On-board Drowsiness Detection using EEG: Current Status and Future Prospects

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***Abstract*— Drowsiness is a transition of psychophysiological state from alert towards sleep causing degradation in concentration, thereby increasing the response time. Drowsy driving is one of the leading causes of accidents in transportation sector. An on-board warning system which helps drivers with essential feedback about the onset of drowsiness by continuously monitoring divers' psychophysiological state can help to reduce the drowsy driving related accidents. Physiological signals are found to be most effective for continuous monitoring and better detection of drowsiness. Among all the frequently used physiological signals, Electroencephalogram (EEG), a record of the electrical activities of the brain, showed the strongest relation with drowsiness. Hence, EEG is widely considered as a reliable measure for drowsiness, fatigue, and performance evaluation. In this paper, EEG analysis for drowsiness studies, current findings and future directions of this field are briefly reviewed. Power spectral density (PSD) based features are found to be the most commonly used features for EEG based drowsiness studies. EEG low-frequency bands (delta, theta, and alpha), especially alpha band, shows an increase in band power during the drowsy state compared to alert state. In contrast, high-frequency bands (beta and gamma), specifically beta band shows a decrease in band power during drowsiness. In terms of brain regions, frontal, parietal, and occipital are suggestively informative, especially, alpha from occipital and beta from frontal are two potential indicators. Therefore, identifying informative brain regions with specific frequency bands will help to reduce the number of electrodes required to develop an effective EEG based drowsiness detection and warning system.**

Keywords: Drowsiness, EEG, PSD, alpha, beta, frontal, occipital

I. INTRODUCTION

Drowsiness is a transitional state from alertness to progression towards falling asleep with decreased vigilance level and increased response time [1]. Long monotonous driving combined with circadian rhythm disruption, insufficient sleep, irregular duty periods and work overload are some of the reasons for drowsiness and fatigue on the wheel [2]. The National Highway Traffic Safety Administration (NHTSA) estimated that each year drowsy driving is responsible for about 100,000 crashes, resulting in more than 1,550 deaths, and huge monetary loss [3]. Therefore, there is a necessity for continuous monitoring of drivers' vigilance state and a timely warning can be helpful for accident avoidance. Mainly three approaches (i.e., vehicular, behavioral and physiological signal based) are used for on-board drowsiness monitoring. Among them, physiological signal based measure is appeared to be the most reliable for early drowsiness detection with higher accuracy [4][5]. Physiological signal-based drowsiness monitoring analyzes the changes in body signals during drowsiness compared to alert or baseline state. Physiological signals such as Electrocardiogram (ECG), Electrooculogram (EOG), Photoplethysmogram (PPG), Electromyogram (EMG) and Electroencephalogram (EEG) have been used for drowsiness estimation [1][6][7]. Among them, EEG, a record of the electrical activities of different brain regions is proved as a comparatively reliable indicator for drowsiness and fatigue monitoring [8]-[11]. It uses surface electrodes placed on the scalp to measure the electrical signals of the brain [12][13]. EEG frequency band is subdivided into several frequency bands, which are delta (0.5–4Hz), theta (4–8Hz), alpha (8–13Hz), beta (13–30Hz), and gamma band (>30Hz) [14]. EEG frequency bands within the range of 0.5 to 13Hz are known as low frequency bands whereas greater than 13Hz bands are called high frequency bands.

Sleep stages are categorized as wakefulness, non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. Further, NREM sleep can be subdivided into three stages[15][16], which are:

Stage 1: Transition from alert to sleepy
Stage 2: Light sleep
Stage 3: Deep sleep

For perceiving and exploring driver drowsiness, investigators in this field mainly focus on Stage 1 sleep period [17], at this stage a reduction in brain activity is observed with an abundance of slow EEG waves [18]. By focusing on this transition period and it's relation to EEG signal frequency, it is possible to design a drowsiness detection system [19]. A typical EEG based drowsiness detection and warning scheme is depicted in Fig. 1.

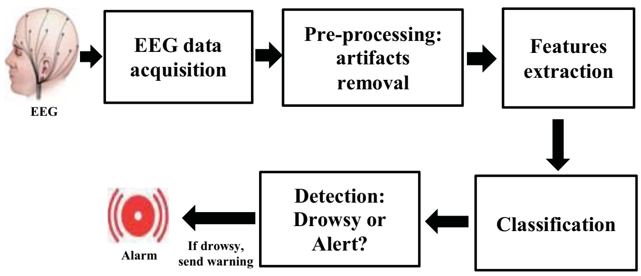

Fig. 1. EEG based drowsiness detection and warning scheme.

However, EEG is highly noise sensitive by nature [20], which makes preprocessing an integral part of signal processing. Then, desired features are extracted in spatial, frequency or temporal domain. Usually, power spectral density (PSD) estimation of EEG frequency bands is performed to observe the changes during drowsy periods compared to baseline. Based on the research goal, classification accuracy, sensitivity, and specificity, a suitable classifier (support vector machine, artificial neural network,

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random forest, or others) is then selected to classify the alert and drowsy periods.

Though EEG is widely used for better drowsiness estimation, the raw data collection involves numerous electrodes placed on the scalp, which is often cumbersome and an obstacle for real-time on board applications. These obstacles can be overcome by identifying the most useful brain regions and frequency bands which will eventually reduce the number of electrodes used for data acquisition. Therefore, extensive research is ongoing in this field, and the goal is to identify the useful brain regions, electrodes, and frequency bands to design an easily wearable universal EEG based drowsiness detection system.

In this review, EEG signal analysis method, current findings (i.e., sensitivity of different brain regions to drowsiness, electrode placement, informative wavebands), and future direction of drowsiness study have been briefly discussed. The rest of this article is structured as follows, in Section II experimental protocol and EEG analysis are briefly presented. Section III focuses on current findings of EEG based drowsiness detection, Section IV describes the limitations and future direction of drowsiness study and Section V is conclusion.

II. Study protocol and signal analysis

A. Experimental protocol and data acquisition

Real-time on-road study is not feasible for research on drowsy driving due to safety concern. Thus, most of the experiments have been conducted in driving simulators under controlled experimental setup [21]. Modern simulators use many projectors and able to provide a 360- degree realistic driving scenario [22]. In this way, a realistic route is displayed on the monitor and the vehicle movement is controlled by using a steering wheel or joystick. It gives the driver an opportunity to immerse himself/herself in a close to real-life driving condition and convenient for the investigators to inspect their algorithms [23]. A snapshot of a driving simulator used for drowsiness and fatigue study is shown in Fig. 2.

Fig. 2. A typical experimental setup for driver drowsiness and fatigue study [24].

Experimental protocols are designed for simulator-based data acquisition to provide a realistic experience in coherence with drowsiness and fatigue. These protocols include strategies like the subject should not to sleep at late night prior to arrival at the study, should avoid anti-fatigue drinks, drowsiness triggering medications, alcohol, smoking, coffee and other beverages for a certain time period before the experiment [25][26]. Moreover, the experiments are usually conducted during a part of the day when subjects are more likely to be drowsy such as dawn, after lunch, early afternoon: 1.00-2.00 PM, 3.00 to 5.00 PM, and late night. Besides, study durations vary from 30 minutes to more than 2 hours to induce drowsiness and fatigue [27][28].

Raw EEG data is acquired during driving using one of the EEG electrode placement methods, such as the international 10-20 system, 10-10 system, 10-5 system [29]. Among them, the 10-20 system or international 10-20 system is the widely used one, where the entire scalp is subdivided into several regions for electrode placement to provide adequate coverage of all the brain regions. Each electrode position is designated by a letter and a number. The letter indicates the region of the brain (i.e., F: frontal, C: central, T: temporal, P: parietal and O: occipital) where the numbering system used to differentiate between the cerebral hemispheres (odd numbering for the left hemisphere and even numbering for the right hemisphere) [12]. The vertex or electrodes placed on the midline are designated as Fz, Cz, and Pz (z for zero) [30]. The 10-20 system of electrode placement is shown in Fig. 3.

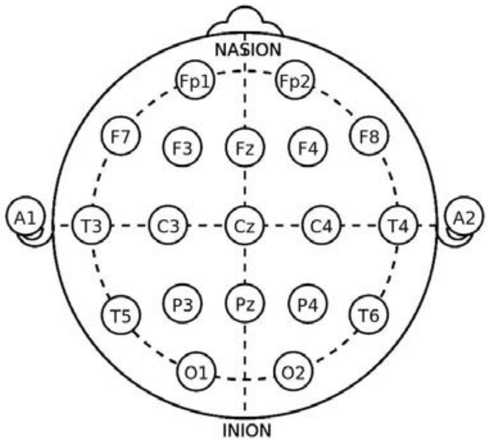

Fig. 3. The international 10-20 system of EEG electrode placement [12].

B. Analysis of EEG

The acquired EEG signal is responsive to various noise and artifacts due to the body and eye movements, heart activities, respiration, and power line interference [31]. Thus, artifacts removal is an essential part of EEG signal processing and EEGLAB toolbox is widely used for signal cleanup [32]. Filtering using a low pass or band pass filter, thresholding and visual inspections are used for signal preprocessing as well. Additionally, independent component analysis (ICA) using linear decomposition method is used for artifacts removal caused by eye blinking and scalp muscle movements [33]. Though ICA is mostly used for offline EEG analysis, it can be used for real-time processing in an online drowsiness monitoring setup [34]. After preprocessing, the most important step is features extraction. Previous studies indicate that there are three types of analysis frequently used for drowsiness studies [35][36], which are 1) PSD analysis, 2) entropy and 3) brain network-based analysis. Among these, PSD estimation is the most widely used technique [37]. Here the basic of PSD analysis is discussed in brief.

Power spectral density (PSD) shows the distribution of the signal power over frequency [38]. It shows the signal power in per unit bandwidth for a specific time series. The PSD estimation methods are mainly classified as parametric and non-parametric methods. The parametric methods are dependent on parametric models of the time series, like autoregressive (AR) models, moving average (MA) models, and autoregressive moving average models (ARMA). So, these are model-based methods.

On the other hand, the non-parametric methods are based on Discrete Fourier Transformation (DFT), which contains periodgram, Welch, Capon, and Bartlett methods. It is not necessary to use the parameters of the time series to implement these nonparametric methods [39]. The Fast Fourier Transform (FFT) algorithm is used to compute DFT, which is advantageous because of robustness, computational efficiency due to the numerical efficacy of FFT and there is no necessity for assumption on the process except its stationarity [40]. The estimated PSDs using this method are free from spurious frequency peaks. However, the primary limitations of this method are the uses of data windowing for computation, which results in the distortion of the estimated PSDs; requirements of stationarity of the studied segments, and a greater length of the data record. In contrast, the parametric methods are not affected by the windowing effect since there is no use of data windowing; it uses a particular model for the selected data [39]. If the selected model and order is correct, parametric method provides high-quality estimation, as well as less data required for its estimation. Further, the physiological signals are nonstationary and nonparametric methods provide limited time-frequency resolution due to the requirement of local stationarity on those signal processing. Improvement of time-frequency resolution is possible by using parametric methods [40]. However, wrong model selection provides incorrect estimation and estimated PSD might show spurious frequency peaks. So, if there is prior knowledge about the whole data generation/recording process, parametric methods can provide a better result, else it is safer to proceed with a nonparametric method.

However, previous studies have shown that the power of the EEG wavebands changes based on subject's alertness, drowsiness, and fatigue level [41], and this relative change in band power can be used for performance analysis and drowsiness detection [42][43]. Hence, PSD estimation has extensive use in this field.

III. Drowsiness detection using EEG: current status

A. *Informative frequency bands*

As mentioned earlier, the frequency domain behavior of EEG is observed in certain frequency bands, they are, delta (δ, 0.5–4Hz), theta (θ, 4–8Hz), alpha (α, 8–13Hz), beta (β, 13–30Hz) and gamma (30–50Hz) [44]-[47]. The waveforms from these frequency bands are depicted in Fig. 4. Usually, PSD analysis is performed on these bands, then absolute and relative power changes are compared between baseline and drowsy or before the drowsy periods. Among these five frequency bands, all of them are not equally useful. Studies have shown that delta, theta, alpha, and beta bands are related

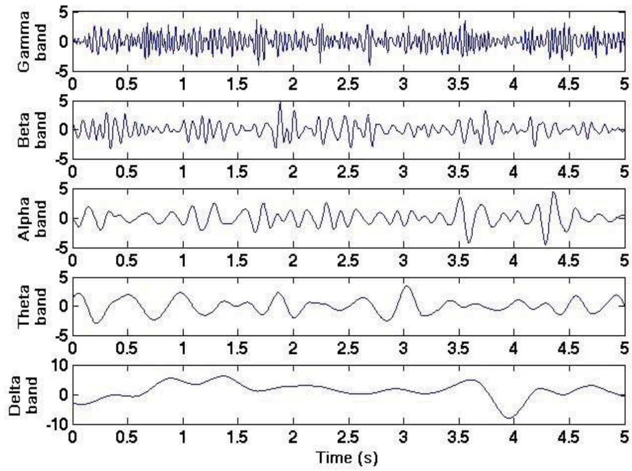

Fig. 4. The frequency bands of EEG [50].

to subjects' vigilance and performance states like fatigue, drowsiness, and sleep [8][48][49]. As a result, one of the goals of current studies in this field is to identify the most informative frequency band, which can help to detect drowsy state faster, precisely, and applicable for real-time applications [44]. Studies have reported an increase in slow frequencies, i.e., delta, theta, and alpha (frequently in the frontal, parietal, and occipital sites) during the onset of drowsiness. This contrasts with fast frequencies, especially beta band, which showed a decrease in activity with the onset of drowsiness. Besides the absolute and relative power of the frequency bands, several ratio indices have been used as well [51][52]. The relation of different brain regions with EEG frequency bands and their response (increase or decrease) to drowsiness are summarized in Table I.

a. *Alpha band*

Though there is no explicitly approved definition of what consists 'alpha activity,' studies showed that it is associated with arousal, attention, perceptual processing, and semantic memory of the cortical system required to perform a critical task [53]. It reflects the cortical activation underlying different brain regions, increased alpha activities assumed as preparedness for information processing or task completion. Investigations in this field found that in most of the cases there is an increase in alpha activities during drowsiness, fatigue or poor attention level [43][54]-[56]. Low alpha band (7.5 Hz to 9.25 Hz) showed an evident change in the power spectrum during drowsy condition; its average magnitude increases noticeably [57]. The high alpha band with a frequency more than 10 Hz also found to change (increase) during poor driving performance [58]. As well as, alpha spindles, which is a short (0.5-2s) bursts of high-frequency alpha activity found to be related to drowsiness and fatigue [59]. Hence, the alpha band has potential to indicate drowsiness and should be carefully studied during drowsiness related system design and implementation.

b. *Delta and Theta band*

Previous studies showed that during drowsy state there was an increase in the relative power of the delta and theta band [34][44][60]. Though delta and theta band experience an increase during drowsiness, the rise is not as significant as the alpha band. Another study mentioned, theta band power increased more compared to the delta band following the alpha band [54]. More findings about delta and theta band response to drowsiness are summarized in Table I. These findings suggest that theta band has more potential for drowsiness indication compared to the delta band and both frequency bands should be studied during drowsiness studies.

c. Beta band

In contrast to the increase in low frequency bands power, during drowsiness the high-frequency bands (especially beta) show just opposite behavior. Most of the studies found that there is a decrease in high-frequency bands' activity during the drowsy state compared to alert state [42] [44]. Beta and gamma both found to show reduced relative power during the drowsy state [44]. In particular, the beta waveband showed just the opposite behavior of the alpha band, i.e., the beta band activity decreased significantly during drowsiness or reduced alertness state [61]. The beta band power shows a higher level during the zero or minimum eye closure i.e., alert condition but reduces as the eye closure increases with drowsiness [62]. Hence, besides alpha, theta, and delta, beta band should be used as an indicator of drowsiness. Moreover, continuous monitoring of the relative change of beta band power compared to the alpha band power can be useful for the systems focusing on drowsiness prediction.

TABLE I. EEG WAVEBANDS FROM DIFFERENT BRAIN REGIONS AND THEIR RESPONSE TO DROWSINESS

	Frontal	Parietal	Temporal	Occipital	Central
Alpha (α)	↑[8] ↑[9]	↑[8] ↑[44] ↑[48] ↑[65] ↑[66] ↑[67] ↑[68]	↑[61] ↑[68]	↑[9] ↑[20] ↑[42] ↑[48] ↑[58] ↑[59] ↑[61] ↑[66] ↑[67] ↑[69] ↑[70]	↑[58]
Theta (θ)	↑[8] ↑[9] ↑[42] ↑[48] ↑[65]	↑[8] ↑[9] ↑[48] ↑[68]	↑[42] ↑[61] ↑[68]	↑[42] ↑[48] ↑[61] ↑[70]	↑[48]
Delta (δ)	↑[8] ↑[9] ↑[48]	↑[48]		↑[48]	↑[8] ↑[9] ↑[42] ↑[48]
Beta (β)	↓[42] ↓[44] ↓[61]	↑[9]	↓[42] ↓[61]	↑[9] ↓[61]	

'↑' indicates increase and '↓' indicates decrease

d. Ratio indices

In addition to depending on the separate waveband measures, ratio indices are also introduced to get a better idea about the relative changes of the band power. Frequently used ratio indices using four wavebands are $(\alpha+\theta)/\beta$, α/β, $(\alpha+\theta)/(\alpha+\beta)$ and θ/β. Among these indices, $(\alpha+\theta)/\beta$ is proved to be highly useful and consistent with previously mentioned findings, i.e., shows an increase in low frequency band power and decrease in high frequency band power during drowsiness [61][63]. Besides these indices, sometimes two other ratio indices are used including spectral power of the gamma (γ) band, which are γ/δ and $(\gamma+\beta)/(\delta+\alpha)$; the second one is proved to be more sensitive to drowsiness [64].

B. Useful brain regions for drowsiness study

Information about the behavior of frequency bands during drowsiness is not enough to design an easily wearable system; it is essential to identify which regions of the brain should be targeted to get useful information with fewer electrodes placement. Though it is not clear which brain region is the most effective one for drowsiness detection, previous studies suggest frontal, central, parietal, and occipital regions are useful for drowsiness and fatigue related studies [71]. The occipital lobe is the visual processing center of the mammalian brain containing most of the anatomical region of the visual cortex. Hence, the occipital region is deeply related to vision-related changes and drowsiness. Alpha rhythms originated from posterior brain regions (i.e., parietal and occipital) are seen to experience an escalation during responsiveness lapses [66] and drowsiness [67][69]. Previous studies found that the power spectrum change of the occipital region was related to drowsy state [20], and alpha activity with close relation to microsleeps was found in occipital and central regions [58], though another research group claimed the parietal region as the most useful compared to other brain sites [48]. Lal and Craig [9] found increased delta and theta magnitude for entire head regions during the transition to fatigue state. Whereas, Poudel et al. [72] found microsleeps were related to the reduced neural activity of arousal-related brain sites like the thalamus, midbrain, and posterior cingulate cortex, but had a relation to increased activates of frontoparietal, and temporo-occipital cortices. They also experienced that poor performance with struggling to stay awake was related to increased activities of the frontoparietal cortical region. During the transition to drowsiness lower delta and theta activity in the cingulate cortices, medial portions of the frontal, parietal and occipital cortices were experienced by another group [73]. Another group found that during drowsy state both delta and theta band power were high in most of the brain regions, whereas for the alpha band it was high in parietal and for the beta band, it was low in the frontal lobe [44]. More findings related to brain regions are outlined in Table I.

Based on the findings, it is hard to conclude which brain region is the most informative for drowsiness detection. However, it is also apparent that some of the brain regions (like occipital, parietal, and frontal) have a significant relationship to drowsiness, and must be targeted during drowsiness study and system design.

C. Informative electrodes identification

EEG data acquisition requires numerous electrodes compared to other physiological signal acquisition techniques (i.e., ECG (3), PPG (1), EOG (2) or EMG (2)), hence, identifying comparatively more informative electrodes will reduce the total number of electrodes, increase comfort and likelihood of adoption for on-board monitoring. It is logical to assume that the useful electrodes should belong to those informative brain regions as discussed earlier. For example, a study on fatigue influenced by 3DTV watching found Fp1 electrode as the most informative electrode [63], though the study was not conducted on drivers, the assumption is that the outcome might be similar to on-road fatigue study. In congruence with the previously mentioned outcome, another group found Fp1 and O1 as the two most significant electrodes for driver fatigue evaluation [53], whereas another group mentioned a single EEG channel (Pz-Oz) as the most useful electrode [64]. Midline EEG channels (Cz, Pz, and Fz) are also useful for drowsiness studies [74]. Schier used four electrodes F3, F4 (Frontal) and P3, P4 (Parietal), and among them, F4 electrode seemed to be the most useful one [55]. Nguyen et al. also found frontal electrodes as more informative with beta as the targeted waveband [44]. Pz and P4 electrodes were found to be more beneficial in another drowsiness and poor driving performance study [58]. As it is mentioned earlier, the useful electrodes' positions should be directly related to informative brain regions; the findings from previous investigations also support it. Although it is hard to suggest a specific number of electrodes, the electrodes from the frontal, parietal, and occipital regions are highly informative for drowsiness related studies.

D. Classifiers used for drowsiness detection

To check significant differences between baseline and drowsy periods, many groups applied the popular statistical analysis methods, like t-test [44], paired t-test, and analysis of variance (ANOVA) [26]. For classification purpose, machine learning algorithms have been used by many groups. As a classifier, Support Vector Machine (SVM) is widely used, which is beneficial for its capability to reduce the structural as well as empirical risk [75], and proved as a better classifier for drowsy epochs detection [47]. Most of the cases claimed accuracy for SVM was around 85%-90%. Another classifier, Extreme Learning Machine (ELM) has appeared as a faster learning algorithm with an accuracy comparable to SVM. ELM algorithm with radial basis function showed better accuracy than SVM using features such as wavelet sample entropy, recurrence quantification analysis and their fusion [76]. However, in a rigorous assessment, Delgado et al. assessed 179 classifiers from 17 families and found Random Forest (RF) version classifiers were most likely to be the best of them, followed by the SVM with a Gaussian kernel [77].

Bayesian-Copula Discriminant Classifier (BCDC), which is an extension of traditional Bayesian decision theory was applied by a group and found to provide better classification accuracy than traditionally used classification algorithms, including Gaussian discriminant classifier, logistic regression, as well as linear and Gaussian kernel SVM [1].

Finally, for precise detection and automated system design, it is of utmost importance to select a classifier which can separate drowsy and alert periods with better accuracy, sensitivity, and specificity. The selection of a classifier also depends on the collected data characteristics and whether the desired system will deal with a drowsiness detection or prediction problem.

IV. Limitations and Future Prospects

Driving is an intricate task that requires motor driving skill, high attention level, rapid decision-making capability, planning, visual perception and object detection ability [78]. EEG has been used for a long time to quantify drowsiness during driving and at the workplace. EEG can track the mental states, progression of fatigue and drowsy state over time [65]. This review paper only focused on the PSD analysis which is the most widely used technique for EEG signal analysis used for drowsiness detection. However, there are other analysis techniques, which also appear useful. Like Hilbert-Huang transform (HHT) has been used for being more advantageous for nonlinear and non-stationary signal processing [79]. Grey Relational Analysis (GRA) was used by some researchers to identify the optimal indicator of driver fatigue [53]. Therefore, in addition to the basic PSD analysis, other methods can be incorporated for better analysis outcome.

Based on the reviewed papers, it can be mentioned that there is a tendency to reduce the number of EEG electrodes which is helpful to reduce the cumbersome of the system [79][80]. Previous studies showed that the use of two EEG electrodes could provide satisfactory drowsiness estimation as well as statistically reliable compared to use only one EEG electrode [81][82]. It is advisable to be cautious during an extreme reduction of EEG electrodes since it can only reflect the brain activities of a limited area [26] and can be misleading.

EEG is used with other techniques of physiological measurements as well, like Near-Infrared Spectroscopy (NIRS), EOG, and ECG [44] which are helpful to increase the overall detection accuracy. Further, combination of different techniques and classifiers showed improved detection accuracy and reliability [83]. Easily assessable signals such as ECG and PPG are being studied to check their ability for early drowsiness detection either solely or combining with EEG [5] [68][80]. Hence, in future, there might be increased application of ECG and PPG for on-board drowsiness detection.

Notably, most of the research outcomes in this field are based on driving simulator-based study, hence, the participants were aware that any driving errors would not lead to any severe or life threating consequences. Previous studies also mentioned that subjects were more likely to feel drowsy during a simulated study [84]; therefore, outcomes based on simulated driving may not be generalized to real life driving [34][85]. Most of the studies focused on drowsiness detection instead of drowsiness prediction. Since a short period of inattention during driving can lead to a fatal accident, predicting drowsiness ahead of time will be a significant improvement compared to detecting it when the person is already drowsy. Besides, the amplitude of EEG wave fluctuates within the microvolt level, which makes EEG an extremely noise sensitive signal [20], and the variability of the brainwaves among individuals made it difficult to use for broad and generalized applications [86].

However, in the near future, nonobtrusive sensors like wireless dry electrodes will play an important role in this research arena to measure brain activities with less contact and more comfort. Hence, it is expected that soon there will be some on board setup for drowsiness and mental fatigue detection that will help to mitigate drowsiness related road accidents [87].

V. Conclusion

Current findings and future prospects of EEG based drowsiness detection have been briefly discussed here. PSD estimation is found to be the mostly used analysis for EEG waveband power based features extraction. It provides useful information about the changes in relative power of different EEG frequency bands during drowsy periods compared to alert periods. Brain regions like frontal, occipital, and parietal lobe are appeared to be more sensitive to drowsiness than other regions. Consequently, Fp1 and O1 electrodes appeared as more informative electrodes and should be included during drowsiness related studies. In the case of useful frequency bands, most of the studies found that alpha, theta, and beta band showed a clear indication for drowsiness and fatigue. The alpha band shows an increase in band power during drowsiness, fatigue, and inadequate attention. Whereas, the beta band shows antagonistic characteristic, a declination in its activity and relative band power. Hence, comparative and continuous behavioral checking of alpha and beta band power can be helpful for better drowsiness detection system design. This review also identifies that in recent studies there is a tendency to reduce the number of EEG electrodes by recognizing the most informative brain regions. Moreover, other easily obtainable physiological signals (like ECG and PPG) are getting attention to assist or substitute EEG for drowsiness study. However, other psychophysiological factors like anxiety, personality, temperament and their relations with drowsiness and fatigue need to be thoroughly studied.

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