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# Feature extraction method for classification of alertness and drowsiness states EEG signals

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ABSTRACT

Drowsy driving is one of the major causes of road accidents. The road accidents can be avoided by the discrimination of alertness and drowsiness states of the drives. The neurological changes in alertness and drowsiness states can be asses by electroencephalogram (EEG) signals. In this paper, the non-stationary characteristic of the EEG signal is explored by tunable Q-factor wavelet transform (TQWT). TQWT decomposes the EEG signal into sub-bands, which further used for the extraction of features. Statistical features of the Hjorth mobility such as minimum value, maximum value, mean and standard deviation (SD) are used for characterization of the alertness and drowsiness states. Various classifiers such as decision tree, logistic regression, fine Gaussian support vector machine, weighted KNN, ensemble boosted trees and extreme learning machine (ELM) are considered. The alertness and drowsiness EEG signals discriminative performance of TQWT-based features are assessed by the Kruskal-Wallis (KW) test. The results of KW-test show that the proposed features are effectively discriminative of the alertness and drowsiness states. According to the obtained results, the best accuracy score of 91.842% is produced by the ELM classifier.



## 1. Introduction

According to the statistics of the U.S. National Highway Traffic Safety Administration (NHTSA), the drowsiness is one of the main causes of deadly traffic accidents and injuries [1]. So, the drivers are asked to have a clear sleep before having a long period driving. In addition car manufacturing companies have been working on new embedded drowsiness detection systems for various conditions. These new designed cars will warn the drivers if any drowsiness indication is detected. A camera mounted on the rearview mirror can detect the yawning and blinking which can be seen as the indications of the drowsiness. The electroencephalogram (EEG) recordings are another solution for the discrimination of the drowsiness and alertness states [2,3]. Various works about EEG based drowsiness detection have been performed by the researchers in the last decades. In that works, authors have used various feature extraction methods for the detection of alertness and drowsiness states.

In [4], the authors opted to use the fast Fourier transform (FFT) based features for EEG based drowsiness detection. Nine dimensional feature vectors and two well-known classifiers namely support vector machine (SVM) and artificial neural network (ANN) were used by the authors. The authors mentioned that ANN was outperformed where the accuracy was 83.5%. Detection of drowsiness using respiratory signal analysis was presented in [5]. The analysis of respiratory rate variability was carried to monitor the state of drivers drowsiness. In [6], detection of drowsiness was carried out by blood volume pulse, eye blink and yawning signals captured from different sources. In [7], the authors proposed an EEG based drowsiness detection system that uses the alpha rhythm of the EEG recordings. A simple thresholding mechanism was adopted for detection of the drowsiness and alertness states. Authors mentioned that their method was independent of drivers and almost 85% accuracy was obtained. In [8], the authors used wavelet transform (WT) in order to detect the drowsiness and alertness states of EEG signals. The alpha and beta channels of the EEG signals were considered and the most significant m-terms from the WT were investigated. 84.98% sensitivity and 98.65% precision scores were reported by the authors. In [9], the EEG signals have been decomposed into sub-bands and various non-linear features used in extreme learning machine (ELM) classifier. In [10], the spectral features and multiple classifiers were used to discriminate the drowsiness and alertness states of the

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EEG recordings. In [11], authors used time, spectral and WT based features in order to detect the drowsiness state in EEG signals. A nineteen dimensional feature vector has been constructed and classified into drowsiness and awake states. The obtained accuracy scores were 87.4% and 83.6%, respectively. In [12], authors used empirical mode decomposition (EMD) based method which uses AM-FM components to extract the rhythm-based features that have been used for the discrimination of alertness and drowsiness EEG signals. To categorize the awekening and sleep transition over EEG epochs Higuchi's fractal dimension and Petrosia's fractal dimension have been proposed using ANN classifier [13].

In [14], the Parseval's energy theorem obtained energy coefficients revised by input-output clustering and applied to ANN classifier for the recognition of alertness and drowsiness states. The reported accuracy was 90.27%. In [15], an adaptive Hermite decomposition (AHD) based features have been proposed for the detection of drowsiness state from EEG signals. The authors used ELM in classification of the AHD features into drowsiness and alertness states with an accuracy of 92.28%. In [16], power spectral density (PSD) and WT were used for EEG based drowsiness detection. The alpha and theta rhythms were used for PSD features. Four PSD features were extracted and the numbers of zero crossings were considered on the WT. 84.1% accuracy score was reported by the authors. In [17], authors used RR time series for EEG based drowsiness detection. The RR time series were decomposed into intrinsic mode functions by using an iterative filtering process. The deep neural network classifier was adopted and 73.70% overall classification accuracy was reported. A multimodal analysis has been explored for detection of drowsiness [18]. Determinism features by recurrence qualification analysis with SVM and Bayes classifiers have been proposed for drowsiness identification in [19].

In this paper, tunable Q-factor wavelet transform (TQWT) for the identification of drowsiness EEG signals is explored. Time domain features are extracted from the sub-bands of TQWT are used in different type classifiers for classification of the alertness and drowsiness states.

## 2. Methodology

### 2.1. Dataset

This work uses the MIT/BIH Polysomnographic database [20]. The database contains multiple physiological signals recording. The EEG recordings are used for discrimination of alertness and drowsiness states. The detail description of the used dataset is available in [20]. Fig. 1 shows, the alertness and drowsiness EEG signals, while the method for illustration example of alertness and drowsiness EEG signal classification is shown in Fig. 2.

### 2.2. Tunable Q-factor Wavelet Transform (TQWT)

For processing and analysis of oscillatory signals TQWT proved to be a powerful technique [21]. The input signal can be decomposed into multiple low pass sub-bands and high pass sub-bands with TQWT with very fast response time. $N$ + 1 sub-bands are obtained by decomposition of input signal, where $N$ is the number of stages of two channel filter banks. The decomposition of an input signal into $N$ + 1 sub-bands is shown in Fig. 3a. and Fig. 3b. shows the structure of first level filter bank. The TQWT is specified by three parameters: Q-factor ($Q$), redundancy ($r$), and the number of stages (or decomposition levels) ($J$) which are known as tuning parameters of TQWT. The parameter $J$ denotes the number of filter banks. The TQWT provides the sub-bands of EEG signals are shown in Fig. 4. After, $N$ stages the frequency response of low pass $H_0^N(\omega)$ and high pass $H_1^N(\omega)$ sub-bands can be given as [21],

$$H_0^N(\omega) = \begin{cases} \prod_{m=0}^{N-1} H_0\left(\frac{\omega}{\alpha^m}\right), & |\omega| \leqslant \alpha^N \pi \\ 0, & \alpha^N \pi < |\omega| \leqslant \pi \end{cases} \quad (1)$$

$$H_1^N(\omega) = \begin{cases} H_1\left(\frac{\omega}{\alpha^{N-1}}\right) \prod_{m=0}^{N-2} H_0\left(\frac{\omega}{\alpha^m}\right), & (1-\beta)\alpha^{N-1}\pi \\ & \leqslant |\omega| \leqslant \alpha^{N-1}\pi \\ 0, & \omega \in [-\pi, \pi] \end{cases} \quad (2)$$

Filter bank high pass and low pass filters scaling factors $\alpha$ and $\beta$ are respectively defined as:

$$\alpha = 1 - \beta/r \quad (3)$$

$$\beta = 2/(Q+1) \quad (4)$$

TQWT decomposes the alertness and drowsiness EEG signals into sub-bands. The time domain measures of sub-bands of TQWT are used as features for alertness and drowsiness states. The discrimination ability of extracted features from both the classes is evaluated using the Kruskal-Wallis (KW) test. The advantage of using the KW-test for features, it is a non-parametric method that does not require the normal distribution assumption for test samples.

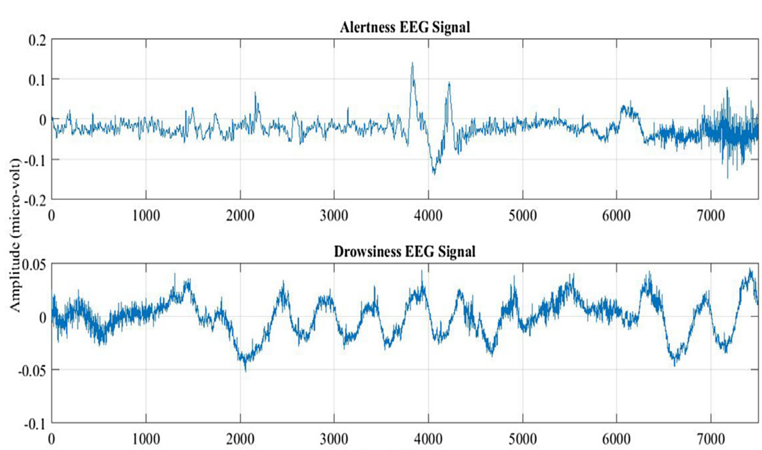


**Fig. 1.** The alertness and drowsiness EEG signals.

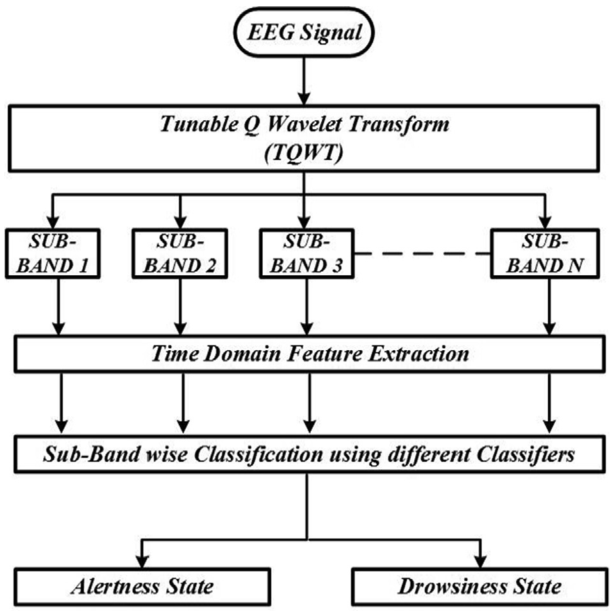


**Fig. 2.** TQWT based method for classification of Drowsiness and Alertness stages of EEG signal.

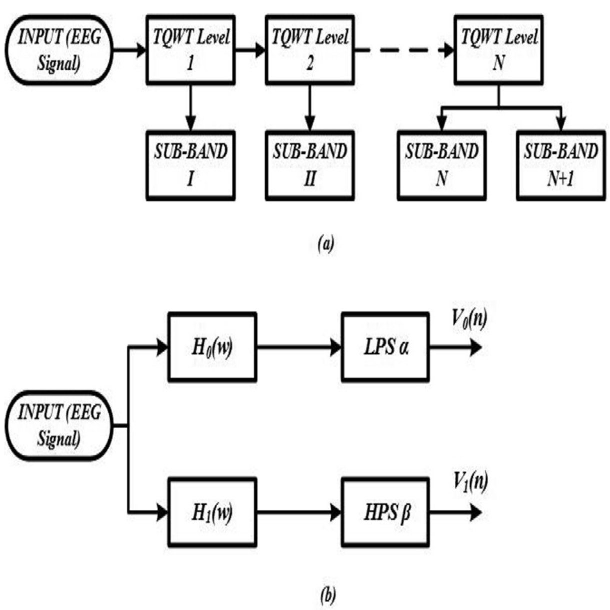


**Fig. 3.** a. TQWT based decomposition level of input signal. b. First stage of filter bank.

### 2.3. Feature extraction

The statistical measures of sub-bands of TQWT are used as the features for classification of the activity. The statistical measures used in this work are Hjorth mobility (HM), minimum value (Minima), maximum value (Maxima), mean and standard deviation (SD). Maxima, minima, mean and standard deviation are the features that can access the variation in the data points.

#### 2.3.1. Hjorth mobility (HM)

Hjorth mobility [22] is the representation of the mean frequency or the portion of the standard deviation of the power spectrum, and it is the square root of the ratio of variance of first derivative to the variance of the signal.

$$HM = \sqrt{\frac{\left(var\left(\frac{dy(t)}{dx}\right)\right)}{(var(y(t)))}} \tag{5}$$

#### 2.3.2. Minima

It is the minimum value among all the instances.

$$Minima = min(y(t)) \tag{6}$$

#### 2.3.3. Maxima

It is the maximum value among all the instances.

$$Maxima = max(y(t)) \tag{7}$$

#### 2.3.4. Mean

Mean is the average of all the instances.

$$Mean(\hat{y}) = \frac{\sum y(t)}{N} \tag{8}$$

#### 2.3.5. Standard deviation

.

$$Standard\,Deviation\ (\sigma) = \sqrt{\frac{\sum [y(t) - \hat{y}]^2}{N}} \tag{9}$$

where N is the total number of instances.

### 2.4. Classifiers

In this paper, different types of classifiers namely decision tree (DT), logistic regression (LR), fine Gaussian support vector machine (FG-SVM), weighted K-nearest neighbour (W-KNN), ensemble boosted trees (EBT) and extreme learning machine (ELM) are explored. Decision tree classifier [23] uses a tree like structure to make the decision based on the human behavioral interpretation to choose correct one from a group of two. Logistic regression uses a sigmoid activation function in order to classify the two classes using non linear relationship. Fine Gaussian support vector machine [24] can be used for binary classification or for multi-class classification that offers fast prediction and medium memory usage in case of binary and slow in multiclass classification problems. Weighted KNN [25] is another efficient classifier that uses sum of the weights of associated classes, where the element is assigned to the class which has got highest sum of the weights among the target classes. EBT [26] does not require input features to be whitened or normalized, they are flexible as they are supported by custom loss functions, can attack arbitrary classification and regression tasks. Also, EBT produces compact model with fever parameters for the same accuracy as compared to other classifiers. Extreme learning machine [27,28] is a feed forward single layer hidden layer neural network which is developed to handle data having high dimensionality and mostly preferred for multiclass classification. It requires very fever number of hidden nodes due to which it has got shorter response time compared to other classifiers.ELM works with linear as well as non linear activation functions.

## 3. Results and discussion

The dataset contains EEG signals of 480 subjects with drowsiness and 660 subjects in an alert state. Tunable Q- wavelet transform decomposes the signal into subbands. The signal have been

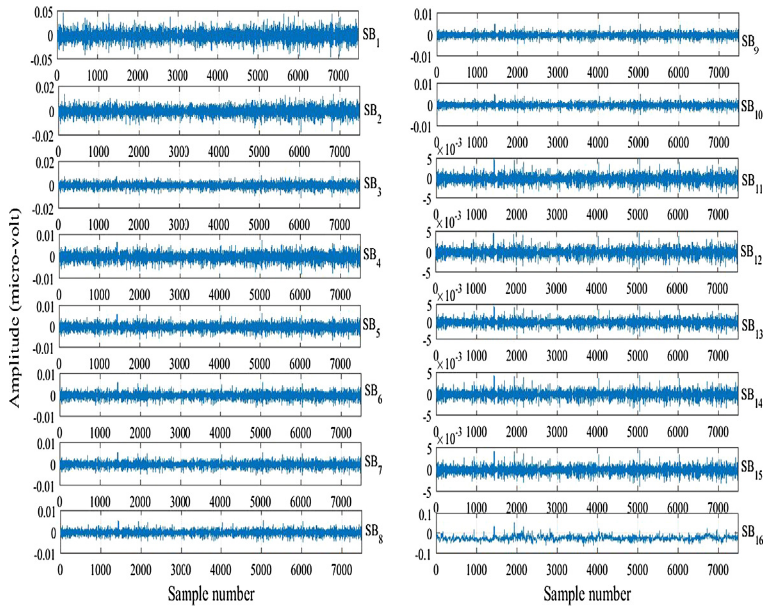

**Fig. 4.** TQWT provided sub-bands of an EEG signal.

decomposed by selecting the parameters of TQWT with values *Q = 1, r = 3, J = 7*. From the 8 sub-bands five time-domain features are extracted namely Hjorth mobility, Maxima, Minima, Mean and Standard deviation. The Kruskal Wallis (KW) test, which is non-parametric analysis of variance test, calculates the probabilistic values of the features for each sub-band. Table 1 shows probabilistics values comparison of sub-bands with each time domain feature. Feature matrix is formed by using these five features for the two classes making the matrix of size $5 \times 480$ and $5 \times 660$ for drowsiness and alertness respectively, representing rows as features and columns as the observations. The matrix used as input to different classifiers to evaluate the performance, performance parameters are compared with other existing methods.

Classification accuracy of six different classifiers is compared with different sub-bands whose comparison is shown in Table 2. The different classifiers have been used 10 cross-validation technique. Table 3 gives the values of different performance parameters for different sub-bands with the ELM classifier. In this method has been evaluated by 7 different parameters namely Accuracy (ACC), Sensitivity (SSE), Specificity (SPE), F1-Score, False Positive Rate (FPR), Recall (RCL) and Error (ERR) to compute the performance of classifier. Values in bracket beside every performance parameter in Table 3 denotes the ideal values of each parameter. Table 4 shows the performance report of the proposed method with other existing methods performed over same dataset. Table 4 compares the method proposed in this paper with other methods existing along with the technique used in classification. The performance of the proposed TQWT based method with Extreme Learning Machine classifier gives the highest classification accuracy of 91.842%, sensitivity of 96.515%, specificity of 85.417%, F1-Score of 0.933 and Recall of 0.965 in sub-band 1 while gives the lowest values of False Positive Rate 14.583% and Error of 8.158% corresponding to the same sub-band.

## 4. Conclusion

Early detection of driver drowsiness and developing an early warning system may prevent some of the car accidents worldwide. The research groups of the car companies have been working on such systems long ago. This paper proposed TQWT-based features for discrimination of drowsiness and alertness EEG signals. TQWT decomposed the EEG signals into band-limited sub-bands. The drowsiness and alertness EEG signals characteristics from TQWT provided sub-bands are extracted using the time domain measures. These measures are based on the statistics of Hjorth mobility. The minimum and the maximum values, the mean and the standard deviation are statistical measures that are used. In addition, various classifiers such as DT, LR, FG-SVM, W-KNN, EBT, and ELM are used. The KW plot analysis of TQWT-based features confirms that the proposed features effectively discriminate the drowsiness and alertness states. The obtained results show that sub-band 1 is the most convenient band for drowsiness detection where ELM produced 91.842% accuracy score. The performances of the classifiers are compared it is notice that the ELM provides

**Table 1**
p-Values of the features of sub-bands.

| Features | Maxima | Mean | Minima | Mobility | SD |
|---|---|---|---|---|---|
| SB-1 | $7.078 * 10^{-18}$ | $3.630 * 10^{-13}$ | $1.504 * 10^{-16}$ | $9.090 * 10^{-04}$ | $2.407 * 10^{-35}$ |
| SB-2 | $7.233 * 10^{-23}$ | $2.314 * 10^{-10}$ | $1.609 * 10^{-21}$ | $1.535 * 10^{-04}$ | $6.237 * 10^{-45}$ |
| SB-3 | $2.752 * 10^{-24}$ | $2.149 * 10^{-09}$ | $1.200 * 10^{-22}$ | $8.781 * 10^{-04}$ | $8.691 * 10^{-48}$ |
| SB-4 | $2.195 * 10^{-25}$ | $2.713 * 10^{-12}$ | $1.175 * 10^{-23}$ | $6.596 * 10^{-04}$ | $3.576 * 10^{-49}$ |
| SB-5 | $2.104 * 10^{-26}$ | $7.076 * 10^{-09}$ | $1.814 * 10^{-24}$ | $2.760 * 10^{-04}$ | $5.580 * 10^{-50}$ |
| SB-6 | $3.288 * 10^{-27}$ | $1.281 * 10^{-09}$ | $3.982 * 10^{-25}$ | $9.968 * 10^{-05}$ | $1.238 * 10^{-50}$ |
| SB-7 | $8.523 * 10^{-28}$ | $1.889 * 10^{-09}$ | $9.312 * 10^{-26}$ | $4.299 * 10^{-05}$ | $3.919 * 10^{-51}$ |
| SB-8 | 0.17 | $5.938 * 10^{-26}$ | $1.599 * 10^{-03}$ | $8.480 * 10^{-51}$ | $5.694 * 10^{-05}$ |

**Table 2**
The proposed method classification accuracy (%) with different classifiers.

| Subband | DT | LR | FG-SVM | W-KNN | EBT | ELM |
|---|---|---|---|---|---|---|
| SB1 | 74.7 | 72 | 74.2 | 73.1 | 75.8 | 91.842 |
| SB2 | 73.1 | 71 | 75 | 71.9 | 74.6 | 86.140 |
| SB3 | 74.4 | 71.5 | 73 | 71.7 | 75.8 | 85.008 |
| SB4 | 74 | 72.5 | 72.5 | 70.6 | 75.8 | 84.737 |
| SB5 | 73.9 | 73.5 | 72.3 | 71.2 | 75 | 86.228 |
| SB6 | 72.1 | 73.3 | 73 | 72.2 | 73.9 | 86.579 |
| SB7 | 74.6 | 73 | 74.6 | 72.6 | 74.7 | 87.368 |
| SB8 | 73.8 | 75.5 | 76.7 | 75.6 | 77.3 | 78.158 |

**Table 3**
Different Performance Parameter for different Sub-Bands for Extreme Learning Machine Classifier.

| Subband | ACC (100) | SSE (100) | SPE(100) | F1-Score(1) | FPR(1) | RCL(1) | ERR(0) |
|---|---|---|---|---|---|---|---|
| SB1 | 91.842 | 96.515 | 85.417 | 0.933 | 14.583 | 0.965 | 8.158 |
| SB2 | 86.140 | 93.182 | 76.458 | 0.886 | 23.542 | 0.932 | 13.860 |
| SB3 | 85.008 | 89.091 | 79.375 | 0.873 | 20.625 | 0.891 | 14.992 |
| SB4 | 84.737 | 88.182 | 80.00 | 0.870 | 20.00 | 0.882 | 15.263 |
| SB5 | 86.228 | 90.152 | 80.833 | 0.883 | 19.167 | 0.902 | 13.772 |
| SB6 | 86.579 | 90.00 | 81.875 | 0.886 | 18.125 | 0.900 | 13.421 |
| SB7 | 87.368 | 90.445 | 83.125 | 0.893 | 16.875 | 0.905 | 12.632 |
| SB8 | 78.158 | 83.182 | 71.250 | 0.815 | 28.750 | 0.832 | 21.842 |

**Table 4**
Classiifcation performance report of the same dataset.

| Authors | Method | Classiifer | No of Features | Accuracy |
|---|---|---|---|---|
| Correa 2010 [16] | PSD | Artificial neural network | 12 | 84.1 |
| Correa et al. 2014 [9] | MA | Artificial neural network | 7 | 85.66 |
| Boonnak et al. 2015 [13] | ECPD | Artificial neural network | 7 | 90.22 |
| Belakhdar 2016 [4] | FFT | Artificial neural network | 9 | 84.75 |
| Tripathy 2018 [17] | BPF | Deep neural network | 10 | 85.51 |
| Anitha 2019 [18] | Mutimodel | Support vector machines | 8 | 87.2 |
| Proposed method | TQWT | ELM | 5 | **91.842** |

best classifier. While comparing the different performance parameters of the ELM classifier for different sub-bands, sub-band 1 produces the best result of ACC with 91.842%, SSE of 96.515%, SPE, F1-Score and Recall with 85.417%, 0.933 and 0.965 respectively. Also lowest values of Error and FPR produced for the same sub-band with values 8.158% and 14.583% respectively. The output of the proposed method with suitable classification algorithm can be used for drowsiness detection system for avoiding the road accidents.

## Conflict of interest

There is no conflict of interest.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.apacoust.2020.107224.

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