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Sub-band decomposition of EEG signals and Feature Extraction for Epilepsy Classification

Aarti Ashok Deshprabhu[1], Nayana Shenvi[2]

Master of Electronics, Electronics and Telecommunication Engg., Goa College of Engineering, Goa, India [1]

Assistant Professor, Electronics and Telecommunication Engg., Goa College of Engineering, Goa, India [2]

Abstract: Electroencephalogram (EEG) is the recording of brain electrical activity and it contains valuable information related to the different physiological states of the brain. Hence, EEG is considered an indispensable tool for diagnosing epilepsy in clinic applications. Epilepsy keeps its importance as a major brain disorder. In this paper, we aimed to classify the EEG signals and diagnose the epileptic seizures directly by using wavelet transform and an artificial neural network model. EEG signals are separated into their spectral components by using wavelet transform, by a method of sub-band decoding. These spectral components are applied to the inputs of the neural network which is then trained to give two outputs to classify whether the signal is epileptic or not. In this paper, the features extracted and the accuracy obtained from this feature set in classifying the data sample as epileptic or not is explained.

Keywords: Wavelet transform, Sub-band decomposition, Feature Extraction, Back-propagation, Neural network, Accuracy.

I. INTRODUCTION

EEG signals are the signatures of neural activities. They are captured by multiple-electrode EEG machines either from inside the brain, over the cortex under the skull, or certain locations over the scalp, and can be recorded in different formats. The signals are normally presented in the time domain, but many new EEG machines are capable of applying simple signal processing tools such as the Fourier transform to perform frequency analysis and equipped with some imaging tools to visualize EEG topographies.

Temporary electrical disturbance of the brain causes epileptic seizures. Sometimes seizures may go unnoticed, depending on their presentation, and sometimes may be confused with other events, such as a stroke, which can also cause falls or migraines. Approximately one in every 100 persons will experience a seizure at some time in their life (Adeli, Zhou, & Dadmehr, 2003). Research is needed for better understanding of the mechanisms causing epileptic disorders. Careful analysis of the electroencephalograph (EEG) records can provide valuable insight into this widespread brain disorder. The EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands–delta (<4 Hz), theta (4 -8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric power spectrum estimation methods such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. But, since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals.

Spectral analysis of the EEG signals produces information about the brain activities. A powerful method was proposed to perform time-scale analysis of signals is the wavelet transforms (WT). This method provides a unified framework for different techniques that have been developed for various applications. Since the WT is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis, it is well suited to locating transient events, which may occur during epileptic seizures. Through wavelet decomposition of the EEG records, transient features are accurately captured and localized in both time and frequency context. The capability of this mathematical microscope to analyze different scales of neural rhythms is shown to be a powerful tool for investigating small-scale oscillations of the brain signals.

Many techniques from the theory of signal analysis have been used to obtain representations and extract the features of interest for classification purposes. Neural networks and statistical pattern recognition methods have been applied to EEG analysis. Neural network detection systems have been proposed by a number of researchers. Artificial neural networks (ANNs) may offer a potentially superior method of EEG signal analysis to the spectral analysis methods. In contrast to the conventional spectral analysis methods, ANNs not only model the signal, but also make a decision as to the class of signal (Subasi, 2005a; Subasi & Ercelebi, 2005).

In this paper, we have reduced the size of the data using sub-band decomposition and then extracted the features from each of these sub-bands. Then, these features are fed into an artificial neural network(ANN) to classify the data samples as epileptic or not. The feed to the ANN is a set of four features for each sample data that we have extracted and fed the algorithm to obtain hundred percent of accuracy to classify the test samples into epileptic or non epileptic samples.

II. WAVELET TRANSFORM

A. *Data Selection*

We have used the publicly available data described in Andrzejak et al. (2001). The complete data set consists of five sets (denoted A–E) each containing 100 single channel EEG segments. These segments were selected and

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cut out from continuous multi-channel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme (Fig. 1).

Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from EEG archive of pre-surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone.
In this study, we used two dataset (A and E) of the complete dataset. Set A is taken as non- epileptic and set E as epileptic data set.
While recording the data, the 10/20 electrode placement pattern has been used.

Brain Area	Left Hemisphere	Midline	Right Hemisphere
Pre-Frontal	Fp1		Fp2
Frontal	F3		F4
Inferior Frontal	F7		F8
Mid-Frontal		Fz	
Mid-Temporal	T3		T4
Posterior Temporal	T5		T6
Central	C3		C4
Vertex (Mid-Central)		Cz	
Parietal	P3		P4
Mid-Parietal		Pz	
Occipital	O1		O2
Ear (Auricular)	A1		A2
Ground		G	

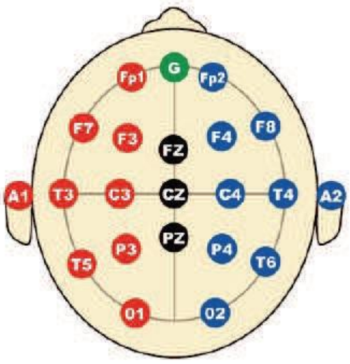

Figure.1: 10/20 Electrode placement for EEG measurement

B. Analysis of Discrete Wavelet Transform

The 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 different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal. The original signal x[n] is first passed through a half band high pass filter g[n] and a low pass filter h[n]. At every level, the filtering and sub sampling will result in half the number of samples (and hence half the time resolution) and half the frequency band spanned (and hence doubles the frequency resolution).

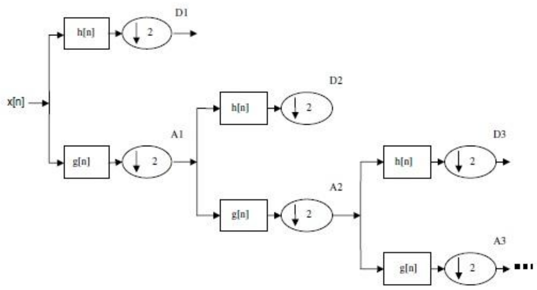

Figure.2: Sub-band decomposition

There are many orthogonal wavelets such as Haar, Meyer and Shannon. Using the Daubechies Wavelet which is also orthogonal wavelet we can extract the features of EEG. As WT has the feature of Multi Resolution Analysis (MRA) i.e. expressing the given signal by dilates and translates of a wavelet function at multiple scale but at one particular scale(of interest depends on the characteristic of signal being analyzed) at a time. The operators h and g are called perfect reconstruction or quadrature mirror filters (QMFs) if they satisfy the orthogonality conditions-

$$G(z)G(z^{-1})+G(-z)G(-z^{-1})=1 \qquad (1)$$

where G(z) denotes the z-transform of the filter g.
DWT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1, respectively. The first approximation, A1 is further decomposed and this process is continued as shown in Fig. 2. Since the EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 5. Thus, the EEG signals were decomposed into details D1–D5 and one final approximation, A5. The smoothing feature of the Daubechies wavelet of order 4 (db4) made it more appropriate to detect changes of EEG signals. Hence, the wavelet coefficients were computed using the db4 in our paper.
The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 1 presents frequencies corresponding to different levels of decomposition for Daubechies order 4 wavelet with a sampling frequency of 173.6 Hz. We have extracted four sets of features for the data as one Set X after sub-band classification, these features are:
1) Mean of the wavelet coefficients in each sub-band
2) Minimum of the wavelet coefficients in each sub-band
3) Maximum of the wavelet coefficients in each sub-band
4) Energy in the sub-band .
These coefficients are then fed to the artificial neural network to classify the data samples as epileptic or not.

C. Artificial Neural Network (ANN)

ANNs consist of a great number of processing elements (neurons), which are connected with each other; the strengths of the connections are called weights. The

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network topology is the standard Gradient descent back propagation algorithm. The number of output neuron is two, and the number of hidden unit neuron is chosen as 10. Since the intermediate layers do not interact with the external environment, they are called hidden layers and their nodes called hidden nodes.

The addition of intermediate layers revived the perceptron by extending its ability to solve nonlinear classification problems. In ANNs, the knowledge lies in the interconnection weights between neurons. Therefore, training process is an important characteristic of the ANN methodology, whereby representative examples of the knowledge are iteratively presented to the network, so that it can integrate this knowledge within its structure. No assumption is needed about the underlying data probability distributions when ANN is used for pattern classification. Once trained, it can be configured to perform adaptively to improve its performance over time. The gradient descent back-propagation is a training function that updates weights and bias values according to gradient descent.

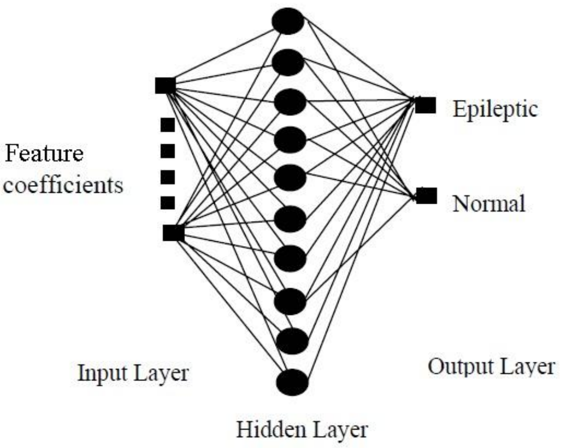

Figure 2 : ANN Architecture

The weights are determined by means of the backpropagation algorithm, which is based on searching an error surface (error as a function of ANN weights) using gradient descent for points with minimum error. During the training phase, the weights are successively adjusted based on a set of inputs and the corresponding set of desired output targets. Each iteration in back propagation constitutes two sweeps: forward activation to produce a solution, and a backward propagation of the computed error to modify the weights. The forward and backward sweeps are performed repeatedly until the ANN solution agrees with the desired value within a pre-specified tolerance. The back propagation algorithm provides the needed weight adjustments in the backward sweep. The back propagation algorithm is a nonlinear procedure because of the nonlinear threshold element contained in each node, and its behavior is very complex because of the layered structure. However, this nonlinear behavior allows a perceptron to generate highly complex decision regions, which is a desirable property for pattern classification.

All representations were classified using different random selections of train, validation, and test sets and initial weight values.

III. SIMULATION AND RESULTS

The total recording time was 23.6 seconds, corresponding to a total sampling of 4,096 points. From these sub-samples, the DWT was performed and derived measures of dispersion statistics from these windows. The DWT was performed at 4 levels, and resulted in five sub-bands: D1 to D4 and A4 (detail and approximation coefficients respectively).These values are tabulated in Table 1. For the data samples used, from each of these sub-bands, a set X of four parameters were extracted and were given to the ANN network.

DECOMPOSED SIGNAL	FREQUENCY RANGE(Hz)
Non-useful freq(noise)	43.4-86.8
D1 (gamma)	21.7-43.4
D2 (beta)	10.8-21.7
D3 (alpha)	5.4-10.8
D4 (theta)	2.7-5.4
A4 (delta)	0-2.7

Table 1: Decomposed signal values after Sub-Band Decomposition using Daubechies wavelet.

The coefficients extracted from the individual sub-bands for the epileptic Set A and non-epileptic Set E are as shown in the Table 2 below.

Data	Features Extracted	D1	D2	D3	D4	A5
Set A	Mean	-9.325	-13.180	-18.576	-26.108	-0.2218
	Min	-284.677	-339.241	-371.35	-422.039	-223.62
	Max	252.779	297.518	328.785	361.860	223.708
	Energy	5721.07	11656.7	22629.76	45056.47	4.771
Set E	Mean	-12.969	-18.599	-27.0542	-40.2366	-11.409
	Min	-1737.31	-1928.63	-2017.79	-2092.02	-1885.35
	Max	1680.14	1854.56	1935.234	1940.072	1838.427
	Energy	584121.96	990618.45	2000384	3842677	577.2458

Table 2: Extracted Feature Coefficients of set X for Epileptic and Non-Epileptic data

It was seen that the accuracy achieved for set X with four parameters was found to be cent percent. The parameters obtained for the set X are shown in Table 3.

SET	Time (sec)	Accuracy(%)
Set X	15	100

Table 3: Results of Extracted Feature Coefficients of set X after neural network classification for Epilepsy

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The graph for the best validation performance is as shown below.

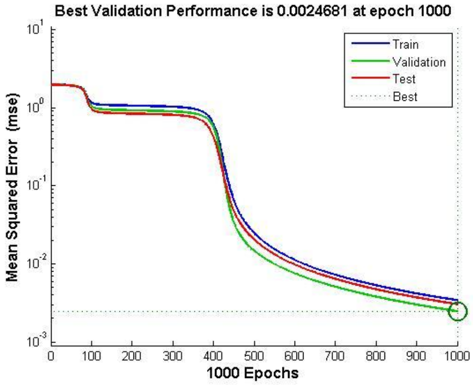

Figure 3: Performance for Set X

IV. CONCLUSION

We have designed an algorithm to classify the EEG signal into its respective sub-bands and also extract features from these bands for data compression. The sub-band coding gives different frequency bands which are Gamma (D1), Beta (D2), Alpha (D3), Theta (D4), Delta (A4) as shown in the Table 1. Two sets were made of the features extracted reducing the size of the data to represent the signal. The set X had four parameters extracted. It gave cent percent accuracy for classification of epileptic samples as shown in Table 3.

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