A Time-Frequency Based Method for the Detection of Epileptic Seizures in EEG Recordings

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Abstract

A novel three-stage method for the analysis of electroencephalographic (EEG) signals, concerning epileptic seizures, is proposed. First, segments of the EEG signals are analyzed using a time-frequency distribution and then, several features are extracted for each segment, representing the energy distribution over the time-frequency plane. Those features are used as an input in an artificial neural network (ANN), which provides the final classification of the EEG segments (existence of epileptic seizure or not). The evaluation results are very promising, indicating overall accuracy from 89.4% to 99%.

1. Introduction

Epilepsy is one of the most common neurological disorders with a prevalence of about 1% of the world's population [1]. The epilepsy is characterized by a sudden and recurrent malfunction of the brain which is termed "seizure". An epileptic seizure is a sudden synchronous and repetitive discharge of brain cells with symptoms depending on the location within the brain of the seizure onset, and the spread of the seizure. Long-term EEG (LTEEG) monitoring is used to closely monitor patients over extended periods, who have relatively infrequent but recurring atypical "turns" or seizures. LTEEG monitoring comprises continuous multichannel EEG and video recording over several days. This allows the seizures to be "captured" for in-depth off-line analysis. This information enables the expert to determine whether or not such seizures are of epileptic origin and, if so, determine the type and location of the epileptogenic activity.

Research in automated epileptic seizure detection began in the 1970s and various algorithms addressing this problem have been presented [2]. Methods for automated detection of epileptic seizures may rely on the identification of various patterns such as an increase in amplitude [3], sustained rhythmic activity [4], or EEG flattening [5]. Several algorithms have been developed based on spectral [6-9] or wavelet features [10-14], amplitude relative to background activity [15] and spatial context [15,16]. Chaotic features [17,18] such as correlation dimension [19], Lyapunov exponents [14,20] and entropy [21] have also been proposed to characterize the EEG signal. These features can then be used to classify the EEG signal using nearest neighbor classifiers [22], decision trees [8], ANNs [14,20], support vector machines (SVMs) [9,14] or adaptive

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neuro-fuzzy inference systems [12,13,20] in order to identify the occurrence of seizures. It is crucial for seizure detection systems to result in high sensitivity, even if this results in a large number of false detections. Such systems can then be used to considerably reduce the amount of data that need to be reviewed; experts can then easily discard false detections. Therefore, epileptic seizures give rise to changes in certain frequencies bands. Recent works have focused on the analysis of the δ (0.4–4 Hz), θ (4-8 Hz), α (8–12 Hz), and β (12–30 Hz) rhythms and their relation to epilepsy. An epileptic signal has components in both time and frequency, but the conventional time and frequency representations present only one aspect. A time-frequency (TF) distribution combines both time and frequency information into a single representation. Thus, TF analysis, which can be carried out with one of the several proposed TF distributions, has proven to be the most suitable tool for the analysis of EEG signals.

In this work, we use a TF distribution in order to analyze EEG segments and extract several features from them. Then, these features are used to classify the segments concerning the presence or absence of epileptic seizures. The method is divided into three stages: (i) TF analysis and calculation of the power spectrum density (PSD) of each EEG segment; (ii) feature extraction, measuring the signal segment fractional energy on specific TF windows and (iii) classification of the segment, using an ANN. The method is evaluated for three different classification problems. To our knowledge, there is no study in the literature related to TF analysis and feature extraction reflecting the energy distribution over the TF plane, for epileptic seizure detection. In addition, no work addresses all three classification problems, which are directly related to the diagnosis provided by an expert. The obtained results indicate high accuracy.

2. Materials and methods

2.1. Dataset

We used the dataset described in reference [23]. The complete dataset consists of five sets (denoted as Z, O, N, F and S) each containing 100 single-channel EEG segments each having 23.6 sec duration. Sets Z and O have been taken from surface EEG recordings of five healthy volunteers with eye open and closed, respectively. Signals in two sets have been measured in seizure-free intervals from five patients in the epileptogenic zone (F) and from the hippocampal formation of the opposite hemisphere of the brain (N). Set S contains seizure activity, selected from all recording sites exhibiting ictal activity. Sets Z and O have been recorded extracranially, whereas sets N, F and S have been recorded intracranially.

In our analysis we use the above described dataset to create three different classification problems and then we tested our method with each of them. In the first problem, two classes are examined, normal and seizure. The normal class includes only the Z type EEG segments while the seizure class includes the S type. The second problem includes three classes, normal, seizure-free and seizure. The normal class includes only the Z type EEG segments, the seizure-free class the F type EEG segments and the seizure class the S type. In the third problem, all five classes are used, including all EEG segments from the initial dataset. According to the previous description, the datasets consist of 200, 300 and 500 EEG segments, for the three problems, respectively. The different problems, related to the classes which are included in the classification were constructed since there is different medical interest for each problem, i.e. it is very important to evaluate the proposed method on the classification of seizure and normal classes. Furthermore, these three problems are the most widely used in the literature and therefore we have used all three in order to be able to compare our approach with several others, proposed in the literature.

2.2 Time-frequency analysis

The smoothed pseudo Wigner-Ville distribution (SPWVD) [24], defined as:

$$SPWVD_x(t,\omega)=\int_{-\infty}^{+\infty}h(s)\left(\int_{-\infty}^{+\infty}g(\tau)x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi\omega\tau}d\tau\right)ds, \tag{1}$$

is applied in each EEG segment. $x(\cdot)$ is the signal, t is the time, ω is the frequency and $g(\cdot)$ and $h(\cdot)$ are window functions centred at time τ and frequency s, respectively. The time window was selected to be a Hamming 64-point length window. The length of the frequency window is not always the same; we have tested several different frequency resolutions: 64, 128, 256 and 512 points length windows; results are presented for all them. TF analysis results in the PSD, which represents the distribution of the signal's energy over the TF plane.

2.3 Feature extraction

The PSD is used to extract several features. A grid is used, based on a partition in the time and in the frequency axis. In the time domain three equal sized windows were used while, in the frequency domain, two different partitions were employed, which divide the frequency domain in 4 and 7 subbands. These subbands, which are not necessarily equal, are defined using medical knowledge about the EEG and the features that are expected to be found in certain frequency subbands for the specific types of EEG segments included in the original dataset. Both combinations, between the time partition and the frequency partitions are used (3x4 and 3x7). Each feature, $f(i,j)$, is calculated as:

$$f(i,j)=\int_{t_i}\int_{\omega_j}SPWVD_x(t,\omega)\,d\omega dt, \tag{2}$$

where t_i is the i^{th} time window and ω_j is the j^{th} frequency band. Each feature represents the fractional energy of the signal in a specific frequency band and time window; thus, the total feature set depicts the distribution of the signal's energy over the TF plane. Therefore, it is expected that a feature set carries sufficient information related to the non-stationary properties of the signal, due to the fact that each feature represents the total energy related to specific EEG activities (δ, θ, α and β rhythms).

Two different feature sets are extracted, one for each TF grid. In both cases, an additional feature is used, which is the total energy of the signal. Therefore, each feature set is a $3M$+1 size vector, where M is the number of frequency sub bands (4 or 7). Thus, the size of the feature vector is 13, when 4 frequency subbands are employed, and 22, in the case of 7 frequency subbands.

2.4 Classification

The calculated features are fed into a feed-forward artificial neural network (ANN). The architecture of the neural network is the same for all problems: N inputs (N is the size of the feature vector), one hidden layer with 20 neurons and K outputs (K is the number of the classes), each of them being a real number in the interval [0,1]. The units in the hidden layer are sigmoid units with hyperbolic tangent as activation function, while the outputs are linear. Each network is trained using the standard backpropagation algorithm [25].

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3. Results

The three classification problems, described above, are used to evaluate the proposed method. For each of them, all combinations between frequency resolutions (64, 128, 256 or 512) and TF grids (3x4 or 3x7) were tested; totally 8 different combinations for each classification problem. The ten fold stratified cross validation method was employed, while the final result is the average of all of them. The size of the confusion matrix is KxK and therefore depends on the classification problem: 2x2 for the first classification problem, 3x3 for the second and 5x5 for the third. The accuracy (Acc), defined as:

$$Acc = Trace\{confusion\ matrix\}/S, \quad (3)$$

where S is the number of EEG segment in the dataset, can be calculated for each confusion matrix. The computed accuracies for all classification problems and all combinations between frequency resolutions and TF grids are presented in Table 1. Also, for each classification problem, overall results have been derived, i.e. the maximum and minimum accuracy (for all combinations between frequency resolutions and frequency subbands) as well as the average accuracy and the standard deviation.

For the first classification problem, the best obtained accuracy is 99%, achieved for 64 frequency resolution and 4 or 7 frequency subbands. For the second classification problem, the best obtained accuracy is 98.6%, achieved for 64 frequency resolution and 7 frequency subbands. Finally, for the third classification problem, the best obtained accuracy is 89.4%, achieved for 256 frequency resolution and 7 frequency subbands. For all classification problems, the obtained accuracies of the different evaluations do not vary significantly; almost 2% for all three of them. Also, the standard deviation is not large, being 0.76, 1.03 and 0.53, for the three classification problems, respectively.

Table 1. Accuracy (%) for all classification problems, different frequency resolutions and TF grids.

	Frequency resolution								Total			
	64		128		256		512					
TF grid	3x4	3x7	3x4	3x7	3x4	3x7	3x4	3x7	min	max	average	stdv
Classification problems 1	99.0	99.0	97.8	97.8	98.8	98.0	98.4	96.8	96.8	99.0	98.20	0.76
Classification problems 2	97.8	98.6	97.2	96.8	97.2	97.2	96.8	95.0	95.0	98.6	97.08	1.03
Classification problems 3	89.0	88.8	88.6	87.8	88.6	89.4	88.2	88.0	87.8	89.4	88.55	0.53

4. Discussion

We have proposed an automated method for seizure detection in EEG recordings. The method is based on TF analysis of the EEG segments and extraction of several features from the PSD of the signal. These features are fed into a neural network, which provides the classification of the EEG segments. The method is evaluated using three different classification problems, originated from the type of medical diagnosis which is followed. The effect of different parameters of the method on the classification accuracy is examined. Those parameters are: the frequency resolution of the TF analysis and the TF grid used for feature extraction. Results are presented for all the different combinations of them.

The frequency resolution, used in the TF analysis, does not greatly affect the accuracy of the proposed method; the average accuracy of all classification problems with both TF grids is 95.37%, 94.33%, 94.87% and 93.87% for 64, 128, 256 and 512 points length windows, respectively. It is obvious that the use of 64 points length window slightly improves the results, while the incorporation of the 256 points length window has the second better results. Also, the incorporation of different TF grids did not have a major impact on the results; the average accuracy of all test that were made using 3x4 TF grid (for all classification problems and frequency resolutions) is 94.78%, while, in the case of 3x7 TF grid, 94.43%.

To our knowledge, TF analysis and feature extraction, which reflect the energy distribution over the TF plane, have not been applied in the analysis of EEG signals. Moreover, the quality of the proposed method can be proven from the obtained results. The accuracy achieved by our method for the epileptic seizure detection is more than satisfactory and also its automated nature makes it suitable for real clinical conditions. Besides its feasibility for real-time implementation, diagnosis can be made more accurate by increasing the number of parameters. A system that will be developed as a result of this study may provide feedback to the experts for classification of the EEG signals quickly and accurately.

Table 2 presents a comparison between our method and other methods proposed in the literature. Only methods evaluated in the same dataset are included. For the two classes' problem, the results obtained from the evaluation of our method are the second best presented for this dataset. It is worth to mention here that a method that discriminates EEGs into non-seizure and seizure is much closer to the expert needs. For the three classes problem, the results obtained from our method are the best presented for this dataset; the difference between our results and other results varies from 1.8%-12.7%. However, in the case of using the third classification problem to evaluate our method our results are not satisfactory, being almost 90%, while the best reported results for this dataset is 99.28%.

Table 2: The classification accuracy (%) of our method for the detection of epileptic seizures compared to the classification accuracies (%) obtained by other methods.

Authors	Method	Dataset	Accuracy
Nigam et al. [7]	Nonlinear pre-processing filter-Diagnostic neural network	Z, S	97.2
Srinivasan et al. [6]	Time & frequency domain features-Recurrent neural network	Z, S	99.6
Kannathal et al. [21]	Entropy measures-Adaptive neuro-fuzzy inference system	Z, S	92.22
Kannathal et al. [18]	Chaotic measures-Surrogate data analysis	Z, S	~90
Polat et al. [8]	Fast fourier transform-Decision tree	Z, S	98.72
Subasi [11]	Discrete wavelet transform-Mixture of expert model	Z, S	95
This work	**Time frequency analysis-Artificial neural network**	**Z, S**	**99**
Guler et al. [20]	Lyapunov exponents-Recurrent neural network	Z, F, S	96,79
Sadati et al. [12]	Discrete wavelet transform–Adaptive neural fuzzy network	Z, F, S	85,9
This work	**Time frequency analysis-Artificial neural network**	**Z, F, S**	**98.6**
Guler et al. [13]	Wavelet transform-Adaptive neuro-fuzzy inference system	Z, O, N, F, S	98.68
Guler et al. [14]	Wavelet transform, Lyapunov exponents-Support vector machine	Z, O, N, F, S	99.28
Übeyli et al. [26]	Eigenvector methods–Modified of Mixture of expert model	Z, O, N, F, S	98.60
This work	**Time frequency analysis-Artificial neural network**	**Z, O, N, F, S**	**89.4**

There are several other aspects either technical or medical which much be addressed. From the technical point of view, although we have examined the effect of various parameters (frequency resolution, TF grid), some other, like TF distributions (e.g. reduced interference distributions), have not been explored. From the medical point of view, the most important feature is that currently the method is used to characterize predetermined (with respect to their length) EEG segments. An important aspect is also the modification of the proposed method in order to be able to automatically detect highly suspicious segments (regardless of their length) into long time EEG recordings and classify them.

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