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WAVELET BASED EEG FEATURE EXTRACTION TECHNIQUE FOR NEUROFEEDBACK SYSTEM: A REVIEW

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ABSTRACT

In this paper, we present two new methods for the Electroencephalography signal analysis and those are Discrete Wavelet Transform and Daubechies Wavelet Transform and their comparison is done as to find the better efficient signal analysis technique. And the signals are classified into seizure and non-seizure signals by applying neural network classifier which is easier to implement and more efficient.

I. INTRODUCTION

A chronicle disorder of the nervous system will be termed as Epilepsy and if a bulk of neurons undergo some synchronized eruptible changes then is will be noted that the person is a seizure person. Sometimes it is also called that an ictal activity is taking place. We very well know that Electroencephalography, popularly known as EEG signals are the set of signals which consists of the recordings of the activities of the human brain. In this paper, different EEG signals are taken and these signals are first to be analyzed using two different signal analysis techniques i.e. Discrete Wavelet Transform and Daubechies Wavelet Transform and then the classification of these signals are to be done using neural network as in to determine whether the applied signal is seizure or non-seizure [1].

1.1 EEG based BCI (Brain Computer Interface) System

In Fig (1) the general model of EEG based BCI system is shown where initially we take the signals from the database or real time data acquisition from the electrodes can be done and these signals will be preprocessed and then segmented where Discrete Wavelet Transform and Daubechies Wavelet Transform theory is applied for the signal analysis by which the features are extracted and then a neural classifier is applied for the detection of the seizure and non-seizure signals [2].

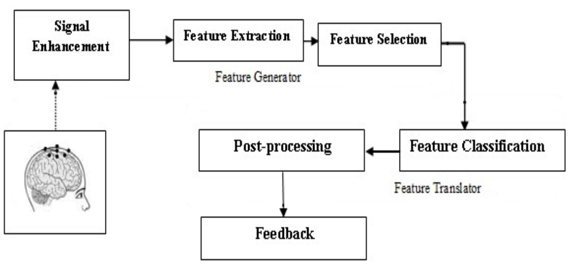

Fig.1: General model of EEG based BCI system

So in this paper first we deal with the two types of signal analysis techniques, Discrete Wavelet Transform and Daubechies Wavelet Transform in II. And then Types of Neural Networks used to classify the given EEG data into seizure and non-seizure EEG signals are dealt in III. And finally we conclude with the conclusion IV which decides which among the two is better [3].

II. SIGNAL ANALYSIS TECHNIQUE

2.1 Discrete Wavelet Transform (DWT)

The DWT is an advantageous tool for signal processing. It comprises of two sets of functions called wavelet functions and scaling functions, which are related to low-pass and high-pass filters respectively. By decomposing the signal into detail information and coarse approximation, the signal at different frequency bands with different resolutions is analyzed. This decomposition of the signal of different frequency bands is obtained by consecutive low-pass and high-pass filtering of the time domain signal. This is called as Mallat algorithm or Mallat-tree decomposition [4]. The DWT is also based on sub-band coding which is found to yields a fast computation of wavelet transform. This makes easy to implement and reduce the computation time and resources required. One application in which the DWT is particularly successful in the epileptic seizure detection because it captures transient features and localizes them in both time and frequency content accurately. Thus, the wavelet transform can be computed discretely on the time-frequency plane, to reduce the redundancy. The signal is denoted by the sequence x(n) where n is an integer. The high-pass filter is denoted by H_0 and the low-pass filter is denoted by G_0. Detail information d(n) is produced at each level of the high-pass filter while the coarse approximations a(n) is produced at each level of the low-pass filter associated with scaling function as shown in fig. 2. At each level decomposition, signals spanning only half the frequency band are produced by the half band filters. Thus doubles the frequency resolution as the uncertainty in frequency is reduced by half. According to Nyquist's rule, if the highest frequency of the original signal is ω then sampling frequency required will be 2ω radians therefore the highest frequency now it has is ω/2 radians. Thus, at sampled frequency of ω radians it discards half the samples without any loss of information. Here, the entire signal as the time resolution by decimation by 2 halves is represented as only half the number of samples. Thus, the decimation by 2 doubles the scale and the half band low-pass filter removes the half of the frequencies therefore halves the resolution. The very important aspect is in the selection of suitable wavelet and number of decomposition levels in the analysis of signals using the DWT. Based on the dominant frequency components of the signal the number of decomposition levels are chosen. The levels are chosen such that those parts of the signal that correlate well with the frequencies that are necessary for classification of the signal are retained in the wavelet coefficients [5].

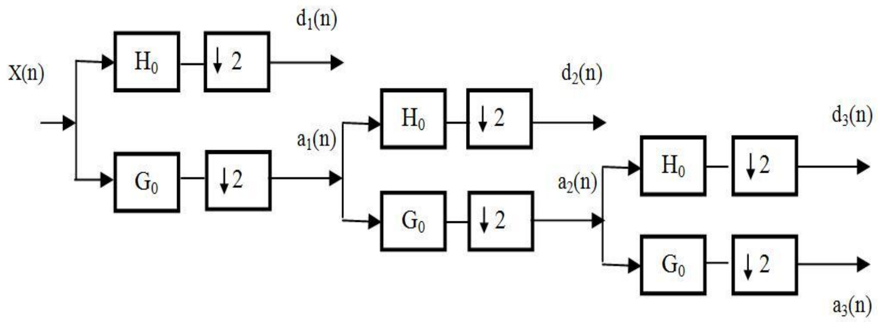

Fig. 2: Approximation and detail decomposition of three level DWT

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2.2 Daubechies Wavelet Transform

The Daubechies wavelet commonly belongs to the family of orthogonal wavelets which defines a discrete wavelet transform. This family of wavelet transforms is discovered by Ingrid Daubechies. The difference between the Daubechies and Haar wavelet transform is only that how the scaling signals and wavelets are defined. In this class with each wavelet type, there is a scaling function called as the father wavelet which generates an orthogonal multiresolution analysis. The Daubechies wavelet transform produces an average and differences using just a few more values from the signal which makes the scaling signals and wavelets to have slightly longer supports. Because of this slight change, it produces a great improvement in the capabilities of these new transforms. For performing basic signal processing tasks these provide us with a set of powerful tools [6].

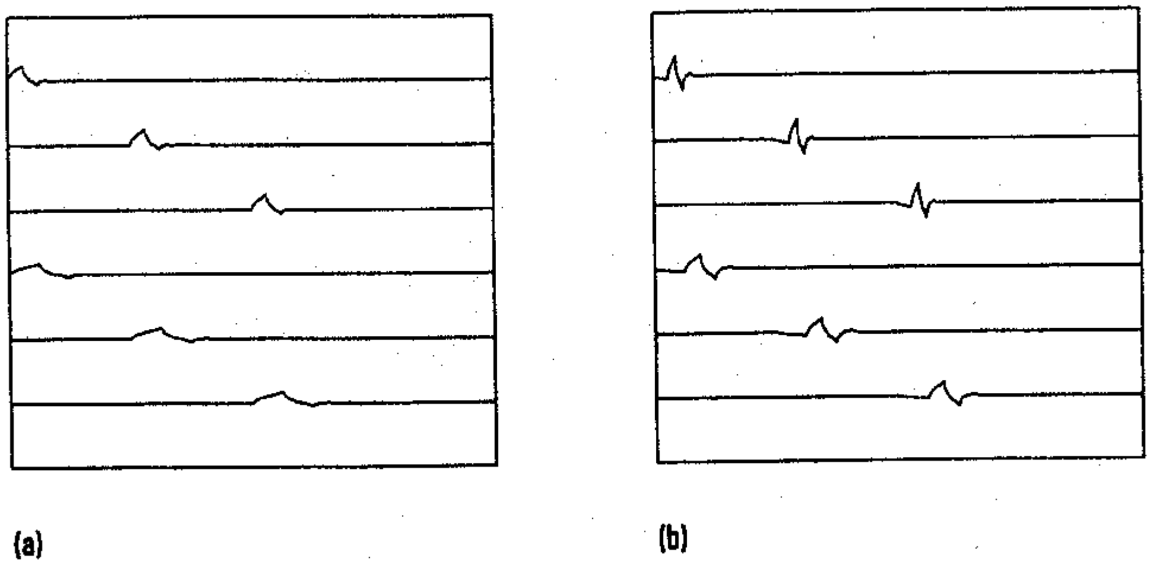

Fig.3: a) Scaling Function and b) Wavelets

Figure 3 a) illustrates that, the top three signals are 5-level Daub4 scaling signals and the bottom three signals are 6-level scaling signals. Figure 3 b) shows that, the three signals are 5-level Daub4 wavelets and the bottom three signals are 6-level wavelets.

The scaling numbers are defined by,

$$\alpha_1 = \frac{1+\sqrt{3}}{4\sqrt{2}}, \alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, \alpha_3 = \frac{3-\sqrt{3}}{4\sqrt{2}}, \alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

Then the wavelet numbers are defined by,

$$\beta_1 = \frac{1-\sqrt{3}}{4\sqrt{2}}, \beta_2 = \frac{\sqrt{3}-3}{4\sqrt{2}}, \beta_3 = \frac{3+\sqrt{3}}{4\sqrt{2}}, \beta_4 = \frac{-1-\sqrt{3}}{4\sqrt{2}}$$

Where, the relation between the wavelet numbers and scaling numbers are given by [7],

$$\beta_1 = \alpha_4, \beta_2 = -\alpha_3, \beta_3 = \alpha_2 \text{ and } \beta_4 = -\alpha_1$$

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III. CLASSIFICATION OF THE EEG SIGNALS USING NEURAL NETWORKS

3.1 Types of Neural Networks used to classify the given EEG data into seizure and non-seizure EEG signals

Over the last few decades neural network architecture has become a most popular in a various domains for application purpose. It is also a powerful technique for to solve a wide variety of problems. There was much advancement made to improve the performance and for better understanding that how these neural networks operate. Here DWT and Daubechies wavelet transforms are used for feature extraction of EEG signals then these signals has to be classified. That is done by neural network classifiers. The two type's of neural network classifier are as follows,

3.1.1 Multilayer Perceptron Neural Network Model: Multilayer perceptron neural network is classical supervised neural network architecture. It consists of an input layer with multiple neurons (X1-Xm), hidden layer with multiple neurons (Z1-Zp) and output layer with multiple neurons (Y1-Yn) as shown in the fig.4. Neurons are referred as nodes. Here all the multiple input signals are connected to X1-Xm neurons respectively. Then these input signals are fed to one or more hidden layers which contains several hidden layer nodes which helps to facilitate nonlinearity to determine an efficient multidimensional nonlinear mapping between input and output layer which is then fed to output layer to generate the output of the neural network. The neural network has to be trained before it is used as the final output. In order to adjust the weights of the signals backpropagation algorithm will be used for mapping of valid input to the correct output [8].

Lets now represent a neural network with single real input 'X' and network function 'f'. Then the computation of derivative f'(X) is done in 2 phases as given below:

1. Feed-Forward: The input X is given to the network. At each neuron the primitive functions and their derivatives at the neurons are calculated and then these derivatives are accumulated.

2. Backpropagation: The network runs backwards feeding constant 1 to the output unit. To the neuron the entering data is added and that outcome value is multiplied by the left accumulated value and then, the obtained result is accumulated in the left part of the unit. We will get a result at the input unit which will be the derivative of the network function w.r.t X [9].

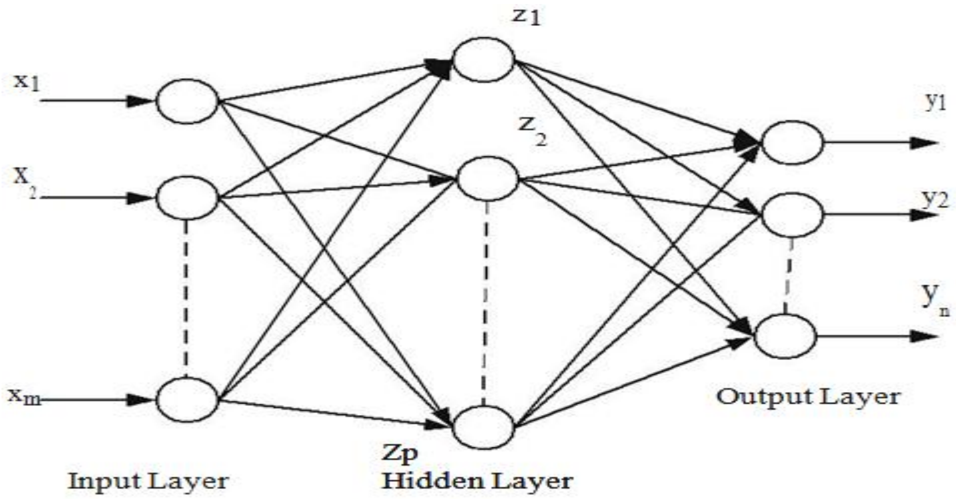

Fig. 4 A typical architecture of MLPNN

3.1.2 Probabilistic Neural Network: A radial basis function networks (RBFN) with variations will be termed as Probabilistic neural networks (PPN) which is used for resolving classification problems. Within the pattern layer a supervised training set is used for the production of probability density functions (PDF's). They are used to resolve binary as well as multi-class classification problems which provide good generalization ability. Probabilistic neural network architecture consists of four layers in which middle two layers are called radial basis layer and competitive layer along with input and output layers as shown in fig.5. In order to estimate the distance between the input vector and training input vector the radial basis layer is used and by this the output vector layer will be formed which will display the proximity distance between input and the training input. The fig.5 shows the architecture of probabilistic neural network [10].

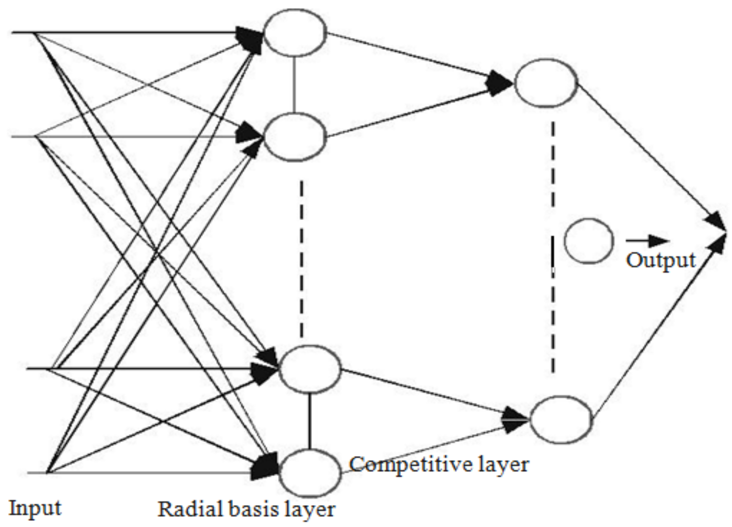

Fig.5 The architecture of PNN

IV. CONCLUSION

I can conclude by saying that Discrete Wavelet Transform is better than Daubechies Wavelet Transform because DWT is based on sub-band coding which yields fast computation and particularly successful in epileptic seizure detection. Hence, it is very useful in feature extraction of EEG signals. The above discussed classifiers are important in classification of seizure and non-seizure signals.

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