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Detection of Epileptic Seizures by the Analysis of EEG Signals Using Empirical Mode Decomposition

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***Abstract*— The detection of epileptic seizure has a primary role in patient diagnosis with epilepsy. Epilepsy causes sudden and uncontrolled electrical discharges in brain cells. Recordings of the abnormal brain activities are time consuming and outcomes are very subjective, so automated detection systems are highly recommended. In this study, it is aimed to classify EEG signals for the detection of epileptic seizures using intrinsic mode functions (IMF) and feature extraction based on Empirical Mode Decomposition (EMD). These records have been acquired from the database of the Epileptology Department of Bonn University and consisting of 5 marker groups A, B, C, D, E in this study. These records taken from healthy individuals and patients are decomposed into IMFs by EMD method. Feature vectors have been extracted based on Tsallis Entropy, Renyi Entropy, Relative Entropy and Coherence methods. These features are then classified by K-Nearest Neighbors Classification (KNN), Linear Discriminant Analysis (LDA) and Naive Bayes Classification (NBC). Significant differences were determined between healthy and patient EEG data at the end of the study.**

Keywords—EEG Signal; Epileptic Seizures; Empirical Mode Decomposition; Feature Extraction; EEG Signal Classification

I. INTRODUCTION

Biological signals that represents the electrical activity of the brain are also called the electroencephalogram (EEG) [1]. Generally, brain electrical activity consists of Na+, K+, Ca++, and Cl- ions. Pumping of these ions through channels in neuron membranes creates the electrical current by membrane potential [2]. Recordable electrical activity on the head surface may be generated by the large populations of active neurons. Electrical current is weakened by skin, skull and some layers between electrode and neuronal layers. Scalp electrodes detect the weak electrical signals which are amplified, and then displayed on the monitor or paper, finally stored on a computer [3].

Epilepsy is one of the best-known neurological disease which affects 50 million people worldwide [4]. The activities of the neurons are usually very well organized and they have mechanisms which regulate itself. Neurons are also responsible for a wide range of functions such as consciousness, movement, speech, memory, excitement, body posture. These functions are performed by a very small amount of electrical charges which flows between the brain cells and all parts of the body. Temporary interruptions or involuntary irregularities that may occur in one or more functions are possible to define as 'seizure'. The epileptic seizure is an abnormal electrical activity that temporarily occurs in the nerve cells. Uncontrolled electrical discharges of cerebral neurons interrupt cerebral cortex function and cause the seizures [5].

EEG is painless and non-invasive method that contains diagnostic information on several neurological disorder [6]. Brain electrical activity is measured by using EEG which one of the most valuable outset of information for epilepsy research and treatment. Intracranial electrodes can be used to stimulate the brain and monitorize cortical and subcortical neurologic functions, such as function of motor and language in preparation for epilepsy surgery [7]. Then this information is used in determination of risk-benefit profile of the surgery. In some cases, seizures may be triggered by stimulation of electrodes during this functional mapping. Epileptic EEG waves which includes spikes, sharp waves, poly spikes, spike wave complexes are considered during the detection [8].

Seizure detection systems could be detecting the beginning of seizures and provide the more detailed data to control of epilepsy. These systems must be able to detect the presence or absence of seizures and provide a rapid therapy.

II. MATERIAL AND METHOD

A. Materials

The EEG dataset in this study is taken from Department of Epileptology at the University of Bonn, Germany [9]. Many detections of epileptic seizure method have been utilized in this dataset. The complete dataset *consists* of five sets as Z, O, N, F and S which containing 100 single-channel EEG signals, each one having 23.6 s duration. Eyes open (Z) and eyes closed (O) volunteers were relaxed awake position that contains normal EEGs. N and F seizure free data (set C and D) were taken from the epileptic patients by intracranial electrodes within epileptogenic zone. S data (set E) were recorded from epileptic subjects using intracranial electrodes which include the epileptic activities. The sampling rate of data is also (Fs) 173.61

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Hz and each segment comprises of 4,096 samples. 40 Hz low pass filter is used to remove the artifacts. In this study, we used the A and E dataset because they classify the epileptic attacks from normal healthy subjects.

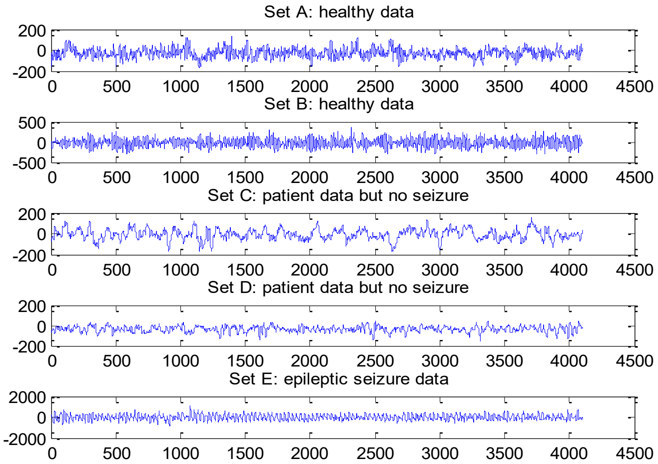

Fig. 1. An example of EEG signals from each of the five subsets (Z, O, N, F, and S).

B. Methods

1) Empirical Mode Decomposition

In 1998, Hilbert Huang introduced the EMD method which obtains the instantaneous frequency data in signal processing [10]. EMD is a signal processing method which decomposes the nonlinear and nonstationary signals [11]. Based on this model, any signal consists of various intrinsic mode oscillations which represents instantaneous frequency data as band-limited functions of time. These amplitude and frequency modulated (AM-FM) oscillating components are called an intrinsic mode decompositions (IMFs) [11]. These methods provide a signal as the sum of a finite number of IMFs and a final residual.

Each IMF satisfies two basic principles: i) In the whole dataset, the number of extrema and the number of zero crossings must be the same or differ at most one by one (adaptation of narrow band concept). ii) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero (new - adoption of local properties).

2) Signal Analysıs Method-IMF Selectıon Algorithm

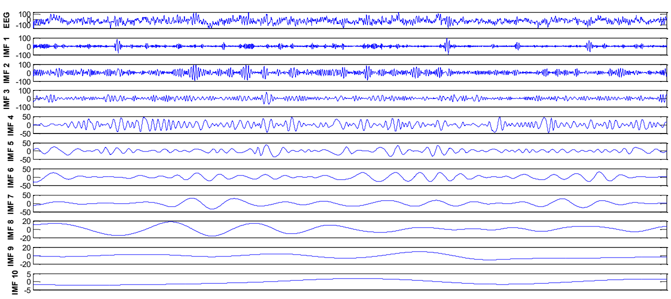

Fig. 2. Empirical mode decomposition of the 23.6 seconds normal EEG signal.

a) Fast Fourier Transform Method

Fourier transform is the most commonly used method for signal analysis and is used to obtain the distribution of the signal energy into frequencies [12]. While the frequencies of stationary signals do not change with time, the peaks during seizures play an important role in the detection of diseases in non-stationary signals such as EEG.

The Fourier Transform separates a signal into a weighted sum of sinusoids for effective extraction of information [12]. Spectral analysis of signal based on separation of the signal into frequency components. Fast Fourier Transform (FFT) provides a fast and efficient implementation of the Fourier transform with sufficient spectral resolution.

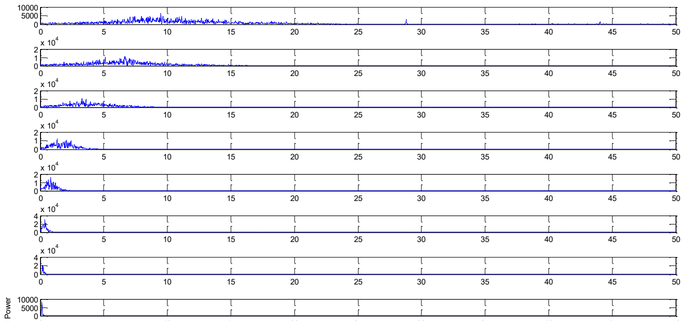

Fig. 3. Magnitude spectra of IMFs

Magnitude spectrum provides the simplest way to estimate the most significant IMFs. Hence, IMF1 above yields the highest frequency content.

b) Correlation

Correlation is a measure of similarity between two signals. Relationships between signals can be just as important as characteristics of individual signals. The equation for correlation is as in (1).

$$R_{x_1x_2}(\tau) = \int_{-\infty}^{+\infty} x_1(\tau)\, x_2(t-\tau)dt \qquad (1)$$

Auto correlation and cross correlation are two types of the correlation: Auto correlation is defined as correlation of a signal with itself and also is a measure of similarity between a signal and its time delayed version. Cross correlation function is a measure of similarity between two different signals.

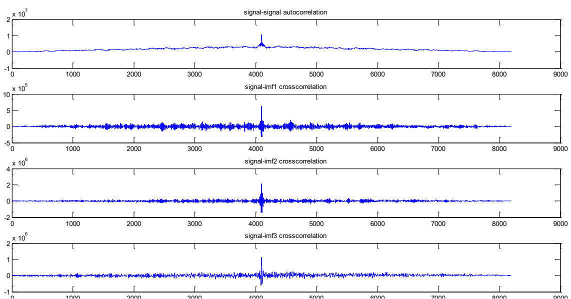

Fig.4. Correlation of IMFs and original signal

Then the correlation process, the variance of the correlations is calculated and it is observation that the cross correlation of IMF2-original signal is closest the autocorrelation of original signal.

C. Feature Extraction

IMFs was selected through the above-described process contain FFT and correlation, they can be utilized for the feature extraction. Purpose of the feature extraction which classification based on some criterions described in the following sections.

1) Estimated Probability Density Function using histogram function

The characteristic of random variable can be interpreted from the histogram. It is presented a simple and reliable histogram-based method to estimate probability density function (PDF). PDF is a very useful tool that identifies oscillatory signals in time series data and help to know their amplitude. In addition, PDF provide information about that frequency ranges variations by computing the sum of FFT of a signal. The time-frequency domain based our method for epileptic seizure detection includes time-frequency distribution.

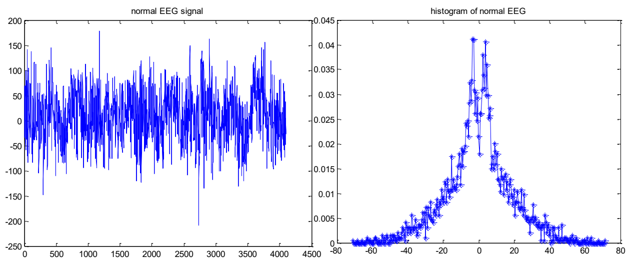

Fig 2. EEG data and histogram of the signal

As shown in Fig. 5, probability is area under the curve. Every random variable is associated with a probability density function. The normal data distribution is more regular.

2) Entropy Based Feature Extraction

Originally arose from thermodynamics is entropy which applied to EEG analysis. Entropy has recently developed as a suitable complexity measure in the processing of time series from biological systems such as brain. Because of the unpredictable characteristic of the EEG signals at any point, they are the best known random biosignals. A higher rate of the entropy represents the more uncertain result and prediction is more difficult [13]. Many complexity processes are related to entropy. The nonlinear arguments can be practical to characterize the dynamics of the nonlinear and non-stationary EEG signals.

a) Shannon Entropy

Shannon Entropy is called as an information entropy which was suggested Shannon et al. in 1949. Information entropy defined as [14];

$$Sen = \sum_{i=1}^{n} p(x_i)\log_a \frac{1}{p(x_i)} \quad ,a > 1 \tag{2}$$

with random variable X that consist of the values $x_1, x_2 \ldots, x_N$. $p(x_i)$ is the probability of random variable X values x_i..

The predictability of future amplitude values of the EEG is measured by Shannon Entropy based on already observed probability distribution of amplitude values in the signal. Higher values represent at more complex and more difficult to predict signals because that entropy is degree of uncertainty.

b) Tsallis Entropy

Consider a system with n values and pi is the probability of given symbol where q is a measure of how strong correlations are. The parameter q is a measure of nonextensivity [6-15] of the approach. There are continuous and discrete versions of this entropic measure.

$$TsEn(q) = 1 - \frac{\sum_{i=1}^{n}(p_i)^q}{q-1} \tag{3}$$

where $TsEn(q)$ is entropy. These entropies represent the measure of uncertainty about the event i.

c) Renyi Entropy

In the information theory, the Renyi Entropy measure is used for estimating the spectral complexity of the time series [16]. It can be defined as:

$$RenEn(q) = \frac{1}{1-q}\left(log\sum_{i=1}^{n}(p_i)^q\right), \quad q > 0, q \neq 1 \tag{4}$$

Higher values of q, approaching infinity. It gives Renyi entropy which is increasingly determined by consideration of only the highest probability events. Lower values of q, approaching zero. It gives Renyi entropy which increasingly weights all possible events more equally, regardless of their probabilities [17].

d) Relative Entropy

Relative entropy is also called Kullback–Leibler divergence between p and q which defined by

$$RlEn = \sum_{i=1}^{n} p(i)log\left(\frac{p(i)}{q(i)}\right) \tag{5}$$

p and q are two probability distributions on a random variable. *p(i)* is first probability function and *q(i)* is second probability function. We used the healthy person data for *p(i)* and healthy and patient data for *q(i)*. The results are compared between Z-Z and Z-S.

3) Coherence Based Feature Extraction

EEG coherence is a degree of association and also called 'magnitude-squared coherence'. Within frequency band, coherence is an approximation of the consistency of association amplitude and phase between signals detected in electrodes [18].

$$Cxy(f) = \frac{|\mathrm{Gxy(f)}|^2}{\mathrm{Gxx(f)\ Gyy(f)}} \qquad (6)$$

Gxy(f) is cross spectral density between x and y. Gxx(f) and Gyy(f) are auto spectral density of x and y.

III. CLASSIFICATION

In order to classify epileptic and normal data, three classifiers were used **(i)** K-Nearest Neighbor Classification (KNN), **(ii)** Linear Discriminant Analysis (LDA), **(iii)** Naive Bayesian Methods.

The classifier performance is calculated by using sensitivity, specificity and accuracy parameters.

IV. RESULT AND DISCUSSION

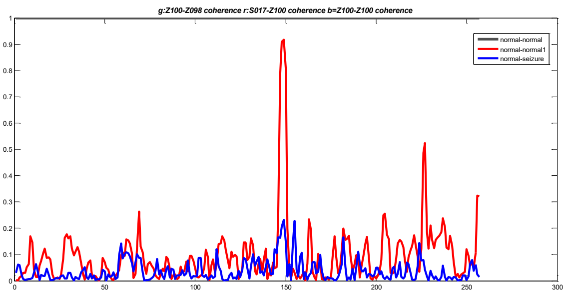

Fig. 6. Outcome assessment of coherence analysis.

In Fig. 6, 'the normal line' shows that coherence of the same data. 'The normal1 line' represent coherence of two different normal data. 'The seizure line' also shows that coherence of normal and seizure data.

TABLE I. Renyi Entropy and IMFs values

RENYI	Z(normal)	S(epileptic)
	IMF2	IMF2
100	3.1996	6.8257
96	3.5016	5.6521
93	3.2583	7.1636
90	3.6673	7.2649
86	2.9300	6.7384
83	2.2359	5.0679
80	1.8378	7.2092
76	2.9250	7.9637

Renyi entropy values were calculated from EEG data. As shown in Table 1, rapid frequency change was observed after seizure which also increased the entropy. The entropy of epileptic data is higher than normal data entropy. Because the irregularity is much more in seizure leading to increased levels of mental activity and epileptic signal has higher variations. The significant difference was obtained in the Renyi Entropy.

The extracted features were taken into the classifiers. In our study, we obtained that the highest accuracy value is 96.97%, sensivity value is 96.97%, specify value is also 96.97%, respectively. From the classification results, it is shown that the entropy and coherence measures can significantly recognize and classify normal and epileptic EEG signals

It has been observed that the proposed method can be used for classifying healthy data and epileptic data. This method can be used as detection tool for clinicians during monitoring the epilepsy. From the above discussion, it is clearly shown that two types of EEG signals (normal and epileptic) can be obviously distinguished by these above described analysis techniques. They can be used as a cost and time effective, approach to detect the epilepsy method.

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