Human-Centric Detection and Mitigation Approach

for Various Levels of Cell Phone-Based Driver Distractions

by

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ABSTRACT

Driving a vehicle is a complex task that typically requires several physical interactions and mental tasks. Inattentive driving takes a driver's attention away from the primary task of driving, which can endanger the safety of driver, passenger(s), as well as pedestrians. According to several traffic safety administration organizations, distracted and inattentive driving are the primary causes of vehicle crashes or near crashes. In this research, a novel approach to detect and mitigate various levels of driving distractions is proposed. This novel approach consists of two main phases: i.) Proposing a system to detect various levels of driver distractions (low, medium, and high) using a machine learning techniques. ii.) Mitigating the effects of driver distractions through the integration of the distracted driving detection algorithm and the existing vehicle safety systems. In phase-1, vehicle data were collected from an advanced driving simulator and a visual based sensor (webcam) for face monitoring. In addition, data were processed using a machine learning algorithm and a head pose analysis package in MATLAB. Then the model was trained and validated to detect different human operator distraction levels. In phase 2, the detected level of distraction, time to collision (TTC), lane position (LP), and steering entropy (SE) were used as an input to feed the vehicle safety controller that provides an appropriate action to maintain and/or mitigate vehicle safety status. The integrated detection algorithm and vehicle safety controller were then prototyped using MATLAB/SIMULINK for validation. A complete vehicle power train model including the driver's interaction was replicated, and the outcome from the detection algorithm was fed into the vehicle safety controller. The results show that the vehicle safety system controller reacted and mitigated the vehicle safety status-in closed loop real-time fashion.

The simulation results show that the proposed approach is efficient, accurate, and adaptable to dynamic changes resulting from the driver, as well as the vehicle system. This novel approach was applied in order to mitigate the impact of visual and cognitive distractions on the driver performance.

DEDICATION

I dedicate my work to my wife, Israa, my new son, Omar, my parents and my siblings. Without their support, encouragement and love, I would not have reached to this level! I am blessed to have you all in my life. Whenever I lost strength and motivation, they dedicate time and effort to stand next to me supporting and encouraging. I love you all!

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INTRODUCTION

Driving Distractions

Driving a car is a complex process that typically involves several physical and mental tasks. A proposed “Theory of Action” by Donald Norman identifies two major gaps (or Gulfs) in the interaction between humans and computer systems, the Gulf of Evaluation, and the Gulf of Execution. These gaps contain multiple stages of user activities (Norman, 1986). Following a simplified projection of the same principles, we can broadly identify three distinguishable stages a driver goes through when dealing with mental tasks. The first stage is the perception phase: large amounts of information are perceived simultaneously from different sources including car instrumentation displays, passengers, and environment. The second stage is the processing phase: information is processed continuously by filtering, sorting and prioritizing. The last stage is the decision and execution phase: the driver executes several functions and decisions in fractions of a second.

In an ideal situation, drivers continuously focus on the road and pay full attention to relevant information through perceptual processes and ultimately make appropriate decisions. In reality, drivers may be paying attention to less important or irrelevant information as well as executing irrelevant tasks while driving. This could draw their attention away for shorter or longer periods of time causing distractions, which are one of the major causes of road accidents and fatalities (Norman, 1986). We can broadly refer to this complex driving activity as having a cognitive load on the driver’s side, which requires great attention and focus most of the time (Gerven, Paas, Merriënboer, Hendriks, & Schmidt, 2003; Hamish & Merat, 2005). Thus, distractions can cause a decrease in driver attention to actual driving and increase the cognitive load which can raise the probability and severity of accidents (McEvoy, Stevenson, & Woodward, 2007). In addition to the cognitive distractions (i.e. the extra load mental load caused by a secondary task), visual driving distraction is another serious issue. Visual distraction occurs when the driver's eyes are off the roadway (e.g., texting while driving), which can negatively affect the substantial role of visual attention in driving. In other words, visual distraction is "eye-off-road" and cognitive distraction is "mind-off-road" (Victor, 2005).

As bad as they are, distractions are an inherent part of driving, and cannot be fully eliminated – at least not in the foreseeable future. Therefore, a major goal for safety is to continuously manage and reduce distractions.

Motivation

With the growing number of distractions, detection of abnormal driver behavior becomes a significant topic that should be addressed and taken into account at the design and evaluation phase of in-vehicle driving systems. The importance of driver behavior detection comes from the advantages associated with it, which include improving safety on the road and increasing energy efficiency. According to many official reports, a large number of road accidents are caused by driver fatigue, aggressiveness, intoxication, drowsiness, texting or recklessness. For instance, in 2008 a report conducted by the National Center for Statistics and Analysis (NHTSA) found that 5,870 people died and approximately 515,000 people were injured in police-reported traffic accidents in which at least one type of driver distraction was reported on the traffic accident reports (Ascone, Lindsey, & Varghese, 2009). In 2014, another report by NHTSA shows that approximately 3,179 people were killed and an estimated additional 431,000 injured in motor vehicle crashes involving distracted drivers (NHTSA, 2014). The same report shows that the percentage of driver's text-messaging or using electronic devices while driving increased from 1.7% in 2013 to 2.2% in 2014. Driver distraction is a global issue that exists in many counties over the world and is not just limited to the USA. A research by Volvo shows that human errors caused by distractions are the main cause of 90% of the accidents in Europe (Internal Communication Newsdesk, 2005). According to the same report, speed, risk awareness, and distraction represent the largest source of human errors.

Problem Statement

Distracted driving redirects a driver's attention away from the primary task of driving, which jeopardizes the safety of driver, passenger(s), as well as pedestrians. Furthermore, with the development of new in-vehicle technologies, the next generation of automobiles involves more distractive in-cabin systems. As a result, drivers are exposed to more sources of distraction, which can lead to more road accidents. Hence, monitoring driver attention levels has become a growing research interest and challenge. It has been proven that institutional approaches which introduce new laws as preventive tools to reduce traffic accidents caused by distractions (such as texting while driving, adjusting the navigation system etc.) are ineffective due to multiple reasons (Dotzer , Fischer, & Magiera, 2005; Leen, Heffernan, & Dunne, 1999). These reasons include:

i) The number and complexity of in-cabin control and entertainment systems have increased drastically and associated regulations would prevent users from utilizing the technology.

ii) Such regulations (i.e. laws to reduce traffic accidents) will bar the development of advanced technologies pursued by the industry and keep them from being merged into the next generation of automobiles

Due to lack of a driver behavior context aware solution, most of the current vehicle safety systems act during or shortly before a critical incident occurs. This limitation can negatively affect drivers' safety. Therefore, one of the goals behind this research is to propose a solution that is able to detect the distracted driving at the early stage, and then educate the current vehicle safety systems with the driver status to act accordingly.

It has been proved that using the institutional approach of introducing new laws as a preventive tool to reduce traffic accidents due to driver behaviors that cause distraction (such as texting while driving, adjust the navigation system …etc.) is inefficient due to the following reasons: first, number and complexity of in-cabin and entertainment systems increases drastically and such regulations will prevent the users from using this technology. Second: such regulations will create a barrier for the development of advanced technologies pursued by the industry from being merged into the next generation of automobiles. Nonetheless, recent advancement in vehicle's safety systems is transforming vehicles from human-controlled passive devices into human-centric intelligent/ active systems. There is a wide range of systems from fully autonomous vehicles to human augmented control devices which have emerged in this field.

Therefore, vehicle active safety systems that have the driver in the decision and control processes are preferred due to their ‘human-centric’ approach. However, most of uncertainty exists in the driving scenario due to the long term as well as instantaneous ability of the driver, changing environment and their interaction. Therefore, the complete solution to decrease road accidents is only achievable by making the vehicles active safety system 'aware' of the driving context, as well as the driver status (distracted, neutral, aggressive, drunk, drowsy etc.). This can be achieved by analyzing driver behavior signals including driver inputs to be part of the control process. However, such systems place a challenge on the design process due to the fact that obtaining reliable human behavior models are difficult due to the complex nature of the driving task in a dynamic traffic environment. From a control theory perspective, driving can be seen as a combination of continuous control segments combined with a discrete decision process (Leen et al., 1999).

Research Objectives

The objective of this research effort is to develop an efficient, robust, and intelligent approach to detect and mitigate various levels of driver distractions. The proposed approach should be capable of distinguishing between various levels of driving distractions that require different amounts of visual and mental load to perform a secondary task. The suggested solution consists of two major phases: i.) Detecting various levels of driver distractions (low, medium, and high) using a learning machine system. ii.) Mitigating the effects of driver distractions by educating the vehicle active safety systems with the detected driver status. Based on the detected level of distractions, time to collection (TTC), lane position (LP), and steering entropy (SE) the active safety system will provide appropriate actions to maintain drivers' safety. Another main objective of this effort is to increase the efficiency of the current vehicle active safety systems by feeding it with driver distraction levels.

Research Questions

The goal of this research effort leads to the following research questions:

- Will the suggested approach be able to efficiently detect and distinguish different levels of cell phone-based driving distractions?
- Can we integrate the early detected operator status into the current vehicle active systems to increase safety?

Outline

Chapter 2 includes a highly focused literature review that discusses and analyzes the research in this area, and also contains a suggested categorization of the current solutions. Chapter 3 discusses the proposed approach; design, implementation, and the methodology in detail. Chapter 4 provides the implementation and the outcomes. In addition, results and evaluation also are included in this chapter. Finally, chapter 5 represents the conclusions, and the future work.

LITERATURE REVIEW

Most of the uncertainty in a driving scenario stems from variations in the sudden situations, as well as long term capability of the driver, changing environment, and their interaction. Therefore, the optimal solution to decrease road accidents would be significantly beneficial by making the vehicles active safety system 'aware' of the driving context as well as driver status (distracted, neutral, aggressive, drunk, drowsy etc.). This can be achieved by analyzing driver behavior information, including driver input, as part of the control process. However, such systems create a challenge in the design process because obtaining reliable human behavior models are difficult due to the complex nature of driving in a dynamic traffic environment (Al-Sultan, Al-Bayatti, & Zedan, 2013). From a control theory perspective (Doyle, Francis, & Tannenbaum, 1992), driving can be seen as a combination of continuous control segments combined with a discrete decision process.

In general, the main goal of detecting abnormal driver behavior is to reduce the number of traffic accidents, decrease fatalities, and increase safety on the roads. Research in this area suggests a solution to detect different kinds of abnormal driver behavior. The importance of abnormal driver detection studies is based on identifying whether or not a driver is responsibly driving. Therefore, detection that a driver is drunk, aggressive, drowsy, tired, or distracted is not as significant as detecting nonstandard driving behavior regardless of the reason. The majority of these behaviors are overlapping with each other. According to federal motor carrier safety administration (FMCSA), excessive driver fatigue can lead to drowsiness (FMCSA, 2016). Another example of overlap between driver behaviors is the overlap between drowsiness and distractions as shown in figure 2.1 (Transportation Research Board, 2009).

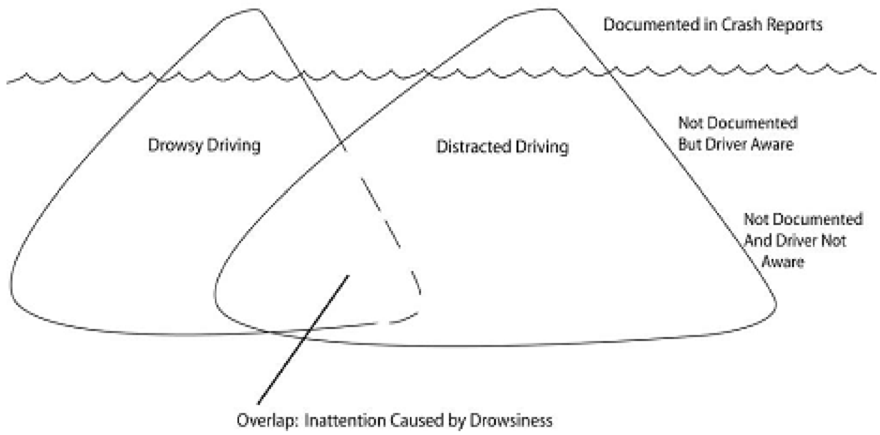

Figure 2.1. The relation between drowsiness and distraction (Transportation Research Board, 2009)

An intelligent interactive safety system can generally have three main stages: Input Processing, Modeling and Simulation, and Output (see figure 2.2). The input stage focuses on collecting pertinent information from the user, the vehicle, and the environment. The modeling stage detects the presence of specific event occurrences in the input data, and deduces certain logical conclusions based on those occurrences. Identified events in the input can be single events, sets of concurrent events (composite events), or repeated sequences (patterns). The modeling stage often arrives at specific conclusions based on the inputs. The output stage typically involves one or more executable actions that are based on the conclusion of the modeling stage. They could activate or deactivate certain systems in the car, or simply generate a warning. Our literature review revealed extensive research covering different parts of the landscape just described. Most current research focuses on the first stage, or a combination of the first and second stages. Few researchers addressed the output stage in their work.

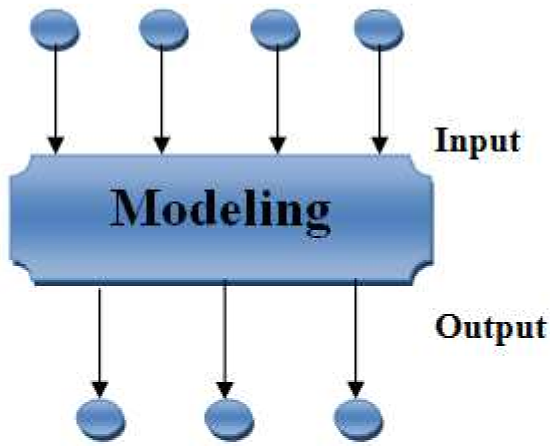

Figure 2.2. Intelligent interactive safety system

A driver's actions are a primary factor in the driving activity as the driver continuously interacts with certain vehicle control/auxiliary parts and the vehicle's environment. These interactions create observable patterns related to the driver's actions. The patterns could be used to detect abnormal driver behavior.

Due to the significance of this research area, several researchers from various educational and relevant backgrounds have studied and proposed approaches to detect abnormal driver behavior. As a result, driver behavior detection has been addressed from different perspectives that include: engineering, cognitive science, and physics. In order to review several driver behavior detection approaches, this study categorized the current solutions into four categories: behavioral measures-based detection approaches, physiological conditions-based detection approaches, in-vehicle measure-based approaches, and hybrid-based approaches.

Behavioral Measures-Based Detection Approach

The behavior measured based solutions are the most popular solutions. Most of behavioral-based detection approaches share the idea that the facial expressions of a driver could be monitored through a camera and could be used to detect driver behavior (as shown in figure 2.3). In other words, the thought behind these kinds of solutions is to seek and record physical driver behaviors and features, which includes: eyes status (open/closed), eye gaze, head nodding, face color, or any other driver behaviors that can help detect nonstandard driving. In order to identify driver behavior, physical sensors combined with image processing technology have been used to monitor, collect, and detect a driver's facial expression.

Figure 2.3. Driver eye and gaze tracking (Collett, 2016)

Particular methods or techniques have been used to extract certain features. Behavior measures-based approaches are widely adopted by many researchers due to the fact that most driver behaviors can be detected by observing and collecting driver's visual information (Hartley, 2000). Therefore using the measurements based on driver behavioral observations to detect driver behavior has been found to be a reliable method to predict driver behavior and has been used in commercial products such as SeeingMachines and Lexus. Figure 2.4 represents the backbone of the behavioral-based detection approach. As shown in the figure, the main processes of this approach are: driver face detection, driver eye and facial part detection, eye and other facial parts tracking, features extraction, abnormal driver detection, and finally decision making process.

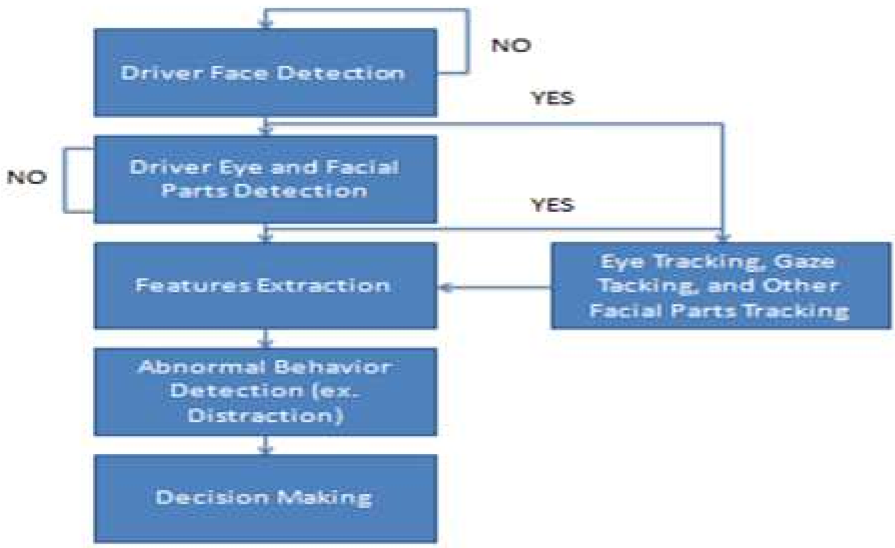

Figure 2.4. Behavioral measures-based approach

Some of the behavior-based detection approaches rely on a single factor to detect abnormal behavior (i.e. single factor-based solutions). In 2001, Veeraraghavan & Papanikolopoulos proposed a behavior measure-based approach to detect driver fatigue. The proposed solution employs image processing and eye tracking techniques to detect the driver's face and extract features such as eye state (open or closed). In order to capture the driver's face in real time, a video camera was directly mounted towards the driver’s face. The collected output of the camera, which represents continued stream of images, was the main input to the proposed approach. These collected images were processed to monitor the driver's eyes by comparing the consecutive frames to detect micro-sleeps, defined in the paper as short periods of sleep.

The main drawback of this approach is neglecting certain realistic scenarios such as the fact that many drivers wear sunglasses while driving, which make the suggested approach unusable (Sahayadhas, Sundaraj, & Murugappan in 2012 ;Veeraraghavan & Papanikolopoulos, 2001). Also, instead of using the entire face as an input to extract eyes state (open or closed) several eye tracking approaches could achieve the same work with better performance and accuracy. Moreover, execution times for some typical image-processing techniques are associated with high computational time while real practical problems in image processing requires high end parallel computing to avoid significant delays in the processing time. In 2009, Yu Xun suggested a solution to detect drowsiness by monitoring whether the driver's eyes are open or closed (Yu, 2009). If the driver's eyes are opened, the degree of eye openness will be calculated and compared to threshold values before making the decision.

Dong and Wu proposed an algorithm to detect driver fatigue based on the distance between the driver's eye lids while driving (Dong & Wu, 2005). The study relies on computer science and image processing to locate and extract body features. An image processing technique that depends on skin colors has been used to locate a driver's face, then the driver's eyes are recognized by projections and finding connected components. The study includes a comparison between the proposed approach and other behavior measures-based detection approaches. The results show high eye detection rates and high fatigue detection rates compared with other methods. However, like most eye tracking-based driver behavior detection approaches, the issue with the proposed solution is neglecting many realistic scenarios such as wearing sunglasses or a cap while driving. Currently, eye tracking could be done using electronic potentials measured with electrodes placed around the eyes (Sahayadhas, et al., 2012). Nevertheless, using electrodes to monitor a driver's eyes status is considered an intrusive and unpractical solution.

In order to overcome the limitations and drawbacks of using eye tracking techniques to detect driver behavior, several researchers addressed the problem from different perspectives. The correlation between gaze directions and the external traffic environment (such as pedestrians, traffic signs, and road status; straight, and curved) has been used to detect abnormal driving (Apostoloff, & Zelinsky, 2004; Fletcher, Loy, Barnes, & Zelinsky, 2005; Hirayama, Mase, & Takeda, 2012). For instance, in 2004, Apostoloff & Zelinsky could track the visual behavior of the driver to the road by tracking the driver's gaze direction and using a lane tracker system. Due to using gaze direction and lane detection systems, the proposed solution represents an example of integration between vision inside and outside the vehicle.

An alternative approach that does not rely on a driver's visual observations was conducted to determine the alertness level of the operator (Desai & Haque, 2006). The research suggested an approach to overcome many issues related to previous work such as the influence of the external environment (traffic, weather, and lightness, etc.) on the performance of the system. The proposed solution is based on the idea that the pressure on the accelerator pedal can be used to determine the level of driver alertness. The research installed a pressure sensor on the accelerator pedal to detect driver fatigue. Baek, Chung, Kim, and Park, (2012), Yu, (2009) applied the same idea in which angle sensors were mounted on the steering wheel to measure the driver's steering activities. A distracted driver would cause high jitter in steering angles that can be captured by steering wheel angle sensors. In fact, rather than using mounted sensors to collect vehicle data, CAN-bus can be easily utilized to access most of in-vehicle data such as speed, acceleration, steering angle, and accelerator pedal pressure (in-vehicle measure-based approach will discuss this part). CAN-bus is a vehicle that is used by a vehicle's microcontroller parts to communicate and exchange data. Therefore, bus data would be more accurate and reliable than the collected data pressure or angle steering sensors because of the influence of the external environment on the sensors' readings.

The idea of mounting pressure sensors on the steering wheel is a significant invention that is related to a vehicle's safety system. This invention was registered as a patent “Steering Wheel with Hand Pressure Sensing" (Lisseman, Andrews, & Bosch, 2011). This invention aimed to mitigate the increase of potential distractions that are associated with portable devices such as cell phones, mp3 players and iPods. In many cases, the interaction with these electronic devices requires drivers to take their hands off of the steering wheel. Therefore, identifying the presence of the driver's hands on the steering wheel is a significant factor in detecting distracted drivers. In order to overcome the main limitations and drawbacks of single factor-based approach, multiple factors-based approach appeared to increase the accuracy of the detection algorithms of driver distractions.

On the other hand, multiple factors-based approaches appeared as a result of accuracy issues associated with some of single factor-based solutions. Including more than one factor into the design would increase the detection accuracy of (Sigari, Fathy, & Soryani, 2013). Besides the low accuracy rate, relying on a single factor would cause a high false positive rate (Sigari, Fathy, & Soryani, 2013). For example, Apostoloff and Zelinsky (2004), Dong and Wu (2005); Fletcher, et al., (2005); Hirayama, et al. (2012); Veeraraghavan and Papanikolopoulos (2001) were successfully able to extract the driver's visual features, yet they suffered low detection accuracy and false positives compared to other multiple factor based detection approaches. As an alternative method, Sigari, et al., (2013) suggested a driver's face monitoring system for fatigue distraction detection using multiple factors extracted from a driver's face and eyes rather than a single factor. The study used the following factors: head rotation, percentage of eye closure, eyelid distance change with respect to the normal eyelid distance, and eye closure rate. Similar to Sigari, Fathy, and Soryani (2013); Batista (2007) suggested a solution based on a computation of eyelid movement parameters such as eye blinking and head orientation that represents point of attention. Sigari, et al., (2013); Batista, (2007) distinguished their work from other multiple factor based eye tracking approaches by having multiple factors from different visual expressions (driver's head gaze and eye movements). Contrasting, Hirayama, et al., (2012) suggested a solution to monitor two different factors from the same visual expression (driver's eyes blinking and closure rate). However, relying on more than one visual expression would increase the overall detection accuracy and reduce the false positives of the proposed approach (Batista, 2007).

Desai and Haque, (2006); Krajewski, Sommer, Trutschel, Edwards, and Golz, (2009); Lee, Li, Liu, and Chen, (2006) followed the same approach, in which visual observations such as eye~~s~~ conditions and movement, head movement, and facial expression have been used to identify driver behavior as well. Physical sensors were used to collect data and then a specific method such as image recognition to extract certain features was applied. (Lee, et al., 2006) used multiple fixed cameras to capture facial expressions, eye movement, head movement, and gaze movement. The collected data was processed and then patterns were generated to identify the driver's behavior.

Although behavior measures-based approaches have several advantages, some performance, applicability and intrusion issues are still related to some of them. According to Sahayadhas, et al. (2012), the accuracy of behavioral measures-based detection approaches would be negatively affected by many factors. These factors include: driver activities (e.g. adjusting the radio, talking to passengers, or picking up a beverage), environmental backgrounds, and driving conditions. In addition, these approaches require a very precise camera for drivers.

Physiological Conditions-Based Approach

Due to the limitations and detection accuracy issues that are related to facial expression and eye/head tracking solutions, other studies addressed the distracted driving issue from different perspectives. The thought behind these approaches is to track and monitor the physiological changes of a driver while driving. Such physiological changes include: heart rate, blood elements, skin electric potential, and electroencephalographic activities (EEG).

Electroencephalogram activities-based approach. Several researches proved that the EEG signals could be used as a sign of a driver's alertness level (Akin, Kurt, Sezgin, & Bayram, 2005; Keren, Yuval, & Deouell, 2005; Tagluk, Sezgin, & Akin, 2010). The changes in the EEG spectrum accompanying performance are correlated with abnormal behaviors such as distraction, drowsiness or fatigue. Similar to the EEG spectrum itself, the precise pattern of correspondence between the EEG and behavior is different for each individual. This correlation shows stability within individuals across sessions, which can lead to practical applications such as monitoring and detecting abnormal driver behavior. Several researchers proved that it is feasible to accurately detect driving errors using a multi-channel EEG power spectrum (Akin, Kurt, Sezgin, & Bayram, 2005; Keren, et al., 2005). Figure 2.5 portrays a flowchart of processing EEG signals to evaluate the alertness level of the driver.

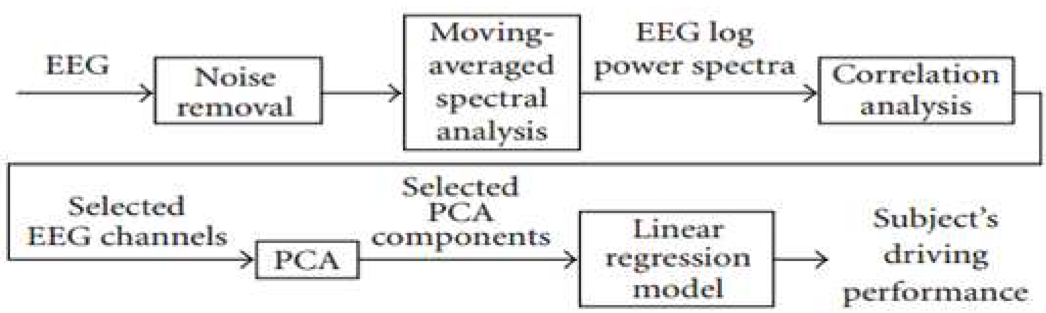

Figure 2.5. Flowchart of EEG signals processing (Sezgin, & Bayram, 2005).

The first 3 phases are common in most EEG approaches. In the noise removal phase, a simple low pass filter was used to remove low and high frequency noises. Then the researcher calculated the average power spectrum for all the channels they used. The calculated average was used in the next phase by calculating the correlation coefficient between the driving performance of the driver and the log power spectrum of all EEG channels at certain frequencies. Finally, the Principle Component Analysis (PCA) was used to decompose the highest correlation coefficients while the highest Eigen values were chosen to be the inputs to the linear regression model to estimate the driving performance of the driver. The study shows the feasibility of using multichannel EEG power spectrum to detect drivers' errors and to estimate drivers' performance.

Healey and Picard (2005) conducted research consisting of multiple experiments to propose a solution to monitor the relative stress levels in daily car driving tasks. The paper suggested an approach for measuring stress using physiological signals. These signals include: electrocardiogram, electromyogram, skin conductance and respiration. Data were collected from various drivers in a real time driving environment. The recorded data were used as an input of linear discriminant analysis to detect stress levels. The drivers were instructed to follow certain routes where certain levels of stress were planned to occur. Similar to other physiological-based approaches, this approach provided feedback about a driver by continuously collecting data without interfering with the driver’s task performance. The high detection and accuracy rates in this study were due to include multiple physiological signals in the detection algorithm rather than a single factor.

Although approaches based on EEG signals have some advantages over other abnormal driver behavior detection approaches, the main issue with the EEG approach is being an intrusive solution and requiring a high collaboration from the driver. The possibility of using multi-channel EEG data to predict the inconstant global level alertness by measuring the driving performance index (i.e. the deviation between the center of the vehicle and the center of the cruising lane) was also investigated (Sezgin, & Bayram, 2005).

Vital signs-based approach. In order to limit the intrusiveness problem in EEG-based approaches, driver behavior detection has been addressed from different perspectives. One of these perspectives is vital signs. Chieh and Isa (2011) followed an approach that depends on vital signs where the abnormal driver behavior was detected based on three different human factors. These factors are: facial expression, thermal imaging, and heart rate. In order to collect the required data a visual camera, a thermal camera, and a wireless heart rate were used. In addition to these physical sensors, an artificial intelligence system has been implemented to predict abnormal and dangerous driver behavior incidents and to alert the driver. The main impact of this solution is the inclusion of an artificial intelligence system with multiple human factors to detect if the driver portrays abnormal states and then acquire a decision on whether the driver behavior showed any abnormality. As a result, the accuracy of the detection would increase. On the other hand, having many inputs in this study increased the amount of collected data, which could lead to reducing the processing time. In order to resolve this issue the paper suggested parallel processors instead of using a single CPU. One of the issues the study does not address is a driver with an elevated heart rate caused by disease and not related to driving intoxicated. Unlike other approaches, no false negative or positive was addressed or measured in this study. In addition to previous drawbacks, usability of the proposed approach is a major issue since not all drivers feel comfortable monitoring their heart rate while driving.

Dissimilar to the other physiological based driver behavior detection approaches, Intelligent Transport System at Minnesota University suggested a non-intrusive solution (Malik, et al., 1996). Instead of placing the sensors and electrodes on the body of the driver; each part of the steering wheel was covered with conductive fabric (biosensors and electrode) that is used to collect physiological data. Besides using the steering wheel, the conductive fabric was placed on the driver's seat backrest as a second non-intrusive method. The driver's heart rate was measured to generate the power spectral density (PSD) (Malik, et al., 1996). The suggested non-intrusive methods in the study were used to collect the physiological data and then the researchers applied other findings attained from further researchers that portray the ratio between low frequency band to high frequency band decreases when human condition changes from awaking to drowsiness (Elsenbruch, Harnish, & Orr, 1999; Tsunoda, Endo, Hashimoto, Honma, & Honma, 2001). Similar to solution Malik, et al., (1996), Baek, et al., (2012) suggested a non-intrusive solution using biosensors that were installed in the back of the driver's chair that contained high-input impedance amplifiers, and specific kind of conductive textiles installed in the seat capable of collecting electrocardiogram data through clothing. Several limitations and issues such as practicality, accuracy, and driver comfortability could be negatively affected by these approaches. According to Yu, (2009), the pulse wave sensor measurement could be sensitive to hands where the method and the strength of holding the steering wheel by a driver could affect the sensors' readings. Besides, heart rate variability (HRV) is a unique metric for individuals that would lead to difficulties in creating a general detection pattern. One of the other issues is the other parameters that could affect the driver behavior, which make physiological conditions solely incapable of detecting driver behavior (Yu, 2009). For example, a driver might suffer a disease that can cause an increase in heart rate preventing this method from creating a general pattern of abnormal driver behavior.

In-Vehicle Measures-Based Approach

The main thought behind in-vehicle measure-based approaches is using a series of data analysis methods to evaluate the driving proficiency and detecting driver errors. Such approaches use in-vehicle operating data as an input of abnormal driver behavior detection algorithm. These data include: speed, acceleration, engine torque, the brake pressure, steering angle, traction, and yaw rate. Many researches who addressed this topic from an engineering perspective have conducted their studies based on the hypothesis that driver behavior can be characterized as a sequence of basic actions. These actions can be associated with a specific state of the driver-vehicle- environment and characterized by a set of observable features. The presence of repeated sequences of the driver actions are called patterns, which are generated by collecting different kinds of data such as speed, acceleration and steering angle at a certain time.

Al-Sultan, et al., 2013 proposed a solution to detect four types of driver behavior in real time driving. The driver behaviors that have been addressed in this paper include: normal, fatigued, drunk and reckless driving. The proposed approach used the Bayesian network model to perform probabilistic reasoning to infer with the behavior of the driver. The input of this model has been collected from different research papers and the collected data has been gathered from different kinds of sensors to create certain patterns. The inputs were collected by physical equipment such as cameras, speed sensors, GPS, alcohol and the accelerometer sensor. The proposed approach was implemented based on three phases: the sensing phase, reasoning phase, and the application phase. The contextual information that was collected in the sensing phase represents the input of the reasoning phase which used a Dynamic Bayesian network algorithm to detect the behavior of the driver. The study also proposed a corrective action algorithm, which aims to suggest the proper actions for other vehicles in the road in case the detection algorithm detects abnormal behaviors for the driver.

The study neglects many details of the action algorithm and instead focuses more on the detection algorithm. Moreover, the study did not mention the structure, content and format of warning messages that have been used in the proposed action algorithm besides the dissemination methods. Another issue in this study is using data from other literatures rather than collecting the data directly, which could be unreliable.

The Hidden Markov Model and Gaussian Mixture Models were used to establish a pattern of driver characteristics based on the collected data from the CAN-bus (Choi, Kim, Kwak, Angkititrakul, & Hansen, 2007). These data include steering wheel angle, brake status, speed, and acceleration. Five actions were considered as driver distraction tasks: calling a video portal, controlling the radio, controlling the window, talking with an assistant, or performing some common tasks. In addition to distraction tasks, the researchers specify six long term behaviors: turn left, turn right, lane change left, lane change right, stop, and neutral driving. The main issue was low accuracy for driver identification and distraction detection besides the limited number of distraction tasks that were addressed. Similar to Choi, et al., (2007), Mitrovic (2005) conducted a research using Hidden Markov Model to recognize driving events. The study refers to driving events as any significant change in vehicle speed or attitude such as stop, or turn right or left. The researchers developed a data acquisition system which includes: accelerometers, gyroscopes, and a GPS. The idea behind this study is to observe frequently occurring patterns in driving since most drivers visit similar locations (school, job, friends' houses, and relative's houses). By identifying a driver's patterns, lots of useful information could be gathered to assist in event driving detection. The main challenge in this approach is the more places the driver visits, the more patterns there are. Assigning a pattern to each place a driver visits can be an impractical way of detecting the driver's behavior since individuals may visit new places daily.

To overcome some drawbacks of other in-vehicle measure-based approaches, another study was conducted by Jensen, Wagner, and Alexander (2011) to evaluate driver performance and detect driver behavior. An in-vehicle measure -based approach was proposed to evaluate driver performance based on three analysis methods: data threshold violations, phase plane analysis with limits and a recurrence plot with outlier limits. In this research, six different driver classifications were studied: timid, cautious, conservative, neutral, assertive and aggressive. This study establishes a single and multi-variable threshold analysis methodology, as well as a recurrence plotting strategy to assess drivers during their ordinary driving conditions. Every instant value that is larger than the specified threshold was considered a violation. Real data were collected by having the participants drive for two weeks after equipping their vehicles with the Engine Control Unit (ECU) data device. The CAN data recorder was used when driving to collect data such as speed and acceleration. The research model was implemented based on various gathered inputs, which include: the vehicle speed, engine speed, coolant temperature, and throttle percentage. As a result of input variations, the detection accuracy was high. In addition, an important advantage of the proposed approach is the suggested data collecting method. Using an in-vehicle data acquisition device mounted to the OBD-II diagnostic port with no interaction with drivers makes them more comfortable. In spite of several advantages of this study, the research includes some drawbacks such as the limited number of participants which could affect the accuracy of the results. Another extended study that investigates such concepts with a larger number of participants and refinements of the methodology would be needed.

To employ standard measurable safety parameters Lu & Wang, (2011) conducted research in which a K-means clustering algorithm was used combined with measurable safety parameters to distinguish four different longitudinal driver behaviors. These behaviors included: aggressive versus prudent, unstable versus stable, risk prone versus safety prone, and non-skillful versus skillful. The paper included several measurable safety parameters from automotive engineering perspective including:

- Average level of time headway during car-following (T_{HW})
- Fluctuation level of the time headway during car-following (σ_{THW})
- Fluctuation level of the time headway during car-following using standard deviation (σ_{TTCi})
- Brake response time of the driver to the lead vehicle deceleration (T_{RESB})
- Accelerator release response time of the driver to the lead vehicle deceleration (T_{RESA})
- Preferred danger estimation level to trigger brake pedal activation (T_{TCi})

- Preferred danger estimation level to trigger accelerator pedal release (TTCi)
- Pedal switch urgency level (Tsw)

Using these standard measurable parameters increased the accuracy and efficiency of the proposed approach as well as led to high detection accuracy and more reliable results. According to Lu and Wang (2011), carrying out the same concepts by real world environment instead of simulation would validate and evaluate such work.

Unlike other research that depends on biometrics features to detect drunk drivers, a more applicable approach was proposed using specific smart phones (Fazeen, Gozick, Dantu, Bhukhiya, & González, 2012). The main idea was to use a smart phone equipped with an accelerator and orientation sensors to read the data and compare it with distinctive drunk driver patterns. The proposed detection algorithm relies on extracting and analyzing drunken behavior based on lateral and longitudinal accelerations and the lane position maintenance. Currently, many smart phones are equipped with accelerator and orientation sensors, which make this solution convenient and realistic to detect drunk drivers in a real time manner. However, the increase in smart phone power consumption caused by the proposed algorithm negatively affected battery life (Fazeen, et al., 2012). In order to overcome this limitation, the proposed approach can be implemented in the vehicle itself using available sensing data such as location by GPS, speed and acceleration by the CAN-bus and lateral acceleration by a gyroscope. (Imkamon, Saensom, Tangamchit, & Pongpaibool, 2008) addressed the issue from different perspectives. One of these perspectives was slightly different from previous in-vehicle measure-based approaches. An On-Board Diagnosis II (OBD-II) reader was used to collect the engine speed and velocity of the vehicle. A fuzzy logic system was used to classify three different levels of danger. In order to train the fuzzy interface, a survey was used to collect the opinions of passengers to rate how safe they feel. Using the fuzzy interface helped build an accurate and learning intelligent system to detect variant levels of danger. Although a large number of information could be collected from the CAN-bus, most of the current studies in driver behavior and distraction detection utilized limited inputs from the various available data.

Hybrid-Based Approach

The idea behind these types of approaches is to combine the advantages of two or more different categories (i.e. Behavioral measures-based, Physiological-based, and In-vehicle measure-based) together in one solution. For example, the approach using the CAN-bus data (i.e. vehicle data) combined with driver's eyes status (behavior measures-based) to detect driver behavior would be considered a hybrid-based approach. Unlike behavior measures-based approaches, hybrid-based approaches depend on more than a single factor from different categories. The main advantage of hybrid-based approaches is combining the strength of two or more different categorized driver detection approaches into one behavior detection approach.

UTDrive project is a platform for a human- machine interactive system (Angkititrakul, et al., 2009). This platform is an ongoing project to collect and analyze multimodal data gathered for modeling driver behavior while the driver is performing other secondary task such as talking on the cell-phone or operating a navigator (GPS). In order to build such platform to recognize driver behavior, a comprehensive understanding of human behavior besides mathematical models is required. Li, Jain, and Busso, (2013) suggested one of the best examples of the hybrid driver behavior detection approaches that used the UTDrive platform to detect a distracted driver. A solution to detect a distracted driver was proposed by using a video camera to capture the driver's face, a microphone to capture the driver's audio, a road camera for lane tracking, and a data bus reader to collect the vehicle activity. Figure 2.6 shows the proposed multimodal information to monitor driver behavior.

Figure 2.6. Monitoring driver behavior model

Figure 2.6 shows the combination of all visual and acoustic observations and CAN-bus activity in one solution. In this paper, a distracted driver was defined as a driver who is voluntarily or involuntarily involved in a secondary task that causes diversion of attention from the primary task (driving). These secondary tasks include: operating a radio, operating and following a navigation system, talking to a passenger, and talking on the phone. The distractions generated by fatigue, drowsiness, alcohol, aggressiveness or other sources of distraction were neglected in this study.

The CAN-bus information used to detect a distracted driver includes: steering wheel angle, vehicle speed, and, brake pedal pressures. Furthermore, the acoustic information that is relevant to secondary tasks recorded talking on a cell phone or following a GPS. Finally, a video camera mounted inside the vehicle facing the driver is used to collect visual observations which consist of: head yaw and pitch values, eye movements and closure rate, and blink frequency. These values were estimated with CERT algorithm, which was developed by (Whitehill & Movellan, 2008). The proposed approach was tested and evaluated based on a real world driving environment involving conditions that are hard to replicate in simulation. Using a real driving environment is considered one of the major advantages of this approach. In addition to a real world environment, multiple factors were taken into consideration from different perspectives, including vehicle measures and visual and acoustic observations that would combine the advantages of both approaches in one solution. On the other hand, the proposed approach suffers from a few issues and limitations that include: neglecting the learning effect of the driver, and neglecting the driver behavior changes due to weather and illumination conditions (Whitehill & Movellan, 2008). Additionally, the corpus was recorded using a predefined route (Whitehill & Movellan, 2008). Cheng, Zhang, Lin, Feng, and Zhang (2012) proposed another hybrid-based driver behavior detection approach in which a drowsy driver was detected using many factors that include: abnormal eye behaviors, steering wheel activity, and vehicle trajectory. However, this approach still experiences some limitations of behavior measures-based detection approaches.

Discussion

The detailed review of several research papers in regard to the inattentive driver behavior detection approaches, showed that the current approaches could be classified under certain categorizes. This classification is based on the measures that are used in the proposed algorithm. For example: the measures that are used in behavior measures-based approaches include: head pose, eye blinking, yawning, and eye closure. Physiological measures-based approaches measures include: heart rate, blood pressure, and physiological signals. In-vehicle data measures-based approaches include: steering wheel, acceleration, speed, and brake value. Meanwhile, the hybrid approach measures include the combination of two or more of other categories measures.

Behavior Measures-Based Approach: due to the large quantity of research work in behavior measures-based driver approach, many methods are used in data acquisition and feature extraction. This variance of methods led to both a high detection accuracy rate and a low false positive rate. Because an image process and computer vision techniques were used to extract a driver's visual features in most behavior measures-based approaches, these solutions can be considered computerized approaches. Furthermore, behavior measures-based approaches are considered non-intrusive behavioral approaches because they lack of a direct contact/interact with the driver.

Although behavior measures-based approaches have many advantages, these approaches suffer from certain limitations and disadvantages. Data acquisition methods are one of the limitations that could significantly impact behavior measures-based approaches. For example, a driver who wears glasses would cause a serious problem to eye based detection approaches, and a driver who wears a cap or scarf would cause issues to head based detection approaches. Another main issue with the eye and head movement tracking approaches is the need to perform an intensive calibration process for each individual. For instance, to evaluate some approaches, applicants were not allowed to move their heads and only very slight head motions were allowed whereas recalibration was needed whenever users moved their heads. In addition to an intensive calibration, lighting is another limitation, because regular cameras could contain issues with acquiring detailed data. Instead, some researchers used infrared light emitting diode to overcome regular camera limitations. However, infrared light emitting diodes do not operate well during the day. Due to this limitation, most researchers used a regular camera during the day and an infrared camera during the night.

Physiological Measure-Based Approach: unlike in-vehicle data and behavior measures-based driver behavior detection approaches, physiological based approaches can detect driver behavior in very early stages. This early behavior detection helps take early proper action such as alerting a driver in a timely manner to prevent road accidents. One of the other advantages of physiological condition-based approaches besides early behavior detection is the high reliability and accuracy of these approaches. The main disadvantage of a physiological condition-based approach is the intrusive nature of these approaches. In order to collect physiological conditions such as heart rate or blood pressure wired or wireless devices need to be attached to the driver's body which makes these approaches intrusive and non-practical. To overcome the intrusive nature of these solutions, some researchers added wireless sensors on steering wheels or on the driver's seat rather than on the body of the driver. However, these solutions are still considered as none fully comfortable solutions for the drivers. In addition, sensitivity of bio and EEG sensors to impedance changes and disturbance caused by external environment noise, could negatively affect these solutions.

In-vehicle data measures-based approach: unlike physiological-based approaches, in-vehicle data based approaches are considered fully non-intrusive approaches because they use in-vehicle data operating data that is available on the CAN-bus as an input of the driver behavior detection algorithm. The CAN-bus is one of the important and rich resources of information that includes vehicle speed, vehicle acceleration, brake pressure value, steering wheel angle, and gas pedal pressure. These available data have been exploited by many researchers to create patterns associated with abnormal driver behavior such as distraction, drowsiness, and fatigue. However, most of the current in-vehicle data based detection approaches have a limited number of inputs. The CAN-bus has thousands of available data that could be correlated with the driver's condition and be used to detect driver behavior. As a result, this can increase the accuracy of detection rate and decrease the false positive rate as well.

Hybrid measures-based approach: the hybrid-based driver behavior detection approach combines two or more different detection categories in one solution. Therefore, these approaches would include the advantages of more than one category. The hybrid based approaches have a high accuracy detection rate and low false negative rates due to include several inputs from different perspectives such as combine the visual observations and the CAN-bus inputs. On the other hand, having several inputs from different perspectives would increase the complexity of the system besides having limitations of each detection category.

Despite of these limitations of the hybrid driver distraction detection approaches, these approaches are still considered reliable and efficient due to the fact of having high accuracy rate and low false negative rate.

Driver Simulators to Investigate Distractions

Driving simulators provide researchers with various advantages to help them conduct their research in comparison to real vehicles. According to Winter, Van, and Happee (2012), these advantages include: controllability, reproducibility, and standardization: most driver simulators are capable of adjusting and manipulating visual traffic, road status (congestion level, traffic light, kind of roads), and weather conditions as a function of research aims. The ability to generate different driving scenarios enables the researcher to investigate the research question from different perspectives in a shorter time compared to the real environment. Also, simulators used for training enable trainees to be exposed to different driving scenarios, weather conditions, road status and hazards which can be risky and hard to create in a real world environment.

1. Ease of data collection: Many of the current driving simulators can measure driving performance accurately and efficiently. In most cases, conducting the study in a real environment can be a fundamental challenge to obtain accurate, complete, and synchronized measurement data. For instance, in one study using an equipped vehicle and a driving simulator, it was not feasible to calculate the distance between the car and a stop line on the road, whereas the simulator was able to readily obtain this information (Plantec, 2004). Also, Roskam, Brookhuis, Waard et al., (2006) pointed to the challenge of calculating the vehicle lateral position because it requires visible

and clear lane markers while weather conditions and shades can affect the correctness of the measurement.

2. Risk-free simulation of potential dangerous situations: Simulators can be used to train operators on how to deal with unpredictable or safety-critical tasks that may be improper to practice on the road, such as collision avoidance (Hoeschen, Verwey, & Bekiaris, 2001). Furthermore, simulators allow researchers to investigate different kinds of hazards perception by exposing drivers to several dangerous driving situations, which can be an ethically unacceptable endeavor in a real environment (Underwood, Crundall, & Chapman, 2011).

Driver simulators disadvantages. On the other hand, the current driver simulators still suffer from known disadvantages and challenges. According to Winter, Van, and Happee (2012), these disadvantages include:

1. Limited perceptual, physical, and behavioral fidelity: low fidelity simulators may induce unrealistic driving behavior and consequently result in invalid research conclusions. Simulator fidelity is known to affect user opinions. Low fidelity simulators can also demotivate participants and make them prefer a real environment. Käppler (2014), debates that the safety features that are considered one of the advantages of driving simulations can be interpreted as a disadvantage in some cases. For example, the real danger feeling and the real consequences of actions we experience are not the same in a driving simulator.
2. Lack of research investigating validity of simulation: a rising body of evidence points out that driving simulator measures are predictive for on the road driving performance (Bédard, Parkkari, Weaver et al., 2010). However, only a few studies have

investigated whether the learned skills in a driving simulator can be completely or partially transferred to the road (Strayer & Drews, 2003).

3. Simulator sickness (e.g. dizziness, headache, and nausea): this issue can ruin training effectiveness and also negatively affect the usability of driver simulators. Research shows that simulator sickness is more prevalent for old people than for young drivers (Brooks, Goodenough, Crisler, Klein, Alley et al., 2010). Studies also show that limiting the horizontal field of view, avoiding sharp curves or continuing to stop during the simulation experiment, along with using short sessions (less than 10 min), with enough breaks between sessions, significantly decreases simulator sickness (Brooks, Goodenough, Crisler, Klein, Alley et al., 2010).

Driver simulators evaluation. Using simulation to conduct research on operator behavior and to train operators has been around since the early days of flight history (Allen & Jex, 1980; Moroney & Lilienthal, 2009). Because training pilots in the real world environment is too expensive, the use of simulation is justified. However, it is more challenging to defend using driver simulation in investigating different driver behaviors, conducting research, and training drivers based on the cost. The most obvious advantage of using driver simulators is not related to the cost, but rather safety. During the last decade because driving simulators started being accepted practice to conduct research and training, many features and enhancements in terms of design, display, and capabilities were supplemented (Moroney & Lilienthal, 2009). These features aim to increase both validity and reliability of driving simulators. However, validity of many current driving simulators that are used to study driver behavior and conduct research is still a critical issue (Moroney & Lilienthal, 2009).

Simulation validity. Validity in behavioral studies refers to how well a measure and procedure does what it is supposed to do (Graziano & Raulin, 1989). Using a driving simulator as a research measure or training tool provides the researcher with a high flexibility represented by the capability of creating different scenarios under different conditions. As a result, the researcher can save more time, cost, and effort compared with conducting the research in a real world environment. Despite the huge benefits and wide use of driving simulators, some important technical details are still neglected by researchers. These technical details are related to how well the simulator represents the real environment (Graziano & Raulin, 1989). The decision of whether to use driver simulation to investigate a particular driver behavior should be based on whether the simulator is adequately valid to conduct that research (Kaptein, Theeuwes, & van der Horst, 1996). In Kaptein, Theeuwes, and van der Horst, (1996), the researchers discussed two different factors that can significantly affect the validity of driving simulators. These factors are physical validity and behavioral validity.

Physical validity. Driving simulators have different shapes, designs, capabilities, and sizes. Physical fidelity is the level in which the simulator replicates the physical properties of the driving situation, unlike behavioral fidelity, which is related to the ability of the simulators to replicate drivers behavior observed in the world. Low fidelity simulators~~:~~ consist~~s~~ of: personal computers with a gaming steering wheel, and pedal components with a normal chair. Figure 2.7 represents two different examples of low fidelity driver simulators that are used for video gaming and to conduct very limited research and training.

	
Narrow Field of View Desktop (NFOVD): Single monitor, desktop; 45° field of view; 50% image size; Sidewinder game controls; Iconic side view mirrors; Two School Districts; Students in driver education classes; One trained in computer lab; Second trained in back of classroom	**Wide Field of View Desktop (WFOVD):** Three monitor, desktop; 135° field of view; 50% image size; Sidewinder game controls; Real image side-view mirrors; Students recruited at local DMV office; Trained in laboratory environment and supervised by researchers

Figure 2.7. Low fidelity driver simulators (Allen, Park, & Cook, 2007)

Furthermore, medium fidelity simulators demonstrate a better level of driving experience that is close to real world environment by using advanced technologies utilizing comprehensive graphics and providing motion feedback to the driver. Figure 2.8 represents an example of medium fidelity driver simulator that is used for research in several universities such as Arizona State University, and Ohio State University. This simulator consists of: half of a vehicle (Ford Focus) that is connected to workstation simulation system, three outsized screens that project traffic scenes, and its rearview and side view mirrors display additional real-time images. These kinds of simulators can create hundreds of different driving scenarios, from a rural road with emergency vehicles to a city highway.

Figure 2.8. Medium fidelity driver simulator

Finally, high fidelity simulators can provide the driver with approximately a 360-degree view by the advanced sophisticated visual graphics, and dynamic feedback corresponding to the driver speed and acceleration. These kinds of simulators provide the driver with a high level of driving experience close to driving in real environment by using the following systems (Salaani, Heydinger, & Grygier, 2002):

- Control Feel System: accelerator and brake pedals apply software-controlled electrical motors to provide feedback.
- Motion System: it can rotate the physical part of the simulator around its vertical axis by a value close to 360 degrees in each direction.
- Visual System: comprehensive and sophisticated graphics with 3-D with and no edges.
- Audio System: The simulator acoustic system provides different kinds of sounds that emulate engine, tire, wind, and other vehicle noise, as well as special effects.

National Advanced Driving Simulator (NADS) is one of the most popular examples of high fidelity simulators and is located at the University of Iowa (NADS, 2009). This simulator consists of: a large dome that contains entire vehicle cab, which is mounted to a motorized turntable allowing 400 square meters of horizontal and longitudinal travel and close to a 360 degree view (sees figure 2.9).

Figure 2.9. High fidelity driver simulator (Salaani, Heydinger, & Grygier, 2002)

Behavioral validity. To ensure the results of driver simulator research equate to driving in the real world, simulators should be validated. Behavioral validity refers to the level to which the simulator creates the same driving experience that happens in the real driving environment (Mullen, Charlton, Devlin, & Bedard, 2011). In addition to comparing the performance in simulation and real environments, behavioral validity is defined in terms of absolute and relative validity (Mullen et al., 2011). Although absolute validity entails producing the same numeric values in both the simulation and real world driving, relative validity is established by whether the conclusions of the two environments are in the same direction and magnitude (Mullen et al., 2011). Many simulator-based studies rarely achieve absolute validity, but achieving relative validity is both highly possible and sufficient for researchers in most cases to draw their conclusions (Mullen et al., 2011).

According to Godley et al., 2002; Liu et al., 2009, it is possible for a high fidelity driving simulator to have the same behavioral validity as a low fidelity driving simulator, and draw the same conclusions (i.e. relative validity) from the same research conducted using both simulators. According to the same study, physical validity of a simulator is the one that is reported in most cases, and the behavioral validity is the neglected one. Also, the study discusses how methodological considerations related to research validation can affect the validity, including: research questions, dependent and independent variables, task conditions, simulator equipment, participant's characteristics, and how driver behavior is measured in the simulator

Advanced Driver Assistance Systems (ADAS)

Advanced driver assistance systems (ADAS) are technologies that mainly increase in-vehicle safety by alerting a driver in critical situations, providing a driver with information regarding the road, or automate and adapt vehicle systems. These technologies are either built-into the vehicle such as adaptive cruise control in modern cars, or an add-on such as a navigator. According to statistics and research, ADAS is one the fastest growing technologies compared to other automotive electronics systems in the vehicle (Hojjati-Emami, Dhillon, & Jenab, 2012). Some of ADAS technologies have been around for a long time such as built-in GPS navigator system that first appeared in 1995 Oldsmobile Eighty Eight. The importance of ADAS technologies are based on two different perspectives that include: send visual or/and acoustic alerts to the driver in potential conditions or implementing vehicle active system controllers that can take control of the vehicle in a critical situation (Hojjati-Emami, Dhillon, & Jenab, 2012; Lundgren & Tapani, 2006). An example of the first type of ADAS that provides information and alerts the driver, is to incorporate a GPS that provides the driver with information about the speed, traffic and the status of the road. On the other hand, adaptive cruise control is an example of active/intelligent system in which the basic functionality of cruise control system (i.e. maintaining a constant speed) has changed. These adaptive systems are capable of adjusting the throttle and brake to maintain a safe distance between vehicles. As a result, this mechanism can help prevent traffic collisions that are caused by distracted driving without intervention from the driver.

Next generation of ADAS and challenging. ADAS technologies are based on vision/camera systems, sensor technology, and in-vehicle data, or vehicle to vehicle/infrastructure communications (ex. GPS). Vehicle- to vehicle (V2V) and vehicle to infrastructure communication technology is the new promising domain to increase the safety on the roads. This next version where the vehicle passengers and the driver would be connected together to the external world requires the addition of intensive instruments that include many embedded devices, chips, and sensors. In fact, on September 5, 2014 Delphi Automotive PLC announced Delphi's wireless vehicle communication technology to extend the current ADAS technologies. Their system will be able using the radio signal to exchange traffic data between vehicles. According to this article, the vehicle that equipped with a certain ADAS technology will be able to notify the drivers about road conditions, traffic congestion, accidents, or any other emergency situations. Also, General Motor (GM) announced that they will launch Super Cruise advanced driver assistance system and vehicle to vehicle communications in 2017 model cars. According to GM, Super Cruise can control the car when a congestion alert is received and the driver will be able to drive hands free.

The most challenging issue is to secure the communication between vehicle to vehicle and vehicle to infrastructure (Leinmüller, Buttyan, Hubaux, Kargl, Kroh, Papadimitratos, & Schoch, 2006; Bai, Elbatt, Hollan, Krishnan, & Sadekar, 2006). What will happen if an intruder was able to send a false alert to other vehicles? What if these automotive systems got jammed by various false alerts by intruders? How is the identity of the message senders validated? Another serious issue is the intensive computation process and the high communication overhead and latency which can affect the performance of ADAS technology. In 2012, Schönwald, Viehl, Bringmann, & Rosenstiel suggested an approach to reduce both the communication overhead and computations that is caused by exchange messages between vehicles in order to be used by ADAS technology.

Finally, one of the most important ADAS technologies is to reduce the driver distractions, which eventually leads to reduction of accidents and an increase in safety. I would like to say that until self-driving vehicles are available to use, driver distractions will continue to be a significant issue.

Machine Learning

Machine learning is a fairly new discipline of artificial intelligent that gives machines the ability to learn and adapt without being directly programmed (Ayodele, 2010). Machine learning mainly focuses on dynamic environments, which change when exposed to new conditions or data. Similar to data mining, machine learning searches through data to observe and extract patterns. Unlike the data mining case in which the system extracts data for humans, machine learning model uses that data to extract patterns from trained data and to make predictions on new data. Machine learning algorithms were categorized as being supervised or non-supervised. In supervised algorithms case, the computer is provided with data that include inputs and desired output (training phase). Then, supervised algorithms will apply the knowledge that was established from the training phase to new data. On the other hand, neither labels nor desired outputs are given to the computer and its function to find the correlation, interference and data structure.

Several studies applied machine learning to implement a model that is able to distinguish between distracted driving and normal driving. Several of these studies used neural networks, Bayesian network, or support vector machine (SVM). Neural networks are an example of a learning algorithm that is inspired by our understanding of how the brain learns. One of the significant applications of neural networks is pattern recognition. During the training phase, the network is trained to associate outputs with certain input patterns. When the neural network is implemented, it recognizes the input pattern and tries to associate it with a specific output (see figure 2.10).

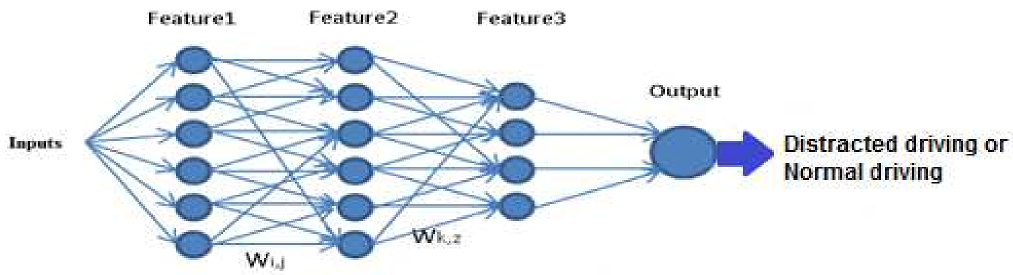

Figure 2.10. Neural networks to detect driving distractions

According to Akin, Kurt, Sezgin, and Bayram, (2008), the main advantages of neural networks can be summarized in:

1. Adaptive learning: an ability to achieve tasks based on the data given in the training phase while the initial experience processes
2. Self organization: neural networks can establish its own representation of the information it receives during learning phase.
3. Real time operation: neural network computations can be carried out in parallel, and the current hardware devices are designed and manufactured in a way to take advantage of this capability.
4. Fault tolerance: partial destruction of a system can negatively affect the performance of the system. However, some systems capabilities may be preserved even with major system damage.

In addition to use neural networks to detect driving distractions, other researchers used Bayesian network to recognize and observe the specific patterns associated with distracted driving. Bayesian networks algorithm is based on the joint probability distribution that can be computed over all the variables $X_1 \ldots X_n$ by using the formula:

$$P(X_1 = x_1, ..., X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i \mid Parents(X_i))$$

Where Parents (X_i) means the values of the Parents of the node X_i with respect to the graph

$$P(X_1 = x_1 \mid X_n = x_n) = P(X_1 = x_1, X_n = x_n) / P(X_n = x_n)$$

In order to support understand how Bayesian networks can be used to detect driver distractions, we analyzed one of the distraction scenarios. Figure 2.11 represents a backbone of Bayesian networks that was built for testing. In this figure, we represent the distraction as the first state (the parent node). We assumed that if the driver is distracted that will be reflected on in-vehicle data including velocity, steering angle, acceleration, and lane position. We applied the joint probability distribution formula to detect distractions. According to previous knowledge (training phase), when the driver is distracted the speed and acceleration goes down, start unintentionally departure the current lane, and moving steering unsmooth.

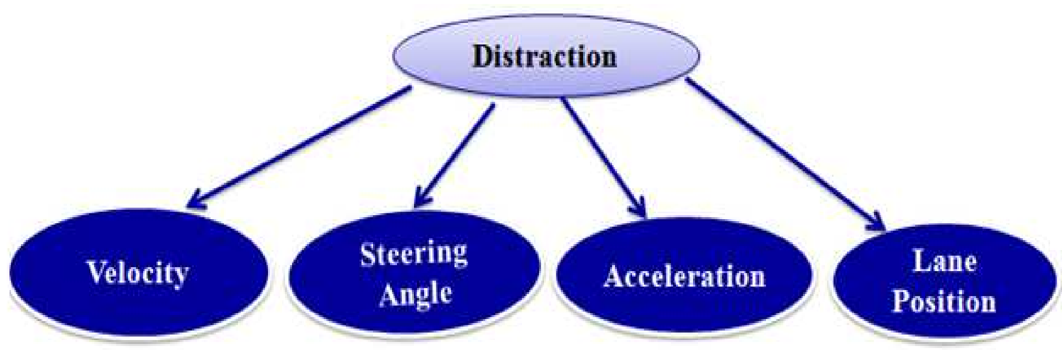

Figure 2.11. Driver Distraction and In-vehicle Data

By Applying Bayesian,

P (Distracted = True | Velocity went down = True, Steering Angle unsmooth = True, departure Lane Position = True, Acceleration went down = True) = P (Distracted = True & Velocity went down = True & Steering Angle unsmooth = True & departure Lane Position = True & Acceleration went down =True) / P (Velocity went down = True & Steering Angle unsmooth = True & departure Lane Position = True & Acceleration went down =True)

Now, by applying

$$P(X_1 = x_1,\ldots,X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i \mid Parents(X_i))$$

The output (All numbers are not real, it just to demonstrate distracted driving detection using Bayesian network)**:**

Table 2.1

Distraction certainty (numbers are not real)

Velocity	Accelaration	Lane position	Steering Angle	Distraction
T	T	T	T	0.92
T	T	T	F	0.87
T	T	F	T	0.85
T	F	T	T	0.87
T	F	F	T	0.84
T	F	T	F	0.85
T	T	F	F	0.81
T	F	F	F	0.12
F	F	F	T	0.18
F	F	T	F	0.12
F	T	F	F	0
F	T	T	F	0.7
F	T	F	T	0.5
F	F	T	T	0.37
F	T	T	T	0.42
F	F	F	F	0

As table 2.1 shows, if the velocity distracted pattern is true and acceleration distracted pattern is true, and lane position driver pattern is true the probability that the driver is distracted is 0.92 (high level distraction). Otherwise, if all of the driver patterns are false the probability of the distraction is zero.

The last machine learning algorithm that we would like to discuss in this section is support vector machine (SVM). It is an example of supervised machine algorithm that can be used for classification and regression challenges. In 1995, Cortes and Vapnik published a paper to introduce SVM algorithm to be used mainly for classification defined by separation hyberplane. The output of SVM is a hyberplane that can categorize new data. In this algorithm, each data item will be plotted as a point in n-dimensional space (where n is number of features) with the value of each feature being the value of a particular coordinate. Then, classification process will be performed by finding the best hyper-plane that well differentiates the classes. Support vector machine (SVM) is basically started as a method for binary classifications. The main idea is to find a hyperplane that can well separate the d-dimensional data into two classes. However, because realistic data are often not linearly separable, SVM proposed the notion of a "kernel induced feature space" that casts the data into a higher dimensional space (see figure 2.12).

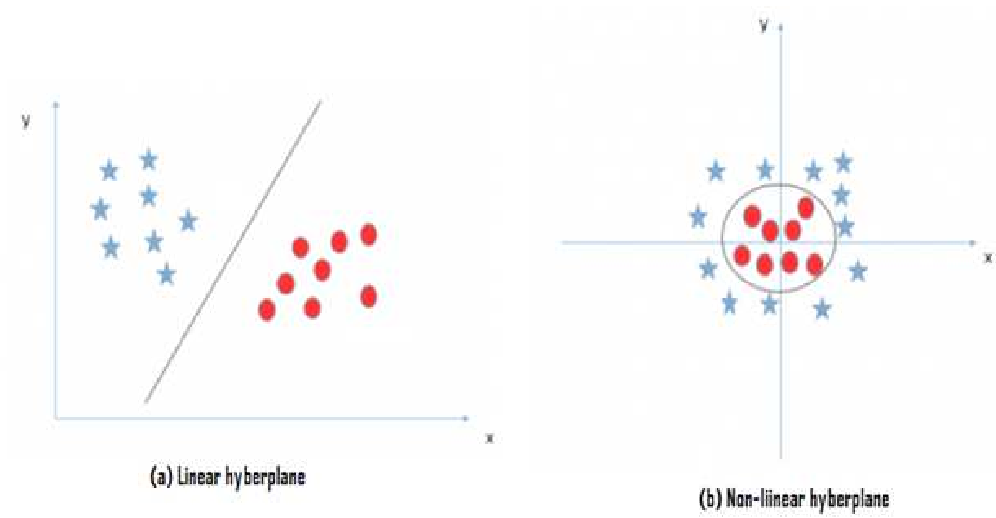

Figure 2.12. Linear and Non-linear hyperplane (SVM)

SVM were initially designed for binary (two-class) problems. When dealing with multiple classes, an appropriate multi-class method is needed. Cortes and Vapnik suggested comparing one class with the others taken together. This strategy generates n classifiers, where n is the number of classes. The final output is the class that corresponds to the SVM with the largest margin, as defined above. Although SVM is mainly for binary classifications, several researchers suggested methods to deal with multiclass problems. The most known strategy for multiclass problem is one against all (OAA). In this approach we should implement M (i.e. M is number of classes) binary SVM classifiers, each one of these classifiers should be able to separates one class from the rest. In order to achieve that, the ith SVM is trained with all dataset for that class is positive labels, and all the other classes with negative labels (Hsu & Lin, 2002).

The following advantages of the SVM approach were largely adopted from Auria & Moro, 2008:

1. SVM maximizes margin, so the model is highly accurate and more robust to noise.
2. SVM supports non-linear relations, so you can model linear and non-linear relations.
3. SVM usually offers a good out-of-sample generalization. In other words, by selecting a proper generalization grade, SVM can provide a less noise and more robust solution; even in case of the training sample has some bias.
4. Because the optimality problem is convex, SVM can easily find global optimum and exclusive solution. This is considered a big advantage compared to Neural networks that provide multiple solutions.

METHODS

This proposed approach consists of two main phases: Phase- 1 and Phase- 2. The first phase proposes a system to detect various levels of driver distractions (low, medium, and high) using Support Vector Machine (SVM). The second phase is to mitigate the effects of driver distractions through the integration between the distracted driving detection system (i.e. phase- 1) and the current vehicle active safety systems. In phase- 1, vehicle data were collected from advanced driving simulator, and face monitoring systems using visual based sensor (webcam). Then the model was trained and validated to detect different human operator distraction levels. In phase 2, several parameters were used as an input to the vehicle safety controller to determine the proper actions that maintain vehicle safety systems. These parameters include: level of distraction, time to collision (TTC), lane position (LP), and steering entropy (SE).

The DS-600c Advanced Research Simulator by DriveSafety™ similar to (Gilchrist and Winter, 1996) was used to investigate the driver cell phone-based distractions in different scenarios. The distraction was simulated through performing a secondary task while driving. In this study, the suggested secondary tasks were categorized based on the simplicity of the task and the visual and cognitive demands. Moreover, the suggested categorization was supported by previous studies (Klauer, Guo, Simons-Morton, Ouimet, Lee, & Dingus, 2014; Hosking, Young, & Regan, 2009; Cook & Jones, 2011). Other studies show that manipulating the phone while driving has higher risk than performing phone conversation. Therefore, task that does not require the drivers to take eyes off the road with low cognitive load too was considered to be a low distraction level.

Phase- 1 includes three sub phases: data collection, extract features, and then classification, which represents detection specific distraction levels. Figure 3.1 illustrates the main stages of phase- 1.

Figure 3.1. Phase- 1 main stages

First, data collection includes gathering all raw data that are required to identify the distraction levels. Second, feature extraction that includes finding and deriving interesting values and features from the initial set of the measured data. Finally, classification phase in which a trained classifier using machine learning strategy was implemented to be capable of identifying different levels of cell-phone driving distractions.

On the other hand, phase- 2 basically is a controller that fully integrated with the current vehicle safety systems. The main purpose of this controller is to provide appropriate actions corresponding to different levels of driver distractions. These actions can be variant from a simple action as acoustic signal or/and a visual signal, to more sophisticated actions including auto applying the emergency brake. The suggested actions mainly depend on the detected level of distraction (phase- 1). Figure 3.2 is a simple part of the controller that is described in later section in this chapter.

```
WHILE (Driving) //speed is greater than zero
{
        IF (Distraction Level- 1)
                Nothing; //normal driving
        IF (Distraction Level- 2)
                Alert- 1; //first level of alert
        IF (Distraction Level- 3)
                Alert- 2;
                Deceleration;
        IF (Distraction Level- 4)
        Alert- 4; //maximum level of alert
        Deceleration;
}
```

Figure 3.2. Part of phase-2 implementation

After phase- 1 was implemented, and the trained model was affectively capable of classifying various levels of cell phone-based distractions, phase 2 took place to mitigate the effect of the detected distractions. Figure 3.3 represents a top level abstract of the integration between phase- 1 and phase- 2. As described later in this chapter, MATLAB and Simulink were used to implement dashboard, alert systems, and simulate different safety actions.

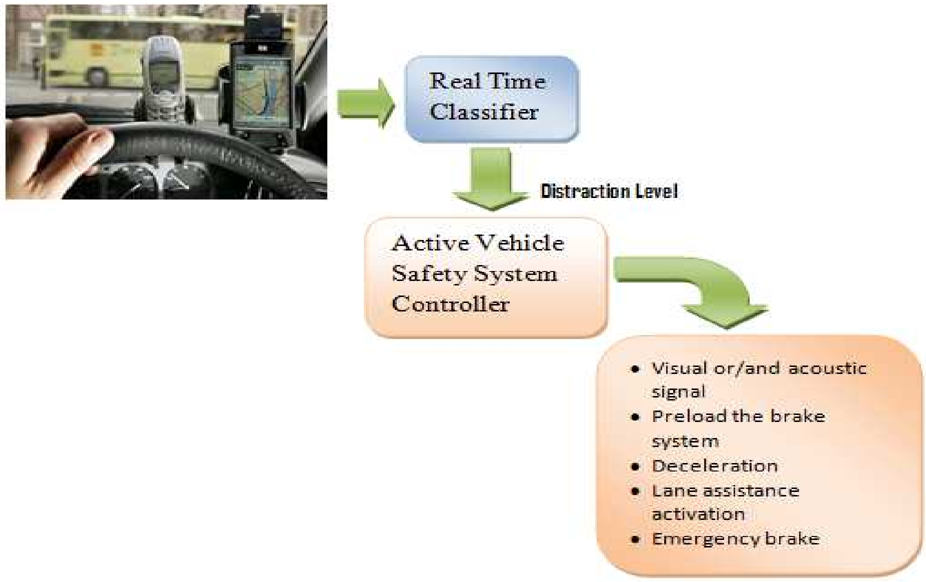

Figure 3.3. Top level of Phase- 1 and Phase- 2 integration

The next sections describe dependent and independent variables, design and implementation, phase -1and phase 2, software and simulation environment, and different distractions scenarios in detail. After well clarifying the adapted methodology, approach evaluations and results analyses were performed to draw the final conclusions.

Predictors and Responses

Predictors:

- Entity Acceleration: The forward acceleration of the monitor entity in meters per second squared.
- Entity Velocity: The forward speed of the monitor entity in m/s
- Lane Position: The lane offset in meters within the current lane. It will be '-' if the subject is not in a lane. Positive is to the right, negative is to the left.

- Latitudinal Acceleration: component for the acceleration of the subject vehicle. The lateral and longitudinal acceleration are the total acceleration of the vehicle with respect to inertial coordinates expressed in the local frame, i.e. this is the acceleration that would be measured by an accelerometer in the vehicle, and except that gravity is not included (gravity would also be measured by an accelerometer).
- Longitudinal Acceleration: component for the acceleration of the subject vehicle. The lateral and longitudinal acceleration are the total acceleration of the vehicle with respect to inertial coordinates expressed in the local frame, i.e. this is the acceleration that would be measured by an accelerometer in the vehicle, and except that gravity is not included (gravity would also be measured by an accelerometer)
- Steering Input: is a value in degrees. A steering wheel can make three complete revolutions, with each revolution containing 360 degrees. Starting at the rest position (0 degrees), the steering wheel can turn one and one half revolutions to the right (+540 degrees) and the same to the left (- 540 degrees).
- Velocity: The speed of the subject vehicle in m/s.
- Gaze (x, y locations): Head x, and y directions to monitor visual distraction.

Responses:

- Distraction Levels with four degrees:
  - ❖ Distraction Level- 1: normal driving.
  - ❖ Distraction Level- 2: minimal distraction.
  - ❖ Distraction Level- 3: moderate distraction.
  - ❖ Distraction Level- 4: high distraction.

Participants

Thirty participants were recruited to participate in the experiment. They were English speakers; Arizona State University (ASU) students, randomly selected, valid U.S. driver's license holders, and each participant needed to own a smart phone. Each participant was willing to provide his/her number and ASU email account. All participants gave informed written consent, and also the experiment was given ethics approval by the Arizona State University Institutional Review Board (IRB). Nineteen participants were used to train the model, and the rest of the participants were used to validate the model.

Experimental Design

The experiment used within-subject design. The experiment consisted of four different driving distractions scenarios and one baseline driving with no distraction. The visual and cognitive driving distractions were implemented by asking drivers to engage in a secondary task using a smart phone while driving. Each participant completed five five-minute sessions of driving. Excluding the baseline driving, each drive contained one distraction task; and each distraction task had a different completion time. The order in which the participants received these distraction tasks was randomly selected. Each participant drove for the first two minutes with no distractions and then the participant was given a secondary task.

Driving Environment

The DS-600c advanced research simulator by DriveSafety™ was used to conduct this study.

This simulator was comprised of a 300 degree wraparound display, a full-width automobile Ford Focus cab and a motion engine platform as shown in figure 3.4.

Figure 3.4. The Driving Simulator at Arizona State University (Mcnabb & Gray, 2016)

A dynamic torque feedback from the steering wheel and vibration transducers mounted under the driver's seat to provide tactile and deep sensing of feedback cues. The motion platform provided coordinated inertial cues for the onset of longitudinal acceleration and deceleration. The driver simulator was adjusted to record data with 60 Hz rate. During the drive, the participant's face was video recorded using a Logitech C920 Webcam. The roadway used in this experiment was a zigzag, two-lane freeway separated by a marked line. Traffic in the left lane approached the subject vehicle from behind and in front. Participants were instructed to maintain the speed around the speed limit. A lead vehicle (LV) was driving with a speed around the speed limit (55 mph – 60 mph).

Software Platform

To design and implement the trained classifier and phase- 2 MATLAB and Simulink software platform were used. MATLAB is a high-performance programming language and interactive environment developed by MathWorks.inc for engineers and scientists to model and visualize ideas across different disciplines (Guide, 1998). Furthermore, MATLAB integrates computation, visualization and high level language, and interactive environments for research purposes. In fact, this software is considered as one of the most well-known tools for scholars and researchers worldwide.

Simulink is a block diagram environment built on top of MATLAB for simulation and modeling based design. It is fully incorporated with MATLAB and other Mathworks objects, as well as a capability to establish real time testing by connecting with hardware. Using Simulink, complete vehicle model incorporating was developed using a bottom-up approach. This model is illustrated in the illustrative top level vehicle model shown below.

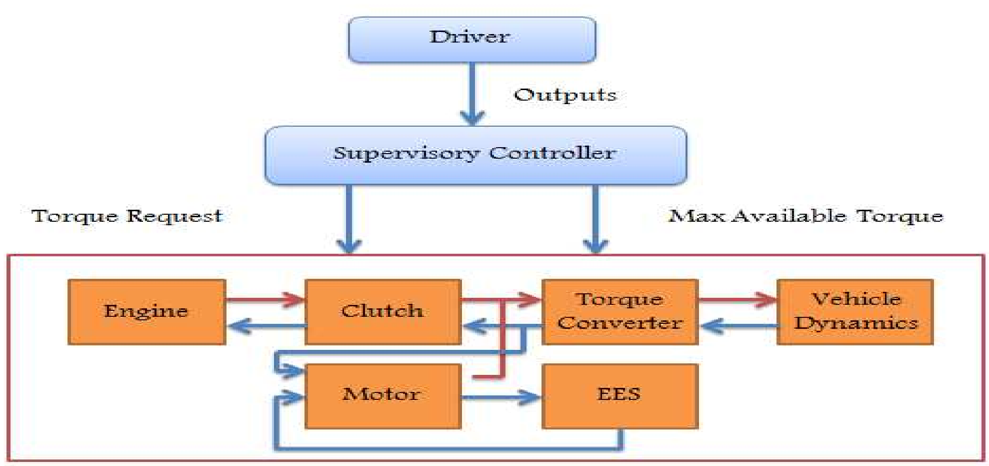

Figure 3.5. Top level of the vehicle model

The major components for the implemented vehicle model are shown in figure 3.5. The fundamental operations for each individual component are either calculated by the physical equations to control the dynamic response of the component, or by implementing the empirical data provided by the component manufacturer or found in the literature. The supervisory controller model is considered one of the major parts of the entire vehicle system. However, it can be the simplest or the most complex part of the vehicle depending upon the tasks embedded into its operations. Generally, the controller calculates the total torque required from the power train to achieve the driver request by having both acceleration and brake commands from the driver as inputs to torque calculation algorithm.

Procedure

The experiment took place in the previously described driving simulator and included five 5-minute drives: five with secondary tasks and one as a baseline drive. During each secondary task drive, participants completed 1-4 minutes of a certain secondary task while driving. Each participant had a short break in between. In the baseline drives, participants did not perform any secondary task. Each secondary task had different level cognitive and visual loads. Head movement and driving performance data were collected at a rate of 60 Hz for thirty participants using a web cam and a driving simulator, respectively.

Assumptions

The experiment has four different scenarios. Each scenario has different level of simplicity and load of visual and cognitive demands. In this study a valid assumption was made in which the distraction levels were suggested based on the simplicity of the secondary task. For example, the scenario that requires more visual interaction and cognitive load had a higher distraction level. This assumption is supported by other studies, which confirmed that the secondary tasks associated. According to the studies, the high risk of a crash or near crash all is related to driver visual attention diversion from the road ahead (Klauer, Guo, Simons-Morton, Ouimet, Lee, & Dingus, 2014; Hosking, Young, & Regan, 2009; Cook & Jones, 2011). Other studies show that manipulating the phone while driving has a higher risk than performing a phone conversation.

The Proposed Approach: Phase- 1 and Phase- 2

Five different secondary tasks were implemented and categorized into three different levels of driving distraction. This classification is mainly based the simplicity of the task and the amount of visual and cognitive load that drivers need to accomplish a secondary task. Figure 3.6 represents the secondary tasks scenarios with the corresponding level of distractions (distraction Level- 1 is the non-distraction driving scenario or the baseline).

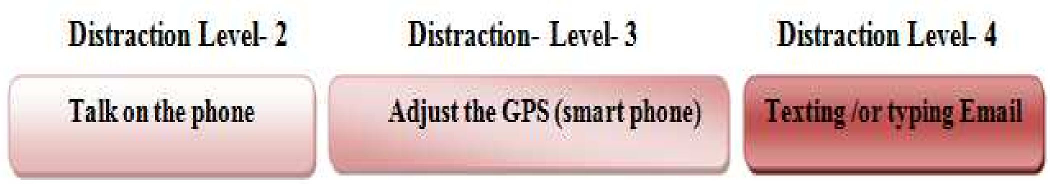

Figure 3.6. Secondary tasks with different levels of distractions

A driving simulator shown in figure 3.4 was used to investigate driver distraction patterns and identify the levels of distractions shown in figure 3.6. The driving scenarios were implemented with the described simulation environment in the previous sections. These scenarios include:

Baseline:

- Each participant was asked to drive for 5 minutes, and try maintaining the lane position.
- Each participant was asked to focus on the primary task (driving) and to not engage in any secondary task during the 5 minutes.
- This scenario represents the baseline for other scenarios and has distraction Level- 1.

Scenario 1:

- Before starting the driving session, the participant was informed that he/she is going to receive a phone call from one of the companies regarding an available position he/she applied for. The participant received a screening interview call for approximately 3 minutes long.
- Each participant was asked to try maintaining the lane position. After 2 minutes of driving, the participant received and engaged with the inbound call. This task represents distraction level- 2 because this task is a simple task with most likely yes/ no answers. In addition, the task does not require a heavy visual distraction compared to other scenarios.

Scenario 2:

- Before starting the driving session, the participant was informed that he/she is going to be asked to use the GPS on the phone to navigate to a specific location. The specific location was passed to the participant verbally during driving. The participant was asked to try to observe the destination path to find the shortest path to the destination.

- Each participant was asked to drive for 5 minutes, and try maintaining the lane position. After 2 minutes of driving, the participant was asked to navigate to Arizona State University downtown campus and observe the shortest path.
- This task represents distractions level- 3 since the task is more complicated than the previous task. The task included manipulating the cell phone, which requires higher visual demands than the previous scenario.

Scenario 3:

- The participant was informed that he/she is going to receive an email while driving. The email includes questions about a job the participant applied for. The participant was asked to reply with the answers.
- Each participant was asked to drive for 5 minutes, and try maintaining the lane position. After 2 minutes of driving, the participant received the email below:

  Hello Sir/Madam

Thank you for your interests in human factors position that we have posted recently. If you are still interested please reply with answers for the following questions:

- ❖ Are you willing to relocate?
- ❖ Are you currently employed?
- ❖ Are you okay with traveling/ if yes what is the acceptance percentage?
- ❖ When can you start working?
- ❖ What is the minimum salary you are looking for?

- This task represents distractions level- 4 since the task is apparently requires higher visual attention than previous tasks and also more cognitive demands needed.

Scenario 4:

- Each participant was informed that we are going to assume that the participant posted his car on craigslist for sale. The participant was asked to reply to the messages that he /she is going to receive from a buyer.
- Each participant was asked to drive for 5 minutes, and try maintaining the lane position. After 2 minutes of driving, the participant started receiving the following messages about the car:
  - ❖ Is the car still available for sale?
  - ❖ Any dents or scratches?
  - ❖ Final price?
  - ❖ Can we meet to take a look at the car?
- This task also represents distractions level- 4 since the task is apparently requires high visual attention cognitive demands.

Phase- 1: Detection Algorithm

The main purpose of Phase- 1 is to implement a trained and efficient model that is capable of detecting different levels of driving distractions level. In order to achieve that sufficient data were collected and normalized to be used as inputs of machine learning algorithm. This process of Phase-1 consists of three sub phases: sensing and data collection, feature extraction, and classification.

- **Data collection:** is based on reading data from the driver simulator main controller (CAN-bus) in real time while driving. These data include: velocity, acceleration, steering angle, and lane position. The main hypothesis is that all human interactions with the vehicle system controls appear as a response on the vehicle systems/subsystems. All vehicle sensory networks are attached to one or more nodes on the CAN-bus. Therefore, the CAN-bus is the most effective node to be used as an input to the driver behavior detection algorithm. In addition to the CAN-bus, a Logitech C920 Webcam was used to record drivers' head movements. The collected videos were analyzed using CascadeObjectDetector function in MATLAB to detect drivers x, and y gaze while driving with and without distractions.
- **Feature extraction:** is the process of reducing the amount of collected data required to describe a large set of data. Instead of performing analysis of complex and large set of data with high number of variables involved, a subset of data intended to be more informative and non redundant can be used. The process of performing analysis with a large number of variables usually requires a large amount of memory and computation power. Thus, feature extraction was used to get around these problems while still describing the data with sufficient accuracy. For example, the recorded videos for the drivers were used to extract drivers gaze (x, and y locations) and the rest of the data that is associated with the videos were discarded.
- **Classification:** as a result of having several unique patterns for a distracted driver: speed, lane position, steering angle, and driver's gaze, one of the machine learning techniques was utilized to detect driver distractions. Several studies were successfully

able to identify and detect driver distraction using support vector machine (SVM), and Bayesian Networks (BNs) (Al-Sultan, et al., 2013; Liang, & Lee, 2010; Yang, Chang, & Hou, 2010). As previously discussed, most of the hybrid based driver distraction detection approaches show better detection accuracy rate compared other measures approaches. In the proposed approach a support vector machine (SVM) algorithm similar to the study in (Chang, & Hou, 2010) was used. Thus, a trained model that is capable of detecting different levels of distraction was implemented. The Fine Gaussian training algorithm had six predictors and 4 responses were used. These predictors include: speed, lane position, steering angle, driver's x-gaze, and driver's y-gaze. The responses are distraction level- 1, distraction level- 2, distraction level-3, and distraction level- 4. Figure 3.7 represents the classifier.

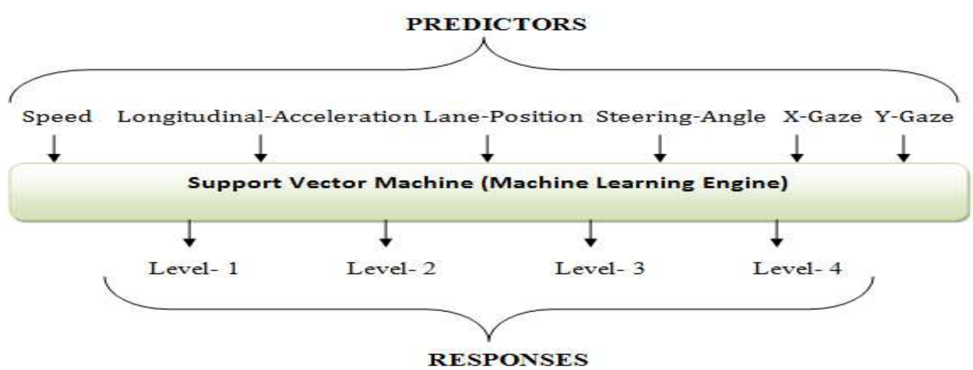

Figure 3.7. Predictors and responses of the suggested classification

Phase- 2: Correction Algorithm

Phase- 2: is the last phase of the proposed model. In this phase the output of the driver behavior detection algorithm is sent to intelligent/active safety system controller. This controller manages some active driving safety systems to help vehicle stay under control and avoid accidents. The safety vehicle's systems that the detection algorithm feeds include:

- **Lane departure warning system:** a strategy designed to alert the driver when the vehicle begins unintentionally departure the lane (unless the right direction blinker is ON). The main purpose of these systems is to decrease number of accidents by addressing main causes of collisions such driver errors, distractions and drowsiness.
- **Anti-collision or Collision avoidance system:** these systems are considered pre-crash safety systems. One of main examples of these kinds of systems is sending visual/auditory warning messages to the driver. In our proposed approach, if the driver is distracted, visual/auditory warning messages will be sent to the driver to maintain normal driving.
- **Advanced Emergency Braking System (AEBS):** is a safety system that is able to take action (i.e. brake) automatically in case the driver did not respond to the warning messages that are generated from the collision avoidance system. In our proposed approach, if time to collision is low and the driver is distracted with high level, the safety control system may deploy emergency brake to avoid collisions. In some cases deceleration was applied rather than full brake deployment.

Phase- 1 and Phase- 2 Integration

Figure 3.8 represents a top level of the proposed solution that demonstrates phase- 1 and phase- 2 in a high level. As shown in the figure, in a real time driving, the implemented model that was trained and tested is performing detection for various levels of driver distractions. The detected level goes to vehicle safety systems that should act based on both: distraction level, and other in-vehicle data. The taken actions are perceptible by the driver so he/she are going to be aware of the situation and further actions may be taken by the driver to correct it.

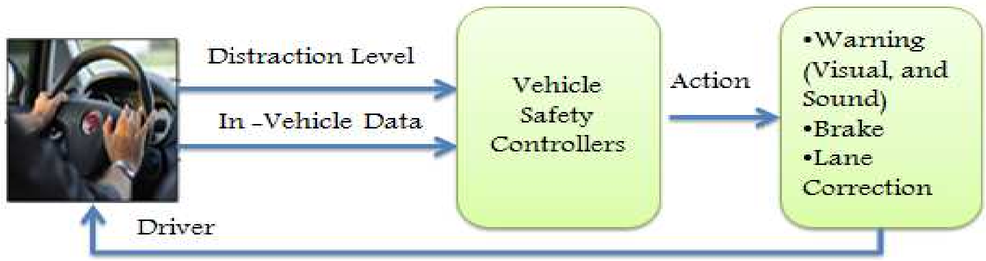

Figure 3.8. Top level of phase- 2 implementation

Figure 3.9 represents an a low level presentation of the proposed solution in which phase- 1 output (level of distraction) is an input along with other in-vehicle data to intelligent/safety controller that provides appropriate actions and eventually minimize road accidents (phase- 2).

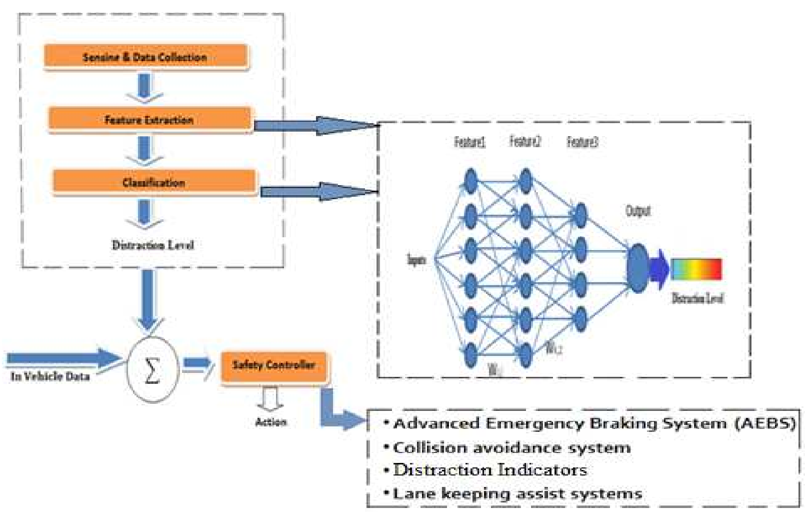

Figure 3.9. The low level of the proposed approach

Because any trained model suffers from false positive and false negative, relying on the detected distraction level only can cause serious issues. For example, if the trained model detects a distraction level- 4 (the highest), but in reality the true distraction level was less than 4, this false positive can lead to wrong actions. Furthermore, if the vehicle safety systems deploy an emergency brake due to false detected distractions, this can seriously jeopardize drivers' safety. Therefore, other parameters were considered in the design to overcome the false alarms problem and create a context aware system that response with appropriate actions at the right time. The parameters that were added to enhance the proposed model and make the model more realistic include: time to collision (TTC), lane position (LP), and steering entropy (SE).

Figure 3.10, illustrates the conditions with the corresponding appropriate actions. The figure shows various actions. These actions include:

- Emergency brake: The action is the highest level of actions in which the safety controller will apply emergency brake if and only if TTC less than or equal 1 sec.
- Deceleration: this action will be taken in one of the following scenarios:
- TTC between 1 and 1.3 sec.
- Distraction level- 3
- Distraction level- 4
- Lane Keep Assistance: The designed dashboard includes an indicator for unintentionally lane departure.
- Alerts system: a multimodal alert system consists of acoustic and visual messages were implemented. These messages include:

- Alert- 1: This is a first level alert. The alert includes a orange color indicator with minimal non-continues volume peep.
- Alert -2: This is a second level alert. The alert includes an orange color indicator with moderate non-continues volume peep.
- Alert -3: This is a highest level alert. The alert includes a red color indicator with high non-continues volume peep.

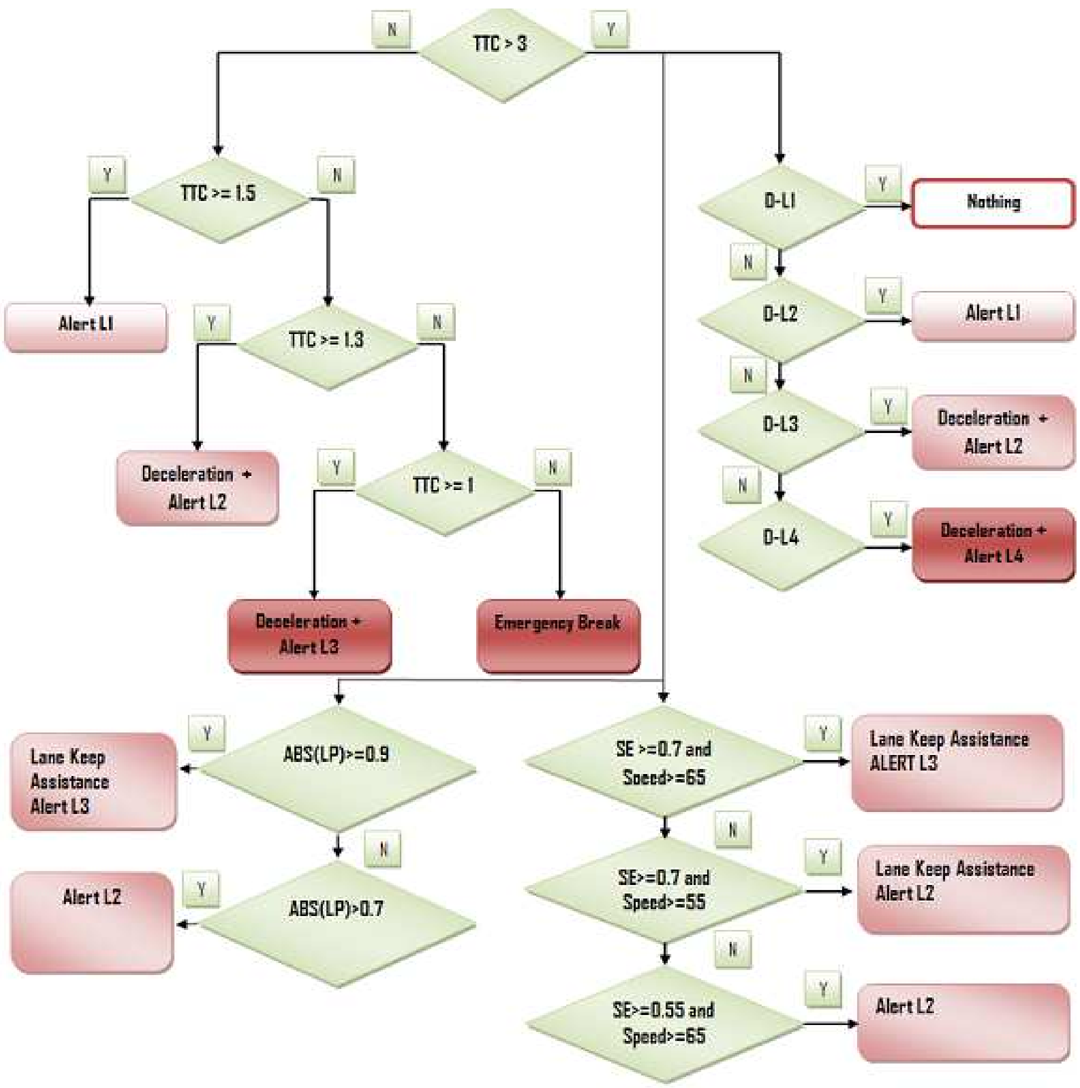

Figure 3.10. Flowchart of phase- 2

The most critical parameter in figure is TTC so when the time to collision is short (less than one sec) the emergency brake was immediately applied to avoid a crash. If time to collision between 1 and 1.3 seconds, the situation is still critical so deceleration and Alert- 3 were deployed. The final situation is TTC between 1.5 and 3 seconds, in this case Alert- 1 will be triggered. The TTC threshold values are adapted from the literature and other studies. On the other hand, the actions that are related to distractions driving should not include an emergency brake or any another severs action due to false positive detection. Other parameters include steering rate, and steering entropy is discussed on next sections.

Steering Entropy (SE)

Steering entropy (SE) is a measure of high-frequency steering corrections (Boer et al., 2005). In other words, steering entropy measures how steady or arbitrary the steering wheel angle is in different driving scenarios compared to baseline driving. In addition to steering variance and frequency, steering entropy mainly focuses on the derivation, which represents the prediction errors. In non-distraction driving scenario, drivers mainly focus on driving and monitor environment effectively and instinctively deploy smooth and predictable steering control. On the other hand, distracted drivers deploy random and non smooth steering control due to the lack of effectively monitoring the environment.

To calculate steering entropy (SE) values, the SE calculation method was adopted from Nakayama et al. (1999). The steering angle was reported every 16.7 milliseconds for each 5 minute driving scenario. After obtaining the data, a second-order Taylor expansion in MATLAB was performed to make a prediction of the steering angle at a given time. The SE equation that was adopted from Nakayama et al. (1999) is:

$$SE = \sum_{i=1}^{9} \left(-Pi\,.Log\,(Pi)\right) \quad where\; i = 1 \ldots .9$$

Where pi represents the proportion of steering prediction errors, e(n). The prediction errors, e(n), as defined by Nakayama et al. (1999) is :

$$e(n) = \theta a(n) - \theta p(n)$$

Where $\theta_\alpha(n)$ is the actual steering angle and $\theta_p(n)$ is the predicted steering angle at time n. To calculate the predicted steering angle value a second-order Taylor expansion series was used (Weisstein, 2002).

After obtaining the data, a second-order Taylor expansion was performed to make a prediction of the steering angle at a given time. This was done by using three preceding data points using the following formula:

$$\theta p(n) = 5/2\,\theta\alpha(n-1) - 2\theta\alpha(n-2) + 0.5\theta\alpha(n-3)$$

Figure 3.11 illustrates the difference between $\theta_\alpha(n)$ (actual) and $\theta_p(n)$ (predicted), which represents the prediction error e(n).

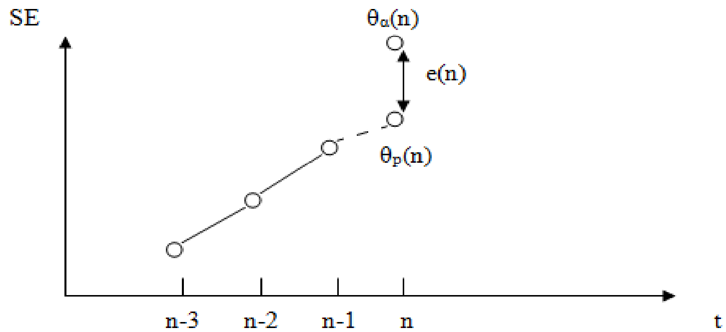

Figure 3.11. Steering entropy prediction

In order to evaluation the proposed approach, all collected data from the previously described scenarios using advanced driving simulator, were analyzed on the next chapter. In addition to the collected results, all the implemented vehicle dashboards, alert systems, states flow (SF) were provided and described.

RESULTS

This chapter discusses the implementation of the proposed approach, and the integration between the designed distraction classifer and the current vehichle saftey systems. Also, the suggested vehicles human vehicle interface (HVI), alerts system, and state flow (SF) were included in detail. Moreover, results from phase- 1 and phase- 2 were added to evaluate the proposed approach.

Phase- 1: Lane Position (LP) and Steering Values Analysis:

Many researchers who addressed this topic from an in-vehicle measure perspective have conducted their studies based on the hypothesis that driver behavior can be characterized as a sequence of basic actions. These actions can be associated with a specific state of the driver-vehicle- environment and characterized by a set of observable features. These repeated sequences of the driver actions are called patterns. In this section, analysis of each signal (speed, lane position, steering angle, and driver gaze) is analyzed in order to observe these patterns.

Figure 4.1 represents the average of all participants' lane position values for each distracted driving scenario compared to the baseline scenario. As shown in the figure, the changes of lane position are unsmooth and random in the phone manipulating scenarios (i.e. texting, emailing, and GPS). Unlike phone manipulating scenarios, talking over the phone while driving shows less randomness in steering values. Also, the figure shows that drivers maintain lane position in better way while engaging with a simple task (i.e. talking) compared to more complicated tasks.

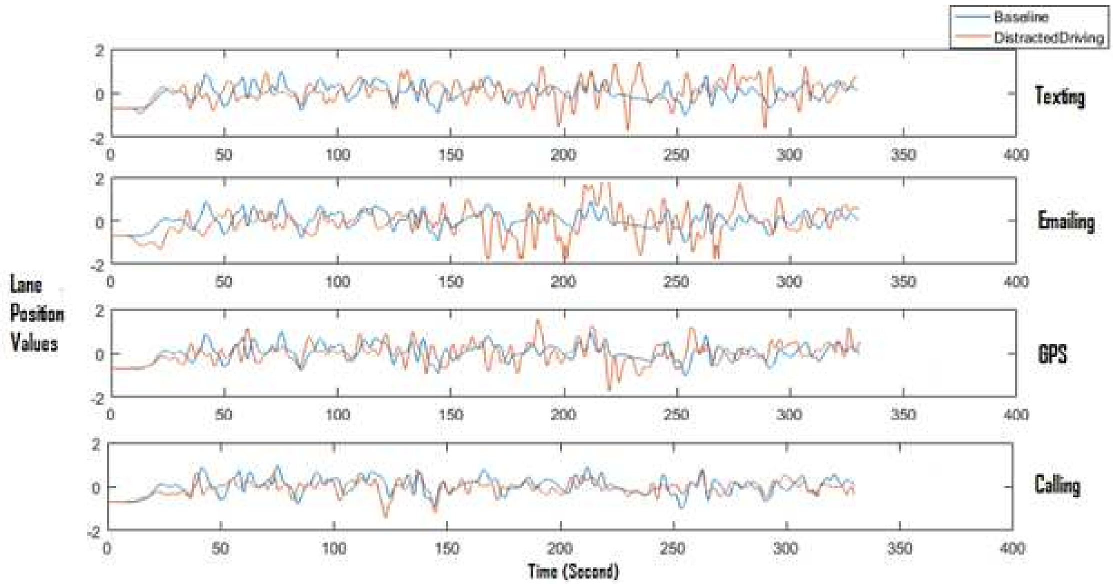

Figure 4.1. Lane position (LP) average of distracted vs. non-distracted drivers

Figure 4.2 represents the average steering values for all participants with and without distractions. As shown in the figure, the changes in steering values are random in distracted driving scenarios compared with the base driving scenarios. Similar to the previous discussion, the changes in steering angle values in the phone manipulating scenarios (i.e. texting, emailing, and GPS) are more than talking scenario. Unlike, phone manipulating scenarios talking over the phone while driving shows less randomness in steering values. As a result, drivers engaged with a simple task such as talking over the phone seem to control the steering wheel better than performing a more complex secondary task such as texting. These findings confirm the previous defined assumptions in which phone manipulating tasks while driving can lead to more distractions more than non- manipulating phone tasks. Also, these results are in line with of the previous studies.

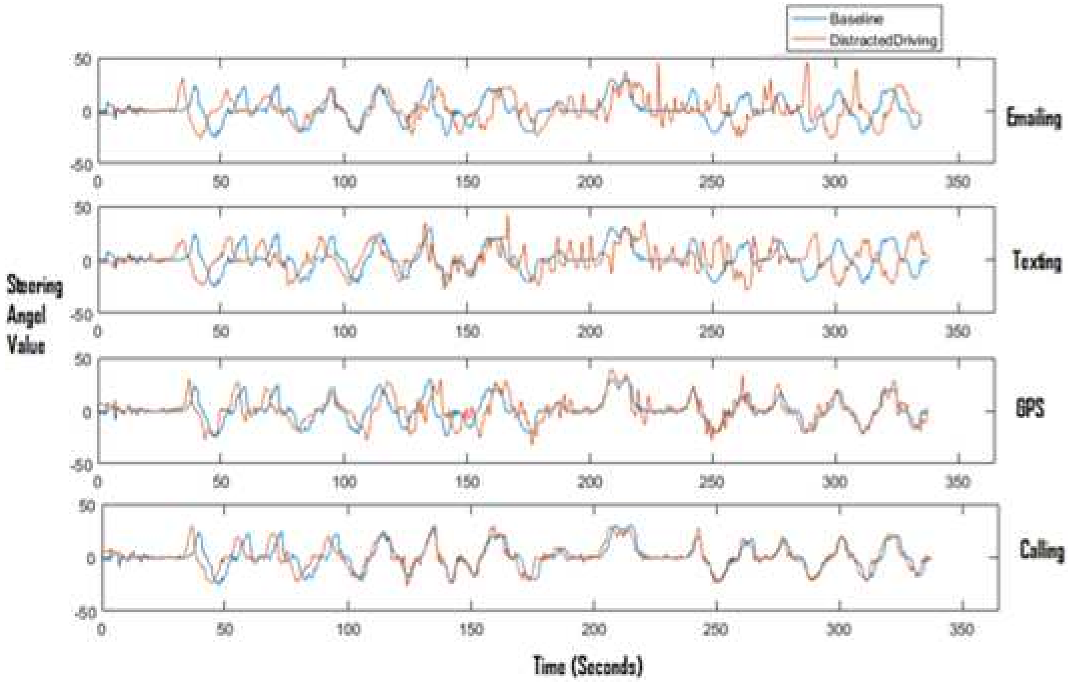

Figure 4.2. Steering values average of distracted vs. non-distracted drivers

In order to invesitage the randomness in steering values under different speeds, figure 4.3 shows the average steering angle values for all participants along with the speed for each scenario.

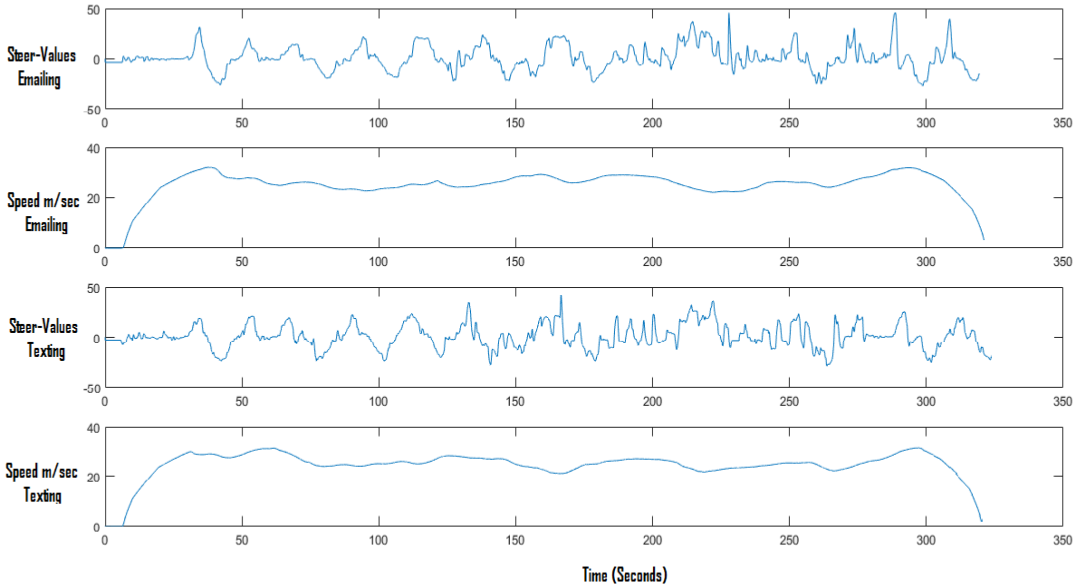

Figure 4.3. Steering values and speed for emailing and texting senarios

Similar to the previous figure but for GPS and talking on the phonescenarios.

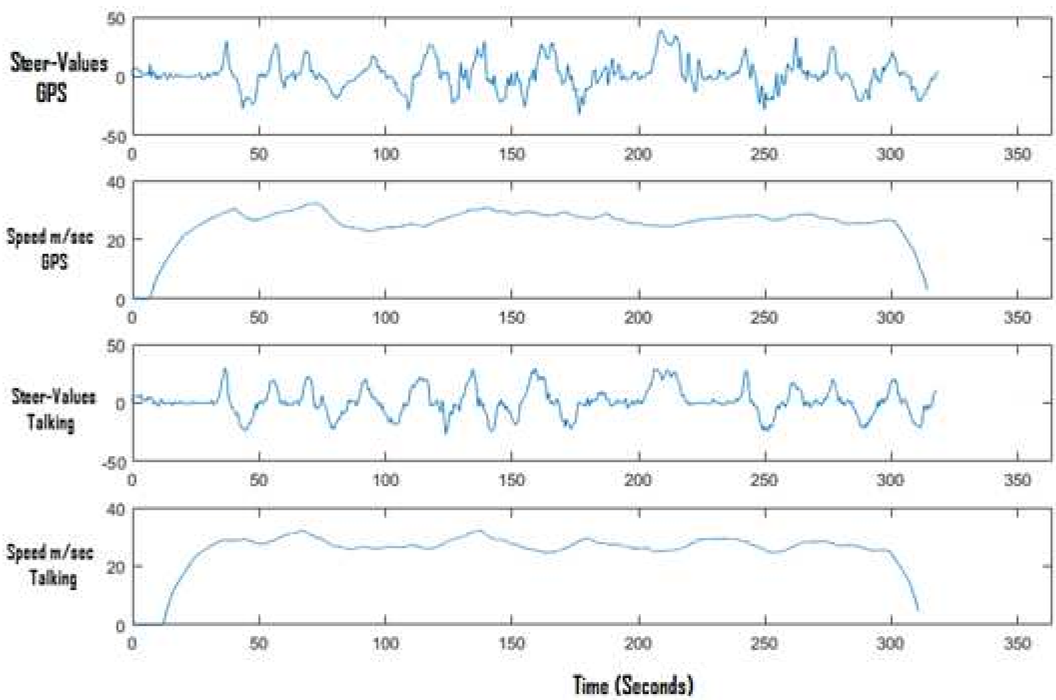

Figure 4.4. Steering values and speed for the GPS and talking on the phone senarios

Due to the high sensitivey of the steering at high speed, studies shows that randomness of steering angle values with a high speed profile can put driver at high risk. On the other hand, low speed profile leads to low sensitivity of the steering. For instance, drivers need to provide large steering input while planning for parking, but not while driving on freeway at high speeds. Table 4.1 shows the horizontal curvature and designed speed. As shown in the table, increasing in the speed requires to increase raduis of the curve for safety. Therfore, if drivers exceeds the designed speed limit for that curve, they will be at high risk.

Table 4.1

Horizontal curvature of high speed highways and connecting roadways with supervelation (Rene, 2014)

Design Speed (mph)	Usual Min.[1,2] Radius of Curve (ft)	Absolute Min.[1,3] Radius of Curve (ft)
	[based on emax = 6%]	
45	810	643
50	1050	833
55	1635	1060
60	2195	1330
65	2740	1660
70	3390	2040
75	3750	2500
80	4575	3050
	[based on emax = 8%]	
45	740	587
50	955	758
55	1480	960
60	1980	1200
65	2445	1480
70	3005	1810
75	3315	2210
80	4005	2670

[1] For other maximum superelevation rates refer to AASHTO's *A Policy on Geometric Design of Highways and Streets.*

[2] Applies to new location construction. For 3R or reconstruction, existing curvature equal to or flatter than absolute minimum values may be retained unless accident history indicates flattening curvature.

[3] Absolute minimum values should be used only where unusual design circumstances dictate.

Phase- 1: Gaze Analysis

For gaze analysis, a Logitech C920 Webcam was used to record drivers' eye~~s~~ and head movements. The collected videos were analyzed using CascadeObjectDetector function in MATLAB to detect drivers x, and y head location while driving with and without distractions. Figure 4.5 represents average Y-locations of the drivers head for all scenarios. As shown in the figure, the drivers attend to move their heads up and down (Y-axes) in emailing, GPS and texting scenarios more than the baseline and talking. Unlike phone manipulating scenarios, drivers appear not to move their heads vertically so often in talking scenario. Because the texting scenario has certain intervals in which the driver was waiting for a reply, the texting scenario shows smooth changes during these intervals. Unlike texting, emailing is a long text with no waiting reply intervals which make the graph looks unsmooth for the most of time.

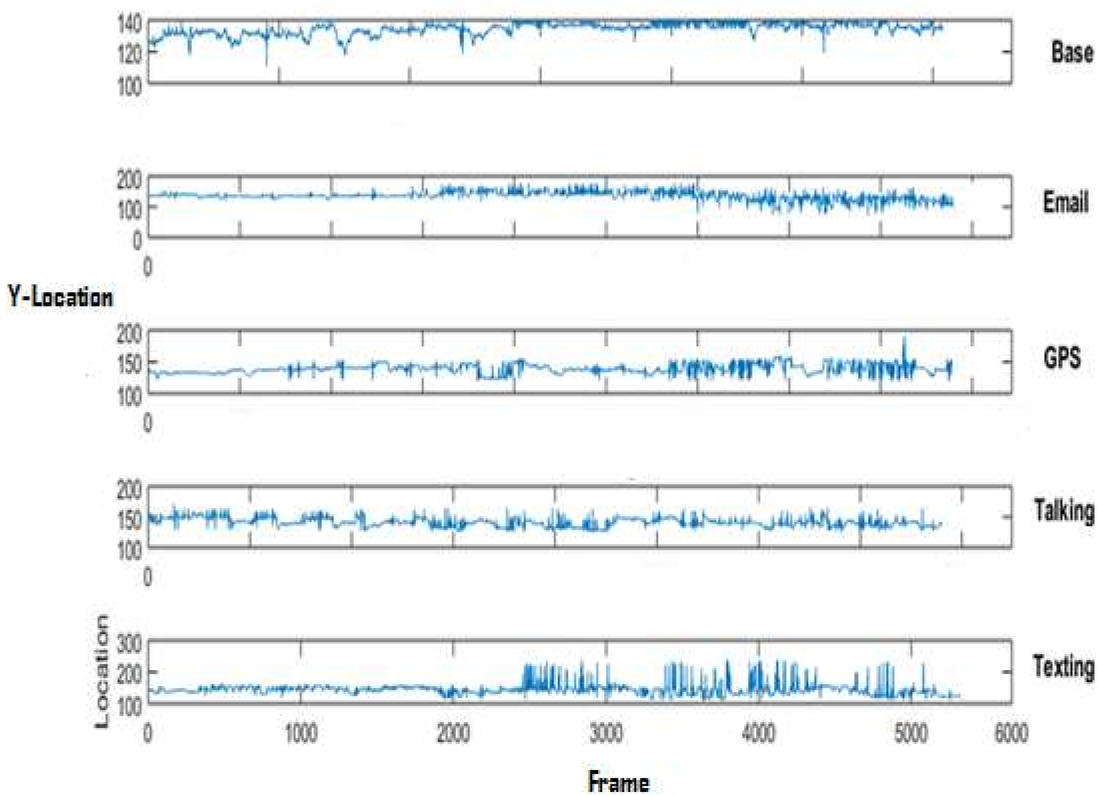

Figure 4.5. Average drivers heads Y-locations for all scenarios

On the other hand, Figure 4.6 represents the average drivers head X-location while driving with and without distractions. The figure shows that the changes in X-locations were smoother in case of baseline and talking. Unlike the scenarios that do not require typing, GPS, texting, and emailing shows unsmooth and random changes in x-locations.

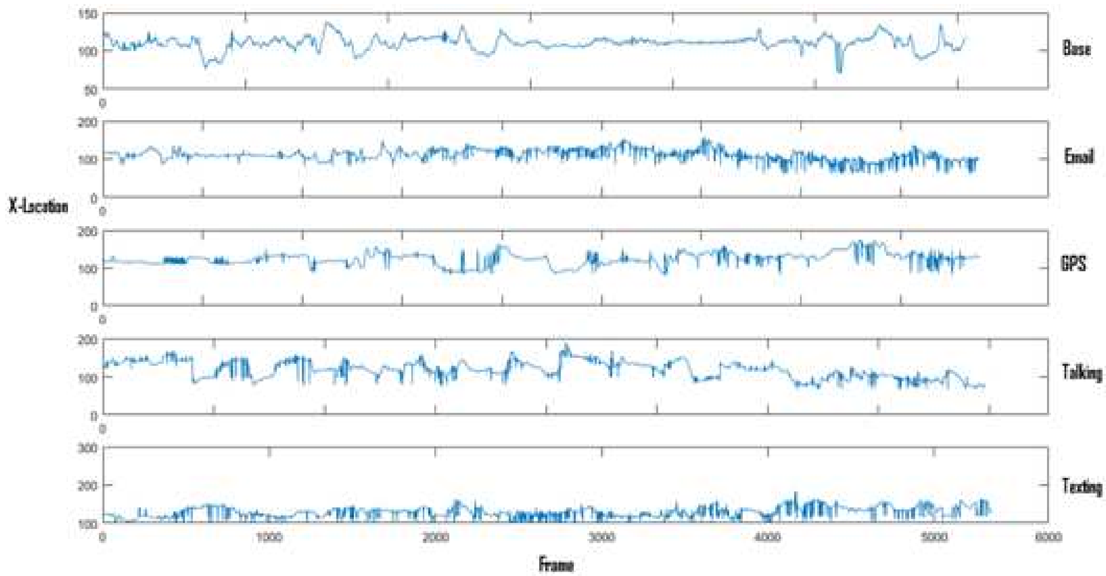

Figure 4.6. Average drivers head X-locations in all scenarios

Phase- 1: Machine Learning and Classification Stage

As a result of having several unique patterns for a distracted driver: speed, lane position, steering angle, and driver's gaze, support vector machine (SVM) algorithm similar to the study in (Chang, & Hou, 2010) was utilized to detect and classify several levels of driver distractions. Thus, a trained model that is capable of detecting different levels of distractions was implemented.

In general, M-class problem, we have N training samples: $\{X_1, Y_1\}. . . \{X_N, Y_N\}$. Here $X_i \in R^m$ is a m-dimensional feature vector. $Y_i \in \{1, 2 . . . m\}$ is the corresponding class label. One-against-all approach builds d binary SVM models; each classifier will separate one class from all the others. The Yi classifier was trained with all the training samples in which Yi class has positive labels, and the rest with negative labels. In this case the Yi SVM explains the following problem that yield the Yi decision function (Liu & Zheng, 2005):

$$f_i(x) = w_i^T \phi(x) + b_i:$$

$$\text{minimize:} \quad L(w, \xi_j^i) = \frac{1}{2}\|w_i\|^2 + C\sum_{l=1}^{N} \xi_j^i$$

$$\text{subject to:} \quad \tilde{y}_j(w_i^T \phi(x_j) + b_i) \geq 1 - \xi_j^i, \ \xi_j^i \geq 0,$$

Where,

$$\tilde{y}_j = \begin{cases} 1, & y_j = 1 \\ -1, & \mathit{Otherwise} \end{cases}$$

A sample x is classified as in class i^* whose f_{i^*} is produces the largest value

$$i^* = \underset{i=1,\ldots,M}{\arg\max}\ f_i(x) = \underset{i=1,\ldots,M}{\arg\max}\ (w_i^T \phi(x) + b_i)$$

In our case we have 4 classes figure 4.7. Fine Gaussian training algorithm that had six predictors and 4 responses were used. These predictors include: speed, lane position, steering angle, driver’s x-gaze, and driver’s y-gaze. The responses are distraction level- 1, distraction level- 2, distraction level- 3, and distraction level- 4.

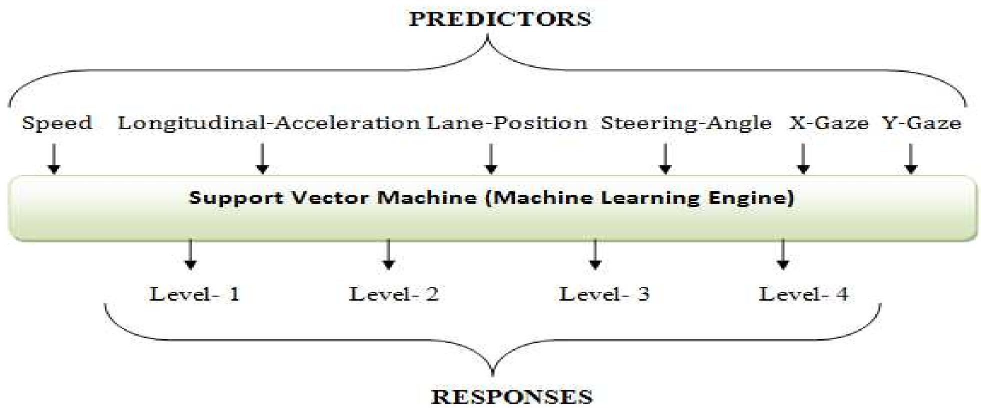

Figure 4.7. Predictors and responses of the fine Gaussian model

After training the model with the collected data, the model shows 98.7% overall accuracy, and 1.3% overall error. In addition to overall accuracy, Figure 4.8 demonstrates more than 99% of true positive rate (TPR) for non-distracted driving detection and 97%, 96%, and 98 for distractions level 2, 3, and 4 respectively. On the other hand, false negative rate (FPR) is less than 0.1% for non-distracted driving detection, and 3%, 4%, and 2% for distractions level 2, 3, and 4 respectively.

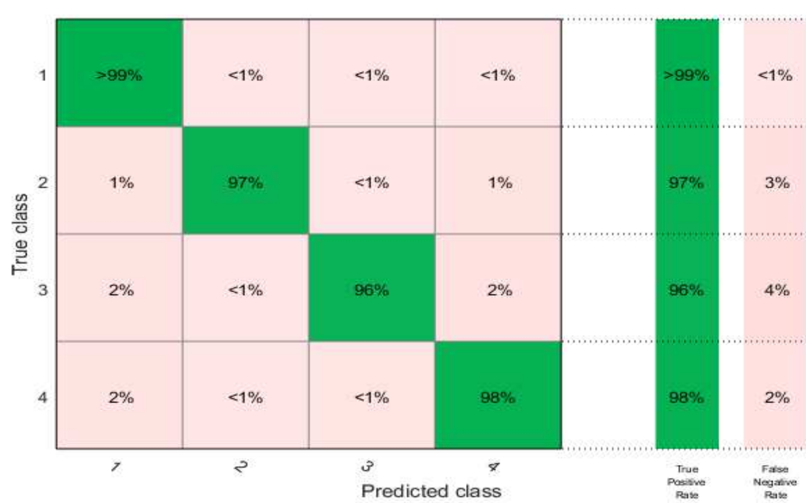

Figure 4.8. Confusion matrix of the proposed model

Figure 4.9 represents ROC graphs for the model where true positive (TP) rate is plotted on the Y axis and false positive (FP) rate is plotted on the X axis. An ROC graph portrays relative compromise between benefits (true positives) and costs (false positives). The Area under curve (AUC) is a measure of the overall quality of the classifier. The model demonstrates a high performance due to the larger area under curve.

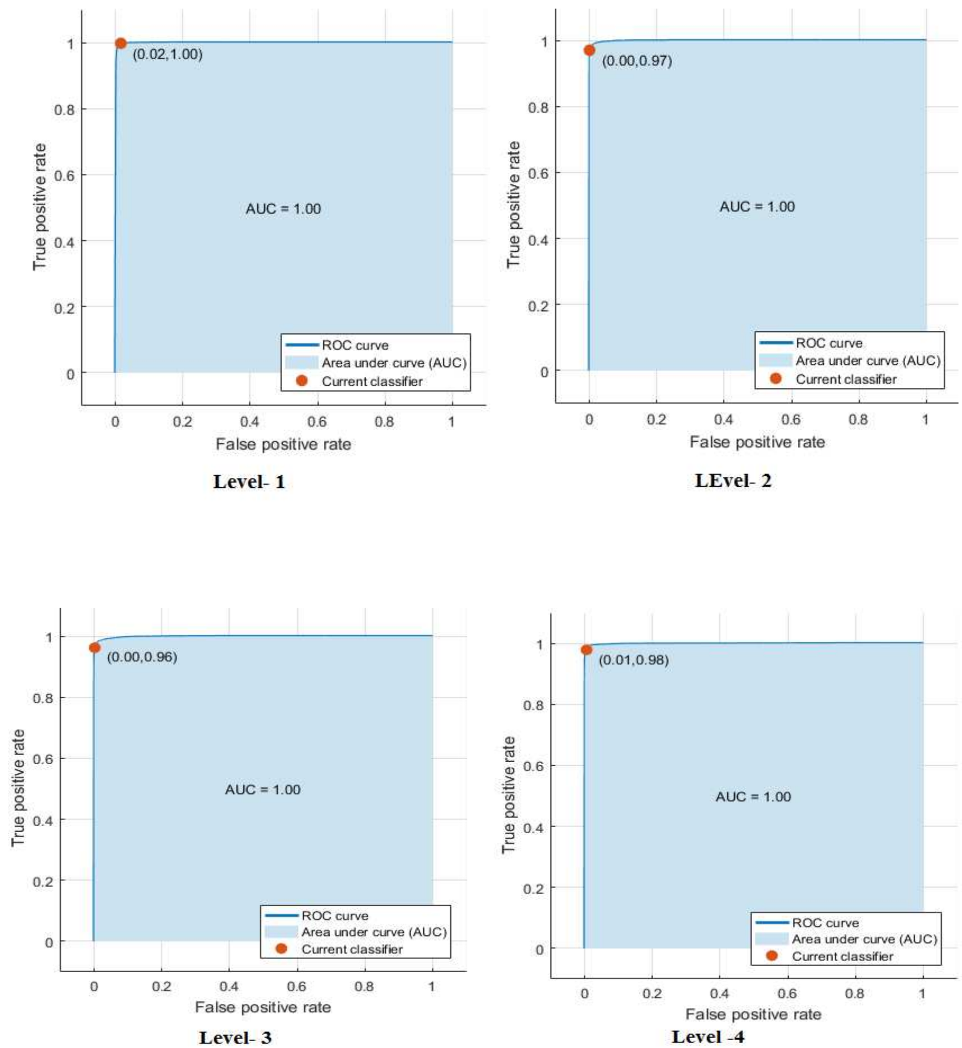

Figure 4.9. ROC for all distraction levels

As confusion matrix and ROC graphs demonstrate, the trained generated model (TrainedDrivingDistraction.mat) shows high accuracy rate, and low false positive and negative rates. The last step is to test and validate the model. In order to validate the model the collected data from 11 participants were used as inputs to the model (TrainedDrivingDistraction.mat). The model was able to detect scenario 1 (no distraction), scenario 2 (distraction level- 2), scenario 3 (distraction level- 3), and scenario 4 (distraction level- 4) with accuracy 99.3%, 96.1%, 95%, and 97.7% respectively.

The implementation of phase- 2 which includes the designed human vehicle interface (HVI) is described in the following sections. Also, the integration between the distraction detection model and vehicle safety systems is explained in detail.

Phase- 2 Implementation

In this phase, a complete vehicle model is developed in order to mimic: driver behavior (i.e. brake and acceleration pedals input), power train, vehicle longitudinal dynamic, Vehicle Interactive Safety System. The driver behavior detection algorithm is interfaced with the vehicle safety controller. The signal exchange between both is depicted in figure 4.10.

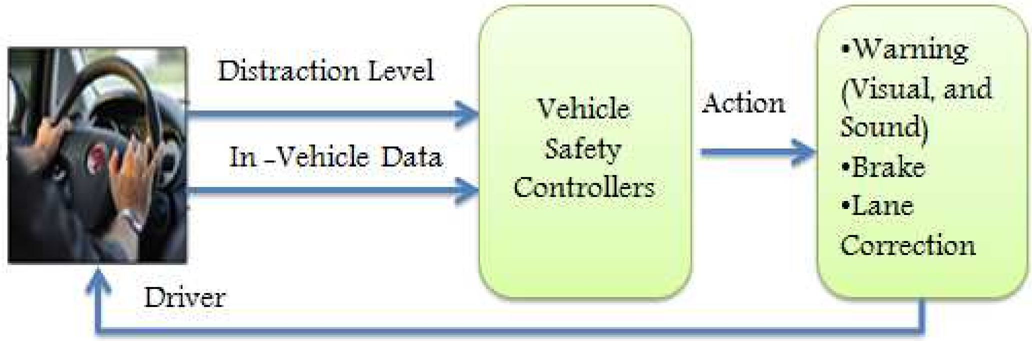

Figure 4.10. Top level of phase- 1 and phase- 2 integration

Figure 4.11 represents the low level abstract of the proposed model. This abstract was built using MATLAB/Simulink. As shown in the figure, the abstract has 2 major components; the first one left side represents the real time distracted driving classifier including the previously mentioned six inputs and one output (distraction level). The second component represents the controller that responds to certain conditions (e.g. distraction level- 4) by providing appropriate actions to increase drivers' safety. This component consists of inputs, outputs, and flow states (FS) that determine the relation between these inputs and outputs. The inputs include: distraction level (DL), steering entropy (EN), lane position (LP), steer value, time to collision (TTC), speed (alpha), and brake value (beta). The outputs include: distraction level indicator (4 levels), time to collision indicator (4 levels), lane assist indicator, sounds indicator, actual speed, and actual brake value.

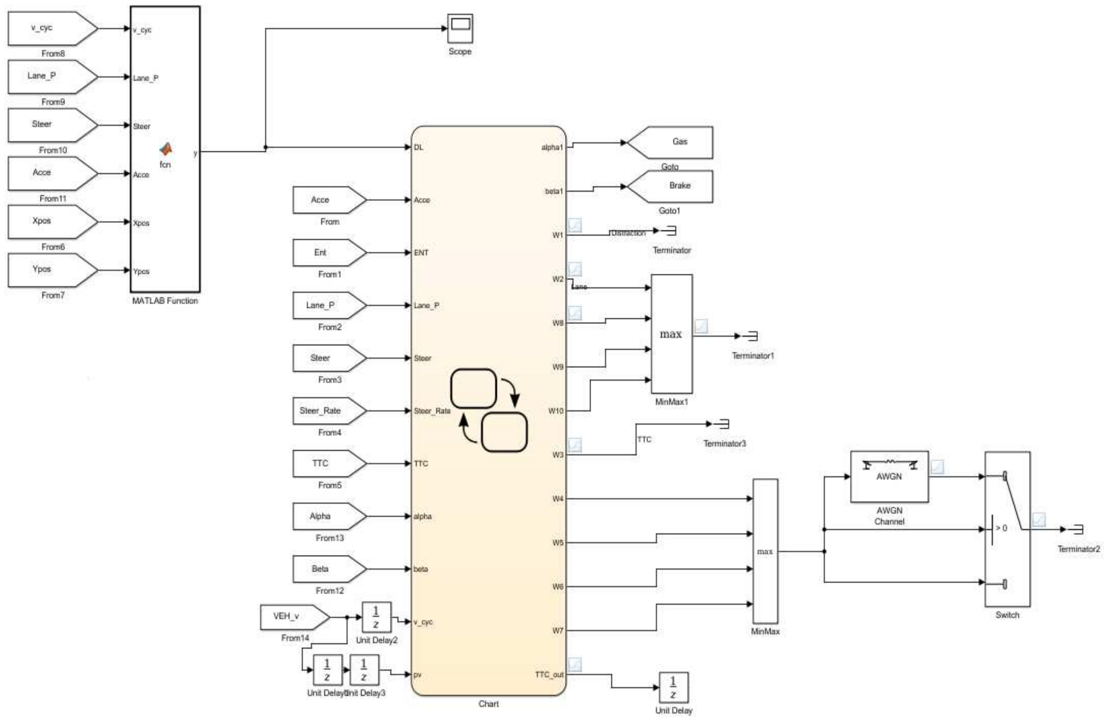

Figure 4.11. Low level design of phase-1 and phase -2

Figure 4.12 represents the implemented human vehicle interface (HVI). This dashboard was implemented using MATLAB/Simulink. The HVI consists of: distractions level indicator, time to collision indicator (TTC), and lane assist Indicator, sounds volume indicator, actual speed, and finally RPM. The main purpose of HVI is to simulate different driving scenarios and evaluate the suggested model. For instance, a baseline scenario (i.e. no distraction) was generated to be as an input to the model and no alerts or actions were applied during this scenario.

Figure 4.12. Human Vehicle Interface (HVI)

Each alert indicator has different state that represents a certain condition. These states include both a specific color associated with each condition and different level of sound (see figure 3.13 and figure 4.14).

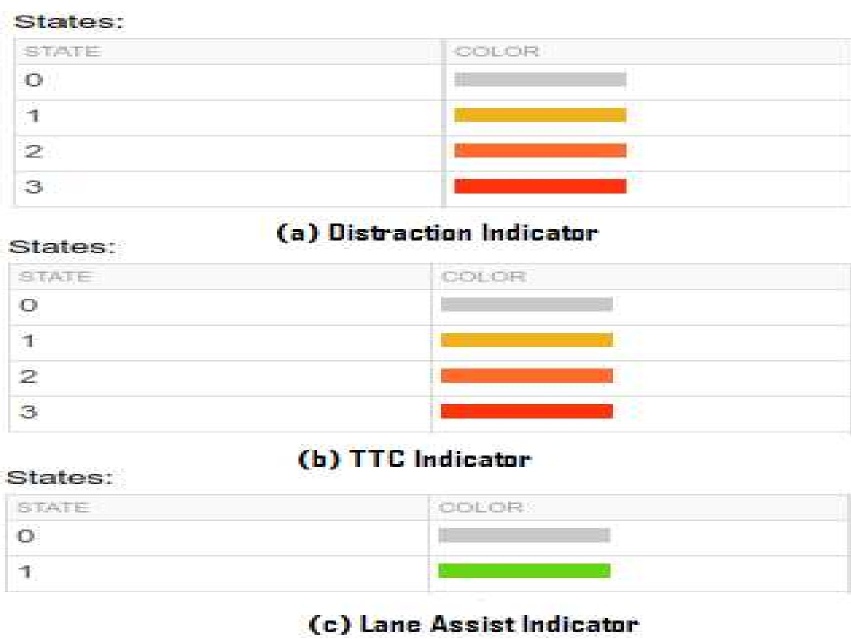

Figure 4.13. Color coded system for different alarm levels

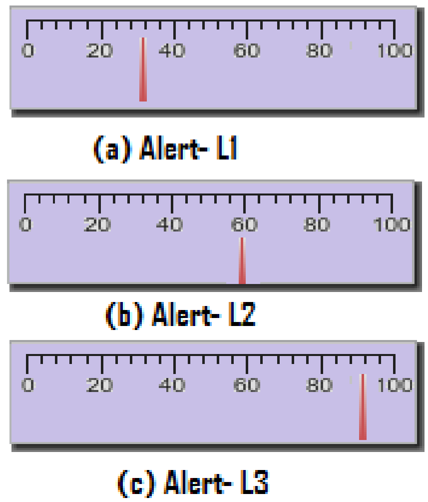

Figure 4.14. Sound indicator levels

Phase- 2: State Flow (SF) Implementation

Figure 4.15 represents the backbone of the design. The flowchart shows various conditions and actions associated with them. As shown in the figure, TTC is the first parameter that the system should check to avoid accidents. If TTC is larger than 3 seconds the system start checking other conditions such as distraction levels, lane position, and steering entropy. Distraction level means normal driving so no action will be taken. Distraction Level -2 means a low level of distracted driving (e.g. talking over the phone where no phone manipulating involved). In this case the system will activate alert level 1 and non-continuous peep with 30db level to notify the driver. Another example when the classifier detects level- 4 of distracted driving; active vehicle safety system will force deceleration (the amount of deceleration is discussed later in this chapter) and alert level-4 with non-continuous peep with 30db level to notify the driver.

Similar to distraction and TTC, steering entropy and lane position parameters are frequently checked by the system to make sure drivers safety.

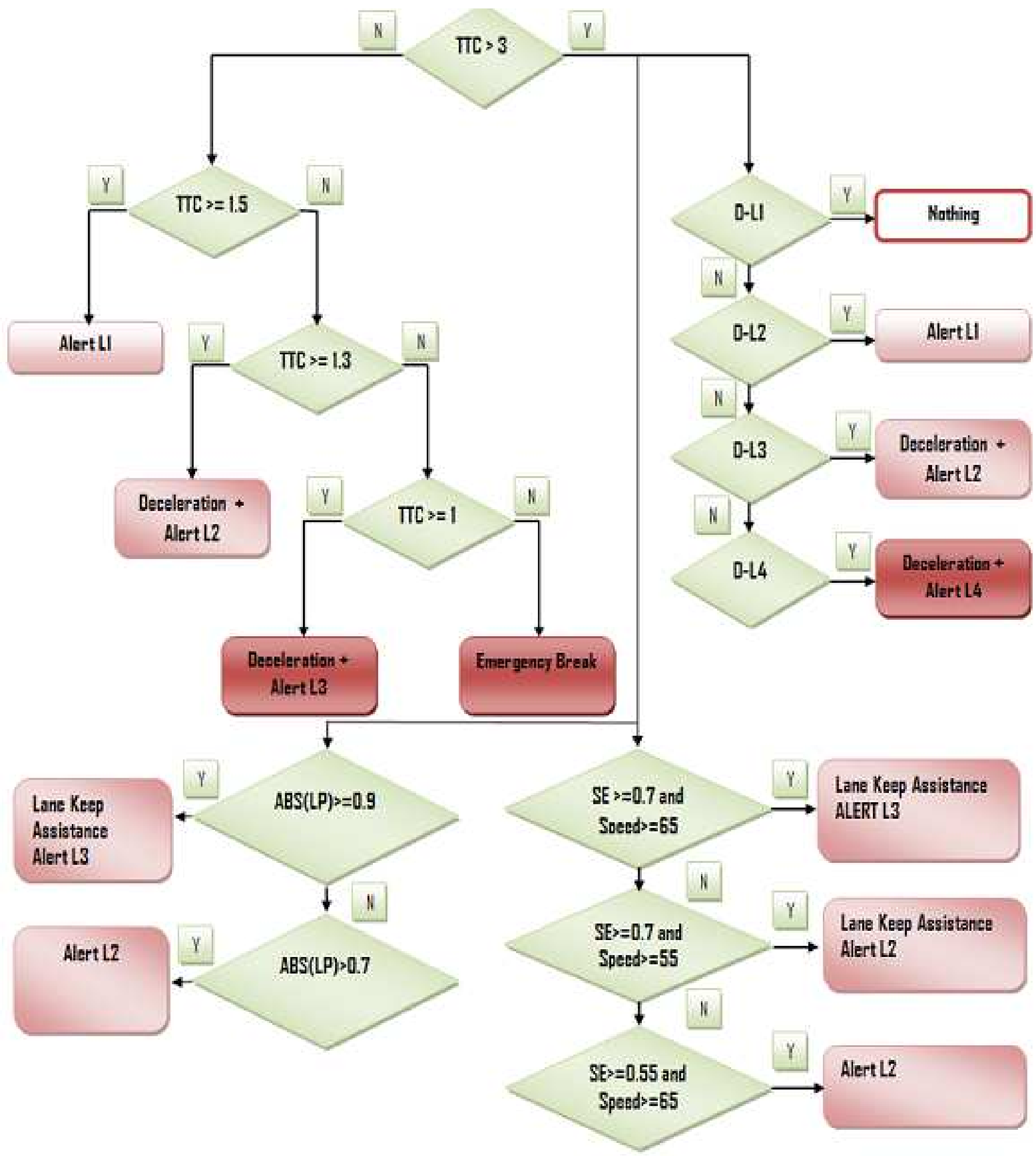

Figure 4.15. Flowchart representation of the different conditions and actions

Distraction levels state flow (SF). To implement the suggested platform, state flow (SF) to control the transition from a state to another was implemented using MATLAB/Simulink. Each state includes different actions (e.g. alert) and a default state (i.e. the state that represents the normal and stable conditions) is always implemented where the system starts with. To transit from a state to another, a specific condition (e.g. if distraction level- 2 is detected) should be met. Figure 4.16 represents the state flow (SF) of distracted driving levels that control transition from the normal state (no distraction) to another states (i.e. distracted level-2, 3, and 4) once distracted driving detected. The state in the middle is the normal state in which no distractions involved. Then, when distraction- L2 (level 1 is normal driving) is detected, the controller switches to the right state (state L2 in the upper side). In this state the distraction indicator will be activated (W1 is the defined distraction signal) with orange color and 30 db non-continues peep sound (W4 is the defined sound indicator). The driver stays in the same state until the driver responds to the indicator and pay attention to the road. As a result of the real time distracted driving classifier (i.e. the one implemented in phase -1) starts detecting a normal driving again (i.e. the controller will switch back to the normal state). In some cases, the controller may transit from distraction- L2 state to distraction- L3 or L4 states. The concept of transition from one state to another is similar in all scenarios; in which specific conditions should be existing to transit.

L3 and L4 states show deceleration as an action once distraction Level 3 or Level 4 is detected. Deceleration amount of 0.1 and 0.05 from the original speed is applied when distraction- L4, and L3 respectively detected. Due to fact of the classifier suffers from false negatives and positives; the amount of deceleration was little. Unlike distraction Level- 3 and 4, no deceleration are involved in distraction level- 2 and only alert will be applied.

Due to the fact that there is no free false positive and negative classifier, we included other parameters to provide more appropriate actions for different realistic driving scenarios. These parameters include time to collision (TTC), lane position (LP), and steering entropy (SE). The state flow for each parameter is included on the next sections.

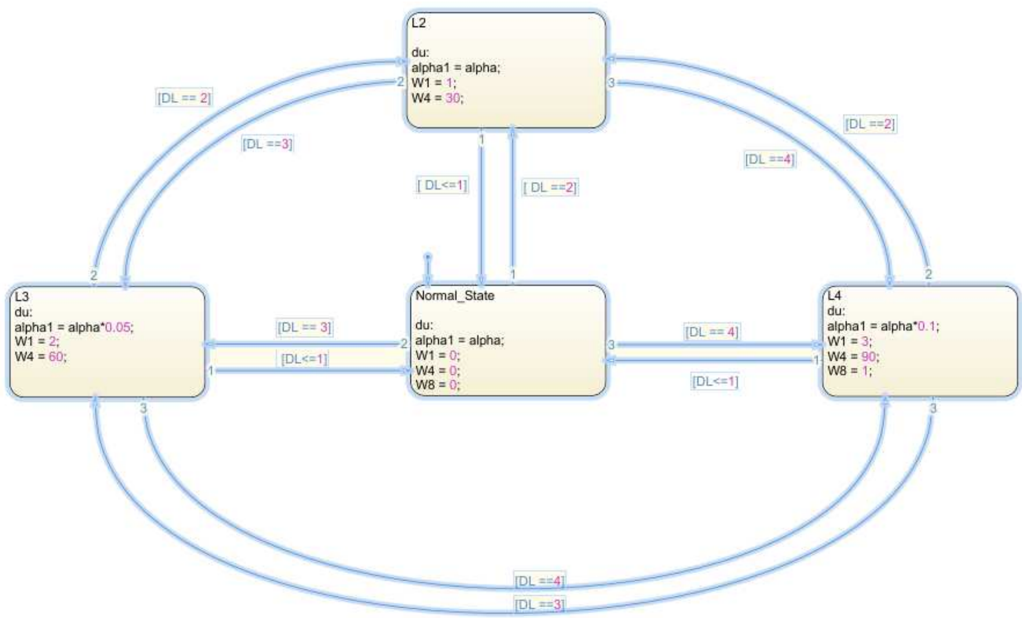

Figure 4.16. State flow (SF) diagram for L1-L4 driving distractions

Time to collision (TTC) state flow (SF). Similar to the previous scenario, figure 4.17 represents the state flow (SF) of time to collision (TTC) that control transition from the normal state to other states. The default state in this scenario is the normal state, which represents the condition of TTC is greater than 3 seconds. Once TTC becomes less than or equal 3 seconds the controller starts checking other states. When the value is less than or equal 3 and greater than1.5 seconds the controller transits to another state (du_L2 state in the lower side). In this state the TTC indicator will be activated (W =2) with orange color and 30 db non-continues peep sound.

In a real time scenario, we expect the driver to respond to the alarm and pay attention to the road, and then the controller will transit back to the normal state. In some cases, the controller may move from the current state to worse state (e.g. TTC<1.3 sec) if the driver is not positively responding. The concept of transition from one state to another is similar in all scenarios; the only difference is the condition and the actions in that state.

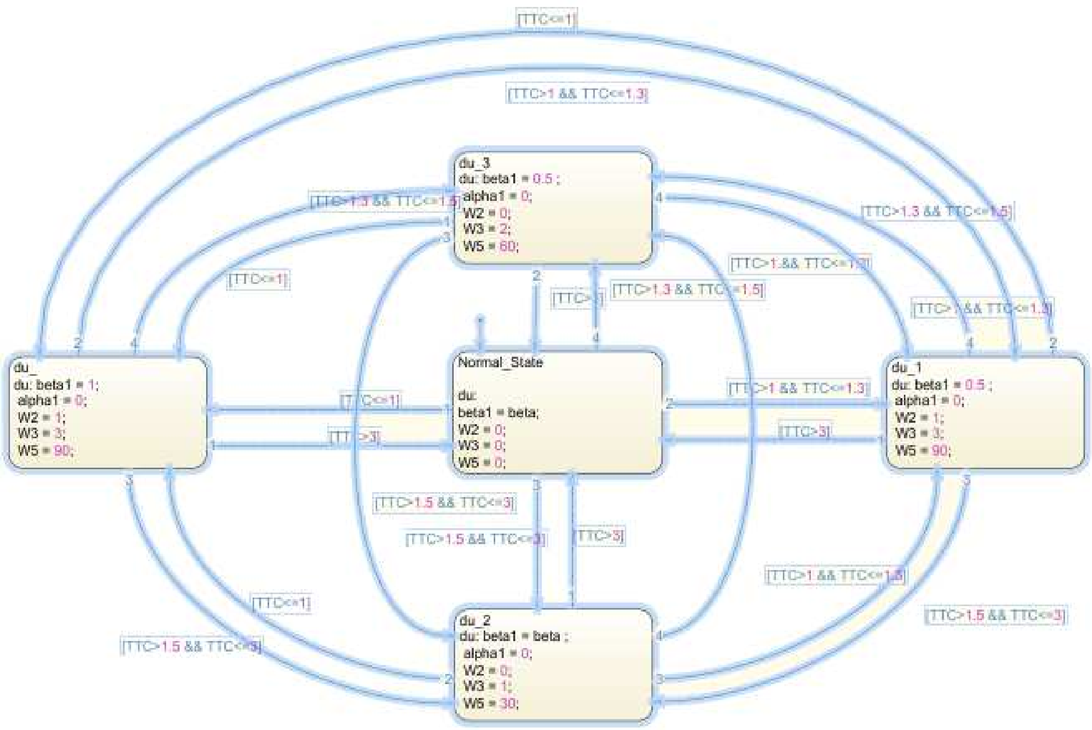

Figure 4.17. State flow (SF) diagram based on TTC threshold

Lane position (LP) state flow (SF). Figure 4.18 represents the state flow (SF) of lane position (LP) that controls transition from the normal state to other states based on LP values. The default state in this scenario is the normal state, which represents the condition of LP absolute value (-/+ represents the direction of the displacement) is greater than 0.7. Once LP becomes greater than or equal 0.9 seconds the controller transit to state on the left side. In this state the controller will activate lane position assist indicator along with 30 db non-continues peep sound. When the LP value is less than 0.7 and greater than 0.9, the controller will transit to another state (M on the upper side). In this state, sound alert with 30 db non-continues peep will be applied. In a real time scenario, we expect the driver to respond to the alarm and pay attention to the road, and then the controller will transit back to the normal state. In some cases, the controller may move from the current state to worse state (e.g. unintentionally departure the lane) if the driver is not positively responding. The concept of transition from one state to another is similar in all scenarios; the only difference is the condition and the actions in that state.

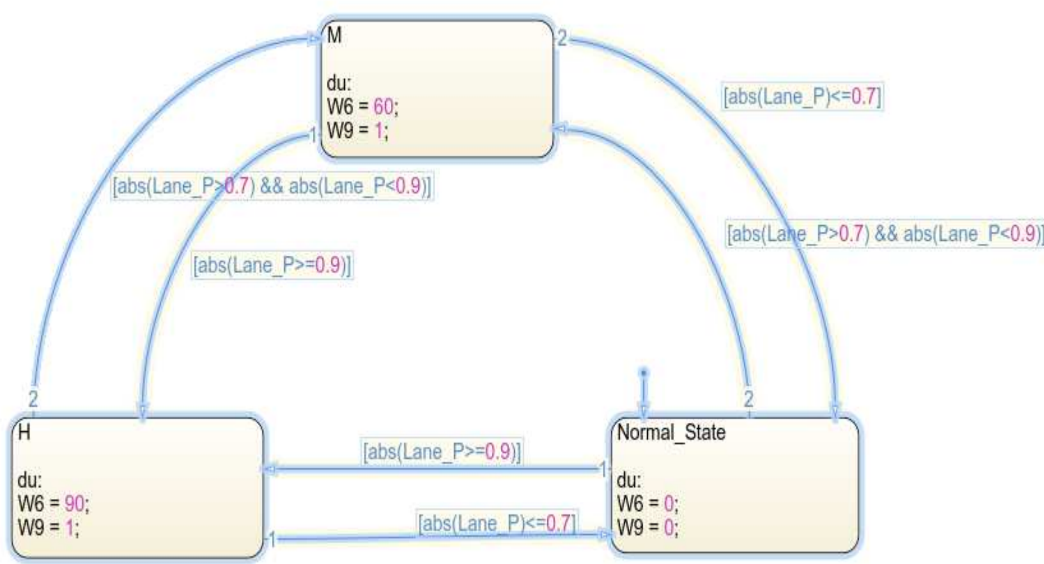

*Figure 4.18***.** State flow (SF) diagram based on LP threshold

Steering entropy (SE) state flow (SF). Figure 4.19 represents the average of steering entropy values for the five driving scenarios. Due to the fact that the drivers were not engaged with any secondary task during the baseline scenario, the baseline steering entropy value was the minimum (49.1%). Also, SE value of the talking while driving scenario shows the minimum among all other distraction scenarios (56.7%). Furthermore, the scenarios that require a phone manipulating while driving showed high steering entropy values (GPS: 66.7%, texting: 73.4%, and emailing: 73.6%) . Based on these values, state flow (SF) was implemented.

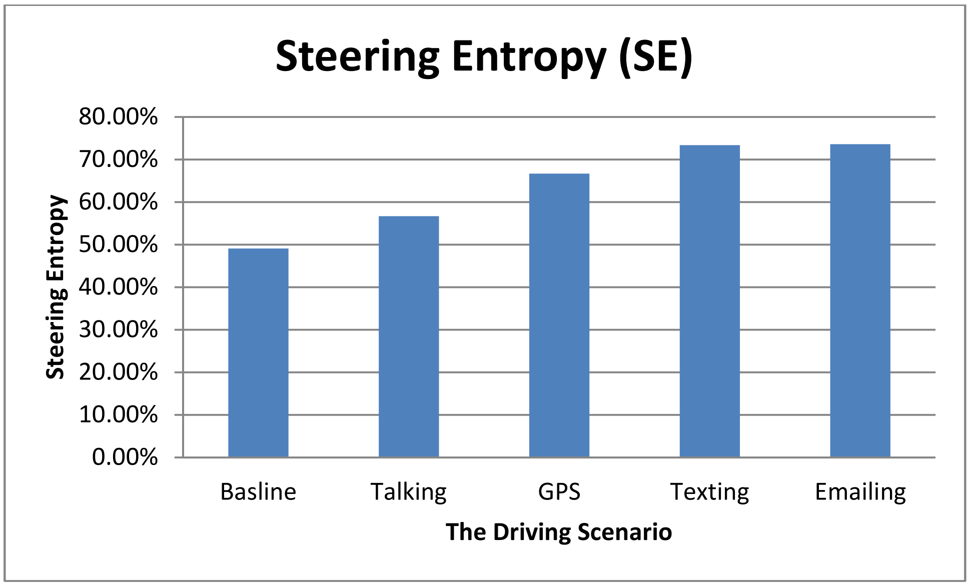

Figure 4.19. Average steering entropy values for all scenarios

Figure 4.20 represents the state flow (SF) of steering entropy (SE) that controls transition from the normal state to other states based on both SE and the speed values. We included the speed value in the controller implementation since a high steering entropy value along with a high speed profile is riskier than high SE with low speed profile. As shown in the figure, the default state in this scenario is the normal state, which represents the condition of SE is less than 55% .Once SE becomes greater than or equal

70% with high speed (65m/h) the controller transits to another state (the state on the right side). In this state, the controller will activate lane position assist indicator along with 90 db non-continues peep sound. When the SE value becomes greater than or equal 70% with speed greater than or equal 55m/h, the controller will transit to another state (the one in the middle). In this state, lane position assist indicator along with 60 db non-continues peep sound. Finally, if the SE value is between 55% and 70% with high speed profile greater than or equal 65m/h, non-continues sound alert with 60 db will be applied. In real time scenario, we expect the driver to respond to the alarm and pay attention to the road, and then the controller will transit back to the normal state. In some cases, the controller may move from the current state to worse state (e.g. increasing of steering entropy value) if the driver is not positively responding. The concept of transition from one state to another is similar in all scenarios; the only difference is the condition and the actions in that state.

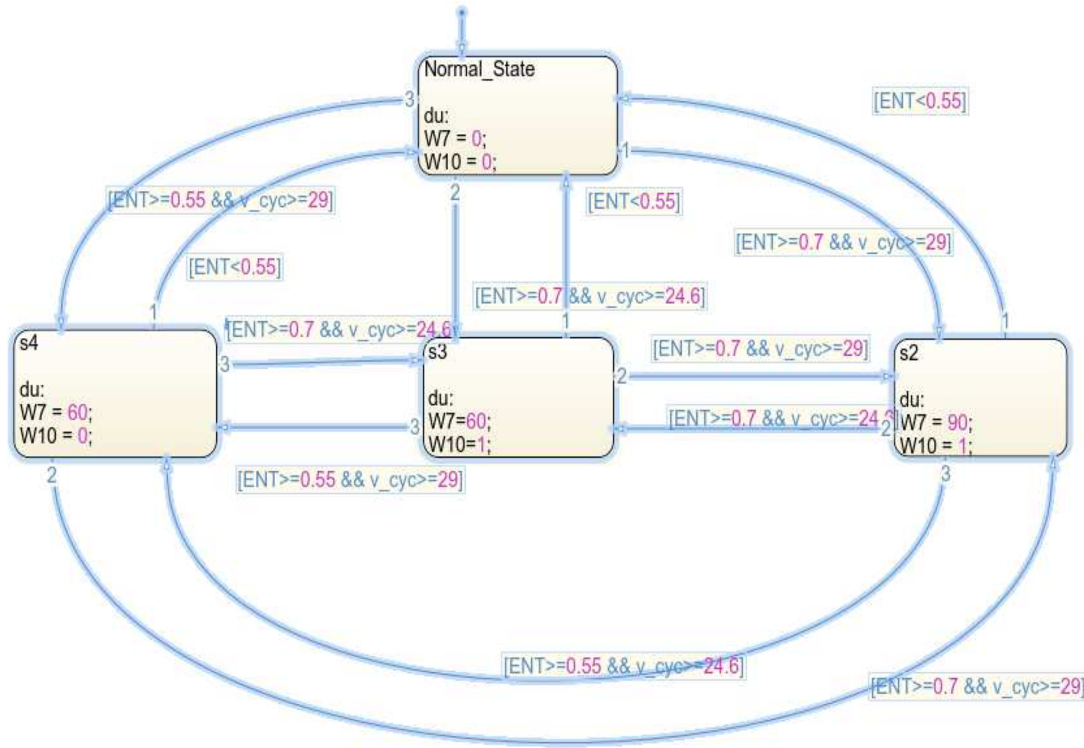

Figure 4.20. State flow (SF) diagram based on SE threshold

Driving Scenarios

In this section several scenarios were simulated to test the implemented model. These scenarios include: distraction level-2, distraction level- 3, distraction level-4, and TTC less than 1 sec. In each scenario, the driving profile (includes speed, acceleration, lane position, steering angle, and drivers gaze) was an input to the proposed model. We expect from the model to detect distractions level and take appropriate actions.

Talking on the phone while driving. In this scenario, a talking and driving profile was taken and tested. As shown in the previous chapter, talking and driving task represents a distraction level- 2. The driving profile of this task (i.e. talking and driving) includes: speed, longitudinal acceleration, lane position, steering angle, gaze-x location, and gaze-y locations. As shown in figure 4.21, once the driver engaged with a call, the model detected a distraction level-2. The figure shows some distraction level -1 and 4 were detected in a very short period of time.

Figure 4.21. Changes of distraction levels in a real time driving with talking on the Phone

As a result of distracted driving detection, the controller act based on the previously implemented flow states. In this scenario, distraction level- 2 was detected, so that the distracted indicator was activated with light orange color and 30 db non continuous peeps. Figure 4.22 represents a snapshot of the model while was running talking and driving profile. Due to the very short time of the detected false positives (fraction of seconds), the actions were not observed and the driver should not be affected.

Figure 4.22. Indicators Status in A real Time Driving with Talking over the Phone

Using GPS. In this scenario, a random profile of using GPS while driving was taken and tested. According to the valid assumptions in the previous chapter, using GPS task represents a distraction level- 3. The driving profile of this task (i.e. using GPS while driving) includes: speed, longitudinal acceleration, lane position, steering angle, gaze-x location, and gaze-y locations. As shown in figure 4.23, once the driver started using GPS, the model detected a distraction level-3. The figure shows some distraction level -1 and 4 were detected in a very short period of time.

Figure 4.23. Changes of distraction levels in a real time driving with using GPS

As a result of distracted driving detection, the controller act based on the previously implemented flow states. In this scenario, distraction level- 3 was detected, so that the distracted indicator was activated with dark orange color as well as 60 db non continuous peeps. Figure 4.24 represents a snapshot of the model while was running using GPS while driving profile. Due to the very short time of the other detected levels of distractions, the actions were not observed and the driver should not be affected.

Figure 4.24. Indicators status in a real time driving with using GPS

Texting and emailing while driving. Since both texting and emailing both scenarios represents distraction level- 4 we have merged both in one section. In this scenario, a random profile of emailing while driving was taken and tested. According to the valid assumptions in the previous chapter, texting and emailing while driving tasks represent a distraction level- 4. The driving profile of this task (i.e. emailing while driving) includes: speed, longitudinal acceleration, lane position, steering angle, gaze-x location, and gaze-y locations. As shown in figure 4.25, once the driver started texting, the model detected a distraction level- 4. The figure shows some distractions level -1 and 3 were detected in a very short period of time.

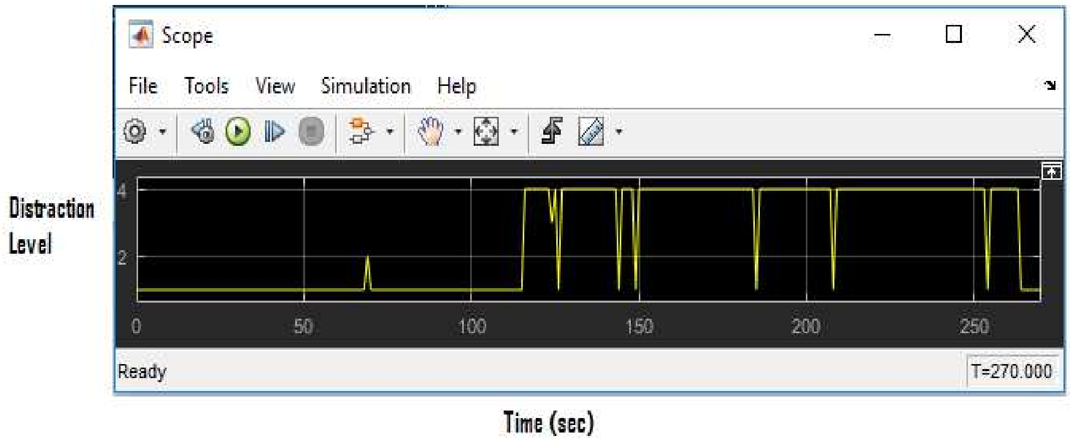

Figure 4.25. Changes of distraction levels in a real time driving with emailing

As a result of distracted driving detection, the controller act based on the previously implemented flow states. In this scenario, distraction level- 4 was detected, so that the distracted indicator was activated with red color as well as 90 db non continuous peeps. Also, deceleration was applied. On the other hand, lane assist was activated with green color due to the high steering entropy. This system should active lane keep assist in the vehicle that helps drivers maintain the lane. Figure 4.26 represents a snapshot of the model while was running texting and driving profile. Due to the very short time of the other detected levels of distractions, the actions were not observed and the driver should not be affected.

Figure 4.26. Indicators status in a real time driving with emailing

According to previously implemented flow states (FS) of the driver distraction levels, level 4 also includes deceleration action with 1 percent. Figure 4.27 represents the deceleration when distracted level- 4 is detected (the figure includes both the main speed profile and the one when the controller applies braking).

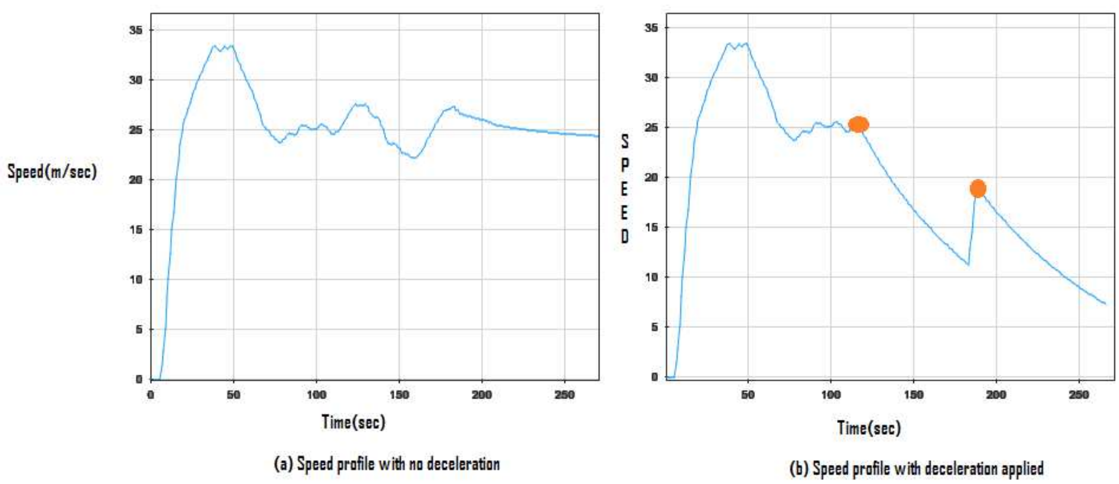

Figure 4.27. Applying brake in a real time driving with emailing

Time to collision (TTC) and texting. In this scenario, a profile of texting while driving was taken and tested. Besides texting, the scenario includes time to collision values less than 3 seconds. Texting and emailing while driving tasks represent a distraction level- 4. The driving profile of this task (i.e. texting while driving) includes: speed, longitudinal acceleration, lane position, steering angle, gaze-x location, and gaze-y locations. In Phase- 2 implementation, TTC represents an input to the model along with steering entropy, and lane position. As shown in figure 4.28, once the driver started texting, the model detected a distraction level- 4. The figure shows that level -1 and 3 were detected in a very short period of time.

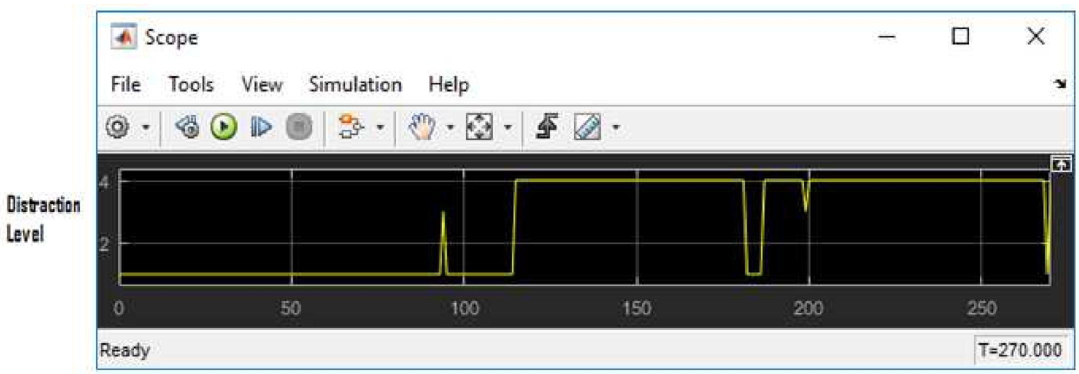

Figure 4.28. Changes of distraction levels in a real time driving with texting

As a result of distracted driving detection, the controller act based on the previously implemented flow states. In this scenario, distraction level- 4 was detected, so that the distracted indicator was activated with red color as well as 90 db non continuous peeps. Also, lane assist indicator was activated with green color because of high steering entropy. This system should active lane keep assistance in the vehicle that helps drivers maintain the lane. Figure 4.29 represents a snapshot of the model while was running texting and driving profile. The snapshot shows TTC indicator in a red state which means TTC was less than or equal 1 sec. Due to the very short time of the detected false positives (fraction of seconds), the actions were not observed and the driver should not be affected.

This scenario represents a hybrid scenario since more than one condition was applied at the same time. For instance, the system detected distraction level- 4 and applied all the actions associated with that level of distraction, and then the system detect TTC less than 3 seconds while distraction level- 4 state is still active. In realistic scenarios, we expect that the driver responds immediately for the indicators before the situation becomes worse.

Figure 4.29. Indicators status in a real time driving with texting scenario

On the other hand, Figure 4.30 represents another snapshot from the same scenario in which the system detects TTC value between 1 and 1.5 seconds. Based on the flow states, a TTC indicator was turned orange with 60 db non continuous peeps, lane assist also was activated, and finally braking with 0.2 was applied. During the whole driving scenario the dashboard dynamically changes based on the detected conditions. Again, we expect in real driving scenario that the driver will respond positively and pay attention to the road from first indicator to avoid worse situations.

Figure 4.30. Indicators status in a real time driving with texting

The implemented states flow (SF) of the driver distraction levels shows another action for distraction level- 4, which includes deceleration with 1 percent. On the other hand, once the model detected TTC value less than or equal 1.5 seconds, the deceleration was applied. The red line shown in the figure 4.31 represents the area that represents TTL <=3 sec. Once TTC is less than 1.5 and greater than 1 second deceleration was applied to avoid accidents. Finally, when TTC became less than or equal 1 second, the emergency brake is applied.

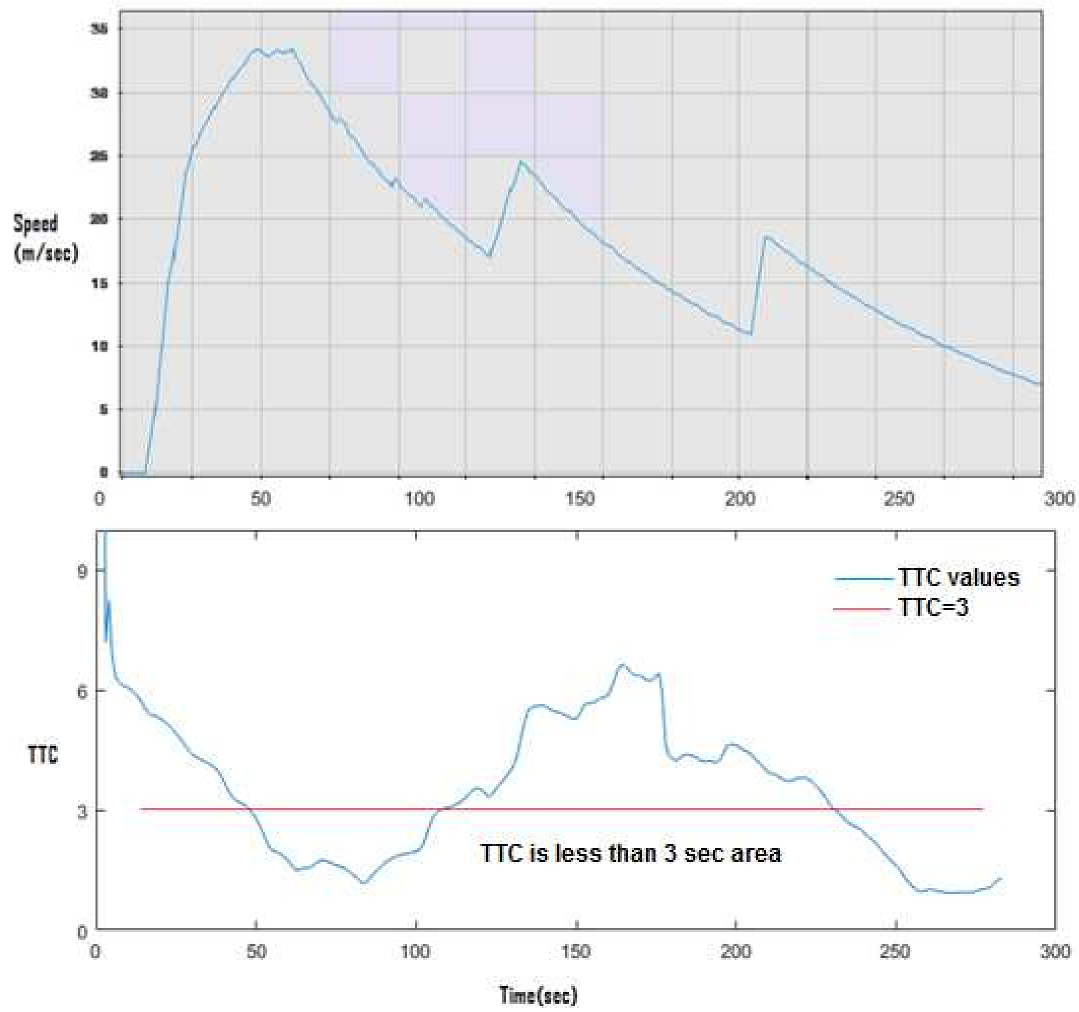

Figure 4.31. Different TTC values and speed profile

According to the tested real time scenarios described in this chapter, the implemented driving distractions detection model is efficiently capable of identifying various levels of cell phone based driving distractions. In addition, the integration between detection algorithm and the current vehicle system systems is achieved in a novel method. Since this result shows such kind of integration we expect this amalgamation to improve safety and significantly decrease accidents on roads.

CONCLUSION

Conclusions

This research contributes to the science related to abnormal driving behaviors detection and mitigation. Specifically, this work emphasizes cell-phone driving distraction detection and mitigation. This research was conducted with a combination of human in-the-loop experiments using an advanced driving simulator, machine learning modeling and classification, and MATLAB/Simulink to simulate different actions.

Although several researchers have addressed abnormal driver behavior and inattentive driving issues from different perspectives that include: engineering, cognitive science, and physics. Issues include: practicality, performance, accuracy rate, false negative rate, and usability were analyzed, and a comprehensive driver behavior detection solution that takes into consideration the effectiveness and usability of the system is proposed. The approach handles and mitigates other issues including low performance, detection rate, and high false positive rate that can directly affect the usability of the system.

Also, we conclude that lacking the context of the driver status system can negatively affect drivers as well as vehicle safety. Therefore, a complete solution to decrease road accidents is only promising by making the vehicles active safety system 'aware' of the driving context as well as the driver status. Driver behavior signals including driver inputs to be part of the control process are analyzed. The suggested approach focuses on the driver distraction levels detection and feeds the vehicle active safety controller in order to avoid severe accidents.

Furthermore, results show that the proposed hybrid driver distraction detection approach is considered a highly reliable and effective compared to other approaches. A hybrid approach combines the advantages of other approaches in one conciliated solution, which can lead to both; high accuracy detection rate and low false positive rate. The validated hybrid model in this research shows 98.7% overall accuracy, and 1.3% overall error. It also demonstrates more than 99% (TPR) for non-distracted driving detection and 97%, 96%, and 98 for distractions level 2, 3, and 4 respectively. Similarly, false negative rate (FPR) associated with hybrid approach is less than 1% for non-distracted driving detection, and 3%, 4%, and 2% for distractions level 2, 3, and 4 respectively.

Upon successful validation using MATLAB/SSIMULINK platform; this work demonstrated that the integration between detection algorithm and the existing vehicle safety system can be achieved in a novel real-time driving scenarios. The integrative driver behavior mitigation strategy and the vehicle safety controller were able to generate visual and audible dashboard alerts, activate vehicle lane assist, decelerate the vehicle to a safe/reasonable speed and/or apply emergency stop.

Future Work

The human vehicle interface (HVI) that includes the warning systems can be implemented on the dashboard of the driving simulator where participants can experience a real world alert scenario. Hence, while participants are driving and based on their driving performance, the system can be evaluated for re-action with an appropriate action. Also, how the drivers react to designed human vehicle interface (HVI) can be investigated and evaluated to suggest improvements to the current HVI.

Also, Vehicle- to vehicle (V2V) and vehicle to infrastructure communication technology is the new promising domain to increase the next generation of vehicle's safety on roads. This next version or domain, in which vehicle passengers and the driver would be connected together and to the external world, requires the addition of intensive instruments that include many embedded devices, chips, and sensors. These instruments will be added to almost every part of the vehicle (to name few: brake system, airbag, cruise control, power seat, and electronic stability control ...etc). Consequently, various data could be exchanged between vehicle systems as well as between the vehicle and the external environment. This intensive communication would create more data available on the CAN bus that could be used to detect abnormal driver behaviors. These available data can significantly be used in real time to generate the patterns associated with different kinds of driver behaviors.

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APPENDIX A

IRB APPOVAL

Abdel Ra'ouf Mayyas
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Dear Abdel Ra'ouf Mayyas:

On 7/13/2015 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Human-Centric Approaches for Abnormal Driver Behavior Detection
Investigator:	Abdel Ra'ouf Mayyas
IRB ID:	STUDY00002785
Category of review:	(6) Voice, video, digital, or image recordings, (7)(b) Social science methods, (7)(a) Behavioral research
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• Methodology , Category: IRB Protocol; • Consent (tracked) (1).pdf, Category: Consent Form; • Template HRP-503a, Category: IRB Protocol; • Recruiting Document, Category: IRB Protocol;

The IRB approved the protocol from 7/13/2015 to 7/12/2016 inclusive. Three weeks before 7/12/2016 you are to submit a completed Continuing Review application and required attachments to request continuing approval or closure.

If continuing review approval is not granted before the expiration date of 7/12/2016 approval of this protocol expires on that date. When consent is appropriate, you must use final, watermarked versions available under the "Documents" tab in ERA-IRB.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).