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Detection Of Epileptic Seizure From EEG Signal Using Wavelet Transform And Artificial Neural Network

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ABSTRACT
Epilepsy is the fourth most common neurological problem in which brain activities becomes abnormal, causing seizure or unusual behavior and sometimes loss of awareness. An electroencephalogram (EEG) signal is used to detect problems in electrical activity of the brain that is associated with certain brain disorders. In this paper, electroencephalogram signals were decomposed into the frequency sub-bands using DWT and set of statistical features were extracted from the sub-bands to represent the distribution of wavelet coefficients. Later, extracted features are given as an input to the neural network for classification of normal and epileptic signal. EEG signal is collected from the publically available Bonn dataset. Experimental results show that 99.8% accuracy is achieved in the classification using the proposed method.
Keywords – Artificial Neural Network, Back Propagation Neural Network, Discrete Wavelet Transform (DWT), Electroencephalogram (EEG), Epilepsy.

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders which affecting more than 65 million number of people around the world. It is a neurological disease affecting the nervous system. Epilepsy is also known as a seizure disorder. It is usually diagnosed after a person has had at two seizures or more, that were not caused by some known medical condition. The seizures in epilepsy related to abnormal activity of brain signal.

Brain waves or neural signals obtained by Electroencephalogram (EEG) recordings is an important research area and plays a vital role in medical, health applications and Brain Computer Interface (BCI). There are two categorize in which the BCI systems can be categorized; invasive and non-invasive. These are the used categorized in which to measure the activity of the brain. For the system to be considered invasive BCI system the sensors used to measure the brain activity is placed inside the skull. The opposite of that is non-invasive system, which is having the sensors that measure brain activity be put outside the brain or surrounding the skull [2].

EEG activity can be broken down into 4 distinct frequency bands: Delta (<4Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), Gamma (>30 Hz).Analysis of EEG activity has been achieved in clinical settings to identify pathologies and epilepsies since Hans Berger's recording of rhythmic electrical activity from the human scalp. In the past, interpretation of EEG was limited to visual inspection by a neuro physiologist, an individual trained to qualitatively make a distinction between normal EEG activity and abnormalities contained within EEG records. The advance in computers and the technologies related to them has made it potential to successfully apply a host of methods to quantify EEG changes (Bronzino,2000).There is a strong demand for the development of automated device to diagnosis neurological disorder. The entire process can be generally subdivided into a number of disjoint processing modules: segment detection, feature extraction/selection and classification.

Wavelet Transformation (WT) is designed to address the problem of nonstationary signals (EEG is a nonstationary signal). It involves representing a time functions in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. The main advantage of WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges. The property of time and frequency localization is known as compact support and is one of the most attractive features of WT.

The EEG signal consisting of many data points, can be compressed into a few features by performing spectral analysis of the signals with the

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wavelets. The features characterize the behavior of EEG signal. Using small number of features to represent the EEG signals is particularly important for recognition and diagnosis purpose. Therefore, EEG signals were decomposed into time-frequency representation using discrete wavelet transform (DWT). Wavelet coefficients were used as a feature vectors to classify frequency bands of eeg signal and to identify the characteristics of the signal.

Artificial neural network (ANN) have been used in a great number of medical diagnostic decision support system application because that they have great predictive power. In this work, EEG dataset is analyzed completely by using wavelet transformation and to extract all the fundamental frequency components of EEG signal that is Alpha, Beta, Gamma, Delta and Theta. In order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients were used. Artificial neural network is trained with the extracted feature to classify signal into normal and epileptic.

The rest of the paper is organized as follows. Section II describes a review on previous methods. Summary of dataset and methods used is given in section III. Section IV gives result with discussion and Conclusion is given in Section V.

II. LITERATURE REVIEW

In the last two decades, many researchers addressed the problem of automatic seizure detection. It has been shown that all the methods fall into four categories: (a) time domain, (b) frequency domain, (c) time-frequency domain and (d) nonlinear methods. Abdulhamit et al. [4] used principal, independent, linear discriminate and support vector machine for the classification of epileptic EEG signals. Rafik et.al. [2] proposed Empirical mode decomposition (EMD) for feature extraction of EEG signal and artificial neural network for the classification. Arun chavan et al. [5] used wavelet transform and neural network for diagnosis and classification of EEG signal.

III. MATERIALS AND METHODS
3.1 Dataset Description

The dataset used in our experiments is from the department of epileptology at the University of Bonn, which is publically available and described with more details in [21]. The dataset consists of five sets (denoted A-E), each containing 100 single-channel EEG signals of 23.6, sampled at frequency of 173.61 Hz with bandpass filter settings at 0.5-40 Hz (12 db/octave). Set A and B have been taken from surface EEG recordings of five healthy volunteers, while sets C and D have been measured in seizure-free intervals from five patients. Set E contains seizure activity selected from all recording

sites exhibiting ictal activity. Therefore, in the present work three dataset A, D and E corresponding respectively to normal EEG recordings (healthy subjects set A), interictal activity (set D) and ictal activity (set E) was classified. Note that the signals of set E are taken from patients during a seizure activity, while the signals of set D are from the same patients in seizure-free intervals.

3.2 Wavelet Transform

The wavelet transform is similar to the Fourier transform with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\Psi_{(a,b)}^{*}(x)dx \qquad (1)$$

where the * is the complex conjugate symbol and function ψ is some function. Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation. There are different types of wavelet transforms are available and it has been mainly classified into two major types: Orthogonal wavelets for Discrete Wavelet transform and Non-Orthogonal wavelets for Continuous Wavelet transform. In this work, discrete wavelet transform is used as it reduce the redundancy and decompose the signal into multiple level which would be helpful to find out the different range of hidden frequency band from the eeg signal.

3.3 Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) decomposes the signal into mutually orthogonal set of wavelets. The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies mathematical conditions as follows:

$$\varphi(x) = \sum_{k=-\infty}^{\infty} a_k \, \varphi(S - k) \qquad (2)$$

where S is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty} \varphi(x)\varphi(x + l)dx = \delta_{0,l} \qquad (3)$$

For most signal and image processing applications, DWT-based analysis is best described in terms of filter banks. The use of group of filters to divide up a signal into various spectral components is termed as

sub-banding. This procedure is known as multi-resolution decomposition of a signal. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, h[] is the discrete mother wavelet, high-pass in nature, and the second, g[] is its mirror version, low-pass in nature. The down-sampled outputs of first high-pass and low-pass filters provide the details D1 and the approximation A1 respectively. (Abdulhamit et al.)

3.4 Artificial Neural Network

Artificial neural networks (ANN) were successfully used in a wide variety of medical applications. Neural Networks are highly interconnected and simple processing units which are designed to model the way human brain perform a particular task. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, it has three important layers: input, hidden and output. The choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems. In order to find the optimal network architecture, several combinations should be evaluated [10].

IV. RESULTS AND DISCUSSION

4.1 Proposed Method

The method proposed in this paper is illustrated in Fig.1
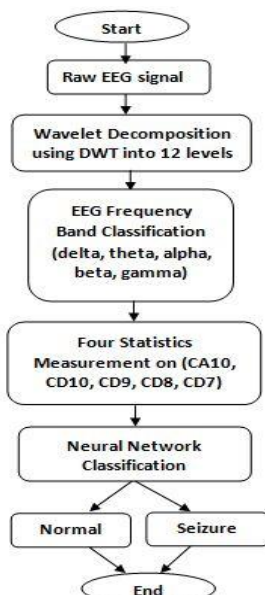

Fig. 1 – Flow chart of the proposed seizure detection method.

EEG signal is decomposed into 12 levels using db1 filter, where CA10 (0-3.5 Hz), CD10 (3.5-7.8 Hz), CD9 (7.8-11.4 Hz), CD8 (11.4-31.6) Hz), CD7 (31.6-43.2) and rest of the decomposition contain the frequency >43.2 Hz. Since the EEG signals do not

have any useful frequency components above 30 Hz, the decomposed level chosen for feature extractions are CA10 to CD7. In order to further decrease the dimensionality of the extracted feature vectors statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time-frequency distribution of the EEG signals:

1. Maximum wavelet coefficients in each subband.
2. Minimum wavelet coefficients in each subband.
3. Mean of the wavelet coefficients in each subband.
4. Standard deviation of the wavelet coefficient in each subband.
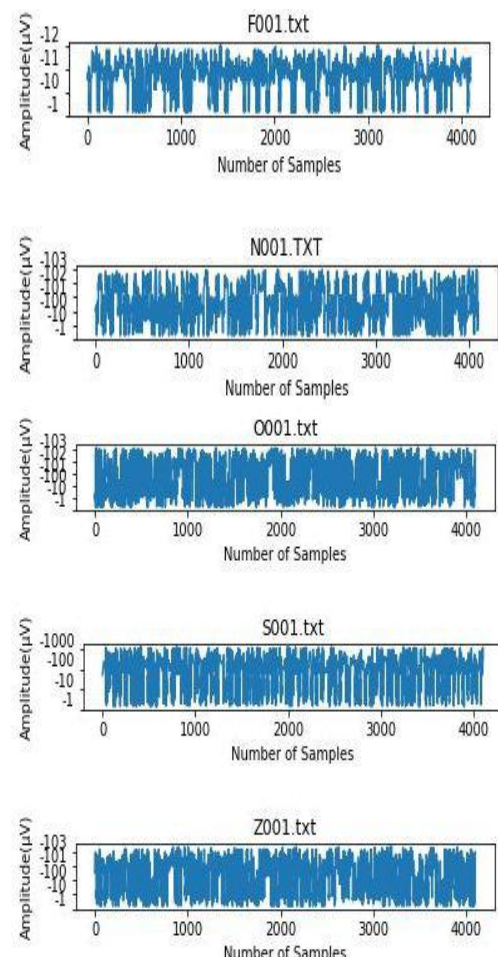
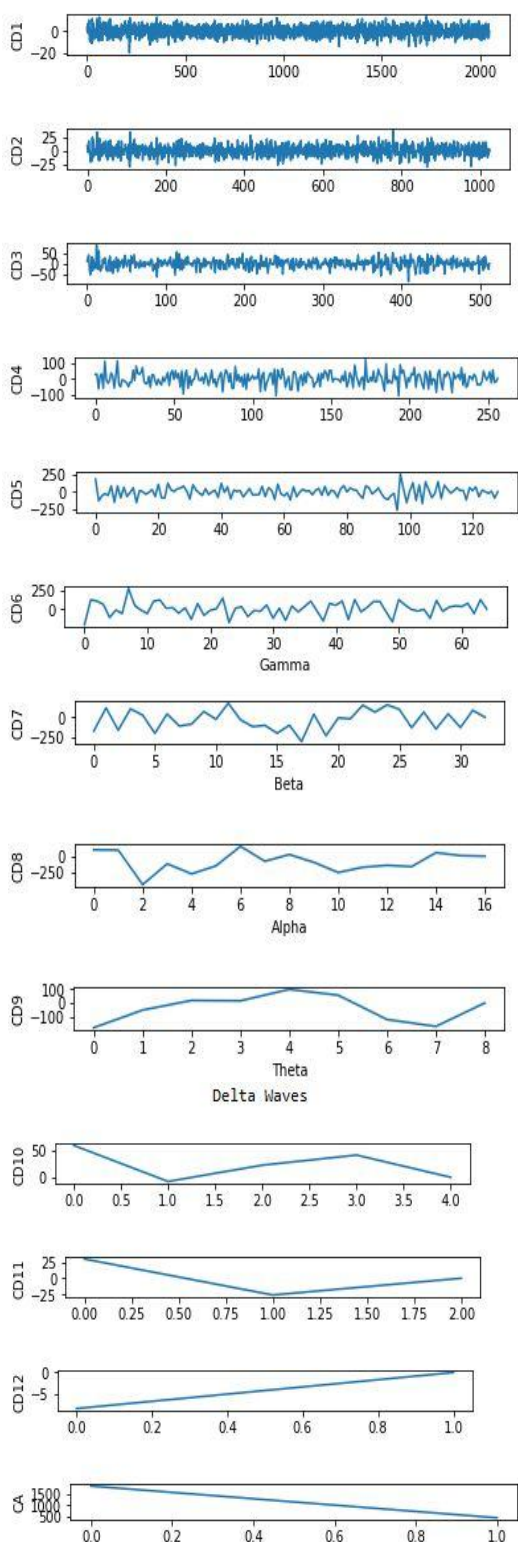**Fig. 2.** Five different sets of EEG signals from different subjects.

Fig. 3. Gamma, Beta, Alpha, Theta, Delta Frequencies.

4.2 Classification using BPN
  The Back Propagation neural network (BPN) used for classification of EEG segments. The network topology has two hidden layer with 20 input

neurons, equal to the number of input feature vectors. The number of hidden layer was 15, 10 and the number of output unit is 2. The network is trained with 400 and tested with 100 samples of EEG. Out of 500 samples 400 were normal and 100 were abnormal samples. The network correctly able to classify EEG signals with an accuracy of 99.80%.

4.3 Classifier Performance Assessment
  Classification results of the Artificial Neural Network were displayed by confusion matrix. (Table 1) The test performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy.

Table 1: Confusion Matrix

n = 100	Predicted: NO	Predicted: YES	Total
Actual NO	TN = 74	FP = 1	75
Actual Yes	FN = 0	TP = 25	25
Total	74	26	100

Specificity: number of true negative decisions / number of actually negative cases
Sensitivity: number of positive decisions / number of actually positive cases
Classification Accuracy: number of correct decisions / total number of cases

- **True Positive (TP):** These are cases in which we predicted yes (they have diseases), and they do have diseases.
- **True Negative (TN):** We predicted no, and they don't have the diseases.
- **False Positive (FP):** We predicted yes, but they don't actually have disease.
- **False Negative (FN):** We predicted no, but they actually do have the diseases.

Table 2: The classification accuracies

Statistical Parameters	Values
Specificity	98.6
Sensitivity	100
Total Classification Accuracy	99.8

V. CONCLUSION

In this work, dabechie1 is used as a mother wavelet for decomposition of eeg signal. Since other wavelet filters such as symlet, coiflet and biorthogonal with its wavelist gives average of decomposition level as 9 where db1 gives 12 level of decomposition for 4097 data points which properly decompose the

signal upto last level and also it makes the frequency band classification of eeg process as simple. Then statistical features were calculated over the decomposed level to further reduce the dimensionality to train with the neural network. Experimental result shows an accurate classification performance for normal and seizure signal with an accuracy of 99.8%. The future work includes identifying Alzheimer disease using the proposed method.

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