Design Simulation and Performance Analysis of Expert System for Diagnosis of Epilepsy using Wavelet Transform and Soft Computing Techniques

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***Abstract*—Epilepsy is a neurological disease with a prevalence of about 1-2% of the global population. Epilepsy is a neurological disorder that is caused by a chronic abnormality of brain discharge. Monitoring brain activity through electroencephalography (EEG) has become an important tool for the diagnosis of epilepsy. EEG recordings in epileptic patients show two types of abnormal activity: abnormal signals recorded during the epileptic seizure; and seizures, activities recorded during the epileptic seizure. The main goal of our research is to analyze the acquired EEG signals using signal processing tools (such as wavelet transforms) and classify them into different categories. The features from the EEG are extracted using statistical analysis of parameters obtained by wavelet transform.Total 300 EEG data subjects were analyzed. These data were grouped in three classes'i.e, Normal patient class, Epileptic patient class and epileptic patient during non-seizure zone respectively. In order to achieve this we have applied a backpropgation based neural network classifier.After feature extraction secondary goal is to improve the accuracy of classification. 100 subjects from each set were analysed for feature extraction and classification and data were divided in training, testing and validation of proposed algorithm.**

***Index Terms*—EEG, Epilepsy, Wavelet transform; Feature Extraction, Neural network, Backpropogation Neural Network.**

I. INTRODUCTION

In general, detection of epilepsy can be achieved by visually scanning EEG recordings of inter-seizure and seizure activity by experienced neurophysiologists. However, visual assessment of large volumes of EEG data has serious drawbacks. Visual inspection is very time-consuming and inefficient, especially in the long-term record. In addition, there may be disagreements among neurophysiologists in the same record due to subjective nature of the analysis and due to changes in spike morphology during the episode.

In addition, the EEG pattern characterizing seizures resembles waves that are part of the background noise as well as artifacts such as blinking and other eye movement, muscle activity, electrocardiogram, electrode "pop" (especially in extra cranial recordings) and electrical interference . For these reasons, the automated method of detecting interictal spikes and seizures can serve as a valuable clinical tool for reviewing EEG data in a more objective and computationally efficient manner [1].

1.1 Wavelet Transform- Discrete Wavelet Transform (DWT) is a very effective signal time-frequency analysis tool. Wavelet transforms can be defined as spectral estimation techniques, where any general function can be expressed as the sum of an infinite series of wavelets. In DWT, the timing of the signal can be achieved using digital filtering techniques. The method of multi-resolution decomposition of signal x (n) is shown in Figure 1.1. The DWT is computed by successive low pass and high pass filtering of the signal x (n). Each step consists of two digital filters and two down samplers by 2. The high pass filter g[] is the discrete mother wavelet and the low pass filter h[.] is its mirror version. At each level the down sampled outputs of the high pass filter produce the detail coefficients and that of low pass filter gives the approximation coefficients. The approximation coefficients are further decomposed and the procedure is continued as shown in figure.1.1.

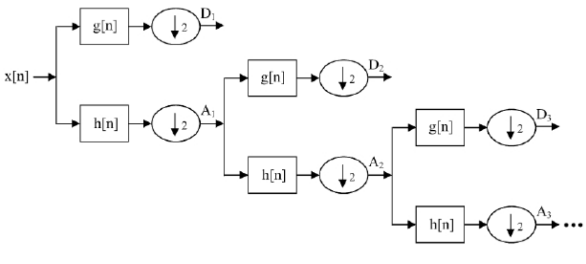

Figure 1.1.Computation process of DWT

The standard equation of Discrete Wavelet Transform is given as-

$$w_{m,n} = \left\langle x(t), \psi_{m,n} \right\rangle = a_0^{m/2} \int f(t)\psi(a_0^m(t) - nb_0)dt \qquad (1.1)$$

Where sub wavelets is given by-

$$\psi_{m,n}(t) = a_0^{m/2}\psi(a_0^m(t) - nb_0) \qquad m,n \in Z \qquad (1.2)$$

The DWT decomposition can be described as

$$a\ k\quad l\ = x\ k\ * \varphi k,l\,(n)$$

$$d\ k\quad l\ = x\ k\ * \psi k,l\,(n)$$

where *a*(*k*)(*l*) and *d(k)*(*l*) are the approximation coefficients and the detail coefficients at resolution k, respectively.

Wavelet transform gives us a multi-resolution description of the signal. It solves the problem of non-stationary signal, so it is especially suitable for the feature extraction of EEG [2]. At high frequencies, it provides a good temporal resolution, which provides better frequency resolution for low frequencies because of the use of a mother wavelet and different bases generated from the mother wavelet by scaling and panning Function to calculate the transform. It therefore has a variable window size, which is low bandwidth and narrow at high frequencies, providing the best resolution at all frequencies.

1.2 Data base-The raw EEG signal is obtained from university of Bonn which consists of total 5 sets (classes) of data (SET A, SET B, SET C, SET D, and SET E) corresponding to five different pathological and normal cases. Three data sets are selected from 5 data sets in this work. These three types of data represent three classes of EEG signals (SET A contains recordings from healthy volunteers with open eyes, SET D contains recording of epilepsy patients in the epileptogenic zone during the seizure free interval, and SET E contains the recordings of epilepsy patients during epileptic seizures) All recordings were measured using Standard Electrode placement scheme also called asInternational 10-20 system. Each data set contains the 100 single channel recordings. The length of each single channel recording was of 26.3 sec.The 128 channel amplifier had been used for each channel [3]. The data were sampled at a rate of 173.61 samples per second using the 12 bit ADC. So the total samples present in single channel recording are nearly equal to 4097 samples (173.61×23.6). The band pass filter was fixed at 0.53-40 Hz (12dB/octave) [4].

II. METHODOLOGIES

DWT successfully analyzed multi-resolution signals in different frequency bands and decomposed the signals into approximate and detail information. The band separation method for epilepsy detection is implemented in MATLAB 2013a. The proposed flowchart for a method of detecting epilepsy data from normal data is shown. Epilepsy testing using EEG requires extracting features from the acquired signal over a specific frequency range of δ, θ, α, β, and γ. Although some researchers have already mentioned DWT decomposition to obtain these bands, the method given is not sufficient to achieve this. First, this study explicitly describes a method of up sampling and recombining multiple decomposition sub bands to achieve the desired frequency.

Data is first pre-processed by removing dc component from the signal thereby achieving different levels of decomposition for Daubechiesorder-2 wavelet with a sampling frequency of 173.6 Hz on each signal of 4096 samples.

The overall process can be explained using following flowchart-

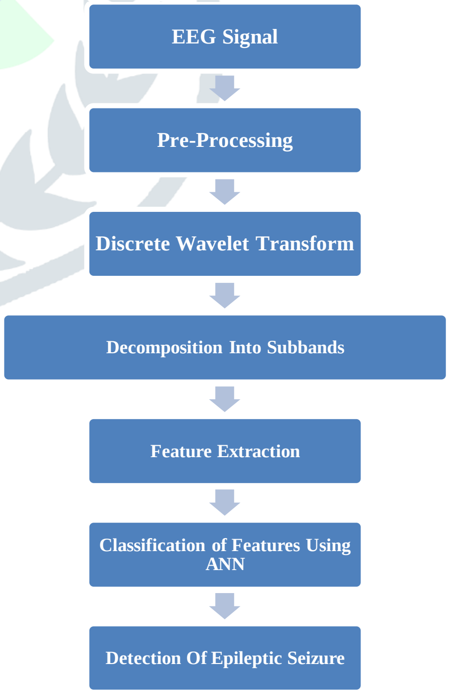

Fig2.1Steps of Detection Of Epilepsy Using EEG

2.1 Feature Extraction using Wavelet Transform– From the data available at [9] a rectangular window of length 256 discrete data was selected to form a single EEG segment. For analysis of signals using Wavelet transform selection of the appropriate wavelet and number of decomposition level is of utmost importance. The wavelet coefficients were computed using daubechies wavelet of order 2 because its smoothing features are more suitable to detect changes in EEG signal. In the present study, the EEG signals were decomposed into details D1-D5 and one approximation A5. After calculating coefficients we can calculate various features using statistical analysis of coefficients. [4]

The feature extraction is shown in fig 2.2-

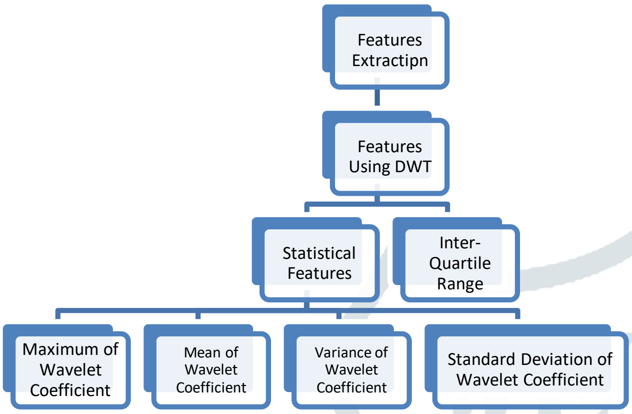

Fig 2.2Feature Extraction using DWT

A rectangular window of length 256 discrete samples is selected from each channel to form a single EEG segment. The total numbers of time series present in each class are 100 and each single channel time series contained 16 EEG signal segments. Therefore total 1600 EEG segments are produced from each class. Hence, total 4800 EEG segments are obtained from three classes. The 4800 EEG segments are divided into training and testing data sets. The 2400 EEG signal segments (800 vectors from each class) are used for testing and 2400 EEG signal segments (800 segments from each class) are used for training.[5]

Figure 2.3,2.4 and 2.5 shows the plot of raw EEG signals from the given set of data. These signals were analyzed using matlab to decompose it using DWT with db2 as mother wavelet and the level of decomposition as 5.

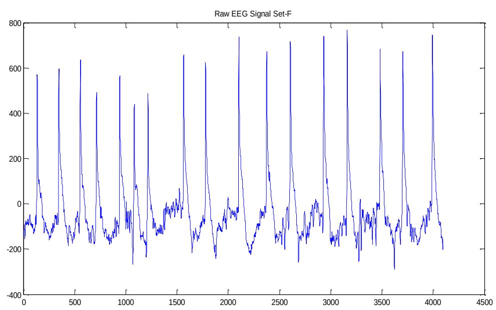

Figure 2.3 Raw EEG Set-F

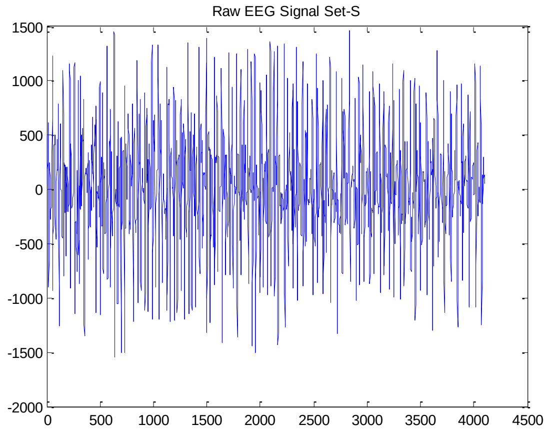

Figure 2.4 Raw EEG Set-S

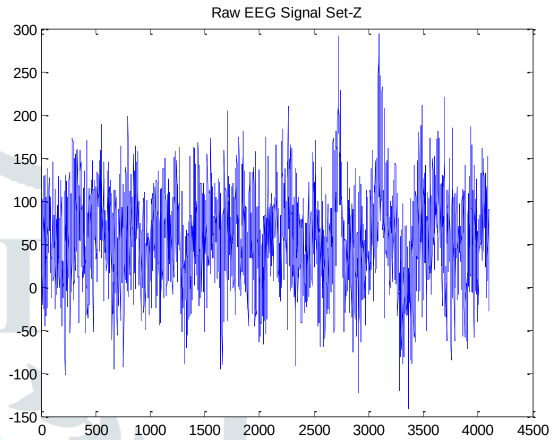

Figure 2.5 .Raw EEG Set-Z

III.CLASSIFICATION USING NEURAL NETWORK

In our work, we have implemented the classification of epileptic EEG with the help of a scaled conjugate back propagation neural network with a hidden layer equal to 10 and initial weights assumed to be zero. In order to classify features using neural networks, we need two important predefined parameters, as follows:

3.1. Input Vector- In our research the feature vector was implemented as input vector. This input vector consists of a matrix of size 25X300 such that rows indicate the features and column indicates number of samples.

and column indicates number of samples to be tested. The overview of target vector is discussed as follows-

- ✓ Class 1 – Epileptic Patient without Seizures- (1 0 0)
- ✓ Class 2 – Epileptic Patient during Seizures- (0 1 0)
- ✓ Class 3 – Normal Patients without Seizures - (0 0 1)

The overall classification was done using input vector and target vector with scaled conjugate gradient based back propagation neural network.

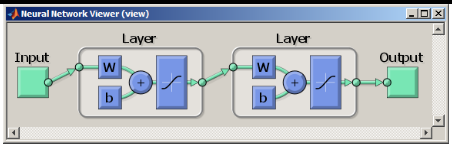

Figure 3.1.Model of Neural Network

In our classification process there are 25 input layers with 10 hidden layer and 3 output neurons for wavelet based features.

- Input Neurons = Number of features
- Output Neuron = Number of Target Classes

IV RESULTS

The overall samples are divided into three categories-

- ✓ **Training Data**-70 % of total 240 samples from given dataset.
- ✓ **Testing Data-** 15 % of 240 samples from given **Validation Data-** 15 % of 240 samples of given dataset.
- ✓ **Unknown Testing Data**-20 samples from each class of EEG samples.(Total 60 samples) .

Type of Dataset	Percentage Accuracy	
	During Training Testing and Validation With 80 Samples of Each Class	During Testing With 60 Unknown Samples (20 from Each Class)
Set-F(Epileptic Patient without Seizures)	98.8%	100%
Set-S(Epileptic Patient with Seizures)	100%	99%
SetZ (Healthy Patient without Seizures)	96.3%	90%
Overall Accuracy of the Network	98.3%	97%

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IV CONCLUSION

In our research work 300 datasets were analyzed with Wavelet Based Statistical Features. In the given table mentioned below we have summarized the classification accuracy of both feature vectors on same epileptic eeg data which can serve as a basis for comparison of their effectiveness.Classification process can be implemented to large number of dataset to enhance accuracy. Neural Network classifier can be replaced by optimized hybrid classifier.Pre-Ictal epileptic data can be analyzed for developing an efficient epilepsy prediction system.

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