Sensor Applications and Physiological Features in Drivers' Drowsiness Detection: A Review

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***Abstract*— Drowsiness in drivers has become a serious cause of concern due to the occurrences of a large number of fatalities on the road each year. Lives of pedestrians and passengers are put to risk as drivers tend to fall asleep at the steering wheel. In the recent past, many researchers have paid attention to the problem of drowsiness detection since safe roads and safe driving are of paramount concern to all societies. This paper has led to the development of several novel and effective methods in detecting drivers' drowsiness. These include: 1) Vehicle based methods; 2) Behavioral methods; and 3) Physiological methods. Since wake-sleep is an intermediate state between two physiologically dissimilar states, physiological signals can define this transition more accurately when compared with approaches that fall in other categories. This paper focuses on the role of physiological signals in detecting driver's drowsiness level. The proposed methods measure the physiological signals by means of various sensors, which monitor the driver's physiological parameters on a continual basis. Multiple sensors can be embedded on the driver or in the vicinity of the driver to capture vital signs indicating the onset of drowsiness. The aim here is to provide an insightful review of all such key approaches that fall in this category. This paper conducts a detailed study in which key physiological parameters that relate to drowsiness are identified, described, and analyzed. Furthermore, the overall advantages and limitations of these physiological based schemes are also highlighted.**

***Index Terms*— Drowsiness, ECG, EEG, EOG, fatigue, GSR, sEMG, ST**

I. Introduction

DROWSINESS can be defined as 'the propensity to fall asleep'. The transition time from awake to sleep can be categorized in three stages: fully awake, Non Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep. NREM and REM sleeps occur cyclically over the period of sleep. NREM sleep can be defined as deep but dreamless sleep [1], [2]. Autonomic physiological activity is found to be very low in this sleep state. NREM sleep covers 75 to 80 percent of total sleep time. NREM sleep is also known as slow-wave sleep. The remaining 20 to 25 percent period is just REM sleep. Sleep episode initializes with NREM I, lasts for 1 to 7 minutes and contributes 2 to 5 percent of total sleep. This is actually a shift from awake to sleep, also known as Sleep Onset (SO) [3], commonly termed as drowsiness. Driver fatigue leading to drowsiness has been identified as one of the major causes responsible for serious road fatalities.

In a report of US National Highway Traffic Safety Administration, it is found that drivers' drowsiness results in 1,550 deaths, 71,000 injuries and $12.5 billion losses in revenue every year [4]. In the state of Victoria in Australia, almost 300 injuries and 50 deaths are caused by drowsiness each year. Research that leads to the development of robust and effective drowsiness detection system is crucial to prevent impending accidents due to driver drowsiness. Various physiological activities during driving such as the activities of central nervous system from ElectroEncephaloGram (EEG) and ElectroOculoGram (EOG), activities of autonomous nervous system from ElectroCardioGram (ECG), Skin Temperature (ST), and Galvanic Skin Response (GSR) and neuromuscular activities as ElectroMyoGram (EMG) are observed and examined to differentiate drivers' drowsiness from wakefulness. Sometimes these signals are combined together to upsurge the accuracy of the detection process. Many different technologies involving the use of novel types of electrodes have been proposed in recent past. From wet to dry electrodes, an upgradation has been observed. The widely used plating material for biofeedback sensors is silver/silver chloride [5]. Beside this, gold, stainless steel and a mixture of silver/silver chloride, aluminium, gold/gold chloride, nickel and titanium are being used in current sensor technologies [5]. There are two types of bio electrodes: one is wet, which requires electrolytic gel to make the surface act as a conductor and the other is dry. Wet electrodes are appropriate for clinical applications as it causes discomfort in real world monitoring. Thus dry electrodes are widely being used in drivers' fatigue related studies [6]. A list of commercially available biosensors has been given in Table I. This paper investigates the role of the physiological measures in drowsiness detection. To the best of our knowledge we have not come across any previous work that has discussed key physiological parameters or markers such as Heart Rate Variability (HRV), and the spectral components of HRV, the EEG band components (delta, theta, alpha, beta), EEG entropies, blink amplitude and frequency, PERCLOS, SEM of EOG, EMG and GSR amplitude and ST, their association (positive/negative) to drowsiness, and the overall effectiveness of such measures as well as challenges present in the use of these schemes. The variations in physiological parameters and

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TABLE I
COMMERCIALLY AVAILABLE DRY ELECTRODE SENSORS THAT ARE USED TO COLLECT PHYSIOLOGICAL SIGNALS

Physiological signals	Commercially available dry electrodes
EEG	MindWave Headsets, Flex Sensors, Drypad Sensors, Imotive Headset, NeuroSky's Dry Sensor, Quasar Sensors
ECG	Alivecor System and ECG Check, EPI mini, Ambulatory ECG, Omron, Flex Sensors, Drypad Sensors, NeuroSky's Dry Sensor, Quasar sensors
EMG	NEURONODE, SX230, Trigno™ Mini Sensor, NeuroSky's Dry Sensor, Quasar Sensors
EOG	NeuroSky's Dry Sensor, Comnoscreen, Google glass, SMI Eye Tracking Glasses, ASL Eye Tracking Glasses
GSR	Empatica wristband, Shimmer 3, Grove – GSR
ST	MAXIM30205, YSI 400 Series Temperature Probe

their effect on drowsiness, along with the overall advantages, and limitations of these schemes are discussed in detail.

A. Drowsiness and Fatigue

In the investigation of [7], fatigue has been classified as mental fatigue and physical or muscular fatigue. The physical fatigue is the effect of continuous physical exertion, which can be induced from physical exercise or from tasks requiring physical labor. The exact cause of mental fatigue is not well defined. According to [7], mental fatigue is a kind of subtle feeling that creates unwillingness toward performing any activity. Conforming to the works of [8] and [9], fatigue is the representation of tiredness, whereas drowsiness is a feeling of hardship in remaining awake. Tasks requiring continuous performance generate reluctance towards the act and degrade the capacity to perform the task over time. This continually increasing reluctance is a process known as fatigue. However, drowsiness is also caused by the factors associated with sleep such as duration of last sleep, sleep quality and the period of having been awake. It is pointed out in [10] that fatigue can be generated from tasks (workload and work period) as well as from sleep (sleep deprivation and time of last sleep). The sleep related fatigue and drowsiness are both influenced by the sleep factors and are used alternately in driving episodes. In our work these two terms have been used synonymously.

B. Factors Contributing Drowsiness

Factors associated with drowsiness are the quality of sleep, the biological clock known as circadian rhythm, age, fitness, and liquor consumption, work circumstances such as noise, in-car temperature and driving schedule, road environments such as monotony, car density and number of lanes [11]. It has been reported that people who are harmonized with circadian rhythm, often found themselves in a drowsy state during 13:00-15:00 h and 1:00-6:00 h in a day [12]. Besides, driving at night increases the risk factor to about 3 to 6 times than day time driving as the propensity to fall asleep increases with reduced vision at night [13]. It is observed that monotonous driving severely impacts the driver's attentional stimulation and it rapidly induces drowsiness when compared to any other contextual features [14].

Drivers often fail to assess their state of drowsiness, leading to fatality [15]. Falling asleep at the wheel reduces drivers' awareness to their surroundings and affects their response time. Furthermore, drowsiness diminishes the decision making capability of the drivers [16].

C. Drowsiness Countermeasures

Drowsiness countermeasure is the behavior adapted by the drivers to combat fatigue in a drowsy state. The most commonly used countermeasures are: stopping for a while to take a short nap or to rest or to eat, drinking coffee or energy drink, washing face, adjusting the ventilation or the airflow, smoking, diverting the thoughts, looking around the view, changing the driver, listening to the music/radio [17]–[19]. Moreover, asking the co-passenger to start conversation and texting or making a phone call are other well known countermeasures, though these activities have been identified as the direct causes of distraction during driving. Beside the driver initiated countermeasures, there are rumble strips which start vibrating whenever the vehicle running off the road or weaving in and out of the lane. According to [13], preventing night and/or prolong driving can automatically reduce road crashes to a great extent. Moreover, providing possible treatment to drivers, who are suffering from various sleep diseases, can further enhance road safety.

A list of commercially available drowsiness detection systems has been illustrated in Table II, where a preference is given to vehicle based measuring techniques over other techniques in detecting drivers' state in real time [20], [21]. Vehicle based drowsiness detection technique works well in controlled environments such as driving simulators, but it may become inefficient in practical situations as the deviation of these parameters from their normal baseline values such as frequent lane changing or weaving in and out may not always be due to drowsiness. Rash driving and road surfaces can be other general causes, which have been highlighted in Table II. Moreover, behavioral measurement requires different image processing techniques, which are highly sensitive to lighting changes. Furthermore, inadequate background-foreground lighting such as illumination due to drivers' spectacles or sunglasses, drivers' motion, speed of the passing vehicles may result in poor image quality.

II. PHYSIOLOGICAL METHODS FOR MEASURING DROWSINESS

A typical block diagram representation of physiological signal based drivers' drowsiness detection system is illustrated in Fig. 1. Since the physiological signals are collected from the electrodes as shown in Fig. 1, and electrodes have negligible internal resistance, the skin-electrode interface may induce motion artifacts [22]. Moreover, nearby power line also results in noise in the original signal [23]. These noise

TABLE II
COMMERCIALLY AVAILABLE DROWSINESS DETECTION TECHNOLOGIES, CURRENT FEATURES AND FUTURE CHALLENGES

Current Technologies	Manufacturing Company	Monitoring Device	Detection parameters	Warning system	Detection category	Important features	Challenges
Driver Alert Control	Ford	Camera	Lane position	Audio-vibration.	Vehicle based measure	1. A reverse steering is applied to direct the vehicle back into the lane	1. Apart from drowsiness, road side obstacle and rash driving are the other two main reasons of lane deviation
Driver monitoring system	Toyota	Charge-coupled camera (CCD)	Eye tracking and head motion	Audio	Behavioural measure	1. Advanced Obstacle Detection (AOD) System pushes the brake automatically by tightening the seat belt during the chance of forward collision	1. Not feasible when the driver wears sunglasses or contact lenses 2. Nodding off has been considered as the final stage of drowsiness when the driver falls asleep at the steering wheel 3. AOD system lessens forward collisions, but no prevention has been offered if the driver in the rear vehicle falls asleep
Attention Assist	Mercedes-Benz	Sensor on the steering column	Steering wheel movement and speed	Audio-visual	Vehicle based measure	1. Individual driving profile is created during the first few minutes of drive to be used as reference 2. Driver's behaviour, road surface, weather and period elapsed behind the wheel have been taken into account to check whether the errors are due to drowsiness or not	1. Apart from drowsiness other factors such as side winds, road bumps and signal indicator may cause steering wheel movements
Driver Fatigue Detection	Volkswagan	Sensor on the steering wheel	Steering wheel movements	Audio-visual	Vehicle based measure		1. Different driving styles and road surfaces are the primary challenges that inhibit the implementation of this system
Driver Alert Control	Volvo	Camera and sensor for steering wheel movement	The distance between the road line marking and the car	Audio-visual	Vehicle based measure	1. Lane departure warning system prevents single vehicle running off the road crashes as well as head-on collisions	1. Good lighting for the visibility of lane marking is required 2. Driving behaviour may not influenced by fatigue for professional drivers

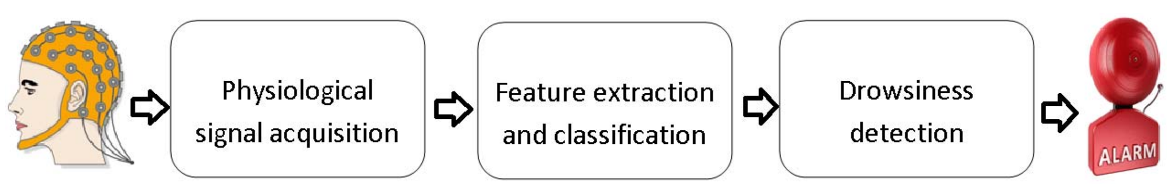

Fig. 1. Block diagram representation of a typical physiological signal based drivers' drowsiness detection system using EEG sensors.

and artifacts have been removed by using median filtering technique [23], independent component analysis [24], low pass filtering [25]–[27] and band pass filtering techniques [28]–[31]. After preprocessing, signal amplitude, mean, median, standard deviation, signal entropies are calculated as time domain features [31], [32]. To extract frequency domain features, Discrete Fourier Transform (DFT) [25], Fast Fourier Transform (FFT) [16], [26], [33], Discrete

Wavelet Transform (DWT) [32], [34] and Wavelet Packet Transform (WPT) [35]–[37] are common in previous works. The parameters are usually classified into alert and drowsy states data. If the recent data is closer to the alert feature set, the epoch is termed as an alert state, otherwise it is classified as a state of drowsiness. The distance between the current state data and the estimated data is measured by probabilistic Bayesian network [11], [25] and various distance matrices such as Mahalanobis distance [26], Artificial Neural Network (ANN) [28], [32], [34], clustering algorithms such as Fuzzy clustering [16], [36], [37] and K Nearest Neighbors (KNN) [35], Support Vector Machine (SVM) [30], [31], [38]. Whenever, the current state data is close enough to the drowsiness baseline data, the driver is considered to be drowsy and a visual as well as an audible alarm is sent to alert him/her. Such physiological features, which have been used to detect drivers' drowsiness, are discussed in detail in the following sections:

A. ECG

The ECG electrodes are used to collect ECG signals from, which we can obtain feedback on critical parameters that relate to Heart Rate (HR), Heart Rate Variability (HRV) or R-R Interval (RRI), and respiration rate or breathing frequency. Each of these is closely related to drowsiness [39].

1) Heart Rate: HR can be defined as the number of heart beats per minute (bpm). A reduction in HR is observed during long duration night driving according to [40]. Mental and physical tasks as well as emotions and physical exertion deeply affect HR [41], [42]. The work in [3] performs an experiment on 34 volunteers of different age groups that include subjects who are normal as well as those who suffer from a variety of sleep diseases. The authors observe a decreasing trend of HR with the induction of fatigue for normal subjects and patients having various sleep disorder. A reduction in HR is also investigated in the works of [39], [43], and [44] when moving from awake to drowsy state.

2) Respiration Rate or Breathing Frequency: Respiration rate or breathing frequency is the number of breaths inhaled and exhaled per minute. The work in [39] obtains a link between respiration rate and drowsiness. According to the authors, respiration rate starts to fall from the normal rate, while fatigue initializes and sets in and continues to fall until sleep onset. However, there is no consensus on this. For example, the experiment conducted in [3] on 34 volunteers could not find any changes in respiratory cycle, while drowsiness sets in.

3) Heart Rate Variability: Another widely used ECG parameter is HRV, which can be defined as the variation in time interval between two consecutive heart beats. This beat-to-beat interval is also known as R-R Interval or simply RRI.

Activities of Autonomous Nervous System (ANS) alter in stress, fatigue and drowsy states. These activities of ANS can easily be described by HRV [45]. There are many studies in literature based on HRV and power spectrum of HRV. Researchers found a link between mental workload and HRV from a large number of experiments [46], [47]. These experiments show a negative correlation between workload and HRV and as workload increases, a reduction in HRV is perceived. The work did not find any significant change in HR during the test. The work of [47] also observes a reduction in HRV with the increasing load. However, this study contradicts the results presented by previous work in terms of HR. They perceived an increased HR with increasing load. The inconsistency in the variation of HR with workload has later been clarified in [48]. There are two categories of workload that are identified and described: one is heavy physical-light mental and the other one is light physical-heavy mental workloads. Finally, it is found that HR increases with physical workload, whereas, HRV reduces.

In addition to HRV alterations, the Power Spectral Analysis (PSD) of HRV is significant in this study as well. The HRV is decomposed into three frequency bands:

a) Very Low Frequency (VLF) is normally in the range from 0.008Hz to 0.04Hz [43]

b) Low Frequency (LF) varies from 0.04Hz to 0.15Hz

c) High Frequency (HF) varies in the ranges from 0.15Hz to 0.5Hz

The power in the LF band is primarily associated with sympathetic nervous system. However, it is further influenced by the parasympathetic activation, whereas HF band power is influenced by only the parasympathetic stimulation. The sympathetic nervous system remains active in tense state, but parasympathetic action upsurges during relaxation. Thus, an increase in the activity of sympathetic nervous system as well as declining levels of activity of parasympathetic nervous system defines wakefulness [45]. Similarly, drowsiness can be characterized by the decreased amount of sympathetic and an increased level of parasympathetic activity.

However, subjects who are in sleep demand state but trying to remain active show an upsurge in LF band power due to sympathetic stimulation. To depict this certain observation adequately, low frequency to high frequency bands power ratio (LF/HF), known as sympatho-vagal balance need to be measured at times [3]. It is explained in [43] that a drop in LF/HF is observed prior to falling asleep (FA) as a symbol of losing alertness. However, an upsurge in LF/HF is observed sometimes after full sleep, which reflects the hardship of driver fighting drowsiness.

A total of 34 patients are studied in the experiment conducted in [3], wherein these patients have broadly been classified into three groups. Normal patients with no sleep abnormality, Obstructive Sleep Apneic (OSAS) patients, and patients having a variety of other sleep disorders so as to check out the deviation of HRV with SO. In these experiments, a significant 2.5 fold decrease in VLF power from its initial baseline value is found in all of the above mentioned groups just 10 minutes before sleepiness. No changes in LF power spectrum is found for OSAS group, but a steady decay is noticed in the other two groups ($p < 0.05$). Again the LF/HF reduces significantly for all throughout SO, especially 1-2 minutes after drowsiness sets in. Though discrimination in the level of variation in ANS is observed, the trend remains the same when the power level of the frequency components of HRV are changed as highlighted in preceding works. These results are further reinforced by studies conducted in [43] with

10 volunteers in the age range 22-40 years and in [45] with 30 volunteers in the age range 25-60 years.

Though many studies have been conducted in the recent past on each of these ECG parameters individually or in a combination, HRV currently gets the first priority to be used as an indicator of early fatigue detection. The main limitation of HRV is its instantaneous variation in observed time domain signal [3], which can be treated by the time frequency analysis of HRV as described in [49] and [50]. It should also be noted that non-contact ECG measurement requires close proximity to the subject as highlighted in [39].

B. EEG

Since, human brain is the center of any response to a certain stimuli, it is said that EEG signals are highly interrelated to vigilance, sleep and cognition, and therefore serves as a perfect tool in defining drivers' drowsiness on board [51]–[54]. The parameters that are common in detecting drivers' drowsiness are the EEG spectral power (delta, theta, alpha and beta bands), the amplitude and latency of the third and highest positive peak (P300) of Event Related Potential (ERP) and the last and final one is the EEG signal entropy. EEG signals are taken basically from different positions of the brain with a view to locating the right position on scalp that gives optimal results in drowsiness detection.

1) EEG Spectral Power: After the frequency transformation of EEG signals, we obtain four basic EEG frequency components, which show the electrical activity of brain in terms of rhythms. Due to a high inter personal variability, no specific frequency limits of these EEG spectral band components has been found in the literature [55]. The defined frequency ranges of the EEG bands in most of literature are as follows:

a) Delta band comprises of frequencies from 1Hz-4Hz
b) Theta band spectrum falls between 4Hz-8Hz
c) Alpha band frequency spectrum lies in 8Hz-12Hz
d) Beta band contains the frequency range of 12Hz-18Hz [56]

Power in the beta region is significant all through the cognitive task demanding high levels concentration [56]. Decreasing alertness results in a gradual rise in alpha band power and this continues to steadily increase as drowsiness gradually sets in [57]. The power in theta band is found in the primary phases of sleep, while alpha band power almost flattens immediately after this wake-sleep alteration. The power for delta band is used to classify brain activity in intense sleep condition [1]. The probability of having delta frequency power in wakeful state is almost zero [58].

To establish a correlation between drowsiness and EEG band power, an experiment has been conducted on 16 healthy subjects in the age range 20-35 years on a driving simulator with 33 EEG channels in [24]. Their test results reveal that power in the range of 8-13 Hz (alpha band) increases with the driving time and so also the driving errors. The works in [16], [59], and [60] also observe a similar increase in EEG alpha power level while drowsiness sets in. Beside alpha power, an increase in spectral power in theta region is perceived in [16].

The scalp site for collecting EEG data is another widely used technique. The experimental results of [24] have concluded that the positions of electrodes are critical when collecting the EEG data from the subjects. The study perceives that the EEG alpha power at central to occipital lobes can be used as an appropriate drowsiness indicator for all subjects who have participated in this experiment. A steady increase in alpha and theta spectra power at occipital region is observed with an accuracy of about 82.8% in a 20 minute driving task of [26]. The experiment described in [56] has generated a database of 12 male volunteers within the 22–27 years age range. This analysis reveals an overall decrease in beta band power in frontal, central and temporal ($p < 0.05$) regions after a 120 minute driving task. In addition to this, a significant increase in alpha (central, occipital, parietal and temporal) and theta (frontal, central and occipital) ($p < 0.05$) power levels is found throughout the task. The experiment also reveals that alpha power follows a slightly reduced trend after a sharp increase, while theta power continues to steadily increase. Occipital alpha power alone has been used in the works of [59] and [60]. According to [59] and [60], it is the occipital cortex, which controls drivers' level of alertness.

The work in [61] measures the temporal and parietal theta, alpha and beta power and obtains 90% accuracy in mental fatigue detection system. The parietal and occipital regions are utilized to measure the alpha and theta spectra power in the experiments of [16]. The work in [62] finds the frontal alpha and theta power as the most appropriate factors to monitor and therefore label them as most preferred drowsiness detectors with an accuracy of about 81%. Though there are a variety of opinions and experimental results on selecting appropriate EEG scalp topology for the purpose of drowsiness detection, the rise in spectral power in alpha band at occipital region has been found to be the classic change of EEG signal in drowsiness [59], [60].

EEG alpha spindle, which is a short burst from 0.5-2 seconds in alpha band, has been detected as another objective indicator of fatigue or drowsiness [63]. Alpha spindle activity has been observed by [64] in car drivers during drowsiness.

2) ERP: An ERP is the response of brain to a certain stimuli, cognition or motor event [65]. Beside EEG band power, ERP has been used in classifying the brain activity with operator performance from alertness to mental workload, in fatigue state to drowsiness and in various phases of sleep for more than 30 years [66]. In particular, the amplitude and latency of P300 of ERP have been of interest to the researchers when dealing with drowsiness. P300 is the third and highest positive peak of ERP. The amplitude of P300 indicates the quantity of available cognitive resources, while the latency reflects the rapidity of response to a certain event [67].

It is evident from the experiment of [66] that P300 can replicate the mental task irrespective of motor stimulus. An inverse relation is noticed between the amplitude of P300 and mental workload, while carrying out an experiment on 20 subjects within an age range 20-33 years ($p < 0.001$). Furthermore, the investigation of [56] reveals that the latency of P300 increases, while the amplitude reduces after a long duration driving session. The induction of drowsiness reduces alertness, thereby reducing the amplitude of ERP. Longer reaction time is another consequence of losing awareness.

3) EEG Entropy (En): Another recent and interesting parameter of EEG signal is Entropy (En), which can be defined as the irregularities in the EEG wave patterns. The greater the degree of uncertainty, the higher is the EEG entropy. Reduction in entropy results in drowsiness as EEG series tends to be uniform, while losing alertness. According to [32], when the subjects (20 male subjects in the age range from 20-35 years) are drowsy, an almost regular pattern in the EEG waveform is observed, which conversely reduces the entropy. A variety of entropy calculations are performed based on a wide range of parameters such as spectral entropy, approximate entropy, sample entropy and fuzzy entropy all of which are negatively correlated with drowsiness and commonly used in EEG based drowsiness estimation [68]. According to [68], fuzzy entropy based EEG analysis in drowsiness detection gives an accuracy of about 93.50% over 12 volunteers with an average age of 21.5 years, which is the highest among all other entropy based drowsiness detection techniques.

Though the EEG signals are most accurate and reliable when compared to other physiological signals in detecting drowsiness, placing electrodes to collect EEG sample data may cause inconvenience to the subject [45]. Moreover, due to its small amplitude, sampling the original EEG signal from noise becomes difficult [24], [58].

C. EOG

EOG signal is the biofeedback taken from the potential of the electric field created between the cornea and the retina and it typically varies from 0.05–3.5 mV [69]. Any kind of eye activity such as eye blink, and eye movement alters this potential difference, thus resulting in a modification in EOG signal [70], [71]. A blink actually happens when the upper lid touches the lower one and lasts for about 200-400 ms [70]. If eye remains closed beyond 0.5 seconds then this is known as microsleep [72].

Naturally, 15-20 blinks per minute are observed in relaxed and calm state. It drops down to 3 blinks per minute in any task requiring tremendous concentration, and this in turn reduces the blink frequency as well [70]. Blink frequency, blink amplitude, blink duration, delay of lid reopening and PERCLOS are generally eye lid movements based indicators of drowsiness. On the other hand, Rapid Eye Movement (REM) and Slow Eye Movement (SEM) are under eye ball based EOG alteration.

Many measuring parameters have been analyzed to detect drowsiness in the domain of eye lid movements based drowsiness detection. These are:

1) Blink Duration: Blink duration can be defined by the period from the beginning to the end of a blink [69]. It is represented in ms.

2) Blink Frequency: The blink frequency is the number of blinks per minute (blinks/min) [69]. Any increase in blink frequency indicates drowsiness being induced, as it is hard to keep eyes open in this state [73].

3) Blink Amplitude: Blink amplitude is the electric potential measured by the EOG electrodes during a blink. The amplitude of a typical blink in EOG varies from 100-400 μV [69].

4) PERCLOS: The proportion of time in a minute that the eyes remain at least 80% closed can also be a drowsiness indicator and is known as PERCLOS [58].

5) Delay of Lid Reopening: It is the duration from full closure to the start of lid reopening [72]. A few ms delay of reopening is typical in wakefulness, while increases during drowsiness and extents to about several hundred ms in microsleep.

6) Eye Ball Movement: The eye ball movements are due to the dislocation of eye ball from its point of fixation [74]. Eye ball movements result in a change in EOG amplitudes collected by the horizontal as well as vertical electrodes.

Considering the blink rate and blink duration, drowsiness has been divided into four stages such as awake, reduced vigilance, fatigued and sleepy in [75]. Increased blink frequency during the transition from wakeful state to a state in which there is reduced vigilance was perceived, while performing an experiment on 11 volunteers using a driving simulator. In addition, it was observed that drowsiness was characterized by long duration blink along with increased blink frequency. In the study of [76], drowsiness has been divided into three stages in terms of EEG band power, blink parameters and eyeball movements. According to this study the first stage towards drowsiness is reduced vigilance, which can be represented by increased EEG theta band power and decreased eye (eye lid and eye ball) movements. Sleep propensity is the second stage and can be characterized by extended blink duration and longer lid reopening. Increased blink rate defines the final stage in which driver almost loses the capacity to react to the traffic events. The impacts of no reactions are: over stepping the red light signal, dangerous steering manoeuvres (over or under steering), veering off the road as well as weaving in and out of the lane.

In order to determine the relationship between these eye lid movements based parameters and drowsiness, an experiment is conducted in [72] involving 129 among 138 participants (mean age 33.4 ± 11.5 years). The outcome is longer blink duration (mean and median blink duration) when gradually moving from alert to the drowsy state. A gradual delay in lid reopening is also perceived with increasing levels of sleepiness. Extended duration is typical in microsleep [77], [78]. Further consequence is the reduction in the blink amplitude [58]. PERCLOS is evident in the works of [79]–[83] for the period of drowsiness. PERCLOS is often noticeable in a situation, where the driver almost loses control over himself and fails to respond to the ongoing traffic situations in a spontaneous and appropriate manner. Thus PERCLOS based detection technique lead to situations that are accident prone [58]. Moreover, all drowsy drivers do not show prolonged periods of lid closure all through the driving episode [72].

If we now examine the performance of eye ball movement, a slower movement of eye ball is observed during drowsiness than in wakeful state [74], [84]–[88]. Some studies have utilized these movements, and have characterized sleep into different stages [89]–[92]. It is apparent from the previous work done in this area for us to conclude that Slow Eye Movements (SEM) can be a reliable indicator of drowsiness.

To check the validity of eye ball movements in drivers' drowsiness detection, the work in [93] has conducted an experiment on 11 volunteers between the age group of 26 to 40 years. A delay is observed in participants' response time in avoiding collisions while they are drowsy, and SEM is common in all participants during this time. The findings also reveal the presence of SEM in 84.6% of the accident cases that occur under drowsy driving ($p < 0.01$). This phenomenon is defined as "thalamic gating", and it actually prevents the communication of sensory information between the thalamus and cerebral cortex, thereby causing sleep onset while eyes remain open.

When collecting EOG data a particular emphasis is given to the placement of EOG electrodes [93]. The farther the distance of the electrodes from the eyes, the weaker is the strength of the received EOG signal [23]. Again attaching electrodes near eye disturbs the driver, and this is very similar to the disturbance caused by the EEG electrodes. Double blink, which implies full blink immediately following a half blink, presents a challenge, when using EOG method [23]. Furthermore, differentiating vertical eye ball movements from the normal eye blink is also very tedious task. Eye ball moves upwards while a blink occurs and causes a change in electric field, which is measured by the vertical EOG electrodes. Furthermore, the same vertical electrodes are also employed to sense the potential difference due to the vertical movements of the eye balls. Thus vertical movements of eye ball may result in artifacts in blink based drowsiness detection and vice-versa. In addition, blink behavior based drowsiness detection may not be suitable for mentally imbalanced people [58] as their eyes remain wide open even in drowsy state or they may exhibit symptoms relating to drowsiness in a non-drowsy state e.g. increased number of blinks with long duration in awake state.

D. EMG

An EMG is the electrical signal generated from the muscle contraction [94]–[96]. In widely used non-invasive EMG collection methods the electrodes commonly referred to as sEMG are placed on the surface of the skin. Much of the previous work in this area has found a link between muscle fatigue and EMG amplitude since the amplitude in this context reflects the strength of the muscles. According to the results furnished, the amplitude decreases progressively with fatigue. Some previous works [97], [98] have observed a shift in center frequency component towards lower spectral band during muscle contraction. While performing an experiment on 11 rower athletes, where electrodes are placed on Posterior Deltoid, Vastus Lateralis, Biceps Femoris and Biceps Brachii, the muscles that are directly involved in rowing [99], a similar center frequency shift is perceived at the time of fatigue. This muscular fatigue or sEMG analysis is later extended to drowsiness detection and some substantial work has already been done in last decade in order to establish a correlation between the two [29], [35], [100]–[103].

The main disadvantage of using EMG signals underlies in its random and complex nature [104]. Furthermore, the collected signals may alter due to the structural and biological properties of the muscle [99].

E. GSR

GSR is the skin conductance measured from the skin, which alters due to the sweat-gland secretion. GSR is also termed as Electro Dermal Activity (EDA), Electro Dermal Response (EDR), Psycho Galvanic Reflex (PGR), Skin Conductance Response (SCR), and Skin Conductance Level (SCL). Secretion of sweat gland is controlled by the sympathetic arousal of ANS. When the activity of parasympathetic nervous system is triggered during drowsiness, sweating reduces, thereby increasing the skin resistivity, and reducing the skin conductivity and vice versa [35], [105]–[107]. The basic problem associated with GSR is its high sensitivity to atmospheric temperature [105].

F. Skin Temperature

The Skin Temperature (ST) measurement techniques measure the temperature of the skin surface, the mean value of which is 32^0 C-35^0C (89.6^0 F-95^0F) for healthy human [108]. On the other hand, the core body temperature is the internal operating temperature of the body organs. The skin temperature (ST) is the direct result of thermoregulation system, which is primarily responsible for the maintenance of the body temperature in humans within a certain range. Drowsiness has been classified into five levels such as awake, slightly drowsy, drowsy, very drowsy and extremely drowsy based on the ST in [27] by measuring the Nasal Skin Temperature (NST), the left and right Forehead Temperature (FHT) and the left and right Tympanum Temperature (TT). The NST and FHT reflect the skin temperature, whereas the TT represents the core temperature. Among the three temperature variables, the experiment reveals an indicative decrease in observed FHT values when transitioning from drowsy to extreme drowsy state. The FHT starts to fall as subjects become drowsy, and the fall continues until an extreme drowsy state is reached.

G. Hybrid Techniques

All Physiological parameters identified and explained above have an impact on drowsiness. Moreover, each parameter has certain advantages and limitations over the others. Depending on a single physiological parameter to detect drowsiness could lead to misclassifications and may impact the detection accuracy. Hence to increase the success rate of detection system, some studies have utilized a combination of several physiological indicators to assess drowsiness. The EEG band power, RRI, HRV spectral power, respiration rate, right/left Anterior Tibialis muscle power are combined together in the experiment of [3], whereas the work in [31] utilizes EEG energy, sample entropy, EEG band power along with HRV spectral components to detect drowsiness. The GSR and EMG signals are both analyzed in the study of [35]. HR, HRV, blink rate, and breathing rate altogether have been used in the work of [39]. HRV and breathing frequency are used in [45]. In addition to EEG spectral power, [56] utilizes the ECG

TABLE III

PHYSIOLOGICAL PARAMETERS ASSOCIATED WITH DROWSINESS, THEIR RELATIONS WITH DROWSINESS, LIMITATIONS AND DETECTION PERFORMANCE

Physiological signals	Amplitude/frequency Range	Correlation of physiological indicators with drowsiness/fatigue		Limitations	Detection accuracy	References in chronological order
		Positive	Negative			
ECG	50μV-50mV [41] 0.05Hz-100Hz		Heart Rate	Detection rate is sensitive to non-intrusive ECG proximity sensors	96% [47] 30 volunteers	41-52
		HRV				
		HF	VLF, LF, LF/HF			
			Breathing Frequency			
EEG	2μV-10μV [41] 10Hz-2kHz	θ and α Bands Power	β Band Power	The low amplitude of EEG signal makes it difficult to separate from noise	96.7% [34] 6 volunteers	53-70
		P300 Latency	P300 Amplitude			
			Entropy			
EOG	0.05mV-3.5mV [71] 0.1Hz-100Hz [41]	Blink Duration		Detection rate depends on the placement of EOG electrodes	81.7% [111] 20 volunteers	71-95
		Blink Frequency				
		Lid Reopening Time				
			Blink Amplitude			
		PERCLOS				
			Eye Movements			
EMG	20μV-10mV [41] 10Hz-10kHz		EMG Amplitude	Muscle amplitude may alter due to muscular biology	94% [30] right anterior deltoid 4 volunteers	96-106
		Centre frequency shift towards lower frequency region				
GSR	10kΩ-10MΩ [108] 1.76V-0.14V	Skin Resistance	Skin Conductance	Very much sensitive to ambient temperature	80% [31] 13 volunteers	107-109
ST	89.6^0 F-95^{0}F [110]		Skin Temperature			110

entropy and amplitude of P300 in fatigue detection. The work in [83] has combined the EEG band power and PERCLOS to detect fatigue or drowsiness.

A summary based on this review has been depicted in Table III, illustrating the amplitude and frequency variations of the physiological signals and the correlation between key physiological parameters and drowsiness. Table III demonstrates how each nominated physiological parameter alters in the presence of drowsiness and their limitations. It also highlights the difficulty in measuring these parameters due to the underlying challenges in collection, sampling and processing of physiological signals in real time situations. It also throws light on detection accuracy of the physiological measure based detection system. From Table III, it can be inferred that with the initialization of drowsiness, the HR falls from its normal value, and the HRV increases. Furthermore, longer duration blink as well as increased blink frequency is observed with respect to wakefulness. Reduced muscular potential indicates the induction of fatigue, while further reduction in muscle amplitude is an indication that sleepiness is taking over. It has been found from this review that among all physiological techniques, EEG power spectrum analysis is the most common, and frequently used technique to detect drowsiness. An increase in EEG alpha band power in occipital region is a primary indicator of drowsiness setting in. The highest success rate of EEG spectral power based drowsiness detection technique is almost 97% over 6 subjects, and is the most accurate when compared to other physiological measures. The basic problem associated with EEG based drowsiness detection system lies in the collection of EEG data, where electrodes are required to be placed on the head. This whole setup is not feasible in real life driving scenario due to its complex arrangement, and may even prove to be a hindrance in driving. To reduce the intrusiveness, in-ear EEG electrodes are currently available in the market [30].

The review also finds the spectrum analysis of HRV as another gold drowsiness detector since the success rate of HRV based drowsiness detection is found to be around 96% over 30 subjects. The key observation is the significant reduction in LF/HF component, while drowsiness gradually sets in. The other components of HRV are the VLF, LF and HF powers. Though the ECG sensors/electrodes can be used in

Fig. 2. Primary setup of driving simulator (FORUM8).

a non-intrusive way, the detection rate primarily depends on the accuracy of the sensors in close proximity to the subject. A similar problem arises while sampling the EOG signal, which gives a success rate of about 81% over 20 subjects in predicting drowsiness using long duration blinks: the typical objective measure of drowsiness. The sEMG and GSR signals can be collected in a less intrusive way, giving success rates of 94% over 4 participants, and 80% over 13 participants, respectively. Human muscles may lose its strength due to reasons other than drowsiness, e.g. due to physical exercise, reduction in the sEMG amplitude, whereas GSR and ST may largely be affected by ambient temperature.

The primary experimental setup consists of a driving simulator, cameras to monitor driver's behavior and data acquisition system. A typical virtual driving simulator has three major parts: simulator software, graphic user interface and 3D visual system as shown in Fig. 2. Participants who have been selected to participate in driving experiments must fall under the age ranges from 18-65 years, not having any mental/physical disabilities, and must have valid driving licenses. Some experimental work use only fully rested subjects, whereas in some other experiments participants can be fully rested, partially sleep deprived and fully sleep deprived [45]. A variation is also observed in driving period in virtual environment. A 90 minute session of test drive is common [29], [109], whereas, 2 hours of continuous drive with 10 mins break after each hour is also a commonly found scenario [45]. Driving in a monotonous highway is typical in most of the previous works [16], [29], [30], [45]. Biggest difference is observed in selecting the number of participants [16], [29], [30], [45], [109].

III. DISCUSSION

If we now visualize the correlation among the critical physiological parameters of drowsiness by taking the vigilance state as reference, we can observe the EEG alpha band power is in its baseline value during this state. The state can be characterized by normal blinks (blink duration and blink frequency) with usual eye movements. During the vigilance state, the sympathetic nervous system remains active over parasympathetic stimuli, which maintains the ECG low frequency to high frequency power ratio (LF/HF) to a moderate level. This actuates the sweat gland secretion, thereby reducing the skin resistance. A drop in vigilance results in irregular occurrences of EEG alpha band power, accompanied by long duration blinks with little eye movements. The blink frequency remains the same but starts to increase with decreasing vigilance. While drowsiness is taking control of vigilance, the alpha band power begins to increase gradually. Longer blink duration with higher blink rate is observed. Moreover, eyes become steady in position. In the initial stages of lapses in vigilance, an increased level of LF/HF is observed as a result of the driver pushing hard to regain normal vigilance levels. As these lapses continue to occur more frequently in the drowsy state, a reduction in LF/HF is observed due to the continuous activation of parasympathetic nervous system. This in turn causes reduction in sweat secretion, giving rise to the skin resistance. Skin temperature falls throughout the process. Muscles are observed to be losing strength due to drowsiness, resulting in the reduction in sEMG amplitude.

Physiological signals are found to be more accurate and consistent in detecting drivers' drowsiness levels. However, there are still some issues that need to be urgently addressed. Real time physiological signal based drowsiness detection system is still not in commercial use due to the invasive nature of biofeedback sensors. These signals require bio sensors to be attached to the driver, which may hinder the concentration of the driver. Moreover, attaching bio sensors impose some restrictions on the driver. For example, if EOG signal needs to be clearly detected, drivers are urged not to wear any kind of glasses. Moreover, they are advised to restrain their movements as much as possible to avoid noise and distortions during the signal collection. Acquiring bio signal from driver, processing and analyzing the signal to ascertain the state of the driver, and finally sending out an alarm needs to be fast enough so that the detection system can generate an alert (early warning sign) before any accident occurs. Individual variability and human factors such as age, gender, experience, sickness (insomnia, fever, hypo and hyper tension, eye sight problem) make it almost difficult to model a real time physiological signal based drowsiness detection system. Again real world driving challenges are very different from the virtual driving environment, where drivers are always trying hard to keep themselves awake to remain alert, which is unusual in virtual driving. As a result, drivers in virtual driving environment offer less resistance and tend to fall asleep easily. Another important factor is the car's internal temperature, which has a great effect on drowsiness induction. However, if we consider a fixed in-car temperature to design a generalized drowsiness model, drivers have to maintain that temperature throughout the driving session, which is not feasible in real life driving scenarios as keeping the internal car temperature to a prescribed level throughout the journey may cause discomfort for the driver.

Future research work can be carried out in two different ways by considering the following:

1) The EEG delta power, which is conspicuous in deep sleep stage is still not taken into consideration in drivers' drowsiness related studies. Only few experiments in the literature have confirmed the existence of EEG

frequency components at 3Hz and 4Hz in drowsy state [55], [110], which provide evidences of the occurrence of EEG delta band power in this state. Thus future research can be directed if there is any incidence of EEG delta band power in this transitional state.

2) A detailed analysis of the role of EDA in drowsiness detection is an area of investigation that requires attention. Investigating the role of EDA could provide an opportunity to classify a variety of transitional states such as resting condition to mental workload, mental workload to mental fatigue and mental fatigue followed by drowsiness. This technique can also help define the general states of drowsiness such as early, middle and late.

IV. Conclusion

This paper presents a thorough review of proposals that currently use sensors to measure physiological signals in drowsiness detection. Though various methods exist to measure drowsiness, the focus of this paper is restricted to the physiological signals based drowsiness detection schemes. With the study and analysis of vast literature, we contribute in identifying key physiological parameters that characterize drowsiness, and describe them in some detail and strive to highlight their advantages and limitations from a practical perspective. In particular, emphasis has been given on the improvisation of the sensing materials such as silver/silver chloride, gold/gold chloride, titanium, nickel, aluminium and stainless steel material are popular as these sensors can be used without any conducting gel. Even though the dry electrodes help to collect physiological data during driving, we observe that the intrusive way of signal collection is still preferred, and is more commonly used. The reason is the precision of the nonintrusive biosensor solely depends on how near/far it has been placed to the user. Apart of this, we find that the inter-individual variability is another big challenge that restricts the commercial use of physiological signal based drowsiness detection system, as generalization is the major problem here. Our study reveals that previous works did not adhere to a standardized experimental setting and as a result noticeable differences were observed in sample numbers, age, gender, driving experiences, length of driving sessions, time of experiments and types of participants (normal, sleep deprived, partially sleep deprived). This lack of uniformity makes it difficult in comparing results from different laboratory settings. Furthermore, several experimental studies are needed in different countries to measure/monitor an individual's physiological parameters to ascertain their impact under different conditions.

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