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# A sleep monitoring method with EEG signals

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**Abstract.** Diagnosis of sleep disorders is still a challenging issue for a large number of nerve diseases. In this sense, EEG is a powerful tool due to its non-invasive and real-time characteristics. This modality is being more and more used for diagnosis such as for epilepsy. It is also becoming widely used for many predictive, Preventive and Personalized Medicine (PPPM) applications.

To understand sleep disorders, we propose a method to classify EEG signals in order to detect abnormal behaviours that could reflect a specific modification of the sleep pattern. Our method consists of extracting the characteristics based on temporal and spectral analyses with different descriptors. A classification is then performed based on these features. Validation on a public available database show promising results with high accuracy levels.

**Keywords:** Sleep disorders prediction, EEG, Signal classification, SVM, PPPM

## 1 Introduction

One of the crucial issues in the development of cognitive and clinical neuroscience is undoubtedly the ability to track over time and to precisely locate human brain activity. Sleep detection is one of the most active research topics in biomedical signal processing. This involves the acquisition and recording of a set of physiological signals, followed by visual analysis to establish the diagnosis. Assessing sleep disorders is also an important step to prevent further physical and mental complications. This could be done for instance to predict and prevent sleep apnea.

Several methods for sleep exploration have been proposed during the last decades. The basic examination, called polysomnography, allows to group the recording of several variables by mentioning for example the electrical activity of the brain, the activity of the muscles of the face and the chin, sometimes muscles legs, the activity of eyeballs and also the electrical activity of the heart.

This study is mainly based on the electroencephalogram (EEG) signal which presents the result obtained by a recording of electrical signals transmitted by means of electrodes applied on the scalp. This recording is a potential difference between the electrodes excited by the neurons.

In 2009 with Li et al [7], the EEG signals are analyzed with the Hilbert-Huang

transformation, the energy frequency distribution of the EEG is used as a function parameter for each sleep stage. This method gave a classification rate of 81.7% using the k nearest neighbor method. In 2010, Tagluk et al [9] used frequency analysis, specifically using the power spectral density. An artificial neural network technique is the used for classification. This system gave a recognition rate up to 76.8%.

In 2012, Fraiwan et al [2] used Hilbert transformations and continuous wavelet transformations to extract the characteristics with an accuracy rate of 83%, relying on a random forest classification method.

In 2013, Lajnef et al [6] used variance, Skewness, Kurtosis and energy permutations as features, and the SVM classification method was considered achieving an accuracy level of 92%. The performance of the method was evaluated using polysomnographic data of 15 subjects (electroencephalogram (EEG), electrooculography (EOG) and electromyogram (EMG) recordings.

In 2015 Kayikcioglu et al [5] reached a 91% classification rate with LPC (Partial Least Squares Regression) using an auto-regressive method. The results were compared with those of other classifiers, such as k nearest neighbor (k-NN), linear discriminant (LDC) and Bayes classifiers.

More recently, Alickovic et al [1] used the decomposition based on iterative filtering with SVM as classifier. This system achieved a classification rate of 91.1%.

In this work, a feature-based method for EEG data classification is proposed with additional features and a dimension reduction strategy.

The rest of this paper is organized as follows. Section 2 formulates the problem. The proposed method is then presented in Section 3, while experimental results are drawn in Section 4. Finally, conclusions and future work are given in Section 5.

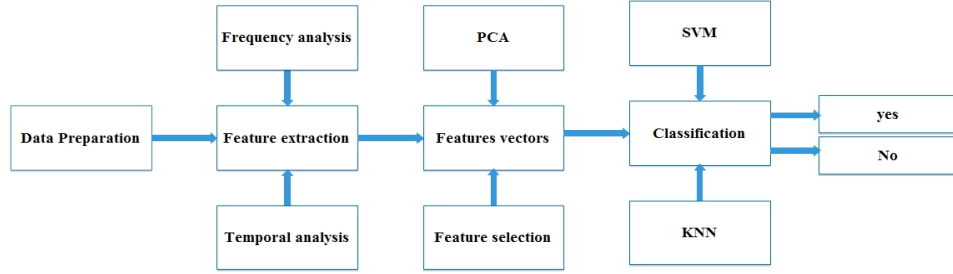
## 2 Problem formulation

The EEG signal is complex, its inspection gives inaccurate information; to improve its sensitivity, the plot is cut into short observation windows. Each window undergoes a mathematical analysis intended to extract quantitative parameters. In this paper, the parameters extracted from EEG signal in order to identify the recognition of the state through a study of classifications. Secondly, we go on to describe the method used in our work that specifies the performance of our research.

## 3 Proposed Method

The basic structure of the method proposed in this paper is given in fig 3. It can be seen that it has three main modules: the first is Data Preparation ; the second is feature extraction; the third is dimension reduction; and finally classification. In this section, we provide detailed explanation of each module.

We performed a windowing with a frame in 2 seconds. Then we varied the size of the window (3s). The best results were obtained for the size of 2 seconds. So we decided to decrease the frame to have a better result we advocated to 1 second and 0.5 seconds. Which leads to deduce that the window a second is the one that suits the most.



**Fig. 1.** Structural diagram of the proposed method for sleep monitoring.

### 3.1 Feature extraction

The main interest in signal processing is to extract as much information as possible on the temporal or frequency structure of these signals. It is therefore necessary to break down the signal on functions well localized in both time and frequency.

**dwt** The discrete wavelet transform analysis the signal at different frequency bands with different resolutions by decomposing the signal with a rough approximation and detailed information. The basic principle of the discrete wavelet transform is to separate the signal into two components, one representing the shape of the signal, the other representing its details. The general appearance of a function is represented by its low frequencies, the details by its high frequencies.

**Energy** The most traditional features among wavelet-based methods is the measurement of energy in each sub-band. Mathematically, it is presented as follows:

$$ED_i = \sum_{j=1}^N |D_{ij}|^2. \quad (1)$$

$$EA_i = \sum_{j=1}^N |A_{ij}|^2. \quad (2)$$

**Shannon's entropy** The entropy here is a reflection of the amount of information present at each sub-band, where  $X$  is a discrete scalar random variable with realizations  $x_1, \dots, x_n$  and the probability distribution  $p_1, \dots, p_n$  measure his disorder. For a source  $X$  having  $n$  symbols, a symbol  $i$  having a probability  $p_i$  to appear, the entropy  $H$  of the source  $X$  is defined as:

$$H(x) = - \sum_{i=1}^n p_i \log_2 p_i. \quad (3)$$

**Variance** Variance is the measure of the dispersion of a set of data points around their mean value, it is defined as follows:

$$v(x) = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}. \quad (4)$$

avec  $\bar{x} = \sum_{i=1}^n p_i x_i$  et  $n$ : total number of data points

**Mean** We can define the mean  $M$  of a data vector  $X$  as follows:

$$M = \frac{1}{n} \sum_{i=1}^n x_i. \quad (5)$$

**Minimum** This is the minimum value of an  $X$  data vector.

**Maximum** This is the maximum value of a data vector  $X$ .

**energy ratio** Each of the brainwaves (delta, theta, alpha and beta) occupy a quantity of the energy of the EEG signal. We proceed to a quantitative study of the energetic ratios of each of the waves compared to the global energy of the signal. The energy ratio is calculated by the ratio between the wave energy ( $E_0$ ) and the total energy of the signal ( $E_s$ ).

$$RE = \frac{E_0}{E_s}. \quad (6)$$

**Frequency analysis** The frequency characteristics of a time series can be written by calculating its power spectral density (DSP).

$$DSP(v) = \lim_{N_k \rightarrow \infty} \frac{1}{2N_k + 1} E(|FFT(v)|^2). \quad (7)$$

### 3.2 dimension reduction

**PCA** which consists of replacing the initial set of data with a new reduced set constructed from the initial set of characteristics.

**Feature selection** which consists in selecting the most relevant characteristics from the dataset of the variables describing the phenomenon studied.

### 3.3 Classification

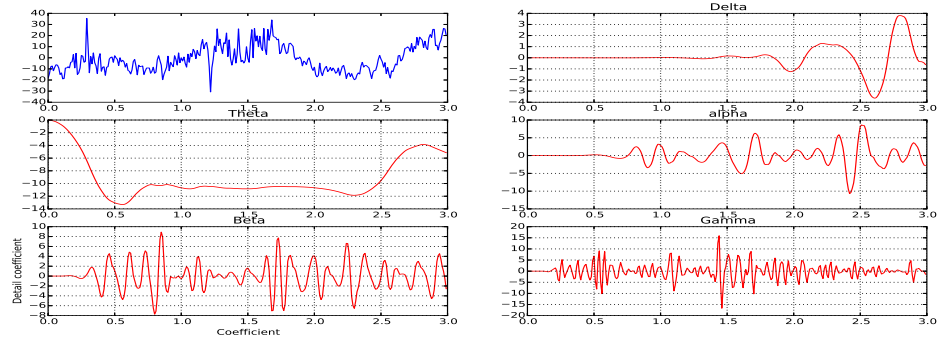
**SVM** is a binary classification method by supervised learning. This method relies on the existence of a linear classifier in an appropriate space. Since this is a two-class classification problem, this method uses a learning dataset to learn the model's parameters.

**KNN** is a method based on memory, which unlike other statistical methods, requires no learning. It works according to the intuitive principle that the closest objects are most likely to belong to the same category. Thus, with the  $k$  nearest neighbors method, forecasts are based on a set of prototype examples that are used to predict new data.

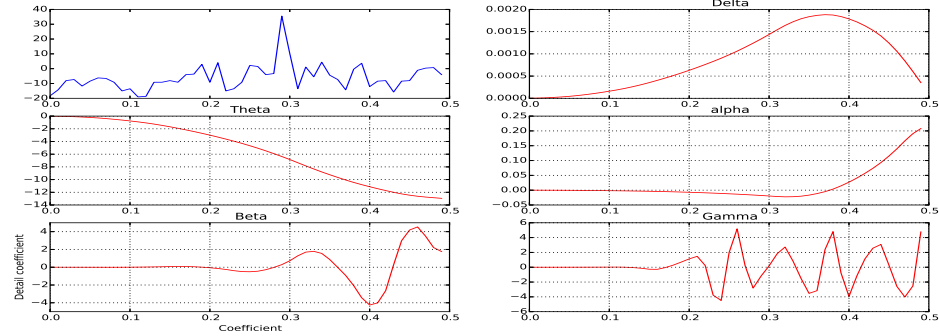
## 4 Experimental Results

**data set** Our database is a record taken from the "Physio Bank" [3], in the form EDF "European Data Format"; EDF is a file that contains separate lines according to the samples. It can have several sampling frequencies as it can contain several signals; in our case he can present an EEG and an EOG together. This database is registered for eight Caucasian people (men and women) between the ages of 21 and 35, healthy (who do not have trouble sleeping) and without medication. The records are named sc4002e0.rec, sc4012e0.rec, sc4102e0.rec, sc4112e0.rec, st7022j0.rec, st7052j0.rec, st7121j0.rec, st7132j0.rec. These signals are recorded through the electrode FpzCz (E1), PzOz (E2) against C4-A1 and C3-A2 according to the alternative placement of the electrodes during the automatic detection of sleep. Four recordings are obtained by four volunteers during 23h: 45 min during their normal lives, while using a modified tap tape cassette. The other four recordings lasted one night of sleep in a hospital, while using a 100 Hz sampling rate miniature telemeter with a frequency response equal to -3 dB per point, a 14-bit representation per sample, and a total noise equal to -2V p-p.

**Experimental Setup** According to the exploitation of the Daubechies wavelet decomposition method (db5) we found the 5 brain waves: alpha, theta, gamma, beta, delta. What the figures sketch



**Fig. 2.** Decomposition with a window of 3 seconds.



**Fig. 3.** Decomposition with a window of 0.5 second .

The calculation of these parameters is done on each EEG rhythm, that is to say for each wave we will calculate the 7 features (energy, variance, maximum, minimum, average, entropy, energy ratio),

From the FFT, we calculated the DSP of our signal. We used this method to subdivide the signal into subband and we started with 2 then 3 then 4 and finally 5 bands. In order to grasp the exact choice we had to try with all the frequencies proposed in the classification.

The following table shows the results without and with reduction. This table shows that we have succeeded, on two levels of reduction, in improving the recognition rate and reducing by more the number of characteristics used. By reducing the characteristics, a small subset of examples containing only those that seem to influence the class separation capability can be selected from the training set. Our contribution comes within this framework. The proposed method makes it possible to significantly reduce the number of characteristics of the database then to make an offline learning. The results obtained show the performance of this solution using the OneClassSVM classification method with electrode 2.

**Table 1.** Best accuracy obtained.

	OneClassSVM	KNN
<b>Without reduction</b>	84%	82.5%
<b>PCA</b>	91.5%	79.7%
<b>SF</b>	<b>93%</b>	88.2%

#### 4.1 Comparison With the Existing Methods

Our detection results are compared with those of the literature to better position our algorithm with other recent methods of sleep detection. The choice of articles



to make the comparison was based on the methods used and their similarities to our algorithm.

**Table 2.** Comparaision of performance of previous studies

Methods	Accuracy
li et al [7]	81.5%
Hassan et al [4]	87.5 %
sharma et al [8]	90%
Kayikcioglu et al [5]	91 %
Proposed method	93 %

## 5 Conclusion

This study proved that statistical eatures can be used with standard accuracy. This proposed methods provides convincing classification accuracy of 93% using statistical parameters of EEG signal. Future work will focus perform parallel analysis using electro oculography (EOG) and electrocardiography (ECG).

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