Seizure Detection in EEG signals: A Comparison of Different Approaches

Hamid R. Mohseni[1], A. Maghsoudi and Mohammad B. Shamsollahi[1]

***Abstract*— In this paper, the performance of traditional variance-based method for detection of epileptic seizures in EEG signals are compared with various methods based on nonlinear time series analysis, entropies, logistic regression, discrete wavelet transform and time frequency distributions. We noted that variance-based method in compare to the mentioned methods had the best result (100%) applied on the same database.**

I. Introduction

EPILEPTIC seizures are the result of the transient and unexpected electrical disturbance of the brain. Approximately one in every 100 persons will experience a seizure at some time in their life [1].

Unfortunately, the occurrence of an epileptic seizure is not predictable and its process is not completely understood yet.

Electroencephalogram (EEG) as a representative signal containing information of the electrical activity generated by the cerebral cortex nerve cells, has been the most utilized signal to clinically assess brain activities, and the detection of epileptiform discharges in the EEG is an important component in the diagnosis of epilepsy.

The detection of epilepsy, which includes visual scanning of EEG recordings for the spikes and seizures, is very time consuming, especially in the case of long recordings. In addition, bio-signals are highly subjective so disagreement on the same record is possible, so the EEG signal parameters extracted and analyzed using computers, are highly useful in diagnostics.

The early methods of automatic EEG processing were based on a Fourier transform. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity.

Parametric methods for power spectrum estimation such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. Since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals.

Gular et al [2] have a study to the assessment of accuracy of recurrent neural networks (RNN) employing Lyapunov exponents in detection seizure in the EEG signals. Dynamical measures especially Lyapunov exponents can serve as clinically useful parameters and contain a significant amount of information about the signal [3],[4]. Therefore, the Lyapunov exponents become a natural complement to our applications of the RNNs.

Non-linear dynamics theory opens new window for understanding the behavior of electroencephalogram (EEG). In the analysis of EEG data, different chaotic measures are used in recent literature. Jing and Takigawa [5] applied correlation dimensions techniques to analyze EEG at different neurological states. Lehnertz and Elger [6] used correlation dimension technique to test whether a relationship exists between spatio-temporal alterations of neuronal complexity and spatial extent and temporal dynamics of the epileptogenic area. Casdagli et al. [7] showed that the techniques developed for the study of non-linear systems could be used to characterize the epileptogenic regions of the brain during the interictal period. Correlation integral, the measure sensitive to a wide variety of non-linearities, was used for detection. In particular, recordings from epilepsy patients have often attracted researchers' attention and they have used non-linear techniques for analysis.

Subasi et al [8] compared the traditional method of logistic regression to the more advanced neural network techniques, as mathematical tools for developing classifiers for the detection of epileptic seizure in multi-channel EEG.

A powerful method was proposed in the late 1980s to Perform time-scale analysis of signals: the wavelet transforms (WT). This method provides a unified framework for different techniques that have been developed for various applications. One of the efficient properties of WT is that it is appropriate for analysis of non-stationary signals, and this represents a major advantage over spectral analysis. Hence the WT is well suited to locating transient events. Such transient events as spikes can occur during epileptic seizures.

Recently, Kiymik et al. presented time–frequency analysis of EEG signals for detecting the information on alertness and drowsiness using spectral densities of DWT coefficients as an input to ANN [9]. As compared to the conventional method of frequency analysis using Fourier transform or short time Fourier transform, wavelets enable analysis with a coarse to fine multi-resolution perspective of the signal [10].

The detection methods which use the characteristics of the EEG seizure in time or frequency domain are based on the assumption that the segments of the signal are quasi

[1] Biomedical Signal and Image Processing Laboratory (BiSIPL), Sharif University of Technology, Tehran. Iran.

stationary. However recent works shows that the EEG signals exhibit non-stationary behavior. For analyzing such signals, time scale and time frequency methods have proved that the most suitable tools [11].

The outline of the paper is as follows: Section II outlines the database which is downloadable from the. This database is the same for papers that we extract the result from them. Also this section summarizes various methods that were used in the detection of seizure in EEG signals. These methods are nonlinear statistics, entropies estimators, wavelet transforms, time frequency distribution and linear statistic (variance). Section III presents the overall accuracy results of the mentioned methods that are elicited from the original papers.

II. Methods and Materials

A. Database

We used the data described in Andrzejak et al [12], which is publicly available. In this section, we restrict ourselves to only a short description and refer to[12] for further details. The complete dataset consists of five sets (denoted A–E), each containing 100 single-channel EEG signals of 23.6 s.

Sets A and B have been taken from surface EEG recordings of five healthy volunteers with eyes open and closed, respectively. Signals in two sets have been measured in seizure-free intervals from five patients in the epileptogenic zone (D) and from the hippocampal formation of the opposite hemisphere of the brain (C). Set E contains seizure activity, selected from all recording sites exhibiting ictal activity. Sets A and B have been recorded extra cranially, whereas sets C, D, and E have been recorded intracranially. In our applications, performance degraded for a more detailed classification which further dissociated between sets A (healthy volunteer, eyes open) and B (healthy volunteer, eyes closed), and sets D (epileptogenic zone) and C (hippocampal formation of opposite hemisphere). Therefore, in the present study we classified three dataset (A, D, E) of the complete dataset.

B. Seizure detection methods

As it is mentioned in previous section, several methods have been proposed for detection of seizure. In this section some of these methods will be introduced and the results will be presented in the next section.

1. Nonlinear-based features

Lyapunov exponents are a quantitative measure for distinguishing among the various types of orbits based upon their sensitive dependence on the initial conditions, and are used to determine the stability of any steady-state behavior, including chaotic solutions. The reason why chaotic systems show aperiodic dynamics is that phase space trajectories that have nearly identical initial states will separate from each other at an exponentially increasing rate captured by the socalled Lyapunov exponent. Numerous methods for calculating the Lyapunov exponents have been developed during the past decade [13]. Generally, the Lyapunov exponents can be estimated either from the equations of motion of the dynamic system (if it is known), or from the observed time series. The first is based on the idea of following the time evolution of nearby points in the state space [14]. This method provides an estimation of the largest Lyapunov exponent only. The second method is based on the estimation of local Jacobi matrices and is capable of estimating all the Lyapunov exponents. Vectors of all the Lyapunov exponents for particular systems are often called their Lyapunov spectra.

In the present study, the technique used in the computation of Lyapunov exponents was related with the Jacobi-based algorithms.

2. Entropy-based features

Entropy is a thermodynamic quantity describing the amount of disorder in the system. From an information theory perspective, the above concept of entropy is generalized as the amount of information stored in a more general probability distribution. First Shannon applied the concept of information or logical entropy to the science of information theory and data communications. Recently, a number of different entropy estimators [15] have been applied to quantify the complexity of the signal. Entropy estimators are broadly classified into two categories spectral entropies and embedding entropies. The spectral entropies use the amplitude components of the power spectrum of the signal as the probabilities in entropy calculations. It quantifies the spectral complexity of the time series. The embedding entropies use the time series directly to estimate the entropy. Kolmogorov—Sinai entropy and the approximate entropy are the embedding entropies discussed here [16].

3. Wavelet-based features

The discrete wavelet transform is a versatile signal processing tool that has many engineering and scientific applications. The wavelet transform (WT) provides a general technique, which can be useful to many tasks in signal processing. The WT can be considered as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. DWT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is simply obtained by successive high-pass and low-pass filtering of the time domain signal.

Subasi [17] deals with a novel method of analysis of EEG signals using discrete wavelet transform, and classification using ANN. In this work the signal decomposed in 5 levels using DB4 wavelet filter .The energy of details and approximation were used as the input features.

4. Time frequency-based features

In this method the first step in processing is to compute a time-frequency distribution. Such a distribution localizes a signal in both time and frequency domains. That is, it provides simultaneous time resolution and inversely proportional frequency resolution. For example, an epileptic signal has component in both time and frequency, but the conventional time and frequency representations present only one aspect.

A time-frequency distribution combines both time and frequency information into a single representation. There are a large number of possible time-frequency distributions; however we will focus only on the two which are most often used. These are the pseudo Wigner-Ville and the smoothed-pseudo Wigner-Ville distribution [18].

For extracting features from the time-frequency plane, the maximum frequency in each point of time axis was obtained so a 1-D signal was acquired (maximum frequency versus time). This signal was fitted with a cubic curve using LMS (Least Mean Square) criterion. The cubic curve which was used is in the form of:

$$y = d_3x^3 + d_2x^2 + d_1x + d_0 \qquad (1)$$

After computing the parameters, d_0, d_1, d_2, d_3 would be taken as features. The number of the parameters d_i can be chosen according to the problem so, the shape of the fitting curve will be changed consequently.

We used this feature as inputs to a feed-forward back propagation neural networks (FBNN).

5. Local variance

One of the simplest statistics that may be used for investigating the dynamics underlying the EEG is the variance of the signal calculated in consecutive nonoverlapping windows [19].

Let denote the EEG signal at time. The variance of this EEG signal is given by

$$\sigma^2 = < s_i^{\,2} > - < s_i >^2 \qquad (2)$$

where $<.>$ is the average taken over the time interval being considered. Esteller *et al* [20] suggest measuring the energy (simply $< S_i^{\,2} >$) of the signal in consecutive windows of the EEG signals.

The detection using variance is as follow: after segmenting the signal using the rectangle window, the variance in each segment is calculated and compared with a constant threshold. If the variance is greater than this threshold the segment is considered as an occurred seizure else, it is a normal section.

6. Power spectrum

Another useful linear approach for investigating the EEG signal is its power spectrum. There are a number of different statistics which aim to summarize the information contained in the power spectrum. These include calculating the total integral of the power spectrum over all nonzero frequencies (note that this equals the variance of the signal), and the median frequency which estimates the “typical” frequency present in the signal [21]. Quasiperiodic fluctuations or “rhythmic” behavior characterized by a peak in the power spectrum at a specific frequency may be used to identify epileptic seizures in some cases [22].

III. Results and Discussion

The EEG database mentioned above has 100 cut of EEG signals from both healthy and epileptic patients. A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single EEG segment. In each segment the mentioned methods were applied and they were considered as the input to classifiers. The reader can refer to [2], [8], [16], [18] and [25] for the details of methods and classifiers. Detection of seizure using variance was completed with a constant threshold and it used no classifier.

For comparison of the results of various algorithms, we used overall accuracy which means the ratio of the number of corrected classified segmented seizure and non-seizure signals to the total number of segmented signals. Table 1 shows the best result of using Lyapanov Exponent, Entropies, Logistic regression, discrete Wavelet transforms, Time frequency distributions and linear statistic (variance) for detection of seizure which, are elicited from [2], [8], [16], [18] and [25].

Table I. Results of classification which were extracted from various papers on the same database.

	Lyapanov Exponent	Entropies	Logistic regression
Overall accuracy	97.38%	93.7%	93.0%

	Discrete wavelet	Time Frequency	Variance
Overall accuracy	86.25%	98.25%	**100%**

These results, the best results, are just reported from these published papers and it can be seen the simplest method (variance-based) have the best result and can classify the signals perfectly. Also it should be noted that in this method no classifier is used and the detection is completed using a fixed threshold on the local variance, however; other methods used modern classifiers which mostly based on neural networks.

IV. Conclusion

In this paper some methods for detection of seizure in EEG signals were described. This methods and their result were elicited from various papers.

The most striking result from this investigation is that using variance for detection of seizure (on a downloadable EEG data) had the best result (100%) in compare of many complicated and modern methods.

To establish the clinical use for any seizure detection scheme it is necessary to test on out-of-sample data sets. This test should include the evaluation of a given statistic on numerous EEG recordings which are known not to contain an epileptic seizure. Comparisons between different statistics could be facilitated by calculating the number of false positives. Whilst there are a number of groups applying various statistical methods to databases of EEG recordings, there has been remarkably little effort made to contrast these methods [23], [24] and to evaluate their performance on different databases. To establish whether any of these methods can be used in a clinical setting will require either the collection of a very large database of recordings of sufficient duration (many hours) and/or increased co-operation between numbers of independent research groups.

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