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A Review on EEG-Based Automatic Sleepiness Detection Systems for Driver

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ABSTRACT Electroencephalography-based sleepiness detection system (ESDS) is a brain-computer interface that evaluates a driver's sleepiness level directly from cerebral activity. The goals of ESDS research are to estimate and produce a timely warning to prevent declines in performance efficiency and to inhibit sleepiness-related accidents. We first, review different types of measures used in sleepiness detection systems (SDSs) and presents their advantages and drawbacks. Second, the review includes several techniques proposed in ESDSs to optimize the number of EEG electrodes, increasing the sleepiness level resolution and incorporation of circadian information. Finally, the review discusses future direction that can be considered in the development of ESDS.

INDEX TERMS Sleepiness, fatigue, countermeasure, accident prevention, alertness monitoring, classification, electroencephalography, multimodal approach, brain-computer interface, multi-modal approach, homeostasis, circadian.

I. INTRODUCTION

Work in shifts is prevalent in many round-the-clock industries (e.g., maritime, military, manufacturing and land transportation) to maintain 24-hour operation. The demand for continuous operation sometimes requires workers to sustain wakefulness throughout the night. Extended wakefulness throughout the night may lead to misalignment between internal biological functions and social needs [1]–[5], which subsequently leads to sleepiness during and after work periods [6]–[8]. The detrimental impact of sleepy/ drowsy driving is significant issue and is strongly associated with many near-misses and driving accidents [9]–[15]. For instance, the US National Highway Traffic Safety Administration analyzed police report and estimated that many vehicle crash are directly related to the driver sleepiness [16]. This is because sleepiness may lead to a slower reaction time that indirectly limits human's ability to respond effectively to spontaneous emergent events [17]–[20]. In addition, humans often provide imprecise estimations when asked to subjectively quantify fluctuations in their alertness level [21].

Development of a continuous real-time sleepiness detection system (**SDS**) to monitor and prevent further drowsiness, which is incompatible with safety-sensitive operations, is thus highly desirable. There are many SDS available to monitor sleepiness levels (See section II for details), and electroencephalography-based sleepiness detection system (**ESDS**) provide the most predictive and reliable estimations [16], [22]–[24]. Although a significant amount of research has been conducted in the development of ESDS, several constraints limit their application in the field. The application in naturalistic driving environment requires that an ESDS be robust, easy to wear and not computationally expensive. One reason for this is that most existing ESDS are based on multiple EEG electrode settings. Effective management of this issue requires minimization of the number of EEG electrodes [25], signifying the need to find the best set of electrode localization, feature and classifier that are most discriminative in classifying different level of sleepiness. Prior research has shown that leveraging the number of EEG electrodes with proper selection of the features and classifier is feasible for monitoring progressive changes in sleepiness [26]–[28].

According to the American Academy of Sleep Medicine [29], sleep can be scored according to different stages: stage W (wakefulness), stage NonREM (stages N1, N2 and N3), and stage R (rapid eye movement). Stage W is the unequivocal stage of high arousal and stage N1 is the ambiguous stage between wakefulness and sleep (i.e., drowsy sleep). Stages N2, N3 and R are unambiguous stages of sleep. Compared with binary cases (i.e., Stage W or stage N1), multilevel (i.e., including intermediate levels between Stage W and N1) ESDSs enable an individual to track their arousal level in incremental steps and allow for ample lead time for appropriate mitigation procedures [30]. For field practicality, a multilevel drowsiness detection system is important for monitoring the dynamic changes in brain activity. In addition, the circadian rhythm is an important consideration for a sleepiness detection system [31]–[33]. However, the circadian system, which is a well-known endogenous influence that affects human cognitive performance differently within a 24-hour cycle [34]–[38], is often neglected in ESDSs. Recent studies have shown that incorporating the circadian rhythm may improve the accuracy of an ESDS [31]–[33].

Sleepiness can be defined as the increasing sleep propensity due to decreased physiological arousal [39]–[41]. According to Borbély's two-process model [42], sleep propensity is influenced by the interaction of circadian and homeostatic processes. The first, the circadian process (P_Circ), generates approximately 24-hour rhythmic fluctuations in sleep propensity. Drivers are usually more alert during the solar day and are more likely to become sleepier throughout the solar night [31], [32]. The second process is the sleep homeostasis process (P_Hom), which represents the progressive build-up of sleep pressure during wakefulness and the progressive decline as recovery occurs during sleep. The interaction of P_Circ and C_Hom oscillation is as depicted in Figure 1.

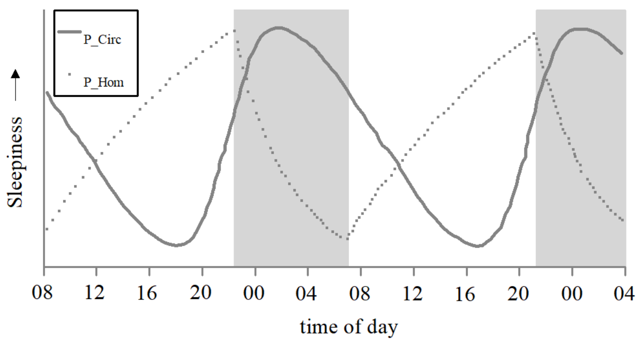

FIGURE 1. The Interaction between circadian and homeostatic process. The grey rectangular box indicated sleep period. The figure adapted from [43] (See text for detail).

Often in the literature, the word fatigue has been used interchangeably or is substituted with the terms sleepiness and sleep propensity [1], [44]. One reason why the term fatigue and sleepiness has been used somewhat loosely might be due to the overlapping features and semiotic between them [45]. In addition, the developers of SDS often used the word fatigue to describe their model in compliance to regulatory requirement [44]. There are numerous work addressing the differences between fatigue and sleepiness both in term of clinical aspect and their exact definition [45]–[47]. Fatigue in general can be defined as a condition in which it is difficult to maintain the motor or mental energy levels with time spend during the mental activity [45]. Rest break is presumably the way to recover from fatigue [45]. With respect to the two reasons mentioned above, the terms fatigue, sleepiness and drowsiness are used interchangeably in this review.

In this article, we present an overview of techniques used in sleepiness detection systems, particularly within the land transportation domain. We review the techniques and classification results obtained for ESDSs with a small number of EEG electrodes and multilevel sleepiness detection. Studies that include a circadian factor to improve the performance of the ESDS are also discussed. Finally, future direction in ESDS research are presented.

II. SLEEPINESS DETECTION SYSTEMS

The evaluation of a driver's sleepiness level can be divided into six main techniques: 1) subjective measures; 2) vehicle-based systems; 3) Driver's behavior-based systems; 4) mathematical models of sleep-wake (**MMSW**) dynamics; 5) human physiological signal-based systems; 6) hybrids of one or more of these techniques. A sleepiness test that fulfills criteria that include: a) easy to use; b) objective; c) reliable; d) robust to the subject's motivation; e) non-intrusive; f) minimally restricts the subject's movement; g) able to continuously monitor the sleepiness state has greater potential for routine use in field environments [48], as summarized in Table 1.

The first technique for tracking sleepiness levels is having the driver subjectively rate their sleepiness at that time [49]–[51]. The most commonly used sleepiness scale used is the Karolinska sleepiness scale (KSS) [52]. Although this technique provides a very straightforward procedure for assessing a drivers' sleepiness level, it is difficult to assess sudden variations in sleepiness level and the ratings may be confounded by misjudgment by the individual [21]. Furthermore, a driver's attention can be distracted if sleepiness feedback is assessed frequently.

The second technique evaluates a driver's sleepiness state according to changes of vehicle-based estimators including steering wheel movement, standard deviation of the lane position, vehicle speed, gear changes, braking and pressure on the steering wheel [53], [54]. Although this technique allows for non-contact detection and eliminates any discomfort to the driver [55], it is difficult to develop a common model due to differences such as vehicle type, driving conditions, driver experience, and the geometric and environmental situations of the road [25], [56]. In addition, changes in driving behavior are not exclusively due to drowsiness but are also influenced by the driver's motivation, experience or personality [57].

The third technique utilizes image acquisition technology to track behavioral changes including eye blink, Percentage of Eye Close (**PERCLOS**), facial position, yawning and gaze direction [58]–[64]. Despite the improvements achieved in recent years, image or video acquisition is sensitive to the illumination of the surrounding area [65]. The accuracy of the

TABLE 1. Summary of the effects that visual and cognitive distraction has on driving performance.

Ref.	Measure	Parameter(s)	Practicality criteria							Comments	
			a	b	c	d	e	f	g	Main advantage(s)	Main limitation(s)
[49-51]	Subjective measures	Sleepiness scale (e.g., Karolinska Sleepiness Scale)	Y	N	N	Y	Y	Y	N	This technique allows the driver to assess their sleepiness level according to their subjective feelings	Not suitable for continuous sleepiness evaluation; self-assessment of sleepiness is often wrong
[53, 54]	Vehicle-based measures	Steering wheel movement, standard deviation of lane position, vehicle speed, gear changes, braking and pressure on the driving paddle	Y	Y	N	N	Y	Y	Y	Non-intrusive	A technique used for a car cannot be applied to airplanes, trains or ships; different drivers might have unique driving styles; driving might vary in different environmental situations
[58-65]	Behavioral measures	Eye-blink, percentage of eye close, facial position, yawning and gaze direction	Y	Y	N	N	Y	N	Y	Non-intrusive; easy to use	This technique is unreliable due to the influence from varying light conditions; inaccurate prediction is possible, especially when SW is sleeping with an open eye
[68, 69]	Bio-mathematical measures	Time awake, sleep duration	Y	Y	Y	Y	Y	Y	Y	Non-intrusive	Reliable only if the input provided is accurate
[71, 73, 74, 77, 80-83, 85]	Physiological measures	Statistical & energy features derived from the electrophysiological signal	N	Y	Y	Y	N	Y	Y	Among the physiological measures, EEG is the most reliable, accurate, and highly reproducible	Obtrusive; prone to unavoidable motion artifacts and noise introduced due to electromagnetic field interferences or poor electrode attachment, which result in unreliable classification results

eyelid closure measurement can be affected by glare reflection from the subject's glasses or by the subject's face being intermittently outside of the detection angle of the recorder during image acquisition [28], [66].

The fourth technique is application of bio-mathematical models (BMMs) of alertness to predict drowsy driving [67], [68]. Most cognitive performance and human alertness models were built using the two-process model (**TPM**) concept [42]. Schedulers and planning staff have utilized BMM to quantitatively forecast and evaluate the likely sleepiness level and cognitive performance of those on a given duty schedule [21], [44], [69]. However, no BMM can forecast any transient changes in sleepiness [21], [22].

The fifth technique emerged from the fact that decrements in an individual's driving performance and alertness state accompany the changes in physiological features [70], [71]. Numerous physiological indicators are used to bridge the physiological-sleepiness relationship such as electrocardiogram (**ECG**) [72]–[75], electrooculography (**EOG**) [76]–[78], functional Near Infrared Spectroscopy (**fNIR**) [79] and electroencephalography (**EEG**) [7], [70], [73], [79]–[86]. Among these modalities, EEG is the most predictive and reliable for continuous evaluation of sleepiness or alertness [16], [23], [24].

EEG is a common technique used in sleep research to record the electrical potential generated from the activity of cortical neurons situated just beneath the scalp. EEG signals can reflect brain activity changes with variation in alertness and arousal states during the transitional phase between stage W and stage N1 [87]. There are different ways to place the EEG electrodes on the scalp such as the 10-20 system, 10-10 system, 10-5 system and et cetera [88]. These relative head-surface-based positioning systems has been designed to allow the use of any number of electrodes with predictable

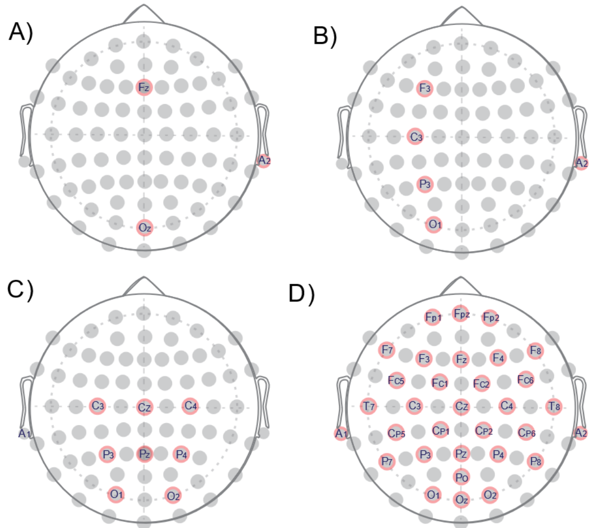

FIGURE 2. **Electrode placement according to the international 10–20 system. F: frontal lobe, T: temporal lobe, C: central lobe, P: parietal lobe, and O: occipital lobe. Z refers to an electrode placed on the midline.**

and easily repeatable position [89]. A commonly used system in driving studies is the 10-20 system. For example, in the study [80], the EEG signal were recorded only from the channel Oz of the international 10-20 system with the reference electrode placement on the Fz and ground electrode was placed on the right ear lobe as depicted in Figure 1a. In addition, other studies has used more electrodes using the 10-20 systems, not limited to, such as the 4 channels [90], 8-channels [25] or 32-channel [20] as shown in Figure 1b and Figure 1c and Figure 1d , respectively.

The EEG signal is divided into several sub-bands: delta (0.1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-36 Hz) and gamma (36-44 Hz). The frequency range is often grouped into each of these sub-bands to compensate for the individual differences and has been shown to correlate well with changes in driving performance during alert or drowsy driving [70], [71], [90], [91]. However, use of EEG as standalone modality do not provide good classification results due to unavoidable motion artifacts [78], noise due to electromagnetic field interference [92], or poor electrode attachment and et cetera.

Lastly, hybrids of these techniques have been designed to complement the limitations of each approach [93]. A hybrid between EEG with one or more sleepiness detection techniques was designed to improve the discrimination power of EEG [56], [76], [79], [81].

III. EEG-BASED SLEEPINESS DETECTION SYSTEM

The sleepiness and performance fluctuations due to the underlying interaction of P_Circ and P_Hom are reflected by frequency-specific circadian and wake duration-dependent changes from the waking EEG [94]–[97]. The dominance of each EEG sub-band at specific times can be used to interpret the brain behavior. The intrusion of low-frequency EEG oscillations such as delta usually indicates the sleep stage and increases in the theta indicate the onset of sleep [98]–[100]. Alpha activities may reflect the increase in mental effort to maintain vigilance and the beta wave is related to high alertness and arousal [101].

The buildup in sleep propensity and drowsiness is commonly characterized by increases in the theta and alpha activities with a parallel decrease of brain activity in the beta band as the alertness level decreases [16], [99]. Nevertheless, many studies were reported to show a significant increase in delta activities [17], [24], [95], [102]–[105]. However, the increased in delta, theta and lower-alpha as demonstrated during an extended wakefulness study was not monotonic and exhibited a predominantly circadian effect [48], [95], [102], [104].

In addition to the above EEG characteristic, other researchers combine the EEG sub-bands to form an equation that served as a more reliable and robust technique to detect and quantify alertness levels [71]. However, depending on the observed dynamic changes in spectral power, different types of ratios have been claimed to be the most sensitive indices to alertness levels such as (1) [theta + alpha]/beta [71], [81], [106], [107]; (2) [theta + alpha]/ [alpha + beta] [81], [107]; (3) and [gamma + beta]/[sigma + alpha] [108]. Observation of the EEG drowsiness-signature paved the way for development of an ESDS that automatically estimates driving performance from brain activity [16], [109].

A. LIMITED NUMBER OF EEG ELECTRODES

To be practical for routine use, an ESDS should apply as few EEG electrodes as possible to reduce the setup time and computational load [87], [110]. Several ESDSs using a single channel or minimal multiple channels have been reported in the literature. These studies were motivated to seek an optimal combination of electrode localization, features and classifiers to improve the performance of the algorithm, as tabulated in Table 2.

In one study [26], Shabani *et al.* extracted a determinism feature using recurrence quantification analysis from only the F8 electrode and used a combination of support vector machine (**SVM**) and Bayes classifiers. SVM is a supervised machine learning algorithm used for classification and regression. The working principle behind SVM is finding the optimal hyperplane that maximize the separation between two classes. More detail about SVM can be referred in [111]. The proposed techniques could differentiate alert to drowsy states with 90.6% accuracy.

In addition, several studies applied features from the occipital region to detect sleepiness while performing a task. For example, some authors [27] proposed support vector regression (**SVR**) to classify an 8-class problem of alert (degrees of vigilance 1, 2, 3, and 4), mildly drowsy (degrees of vigilance 5, 6, and 7) and severe behavioral lapse (degree of vigilance 8). SVR is one of the form of SVM. The main idea of SVR is to compute the linear regression function in the higher dimensional space by mapped the input data through

TABLE 2. Accuracy of classifiers in the ESDS based on single- or minimal-multichannel electrodes. The protocols are arranged by the number of subjects, protocol and total duration of the experiment. The tasks are (t1) a driving simulation, The information in parenthesis after each task is the total time (minute: m or hour = h) required to complete the task. The proposed scalp areas are: (F) frontal, (O) occipital, (OM) occipital midline, (P) parietal. The class problems are (A) alert, (D) drowsy, (S) sleep. NR: not reported, CP: class problem. The SVM multiclass classification can be divided into one-against-all (OA) or one-against-one (OO) method. In some case, the author did not explicitly explain the details of a particular information and this is symbolized as (∗). In study [80] the author did not explicitly explained which EEG sub-band was used to calculate the PSD spectra, while in studies [81], [113], the authors did not explicitly mentioned either they utilized type OA or OO when used SVM for classification.

No.	Subjects	Protocol	Electrode(s)	Feature(s)	Classification	Accuracy [CP]	Ref.
1.	12	t1 (50 m)	F8	EEG (delta & theta)	SVM + Bayes	90.60% [2 CP]	[26]
2.	15	t1 (90 m)	O1 & O2	EEG (theta, alpha and beta)	SVR-RBF	93.10 ± 5.2% [8 CP]	[27]
3.	20	t1 (60 m)	O1 or O2	EEG (theta, alpha and beta)	SVM+posterior probabilistic model	A (91.25%,), Early-warning (83.78%) & D (91.92%)	[28]
4.	10	t1 (120 m)	O1 or O2	EEG (theta, alpha and beta)	K-singular value decomposition	O1 feature (87.05%) & O2 feature (93.87%) [2 CP]	[25]
5.	10	t1 (120 m)	O1 or O2	EEG (theta, alpha and beta)	SVM	O1 feature (92.39% & O2 feature (93.72%) [2 CP]	[55]
6.	15	t1 (NR)	Oz	EEG (Mahalanobis distance feature)	BL	positive predictive value and sensitivity of 76.9% and 88.70%, respectively [2 CP]	[99]
7.	5	t1 (NR)	Oz	PSD spectra*	SVM	98.20 % [2 CP]	[81]
8.	20	t1 (90 m)	O1, O2, and Oz	EEG (Delta, theta, alpha and beta)	RSEFNN	RMSE (0.0997) [CP NR]	[117]
9.	60	t1 (120-180 m)	P3, PZ and P4	EEG (ApEn & SampEn)	SVM	P3 (0.91 %), Pz (0.90 %), P4 (9.89 %) [2 CP]	[116]
10.	20	t1 (2days x 480 m)	Fpz-Cz and Pz-Oz	EEG (Delta, theta, alpha and beta) and respiratory signals	SVM*	Average accuracy rate of 98.00% [5 CP]	[82]
11.	13	t1 (150 m)	Fp1, Fp2, C3, C4, O1, O2	Higher dimension EEG feature extracted based on MVAR	SVM (OA &OO)	SVM (OA) best three-state classification accuracy of 81.64 % [3 CP]	[118]
12.	20	t1 (120 m)	O1 & O2	EEG & EOG wavelet entropy, EEG sample entropy, and EMG approximate entropy	ANN	Average accuracy rate of 99.50-96.50% [4 CP]	[119]
13.	10	t1 (120 m)	19 Channels, NR in detailed	EEG (Delta, theta, alpha and beta)	BL	Percentage error for alert (1.0%), transitional (9.20%), transitional to post-transitional (11.5%) and post-transitional (2.70%), respectively [4 CP]	[92]
14.	31	t1 (120~180 m)	Fz, T8 & Oz	EEG, EOG and ECG signals	LDA	Best classification rate 97.00% [5 CP]	[120]
15.	31	t1 (120~180 m)	Fz, T8 & Oz	EEG, EOG and ECG	SVM (NR)	Best classification rate 92.00% [5 CP]	[56]

the nonlinear function. More detail can be found in [112]. The power spectral density (**PSD**) of the theta, alpha and beta activity were extracted from the occipital (O1 & O2) data and radial basis function kernel SVR was used for classification, with a root mean square error (**RMSE**) of 0.124 ± 0.011. Fast Fourier Transform is a technique used to convert the time domain signal into frequency domain. One author [28] used fast Fourier transform (**FFT**) extraction of the theta, alpha and beta power from O1 and O2 and classified the data using an SVM-based posterior probabilistic model (**SVMPPM**).

The results confirmed accuracies of 91.25%, 83.78% and 91.92% for the alert, early-warning and drowsy groups, respectively. In another study, [25] the alert-drowsy states were classified based on PSD features derived from a FFT using either the O1 or O2 channel and sparse representation classification with k-singular value decomposition (**KSVD**) for classification. KSVD is an iterative approach which switch between the sparse coding of the given signal relying on the current dictionary and keep updating the atoms of the dictionary to get optimum fitting of the data. More detail of KSVD can be found in [118]. The algorithm resulted in classification accuracies of 87.05% and 93.87% using features from O1 and O2, respectively. Recently, researchers [55] applied FFT to extract the power spectrum density features from 01 and O2. For comparison, the SVM classifiers were applied with sensitivities of 92.39% and 93.72% for the PSD features derived from O1 and O2, respectively.

Some studies localized the midline occipital but others such as Chin *et al.* [98] extracted the Mahalanobis distance (**MD**) features from a single Oz EEG channel. The alert-drowsy classification was conducted using a Boolean logic (BL) algorithm in which the summation of the MD features was compared with a pre-determined threshold. The proposed method showed a positive predictive value and sensitivity of 76.90% and 88.70%, respectively. Similarly, drowsy and alert were classified in a study [80] in which the author compared a SVM classifier with a linear discriminant analysis (**LDA**) and MAX classifier. The SVM feed with a PSD feature from the Oz electrode resulted in the most accurate classification of 98.20%. Another [114] Liu *et al.* proposed a new recurrent self-evolving fuzzy neural network (**RSEFNN**) that effectively integrates and considers the past and current (target) EEG states. FFT was applied to extract the PSD from the occipital region (O1, O2, and Oz). The RSFNN as indexed by the RMSE outperformed the SVR, self-organizing neural fuzzy inference network (**SONFIN**), a fuzzy wavelet neural network (**FWNN**), a Takagi–Sugeno–Kang (**TSK**)-type, recurrent fuzzy network (**RFN**).

In addition to the occipital region, features originating from the parietal region were used to discriminate the sleepiness level, as in a study [113] in which the discriminability of parietal (P3, PZ and P4) data was determined using a combination of approximate entropy (**ApEn**) and sample entropy (**SampEn**) and SVM for classification. Approximate entropy and Sample entropy are techniques used to measure the system complexity of the time series related to entropy. More detail can be found in [119]. The averaged accuracies for the two-class problem (i.e., alert & drowsy) in descending order were 0.9128 %, 0.9064 %, and 0.8983 %, for P3, Pz and P4, respectively.

Extreme learning machines (**ELM**) is one step ahead of a conventional artificial learning approach. It is based on the biological learning. In contrast to the neural network, the hidden neurons parameters do not need to be tuned but it is randomly assigned where the learning process is completed in single step. More detail about ELM can be found in this recent article [120]. In some studies, the EOG and EEG data were combined, as in the study by Chen *et al.* [66] in which the author proposed an **ELM** classification based on ApEn, Renyei entropy, SampEn and recurrence quantification analysis (**RQA**) features extracted from the Fz and Oz data of EEG and EOG signals. For comparison, three different classifiers (ELM-SIG, ELM_RBF & SVM) classified the two-class (drowsy and alert) problem from two different sets of features. The first feature set (SF1) was a combination of nonlinear features from the EEG data and the second feature set (SF2) was a combination of nonlinear features from EEG & EOG data. ELM_sig in both combinations (SF1 or SF2) outperformed ELM_RBF and SVM and the combination of ELM_sig and SF2 performed better than ELM_sig and SF1 with an accuracy of 97.30 % versus 95.60 %.

B. MULTICLASS SLEEPINESS CLASSIFICATION

It is advantageous for an ESDS to show progressive changes in arousal level. Compared to the binary case, a multilevel drowsiness system enables an individual to track their arousal level in incremental steps and allows for ample lead time for appropriate mitigation procedures [30]. Several techniques have been proposed to monitor progressive arousal changes at three or more levels. Table 2 summarizes all the studies related to this.

EEG time series analysis can be divided into linear and nonlinear techniques. In linear modeling technique, the simple and commonly used method is auto regressive model (AR). Multivariate autoregressive (MVAR) approach provide the directional and causal flow of information based on Granger's framework [121]. Principle Component Analysis (PCA) and Kernel-PCA (KPCA) are common methods used for data reduction. Both techniques used the singular value decomposition which is applied on data to project it to the lower dimensional space and further detail can be found in [122]. For example, EEG features were extracted based on MVAR. The performance of two dimensionality reductions (PCA & KPCA) and SVM classification implementations (SVM One-Against-One & SVM One-Against-All) were compared in classifying the 3-alertness-state problem (alert, medium drowsy and extreme drowsiness) [115]. Compared with other combinations, the KPCA-SVM One-Against-All method resulted in the best three-state classification accuracy of 81.64 %. Artificial neural networks (ANNs) are based on the structure and functions of biological neural networks. Further detail can be found in [123]. The study [116] utilized an ANN to classify a 4-class problem (normal state, mild fatigue, mood swing, excessive fatigue) based on extracted features including the EEG & EOG wavelet entropy, EEG sample entropy, and EMG approximate entropy. The result showed accuracy of 99.50-96.50%. In another study [91], Larue and Pettitt used statistical EEG features and an algorithmic BL with pre-selected thresholds for classification. The results showed that the percentage error of the algorithm for detecting alert, transitional, transitional to post-transitional and post-transitional states was 1.00%, 9.20%, 11.50% and 2.70%, respectively.

In other study [81], several features obtained from a statistical, interval and frequency analysis of EEG (Fpz-Cz and Pz-Oz) and respiratory signals were extracted and the top features were selected using mutual information (**MI**). Mutual information (MI) can be used for feature selection [124]. The top feature extracted through MI having highest value of MI between the given input features X extracted from the EEG or respiration signals and output class Y of sleepiness level were selected as the most descriptive feature. The significant features are passed to the SVM classifier and yielded an average accuracy rate of 98.00% for the classification of 4 alertness level classes (awake, slightly drowsy, moderately drowsy, and extremely drowsy) [81].

In two studies [56], [117], Khushaba *et al.* proposed two novel features selection techniques to select five-level drowsiness-related features (alert, slightly drowsy, moderately drowsy, significantly drowsy, and extremely drowsy) from EEG, EOG and ECG signals. In one study [117], Khushaba *et al.*proposed a fuzzy MI to evaluate the dependency between the wavelet packet energy and the five-class label. For dimensionality reduction point of view, spectral regression (SR)-based linear discriminant analysis (LDA) and kernel SR-LDA, and four different classifiers, a LDA classifier, linear-SVM, k-nearest neighbors, and kernel-SVM were tested for comparison.

K-nearest neighbor's algorithm (K-NN) is a non-parametric approach used for the classification purposes and considered as simplest algorithm among all the machine learning algorithms [125]. Linear Discriminant analysis (LDA) classifier can be used to find a linear combination of features that separates two or more classes [126].

The LDA classifiers with kernel SR-LDA (97.00%) achieved a higher success rate than the other combinations. In the other study, Khushaba *et al.* [56] maximized the drowsiness-related features from EEG, EOG and ECG signals, including the zero crossing, Hjorth parameters, root mean square autoregressive model, model coefficient, spectral moment, waveform length, and Barlow parameters, resulting in 115 features. The newly proposed uncorrelated fuzzy neighborhood preserving analysis was used to reduce the feature dimension. KNN and linear-SVM were compared and both obtained an averaged recognition rate of 82.30% - 97.50% for the 5-class problem. However, the state discrimination at the intermediate levels (i.e., slightly drowsy, moderately drowsy, and significantly drowsy) was lower than that of the alert and extremely drowsy states in both these studies. It is worth to note that the author in studies [56], [81], [117] did not report whether the classification of SVM is either a type of One-Against-One or One-Against-All.

C. INTEGRATION OF A CIRCADIAN FACTOR

Although the effect of the circadian phase is apparent, very few studies take this factor into account [31]–[33]. In addition, sleep pressure is accumulating over time, due to the homeostasis process [33]. For instance, the driver's sleepiness level in the beginning may be lower and subsequently elevated with the time spent during driving task [127]. Therefore, several studies had proposed ESDS to dynamically monitor alert-drowsy states based on the combination of circadian factor with physiological factors based on Dynamic Bayesian Network (DBN) [31]–[33]. DBN is a probabilistic graphical model used to solve a problem with time dependent stochastic processes [128], [129]. In one study [33], Yang *et al.* implemented a DBN as a classifier for the discrimination of the 2-state (alert and drowsy) problem utilizing contextual and observable physiological information. The algorithm integrated observable features such as the alpha amplitude of eye movement, EEG and ECG activity with contextual information including sleep quality, working environment and P_Circ. The results showed that the decision maker can perform better when physiological (eye movement, EEG and ECG) and contextual information (sleep quality, working environment and circadian rhythm) were incorporated. They also showed the absence of EEG & ECG data (considering only the eye movement + contextual information) reduced the sleepiness estimation accuracy. Another [32] He *et al.* proposed a fusion of EEG and head-based indicators (HB) as the observable feature, the contextual information was represented by P_Circ and P_Hom, and classified the data using a DBN. Compared with the EEG features alone, the fusion of all variables improved the drowsiness state discrimination in that the classification result as (EEG + HB + P_Circ + P_Hom) was better than (EEG + HB), which was better than EEG, and the combination of (EEG + HB + CR + TOT) was better than (EEG + CR + TOT), which was better than EEG data alone. In another study [31], Fu *et al.* imputed both physiological observations (EEG, EMG and respiration) and contextual knowledge (sleep quality, P_Circ and driving conditions) into the Hidden Markov Model to assess the probability of driver sleepiness. Combining all variables achieved a larger Area-Under-Curve than other single features (contextual information + physiological observation (RESP, EMG, EEG) > RESP > EMG or EEG).

IV. DISCUSSION

Developing a single-channel or few-channel ESDS is academically and practically important. The source of electrode localization can be grouped into three area including frontal, occipital and parietal. However, most of the studies utilized the occipital electrodes particularly the O1, O2 or Oz [25], [27], [28], [55], [80], [98], [114], [116]. Occipital component are located within the occipital cortex (Broadmann area 18-20) and mainly involve with visual reception [130]. The selection of occipital cortex with the objective of having limited number of EEG electrodes in most of the reviewed studies is consistent with previous studies on neurophysiological of drowsy driving [130]–[136]. In addition, the signal from forehead is susceptible to the eye movement artifact which make the source from occipital preferable [25]. This thus support the feasibility of using electrical activity from the occipital electrode/s as sole input to predict lapses in driving task. Beside looking for electrode localization, selection of the EEG features is essential to complement different angle of the objective. The frequency domain features, such as PSD spectra of the theta, alpha and beta, seem to be effective for classifying the different sleepiness stages. In terms of the classifiers, SVM was commonly used for the two-class problem and in most of the recent publication [26], [28], [55], [80], [113]. This is due to the strength of SVM in overcoming the problem when the ratio of number of features to number of training data is high [137]. In other word, the SVM is non-sensitive to the small sample size data with a relatively high dimensionality [130], [138]. Nevertheless, in all the review studies related to the minimization of the number of EEG electrodes is limited to the binary class (i.e., sleepy and alert) SDS.

Capturing the intermediate states during the wake-to-sleep onset transition is valuable for activating a warning signal at the optimal time. However, the average performance accuracy decreased when classifying the EEG-derivative features into more than two groups (alert or sleepy). In two of the studies [56], [117], Khushaba *et al.* reported that the computed features could not able to produce desirable discriminative power, especially between the intermediate states of the alert-sleepiness continuum. Another probable reason for the poor performance when classifying the multilevel sleepiness problem is the selection of driving performance measurers as an alertness indicator. In these studies, [56], [117], the system was developed using a driving task in a driving simulator. Therefore, the subject might have assumed that navigation mistakes would not cause any harm, which may compromise the objective assessment [100]. In other cases, some subjects do not exhibit high level of drowsiness. For example, in one study [56], only 6 of 31 subjects whom exhibited all five drowsiness levels.

Introducing various sources of contextual information based on information extracted from sleep quality, working environment and circadian rhythm, inevitably improves the EEG based sleepiness detection system. However, information relating to the hours of wakefulness, work hours, and sleep-wake history is not always available [44]. Even though, the addition of multiple feature from different modalities and contextual features can improve the binary class problem, the construction of Bayesian-based probabilistic methods becomes complicated as more contextual and observational features are introduced, particularly during constructing the appropriate probabilities for the prior, conditional and transitional states of the equation [28].

V. FUTURE DIRECTIONS

There are two issues can be considered in the development of ESDS. Although several techniques have been proposed for achieving the maximum theoretical performance accuracy for alertness fluctuation classification, there are several areas that require attention. With respect to all studies reviewed in this paper, the association between observable features of the EEG signal and driving performance was assessed in the midafternoon (13:00-16:00) after lunch. At this time, there is decrease in performance associated with post-lunch dip phenomenon [4], [139]. However, no studies that being reviewed in this paper have validated their proposed algorithms at different circadian phases. Such validation is needed because neurobehavioral performance and awake EEG are phase locked to the circadian rhythm and are also modulated by the elapsed time awake [97], [102]. It is worth to note that there are numerous neuroscientific studies that only showing this relationship but not covering the development of ESDS [19], [94], [99]. Secondly, as discussed in Section II, a combination of measures can enhance the performance of the SDS. Fusing sleepiness forecasting by the BMM and other sleepiness detection technologies holds a promising future for the research in developing sleepiness detection system [21]. Although mathematical modeling has been used extensively in the industry for shift scheduling [44], [69], there are limited studies investigating their potential when combined with other sleep measures. To date, there are only two studies investigating the fusion between the sleep/wake predictor model [140], which is one of many phenomenological BMM types, integrated with either the vehicle-based performance [68] or eyelid movement [67]. However, the changes in driving behavior are not exclusively due to sleepiness but are also influenced by the subject's motivation or personality. Whereas the accuracy of the eyelid closure performance can be affected by the glare reflection from a subject's glasses or departure of the subject's face from the detection angle of the recorder during image acquisition [28], [66]. In addition, the moving average window for eyelid activity and driving behavior compared to EEG is in minutes and seconds, respectively [141]. From the information transmission point of view, the EEG-based method is superior in updating the subject's state of arousal. Thus, there are open possibilities to investigate the performance of combinations of BMM and EEG.

VI. CONCLUSION

The quest to provide safer environments in land transportation, has been intensively explored in field and laboratory studies. Performance deterioration can be avoided by early detection of sleepiness symptoms. The findings show that brain activity as quantified from scalp EEG can be utilized for measuring sleepiness levels. Continuous improvement to find the best combination between scalp areas, EEG-based features and classifiers are used to improve ESDS classification performance and usability in the field. It is evident that ESDS that utilize features from a limited number of EEG electrodes is feasible. It appears that multilevel sleepiness classification can achieve the best result as a binary class problem and that the performance decreases when classifying the intermediate states. Further, the fusion of EEG features with other physiological features and contextual information would improve the classification performance. Although several techniques have been proposed for ESDSs, several improvements must still be considered for such techniques to be acceptable in practice. We briefly highlight the needs to validate ESDS algorithm for data sets conducted at different circadian phases and the potential hybrids of EEG and BMM that can be investigated in the future.

ABBREVIATIONS AND ACRONYMS

ANN	Artificial neural network
ApEn	Approximate entropy
BL	Boolean Logic
DWT	Discrete wavelet transform
ECG	Electrocardiogram
EEG	Electroencephalography
ELM	Extreme learning machine
EMG	Electromyography
EOG	Electrooculograph
ESDS	EEG-based sleepiness detection system
FFT	Fast Fourier transform
FWNN	Fuzzy wavelet neural network
KSS	Karolinska sleepiness scale
KSVD	K-singular value decomposition
LDA	Linear discriminant analysis
MD	Mahalanobis distance
MI	Mutual information
MMSW	Mathematical model of sleep-wake
P_Circ	Circadian process
P_Hom	Homeostasis process
PERCLOS	Percentage of eye close
PSD	Power spectral density
RBP	Resilient-back propagation
RFN	Recurrent fuzzy network
RMSE	Root mean square error
RQA	Recurrence quantification analysis
RSEFNN	Recurrent self-evolving fuzzy neural network
RWENN	Recurrent wavelet-based Elman neural network
SampEn	Sample entropy
SBP	Standard back-propagation
SDS	Sleepiness detection system
SONFIN	Self-organizing neural fuzzy inference network
SSS	Standford sleepiness scale
SVM	Support vector machine
SVMPPM	SVM-based posterior probabilistic model
SVR	Support vector regression
TPM	Two-process model
TSK	Takagi–Sugeno–Kang
WPD	Wavelet packet decomposition

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