Seizure Detection with Single-Channel EEG using Extreme Learning Machine

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Abstract—
The electroencephalography (EEG) is the most essential tool for the diagnosis and the treatment of the epilepsy. It allows observing events strongly associated with epilepsy or epileptic spikes and locating the brain regions that cause the symptoms of epilepsy. This paper presents an automated classification of EEG signals for the detection of epileptic seizures with Single-Channel using the wavelet transform and the Extreme Learning Machine. The aim is to create a system with reduced computation time and resources with the minimum number of required electrodes. The decision making process is comprised of three steps: (a) Preprocessing, (b) feature extraction based on the wavelet transform, and (c) classification by the Extreme Learning Machine. The proposed algorithm has been tested on three different data sets from the CHB-MIT scalp EEG database using only the FT10-T8 channel. The proposed method achieves a classification accuracy of 94.85%.

Keywords—**EEG; seizures detection; wavelet transform; Extreme Learning Machine.**

I. Introduction

The epilepsy is a disease which results from a cerebral dysfunction. It is characterized by repeated crises during which uncontrolled alterations, often stereotyped, occur in the patient's behavior. This chronic disorder of the brain is characterized by recurrent seizures that are the physical manifestation of excessive and sudden electrical discharges, generally short and repetitive, generated by a population of neurons. The crisis events vary from one individual to another depending on the brain involved structures. The Electroencephalography (EEG) is one of the most used methods in the study and the identification of the epilepsy. This cerebral activities measurement tool allows a medical expert to analyze the brain signals in order to detect the epilepsy. Since the EEG data last for several hours, this technique can be very tiring and consumes a lot of time. For this end, an automatic detection system can be very useful to reduce the effort needed for the data examination. The purpose of this automatic system is to determine the sections of seizures in the EEG signal.

The automatic seizure detection and quantification systems have gained the attention of several research groups in the last decade. For instance, Gotman [1] have presented a frequency based system for the seizures detection; while the method proposed by Qu and Gotman [2] detects the epileptic seizures using the nearest-neighbor classifier with time and frequency domains features. Moreover, Gigola et al. [3] have used a method based on the evolution of accumulated energy using wavelet analysis. E. Ubeyli [4], A. Tzallas et al. [5], and G. Dastidaret al. [6] have proposed a detection system for the diagnosis of the epilepsy using the Artificial Neural Network. Furthermore, Weng and Khorasani [7] have used the average amplitude, the variation coefficient, the dominant frequency, the average duration and the average power spectrum, for the quantification. An adaptive structured neural network was then used for the classification. Pradhan et al. [8] have proposed a method that uses a four features vector of EEG signals as an input to a learning vector quantization network. Kiymiket al. [9] have proposed an automatic detection system of epileptic seizures that uses a back propagation neural network as classifier. The feature extraction method is based on the periodogram and the autoregressive (AR). Srinivasan et al. [10] have introduced a detection system based on a nonlinear feature named approximate entropy, and used artificial neural network as classifier.

In the following sections, the proposed method is presented in details. Then the experimental results are given in order to validate the system. Finally, the last section concludes the paper.

II. Methods

The classification process used in this work can be divided into several stages. First of all, several preprocessing

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techniques are applied on the EEG signals. This stage consists in temporally segmenting the EEG signal. Then, a wavelet transform (WT) is applied to the resulting signal in order to extract time and frequency domain features. Finally, we adopt the Extreme Learning Machine (ELM) classifier to decide if seizure can be detected in the examined data segment or not. Figure 1 depicts the different steps involved in the classification process.

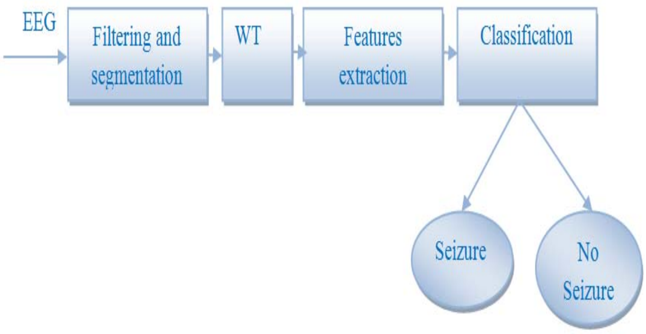

Figure 1. Schematic diagram of the system used in this study.

A. *Database*

The proposed approach is evaluated with EEG signals from the CHB-MIT scalp EEG database using only the FT10-T8 channel [11]. The EEG data were acquired from pediatrics subjects suffering from intractable seizures with a sampling rate equal to 256. The database was collected from 22 subjects (5 males, ages 3–22; and 17 females, ages 1.5–19). In most cases the EEG data were recorded from 23 channels. 21 electrodes with specific nomenclature and coordinates according to the 10-20 international system were used. EEG signals, of one hour length in the majority, were stored in separated file for each subject. The seizure can be detected in several files more than once.

In this study, only the data sets chb_03, chb_08and ch_13 were used. The main details of the three EEG records are presented in Table I.

TABLE I. DETAILS OF THE THREE EEG RECORDS

Patient identifier	Age	Sex	Number of seizure
Chb03	14	F	chb03-01 chb03-02 chb03-03 chb03-04 chb03-34 chb03-35 chb03-36
Chb8	3.5	M	chb08_02 chb08_05 chb08_11 chb08_13 chb08_21
Chb13	3	F	Chb13_19 Chb13_21 Chb13_40 Chb13_55 Chb13_58 Chb13_59 Chb13_60 Chb13_62

B. *Filtering and segmentation*

The occurrence of seizures can be detected as changes of the EEG signals within a frequency range between 0.5 and 30 Hz [12] [11]. In order to retain only frequencies among this range, a band pass linear phase FIR filter is used. On the other hand, in order to decrease the calculation time and improve the real time detection, only 512 samples or 2s data are used at once.

C. *Wavelet Transform*

After the filtering and the segmentation, a WT is applied to the EEG signal. This technique decomposes the temporal signals in the time-scale plane [13]. The WT leads to extract several sub frequency bands from the EEG segments using different wavelet functions. To obtain relevant signal characteristics, the selection of the proper wavelet function and the number of decomposition levels is essential. In this work, we have used the Daubechies wavelet function of order 6 and 6 decomposition levels by referring to the work presented in [12]. The choice of the decomposition level considers the interesting brain rhythms.

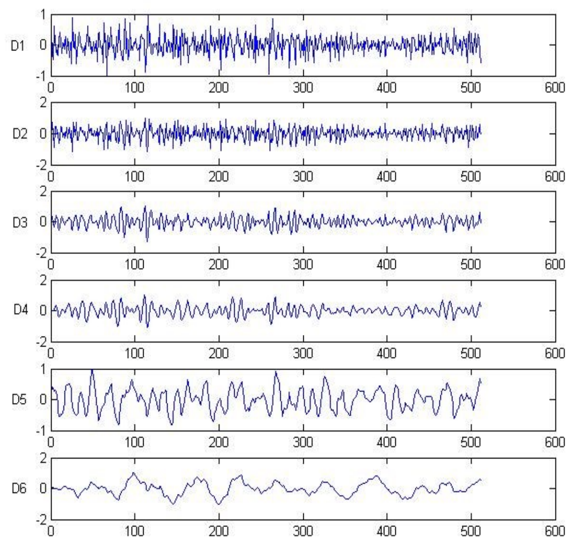

Figure 2. An example of 2s long epoch wavelet.

The WT was calculated for each segment of 2 s. Hence, six decomposition levels or bands (D_i while i is the number of level) were found as shown in figure2 and figure 3. Four WT bands can be considered as relevant since they lie at approximately the same frequency bands as the brain rhythms: β between 13 and 30 Hz, α between 8 and 13Hz, θ between 4 and 8 Hz and δ between 0.5 and 4 Hz [11]. Then, for each band the temporal and spectral features were determined. Table II shows the bandwidth of Wavelet Filters D3, D4, D5 and D6.

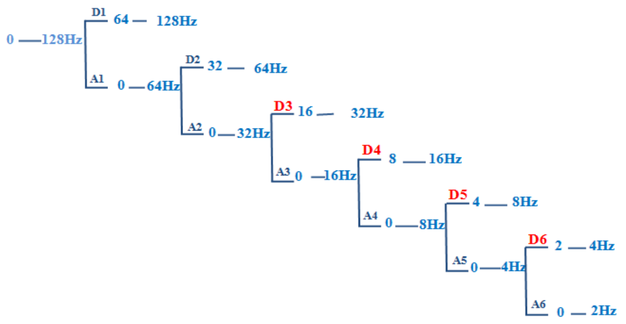

Figure 3. Decomposition level of the EEG signal sampled at 256 Hz

TABLE II. USEFUL WAVELET BANDS FOR THE SEIZURE DETECTION.

Wavelet bands	Frequency range (Hz)	Brain rhythms
D3	12-30Hz	β
D4	8-16Hz	α
D5	4-8Hz	θ
D6	1-4Hz	δ

D. Features extraction

After the decomposition several features were extracted from the levels (D3, D4, D5, and D6). The power spectral density (PSD) based burg method was used to extract the different spectral features. For each level, the PSD is estimated while setting the method order at 16 [12]. Then, the peak and the mean frequencies are considered as features.

TABLE III. LIST OF TEMPORAL AND SPECTRAL FEATURE

Features name		Description
Temporal Features	Mean	The mean value describes the location of the distribution
	NCOV	ratio of variance
	Std	Standard deviation
	skewness	Describes the trend of the probability distribution function of a signal.
	Kurtosis	Describes the trend of the probability distribution function of a signal.
Spectral Features	Mean DSP	The mean value of DSP
	Peak_PSD	Peak Frequencies

The temporal features used in this work are: Mean, NCOV (ratio of variance σ^2), Standard deviation, skewness, and kurtosis [5]. All features are presented in Table III. Thus we have obtained 8 spectral features (4 levels * 2 feature types) and 20temporal features (4 levels * 5 feature types).

E. Classification

The recently proposed neural network algorithm which is the ELM is used as a classification method. The little computation resources needed for this algorithm as well as its high performances level make it a good choice face ordinary techniques [14]. The ELM can be seen as Single Hidden layer Feedforward Neural Networks (SLFNs). The hidden neurons form a link between the input and the output neurons for a direct transfer of the information. The input layer and the output layer are the principal component consisting this network. The connections are established between neurons belong to successive layers and not between neurons in the same layer. The function of the ELM algorithm with a single hidden layer is described in the following steps [15]:

Given a training set $\phi = \{(x_i, t_i) / x_i \in R^n, t_i \in R^m, i = 1, ..., N\}$ where x_i is a training sample and t_i is the corresponding target value, the activation function $g(x)$ and the number of hidden neurons N perform the following steps.

- Step1: Assign arbitrary input weight w_{ij} and bias b_i .
- Step2 : Calculate the output matrix at the hidden layer

$$H = g(w.x + b) \quad (1)$$

- Step 3 : Calculate the output weight β

$$\beta = H^{\dagger} T \quad (2)$$

$H^{\dagger}$ is the Moore-Penrose generalized inverse of the matrix H .

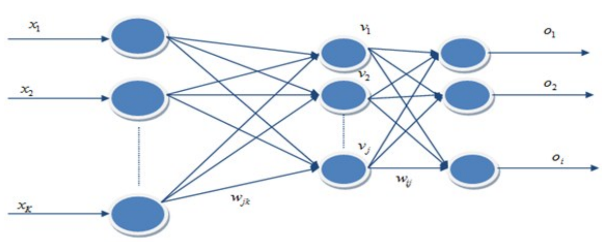

Figure 4. ELM network configuration.

III. EXPERIMENTAL RESULTS

In this study, a seizure detection system based on the EEG signal processing is proposed. During the first step, signals are filtered then segmented using a simple rectangular window. Next, several temporal and spectral features are extracted. This step is considered very crucial as it can dramatically enhance or deteriorate the system performance. Finally, features are feed to the ELM algorithm in order to be classified. The performance of this proposed method was evaluated using the CHB-MIT scalp EEG database. Only signals from the data sets chb_03, chb_08, ch_10 and ch_13 were used for the validation of this detection system. The two classes are: the seizure class and the non- seizure class. For the ELM algorithm parameters adjustment, the number of the input neurons is set at 28 the same as the total number of features. The number of outputs is set at 2 equal to the number of classes. After several configuration tests the number of hidden neurons is fixed at 150 which correspond to the most appropriate value. Moreover, the sigmoid function is selected as the best activation function. The network weights are adjusted by randomly selecting 2/3 of the data set for the training step and the 1/2 left for the test step.

The accuracy rate which corresponds to the number of segments correctly classified divided by the total number of segments, is used as the main criterion representing the system performance.

The effectiveness of the proposed algorithm can be verified via the experimental results given in Table 4. The overall accuracy reached 94.85% and the learning time is equal to 0.0121s.

The algorithm ELM also presents an advantage at the level of speed of learning.

TABLE IV. PERFORMANCES OF THE DESIGNED SYSTEM

Patient identifier	Classification rate (%)	Learning time(s)
chb03	96.88	0.0121
chb08	94.97	0.0121
chb13	95.05	0.0121
Average	94.85	0.0121

The found results show an improvement of the system performances compared to other system with single channel. For example, the system designed by Maragakis and al. [11] have reached an accuracy rate of over 90% with the same data base. For this system, only signals from the channel FT10-T8 were used and very primitive features, namely the log of variance and energy were used after the wavelet stage. The SVM classifier allows to separate the different classes.

IV. CONCLUSION

In the present study, a new Seizure Detection system is proposed. After the filtering and the segmentation processes, spectral and temporal analyses are used in order to extract different features from the EEG recordings. The ELM is used as a classifier. Experimental results found using the three chosen data sets show that an acceptable and practical performance can be reach by mean of the proposed system.

For further works, we can improve the proposed method by the use of multi-channel EEG signals. Another possibility consists in increasing the system accuracy rate using a joint method including several processing techniques. Selecting the relevant system parameters is also a clue to increase the performances.

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