

CRANFIELD UNIVERSITY

ZHAOZHONG ZHANG

Driver Distraction Detection Using Experimental Methods and
Machine Learning Algorithms

SCHOOL OF AEROSPACE, TRANSPORT AND
MANUFACTURING
Ph.D. in Transport Systems

PhD

Academic Year: November 2015 – February 2020

Supervisors: Dr. Efstathios Velenis, Dr. Abbas Fotouhi
Associate Supervisor: Dr. Daniel Auger
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This thesis is submitted in partial fulfilment of the requirements for
the degree of Doctor of Philosophy
***(NB. This section can be removed if the award of the degree is
based solely on examination of the thesis)***

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ABSTRACT

Driver distraction causes numerous road accidents, which is approximately equal to 25% of the total crashes according to the reports by the National Highway Traffic Safety Administration. Warnings can be helpful to mitigate the risks caused by driver distraction. Previous studies on driver distraction detection have not sufficiently found relevant input features to filter insignificant information, thus limiting the improvement of efficiency. Moreover, the disadvantages of driving simulators and public roads pose a challenge in collecting suitable data for feature identification and comparisons of performance among driver distraction detection algorithms. While the previous research focuses on improving prediction accuracy, shortening the prediction time is critical in giving timely warnings to drivers.

This thesis aims at detecting driver distraction, which could provide faster and accurate warnings to drivers. The developed method is implemented by cutting the redundancy and irrelevant information fed to the algorithms and instead selecting suitable algorithms that achieve the balance between the prediction accuracy and prediction time. Moreover, a closed testing field supplies an environment for collecting more accurate information to identify the relevant features and to determine suitable algorithms.

In this study, open-source data and experimental data are used. The results show that a balance between the prediction accuracy and the prediction time is achieved by feeding the relevant features and using suitable machine learning algorithms (e.g. Decision Tree). Compared with existing state-of-the-art methods, the prediction accuracy of the

method proposed in this study has reached approximately the same level. More importantly, the efficiency has improved, including reduced prediction time and fewer input features. Consequently, less computer storage is used.

Keywords: Driver Distraction, Data Visualisation, Decision Tree, Logistic Regression, Machine Learning, Relevancy Analysis, Visual Inspection.

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LIST OF ABBREVIATIONS

APP	Application
CAN	Controller Area Network
CART	Classification and Regression Tree
DT	Decision Tree
DfT	Department of Transport
ECG	Electrocardiography
EDA	Electrodermal Activity
GPS	Global Positioning System
IVIS	In-Vehicle Infotainment System
KNN	K-Nearest Neighbours
LR	Logistic Regression
ML	Machine Learning
MUEAVI	Multi-User Environment for Autonomous Vehicle Innovation
Max	Maximum
Min	Minimum
Std	Standard Deviation
NHTSA	National Highway Traffic Safety Administration
RPM	Revolution Per Minute
Satnav	Satellite Navigation
SVM	Support Vector Machine
5G	Fifth Generation Technology Standard for Broadband Cellular Networks

Nomenclature

G_x	Gaze in x direction
G_y	Gaze in y direction
H_x	Head movement in x direction
H_y	Head movement in y direction
V	Velocity of Vehicle
$\delta_{steering}$	Steering angle
δ_{LD}	Lane Deviation
δ_{LP}	Lane Position
Acc	Percentage of acceleration pedal opening
$F_{braking}$	Braking Force of Braking Pedal
t_p	Prediction Time using a developed algorithm
t_{TW}	Length of a TW
TW	Time Window
$Accuracy$	Detection/Prediction Accuracy of an Algorithm
O	Time Complexity

1 Introduction

1.1 Background

The modern automobile was invented 134 years ago [1], and it has since become the main tool for road transportation. By the end of 2019, the UK had 38.4 million licensed vehicles [2]. The average family had 1.2 cars, and every driver made 1.1 journeys and drove a car for 23.2 minutes a day [3], [4]. While automobiles bring convenience to people's lives and improve their quality of life, they also bring serious problems. According to the Department for Transport (DfT) report in 2019, 1,752 people died, and 25,954 people were seriously injured due to traffic accidents [5].

Among the multitude reasons that cause road accidents, driver distraction is one of the leading causes. According to the National Highway Traffic Safety Administration (NHTSA), driver distraction directly contributes to 25% of the total crashes. The NHTSA also reports that 78% of the recorded crashes and 65% of the near-crashes are indirectly related to driver distraction [6]. Moreover, as reported by the statistics from the DfT in the UK [5], a total of 493 crashes have been caused by driver distraction out of 1,456 crashes, which equals to 33% of all recorded crashes. In a survey conducted in the same country, one in six drivers were found to be involved in certain types of distraction during driving, including talking to a passenger or using a mobile phone. Additionally, in the interviews after the crashes, from the retrospective view, the drivers interviewed typically described themselves as not having focused on driving and having had their minds diverted elsewhere. The crash figures from the NHTSA and other sources prove that driver distraction is common among drivers and is a major cause of crashes and accidents [6].

Given the dangers posed by driver distraction, mitigating such risks is essential to driving safety. Furthermore, improving the safety performance of automobiles is one of the long-term goals of automotive technology development. The rapid advances in technology are represented by the fast development of electrical, connected and automated vehicles. In recent years, the goal for developing

autonomous vehicles is to make the vehicle drive by itself, which can solve the problem of traffic accidents caused by driver distraction. However, the development of fully autonomous vehicles could take decades. In the near future, most autonomous vehicles will need to have a certain level of human intervention during driving until full automation is achieved [7].

Autonomous vehicles have six levels of automation ranging from level 0 to level 5. Level 0 of automation indicates that the driver has full control of the vehicle's operation and driving is not assisted by any systems. Level 1 of automation has intelligent systems to assist driving in one moving direction, such as ABS or cruise control. Vehicles in Level 2 automation have intelligent systems to control the vehicles' movement in both longitudinal and lateral directions. However, these vehicles still need the driver's supervision. In Level 3 automation, the vehicle is capable of driving itself. However, it requires the driver's intervention when indicated by the system. Level 4 automation refers to fully autonomous driving in certain situations but not all. Level 5 automation refers to fully autonomous driving in every situation at all times [8].

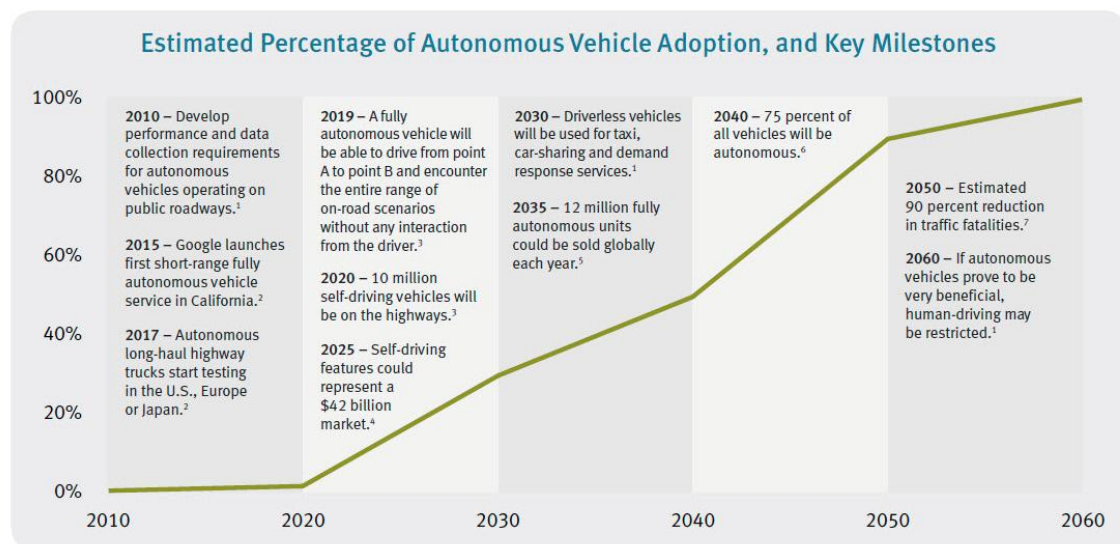


Figure 1-1. Predictions by Victoria Policy Institute

According to the predictions (illustrated in Figure 1-1) for the autonomous vehicle by the Victoria Policy Institute, by the end of 2019, autonomous vehicles can conduct short trips between two points independently. By 2030, there will be ride-

hailing services by autonomous vehicles. However, these progressions may take decades to come into large massive commercial use. Vehicles will need to be equipped with driver monitoring systems to assist the driver's control of vehicles [9].

From level 0 to level 2 of automation, the driver oversees and controls the vehicle. For level 3 automated vehicles, the driver's attention can be diverted with the condition that he/she should be prepared to take over the vehicle whenever prompted. Therefore, the driver's states are important information to autonomous vehicles, as these vehicles need to 'know' the driver's state before a takeover warning is issued. Given the importance of the driver's state information, vehicles must be equipped with a driver monitoring system which is capable of detecting the conditions of the driver [8].

Thus, driver distraction detection is an important part of the driver monitoring system. The distraction is defined as the driver not focusing on the current driving behaviour and having his/her attention diverted from driving into something that is not relevant to the driving task. Driving performances are degraded, and decision-making processes are slowed when the driver is distracted [10].

Generally, the three common types of driver distraction are visual, cognitive and manual distraction [6]. Visual distraction is defined as the driver looking at places that are not relevant to the driving task. Cognitive distraction is induced when the driver is thinking about something that is not relevant to driving. Meanwhile, manual distraction is induced by the hand operation of vehicle systems that are not related to driving.

Among the many facets that can divert the driver's attention, certain tasks involve all three types of distraction. For example, to use a mobile phone, the driver must look away from the road at first and then look at the screen of the mobile phone. This process reduces the information received from the outside environment that is important for safe driving. Moreover, a certain amount of cognitive resources are required for the driver to operate the mobile phone. The driver is also manually distracted because the driver needs to use his/her hands to operate the mobile device.

Three approaches can detect driver distraction. One approach determines the driver's state by installing one or more cameras in the vehicle. The eye and head signals extracted from recorded videos using one or multiple cameras provide valuable information for detecting driver distraction [11]. Driving performance measures, including vehicle speed, steering angle and lane deviation, can also be used to discern driver distraction. Moreover, the signals from invasive sensors, including electroencephalography (EEG) and electrocardiography (ECG), are used to detect driver distraction in relevant research. For real-world applications, these invasive sensors are difficult to install. Therefore, non-invasive sensors are commonly used instead to identify driver distraction in real-world applications. Subsequently, driver distraction detection is an essential step for improving driving safety by collecting relevant signals and inputting them to detection algorithms.

1.2 Motivation

Most of the research on driver distraction detection has focused on improving the prediction accuracy by entering as many signals or features as possible into a certain algorithm, which is shown in Figure 1-2. Little has been done to study relevant features and prediction time. More input signals or features means longer prediction time, especially for engineering applications. Such addition will greatly increase the operation cost and the complexity of signal collection.

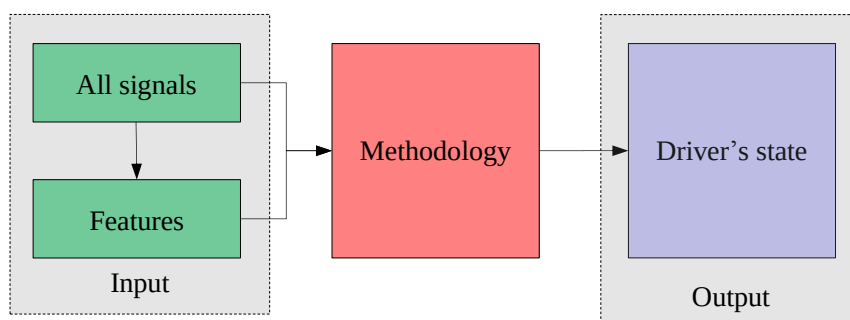


Figure 1-2. Determination of Drivers' states

The motivation for this research is to improve the efficiency of driver distraction detection. High detection efficiency means that despite fewer input features, satisfactory prediction accuracy and shorter prediction time can still be achieved.

This study focuses on identifying relevant features and suitable algorithms for driver distraction detection. The contribution of this study is that when the methods are applied in real applications, computing and storage resources can be greatly saved, and operating costs can be reduced.

1.3 Description of Chapters

The thesis consists of seven chapters, which are listed below.

Chapter 1 introduces the research background and motivations. It also stresses the importance of driver distraction detection in improving road safety.

Chapter 2 states related work and identifies the research gap and objectives. It presents different areas related to driver distraction research.

Chapter 3 describes the methodology used in this study. In this chapter, methods such as the data pre-processing, identification of relevant features and machine learning algorithms, are introduced.

Chapter 4 presents the results using open-source data by applying the methodology. The change in prediction accuracy and time are presented to validate the effectiveness of using relevant features.

Chapter 5 focuses on the driving experiment in a closed testing environment and the results based on collected data. In Chapter 5, the same method used in Chapter 4 is applied to analyse the experimental data collected in the closed environment.

Chapter 6 discusses the results obtained and explores the reasons behind the findings. The results of the open-source data and the experimental data are compared, and the outcomes in this thesis are compared with the typical research in the literature.

Chapter 7 concludes the thesis. Important conclusions are drawn by analysing the changes in prediction accuracy and prediction time to verify whether the detection efficiency has improved or not.

2 Related Work

The research work that relates to driver distraction can be divided into two categories: driver behaviour analysis and driver distraction detection. The former studies driver behaviour in normal driving conditions. It provides the foundation for further research in the identification of a driver's state. The latter detects driver distraction for the driver's state identification by data redundancy removal, feature extraction and prediction. In addition, experimental methods are used in related studies.

2.1 Current Research Progress

In the previous studies, driver distraction research mainly concentrates on driver behaviour analysis and driver distraction detection.

(1) Driver Behaviour Analysis

The driving behaviour analysis in normal driving conditions mainly investigates the visual attention shifts in a straight line and cornering as well as the underlying mechanism that commands the shifts. The factors which influence the eye and head movements during straight-line driving and cornering have been examined. Moreover, the patterns of visual attention shifts have been studied in the literature.

The latest research shows that the driver shifts their attention between the tangent point (i.e., tangent to the road curvature) [12] and a waypoint (i.e., the point located on the future path) [13]. When driving on a straight road, the driver looks at the optimal point, in which the driver could locate the vehicle as well as following the road ahead. Also, the eye gaze and steering angles are strongly correlated during cornering [14].

The driver perceives the movements of vehicles and surrounding environment from multiple sources including the visual information and the vestibular information. The visual information includes the eye movements in yaw pitch and roll, gaze angles in yaw and pitch directions as well as head movements in either nod, tilt and shake or yaw pitch roll motion. The vestibular information refers to the gravitational and lateral accelerations the drivers perceive during driving. The

driver uses both types of information to assist driving. Multiple studies [10], [15] - [24] have proved this theory in naturalistic driving conditions.

Two basic factors are considered in the study of visual attention: the top-down and bottom-up factors. The top-down factors refer to the driver's knowledge and driving skills, which include the driver's characteristics and are not subject to change in a short time. The bottom-up factors refer to the surrounding environments of the vehicle, which are perceived by the driver. The two kinds of factors both have impacts on driver behaviour. The top-down factors could be used to study the gaze directions of the driver [25], [26]. The driving experiments in the literature are mainly based on bottom-up factors which could predict the driver behaviour quantitatively. The environmental factors could be used to assist the study of gaze directions [27] - [30]. For example, when approaching an intersection, the experimental results show that the dwell times in yield and priority conditions do not have much difference [31]. However, in the stop conditions, the dwell times are shorter, and the waiting times at full stop are longer. The results are based on the analysis of top-down factors and bottom-up factors.

When a driver performs different complex tasks, he/she takes certain sequences and strategies to accomplish the task demands. For example, the participants in one study look at the tap and the soap dispenser in the hand-washing task. The fixation at the soap dispenser could be regarded as a look-ahead fixation, as the soap dispenser will be used in the next stage of the task after the water tap. People gather this kind of important information using both temporal and spatial cues. With the increase of proficiency (multiple identical tasks), the fixation at the conscious part decreases. This theory has been proven by several studies [12], [27], [32], [33], [35] - [37].

The look-ahead fixation at important points also exists in driving. Two kinds of models predict where the driver is looking during cornering using the look-ahead fixations theory [13]. In the first model, drivers are focusing on the tangent point of the curve. The second model is that the driver is focusing on the future path or the far zone of the driving environment.

According to the results obtained in corners, the driver fixes his/her gaze on a certain point which lies at the future path. The driver decides the steering angle by fixing at the future points. If the visual flow of the driver is analysed, it will lie at the future path set by the driver, and the directions of visual flow will always be straight. Lehtonen et al. [25] demonstrated that the tangent point, the occlusion point and the waypoints (future path) are where the driver should be looking at during cornering. The tangent point could be used as a control parameter in determining the visual gaze positions of the driver. The future path and the waypoints are difficult to estimate during the current experiments, as the future path is uncertain [25]. In the past, the tangent point was the target of the driver while cornering. However, the eye gaze at the tangent point is more of an empirical conclusion from previous driving experiences. According to the results of cornering, the driver spends more time on the far zone of the future path models.

During the approaching or entry phase of the cornering, the driver has an extensive chance of fixing his/her gaze on the tangent point of the curve. The latest research focusing on the pattern and sequence of where the driver is looking during cornering is undertaken by Lappi et al. [37]. The gaze directions of the driver could be the reference points at which he/she is looking. The future point is another point at which the driver could look to optimise the driving in addition to the tangent point. The driver could look at these points to optimise the steering behaviour. The related research [13], [35] - [39] concludes that gaze positions are slightly above the tangent point during cornering. Additionally, the variation of gaze points is half of the vehicle yaw rate. Moreover, the horizontal movements are beneficial to cornering.

The head movement is strongly correlated to the current driving environment and the state of the drivers [13], [14], [25]. The relevant research investigates the relationship between the head movement and steering angle by estimating the correlation coefficients. These coefficients range from -1 to 1, where -1 indicates a linear negative correlation between the two variables and 1 indicates a linear positive correlation. A 0 value indicates no linear correlation between the two

variables. The correlation index is 0.33 when the driver is driving attentively. The correlation index increases to 0.71 when the driver is drowsy or fatigued, which is a significant increase in terms of linear positive correlation. The head movement patterns also change before a lane change. The head moves both left and right before starting to change lanes. The head tilt has a linear relationship with the road angle.

Yekhshatyan et al. [25] found that the head moves before corners but not during turns. The conclusion is drawn considering several factors, such as the brake pedal pressure, steering wheel pressure, head yaw and roll motions, the tangent of the road curvature and the vehicle positions [14], [40] - [44]. Furthermore, both drowsiness and distraction can be detected from the head movement. The head movement curve obtained by an infrared camera is used for this kind of analysis. The extracted features are the width and range of the peak values of the head movement. When the driver's peak values exceed a certain threshold over a significant time range, the driver is considered distracted while driving.

(2) Driver Distraction Detection

The driver behaviour analysis generally includes the driver behaviour under the circumstance of naturalistic operation and distraction state (i.e. driver behaviour analysis in normal driving conditions and driver distraction detection).

To detect driver distraction, a wide range of signals are used. The input signals could be divided into three categories: the eye gaze and head-related signals, the driving performance measures and the driver physiological signals. To obtain the characteristics of these signals, features can be extracted from signals using statistical measures.

The drivers' eye gaze, head-related features and facial expressions can be used to detect driver distraction. In detail, the eye gaze directions in horizontal and vertical dimensions; the head movement in yaw, pitch and roll motions; the percentage of road centre; the frequency and duration of the eye off the road glances [45] and the eye blink rates [46] are potential signals that can be used to detect driver distraction [47] - [49]. Reyes et al. [50] successfully detected driver

distraction on the basis of eye movements. The driver's facial expressions are also proven to be relevant in detecting driver distraction [51]. Kutila et al. [52] estimated the coarse gaze directions to measure eye-off-the-road glances. In addition, Pohl et al. [53] assessed the eye-off-the-road and lane deviation to detect driver distraction. Similar methods can also be seen in other research [16]. The features extracted from the head movements can also be used in detecting driver distraction. For example, Chui et al. [54] gave coefficients to head movements in their data analysis.

The features extracted from gaze angles, including the off-road glances, gaze concentration and time-sharing between different areas of gaze angles, can be used to detect driver distraction. Finding the relative relationship between driver distraction and the driver's surrounding environment is critical in determining the states of the driver. According to the experiments, the mean speed of the vehicle reduces when the drivers' state shifts from no distraction to visual distraction. However, the complexity of the tasks does not affect the speed of the vehicle significantly. The results prove that a trade-off exists between the vehicle's speed and the operation of the tasks.

To study the impact of visual and cognitive distraction on drivers, the distributions of gaze angles are studied in the literature [30]. The study found that the standard deviation of the gaze angle reduces when the complexity of tasks increases. The eye movement patterns during distracted driving has three different types [55]. The first pattern is the single glance when viewing the rear-view mirror. The second pattern occurs when the driver is operating secondary tasks, such as radio tuning. The third pattern is the variance of eye movements under cognitive distraction. The glance analysis involves the frequencies and time durations of the off-road glance. The combination of the off-road glances and on-road glances could estimate the level of distraction by comparing the average values of these factors.

The main parameters in analysing the distraction induced by in-vehicle activities are the total eye fixation time, the frequency of eye fixation, the accumulated glance time and the accumulated task time [56]. During the operation of

secondary tasks, the driver may divert his/her attention from the on-road driving to the operation of secondary tasks several times, which is called time-sharing.

The relationships between the frequencies of eye fixation, the total time of eye fixation and the secondary task time operated by the driver can be used to estimate the level of distraction and lead to the study of the possibility of crashes. When the driver is cognitively distracted, he/she usually spends a long time on the fixations and a vastly reduced range of gaze angles in both vertical and horizontal directions. Moreover, the driver would check the rear-view mirrors and odometers less frequently. The eye fixation on a dense area dominates the driver behaviour when the subject is under cognitive distraction [57].

Eye fixations have two types: one is the fixation on the surrounding environment, and the other is the attention on the forward road [42]. If the eye gaze is diverted away from the road [58], it could affect the vehicle's lane-keeping performance. If the eye fixations are more on the forward roads, the driver could be cognitively distracted.

The studies on driver distraction detection have mainly focused on driver behaviour, the experimental design and implementation and the analysis of the experimental data. Research on the correlations between feature values and the driver's states also remain limited.

The change in the driver's state is reflected in the values of driving performance measures. Driving performance measures include the speed, acceleration pedal input, the braking pedal input, the engine turning speed (rpm) and the steering angle, which are all tracked by the CAN-Bus system. Usually, the speed is reduced due to cognitive distraction. The braking pedal input is an important signal in detecting cognitive distraction. The values of the steering angle is also correlated with cognitive distraction. In a number of studies [16], [45], [53], [59] – [62], driver distraction is detected using CAN-Bus extracted signals.

The commonly used physiological data includes the electrocardiography (ECG), Electrodermal Activity (EDA) signals, heart rates and breath rates. The electrocardiography signals are closely correlated with the cognitive load of the

driver. Between different driver's status, the heart rates and breath rates of the driver vary. In the research of [63] - [65], driver distraction is detected using physiological signals.

Furthermore, audio recordings, images containing driver behaviour, accelerometers and gyroscopes can provide valuable information in detecting driver distraction. Audio recordings signals are used to detect driver distraction [17]. Recent studies [66] - [68] have suggested that the images containing driver behaviour can be classified into normal driving and texting using Deep Learning. Accelerometers and gyroscopes [60], [69] have been applied to detect distraction using acceleration and angular velocity in x, y and z coordinates.

The eye-gaze-related features, driving performance measures and surrounding environment information can be combined to provide better detection results. The data from the above-mentioned input features can be fused together, which usually improves detection accuracy [62], [71], [72].

Subsequently, machine learning algorithms have been commonly applied to detect driver distraction. Algorithms, such as Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR) and K-Nearest Neighbours (KNN), are used. For example, the detection accuracy of data collected on the public road in Dallas, Texas has reached an average accuracy of 77.2% using SVM [17], which works effectively in classifying the data into different categories by equipping SVM algorithms with linear kernels. A second-order polynomial and a radial basis function kernel have also been used to classify the data when SVM algorithms are applied [73] - [75].

Naïve Bayes and DT are useful for detecting driver distraction. The Naïve Bayes algorithm estimates the probability of classification within each class. It can capture the momentous change of the driver's state. The DT, which is a non-parametric algorithm, can classify the data into different categories. Each point in the dataset follows a set of rules to determine the class into which it falls. Several studies [58], [59], [61], [69], [76], [77] have applied Naïve Bayes and DT and successfully detected driver distraction.

LR and KNN are two efficient methods for classifying the data. LR is a basic algorithm often used to benchmark the performance of other algorithms. KNN is a non-parametric machine learning algorithm and requires fewer computational resources than other algorithms. Several works [17], [65], [69], [78], [79] have successfully applied LR and KNN to classify the collected data.

At present, Deep Learning-based methods, including the convolutional neural network and multi-layer neural network, are also used to categorise the images collected in the cockpit of vehicles and driving simulators. The Deep Learning algorithm can capture the characteristics of the images which are showing the tasks that the driver is undertaking. The classification using Deep Learning is developing rapidly. Recent studies [68], [81], [82] have used this algorithm to classify the images containing the driver behaviour. However, Deep Learning-based algorithms are extremely time-consuming compared with the above-mentioned traditional algorithms.

Besides the feature extraction and machine learning algorithms used in detecting driver distraction, several experiments have been designed to collect the data for the analysis.

The drivers usually conduct two types of driving tasks during the experiment for driver distraction analysis: the primary driving tasks which maintain the vehicle within the same lane and secondary tasks which could potentially distract drivers. The experiments for the analysis can be implemented in the real driving environment and the simulated-driving environment.

Li et al. [17] used secondary tasks in their experiment, which include interaction with the GPS and a mobile phone, talking to a passenger, looking at the passenger side and doing single-digit or double-digit mathematical calculations. Similar secondary tasks have been conducted in the experiments of Du et al. [71] and Ou et al. [85]. The data collected in the real driving environment with different types of distraction can be used to compare the impact of distraction on driver behaviour and to develop detection algorithms. This kind of research can be seen in the literature [50], [52], [53].

A driving simulator is a widely used testing environment to study driver distraction and reduce the potential safety risks caused by distracted drivers. The extraction of signals in driving simulators is easier than the extraction of signals in real driving environments. The environment is strictly controlled with little interference. However, it also faces the problem of including large variability in the testing results and differences between the outcomes obtained from the driving simulator and real driving environments. Several studies [72], [73], [86] have used driving simulators as the main testing environment for the distraction analysis. Secondary tasks, such as eating, drinking and texting, were implemented in a driving simulator in the research by Choudhary et al. [15]. In other studies, drivers were also cognitively distracted to examine driver behaviour in driving simulators [87], [88].

Experiments on driver distraction have been successfully conducted in both driving simulators and real-world driving environments. For example, the research group from the University of Texas in Dallas took the experimental approach [17]. Drivers were required to drive on public roads while undertaking secondary tasks. The signals for analysis were extracted from CAN-Bus, a microphone array and front-facing cameras.

Research groups, including the University of Iowa and the University of Houston, used driving simulators as the main testing environments for the driver distraction research. For example, Liang et al. [75] from the University of Iowa was interested in the changes in driver behaviour after the driver started to interact with in-vehicle infotainment systems. At the University of Houston, researchers published a multi-modal dataset, which contained the data of 68 participants who drove on a four-lane-highway in a driving simulator under different kinds of distractions [89].

To summarise the literature, all signals and features extracted from the experiment are usually fed into detection algorithms. One research included 75 input features [17]. Another research [90] identified the relevant signals in detecting driver distraction as the lane deviation, speed and steering angle.

2.2 Research Gaps

Three gaps are identified in the field of driver distraction detection. The first gap is that limited research has focused on identifying relevant features and reducing the prediction time. One related study is McDonald's research on relevant features using the inference of the variable importance method [90]. Prediction time is a crucial factor in assessing the performance of a detection algorithm. However, the problem is not addressed in the literature. Further research could be conducted to gain a deeper understanding of the features to reduce the prediction time and give prompt warnings to drivers.

The second gap is that to give fast and timely warnings to drivers, a trade-off between the prediction accuracy and the prediction time must be satisfied. However, in the literature, most researchers have concentrated on improving the prediction accuracy, and the prediction time is not widely considered. When selecting suitable algorithms in detecting driver distraction, both the prediction accuracy and the prediction time should be taken into consideration.

The third gap is that driving simulators and public roads are commonly used as the experimental environments in the literature. However, the two environments have drawbacks. Driving simulators suffer from low-fidelity and cause discomfort for test drivers. Meanwhile, the variables are difficult to control in experiments conducted on public roads. Biased data are collected in the two experimental environments, thus challenging the ability to conduct accurate analysis for features and compare the performance between the detection algorithms.

2.3 Objectives

This thesis aims at developing a new driver distraction detection method by removing redundant input features, selecting suitable algorithms and collecting data in an improved environment. The objectives of this thesis are listed below.

The first objective is to identify the relevant signals/features in detecting driver distraction and reduce the prediction time. The relevant features are identified by visual inspection and correlation analysis. The features are ranked, and the most relevant features are fed into detection algorithms.

The second objective is to select suitable algorithms for detecting driver distraction. A balance between prediction accuracy and prediction time should be achieved using suitable algorithms, which are chosen from a wide range of classification algorithms.

The third objective is to validate the usefulness of the developed driver distraction detection method in a closed testing environment. Given that the environment provides more realistic information for drivers, the effectiveness of using relevant signals/features and the selection of suitable algorithms based on the environmental data are worth investigating.

3 Methodology

The methods used in this study are introduced in this Chapter. The methodology applied comprises data pre-processing, identification of relevant features and selection of algorithms, as shown in Figure 3-1. At the first stage, data pre-processing is implemented to covert the raw data into data that are ready to be analysed. At the second stage, features are visualised for a visual inspection, and correlation coefficients are also calculated. At the third stage, the suitable algorithms are selected by comparing the performance of algorithms.

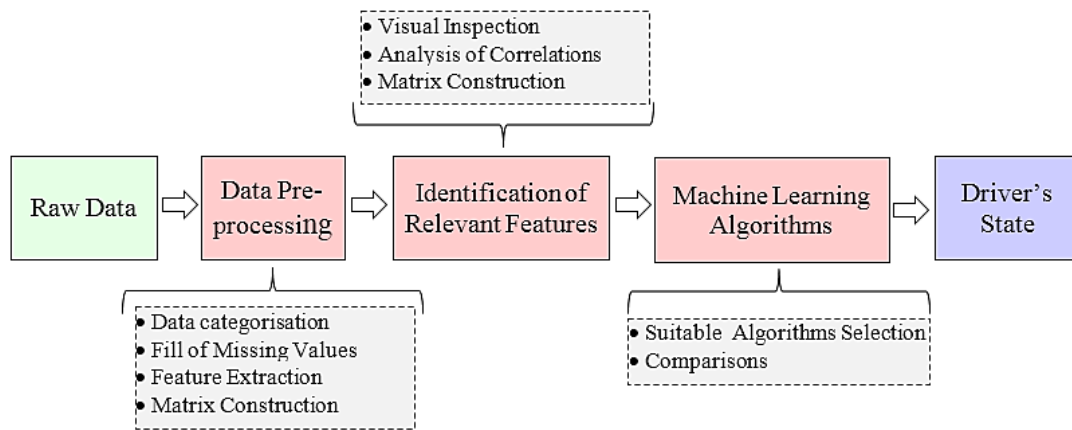


Figure 3-1. Workflow of This Study

3.1 Data Pre-processing

The raw data are pre-processed through data categorisation, filling of missing values, feature extraction and matrix construction to obtain useful information for driver distraction analysis. After the data pre-processing, the extracted features are visualised for a visual inspection and arranged to calculate the correlation coefficients. The matrices are constructed with all available features. The relevant features for detecting driver distraction are fed to a wide range of algorithms. The suitable algorithms are selected based on prediction accuracy and prediction time. The methodology of this thesis is explained in detail in the following paragraphs.

First, data categorisation is implemented by re-grouping data. The raw data contain all the data collected in the experiment. Data categorisation divides the

data into different kinds according to the specific type of distraction. The data are arranged according to their specific type of distraction.

Second, the raw data contain missing values and unavailable information. After the initial categorisation, the missing values and unavailable information need to be filled to refine the data. The missing data are filled through linear interpolation, which is a common means to deal with the missing data.

Third, the feature extraction, which uses Time Window (TW) to extract the values of features for analysis, is applied. The TWs are of different sizes and their values are determined according to the data characteristics. The feature values are calculated based on the values within the TWs.

Fourth, the matrices are constructed and fed to the detection algorithms. The dataset is divided into training and test sets with a ratio of 80 to 20. During matrix construction, the values of features are computed to form the matrix. The use of TWs to extract features and matrix construction are important steps in the identification of relevant features. TWs and matrix construction are introduced in detail as follows.

(1) TWs

TWs are time segments used to extract statistical features. Time segments have various lengths, which are determined by the sampling rate. The typical lengths of TWs are 0.1, 0.2, 0.5, 2 and 5 seconds. The statistical features are mean, maximum, minimum and standard deviation.

A feature is visualised to demonstrate how a TW works. Two figures that present the conditions before and after TWs are given to show the implications of TWs and the extraction of values.

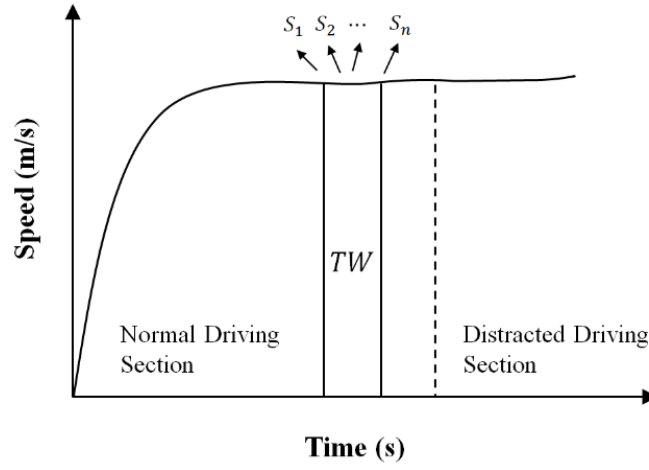


Figure 3-2. Working Principles of TWs

Figure 3-2 shows the working principle of TWs. The signal in Figure 3-2 is vehicle speed. The y -axis shows the speed values. The x -axis is the time in seconds. Normal driving (left part) and distracted driving (right part) sections are presented by applying the TWs, which are shown on two black vertical lines and TW in the middle. In this example, the values are S_1 to S_n . As stated previously, four statistical features are calculated based on the extracted values.

(2) Matrix Construction

Input matrices that will be fed to the detection algorithms are constructed based on the features extracted from the TWs. The values extracted from the TWs are labelled as TW . The locations of the values are subscripted by the value of TW .

$$\begin{bmatrix}
 \text{Feature 1} & \text{Feature 2} & \cdots & \text{Feature } n & \text{Label} \\
 TW_{11} & TW_{21} & \cdots & TW_{n1} & 0 \\
 TW_{12} & TW_{22} & \cdots & TW_{n2} & 0 \\
 \vdots & \vdots & \ddots & \vdots & \vdots \\
 TW_{1x} & TW_{2x} & \cdots & TW_{nx} & 1 \\
 \vdots & \vdots & \ddots & \vdots & \vdots \\
 TW_{1m} & TW_{2m} & \cdots & TW_{nm} & 1
 \end{bmatrix}$$

Figure 3-3. Constructed Matrix

Figure 3-3 shows the matrix constructed by the values extracted from the TWs. Each row of the matrix has values of features extracted from the same TW (i.e., the same time), and each column of the matrix has values from the same feature. The data are also labelled according to the driver's states. The feature values of the normal driving section are labelled as 0. The feature values of the distracted driving section are labelled as 1. The values of features can be visualised to determine the relevant features. The constructed matrices are obtained after data pre-processing and fed to machine learning algorithms to detect driver distraction.

3.2 Identification of Features

The features are analysed after feature extraction. The features are identified as relevant or irrelevant in detecting driver distraction. A relevant feature has useful information for detecting driver distraction. An irrelevant feature is defined as irrelevant or redundant information compared with other features. An irrelevant feature is not helpful in improving the efficiency of driver distraction detection.

The methods for identifying features are visual inspection and correlation analysis. Visual inspection is the main method to identify relevant features, and correlation analysis is a supplementary method to validate the results of visual inspection.

(1) Visual Inspection

The eyes of human beings can identify the defects of and differences between objects. The method of identifying differences is called visual inspection. The visual inspection method can be used to identify relevant features because of its strong capability to spot differences between driving sections.

Initially, the values of features are visualised for normal and distraction driving sections. The differences in features are then detected via visual inspection. The visual inspection process determines the extent of the difference in features between normal and distracted driving sections. Features with large differences are considered to be relevant in detecting distraction, and features with small differences or no observable differences are considered to be irrelevant in detecting distraction.

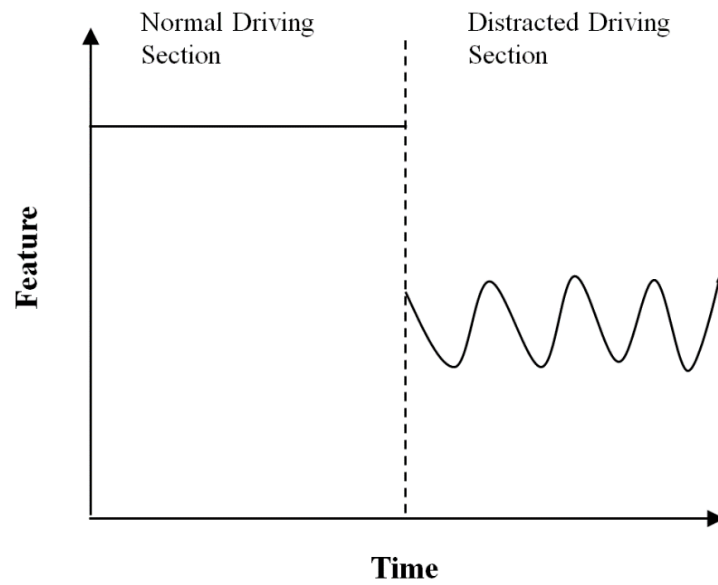


Figure 3-4. Relevant Feature

Figure 3-4 shows the plot of the values of eye gaze direction versus time segment. The values of the normal driving section are shown on the left-hand side, and the values of the distracted driving section are shown on the right-hand side. Figure 3-4 indicates that a large difference exists between the values of eye gaze direction in normal and distracted driving sections. The values of eye gaze direction decrease after the driver is distracted.

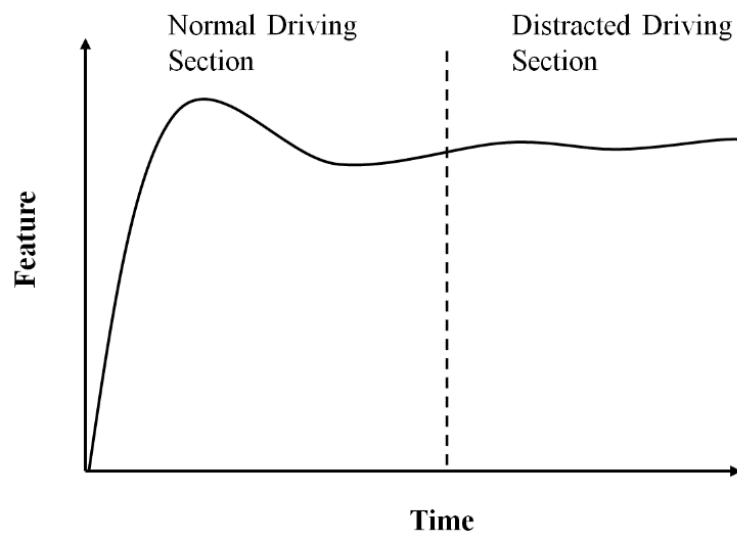


Figure 3-5. Irrelevant Feature

Figure 3-5 shows a plot of the values of an irrelevant feature. Figure 3-5 indicates the velocity of a vehicle during normal and distracted driving. An initial acceleration phase in which the vehicle accelerates from 0 to the cruising speed can be observed. The driver maintains the cruising speed afterward. As shown in Figure 3-5, minor differences exist between normal and distracted driving sections, except for the initial acceleration phase. It is regarded as an irrelevant feature due to the minor differences between the two sections. Irrelevant features provide less valuable information compared with relevant features.

The visual inspection method utilises the capability of human eyes. It is an effective method of detecting relevant features because the values of features change when the driver's states shift from normal to distracted, and the change can be easily observed by human eyes.

(2) Correlation Analysis

The correlation coefficients are a mathematical way to calculate the relevancy between two signals, but not the causal effect of one signal on another. The correlation coefficient ranges from -1 to 1 . An absolute value of 1 indicates a strong correlation between the two variables of interest, and a value of 0 indicates the absence of correlation between the variables. Features with high absolute values of correlation coefficients are relevant features.

Various types of correlations are available for calculating the correlation coefficients, and they include Pearson's correlation coefficient, point-biserial correlation coefficient and Spearman's rank correlation coefficient.

Pearson's correlation coefficient is the primary method to calculate correlation coefficients. The point-biserial correlation coefficient is a specific type of correlation coefficient that is suitable for calculating correlations between a binary variable and a continuous one. The distraction level (0 and 1) is a binary variable, and the features are continuous variables. Therefore, the point-biserial variable is applied in this section.

Originally, the Pearson's correlation coefficient is defined as:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}, \quad (3-1)$$

where $\rho_{X,Y}$ is the correlation coefficient between variables X and Y ; $cov(X,Y)$ is the covariance between X and Y ; and σ_x and σ_y are the standard deviation of variables X and Y , respectively.

One binary variable (the driver's state) is involved, and the point-biserial variable is used; it is calculated as

$$r_{pb} = \frac{M_1 - M_0}{S_n} \sqrt{\frac{n_0 n_1}{n}}, \quad (3-2)$$

where r_{pb} is the correlation coefficients, S_n is the standard deviation of x , M_1 is the mean value of the group where the binary value equals 1, M_0 is the mean value of the group where the binary value equals 0, n_1 is the number of points in the group where the binary value equals 1, n_0 is the number of points in the group where the binary value equals 0, and n is the total number of points.

S_n is the standard deviation of X , x is the values of the sample X .

$$S_n = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}, \quad (3-3)$$

where x is the value of a continuous variable.

The point-biserial variable is used to calculate the relevancy between the features and the driver's states. However, it only estimates the first-order relationship between the two variables, and it cannot detect higher orders of relevancy.

The results of the analysis of correlations complement the results of the visual inspection. Given that correlation coefficients calculate only first-order relevancy, visual inspection, which can identify higher orders of relevancy, is selected as the main method to identify features. The features with first-order and higher-order correlations are identified by comparing the results of the visual inspection and correlation analysis. The common features identified from the visual inspection and correlation analysis are regarded as relevant features. The results of the

correlation analysis are also meaningful. They can validate the results of the visual inspection, whereas different features can make the visual inspector check the results of visual inspection again.

3.3 Machine Learning Algorithms

Machine learning algorithms can learn from data and make predictions and are usually utilised for driver distraction detection. The main applications of machine learning are spam filtering, computer vision, natural language processing, marketing, and bioinformatics.

The two main categories of machine learning are supervised and unsupervised learning. Supervised learning relies on labeled data to build a model that can make future predictions based on new data. The underlying process is known as learning based on labeled data. Unsupervised learning relies on the iteration of models to develop the best models. In other words, the underlying process is a black-box operation.

Classification is an important objective of machine learning, and it aims to divide the output data into different classes. The applications of classification algorithms include spam filtering and tumor classification. Classification algorithms can classify the input data of this study into normal and distracted driving sections (i.e., detection of the driver's states). However, not all classification algorithms are suitable for detecting driver distraction. A suitable algorithm can detect the driver's states with satisfactory accuracy and efficiency.

Suitable algorithms are selected based on their performance using two metrics. The first one is prediction accuracy, which is commonly used in evaluating the performance of algorithms. The second metric is prediction time, which indicates how fast driver's states can be predicted. The suitable algorithms are selected based on the balance between prediction accuracy and prediction time.

The commonly used classification methods for driver distraction detection are DT, LR, SVM and KNN. They are introduced in this section, and several of them will be used to classify the collected data in the subsequent chapters.

(1) DT

DT is a supervised machine learning algorithm that can be applied to classification and regression. DT has a tree-like structure with a cluster of if-then rules. The splitting rules divide the data into different subsets. The splitting stops when all the training instances have reached the smallest inseparable subsets.

The structure of DT is shown in Figure 3-6. A typical DT consists of roots, nodes, branches. The root is the input of all the data. Nodes are of two types: internal and leaf nodes. The internal nodes contain the instances that have not been entirely separated. The leaf nodes are where the outcomes appear. The distraction levels (0 and 1) appear at the leaf nodes. The branches contain the rules that separate the data from the internal nodes or roots.

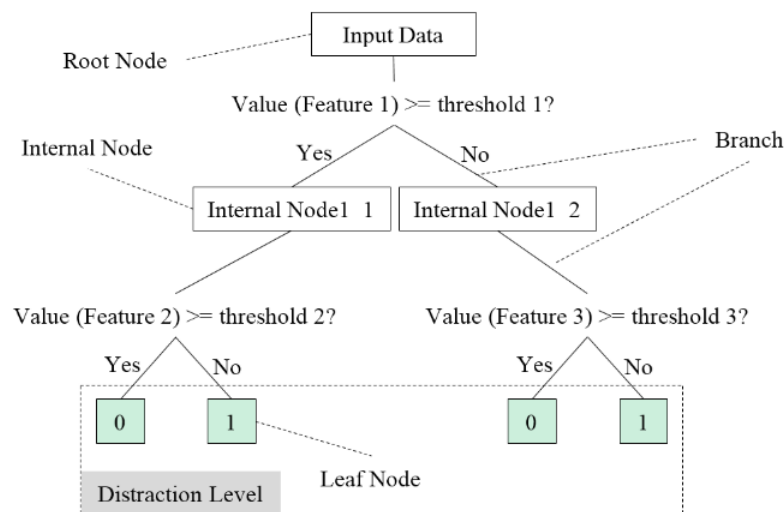


Figure 3-6. Decision Tree

The establishment of DT includes feature selection, generation of a decision tree and the pruning of the decision tree.

Feature selection determines which category or feature to discriminate the data from roots or internal nodes. Information gain or the ratio of information gain is a common way of selecting it.

The information gain is defined as:

$$g(D, A) = H(D) - H(D|A), \quad (3-4)$$

Where $g(D, A)$ is the information gain, $H(D)$ is the entropy of subset D, $H(D|A)$ is the entropy of subset D with feature A.

$$g_R(D, A) = \frac{g(D, A)}{H_A(D)}, \quad (3-5)$$

$g_R(D, A)$ is the ratio of information gain. $g(D, A)$ is the ratio of information gain, and $H_A(D)$ is the entropy of subset D for feature A. The entropies of the above-mentioned equations are as follows:

$$H(D) = - \sum_{k=1}^K \frac{|C_k|}{|D|} \log_2 \frac{|C_k|}{|D|}, \quad (3-6)$$

$$H(D|A) = \sum_{i=1}^n \frac{|D_i|}{|D|} H(D_i) = - \sum_{i=1}^n \frac{|D_i|}{|D|} \sum_{k=1}^K \frac{|D_{ik}|}{|D_i|} \log_2 \frac{|D_{ik}|}{|D_i|}, \quad (3-7)$$

$$H_A(D) = - \sum_{i=1}^n \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|}, \quad (3-8)$$

where $H(D)$ is the entropy of subset D, $H(D|A)$ is the entropy of subset D with feature A, and $H_A(D)$ is the entropy of subset D for feature A.

The process of training DT can be divided into three steps. The first step is to proceed with the data with attributes on the roots of DT. The second step is to divide the input data into subsets. The subset in each internal node has the same attributes. The third step is to repeat the two previous steps until each data point reaches the leaf node. A new data point can be trained and tested by following the three previously mentioned steps.

After the features and branches are determined using the trained data by adopting the process, the obtained DT is tailored for the specific training set. Overfitting is possible in this kind of process. Pruning is applied to eliminate the unnecessary parts of the decision and make the algorithm generalized, thus preventing overfitting.

The main advantages of DT are its simplicity, readability, and high speed. DT is generally a simplified machine learning method. Therefore, its speed is relatively higher than that of other algorithms. DT has a tree-like form, so nodes and branches can be viewed. However, DT can easily overfit data, and a small difference in data could result in a different DT; therefore, the variance of this machine learning method is large.

(2) SVM

SVM is a binary classification algorithm that has been applied to various areas of engineering and proven to be robust. The objective of SVM is to maximise the margins between two classes.

The input to the SVM algorithm is either an $N \times 29$ matrix or an $N \times 7$ matrix, with each column being a different feature at a certain time. The output of the SVM algorithm is binary, indicating the outcome of driver distraction detection (normal or distracted driving).

The three types of SVM are linearly separable, linear, and nonlinear. These three types correspond to the three kinds of condition that separate the classes. The first SVM type is developed by maximising the hard margin between classes. The second SVM type maximise the soft margin between classes. The third type, nonlinear SVM, projects the instances in the training sets into higher feature spaces and separates the instances; it is also called the kernel trick. The three types of SVM are introduced one by one in the following text.

Linear separable SVM

SVM uses a hyperplane to separate two classes. In Figure 3-7, the positive class is marked in blue, and the negative class is marked in red. The equation for the hyperplane is $\omega x + b = 0$, where ω denotes the vectors and b is the biased term. The rule for dividing the instances (training examples) is the sign function, which is $f(x) = \omega x + b$. A training example is classified as positive when the sign function is equal to 1 and classified as negative when the sign function is equal to -1.

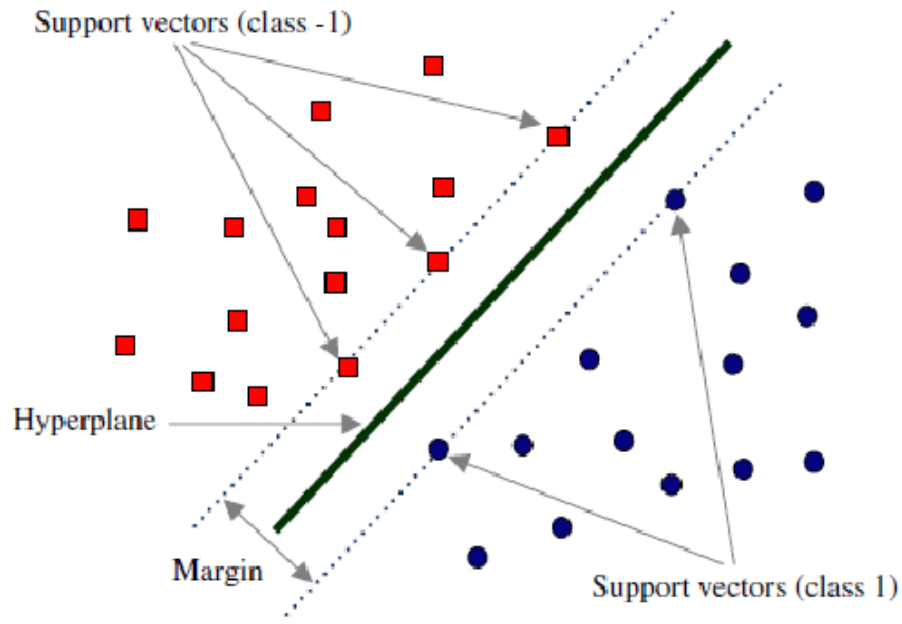


Figure 3-7. Support Vector Machine

Maximum margin classifier

Figure 3-7 shows that an indefinite number of hyperplanes can separate the two classes; for example, a hyperplane can move up and down or twist. To identify the optimal margin, the margin between the two classes should be the largest because the hyperplane with the largest margin can best predict the future classes and has the highest confidence because its margin is the largest.

The standard for determining the best hyperplane is to maximise the distances to the hyperplane.

The training examples can be expressed as $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, and the classes for each training example can be expressed as $y_i \in \{-1, +1\}$ for $i = 1, 2, \dots, N$.

The hyperplane to be determined is

$$\omega x + b = 0. \quad (3-9)$$

The total distances of all the points to the hyperplane are

$$\sum_i^N \frac{|\omega x_i + b|}{\|\omega\|}. \quad (3-10)$$

The goal is to maximise the distance

$$\max \sum_i^N \frac{|\omega x_i + b|}{\|\omega\|} \quad (3-11)$$

because when $\omega x_i + b < 0$, $y_i = -1$, and when $\omega x_i + b > 0$, $y_i = 1$.

Hence,

$$|\omega x_i + b| = y_i(\omega x_i + b). \quad (3-12)$$

Then, the function to maximise the distance becomes

$$\max \sum_i^N \frac{y_i(\omega x_i + b)}{\|\omega\|}. \quad (3-13)$$

Notably, for all hyperplanes, $\omega x + b = 0$ and $\lambda \omega x + \lambda b = 0$. A certain λ can be obtained to equalise all the values of $y_i(\omega x_i + b)$.

Therefore, the maximisation of the distance can be transformed into the minimization of vector ω .

$$\max \sum_i^N \frac{y_i(\omega x_i + b)}{\|\omega\|} \Leftrightarrow \min \frac{1}{2} \|\omega\|^2 \quad (3-14)$$

Thus, the linear separable problem becomes the convex quadratic programming problem

$$\min \frac{1}{2} \|\omega\|^2, \quad (3-15)$$

$$\text{s.t } y_i(\omega \cdot x_i + b) \geq 1, i = 1, 2, \dots, N.$$

The convex quadratic programming problem is solved, and the Lagrange function is introduced as follows:

$$\mathcal{L}(\omega, b, \alpha) = \frac{1}{2} \|\omega\|^2 - \sum_{i=1}^N \alpha_i y_i(\omega x_i + b) + \sum_{i=1}^N \alpha_i. \quad (3-16)$$

The dual problem for the Lagrange function is

$$\max_{\alpha: \alpha_i \geq 0} \min_{\omega, b} \mathcal{L}(\omega, b, \alpha). \quad (3-17)$$

The next step is to solve this dual problem. i.e., $\max_{\alpha: \alpha_i \geq 0} \min_{\omega, b} \mathcal{L}(\omega, b, \alpha)$.

The dual problem becomes

$$\min_{\alpha} \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j (x_i x_j) - \sum_i \alpha_i, \quad (3-18)$$

s.t. $\begin{cases} \sum_i \alpha_i y_i = 0 \\ \alpha_i \geq 0, i = 1, 2, \dots, N \end{cases}$, by partial differentiation of vectors ω and biased term b .

The optimal solution α^* for the dual problem can be obtained by this equation.

The optimal solution ω^*, b^* is

$$\omega^* = \sum_{i=1}^N \alpha^* y_i x_i. \quad (3-19)$$

The optimal biased term b is

$$b^* = y_j - \sum_{i=1}^N \alpha^* y_i (x_i x_j), \quad (3-20)$$

s.t. $\alpha_j^* > 0$.

The final hyperplane is

$$\omega^* x + b^* = 0. \quad (3-21)$$

Linear SVM

In real-life situations, finding linear separable cases is difficult because most cases are linear inseparable. The slack variable (ξ_i) is introduced to tolerate the outliers and classify the rest of the data. One of the constraints becomes

$$y_i (\omega_i x + b) \geq 1 - \xi_i. \quad (3-22)$$

When $\xi_i = 0$, the training example is correctly classified. When $\xi_i > 0$, the training example is classified into the wrong class. The slack variable can be considered an error term because the training example is not correctly classified. The error term is

$$\frac{1}{N} \sum_{i=1}^N \xi_i. \quad (3-23)$$

The minimisation becomes

$$\min_{i=1,2,\dots,N} \frac{1}{2} \|\omega^2\| + \frac{1}{N} \sum_{i=1}^N \xi_i, \quad (3-24)$$

s.t. $y_i(\omega_i x + b) \geq 1 - \xi_i$ for all $i = 1, 2, \dots, N$.

Kernel Trick

One solution for the case where the two classes are linearly inseparable is to project the training examples into a higher-dimensional feature space. The classes are separable in higher dimensions. The three most common types of kernels are linear, polynomial, and Gaussian. Gaussian kernels are introduced here because they are the most commonly seen.

The equation of the Gaussian kernel is

$$k(x_1^i, x_2^j) = \exp\left(-\frac{\sum_{k=1}^n (x_k^{(i)} - x_k^{(j)})^2}{2\sigma^2}\right). \quad (3-25)$$

The Gaussian kernel estimates the distances between training examples and the decision boundary for the classes can be determined by computing the values. The detailed process is not introduced for the sake of simplicity.

(3) KNN

KNN is a classification algorithm. Instead of training a specific model to classify the data, it searches and finds K-nearest neighbors to determine the class of the instance for any given data point. The class of other data points is already known. The definition of distance is crucial in KNN. The types of distance include Minkowski, Euclidean, and Manhattan distances. The formula for measuring these distances are listed below.

The Minkowski distance is

$$L_p(x_i, x_j) = \sqrt[p]{\sum_{m=1}^n |x_i^{(m)} - x_j^{(m)}|^p}. \quad (3-26)$$

When $P = 2$, the formula above is Euclidean distance, as follows:

$$L_2(x_i, x_j) = \sqrt{\sum_{m=1}^n |x_i^{(m)} - x_j^{(m)}|^2}. \quad (3-27)$$

When $P = 1$, the formula becomes Manhattan distance, as follows:

$$L_1(x_i, x_j) = \sum_{m=1}^n |x_i^{(m)} - x_j^{(m)}|. \quad (3-28)$$

After specifying the distance measure, the next step is to find the K nearest neighbors. One way is to calculate all the distances between the data point to be classified and all known data points. The computation is long when the dataset is large. Many algorithms can reduce the computation time, and one of them (i.e., K-D tree) is introduced here.

K is an important algorithm parameter. When K is smaller than the optimal value, noise is present, and the results are unstable. When K is larger than the optimal value, an error occurs because irrelevant data points are also included. The best value requires tuning and is a small number.

Calculating the distance between all the data points and the data point to be classified is computationally inefficient. The K-D tree is an efficient means to store data. The K-D tree has a bisecting form. The data are divided by the branchpoint, which is the median value of a certain dimension. Data that are smaller than the branchpoint are split into the left part of the tree, and data larger than the branchpoint are split into the right part of the tree. The process is repeated until all data points have been split.

The next procedure is to construct the K-D tree by implementing the following steps.

Step 1: Construct the root node, which includes k -dimensional space. The branchpoint is x^1 , which is the median of all data points. All data points are split into left and right according to the rule mentioned above.

Step 2: Repeat the process for the other data points. Assume that the current depth is j , and $x^{(m)}$ is the median value and used to split the data. The superscript $m = j(\bmod k) + 1$. The depth for the next layer is $j + 1$.

Step 3: Repeat the process until no data points are left.

The problem now is how the K-D tree can help search k nearest neighbors for point P . Assume that S stores the k nearest neighbors for P .

The process of searching for k nearest neighbors involves positioning the point p in the K-D tree and searching in the subtree.

Step 4: When the search reaches the leaf node, if S does not have enough points, then the point in the leaf node is added to S . When S does not have enough points, the distance between the current point and point p needs to be calculated and compared with the longest distance in S . The point with a smaller distance is selected.

When the current node is not the root, Step 4 is executed; otherwise, the algorithm stops. The process goes back to the parent node and sets it as the current node. Two conditions are considered. If the node has not been checked yet, then Steps 5 and 6 are executed, and the node is marked as checked. If the node has been checked, then Step 4 is executed.

Step 5: If S does not have enough points, then the current point is added to S . If S is full, then the distance between the current point and p and the longest distance in S are compared; the current best is selected and added to S .

Step 6: The distance between the current data point and the branchpoint is calculated. If the distance is larger than the longest distance in S , then Step 3 is executed. If the distance is smaller than the longest distance in S , then the other child node is executed. Step 4 is executed when only one child node is present.

The main advantage of KNN is that it has no parameters and no model training process. The algorithm is suitable for the multi-class classification problem and not prone to outliers. The main disadvantage of KNN is that it requires excessive prediction time, especially when the training sample is large. Additionally, its prediction accuracy depends largely on data quality. If data quality is not ensured, then the prediction accuracy will be adversely affected.

(4) **LR**

LR can classify data into two classes by using probability theory. The probability ranges from 0 to 1. When the estimated value is near 1, the class is considered to be 1. When the estimated value is near 0, the class is considered to be 0. This type of problem is called soft binary classification. The LR method uses the sigmoid function to achieve its goal.

The sigmoid function is $g(z) = \frac{1}{1+e^{-z}}$, where

$$z = \theta^T x. \quad (3-29)$$

The sigmoid function becomes

$$f(x) = \frac{1}{1+e^{-\theta^T x}}, \quad (3-30)$$

where x is a training example and θ is the parameter.

This function is suitable for LR because it suits the characteristics of the algorithm. The function is monotonically increasing, and its values range from 0 to 1. When $z = 0$, the value of the function is equal to 0.5. The values of the sigmoid function approach upper (1) and lower (0) limits when the absolute values of z are large. In consideration of these characteristics and requirements of LR, the sigmoid function is selected.

The ideal cost function for LR is to penalize the values. For the case where the actual class is 1, the cost is near zero when the estimated probability approaches 1, and the cost is large when the estimated probability approaches 0. For the case where the actual class is 0, the cost is near 0 when the estimated probability approaches 0, and the cost is large when the estimated probability approaches 1.

The cross-entropy cost function satisfies the standard

$$\text{Cost}(y, x) = \begin{cases} -\log(h_{\theta}(x)) & \text{when } y = 1 \\ -\log(1 - h_{\theta}(x)) & \text{when } y = 0 \end{cases} \quad (3-31)$$

The two conditions can be combined to create the single equation

$$\text{Cost}(x) = -y \log(h_\theta(x)) - (1 - y) \log(1 - h_\theta(x)). \quad (3-32)$$

Loss function of LR

The loss function is the sum of the cost of all training examples, as follows:

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m [y^i \log(h_\theta(x)) + (1 - y^i) \log(1 - h_\theta(x))]. \quad (3-33)$$

Gradient descent is used to solve the equation and minimize the loss function.

The equation for updating the parameter is

$$\theta_j = \theta_j - \alpha \left(\frac{\partial}{\partial \theta_j} J(\theta) \right) = \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_\theta(x^i) - y^i) x_j^i. \quad (3-34)$$

This equation is derived as follows:

$$\frac{\partial}{\partial \theta_j} J(\theta) = -\frac{1}{m} \sum_{i=1}^m \left[\frac{y^{(i)}}{h_\theta(x^{(i)})} \frac{\partial(\log(h_\theta(x^{(i)})))}{\theta_j} + \frac{y^{(i)} - 1}{1 - h_\theta(x^{(i)})} \frac{\partial(\log(h_\theta(x^{(i)})))}{\theta_j} \right], \quad (3-35)$$

$$\frac{\partial}{\partial \theta_j} J(\theta) = -\frac{1}{m} \sum_{i=1}^m \left[\left(\frac{y^{(i)}}{h_\theta(x^{(i)})} + \frac{y^{(i)} - 1}{1 - h_\theta(x^{(i)})} \right) \frac{\partial(\log(h_\theta(x^{(i)})))}{\theta_j} \right]. \quad (3-36)$$

The term $\frac{\partial(\log(h_\theta(x^{(i)})))}{\theta_j}$ can be computed individually.

$$\begin{aligned} \frac{\partial(\log(h_\theta(x^{(i)})))}{\theta_j} &= \frac{\partial(\log(\frac{1}{1 + e^{-\theta^T x^{(i)}}}))}{\theta_j} \\ &= \frac{e^{-\theta^T x^{(i)}} x_j^{(i)}}{(1 + e^{-\theta^T x^{(i)}})^2} \\ &= h_\theta(x^{(i)})(1 - h_\theta(x^{(i)}))x_j^{(i)} \end{aligned} \quad (3-37)$$

Substituting the form back to the equation yields

$$\frac{\partial}{\partial \theta_j} J(\theta) = -\frac{1}{m} \sum_{i=1}^m \left[\left(\frac{y^{(i)}}{h_\theta(x^{(i)})} + \frac{y^{(i)} - 1}{1 - h_\theta(x^{(i)})} \right) (h_\theta(x^{(i)}) (1 - h_\theta(x^{(i)})) x_j^{(i)}) \right], \quad (3-38)$$

$$\frac{\partial}{\partial \theta_j} J(\theta) = -\frac{1}{m} \sum_{i=1}^m [(y^{(i)}(1 - h_\theta(x^{(i)})) + (y^{(i)} - 1) h_\theta(x^{(i)})) x_j^{(i)}], \quad (3-39)$$

$$\frac{\partial}{\partial \theta_j} J(\theta) = -\frac{1}{m} \sum_{i=1}^m (y^{(i)} - h_{\theta}(x^{(i)})) x_j^{(i)}. \quad (3-40)$$

Thus, the equation of the updated parameters becomes

$$\theta_j = \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)} - h_{\theta} x^{(i)}) x_j^{(i)}. \quad (3-41)$$

The main advantage of LR is its intuitiveness and simplicity. No tuning is needed, and features do not need to be scaled. It performs well when the input features are carefully selected and relevant to the classification problem. LR is often used as a benchmark method because of its simplicity and good performance.

The main disadvantage of LR is that first, it cannot classify nonlinear data because the decision boundary is linear. Second, when many irrelevant features are present, LR cannot perform well. Relevant features need to be identified beforehand.

3.4 Summary

Chapter 3 mainly introduces the methodology of driver distraction detection. The process of extracting features by using TWs is described in detail. Visual inspection and correlation analysis are combined to identify the relevant features. Visual inspection is a creative means to achieve this goal. The four commonly used algorithms in detecting driver distraction are also discussed.

In the next two chapters, the developed driver distraction detection method is used to process the data from the online experimental environment.

4 Open-Source Data-Based Driver Distraction Detection

Two ways can be used to collect data for driver behaviour analysis. One way is to experiment with driving simulators and the other is to conduct it on public roads. The driving simulator provides a standardised, safe and easy to implement environment for driving experiments.

Researchers from the University of Houston used driving simulators to study driver distraction and published the collected data in *Scientific Data* of the Nature group. The open-source data are available online on the journal website (<https://www.nature.com/articles/sdata20171110>). This dataset [89] is used to study driver distraction. The methodology of this study is introduced in detail in Chapter 3.

Similar to Figure 3-1, the driver distraction detection is conducted using the open-source data and can be mainly divided into three steps: feature identification, selection of suitable algorithms and comparison of results. In the first step, feature identification is conducted; specifically, the relevant features in detecting driver distraction are identified by visual inspection and correlation analysis after data pre-processing. In the second step, an approach is used to find suitable algorithms. In general, we feed relevant features into various algorithms after identifying the features. The final step is to comparatively analyse the results of driver distraction detection. Prediction accuracy and prediction time are the two metrics of result evaluation.

4.1 Description of Open-Source Data

The open-source dataset is collected from experiments in a driving simulator. The drivers conduct several secondary tasks whilst driving. The experiments are divided into different phases. Multiple channels of data are collected during the experiments for further analysis.

The dataset, which is presented in excel worksheets form, contains data files of 68 participants. Although data of 26 participants contain a significant amount of lost data, data from 42 participants are available for analysis. All available signals

are arranged in a specific order. However, only signals from the frontal camera and CAN-Bus data are considered for non-invasive detection of driver distraction. The signals to be analysed are eye gaze in x and y direction, steering angle, vehicle speed, vehicle acceleration, brake force and lane position and deviation. The signals and features are listed in Table 4-1.

Table 4-1. Signals Available in Open-Source Data

Signal Channel	Symbol	Signals	Units
Frontal Camera	G_x	Eye gaze in x direction	m
	G_y	Eye gaze in y direction	m
CAN-Bus Data	$\delta_{steering}$	Steering Angle	$^{\circ}$
	$V_{vehicle}$	Vehicle Speed	km/h
	$a_{vehicle}$	Vehicle Acceleration Pedal Input	$\%$
	$F_{braking}$	Braking Force	N
	$LP_{vehicle}$	Lane Position	m
	$LD_{vehicle}$	Lane Deviation	m

Eye gaze positions of the drivers are recorded and tracked. The videos of the driver's face are recorded with a camera facing the driver. The eye gaze positions are estimated using the camera angles and the distance to the screen. The eye gaze positions are the projected positions on the screen. The gaze positions are measured in metres. The vehicle performance measures are vehicle speed, vehicle acceleration pedal input, vehicle braking force, lane position and lane deviation.

Four types of secondary tasks are considered in the experiment including manual, cognitive and emotional distraction. The driver is manually distracted by texting. The driver is cognitively distracted when answering double-digit math questions

during driving. Two types of emotional distraction are considered: types 1 and 2. Type 1 of emotional distraction is induced by casual questions asked by the passenger to the driver. Type 2 of emotional distraction (type 2) is induced by answering emotionally pointed questions of the driver.

The data pre-processing transfers raw data into data that are ready to be analysed. In other words, this operation removes redundant information. The raw data downloaded online are stored in excel and can be imported to MATLAB. An input matrix is constructed using the four statistical features of different TWs.

4.2 Identification of Relevant Features

The features extracted from the signals include the mean, maximum, minimum, standard deviation values of vehicle speed, acceleration, braking force, steering angle, lane deviation, lane position and eye gaze in x and y directions. A total of 32 features (4 statistics $\times$ 8 signals) that are being visualised. The features are pre-processed with four steps before they are visualised.

(1) Data categorisation divides the collected data into four main categorisations, and each one corresponds to a certain kind of distraction. The data when the driver is driving normally is extracted and stored separately.

(2) Missing values exist in the original dataset during collection. The missing values are filled using interpolated values of adjacent numbers. The method is common amongst the ways to deal with the missing data, and the effects are small in terms of the change to the general characteristics of the dataset. Signals such as brake force and eye gaze in x and y positions contain more missing values than other signals.

(3) The features are extracted through certain TWs. Although the extracted feature values are different using different TWs, the results of identified relevant features are only slightly related to the size of the selected TW. The identification of relevant feature mainly depends on the difference in patterns between normal and distracted driving states rather than the values themselves. The 5-second TW is selected for the visualisation of features, which is selected by observing

the changes between the two driving states, to best compare the differences between the two driving states.

(4) The visual inspection method is used to determine the differences between normal and distracted driving sections in visualised figures. Point-biserial correlations are also calculated to validate the results by visual inspection. The analysis of correlation is additional to the visual inspection method. The analysis of correlations in this study uses the point-serial correlation coefficients because of the capability of this method to calculate correlations between binary variables and features. A feature with a high correlation coefficient indicates a high correlation between feature and driver distraction, which are relevant features in detecting driver distraction. In this section, the correlations are ranked and the features with the 10 highest correlations are listed.

Feature analysis to one driver in this section consists of five figures, that is, from Figure 4-1 to Figure 4-5. Four figures from Figure 4-1 to Figure 4-4 correspond to the plots of features using the four statistical measures, and one figure, that is, Figure 4-5, corresponds to results of correlation analysis. For the four figures, the x axis is the time series. The y axis is the feature values. Notably, the left part is the normal driving section, and the right part is the distracted driving section. Values of features are normalised, and their values are between -1 to 1. For Figure 4-5, the x axis is the statistical features and the y axis shows the correlation coefficients.

For simplicity, only one set of figures for the male young driver (i.e. No. 5), the female young driver (i.e. No. 6), the male old driver (i.e., No. 38) and the female old driver (i.e. No. 25) is presented. Additional plots of driver behaviour are shown in the appendices.

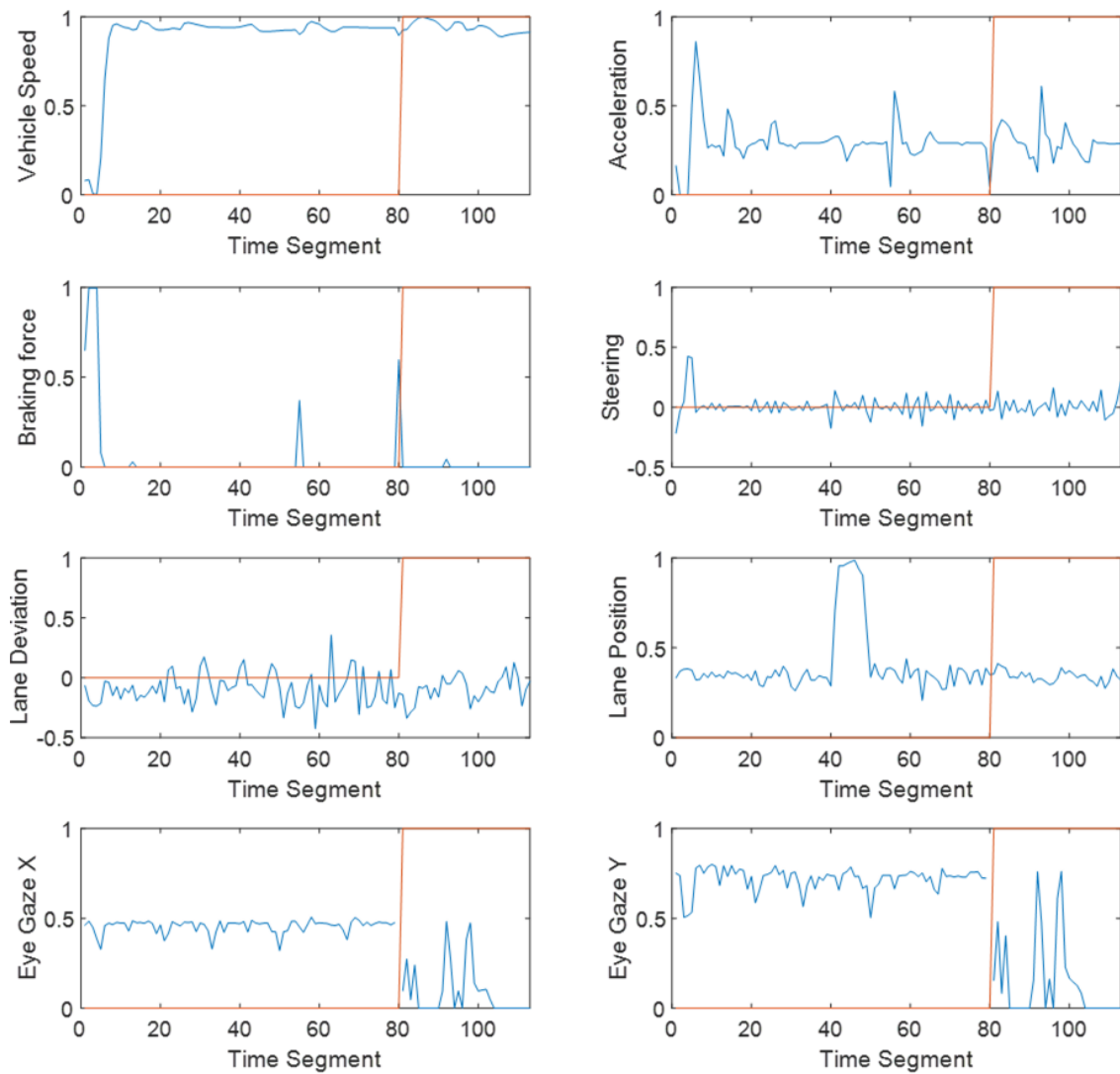


Figure 4-1. Comparisons of Mean Values of Features of Normal Driving and Distracted Driving for Driver No. 5

Figure 4-1 shows the mean values of features of normal and distracted driving for driver No. 5. The relevant features are identified as mean values of eye gaze in x and y directions given that the values of eye gaze in x and y directions reduce when the driver's state shifts from normal to distracted. The values of eye gaze in x and y directions during normal driving maintain a constant value with minor disruptions. However, spikes reflect the rapid change in gaze locations during distracted driving sections.

The difference between normal and distracted driving sections in eye gaze in x and y directions makes them relevant in detecting driver distraction. Significant

changes have not been observed in other features. Therefore, other features are not regarded as relevant.

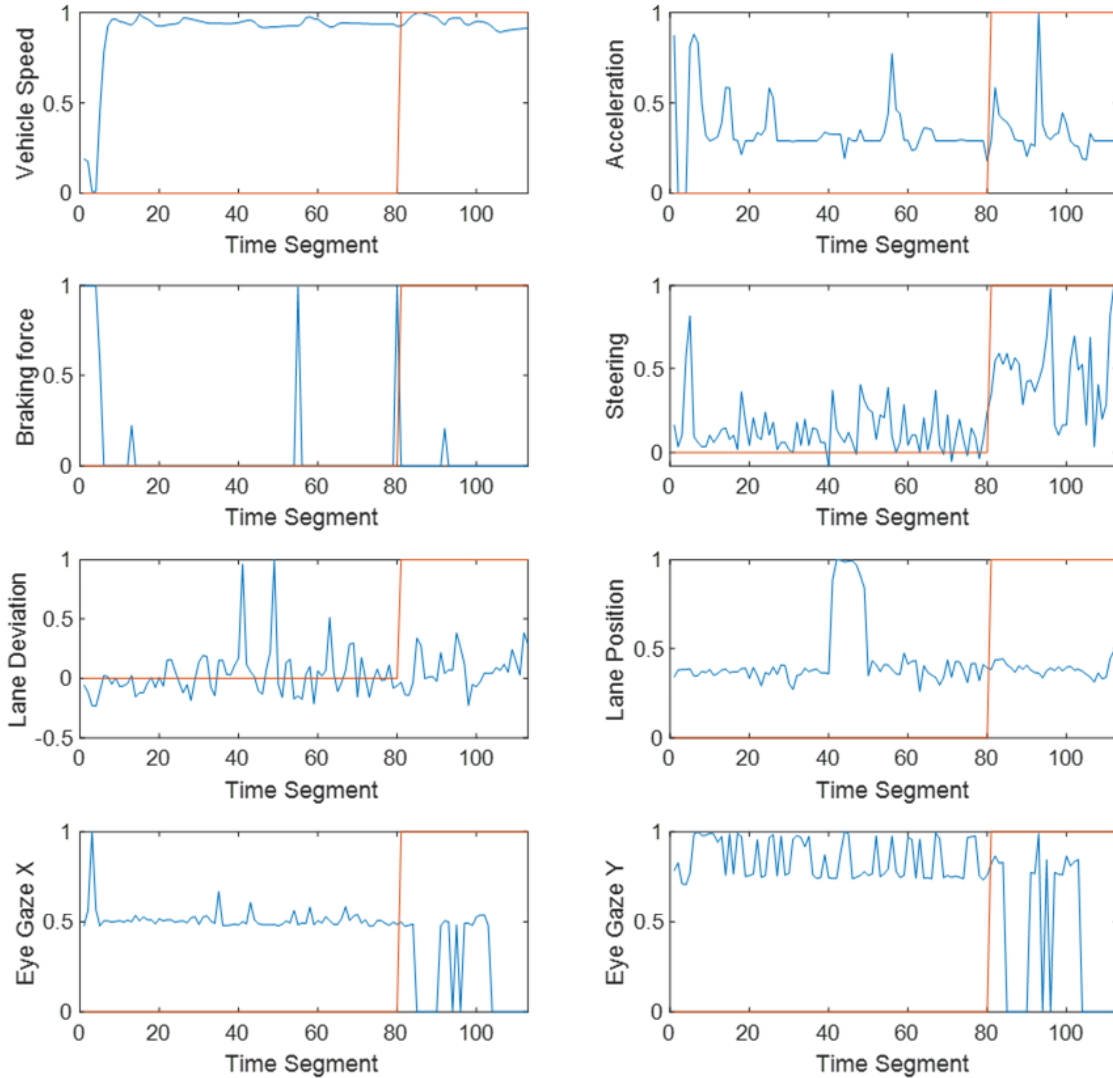


Figure 4-2. Comparisons of Maximum Values of Features of Normal and Distracted Driving for Driver No. 5

Figure 4-2 shows the maximum values of features in normal and distracted driving sections for driver No. 5. The identified features are maximum values of eye gaze in x and y directions and maximum value of steering angle. Maximum values of eye gaze in x and y directions reduce significantly when the driver's state shifts from normal to distracted. The maximum value of the steering angle increases from 0.1 in normal driving section to 0.5 in the distracted driving section.

For other five features, no significant difference has been observed. Therefore, they are regarded as irrelevant features.

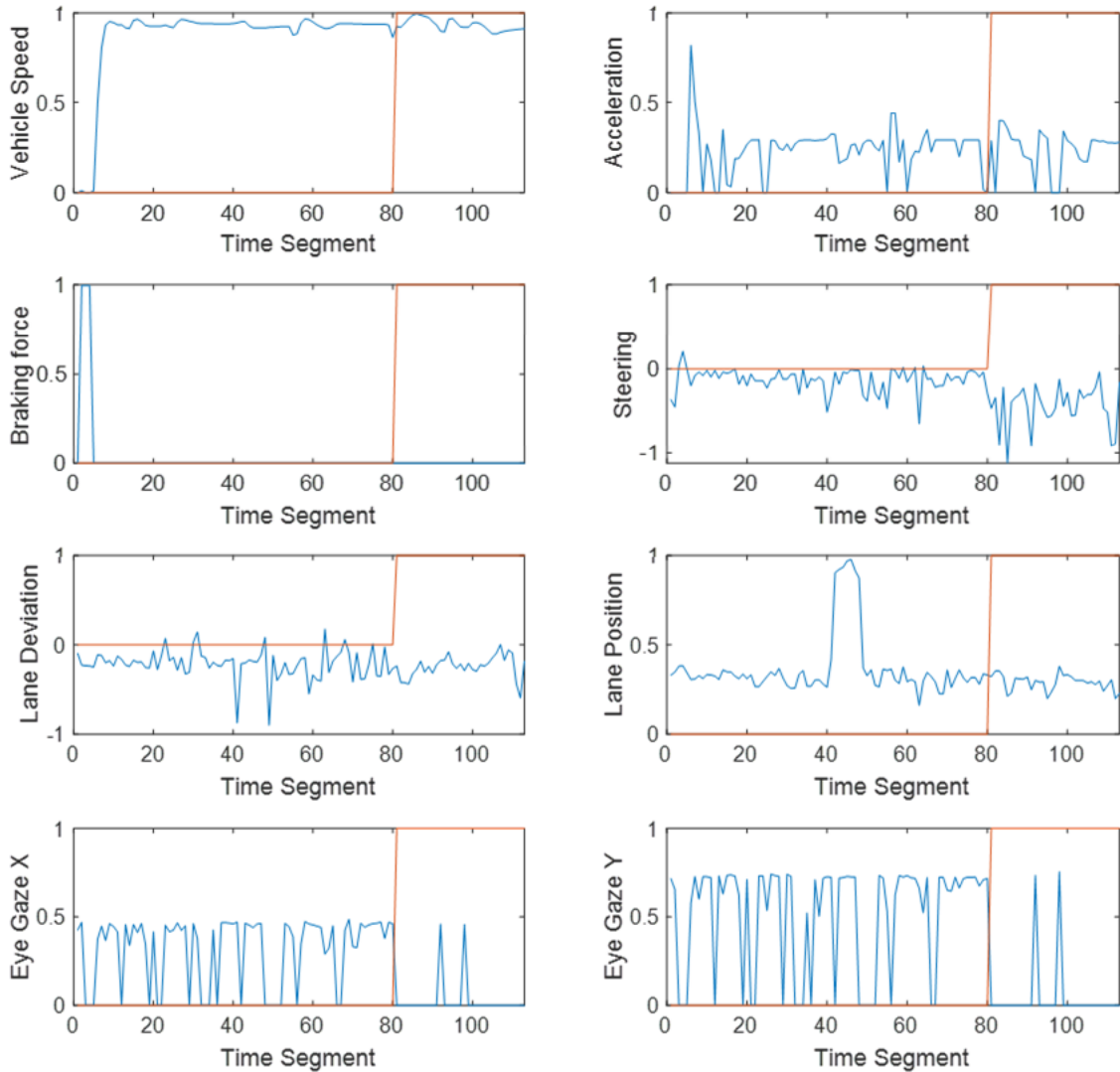


Figure 4-3. Comparisons of Minimum Values of Features of Normal and Distracted Driving for Driver No. 5

Figure 4-3 demonstrates the minimum values of features of normal and distracted driving sections for driver No. 5. The relevant features are minimum values of eye gaze in x and y directions and minimum value of steering angle. The values oscillate between 0 and 0.5 for eye gaze in x direction and between 0 and 0.7 for eye gaze in y direction in normal driving sections. The frequency of oscillation in distracted driving sections reduces significantly without decreasing the range. The reduction in oscillation in frequency indicates a pattern change, which makes

the minimum values of eye gaze in x and y directions relevant features in detecting driver distraction. The minimum value of the steering wheel angle is relevant in detecting driver distraction, because a significant reduction in average values occurs when the driver was distracted.

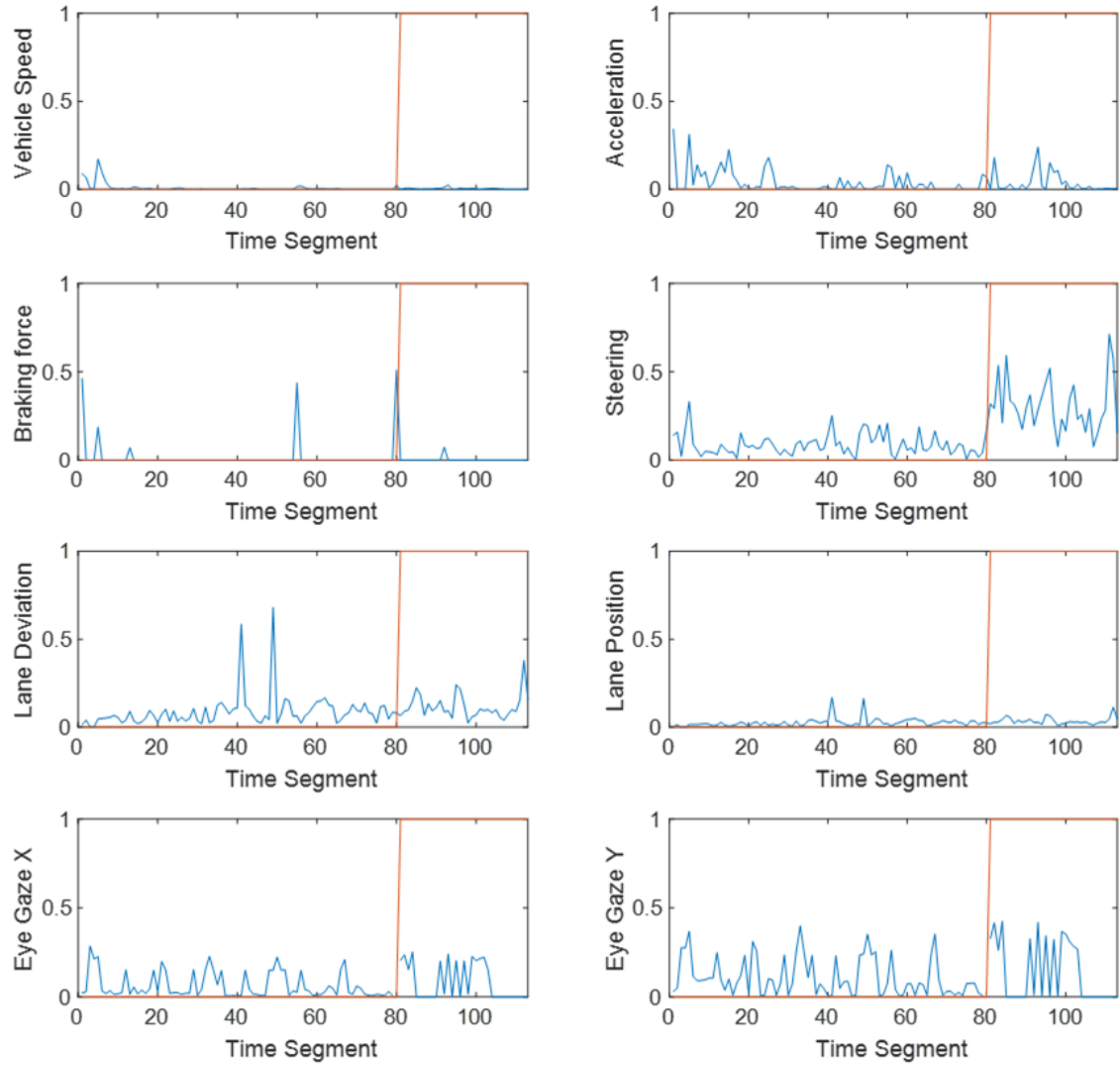


Figure 4-4. Comparisons of Standard Deviation Values of Features of Normal and Distracted Driving for Driver No. 5

Figure 4-4 presents the standard deviation values of features of normal and distracted driving sections for driver No. 5. The identified features in detecting driver distraction are the standard deviation values of steering angle, lane deviation and eye gaze in x and y positions. The values of the standard deviation of steering angle, lane deviation and eye gaze positions increase when the driver

was distracted compared with the values when the driver was driving normally, This finding indicates that driver gazed out of the screen and had less control over the vehicle after the driver was distracted.

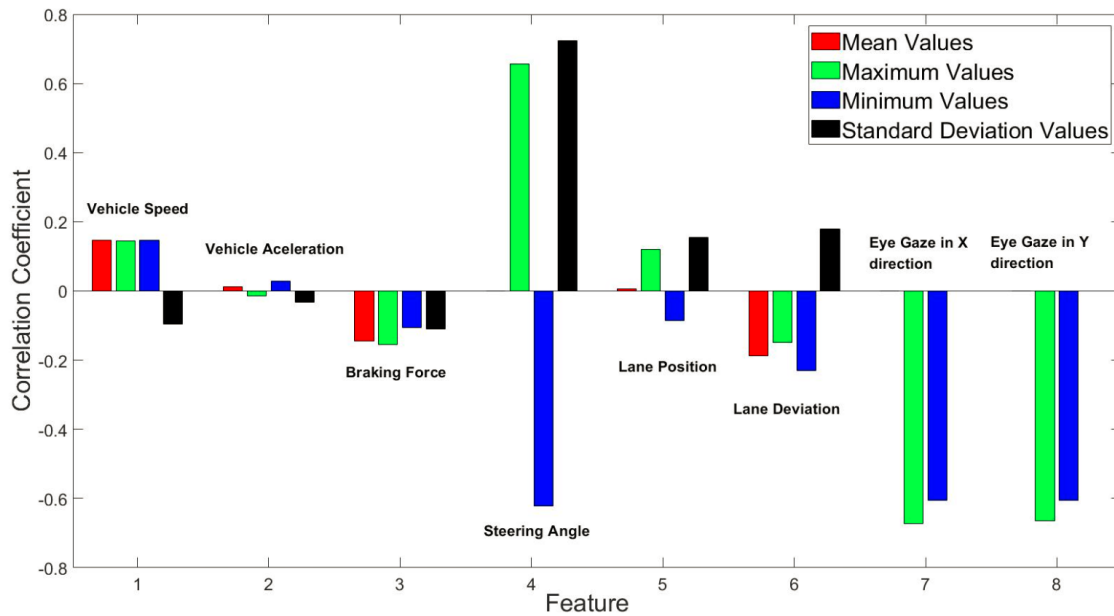


Figure 4-5. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 5

Figure 4-5 demonstrates the correlation coefficients of features. The correlation coefficients estimate the first-order correlation between the feature values and the driver's states. As observed, the relevant features are maximum and minimum values of gaze positions x and y and the maximum value, minimum value and standard deviation value of steering angle because their correlation coefficients are amongst the largest features.

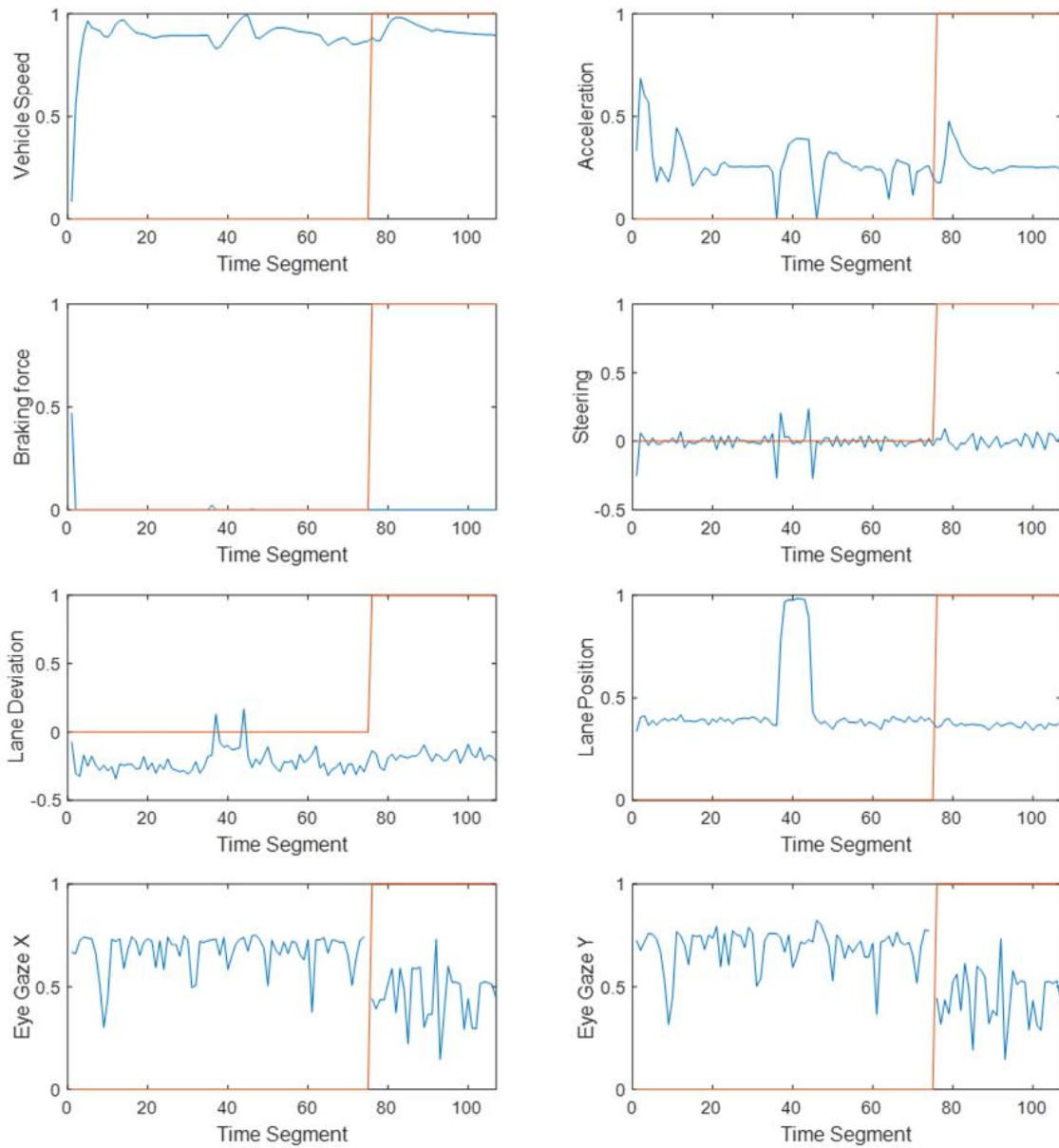


Figure 4-6. Comparisons of Mean Values of Normal and Distracted Driving for Driver No. 6

Figure 4-6 presents the mean values of features of normal and distracted driving sections for driver No. 6. By comparing the normal and distracted driving sections from Figure 4-6, mean values of eye gaze in x and y directions are identified as relevant features in detecting driver distraction for their reduced values after driver was distracted. The mean value of vehicle acceleration is identified as a relevant feature due to more sharp accelerations in the normal driving section, which is not observed in the distracted driving section. The mean value of steering

angle is also relevant in detecting driver distraction with the increased magnitude of oscillations after the driver was distracted.

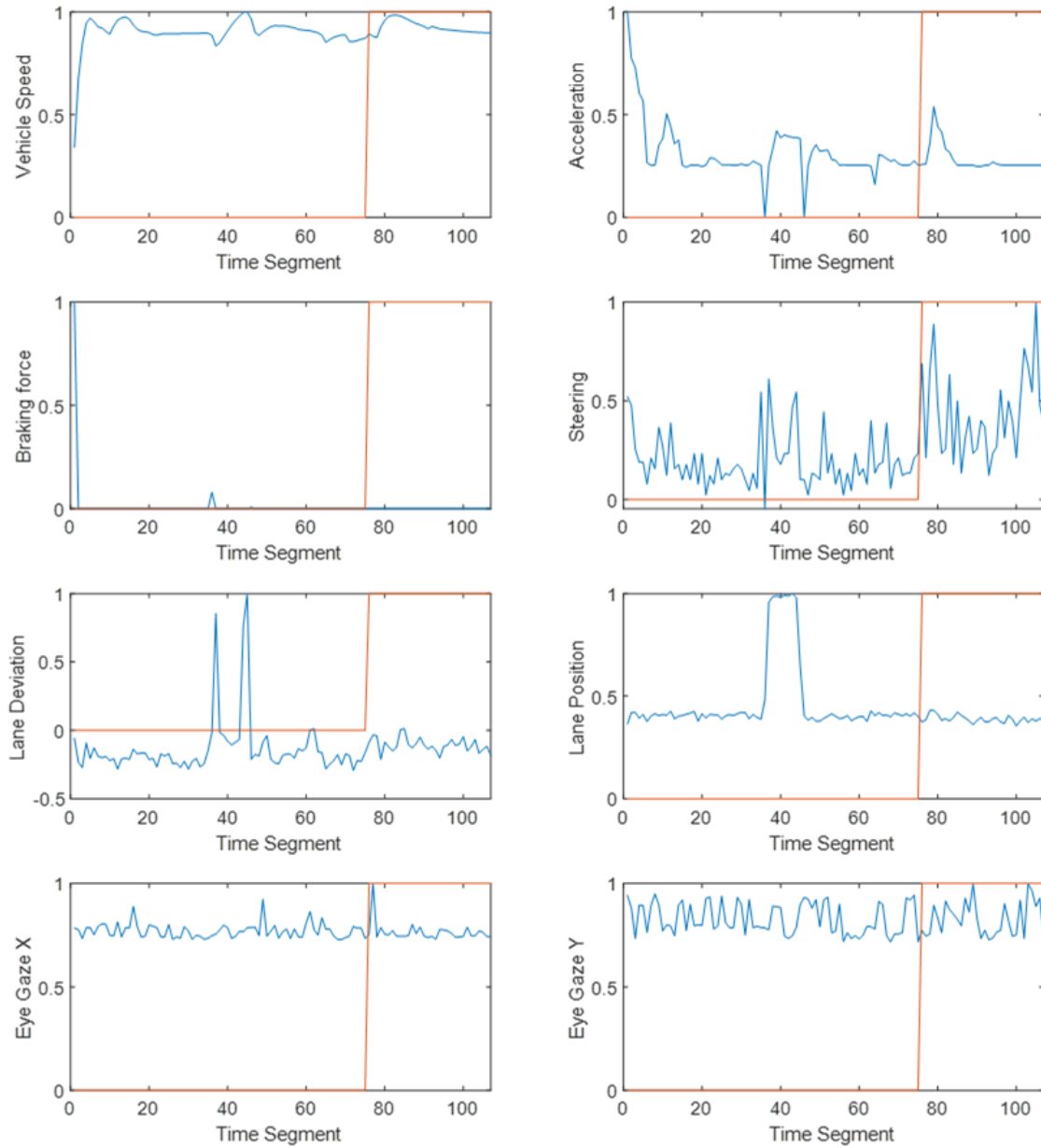


Figure 4-7. Comparisons of Maximum Values of Normal Driving and Distracted Driving for Driver No. 6

Figure 4-7 demonstrates the maximum values of features in normal and distracted driving sections for driver No. 6. The relevant feature in detecting driver distraction is identified as the maximum value of steering angle. This value increases significantly after the driver was distracted compared with the values

when the driver was driving normally. Therefore, the feature is regarded as a relevant feature in detecting driver distraction.

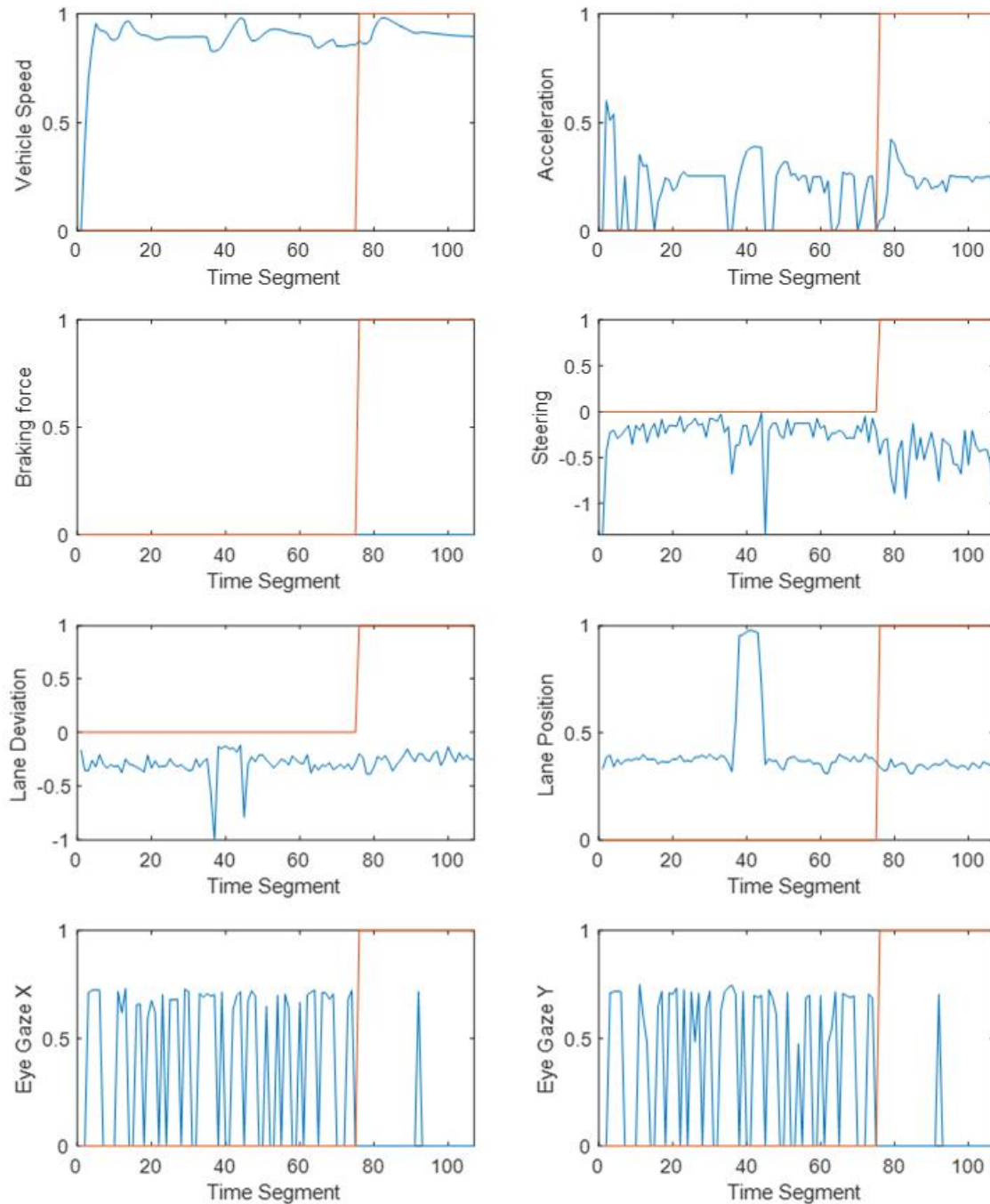


Figure 4-8. Comparisons of Minimum Values between Normal Driving and Manually Distracted Driving for Driver No. 6

Figure 4-8 demonstrates the minimum values of features of normal and distracted driving sections for driver No. 6. The identified relevant features are minimum

values of eye gaze in x and y directions and minimum value of vehicle acceleration. Fewer oscillations and more zero values are observed when the driver was distracted than the mean values of eye gaze in x and y directions when driver was driving normally. The minimum value of vehicle acceleration becomes more stable and fewer oscillations are observed in the distracted driving section than the values in the normal driving section. Therefore, the minimum values of eye gaze in x and y directions and minimum value of acceleration are the three identified relevant features in detecting driver distraction amongst the eight features.

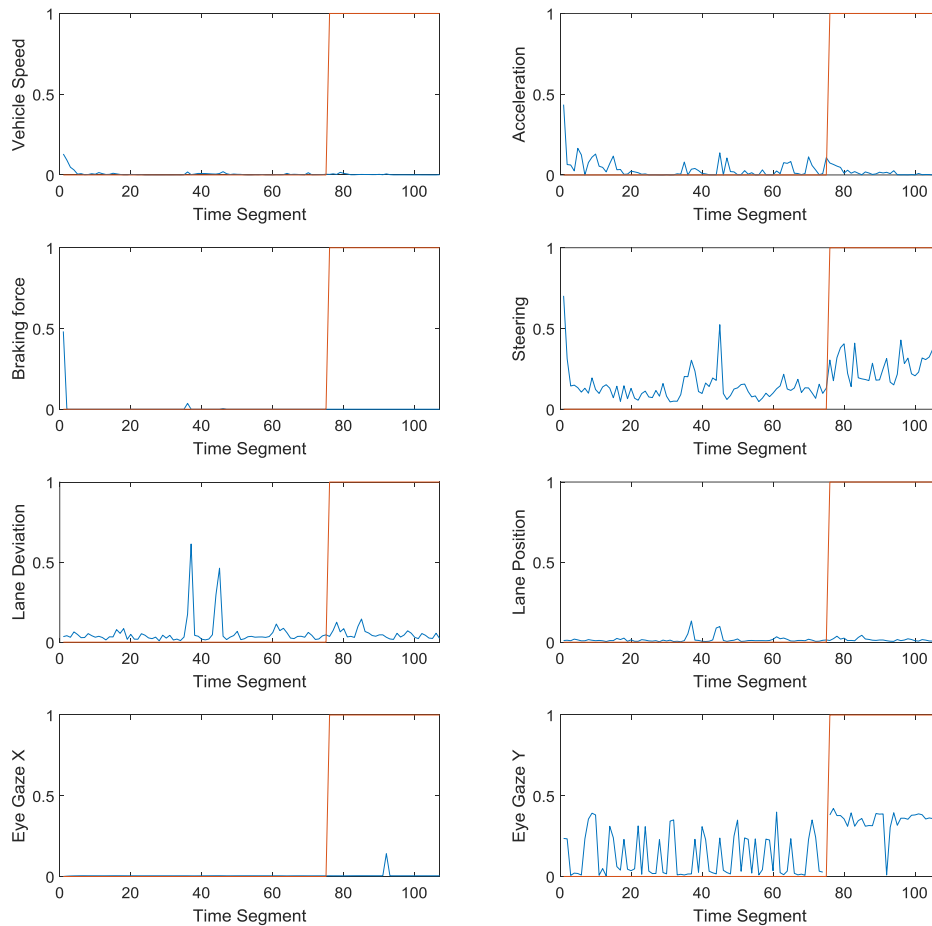


Figure 4-9. Comparisons of Standard Deviation Values of Normal and Distracted Driving for Driver No. 6

Figure 4-9 demonstrates the standard deviation values of features for driver No. 6. The relevant features in detecting driver distraction are the standard deviation of eye gaze in the y direction and steering angle. Oscillations are observed in normal driving sections, and the values become steady and fewer oscillations are observed. The difference is caused by the texting behaviour and that the driver is holding the phone whilst texting. Thus, the standard deviation values of eye gaze in y direction becomes a relevant feature in detecting driver distraction.

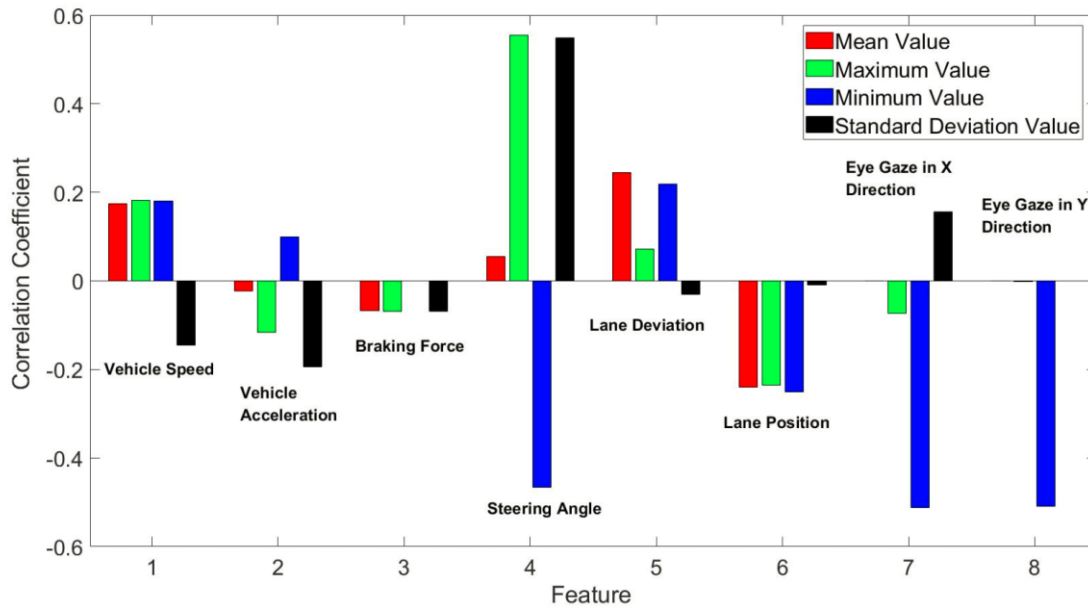


Figure 4-10. Correlation Coefficients between Features and Distraction for Driver No. 6

Figure 4-10 shows the correlation coefficients between the feature values and the driver's states. Figure 4-10 shows that the relevant features are maximum, minimum and standard deviation of steering angle and minimum values of eye gaze in x and y directions. The results in terms of the rankings of the steering angle and eye gaze in x and y directions are in line with the results from the visual inspection. However, the mean and maximum value of acceleration have not been identified by this correlation analysis.

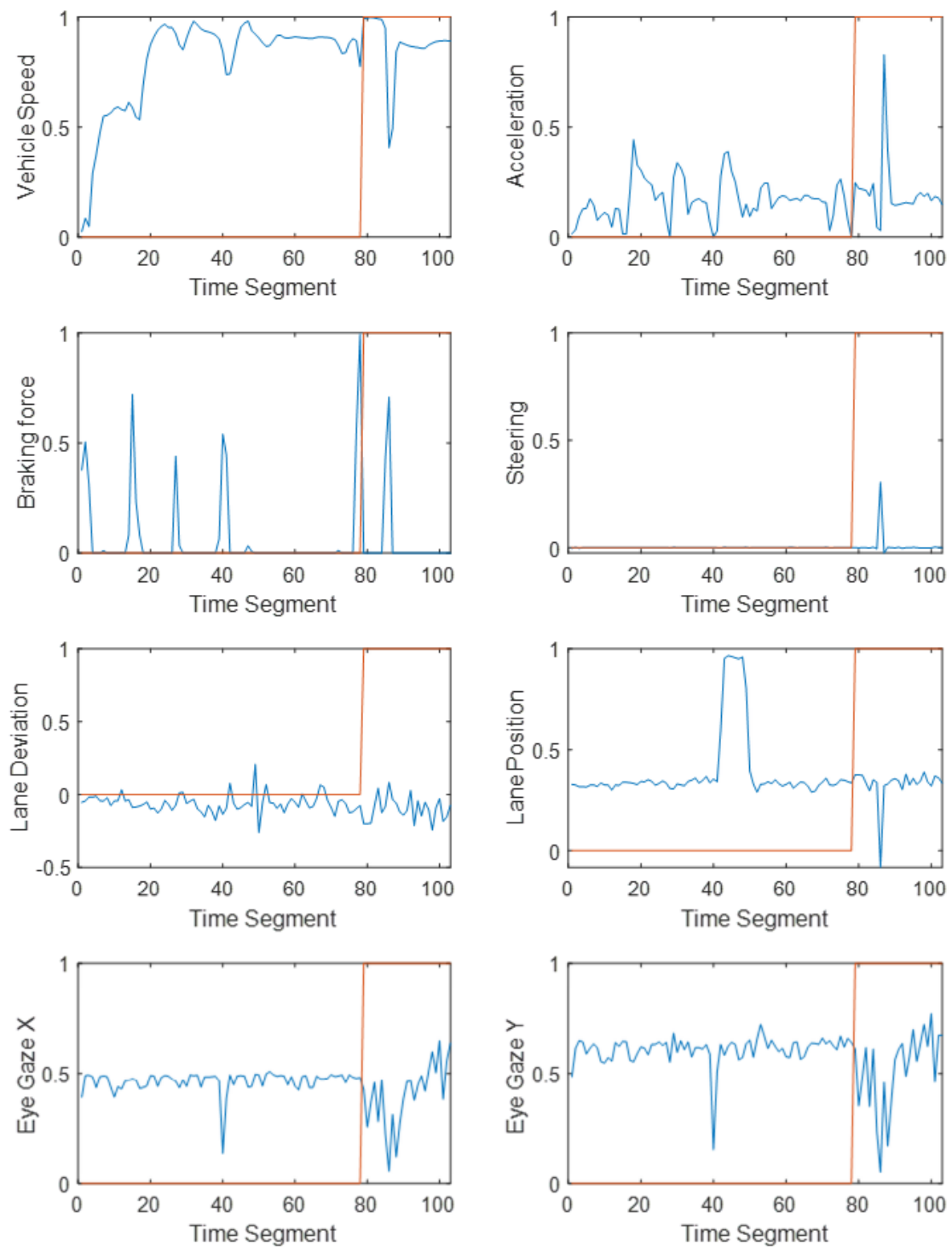


Figure 4-11. Comparisons of Mean Values of Normal Driving and Distracted Driving for Driver No. 25

Figure 4-11 demonstrates features of normal and distracted driving sections for driver No. 25. All features except the mean value of lane deviation are relevant in

detecting driver distraction. Amongst these features, the more relevant features are mean values of speed, acceleration, braking force and eye gaze positions in x and y directions. The eye gaze positions in x and y directions remain steady in normal driving sections and decrease firstly and then increase in distracted driving sections, which indicates the driver moves its gaze directions continuously to text whilst driving. The driver also lost control of the vehicle in a moment, which is indicated by the sharp decrease and then increase in vehicle speed, a spike in vehicle acceleration and a spike in braking force. The momentous change makes the mean values of speed, acceleration and braking force relevant in detecting driver distraction.

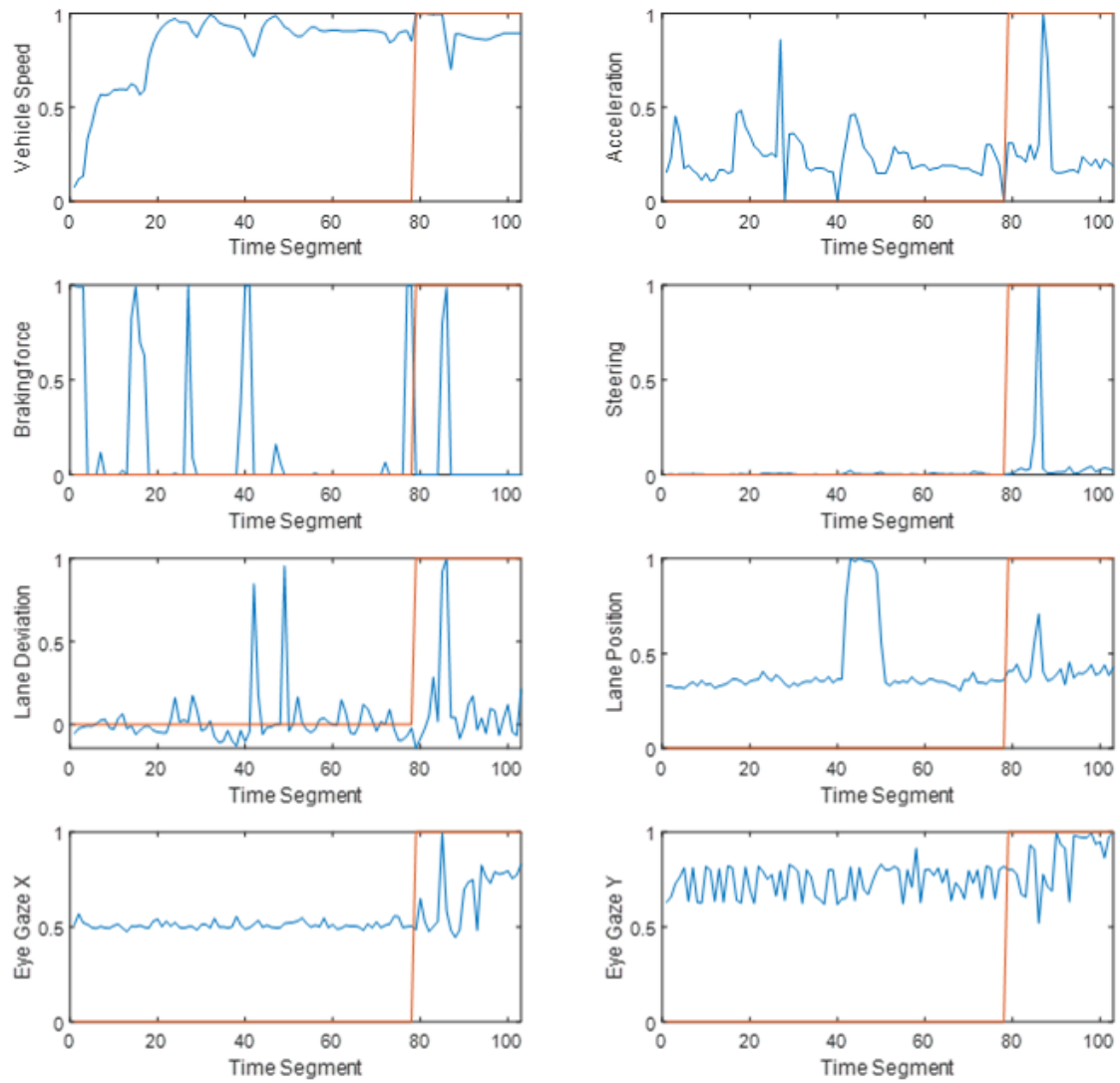


Figure 4-12. Comparisons of Maximum Values between Normal Driving and Distracted Driving for Driver No. 25

Figure 4-12 demonstrates the maximum values of features in normal and distracted driving sections for driver No. 25. As indicated in Figure 4-12, maximum values of steering angle, lane deviation and eye gaze in x and y directions are relevant in detecting driver distraction, because of their differences between the normal and distracted driving sections. The features with the most differences are maximum values of eye gaze positions in x directions, the steering wheel angle, lane deviation and vehicle acceleration. The maximum value of gaze position in x direction increases significantly, which means that this driver looks more to the left during distracted driving than in normal conditions.

When the driver is manually distracted, the angles becomes significantly larger than the rest of the steering wheel angles at one point, which indicates that the driver lost control of the steering wheel. Moreover, the vehicle accelerates sharper when the driver was distracted, which leads to abrupt vehicle speed changes. The lane deviates more significantly when the driver was manually distracted due to the lost control of the steering wheel and sharper acceleration.

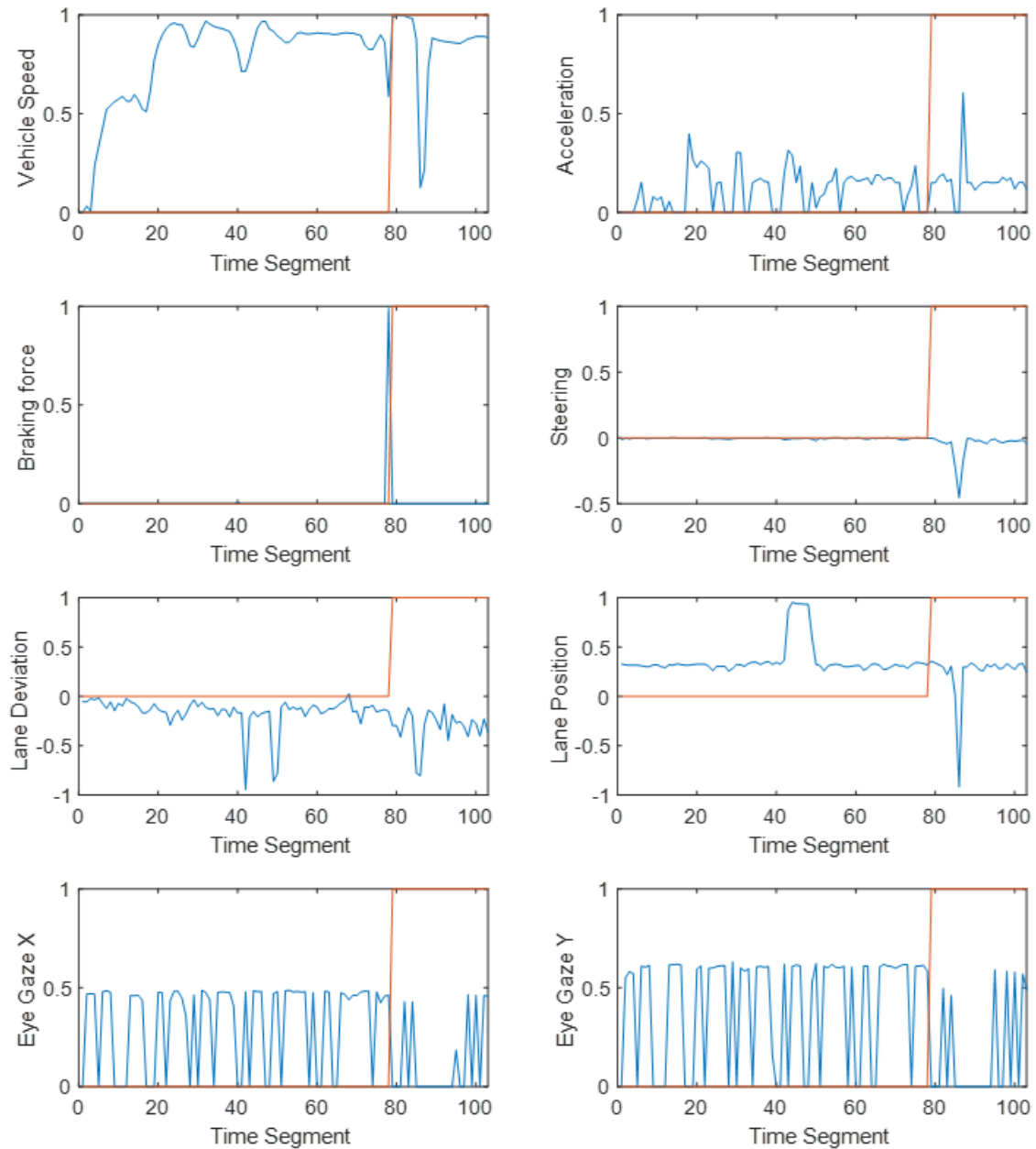


Figure 4-13. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 25

Figure 4-13 demonstrates the minimum values of features in normal and distracted driving sections for driver No. 25. Minimum values of vehicle speed, lane position and eye gaze in x and y directions are relevant features in detecting driver distraction. The driver lost control of the vehicle once during the distracted driving phase. The vehicle speed in the distracted driving section is reduced largely and then accelerates back to normal speed. In the meantime, the steering angle sharply decreases and then returns to the central position. Thus, the minimum values of speed, acceleration and steering angles are relevant in detecting driver distraction. The values of a minimum of eye gaze positions also reduce after the driver was distracted compared to the values of features in normal driving sections. The differences are caused by the texting behaviour of drivers. Therefore, the gaze positions are relevant in detecting driver distraction.

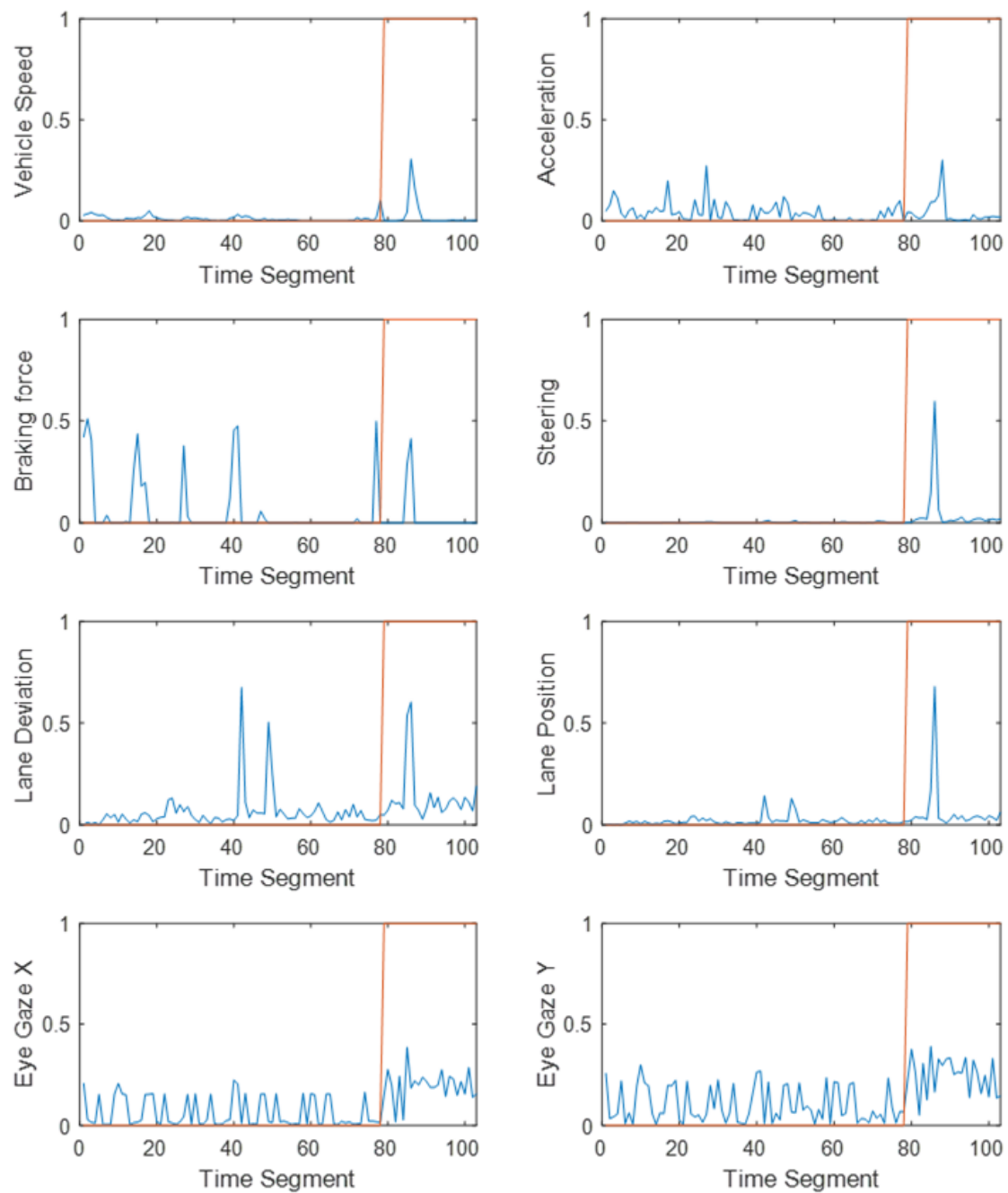


Figure 4-14. Standard Deviation Values between Normal and Distracted Driving for Driver No. 25

Figure 4-14 demonstrates the standard deviation values of features of normal and distracted driving sections for driver No. 25. The standard deviation values of steering angle, lane position and deviation are significantly higher than the values in normal driving sections due to the loss of control of the vehicle. This

result makes them relevant in detecting driver distraction. The standard deviation of eye gaze in x and y directions increases after the driver was distracted due to more frequent and large movement of eye gaze. Therefore, the eye gaze positions are relevant in detecting driver distraction.

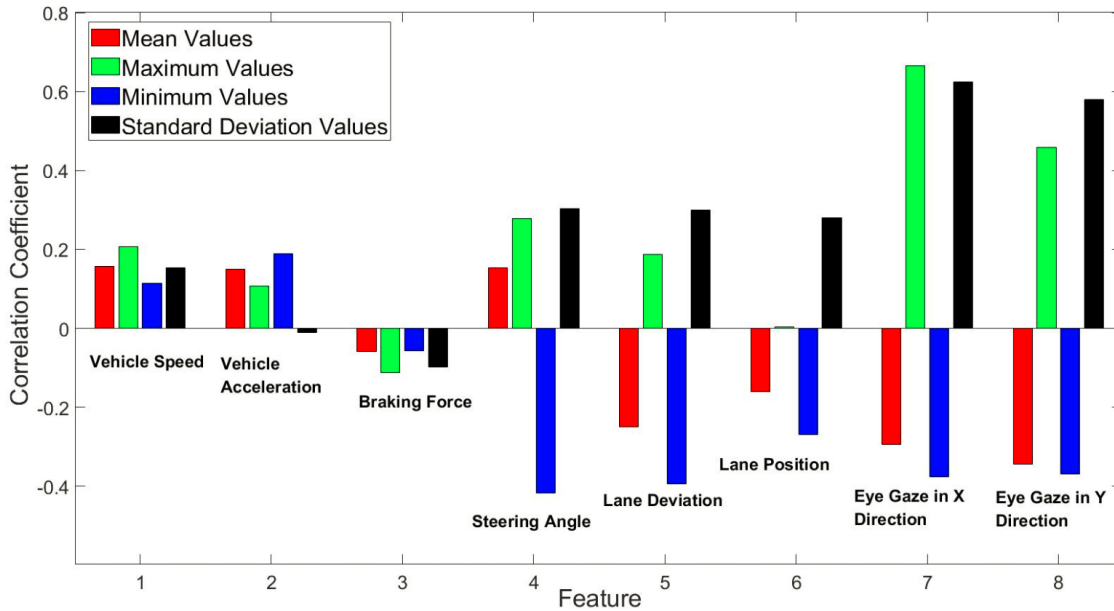


Figure 4-15. Correlation Coefficients between Features and Binary Distraction Levels (0 and 1) for Driver No. 25

Figure 4-15 demonstrates the correlation coefficients between features and binary distraction levels for driver No. 25. Figure 4-15 shows that the signals with high correlation coefficients are steering angle, lane deviation, lane position, and eye gaze in x and y directions. In detail, maximum, minimum and standard deviation of gaze positions are relevant in detecting driver distraction. The minimum values of steering angle, lane position and lane deviation are also relevant in detecting driver distraction with relatively smaller correlation coefficients. The features such as maximum values of eye gaze in x and y directions are successfully identified by the visual inspection. However, the identified features by visual inspection such as vehicle speed and acceleration have not been identified by correlation analysis.

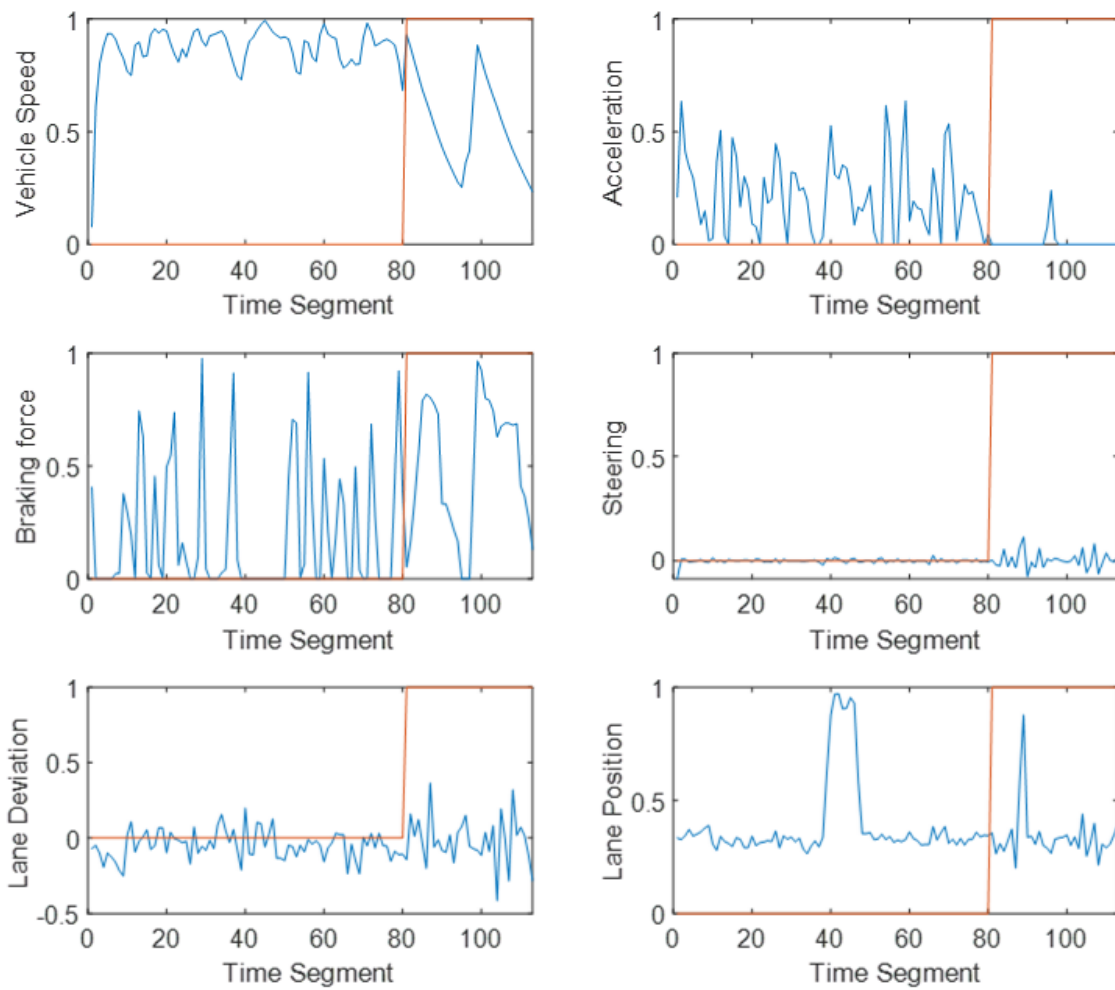


Figure 4-16. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 38

Figure 4-16 demonstrates the mean values of vehicle performance measures of normal and distracted driving for Driver No. 38. The eye gaze positions in x and y directions are not shown due to loss of data. The relevant features in detecting driver distraction are mean values of speed, acceleration, braking force and lane deviation. The mean values of speed changes more abruptly, and the driver applies brakes more often and uses accelerator pedal less frequent. The lane deviates at a larger magnitude when the driver was distracted. These reasons result in that the features of mean values of speed, acceleration, braking, and lane deviation are relevant in detecting driver distraction.

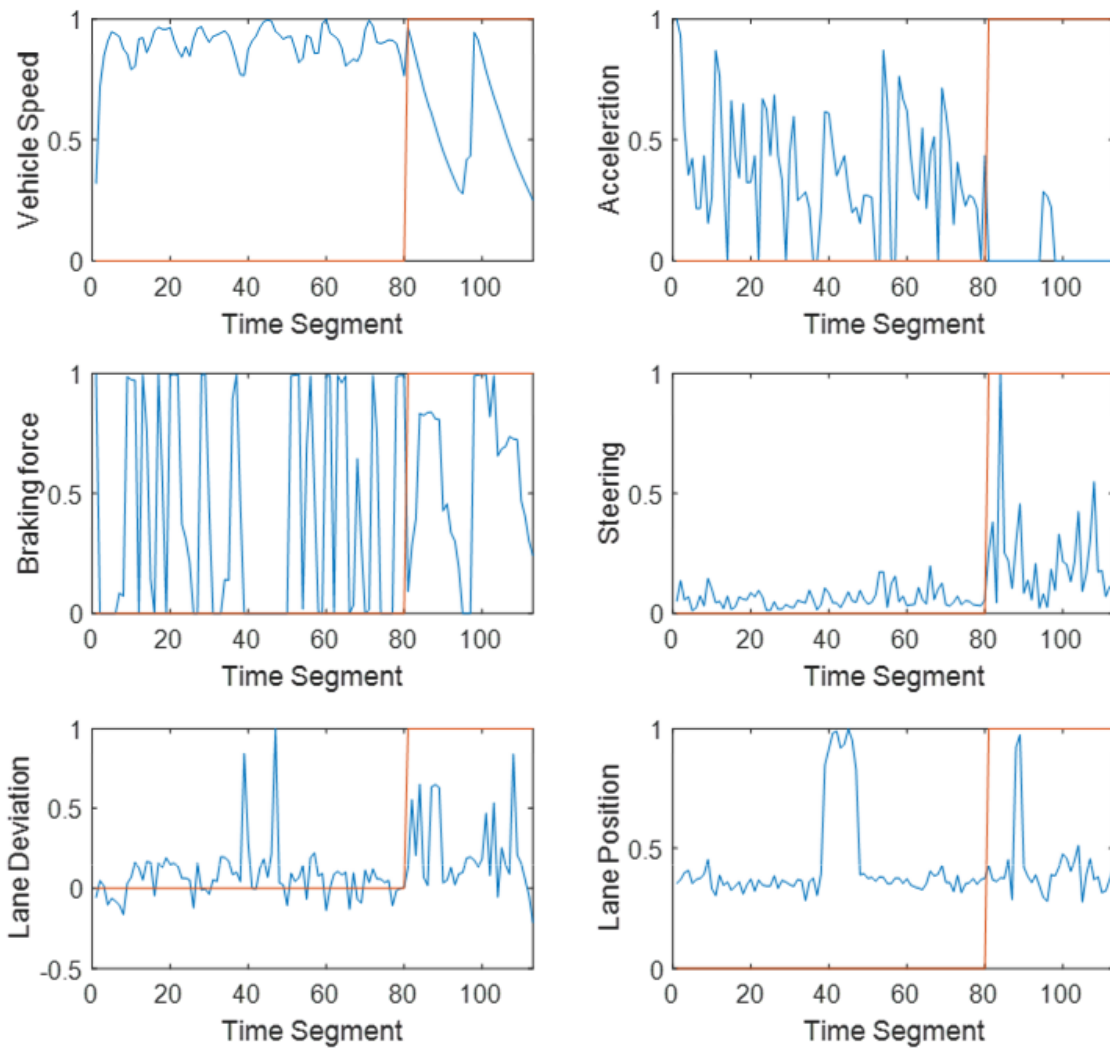


Figure 4-17. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 38

Figure 4-17 demonstrates the maximum values of features in normal and distracted driving sections for Driver No. 38. All six features are relevant in detecting driver distraction. The reasons are that the maximum values of steering wheel angles increase significantly after the driver was distracted. In the meantime, the driver uses the accelerator pedal less frequently and less aggressively, which is indicated with less value. By contrast, the brake force becomes larger and more frequent than before. In conclusion, maximum values of vehicle acceleration, braking force and steering angles are relevant features in detecting driver distraction.

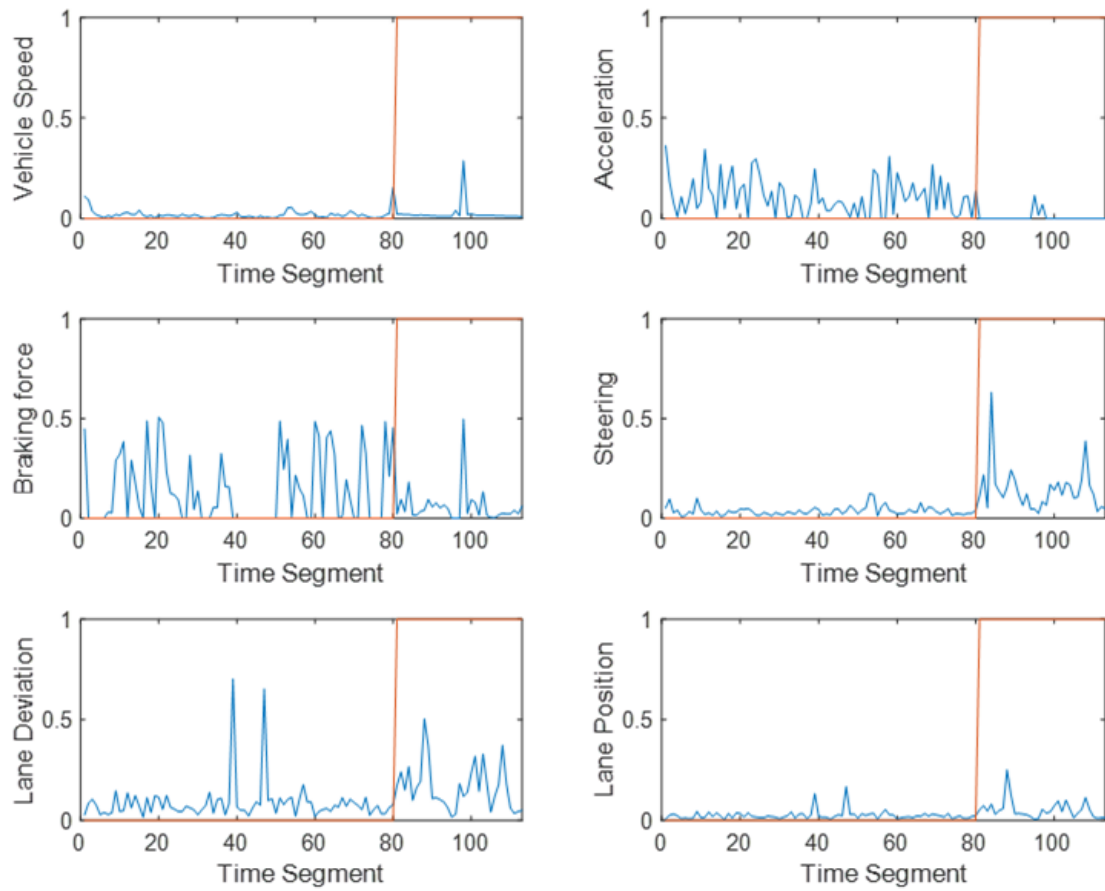


Figure 4-18. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 38

Figure 4-18 demonstrates the minimum values of features in normal and distracted driving sections for Driver No. 38. The minimum values of steering angle, lane deviation and acceleration are identified as relevant features in detecting driver distraction. The minimum values of acceleration decrease after the driver was distracted due to concentration on texting and lack of movements on the acceleration pedal. By contrast, the minimum values of lane deviation and steering angles increase after the driver was distracted. The driver's concentration on texting causes the vehicle to drift more frequently and need to adjust the steering wheel more frequently to compensate for it. Therefore, the minimum values of steering angle, lane deviation and vehicle acceleration are relevant features in detecting driver distraction.

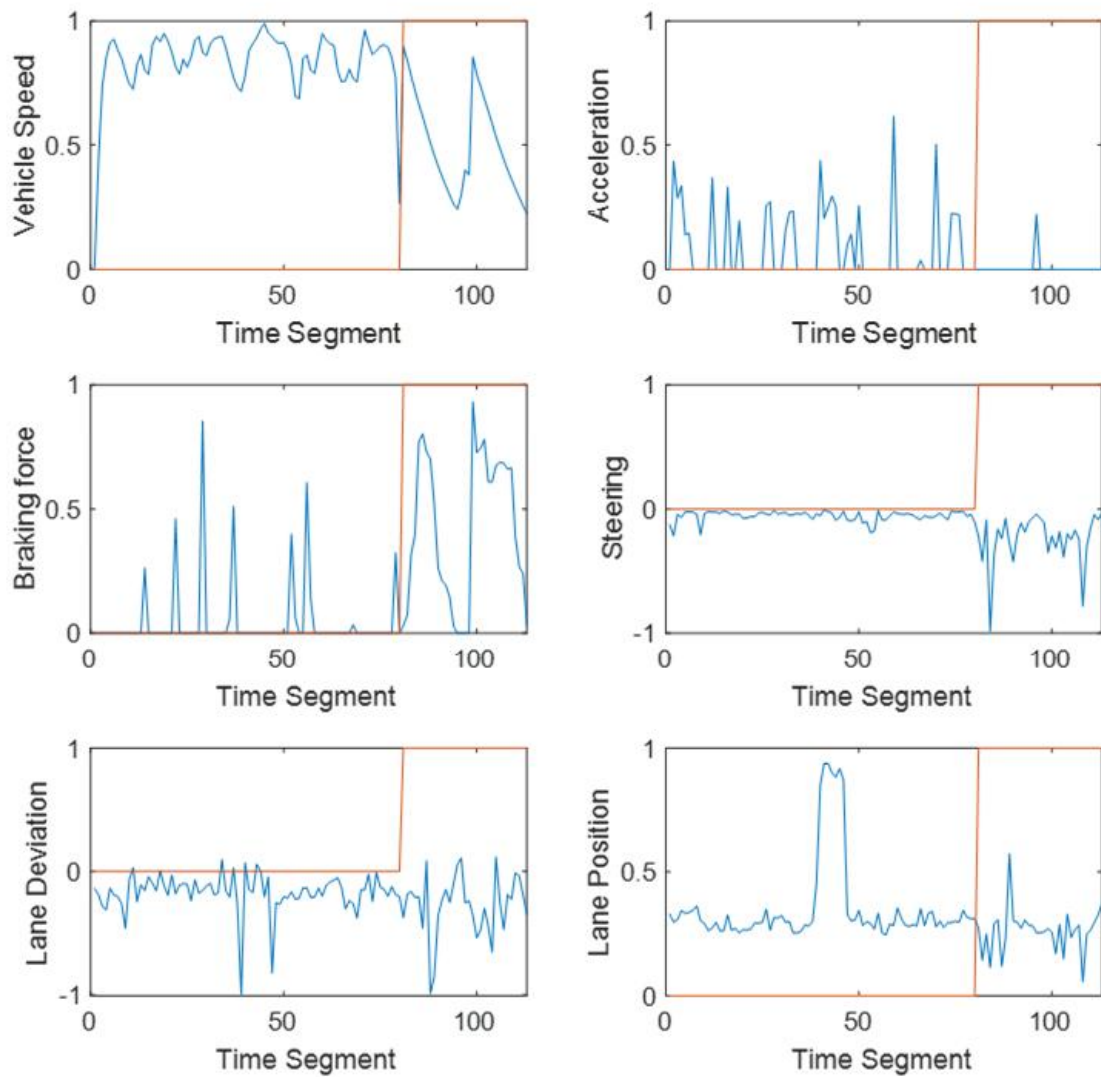


Figure 4-19. Comparisons of Standard Deviation Values between Normal Driving and Distracted Driving for Driver No. 38

Figure 4-19 demonstrates the standard deviation values of features in normal and distracted driving sections for Driver No. 38. The relevant features are identified as the standard deviation of braking force, vehicle speed and steering angle. Compared with the normal driving section, the standard deviation of braking force significantly increases and lasts longer than the time driver applied to brake when the driver was driving normally. For the standard deviation of vehicle speed, its values show a sharp increase and decrease in distracted driving sections. This condition is not observed in normal driving sections. For the standard deviation of steering angle, its values show a sharp increase and frequency oscillations

when the driver was distracted. Therefore, the standard deviations of vehicle acceleration, speed and steering angle are identified as relevant features.

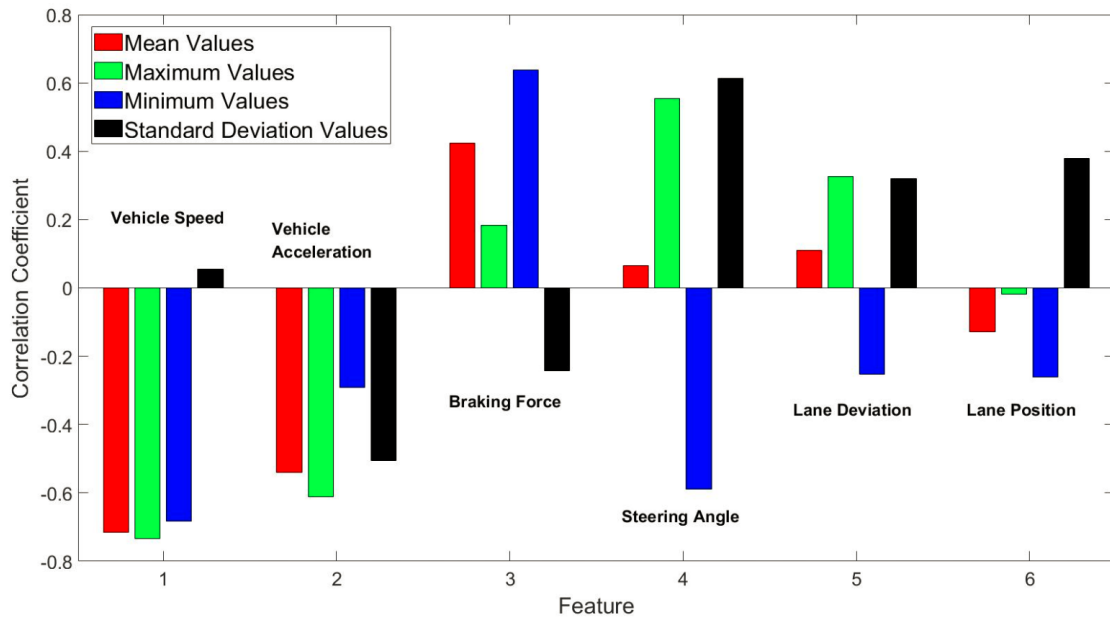


Figure 4-20. Correlation Coefficients between Features and Binary Distraction Level for Driver No. 38

Figure 4-20 demonstrates the mean, maximum, minimum values of speed, maximum values of acceleration, and minimum values of braking force are amongst the most relevant features in detecting driver distraction. These features have the highest correlation coefficients. The relevant features identified by correlation coefficients are also identified in figures including Figure 4-16, Figure 4-17, Figure 4-18 and Figure 4-19.

After the individual extractions of relevant features in detecting driver distraction by visual inspection and correlation analysis, the most relevant features in detecting driver distraction can be identified after concluding the results from 42 participants.

From the visual inspection perspective, each statistical feature will be identified as relevant or irrelevant features. The results of each participant are recorded. The final results of the visual inspection add up all the relevant features according to the specific feature type, such as the maximum of steering angle. The most relevant features in detecting driver distraction are the features with the highest

numbers amongst the 42 participants. A table of relevant features and number of participants with these relevant features is presented.

Table 4-2. Number of Participants with Relevant Features

Ranking	Feature Name	Number of Participants
1	Standard deviation Value of Steering Angle	42
2	Maximum Value of Steering Angle	41
3	Maximum Value of Lane Deviation	36
4	Maximum Value of Vehicle Speed	36
5	Standard Deviation Value of Eye Gaze Position in x Direction	35
6	Mean Value of Eye Gaze Position in y Direction	35
7	Standard Deviation Value of Eye Gaze Position in y direction	35
8	Minimum Value of Vehicle Speed	35
9	Standard Deviation Value of Lane Deviation	31
10	Maximum Value of Eye Gaze Position in x Direction	31

Table 4-2 lists the 10 most relevant features in detecting distraction by visual inspection. The remaining features are not presented because the 10 most relevant features are representative and other features have low relevancy. The standard deviation of steering angle has been identified as the most relevant feature amongst all participants. This is attributed to that the driver is texting whilst driving, and due to the grip and control over the steering wheel. The second most relevant feature is the maximum of steering angle, and the maximum of lane deviation ranks third. The large values of lane deviation indicate that the drivers are less capable of keeping the vehicle in lane given that part of their attention has been diverted to the texting behaviour. As demonstrated in Table 4-2,

features such as maximum and standard deviation of eye gaze position in x directions and mean and standard deviation of eye gaze position in y directions are also relevant in detecting driver distraction. Eye gaze in x and y directions are identified as the relevant features because the driver behaviour (e.g. texting) is reflected on the change in eye gaze directions.

The relevant signals and features fed into detection algorithms can be identified according to Table 4-2. The most relevant signals are steering angle, lane deviation, vehicle speed and eye gaze positions in x and y directions. The 10 features listed in Table 4-2 are extracted from the above-mentioned five signals. The five features fed into detection algorithms are the standard deviation and maximum values of steering angle, maximum of lane deviation, maximum of speed and the standard deviation of eye gaze in x direction. The eight features fed into detection algorithms are mean and standard deviation values of eye gaze in y direction and minimum values of vehicle speed in addition to the abovementioned five features fed into detection algorithms.

Analysis of correlations has been applied to all 32 features. The binary variables are 0 and 1, which denote normal and distracted driving sections.

The mean values for all values of normal driving sections (M_0) and distracted driving sections (M_1) are calculated separately firstly. Then, the standard deviation of all values is calculated, followed by adding the total number of training examples of normal and distracted driving. The next step is to substitute the abovementioned values into the equation (3-2) to obtain the correlation coefficients.

The relevant features from analysis of correlation are ranked from high correlations to low correlations in Table 4-3. This table indicates that the relevant signals are gaze in x and y directions and steering angle. The features with the highest correlation are mean values of eye gaze in x and y direction as well as standard deviation of steering angle. The three features have the highest correlation coefficients for their difference in values between normal driving and distracted driving sections.

Table 4-3. Results from Correlation Analysis

Ranking	Feature Name	Correlation Coefficient
1	Mean Value of Gaze in y direction	0.65
2	Mean Value of Gaze in x direction	0.64
3	Standard Deviation Value of Steering Angle	0.56
4	Maximum Value of Steering Angle	0.54
5	Minimum Value of Steering Angle	0.53
6	Standard Deviation Value of Gaze in y direction	0.47
7	Standard Deviation Value of Gaze in x direction	0.46
8	Minimum Value of Gaze in y direction	0.37
9	Minimum Value of Gaze in x direction	0.37
10	Maximum Value of Gaze in x direction	0.30

Table 4-3 presents the relevant features identified by the analysis of correlations. As mentioned previously, the features are extracted from signals including gaze in x and y direction and steering angle. The top three relevant features are mean values of gaze in x and y directions and standard deviation of steering angle.

Comparing Table 4-3 with Table 4-2 shows that six out of ten features are common including mean and standard deviation values of gaze in y direction, maximum and standard deviation values of gaze in x direction and maximum and standard deviation values of steering angle. The remaining four different features in Table 4-2 and Table 4-3 are maximum and minimum of vehicle speed and

maximum and standard deviation of lane deviation identified by visual inspection, and mean and minimum values of gaze in x direction, minimum value of gaze in y direction and steering angle identified by analysis of correlations. The visual inspection method identifies some features extracted from vehicle speed and lane deviation, which are not identified by the analysis of correlations. Comparing the relevant features identified by visual inspection and analysis of correlations, indicates that some features such as the maximum value of vehicle speed contain higher-order differences between normal and distracted driving sections.

4.3 Identification of Suitable Algorithms

The detection algorithms in this study are selected by comparing the performance of algorithms. In the previous study on the development of detection algorithms, a single algorithm is developed at a time. For example, the SVM is developed with different kernels. This development process relies more on the previous experiences of the researcher considering that algorithms are developed separately. No comparisons between the algorithms in terms of performances are made.

Programmed classification algorithms are available in the MATLAB classification toolbox, which has 25 algorithms. Many of them are unsuitable for detecting the driver distraction but selecting the appropriate algorithms to detect driver distraction becomes a priority. The classification algorithms built in the MATLAB 2019a include DT, LR, KNN and SVM. Each algorithm is developed with several variations. The suitable algorithms can be identified from these programmed algorithms.

The three steps of obtaining the results are data importing, algorithm selection and feature selection, the results including the training accuracy, prediction accuracy and prediction time are recorded.

The first step is to feed the data into the detection algorithm (i.e., data importing). The input and output variables should be specified by selecting the predictors and responses after the target data file is specified. Before selecting the detection algorithms, the way of separating training and validation sets should be selected

from cross-validation, hold-out validation, and no validation. Cross-validation and hold-out validation further tune the algorithm and supply information about the performance of the algorithm.

The second step is to select input features from all extracted features available, which can be specified in feature selection options in the MATLAB classification toolbox. All features in the input matrix are selected by default, specific features can be selected by de-select undesired features.

After the input data are imported to the system, the next step is to select the desired machine learning algorithms. The 'all-quick-to train' or 'All' button could train a series of machine learning algorithms one by one and present the training results in the side window of the MATLAB user interface. One of the two buttons should be selected if the results using the algorithms need to be compared and, the suitable algorithms can be found in this way.

The two metrics in assessing the performance of algorithms are prediction accuracy and prediction time. The suitable algorithms achieve the balance between high prediction accuracy and short prediction time.

All simulations and estimations in this study run on a Lenovo ThinkPad computer, whose processor is Intel i7-5500U and the Ram volume is 8 GB. The operation system of the computer is a 64-bit Windows 7.

The MATLAB code which estimates the prediction time of algorithms runs numerous times (up to 10,000) to obtain the accurate values. The total running time and the times which the MATLAB code runs are recorded. Total running time dividing the running times results in the prediction time for each algorithm. Typical time for predicting once is several milliseconds.

The suitable algorithms can be found by feeding five relevant features into the software and comparing the results for each algorithm. A total of 25 algorithms built in the APP are tested, and the suitable algorithms are selected based on the test results. The choice of the TW is not important between the 2 and 5 s TWs given that both of them have similar results when selecting suitable algorithms.

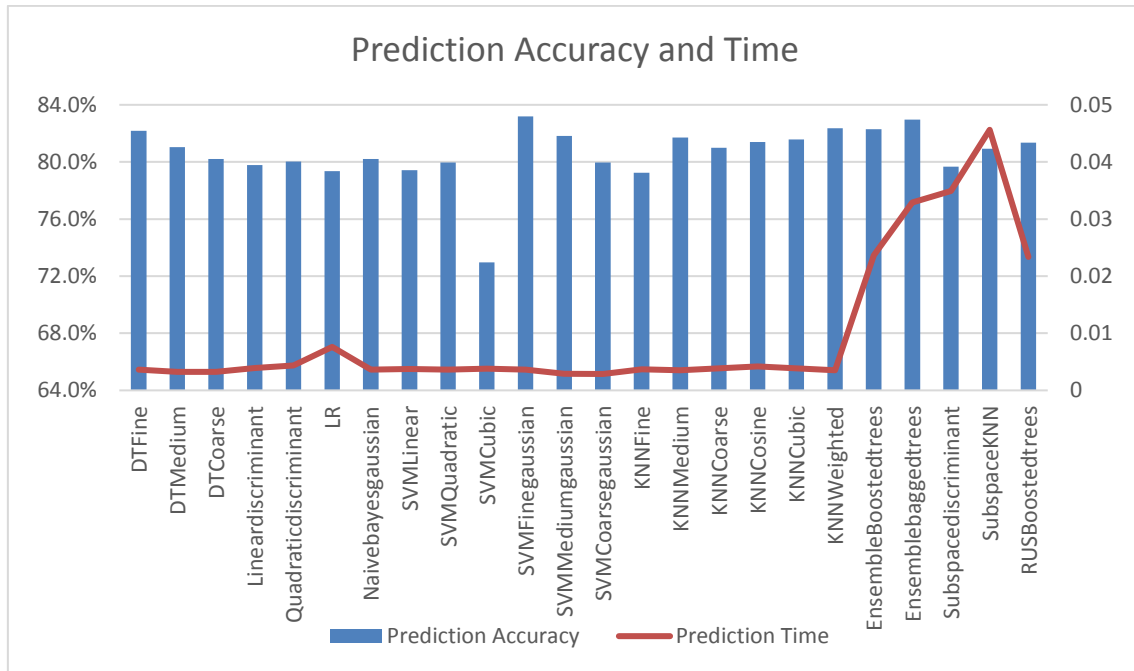


Figure 4-21. Prediction Accuracy and Time

Figure 4-21 presents the prediction accuracy and prediction time for 24 algorithms (naïve Bayes with a linear kernel is excluded for its excessive long prediction time). The input is data when the driver is manually distracted, the number of input features is five and the TW is 5 s. Figure 4-21 shows that the prediction time is close to each other apart from the five algorithms using ensemble methods (i.e., Ensemble Boosted Trees, Ensemble Bagged Trees, Subspace Discriminant, Subspace KNN and RUS Boosted Trees). The remaining 19 algorithms only have a slight difference in terms of prediction time. Thus, the selection of suitable algorithm is based on the comparison between prediction accuracy. One algorithm is chosen for each type of algorithm if the prediction accuracy is high enough to make the top five. The DT (fine), LR, SVM (fine Gaussian) and KNN (weighted) are selected for their higher prediction accuracy and shorter prediction time compared to other algorithms. Although the prediction time for Ensemble Bagged Tree is longer than those of other algorithms, it is considered due to its high prediction accuracy.

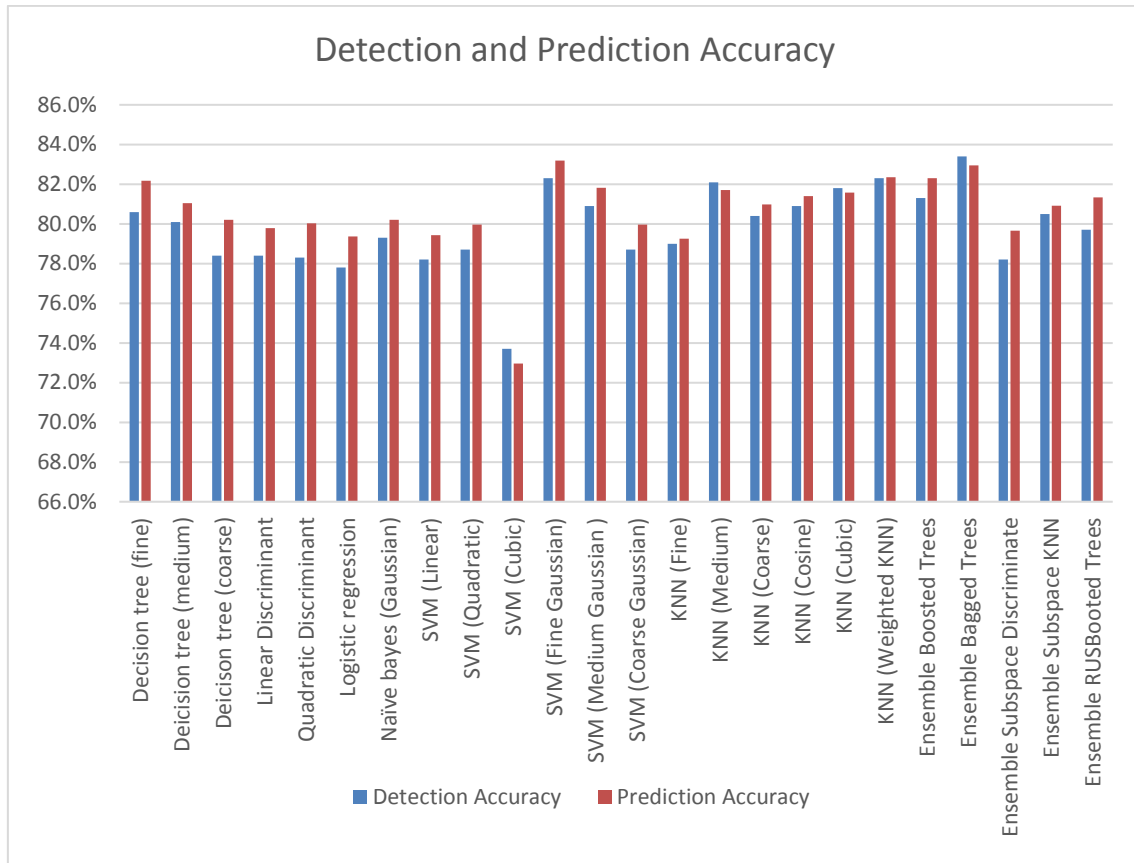


Figure 4-22. Detection and Prediction Accuracy

Figure 4-22 presents the detection and prediction accuracy when the number of input features is 5 and the driver is manually distracted. Figure 4-22 shows that the detection and prediction accuracy are similar for most of the algorithms. In general, the prediction accuracy is 1%–2% higher than the detection accuracy. However, for SVM (cubic), the detection accuracy is around 1% higher than prediction accuracy. Therefore, trained algorithms are stable in terms of their performance. Therefore, they can be used to predict driver's states.

The five potential suitable algorithms need to be further examined with the prediction time, which is important in real applications.

Table 4-4. Prediction Time for Different Numbers of Inputs

Algorithm	t_p (5 inputs)	t_p (8 inputs)	t_p (32 inputs)
DT (Fine)	0.003	0.004	0.005
LR	0.007	0.007	0.009
SVM (Gaussian Kernel)	0.005	0.005	0.006
KNN (Weighted)	0.008	0.010	0.026
Ensemble Bagged Trees	0.051	0.077	0.090

Table 4-4 presents the prediction time for the various numbers of inputs when the t_{TW} is 1 s. The table shows that the prediction time for KNN and Ensemble Bagged Trees increases with the number of inputs, which means the prediction time increases with the data volume. In real applications, the data volume tends to be large when driving data with diverse types of drivers over a long time are included. Therefore, KNN and Ensemble Bagged Trees are unsuitable for real applications. Although the prediction time for SVM (Gaussian kernel) only increases from 0.005 to 0.006 seconds (i.e. 20%) when the number of inputs increases from 5 to 32, the SVM (Gaussian kernel) is not suitable for real applications because computing cost is high when training sets are projected into higher dimensional feature spaces using the Gaussian kernel. The suitable algorithms can be chosen from DT and LR. The selection process can be completed by exploring prediction time with different TWs.

Table 4-5. Prediction Time with Different TWs

Algorithm	$t_p (5 \leq t_{TW})$	$t_p (2 \leq t_{TW})$	$t_p (1 \leq t_{TW})$
DT	0.004	0.004	0.005
LR	0.008	0.008	0.009
SVM (Gaussian Kernel)	0.005	0.005	0.006
KNN (Weighted)	0.006	0.006	0.026
Ensemble Bagged Tree	0.031	0.035	0.090

Table 4-5 presents the prediction time for different TWs (i.e., 1, 2 and 5s) when the number of inputs is 32. The results show that the prediction time for KNN and Ensemble Bagged Trees increases significantly with the increasing size of TWs. Therefore, they are unsuitable for real applications. The choice of suitable algorithms will be made by examining their time complexity. The algorithms without any notable changes in prediction time are DT and LR. The DT is generally quick to predict. No significant change in prediction time occurs when the volume of data increases, which makes DT a suitable algorithm. LR is often used to benchmark the performance of other algorithms. Given that the DT is regarded as a suitable algorithm, LR is also chosen for the benchmarking purpose and because of its short prediction time.

Table 4-6 introduces the time complexity of algorithms of training and prediction. This table reflects the time trends when the data volume is increasing.

Table 4-6. Time Complexity

Algorithm	Time Complexity (Training)	Time Complexity (Prediction)
DT	$O(n \cdot \log(n) \cdot d)$	$O(\text{maximum depth of the tree})$
LR	$O(n \cdot d)$	$O(d)$
SVM	$O(n^2)$	$O(d \cdot s)$
KNN	$O(d \cdot n \cdot k)$	$O(n)$
Ensemble Bagged Trees	$O(n \cdot \log(n) \cdot d \cdot t)$	$O(\text{maximum depth of the tree} \cdot t)$

Notes: n : number of samples, d : number of features, s : number of support vectors, k : number of nearest neighbours and t : number of trees included in Ensemble Bagged Trees

Table 4-6 shows that the time complexity of KNN is the largest. It is proportional to n (number of samples). The prediction time complexity for SVM is proportional to s (the number of support vectors) and d (the number of features). When the data volume increases, the number of support vectors increases. Thus, SVM is unsuitable for real applications. The time complexity for Ensemble Bagged Trees depends not only on the depth of the tree but also on the t (number of trees) included in the algorithm. The time complexity for DT and LR is the smallest; that of the former depends on the depth of the tree, and that of the latter depends on the d (number of features).

4.4 Results

Visual inspection and correlation coefficients have found relevant features in detecting driver distraction. Whether the method of feeding relevant features into the algorithm is effective is unclear. The performance of the algorithms is

unknown. Feeding all available and relevant features into suitable algorithms is important to obtain the prediction results. An analysis of the results is followed.

The input matrix is constructed according to the number of input features, distraction type and the lengths of TWs. The following tables present the prediction results using suitable algorithms. The input matrix is feed into the selected algorithms in the MATLAB classification toolbox to produce the following results. The TWs are 2 and 5 s in length, the numbers of input features are 5, 8 and 32. The four distraction types are manual, cognitive and two types of emotional distraction (types 1 and 2).

The prediction accuracy and prediction time of the same TW and type of distraction are presented in the separate tables. The algorithms chosen to detect driver distraction are the DT and LR.

Table 4-7. Prediction Accuracy and Prediction Time of the DT and LR of Manual Distraction Using 2 s TW

Algorithm	Number of Features	Prediction Accuracy (%)	t_p (s)
DT	5	80.07	0.002
LR	5	79.54	0.004
DT	8	80.95	0.002
LR	8	80.16	0.004
DT	32	82.26	0.004
LR	32	80.74	0.008

Table 4-7 demonstrates the prediction results using DT and LR for manual distraction using 2 s TW. The prediction accuracies using the DT are 80.07%, 80.95% and 82.26% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.004 s for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 79.54%, 80.16% and 80.74% for 5, 8 and

32 features, respectively. The time durations needed are 0.004, 0.004 and 0.008 s.

Table 4-8. Prediction Accuracy and Prediction Time of DT and LR of Manual Distraction using 5 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
DT	5	82.18	0.002
LR	5	79.37	0.004
DT	8	85.35	0.002
LR	8	85.77	0.004
DT	32	86.54	0.004
LR	32	85.77	0.008

Table 4-8 demonstrates the prediction results using the DT and LR for manual distraction using 5 s TW. The prediction accuracies using the DT are 82.18%, 85.35% and 85.54% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.004 s for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 79.37%, 85.77% and 85.77% for 5, 8 and 32 features, respectively. The prediction time is 0.004, 0.004 and 0.008 s.

Table 4-9. Prediction Accuracy and Prediction Time of the DT and LR of Cognitive Distraction of 2 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
Decision Tree	5	72.02	0.002
Logistic Regression	5	71.13	0.004

Decision Tree	8	76.19	0.002
Logistic Regression	8	70.70	0.005
Decision Tree	32	72.90	0.003
Logistic Regression	32	70.99	0.006

Table 4-9 demonstrates the prediction results using DT and LR for cognitive distraction induced by math questions using 2 s TW. The prediction accuracies using the DT are 72.02%, 76.19% and 72.90% for 5, 8 and 32 input features respectively. The prediction time is 0.002, 0.002 and 0.003 seconds for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR is 71.13%, 70.70% and 70.99% for 5, 8 and 32 features, respectively. The prediction time is 0.004, 0.005 and 0.006 s.

Table 4-10. Prediction Accuracy and Prediction Time of the DT and LR of Cognitive Distraction of 5 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
DT	5	70.19	0.002
LR	5	70.55	0.004
DT	8	70.25	0.002
LR	8	68.75	0.005
DT	32	72.23	0.003
LR	32	70.37	0.007

Table 4-10 demonstrates the prediction results using DT and LR for cognitive distraction induced by math questions using 5 s TW. The prediction accuracies using the DT are 70.19%, 70.25% and 72.23% for 5, 8 and 32 input features,

respectively. The prediction time is 0.002, 0.002 and 0.003 s for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 70.55%, 68.75% and 70.37% for 5, 8 and 32 features, respectively. The prediction time is 0.004, 0.005 and 0.007 s for 5, 8 and 32 input features, respectively.

Table 4-11. Prediction Accuracy and Prediction Time of the DT and LR of Emotional Distraction (Type 2) of 2 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
Decision Tree	5	80.59	0.002
Logistic Regression	5	81.29	0.004
Decision Tree	8	81.63	0.002
Logistic Regression	8	81.12	0.004
Decision Tree	32	83.65	0.003
Logistic Regression	32	82.56	0.007

Table 4-11 demonstrates the prediction results using the DT and LR for emotional distraction (type 2) using 2 s TW. The prediction accuracies using the DT are 80.59%, 81.63% and 83.65% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.003 seconds for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 81.29%, 81.12% and 82.56% for 5, 8 and 32 features, respectively. The prediction time is 0.004, 0.004 and 0.007 s, respectively.

Table 4-12. Prediction Accuracy and Prediction Time of the DT and LR of Emotional Distraction (Type 2) of 5 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
DT	5	80.94	0.002

LR	5	81.15	0.004
DT	8	81.15	0.002
LR	8	82.14	0.004
DT	32	82.98	0.003
LR	32	83.76	0.008

Table 4-12 demonstrates the prediction results using DT and LR for emotional distraction induced by emotionally pointed questions using 5 s TW. The prediction accuracies using the DT are 80.94%, 81.15% and 82.98% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.003 s for 5, 8 and 32 input features, respectively. The prediction accuracy using the LR are 81.15%, 82.14% and 83.76% for 5, 8 and 32 features. The prediction time is 0.004, 0.004 and 0.008 s.

Table 4-13. Prediction Accuracy and Prediction Time of the DT and LR of Emotional Distraction (Type 1) of 2 s TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
DT	5	64.92	0.002
LR	5	64.15	0.005
DT	8	64.92	0.002
LR	8	63.82	0.005
DT	32	69.52	0.003
LR	32	64.95	0.008

Table 4-13 demonstrates the prediction results using DT and LR for emotional distraction (type 1) using 2 s TW. The prediction accuracies using the DT are

64.92%, 64.92% and 69.52% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.003 s for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 64.15%, 63.82% and 64.95% for 5, 8 and 32 features, respectively. The prediction time is 0.005, 0.005 and 0.008 seconds.

Table 4-14. Prediction Accuracy and Prediction Time of the Decision Tree and Logistic Regression of Emotional Distraction (Type 1) of 5-Second TW

Algorithm Name	Number of Features	Prediction Accuracy (%)	t_p (s)
Decision Tree	5	66.70	0.002
Logistic Regression	5	65.00	0.004
Decision Tree	8	67.91	0.002
Logistic Regression	8	66.43	0.004
Decision Tree	32	68.52	0.003
Logistic Regression	32	66.21	0.007

Table 4-14 demonstrates the prediction results using the DT and LR for emotional distraction induced by talking using 5 s TW. The prediction accuracies using the DT are 66.70%, 67.91% and 68.52% for 5, 8 and 32 input features, respectively. The prediction time is 0.002, 0.002 and 0.003 s for 5, 8 and 32 input features, respectively. The prediction accuracies using the LR are 65.00%, 66.43% and 66.21% for 5, 8 and 32 features, respectively. The prediction time is 0.004, 0.004 and 0.007 s.

In the experiment, 32 features will be analysed. Each feature would be identified as relevant or irrelevant features in detecting driver distraction using visual inspection and correlation analysis. After individual features are analysed and divided into relevant and irrelevant features, the relevant features are added together and the number of times a feature is regarded as relevant is counted.

The relevant features identified by visual inspection are determined using this method. The most relevant features by correlation analysis are determined by the highest average correlation coefficients.

4.5 Summary

The efficiency of driver distraction detection can be improved by feeding the relevant features into suitable algorithms, which is proven by the obtained results. The processes of identifying relevant features are described in detail. The prediction accuracy and prediction time are presented according to the size of TWs and the type of distraction.

The prediction accuracy is generally not compromised by reducing the number of input features when relevant features are fed into the algorithms. The change in the prediction accuracy is minor compared with the results for 5, 8 and 32 input features.

An example shows that the prediction accuracies of manual distraction by the DT are 80.07%, 80.95% and 82.26% for 5, 8 and 32 input features in 2 s TW, respectively. Only 2.19% difference is observed between the prediction accuracy whilst the number of input features is reduced from 32 to 5. The prediction time reduces from 0.004 to 0.002 s. The results show that the prediction accuracy can retain a high level whilst the number of input features and the prediction time are reduced by feeding the relevant features into the algorithm. Therefore, feeding the relevant features into the algorithms is an effective way to improve detection efficiency.

The developed detection algorithms presented in Chapter 4 can reduce the number of features needed whilst achieving a relatively high prediction accuracy. The results in literature show that the prediction accuracy varies from different experiments and types of distraction. For example, the results collected on the public road at Dallas, Texas have achieved an average accuracy of 83% for manual distraction using 75 features. An accuracy of 81.1% has been achieved for detecting cognitive distraction by using 21 features. The results from chapter 4 show that the prediction accuracy is 82.18% for manual distraction and 72.02%

for cognitive distraction when the number of input features is five. The prediction accuracy of manual distraction using the DT is higher than the highest prediction accuracy found in the literature. The prediction accuracy of cognitive distraction is lower than the highest accuracy in literature, but the number of features needed to achieve the accuracy is 5.

Visual inspection and analysis of correlations are effective methods to identify relevant features, which are proven by the minor reduction in prediction accuracy when correct relevant features are identified. As explained before, the relevant features identified by visual inspection are more trustworthy.

The suitable algorithms based on open-source data are DT and LR, which have achieved a balance between the prediction accuracy and prediction time. The DT is simple to train and easy to interpret and it has achieved a good balance between the prediction accuracy and prediction time. LR has also achieved the balance between the two metrics. Therefore, it is a suitable detection algorithm.

The complexity of the distraction task is related to the obtained prediction accuracy. The prediction accuracy increases when the complexity of the tasks increases, because the feature values deviate more significantly from the normal state.

The prediction accuracies of cognitive distraction and manual distraction are 71.13% and 79.54% using the LR when the number of input feature is 5 and the size of the TW is 2 s. Similar patterns can be found in prediction accuracy across various input features and TWs. The ranking of average prediction accuracy (from the highest to lowest) is manual distraction, emotional distraction (type 2), cognitive distraction and emotional distraction (type 1). Texting is a more complex task than double-digit math questions, which induces the cognitive distraction. Thus, the values of features when the driver is manually distracted deviate more from such values when the driver is cognitively distracted, the detection algorithm can capture the more significant change. Therefore, its prediction accuracy increases.

The prediction accuracy increases when the drivers are more emotionally unstable. The result is mainly due to the same reason why the prediction accuracy of manual distraction is higher than that of the cognitive distraction. The prediction accuracies for emotionally type 2 and 1 are 81.29% and 64.15% using the LR and 2 s TW. Therefore, the prediction accuracy decreases by 17.14%.

The emotionally more unstable driver would drive the vehicle more aggressively. The change would reflect on the more abrupt change in features and changes will be captured by detection algorithms. The algorithm could detect driver distraction at a higher accuracy because the algorithm could easily detect the difference.

The difference between the prediction accuracy of the 2 s TW and 5 s TWs is minor. Overall, the difference is within 3.00%. For example, the prediction accuracies using the LR are 70.70% and 68.75% for 2 s and 5s TWs.

5 Experimental Methods and Results

In the previous chapter, driver distraction is detected using open-source data, and the results obtained are satisfactory. This condition proves the effectiveness of the methodology used in this study. However, the technique is implemented only in a simulated driving environment, the usability of the technique in real-world situations is unknown and needs to be verified further. An experiment in a real-world driving environment is also needed.

The real-world driving environment in this study is a closed testing field located in Cranfield University. The closed testing field is designed for the development of autonomous vehicles and is called Multi-User Environment for Autonomous Vehicle Innovation (MUEAVI) [91].

This chapter introduces the design and implementation of the experiment in detail. The collected data are used for driver distraction detection with the methods described in Chapter 3.

5.1 Experiment Design and Implementation

An experiment is conducted to study driver distraction detection in a real-world driving environment. In Chapter 4, eight signals in four different types of distraction are collected from devices installed on driving simulators. To conduct a comparative analysis, the same signals are collected in this experiment. However, the acceleration pedal input, braking force and lane position are not recorded due to the change in experimental conditions. The head movements in x and y directions are added and compared with the collected signals in Chapter 5. Seven signals are collected as a result. A list of signals is provided in Table 5-1.

In the experiment design, drivers drive in pre-set routes and simultaneously undertake various distraction tasks. The effects of distraction on driver behaviour are investigated by comparing the results of normal driving state and distracted driving states.

The experiment design includes the collection of background information, recruitment of participants and installation of apparatus. The implementation of the experiment consists of the experiment procedures and questions asked in the experiment.

The drivers perform multiple secondary tasks during the experiment. The secondary tasks include talking to a passenger, answering math questions and texting. Relevant signals, which include vehicle performance measurements and the driver's facial information, are recorded to analyse the impact of secondary tasks on driver behaviour.

Previous results have shown that steering wheel angle and the gaze locations are important parameters in determining the driver's state. The algorithms used to detect driver distraction are DT and LR. As indicated in Chapter 4, the detection accuracy of DT can be as high as 82.18%. In this chapter, a real-world driving experiment is conducted to validate the developed method and the usefulness of the relevant features. The experimental apparatus used in this study is shown in Figure 5-1. The figure also shows the recording devices installed on a Land Rover vehicle including video recordings, GPS device, and steering angle and speed sensors. The eye gaze directions and head angles are extracted from video recordings from OpenFace software. Lane deviation can be estimated from the GPS data. The steering angle and speed sensor record the steering angle and speed values.

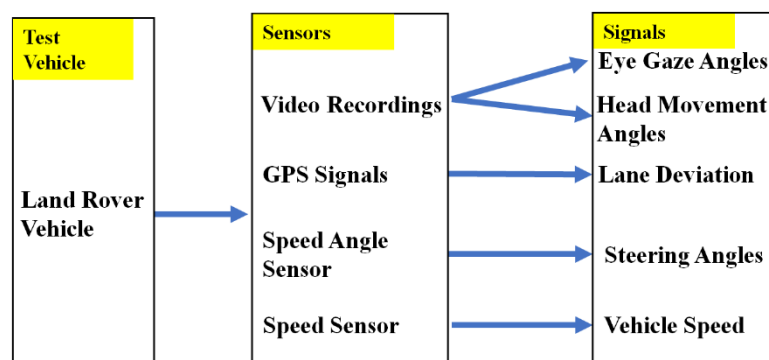


Figure 5-1. Experimental Apparatus for Parameters Acquisition

A Land Rover Discovery 4 installed with a GPS device, steering angle sensor, speed sensor and central control unit is used as the test vehicle. As highlighted by a red square in Figure 5-2, a Logitech C520 web camera is installed on the windscreen facing the driver. In the longitudinal direction, the centre line of the camera is placed in line with the centre line of the driver. Vertically, the camera is placed just higher than the speedometer. To make the camera functional, an additional computer is used to record the videos obtained by the Logitech camera. A LED light is installed beside the B-pillar on driver's side to synchronise the time series in the camera and the time series in the vehicle's CAN-Bus system. The LED light is linked to the computer and set to blink following a certain pattern. The camera can capture the LED light's blinks and determine the time series in the vehicle recording system. The time series in the two different recording systems can be synchronised by setting the blink patterns.



Figure 5-2. Test Vehicle and Apparatus

Figure 5-2 shows the test vehicle (Land Rover Discovery 4) used in the experiment. The GPS antenna is installed on the top of the vehicle. The camera for recording the driver's facial behaviour is highlighted in the red square.



Figure 5-3. Camera Recording the Driver's Behaviour

Figure 5-3 shows the interior of the test vehicle and the camera for recording the driver's behaviour.

The experiment involves 10 male drivers and 1 female driver. All participants are recruited from Cranfield University; they have valid UK/EU driving licenses and driving experiences in the UK. The participants' ages are between 20 and 40. They are considered to be in the same age group.

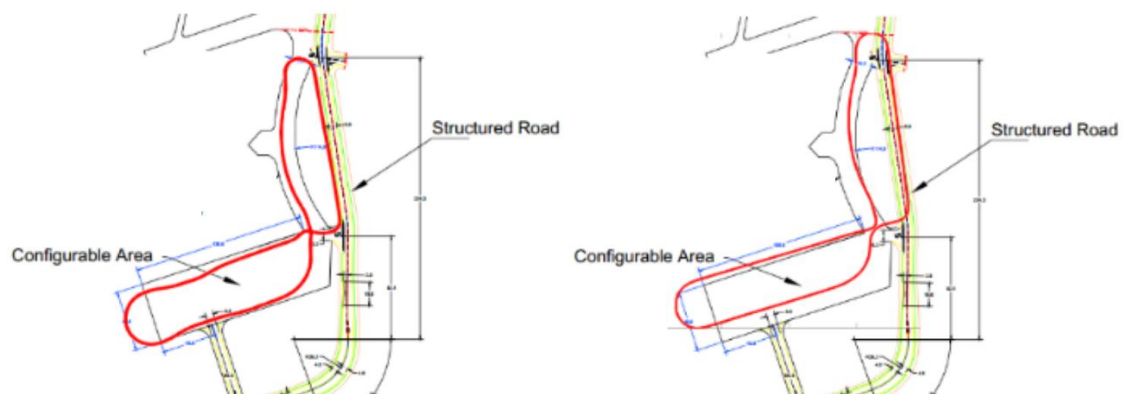


Figure 5-4. Test Routes

Figure 5-4 shows the experimental routes on MUEVAI testing ground in Cranfield University. Equipped with configurable areas and closed roads, the MUEVAI testing ground provides a suitable undisturbed environment for on-road experiments. On-road experiments, which often involve complex secondary tasks (e.g., texting), require a closed testing environment to ensure safety. Additionally, the traffic, traffic signals, and lane positions can be easily controlled on this testing ground, thereby reducing the uncontrolled variables in the experiment. Lane changes, roundabout negotiation, and curved driving are implemented during testing to prevent the driver from becoming familiar with the environment and to create different driving maneuvers.

Drivers who participate in the experiment need to perform secondary tasks while following the pre-set route. The secondary tasks can divert attention from the normal driving state and induce driver distraction. As stated previously, three secondary tasks are adopted in this experiment.

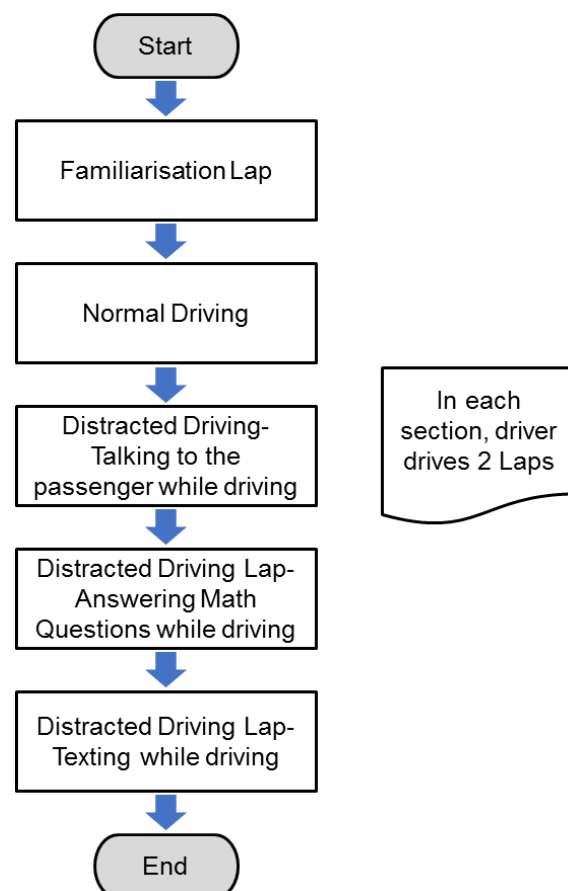


Figure 5-5. Flowchart of the Experiment Process

Figure 5-5 shows the flowchart of the experiment process. A total of 10 laps are considered. Laps 1 and 2 are familiarisation laps that guide the drivers through the route they will be driving on. Laps 3 and 4 are where the experiment, recording of the driver's facial information, and driving response measures begin. In laps 5 and 6, the drivers perform cognitive distraction (talking) tasks, during which they talk to a passenger about several casual questions. The secondary task in laps 7 and 8 is driving while answering math questions. The drivers are considered cognitively distracted when answering math questions because they are thinking about something that is not related to driving. In laps 9 and 10, the drivers are texting and therefore manually distracted because they are operating a cell phone while driving.

Relevant signals are recorded to analyse the impact of secondary tasks on driver behaviour. The measurements include those of vehicle performance and driver facial information. The values of the signals are used to analyse the impact of secondary tasks on driver behaviour.

5.2 Extracted Signals from the Experiment

Two sets of signals are extracted separately from the CAN-Bus and video recordings. The steering wheel angle, GPS signal were measured by the OXTS RT 1003 system. The video was recorded by the Logitech C520 camera. The OpenFace software is used to process the recorded video. The estimation accuracies are listed. Notably, the accuracy of estimating eye gaze and head movement angles is 1 degree. Four statistical measures, namely, mean, maximum, minimum and standard deviation, are extracted for each signal. The detailed signals are listed in Figure 5-1.

Table 5-1. Signals and Features of Experimental Data

Signal Channel	Symbol	Features	Statistics	Accuracy
Video Channel	G_x	Eye gaze in x direction	Mean, Max, Min, Std	1°
	G_y	Eye gaze in y direction	Mean, Max, Min, Std	1°

	H_x	Head Pose in x direction	Mean, Max, Min, Std	1°
	H_y	Head Pose in y direction	Mean, Max, Min, Std	1°
CAN-Bus Data	$\delta_{steering}$	Steering angle	Mean, Max, Min, Std	0.25°
	V	Vehicle speed	Mean, Max, Min, Std	0.5 m/s
GPS Signal	δ_{LD}	Lane deviation	Mean, Max, Min, Std	2 cm

5.3 Analysis of Features

The same pre-processing method used in Chapter 4 is applied in this chapter to process the collected data. Features are extracted and the relevant ones are identified using the same methodology.

The characteristics of the experimental data, with 30 data points in each second, are relatively denser than those of open-source data. Features with a 0.5 s TW are selected to identify relevant features because the data characteristics change.

In the experiment, 28 features ($4 \text{ statistics} \times 7 \text{ signals}$) are analysed. Each feature is identified as relevant or irrelevant features in detecting driver distraction for each participant by using visual inspection and correlation analysis. After identifying the features are identified by visual inspection and calculating them by correlation analysis, the numbers of relevant features for all participants are added to determine the most relevant feature by visual inspection. The relevant features derived by correlation analysis are based on the highest average correlation coefficients.

The 28 features of one participant are presented as an example to demonstrate the analysis of features by visual inspection and correlation analysis. The 28 features are divided into four groups according to their statistical features. A figure showing the correlation coefficients of the 28 features is presented after the four figures showing the 28 features. The seven subplots of the four figures shows the seven features of a statistical measure. Three vertical bars divide a subplot into four parts. The leftmost part shows the feature values when driver is driving normally. The three parts in the right show the feature values of cognitive

distraction (talking), cognitive distraction (math) and manual distraction (texting) states.

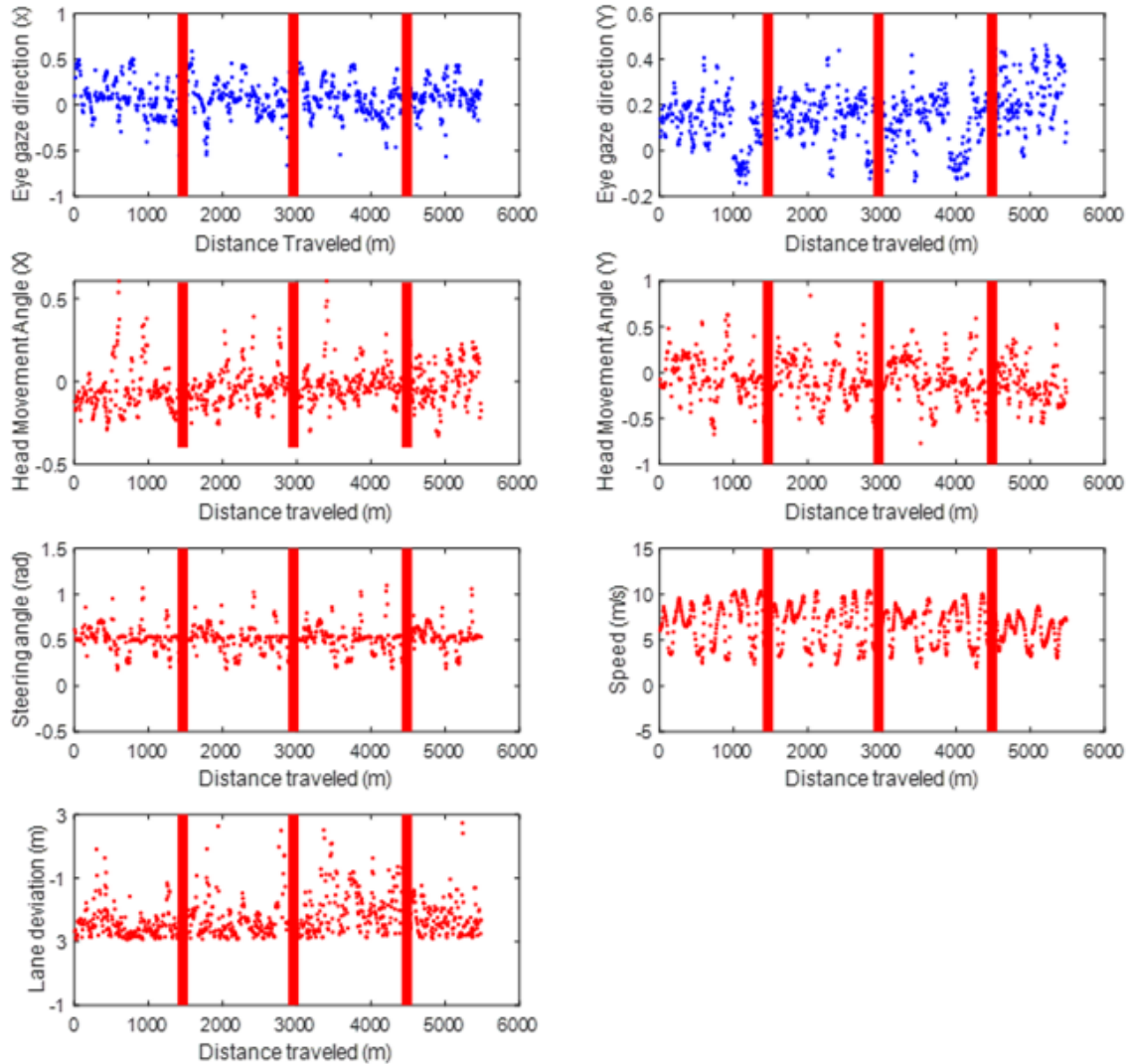


Figure 5-6. Comparisons of Mean Values of Normal and Distracted Driving Sections for Driver No. 4

Figure 5-6 presents the mean values of seven signals in normal and distracted driving sections. The eye gaze in x and y directions is relevant in detecting driver distraction. The distribution of eye movement is measured by the eye gaze in both directions. Additionally, the head movement in the x direction is relevant in detecting driver distraction. These results indicate that the driver spends a considerable amount of time keeping his head still when cognitively distracted and looking upward and downward when texting. The mean value of steering

angle is not related to driver distraction detection because all mean values of steering angle have similar patterns. The mean value of speed is relevant in driver distraction detection because the average speed is significantly reduced when the driver is manually distracted. Moreover, the mean value of lane deviation is relevant in detecting driver distraction because numerous deviations from the normal position are observed when the driver is distracted.

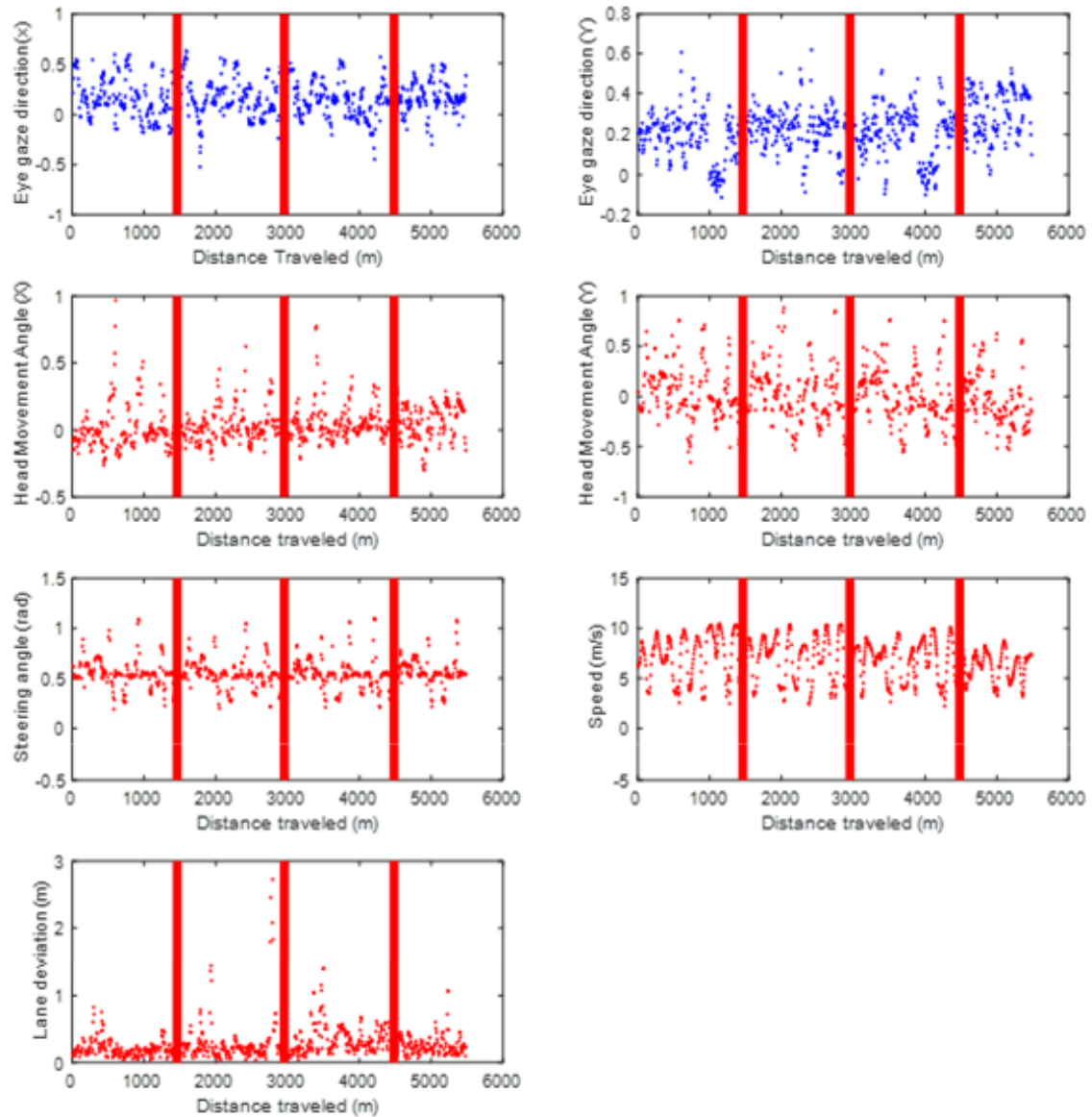


Figure 5-7. Comparisons of the Maximum Values of Normal and Different Types of Distracted Driving for Driver No. 4

shows the maximum values of seven signals in normal and distracted driving sections. The most relevant features in detecting driver distraction are eye gaze in y direction, head movement in x direction, and maximum value of speed, which is particularly relevant when the driver is manually distracted. The maximum values of speed are significantly reduced due to the texting behavior. The three features are identified as relevant in detecting driver distraction.

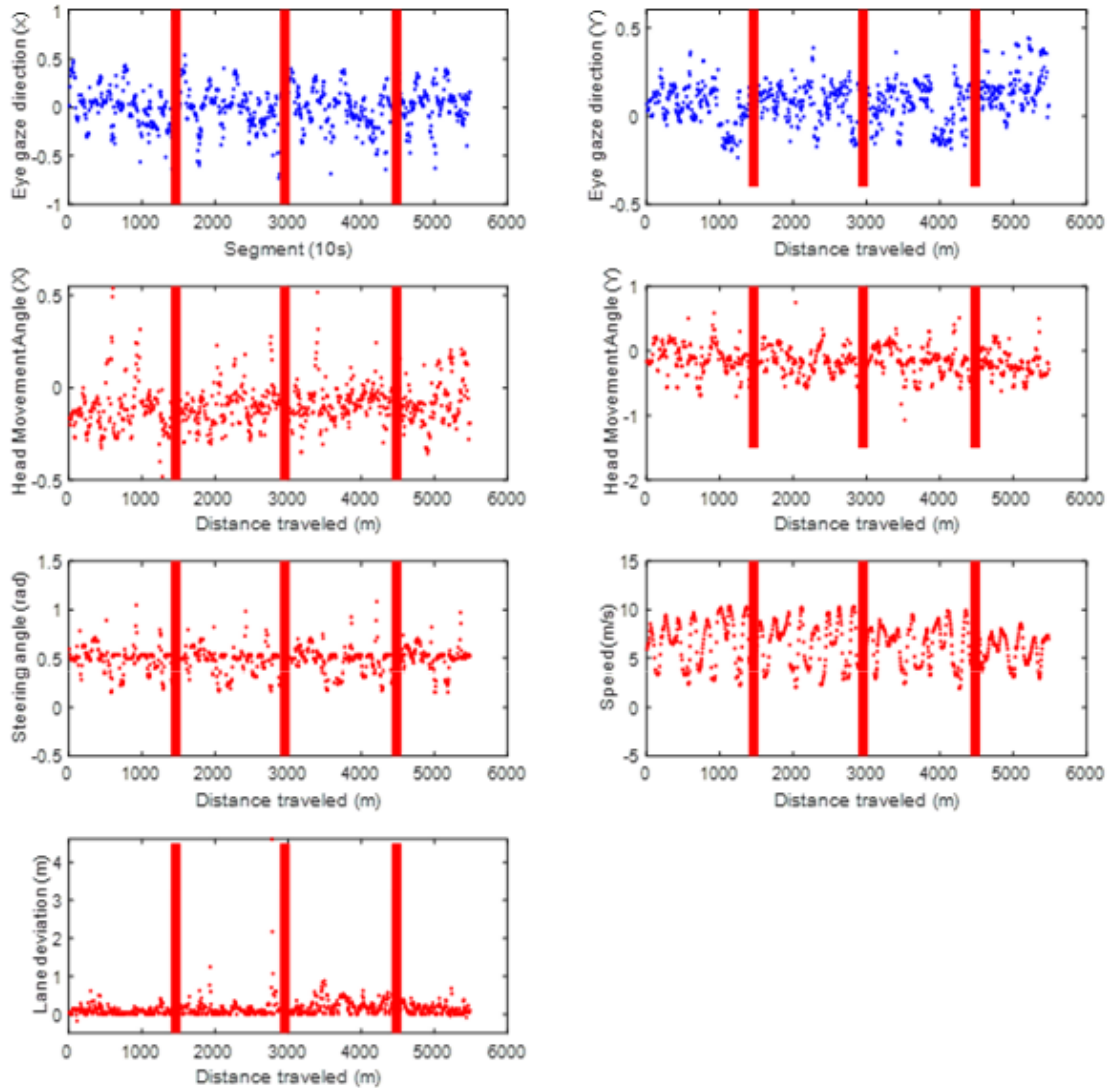


Figure 5-8. Comparisons of the Minimum Values of Normal and Different Types of Distracted Driving for Driver No. 4

The relevant features in detecting driver distraction can be identified from Figure 5-8 by visual inspection. The most relevant features in detecting driver distraction are eye gaze in y direction and head movement in x direction. The minimum

value of eye gaze in y direction and head movement in x direction increase after the driver was distracted. The minimum value of speed is relevant in detecting distraction, especially when the driver is manually distracted.

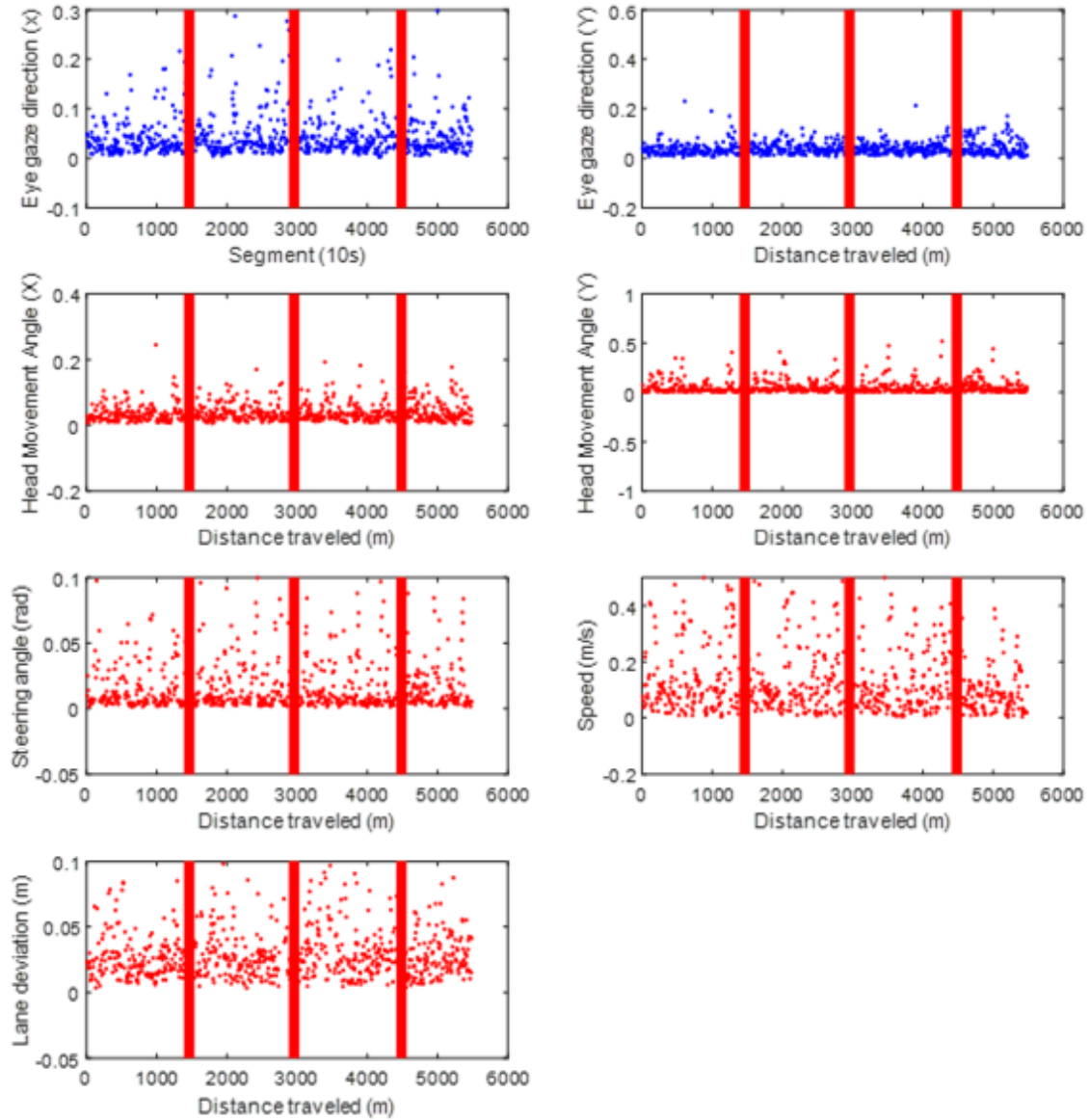


Figure 5-9. Comparisons of Standard Deviations of Seven Features in Normal and Distracted Driving Sections for Driver No. 4

Figure 5-9 presents the standard deviations of seven signals. The relevant features in detecting driver distraction are standard deviation values of steering angle, speed, and lane deviation. The standard deviation of steering angle increases after the driver was distracted partly due to poor control of the vehicle

when the driver’s state changes. The standard deviation values of vehicle speed do not change significantly when the driver is talking and answering math questions but significantly decrease when the driver is texting. The standard deviation value of lane deviation increases because the driver’s attention was diverted from normal driving.

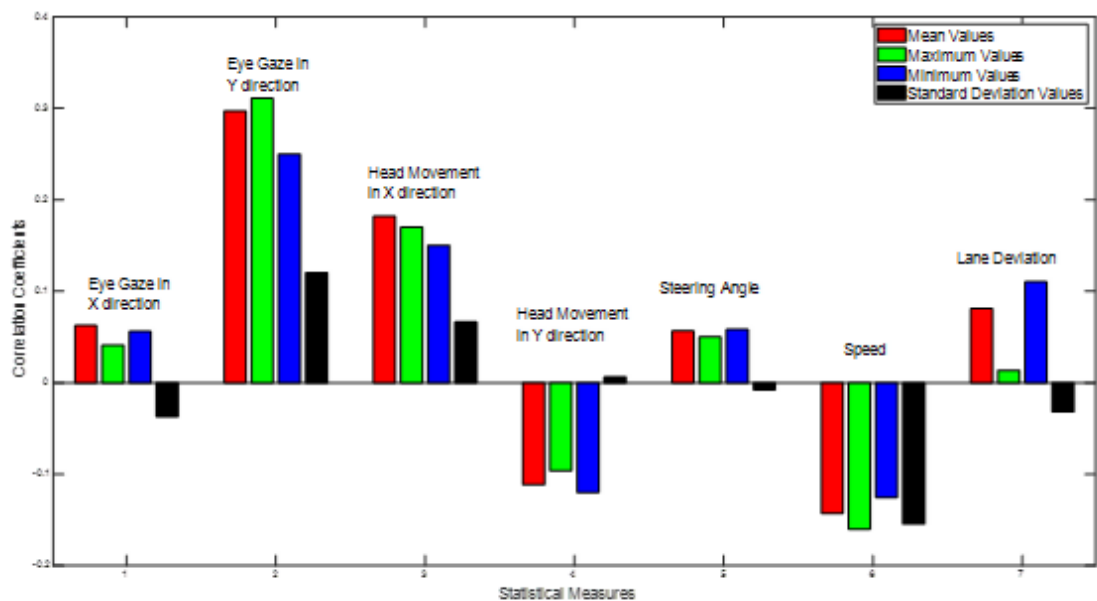


Figure 5-10. Correlation Coefficients between the Statistical Measures and Distraction for Driver No. 4

Figure 5-10 shows the correlation coefficient values of the four statistical measures (mean, maximum, minimum, and standard deviation). The relevant features in detecting driver distraction can be identified through their values. The features with the highest correlation coefficients are the mean and maximum values of eye gaze in y direction. The second most relevant feature is the mean value of head movement along the x direction. Additionally, the mean, maximum, minimum, and standard deviation values of speed are relevant in detecting driver distraction. The results obtained from the correlation coefficients are complemented by the visual inspection results.

The identification results of all the participants are given in Table 5-2. Visual inspection is applied to analyse the figures in the same way as that described in Chapter 3.

Table 5-2. Identification Results of Visual Inspection

Feature Name	Ranking	Number of participants
Maximum Value of Eye Gaze in y Direction	1	10
Maximum Value of Head Movement in x Direction	1	10
Minimum Value of Head Movement in x Direction	1	10
Mean Value of Speed	1	10
Maximum Value of Speed	1	10
Mean Value of Lane Deviation	1	10
Maximum Value of Lane Deviation	1	10
Mean Value of Eye Gaze in y Direction	8	9
Mean Value of Head Movement in x Direction	8	9
Standard Deviation Value of Eye Gaze in y Direction	10	8

Table 5-2 presents the identification results of visual inspection. The relevant features in detecting driver distraction are the mean, maximum, and standard deviation values of eye gaze in y direction; the mean, maximum, and minimum values of head movement in x direction; the mean and maximum values of vehicle speed; and the mean and maximum values of lane deviation. Additionally, correlation analysis is used to identify the relevant features. The most relevant features are listed in the following table.

Table 5-3. Ranking of Relevant Features by Correlation Analysis

Feature Name	Ranking	Correlation Coefficient
Maximum Value of Eye Gaze in y Direction	1	2.03
Mean Value of Eye Gaze y Direction	2	1.88
Mean Value of Head Movement in x Direction	3	1.73
Maximum Value of Head Movement in x Direction	4	1.68
Mean Value of Lane Deviation	5	1.42
Minimum Value of Lane Deviation	6	1.40
Minimum Value of Head in x Direction	7	1.40
Maximum Value of Speed	8	1.36
Mean Value of Speed	9	1.29
Maximum Value of Lane Deviation	10	1.23

The relevant features identified by the correlation analysis are the mean and maximum values of eye gaze in y directions; the mean, maximum and minimum

values of the head in x direction; the mean, maximum and minimum values of lane deviation; and the mean and maximum values of vehicle speed.

Comparison of the results of the visual inspection and correlation analysis indicates that nine out of the 10 identified features are the same. The only different feature is the standard deviation of eye gaze in y direction obtained from the results of visual inspection and the minimum values of lane deviation derived from the results of correlation analysis. Given that visual inspection can identify a higher order of correlations, the standard deviation values of eye gaze in y direction are regarded as relevant.

5.4 Identification of Suitable Algorithms

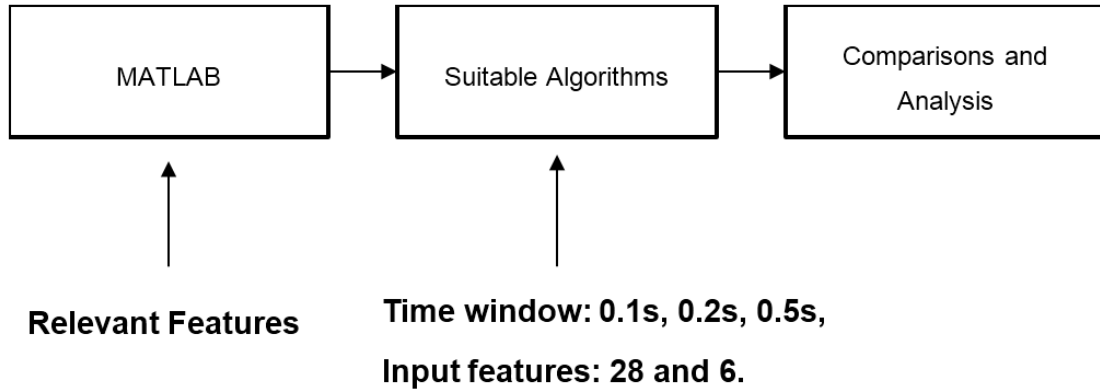


Figure 5-11. Classification of Experimental Data

Figure 5-11 shows the process of classifying the experimental data. The first step is to feed the six relevant features to MATLAB and obtain the prediction accuracy and prediction time of all 25 available algorithms. Only the six relevant features are selected because they are used in real applications. The suitable algorithms for detecting driver distraction are selected based on the results of the two metrics. Second, t_{TW} of 0.1, 0.2, and 0.5 s are used to extract the values of the 28 features and 6 relevant features under the 3 kinds of distraction. Third, the suitable algorithms are used for training. Lastly, prediction accuracy and prediction time are obtained and analysed.

Generally, prediction accuracy and prediction time change with the t_{TW} . However, the change is relatively small when the sizes of TWs are within a suitable range. The results of the overall performance will not be affected, and a suitable algorithm can be selected based on the results of a carefully selected TW.

The selection of an appropriate TW size is based not only on the features that need to be extracted, but also on the characteristics of the data. It is a process of trial and error involving the experience of researchers.

The characteristic of the experimental data is dense (each signal generates 30 data points in one minute). Thus, a small TW of 0.5 s is to be used to select the suitable algorithm. The classification results of the suitable algorithm are analysed and compared by using 0.1 s, 0.2 s and 0.5 s TW.

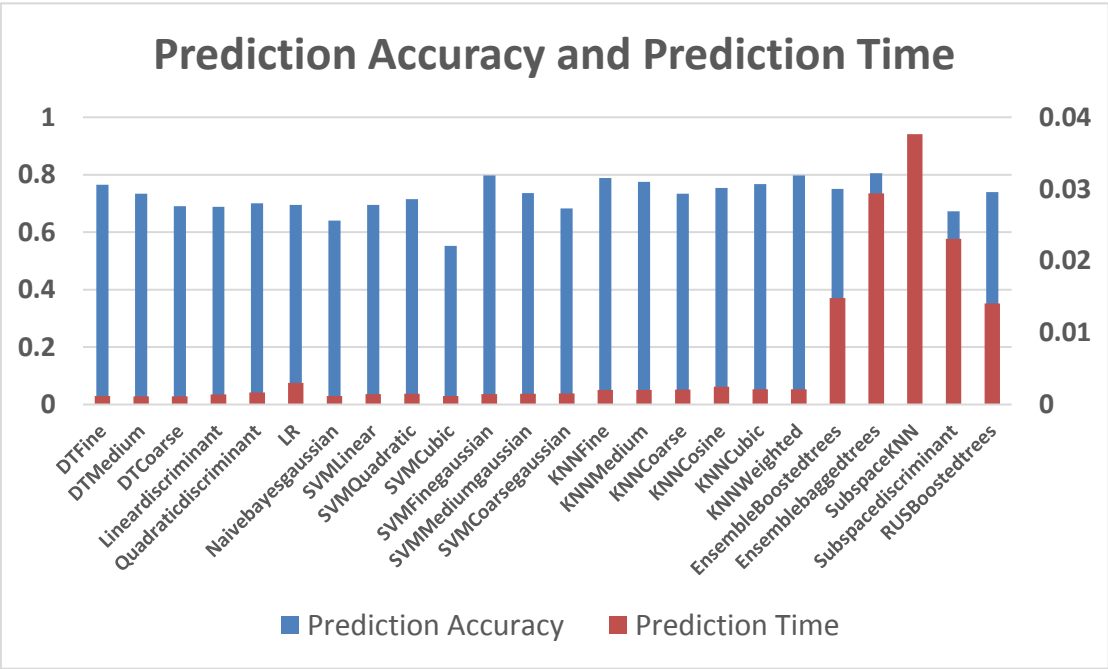


Figure 5-12. Prediction Accuracy and Prediction Time of Manual Distraction in the 0.5-second TW of Six Input Inputs

Figure 5-12 shows the prediction accuracy and prediction time of manual distraction within the 0.5 s TW of the six inputs of 24 algorithms. Naïve Bayes is not presented due to the excessively long prediction time. Suitable algorithms should achieve the balance between high prediction accuracy and short prediction time. Figure 5-12 shows that all of the ensemble methods, such as

Subspace KNN and Bagged Trees, suffer from long prediction time and are therefore not regarded as suitable algorithms. DT (fine), SVM (fine Gaussian) and KNN (fine) achieve balance between prediction accuracy and prediction time. However, SVM (fine Gaussian) and KNN (fine) are not selected due to their rapidly increasing prediction time with the increasing amount of input data.

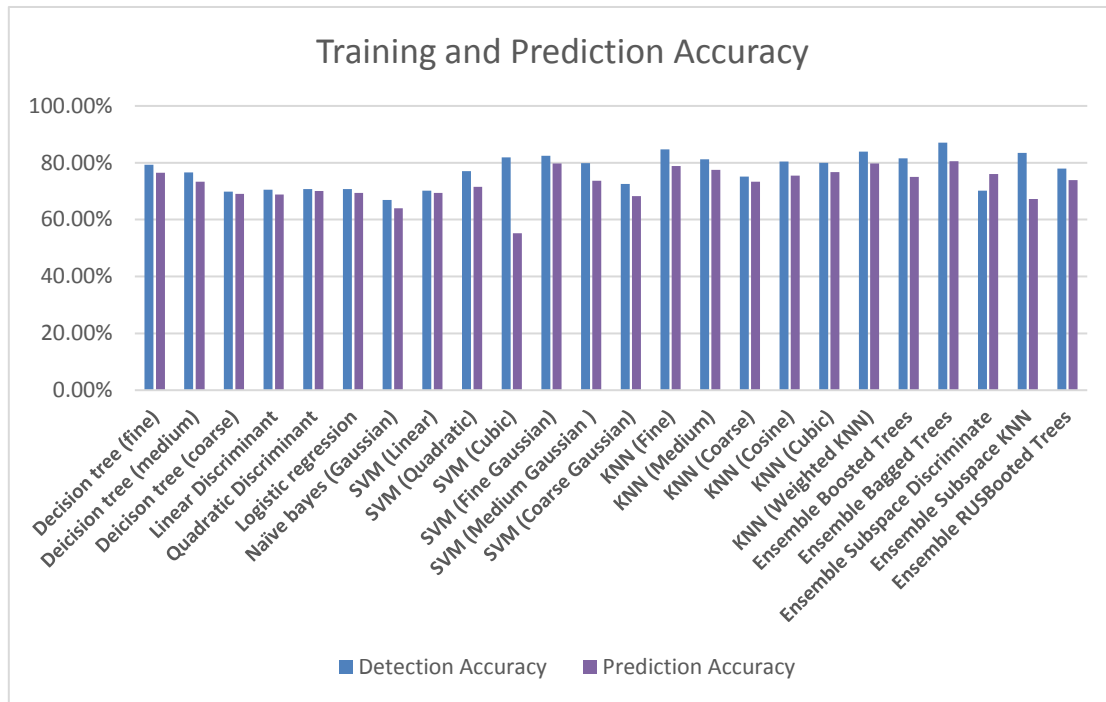


Figure 5-13. Training and Prediction Accuracy of Manual Distraction Within the 0.5-second TW of Six Input Features

Figure 5-13 presents the training and prediction accuracies of manual distraction within the 0.5 s TW of six input features. A prediction algorithm can be verified as suitable or not by comparing the training and prediction accuracies. As indicated in Figure 5-13, most of the algorithms are stable because the difference between the detection and prediction accuracies is small. Although most of the algorithms show a similar detection accuracy, the prediction accuracy is significantly lower than the training accuracy for SVM (cubic); an opposite situation is observed for the Ensemble Subspace Discriminant.

In terms of prediction accuracy, the top four algorithms in each category are DT (fine), SVM (fine gaussian), KNN (fine), and Ensemble Bagged Trees. The logistic regression is not considered in detecting driver distraction for the its lower

prediction accuracy compared to other four algorithms. LR is selected because it is regarded as a suitable algorithm for open-source data. Considering LR for comparison is thus meaningful when analysing the prediction time of experimental data.

Table 5-4. Prediction Time of Six Inputs of Different TWs

Algorithm	0.5 s t_{TW}	0.2 s t_{TW}	0.1 s t_{TW}
DT	0.002	0.002	0.002
LR	0.004	0.004	0.004
SVM	0.003	0.003	0.004
KNN	0.003	0.003	0.005
Ensemble Bagged Trees	0.034	0.054	0.066

Table 5-4 presents the prediction time for manual distraction of 6 inputs in 0.1, 0.2 and 0.5 s TWs. The prediction time of the DT, LR, SVM, KNN and Ensemble Bagged Trees is presented. The prediction time of DT and LR stays unchanged, which is 0.002 and 0.004 s when t_{TW} increases from 0.1 to 0.5 s. The prediction time of SVM and KNN increases slightly when t_{TW} increases from 0.1 to 0.5 s. The prediction time of Ensemble Bagged Trees increases significantly. The values increase from 0.034 to 0.066 s. DT and LR are suitable for real applications for their steady prediction time when data volume increases. The conclusion is obtained by examining the prediction time of the five algorithms.

Table 5-5. Prediction Time for Manual Distraction of 28 Inputs

Algorithm	0.1 s t_{TW}	0.2 s t_{TW}	0.5 s t_{TW}
DT	0.005	0.005	0.003
LR	0.009	0.009	0.007
SVM	0.008	0.007	0.004

KNN	0.013	0.009	0.005
Ensemble Bagged Trees	0.065	0.057	0.030

Table 5-5 presents the prediction time for the manual distraction of 28 inputs. Notably, the prediction time of Ensemble Bagged Trees ranges from 0.030 s to 0.065 s.

The relationship of prediction time with the change in TWs and number of inputs can be determined by comparing the prediction time in Table 5-4 and Table 5-5.

Table 5-6. Prediction Time of 28 and 6 Inputs of the 0.1-second TW

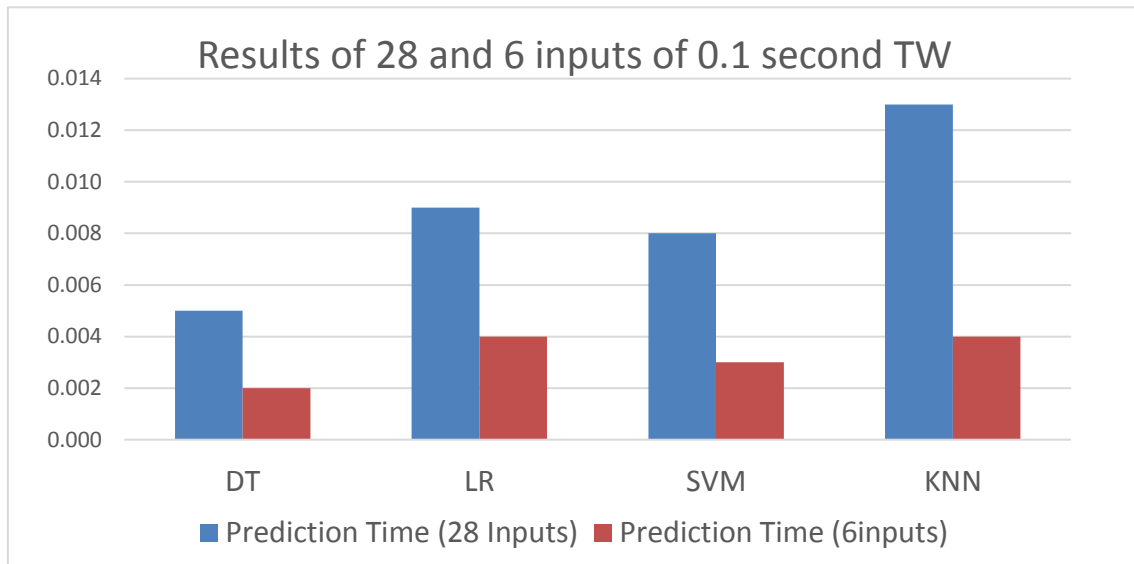


Table 5-6 presents the prediction time of both 28 and 6 inputs in 0.1 s TW. Table 5-6 indicates that for DT, LR, SVM and KNN, the prediction time decreases by more than half when the number of input features decreases from 28 to 6. For example, the prediction time of SVM is reduced from 0.008 s to 0.005 s. The results prove that by inputting the relevant feature into trained algorithms, the prediction time can be reduced; in addition, the prediction time changes with the number of input features.

Table 5-7. Prediction Time in 0.1, 0.2 and 0.5-second TWs

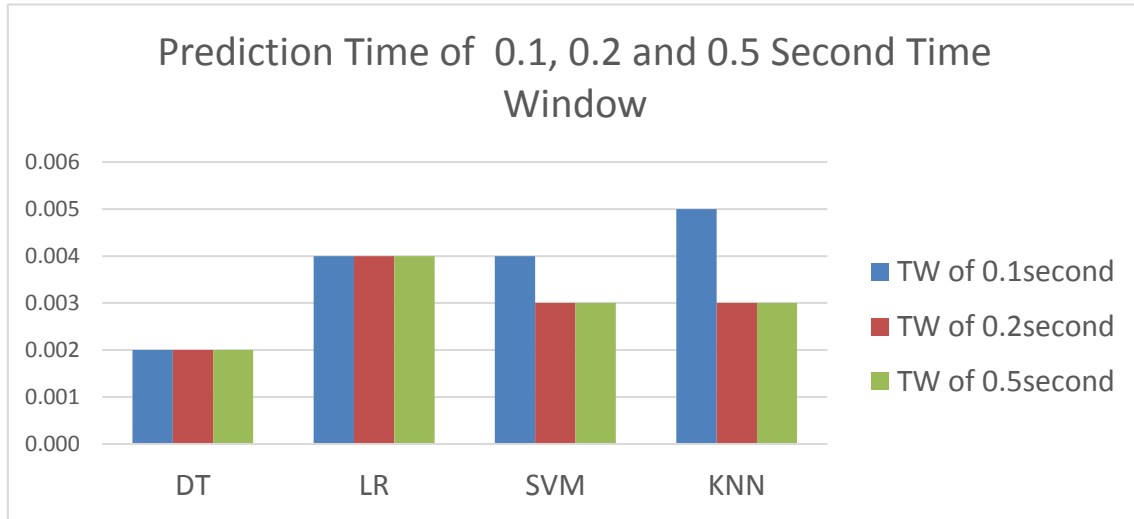


Table 5-7 presents the prediction time in 0.1, 0.2 and 0.5-second TW of six inputs. For DT and LR, the prediction time does not change significantly with increasing TWs. For KNN and SVM, the prediction time in 0.1 s TW is significantly larger than prediction time in 0.2 and 0.5 s TW. This result demonstrates that when the t_{TW} is increased, the prediction time does not change significantly for DT and LR. For SVM, KNN and Ensemble Bagged Trees, the prediction time increases when the t_{TW} increases. The values of Ensemble Bagged Trees are not presented in Table 5-7 due to its excessively long prediction time.

The results in Chapter 4 proved that feeding relevant features and using suitable algorithms can improve driver distraction detection efficiency based on open-source data. However, the condition is unknown for experimental data. Therefore, the results are presented and analysed here.

DT is selected to predict the driver distraction. All 28 features and six relevant features are fed into the DT to predict the driver's states in all three types of distraction. The results are presented in the following tables and figures.

Table 5-8. Prediction Accuracy and Prediction Time for Manual Distraction

t_{TW} (s)	Prediction Accuracy (%)	t_p (s)	Number of features used
0.1	75.50	0.005	28
0.1	73.70	0.002	6
0.2	76.60	0.005	28
0.2	73.20	0.002	6
0.5	82.60	0.003	28
0.5	78.50	0.002	6

Table 5-8 shows the prediction accuracy when the driver is manually distracted. When 0.1, 0.2 and 0.5 s TWs are applied, the prediction accuracies are 75.50%, 76.60% and 82.60%, respectively, for 28 inputs; the respective prediction time is 0.005, 0.005 and 0.003 s. The prediction accuracies are 73.70%, 73.20% and 78.50% for 0.1, 0.2 and 0.5 s TW, respectively, for 6 inputs; the respective prediction time is 0.002, 0.002 and 0.002 s.

Table 5-9. Prediction Accuracy and Prediction Time for Cognitive Distraction (Math Questions)

t_{TW} (s)	Prediction Accuracy (%)	t_p (s)	Number of features used
0.1	68.80	0.003	28
0.1	67.50	0.002	6
0.2	69.00	0.002	28
0.2	67.10	0.002	6
0.5	74.30	0.002	28
0.5	72.10	0.001	6

Table 5-9 presents the prediction accuracy and prediction time for cognitive distraction (math questions). When 0.1, 0.2 and 0.5 s TWs are applied, the prediction accuracies are 68.80%, 69.00% and 74.30%, respectively, for 28 inputs. The prediction time is 0.003, 0.002 and 0.002 s for 0.1, 0.2 and 0.5 s TWs respectively. The prediction accuracies are 67.50%, 67.10%, and 72.10% for 0.1,

0.2, and 0.5 s TWs, respectively, for six inputs; the respective prediction time is 0.002, 0.002, and 0.001 s.

Table 5-10. Prediction Accuracy and Prediction Time for Cognitive Distraction (Talking)

t_{TW} (s)	Prediction Accuracy (%)	t_p (s)	Number of features used
0.1	65.00	0.002	28
0.1	58.10	0.002	6
0.2	67.00	0.002	28
0.2	59.20	0.002	6
0.5	77.10	0.002	28
0.5	60.20	0.001	6

. The prediction accuracies are 67.50%, 67.10%, and 72.10% for 0.1, 0.2, and 0.5 s TWs, respectively, for six inputs; the respective prediction time is 0.002, 0.002, and 0.001 s. shows the prediction accuracy and prediction time for cognitive distraction (talking). When 0.1, 0.2, and 0.5 s TWs are applied, the prediction accuracies are 65.00%, 67.00% and 77.10%, respectively, for 28 inputs; the respective prediction time is 0.002, 0.002 and 0.002 s. The prediction accuracies are 58.10%, 59.20% and 60.20% for 0.1, 0.2 and 0.5 s TWs, respectively, when the number of input features is 6; the respective prediction time is 0.002, 0.002 and 0.001 s.

The prediction results of DT are further analysed by plotting prediction accuracy and prediction time versus various t_{TW} .

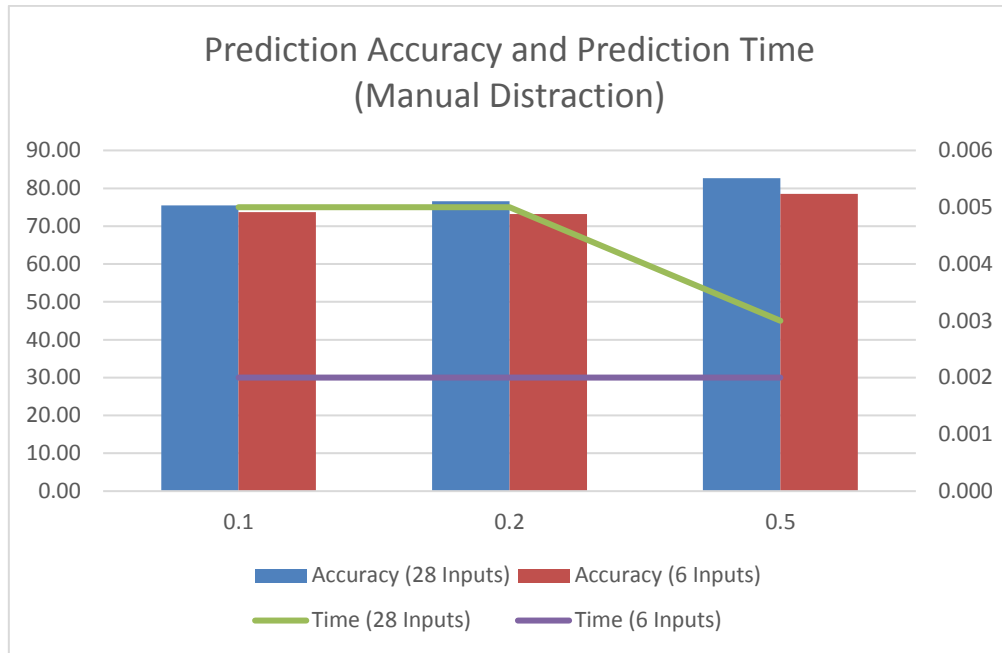


Figure 5-14. Prediction Accuracy and Prediction Time for Manual Distraction

Figure 5-14 demonstrates the prediction accuracy and prediction time for manual distraction obtained using DT. The t_{TW} , shown on x axis, are 0.1, 0.2, and 0.5 s in length. The prediction time of 28 input features decreases when the t_{TW} increases. The prediction time of 6 input features stays unchanged when the t_{TW} increases. Generally, the prediction accuracy decreases when t_{TW} increases. The prediction accuracy of the 0.5 s TW is larger compared with the prediction accuracies of 0.1 and 0.2 s TW. With reduced prediction time compared with the 0.2 s TW, the prediction accuracy of driver distraction is higher accuracy by using the 0.5 s TW. As indicated by the results, 0.5 s is the optimal TW.

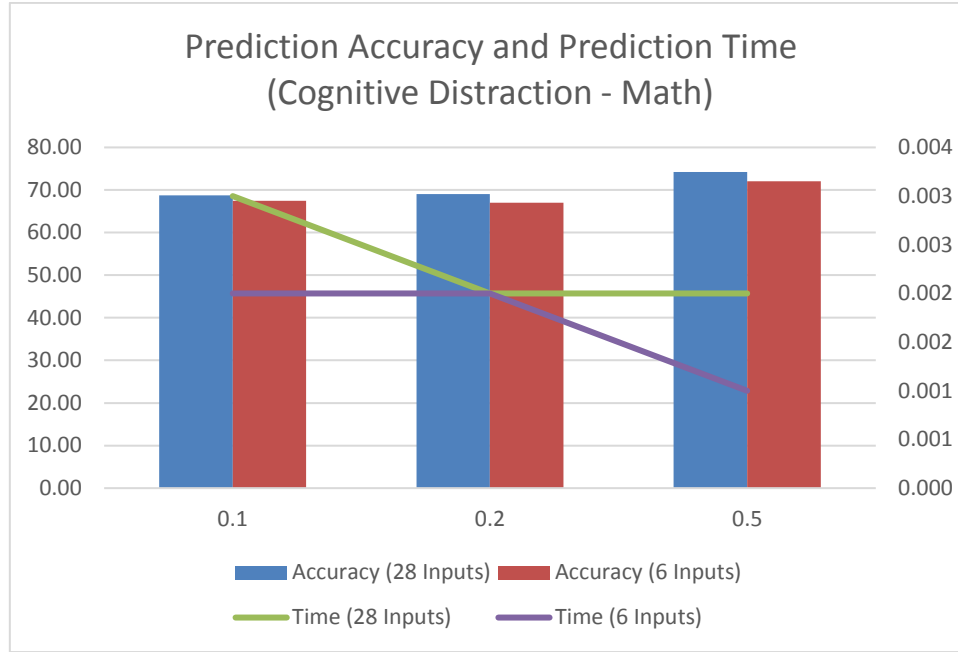


Figure 5-15. Prediction Accuracy and Prediction Time for Cognitive Distraction Induced by Math Questions

Figure 5-15 presents the prediction accuracy and prediction time of cognitive distraction induced by drivers answering math questions. The blue and red bars denote the prediction accuracy. The green and the purple lines show the prediction time. The results show that prediction accuracy increases when the applied TW increases from 0.1 s to 0.5 s. Prediction time generally decreases with increasing TWs, but the trend is not obvious because the prediction time is the same for 0.1 and 0.2 s TW when the number of input features is 6 and for 0.2 and 0.5 s TW when the number of input features is 28. The optimal TW is 0.5 s because prediction accuracy increases, and prediction time reduces compared to the metrics when t_{TW} is 0.1 and 0.2 s.

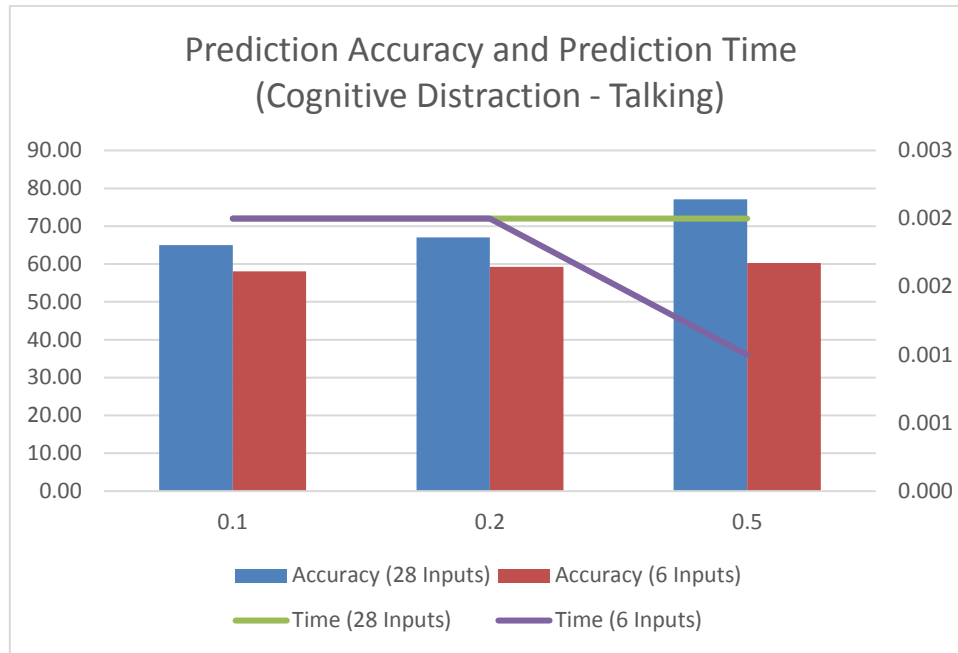


Figure 5-16. Detection Accuracy and Computation Time of Cognitive Distraction Induced by Talking

Figure 5-16 presents the prediction accuracy and prediction time for distraction induced by talking. The blue and red bars denote the prediction accuracy when the number of input features is 28 and 6. The green and the purple line show the prediction time with 28 and 6 input features. Generally speaking, the prediction accuracy decreases with the increasing size of TWs. The prediction accuracy generally increases when the TW size increases from 0.1 s to 0.5 s and the number of inputs is 28 and 6. Comparison of the prediction accuracies of 28 and 6 inputs in various TWs reveals an average of 10% difference between them. This finding is contradictory to the difference in prediction accuracy for manual distraction and cognitive distraction induced by answering math question. Possibly, the effect of feeding relevant features into the detection algorithms when the driver was talking is not as effective as feeding relevant features into detection algorithms when the driver was texting or doing math questions. The prediction time remain unchanged when t_{TW} increases from 0.1 s to 0.5 s and the number of input features is 28. The prediction time remains unchanged when the t_{TW} is 0.1 and 0.2 s and decreases when the t_{TW} is 0.5 s. Therefore, the

optimal t_{TW} is 0.5 s for its significantly increased prediction accuracy and reduced prediction time compared to the same metrics of other algorithms.

Table 5-11. Prediction Accuracy and Prediction Time of the 0.5-second TW

Distraction Scenarios	Number of Features	Prediction Accuracy (%)	t_p (s)
Manual (Texting)	28	82.60	0.003
	6	78.50	0.002
Cognitive (Math)	28	74.30	0.002
	6	72.10	0.001
Cognitive (Talking)	28	77.10	0.002
	6	60.20	0.001

The prediction accuracy and prediction time of the 0.5 s TW in Table 5-8, Table 5-9, and 5-10 . The prediction accuracies are 67.50%, 67.10%, and 72.10% for 0.1, 0.2, and 0.5 s TWs, respectively, for six inputs; the respective prediction time is 0.002, 0.002, and 0.001 s. are merged in Table 5-11. The prediction accuracy and prediction time of the optimal TW are then compared using different types of distraction and different numbers of input features.

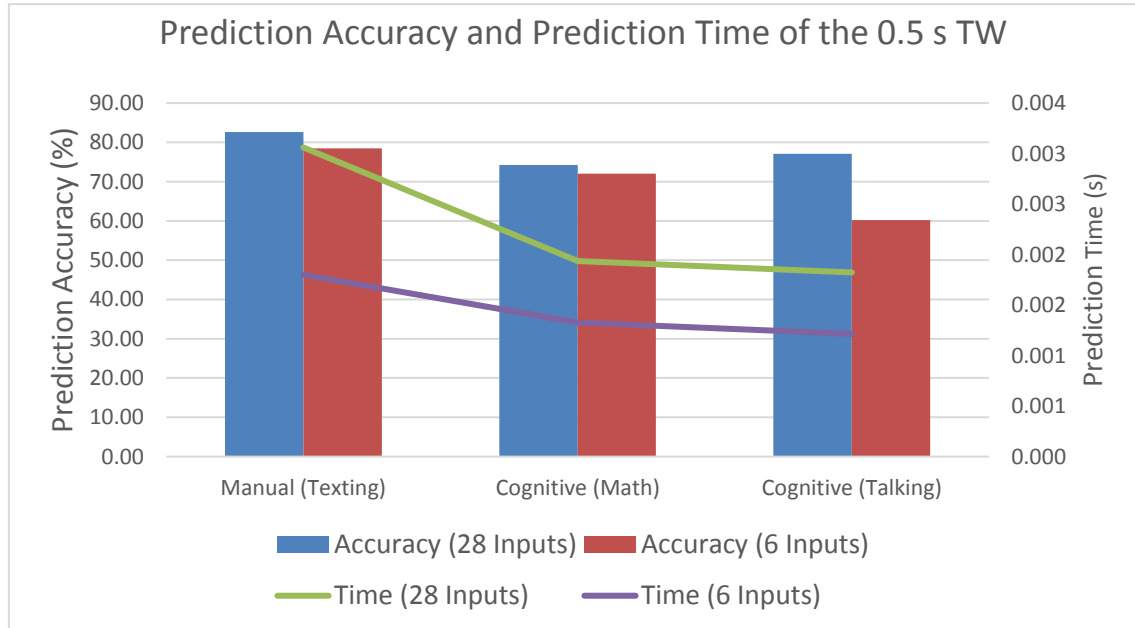


Figure 5-17. Prediction Accuracy and Prediction Time of the 0.5-second TW

Figure 5-17 shows the prediction accuracy and prediction time of the optimal TW (i.e., 0.5 s) across three distraction types. The blue and red bars denote the

prediction accuracy for 28 and 6 inputs, respectively. The green and the purple lines show the prediction time, respectively. The prediction accuracy decreases by a small margin when the number of inputs is reduced from 28 to 6 for manual distraction and distraction induced by math questions. However, for distraction induced by talking, the prediction accuracy decreases significantly when the number of input features is reduced from 28 to 6. This result proves that the identified relevant features are ineffective for cognitive distraction (i.e., talking).

Comparison of the green and the purple lines reveals that by inputting relevant features into the suitable algorithm, the prediction time decreases by more than half, indicating the advantage of the relevant features in reducing prediction time. The reduction of prediction time is critical to the development of algorithms for detecting driver distraction. This aim is achieved here by inputting the six relevant features into the suitable algorithm (i.e., DT).

5.5 Summary

Chapter 5 introduces the design and implementation of the experiment in detail and presents the results obtained when the research methodology in Chapter 3 is applied.

Visual inspection and correlation analysis are proven to be two effective ways to identify the relevant features. Nine out of the 10 common relevant features, namely, $G_{max,y}$, $G_{mean,y}$, $H_{mean,x}$, $H_{max,x}$, LD_{mean} , $H_{min,x}$, V_{max} , V_{mean} , and LD_{max} , are identified. The common signals are eye gaze in y direction, head movement in x direction, speed, and lane deviation.

The study of relevant features can be applied to improve detection efficiency. The prediction time for manual distraction using the 0.5 s TW is reduced by 41.9%, and the number of input features reduces from 28 to 6. The prediction accuracy decreases by a small amount (4%) when 22 irrelevant features are eliminated from the list of input features. This result demonstrates that by inputting the relevant features, the number of input features needed in classification algorithms can be reduced, and the prediction accuracy is generally not compromised.

The most relevant feature is identified as the maximum values of eye gaze in y direction by analysing the experimental data. The DT is selected as the suitable algorithm because of its high prediction accuracy and short prediction time. The prediction accuracy is higher when the is 0.5 s compared to prediction accuracy when the TWs are 0.1 and 0.2 s. The prediction time reduces significantly when the relevant features are fed into the detection algorithm.

By applying different sizes of TWs, the optimal TWs are determined by plotting the prediction accuracy and prediction time. The prediction time generally decreases with increasing sizes of TWs. The prediction accuracy initially increases then decreases. Therefore, the optimal TWs can be determined for each type of distraction.

The effects of the relevant input features and detection algorithms on prediction accuracy are studied by varying the number of input features and using different detection algorithms. Relevant features are fed to suitable detection algorithms to achieve high detection efficiency with same-level prediction accuracy and short prediction time.

6 Discussions

In Chapter 4 and 5, driver distraction detection is studied on the basis of open-source data and experimental data. Similar findings have been drawn from the results of both data. However, variations arise given that the two driving environments are different. Key conclusions obtained in the two conditions will be discussed in this chapter.

The chapter also selects two research papers in this field to discuss the related research work of this thesis. The first paper is 'Classification of Driver Distraction: A comprehensive analysis of feature generation, machine learning and input features'. The study is based on the same open-source data used in Chapter 4. The techniques used in the abovementioned study and the present work have similarities. The second paper is 'Modeling of driver behaviour in real-world driving scenarios using non-invasive sensors'. It is based on on-road experiments in various distracted driving situations. The conclusions are drawn by comparing data from normal driving and distracted driving situations. The design of the experiment and the analysis tools are similar to the methods used in Chapter 5.

Three distraction scenarios are the same for Chapters 4 and 5. The DT is selected as a suitable algorithm for both chapters. Moreover, suitable TWs are chosen on the basis of data characteristics. The comparison between the two results is based on the three distraction scenarios, suitable algorithm and suitable TWs.

Table 6-1. Comparison of Results of Chapters 4 and 5

	Open Source Data			Experimental Data		
	TW	Type of Distraction	Results	TW	Type of Distraction	Results
Prediction Accuracy	5s	Manual	82.18	0.5s	Manual	78.50
		Cognitive (Math)	70.19		Cognitive (Math)	72.10
		Emotional (Type 1)	66.70		Cognitive (Talking)	60.20
Prediction Time	5s	Manual	0.002	0.5s	Manual	0.002
		Cognitive (Math)	0.002		Cognitive (Math)	0.001

	Emotional (Type 1)	0.002	Cognitive (Talking)	0.001
Suitable Algorithm(s)	DT, LR		DT	
Relevant Signals	Eye Gaze in y Direction Speed Land Deviation Steering Angle		Eye Gaze in y Direction Speed Land Deviation Head Position in x Direction Eye Gaze in x Direction	
Top 6 relevant features	Std. Steering Angle Max. Steering Angle Max. Land Deviation Max. Speed Std. Eye Gaze in x Direction Mean. Eye Gaze in y Direction		Max. Eye Gaze in y Direction Max. Head Movement in x Direction Min. Head Movement in x Direction Mean. Speed Max. Speed Mean. Land Deviation	
Suitable Size of TW (s)	2 s, 5 s		0.5 s	
Research Methods	Visual Inspection, Analysis of Correlations, Machine Learning		Visual Inspection and Analysis of Correlations. Machine Learning	

The abbreviation in the relevant features section is explained as follows: the mean values of features are abbreviated as mean, followed by the name of the feature. Similarly, the maximum, minimum and standard deviation values of features are abbreviated as the max, min and std, respectively. The names of the features remain the same.

The prediction accuracy of the DT algorithm is based on the open-source data and the experimental data. The prediction accuracy of the open-source data is higher than the prediction accuracy of the experimental data. For example, the prediction accuracies of the open-source data are 82.18% and 78.50%. However, when the driver is cognitively distracted, the prediction accuracies are near, which are 70.19% and 72.10%, respectively.

The difference in prediction accuracy is caused by the difference in the data. The open-source data are collected in a driving simulator in a two-lane highway with a speed of 70 km/h. The road is straight from start to end and the speed remains at the speed limit (70 km/h). As the experimental data are collected in a closed, low-speed (36 km/h) environment, the two types of gathered data vary. In the first

case, the momentary change of the data is relatively small compared with the second case (closed low-speed environment) due to the difference in the road environment and speed.

The prediction time for driver distraction detection is short across all types of distraction and TWs, as the prediction algorithm has been pre-selected. The average time is 0.002 s for the open-source data and 0.001 to 0.002 s for the experimental data. Differences still remain in the prediction times of different types of distractions and they should be carefully examined.

From the time complexity point of view, the prediction time should be the same for different distraction types, which follows the results of the open-source data. The machine learning models trained by the experimental data are becoming increasingly complex from the distraction induced by talking to answering math questions and to operating cell phones. The complexity of the trained models of various distraction types explains why the prediction time is the longest for manual distraction and shortest for cognitive distraction induced by talking.

The suitable algorithm for detecting driver distraction is DT and LR for the open-source data and DT only for the experimental data. The DT algorithm is a quick-to-train and efficient method for detecting driver distraction.

Three common relevant signals are found when comparing results from the closed driving environment and the open-source data. The results are vastly different when comparing the relevant features. Signals of speed, lane deviation and eye gaze in the y direction are considered relevant signals in both cases. However, the identified features are different. For example, the mean and standard deviation values of eye gaze in the y direction are considered to be relevant based on the open-source data. In addition, the maximum and minimum values of the same signal are considered relevant based on the closed-driving environment.

The eye gaze in the x direction is considered a relevant feature based on open source data but not for experimental data. This outcome is caused by the difference in the driving environment. In the simulated-driving environment, the

driver needs to look at the frontal screen during driving. No obstruction is present between the screen and the driver except for the steering wheel, which makes the driver feel free to move his/her eyes and head. In real-world driving scenarios, the driver's movement is limited because the space between the driver and the car frame is tight even though an SUV is used in this experiment.

The steering angle is identified as a relevant signal in simulated-driving conditions but not a relevant signal in closed-driving conditions. In simulated-driving conditions, the risks of crashes are mitigated by creating an artificial driving environment. Therefore, the room for steering errors is larger than that in the real-driving environment. In the real-driving environment, small steering errors could lead to serious crashes. The driver's control over steering is tight even when the driver is distracted.

The optimal TWs are related to the sampling rate, and the driving environment. Therefore, the data characteristics are different. The sampling rates for the open-source data is 1 Hz and 30 Hz for the experimental data. The driving environments are also different as stated before. The optimal TWs for the two conditions are different in size.

Two related pieces of research exist in the literature. The first research is conducted by the University of Houston on the basis of open-source data. Similar research has been conducted in Chapter 4.

Table 6-2. Comparisons of the Research between Literature and Chapter 4

	McDonald et al.	Chapter 4
Most Relevant Feature	Standard Deviation of Lane Deviation	Standard Deviation of Steering Angle
Identification Method	Inference of Variable Importance	Visual Inspection, Analysis of Correlations

Highest Prediction Accuracy	68.76% (Random Forrest)	85.35% (Decision Tree) 85.77% (Logistic Regression)
Type of Data Used	Driver Behaviour, Physiological Data, Combined.	Combined (Driver Behaviour and Eye Gaze Data)
Most Suitable Algorithm	Random Forrest	Decision Tree Logistic Regression
TW	30 seconds	2 and 5 seconds

The research process of the literature and Chapter 4 are similar. The research is based on open-source data including driver behaviour, physiological factors and eye gaze data. The features are extracted from the open-source data using TWs, and relevant features are identified. These identified features are fed into the detection algorithms. Then the prediction results can be obtained.

Although the research processes of the two studies are similar, the detailed methods and results are different. The TWs used are 30 seconds in the literature and 2 and 5 seconds in our research. The method to identify relevant features is the inference of variable importance in the literature and the visual inspection and analysis of correlations for our research. The results are also different. The prediction accuracies are 68.76% using the random forest in the literature, 85.35% for DT and 85.77% for LR.

The researchers at the University of Texas in Dallas also adapted the method of on-road experiments to investigate the driver behaviour under normal and distracted driving conditions. The secondary tasks in their research, such as phone-operating and conversation, are similar to the secondary tasks of operating cell phone and talking in Chapter 5. Thus, comparing the detection accuracy of the experimental data and the literature is of great value to this work.

Table 6-3. Prediction Accuracy of the Literature and Experimental Results

Task	Li et al	Experimental Results
Phone Operating	75.9	78.5

Table 6-3 presents the prediction accuracy of the literature and the experimental results. The difference between the literature and the experimental results is small in the phone operating task (manual distraction). This observation indicates that our method has an advantage over the average accuracy in the literature.

The most common algorithm used in the literature for detecting driver distraction is the SVM. The SVM can fit the model for driver distraction detection accurately at the cost of time. Meanwhile, the DT is a simplified and efficient algorithm. It can achieve a balance between prediction accuracy and time.

The innovations of this thesis include the select suitable algorithms from 25 variations. Moreover, this thesis applies visual inspection and analysis of correlations to identify the relevant features and prove that the detection efficiency can be improved by feeding the relevant features into suitable algorithms.

Algorithms that are appropriate for detecting driver distraction are defined as achieving the balance between prediction accuracy and time. The prediction time is taken into consideration in this thesis to stress the importance of speedy detection and warning of distraction. No previous literature has been found to consider prediction time. The thesis broadens the horizon in driver distraction detection area.

Visual inspection has been innovatively used to identify the relevant features in detecting driver distraction. The ability to spot the differences visually in higher orders and patterns is reflected in the identified features by visual inspection. The effectiveness of visual inspection on identifying relevant features is validated by the analysis of correlations and the comparison of the prediction results.

The improvement of detection efficiency is represented by faster prediction, simpler hardware and less memory required for the driver distraction detection

system. By identifying the relevant features and feeding them into the algorithms, the prediction time is reduced by half on average. The simpler hardware is achieved by the reduced number of signals collected in real applications. The amount of data is also reduced in the process. Hence, less memory is required in the system.

7 Conclusions and Future Work

This study fills the gap of improving driver distraction detection efficiency by analysing relevant features, selecting suitable algorithms and validating the method in the closed testing environment. Faster warnings can be given to the driver with improved detection efficiency to improve driving safety. The improvement of efficiency of driver distraction detection is equal to high prediction accuracy and shorter prediction time. This goal is completed by feeding the relevant features into a suitable algorithm, which is proved by the obtained results. Visual inspection and analysis of correlations are used to identify the relevant features. The suitable algorithms are selected on the basis of their prediction accuracy and prediction time. The results show that these methods can be applied to simulated-driving and real-world driving environments.

7.1 Conclusions

In this section, some concluding remarks are made to show the improvements.

Firstly, the prediction accuracy remains at the same level, and the prediction time reduces significantly on the condition that relevant features in detecting driver distraction are identified and fed into the algorithm. Generally speaking, high prediction accuracy can be achieved using a smaller number of relevant features, as only minor differences exist between the prediction accuracy when the input features are reduced. At the same time, the prediction time is reduced by more than half. In the future, when Fifth Generation Technology Standard for Broadband Cellular Networks (5G) and cloud computing are widely applied, the detection of driver distraction will be moved to the clouds. A 1 ms reduction in the prediction time can vastly reduce the number of servers needed.

Secondly, the visual inspection and analysis of correlations is a useful tool in identifying the relevant features in detecting driver distraction. The difference between detection accuracy using 5 and 32 features based on the open-source data is minor. The minor difference shows that the most relevant features in

detecting driver distraction have been found. The same conclusion can be drawn from the classification results based on the experimental data.

Finally, the results show that the DT and LR are the suitable algorithms for detecting driver distraction, as their performance balances the prediction accuracy and time. Machine learning algorithms are used to classify the open-source and experimental data after relevant features are identified. The highest accuracies of distraction detection are 82.18% and 78.5% when DT is used to classify the open-source data collected in a driving simulator and the experimental data collected in the closed testing environment, respectively. Both algorithms demonstrate satisfactory results.

This thesis has additional findings.

The identified relevant signals are different based on the data collected in the driving simulator and the real-world driving environment. The mean value of the steering angle is a relevant feature in the simulated-driving environment, which is not identified as a relevant feature in the real-world driving environment. During the tests in the driving simulator, the drivers were less sensitive to the risks posed by distraction. Therefore, less attention was paid to maintain the positions of the vehicle, and the steering control degraded. However, in the real-world driving condition, the risks posed by secondary tasks were immense. The lack of steering control could have lead to crashes. For the safety reasons, the tight steering control in real-world driving scenarios was maintained.

7.2 Future Work

More statistical measures can be applied to identify the relevant features. This thesis has proven that detection efficiency can be improved using the most relevant features. However, only one common feature (maximum of lane deviation) has been found. Thus, a variety of statistical measures should be applied to identify more relevant features.

The detection of driver distraction will be moved to the cloud using the fast-developing 5G and cloud computing technologies. In detail, data containing driver behaviour are transmitted to the cloud and the information on the driver's state is

transmitted back to the vehicle. The prediction time can be reduced, and the vehicle hardware can be simplified.

The results in this thesis can be applied to the development of new hardware that could warn drivers when they are distracted. The system could detect such distraction successfully on the basis of the inputs from the related features on the driver's eye gaze and the lane deviation of the vehicle.

In the future, the driver distraction detection system can be integrated into the brake-by-wire system. Currently, the conventional hydraulic steering columns are gradually being replaced by the steer-by-wire system in newly developed vehicles. Similarly, the brake-by-wire system has been replacing the conventional braking system at a fast rate. This newly updated wire system could be used in such a way that brakes are applied when the driver does not respond to the warnings.

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APPENDICES

Appendices consist of figures and questionnaires.

Appendix A Figures and Plots

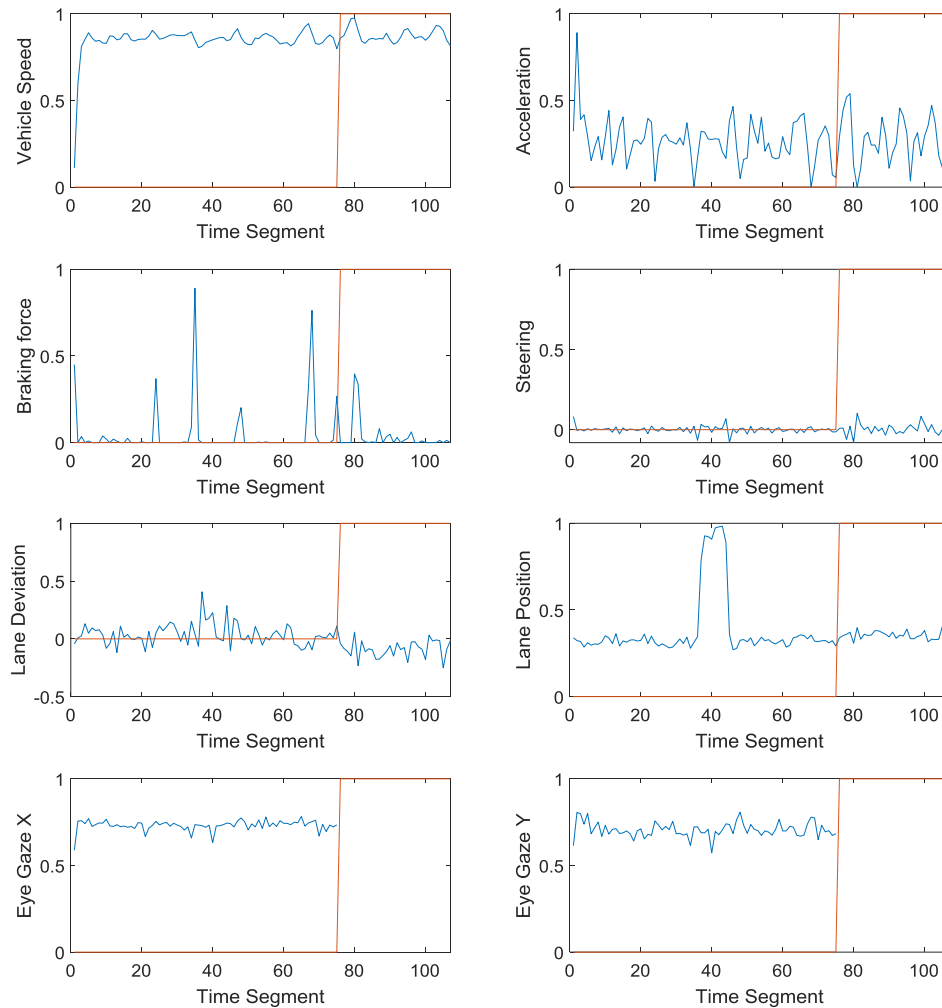


Figure A-1. Comparisons of Mean Values of Normal and Distracted Driving for Driver No. 3

Figure A-1 demonstrates the features between normal driving and distracted driving for driver No. 3. The eye gaze in x and y directions are not shown due to technical issues of the eye tracker. The relevant signals in detecting distraction are acceleration pedal input and braking force. The acceleration pedal input

became more frequent and the mean values of braking force reduced significantly (below 0.5 after scaling) after driver was distracted.

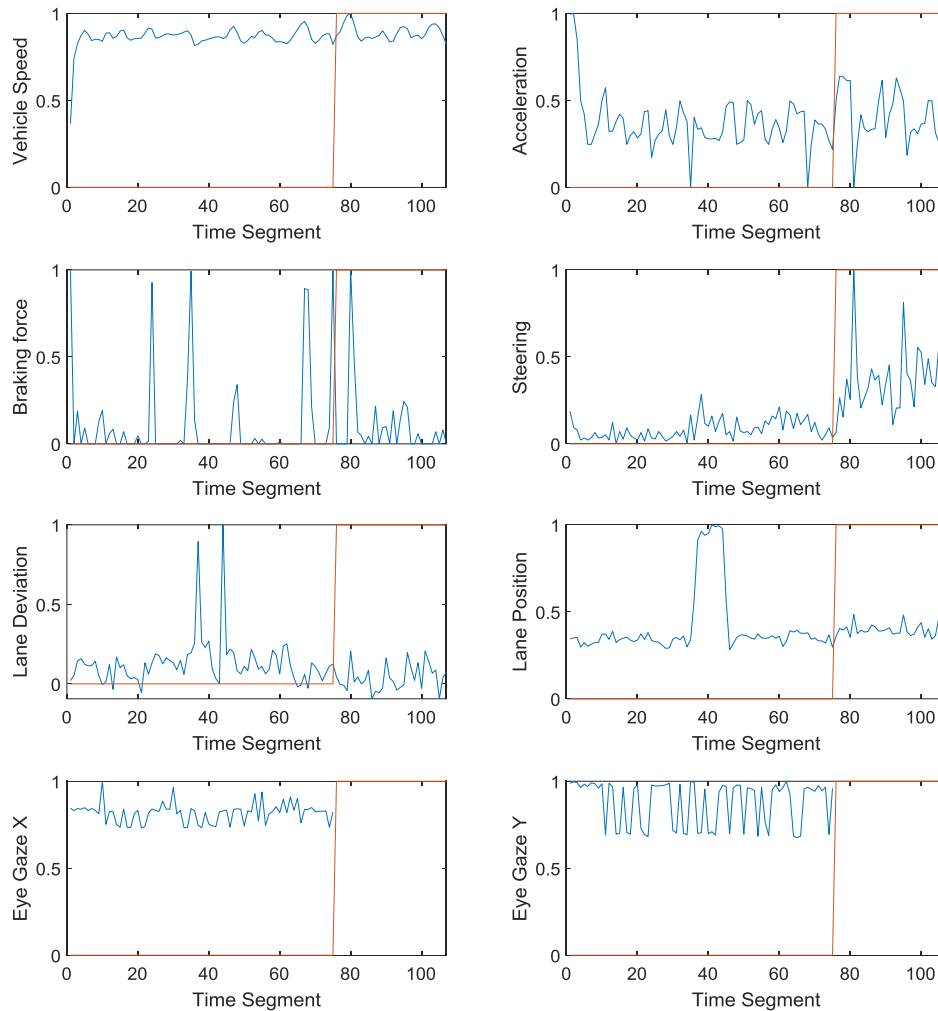


Figure A-2. Comparisons of Maximum Values of Normal and Distracted Driving for Driver No. 3

Figure A-2 demonstrates the maximum features of 32 features between normal driving and distracted driving. The eye gaze in x and y directions are not shown due to technical reasons. The relevant features in detecting driver distraction are maximum values of acceleration, braking force and steering angle. The maximum values of steering angle and acceleration became larger when driver was distracted. The maximum values of the braking force also got larger after the

driver is distracted. Therefore, the three features are relevant in detecting distraction.

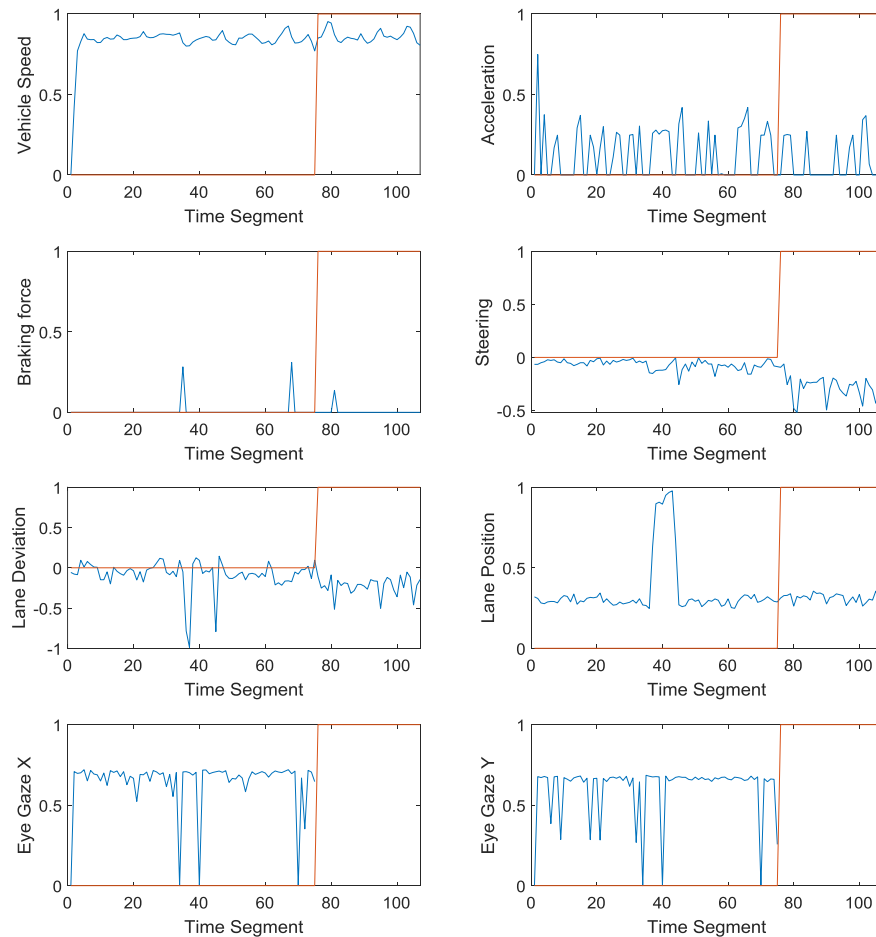


Figure A-3. Comparison of Minimum Values of Normal and Distracted Driving for Driver No. 3

Figure A-3 demonstrates the minimum values of 32 features between normal driving and distracted driving. The relevant features are minimum values of speed and steering. The minimum value of speed increased after driver got distracted, by contrast, the minimum value of steering angle decreased after driver got distracted. The two features are relevant in detecting distraction.

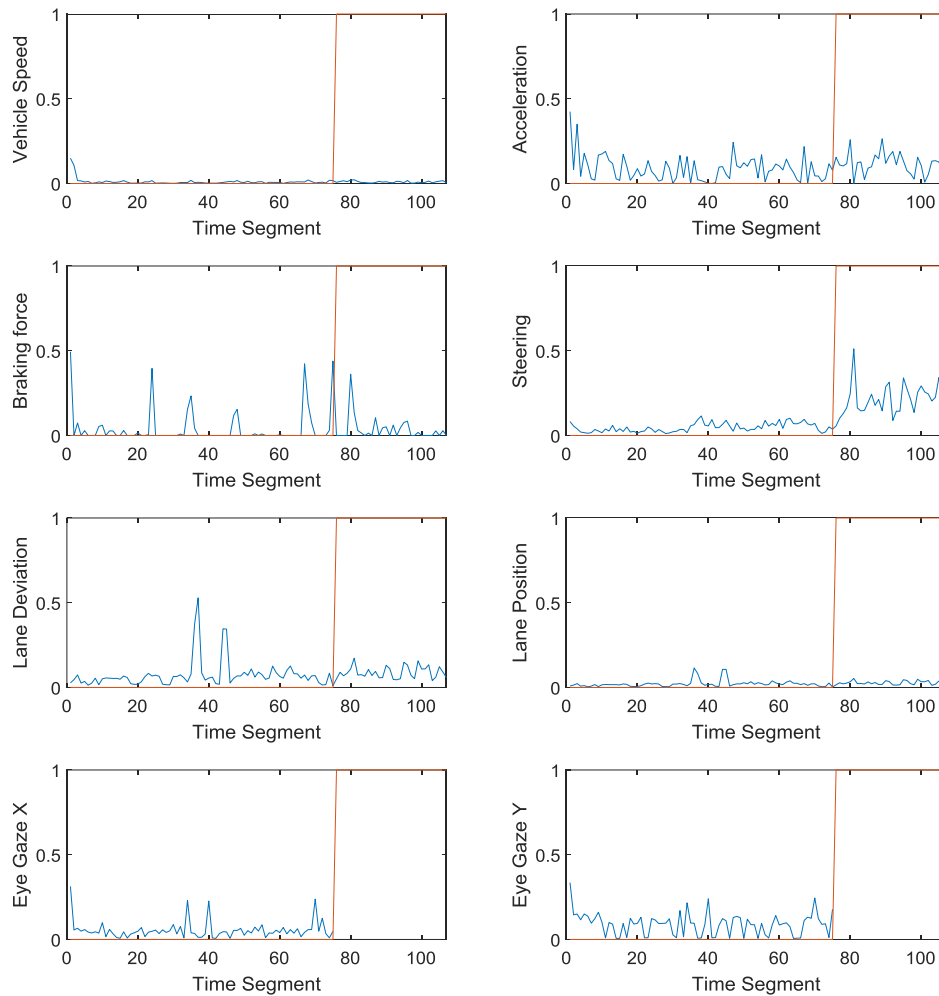


Figure A-4. Comparisons of Standard Deviation between Normal and Distracted Driving for Driver No. 3

Figure A-4 shows that the impact of driver distraction can be investigated. In total there are 8 features available for analysis including speed, acceleration, brake force, steering, lane deviation, lane position, eye gaze direction x and y . Figure A-4 shows that there is a significant difference in mean speed between normal driving and distracted driving. The distracted driving pattern has significant fluctuations but with the normal driving the speed remains steady and does not change much. It is labelled as relevant in detecting driver distraction. Taking acceleration into consideration, there is not significant difference between

distracted and non-distracted driving. It is labelled as not relevant. The brake force is considered to be relevant in detecting distraction due to the factor that the frequency of brakes changes from non-distracted drivers to distracted drivers. Steering angle is considered to be minimal with little change between distracted and non-distracted drivers. The same situations fit into lane position and lane deviation, which are irrelevant to detecting driver distraction. For gaze locations x and y , due to the vast difference between the gaze locations x and y , it is classified as relevant in detecting driver distraction.

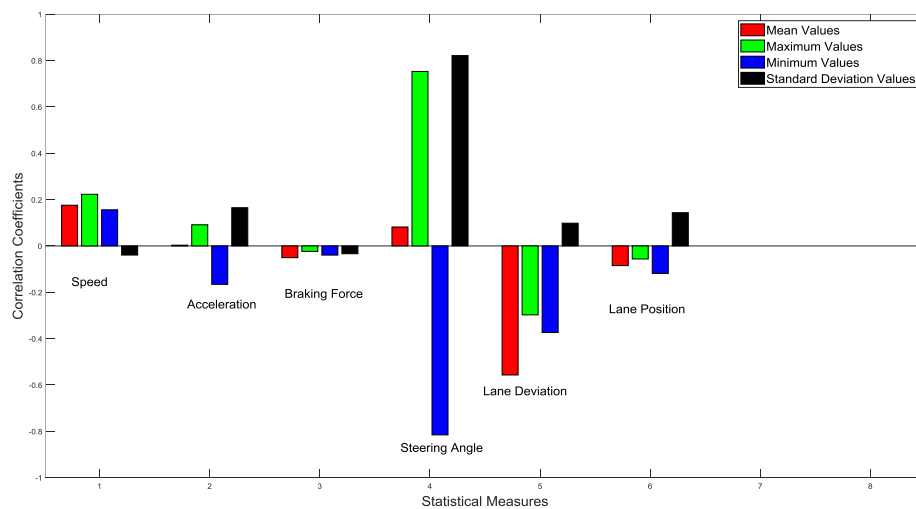


Figure A-5. Correlation Coefficient between Statistical Measures and Distraction for Driver No. 3

Figure A-5 shows that the most relevant features are standard deviation of gaze x and y , the mean value of lane deviation and the minimum value of brake force and maximum value of steering angle are also large in terms of correlation coefficient. These represents the relevant signals/features in detecting driver distraction.

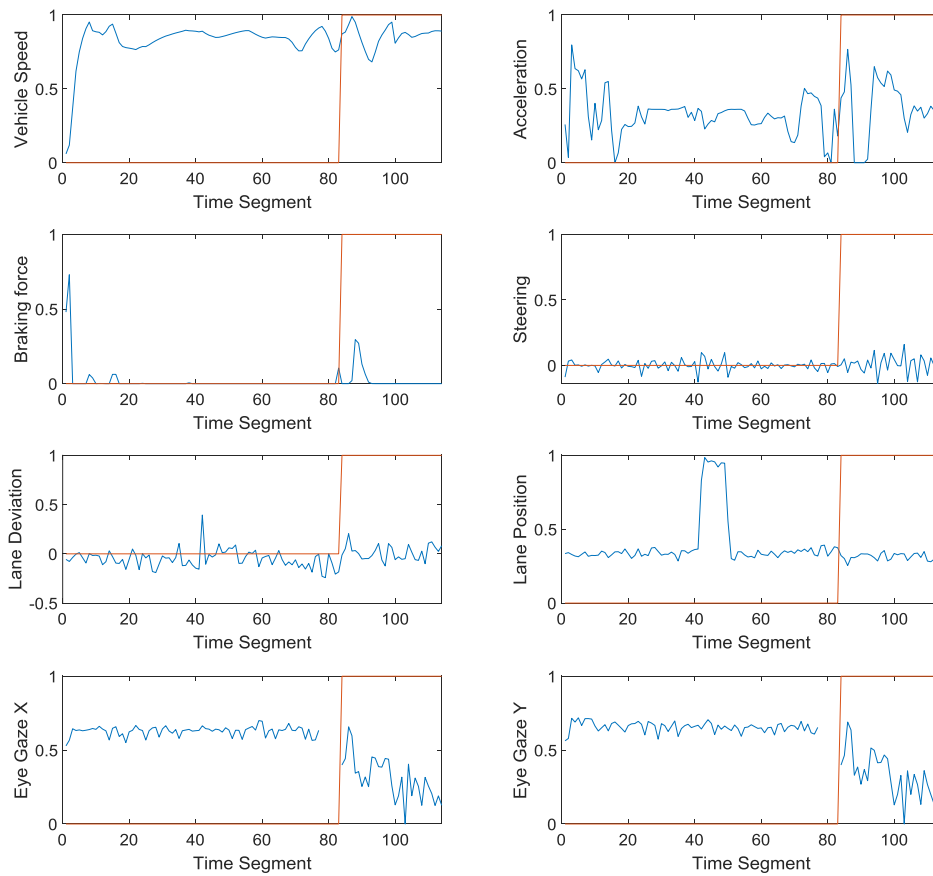


Figure A-6. Comparisons of Mean Values between Normal and Manually Distracted Driving for Driver No. 4

Figure A-6 shows that the mean values of vehicle speed, vehicle acceleration and gaze in x and y directions are the relevant features in detecting driver distraction. The mean values of brake force, steering angles, lane deviation and lane position are less relevant.

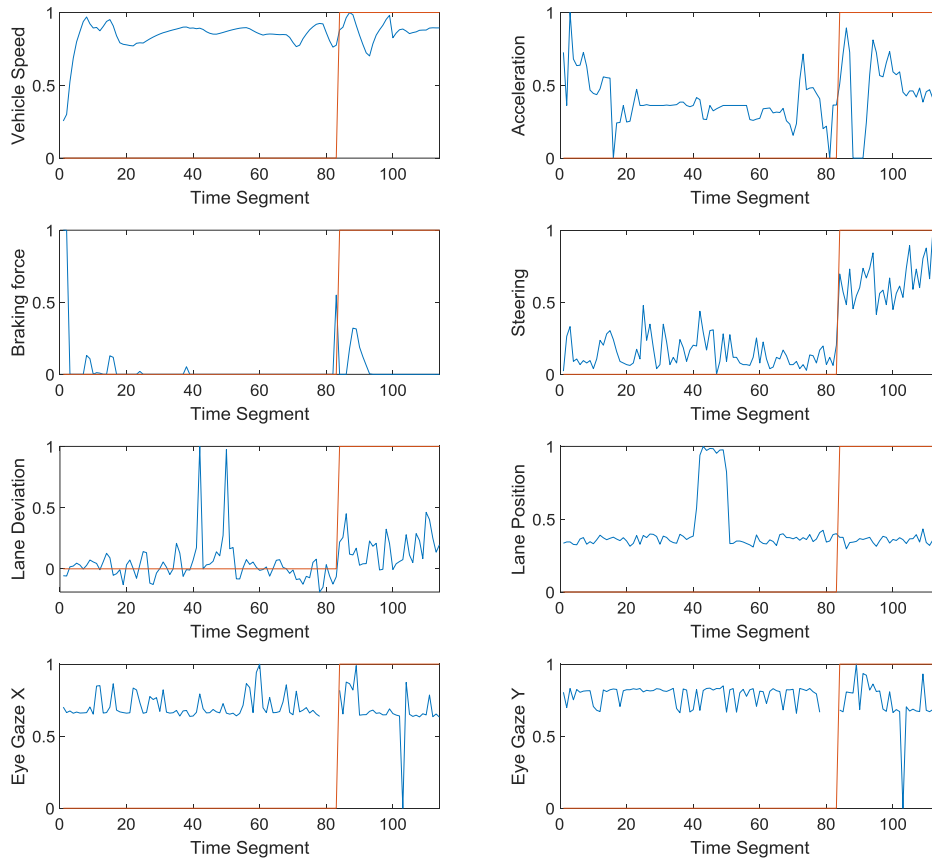


Figure A-7. Comparisons of Maximum Values between Normal and Manually Distracted Driving for Driver No. 4

Figure A-7 shows that the maximum value of steering angle is the most relevant feature in detecting driver distraction, followed by maximum value of vehicle speed, acceleration and eye gaze in x and y directions. Maximum value of lane deviation is also relevant in detecting driver distraction. The maximum values of steering wheel angle increase dramatically after the driver is distracted. The acceleration changes become more sharp comparing to those changes in normal driving. Correspondingly, the vehicle speed changes more frequently and in large amount compared to vehicle speed during normal driving. Also, the lane deviation increases significantly after the driver is distracted.

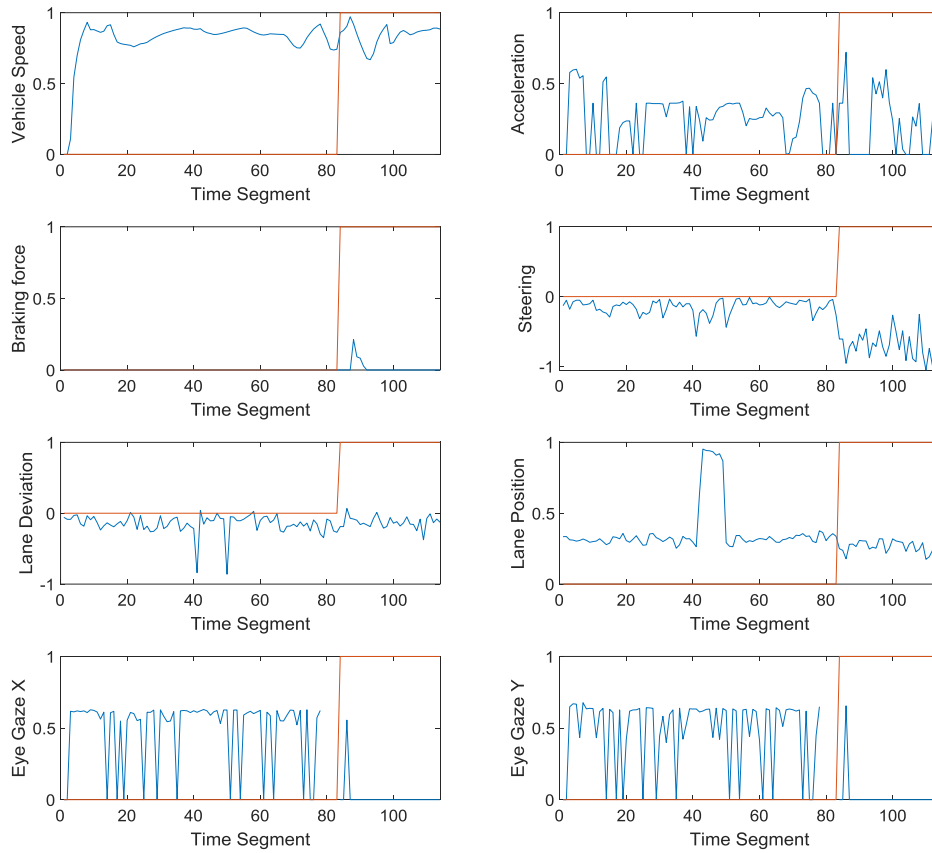


Figure A-8. Comparisons of Minimum Values between Normal and Manually Distracted Driving for Driver No. 4

Figure A-8 shows that minimum values of vehicle speed, vehicle acceleration, steering angle and eye gaze in x and y are relevant features in detecting driver distraction. The vehicle accelerates more abruptly according to the minimum values of accelerator positions. The vehicle speed oscillates more frequently after the driver is distracted. The minimum values of steering angle drop rapidly after the driver is distracted. The minimum values of gaze in x and y indicates that the eye tracker lost tracking of eye gaze frequently.

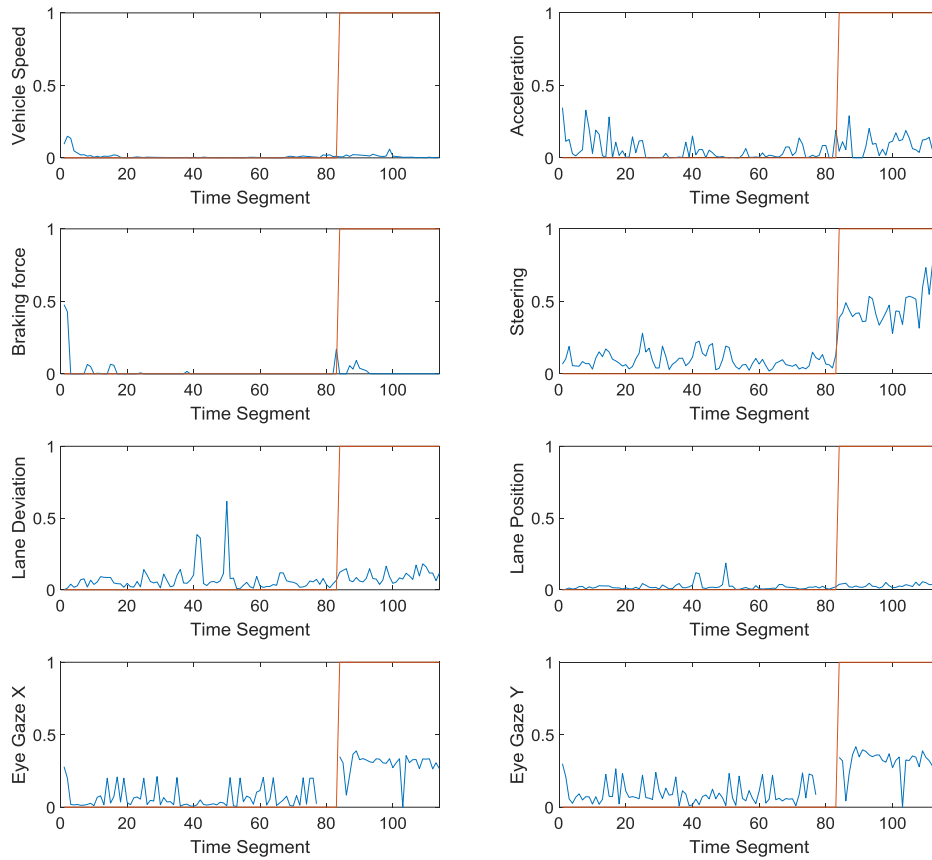


Figure A-9. Comparisons of Standard Deviation Values between Normal and Manually Distracted Driving for Driver No. 4

Figure A-9 shows that the standard deviation of steering angle, the eye gaze in x and y directions increases significantly after the driver is distracted. The steering angle oscillates more due to the poor control of the steering wheel caused by driver distraction. The gaze in x and y directions oscillates more due to the texting behaviour.

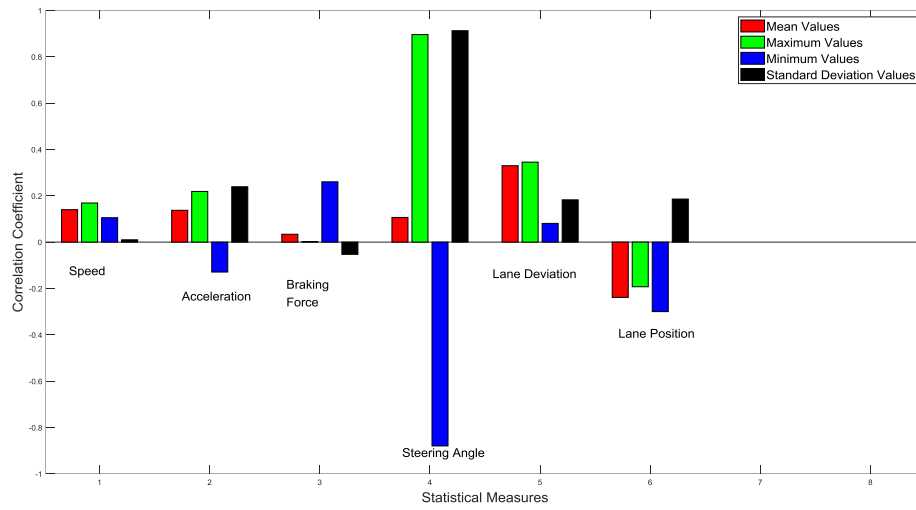


Figure A-10. Correlation Coefficients between Features and Distraction for Driver No. 4

Figure A-10 estimates the correlation coefficients between features of each signals and the binary state of distraction (no distraction and distraction). It indicates that the maximum, minimum and standard deviation of steering angle is the most relevant in detecting driver distraction, followed by the mean and maximum lane deviation. Also, the minimum of lane position and maximum of acceleration are relevant in detecting driver distraction.

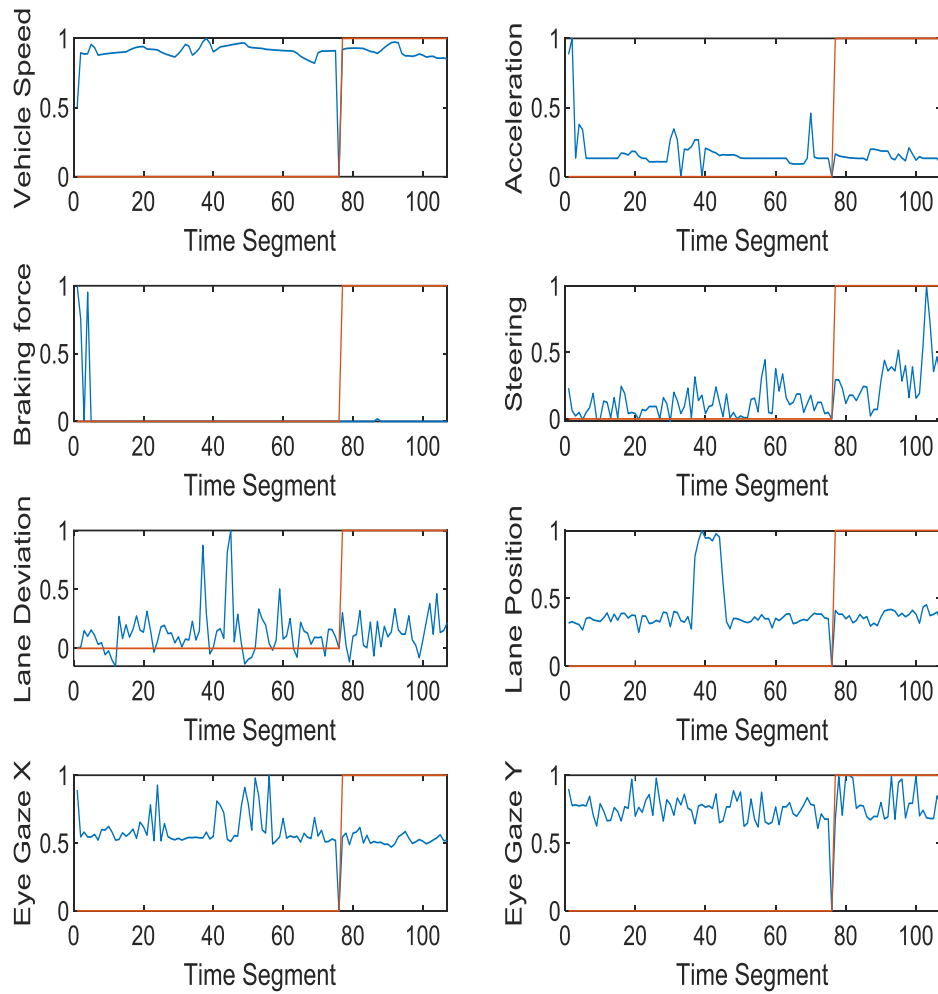


Figure A-11. Comparisons of Maximum Values between Normal and Manually Distracted Driving for Driver No. 9

Figure A-11 shows that the most relevant feature in detecting driver distraction is maximum of steering angle. The second relevant feature is the gaze in y direction, followed by the gaze in x direction. Other features are not relevant in detecting driver distraction by visual inspection. Notably, the vehicle speed is reduced to zero before normal driving section ends and increased to around 70 km/h after manual distraction section starts.

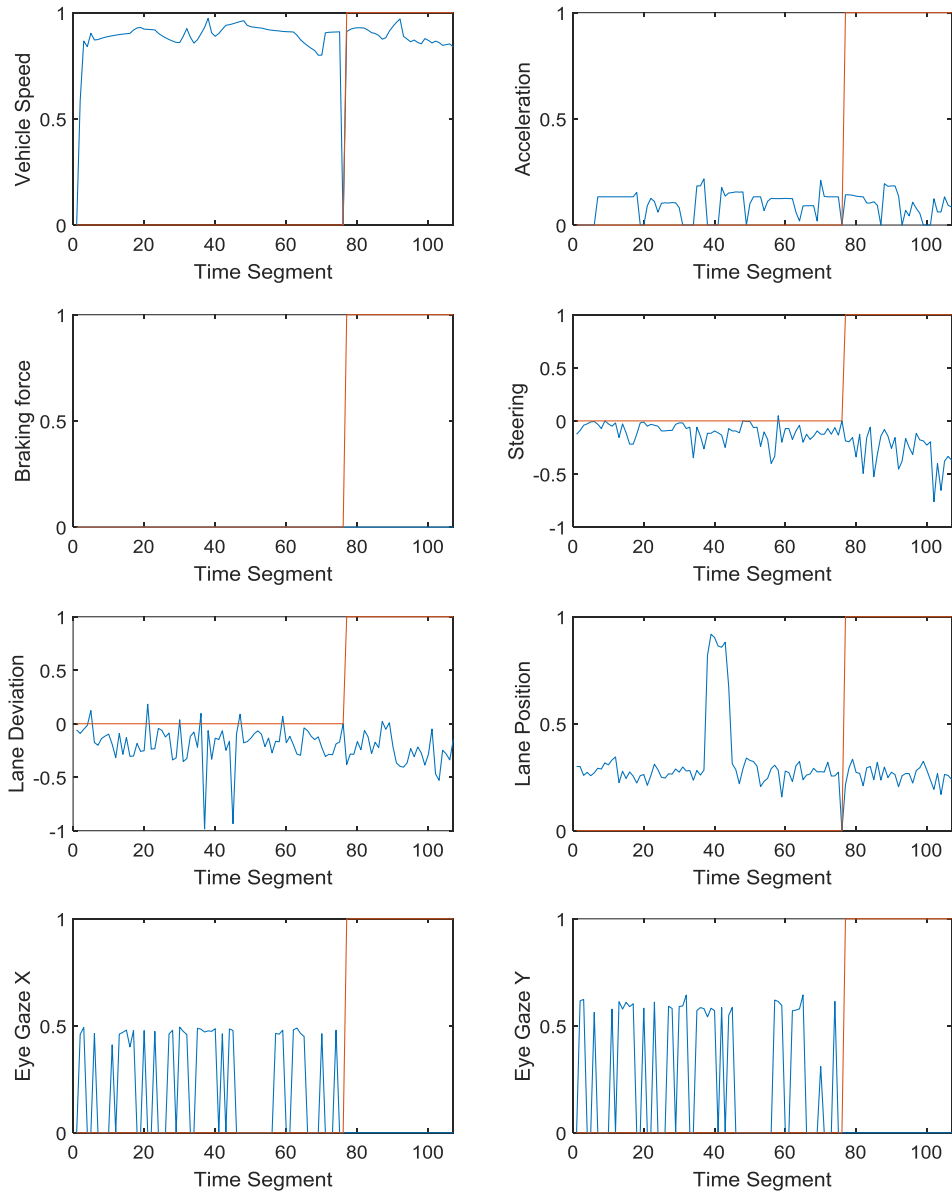


Figure A-12. Comparisons of Minimum Values between Normal and Manually Distracted Driving for Driver No. 9

Figure A-12 shows that the most relevant features in detecting distraction are gaze positions in x and y directions. With gaze out of the screen for large amount of time in distraction section, the driver gazes out of the screen for a short period of time in normal driving section. Other relevant features are maximum value of

steering angle and maximum value of lane deviation, both values are reduced when the driver gets distracted.

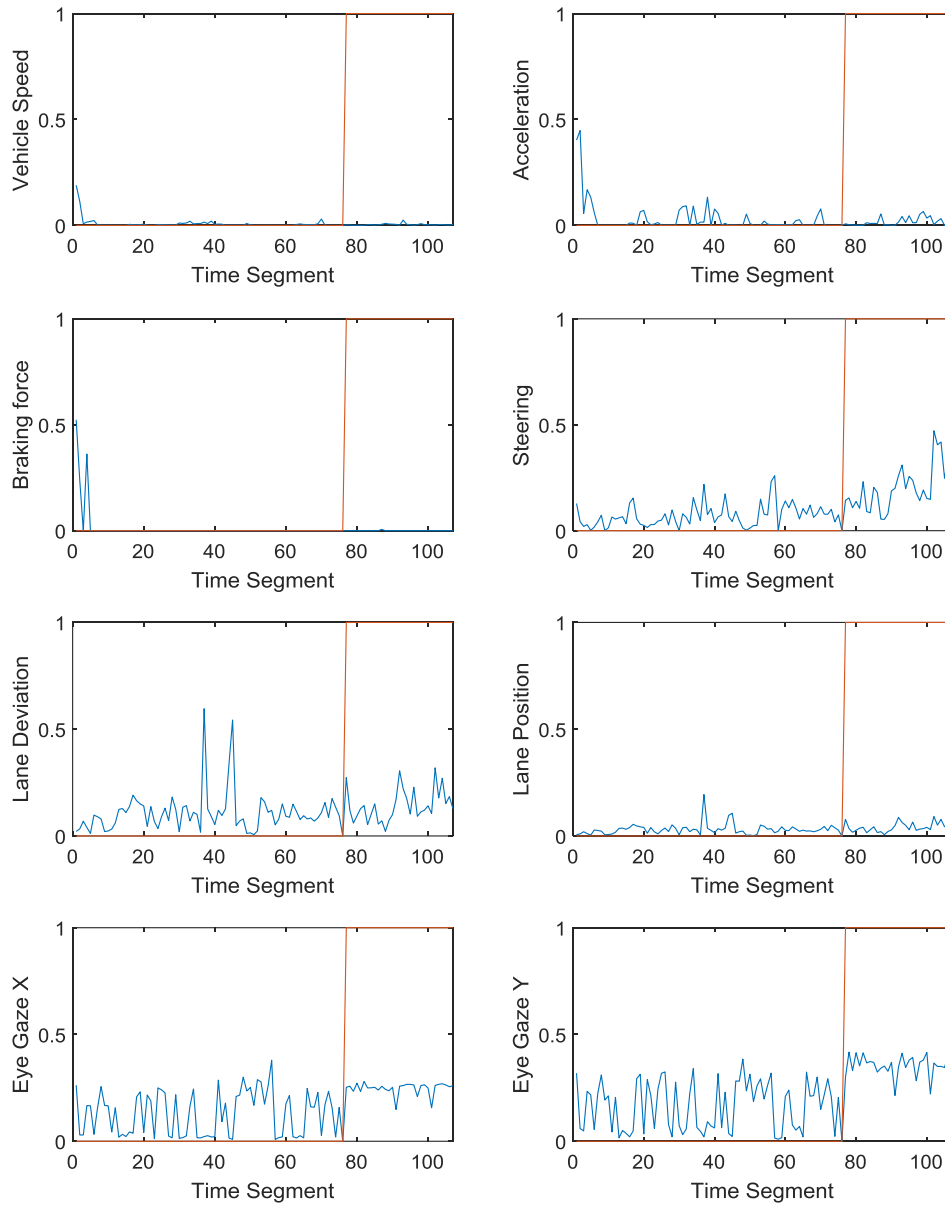


Figure A-13. Comparisons of Standard Deviation Values between Normal and Manually Distracted Driving for Driver No. 9

Figure A-13 shows that the features with the largest difference are standard deviation values of gaze positions in x and y directions, as well as standard

deviation of steering angle and lane deviation from middle of the lane by comparing the normal driving and distracted driving. In other features, there are minor changes from normal driving to distracted driving, since it is not obvious, they are not relevant in detecting driver distraction.

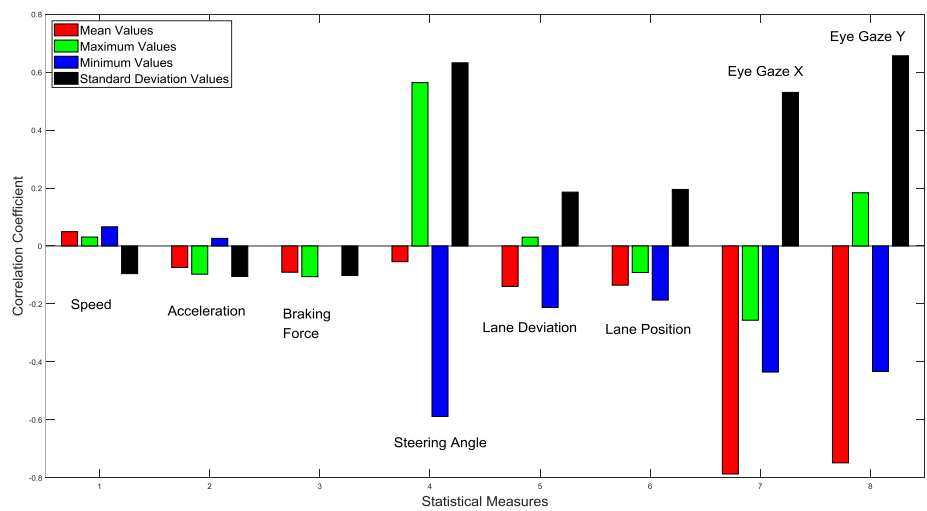


Figure A-14. Correlation Coefficients between Features and Distraction for Driver No.9

Figure A-14 indicates the correlation coefficients between 8 features and binary distraction level (0 and 1). As shown in Figure A-14, the features with the largest correlation coefficients are the maximum, minimum and standard deviation of steering angle, as well as the minimum and standard deviation of gaze positions in x and y directions. Features with relatively smaller correlation coefficients are minimum and standard deviation of lane deviation and lane position. The above-mentioned features are relevant in detecting driver distraction.

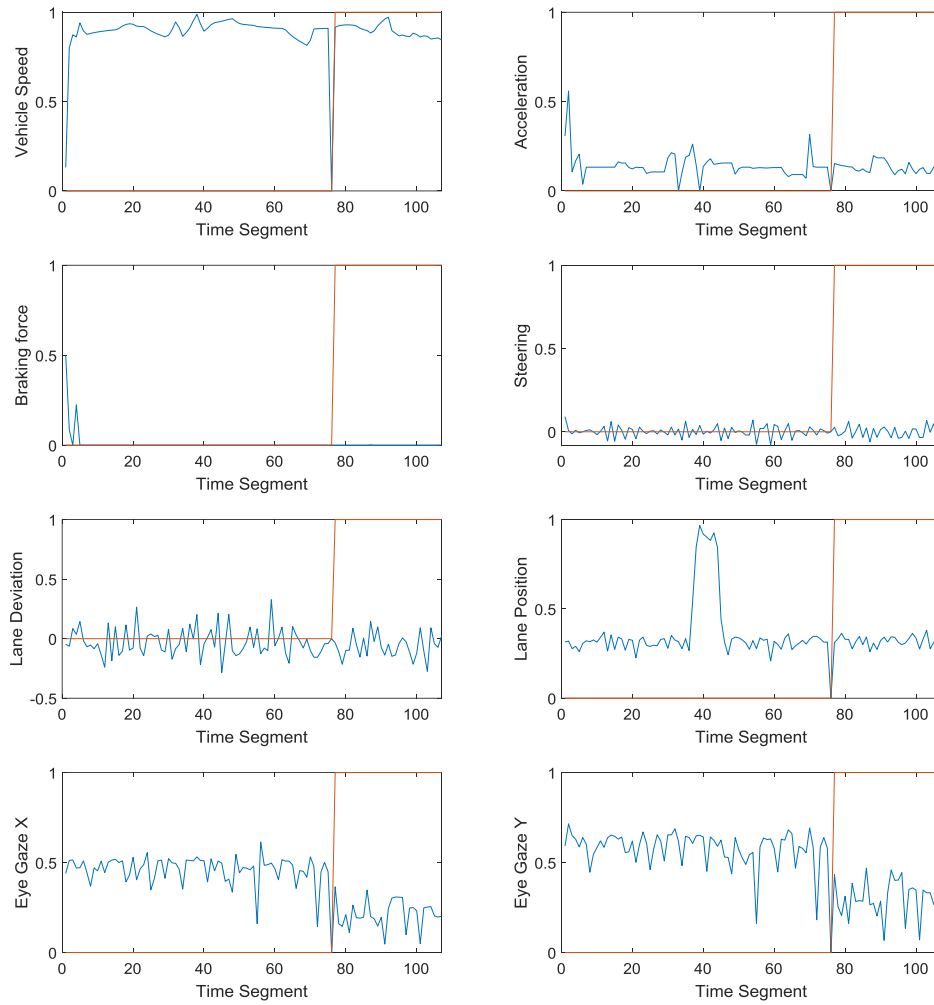


Figure A-15. Comparisons of Mean Values between Normal and Manually Distracted Driving for Driver No. 10

Figure A-15 shows that the most relevant features in detecting driver distraction are mean values of gaze positions in x and y directions. There are no significant differences between normal driving and distracted driving in other features.

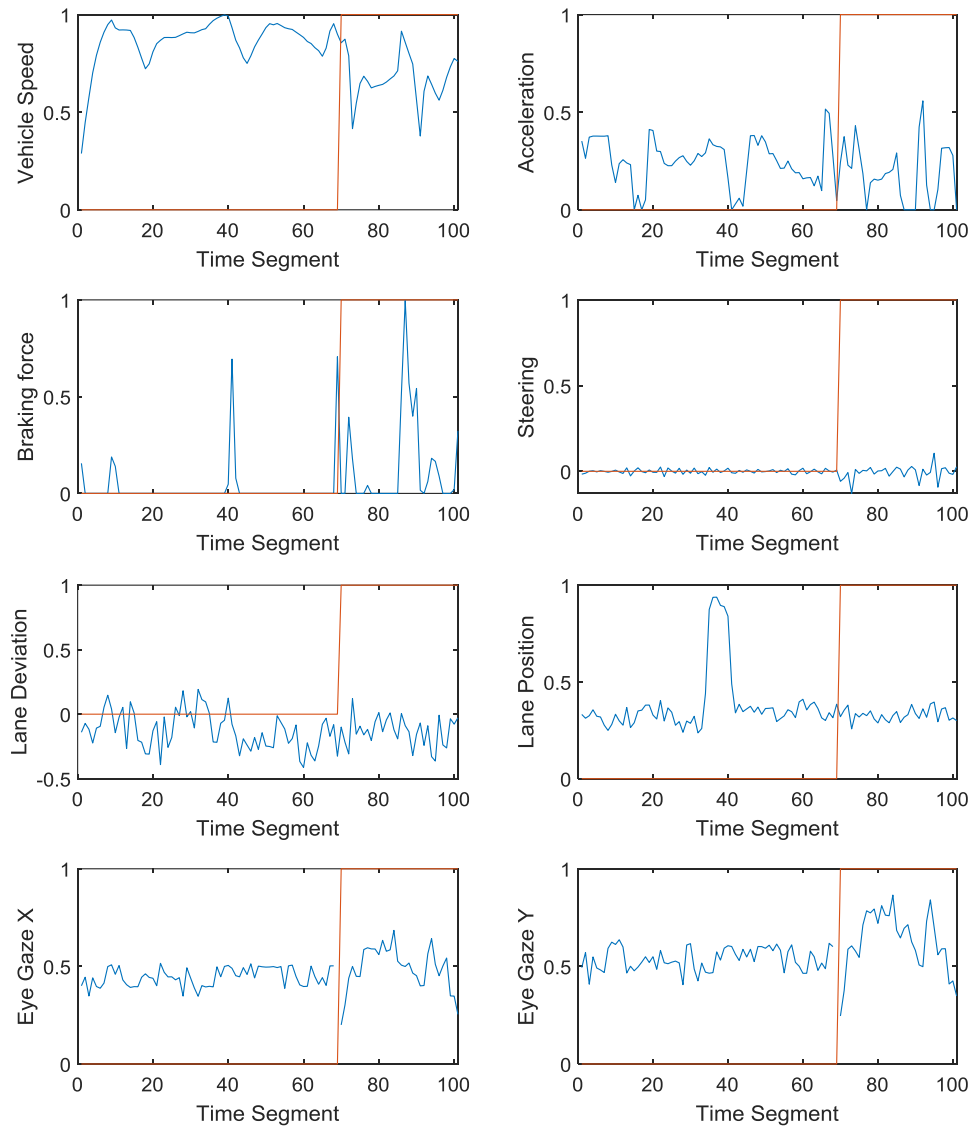


Figure A-16. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 10

Figure A-16 indicates the mean values of 8 recorded features with both normal driving and distracted driving. By comparing the changes of features in normal driving and distracted driving, the features that are relevant in detecting driver distraction can be determined. The most relevant feature with largest difference is the mean brake value, whose value increases significantly after the driver gets

distracted. In addition, the mean values of gaze positions in x and y directions are also relevant in detecting driver distraction.

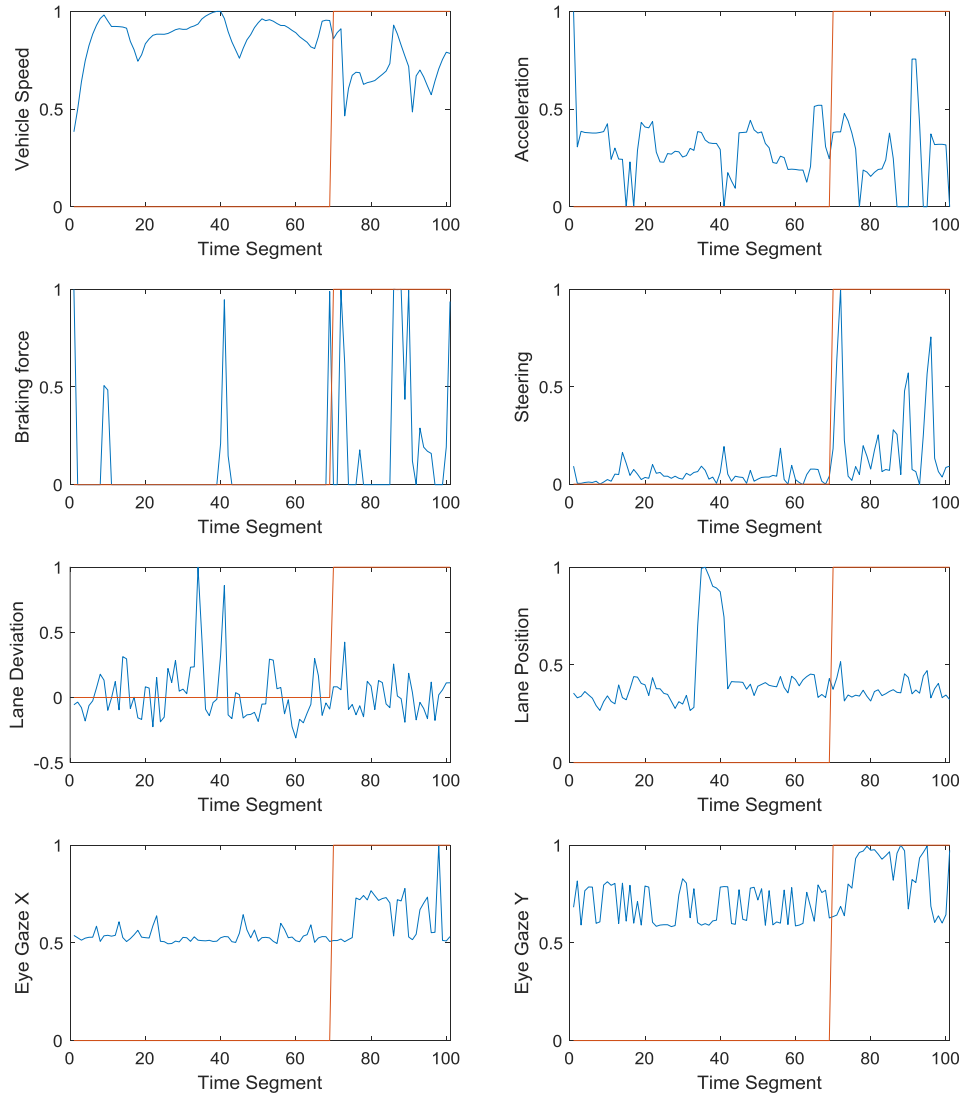


Figure A-17. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 10

Figure A-17 shows maximum value of the 8 recorded features including both normal driving and distracted driving sections. By comparing the normal driving and distracted driving sections (left and right), the most relevant features in detecting driver distraction can be determined. Figure A-17 shows that significant

differences are present in all 8 features, among these features, the most significant features are maximum of braking force, steering wheel angle and gaze in x and y directions. The maximum of vehicle acceleration and speed are also relevant in detecting driver distraction due to the more abrupt acceleration and fast speed changes. In addition, the maximum of lane deviation trends to reduce as the changes mainly happen in longitudinal direction rather than the lateral directions.

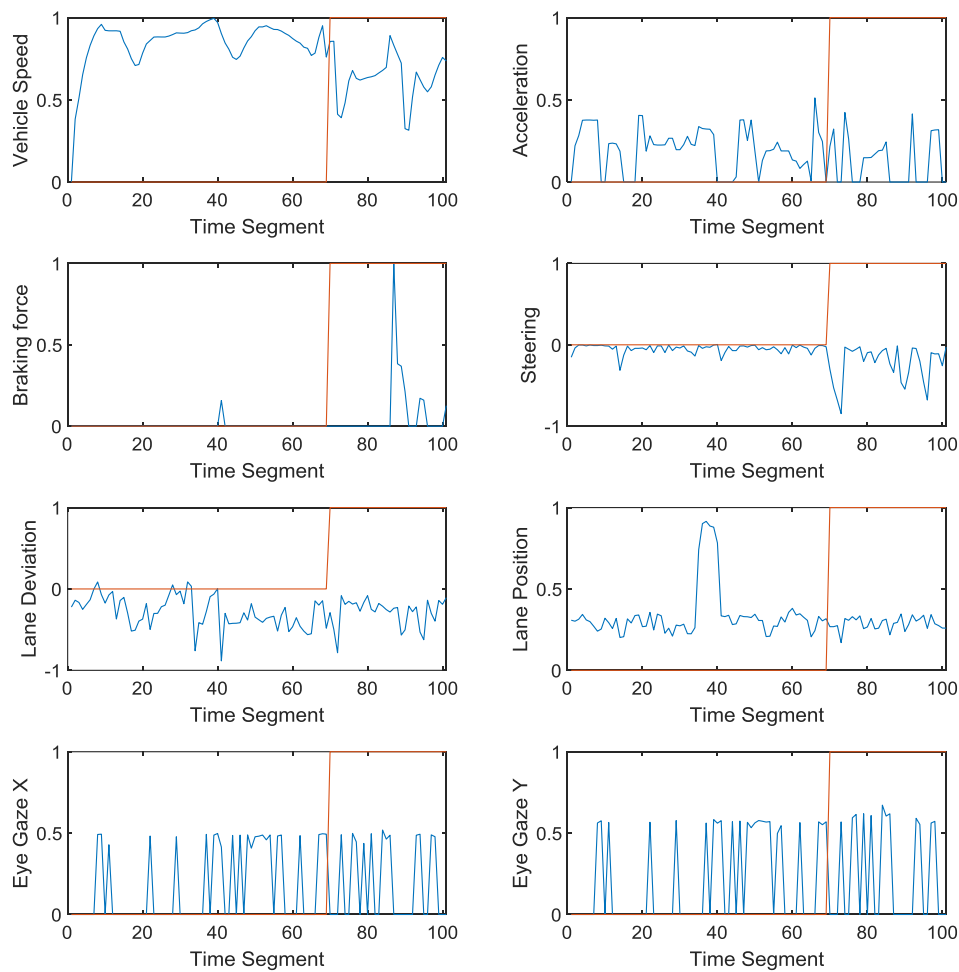


Figure A-18. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 10

Figure A-18 indicates the minimum values of 8 features in normal driving and distracted driving sections. By comparing the normal driving and distracted

driving sections (left and right), the most relevant features in detecting driver distraction can be identified by visual inspection. The relevant features include the minimum value of vehicle speed, acceleration and steering angle, as well as gaze in x and y directions.

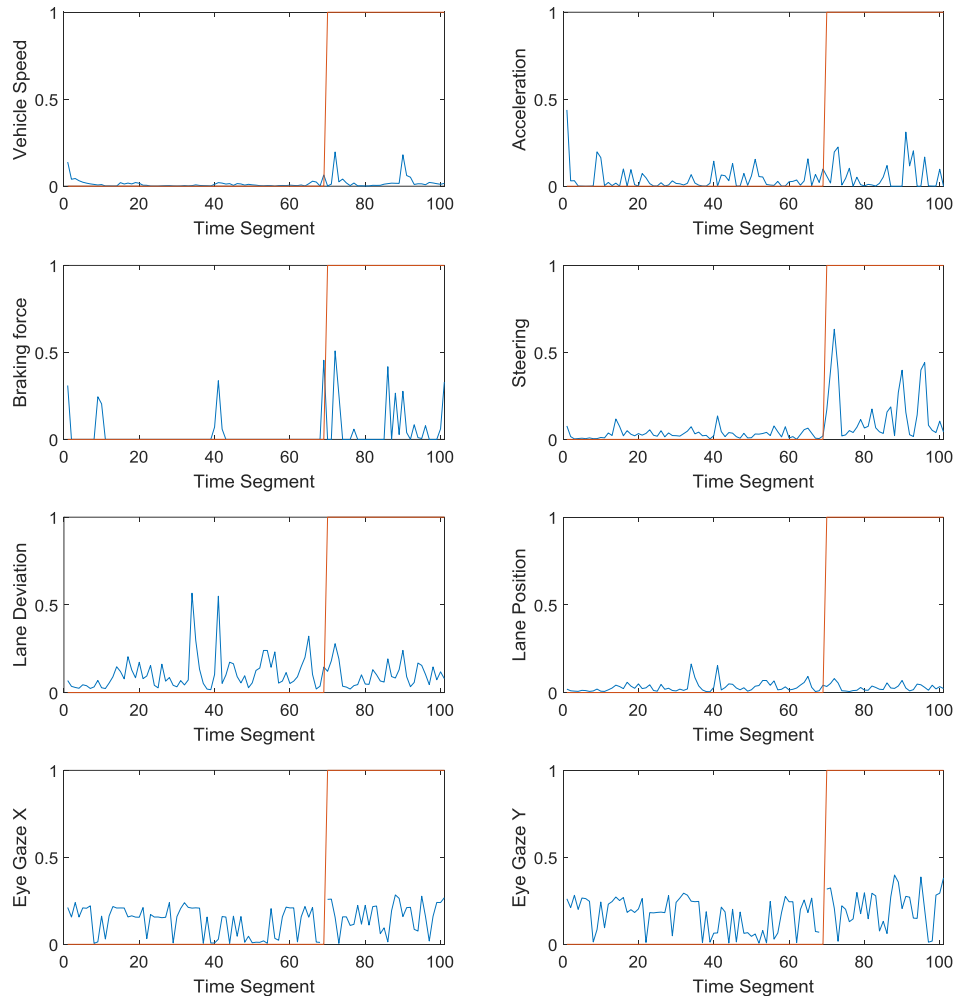


Figure A-19. Comparisons of Standard Deviation between Normal and Distracted Driving for Driver No. 10

Figure A-19 shows the standard deviation value of 8 features in both normal driving and distracted driving. By comparing the normal driving and distracted driving sections, the most relevant features in detecting driver distraction can be identified. The most relevant feature in detecting distraction is the standard

deviation of steering angle due to increased oscillations. Other relevant features are maximum value of eye gaze positions in x and y directions as well as maximum value of driver braking force and vehicle acceleration.

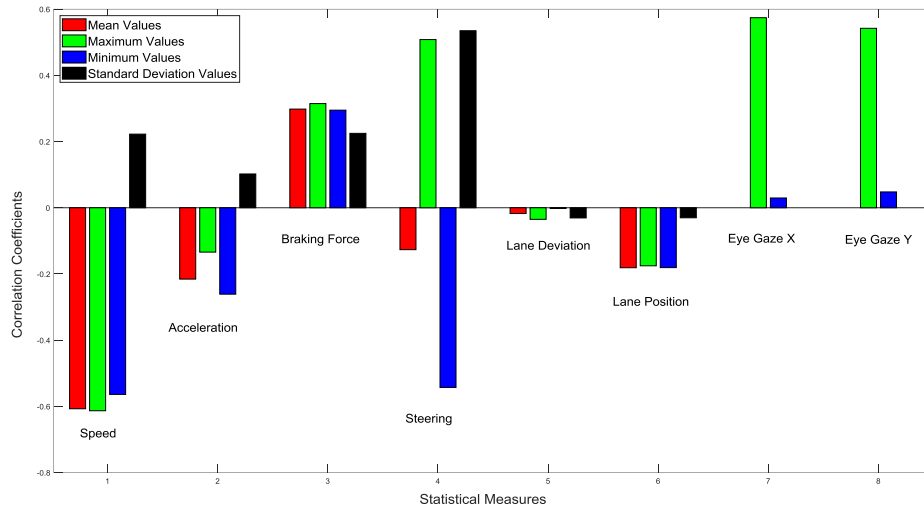


Figure A-20. Correlation Coefficients between Statistically Measures and Distraction for Driver No. 10

Figure A-20 demonstrates the correlation coefficients between statistically measures and binary distraction level. Higher correlation coefficients indicate a higher relevancy in detecting driver distraction. Figure A-20 shows that the most relevant features are mean, maximum and minimum values of vehicle speed as well as maximum value of gaze angles, followed by the maximum, minimum and standard deviation of steering angle. All 4 statistical measures of braking force are also relevant in detecting distraction.

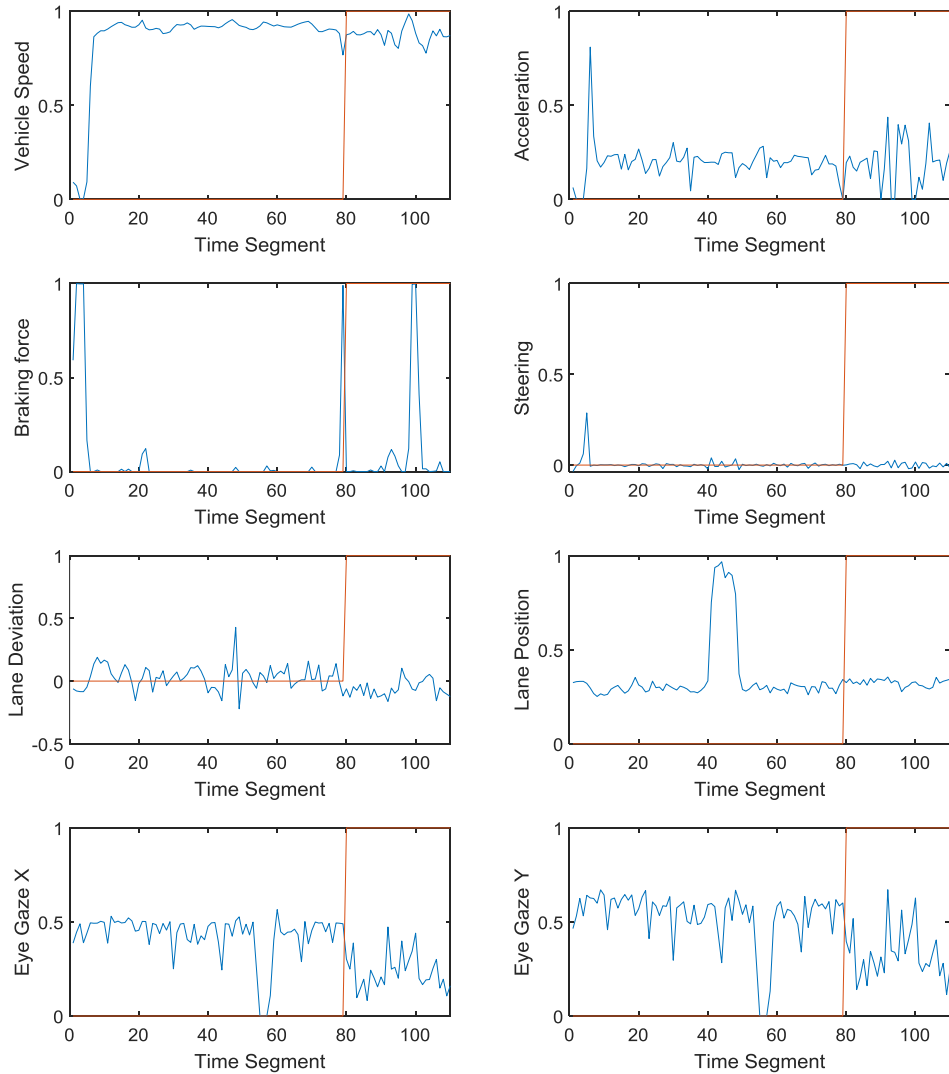


Figure A-21. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 12

Figure A-21 shows the mean values of 8 features in both normal driving and distracted driving sections for driver No. 12. Features that are relevant in detecting distraction can be identified by comparing the features in normal driving and distracted driving sections. Figure A-21 shows that the most relevant features in detecting distraction are mean values of acceleration, braking force and eye gaze in x and y positions. The mean values of acceleration and braking forces increased after driver got distracted while the mean values of eye gaze in x and

y positions decreased after driver got distracted. The control over acceleration pedal and brake pedal became more abrupt for Driver No. 12. Meanwhile, there were more shifts of attention during driving.

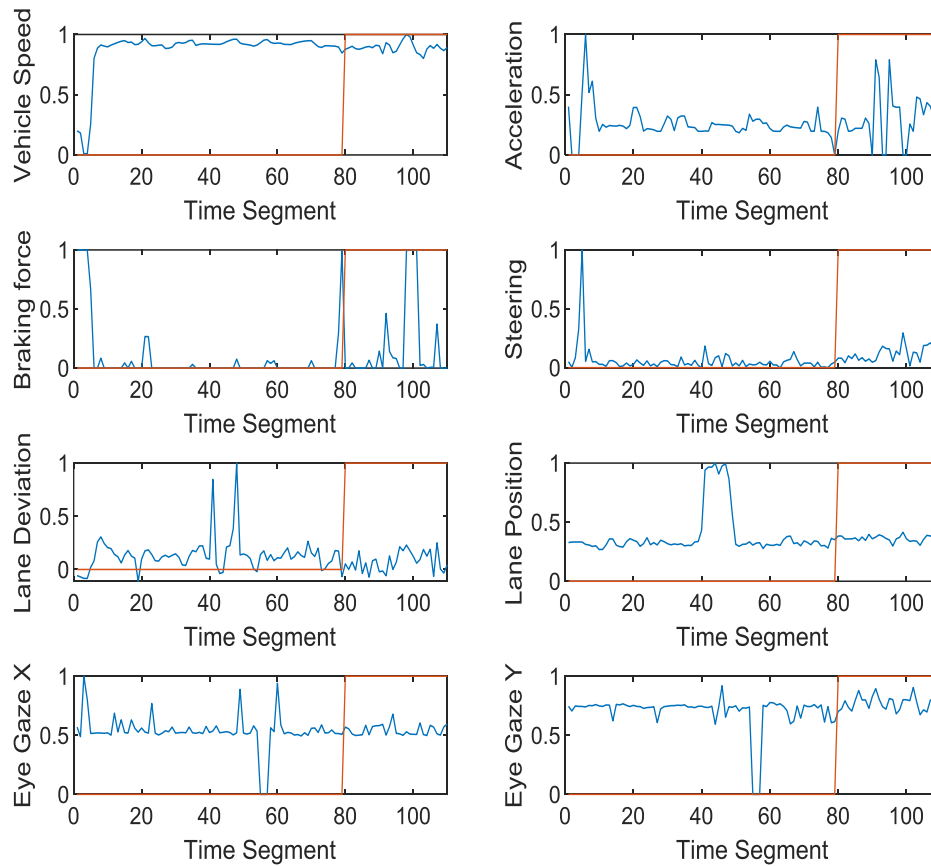


Figure A-22. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 12

Figure A-22 demonstrates the maximum values of 8 features for driver No. 12. The relevant features in detecting driver distraction are maximum values of acceleration and braking forces. The maximum values of the two features increased after driver got distracted. There were more abrupt acceleration and braking forces when driver is manually distracted.

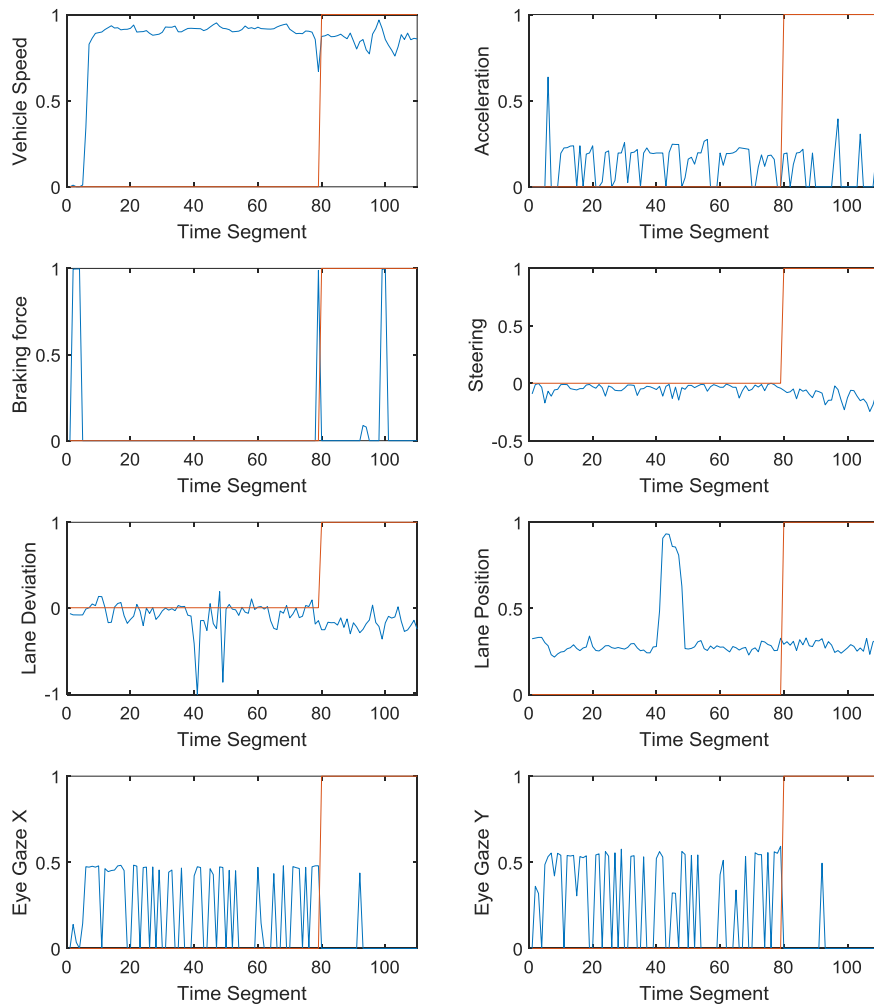


Figure A-23. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 12

Figure A-23 demonstrates the minimum values of 8 features for driver No. 12. The relevant features in detecting distraction are eye gaze in x and y directions. The changes after distraction in other six features listed in Figure A-23 are not obvious, therefore, they are not relevant in detecting driver distraction by visual inspection. There are a series of zero values recorded as a result of lost track of the eye positions of the eye tracker when the driver was texting.

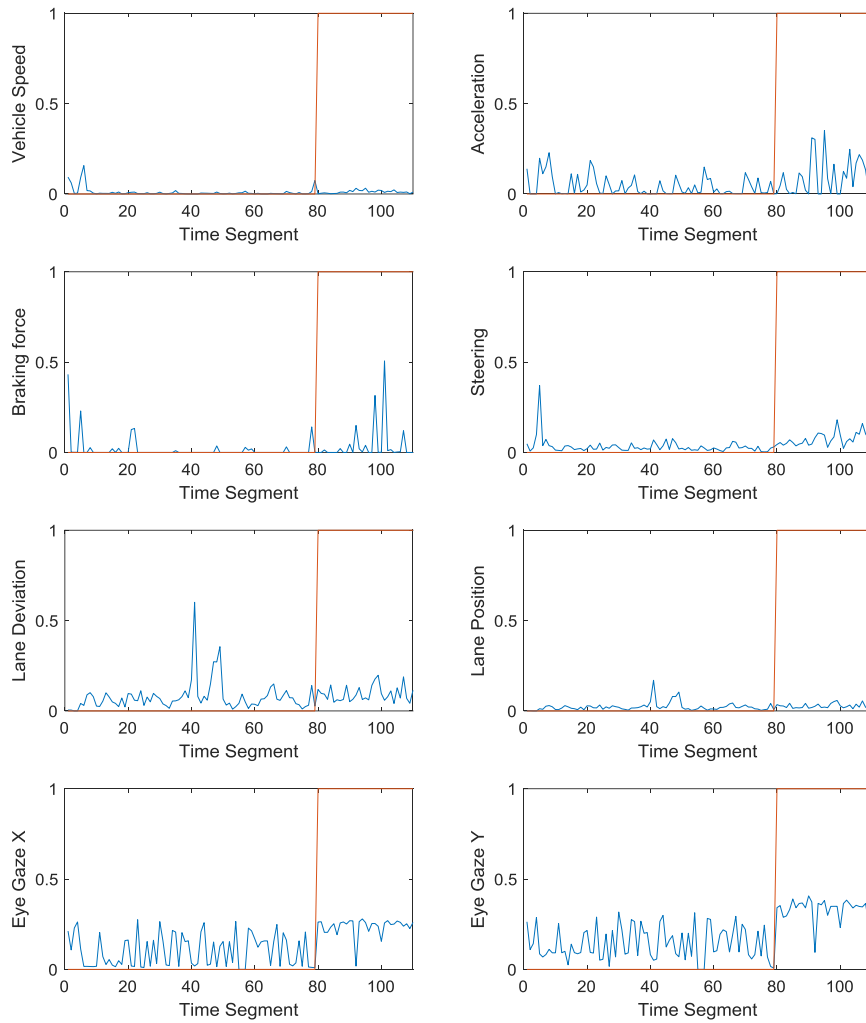


Figure A-24. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 12

Figure A-24 demonstrates the standard deviations of 8 features for driver No. 12. The relevant features in detecting driver distraction are standard deviations of acceleration, braking force, lane deviation and eye gaze in x and y positions, whose values increased as a result of distraction. The increased values of acceleration and braking force are a result of aggressive use of acceleration and braking pedals. The increasing values of lane deviations indicated that the control of the vehicle was degraded due to distraction. The standard deviation of eye gaze in x and y direction increased for the reason that occasionally eye tracker

lost track of the gaze positions and in this case the system recorded values of eye gaze as zeros.

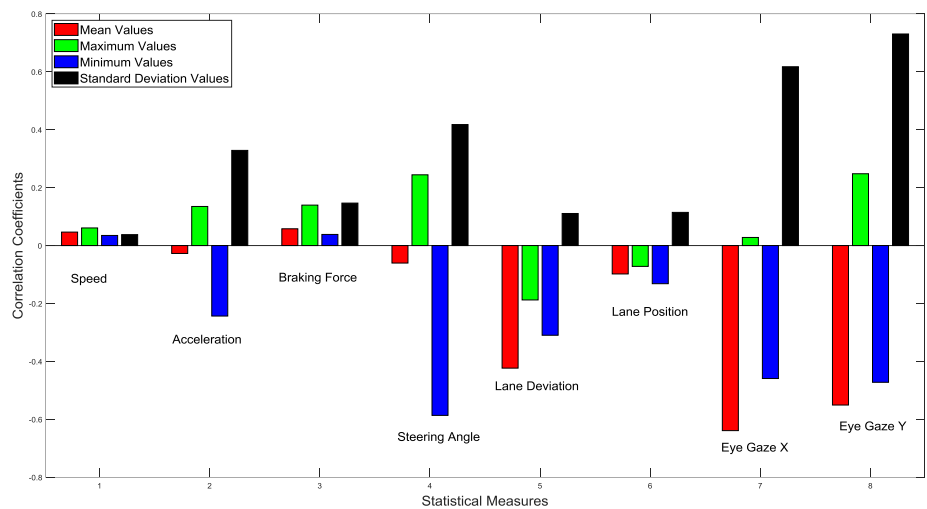


Figure A-25. Correlation Coefficients between Features and Distraction for Driver No. 12

Figure A-25 demonstrates the correlation coefficients between 8 features and distraction level for driver No. 12. As Figure A-25 indicates, the relevant features in detecting distraction are mean and standard deviations of eye gaze in x and y positions as well as the minimum and standard deviation of steering angle. The mean value of lane deviation is also relevant in detecting distraction.

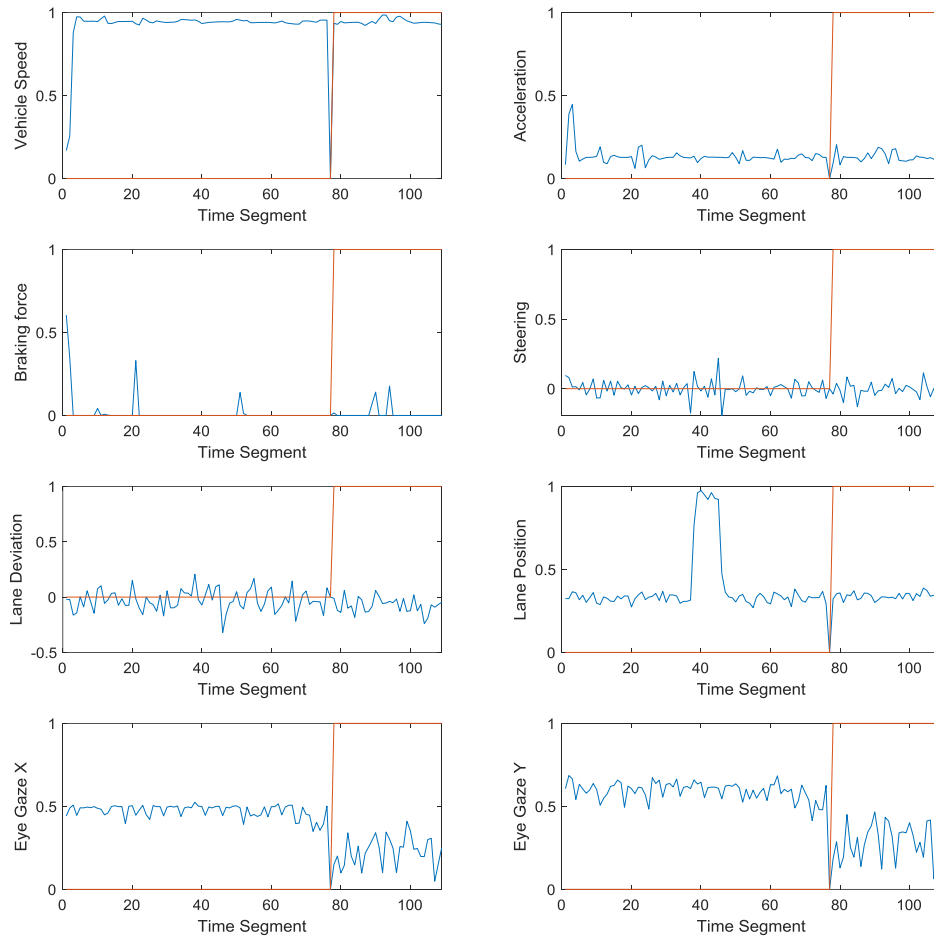


Figure A-26. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 15

Figure A-26 shows that gaze in x and y directions are most relevant features in detecting driver distraction due to the reduction in mean values of gaze positions. For other features, the differences between normal driving and distracted driving of vehicle performance features are minor, therefore these features are not relevant in detecting driver distraction by visual inspection.

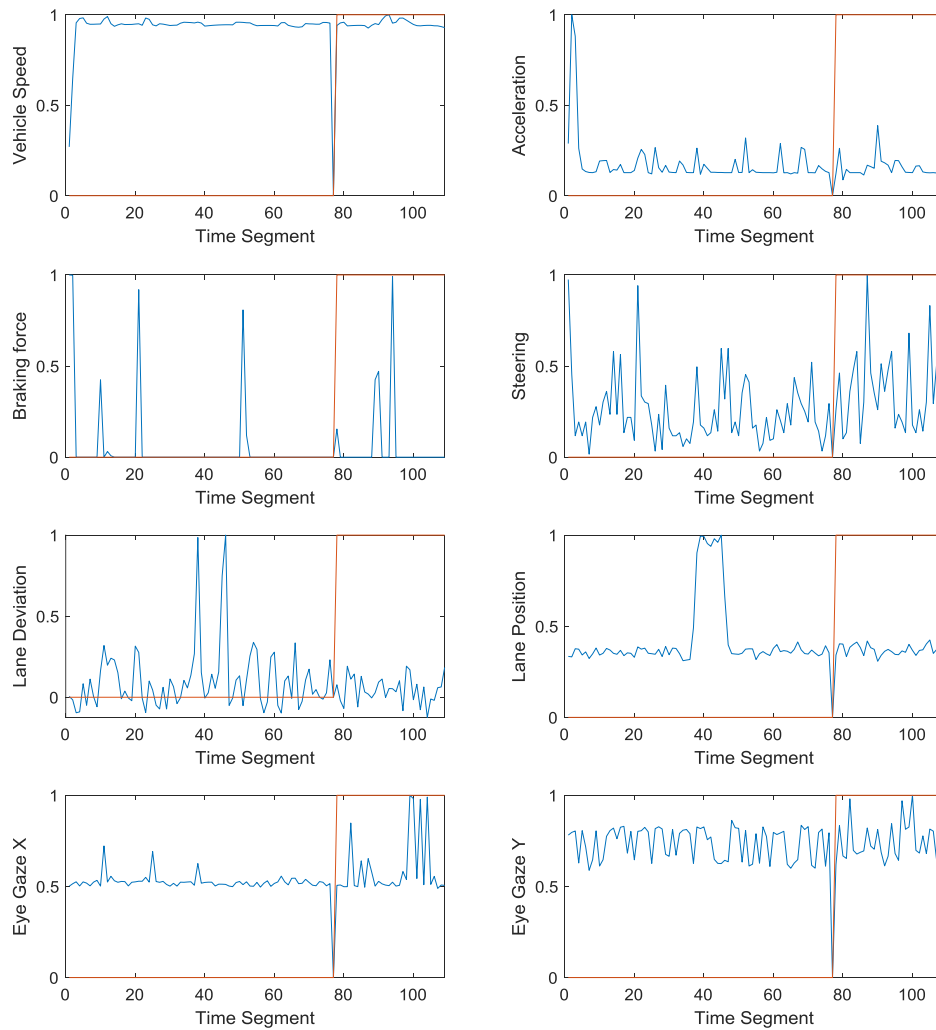


Figure A-27. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 15

Figure A-27 demonstrates the maximum values of eye gaze directions and vehicle performance features. By visual inspecting the features, steering angle, lane deviation and eye gaze in x and y directions are regarded as relevant in detecting driver distraction. Other features such as the maximum values of lane deviation and braking force are also relevant in detecting driver distraction. Driver No. 13 trends to brake more often and increase the brake force after he/she is distracted.

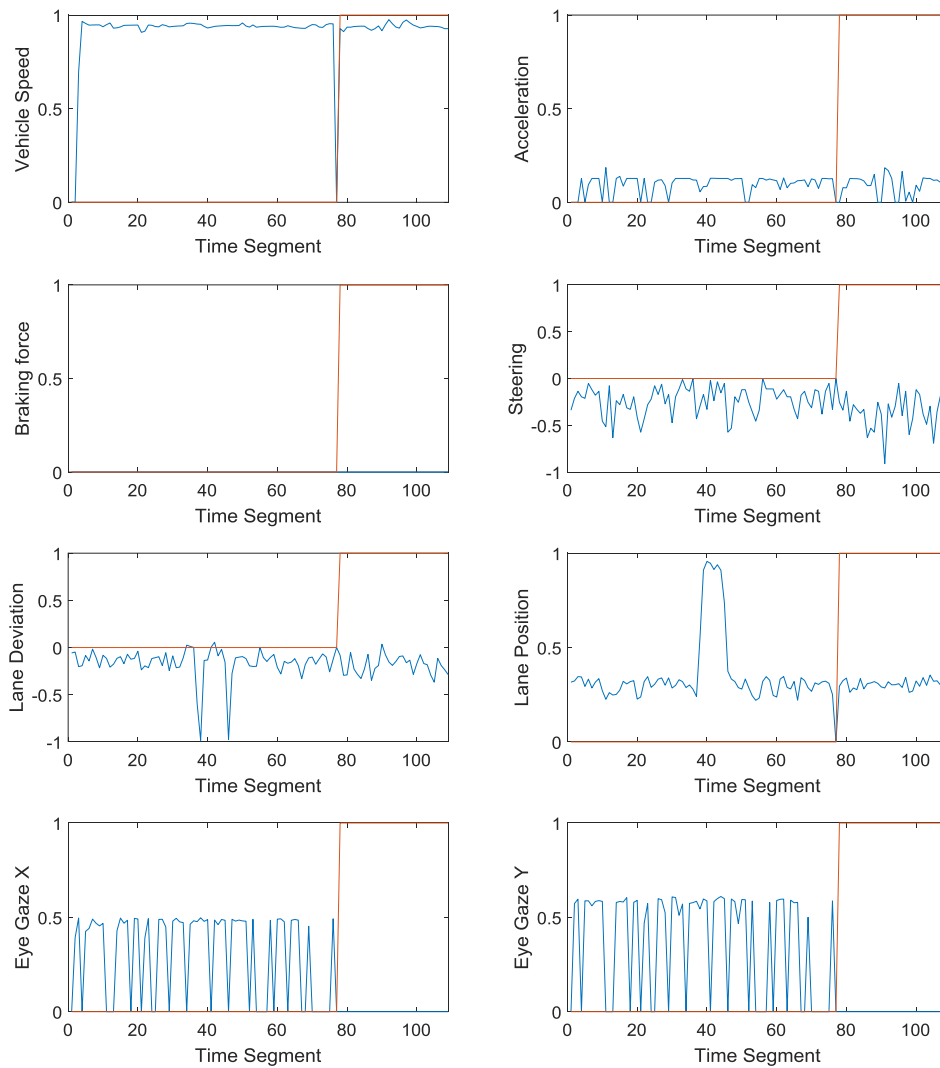


Figure A-28. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 15

From Figure A-28, relevant features in detecting driver distraction are steering wheel angle, gaze in x and y directions. The minimum values of steering angles reduce when the driver is manually distracted. The eye tracker lost track of the eye gaze points during each time segments when the driver is texting.

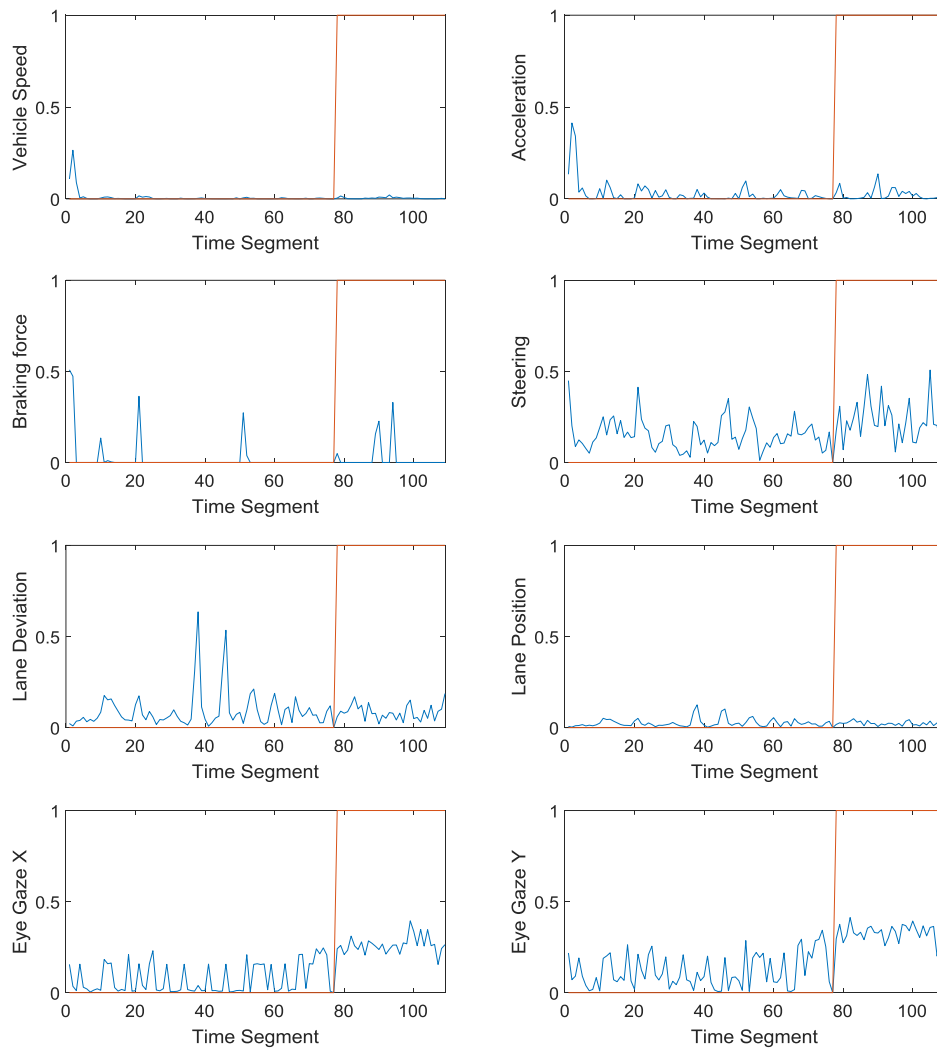


Figure A-29. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 15

Figure A-29 demonstrates that standard deviation values of braking forces, steering angles, gaze in x and y directions are relevant in detecting driver distraction. Driver brakes more often and in larger forces when the driver is manually distracted. The standard deviation values of eye gaze in x and y directions are larger when driver is distracted than the standard deviation values when they are driving normally.

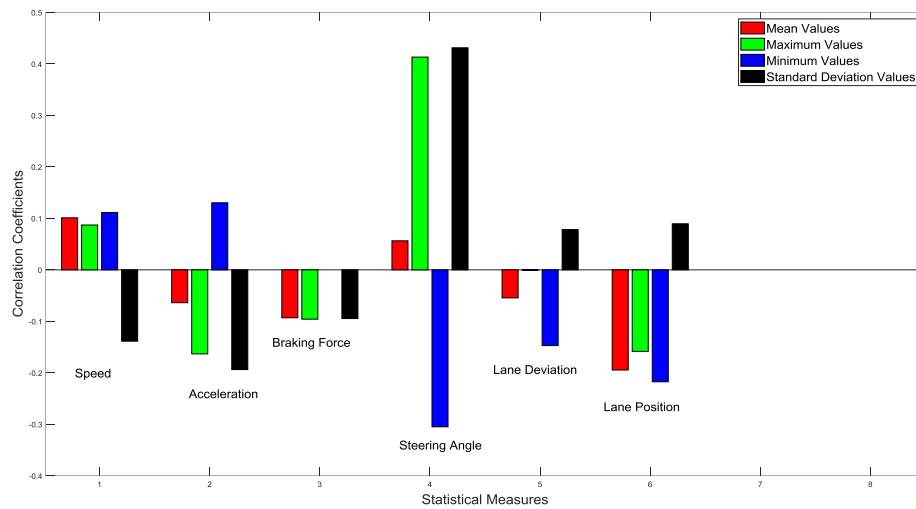


Figure A-30. Correlation Coefficients between Features and Distraction for Driver No. 15

Figure A-30 demonstrates the correlation coefficients between distraction level and features. The most correlated features are minimum values and standard deviation values of eye gaze in x and y directions, as well as the maximum, minimum and standard deviation values of steering angles.

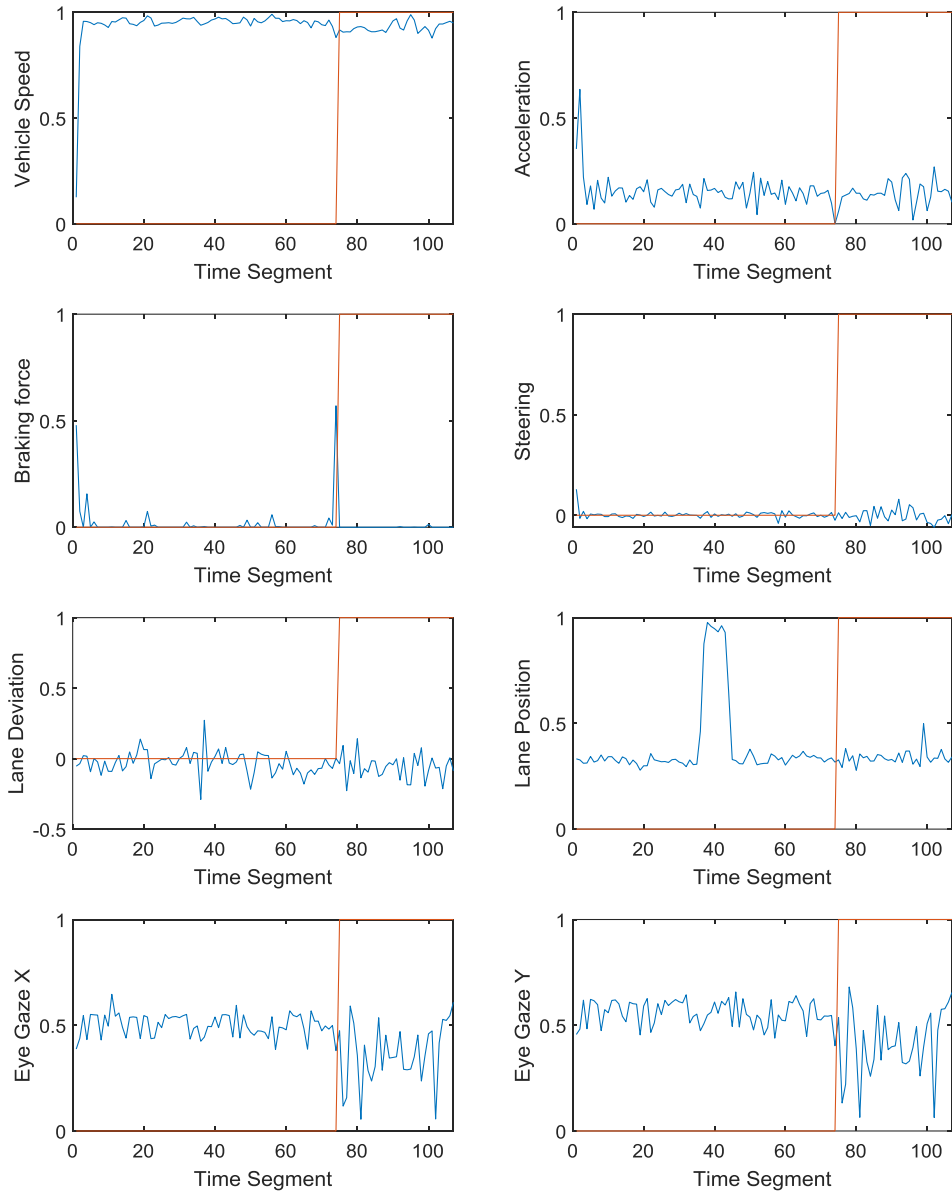


Figure A-31. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 34

Figure A-31 demonstrates the standard deviation values of eye gaze positions and vehicle instrumentation features for both normal driving and distracted driving. Figure A-31 shows that the most relevant features in detecting driver distraction are mean values of eye gaze in x and y directions. Other features

have minor differences between normal driving sections and distracted driving sections.

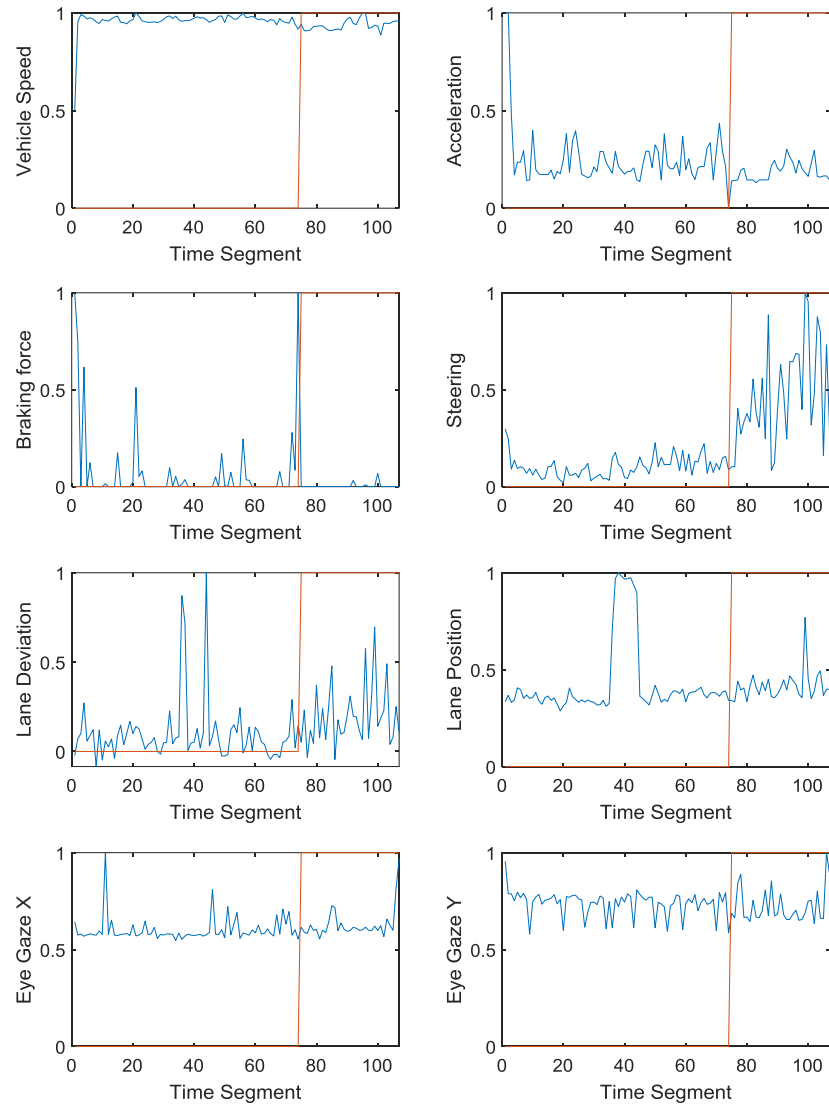


Figure A-32. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 34

Figure A-32 demonstrates the maximum values of features of both distracted driving and attentive driving. The most relevant features in detecting driver distraction are maximum values of braking force, steering angle and lane deviation. The brake force and frequency reduced significantly when the driver is

distracted compared to the force and frequency when they were driving attentively. The maximum values of steering angle and lane deviation increases when the driver was distracted. This may be caused by the reduced control of the vehicle. The gaze positions in x and y directions did not change significantly, which proves that texting behaviour did not change the gaze positions.

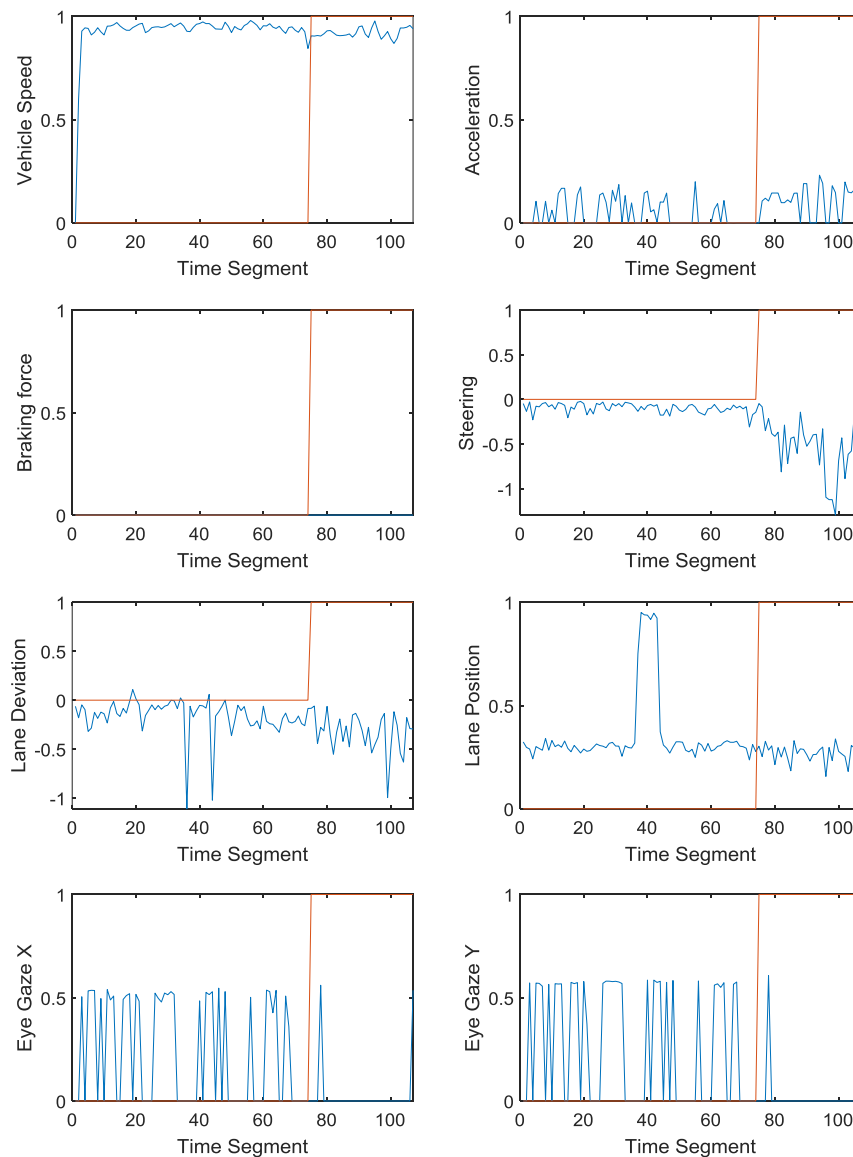


Figure A-33. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 34

Figure A-33 demonstrates the minimum values of eye gaze positions and vehicle performance features. By comparing the normal driving sections with the distracted driving sections, it can be found that minimum values of steering angle, and gaze positions in x and y are relevant in detecting driver distraction. The three features reduced when the driver was distracted, reflecting a large amount of movement in gaze and steering.

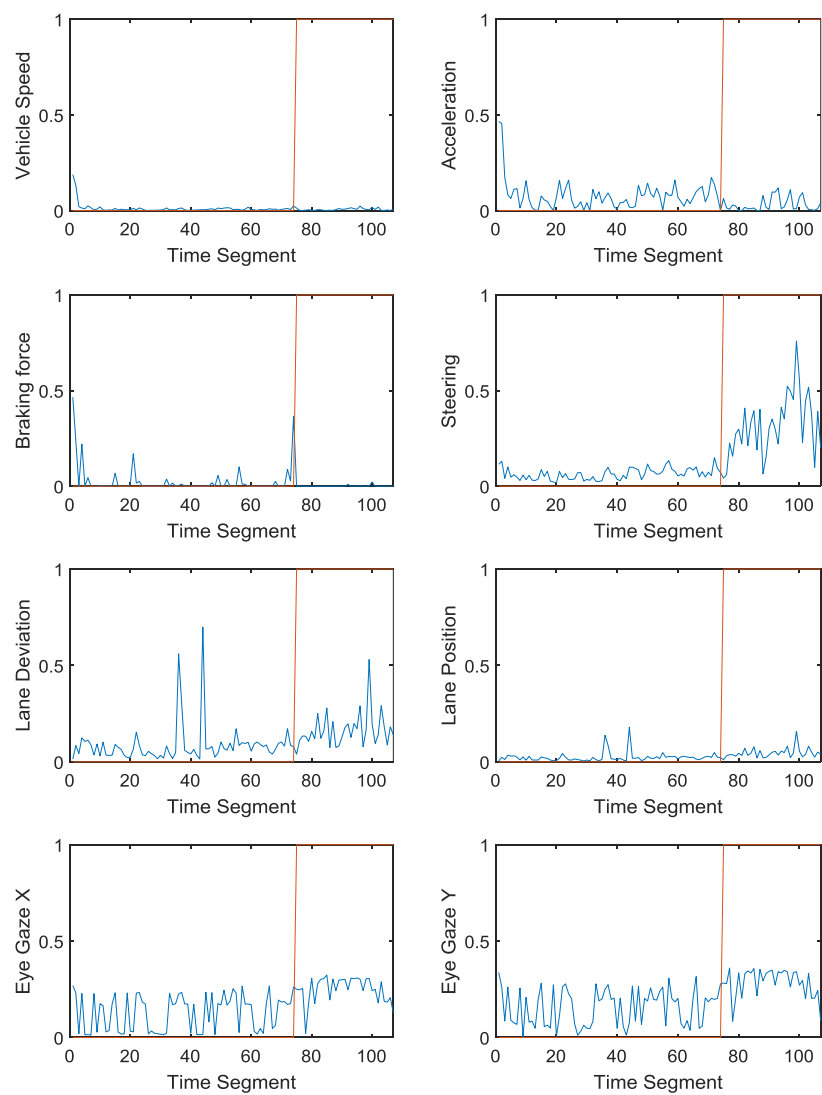


Figure A-34. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 34

Figure A-34 demonstrates the standard deviation values of eye gaze positions and vehicle performance features. From the figure it can be seen that standard deviation of steering angles and lane deviation increases and vehicle acceleration decreases. The mean values of standard deviation of eye gaze in x and y directions increase due to large gaze shifts in texting behaviour. As a result, the standard deviation of eye gaze in x and y directions, steering and lane deviation are relevant in detecting driver distraction.

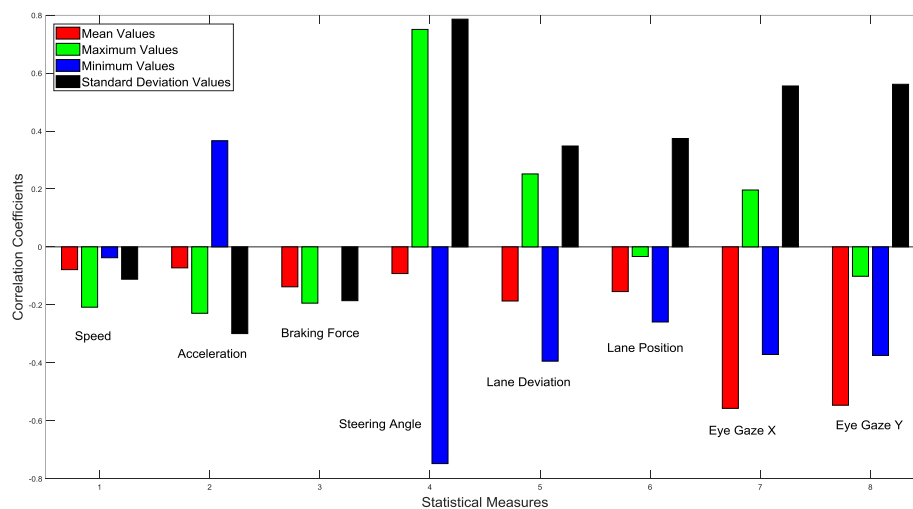


Figure A-35. Correlation Coefficients between Features and Binary Classification Level (0 and 1) for Driver No. 34

Figure A-35 demonstrates the correlation coefficients between features and vehicle performance features and binary classification level (0 and 1). Figure A-35 shows that the maximum, minimum and standard deviation of steering angles are relevant features in detecting driver distraction as they have the highest correlation coefficients. In addition, minimum and standard deviation of gaze positions in x and y directions are also relevant in detecting driver distraction.

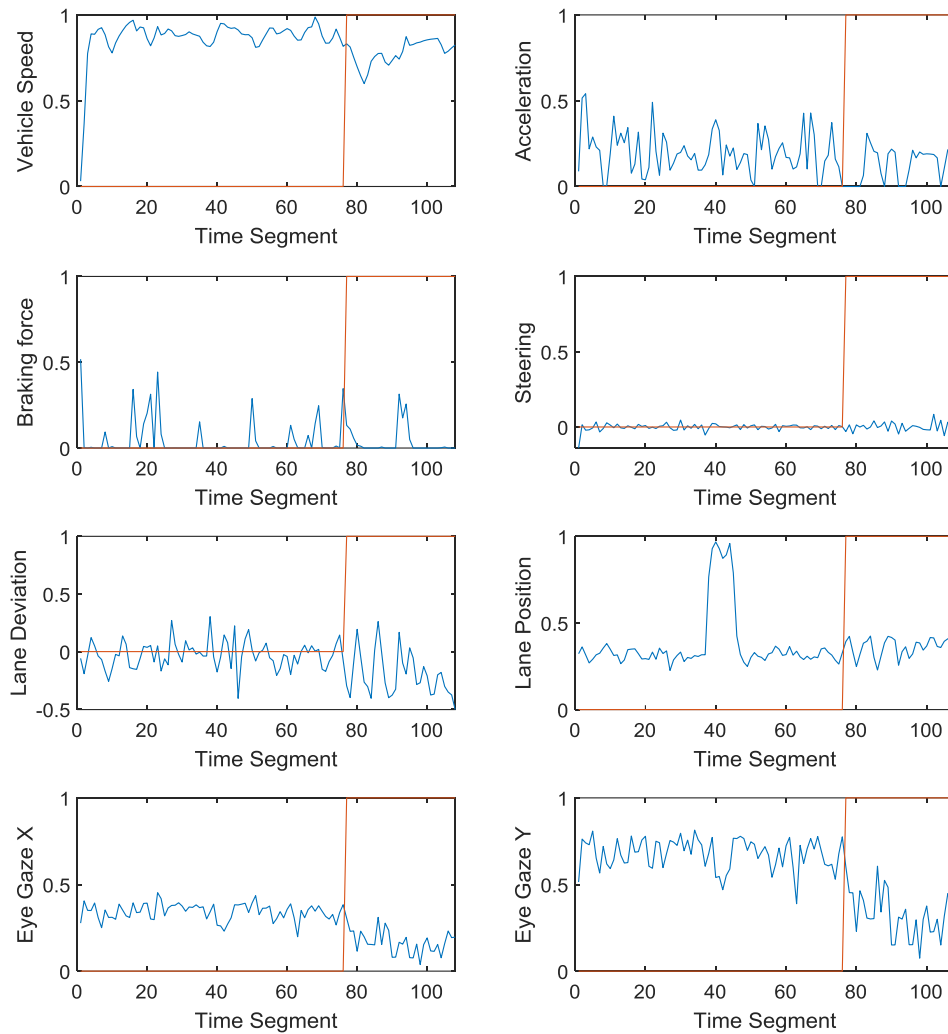


Figure A-36. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 39

Figure A-36 presents the features between normal driving and distracted driving. Figure A-36 shows that the mean values of vehicle speed, acceleration, lane deviation and eye gaze positions in x and y are relevant in detecting driver distraction. The average of vehicle speed decreased, with a smaller distraction. In addition, the lane deviation increased after the driver is distracted. The eye gaze positions in x and y directions moved less frequently. The driver concentrated on texting with little gaze movement.

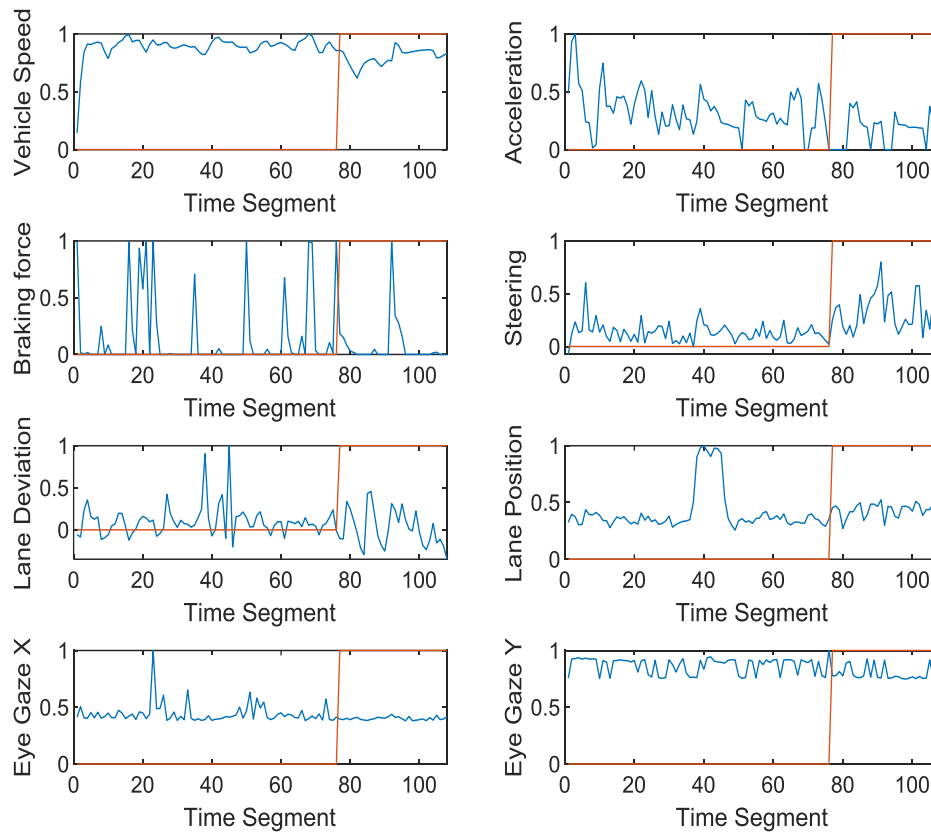


Figure A-37. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 39

Figure A-37 shows that the maximum values of vehicle acceleration, steering, lane deviation and eye gaze in x and y directions are relevant in detecting driver distraction. The maximum values of vehicle acceleration decreased after driver was distracted. However, the maximum values of steering angle and lane deviation increases after driver was distracted. The level of driver's control over the vehicle was reduced due to the distraction. The mean values of eye gaze positions do not change significantly.

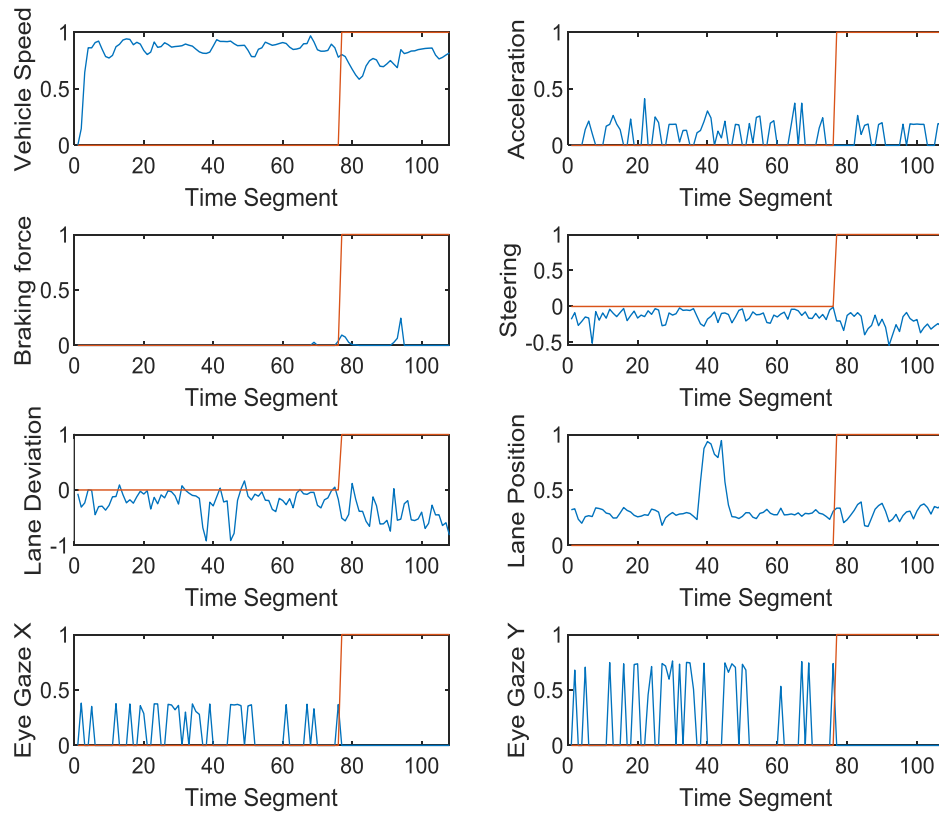


Figure A-38. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 39

Figure A-38 demonstrates the minimum values of eye gaze and vehicle performance features for driver No. 39. It shows that the minimum values of lane deviation, eye gaze in x and y directions are relevant in detecting driver distraction. The minimum values of lane deviation reduced as the driver got distracted which indicates that the vehicle was approaching the right kerb. The driver looked other places in order to text back the messages and the tracking of the eye gaze lost. Features with significant changes after distraction are relevant in detecting driver distraction.

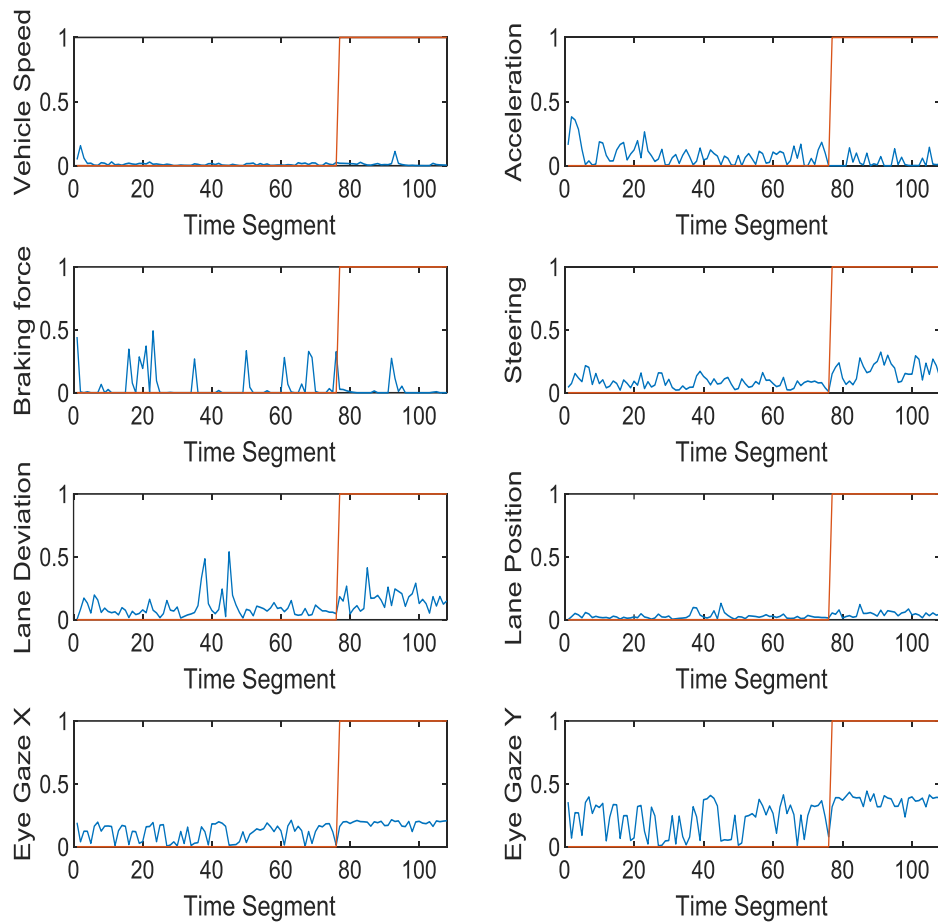


Figure A-39. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 39

Figure A-39 demonstrates the standard deviation values of eye gaze positions and vehicle performance features for driver No. 39. The standard deviation of eye gaze in x and y directions increase after driver was distracted. The same pattern can be found in the curve of standard deviation of steering angles. The above-mentioned three features are relevant in detecting driver distraction.

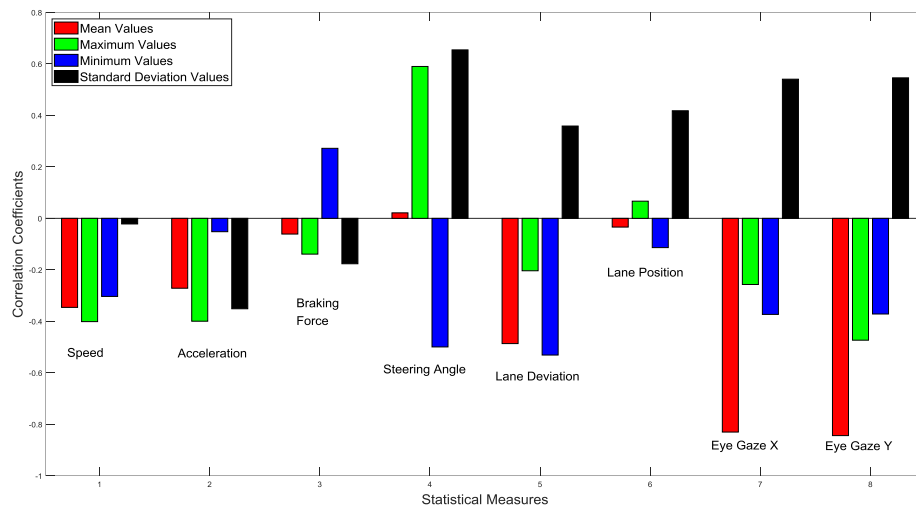


Figure A-40. The Correlation Coefficients between Features and Distraction for Driver No. 39

Figure A-40 shows that the relevant features in detecting driver distraction are the maximum, minimum and standard deviation of steering angle, mean and minimum values of lane deviation and standard deviation of eye gaze in x and y positions. The above-mentioned features have high correlation coefficients between features and binary distraction levels. The results are in-line with the results from the previous four plots.

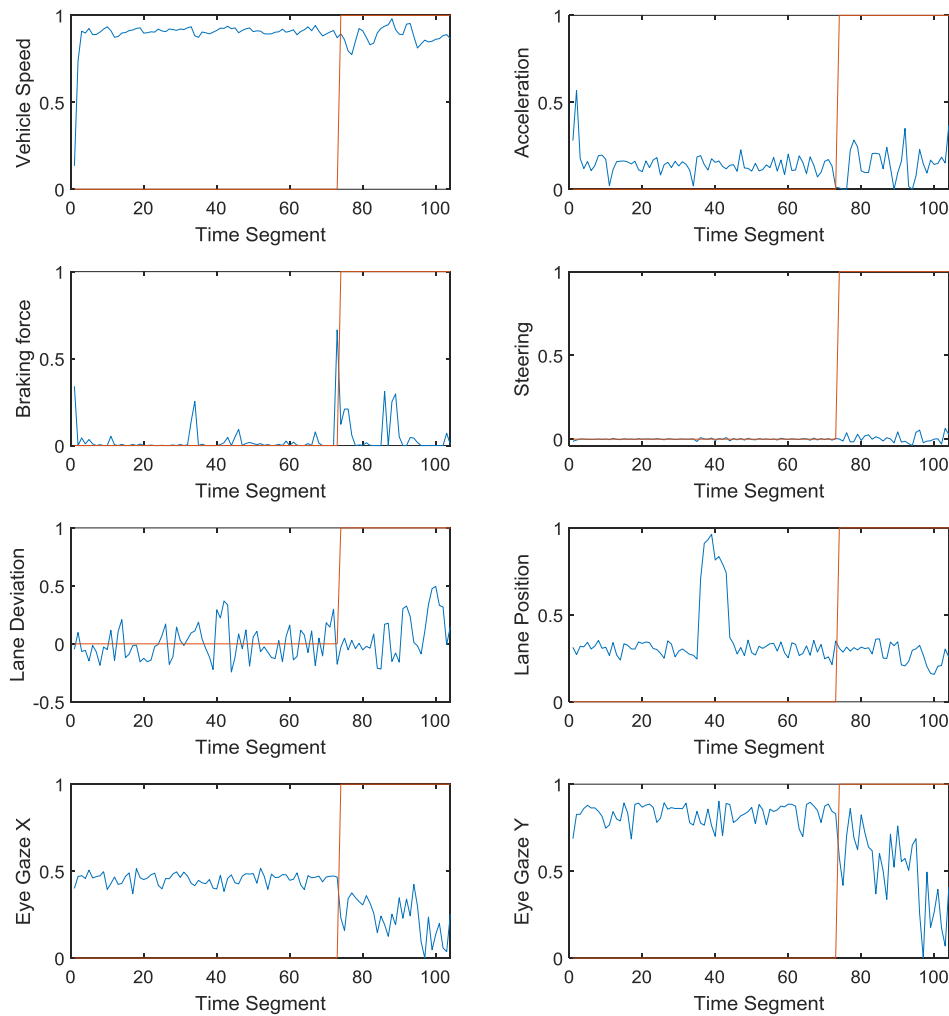


Figure A-41. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 43

Figure A-41 demonstrates the mean values of eye gaze positions and vehicle performance features for driver No. 43. The relevant features in detecting driver distraction are mean values of eye gaze in x and y positions, the mean values of vehicle acceleration, braking force and lane deviation. The change of mean values of vehicle acceleration is more significant when driver was distracted. Without significant movement of steering wheel, the mean values of lane deviation become larger. The mean values of eye gaze in x and y directions

reduced after the driver got distracted, which indicates that driver trends to look top right of the screen.

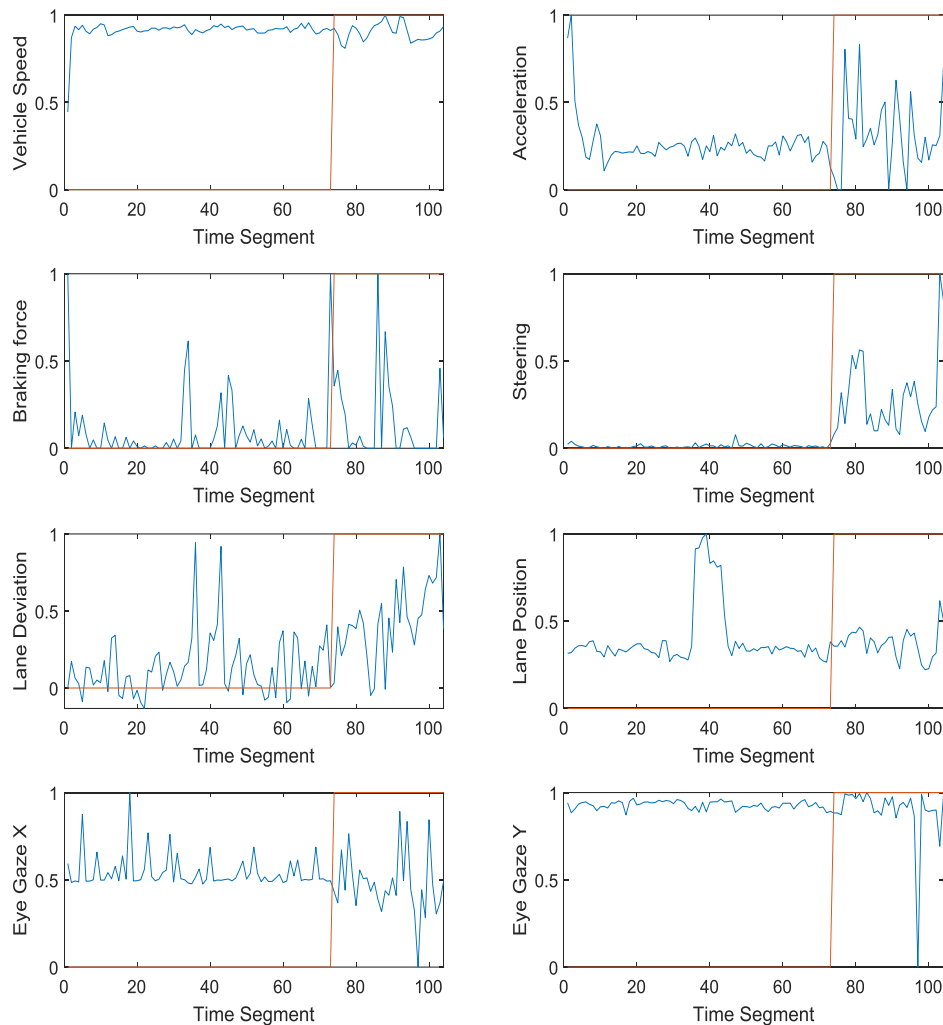


Figure A-42. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 43

Figure A-42 demonstrates the maximum values of eye gaze positions and vehicle performance features for driver No. 43. The figure also shows that maximum values of vehicle acceleration, braking force, steering angle, lane deviation and eye gaze in x directions are relevant in detecting driver distraction. The vehicle accelerated more abruptly and braked more firmly during distracted driving

sections. In addition, the maximum of steering angle also increased due to the driver's texting behaviour. Moreover, the mean values of eye gaze in x directions oscillated more frequently and in a larger magnitude after driver got distracted. The frequent movement in x direction was caused by the texting behaviour of driver.

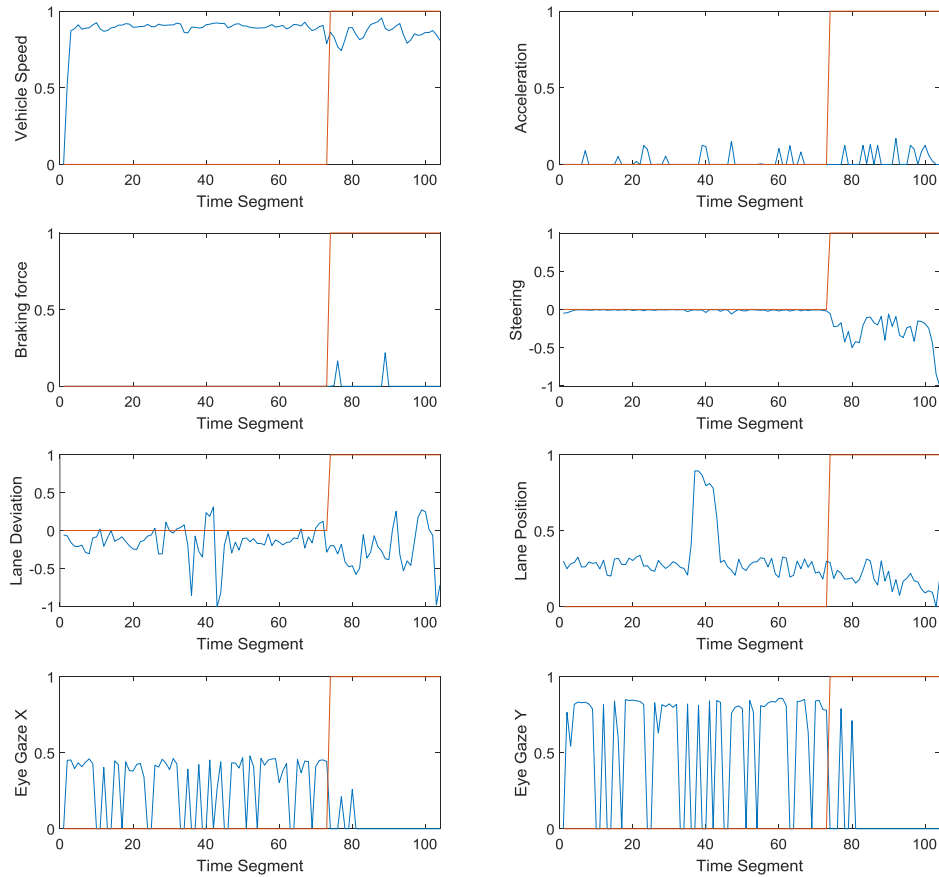


Figure A-43. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 43

Figure A-43 demonstrates the minimum values of eye gaze positions and vehicle performance features for driver No. 43. The figure also shows that minimum values of steering wheel, lane deviation and eye gaze in x and y directions are relevant in detecting driver distraction. The minimum values of steering angle reduced significantly after driver was distracted while remained 0 while driving

normally. The minimum value of lane deviation oscillated to a larger extent during distracted driving compared to the lane deviations during normal driving.

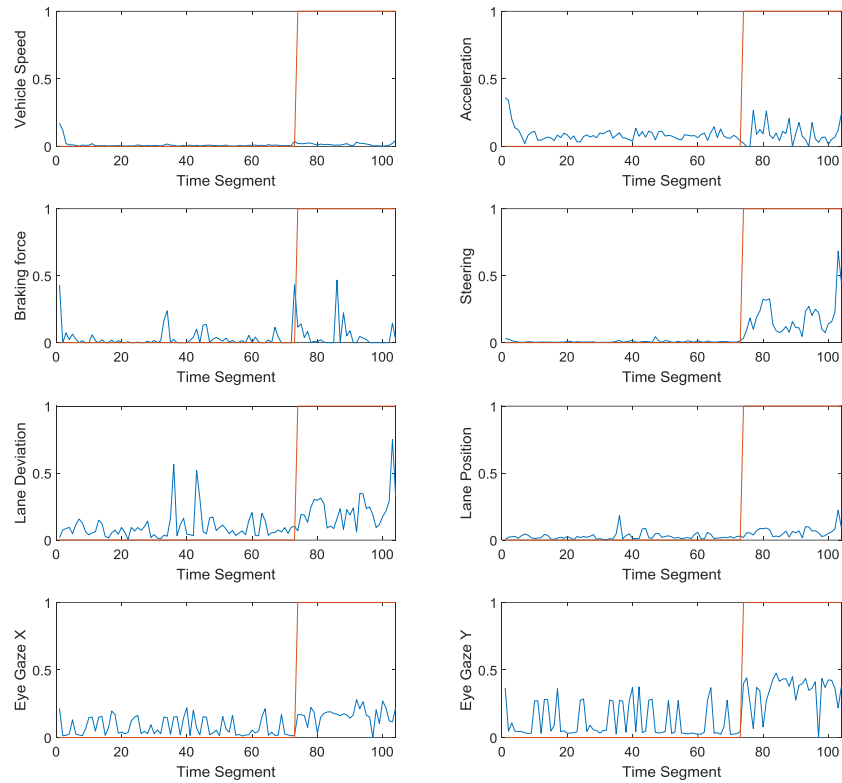


Figure A-44. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 43

Figure A-44 presents the standard deviation values of eye gaze positions in normal driving and distracted driving. Relevant features in detecting driver distraction are standard deviation values of steering angle, lane deviation and eye gaze in x and y directions. The standard deviation values of above-mentioned features increased due to distraction, indicating a more aggressive driving behaviour and less control over the vehicle.

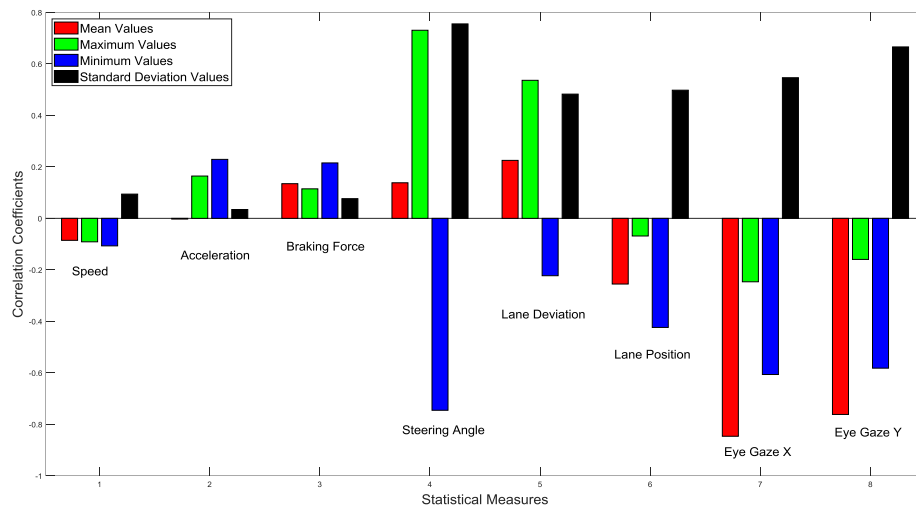


Figure A-45. Correlation Coefficients between Features and Binary Classification Level for Driver No. 43

Figure A-45 demonstrates the correlation coefficients between features and binary classification level. The figure also shows that maximum, minimum and standard deviation of steering angle, minimum and standard deviation of eye gaze positions in x and y directions and minimum and standard deviation of lane positions are relevant in detecting driver distraction. The above-mentioned features are relevant in detecting driver distraction for their high correlation coefficients, which is consistent with results found in previous four figures. What have not been found is that standard deviation of lane position is a relevant feature in detecting driver distraction.

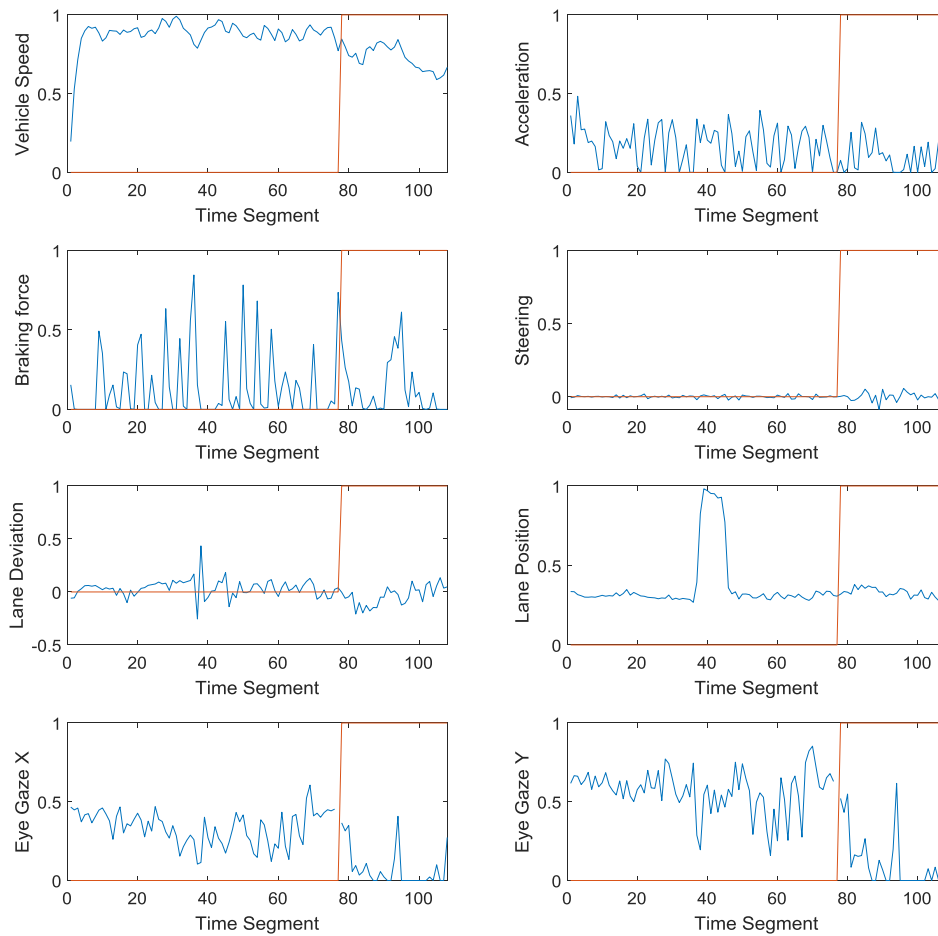


Figure A-46. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 44

Figure A-46 presents the mean values of eye gaze positions and vehicle performance features in normal driving and distracted driving sections. The figure also shows that the mean values of speed, braking force, lane deviation and eye gaze in x and y directions are relevant in detecting driver distraction. The mean speed reduced after the driver was distracted, with more frequent use of braking pedal. The eye gaze in x and y directions reduced when driver was distracted, which indicated that driver gazed out of the screen more often when texting.

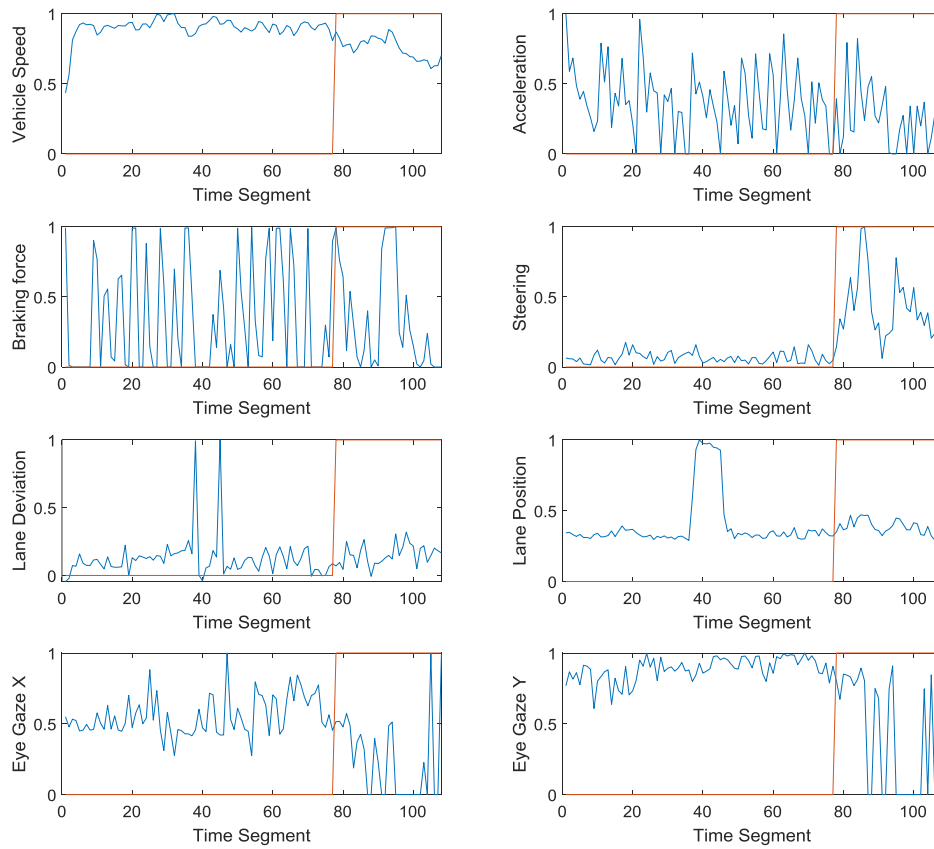


Figure A-47. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 44

Figure A-47 presents the maximum values of eye gaze and vehicle performance features between normal driving and distracted driving. The relevant features in detecting driver distraction are maximum values of steering wheel angle, brake force, vehicle speed and acceleration and eye gaze in x and y directions. The most significant changes after distraction is that maximum values of steering angle became larger and vehicle speed and acceleration reduced. The change of features indicates that driver shifted attention to texting from driving.

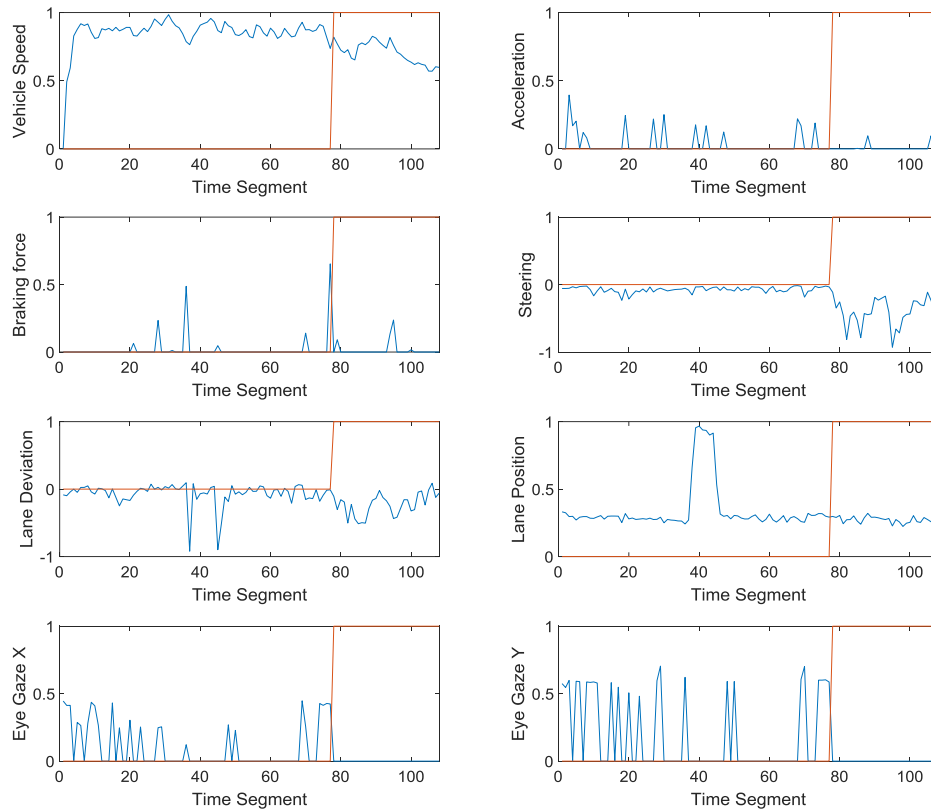


Figure A-48. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 44

Figure A-48 presents the minimum values of eye gaze and vehicle performance features in normal driving and distracted driving sections. The relevant features are minimum values of vehicle speed, steering angle, lane deviation and eye gaze in x and y directions. The minimum values of vehicle speed, steering angle and lane deviation reduced after driver was distracted. The changed vehicle performance measures indicate that driver shifted the attention away and the changed eye gaze positions (including the lost tracking of eye gaze) indicated that the driver was gazing out of the screen.

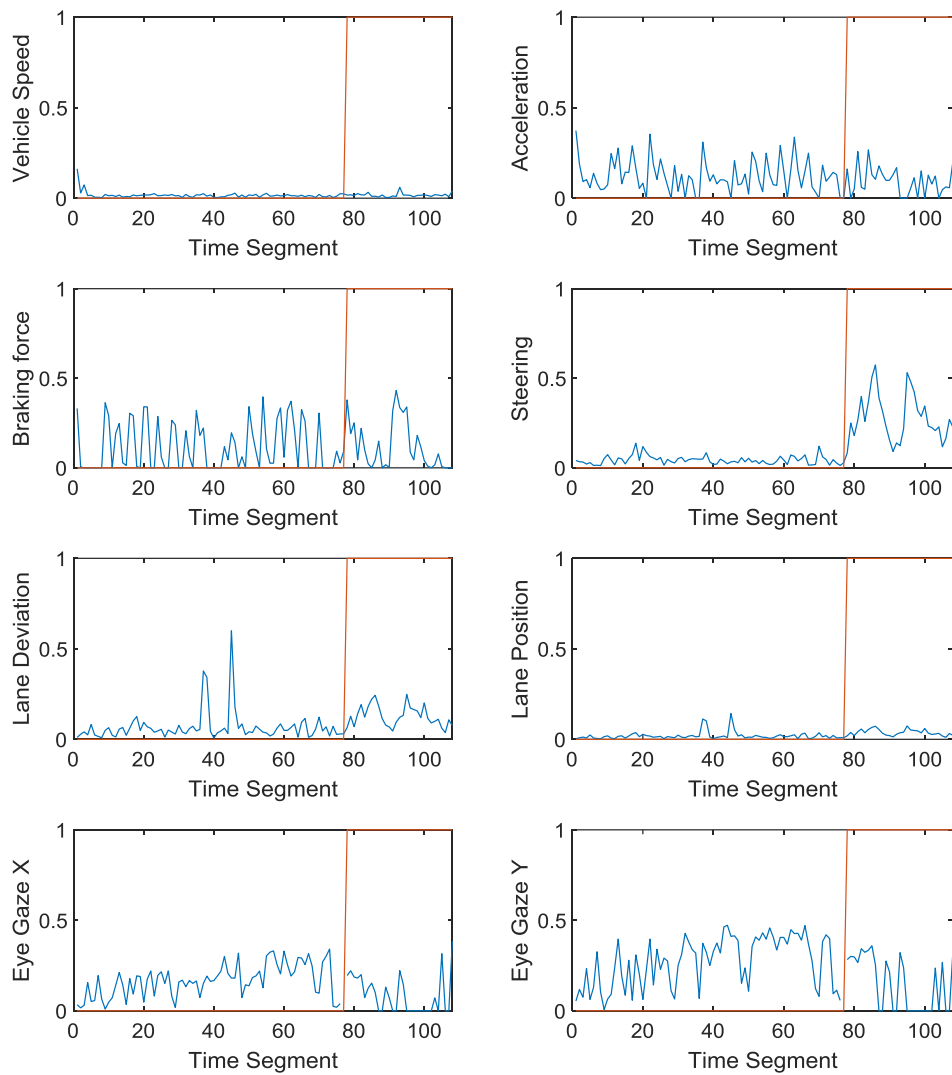


Figure A-49. Comparisons of Standard Deviation Values between Normal and Distracted Driving or Driver No. 44

Figure A-49 presents the standard deviation values of eye gaze features and vehicle performance features in detecting driver distraction. The standard deviation of braking force and steering wheel angle increased after driver was distracted. The standard deviation of eye gaze positions reduced after driver was distracted, indicating a gaze shift towards the screen of the phone.

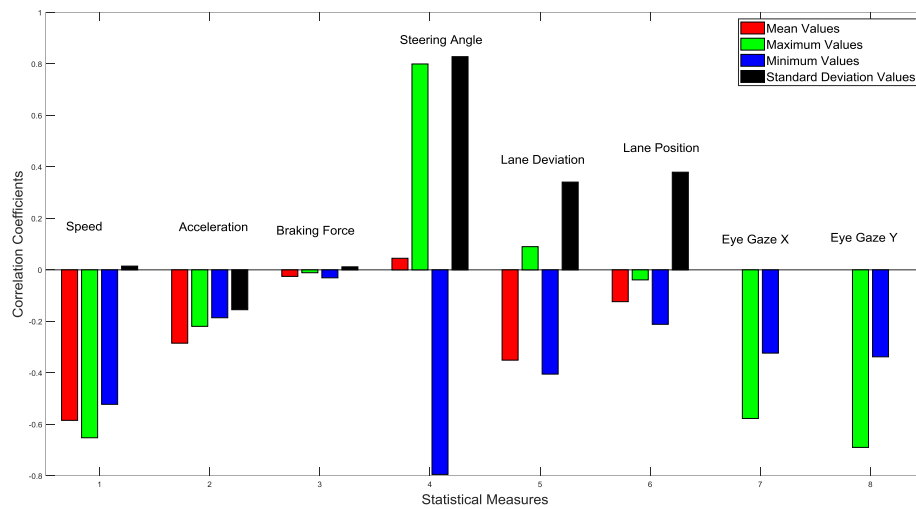


Figure A-50. Correlation Coefficients between Features and Binary Classification Level for Driver No. 44

Figure A-50 presents the correlation coefficients between eye gaze and vehicle performance features and binary classification level. It also shows that the maximum, minimum and standard deviation of steering angle, mean, maximum and minimum values of speed and maximum values of eye gaze in x and y directions are relevant in detecting driver distraction.

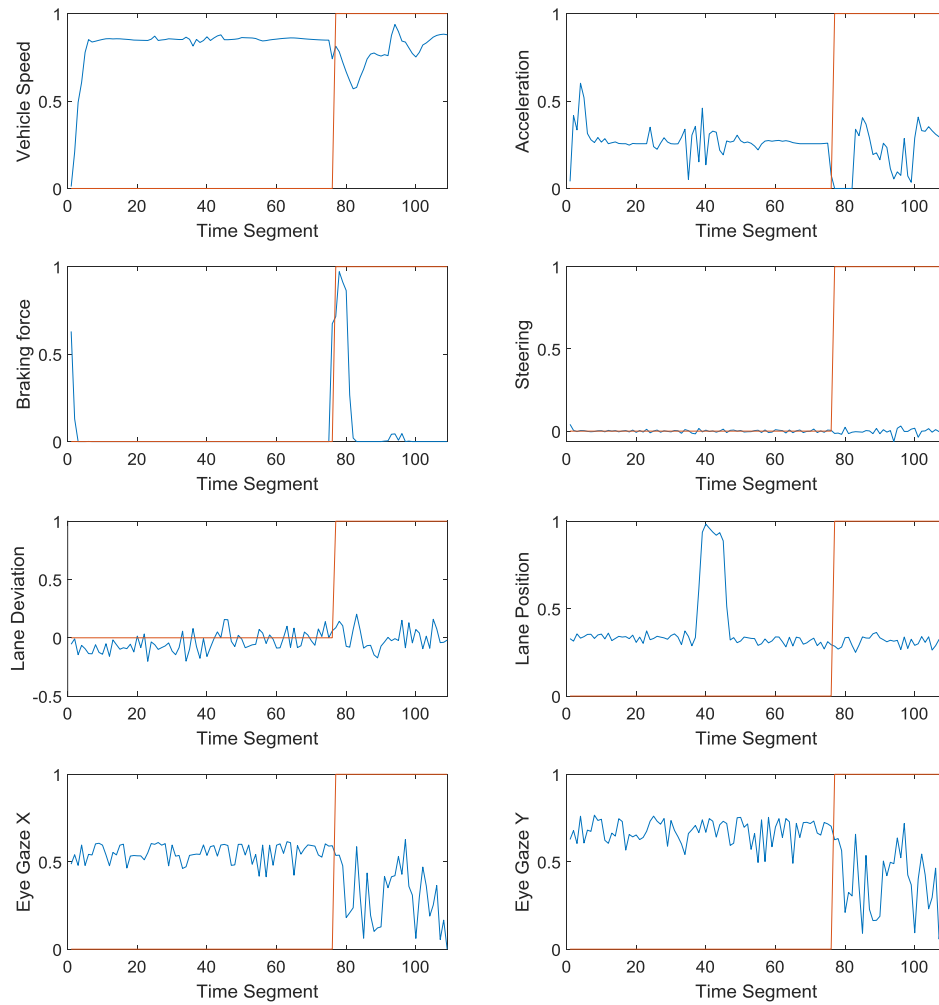


Figure A-51. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 45

Figure A-51 shows that the mean values of eye gaze positions and vehicle performance features between normal driving and distracted driving for driver No. 45. The relevant features in detecting driver distraction are mean values of speed, braking force and eye gaze in x and y directions. There are more oscillations in vehicle speed after driver was distracted. The braking force increased significantly after driver was distracted. Notably, the mean values of gaze angles reduced significantly, partly due to the lost tracking of eye gaze directions.

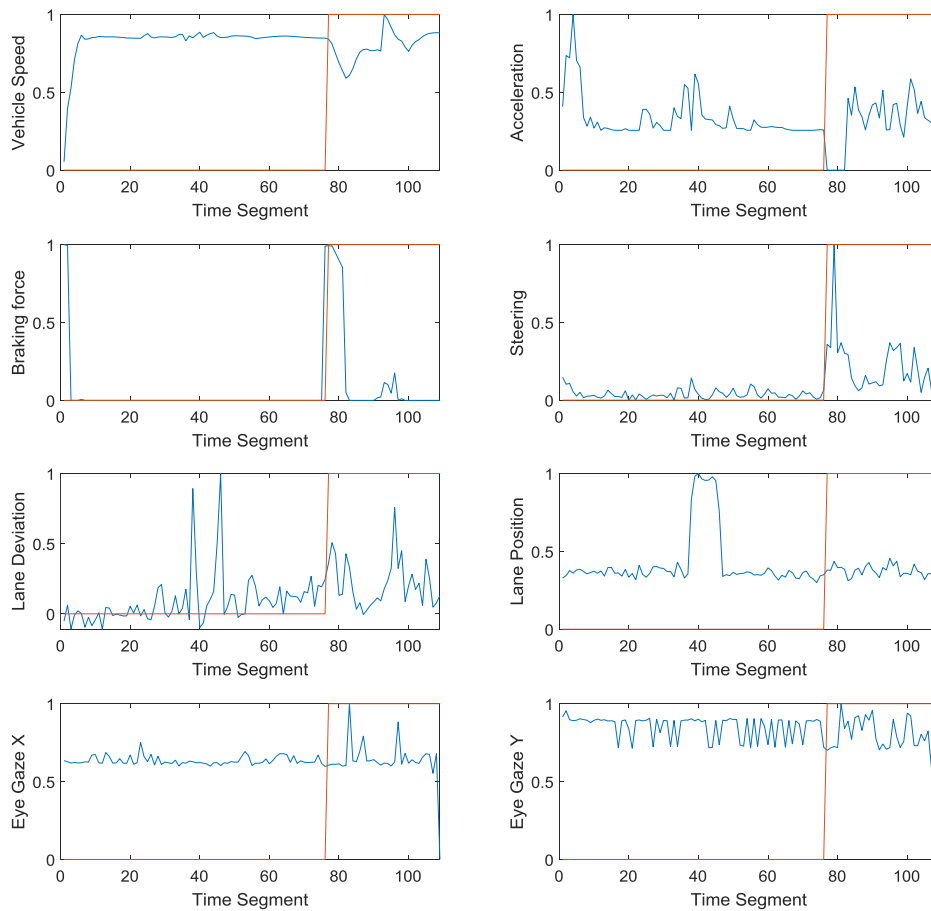


Figure A-52. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 45

Figure A-52 presents maximum values of the eye gaze and vehicle performance features between normal driving and distracted driving for driver No. 45. The figure also shows that features such as maximum values of vehicle speed, acceleration, steering angle and lane deviation are relevant in detecting driver distraction. Their values increased significantly after driver was distracted which indicates that driver's control over vehicle was degraded after driver was distracted.

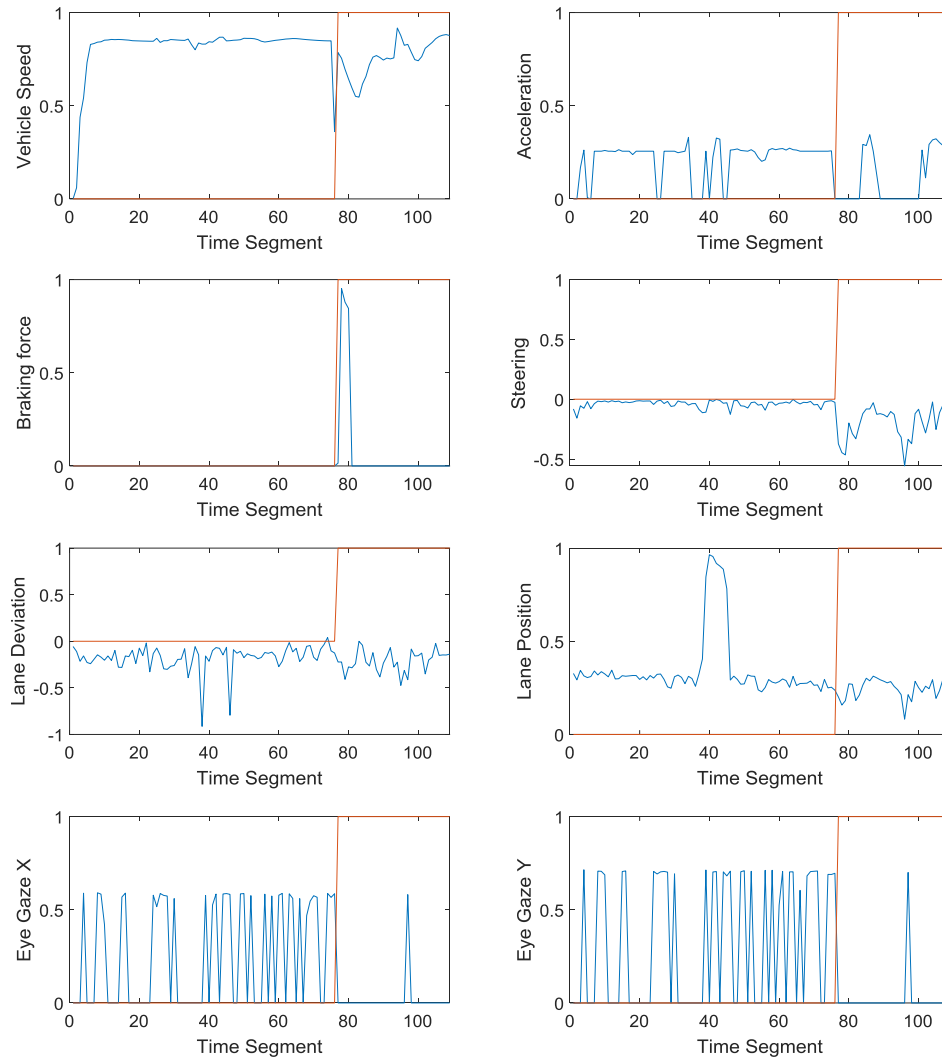


Figure A-53. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 45

The above figure demonstrates the minimum values of eye gaze and vehicle performance measures including normal driving and distracted driving sections for driver No. 45. The relevant features in detecting driver distraction are minimum values of vehicle speed and acceleration, steering and eye gaze positions in x and y directions. The speed accelerated and decelerated frequently; the

minimum steering angle decreased during distraction compared to zero movement when driver was driving normally.

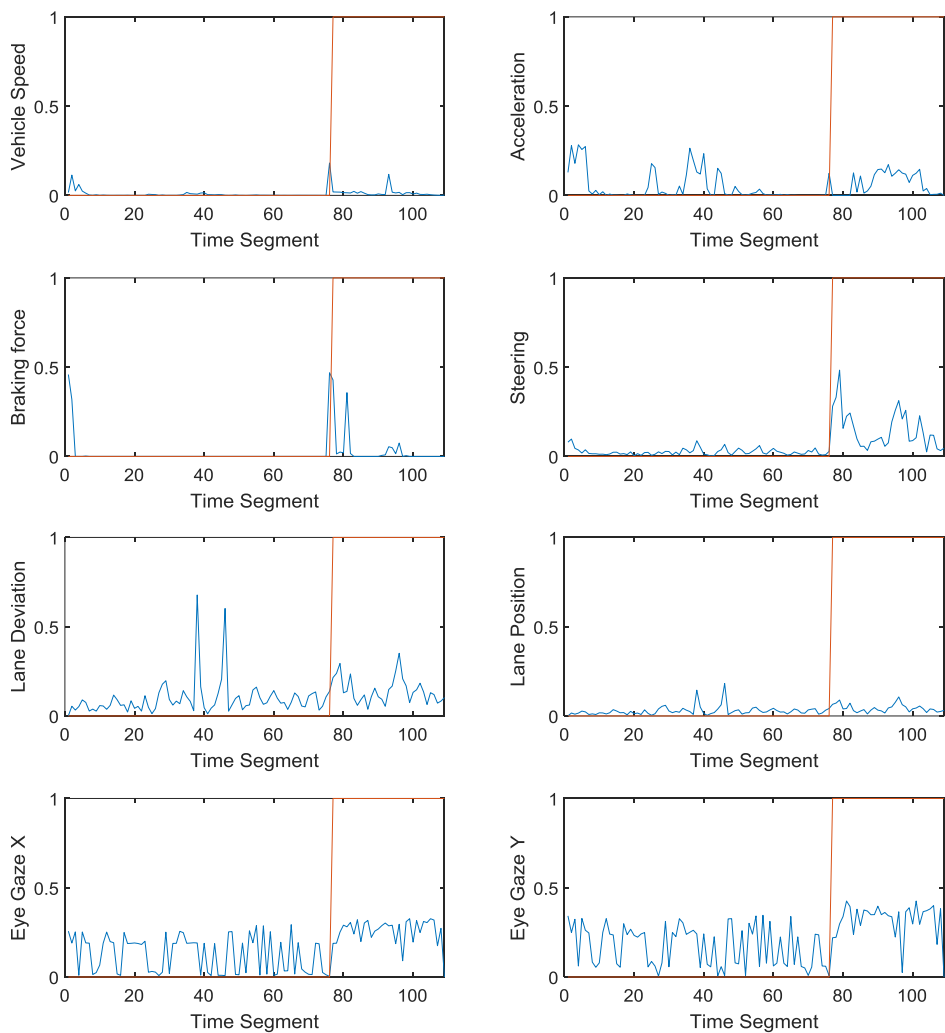


Figure A-54. Standard Deviation between Normal and Distracted Driving for Driver No. 45

Figure A-54 demonstrates the standard deviation of eye gaze and vehicle performance measures for driver No. 45. The standard deviation of braking force, steering, lane deviation and eye gaze positions in x and y directions increased after driver was distracted. These features are relevant features in detecting

distraction. The increased values also indicated that driver’s control over the vehicle degraded.

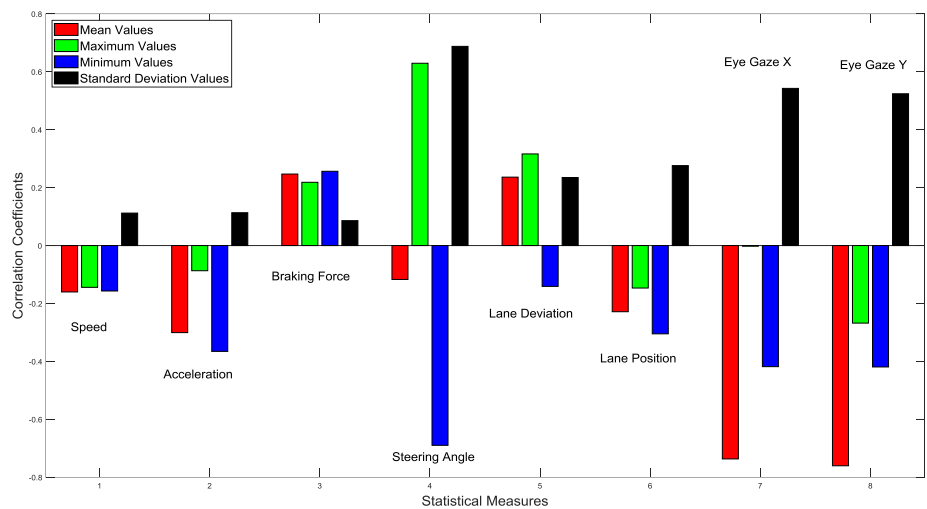


Figure A-55. Correlation Coefficients between Features and Binary Distraction Level for Driver No. 45.

Figure A-55 presents the correlation coefficients between features and binary distraction level. The features with the maximum correlation coefficients are maximum, minimum and standard deviation of steering angle, the maximum and standard deviation of eye gaze in x and y directions.

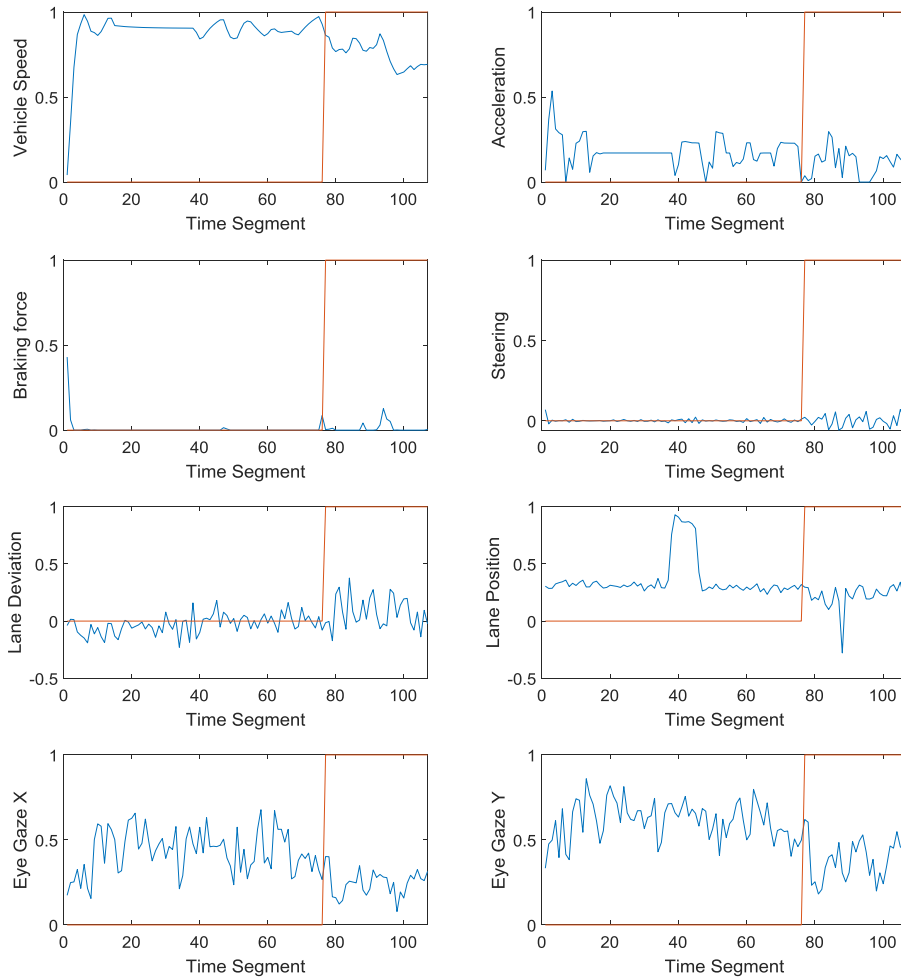


Figure A-56. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 51

Figure A-56 presents the mean values of normal driving and distracted driving for driver No. 51. The relevant features in detecting driver distraction are mean values of speed, lane deviation, lane position and eye gaze in x and y directions. The mean values of vehicle speed, acceleration, eye gaze in x and y directions reduced after driver was distracted, in contrast, the mean values of lane deviation increased. The driver's control became weaker after driver was distracted since lane deviation increased. The vehicle speed was reduced to compensate the effect of texting.

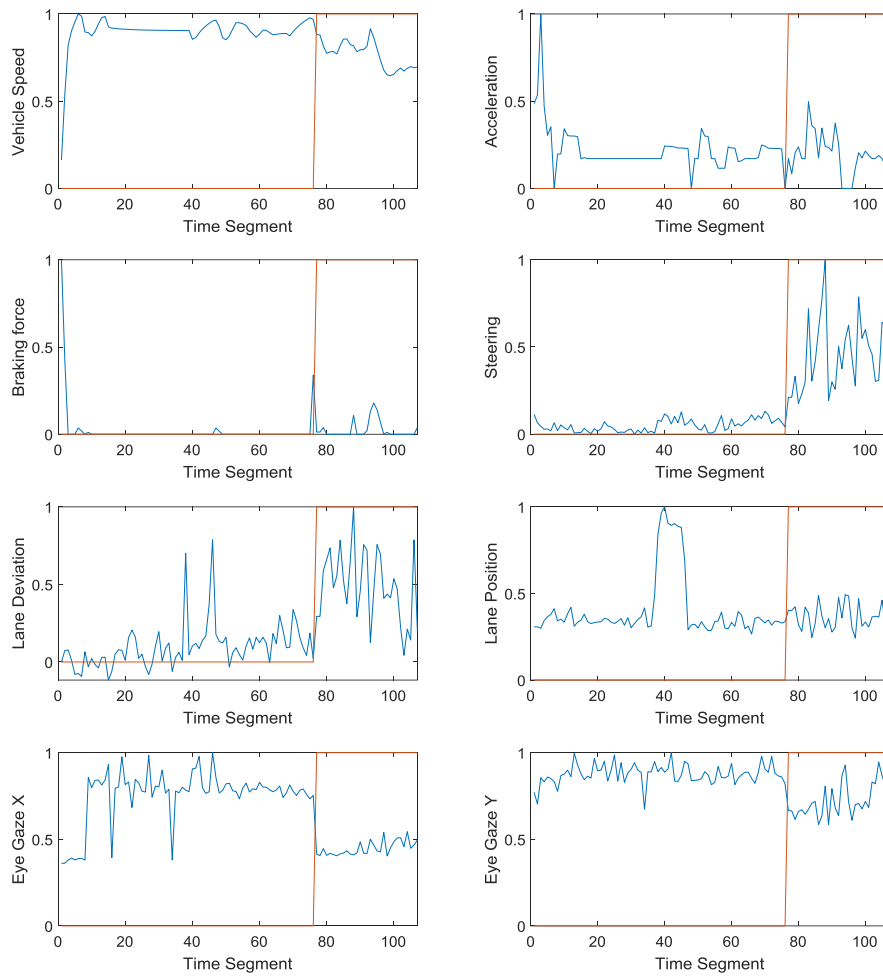


Figure A-57. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 51

Figure A-57 presents the maximum values of eye gaze and vehicle performance features in detecting driver distraction. The relevant features in detecting driver distraction are vehicle acceleration, steering angle, lane deviation and eye gaze in x and y directions. There are more abruptly accelerations after driver was distracted. The maximum of steering angles increased dramatically after driver was distracted. The maximum values of eye gaze in x and y directions decreased and remained steady, which could be caused by the texting behaviour.

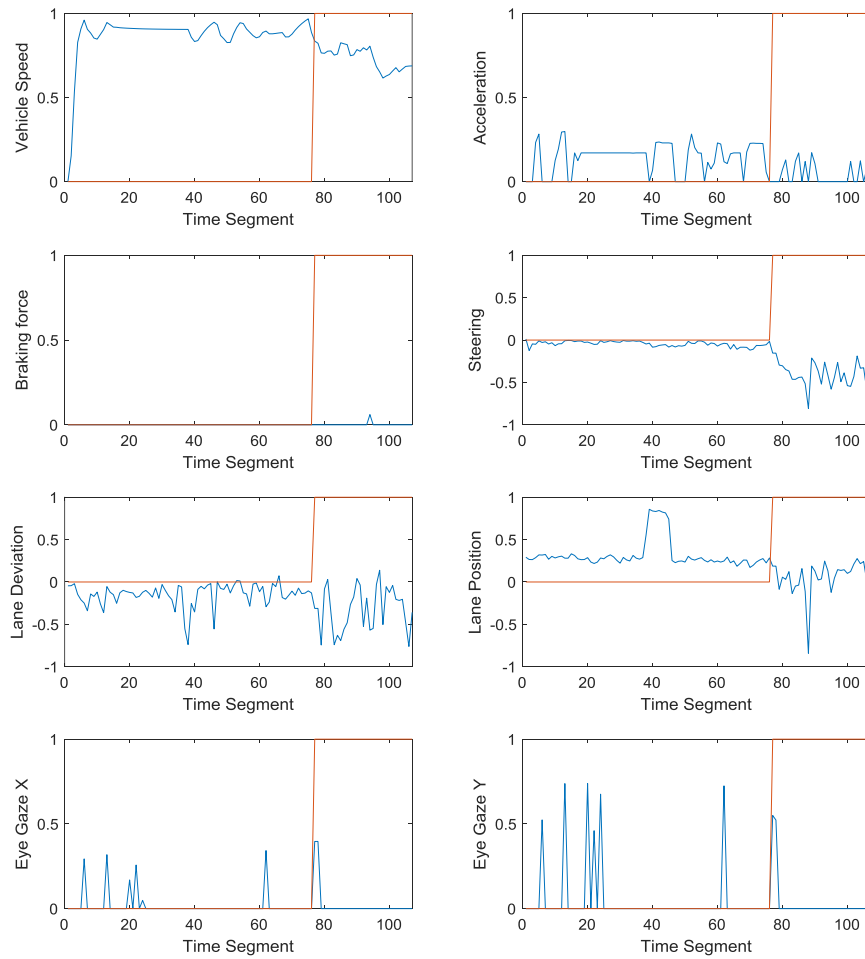


Figure A-58. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 51

Figure A-58 demonstrates the minimum values of eye gaze and vehicle features for Driver No. 51. The relevant features in detecting driver distraction are minimum values of vehicle speed, steering angle, lane deviation, lane position and eye gaze in x and y directions. The minimum values of speed and steering and lane deviation reduced after driver was distracted. The driver gazed out of the screen most of the time during distracted driving.

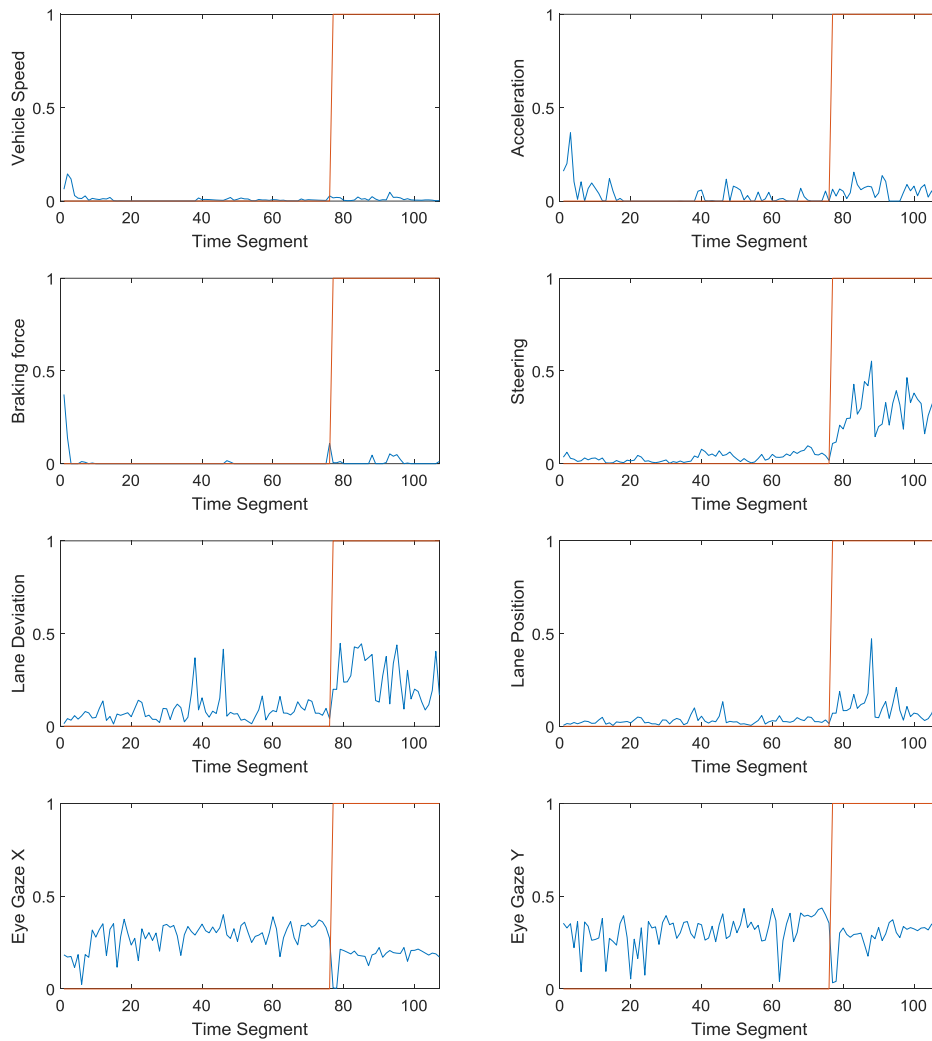


Figure A-59. Comparisons of Standard Deviation Values between Normal and Distracted Driving for Driver No. 51

Figure A-59 demonstrates the standard deviation values of eye gaze and vehicle performance features in detecting driver distraction for driver No. 51. The relevant features in detecting driver distraction are standard deviation of steering angles, lane deviations, lane positions and eye gaze positions in x and y directions. The standard deviation of eye gaze in x and y directions reduced after driver is distracted, partly due to the texting behaviour with no gaze movements.

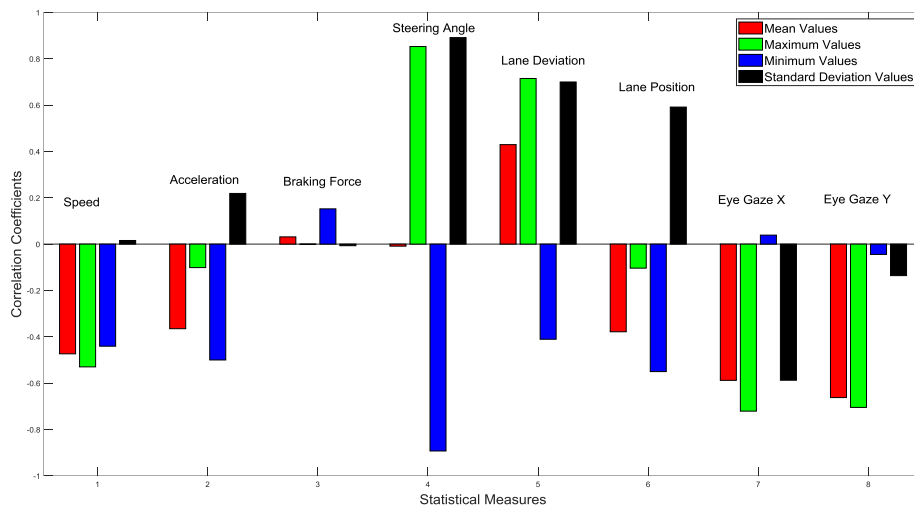


Figure A-60. Correlation Coefficients between Features and Distraction for Driver No.51

Figure A-60 presents the correlation coefficients between normal driving and distracted driving. The features with the highest correlation coefficients are maximum, minimum and standard deviation of steering angle, maximum and standard deviation of lane deviation, maximum and standard deviation of eye gaze in x direction and maximum values of eye gaze in y directions. Features with high correlation coefficients identified in Figure A-60 are consistent with the relevant features identified from Figure A-56, Figure A-57, Figure A-58, Figure A-59 with majority relevant features from steering angle, lane deviation and eye gaze in x directions.

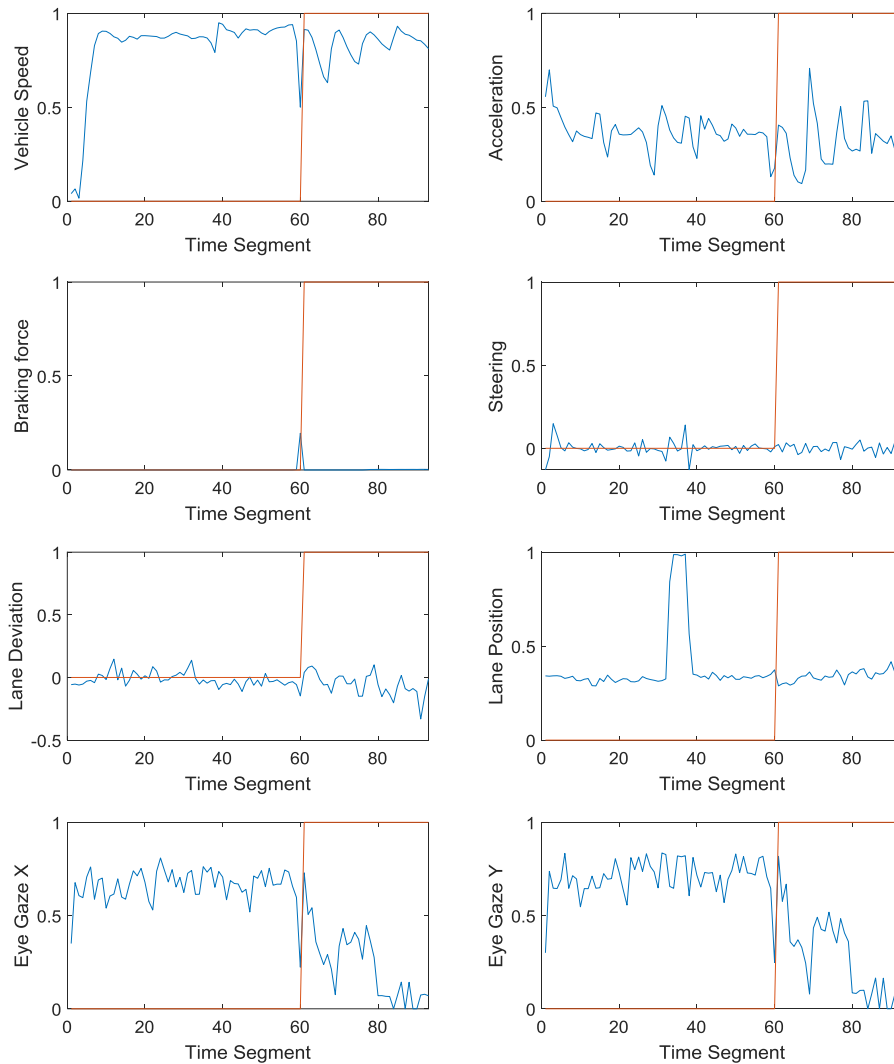


Figure A-61. The Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 77

Figure A-61 presents the mean values of eye gaze positions and vehicle performance features in detecting driver distraction. The relevant features in detecting driver distraction are mean values of vehicle speed, acceleration and eye gaze in x and y directions. The mean values of speed and acceleration changed more abruptly after driver was distracted. The mean values of gaze positions decreases due to the lost track of gaze positions while driver was texting.

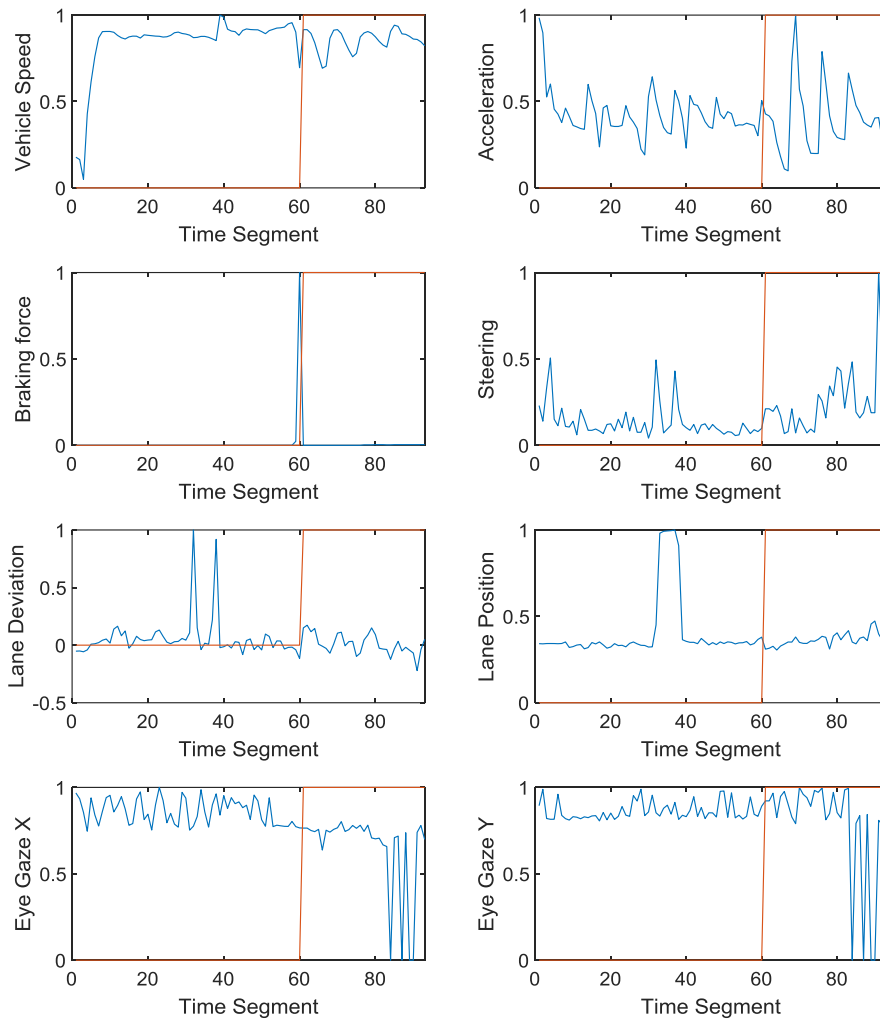


Figure A-62. The Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 77

Figure A-62 presents the maximum values of eye gaze positions and vehicle performance measures for driver No. 77. From the figure, the relevant features for detecting driver distraction are maximum values of acceleration, steering and eye gaze positions in x and y directions because the values changed significantly after driver was distracted. The maximum values of acceleration oscillated between 0.2 and 1 after driver go distracted compared to the maximum values oscillating between 0.4 to 0.6. The maximum of values of steering angle

increased significantly after driver is distracted, making it relevant in detecting driver distraction.

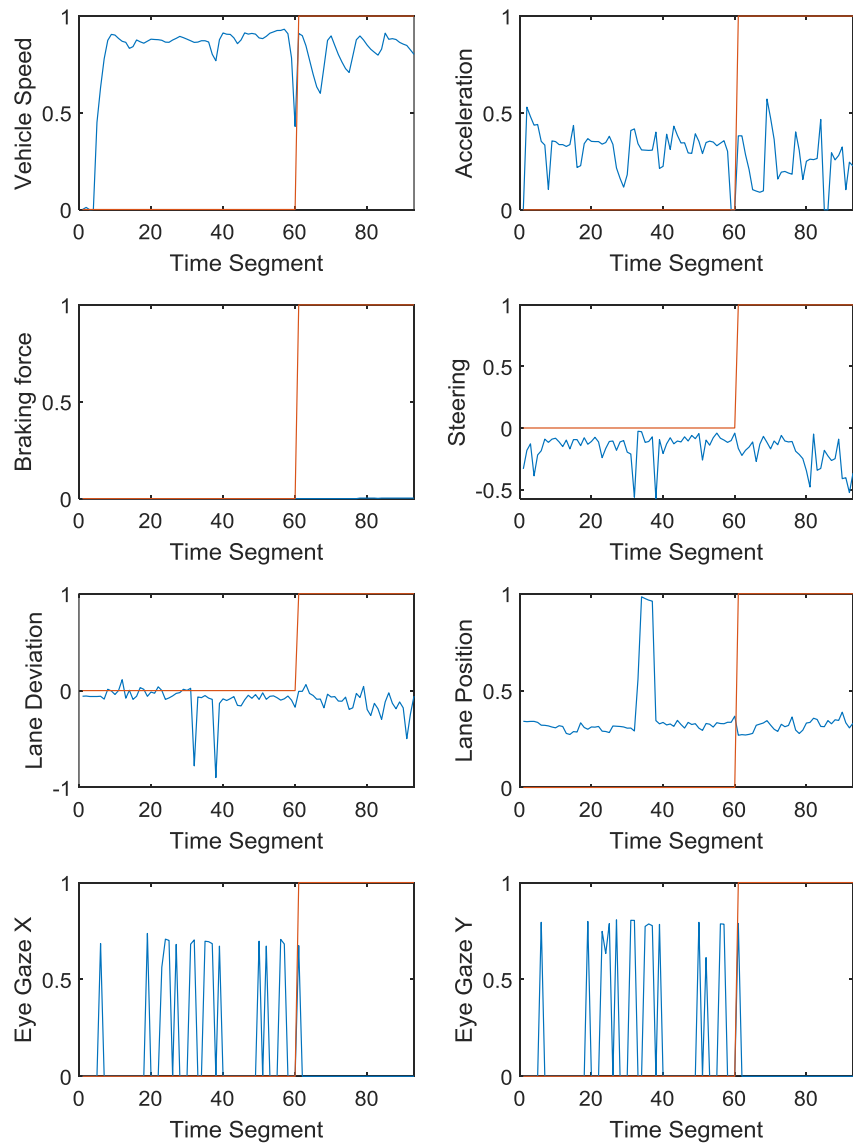


Figure A-63. Comparisons of Minimum Values between Normal and Distracted Driving for Driver No. 77

Figure A-63 presents the minimum values of eye gaze positions and vehicle performance features for driver No. 77. The relevant features are minimum values of vehicle speed, acceleration and eye gaze in x and y directions. There are

more and larger oscillations in vehicle speed when driver go distracted, meanwhile, the vehicle accelerated more abruptly, making both relevant in detecting driver distraction. The minimum values of eye gaze in x and y directions are zero after driver got distracted, indicating that driver gazed out of the screen (texting).

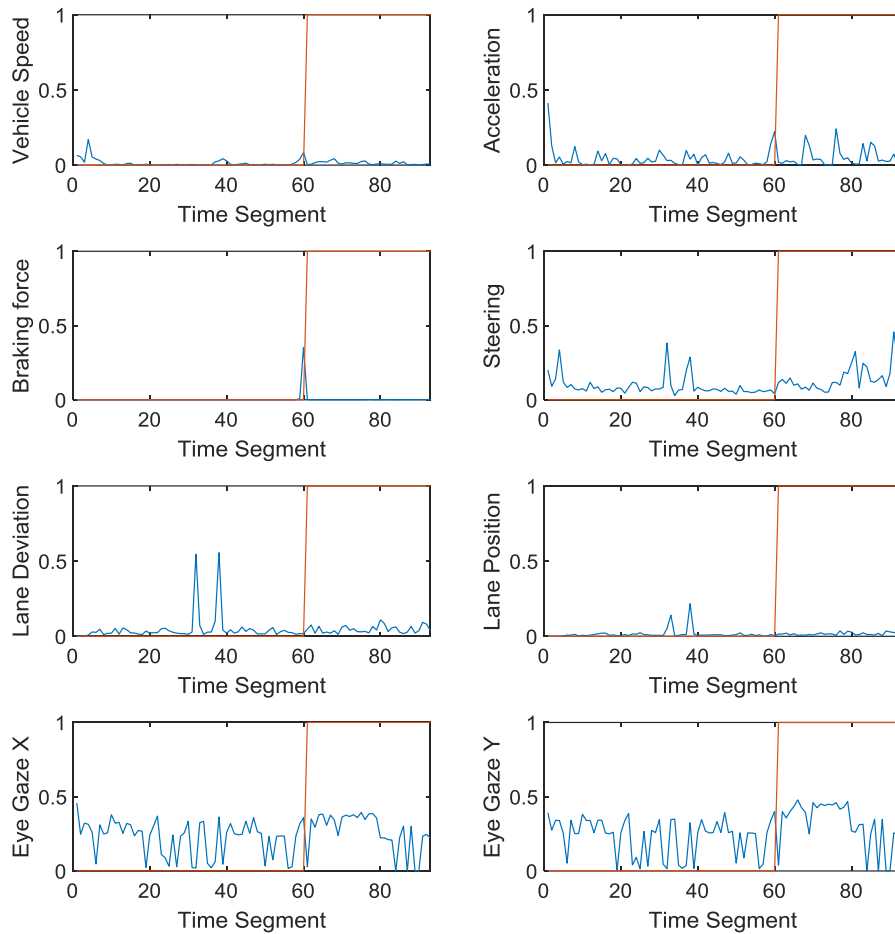


Figure A-64. Comparisons of Standard Deviation between Normal and Distracted Driving for Driver No. 77

Figure A-64 presents the standard deviation of eye gaze and vehicle performance features for driver No. 77. The relevant features in detecting driver distraction are standard deviation of steering wheel, eye gaze in x and y directions because

they increased significantly after driver was distracted. The results indicate that there were more oscillations in steering and gaze behaviour of driver No. 77.

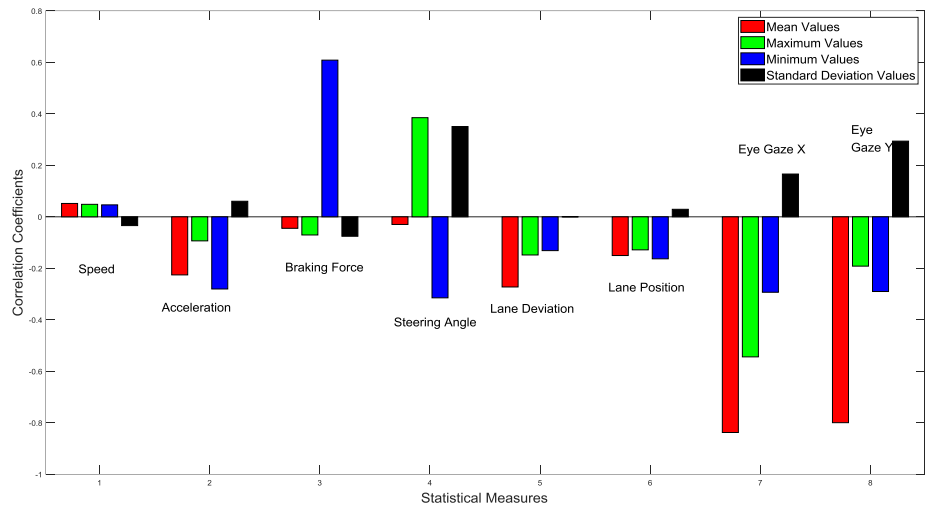


Figure A-65. Correlation Coefficients between Features and Distraction for Driver No. 77

Figure A-65 demonstrates the correlation coefficients between eye gaze and vehicle performance features for driver No. 77. The features with highest correlation coefficients are maximum of eye gaze in x positions and minimum of braking force. The standard deviation of eye gaze in y directions and maximum and standard deviation values of steering angle are also relevant in detecting driver distraction.

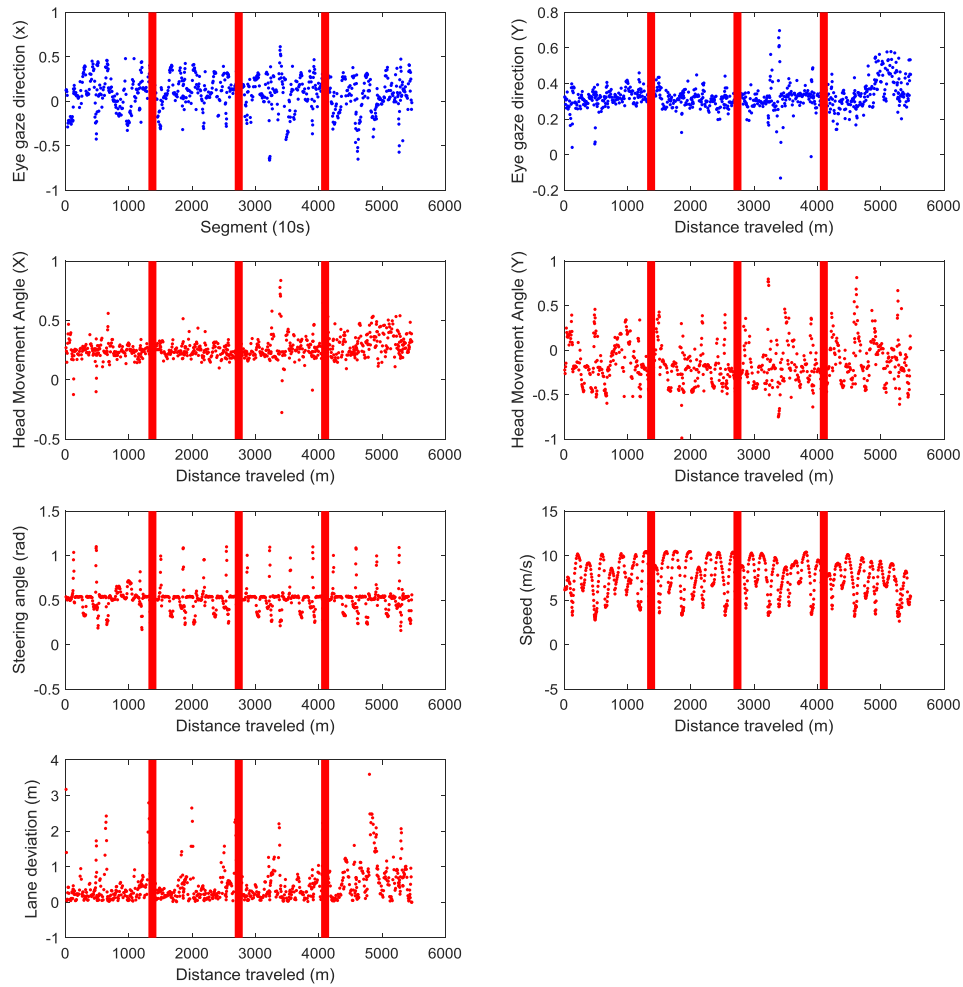


Figure A-66. Comparisons of Mean Values between Normal and Different Types of Distraction for Driver No. 6

Figure A-66 demonstrates the mean values of seven features for driver No. 6. The relevant features in detecting driver distraction are the mean values of eye gaze in y directions, head movement in y directions and lane deviations, whose values increase after driver was distracted. The mean speed of driver No. 6 decreases when the driver was manually distracted. There is no significant change in mean speed when the driver was under cognitive distraction.

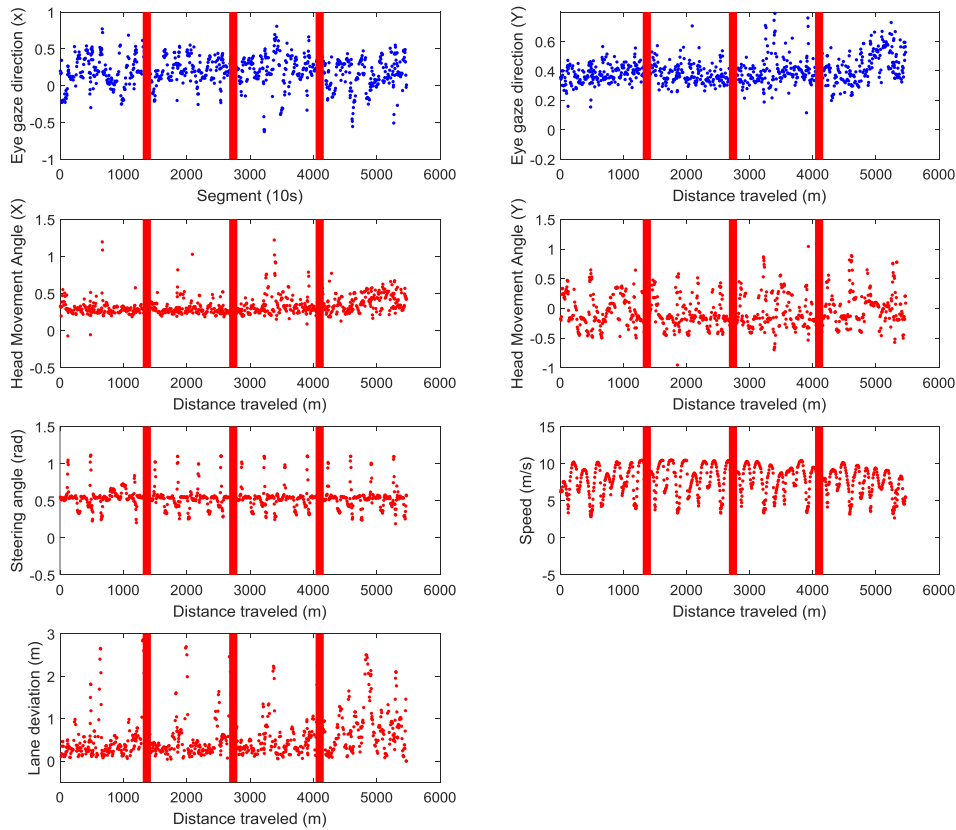


Figure A-67. Comparisons of Maximum Values between Normal and Different Types of Distracted Driving for Driver No. 6

Figure A-67 presents the maximum values of seven features for driver No. 6. The relevant features in detecting driver distractions are maximum values of eye gaze in y directions, head movement in y direction and lane deviation. All three features increase after driver was distracted because the driver frequently gazes upward and degrades control of the vehicle. In particular, the maximum values of lane deviation and head movement in y direction increase significantly after driver is manually distracted. The maximum values of lane deviation and head movement in y direction is suitable for detecting manual distraction because the difference between normal and distracted driving is significant.

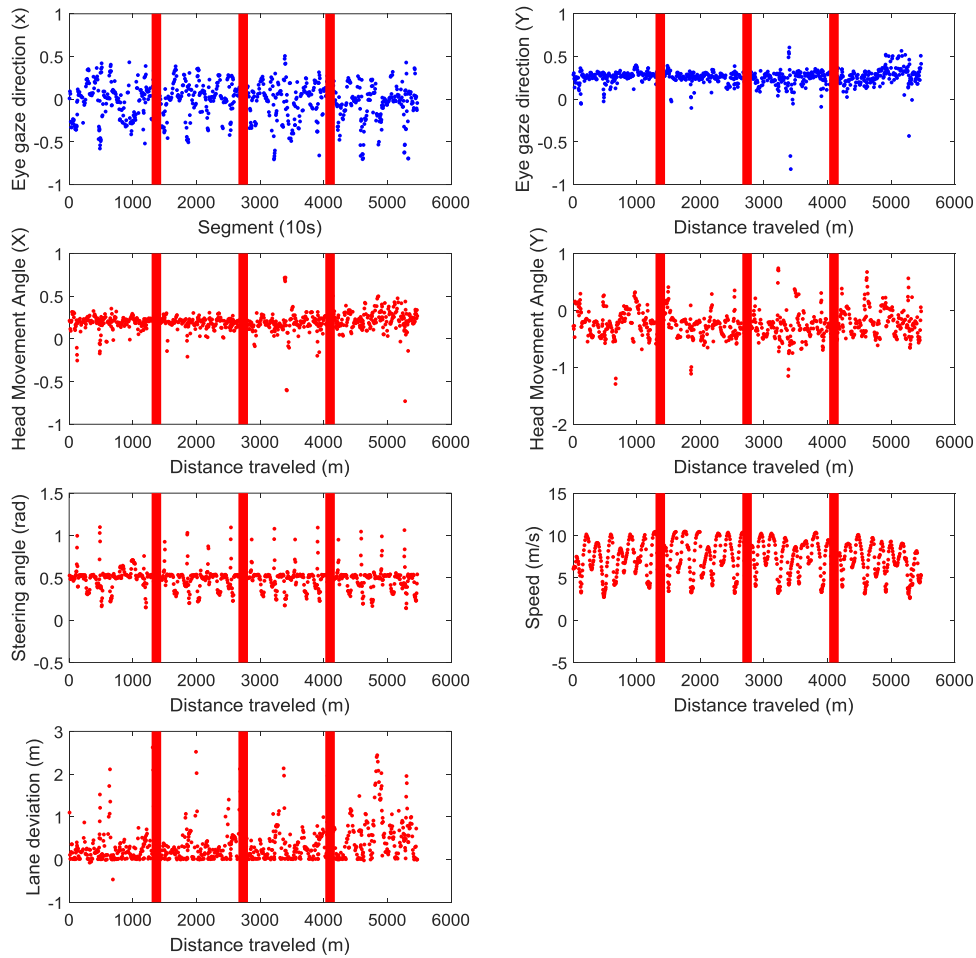


Figure A-68. Comparisons of Minimum Values between Normal and Different Types of Distracted Driving for Driver No. 6

Figure A-68 demonstrates the minimum values of 7 features for driver No. 6. The relevant features in detecting driver distraction are minimum values of eye gaze in x direction, head movement in x direction and lane deviation. The lane deviation became smaller when driver was taking to passenger and doing math, while larger when driver was texting. The patterns of change of minimum values of eye gaze in x direction change when the driver was distracted, with reduced values when driver was talking to passenger, frequent changes when driver was doing math and increased values when driver was texting. It is worth noting that the minimum values of eye gaze in y directions, head movement in x directions

and lane deviation became higher after driver got manually distracted while minimum values of speed decreased significantly when driver was under manual distraction.

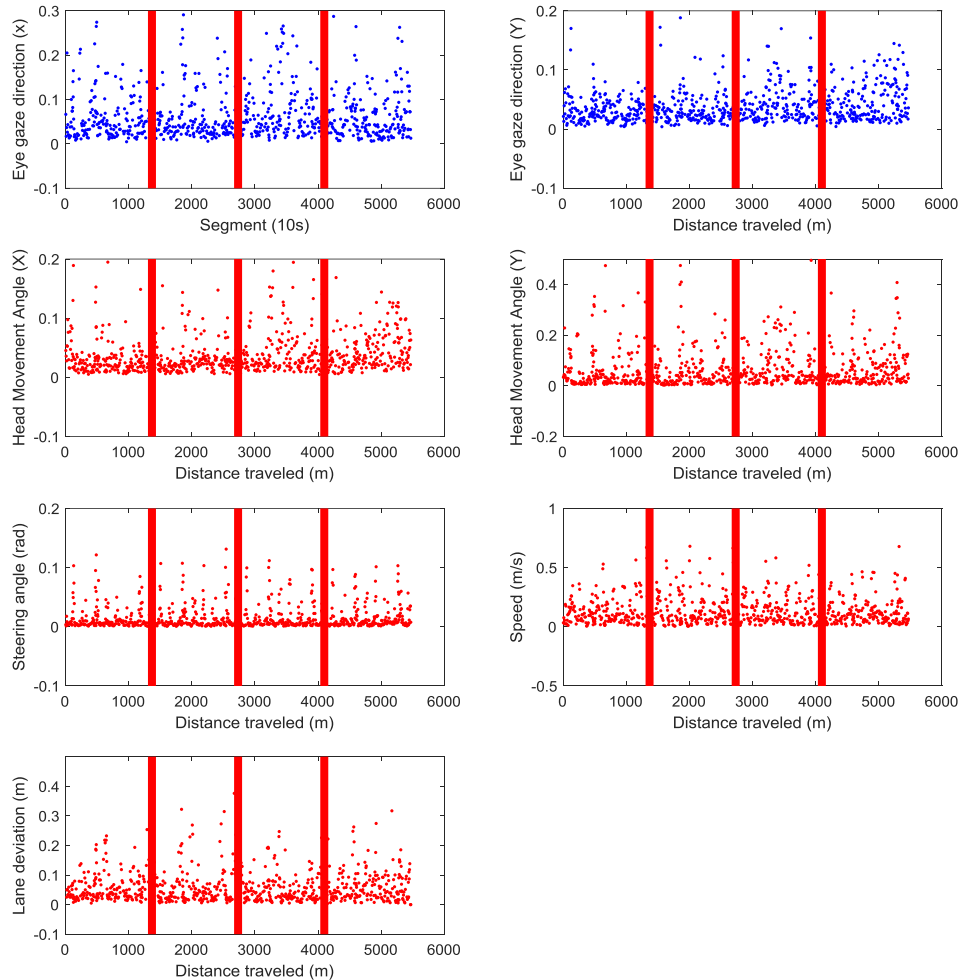


Figure A-69. Comparisons of Standard Deviations between Normal and Different Types of Distracted Driving for Driver No. 6

Figure A-69 demonstrates the standard deviations of features for driver No. 6. The relevant features in detecting distraction are standard deviation values of eye gaze in y directions because the values increase after the driver was distracted. Other features are not relevant in detecting driver distraction.

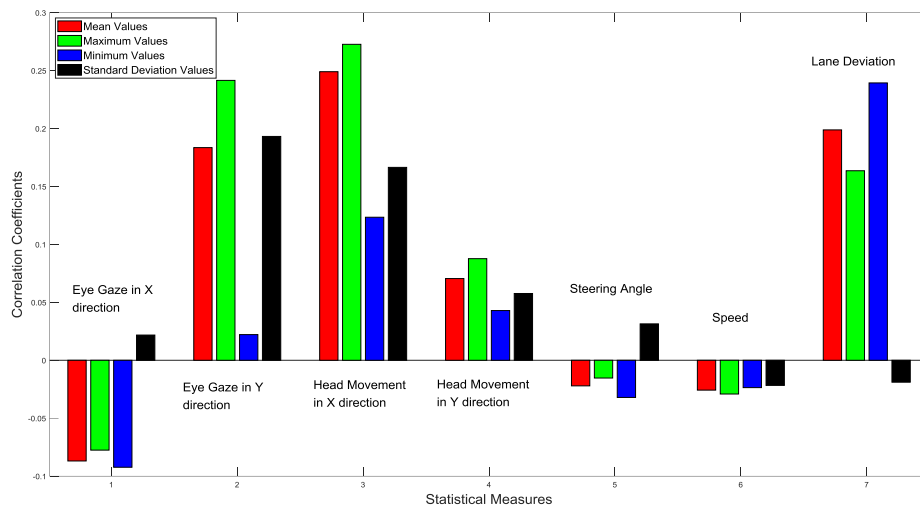


Figure A-70. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 6

Figure A-70 presents the correlation coefficients between mean, maximum, minimum and standard deviation of seven different features and distraction level (0 and 1). The features with large correlation coefficients are maximum values of eye gaze in x direction and eye gaze in y direction and the minimum values of lane deviation. The above-mentioned three features are relevant in detecting driver distraction.

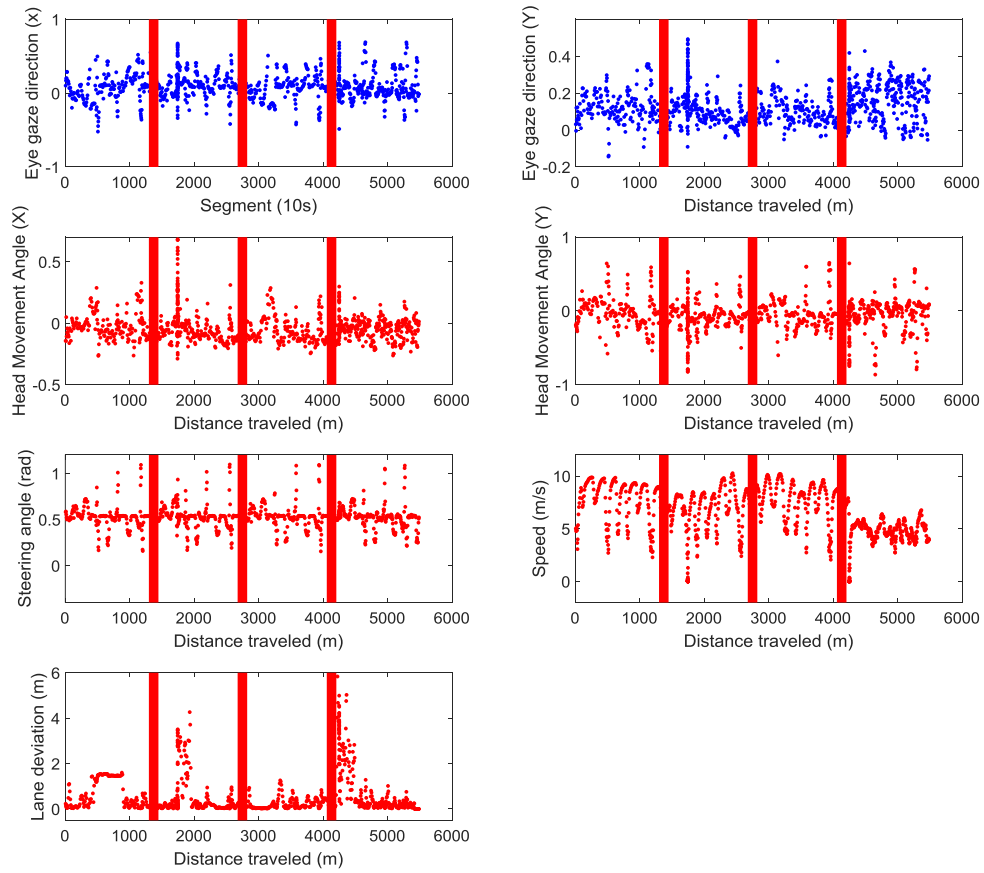


Figure A-71. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 7

Figure A-71 shows the mean values of 7 features for driver No. 7. The relevant features in detecting distraction are mean values of eye gaze in x and y directions, the lane deviation. There are less variations in mean values in eye gaze in x direction and more variations in eye gaze in y direction. The mean value of speed reduces significantly when the driver was texting, while the mean values of lane deviation increases significantly at same time.

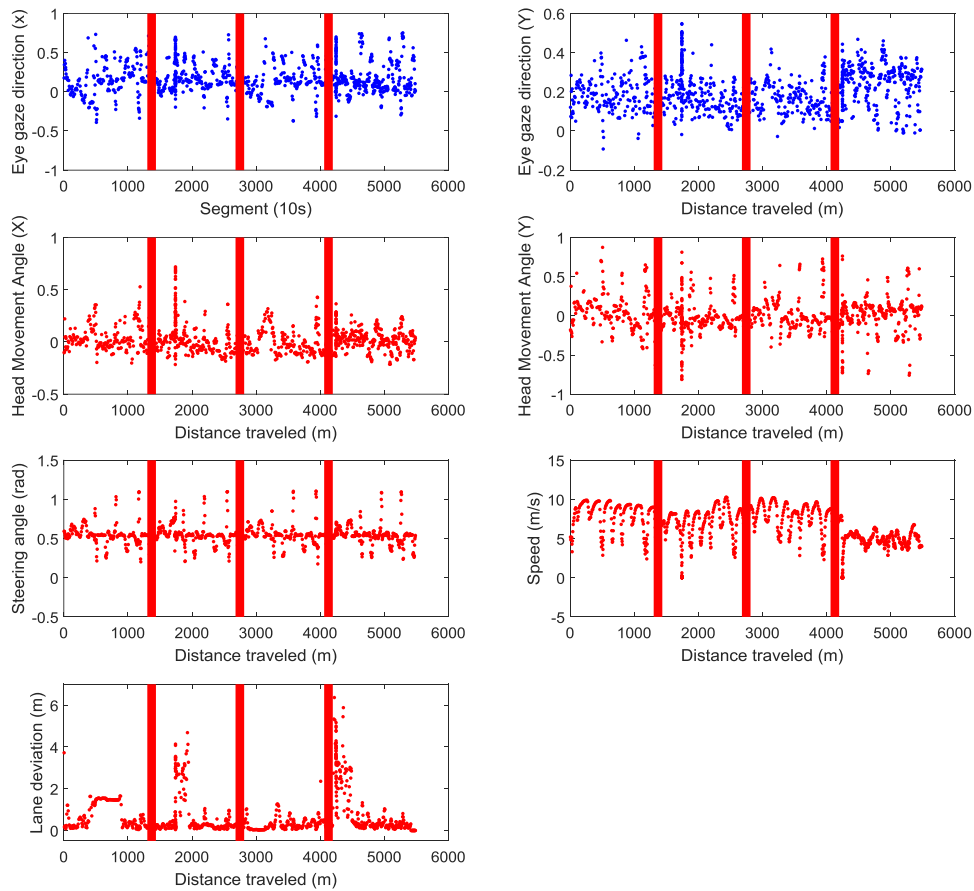


Figure A-72. Comparisons of Maximum Values between Normal and Different Types of Distracted Driving for Driver No. 7

Figure A-72 presents the maximum values of seven features for driver No. 7. The relevant features in detecting distraction are the maximum values of eye gaze in y direction, lane deviation, whose values increases after driver was distracted. The maximum value of vehicle speed decreases significantly after the driver was manually distracted. The above-mentioned three features are relevant in detecting distraction.

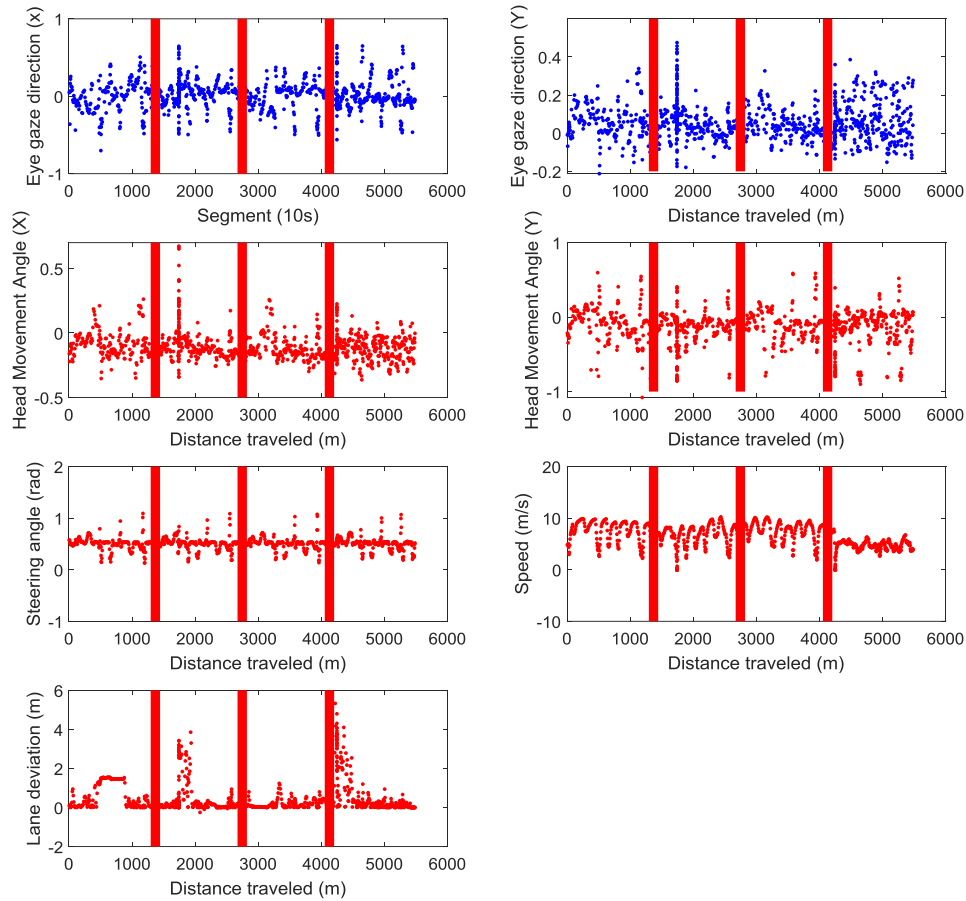


Figure A-73. Comparisons of Minimum Values between Normal and Different Types of Distracted Driving for Driver No. 7

Figure A-73 presents the minimum values of seven features for driver No. 7. The relevant features in detecting distraction are minimum values of eye gaze in x and y direction, head movement in y direction and the lane deviation. The patterns of eye gaze in x and y directions and head movement in y direction changed significantly after driver was distracted compared to the patterns in normal driving. The above three features can be used to detect driver distraction.

It is worth observing that the minimum values of head movement in x and y direction and lane deviation increase significantly after driver was manually distracted. The minimum values of head movement in x and y directions and lane deviation can detect driver manual distraction efficiently.

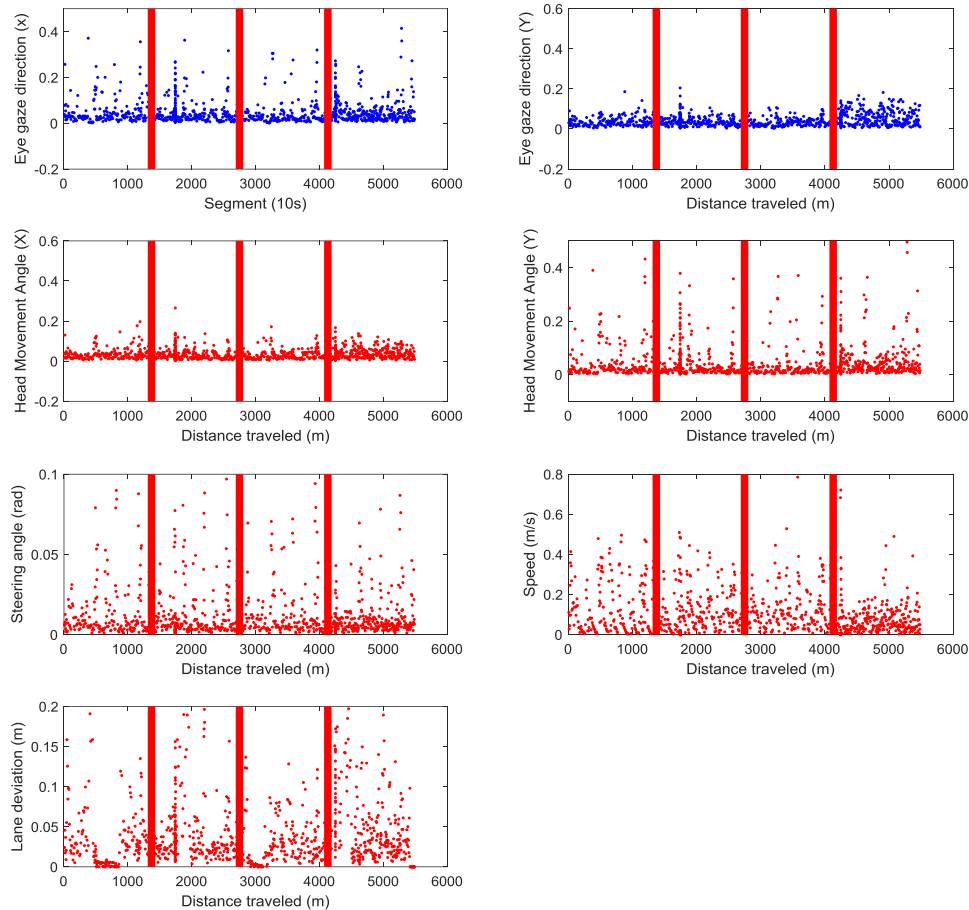


Figure A-74. Comparisons of Standard Deviation Values between Normal and Different Types of Distracted Driving for Driver No. 7

Figure A-74 presents the standard deviations of seven features between normal and different types of distracted driving. The relevant features in detecting distraction are standard deviations of speed and lane deviation. The standard deviation of speed reduced when driver was distracted. The level of reduction became more significant as the driver was more distracted (from talking, doing

math to texting). The standard deviation of lane deviation increases significantly when driver was talking to the passenger and texting.

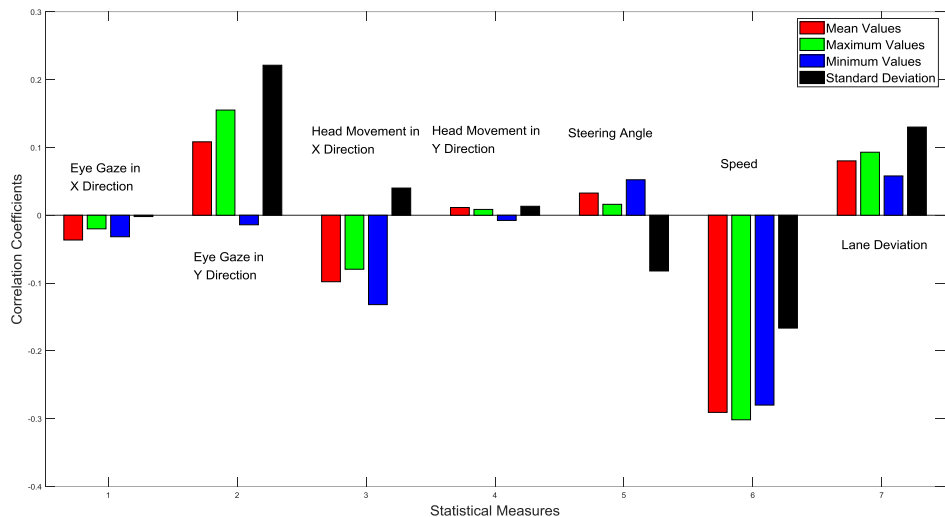


Figure A-75. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 7

Figure A-75 presents the correlation coefficients between the statistical measures of seven features and distraction level for driver No. 7. The features with the largest correlation coefficients are mean, maximum, minimum of speed and standard deviation of eye gaze in y direction. The four features are relevant in detecting driver distraction.

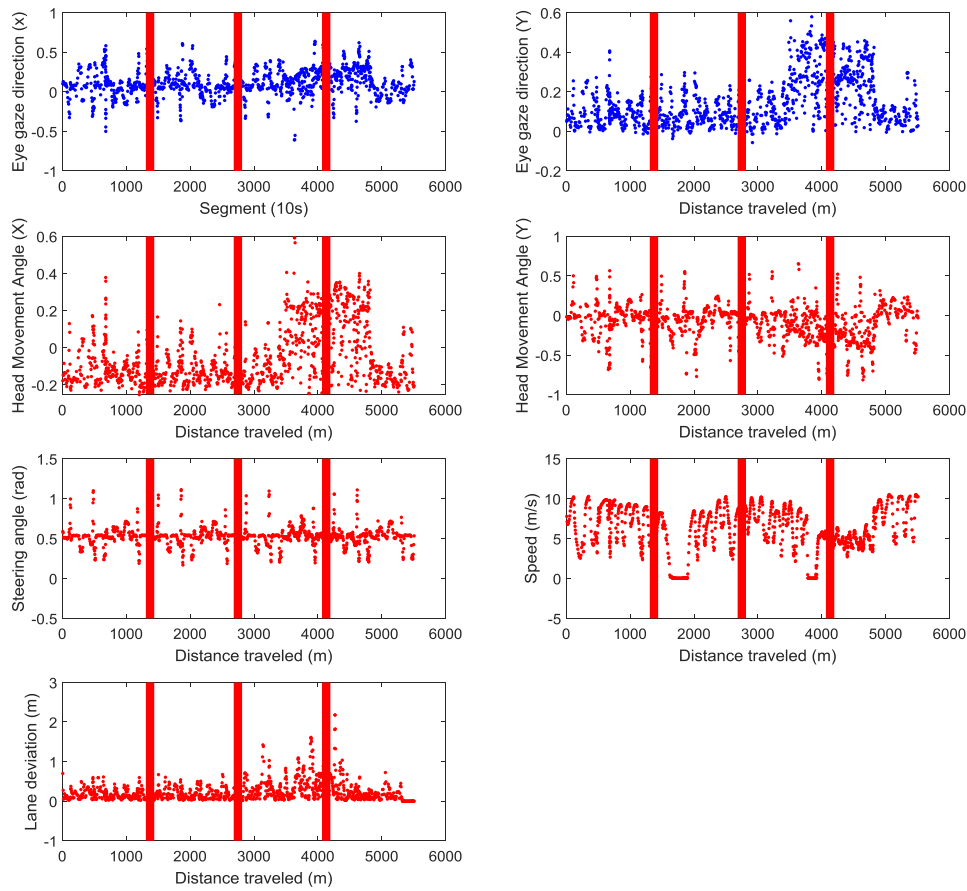


Figure A-76. Comparisons of Mean Values between Normal and Different Types of Distracted Driving for Driver No. 9

Figure A-76 presents the mean values of seven features for driver No. 9. The relevant features in detecting driver distraction induced by math calculation and texting are mean values of eye gaze in y direction, head movement in x direction, speed and lane deviation. For distraction induced by secondary tasks including the math calculation and texting, the mean values of eye gaze in y direction, head movement in x direction and lane deviation increased significantly compared to the normal driving state. The patterns of speed change were different when driver was distracted compared to the pattern of change in speed when driver was in normal driving state. The above-mentioned features can be used to detect distraction caused by math calculation and texting. For the distraction caused by talking with the passenger, the change in features listed in Figure A-76 is too

small to be detected by visual inspection. The effectiveness of detection of talking-induced distraction by eye gaze related features and vehicle performance measures are limited due to the similarity between features in normal driving state and distracted driving state.

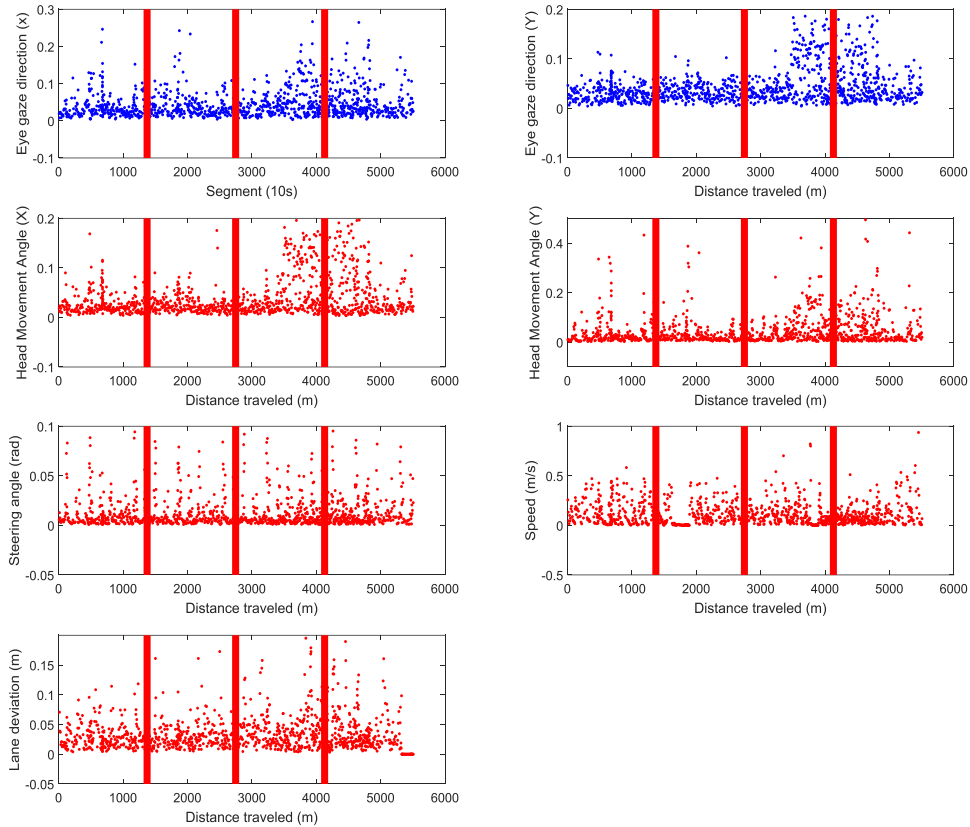


Figure A-77. Comparisons of Maximum Values between Normal and Different Types of Distracted Driving for Driver No. 9

Figure A-77 presents the maximum values of 7 features for driver No. 9. For distractions induced by math calculation and texting, the maximum values of eye gaze in x and y directions, the head movement in x and y directions and lane deviation. The values of above-mentioned features increase after driver was distraction. For cognitive distraction induced by the talking, the difference of features between normal and distracted driving is less obvious than the other two types of distraction.

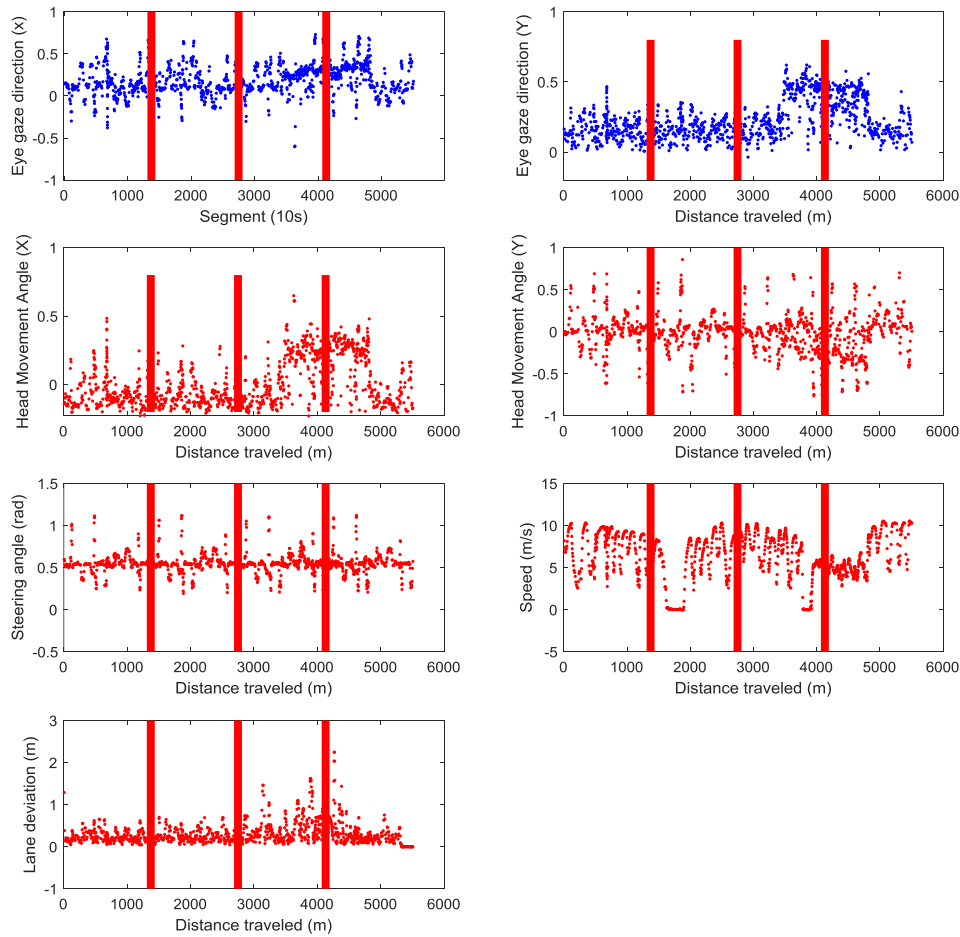


Figure A-78. Comparisons of Minimum Values between Normal and Different Types of Distracted Driving for Driver No. 9

Figure A-78 presents the minimum values of seven features for driver No. 9. For distractions induced by texting and math operations, the relevant features in detecting distraction are minimum values of eye gaze in x direction and head movement in y direction, for their increased values when driver is distracted. The minimum values of eye gaze in x direction, head movement in y direction and lane deviation are also relevant in detecting driver distraction. There are more oscillations in eye gaze in x direction and head movement in y direction when driver was driving while doing math calculations or texting, making them relevant

in detecting the two types of distraction. The minimum values of lane deviation increased after driver was distracted. The minimum values of lane deviation can be used to detect driver distraction. For distraction induced from talking, the difference between it and normal driving is not significant among the seven features, making the detection harder.

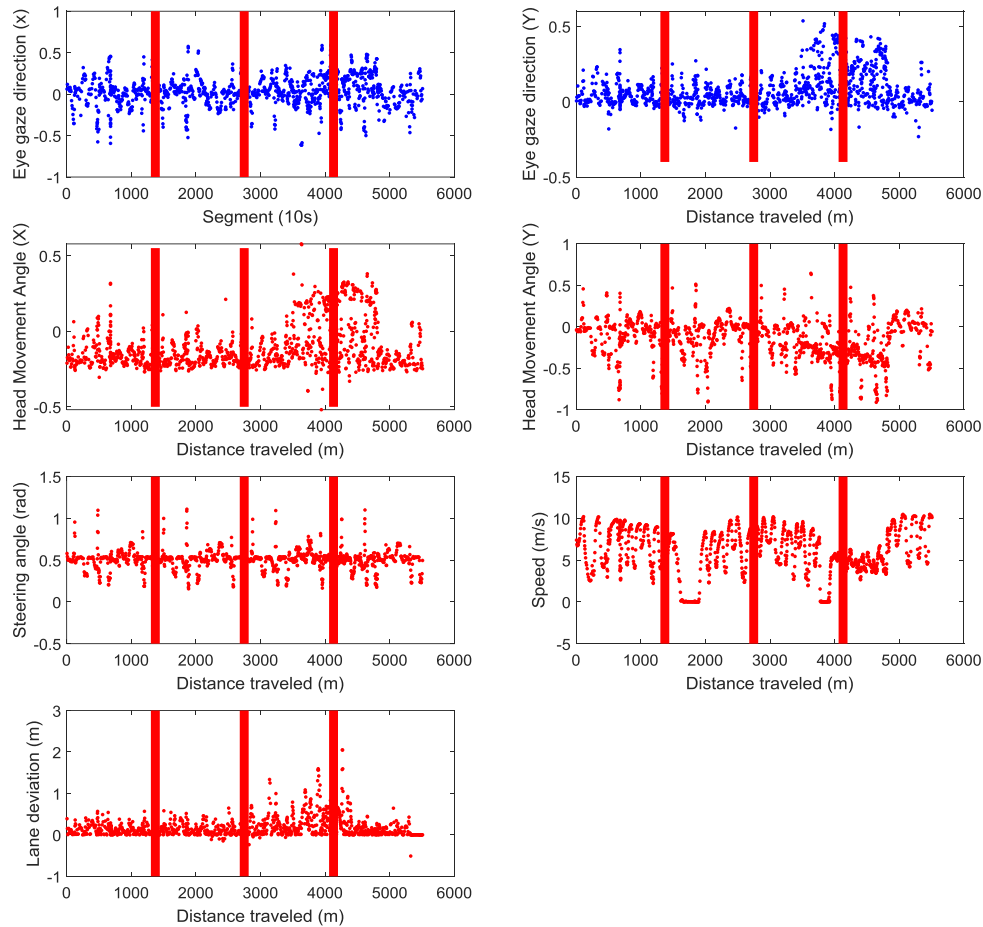


Figure A-79. Comparisons of Standard Deviation Values between Normal and Different Types of Distracted Driving for Driver No. 9

Figure A-79 presents the standard deviation values of seven features for driver No. 9. For distractions induced by doing math calculations and texting, the relevant features to detect these two types of distraction are standard deviation eye gaze in y directions, head movement in x directions and lane deviation. The values of standard deviations of the above-mentioned three features increases

when driver is distracted. The impact of cognitive distraction induced by talking is less significant, since the differences between features are small between the normal driving and cognitive distraction induced by talking.

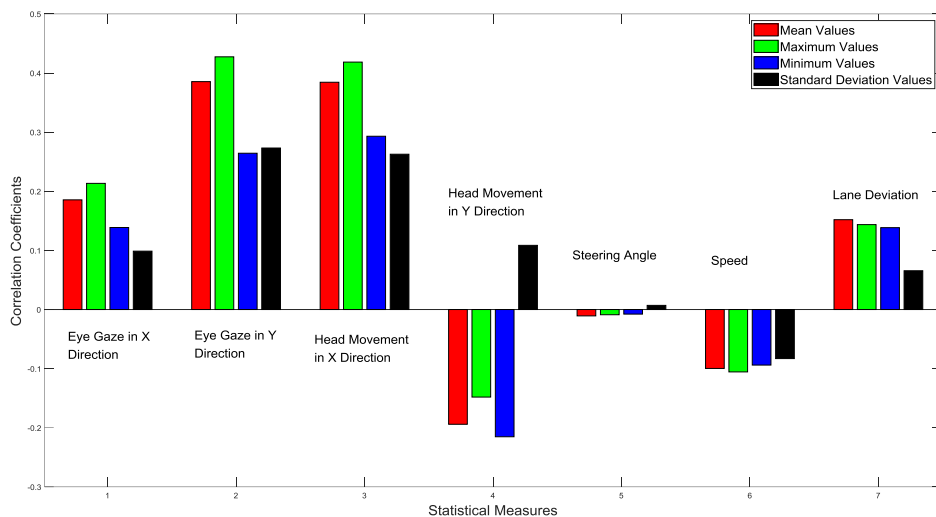


Figure A-80. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 9

Figure A-80 presents the correlation coefficients between statistical measures of seven features and distraction level. The features with large coefficients are mean and maximum of eye gaze in y direction and head movement in x direction. The above-mentioned four features are relevant in detecting distraction.

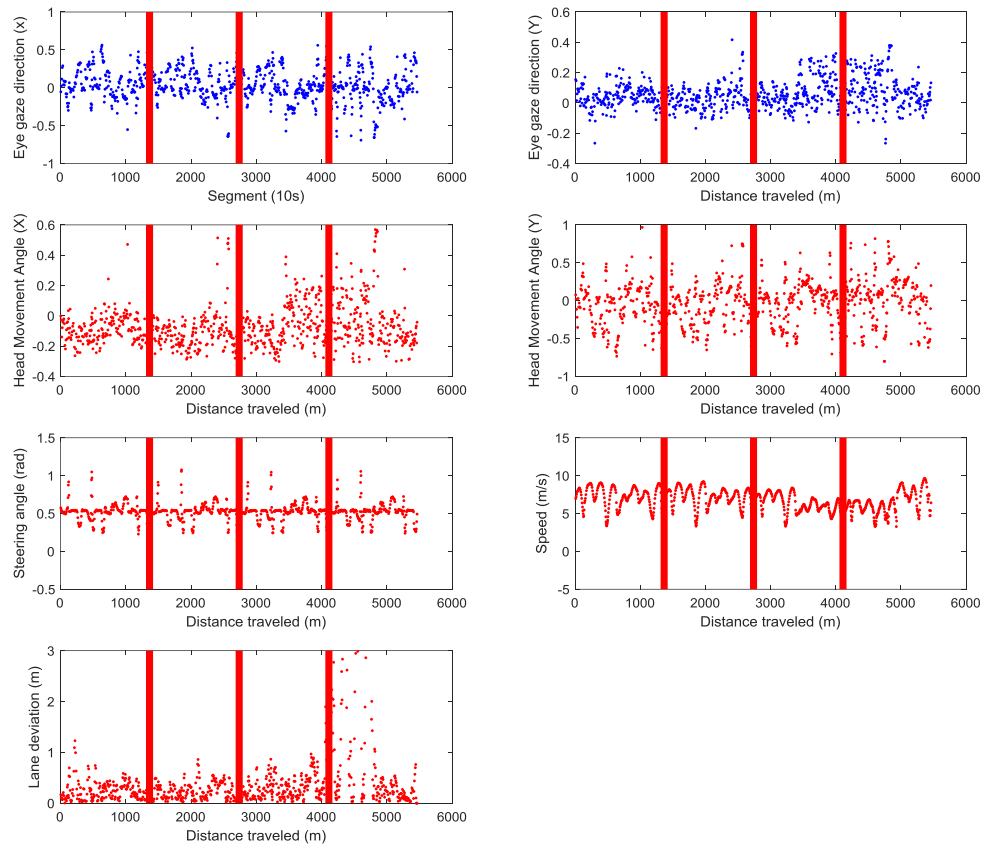


Figure A-81. Comparisons of Mean Values between Normal and Distracted Driving for Driver No. 10

Figure A-81 presents the mean values of seven features for driver No. 10. For distractions induced by texting and doing math calculations, the relevant features are mean values of eye gaze in y direction and head movement in x direction. Their values increased significantly after driver got distraction, which make them relevant in detecting driver distraction. For manual distraction, the mean values of vehicle speed reduce, and mean values of lane deviation increases. The two features are relevant in detecting driver distraction.

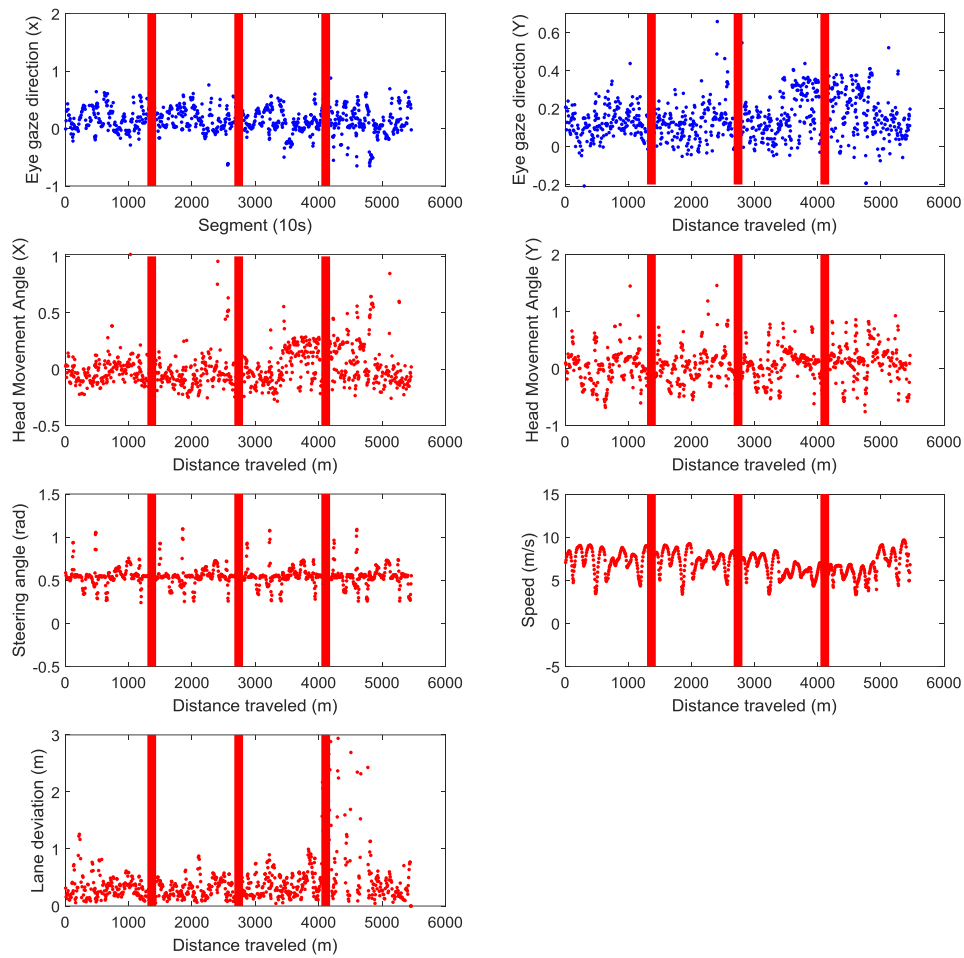


Figure A-82. Comparisons of Maximum Values between Normal and Different Types of Distracted Driving for Driver No. 10

Figure A-82 presents the maximum values of seven features for driver No. 10. The relevant features for detecting driver distraction are eye gaze in y direction and head movement in x direction, for their increased values after driver was distracted. The features for detecting distraction induced by talking is not obvious, for the difference between the normal driving state and distracted driving state is small.

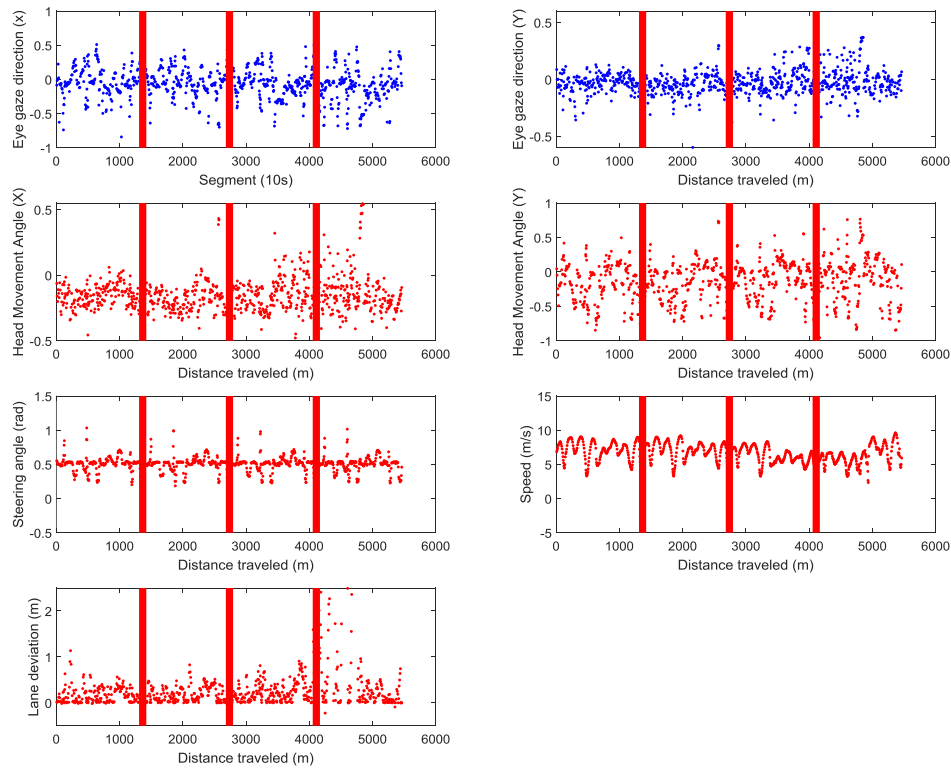


Figure A-83. Comparisons of Minimum Values between Normal and Different Types of Distracted Driving for Driver No. 10

Figure A-83 presents the minimum values of seven features for driver No. 10. The relevant features to detect manual distraction are minimum values of head movement in x direction, vehicle speed and lane deviation. For the other two types of distraction, the relevant features are not obvious, for there is a small difference between normal driving state and distracted driving state shown in features.

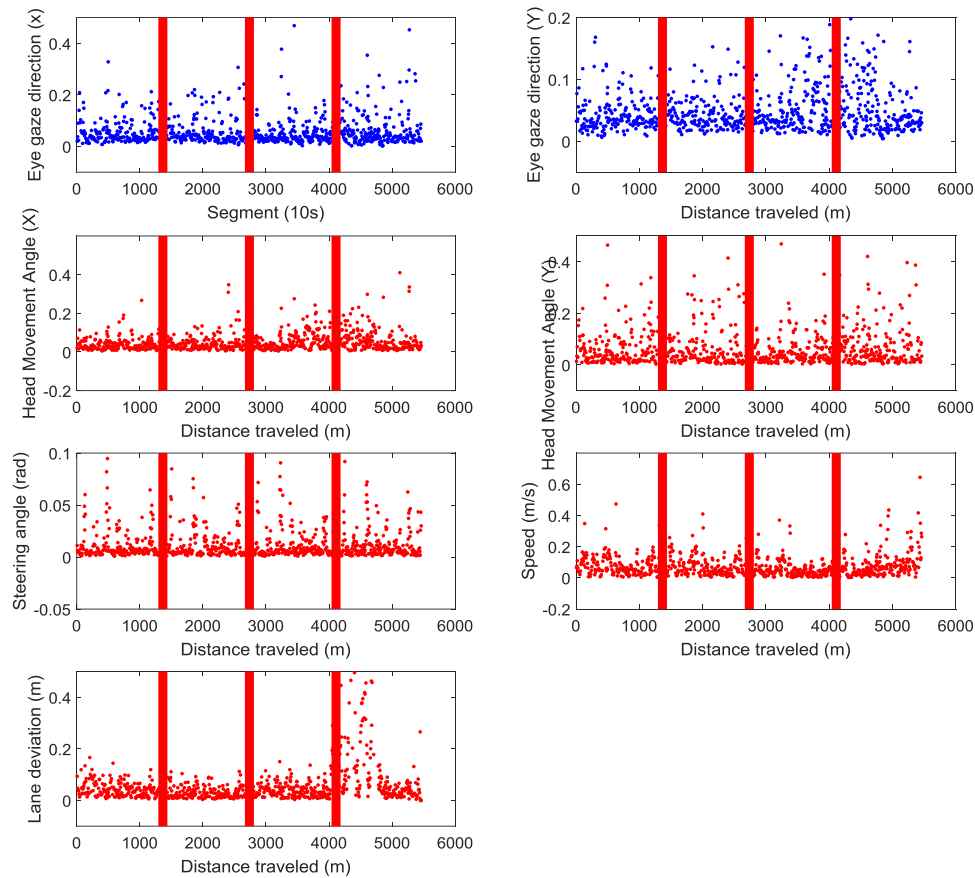


Figure A-84. Comparisons of Standard Deviations between Normal and Different Types of Distracted Driving for Driver No. 10

Figure A-84 presents the standard deviation of 7 features for driver No. 10. The most relevant feature to detect distractions induced by texting and doing math calculations are eye gaze in y directions, for their increased values after driver was distracted. It is worth noting that the standard deviation value of lane deviation increases significantly when driver was under manual distraction. The standard deviation of lane deviation is suitable for detecting driver manual distraction.

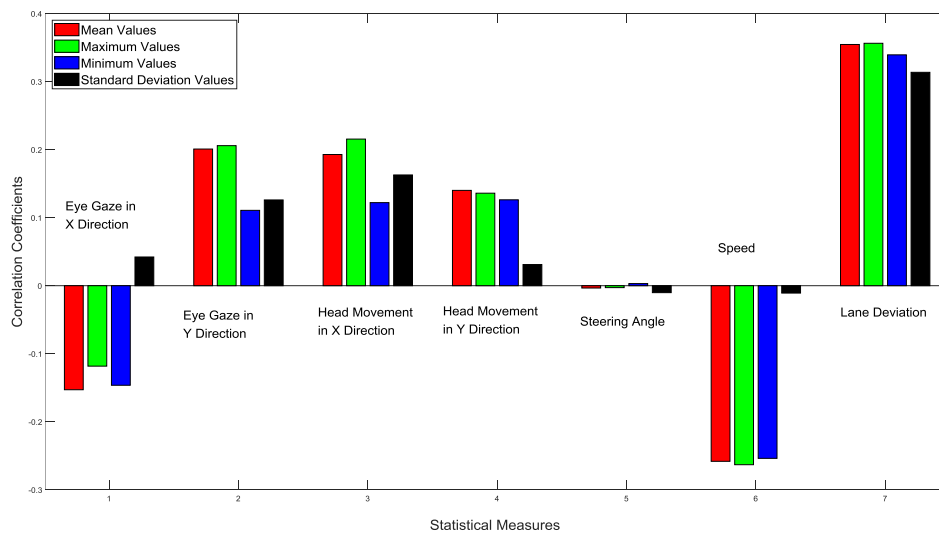


Figure A-85. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 10

Figure A-85 presents the correlation coefficients for driver No. 10. The features with largest correlation coefficients are the mean, maximum and minimum values of speed, lane deviation, followed by the mean and maximum of eye gaze in y direction and head movement in x direction. The above-mentioned features are relevant in detecting distraction.

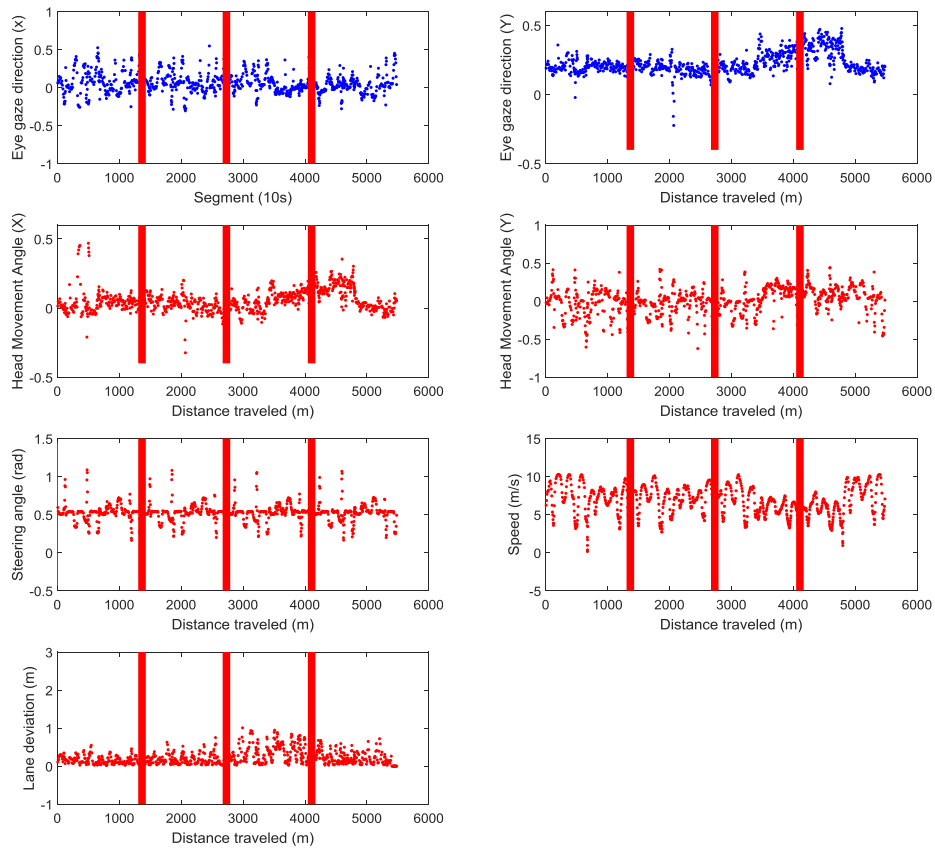


Figure A-86. Comparisons of Mean Values between Normal Driving and Different Types of Distracted Driving for Driver No. 11

Figure A-86 presents the mean values of 7 features for driver No. 11. The relevant signals in detecting driver distractions are mean values of eye gaze in y direction and head movement in x direction. Their values increased significantly when driver was cognitively distracted or manually distracted compared to the normal driving state. The mean values of lane deviation increase significantly when driver was distracted by doing math compared to the normal driving condition. The mean values of lane deviation can efficiently detect cognitive distraction induced by doing math calculations.

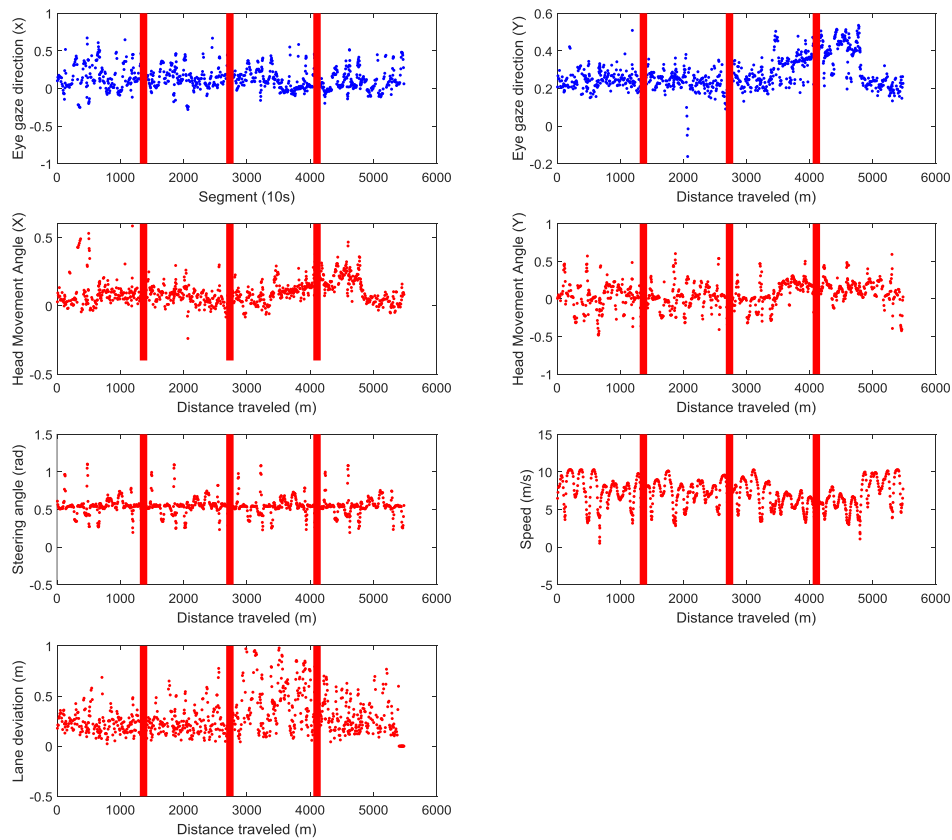


Figure A-87. Comparisons of Maximum Values between Normal and Different Types of Distracted Driving for Driver No. 11

Figure A-87 presents the maximum values of seven features for driver No. 11. For distractions induced by texting and doing math calculations. The relevant features in detecting distraction are the maximum values of eye gaze in y directions and head movement in x directions. In particular, the maximum values of lane deviation increased significantly when driver was doing math calculations while driving. For distraction induced by talking, the features listed in Figure A-87 are not relevant because the difference between the normal driving state and distracted driving state is small.

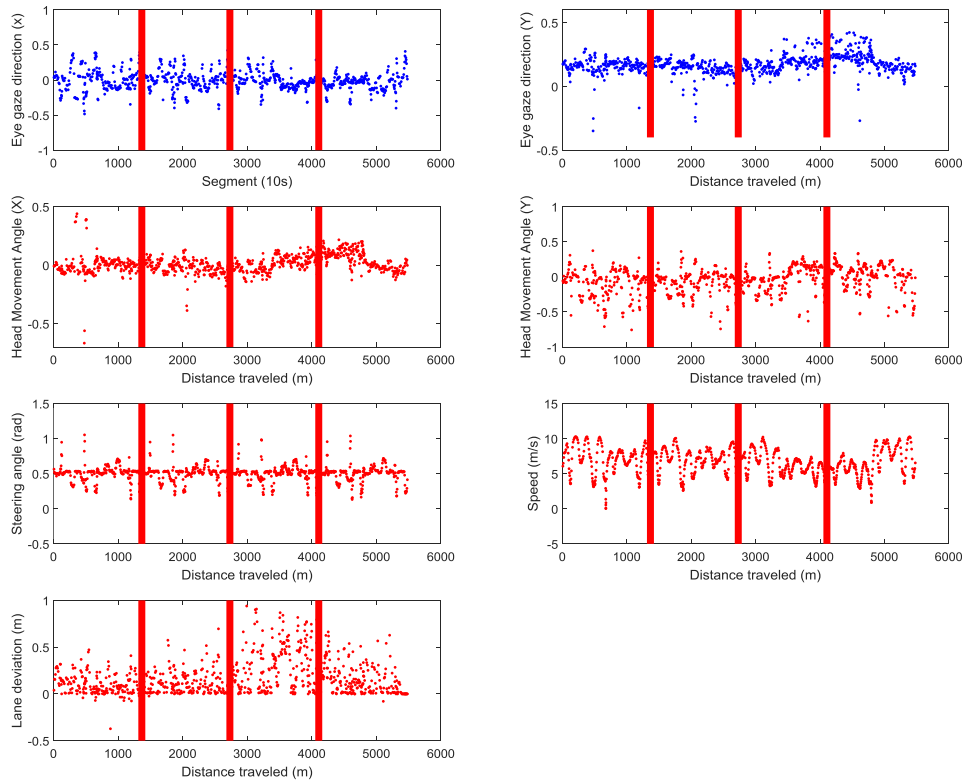


Figure A-88. Comparisons of Minimum Values between Normal Driving and Different Types of Distracted Driving for Driver No. 11

Figure A-88 presents the minimum values of seven features for driver No. 11. For the distraction induced by the texting, the most relevant feature is the minimum values of speed, followed by the minimum values of eye gaze in y direction and head movement in x direction. Vehicle speed is also relevant in detecting this type of distraction. For the cognitive distraction induced by math questions, the relevant features are lane deviations, head movement in x and y directions. For the cognitive distraction induced by talking, the minimum values of speed are relevant.

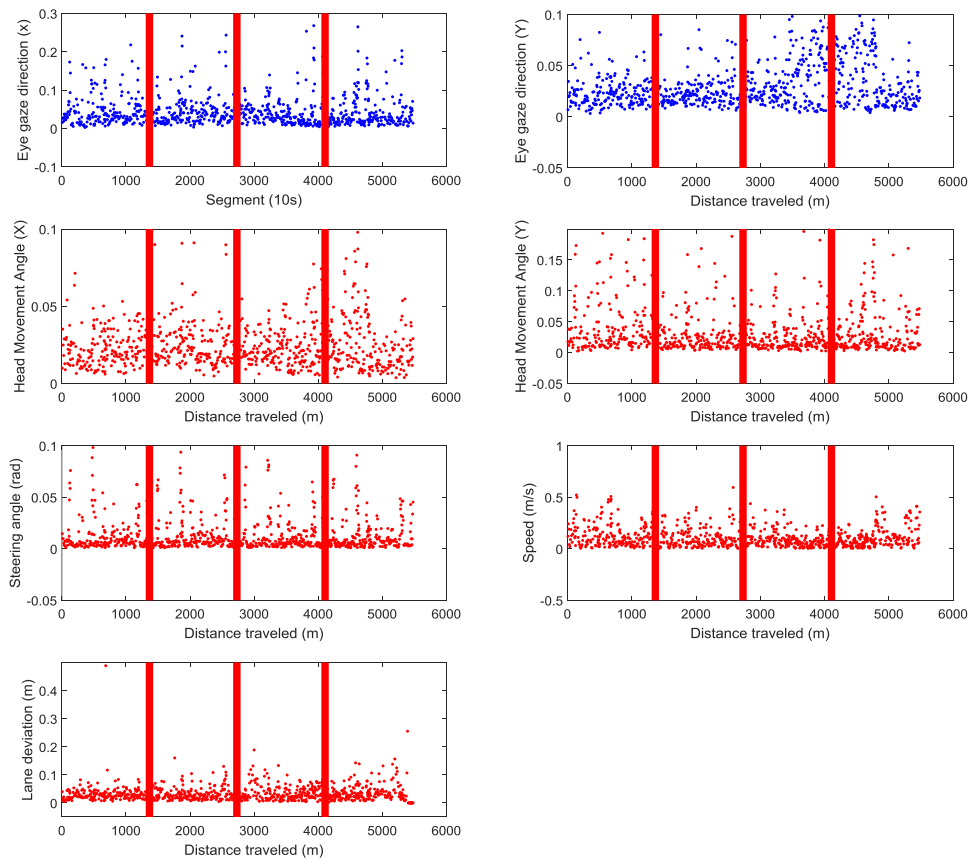


Figure A-89. Comparisons of Standard Deviation Values between Normal Driving and Different Types of Distracted Driving for Driver No. 11

Figure A-89 presents the standard deviation values of seven features for driver No. 11. For distractions induced by texting and math questions, the relevant features in detecting these two types of distraction are standard deviations of eye gaze in y directions and head movement in x directions, for their increased values after distraction. For cognitive distraction induced by talking, no relevant features are found because the similarity between the two states within each feature is small.

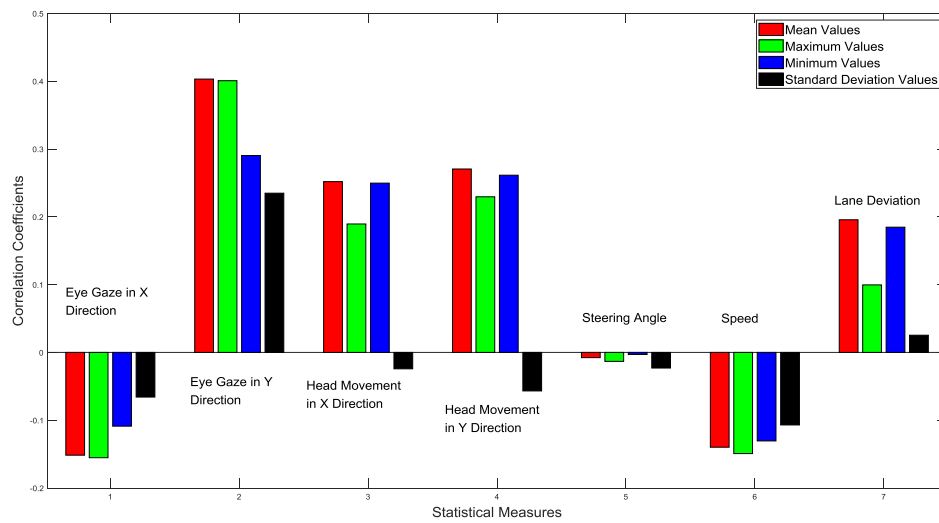


Figure A-90. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 11

Figure A-90 presents the correlation coefficients for driver No. 11. The features with largest correlation coefficients are mean, maximum values of eye gaze in y direction and head movement in x direction, followed by the mean values of head movement in y direction and lane deviation. The above-mentioned features are relevant in detecting distraction for the specific case of driver No. 11.

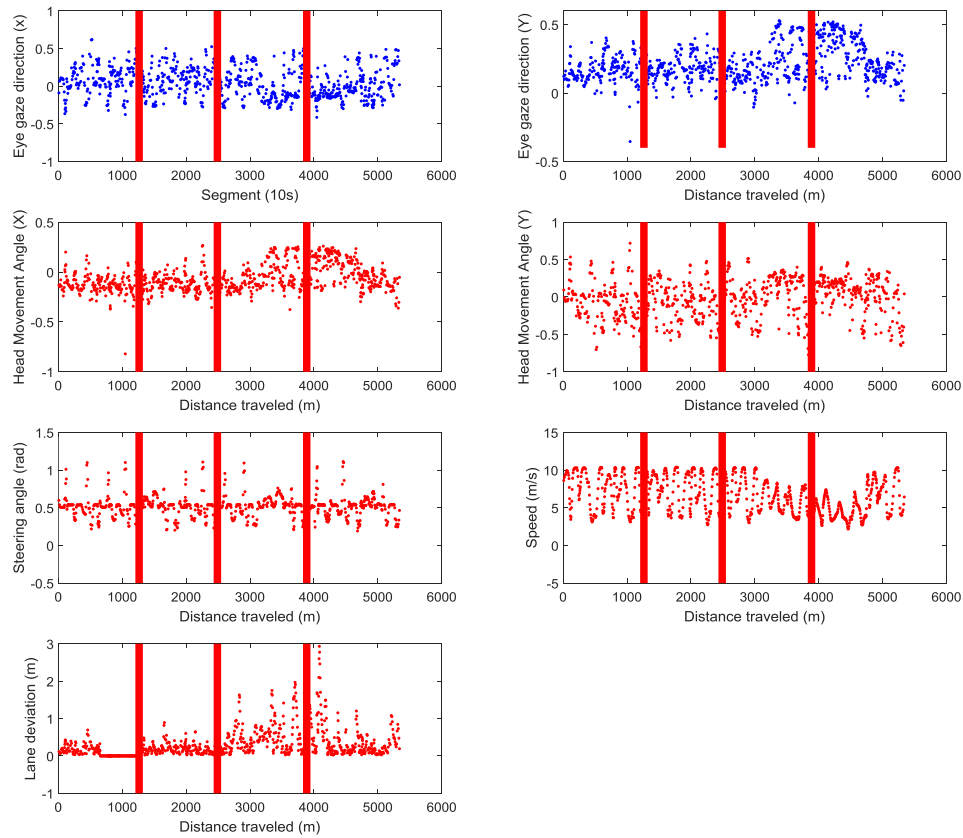


Figure A-91. Comparisons of Mean Values between Normal and Different Types of Distracted Driving for Driver No. 12

Figure A-91 presents the mean values of seven features for driver No. 12. For the manual distraction, the relevant features are mean values of eye movements in x and y directions, head movements in y direction, vehicle speed and lane deviation. The eye gaze related features have more oscillations when the driver was under manual distraction. The mean values of lane deviation increased due to manual distraction.

For cognitive distraction induced by the math questions, the relevant features are mean values of eye gaze in y direction and head movement in x direction. The mean values of lane deviation and vehicle speed are also relevant.

For cognitive distraction induced by talking, the relevant features are hard to find because the feature values between the two driver states are also identical.

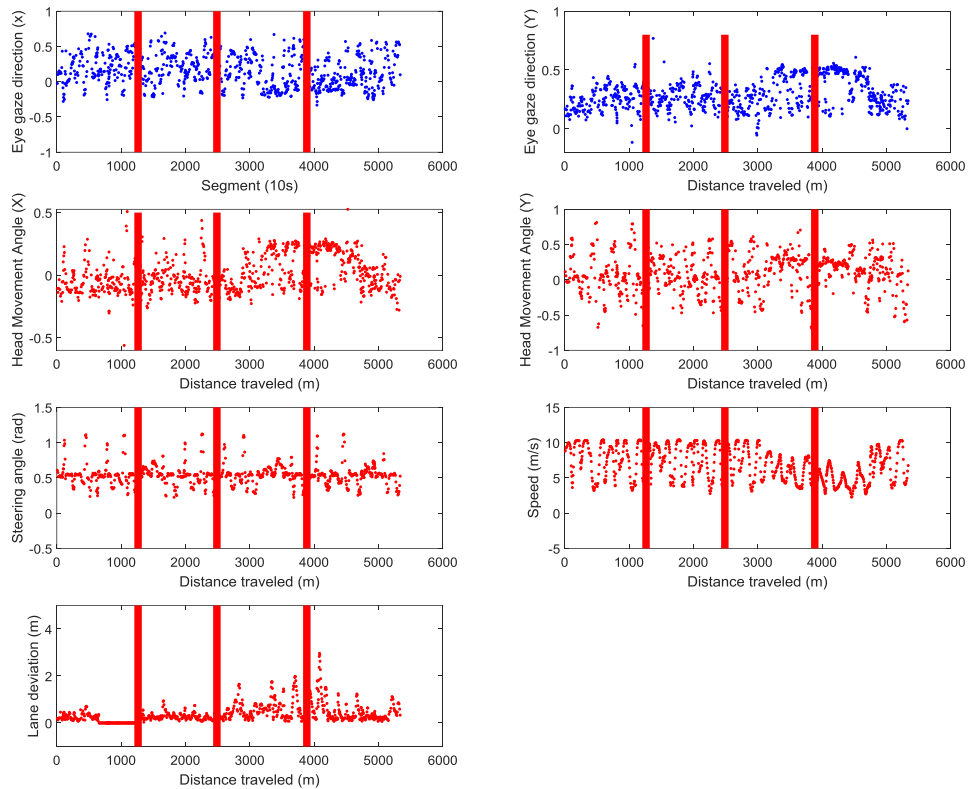


Figure A-92. Comparisons of Maximum Values between Normal and Distracted Driving for Driver No. 12

Figure A-92 presents the maximum values of seven features for driver No. 12. For the distraction induced by texting and math questions, the relevant features are maximum values of eye gaze in y direction, head movement in x direction and lane deviation, whose values increased significantly after distraction.

For the cognitive distraction induced by talking, the relevant features are eye gaze in x direction and head movement in y direction. Their values increase after driver was cognitively distracted.

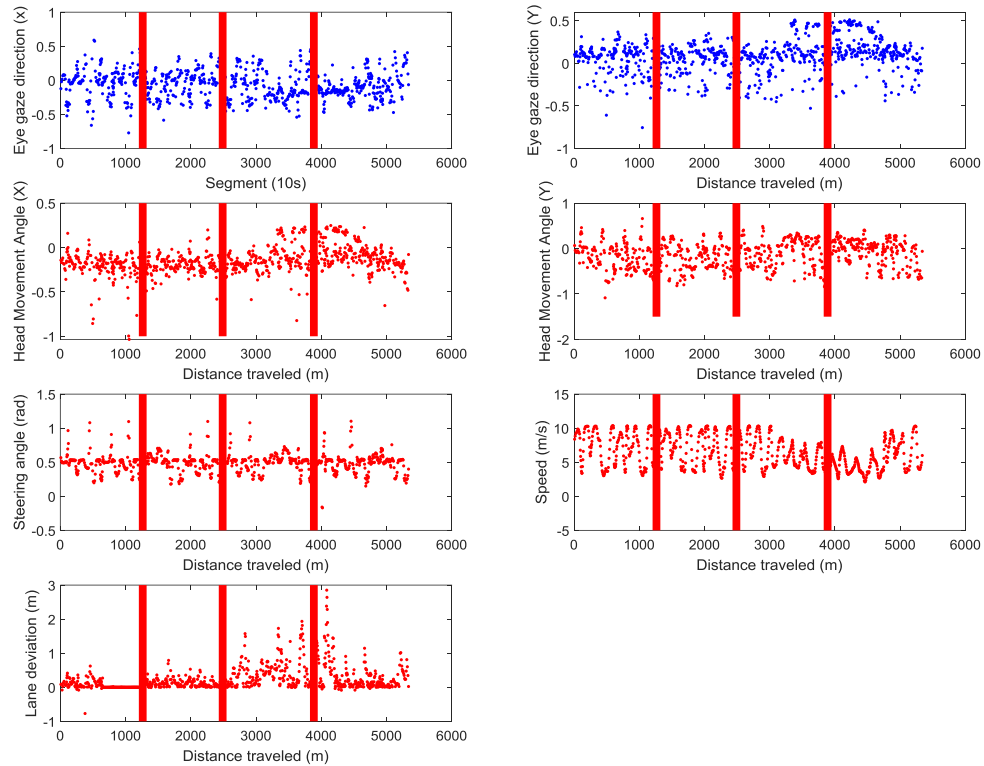


Figure A-93. Comparisons of Minimum Values between Normal and Different Types of Distracted Driving for Driver No. 12

Figure A-93 presents the minimum values of 7 feature for driver No. 12. For distractions induced by the texting and math questions, the relevant features are minimum values of head movement in x and y directions and lane deviation, whose values increased when driver was distracted compared to the normal state. The minimum values of vehicle speed can also be used to detect driver distraction, whose values decreases when driver was distracted. For the distraction induced by talking, the relevant features are not found for the close similarity between the patterns of normal state and cognitive distraction state.

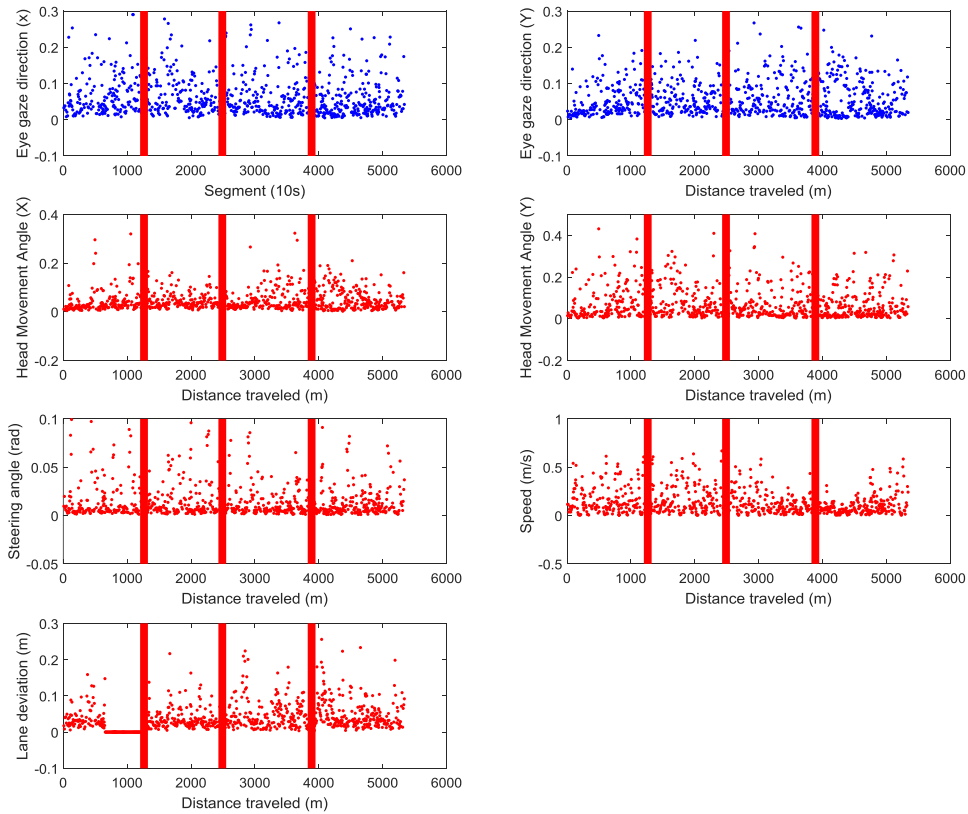


Figure A-94. Comparisons of Standard Deviation Values between Normal and Different Types of Distracted Driving for Driver No. 12

Figure A-94 presents the standard deviation values of 7 features for driver No. 12. For distraction induced by the texting and math questions, the relevant feature is head movement in y direction, for their decreased values after driver was distracted. The standard deviation of lane deviation could also be used to detect driver distraction, for its increased values when driver was distracted.

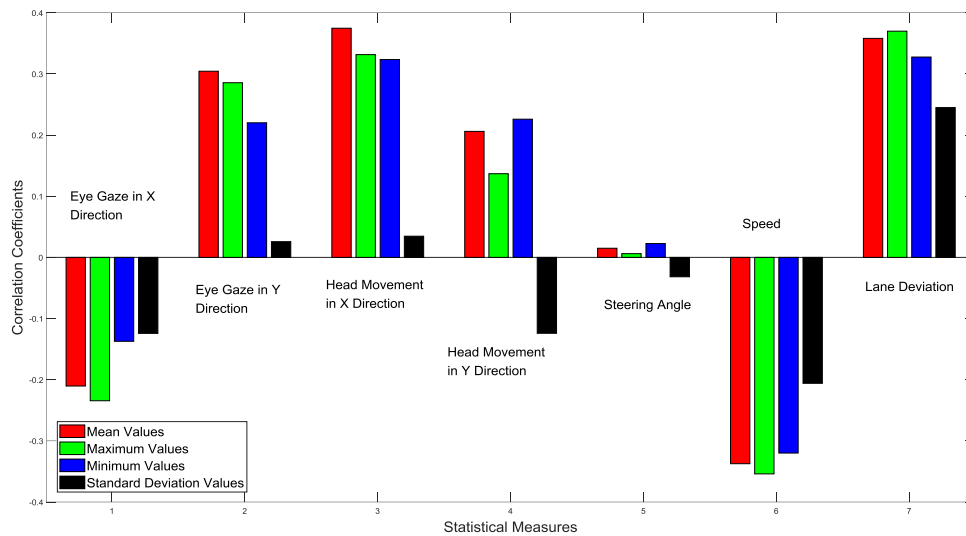


Figure A-95. Correlation Coefficients between Statistical Measures and Distraction for Driver No. 12

Figure A-95 presents the correlation coefficients for driver No. 12. The features with largest correlation coefficients are the mean, maximum and minimum values of head movement in x direction, speed and lane deviation. The above-mentioned features are considered to be relevant in detecting distraction for the specific case of driver No. 12.

Appendix B Experiment Procedures and Questionnaires

Lap 1:

The first lap aims at introducing the experiment and improving the familiarisation

The driver is instructed by the experimenter to drive around for one lap. The vehicle firstly will be driven to the starting point. Then the driver receives following instructions:

- 1: Start, follow the curved road.
- 2: Turn right, where you can see the road ahead.
- 3: Go straight and follow the road.
- 4: Change lane to the right and then go back to left lane.
- 5: Go around the hill to the other side of the road.
- 6: Bypass the truck/lorry parked by the side of the road
- 7: Go straight and prepare for the 180 degree left turn
- 8: Go straight and look at the left/right sign.
- 9: Follow the direction sign. (right in this case)
- 10: Go around the hill to the other side of the road (180 degree left turn)
- 11: Follow the road ahead (Bypass a vehicle)
- 12: When reaching the end of the road, go right and exit the rectangular area to the main road.
- 13: Follow the road ahead till the next intersection
- 14: Turn left and reach the starting point.
- 15: Stop the vehicle.

Lap 2:

The second lap aims at introducing the experiment to the driver and improve the familiarisation of the driver to the road.

The driver is instructed by the experimenter to drive around for one lap. The vehicle firstly will be driven to the starting point. Then the driver receives following instructions:

- 1: Start, follow the curved road ahead.
- 2: Turn left, where you can see the road ahead.
- 3: Go straight and follow the road ahead.
- 4: Double lane change, firstly change to the right lane and then change back to left turn.
- 5: 180-degree left turn. Go around the hill to the other side of the road.
- 6: Bypass the lorry/truck parked by the side of the road.
- 7: Go straight and prepare for the 180 degree left turn
- 8: Go straight and look at the left/right sign.
- 9: Follow the direction sign. (left in this case)
- 10: By pass the vehicle.
- 11: 180-degree right turn. Go around the hill to the other side of the road.
- 12: Follow the road ahead until the end of the road to the main road
- 13: Follow the main road until reaching the next intersection.
- 14: Turn left to the curved road.
- 15: Reach the stopping point. End.

Lap 3:

Notes:

This is now the start of the experiment.

Please focus on driving and follow the direction sign.

Please continue to drive and this is the first lap of normal driving.

No distraction task is applied.

Lap 4:

Notes:

This is the second lap of the experiment.

Please focus on driving and follow the direction sign.

Please continue to drive and this is the second lap of normal driving.

No distraction task is applied.

Lap 5 (Talking to the passenger):

Notes:

This is the first lap of the experiment (Talking to the passenger).

Please driving and talking to passenger at the same time.

Please continue to drive and this is the first lap of distracted driving (Talking to the passenger).

Table B-1. Questions in Lap 5

Phase 1:	Phase 4
Where were you born?	Do you like cats?
Are you male or female?	What is your hair colour?
What is your nationality?	Do you like burgers?
Did you have lunch today?	Do you have a bank account?
What is your first name?	Where do you live now?

What year were you born?	How many cars do you own?
Can you speak mandarin?	What is your eye colour?
Do you have a TV at home?	
Do you have children?	
Have you been to Asia before?	

Lap 6 (Talking to the passenger):

Notes:

This is the second lap of the distracted driving phase (Talking to the passenger).

Please driving and talking to passenger at the same time.

Please continue to drive and this is the second lap of distracted driving.

Table B-2. Questions in Lap 6

Phase 1:	Phase 6:
Did you go to the movies this week?	Have you ever been to Edinburgh?
Do you have siblings?	Do you like to play video games?
Have you ever been to Edinburgh?	Do you like sports?
Are you good at playing guitar?	What's your favourite movie?
Have you eaten Subway sandwich before?	What's your favourite colour?
Did you watch Formula 1 this year?	Do you like the outdoors?
Do you have a bachelor's degree?	Do you live in Cranfield?

Lap 7 (Cognitive distraction – Mathematical Questions):

Notes:

This is the first lap of the cognitive distraction –mathematical questions.

Please driving and answer to passenger's questions at the same time.

Please continue to drive and this is the first lap of cognitive distraction – mathematical questions.

Table B-3. Math Questions in Lap 7

Phase 1:	Phase 4:
What is the sum of $3+7$?	What is $11*4$?
What is $12*3$?	What is $84/21$?
What is $15-30$?	What is $67-23$?
What is $14*2$?	What is $45/15$?
What is the sum of $25 + 23$?	What is the sum of $41+21$?
What is the sum of $4 - 31$?	What is $80-27$?
What is $94-33$?	What is $72/12$?

Lap 8 (Cognitive distraction – Mathematical Questions):

Notes:

This is the second lap of the cognitive distraction –mathematical questions.

Please driving and answer to passenger's questions at the same time.

Please continue to drive and this is the second lap of cognitive distraction – mathematical questions.

Table B-4. Math Questions in Lap 8

Phase 1:	Phase 6:
What is $14*4$?	What is the sum of $52+38$?
What is the sum of $43+87$?	What is the sum of $84+36$?

What is 2×27 ?	What is $93 - 37$?
What is $75 - 32$?	What is 58×2 ?
What is 6×15 ?	What is 34×3 ?
What is the sum of $58 + 32$?	What is $76 - 43$?
What is 6×17 ?	What is 3×32 ?

Lap 9 (Manual distraction – Texting):

Notes:

This is the first lap of the manual distraction – texting.

Please driving and texting the same time.

Please continue to drive and this is the first lap of manual distraction – texting.

Please type in follow sentences:

Table B-5. Text Messages in Lap 9

Phase 1:	Phase 4:
I am doing driving experiment now	The nearest town to Cranfield is Bedford
The test is on MUEAVI road	46% of Cranfield students are from outside the UK
Today's weather is _	Half of our students are over 30 years of age.
Cranfield University has an airfield	There is one member of academic staff to every seven students.

Lap 10 (Manual distraction – Texting):

Notes:

This is the second lap of the Manual distraction – Texting.

Please driving and texting at the same time.

Please continue to drive and this is the second lap of Manual distraction – Texting

Please type in follow sentences:

Table B-6. Text Messages in Lap 10

Phase 1:	Phase 6:
Over 10,000 people come to Cranfield each year to benefit from our executive and professional development programmes.	We have 30 international alumni communities across the world, including Australia (which sponsors an annual MBA scholarship), China (Beijing and Shanghai), India and Switzerland (Zurich).
More than half of our students and learners study part-time.	We are ranked in the top ten in the UK for commercial research, consultancy and professional development. According to the Research Excellence Framework 2014, 81% of our research is classed as world-leading or internationally excellent. We're number one in the UK for research income from industry per academic (<i>Times Higher Education</i> , 2017).
In a typical year, our academics deliver courses in 45 countries outside the UK.	
There are over 100 universities in the UK	

Lap 11

The third lap involves the independent driving of driver.

The driver should follow the same route as in the first lap.

The lap is to test whether driver could follow the route correctly. Driver should turn right before the direction sign.

Lap 12:

The fourth lap involves the independent driving of driver.

The driver should follow the same route as in the second lap.

The lap is to test whether driver could follow the route correctly. Driver should turn left before the direction sign.