Discrete Wavelet Transform Coefficients for Drowsiness Detection from EEG Signals

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***Abstract*— This paper proposes an effective approach to detect drowsiness from EEG signals by using Discrete Wavelet Transform (DWT) coefficients as features. The majority of drowsiness detection systems extract features using FFT to calculate the power spectral density or the DWT to calculate entropy from EEG sub-bands. Although these techniques excel in capturing valuable features in the frequency domain, they omit temporal details essential to the analysis of EEG signals. These details are integrated into coefficients indicating the correlation between the wavelet function and the EEG signal at different times. In our work, we perform a time-frequency analysis of EEG signals using DWT coefficients to preserve this temporal context. Furthermore, the study explores the influence of time segment size on system performance. Subsequently, we determine the most suitable technique to minimize input feature redundancies. Our approach employs just two EEG electrodes, C3 and C4, mirroring common setups for detecting wakefulness and drowsiness. Four classifiers were assessed: decision tree, random forest, multilayer perceptron, and support vector machine. The findings reveal that DWT coefficients enhance drowsiness detection performance, surpassing previous methods.**

Keywords—EEG, Drowsiness, DWT, Time-frequency features

I. INTRODUCTION

In this era, cars are the most used means of daily transport. According to Statista, cars account for more than 75% of the means of transport in 2022. Thanks to this great demand, several brands have appeared, reaching autonomous cars that propose several services and improve traditional driving conditions. This development has a direct impact on accident rates in road traffic. However, according to a study conducted by the U.S. Highway Traffic Safety Administration (NHTSA), traffic accident rates still exceed 42,000 fatalities annually [1]. Over 90% of accidents involve the human factor. Few accidents occurred due to purely meteorological or technical causes. Based on [2], it could be said that the majority of road accidents were related to reduced vigilance. Several factors, such as alcohol and drugs, accounted for the direct cause of decreased alertness, but the most difficult to detect is drowsiness. According to Statista, more than 28,000 people died on the road in 2022 because of drowsiness.

Drowsiness [3] is characterized by the gradual decline in cortical processing efficiency, necessitating a larger neural capacity for similar task execution. This loss of efficiency results in the inability to maintain network functions of a higher level of complexity, causing a gradual decline in cognitive abilities. This occurrence is driven by a compelling biological need for sleep. This phenomenon results in several signs such as struggling to keep eyes open, yawning, frequent eye blinking, and difficulty to concentrate. These indications progressively intensify as the level of drowsiness is gauged.

Drowsiness can occur for many reasons, such as medication, extended work hours or prolonged wakefulness, sleep disturbances, or poor sleep quality. To avoid the problem of drowsiness at the wheel, several detection methods have appeared. Generally, there are two main detection methods for drowsiness [4]: The first focuses on the driver, and the second is based on the vehicle. Driver-based measurements are the most effective, especially those based on physiological signals, and more specifically EEG signals, which represent the most accurate indicator of drowsiness [5].

There are several ways to extract the characteristics of EEG signals. Nevertheless, frequency range characteristics (spectral analysis) are most commonly used [6]. On the other hand, this method has limitations for simultaneous time-frequency analysis of EEG signals, which is a necessary prerequisite for the analysis of transient, non-stationary, signals. Several modern techniques have appeared to solve this limitation in the analysis of non-stationary signals like the short time Fourier transform [7] and the Discrete Wavelet Transform (DWT). Among these techniques, the time-frequency insights derived from the DWT appear particularly valuable. DWT represents a very effective tool in the extraction of features from EEG signals for the detection of drowsiness, but most of the studies have used DWT to extract the frequency EEG bands, which eliminates the temporal information [8].

In this work, we propose to use the DWT coefficients directly to detect drowsiness from EEG signals. The different DWT coefficients represent the correlation degree between the wavelet function and the analyzed EEG signal at different instances of time. The DWT coefficients help us to conserve temporal information and extract useful time-frequency features in contrast to other methods. In addition, we investigated the impact of the time segment size on the drowsiness detection performance as well as the effect of different feature selection methods as k-PCA and PCA on approach accuracy [9]. In order to create a drowsiness detection system adaptable to real-life conditions, we work with just two EEG channels: C3 and C4. This proposed extraction method was also compared with two recent feature extraction methods: Tunable Q-Wavelet Transform (TQWT) and Power Spectral Density (PSD) and Entropy.

The rest of this paper is divided as follows: Section II provides a clear description of the EEG-based drowsiness detection system. Sections III describes the EEG data used in this work and the EEG preprocessing. Section IV presents two relevant studies. Section V represents the proposed feature extraction method. Section VI presents the final data and the classification algorithms. Section VII presents the experimental results. The conclusion is presented in section VIII.

II. Drowsiness detection from EEG

In this section, we present the steps required to detect drowsiness from EEG signals.

The initial phase involves EEG data acquisition. Here, we record five EEG signals from diverse subjects exhibiting varying levels of drowsiness. However, EEG signals are susceptible to various artifacts. To address this issue, the subsequent step encompasses the utilization of artifact removal techniques. We employ a low-pass FIR filter [10] and Independent Component Analysis (ICA) [11] to eliminate physiological and non-physiological artifacts. Subsequently, we perform feature extraction, which involves extracting characteristics from EEG signals useful for drowsiness detection. To achieve this, we utilize DWT to extract features in the time-frequency domain. These feature vectors are then fed into classification algorithms [12], enabling the classification of subjects into different states like awake or drowsy. Figure 1 represents the flow chart for detecting drowsiness from EEG signals.

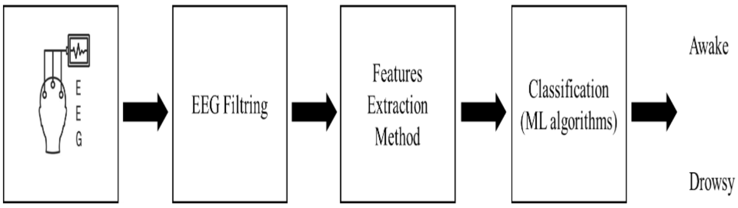

Fig. 1. Flow chart of drowsiness detection system from EEG.

III. Methodology

A. Data description

The data used in this work is referred to the ULg multimodality drowsiness (DROZY) database [13]. The multimodality data of DROZY were collected by the INTELSIG laboratory of the Department of Electrical Engineering and Computer Science of the University of Liège, Belgium. The dataset contains mixed data types of 14 young subjects (3 males, 11 females), composed of physiological signals, EEG, EOG, ECG, and EMG, in addition to videos of each subject. The protocol of the data collection is represented in Figure 2.

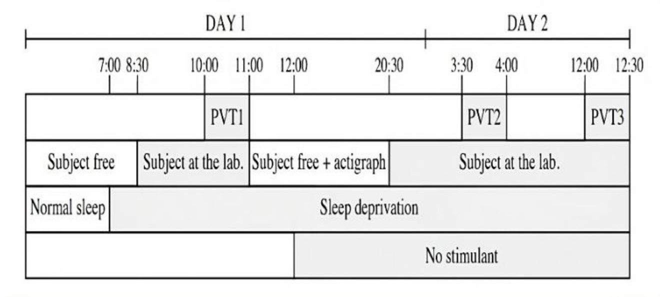

Fig. 2. Protocol of data collection.

The physiological signals of DROZY were recorded by the Polysomnography (PSG) Embla Titanium system. PSG signals are recorded in EDF form, where each EDF file contains five EEG channels: Fz, Cz, C3, C4, and Pz referenced at A1 in the international 10-20 system, as well as two EOG channels (vertical and horizontal), in addition to one ECG channel and an EMG channel. All signals were recorded at a sampling rate of 512 Hz. Figure 3 represents the location of each EEG channel.

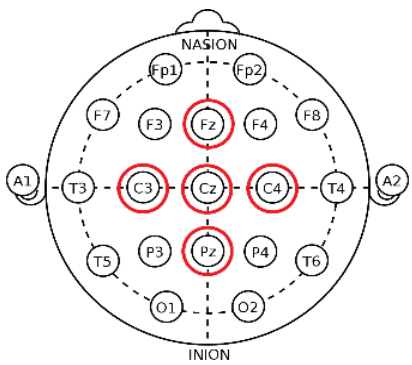

Fig. 3. Location of EEG electrodes.

The experiment is conducted for ten minutes, and the EEG signal contains information for up to six hundred seconds.

Each subject estimates his or her level of vigilance using the KSS scale.

Our work attempts to detect drowsiness at different levels. For this reason, we focus on four subjects (1, 4, 6, and 8) with different KSS scores to explore different arousal states.

B. EEG pre-processing

EEG signals are a non-invasive means of measuring brain activity. On the one hand, multiple types of artifacts can easily infect this type of data. In general, we can distinguish between two types of artifacts: physiological, such as eye activity, breathing, and heart activity, and non-physiological artifacts, caused by cable or body movement, AC electrical, and electromagnetic interference.

In order to remove artifacts [14], four main techniques are available: EEG artifact rejection, source decomposition, filtering, and blind source separation. However, the two first methods are very complex and risk removing several useful EEG pieces of information.

For this reason, and to preserve as much useful EEG information as possible, we use a low-pass FIR filter. This technique helps to remove 50Hz artifacts, known as AC electrical interference. This also removes EEG information, although such frequencies are not usually the focus of studies based on EEG signals. Thereafter, we apply the blind source separation method by using ICA to eliminate EMG and EOG artifacts and reconstruct the clean EEG from the remaining components.

EEG signals in the database are recorded for 10 minutes. Therefore, to effectively study drowsiness, the signal should be divided into smaller time intervals. These time windows are called EEG epochs [15]. The size of the window is chosen based on performance metrics. In this approach, we tested two epoch sizes to see their effects on drowsiness detection efficiency, by applying a sliding window of 30s and then 10s.

IV. RELATED WORK

This section highlights two pertinent studies utilizing TQWT and PSD/Entropy for feature extraction from EEG data, serving as benchmarks for comparison in drowsiness detection.

A. TQWT

The Wavelet Transform (WT) represents an effective tool to analyze EEG signals. Abidi et al. in [16] introduced a novel drowsiness detection approach based on 10s segments from two EEG derivations (C3, O1). Their work consisted in applying the TQWT to extract two EEG sub-bands, Alpha and Theta, and nine temporal features. Finally, they applied kernel Principal Component Analysis (k-PCA) to reduce the characteristics extracted from EEG signals without decreasing the performance of the system. For the detection of reduced vigilance, two different machine learning techniques were used: the k Nearest Neighbors (k-NNs) and the Support Vector Machine (SVM). The classifiers were applied to laboratory subjects. This system indicated about 94% accuracy in the intra-subject mode and 83% in the inter-subject mode.

B. PSD and Entropy

The Fourier analysis represents the most popular feature extraction method for drowsiness detection from EEG signals. Lachtar et al. in [17] used PSD and Entropy as the feature vector to classify two drowsiness states: "Alert" and "Drowsy". In their work, they focused on two EEG sub-bands, Delta and Alpha, from seven subjects. The sampling frequency was set at 500 Hz and EEG data was segmented into 30s segments using a sliding window. After segmentation, they applied the FFT to calculate the PSD and entropy every five seconds. For the classification process, they used SVM with a single EEG derivation (C4). Their proposed method achieved an average classification accuracy of 91.39%.

V. PROPOSED FEATURE EXTRACTION METHOD

This section introduces our proposed feature extraction technique, employing DWT for coefficients extraction. This approach retains vital temporal details, as the DWT coefficients denote the correlation between the EEG signal x(t) and the wavelet function $\psi_{(l,n)}$(t) at distinct time points. Moreover, these coefficients capture valuable insights into the transient activity of EEG signals. Indeed, we utilize the DWT coefficients as features to detect decreased vigilance.

The proposed approach utilizes the 'db4' Daubechies wavelet function for coefficient extraction, as it effectively captures drowsiness-related information from EEG signals [18]. The DWT coefficients are calculated as follows (1) (2):

$$C_{x(t)}(l,n) = \int_{-\infty}^{+\infty} x(t)\ \psi_{l,n}(t)dt \qquad (1)$$

$$\psi_{l,n}(t) = 2^{-(l+1)}\psi(2^{-(l+1)}(t-2^{-l}n)) \qquad (2)$$

where x(t) represents the EEG signal, and l and n represent the scale and translation variables of the wavelet function, respectively.

In the DWT output, we identify two coefficient ranges. The 'Detail' coefficients pertain to high-frequency details, while the 'Approximation' coefficients correspond to the approximation of the time domain original signal. Refer to Figure 4 for the wavelet function's coefficient decomposition from the EEG signal.

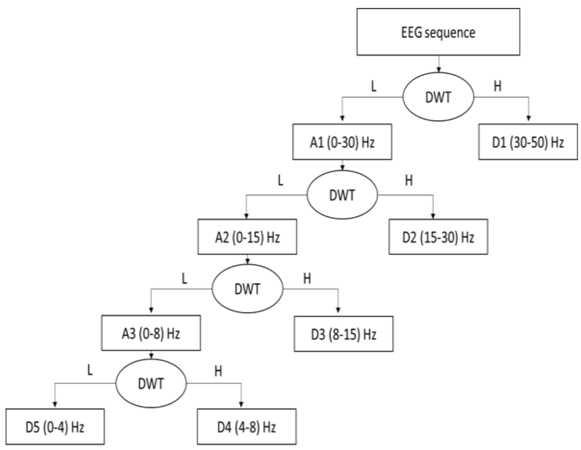

Fig. 4. Four-level wavelet decomposition of EEG.

After extracting the DWT coefficients, we calculate the energy, the entropy, the standard deviation, and the mean of the range of all coefficients (cD and cA). Table I represents all these features.

TABLE I. ALL FEATURES

DWT Detail coefficients (cD)	DWT Approximation coefficients (cA)
Energy	Energy
Entropy	Entropy
Standard deviation	Standard deviation
Mean	Mean

The DWT coefficients $C_{x(t)}(l, n)$ often exhibit redundancies, potentially carrying information not related to drowsiness. To address this, we suggest evaluating two feature selection techniques, k-PCA and PCA, aimed at mitigating redundancies and retaining pertinent drowsiness-related features. Through this process, DWT coefficients with minimal variance across training samples are discarded, while those with substantial variance are emphasized. The selection of the principal components is determined by accuracy classification.

VI. FINAL DATA AND CLASSIFICATION ALGORITHMS

Each DROZY subject possesses one record during wakefulness and two records during drowsiness, all rated on the KSS scale. In this work, we extract features from the trials of alertness marked as stage '1' after applying a normalization operation. Similarly, for drowsiness, we undertake the same procedure, labeling features as characteristics of stage '2' to ensure a binary classification. DROZY EEG signals, captured with five electrodes, yield eight features each, resulting in a cumulative feature count of 40.

EEG signals exhibit the ability to preemptively detect decreased alertness, devoid of physical cues. However, their intricacy, substantial size, and non-linearity pose challenges. To overcome these issues, we opted to test four classifiers capable of handling nonlinearity, complexity, and high-dimensional data. These classifiers also excel in feature selection and noise resilience, rendering them ideal for establishing a binary classification approach to identify drowsiness from EEG features. These classifiers are respectively the Decision Tree (DT), the Random Forest (RF), the Multilayer Perceptron (MLP), and the Support Vector Machine (SVM) [19].

Since each individual reacts differently to drowsiness, the classification algorithms were trained separately for each subject. The input data from each subject is partitioned into 70% for training and 30% for testing, yielding the overall classification accuracy through mean calculation across subjects. To assess the efficiency of the classifiers, the confusion matrix, shown in Figure 5, was used.

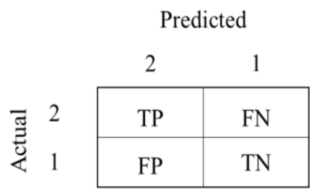

Fig. 5. Confusion matrix of binary drowsiness classification.

- True Positive (TP): Prediction of drowsiness when the real state is drowsiness;
- False Positive (FP): Prediction of drowsiness when the real state is alertness;
- True Negative (TN): Prediction of alertness when the real state is alertness;
- False Negative (FN): Prediction of alertness when the actual state is drowsiness.

The equations of the performance indicators are presented in (1), (2), (3), (4):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score} = \frac{TP}{TP+(\frac{FN+FP}{2})} \quad (4)$$

VII. RESULTS AND DISCUSSION

In this section, we discuss the effect of segment size on the accuracy of the drowsiness detection system, followed by an exploration of the impact of the different feature selection methods on accuracy. Subsequently, we rationalize the system by reducing the number of electrodes to create a system better suited to real-world use.

We first evaluate the impact of two segment sizes (30s and 10s). Results for segments 30 and 10 are shown in Table II. Based on these results, we can say that 10s segments provide better accuracy regardless of the classifier used.

TABLE II. CLASSIFICATION ACCURACY WITH 30S AND 10S SEGMENTS

Classifier	Classification accuracy (%) (average for 4 subjects)	
	30s segments	*10s segments*
DT	88	93
RF	90	96
MLP	82	97
SVM	91.25	97

DWT coefficients can encompass superfluous information, unrelated to drowsiness, so we used two feature reduction techniques (k-PCA and PCA) to choose the most effective alternative for drowsiness detection. The classification results with PCA and k-PCA are shown in Table III.

TABLE III. CLASSIFICATION WITH PCA AND K-PCA

With PCA				
Classifiers	**Precision (%)**	**Sensitivity (%)**	**F1-score (%)**	**Accuracy (%)**
DT	93.4	94.7	94.2	94.5
RF	96,5	97	96.7	97.2
MLP	95.8	96.8	97.3	97.2
SVM	**97.8**	**97.5**	**96.8**	**98**
With k-PCA				
Classifiers	**Precision (%)**	**Sensitivity (%)**	**F1-score (%)**	**Accuracy (%)**
DT	93.2	92.7	93.8	94
RF	97.3	97.7	98	98
MLP	96.7	97.8	97.3	98
SVM	**97.9**	**98.3**	**98.7**	**99**

From the results presented in Table III, we can see that, compared to PCA, k-PCA is slightly more efficient in eliminating redundancies in DWT coefficients. In both cases, SVM represents the classifier with the highest accuracy (99%).

Employing five electrodes lacks real-life adaptability. However, using a single electrode for drowsiness detection, as some approaches propose, is not robust enough as system failure can occur if the electrode malfunctions or loses scalp contact. For these reasons, in particular computing energy efficiency, we opt for two electrodes. Thus, to identify the suitable channels, we evaluated the SVM performance using individual channels. Table IV showcases the outcomes for each EEG derivation. As detailed in Table IV, when evaluated individually, derivations C3 and C4 give us the best accuracy. When combined, the SVM classifier shows 97% accuracy, which is 2% less than using all 5 electrodes.

TABLE IV. AVERAGE ACCURACY IN DIFFERENT EEG DERIVATIONS

EEG derivation	**SVM accuracy (%)**
Fz	84
Cz	84
C3	**88**
C4	**95**
Pz	86

We also compared our approach with two other drowsiness detection methods [16] [17] and, according to the results, it seems that the proposed method offers higher accuracy even with a single EEG channel.

TABLE V. PERFORMANCE COMPARISON

Method	**Features**	**Classifier**	**Accuracy (%)**
[16]	TQWT (band power + statistics features)	SVM	94
[17]	PSD + Entropy	SVM	91.39
Proposed method	**DWT coefficients**	**SVM**	**95**

VIII. CONCLUSION

This study introduced a novel approach for drowsiness classification using EEG signals. In this approach, DWT coefficients are employed as features extracted from just two EEG derivations.

The publicly accessible DROZY database from ULg was chosen due to its multimodal signals. Five EEG channels (C3, C4, Cz, Pz, Fz) were extracted from that database. To filter out high-frequency components and eliminate EOG and EMG artifacts, a low pass filter with a 50 Hz cutoff is applied alongside ICA. Given the ten-minute recording duration of the Drozy EEG signals, the signal was divided into frames via a sliding window to facilitate analysis. This study also assesses the impact of two epoch sizes on drowsiness detection precision.

In our approach, features were computed in the time-frequency domain through DWT coefficients. As the database contained one alertness trial and two drowsiness trials, extracted feature sets were normalized and labeled '1' for alertness and '2' for drowsiness. These combined trials constituted the evaluation dataset. Utilizing this dataset, DT, RF, MLP, and SVM models were trained to evaluate the efficacy of DWT coefficients in detecting decreased alertness in the intra-subject mode. Notably, SVM outperformed other algorithms with a 97% classification accuracy using just two electrodes, C3 and C4.

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