Methods to Detect and Reduce Driver Stress: A Review

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ABSTRACT - Automobiles are the most common modes of transportation in urban areas. An alert mind is a prerequisite while driving to avoid tragic accidents; however, driver stress can lead to faulty decision-making and cause severe injuries. Therefore, numerous techniques and systems have been proposed and implemented to subdue negative emotions and improve the driving experience. Studies show that conditions such as the road, state of the vehicle, weather, as well as the driver’s personality, and presence of passengers can affect driver stress. All the above-mentioned factors significantly influence a driver’s attention. This paper presents a detailed review of techniques proposed to reduce and recover from driving stress. These technologies can be divided into three categories: notification alert, driver assistance systems, and environmental soothing. Notification alert systems enhance the driving experience by strengthening the driver’s awareness of his/her physiological condition, and thereby aid in avoiding accidents. Driver assistance systems assist and provide the driver with directions during difficult driving circumstances. The environmental soothing technique helps in relieving driver stress caused by changes in the environment. Furthermore, driving maneuvers, driver stress detection, driver stress, and its factors are discussed and reviewed to facilitate a better understanding of the topic.

KEY WORDS: Driver stress, Intelligent transportation, Transportation, Stress detection, Stress reduction

1. INTRODUCTION

In the second largest populated country, the United States of America, people spend an average of 46 min per day driving to school or work (Tripplett and Rosenbloom, 2015). In fact, the number of vehicles on the road increases by 100% every 10 to 15 years worldwide (Tripplett and Rosenbloom, 2015). The drastic increase in the number of vehicles, the driving population, and the number of road accidents globally is critical concern. It has also triggered technological advancements in the automobile industry that aid in providing road safety and reducing probable accidents (Meiring and Myburgh, 2015). Driver stress can cause the driver to make faulty and wrong decisions, which can be extremely dangerous (Westerman and Heigney, 2000; Kontogiannis, 2006). Besides its effect on road safety, driver stress can also affect a driver’s personal health. According to Kompier and Di Martino (1995), prolonged stressful driving increases the risk of high blood pressure and other stress-related disorders significantly. Hence, methods to detect and reduce driver stress are discussed in this present paper. Several strategies for coping with driver stress were developed and introduced in the automobile industry (Stanton and Young, 2005; Reimer et al., 2010; T. C. Harrison Ford, 2017). These strategies are specially designed to avoid traffic accidents as well as improve the driving experience. The aim of this paper is to review the existing techniques for reducing and coping with driver stress.

This paper is organized as follows. Definition of stress and how the factors of driver stress are presented in the Section 2. In the following section, state-of-the-art methods for stress detection are categorized into four groups; then each category is presented and discussed. Section 3 shows two difference driving stress maneuvers that are widely used by researchers, and their effect on driver stress is discussed. In Section 4, methods of driver stress reduction are presented in detail. In the last section, a conclusion and recommendations for future studies on driver stress detection and reduction are highlighted.

2. DRIVER STRESS AND FACTORS

Stress is a generally well-understood term that can be hard to define. Stress is a state of physical, psychological, or emotional strain experienced by a person when actual or perceived demands results in an elevated mobilization of resources in an attempt to cope with those demands (Lazarus and Folkman, 1984; The American Institute
dangerous. These unforeseen events may indirectly increase the driver’s physical and mental stress. However, a driver’s capability is defined by his driving experiences and skills as driving requires a good command over one’s emotions, disposition, and particularly, unforeseen emergencies (Westerman and Heigney, 2000). Therefore, some drivers are not comfortable or confident while driving. Such drivers use extra effort to overcome physical and psychology obstacles (Wiesenthal et al., 2000).

Hill and Boyle (2007) suggested that driver stress is not only related to the driver’s characteristics, but also to the driving environment. Road and traffic conditions significantly affect the driver stress levels according to Wiesenthal et al. (2000), who observed that driver stress is significantly higher on highly congested traffic roads as compared to low-congestion roads. Further, road width is one of the environmental factors that affects a driver’s stress levels. Driving on a narrow and curvy road increase the driving workload (Schießl, 2007).

Moreover, driving in bad weather conditions requires higher concentration and simultaneously burdens the driver’s concentration. For example, drivers are subjected to higher workload while driving in heavy rain and foggy conditions (low visibility) as compared to driving on a clear sunny day (Hill and Boyle, 2007); the worse the weather condition, the higher the driving workload. In Rimini-Doering et al. (2001) a foggy driving condition was simulated to induce fatigue and stress. The results proved that driving at night (low visibility) can be considered as one of the factors that affect a driver’s stress level.

Passengers may assist the driver through actions, such as navigating, talking, and warning the driver of approaching hazards. Good passengers assist drivers and reduce their workloads; however, some passengers become key stress factors. Regan and Mitsopoulos (2001) and Engström (2008) studies showed that passengers are good at assisting drivers while driving; however, they should remain silent to avoid disturbing the driver’s concentration during highly stressful driving situations. Similarly, poorly designed driver assistance systems and navigation prompts that are delivered at inopportune times may annoy the driver (Reimer et al., 2010) and contribute to, rather than reduce, stress.

3. STRESS DETECTION METHODS

To accurately acquire and measure a driver’s stress levels and observe changes under different driving situations respectively, numerous metrics to measure stress levels and driver workload have been proposed and executed. In general, four approaches are widely used by researchers in the advanced automobile industry. Table 2 provides summary of the driver stress detection methods and their limitations. Table 4 shows a list of sensors for stress detection.
3.1. Self-report Questionnaire Assessment
The self-report questionnaire was designed to focus on the driver’s behavior in various driving situations and while carrying various tasks. The questionnaire studies the driver’s behavior and his/her respective coping strategies. Accordingly, drivers react differently to different kinds of stressful events. Additionally, driver stress is the outcome of a combination of driver characteristics such as age, driving experience, and crash history (Reimer et al., 2010). Therefore, this information is important for the assessment. According to Hill and Boyle (2007), drivers with a history of crashes reported higher stress levels while driving. Drivers with a crash history are more likely to report travel anxiety (Mayou and Bryant, 2003) and suffer from post-traumatic stress disorder (Blanchard et al., 2011). Therefore, the driver behavior inventory (DBI) is widely used in many experiments. In DBI, driver stress is defined by five factors: i) driving aggression, ii) dislike of driving, iii) tension and frustration connected with successful or unsuccessful overtaking, iv) irritation when overtaken, and v) heightened alertness and concentration. A five-point Likert scale (Mcleod, 2017) (0 = Never, 1 = Rarely, 2 = Occasionally, 3 = Frequently, 4 = Very Frequently) is usually associated with a self-report inventory to describe and measure each inventory item. In this questionnaire, all assessment questions are correlated to each other. Stressful events in everyday life are mentioned as one of the factors as well.

Most self-report questionnaires are separated into two types; pre-experiment assessments and post-experiment assessments. Pre-experiment assessments are carried out to observe the driver’s condition before the driving simulation and real-world driving studies. In some cases, only post-simulation assessment data is collected for analysis. To obtain the assessment data simultaneously, researchers can collect verbal reports. In Mehler et al. (2016) and Reimer et al. (2010), participants were asked to subjectively rate their stress level verbally on a scale of 0 to 10 where 0 is not stressed at all and 10 is totally stressed during the experiment; whereas, in Hennessy and Wiesenthal (1999), participants were interviewed over a cellular telephone to report their driver stress levels. The driving stress inventory (DSI) (Costin et al., 2012), stress arousal checklist (SACL) (Matthews et al., 1996), and Dundee stress state questionnaire (DSSQ) (Matthews et al., 1999) were designed to assess driver stress levels, whereas the NASA task load index (NASA-TLX) (Hart and Staveland, 1988; De Waard, 1996) and driving activity load index (DALI) (Pauzié, 2008a, 2009) are widely used to obtain workload ratings in different simulation experiments. Each questionnaire has its own aim. A few sets of questionnaires could be provided in a single experiment for specific research purposes. For example, in Funke et al. (2007), participants were asked to complete the DSI before the experiment and DSSQ was conducted pre- and post-task. DSI is used to assess the driver’s vulnerability to stress (i.e. aggression; dislike of driving; hazard monitoring; thrill seeking; fatigue proneness) with scores scaled from 0–100. Workload items within the DSSQ are incorporated with NASA-TLX to observe the degree of mental, physical and temporal demand, as well as, the performance, effort, and frustration associated with a task through a six 10-point rating scale. Therefore, Pauzie (2008a, 2009) developed a specific rating scale to access mental workload while driving.

Brookhuis and De Waard (2002) have discussed the use of mental workload assessments and other subjective qualifications. Brookhuis and De Waard (2002) mentioned that subjective measures and scales are rather common in traffic and transport research studies. Nevertheless, predictive validity, timing and memory, and context and consciousness are important and crucial for correct assessment of the self-report questionnaire. This especially occurs in the traffic and transport field, where the

| Stress factor                              | Examples                                                                 |
|-------------------------------------------|--------------------------------------------------------------------------|
| Driver’s physical and mental condition    | Lack of sleep, driver fatigue (Kompier and Di Martino, 1995)             |
|                                           | Driving phobia and impatient                                             |
|                                           | Curved narrow roads (Schießl, 2007)                                      |
| Road and traffic conditions               | Congestion and heavy traffic (Wiesenthal et al., 2000)                   |
|                                           | Motorist disturbances                                                    |
|                                           | Machine noise (Wiesenthal et al., 2000)                                  |
| Vehicle condition                         | Engine malfunction                                                       |
| External disturbance                      | Passengers in the vehicle (Regan and Mitsopoulos, 2001; Engström, 2008)|
|                                           | Gadgets (Mobile Phone) (Reimer et al., 2010)                            |
|                                           | In-car smart applications (Navigation prompt)                           |
|                                           | Weather condition (Low visibility, slippery road)                       |
|                                           | (Rimini-Doering et al., 2001; Hill and Boyle, 2007; Hu et al., 2011)   |

Table 1. Stress factors and examples.
experiments are carried out in dynamic situations and extremely variable conditions (Brookhuis and De Waard, 2002).

3.2. Physiological Measures

Physiological sensors are used to detect the human body’s physiological changes, such as brain activation, electrodermal activity (skin conductance or galvanic skin response (GSR)), heart rate, heart rate variability (HRV), muscle tension, and respiration rate (Healy and Picard, 2005; Yamakoshi et al., 2008; Mehler et al., 2009; Munla et al., 2015). For instance, electroencephalography (EEG) is widely used by researchers to detect human brain waves; the electrocardiograph (EKG) is used to record heart rate and skin temperature; photoplethysmography (PPG) to measure changes in peripheral blood flow; electromyography (EMG) to measure muscle activity; and electrodermal sensors are used to measure the electrical conductance of the skin which changes largely as a function of sweat gland activity. For stress detection, as we unable to monitor the internal representation of perception of a driver, we have to rely on a subtle and detailed analysis of physiological measurement (Koolhaas et al., 2011). Physiological measurements for stress detection are proposed by Wijsman et al. (2011) and Sun et al. (2010) In Horvath (1978), an experimental comparison of the psychological stress evaluator and GSR was executed.

According to Reimer et al. (2010) and Westerman and Heigney (2000), stress from driving is associated with an increase in heart rate and blood pressure. Bakker et al. (2011) monitored human stress using the GSR sensors. Castin et al. (2012) observed stress using electrocardiogram (ECG) signals. Physiological sensors can record data during the driving experiment (Coughlin et al., 2009). They monitor physiological changes, and could potentially provide drivers with useful reference information about their body’s conditions while driving (Coughlin et al., 2009). Healy and Picard (2005) mentioned that real-time driver stress can be detected, after a training segment has been completed, by the use of machine learning. GSR, HRV, and methods to measure heart rate were suggested as the best real-time correlates of stress (Healy and Picard, 2005). Each physiological sensor has its own advantages and limitations. Sensor artifacts or coding metrics can cause latency issues. For instance, anticipatory electromyography (EMG) has been measured in the laboratory at 30 ms (Barniv et al., 2005); however, skin conductivity latency was of the order of 1.4 s (Lockhart, 1972). Although, skin temperature can show a decrease with stress, it can also show delays and directional shifts that can exceed 60 s. Moreover, GSR signals vary among individuals and on a daily basis, even for the same individual (Bakker et al., 2011). Therefore, Kurniawan et al. (2013) suggested that other forms of measurements, instead of relying only on GSR-based detection of stress, are needed to obtain more reliable data. Therefore, researchers now detect stress via multi-physiological sensors (Healy et al., 1999; Healy and Picard, 2005). In a stress detection experiment conducted by Healy et al. (1999), four types of physiological signals were recorded, namely, skin conductance, heart activity, respiration, and muscle activity. Moreover, Mehler et al. (2012) found that individuals whose measurements vary will show the most reactivity and suggested that hybrid detection systems that consider multiple measures might be more sensitive than those dependent on a single measure.

Advanced technologies enable researchers to design and develop non-invasive sensors to acquire data accurately without any contact with the driver. Use of several non-invasive sensors to collect physiological data to avoid obstructing the driver while driving has been proposed (Vavrina et al., 2012; Mizuno and Hiep, 2013). These sensors often come with the vehicle and, therefore, no extra setup to activate the sensors is needed.

3.2.1. Challenges of sensor system design

Despite the debut of a non-invasive sensor system that successfully avoids obstructing to the driver, three key elements of sensor system design should be considered, namely, size and dimension, accuracy, and power consumption. Ideal sensor systems should be lightweight and tiny in size to reduce the intrusiveness, but also highly accurate with a low power consumption. However, in reality, a tiny sensor system could be highly costly owing to the difficulty of its production process. Additionally, accuracy and power consumption are usually directly related, i.e., high performance sensor system often requires a considerable amount power consuming for data processing and analysis. From the perspective of driver stress detection sensor system design, driver safety should be prioritized; therefore, tiny and non-invasive sensor systems are recommended.

However, there are some physiological sensors (PPG, GSR, and skin temperature sensors) that have to be attached to the participants’ body directly to acquire reliable signals (Jimenez, 2013). Although wearable sensors may cause drivers to experience some encumbrance in normal activity, the dimension and size of the sensors could be sufficiently optimized to lower the degree of intrusiveness.

Furthermore, physiological sensor signals are often corrupted owing to electrode contact noise, motion artifacts, power line interference, baseline drift, contraction, etc. (Munla et al., 2015). Specifically during driving, motion artifacts can be contaminated easily by movement and other interferences. To avoid signal noise and interferences that could potentially mislead the results and accuracy, filtering of raw signals and further signal processing is vital during the preprocessing stage because sets of raw captured data can be incomprehensible (Munla et al., 2015). To remove the noisy signal caused by motion artefacts, Healy (2009) suggested two solutions: track
activity and only attempt affective analysis during periods of relative rest or attempt to model the effects of motion and factor them out.

3.3. Driving Behavior Monitoring
Lee et al. (2017) mentioned that driver stress detection is achievable by monitoring driving behavior, and Lanatà et al. (2015) reported that the autonomic system (ANS) and driving style changed under driving stimulations with incremental stress levels. Stressful and non-stressful driving events are statistically detected by dynamic steering wheel correction and vehicle velocity (Lanatà et al., 2015). Instead of observing the driver’s body conditions, driving behavior monitoring systems observe his/her driving performance. Lee et al. (2017) developed a wearable pair of gloves that has a 9-DOF inertial motion unit (IMU) sensor to calculate steering wheel motion (SWM). Moreover, by implementing a multi-sensor integrated system, vehicle movement parameters on roads with different conditions can be recorded and analyzed. In most of the studies, the GPS unit, cameras, and ranging sensors, such as the ultrasonic sensor and laser scanner unit, were installed in the vehicle to observe driving behavior (Schießl, 2007; Takeda et al., 2009; Meiring and Myburgh, 2015). Figure 2 shows an example of how the sensors were installed in the vehicle (Ohn-Bar et al., 2014). In steady driving conditions, the driver aims to consistently maintain a constant velocity (Lanatà et al., 2015). A preprogrammed camera is used to execute lane recognition to observe the vehicle’s locus to monitor driving behavior (Schießl, 2007). A laser scanner and radar sensor are used to capture data from the surrounding environment and detect the distance between the vehicle and obstacles (Schießl, 2007). A computer is required to direct the sensors capturing vital information (Takeda et al., 2009). ViewCar (Schießl, 2007), NU-Drive (Meiring and Myburgh, 2015), and Uyanik (Takeda et al., 2009) are three examples of intelligent vehicle systems embedded in real vehicles to observe driving behavior in the real world. They can monitor the turning patterns of the steering wheel and recognize lanes and accelerating patterns. All those data are recorded and analyzed to detect and measure the driver’s stress arousal state.

3.4. Visual-based and Speech Detection
Physiological sensors have to be attached to the driver’s body directly, whereas visual-based sensors are installed on the vehicle rather than on driver’s body. Visual-based sensors have a greater potential of measuring driver stress and mental workload as they are non-invasive and can assess real-time and automated workload (Or and Duffy, 2007). For instance, visual-based thermography to detect facial skin temperature (Yamakoshi et al., 2008) and pupil dilation have been implemented in several driver stress studies (Pedrotti et al., 2014; Baltaci and Gokcay, 2016). In a study conducted by Or and Duffy (2007), nose and forehead skin temperature were captured via thermography. Nose skin temperature is found to respond to stimuli, i.e., the higher the stimuli, the greater the decrease in nose skin temperature (Or and Duffy, 2007). Pedrotti et al. (2014) proved that the pupil diameter (PD) increases during stressful events. For the acquisition and analysis of the PD parameters, six different steps were taken from preprocessing to classification (Lee et al., 2017). PD changes have been found to be very sensitive in response to stress in the laboratory under controlled lighting conditions, however, the technique has several limitations under real-world driving scenarios as PD reacts to light intensity as well as stress stimuli. Gao et al. (2014) introduced a method for detecting driver’s stress via the analysis of facial expressions that can be captured by a NIR-camera. However, illumination and occlusion become an issue in data collection for facial features (Fernández et al., 2016). Therefore, computer vision technology is applied for accurate facial detection and data correction. Gao et al. (2014) proposed a data normalization step that is applied using the 3D cylindrical head model to increase the accuracy and decrease the impact of driver pose mismatch due to variations in camera setup and driver position. Alternatively, Yin et al. (2007) determined driver stress by analyzing the changes in pitch in a subject’s speech. A set of speech data for stress detection has been presented by Hansen (1996), Boril et al. (2010) and Fernandez et al. (2003) found that driver stress could be observed by speech. Boril et al. (2010) recommended that subject complete several tasks by verbally answering into the voice recorder while driving. The collected speech data were then subjected to signal processing for further analysis and emotional stress classification. Driver stress detection by speech was found to be obstructive for the driver while driving, as the driver needs to perform additional tasks in order to do the required speech recording. Fernandez et al. (2003) suggested drivers perform a secondary task by answering while driving in a simulator. The additional secondary task was a distraction in this case as well.

As the raw data for facial skin temperature, PD, and
4. DRIVING STRESS MANEUVERS - A REVIEW

To detect and collect necessary data on driving stress, two different assessment approaches are commonly used: driving simulations and real-world driving tasks. Sahayadhas et al. (2012) adapted a low-level simulator with basic driving simulator equipment, facilities, and multi-screens, while Pradhan et al. (2005) adapted an immersive driving simulator using a real vehicle and high-quality realistic graphics that are projected onto big screens; and English (2009) utilized a highly immersive 360-degree professional driving simulator that mimics all driving circumstances inside a 360-degree motion simulation space. In the section below, their purpose and limitations are discussed and reviewed. Although driving simulators in the current market offer a realistic driving experience and allow researchers to reproduce driving situations consistently for each participant during the experiments, from the perspective of investigating the driver behaviors, it is unsafe and unethical to mimic certain driving situations, such as road accidents and road safety violations, while driving in the real world. Hence, in an experiment conducted by Yamaguchi and Sakakima (2007), stress was evaluated by using driving simulators, while Parsons et al. (1998) conducted an experiment using real-world driving tasks. Both driving stress maneuvers served different study purposes. A virtual and a real driving task were compared by Sena et al. (2014), who used similar driving scenarios for both driving task, and a lower variant of the heart rate was found in a fixed base simulator but not in the real driving task. Reimer and Mehler (2011), found that absolute heart rate values were higher during real-world driving tasks but showed very similar relative increases in heart rate during both the simulator and real-world driving task in response to increased levels of cognitive demand. For facial skin temperature, Or and Duffy (2007) found that the driving simulator resulted in a higher level of driver stress and a greater drop in nose temperature than the real-world driving task. The studies highlighted above observed and showed physiological changes in both driving simulator and real-world driving.

However, in a laboratory, a large degree of control can be exerted over the subject’s behavior and better results can be expected (Healy, 2009). While driving on the road, the subjects were expected to encounter unpredictable stress stimuli; Reimer and Mehler (2011) found that absolute levels of heart rate and skin conductance were lower for participants in the simulator than they were for participants in real-world driving scenarios. However, the relative increases in heart rate were very similar in both, the simulator and real-world driving tasks. Thus, simulation is

Table 2. Summary of stress detection methods.

| Refs. | Methods | Examples | Limitations |
|-------|---------|----------|-------------|
| (Hart and Staveland, 1988; Matthews et al., 1996; Westerman and Heigney, 2000; Kontogiannis, 2006) | Self-report questionnaire assessment | Driving Stress Inventory (DSI), Driving Behavior Inventory (DBI), Stress Arousal Checklist (SACL), Dundee Stress State Questionnaire (DSSQ), NASA Task Load Index (NASA-TLX) | Questionnaire is commonly known as subjective. A specific purpose set of question and variety have to be implemented. |
| (Healey et al., 1999; Meiring and Myburgh, 2015) | Physiological measures | Photoplethysmography (PPG) sensor, Galvanic Skin Response (GSR) sensor, Electrocardiogram (ECG) sensor, Electroencephalography (EEG) sensor | Problematic influence on accuracy and sensitivity along with being intrusive. |
| (Alvarsson et al., 2010; Lanatà et al., 2015; Meiring and Myburgh, 2015) | Driving behavior monitoring | Lane recognition, steering movement, braking and accelerating recorder | Vehicle types, driver experience and road conditions are dynamic and affecting the data acquisition. |
| (Matthews et al., 1996; Yamakoshi et al., 2008; and speech Kurniawan et al., 2013) detection | Facial temperature changes, pupil dilation and speech | Visual-based: easily disturbed when occlusion or illumination changes appear. |

speech are not suitable for analysis directly. The collected data and extracted features are subject to signal processing, such as normalization or noise cancelation, which is important for speech detection (Hansen, 1996). Furthermore, several classification techniques have been performed using several classifier and machine-learning algorithms (Lee et al., 2017). Neural network was applied in Alvarsson et al. (2010), while a SVM classifier was applied in Fernandez et al. (2003).
very useful for assessing relative levels of stress associated with different tasks. However, it is not as good at showing what the absolute values of various physiological measures might be under real-world driving conditions. Moreover, Healy (2009) found that the human system might respond differently to stimuli, so a model of history and person-dependent specifications are necessary for accurate signal interpretation. However, differences in maneuvers and real-life driving were investigated by Reimer and Mehler (2011), who found that driving simulators can produce convincing and reliable results as well. Most importantly, Wang et al. (2010) stated that a fixed-base driving simulator provides a safe and structured environment for evaluating performance on several tasks. Table 3 demonstrates the advantages and limitations of the virtual and real-world driving tasks. Although driving simulators have several limitations, they still provided reliable and valid data. In most cases, driver stress detection experiments are carried out under highly dangerous situations to trigger and observe driver stress. Therefore, a driver simulator is highly recommended for future driver stress investigation studies.

5. STRESS REDUCTION AND RECOVERY

Stress reduction and recovery is defined as the act of relieving stress arousal to an optimal level to improve driving performance and potentially increase driver wellness. This paper targets driver stress; therefore, the coping strategies mentioned in this paper are only designed for drivers. Driver stress reduction and recovery techniques ameliorate driver stress via several aspects, such as assisting with driving at a slow-pace in high-congestion traffic, or autopilot navigation systems that reduce the driver’s workload. There are numerous stress reduction and recovery strategy systems that have been developed by vehicle manufacturers and researchers (Stanton and Young, 2005; Reimer et al., 2010). In this section, stress reduction and recovery techniques are categorized into three major categories: (1) driver assistance systems, (2) notification alerts, and (3) environmental soothing. Table 5 lists these three categories, as well as methods for stress reduction, stress detection, and the results; limitations are discussed in the section below.

5.1. Driver Assistance Systems

Driving assistance systems are a collection of systems and subsystems that assist or take over part of driver’s task to reduce or even eliminate driver errors, and enhance efficiency (Brookhuis et al., 2001). However, this paper focused on driving tasks in high-stress situations for the purpose of reducing the driver’s workload and stress levels. Such systems may employ several types of ranging sensors, such as an ultrasonic sensor, a radar sensor, and a laser scanner installed in the vehicle to capture data from the surrounding environment (Reimer et al., 2016).
Therefore, driving behavior monitoring techniques are often applied in driver assistance systems to observe the surrounding conditions. Once the surrounding environment has been captured and analyzed, the system will prompt a set of steps or actively assist the driver in performing the task easily (T. C. Harrison Ford, 2017). For example, active park assist (APA) is an automation system that assists drivers with parking (Reimer et al., 2016; Active Park Assist, 2017), while adaptive cruise control (ACC) is based on a range sensor and distance control system (Stanton and Young, 2005). The control system has authority over the throttle and brakes to switch between speed and headway control in response to the range sensor. As reported, driver assistance systems mentioned above assisted the driver in performing stressful driving tasks effectively and reduced driver stress level relatively (Reimer et al., 2016). Reimer et al. (2016) confirmed that driver stress is reduced while using the driver assistance system and that the average heart beats is significantly reduced by 12.6 bpm when using the APA system. Moreover, there are numerous vehicle assistance systems available, such as active city stop (ACS) (T. C. Harrison Ford, 2017), lane keeping aid (Ford Europe, 2011), and ACC (Stanton and Young, 2005). Different driver assistance systems provide different types of assistance in different driving situations; for example, the ACS is suitable for slow speeds in high city traffic areas (T. C. Harrison Ford, 2017), whereas the ACC targets stressful driving events (Stanton and Young, 2005). Nevertheless, the ACC system is reported to have successfully reduced driver mental workload and improved driving performance in multiple dimensions (Ma and Kaber, 2005).

5.2. Notification Alert
A notification alert system is a warning system that notifies the driver when a hazard is detected (Howard, 2017). There are two types of potential notification alert systems: driver physiological condition notification alert system and road situation notification alert system. Driver will be notified once the his/her stress levels are susceptible to be high. The notification message may request the driver to reduce his/her driving speed and drive safely. On the other hand, road situation notification alert systems warn the driver when a hazard is detected. A series of ranging sensors are installed

| Refs. | Stress reduction Methods | Stress stimuli | Detections | Results |
|-------|--------------------------|----------------|-------------|---------|
| Reimer et al. (2016) | Driver assistance systems | Active Park Assist (APA) | Car parking | Self-report assessment and physiological signal | Stress level significantly lower (12.6 bpm lower) |
| T. C. Harrison Ford (2017) | Driver assistance systems | Active City Stop (ACS) | Traffic jam, high congestion traffic | - | Assist driver and reduce driver’s workload |
| Ma and Kaber (2005), Stanton and Young (2005) | Driver assistance systems | Adaptive Cruise Control (ACC) | High-demand driving situations | Dundee Stress State Questionnaire (DSSQ) | Alleviate stress and workload in high-demand driving situations |
| Reimer et al. (2010) | Notification alert | Cross Traffic alert (CTA) | Backing out from parking | Self-report assessment and physiological signal | Warn drivers during hazards |
| Wiesenthal et al. (2000) | Environmental soothing | Listen to preferred music | High congestion traffic | Driving Behavior Inventory-General (DBI-Gen) | Music constrain the stress arousal level |
| Jimenez (2013) | Environmental soothing | Driver seat massage | Driving on road | Physiological signal (Heart rate and respiration rate) | Relief on driver’s tension |
| Coughlin et al. (2009) | Environmental soothing | Natural-dominated road view | Nature-dominated and artifact-dominated road view | Physiological signal (facial EMG, ECG, and blood pressure) | Quicker recovered from stress |
| Alvarsson et al. (2010) | Environmental soothing | Nature sound | Mental arithmetic task | Physiological signal | Stress recovered quicker |
in the vehicle to collect road situation data. The lane departure warning (LDW) system is a lane recognition system that detects driving behavior (Howard, 2017). A warning notification is activated to warn the driver when his or her vehicle is moving past the boundaries of the lane (Jadhav and Jadhav, 2015). Image processing and signal processing techniques are applied in the system to perform measurements. Additionally, laser scanners and ultrasonic sensors are widely used to detect and measure the distance between the vehicle and surrounding obstacles. Notifications are prompted if the vehicle approaches an obstacle. Both road situation and driver physiological state alert systems have been proven to improve a driver’s situational awareness and reduce driver stress effectively while operating the vehicle. Reimer et al. (2010) reported that a majority of the participants are reported to have a better performance while backing out of a parking space with limited visibility by activating the cross traffic aid (CTA) system.

5.3. Environment Soothing
Environmental soothing is a therapy-like system that mainly focuses on alleviating the driver’s physiological stress by altering the in-vehicle environmental condition. To detect driver stress, physiological sensors are often used to monitor the driver’s mental and physical status. Further, signal processing and machine-learning algorithms are often used to detect and measure the driver’s stress level. Once high-stress level is detected, an environment-soothing application is launched to relieve driver stress without any disturbances to the driver. For example, an intelligent car seat has been proposed as a solution for driver stress by Innovation Europe, Faurecia Automobile Seating. The intelligent car seat is an environment soothing system embedded in the car seat (Stock, 2015). The seat actively measures and monitors the driver’s physiological status. Respiration and heart rates are analyzed by a designed algorithm to detect driver stress and energy level (Stock, 2015). The system is embedded seamlessly in the vehicle without causing any disturbance to the driver. Once the system detects the driver is in a high-stress state, a relaxation massage and warm ventilation equipped inside the driver seat are activated to soothe the driver (Stock, 2015). On the other hand, music therapy is known as one of the potential methods for reducing driver stress. Wiesenthal et al. (2000) observed that listening to preferred music decreases heart rate and reduce stress while driving in highly congested traffic. A smart music player that is able to recognize the driver’s identity and select customized, driver-preferred music could help reduce driver stress. In other words, environmental soothing systems create and provide a comfortable driving environment to alleviate the driver’s mental and physiological stress.

5.4. Limitations of Stress Reduction Techniques
As reported by Reimer et al. (2010), some drivers face difficulty with these systems because of their unfamiliarity with new technologies, and, hence, find it difficult to follow the instructions suggested by the smart alert system. The drivers need to completely trust the new driver assistance systems to confidently utilize the system and be assisted (Reimer et al., 2010). Meanwhile, notification alerts may not always effectively reduce driver stress as drivers are allowed to use or ignore the notification (Matthews and Desmond, 2001) and inappropriate notifications could induce, rather than reduce, stress (Reimer et al., 2010). For instance, in a comparison study between APA and CTA conducted by Reimer et al. (2010), participants were uncertain if the CTA technology was active or not because it is only overtly presented a notification when a warning was present. Further, CTA assessment also reported an issue of false and missed alarms (Reimer et al., 2010). Warning systems with 0% failure detection are most likely unrealistic; therefore, accuracy and user’s acceptance of a systems is crucial (Reimer et al., 2010). Although driver stress reduction systems are still under development and, a fully specific driver stress reduction system is yet to be released, many advanced driver assistance systems (ADAS) are equipped to aid and assist drivers during their daily drives. Notification systems can trigger negative emotions in drivers under certain situations (Reimer et al., 2010; Abdic et al., 2016). On the other hand, environment soothing techniques alter the driver emotions by adjusting in-vehicle surroundings. To generalize the environmental soothing technique for the masses is challenging, as it has been specially designed to cater to all aspects of the drivers’ preferences and can be customized by the users.

6. CONCLUSION
This paper discussed the methods of detecting driver stress, including (1) self-report questionnaires, (2) physiological measures, (3) driving behavior monitoring, and (4) visual-and speech-based detection, and also highlighted their advantages and limitations. Self-report questionnaire were found to be subjective; however, the reported physiological measures produced consistent and reliable results. Therefore, researchers are advised to multiple methods in a study to detect driver stress in order to acquire high-reliable result. Stress detection systems and hardware design are some of the key factors that need to be considered. Non-invasive sensors are highly recommended owing to the driver safety issue. An intrusive or second task for a driver during stress detection could cause a deadly traffic tragedy. A great stress detection and reduction system should be embedded in the vehicle seamlessly without asking the driver to perform additional tasks. Meanwhile, several stress reduction methods have been proposed by researchers. Stress reduction methods have been grouped into three categories, namely, (1) notification alerts, (2) driver assistance systems, and (3) environmental soothing.
techniques. Each of the stress reduction methods target to different driver stress stimuli. User friendliness is one of the major factors determining the use of an advanced driver assistance system. Effectively reducing the driver’s mental and physical workload while driving is the most important consideration for the development of systems that aim to reduce driver stress.

Nowadays, people are seeking heather and happier lives. Driver stress reduction technologies not only aid in road safety but also have the potential to provide pleasant trips for drivers and road users daily. A stress reduction enabled smart vehicle that allows the driver or the passengers to relax during a journey will soon be released. Hence, to design an intelligent driving embedded system for driver stress detection and reduction, non-invasive physiological sensors and environmental soothing technique are highly recommended. The key advantage of applying non-invasive physiological sensors and environmental soothing techniques is both of them are non-intrusive to the driver and alter driver stress levels seamlessly. Furthermore, researchers are advised to consider the user interface and user experience associated with these systems to allow the driver to fully utilize the designed system.

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