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Drowsiness Detection using Minimum Discriminated Features and Single EEG Channel

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Abstract:

Driver drowsiness is one of the top causes of road fatalities and transportation industry risks. Electroencephalography (EEG) has been regarded as one of the most reliable physiological signs for detecting drowsiness in drivers since it directly assesses neurophysiological brain activity. If possible, a system that monitors driver drowsiness and warnings can prevent the greatest number of traffic incidents. This study presents a simple and inexpensive method for detecting driver drowsiness or sleep onset with single-channel EEG signal processing. The primary contribution of this study is the identification of sleepiness detection from a publicly available graph signal dataset using only two discriminated features (standard deviation and entropy) and a filter that is easily implementable in any microcontroller device or smartphone. This study employed the least square support vector machine to categorize driver status into two groups (awake or drowsy). The proposed method can be implemented in real-time with high efficiency and precision. Furthermore, this method can be readily applied on a smartphone to create and expand a sleepiness detection and alert system for vehicle drivers. The trial findings indicate an accuracy of 95.5 percent.

Keywords: Drowsy driving detection, Electroencephalography, wavelet transform.

Introduction:

All over the world, there has been an increase in car accidents, and one of the main causes is sleepy drivers. Three times as many crashes as are reported by police departments (NHTSA)[1] are caused by drowsy drivers, according to the AAA Foundation for Traffic Safety. The automotive industry is constantly working to improve drowsiness detection methods by incorporating subjective, in-vehicle, behavioral, and physiological indicators. Questionnaires can be used to assess levels of alertness and drowsiness using data from the Karolinska sleepiness scale (KSS). Participants in the KSS are polled on a scale from 1 to 9 regarding how exhausted they feel (1 indicates a high level of alertness, whereas 9 indicates a high level of drowsiness). SD of steering-wheel motion and lane position can be calculated using a vehicle-based approach. The degree to which a person's eyes are closed, the frequency with which they blink, and the orientation of their head are all taken into account when trying to diagnose drowsiness. Nonetheless, subjective, vehicular, and behavioral evaluations are hampered by real-time modeling, unreliability, and a lighting situation in the background[2]

Numerous methods have been developed for detecting drowsiness using EEG data. [3] proposed employing convolutional neural networks (CNNs) for drowsiness detection. A support vector machine (SVM) has been used to differentiate between sleep and awake in EEG patterns [4]. Both decision tree (DT) and random forest (RF) algorithms have been used for Fatigue Driving Vigilance Monitoring [4]. To identify drowsiness, scientists have considered employing step-wise linear discriminant analysis (SWLDA) and support vector machines (SVMs) using a radial basis function (RBF) kernel [5]. Driver fatigue detection by pulse-coupled neural network (PCNN) clustering [6],[7]. Before now, a multi-source signal alignment (MSSA) and multi-dimensional feature classification framework was used for sleep and wake detection [8]. Researchers have looked into a self-attention based Long Short-Term Memory (LSTM) deep learning model for recognizing tiredness, and found it to be very accurate [9]. A multiscale convolutional neural network-dynamical graph convolutional network (AMCNN-DGCN) model has been proposed for Driving Fatigue Detection [10]. A flexible analytic wavelet transform (FAWT) and extreme learning machine (ELM) are used to improve the separability of drowsiness and alert EEG signals [11]. Tunable Q-factor wavelet transform (TQWT) and ELM have been used to classify alertness and drowsiness states EEG signals [12]. Adaptive variational mode decomposition (AVMD) and ensemble boosted tree (BT) have been used for the detection of drowsiness [13]. Multi-criteria optimization-based multi-channel frequency-domain ratio indices for detecting drowsiness [14]. The KNN classifier has been used to the use of Short-time Fourier Transform and Relative Band Power to detect drowsiness [15]. EEG and BT-bagged tree instantaneous rhythms separation for sleep and wake detection was investigated [16]. For sleepiness diagnosis, K-Nearest Neighbors (KNN) is used with band power and log energy entropy characteristics [17]. Both the Common Spatial Patterns (CSP) and the Extreme Learning Machine (ELM) are utilized to detect sleepiness [18]. The detection of alertness is carried out with the use of Support Vector Regression (SVR) and Random Forest (RF) [19]. Recognition of sleepiness and wakefulness was investigated using Wavelet packet transform (WPT) and Extra Trees (ET) [20]. When it comes to snoozing detection, we turn to a genetic algorithm-based support vector machine (GA-SVM) [21]. K-Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) for Driver Drowsiness Detection [22]. In order to detect drowsiness, LSTM and TQWT are utilized [23]. The purpose of this study is to identify EEG signals as either drowsy or alert using a proposed discrete wavelet transform of depth 5 with Daubechies order four (db4) employed for features extraction and LSSVM. With only two differentiated parameters (SD and entropy), this paper's contribution is a straightforward and low-cost method for detecting driver drowsiness with a single EEG channel, suitable for implementation in any microcontroller device or smartphone .

In this study, we have used C3-A2 as the best channel to obtain optimal accuracy, as shown in table (3). Furthermore, we tested many linear and non-linear features as individuals or in different groups, such as max, min, mean, SD, energy, variant, skewness, and sample entropy. As a result, we found SD and sample entropy are the discriminant features in this study to obtain optimal results. In addition, many levels of wavelet transformation are tested.

Materials and Methods:

This section presented the main datasets used in the study and explained the methodology steps. In addition, the features extraction technique and classification method are examined in this section.

ISRUC-Sleep database

The ISRUC-Sleep database from the Hospital of Coimbra University was used in this work for one set of EEG data. It is divided into three sections[24]. It consists of a variety of participants in each subgroup, including healthy individuals, those with sleep disorders, and those taking medication: eight, ten, and 100 volunteers in each sub-group whose data was recorded. There are 19 channels in each recording. European Data Format (EDF) files were used to hold the 200 Hz sampled EEG, EMG, and EOG signals. This study's EEG data from the C3-A2 channel is demonstrated to improve classification outcomes. Following the AASM guidelines, two experts rated the recordings. According to AASM criteria, all recordings were divided into 30-second segments, and each segment was allocated to a specific stage of sleep[25]. For sleep research, the dataset is available online. Ten healthy people in the original dataset provided EEG recordings for this study. Their demography information was as follows: 15 males and four females, aged between 22–76, with a weight from 41 kg to 110 kg and height from 68 cm to 178 cm. Table 1 shows the number of segments (epochs) that were used in this study.

Table (1): Distribution of the sleep stages in the ISRUC dataset

Sleep stage	AWA	S1	Total number of epochs
No. of epochs	4102	1908	6010

Methodology

In this study, each raw file contains 30 seconds of EEG data. Decrease the number of dimensions that each EEG segment occupies to improve the efficiency and effectiveness of your algorithm. Every 30 seconds, a wavelet transform of depth 5 with Daubechies order 4 (db4) was performed at a frequency of 200 Hz. As a result, a wavelet filter with five levels was used for optimal performance. Finally, the least square support vector machine (LS-SVM) classifier was used to categorize the single EEG segment into awake or stage one, as shown in the figure. The vector of standard deviation and entropy characteristics represents one 30-second EEG segment.The classification of EEG signals is illustrated in Figure (1).

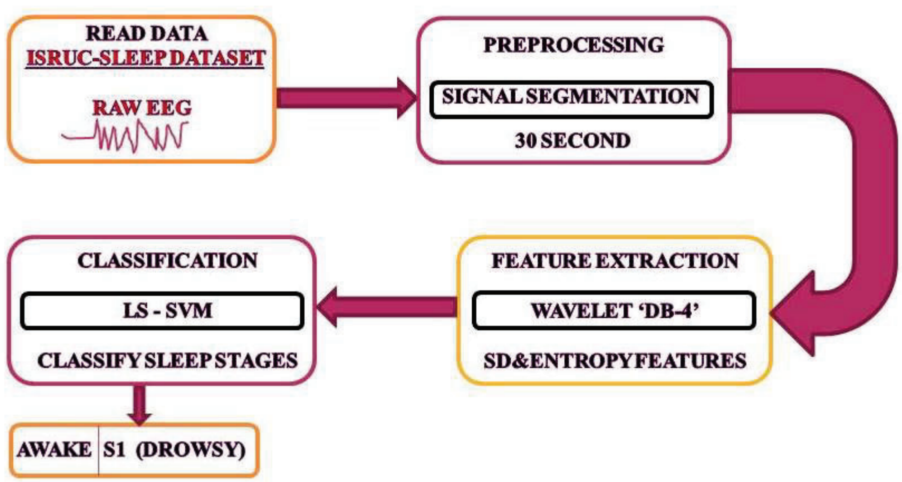

Figure (1): The block diagram of the proposed method

Features Extraction

The statistical measurements of the EEG signal's subbands are known as features. SD and sample entropy features were extracted using a wavelet transform with a five-level. Segments of 30 seconds each with a sampling rate of 200. This means that the length of a segment is 6000. For the Daubechies D4 technique, the Daubechies wavelet transform contains four wavelet and scaling function coefficients. Each cycle of the wavelet transform involves scaling the input data. If an initial set of N values is utilized in the wavelet transform stage, an N/2 smoothed value will be produced. In the ordered wavelet transform, the smoothed values are placed in the lower half of the N-element input vector. When performing a wavelet transform, the resultant data is constantly subjected to the wavelet function. If the original data set has N values, the wavelet function will compute N/2 differences (reflecting the change in the data). In the ordered wavelet transform, the wavelet values are stored in the upper half of the N-element input vector. The scaling and wavelet functions are generated using the inner product of the coefficients and the four data values. The following equations describe the scaling process of Daubechies D4:

$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3] \quad (1)$$

And Daubechies D4 wavelet function:

$$c[i] = g_0 s[2i] + g_1 s[2i+1] + g_2 s[2i+2] + g_3 s[2i+3] \quad (2)$$

Least Square Support Vector Machine (LS-SVM)

The least-square support vector machine (LS-SVM) was invented by Suyken and Vandewalle[26], the creators of the first support vector machine. In the case of epileptic EEG signals, it was employed by Al Ghayab et al., while in the case of motor image classification, it was used by Li and Wen. Two crucial parameters must be adjusted appropriately to get the desired classification results from the LS-SVM. These two factors can either enhance or hinder the effectiveness of the proposed strategy. Empirical values for and were selected for the LS-SVM algorithm's training set to classify distinct pairs of sleep stages. The optimal settings for determining the awake and drowsiness pair were: (3.9718, 1.1961).

Experimental Results and Discussion

A series of experiments determined the effectiveness of the proposed method. Experiments made use of the dataset discussed in Section 2. With the help of Wavelet Transform Daubechies four (WTDB4) and the LSSVM classifier, we can identify who is awake and who is in stage 1. All experiments were run in the appropriate MATLAB 2018b conditions on a Windows 10 computer: A system with an Intel(R) core(TM) i7 processor running at 3.40 GHz and 8.00 GB of RAM. A 10-fold cross-validation procedure was used for both the testing and training phases. By carefully tweaking WDB4, they can breakdown the signal. WTDB4 is recommended for the sub-band decomposition of EEG signals in this system.

Table (2): Performance Parameter for different Sub-Bands with LS-SVM

SB	ACC	SEN	F1-score	PRE
SB1	96.51	97.39	96.62	96.22
SB2	91	96.23	93	94.67
SB3	92.32	93.24	93.71	95
SB4	92.61	95.74	95.45	94.32
SB5	94	93.31	96	93.52
SB6	89.83	92	94.33	94.31

Two features (SD and entropy) useful in the signal analysis are derived from the sub-bands of EEG data. First, a feature matrix is fed into classifiers using a 10-fold cross-validation strategy. The input data is split into ten random subsets over several iterations, with nine subsets used for training. The LS-SVM classifier is used to classify the bands. Table (2) shows the test results for the suggested model's compliance with four performance metrics: accuracy, sensitivity, specificity, and F1-score. A classification system's accuracy (ACC) is measured by the number of instances in which it correctly classifies objects. We obtain 96.5 percent in sub-band 1, the highest possible classification ACC, and the lowest is 89.8 percent in sub-band 6. The proportion of correctly identified positive and negative instances is measured by sensitivity (SEN) and specificity (SPE). SB1 has the greatest SEN at 97.39%, while SB5 has the lowest SEN at 96.39%. Using the F1-score, the harmonic mean of precision and recall, the highest and lowest values for SB1 with a score of 96.6, respectively. Table (3) displays the confusion matrix for an awake and drowsy class. Awake state has 95.9 percent correct prediction and 4.1 percent misclassification, according to Table (3).

On the other hand, drowsiness is correctly identified in 95.2 percent of cases, whereas just 4.8 percent of cases are misclassified. Table (4) compares the existing algorithms' accuracy with the proposed framework. The comparison goes along with methods used for decomposition, classification techniques, number of features, and accuracy. Guarda et al.,2022; Cui et al.,2022; Stancin et al.,2021; Shen et al.,2021; H Wang, Zhang, et al.,2021 and Chaabene et al., 2021, using Power spectral density (PSD) methods for Feature extraction with CNN and SVM use 5 and 7 features with an accuracy of below 90%. The multimodal analysis used for feature extraction in Gangadharan K & Vinod,2022; Moura et al.,2022; Sivakumar et al.,2021, with SVM, RF, and KNN claims classification accuracy of 78.3%, 90%, and 92%, respectively. Fixed tuning settings are used in the WTDB4 approach to claim 95.5 percent accuracy. Table (4) shows that the suggested WTDB4 method for detecting drowsiness has the highest classification accuracy of all the preceding state-of-the-art, as can be seen. When combined with WTDB4 and LS-SVM classifiers, the suggested system is 95.5 percent more accurate than any other method for detecting drowsiness. Comparing the proposed work to existing methods also demonstrates its advantages. Table (5) shows a variety of channels from the two datasets being examined; as shown, C3-A2 is the best channel from the ISRUC-Sleep dataset.

Table (3): Confusion matrix of alertness and drowsiness

Classes	Awake	Drowsiness
Awake	95.9	4.1
Drowsiness	4.8	95.2

Table (4): Performance Comparison with previous studies

Authors	Year	Method	Features	No. of Features	ACC
Guarda et al.	2022	CNN	PSD	5	86,44%
Cui et al.	2022	CNN	PSD	5	73.22%
Gangadharan K & Vinod	2022	SVM	Entropy, Envelope mean, Hjorth parameters, SD, spectral Entropy	8	78.3%
Moura et al.	2022	RF	Hjorth parameters	3	90%
Stancin et al.	2021	ratio indices	PSD	5	86%
Sivakumar et al.	2021	KNN	statistical features	11	92%
Shen et al.	2021	MSSA + TN	PSD	5	72%
H Wang, Zhang, et al.	2021	GA-SVM	PSD	5	80%
Chaabene et al.	2021	CNN	PSD	7	90%
Proposed method		WTDB4+LS SVM	Entropy, SD	2	95.5%

Table (5): Accuracy comparison of different channels

Dataset	Channel	ACC
ISRUC-Sleep	C3-A2	95.5
ISRUC-Sleep	O1-A2	91.91
ISRUC-Sleep	F4-A1	90.42
ISRUC-Sleep	C4-A1	89.93

4. Conclusion

This study attempts to represent sleep EEG patterns using a minimum number of features without significant performance loss. The advantages of this method were decreasing the features to two only and improving the model performance. The non-stationary nature of EEG signals makes extracting information from raw signals difficult. Decomposition of the signal into sub-bands is necessary to obtain confidential information. The proposed method provides a better separation of the alert and the drowsy state than previous studies. WTDB4 is presented in this framework to decompose the EEG signals into sub-bands. Two features (SD and entropy) are extracted from the sub-bands of EEG signals. LS-SVM classifier is used to classify the bands into two classes with high accuracy

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