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A Comparative Study on Features and Classification Techniques in Real Time Sleep Onset Detection

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Abstract: *In recent years, driver's drowsiness has been one of the major causesof mortality in roadaccidents worldwide and can lead to severe physical injuries,deaths and significant andnoticeable economic losses. Many of these road accidentsand deaths could be avoided, ifdriver's drowsiness could be properly monitored anddrivers are given early warnings. Inthis work, we have made a comparative study on different features used in sleep detection studies. Also a comparative study on different classification techniques used in real time sleep onset detection has been made.*

Keywords: *Sleep Onset, Sleep Detection, Drowsiness, EEG, Electroencephalogram,Threshold Based Classification.*

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I. Introduction

Sleep is the primary function of the human brain and plays an essential role in an individual's performance, mode, learning ability and physical movement. Sleep is an active and regulated process with an essential restorative function for physical and mental health, a period of consolidation of memory and brain recovery. In human beings, sleep is a universal recurring dynamical and physiological activity that influences our daily lives in diverse ways. Performances at work, morale, mood and relationships with other individuals are but a few of them. Sleep can impacts negatively on aspects of cognition, like vigilant attention, and public health. Sleep deprivation makes a person drowsy and unable to concentrate. The term "drowsy" is synonymous with sleepy, which simply means an inclination to fall asleep. Drowsiness, also referred to as sleepiness, can be defined as "the need to fall asleep". In order to analyze driver drowsiness, researchers have mostly studied Stage I, which is the drowsiness phase. Sleep restriction or disorders can lead to sleepiness and may result in the involuntary onset of sleep, (falling asleep) causing car/truck accidents.

In recent years, driver drowsiness has been one of the major causes of mortality in traffic accidents worldwide and can lead to severe physical injuries, deaths and significant and noticeable economic losses.

Based on Bangladesh Road Transport Authority (BRTA), 1422 people were killed and 1289 injured in road accidents in January, 2016 to July 2016 and 2376 people were killed and 1958 injured in road accidents in 2015 in Bangladesh [1]. **A**t least2,297 people were killed and 5,480 injured in road accidentsin January, 2017 to June 2017, a sharp rise in the death toll compared to the same period last year, National Committee to Protect Shipping, Roads and Railways (NCPSRR), an organization campaigning for safety in the transport sector, said in a report.National Committee to Protect Shipping, Roads and Railways (NCPSRR) in a report said casualties in road mishaps has increased by 18.35 percent and the number of accidents increased by 8.6 percent. The report was prepared on the basis of reports in 22 national and 10 regional dailies and eight online news portals and news agencies [2]. According to this report, The 2,297 victims, including 315 children and 292 women, were killed in 1,983 accidents between January and June this year. Last year, a total of 1,941 people, including 261 children and 262 women, were killed and 4,794 injured in the first six months [3]. Nevertheless, many run-off-roadway crashes are not reported or cannot be verified by police, suggesting that the problem is much larger than previously estimated. A significant number of surveys, studies and reports suggest that drowsiness is one of the biggest causes of road accidents.

Many of these road accidents and deaths could be avoided if driver drowsiness could be properly monitored and drivers are given early warnings. Driver drowsiness, that is, excessive sleepiness, is more likely to happen when a person is driving for extended periods in monotonous environments, such as on a highway. The standard clinical tests for measuring sleepiness are the Multiple Sleep Latency Test (MSLT) and the Maintenance of Wakefulness Test (MWT), combined with Polysomnography datasets. These measurements are very expensive and cumbersome to perform (at least eight channels are needed: four EEG, two Electrooculogram (EOG), one electromyogram, and one electrocardiogram (ECG); it would be practically impossible to use these methods to detect driver drowsiness in an actual driving environment. For instance, the use of multiple sensors would be uncomfortable for the driver and could even impede his or her movement. Thus, there is a strong demand for an easy-to-use driver drowsiness detection (DDD) system.

To enable the detection of driver drowsiness both simply and inexpensively, many methods have been proposed, including vehicle-based methods (such as the lane departure warning system and the steering wheel movement system), video-based methods (such as the detector of the degree (percentage) of eyelid closure over the pupils over time, and physiological-signal-based methods (such as those based on the ratio of low frequency to high frequency of heart rate variability and EEG (brain waves). Among these methods, physiological-signal-based methods are considered to be the most reliable means of detection as these signals provide an indication of the true internal state of the driver [4]; and compared to other physiological signals, the EEG, that is a non-invasive physiological means of measuring brain activity, is considered to have the closest relationship with drowsiness [5].

Electroencephalogram (EEG) Signal

The human brain is considered a complex dynamic system that consists of millions of neurons interconnected by axons and dendrites. These neurons are responsible for communicating information to and from the brain.

According to [6], the brain can be divided anatomically into three primary structures: the cerebrum, cerebellum and brain stem. The cerebrum, which is the largest of these three parts, is divided into two hemispheres that have an outer surface called the cerebral cortex. The cerebral cortex is organized into four lobes: the frontal, parietal, temporal and occipital lobes.

Various methods have been developed to measure the signal activity generated in the human brain, including EEG, Magneto encephalography (MEG), functional Magnetic Resonance Imaging (f-MRI), function Near-Infrared Spectroscopy (fNIRS) and Positron Emission Tomography (PET). Among them, EEG is one of the strongest biomedical signals that has significance and a high practical value for applications in clinical neurology [7]. EEG is a noninvasive method for measuring the electrical activity of the cerebral cortex. EEG has been widely used since its discovery by Berger in 1929. EEG is measured using multiple electrodes that are placed on the scalp at multiple locations according to the international 10/20 placement system. This system was extended to the 10/10 system with more electrodes since the multi-channel EEG hardware systems have been developed.

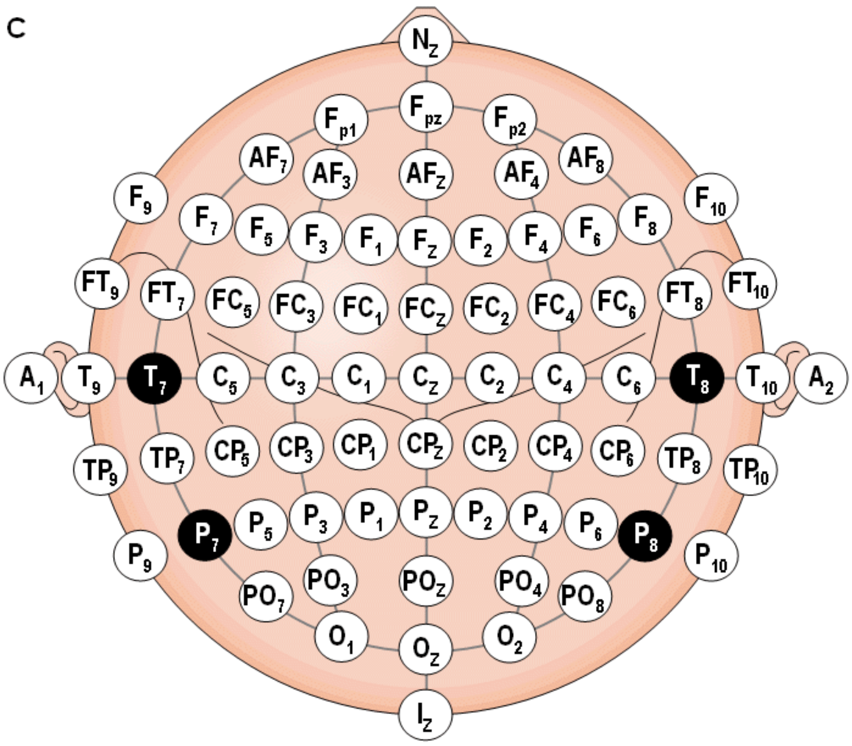

Figure 1 EEG electrode placement [8].

The EEG waveform can be differentiated into five frequency bands, namely $\delta, \theta, \alpha, \beta$and γ. These bands can provide valuable information for diagnosing, monitoring, and managing neurological characteristics and disorders. Table 2.1 shows the amplitude and frequency ranges of the decomposed EEG signal in different frequency bands.

Table-01 Amplitude and frequency range of decomposed EEG signal.

Bands	Frequencies (Hz)	Amplitude (μV)
Delta (δ)	0 – 4 Hz	20 – 100
Theta (θ)	4 – 8 Hz	10
Alpha (α)	8 – 12 Hz	2 – 100
Sigma (σ)	12 – 15 Hz	5 – 10
Beta (β)	15 – 30 Hz	5 – 10
Gamma (γ)	> 30 Hz	-

State of the Art

Electroencephalogram (EEG) signal has been used to detect the stages of sleep since the early 1930s. It has also been clinically used to monitor vehicle driver and pilot drowsiness [9,10]. However, these EEG devices were impractical for everyday driver drowsiness detection because of the use of medically grade expensive equipment that needed specific conditions and preparations for effective monitoring. Many Sleep researchers used EEG data for detecting drowsiness of drivers. Some of the used public database like Sleep EDF [Expanded] database, Dreams database, while others used virtual reality based highway simulation database. Most of the simulation database are private and protected databases.

Also, in [11], the authors proposed an algorithm for detecting drowsiness of drivers. The algorithm classified drowsiness EEG signals into five phases that were early fatigue phase, medium fatigue phase, extreme fatigue phase, early Stage one of sleep and arousal phases. EEG baseline was recorded before the drowsiness of the subject. From this recording, the mean and standard deviation for each of the frequency bands were computed. This algorithm showed a 10% error rate in sleep detection. The existing literature is reviewed here.

In [12], it was found that the transition between sleep and wakefulness was a gradual transition. A gradual increase was noticed in delta waves along with a gradual decrease of beta waves when the subject under test was falling into sleep. Frequencies from 1 Hz to 16 Hz increase while falling into sleep and frequencies 17 Hz and above decrease. Another study to establish a method for automatic recognition of the alertness level from full spectrum EEG recordings is presented in [13].This method used power spectral density (PSD) of discrete wavelet transform (DWT) of full spectrum EEG as an input to an artificial neural network (ANN) with three discrete outputs: alert, drowsy and sleepy. The back propagation neural network was selected as a classifier to discriminate the alertness level of a subject. EEG signals were obtained from 30 healthy subjects. Alertness level and classification properties of artificial neural networks (ANN) were tested using the data recorded in 12 healthy subjects. The accuracy of the ANN was 96 ± 3% alert, 95 ± 4% drowsy and 94 ± 5% sleep.

In [14], a study that developed a Virtual-Reality (VR) –based interactive highway scene to monitor the driver's alertness based on the driving performance estimation and the EEG power spectrum analysis was presented.In this study, an EEG-based drowsiness estimation system that combines EEG log Subband power spectrum, correlation analysis, principle component analysis and linear regression models to indirectly estimate driver’s drowsiness level in a virtual-reality-based driving simulator.A total of 16 subjects (ages from 20 to 40 years) participated in the VR-based highway driving experiments. They concluded that multichannel EEG power spectrum estimation and principal component analysis algorithm can be used to estimate driving errors with good accuracy. The major drawback of this approach is its complexity that makes it inappropriate for real-time fatigue detection. Also, it is expensive, and the device is inconvenient.

In [15], Micro-Electro-Mechanical Systems (MEMS), namely dry electrodes, were fabricated and characterized to bring EEG monitoring to the operational environment without requiring gel or other preparation. The results suggested that the dry electrodes have advantages in electrode skin interface impedance, signal intensity and size over the conventional (wet) electrodes.

In [16], an Intelligent Transportation System (ITS) was developed to warn drivers of their low arousal state to reduce traffic accidents. The EEG during a monotonous task was measured, and it was investigated how these measures change under the low arousal (drowsy) state. This study plotted the time series of mean power frequency of EEG on X-bar control chart. The mean power frequency tended to be lower than the central line (CL) and range between CL and lower control limit (LCL) in the drowsy state. The mean power frequency was lower than LCL under the worst case. The ratio of such intervals to total measurement period increased under the drowsy state. The mean power frequency was found to be effective for evaluating drowsiness of drivers.

In [17], an online drowsiness detection algorithm using a single EEG channel was presented. This algorithm was based on a mean comparison test to detect changes of the relative alpha power ([8-12] Hz band). This algorithm was tested on a huge dataset representing 60 hours of driving and gave good 80% of good detections and 20% of false alarms.

Moreover, in [18], the artificial neural network has been used to detect the driver drowsiness level. This system gave very promising results, but it was not the online system.

A study to design and test real-time stage-one sleep detection and warning system using a single dry sensor EEG headset was performed in [19]. Stage one sleep was indicated when the amplitude of the signal transmitted was low, and signal power at higher frequencies has been attenuated. When the EEG transitions resembled that of stage one sleep, the device produced an auditory alarm. The system proved 81% effective at detecting sleep in a small sample group. In 62% of the cases, stage stage-one sleep was detected after an average of 8.4 seconds. In 19% of the cases, the sleep algorithm indicated sleep in 30 seconds to 20 minutes before stage I sleep was indicated by estimated visual scoring. This system has a risk of high false alarm rate (up to 14%), limited number of test subjects (only 16), and the test was not performed on sleep deprived subjects who were trying to stay awake.

Many single- or multichannel-based techniques for automated sleep stage scoring have been reported in literature. The study by [59] segmented two-channel (Fp1 and Fp2) EEG signals in quasi-stationary components, extracted features based on Short Time Fast Fourier (STFT), performed Fuzzy C-Means (FCM) algorithm based dimension reduction and used multiclass SVM to develop an ASSC system. The result of this work provided 70.92% accuracy.

Mustfa et al. [21] employed six different EEG signals and various signal processing features, such as time domain, frequency domain and non-linear features. Additionally, Random Forests (RF) and SVM were considered as classifiers for five sleep stages. The aim of this work was to develop an online algorithm for an automatic sleep stage classification using a single EEG channel. The results showed that the best performance has been found using the frontal EEG signals, with spectral linear features and a RF led to the optimal performance higher than SVM.

A Bootstrap Aggregating (Bagging) algorithm with various statistical and spectral features extracted from a single EEG channel was used by [22] to classify different sleep states. The authors reported the accuracy results of 6-stages, 5-stages, 4-stages, 3-stages and 2-stages as 85.57%, 86.53%, 87.49%, 89.77% and 95.05%, respectively.

Similarly, a study by [23] proposed a single-channel-EEG-based method for sleep stage scoring using Complete Ensemble Empirical Mode Decomposition (EMD) with Adaptive Noise (CEEMDAN). Bagging was employed to classify the sleep states. This work achieved an accuracy of 86.89%, 90.69%, 92.14%, 94.10% and 99.48% for 6-Class, 5-Class, 4-Class, 3-Class and 2-Class, respectively.

Sotelo et al. [24] used entropy metrics features, the Q-algorithm as a dimensionality reduction method and J-mean clustering as a classifier for two EEG-channel-based automatic sleep stage scoring. The performance for the automatically discriminated data achieved an optimal classification accuracy of up to 80%.

Another study from [25] extracted many spectral features based on Fast Fourier Transform (FFT) of multichannel PSG data to classify the sleep stages using a rule-based DT classifier and achieved an accuracy of 84%.

In [26], an SVM classifier based approach was used to distinguish between wake and drowsy states using three channels of EEG waveforms. The drowsy state was defined as a combination of both sleep Stage 1 and Stage 2. The results of the drowsiness detection approach indicated a high accuracy and precision of 98.01% and 97.91%, respectively.

Fraiwan et al. [27] developed a methodology for automatic sleep stage scoring based on extracted entropy features of the Wigner–Ville Distribution (WVD), Hilbert–Hough Spectrum (HHS) and Continuous Wavelet Transform (CWT) using a single EEG channel and ANN. The classification accuracy of the WVD was 84%, which outperformed the other approaches using the other features in their work.

Renyi’s entropy features were extracted from a single EEG channel for sleep stage identification [28] using three time-frequency techniques. The performance of the proposed approach was tested by a RF classifier and attained an accuracy rate of 83%.

Moreover, the study from [29] performed sleep stage classification based on extracting nine graph domain features from a Visibility Graph (VG) and a Horizontal VG (HVG) using a single channel of the EEG signal, and multiclass SVM as the classifier. The accuracy of the classification of six sleep stages achieved 87.5% using the SVM classifier.

Hsu et al. [30] classified five sleep stages based on six energy features from a single EEG channel using the Elman recurrent neural classifier with 87.2% classification accuracy.

Shuyuan et al. [31] utilized 4 EEG, 2 EOG and 1 EMG signals to extract ratio, power and Zero Crossing (ZC) features, respectively. Then, an enhanced k-means clustering algorithm was used to classify the sleep data into five stages. The algorithm showed an accuracy of 75%, which was higher than the original k-means clustering algorithm.

A wide range of time and frequency-domain features have been explored by [32] from PSG signals that included two EEG channels, two EOG channels and one EMG channel for automatic sleep stage scoring. The proposed method led to 94% specificity, 82% sensitivity and 92% accuracy using a Dendrogram-SVM (DSVM). Correspondingly, an ASSC addressed by Karkovská and Mezeiova [33] extracted 14 features of PSG signals such as entropy, variance, coherence, prediction error and ZC from 6 EEG, 2 EOG and 1 EMG channel and classified the data using a quadratic discriminant analysis. The results confirmed an accuracy of 81%.

In [34], a total of 39 features obtained from time-domain, frequency-domain and nonlinear parametric analyses were extracted and then applied to a certain combination of optimum feature subsets that were selected to help binary SVM classify five different sleep stages from a single-channel EEG signal. The algorithm was capable of achieving an average sensitivity, specificity and accuracy of 88.32%, 97.42% and 95.88% respectively; and reported an error rate of 10.61%.

According to [35], a machine learning approach for ASSC based on a single-channel of EEG data was introduced. A two-step classification based on the KNN method was used to first classify wake/sleep and then four sleep stages consisting of wake, Stage 1 + REM, Stage 2 and SWS. The achieved accuracies were 98.32% and 94.49%, respectively.

Kayikcioglu et al. [36] extracted Auto-Regressive (AR) coefficient features from a single EEG signal to classify both sleep and wake stages with an accuracy of 91% using a Partial Least Squares Regression (PLSR) classifier. Spectral analysis, Wavelet Transform (WT) and fuzzy clustering based on the FCM algorithm were used by [37] in an automatic sleep stage detector, which was able to distinguish the wake stage, as well as stages 1–4 and REM sleep stage, using single-channel EEG signals. The results showed that the algorithm could provide a 92.27% success rate when using wavelet packets.

Cic et al. [38] generated time-frequency features using the EMD method and applying the Generalized Zero Crossing (GZC) method on the obtained Intrinsic Mode Functions (IMF) for sleep stage classification based on a single EEG channel. The approach performed with an overall 90% accuracy using the SVM classifier.

Another sleep stage classification study was conducted by Chen et al. [39] to estimate sleep stages, including the wake stage, Stage 1 and Stage 2, during daytime naps using four recorded EEG signals. The proposed method achieved an 80.6% accuracy rate based on the Hopfield Neural Network (HNN) classifier.

A multiclass SVM based on three EEG and two EOG channels was used by [40] for an automatic sleep stage detector, to automatically separate wakefulness, REM and NREM sleep stages in young healthy subjects and elderly patients. The experimental results showed that this algorithm could achieve a 91% success rate.

In [41], three features obtained from the Cross-Frequency-Coupling (CFC) method, average power method and preferential frequency band method, using a single-channel EEG were fed as inputs to an LDA classifier for sleep stage classification. The proposed method correctly classified up to an average of 75% of the stages using a combination of both average power and CFC features, which outperformed either approach used individually.

Koch et al. [42] addressed the sleep stage classification problem by using the Latent Dirichlet Allocation model from multiple PSG signals that included 2 EEG and 2 EOG channels. The model scored an overall 68.3% accuracy.

In [43], NinahKoolen et al. collected 231 EEG recordings from 67 infants between 24 and 45 weeks of postmenstrual age. Ten minute epochs of 8 channel polysomnography (N = 323) from active and quiet sleep were used as a training dataset. They extracted a set of 57 EEG features from the time, frequency, and spatial domains. A greedy algorithm was used to define a reduced feature set to be used in a support vector machine classifier. Performance tests showed that their algorithm was able to classify quiet and active sleep epochs with 85% accuracy, 83% sensitivity, and 87% specificity. The performance was not substantially lowered by reducing the epoch length or EEG channel number. The classifier output was used to construct a novel trend, the sleep state probability index that improves the visualization of brain state fluctuations.

Features and Feature Extraction Techniques in EEG-based Sleep Detection

Feature extraction is considered the most important procedure for any type of PSG-related analysis. From our literature survey, ninety of the reported sleep stage detection schemes employed feature extraction algorithms. All the sleep stage related features can be meticulously categorized into four main groups: time, frequency, time-frequency domain and nonlinear features. Based on the no. of papers we have reviewed, approximately 40% use non-parametric-based frequency-domain features, 25% use the wavelet-transform-based time-frequency domain, 25% use statistical standards based on the time domain and 10% use Approximate Entropy (ApEn) based on nonlinear, domain feature, extraction measures. The standard statistics of the temporal domain, non-parametric statistics of the spectral domain and WT of the time-frequency domain are the top three feature extraction methods that have received more attention in ASSC schemes. In the following section, we discuss the above feature extraction techniques.

Standard Statistics

Many time-domain features have been reported in literature. The statistical measures are among the simplest features that can be derived from the time domain analysis. These statistical parameters are well recognized for their ability to express the underlying statistical moments of the EEG signal. When applying these measures, each epoch is considered as a univariate process that ignores the correlations between epochs. Examples of statistical moments include the mean, variance, skewness and kurtosis. The characteristics of such features are obtained directly from the EEG epoch X(n) to measure certain tasks, such as central tendency, degree of dispersion, asymmetry, data peaks, troughs and flatness respectively. Examples of statistical moments are shown in previous studies [44,45].

Non-Parametric Statistics of the Spectral Domain

Some of the most commonly extracted features from PSG signals are frequency-domain features which characterize the spectral structure of the signal. The spectral estimation such as power spectrum and the Power Spectral Density (PSD) are meaningful when the signal is stationary. Because the EEG signal is non-stationary, the calculation of the spectral estimation involves prior segmentation of the EEG signal. This requires applying a special transform, typically based on the Fourier Transform (FT), to convert EEG signals from the time domain to a representation in the frequency-domain for acquiring the spectrum components of such signals. The most general form of spectral estimation uses non-parametric methods. Welch's spectral analysis method and periodogram are examples of non-parametric approaches. The non-parametric approach is a commonly used technique in EEG-based sleep analysis because they are simple to implement and interpret, as stated by [46]. However, the frequency resolution may be lost due to smearing and leakage problems that appear when FT-based methods are implemented. Therefore, the non-parametric methods require long records to achieve proper resolution [46].

Table 2Features and feature extraction techniques in EEG-based signal processing of sleep studies.

Techniques	Features	References
Time Domain	Standard statistics	[60,61,62,63,64,68,71,82,84,85,87,88,89,90,93,95,99,105,108,109]
	Zero crossing	[61,62,69,71,72,83,85,88,108]
	Hjorth parameters	[60,61,62,81,87,88,93,108]
	Integrated EEG	[69,71,72]
	Mutual information	[101,110]
	Detrended fluctuation analysis	[67,88]
	Renyi entropy	[60,61,75,93]
	Tsallis entropy	[60,93]
	Shannon entropy	[60,67,74,87,93]
Frequency Domain	Parametric analysis	[69,71,91,94,109]
	Non-parametric analysis	[60,62,69,66,68,73,79,80,81,83–88,89,92, 93, 95, 97, 100,103,104,106]
	Coherence analysis	[85]
	Harmonic Parameter	[60,72]
	Spectral entropy	[61,62,81]
	Median frequency	[81]
Time-frequency Domain	WT	[60,61,70,74,75,76,77,89,92,93,96,100,102,106]
	STFT	[106]
	WVD	[61,74]
	EMD	[64,74,75,98,103]
	Choi-williams	[75]
Complexity measures & non-linear parameters	Lempel-Ziv	[62,88,101]
	Correlation dimension	[88]
	Fractal dimension	[61,62,67,85,88]
	Lyapunov exponent	[88]
	Sample Entropy	[67,102]
	Approximate Entropy	[61,67,88]
	Permutation entropy	[61,65,84,90]
	Multiscale Entropy	[67]
	Phase space	[78]
	Autoregressive	[60,65,93,108]
	Energy operator	[61,84,109]
	Hurst exponent	[61,97]

Wavelet Transforms

WT is a well-known form of the time-frequency distribution and has been widely deployed in signal processing and analysis of many fields over the past two decades. WT uses functions that are localized in both time and frequency scales. Because of its flexible way to represent the time-frequency domain of a signal, WT is suitable for non-stationary signal analysis. Therefore, it is a powerful tool for the analysis and feature extraction of the EEG signal. The WT breaks down the input signal by shifting and scaling wavelets over different frequency bands. By applying the multi-resolution, the vector of coefficients can be obtained and used as an input for the classifier.

Classification Techniques in EEG-based Sleep Detection

Various classifiers are utilized to classify the elicited features and assign a sleep stage into each epoch. These classifiers are learned to construct linear/non-linear boundaries to separate feature vectors of different classes. Table 1.2 summarizes a number of Automatic Sleep Stage Classification (ASSC) schemes that use the different classification algorithms. Approximately 35% of the ASSC methods use classification schemes that are based on SVM classifiers, 25% based on NN classifiers, 10% based on LDA, 5% based on KNN, 5% based on DT, 5% based on NB classifiers and less than 5% based on other types, such as HMM, Adaboost, Bagging, quadratic, RF and K-means. Approximately 5% are also based on other types, such as fuzzy classification and combined classification. Some of the prominent and broadly used classifiers are briefly explained below.

Artificial Neural Network (ANN)

Artificial neural network (ANN) is a network composed of artificial nodes that process input activation for transmission to connected nodes. Input vectors to the ANN are treated as a temporal sequence whose analysis requires consideration of a set of prior input vectors. ANNs are widely applied to automatic classification of sleep stages using an EEG signal. They are popular for their high classification efficiency and relatively simple implementation. A very important task when creating an ANN is selecting a type and architecture of the network. Generally, an ANN consists of several layers of neurons: the input layer, one or more hidden layers and the output layer. The numbers of hidden layers and neurons within them influence the ANN classification capability. It is known that an ANN with two hidden layers can approximate any continuous mapping arbitrarily well. Also, most of classification problems can be solved by ANNs with only one hidden layer. ANN is highly tolerant to noisy data and also has the ability to classify pattern on which they have not been trained.

Table 3. Classification techniques in EEG-based signal processing for sleep studies.

Technique	Technique Variations	References
ANN		[61,64,67,69,71,72,74,82,87,89,96,98, 99,101,104]
Statistical	SVM	[60,61,62,73,76, 77, 78,80,81,84,88,92,93,95,102,103,105,107,110]
	LDA	[60,64,65,84,91,92,97,106]
	Bayesian	[60,64,91]
	Hidden Markov Model	[111]
	Quadratic	[89]
Decision tree	DT	[61,66,68,86]
Instance base	KNN	[64,76,81,86,89,90,91]
Clustering	K-means classifier	[70,83,109]
Ensemble	Adaboost	[60,64]
	Bagging	[63,64]
	Random Forest	[61,62,75]
Other classifiers	….	[67,76,78,79,91,94,100]

Table 4. List of Previous Works on Drowsiness/Sleep Onset Detection using Training based classifiers.

References	Sensors	Preprocessing	Feature Extraction	Classification	Classification Accuracy (%)
[48]	EEG ECG EoG	Optimal Wavelet Packet, Fuzzy Wavelet Packet	The Fuzzy MI-based Wavelet-Packet Algorithm	LDA, LIBLINEAR, KNN, SVM	**95–97% (31 drivers)**
[49]	ECG	Band Pass Filter	Fast Fourier Transform (FFT)	Neural Network	**90% (12 drivers)**
[50]	EEG	Independent Component Analysis Decomposition	Fast Fourier Transform	Self-organizing Neural Fuzzy Inference Network	**96.7% (6 drivers)**
[51]	EEG EMG	Band Pass Filter & Visual Inspection	Discrete Wavelet Transform (DWT)	Artificial Neural Network (ANN) Back Propogation Algorithm (Awake, Drowsy, Sleep)	**98–99% (30 subjects)**
[52]	EEG	Low pass filter 32 Hz	512 point Fast Fourier Transform with 448 point overlap	Mahalanobis distance	**88.7% (10 subjects)**
[53]	EoG EMG	Filtering & Thresholding	Neighborhood search	SVM	**90% (37 subjects)**

[54]	EEG EoG EMG	Low pass pre Filter and Visual Inspection	Discrete Wavelet Transform	ANN	**97–98% (10 subjects)**
[55]	EEG	Least mean square algorithm and Visual Inspection	Wavelet packet analysis with Daubechies 10 as mother wavelet	Hidden Markov Model	**84% (50 subjects)**

Table 5. Non-Training Based Sleep Classification Techniques

Reference	Database	Sensors	Features Extraction	Classification	Accuracy
[56]	CEPA Database (40 Recordings, 20 Subjects)	EEG	Relative Power of α, θ and β	Threshold based Classification	**85%**
[19]	Three Datasets from Physionet.org	EEG	Mean and standard deviation	Threshold based Classification	**81%**

Support Vector Machines

For the first time, a generalized classifier trying to minimize the risk of error instead of minimizing the classification error is proposed by Vapnic [57]. SVM considers a margin around its hyperplane while other conventional classifiers just attempt to form a boundary, weather linear or nonlinear, between two classes. In fact, SVM tries to maximizing the margin width simultaneous to minimizing the classification error of samples, within that margin. Therefore, finding the separating plane of SVM needs to solve the constrain optimization problem. Since the objective function of SVM is convex, SVM will be a stable classifier in terms of boundary learning. Since SVM optimization formula has a constraint, Lagrange coefficient is inserted into its objective function; whereby in each sample a Lagrange coefficient is determined.

$$L(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \; \phi(x_i)\phi(x_j)$$

whereα_i is the Lagrange multiplier of the i^{th} sample, $\phi(x_i)$ is the kernel function, x_i is the i^{th} input and y_i is its corresponding label.

The values of Lagrange coefficients belong to the samples located within the margin space (support vectors) are positive values bounded within:

$$0 \leq \alpha_i \leq c$$

Where,c is a user-defined parameter.

In contrast, other samples (majority of instances) located outside of the margin space do not have any role in determining the SVM hyperplane, since their Lagrange coefficients become zero. The boundary of SVM is determined by:

$$W = \sum_{i=1}^{N} \alpha_i y_i x_i$$

where N is the number of samples.

In the case of nonlinear classification, kernels, such as radial basis functions (RBF), are used to map the data into a higher dimensional feature space in which a linear separating hyperplane could be found. When the number of samples is less than the number of features, nonlinear learning methods do not significantly affect the results and it may be better to simply use linear learning method.

Linear Discriminant Analysis (LDA)

LDA is developed by Fisher in 1936 and optimized by a very popular criterion function, called as Fisher criterion. In two-class problems LDA can be considered as a classifier whereas in multi-class problems, LDA is acted as a feature-extraction method. Since sleep EEG contains 5 classes, LDA provides more separable features for the next classifier. LDA tries to maximize the ratio of between-to-within classes' scatter matrices. This is done by projecting input samples onto a few number of hyperplanes (depends on the number of classes) such that the separability among the samples is maximized in the projected space. The Fisher criterion is described as:

$$J(W) = \frac{W^T S_B W}{W^T S_W W}$$

where W is potentially a hyperplane (in two-class problems) or a matrix of hyperplane (in multi-class problems). Incidentally, S_W and S_B are between and within class scatter matrices, defined as:

$$S_{W_i} = \sum_{x \epsilon c_i} (x - m_i)(x - m_i)^T, \quad i = 1,2,3,\ldots\ldots.c_i$$

$$S_W = \sum_{k=1}^{c} S_{W_i}$$

where x is the input vector, c is the number of classes and m is mean value.

$$S_{W_i} = \sum_{x \epsilon c_i} (x - m_i)(x - m_i)^T, \quad i = 1,2,3,\ldots\ldots.c_i$$

The final decision is made by applying a distance-base classifier (NC) to the LDA outputs. In other words, LDA acts as a feature extractor and the projected features are assigned to the corresponding classes according to the minimum distance of the project sample to the center of each class, separately.

II. Conclusion

In this research work, a comparative study has made to develop a novel approach that can be easily implemented in hardware to differentiate between wakefulness and stage 1 sleep using EEG signals. After a thorough review, we can conclude that, training based sleep onset detection is not practically implementable. Rather, we need threshold based classifier. Threshold based approach is attractive for easy implementation in any smartphone or embedded microcontroller device to identify driver's drowsiness in real time. In comparison with several recently available studies on the classification of sleep stages and drowsiness detection, the present study reveals that threshold based approach of real time sleep onset detection has certain advantages in terms of the accuracy and feasibility, which allows this research to be considered as an important step towards design and development of a fully automated, convenient and efficient drowsiness detection system.

Most of the existing sleep detection technologies are based on training based classifiers. The most commonly used techniques for automatic sleep stage classification are still supervised and they require user intervention or manual data annotation. Although, training based classifiers show better accuracy, building a training based classifier requires a lot of times to train the model. Moreover, training based classifier does not work efficiently and effectively in real time since each time a new subject use the device, it requires training which kills a huge time. Also, training based classification requires a huge training data for obtaining better accuracy. All these supervised approaches strongly depend on the predefined scorers labels and therefore they lack of flexibility, adaptability and reusability.

Threshold based classification approach requires very little time for subject adaptation. Most of the prominent classifiers require training phase before the testing phase but thresholding based classifiers require a short period of baseline data for subject adaptation and threshold calculation. These motivated us to develop a non-training based classifier which can work online. Real time application requires little training time, little baseline data, little number of features to be extracted and classification within very short period of time. Threshold based classifiers hold all these properties whereas training based classifiers does not. These reason leads us to develop a novel and innovative approach for sleep onset detection based on thresholding technique.

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