Driver Fatigue Detection Systems: A Review

Gulbadan Sikander and Shahzad Anwar

***Abstract*—Driver fatigue has been attributed to traffic accidents; therefore, fatigue-related traffic accidents have a higher fatality rate and cause more damage to the surroundings compared with accidents where the drivers are alert. Recently, many automobile companies have installed driver assistance technologies in vehicles for driver assistance. Third party companies are also manufacturing fatigue detection devices; however, much research is still required for improvement. In the field of driver fatigue detection, continuous research is being performed and several articles propose promising results in constrained environments, still much progress is required. This paper presents state-of-the-art review of recent advancement in the field of driver fatigue detection. Methods are categorized into five groups, i.e., subjective reporting, driver biological features, driver physical features, vehicular features while driving, and hybrid features depending on the features used for driver fatigue detection. Various approaches have been compared for fatigue detection, and areas open for improvements are deduced.**

***Index Terms*—Intelligent transportation, fatigue detection, driver monitoring.**

I. Introduction

DRIVING involves the performance of a set of actions along with situation awareness, as well as, quick and accurate decision making. Situational awareness is critical in driving, as direct attention is required to process the perceived cues. Monitoring attention status is considered one of the most important parameter for safe driving [1]. Fatigue slows down human response time which leaves the human unable to drive efficiently. Research in the field of driver monitoring has gained momentum, specially for driver workload estimation [2], driver activity identification [3], secondary task identification [4] and driving style recognition [5]. Many techniques (to detect driver fatigue) are presented in literature [6]–[10]. Some of these methods have been implemented by various multinational companies for driver assistance. In a survey in Canada [11], it has been reported that 20% of fatal collisions involve fatigue. In another survey, it is documented that in Pakistan 34% of road accidents were related to fatigue [12]. According to US survey, 20% of fatal crashes involved a drowsy driver [13]. In the EU, 20% of commercial transport crashes are attributed to fatigue [14]. All the statistics and numbers are alarming and seek serious research community attention to address the issue. Fatigue symptoms include yawning [15], slow reaction time [16], eyelid closure [17], loose steering grip [18], etc. Humans may exhibit multiple symptoms and levels of fatigue [19], therefore one symptom may not singly and accurately be employed for fatigue detection.

This study presents an in-depth review of scientific research and existing technologies for fatigue detection. This paper is organized into seven sections. Section I introduces the concept of driver fatigue. Section II presents the effects of fatigue on driving performance. Section III illustrate the existing commercial products available in the market for fatigue detection. Section IV explains the scientific methods deployed for fatigue detection. Section V covers a detailed investigation of the scientific research on driver fatigue detection. Section V has been subdivided into 5 parts; subjective reporting, biological features, physical features, vehicular features and hybrid features. Section VI presents a discussion on the methods presented in section V and finally Section VII concludes this article.

II. Effect of Fatigue on Driver Performance

Fatigue can be classified into active, passive and sleep related fatigue [20]. Active fatigue is mental depletion caused by active engagement in a task. Humans with intense long hours of work, experience, active fatigue. Passive fatigue is caused by a monotonous task or inattention. Even if a human is not tired a monotonous task will distract from the primary task. Prolong episodes of driving cause the driver to lose interest and mind will wonder, consequently accidents might occur not due to the fact that driver is tired but the driver being distracted from the road. In driving, blink duration and reaction time show direct relation to passive fatigue [21]. A study in [22] has suggested that the sensitivity of driving performance to fatigue is higher on straight roads such as highways as compared to curved roads because driving on highways is monotonous and causes passive fatigue.

The circadian rhythm is a 24-hour sleep/wake cycle and a human will feel sleepy during the same period in the circadian cycle. For adults the largest dip in energy is at midnight (02:00 to 04:00 hours) and midday (13:00 to 15:00 hours) [23]. If driving phenomena is occurring in between these timings, there is a high possibility of experiencing sleep-related fatigue. Sleep-related fatigue and its effect on driver performance is further explained in [24]. Their study suggested that the driver's manoeuvring ability decreases with increasing fatigue levels and break distance is also dependent on the time of day. As sleep-related fatigue is higher at

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night (20:00 to 05:00 hours) and early morning (06:00 to 10:00 hours), driving efficiency is compromised during these timings. Philip *et al.* [25] elaborate on the dependence of driving performance on time of day and time slept in the last 24 hours. If sleep is restricted to two hours in a 24-hour time frame, the inappropriate line crossing increase multi-fold.

Matthews and Desmond [26] present the effect of task induced fatigue or active fatigue on driving performance. While experiencing fatigue vehicle control, signal detection and pedestrian detection all deteriorate. Driver age and drive duration play an important role in performance [27]. When the duration of driving task increases the steering error and reaction time both increase. After long working hours the driving performance falls significantly [28].

Therefore, the adverse effect of fatigue on driving performance highlights the importance of timely fatigue detection. Some existing technologies used for driver fatigue detection are explained in Section III.

III. Existing Technologies for Driver Fatigue Detection

A. Implemented Driver Fatigue System by Automobile Companies

Many well-known multinational automobile companies such as Toyota, Volkswagen and Nissan are currently performing research on driver inattention systems.

In 2008 model Crown, Toyota's first fatigue detection module was installed which detects drowsiness based on eyelid activity. Recently, Toyota has deployed Toyota Safety Sense P [29] in both compact and large vehicles. Toyota Safety Sense P includes vehicle detection, lane deviation, and pedestrian detection.

Nissan [30] driver attention alert implemented in 2016 Nissan Maxima model tracks the driver's steering patterns and once it detects any unusual deviation from the pattern a warning signal is generated, in order to alert driver, if break is required. The Nissan driver attention alert adapts to driver's behaviour by establishing a baseline. Continuously statistical analysis of steering correction errors is performed for the detection of deviation from baseline. A sign is displayed on the console once fatigue is detected.

Rest Assist in Volkswagen [31] offers lane tracking system, pedal use and erratic steering wheel movements to judge driver fatigue level. Once fatigue is detected the system warns the driver in the form of (i) visual message, (ii) acoustic signal and (iii) steering wheel vibration.

Many of the current fatigue detection methods implemented by various automobile companies are based on vehicle based features, whereas third party commercial products (described in the following section) are based on driver's physical features.

B. Third Party Commercial Products

Many third-party companies have designed, developed and implemented products for fatigue identification. Smart Eye AB has designed AntiSleep specially for real-time driver fatigue detection. AntiSleep employs features such as eye gaze, head movement, eye position and blinking for driver fatigue detection [32]. Additionally, Smart Eye AB has designed Smart Eye Pro 3.0, which detects fatigue and inattention employing eyelid activity and gaze direction respectively.

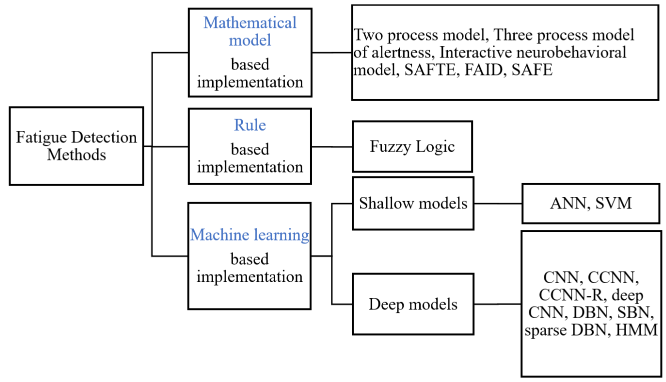

Fig. 1. Driver fatigue detection methods.

Applied Science Laboratories (ASL) [33] has designed and developed a video-based eye tracking software which observe pupil reflection to measure eye movement. ASL has designed various tracking softwares for different applications such as psychology/cognition, human factors/ergonomics, education/training and marketing research.

Sleep Diagnostics Pvt Ltd designed OPTALERT [34] for fatigue monitoring. OPTALERT utilizes wireless glasses to monitor eyelid and pupil activity. The glasses are equipped with a small-scale LED mounted on frame which measures operator eyelid velocity and eye openness. OPTALERT is currently deployed in commercial vehicles in Australia.

Care Drive's [35] driver fatigue monitor MR688 incorporates an infrared camera sensor to detect fatigue and tracks pupil changes and head movements. The output video is connected to the customers MDVR and fatigue signals are also sent through GPS to the customer so that the supervisor can monitor driver's state in real time.

GuardVant has designed OpGuard [36] which is an installable system for driver fatigue detection. OpGuard's infrared camera monitors driver's eyelid closure, head and facial movements and behaviour, such as, cell phone use and reading while the vehicle is moving. The OpWeb software allows supervisory team to keep real time check on the driver.

Third party companies have mostly concentrated on fatigue detection using driver physical features such as yawning, blink rate, blink duration and head movement. Even though much progress has been made in driver monitoring technologies, there is still a long way to achieve a highly accurate system.

IV. Fatigue Detection Methods

Driver fatigue detection methods are implemented via mathematical models, shallow models or deep models as summarized in Fig. 1.

A. Mathematical Models Based Implementation

Bio-mathematical models offer a quantitative analysis of the effect of sleep cycle on individual performance.

Bio-mathematical models incorporate inputs, such as, circadian cycles, duration of sleep, duration of wakefulness and sleep history to predict risk of fatigue and performance quality. One of the earliest models is the Two Process Model [37]. This model is based on the interaction of two processes namely the circadian Process '*C*' and the homeostatic Process '*S*'. These processes predict performance and fatigue levels. An upgrade to the two process model is the Three Process Model of Alertness [38]. The Three Process Model utilizes the duration of sleep and wakefulness as input to predict fatigue risk and alertness. This computer based model considers both circadian and homeostatic component. The Interactive Neurobehavioral Model is targeted for agencies that suggest regulating their working hours, such as aviation, railway and bus transportation. This model is based on homeostatic, sleep and circadian features [39]. The Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) [40], [41] Model is a neurobehavioral model and works on similar features as the SAFE model. However, the difference between SAFE and SAFTE is that SAFE is based on real life generated data while SAFTE is based on both real life data and data generated by auto sleep algorithm. SAFTE has applications in military, medical and the industrial field. Fatigue Audit InterDyne (FAID) [42] Model only incorporates the hours of sleep as an input and predicts fatigue levels. FAID is applicable to a workplace setup, it associates fatigue levels to past sleep durations. The models discussed above are general purpose models and are used to regulate work hours and increase efficiency. The system for Aircrew Fatigue Evaluation (SAFE) Model [43] was developed for air travel crew and is based on laboratory experiments. SAFE presents alertness levels during flight duration.

Most mathematical model based approaches are designed for generic setups, such as, workplace and factory worker workload. Recently, due to the development in intelligent systems, researchers have shifted their attention towards intelligent systems, which is discussed in the following section.

B. Rule Based Implementation

Rule based implementation is considered as one of the lesser challenging approaches in expert system implementation. For complicated expert systems Fuzzy Inference Systems (FIS) [44] is preferable over simple rule base systems. FIS use fuzzy rule base in combination with fuzzy membership functions to take decisions. FIS offers built-in expert knowledge and maps inputs to outputs employing the IF-THEN base rule. Devi and Bajaj [45] proposed one such method for driver fatigue detection. Mouth and eye state were fed to FIS and the FIS deduced the driver state as fit, fatigue or dangerous. The eyes state is categorized as blink, sleepy and slept, while mouth state have been categorized as normal and yawning. In a more recent study [46] characteristics such as eye state and mouth state are fed to two layered FIS to deduce the level of fatigue of driver. Each layer of FIS has its own IF-THEN rules to deduce the output from the specific inputs.

FIS provide a high degree of flexibility and is useful in many vision based applications. FIS offers data less training and provides parallel processing as all the rules are applied simultaneously. FIS also have the ability to learn by incorporating additional rules and knowledge base.

C. Machine Learning Based Implementation

Machine learning based implementations are data driven algorithms trained on extensive driving data acquired in laboratory and on the road testing. The category can be broadly divided into shallow and deep models based on the levels of representation and the technique used for feature derivation.

1) Shallow Models: Shallow models provide reasonable predictive ability with minimal complexity. Shallow models consist of a few layers and requires limited training data; however it requires predefined discriminative features. Artificial Neural Networks (ANN) with one hidden layer and Support Vector Machine (SVM) can be considered as well known shallow models.

ANN processes information mimicking the human brain. The learning mechanism can be supervised, non-supervised or reinforced learning [47]. ANN has been widely incorporated in fatigue detection systems [48], [49]. ANN can be trained on various parameters such as EEG [50], Steering angle [51] and PERCLOS [52] to predict driver state as either fatigued or alert. In [50] to deduce fatigue from EEG signal, EEG signal's time series of both inter-hemispheric and intra-hemispheric cross spectral densities were fed to ANN as input and the ANN classified the driver state as fatigued or alert. In another approach [53] the time domain EEG data was converted to frequency bands i.e. alpha, theta, beta and delta bands and the frequency domain data was fed to an ANN for fatigue detection. Friedrichs and Yang [51] utilized lane based features and steering based features together for better results. The selected features were passed on to ANN for classification of driver state as awake, fatigued or questionable.

Support Vector Machine (SVM) is specially designed for two group classification problem. SVM has been employed in many fatigue detection systems to classify the driver state according to different levels of fatigue. Various parameters such as EEG [54], ECG [55], PERCLOS [56] and EoG [57] can be used in tandem with SVM to classify fatigue state. Mervyn *et al.* [54] trained SVM for two class fatigue classification. Prominent beta activity represents alert EEG and dips in Alpha wave represents drowsy EEG. This method had a classification accuracy of 99.2%. Alternatively, features, such as, cardiovascular blood volume pulse and heart rate variability (HRV) are extracted from Photoplethysmography (PPG) to train an SVM [55]. Fast Fourier Transform (FFT) and wavelet decomposition was simultaneously performed on HRV data. LF:HF was extracted, and feature selection was performed on the data achieved through wavelet decomposition, subsequently the LF:HF and feature selected through feature selection were fed as input to the SVM. Subsequently, SVM classify the driver state (as either alert or fatigued).

Eyelid related parameters extracted from electro-oculography (EoG) fed to SVM was intended to perform fatigue prediction in [57]. Data was collected to train the

SVM with a driving simulator. The driver state was classified into three states i.e. alert, sleepy and very sleepy by the SVM. The development of deep models (in the last decade) has influenced the usage of deep models for driver fatigue detection.

2) Deep Models: Deep learning models are machine learning techniques which incorporate learning representation of data instead of task specific methods. In contrast to shallow models, deep models have the ability to extract the features from the training data. Convolutional neural networks (CNN) [58] are the earliest deep learning models that have been incorporated for driver fatigue detection. In [59] CNN was utilized to learn features for drowsiness detection. A softmax layer classifies the driver state as either drowsy or non-drowsy. Face was extracted from the frame using the Viola-Jones method and fed to a CNN for feature extraction. The output of the hidden layers is considered as the extracted features. The softmax layer is trained on the features extracted. In experimentation 20% of the data was utilized for testing. Channel-wise convolutional Neural Networks (CCNN) and CCNN-R show better results than CNN for fatigue detection of drivers [60]. CCNN-R utilizes Restricted Boltzmann Machine instead of convolutional filter and incorporate bagging classifiers as an alternative to the conventional DL solutions. Yawning is considered a prominent feature of fatigue and plentiful research has been dedicated to detecting driver fatigue using yawn detection, one such technique is presented in [61] employing a deep CNN. A deep CNN was deployed for face detection and a second deep ANN is incorporated for nose detection. As a nose offers distinct features in tracking therefore, nose tracking was preferred over mouth tracking. From the location of the nose the mouth location can be inferred. Finally, an ANN was developed for yawn classification.

Another class of deep learning models is Deep Belief Networks (DBN), which consists of multiple layers with hidden units. The layers are connected, however units within a single layer are not connected. Chai *et al.* [62] investigate the effectiveness of Sparse-DBN for EEG based fatigue detection. Sparse-DBN is a semi-supervised learning method. Sparse-DBN incorporates a combination of both supervised and unsupervised learning for modelling features in pretraining layer and for discriminating features in the next layer respectively. In their experimentation it was concluded that fatigue detection accuracy of Sparse-DBN is higher than ANN and DBN classifiers.

A probability based approach would be a Bayesian network which can be built from either training data or expert opinion. Bayesian models are built on laws of probability and probability distribution functions. Static Bayesian Network (SBN) was incorporated in [63] to predict fatigue however, SBN offers relatively lesser suitability for systems that change over time. To resolve the issue Dynamic Bayesian Network (DBN) [64] were considered for driver fatigue detection to dynamically model the drivers state [65]. The model proposed in [65] does not take into consideration physiological features and relay on visual features for fatigue detection. Yang *et al.* [66] present an approach based on both visual and physiological features using DBN.

The simplest DBN can be modelled as the Hidden Markov Model (HMM). HMM is a statistical model based on the Markov process with hidden states. The model will move in-between states taking into consideration transition probabilities. To predict future state of the driver from current and previous states first order HMM is utilized in [67]. Sleep history, driving conditions and circadian rhythm are used to predict fatigue. The techniques mentioned in this section are applied in various ways for driver fatigue detection. In the following section driver fatigue detection methods are classified based on input features.

V. Scientific Research in the Field of Driver Fatigue Detection

Driver fatigue detection can be categorized based on input features into five categories: subjective reporting; biological; physical; vehicular; and hybrid. Further classification is summarized in fig.2.

A. Subjective Reporting

One of the earliest technique to assess sleepiness is the Karolinska Sleepiness Scale (KSS) [68]. KSS is a self assessment questionnaire that can be implemented to access the fatigue levels of factory workers and long haul drivers. KSS is a nine point assessment list, where one represents highest level of alertness while nine represents lowest level of alertness (high level of sleepiness). Since the questionnaire data was recorded after a long period of time therefore, the technique is less suitable for real time detection and prevention. However, KSS has been used as a benchmark to check the accuracy of other systems [57], [69].

B. Biological Features Based Driver Fatigue Detection

Biological signs offer good indication of early onset of fatigue and can be utilized to prevent accidents well on time. Biological signals can be categorised into heart, brain, eyes and skin based signals. Changes in biological signals such as electroencephalography (EEG) [70], electrocardiogram (ECG) [71], electro-oculography (EoG) [72] and surface electromyogram (sEMG) can be an accurate method to detect fatigue [68].

1) Heart Signal Based Implementation: Even though, heart signals such as ECG and PPG (Photoplethysmogram) were considered as accurate measures of fatigue, their feasibility in driver fatigue detection was limited because of the intrusive nature of the heart signal sensors. However, due to the advancement in the field of non-intrusive sensors, current sensors can be embedded in the steering wheel or the seat belt, due to which driver fatigue detection based on heart signals has gained popularity. Initially, non-intrusive ECG sensors were embedded in the driver seat or worn as a belt, however, both these methods are prone to error due to fabric thickness. To overcome this problem, Jung *et al.* [73] proposed to embed the electrodes in the steering wheel. Two important parameters extracted from ECG for fatigue detection is the Heart Rate (HR) and Heart Rate Variability (HRV). Visual cues

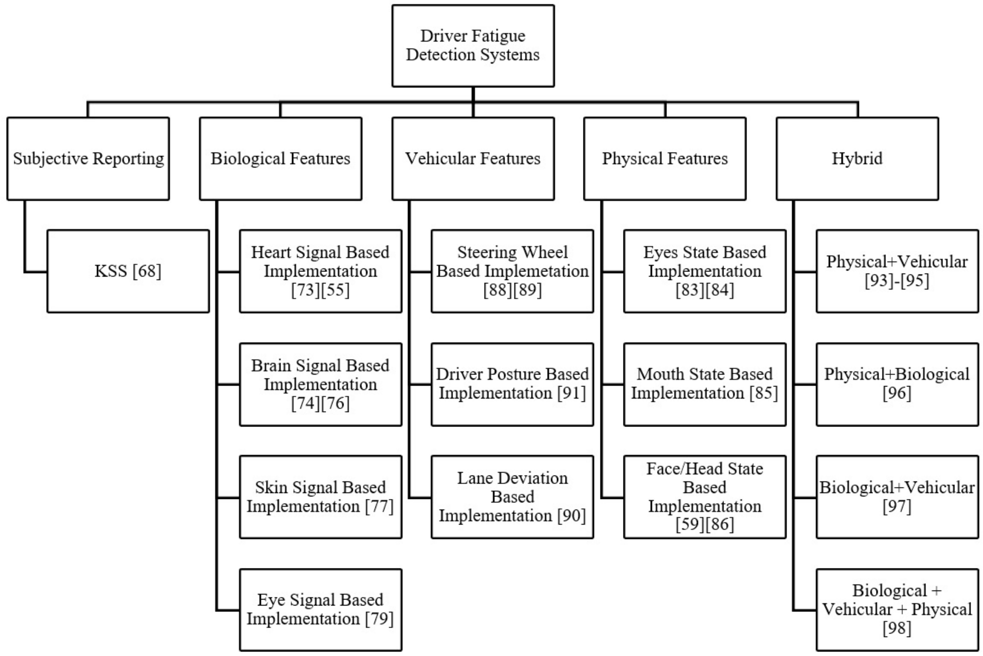

Fig. 2. Input feature based classification of driver fatigue detection system.

exhibited by the driver such as yawning and deep respiration are considered as ground truth. Two subjects participated in the study where tests were performed in a real environment. The study concludes that HRV increases with fatigue. The method shows promising results however, highly accurate sensors are required for this because minute changes need to be observed as the state of the driver changes from normal to fatigued. Secondly, position of the driver's hands on the steering wheel is crucial and prone to human error.

In addition to ECG, PPG has also been tested to estimate driver fatigue level. Li and Chung [55] proposed a PPG sensor based driver fatigue detection method. PPG sensor was placed on the steering wheel of the vehicle, HRV was extracted from the raw PPG signal and SVM was trained to classify the driver state as fatigued or alert. PERCLOS and KSS are considered as ground truth. In their study, four volunteers (three male and one female) participated in a laboratory controlled environment. The method offers 95% fatigue detection accuracy. Even though, this method is non-intrusive, it is susceptible to human error and natural movements.

2) Brain Signal Based Implementation: EEG is the golden standard for brain activity measurement and is considered a good indicator of fatigue and generally of the transition between wakefulness and sleep. EEG can be extracted using flat electrodes attached to the scalp. In the frequency domain EEG signal can be divided into five bands ie. the Gamma (30-42 Hz), Beta (13-30 Hz), Alpha (8-13 Hz), Theta (4-8 Hz) and Delta (0.5-4 Hz) waves as shown in fig 3. Beta waves are present when a person is alert e.g. if a cognitive task is being performed. It may also be present in early stages of sleep. Theta wave is associated with early stage of sleep and deep sleep is represented in delta waves. Alpha waves are present in relaxed condition and hence exhibit the first sign of fatigue. Borghini *et al.* [74] introduced EEG based fatigue index

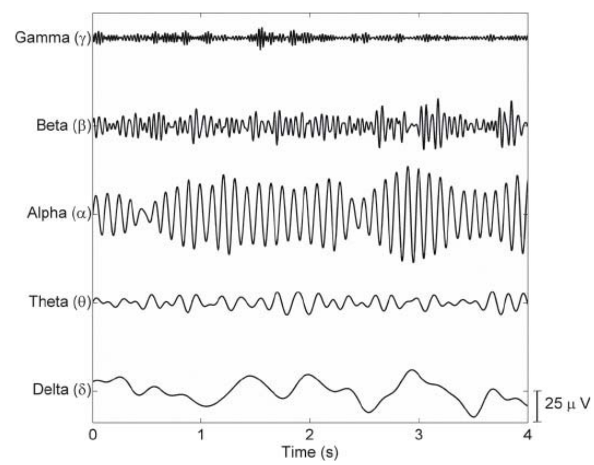

Fig. 3. Types of EEG signals.

based on alpha spindles (spikes). EEG was extracted from the participants in a real monotonous driving environment. It has been concluded that the EEG alpha band spindles increase with fatigue. Even though the results were promising, the number of participants were not mentioned in their experimentation hence, accuracy for users is compromised [75]. A more recent study in [76] suggested the use of a three layered feed-forward Bayesian neural network structure for data classification (as either fatigued or non-fatigued), features were separated by ICA-ERBM prior to feeding to the classifier. The data was segmented and features were extracted from the segmented data with an autoregressive (AR) model. EEG was extracted from 43 participants in a simulated environment and the result was validated against visual signs of fatigue, EoG, lane deviations and through a questionnaire. This method has fatigue detection accuracy of 89.7%.

TABLE I
BIOLOGICAL FEATURES BASED FATIGUE DETECTION

Signal	Feature	Parameter	Placement	Participants	Test Environment	Ground Truth	Method	Result
Heart	ECG [73]	HR, HRV	Steering wheel	2	Real time	Visual cues	HRV analysis	HRV ↑
	PPG [55]	HRV	Steering wheel	4	Simulation	PERCLOS, KSS	SVM	Accuracy (95%)
Brain	EEG	α spindle [74]	Head	N/A	Real time	N/A	No. of α spindles	α spindles ↑
		AR extraction [76]	Head	43	Simulation	Visual	BNN	Accuracy (89.7%)
Skin	sEMG [77]	15-30Hz band	Muscle	11	Simulation	time elapsed	Power in band	Power ↑
Eyes	EoG [78]	Extracted by CNN	Around eye	22	Simulation	Response error	CNN	Performs better than statistical models
Multiple	ECG	HRV	Chest	30	Real time	Visual cues	LF/HF and SDNN	LF/HF and SDNN ↓
	EEG	α and β band	Cap				Power α and β bands	power ↑
	EoG [79]	Eyelid activity	Contactless				Blink duration	Blink duration↑

↑ indicates increase, ↓ indicates decrease

Changes in EEG have high correlation with fatigue however, the extraction of EEG from the driver is highly intrusive and a contactless method for EEG extraction has yet to be proposed.

3) Skin Signal Based Implementation: EMG sensors record electric potential generated by muscle cells through electrodes. sEMG is the measurement of electric potential created by the muscles on the surface of the skin. Features extracted from the time and frequency domain signal of sEMG could be utilized to predict muscular fatigue. Features such as change in mean and median frequency, electrical activation and root mean squared (RMS) amplitude have been used for fatigue detection. In [77], signal power in the 15-30 Hz frequency band was used for muscle fatigue detection. sEMG was extracted from the driver by placing sEMG electrodes on the neck, back, shoulders and wrists in a simulated environment. Eleven individuals participated in the study and it was concluded that the power in 15-30 Hz frequency band increases with fatigue. The results have not been authenticated with any feature other than driving elapse time. sEMG sensors are highly intrusive and their applicability in real time driver fatigue detection is limited.

4) Corneo-Retinal Signal Based Implementation: EoG is the measurement of the corneo-retinal potential difference between the back and front of the eye. EoG measures the movement of the eye using electrodes attached to left and right side of the eye. The entropy based on energy distribution classified the EoG data. In [78] EoG is extracted from 22 participants of a stimulated study with precisely placed electrodes around the eye. Features are extracted from the raw EoG using CNN. To comprehend fatigue correctness of response is measured and it is deduced that response error increased with fatigue. As electrodes were mounted close to eye it may cause nuisance to the driver. Zhang *et al.* [80] present a technique to measure EoG from electrodes placed on forehead, the results are promising however, the application of EoG sensor based methods is limited in real time driver fatigue detection.

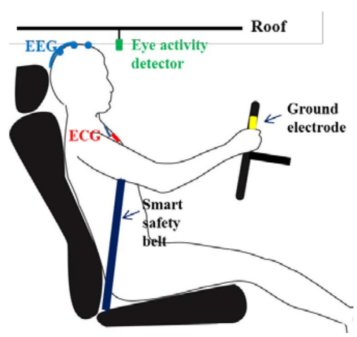

Fig. 4. Electrode placement by [79] for non intrusive acquisition of EEG, ECG and EoG.

5) Multiple Biological Feature Based Implementation: If multiple biological features are utilized better performance can be achieved. Sun and Yu [79] utilize non-intrusive electrodes to measure ECG through clothes, EEG with electrodes attached to a cap and EoG from an electrode hanging from the vehicle ceiling as shown in fig. 4. Thirty individual (eight female and twenty two male) participated in the experiment. Wierwille and Ellsworth criterion (based on visual cues of fatigue) was used as ground truth to assess fatigue. Eyelid activity, EEG and HRV were recorded to deduce fatigue. It was deduced that blink duration and frequency increase with fatigue, power density of alpha and beta wave decrease with fatigue and LF/HF and SDNN decrease with fatigue while RMSSD, LF and HF increase with fatigue. Other studies also suggest the use of multiple biological features for driver fatigue detection [81].

Biological feature based fatigue detection techniques are summarized in table I. Biological features are a direct measure of fatigue however, their application in real-time driver fatigue detection is limited due to intrusive sensors. The subsequent section illustrates fatigue detection methods that incorporate driver physical features. Eyelid opening, yawning, blink rate and blink duration are some of the physical features used for fatigue detection.

C. Physical Feature Based Driver Fatigue Detection

Features exhibited on the drivers face and through head movements are some of the most obvious symptoms of fatigue. Physical features include blink frequency, eye closure duration, percent of time the eyes are close (PERCLOS), pose, gaze and nodding frequency. Physical feature based systems for fatigue detection can be broadly divided into techniques based on eyes, mouth and face/head.

1) Eye State Based Implementation: Features such as eye closure rate, eyelid distance and percentage eye open prove to suitable indicators of fatigue. In [82] a fuzzy system classifies the fatigue levels into low, normal and high. The face was detected in the image using Haar-like feature detector. The features were extracted from the image using template matching and horizontal projection of face image. This method has been tested on five individuals in a real driving environment. Feature is classified for fatigue using objective evaluation as ground truth. The face tracking method is inaccurate, very computationally complex and the accuracy is reduced considerably with low illumination.

In a recent approach [83], fatigue detection system was designed specifically for bus drivers using the dome camera already installed in buses to monitor driving behaviour. Estimated eye open and PERCLOS are incorporated as features to detect fatigue. The head and shoulders are detected using a Histogram of Gradients (HoG) descriptor and driver detection is performed by SVM. Face and eye detection is performed by OpenCV face detector and eyes detector respectively. Eye openness is calculated using linear and spectral regression. The technique has been tested on 23 drivers in a real driving environment. No ground truth method was incorporated as fatigue was self simulated. The fatigue detection works for low resolution images however, the technique is designed for the dome camera installed in buses and is not applicable to all vehicles.

2) Mouth State Based Implementation: Eye activity is a popular method for fatigue detection however, yawning and mouth opening can also prove to be good indicators of fatigue. In [84] yawning was detected for driver fatigue identification. SVM based technique detected the face in the frame and gradient edge detectors located the mouth. Further, the circular hough transform detected if the mouth was in the state of yawning. A yawn counter decided about driver fatigue level. The technique has been tested in a real environment, however fatigue was simulated by the participants and the number of participant are not mentioned. The system has 98% accuracy however needs more features to be included to detect fatigue.

3) Face/Head Based Implementation: Features, instead of being predefined, can be learnt through deep learning techniques. In [59] feature selection is performed by deep learning for visual fatigue detection. The selected features are then classified as fatigued and not fatigued using a softmax layer classifier. CNN classifies the drivers as either fatigued or non-fatigued. Thirty individuals with different features, skin tone, facial hair and fatigue level participated in a simulator based study. The system had a 92.33% validation accuracy. More accurate results are presented in [85]. In their experiment 500 fused Gabor feature vectors were extracted from facial image sequences. The video of the driver was collected at different times of the day, at different illumination level and in different poses. To mine the fatigue patterns from the facial image the frequent patterns mining algorithm is deployed. Even though this method has a high detection accuracy of 99.2%, the technique has been tested on only a single participant. Further testing is required as results from a single participant is not enough, testing the method on multiple participants might give a more accurate portrayal of the true accuracy of the system.

4) Multiple Physical Feature Based Implementation: For improved accuracy multiple physical features are used in tandem for fatigue detection. Bergasa *et al.* [86] predict fatigue from eye, face and head features. PERCLOS, eye closure duration, blink frequency, head nodding frequency, face position and gaze are fed to a FIS for fatigue detection. The method has been tested with ten participants in real driving scenarios. The system works well at night; however, the performance of the system decreases during daytime, especially on bright days. The system has limited applicability for drivers glasses wearing. Further improvement is required as the method has limited applicability under varying illumination. A summary of the physical feature based fatigue detection is stated in table II. The following section will explain the fatigue detection techniques using features extracted from the vehicle. Vehicular features include break distance, lane deviation, speed and steering control.

D. Vehicular Features Based Fatigue Detection

Fatigue reduces the driver's ability to perform. The deviation in features such as lane crossing and steering wheel angle are indicators of deteriorating driving ability. Unusual activities such as pressure changes on brake and accelerator, load distribution on the driver's seat and vehicle speed are also strong indicators of fatigued driver. Vehicular features can be divided into steering wheel angle, lane deviation and posture change.

1) Steering Based Implementation: Steering angle is a popular method of identifying driver fatigue, McDonald *et al.* [87] detected lane departures using steering wheel angle and random forest algorithm. In comparison to PERCLOS, this method is more accurate and can predict fatigue related lane departure six second in advance. The algorithm was tested on a data set from the National Advanced Driving Simulator, University of Iowa. Seventy two participants participated in the study. Drowsiness related lane departures were extracted

TABLE II
PHYSICAL FEATURES BASED FATIGUE DETECTION

Feature	Parameter	Participants	Test Environment	Ground Truth	Method	Result
Eyes	PERCLOS, change in eyelid distance [82]	5	Simulation and real time	Objective evaluation	Fuzzy expert system	Computationally expensive and illumination dependent
	PERCLOS and eye openness [83]	23	Real time	Self simulated	HoG and SVM	Works on low resolution images
Mouth [84]	Yawn frequency	N/A	Real time	self simulated	Circular Hough transform (CHT) and SVM	Accuracy (98%) however more features are required for fatigue detection
Face	Learned through CNN [59]	30	Simulation	Manually labelled	Convolutional Neural Network	Does not work under all illumination
	Gabor feature sequence [85]	1	Real time	Self classification	Gabor Translation and frequent patterns mining	Works better compared to Gabor-based dynamic representation with AdaBoost
Multiple Physical Features [86]	PERCLOS, Nodding gaze, face position	10	Real time	Self simulated	Fuzzy Inference System	The system works well at night.

from raw simulator data by reviewers using modified Observer Rating of Drowsiness (mORD) scale. Reading was taken once every minute up to a lane departure. PERCLOS was extracted from the eye detection video captured with the eye detecting FaceLab software. The random forest is trained by a series of decision trees with features selected randomly. The study does not disregard PERCLOS as a fatigue measure; however, it is suggested that SWA is a more robust metrics for fatigue detection.

A more recent method based on SWA is presented in [88]. Approximate Entropy (ApEn) was calculated from the steering wheel angle data. From the ApEn the Adaptive piecewise linear approximation (APLA) was calculated to estimate the similarity to fatigue state. The driving test was conducted on the Beijing to Qinhuangdao, China motorway as high level of monotony on motorways makes it easier for the driver to feel fatigued and visual cues are incorporated as ground truth. This method has an accuracy of 78.01% which has to be improved to be applicable to fatigue detection.

2) Lane Deviation Based Implementation: Apart from SWA, lane deviation has also been widely used for driver fatigue detection. In [89] Yang *et al.* designed a test bed using a driving simulator with twelve participants. Sleep deprivation was kept as the only independent variable in the experiments. Four stimulus response tasks were given to the driver: 1) change lane when an overhead lane changing sign appears (APVT); 2) change two lanes when the two lane changing sign appears (VPVT); 3) press a green button after hearing a ring tone (SLCT); 4) press a green button after hearing seeing a red stimulus on the screen (DLCT). The mean value and standard deviation (SD) of APVT, VPVT, SLCT and DLCT show mark deterioration in response time of the participants in sleep deprived state. The method has only been tested on a simulator and further testing on the road would be preferable.

3) Posture Based Implementation: Drowsiness has a direct effect on the driving patterns of the driver such as load centre position (LCP). LCP can be measured by pressure sensors in the seat. In [90] body pressure sensors were installed in the driver seat of a vehicle. It was found that in the beginning the pressure was distributed throughout the seat however, as time passes the pressure starts to concentrate at one point on the back of the seat. Pressure reading was taken every 20 minutes for 15 minutes. Only one participant has performed the experiment. Further experimentation is required as method has only been tested on a single participant.

4) Multiple Vehicular Feature Based Implementation: To improve accuracy, multiple vehicular features could be utilized for driver fatigue detection. Wakita *et al.* [91] utilize features such as vehicle velocity, brake pedal, accelerator pedal and distance from car in-front to identify fatigue. The features are fed to a Gaussian mixture model (GMM) and Helly model. Comparative studies show that Gaussian model worked better compared to Helly model as a velocity model. The proposed method has 81% accuracy on a simulator and 73% accuracy on a real vehicle. The accuracy of the method for real vehicle is not adequate and further improvement are required to increase accuracy. The methods discussed above are summarized in table III. Hybrid feature based systems as discussed in the proceeding section incorporate a combination of physical, biological and vehicular features to detect fatigue. Hybrid systems demonstrate better results as compared to using a single type of features.

TABLE III
VEHICULAR FEATURES BASED FATIGUE DETECTION

Feature	Parameter	Participants	Test Environment	Ground Truth	Method	Result
Steering	SWA [88]	6	Real time	Visual cues	Dynamic time warping (DTW)	Accuracy (78.01%), More features needed to improve accuracy
	SWA [87]	72	Simulation	mORD	Random forest algorithm	Predict lane-departures associated with fatigue six seconds prior to occurrence, works better than PERCLOS
Lane Deviation [89]	APVT, VPVT, SLCT and DLCT	12	Simulation	Sleep deprivation	Mean and SD of APVT, VPVT, SLCT and DLCT	Mean and SD increase for all features with fatigue.
Posture [90]	LCP	1	Real time	Time elapsed	Pressure sensors on seat	Change of the load centre correspond to fatigue
Multiple Features [91]	pedals, speed, distance from the vehicle in front	8	Simulation	Not stated	Gaussian Mixture Model	Identification rate (73%), Merge physical model and statistical model for better results

E. Hybrid Feature Based Fatigue Detection

Even though methods based on a single type of feature give satisfactory results however, recently research has been geared towards the fusion of various features for fatigue detection.

1) Physical and Vehicular Features Based Implementation: Combining physical features and vehicular features to detect fatigue could drastically increase the accuracy of fatigue detection. Cheng *et al.* [92] proposed a technique which incorporates both driver characteristics as well as vehicle characteristics. Eight features were chosen for fatigue detection including PERCLOS, blink rate, maximum time eyes are close, non-steering percentage, percentage of on-centre driving, standard deviation of steering wheel angle and standard deviation of lane position. Twenty participants took part in the experiment. A multi-source data fusion model was also developed to fuse information from both the driver and vehicle. Vehicle dependent measures were 81.9% accurate, driver dependent measures were 86.9% accurate while the fusion of both driver and vehicle oriented measures were 90.7% accurate. Fatigue is determined against ANOVA and Johns Drowsiness Scale (JDS) as ground truth.

In a more recent study [93] a self-adaptive dynamic recognition model was proposed which used the most effective features for feature fusion to detect fatigue. Physical features include blinking frequency (BF), eye-closed duration (ECD), mean of eye-opened level (MEOL) and yawning frequency (YF). Vehicular features include percentage of non-steering (PNS), standard deviation of steering-angle (SDSA), frequency of abnormal lane deviation (FALD) and standard deviation of vehicle speed (SDVS). The feature fusion was based on Takagi-Sugeno fuzzy neural network (T-SFNN). The features were based on the driver visual measures as well as the vehicle behaviour. By using only, the vehicle behaviour features the system offers an accuracy of 90.8% while facial features offers an accuracy of 91.6%. The fusion of all fatigue features offers an accuracy of 92.1% and using only most effective features offers an accuracy of 93.8%. This shows it is not important to fuse all possible features but only the effective features.

2) Physical and Biological Features Based Implementation: Features directly extracted from the driver have the potential to give highly accurate results and one such method is proposed in [95]. Eye and PPG related features are extracted from the driver and wirelessly send to an android based smartphone. The features are fed to a DBN, the DBN outputs a probabilistic value that represents the drivers fatigue level. The method has been tested on 10 participants in a real driving experiment. Better results are achieved by the fusion of physical and biological features compared to using just physical or biological features.

3) Biological and Vehicular Features Based Implementation: The fusion of direct and indirect features i.e. biological and vehicular features has attracted researchers for driver fatigue detection. Lee *et al.* [96] present a smart watch based approach incorporating PPG and steering motion. Steering motion is estimated from the built in gyro meter in the watch and PPG sensor data is transmitted to the smart watch via Bluetooth. Twelve participants participated in a simulator based study, visual cues and KSS were utilized as ground truth. A mobile-based Support Vector Machine (M-SVM) classifies the driver state with an accuracy of 95.8%. The accuracy is high however, on road experimentation is missing.

4) Physical, Vehicular and Biological Features Based Implementation: Keeping in view the results from previous methods it would be a natural progression to fuse physical, vehicular and biological features for driver fatigue detection. In [97] data fusion was performed using a decision making module to fuse the decision made by three neural networks, each of which detect fatigue using a different feature. Fatigue detection was performed by utilizing eye status, lateral position, SWA, ECG, EEG and sEMG. The experimentation was performed on twelve individuals on a simulator.

TABLE IV

HYBRID FEATURES BASED FATIGUE DETECTION

Features	Parameters	Participants	Test Environment	Ground Truth	Method	Result
Physical and Vehicular	Eye, SWA and lane deviation [92]	20	Real time	JDS and ANOVA	Fisher's linear discriminant and Dempster-Shafer evidence theory	Fusion has better result than just using eye or vehicle features
	Eye, SWA and lane deviation [94]	9	Simulation	KSS	ANN	PERCLOS and lane deviation give best results
	Eye, mouth, SWA, lane deviation and speed [93]	5 (3m 2f)	Real time	Observer assesment	T-SFNN (feature level fusion) and D-SET (decision level fusion)	Works even if some features fails
Physical and Biological	PPG and eye [95]	10	Real time	Not stated	DBN	Best result by fusing all features
Biological and Vehicular	PPG and SWA [96]	12 (8m 4f)	Simulation	Visual cues and KSS	M-SVM	System accuracy (95.8%)
Biological, Physical and Vehicular	SWA, lane deviation, pedal force, Eye, EEG [97]	12	Simulation	KSS	ANN	Worst case accuracy (87.78%)

Fatigue detection comparisons were made with KSS (ground truth). The system had an accuracy of 94.63%. The accuracy is high however, on road experimentation is missing. A summary of hybrid techniques is given in table IV.

VI. COMPARISON OF VARIOUS DRIVER'S FATIGUE DETECTION TECHNIQUES

The numerous features driver fatigue reviewed in this study are dependent on the level of drowsiness, which further depends on the time of day, duration of the task and the time that has elapsed since the last sleep. Nevertheless, when developing an improved fatigue detection system, several other essential issues are required to be addressed. The conditions that are of utmost importance in designing a driver fatigue detection system are that the sensors should not interfere or hinder the driving process, the detection process should be autonomous and must support real-time processing. Subjective reporting can reasonably detect and categorize fatigue however, it requires the driver to frequently report their state which interferes in driving and also causes error in the report. It is also worth noticing that the driver's ability to efficiently judge their fitness considerably deteriorates after three hours of driving activity [98] and hence, subjective reporting has limited applicability for driver fatigue detection.

Biological features provide reliable and accurate results as they represent the true internal state; however, for data acquisition such as EEG, ECG and sEMG multiple electrodes have to be connected to the body. Electrodes connection to the body makes the system intrusive in nature which is less desirable for real time driver fatigue detection [99]. Another contributing factor might be that EEG signal retrieval through numerous electrodes is highly susceptible to noise from external factors [100]. Furthermore, EoG signals are retrieved through electrodes placed near the eye which can hinder driving. Among all biological features investigated (in this study), ECG can be measured in a less intrusive method; however ECG are interpersonal and show much diversity for individual to individual that it can be used for human identification [101], [102].

Biological sensors are complex and expensive, the signals require much of pre-processing (to avoid noise) and is prone to driver movement. For real time driver fatigue detection physical features and vehicular features seem to be more desirable as neither is intrusive. Vehicular feature based methods are expedient in determining drowsiness, as lack of vigilance effects vehicle control or deviation. However, as demonstrated in [103] fatigue might not always affect vehicle-based features similarly for each individual. Similarly, in comparison to blink rate, significant individual differences were observed in the standard deviation of lateral position. Vehicular features are easily influenced by personal driving attributes, weather and traffic conditions. Steering and lane deviation will become erratic in an urban traffic scenario and standard deviation will increase even without the onset of fatigue. Therefore, physical features can be considered as an efficient feature to detect fatigue and certain real time products have been established [104]. Barr *et al.* [104] observed that illumination has a considerable effect on measurement's reliability and accuracy. One of the most widely employed technique for fatigue detection is PERCLOS, however, it does not consider individual differences. A method that is based on driver physical features relies on image processing hence, it needs to be robust under all outdoor conditions such as day, night, rainy, sunny and cloudy days. To minimize the effect of outdoor conditions, researcher incorporated IR cameras. IR cameras make the detection of pupils easier due to bright pupil effect, however IR cameras do not cause a bright pupil under all illumination.

TABLE V
A COMPARISON OF DRIVER FATIGUE DETECTION

Category	Signal	Parameter	Contact	Sensor Cost	Real-time Applicability	Limitations
Subjective Reporting	KSS[68]	KSS	No	low	No	Offline, not suitable for real-time detection
Biological	Brain[74][76]	EEG	Yes	High	No	Extremely Intrusive
	Heart	ECG [73]	Yes	High	No	
		PPG[55]	Yes	High	Yes	
	Skin[77]	sEMG	Yes	High	No	Prone to human movement
Vehicular	Steering [87][88]	SWA	Yes	Low	Yes	Driver and environment dependency
	Lane[89]	Lane deviation	No	Low	Yes	
	Posture[91]	Pressure sensors	Yes	High	Yes	
Physical	Eyes [82][83]	PERCLOS, Blink, etc	No	Low	Yes	Illumination and background dependent
	Mouth[84]	Yawning	No	Low	Yes	
	Face/Head [59][85]	Nod	No	Low	Yes	

De Naurois *et al.* [105] performed comparative analysis of biological, physical and vehicular features based fatigue detection. Features, such as, heart rate, eye state, head position, steering wheel, lane deviation, pedal force and vehicle speed were utilized in the study to detect driver fatigue. Artificial neural networks were incorporated for the detection process. The ANN were trained with either biological, physical, vehicular or all features. The ANN were also trained using additional parameters, such as driving time and participant information in some cases. The best result for fatigue detection was acquired once physical features, driving time and participant information were employed.

Due to advancement in the field of contactless heart rate measurement in the past decade, the measurement of remote PPG (rPPG) has become a possibility [106]. RPPG is extracted from facial colour variation and could be easily measured by a normal RGB camera, which makes its easy to be integrated with physical features for driver fatigue detection. Currently the use of rPPG is relatively less explored for driver fatigue detection.

As per the study conducted by Horne and Reyner [107] driver's age and time of driving plays an important role in sleep related accidents; therefore, external signs can also be attributed to fatigue. Other factors, such as speed limits and scenery could also be considered for driver safety and incorporated in driver fatigue detection systems [108].

The investigation in this study determines that no single feature can be used reliably for fatigue detection. Hence, a combination of multiple features would give accurate results. However, intrusive features, such as, EEG and ECG are relatively less feasible for real-time implementation to deduce fatigue. Vehicular features are dependent on some other features, such as, weather, driving style, and traffic conditions and may not offer reliable results in an urban environment; however, vehicular features can be utilized for driver fatigue detection in long haul drivers that drive on the highways.

Driver fatigue detection requires real-time processing and accurate results. The suitability of fatigue detection methods varies for real-time processing as fast and accurate results are desired for fatigue detection. A comparison of the fatigue detection techniques is presented in table V.

It is deduced that the most suitable features for driver fatigue detection are physical features and to improve the results fusion with driver characteristics, time of day, duration of drive and rPPG would be desirable.

VII. CONCLUSION

This paper is a review and comparison of state of the art and recent advancement in the field of driver fatigue detection. High risk is associated with driver fatigue because fatigue causes severe threat to human life and the surroundings. Fatigue can be divided into active, passive and sleep related fatigue, a driver can experience any of the three types of fatigue. Under fatigue, a driver is no more capable of driving a vehicle. Recently many automobile companies such as Volkswagen, Nissan and Toyota have installed and updated driver assistance technologies in their vehicles for accident prevention and driver assistance. Third party companies are also manufacturing fatigue detection devices however, research community attention is required to improve results. Continuous research is being performed in the field of driver fatigue detection and several articles propose promising results in constrained environments, still much progress has to be made to develop a robust, real-time and accurate technique that works well in all possible scenarios. In this paper the features for fatigue detection are categorized into subjective reporting, driver biological features, driver physical features, vehicular features and hybrid features. A comparison of the technologies points out that the suitability of subjective reporting and biological features for real time processing are limited and therefore have restrained utilisation in real world driver fatigue monitoring. Physical features and vehicular features could be used for real time fatigue detection however, both have their own pros and cons. It is suggested that physical features fused with driver characteristics, time of day, duration of drive and rPPG could provide better accuracy and could be incorporated to manufacture reliable systems.

References

[1] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 37, no. 1, pp. 32–64, 1995.

[2] Y. Xing, C. Lv, D. Cao, H. Wang, and Y. Zhao, "Driver workload estimation using a novel hybrid method of error reduction ratio causality and support vector machine," *Measurement*, vol. 114, pp. 390–397, Jan. 2018.

[3] Y. Xing *et al.*, "Identification and analysis of driver postures for in-vehicle driving activities and secondary tasks recognition," *IEEE Trans. Comput. Social Syst.*, vol. 5, no. 1, pp. 95–108, Mar. 2018.

[4] Y. Zhao *et al.*, "An orientation sensor-based head tracking system for driver behaviour monitoring," *Sensors*, vol. 17, no. 11, p. 2692, 2017.

[5] C. M. Martinez, M. Heucke, F.-Y. Wang, B. Gao, and D. Cao, "Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 13, pp. 666–676, Mar. 2016.

[6] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 596–614, Jun. 2011.

[7] S. Kaplan, M. A. Guvensan, A. G. Yavuz, and Y. Karalurt, "Driver behavior analysis for safe driving: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 6, pp. 3017–3032, Dec. 2015.

[8] V. Saini and R. Saini, "Driver drowsiness detection system and techniques: A review," *Int. J. Comput. Sci. Inf. Technol.*, vol. 5, no. 3, pp. 4245–4249, 2014.

[9] A. Sahayadhas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: A review," *Sensors*, vol. 12, no. 12, pp. 16937–16953, 2012.

[10] Q. Wang, J. Yang, M. Ren, and Y. Zheng, "Driver fatigue detection: A survey," in *Proc. IEEE 6th World Congr. Intell. Control Autom. (WCICA)*, Dalian, China, vol. 2, Jun. 2006, pp. 8587–8591.

[11] (2011). *Road Safety in Canada*. Accessed: Mar. 24, 2017. [Online]. Available: https://www.tc.gc.ca/

[12] K. Azam, A. Shakoor, R. A. Shah, A. Khan, S. A. Shah, and M. S. Khalil, "Comparison of fatigue related road traffic crashes on the national highways and motorways in Pakistan," *J. Eng. Appl. Sci.*, vol. 33, no. 2, pp. 47–54, 2014.

[13] *AAA Foundation for Traffic Safety*. Accessed: Jan. 10, 2017. [Online]. Available: https://www.aaafoundation.org

[14] *Fatigue*. Accessed: Jan. 21, 2017. [Online]. Available: https://ec.europa.eu/transport/road_safety/

[15] M. Kamieńska-Żyła and K. Prync-Skotniczny, "Subjective fatigue symptoms among computer systems operators in Poland," *Appl. Ergonom.*, vol. 27, no. 3, pp. 217–220, 1996.

[16] R. J. Kosinski, "A literature review on reaction time," Clemson Univ., Clemson, SC, USA, Tech. Rep., Sep. 2008. [Online]. Available: http://biae.clemson.edu/bpc/bp/Lab/110/reaction.htm

[17] R. Schleicher, N. Galley, S. Briest, and L. Galley, "Blinks and saccades as indicators of fatigue in sleepiness warnings: Looking tired?" *Ergonomics*, vol. 51, no. 7, pp. 982–1010, 2008.

[18] E. Bekiaris, A. Amditis, and K. Wevers, "Advanced driver monitoring: The awake project," in *Proc. 8th World Congr. ITS*, Sydney, NSW, Australia, 2001, pp. 1–9.

[19] I. D. Brown, "Prospects for technological countermeasures against driver fatigue," *Accident Anal. Prevention*, vol. 29, no. 4, pp. 525–531, 1997.

[20] J. F. May and C. L. Baldwin, "Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies," *Transp. Res. F, Psychol. Behav.*, vol. 12, no. 3, pp. 218–224, 2009.

[21] M. Körber, A. Cingel, M. Zimmermann, and K. Bengler, "Vigilance decrement and passive fatigue caused by monotony in automated driving," *Procedia Manuf.*, vol. 3, pp. 2403–2409, Oct. 2015.

[22] P. Thiffault and J. Bergeron, "Monotony of road environment and driver fatigue: A simulator study," *Accident Anal. Prevention*, vol. 35, no. 3, pp. 381–391, 2003.

[23] *What is Circadian Rhythm by National Sleep Foundation*. Accessed: Feb. 21, 2017. [Online]. Available: https://sleepfoundation.org/

[24] C. Bougard, S. Espié, B. Larnaudie, S. Moussay, and D. Davenne, "Effects of time of day and sleep deprivation on motorcycle-driving performance," *PLoS ONE*, vol. 7, no. 6, pp. e39735-1–e39735-11, 2012.

[25] P. Philip *et al.*, "Effect of fatigue on performance measured by a driving simulator in automobile drivers," *J. Psychosomatic Res.*, vol. 55, no. 3, pp. 197–200, 2003.

[26] G. Matthews and P. A. Desmond, "Task-induced fatigue states and simulated driving performance," *Quart. J. Exp. Psychol.*, vol. 55, no. 2, pp. 659–686, 2002.

[27] P. Philip *et al.*, "Fatigue, sleep restriction and driving performance," *Accident Anal. Prevention*, vol. 37, no. 3, pp. 473–478, 2005.

[28] T. Åkerstedt, B. Peters, A. Anund, and G. Kecklund, "Impaired alertness and performance driving home from the night shift: A driving simulator study," *J. Sleep Res.*, vol. 14, no. 1, pp. 17–20, 2005.

[29] Toyota. (2014). *The Future of Safety is Here*. Accessed: Sep. 22, 2017. [Online]. Available: https://www.toyota.com/

[30] (2016). *Nissan Intelligent Safety Shield Technologies*. Accessed: Aug. 5, 2017. [Online]. Available: https://www.nissanusa.com/blog/safety-shield-technology

[31] *Driver Alert System*. Accessed: Oct. 13, 2017. [Online]. Available: http://www.volkswagen.co.uk/technology/car-saftey/driver-alert-system

[32] L. Bretzner and M. Krantz, "Towards low-cost systems for measuring visual cues of driver fatigue and inattention in automotive applications," in *Proc. Int. Conf. Veh. Electron. Saf.*, Shaan'xi, China, Oct. 2005, pp. 161–164.

[33] C. H. Morimoto, D. Koons, A. Amir, and M. Flickner, "Pupil detection and tracking using multiple light sources," *Image Vis. Comput.*, vol. 18, no. 4, pp. 331–335, Mar. 2000.

[34] *Optalert Driver-Drowsiness Monitoring Systems*. Accessed: Apr. 24, 2017. [Online]. Available: http://www.optalert.com/

[35] *Driver Fatigue Monitor MR688 by Care Drive*. Accessed: May 3, 2017. [Online]. Available: http://www.care-drive.com/

[36] *OpGuard by GuardVant*. Accessed: Aug. 11, 2017. [Online]. Available: https://www.guardvant.com/opguard/

[37] A. A. Borbély, "A two process model of sleep regulation," *Hum. Neurobiol.*, vol. 1, no. 3, pp. 195–204, 1982.

[38] T. Åkerstedt and S. Folkard, "Validation of the S and C components of the three-process model of alertness regulation," *Sleep*, vol. 18, no. 1, pp. 1–6, 1995.

[39] D. F. Dinges, "Critical research issues in development of biomathematical models of fatigue and performance," *Aviation, Space, Environ. Med.*, vol. 75, no. 1, pp. 181–191, 2004.

[40] S. R. Hursh *et al.*, "Fatigue models for applied research in warfighting," *Aviation, Space, Environ. Med.*, vol. 75, no. 3, pp. A44–A53, 2004.

[41] C. Fox, V. Hall, T. Schaefer, and R. Wolford, "407 EMF identification of emergency medicine fatigue at-risk periods using actigraphy and computer modeling: A pilot study," *Ann. Emergency Med.*, vol. 66, no. 4, pp. S146–S147, 2015.

[42] G. D. Roach, A. Fletcher, and D. Dawson, "A model to predict work-related fatigue based on hours of work," *Aviation, Space, Environ. Med.*, vol. 75, no. 3, pp. A61–A69, 2004.

[43] A. J. Belyavin and M. B. Spencer, "Modeling performance and alertness: The QinetiQ approach," *Aviation, Space, Environ. Med.*, vol. 75, no. 3, pp. 93–103, 2004.

[44] S. Cateni, V. Colla, M. Vannucci, and A. Borselli, "Fuzzy inference systems applied to image classification in the industrial field," in *Fuzzy Inference System: Theory and Applications*. Rijeka, Croatia: InTech, 2012.

[45] M. S. Devi and P. R. Bajaj, "Fuzzy based driver fatigue detection," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Istanbul, Turkey, Oct. 2010, pp. 3139–3144.

[46] T. Azim, M. A. Jaffar, and A. M. Mirza, "Fully automated real time fatigue detection of drivers through fuzzy expert systems," *Appl. Soft Comput.*, vol. 18, pp. 25–38, May 2014.

[47] F. O. Karray and C. W. De Silva, *Soft Computing and Intelligent Systems Design: Theory, Tools, and Applications*. London, U.K.: Pearson Education, 2004.

[48] R. Sayed and A. Eskandarian, "Unobtrusive drowsiness detection by neural network learning of driver steering," in *Proc. Inst. Mech. Eng. D, J. Automob. Eng*, vol. 215, no. 9, pp. 969–975, Sep. 2001.

[49] M. Patel, S. K. L. Lal, D. Kavanagh, and P. Rossiter, "Applying neural network analysis on heart rate variability data to assess driver fatigue," *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7235–7242, 2011.

[50] A. Vuckovic, V. Radivojevic, A. C. Chen, and D. Popovic, "Automatic recognition of alertness and drowsiness from EEG by an artificial neural network," *Med. Eng. Phys.*, vol. 24, no. 5, pp. 349–360, 2002.

[51] F. Friedrichs and B. Yang, "Drowsiness monitoring by steering and lane data based features under real driving conditions," in *Proc. 18th Eur. Signal Process. Conf.*, Aalborg, Denmark, Aug. 2010, pp. 209–213.

[52] M. J. Flores, J. M. Armingol, and A. de la Escalera, "Real-time warning system for driver drowsiness detection using visual information," *J. Intell. Robot. Syst.*, vol. 59, no. 2, pp. 103–125, 2010.

[53] L. M. King, H. T. Nguyen, and S. K. L. Lal, "Early driver fatigue detection from electroencephalography signals using artificial neural networks," in *Proc. 28th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, New York, NY, USA, Aug. 2006, pp. 2187–2190.

[54] V. M. Y. Mervyn, X. Li, K. Shen, and E. P. V. Wilder-Smith, "Can SVM be used for automatic EEG detection of drowsiness during car driving?" *Saf. Sci.*, vol. 47, no. 1, pp. 115–124, 2009.

[55] G. Li and W.-Y. Chung, "Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier," *Sensors*, vol. 13, no. 12, pp. 16494–16511, 2013.

[56] T. Azim, M. A. Jaffar, and A. M. Mirza, "Automatic fatigue detection of drivers through pupil detection and yawning analysis," in *Proc. 4th Int. Conf. Innov. Comput., Inf. Control (ICICIC)*, Kaohsiung, Taiwan, Dec. 2009, pp. 441–445.

[57] S. Hu and G. Zheng, "Driver drowsiness detection with eyelid related parameters by support vector machine," *Expert Syst. Appl.*, vol. 36, no. 4, pp. 7651–7658, 2009.

[58] Y. LeCun and Y. Bengio, "Convolutional networks for images, speech, and time series," in *The Handbook of Brain Theory and Neural Networks*, vol. 3361. Cambridge, MA, USA: MIT Press, 1995.

[59] K. Dwivedi, K. Biswaranjan, and A. Sethi, "Drowsy driver detection using representation learning," in *Proc. IEEE Int. Adv. Comput. Conf. (IACC)*, Gurgaon, India, Feb. 2014, pp. 995–999.

[60] M. Hajinoroozi, Z. Mao, and Y. Huang, "Prediction of driver's drowsy and alert states from EEG signals with deep learning," in *Proc. 6th IEEE Int. Workshop Comput. Adv. Multi-Sensor Adapt. Process. (CAMSAP)*, Cancun, Mexico, Dec. 2015, pp. 493–496.

[61] W. Zhang, Y. L. Murphey, T. Wang, and Q. Xu, "Driver yawning detection based on deep convolutional neural learning and robust nose tracking," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Killarney, Ireland, Jul. 2015, pp. 1–8.

[62] R. Chai *et al.*, "Improving EEG-based driver fatigue classification using sparse-deep belief networks," *Frontiers Neurosci.*, vol. 11, no. 103, pp. 1–14, Mar. 2017.

[63] Q. Ji, Z. Zhu, and P. Lan, "Real-time nonintrusive monitoring and prediction of driver fatigue," *IEEE Trans. Veh. Technol.*, vol. 53, no. 4, pp. 1052–1068, Jul. 2004.

[64] X. Li and Q. Ji, "Active affective State detection and user assistance with dynamic Bayesian networks," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 35, no. 1, pp. 93–105, Jan. 2005.

[65] Q. Ji, P. Lan, and C. Looney, "A probabilistic framework for modeling and real-time monitoring human fatigue," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 36, no. 5, pp. 862–875, Sep. 2006.

[66] G. Yang, Y. Lin, and P. Bhattacharya, "A driver fatigue recognition model based on information fusion and dynamic Bayesian network," *Inf. Sci.*, vol. 180, no. 10, pp. 1942–1954, May 2010.

[67] R. Fu, H. Wang, and W. Zhao, "Dynamic driver fatigue detection using hidden Markov model in real driving condition," *Expert Syst. Appl.*, vol. 63, pp. 397–411, Nov. 2016.

[68] K. Kaida *et al.*, "Validation of the Karolinska sleepiness scale against performance and EEG variables," *Clin. Neurophysiol.*, vol. 117, no. 7, pp. 1574–1581, 2006.

[69] E. Portouli, E. Bekiaris, V. Papakostopoulos, and N. Maglaveras, "On-road experiment for collecting driving behavioural data of sleepy drivers," *Somnology*, vol. 11, no. 4, pp. 259–267, 2007.

[70] S. Makeig and T.-P. Jung, "Tonic, phasic, and transient EEG correlates of auditory awareness in drowsiness," *Cogn. Brain Res.*, vol. 4, no. 1, pp. 15–25, 1996.

[71] A. Tsuchida, M. S. Bhuiyan, and K. Oguri, "Estimation of drowsiness level based on eyelid closure and heart rate variability," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Minneapolis, MN, USA, Sep. 2009, pp. 2543–2546.

[72] V. Häkkinen *et al.*, "The effect of small differences in electrode position on EOG signals: Application to vigilance studies," *Electroencephalogr. Clin. Neurophysiol.*, vol. 86, no. 4, pp. 294–300, 1993.

[73] S.-J. Jung, H.-S. Shin, and W.-Y. Chung, "Driver fatigue and drowsiness monitoring system with embedded electrocardiogram sensor on steering wheel," *IET Intell. Transport Syst.*, vol. 8, no. 1, pp. 43–50, 2014.

[74] G. Borghini *et al.*, "Assessment of mental fatigue during car driving by using high resolution eeg activity and neurophysiologic indices," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, San Diego, CA, USA, Aug. 2012, pp. 6442–6445.

[75] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neurosci. Biobehavioral Rev.*, vol. 44, pp. 58–75, Jul. 2012.

[76] R. Chai *et al.*, "Driver fatigue classification with independent component by entropy rate bound minimization analysis in an EEG-based system," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 3, pp. 715–724, May 2016.

[77] V. Balasubramanian and K. Adalarasu, "EMG-based analysis of change in muscle activity during simulated driving," *J. Bodywork Movement Therapies*, vol. 11, no. 2, pp. 151–158, 2007.

[78] X. Zhu, W.-L. Zheng, B. L. Lu, X. Chen, S. Chen, and C. Wang, "EOG-based drowsiness detection using convolutional neural networks," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Beijing, China, Jul. 2014, pp. 128–134.

[79] Y. Sun and X. B. Yu, "An innovative nonintrusive driver assistance system for vital signal monitoring," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 6, pp. 1932–1939, Nov. 2014.

[80] Y.-F. Zhang, X.-Y. Gao, J.-Y. Zhu, W.-L. Zheng, and B.-L. Lu, "A novel approach to driving fatigue detection using forehead EOG," in *Proc. 7th Int. IEEE/EMBS Conf. Neural Eng. (NER)*, Montpellier, France, Apr. 2015, pp. 707–710.

[81] C. Zhang, H. Wang, and R. Fu, "Automated detection of driver fatigue based on entropy and complexity measures," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 168–177, Feb. 2014.

[82] M.-H. Sigari, M. Fathy, and M. Soryani, "A driver face monitoring system for fatigue and distraction detection," *Int. J. Veh. Technol.*, vol. 2013, Nov. 2013, Art. no. 263983.

[83] B. Mandal, L. Li, G. S. Wang, and J. Lin, "Towards detection of bus driver fatigue based on robust visual analysis of eye state," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 3, pp. 545–557, Mar. 2017.

[84] N. Alioua, A. Amine, and M. Rziza, "Driver's fatigue detection based on yawning extraction," *Int. J. Veh. Technol.*, vol. 2014, Aug. 2014, Art. no. 678786.

[85] L. Wang, H. Yang, X. Jiang, and X. Feng, "Gabor-based facial image sequential pattern mining for human fatigue monitoring," *Int. J. Adv. Comput. Technol.*, vol. 3, no. 6, pp. 26–33, 2011.

[86] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea, and M. E. Lopez, "Real-time system for monitoring driver vigilance," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 63–77, Mar. 2006.

[87] A. D. McDonald, C. Schwarz, J. D. Lee, and T. L. Brown, "Real-time detection of drowsiness related lane departures using steering wheel angle," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, vol. 56, no. 1. Los Angeles, CA, USA: Sage, 2012, pp. 2201–2205.

[88] Z. Li, S. E. Li, R. Li, B. Cheng, and J. Shi, "Online detection of driver fatigue using steering wheel angles for real driving conditions," *Sensors*, vol. 17, no. 3, p. 495, 2017.

[89] J. H. Yang, Z.-H. Mao, L. Tijerina, T. Pilutti, J. F. Coughlin, and E. Feron, "Detection of driver fatigue caused by sleep deprivation," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 39, no. 4, pp. 694–705, Jul. 2009.

[90] S. Furugori, N. Yoshizawa, C. Iname, and Y. Miura, "Estimation of driver fatigue by pressure distribution on seat in long term driving," *Rev. Automot. Eng.*, vol. 26, no. 1, pp. 053–058, 2005.

[91] T. Wakita *et al.*, "Driver identification using driving behavior signals," *IEICE Trans. Inf. Syst.*, vol. 89, no. 3, pp. 1188–1194, 2006.

[92] B. Cheng, W. Zhang, Y. Lin, R. Feng, and X. Zhang, "Driver drowsiness detection based on multisource information," *Hum. Factors Ergonom. Manuf. Service Ind.*, vol. 22, no. 5, pp. 450–467, Oct. 2012.

[93] W. Sun, X. Zhang, S. Peeta, X. He, Y. Li, and S. Zhu, "A self-adaptive dynamic recognition model for fatigue driving based on multi-source information and two levels of fusion," *Sensors*, vol. 15, no. 9, pp. 24191–24213, 2015.

[94] I. G. Daza, L. M. Bergasa, S. Bronte, J. J. Yebes, J. Almazán, and R. Arroyo, "Fusion of optimized indicators from advanced driver assistance systems (ADAS) for driver drowsiness detection," *Sensors*, vol. 14, no. 1, pp. 1106–1131, 2014.

[95] B.-G. Lee and W.-Y. Chung, "Driver alertness monitoring using fusion of facial features and bio-signals," *IEEE Sensors J.*, vol. 12, no. 7, pp. 2416–2422, Jul. 2012.

[96] B.-G. Lee, B.-L. Lee, and W.-Y. Chung, "Smartwatch-based driver alertness monitoring with wearable motion and physiological sensor," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Milan, Italy, Aug. 2015, pp. 6126–6129.

[97] S. Samiee, S. Azadi, R. Kazemi, A. Nahvi, and A. Eichberger, "Data fusion to develop a driver drowsiness detection system with robustness to signal loss," *Sensors*, vol. 14, no. 9, pp. 17832–17847, 2014.

[98] E. A. Schmidt, M. Schrauf, M. Simon, M. Fritzsche, A. Buchner, and W. E. Kincses, "Drivers' misjudgement of vigilance state during prolonged monotonous daytime driving," *Accident Anal. Prevention*, vol. 41, no. 5, pp. 1087–1093, 2009.

[99] K. Grauman, M. Betke, J. Gips, and G. R. Bradski, "Communication via eye blinks—Detection and duration analysis in real time," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Kauai, HI, USA, vol. 1, Dec. 2001, p. 1.

[100] P. Bouchner, "A complex analysis of the driver behavior from simulated driving focused on fatigue detection classification," *WSEAS Trans. Syst.*, vol. 5, no. 1, pp. 84–91, 2006.

[101] S. A. Israel, J. M. Irvine, A. Cheng, M. D. Wiederhold, and B. K. Wiederhold, "ECG to identify individuals," *Pattern Recognit.*, vol. 38, no. 1, pp. 133–142, Jan. 2005.

[102] P. Sasikala and R. S. D. Wahidabanu, "Identification of individuals using electrocardiogram," *Int. J. Comput. Sci. Netw. Secur.*, vol. 10, no. 12, pp. 147–153, 2010.

[103] M. Ingre, T. Åkerstedt, B. Peters, A. Anund, and G. Kecklund, "Subjective sleepiness, simulated driving performance and blink duration: Examining individual differences," *J. Sleep Res.*, vol. 15, no. 1, pp. 47–53, 2006.

[104] L. Barr, S. Popkin, and H. Howarth, "An evaluation of emerging driver fatigue detection measures and technologies," Federal Motor Carrier Saf. Admin., Washington, DC, USA, Tech. Rep. FMCSA-RRR-09-005, 2009.

[105] C. J. de Naurois, C. Bourdin, A. Stratulat, E. Diaz, and J.-L. Vercher, "Detection and prediction of driver drowsiness using artificial neural network models," *Accident Anal. Prevention*, to be published.

[106] P. V. Rouast, M. T. P. Adam, R. Chiong, D. Cornforth, and E. Lux, "Remote heart rate measurement using low-cost RGB face video: A technical literature review," *Frontiers Comput. Sci.*, vol. 12, no. 5, pp. 858–872, 2016.

[107] J. A. Horne and L. A. Reyner, "Sleep related vehicle accidents," *Brit. Med. J.*, vol. 310, no. 6979, pp. 565–567, Mar. 1995.

[108] A. Eskandarian, R. Sayed, P. Delaigue, A. Mortazavi, and J. Blum, "Advanced driver fatigue research," Federal Motor Carrier Saf. Admin., Washington, DC, USA, Tech. Rep. FMCSA-RRR-07-001, 2007.

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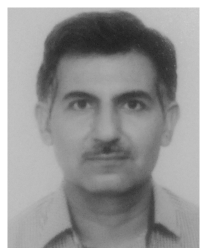

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