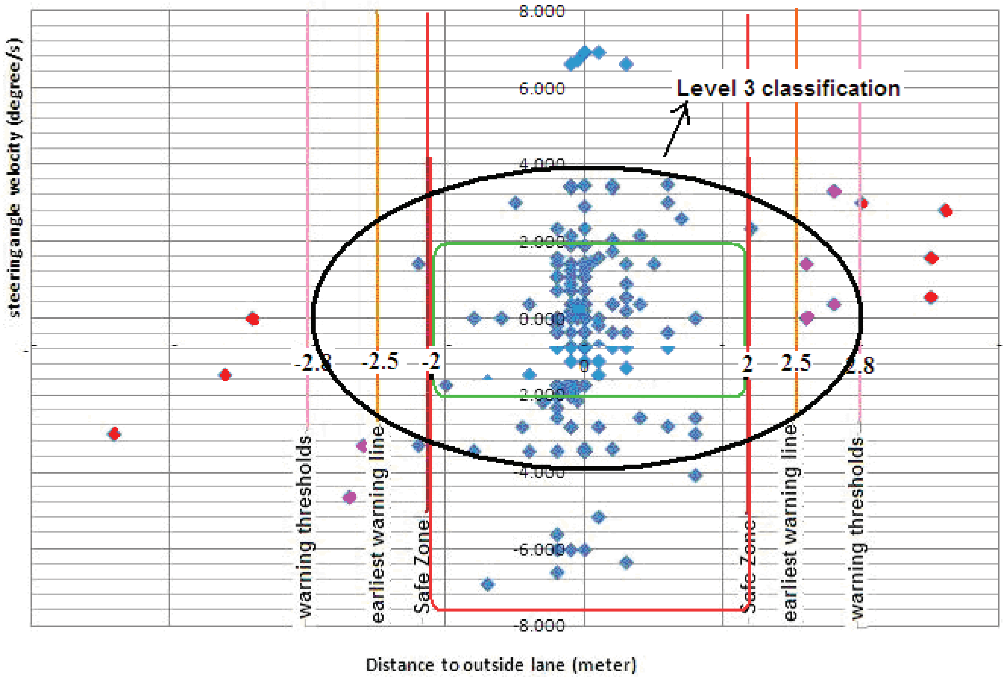


**Figure 5.22: Drowsiness stage on level 3.**

Level 3 classifications consider the data within the warning zone. The idea is to classify the drowsiness state associated with the warning mode. The idea is illustrated in Figure 5.22.

## 5.7 SVM experiment results

The SVM model (classifier) we constructed in this thesis has been trained with several attributes, and then it has been used to detect the driver's condition with the validation dataset. A set of experiments was conducted using different kernels to identify the best one for our application. From these experiments the RBF kernel function was selected. In order to determine the parameters *C* and gamma to get the highest predictive accuracy, a five-fold cross-validation is done with LibSVM. After conducting the grid search on the training data, the optimal (*C*,gamma) is (0.03125, 0.0078125) with a cross-validated accuracy of 92.4%.

The data was further normalized before being used for SVM training. The normalization data is shown in Figure 5.23 and Figure 5.24 where both un-normalized and normalized data is used for testing the classifier.

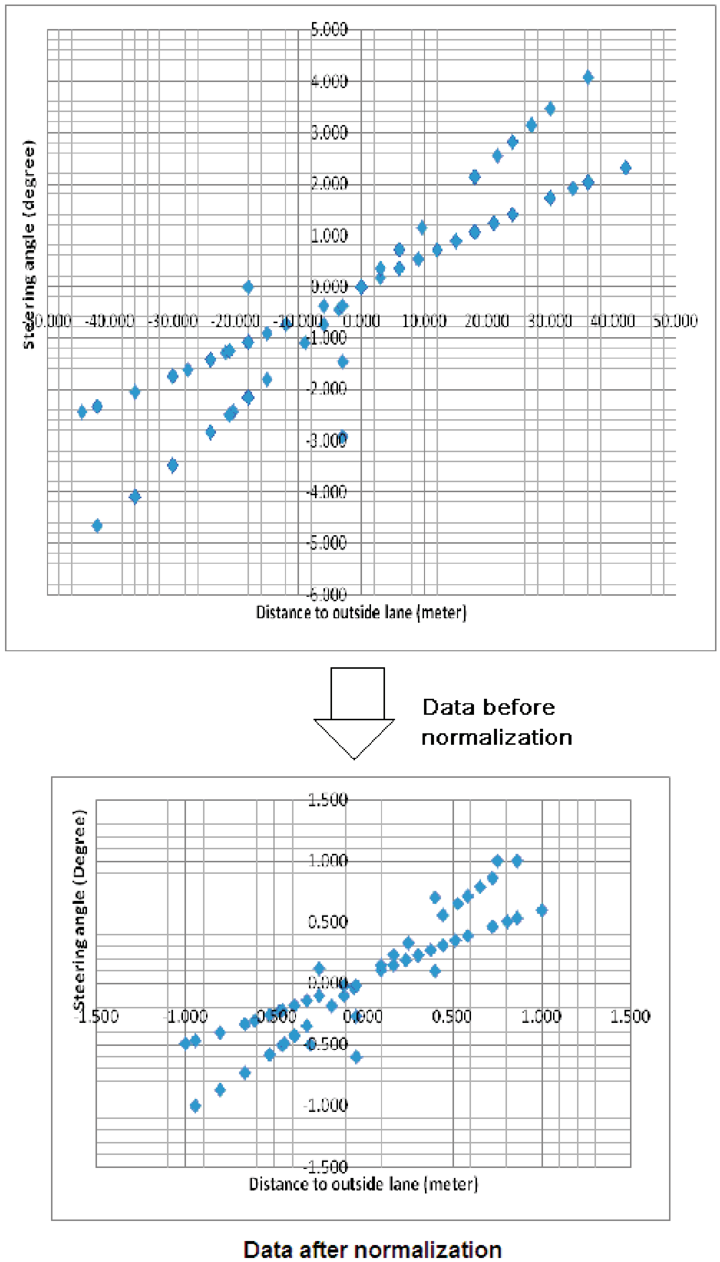


**Figure 5.23: Data representation before and after training (set 1).**

In set 1 we pick distances to boundary lane and steering angle (deg) as training and testing data.

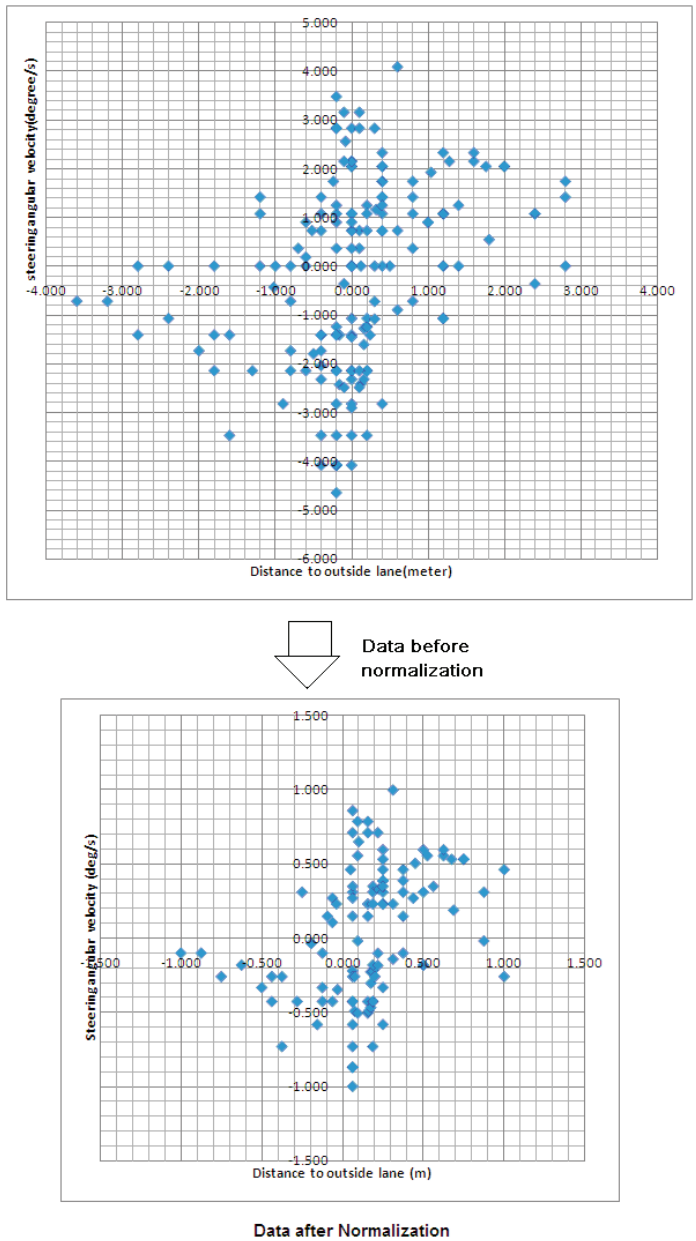


**Figure 5.24: Data representation before and after training (set 2).**

In set 2 we pick distances to boundary lane and steering angle (deg/s) as training and testing data.

**Table 5.1: Kernel types that were employed while training using SVM.**

| Kernels | Formula |
|---|---|
| linear | $k(x, y) = x.y$ |
| sigmoid | $k(x, y) = \tanh(ax.y + b)$ |
| polynomial | $k(x, y) = (1 + x.y)^d$ |
| RBF | $k(x, y) = \exp(-a\|x - y\|^2)$ |
| exponential RBF | $k(x, y) = \exp(-a\|x - y\|)$ |

In the training and testing data we use only RBF kernel, table of kernel can be viewed in Table 5.1.

**Table 5.2: Testing different kernel functions.**

| Kernel | Accuracy w/o normalization (%) | Accuracy with normalization (%) |
|---|---|---|
| LINEAR | 10% | 12% |
| POLY | 50% | 55% |
| RBF | 85% | 92.4% |

The parameters in Table 5.2 are of different types and can take very different values. To make the discriminators suitable to the SVM algorithm, these parameters are pre-treated using the normalization technique so that they are all distributed in the same value range between 0 and 1. Normally accuracy can be improved 7%-10% by normalization with best c and gamma.

To evaluate the effects of the kernel functions, three commonly used kernel functions LINEAR, POLY, RBF were used.

The data were selected from several drivers and all features were used for the discriminators to help the SVM method evaluate their classification accuracy.

## 5.8 Analysis on Set 1 by using SVM

The following results show the evaluation of our data using the SVM with RBF kernel. For these we are looking to see if the steering angle is a useful measure for detecting drowsiness. In Figure 5.25 below shows output result after we trained the distances to boundary lane and steering angle (deg).

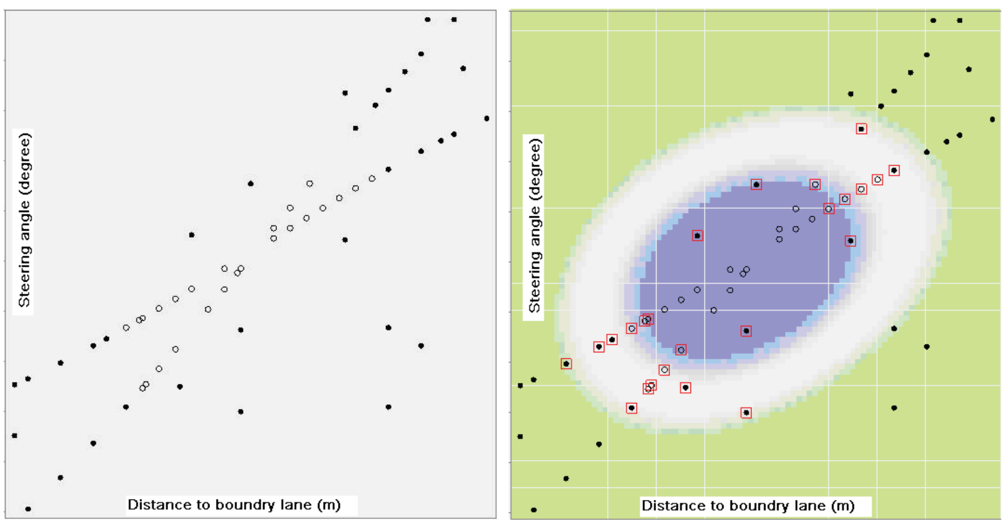


**Figure 5.25: Data classification training for level 1.**

It contains the attributes of distance to lane boundary and steering angle. We train this model using RBF model to classify data within safe zone area only.

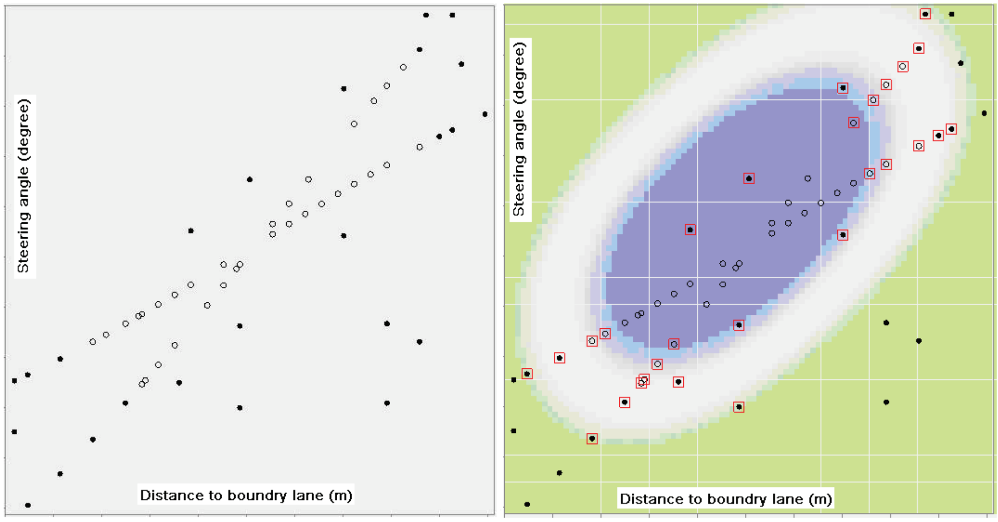


**Figure 5.26: Data classification training for level 2.**

Figure 5.26 shows the result before and after training classification for drowsiness level 2. It contains the attributes of distance to lane boundary and steering angle. We trained this using RBF model to classify data within earliest warning zone area only.

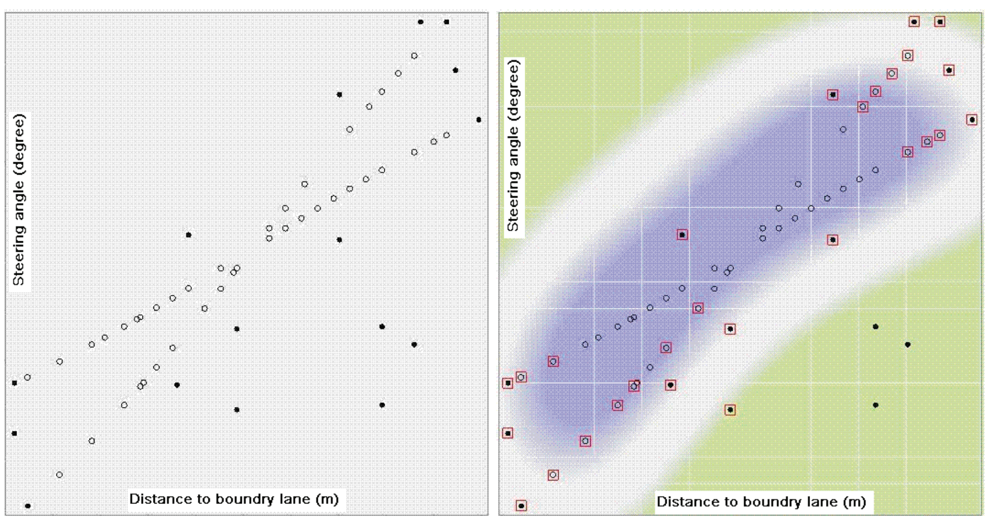


**Figure 5.27: Data classification training for level 3.**

Figure 5.27 shows the result before and after training classification for drowsiness level 3. It contains the attributes of distance to lane boundary and steering angle. We trained this using RBF model to classify data within warning thresholds area only.

Overall we can see that by classifying the data using the one class Support Vector Machine it can discriminate the data easily by employing the RBF kernel method by controlling the margin and the boundary of the system.

## 5.9 Analysis on Set 2 by using SVM

We used the same experimental setup as above, but this time we measured steering angle velocity – the speed with which the driver turns the wheel, as a potential predictor of drowsiness.

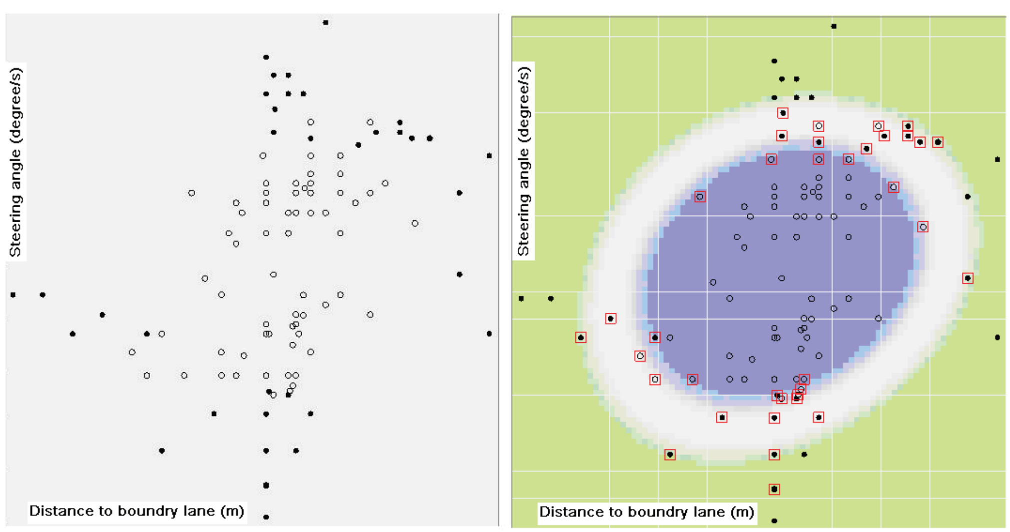


**Figure 5.28: Data classification training for level 1.**

Figure 5.28 shows the result before and after training and classification for drowsiness level 1. It contains the attributes of distance to lane boundary and steering angular velocity were used to train this using RBF model to classify data within safe zone area only.

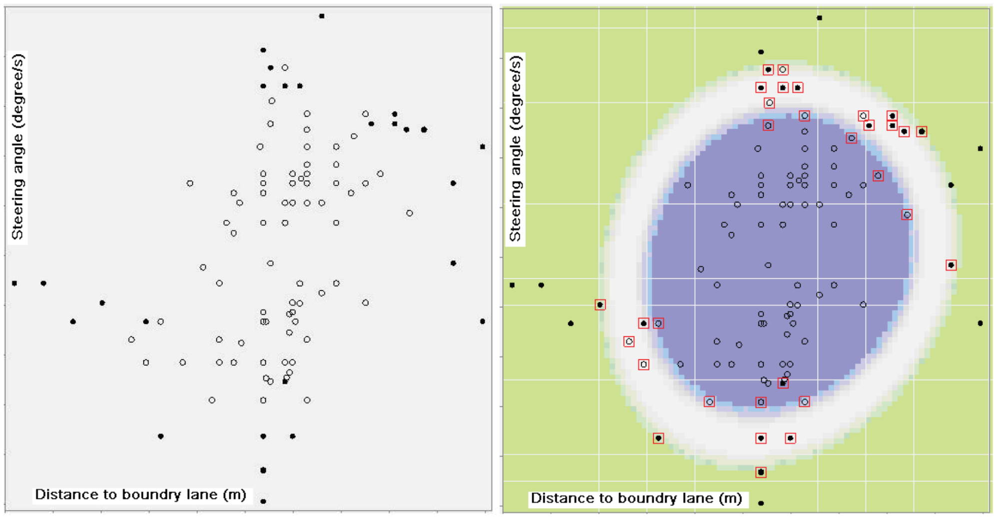


**Figure 5.29: Data classification training for level 2.**

Figure 5.29 shows the result before and after training classification for drowsiness level 2. It contains the attributes of distance to lane boundary and steering angular velocity which were used to train this using RBF model to classify data within earliest warning zone area only.

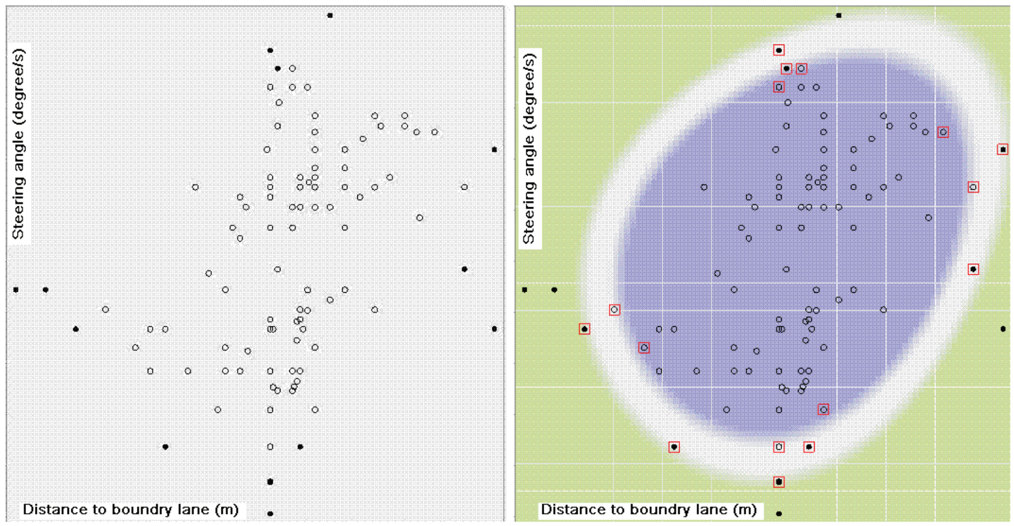


**Figure 5.30: Data classification training for level 3.**

Figure 5.30 shows the result before and after training classification for drowsiness level 3. It contains the attributes of distance to lane boundary and steering angle was used to train this using RBF model to classify data within warning thresholds area only.

By classifying the data using the one class Support Vector Machine, the results of these experiments have clearly shown that the model can discriminate the data easily by employing the RBF kernel method in identifying the margins and the boundaries of the system for various levels of awareness.

# Chapter 6

# Conclusions and future work

Recall from Chapter 3 or the drowsiness system model development. That integrated the drowsiness development system by employing one class support system classification. As mentioned before training and testing of the SVM classification, the data from simulated driving experiments were split into a training set and a testing set, each containing a mixture of 'drowsy' and 'non-drowsy'. Three main attributes of steering angle distance to lane boundary and steering angle velocity being used to train and test the system. OC-SVM system achieved a classification accuracy of 90%, this means that the distinguishing criterion used for training the SVM program could successfully enable it to identify and differentiate between 'drowsy' and 'non drowsy' accurately. The differentiator system really helped the SVM system to work more accurately in the way to classify the drowsiness to specific level.

## 6.1 Summary and conclusions

Chapter 5 demonstrates the effectiveness of the chosen classification system. This part of the study has shown that the early detection of drowsiness leading to the onset of sleep in automobile drivers could be reliably detected by changes in steering angle activity and distance to lane boundary. By referring to the Figure 6.1 we can see the capability of Support Vector Machine (SVM) as a classification tool to control the boundary of the data that tabulated in 2 dimensional (X and Y coordinate).

The steering wheel angle and distance to lane boundary extracted from the driving simulator contains a substantial amount of information about the driver's drowsiness state. By employing the Support Vector Machine the algorithm for drowsiness detection which is based on the incorporation of a road vision system and vehicle performance parameters is performing accurately in detecting the drowsiness. It manages to detect drowsiness at recognition rate of 90%, which is a very high value.

By using different drivers with various conditions in order to build the system which is a robust system and an accurate drowsiness warning system by incorporation of data from the road vision and data logger to provide an efficient method for detecting drowsiness under varying modes and road conditions. A strategy which employed a fault diagnosis technique integrates information from trained classifiers which are used to improve accuracy and reliability.

The improvement of one class Support Vector Machine (OCSVM) system by employing the classification capable to differentiate it into several level of drowsiness. By refining the algorithm to precisely detects the level of drowsiness as illustrated in Chapter 5.

A method of optimizing parameters using the one class Support Vector Machine has been implemented and has proven to work well. Several different driving strategies have been tried in the optimization of the design system. The approach has simulated two modes day and night. An algorithm based on these functions derived from the steering wheel motion is developed to detect the driver condition.

## 6.2 Future work

Future investigation should enhance detection of drowsiness by refining the feature sets with information of steering wheel acceleration, time to lane crossing and pedal movement activity. In addition, performing separate drowsiness prediction models for various driving tasks, geometrical road characteristics and environmental circumstances (e.g. speed, crosswind, road curvature, or lane width) might enhance the comprehensive drowsiness prediction precision. Further work will consider as comparing with other techniques or combined with SVM model.

Another encouraging rectification could be realized by using driver state data such as personal driving performance for the individual of the prediction models. Moreover, considering various driver conditions could be useful, especially when every driver will drive differently, it is likely that there will be a variance in drowsiness steering patterns.

When joining together a low activity state such as drowsiness with high activity, the typical drowsiness driving behaviour might be discovered. To handle this, system modelling verification is necessary. In that situation, it is essential to feed the system with sufficient learning data.

We believe we have identified a system which overcomes all of the shortcomings and difficulties of previous systems. It is non-intrusive, can be built into current vehicles with little change to vehicle technology and at low cost, it is reliable with low levels of false alarms, it automatically adapts to different drivers and driving techniques.

The potential in saving life, injury and cost due to accidents is huge. Clearly some further work is necessary before commercial exploitation, but after forty years of work by many people we feel that a solution is now imminent.

The drowsiness detection by using OCSVM will be enhanced if considering other inputs as the attributes to the SVM system. It was mentioned at the beginning of the thesis where velocity also gave an important impact on the detection.

To consider the velocity, the researchers think several other elements have to be considered due to its correlation with other parameters. The parameters that govern the velocity are heading view, road view, braking, acceleration, environment noise and etc. The road curvature is also play an important factor for the velocity to work well when we want to train the system.

The complete OCSVM system development will have two inputs that called:

- Longitudinal (move forward)
- Lateral (direction control)

It can be used in the future work if the system integrated with satellite navigation system that provides the road system database.

One of the most important aspects of a computational study is its practical usefulness. In other words, how the study can be used by other engineers and researchers. This study can be helpful in many ways. First, it can be used as a basis for future studies of drowsiness detection concepts applied to the driver vehicle behaviour. This study may be referenced to show that classification can be generated by setting up the Support Vector Machine using the RBF kernel.

Further, this research can be used as a preliminary study for the development of a new drowsiness testing procedure. By expanding the idea using the satellite navigation application to do online training system that can be used to generate automatic alertness detection using from the training data from current driver data.

By implementing this concept along with a feedback correction system controller, an automated guidance can be developed to make driving environment more efficient, accurate and finally hope to reduce road accidents.

Simulation such as those presented in this thesis can be used as a tool to perform comparison tests on different vehicle specifications to determine the effects of changing a certain parameter on the drowsiness detection system.

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