

EEG Feature Extraction using Daubechies Wavelet and Classification using Neural Network

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Abstract: Electroencephalography (EEG) is a simple method which gives an idea about the potential generated on the surface of the brain which helps in understanding the functionality of the brain. So EEG signals play a important role in detecting the Human emotions. In this paper, new features are extracted using Discrete Wavelet Transform (DWT) and further the emotions are classified using EEG signals of 10 subjects is collected using 24 electrodes from the standard 10-20 Electrode Placement System which is placed over the entire scalp. Feature Extraction is performed by using DWT and the Decomposition of EEG signals is extracted for 8 levels using “db4” wavelet. Features like Energy Density, Power spectral Density are extracted. The feature extracted signals are then classified using Artificial Neural Network (ANN) and the neural system is trained, evaluated and the classification is performed which can be compared for emotional states classification.

Keywords: Electroencephalogram (EEG), Discrete wavelet transform, Feature extraction, Artificial Neural Network (ANN), Daubechies 4 Wavelet

1. Introduction

Researchers are finding ways to focus on Human computer interaction to empower computers to understand human emotions. Murugappan et. al [1] analysed that emotion perception relates to similar thinking, learning and remembering a consequent of complicated brain activity. These detected emotions can be used as a user input to the brain computer interface system.

Researchers on human EEG signal reveal that brain activity plays a major role in the assessment of emotions. M.A. Khalilzadeh et.al [2], proposed the emotional states from neural responses is an effective way of implementing brain computer interfaces. K. Schaaff et.al [3] relates the studies related to an important functional activity of EEG signals. Many methods are used for estimating human emotions in the past. Different researchers have carried out different methods for feature extraction and classification which is been discussed. Mingyang et.al [4], proposed a novel approach for the Classification of BCI signals. In their work Discrete Wavelet Transform (DWT) was implemented for feature extraction using Daubechies wavelet db4, for a 5 level Decomposition of EEG signals. They have considered 100 samples in a single channel EEG at a sampling rate of 173.61 Hz. The features computed were mean of the envelope spectrum in each sub-band, energy, standard deviation, maximum value of the envelope spectrum in each sub-band. The classification of EEG signals was performed based on bagging method. In this method a Neural Network Ensemble (NNE) Algorithm was developed for the classification of EEG signal by implementing the N-class classification into N independent 2-class classification, which uses Classification accuracy of about 98.78% was achieved. Jasmin Kevric [5] implemented two feature extraction methods namely DWT and Wavelet Packet Decomposition methods.

Both these methods generate several sub-band signals from which six different statistical features, including higher order statistics were extracted. A sampling rate of 100 Hz was considered by using Symlet 4 wavelet. Classification of BCI signals was implemented using K nearest neighbor (K-NN)

algorithm and an average classification accuracy of 92.8% was achieved. Gilsang Yoo et al [6], developed a human emotional state from bio-signal system that can recognize human emotional state from biosignal. The by considering six emotional states. In this work, two methods were proposed namely Multimodal Bio-signal Evaluation and Emotion recognition using Artificial Neural Network. An accuracy of 85.9% was obtained for Back Propagation. The study results can help emotion recognition studies to improve recognition rates for various emotions of the user in addition to basic emotions. Gyanendra et.al [7] has performed the feature extraction of EEG signals using Daubechies Wavelet by considering 32 channels. The physiological signals were recorded at 512 Hz sampling rate and down sampled to 256 Hz, for a 5 level decomposition to obtain the detailed and approximate co-efficients with a sampling rate of 512 Hz to capture the information from signals as it provides good results for nonstationary. The experiments were performed to classify different emotions from four classifiers namely, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbor (K-NN) and Meta Multiclass (MMC). The average accuracies are 81.45%, 74.37%, 57.74% and 75.94% for SVM, MLP, KNN and MMC classifiers respectively. Suwicha Jirayucharoensak et. al [8] implemented a system by collecting 32 subjects of EEG signals. The EEG signals were down sampled from 512 Hz to 128 Hz. The power spectral features of EEG signals on these channels were extracted. The emotion recognition was performed by using a deep Learning Network with 100 hidden nodes in each layer and it was reduced to 50 hidden nodes for investigating the effect of hidden node size in the DLN. The Principal Component Analysis (PCA) extracted the 50 most important components. The extracted features were fed as into the DLN with 50 hidden nodes in each layer. The purpose of PCA is to reduce dimension of input features. The classification accuracy of the DLN with PCA and CSA is 53.42% and 52.05 %. Amjed S. Al-Fahoum et.al [9] has described a mathematical method by considering five different signal extraction methods. The main methods of frequency domain and time-frequency domain methods for linear analysis of one-dimensional signals for EEG signal feature extraction. Noppadon Jatupaiboon et.al [10] considered a wireless EMOTIV Headset for collection of EEG signals, which consists of 14 channels. The sampling rate is set at 128 Hz. The EEG signals were decomposed by implementing Discrete Wavelet Transform. In this paper a real time EEG data is considered to classify happy and normal emotions by giving an external stimulus in the form of pictures and classical music. Different frequencies were analyzed, in that Gamma and Beta band gave a better result than low frequency bands. By using SVM as a classifier, power spectral density was analysed as a feature and an average accuracy of 75.12% and 65.12 % was achieved. Umut Orhan et.al [11] proposed a classification model using Neural Network for epilepsy treatment. An EEG data of about 100 single channel EEG signals were considered which was decomposed into sub-bands by using db2. The decomposition was performed for 11 levels. The wavelet coefficients were clustered using the K-means algorithm for each frequency sub-band. Wavelet coefficients obtained from EEG segments with 4097 samples were clustered by K-means algorithm. In this work, the MLPP Model is supported by the Levenberg–Marquardt (LM) algorithm by considering a single hidden layer of 5 hidden neurons resulting in classification of the EEG segments. Classification accuracy of 95.60% was achieved for normal and abnormal patients using the test data. Abdulhamit Subasi et.al [12], EEG signals were decomposed into the frequency sub-bands using DWT and a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. In this work, DWT has been applied for the time–frequency analysis of EEG signals for the classification using wavelet coefficients. Using statistical features extracted from the DWT sub-bands of EEG signals, three feature extraction method namely PCA, ICA, and LDA, were used with SVM and cross-compared in terms of their accuracy relative to the observed epileptic and normal patterns. According to this result, the application of nonlinear feature extraction and SVMs can serve as a promising alternative for intelligent diagnosis system. Xiao-Wei Wang et.al [13], in this paper, four emotion states, namely joy, relax, sad, and fear are considered. The EEG Signal classification k-nearest neighbor (k-NN) algorithm multilayer perceptron and support vector machines are used as classifiers. Experimental results indicate that an average test accuracy of 66.51% for classifying four emotion states can be obtained by using frequency domain features and support vector machines. In our Research, different classification algorithms have been implemented, to classify three different emotional states, in this paper one Classification of EEG signals

is proposed using artificial neural network. In this work, implementation of Feedforward Back-Propagation Algorithm is performed.

2. Discrete Wavelet Transform (DWT)

Discrete wavelet transform is performed by repeated filtering of the input signal using two filters. The filters are a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The output co-efficient gained by the low pass filter is the approximation co-efficient. The scaling function output is in the form of:

$$\Phi(t) = 2 \sum_{q=0}^M h(q) \Phi(2t - q) \quad \dots\dots\dots (1)$$

The output of the high pass filter is the detailed co-efficient. The wavelet function output is in the form of:

$$w(t) = 2 \sum_{q=0}^M g(q) \Phi(2t - q) \quad \dots\dots\dots (2)$$

The approximation co-efficient is consequently divided into new approximation and detailed co-efficients. By choosing the mother wavelet the co-efficient of such filter banks are calculated. This decomposition process is repeated until the required frequency response is achieved from the given input signals. The selection of an appropriate wavelet function has been a challenge in this research. Among different wavelets, daubechies wavelet has been chosen as they have a maximal number of vanishing moments and hence they can represent higher degree polynomial functions. With each wavelet type of this class, there is a scaling function known as “father wavelet” that generates an orthogonal multi-resolution analysis. Each wavelet has vanishing moments equal to half the number of coefficients. The number of vanishing moments is what decides the wavelet’s ability to represent a signal. Every resolution scale is double that of the previous scale. Daubechies family of wavelets has been chosen because of their high number of vanishing moments making them capable of representing complex high degree polynomials. Thus Daubechies 4 wavelet provides a good signal output.

2.1. Daubechies 4 Wavelet

The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing running averages and differences via scalar products with scaling signals and wavelets the only difference between them consists in how these scaling signals and wavelets are defined.

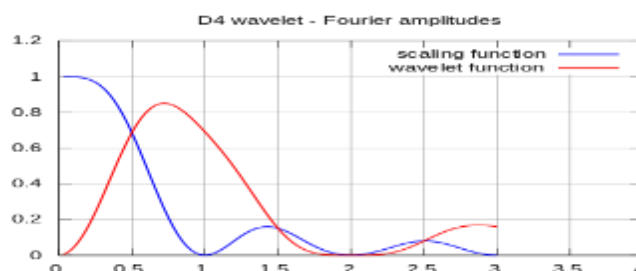


Figure 1. Daubechies Wavelet representing scaling and wavelet function

For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal.

The Daubechies D4 transform has four wavelet and scaling function co-efficients. The scaling function co-efficients are:

$$\{h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}; h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}; h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}; h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}\} \dots\dots\dots (3)$$

Each step of the wavelet transform applies the scaling function to the data input, if the original data set has N values and the scaling function will be applied in the wavelet transform step to calculate N/2 smoothed values in the ordered wavelet transform and the smoothed values are stored in the lower half of the N element input vector. The wavelet function co-efficient values are:

$$\{g_0 = h_3; g_1 = -h_2; g_2 = h_1; g_3 = -h_0\} \dots\dots\dots (4)$$

The wavelet transform applies the wavelet function to the input data if the original data set has N values. The original data set has N values and the wavelet function will be applied to calculate N/2 differences. The scaling and wavelet functions are calculated by taking the inner product of the co-efficients and four data values. The equations are shown as:

Daubechies D4 scaling function:

$$a_i = h_0s_{2i} + h_1s_{2i+1} + h_2s_{2i+2} + h_3s_{2i+3} \dots\dots\dots (5)$$

$$a[i] = h_0s[2i] + h_1s[2i+1] + h_2s[2i+2] + h_3s[2i+3] \dots\dots\dots (6)$$

Daubechies D4 Wavelet function:

$$c_i = g_0s_{2i} + g_1s_{2i+1} + g_2s_{2i+2} + g_3s_{2i+3} \dots\dots\dots (7)$$

$$c[i] = g_0s[2i] + g_1s[2i+1] + g_2s[2i+2] + g_3s[2i+3] \dots\dots\dots (8)$$

Each iteration in the wavelet transform step calculates a scaling function value and a wavelet function value.

3. Neural Network

A neural network consists of formal neurons which are connected in such a way that each neuron output further serves as the input of generally more neurons similarly as the axon terminals of a biological neuron are connected via synaptic bindings with dendrites of other neurons. The number of neurons and the way that they are interconnected determines the architecture (topology) of neural network. The input and output neurons represent the receptors and effectors, respectively, and the connected working neurons create the corresponding channels between them to propagate the respective signals. These channels are called paths in the mathematical model. The signal propagation and information processing along a network path is realized by changing the states of neurons on this path. The states of all neurons in the network form the state of the neural network and the synaptic weights associated with all connections represent the configuration of the neural network shown in Figure 2.

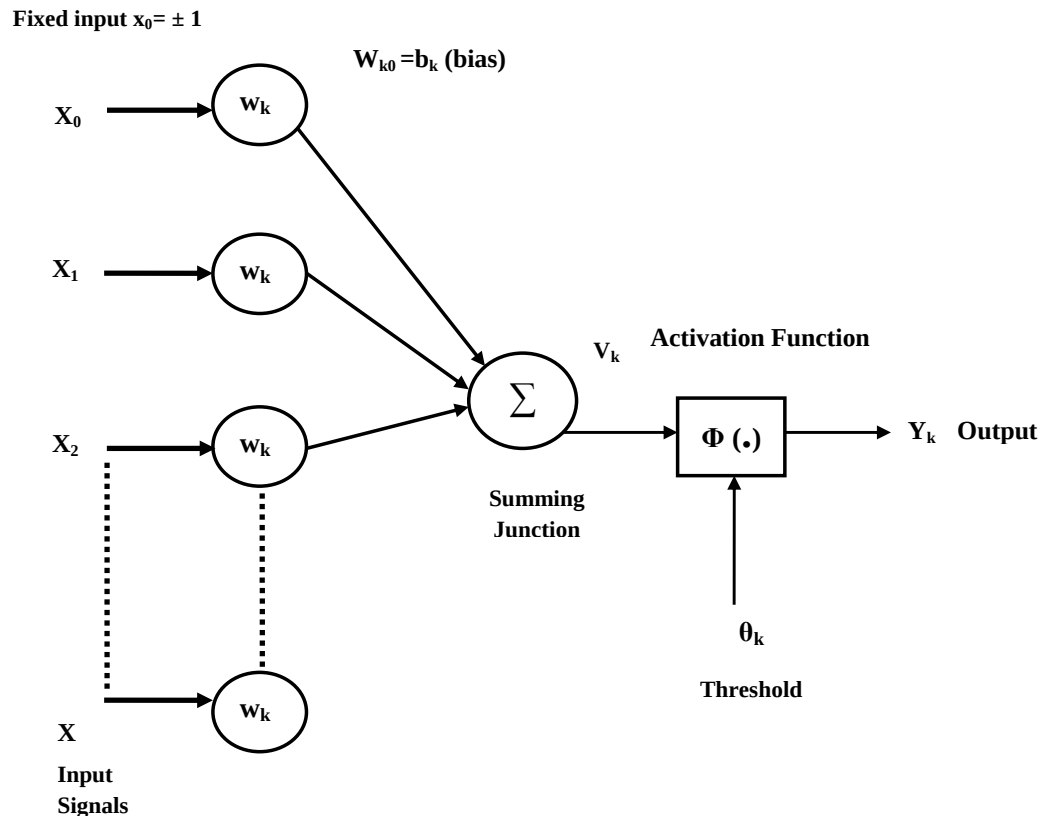


Figure 2. Mathematical Model of Neural Network.

From the mathematical model an artificial neuron has three basic components are. The synapses of the biological neuron are modeled as weights which interconnect the neural network and gives strength to the connection. All inputs are summed together and are modified by the weights. This activity is referred as a linear combination. An activation function controls the amplitude of the output. From this model the interval activity of the neuron is represented as:

$$V_k = \sum_{j=1}^p w_{kj} x_j \quad \dots\dots\dots (9)$$

The output of the neuron, y_k will be the outcome of the activation function on the value of v_k

4. Proposed Work

The proposed work describes the raw EEG which is acquired by using 10-20 electrode placement system. Though there are multiple acquisition system, the acquisition is done using 10-20 electrode placement system and it is found that 10-20 system is the best for the data acquisition with respect to the data

consistency. Since it is a standard system for measuring the electrical activity of a brain with respect to all the standard positions on the scalp therefore it is considered as most suitable method for EEG acquisition.

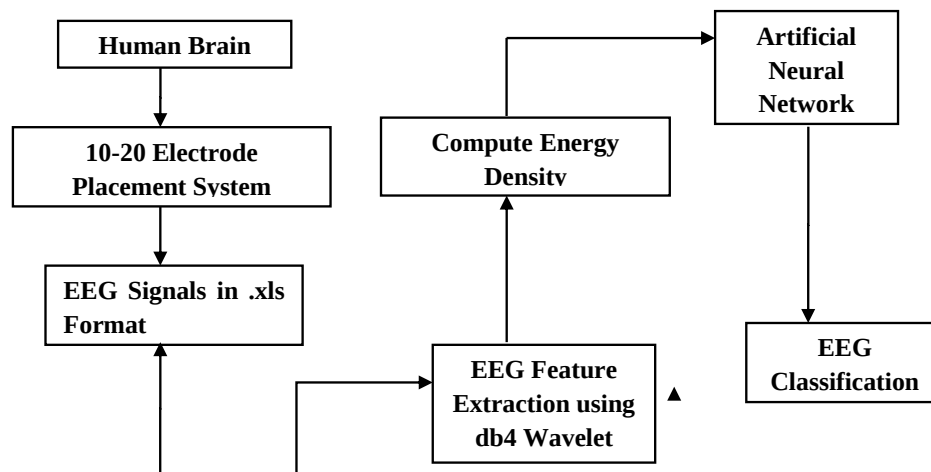


Figure 3. Proposed Block Diagram of Emotion Recognition System

The acquired EEG signal which is in the format of .xls is loaded to the MATLAB workspace and converted to .csv format for further processing. The formatted EEG dataset is analyzed by using Daubechies wavelet transform to extract all the fundamental frequency components of EEG signal i.e. alpha, beta, gamma, delta and theta. EEG frequency bands which relates to various brain states. The extracted EEG bands are further decomposed. After further decomposition, prominent features like Energy and Power Spectral Density are computed. The features extracted are fed as input for Classification using Artificial Neural Networks. The proposed Block diagram is shown in Figure 3.

5. Implementation

Feature Extraction is the process of identifying a particular information form EEG which is been measured by the neuronal activity from the brain. The emotions are detected by analyzing the characteristics of the signals. The main task of feature extraction is to derive the salient features which can map the EEG data into consequent emotion states. The wavelet decomposition of any signal $x(t)$ is represented in terms of its decomposition coefficients given by the equation:

$$x(t) = \sum_{k=-\infty}^{\infty} A(k) \phi_k(t) + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} D(j, k) \psi_{j,k}(t) \quad \dots\dots\dots (10)$$

After obtaining the noise-free signals from the signal enhancement phase. In this work, “db4” (Daubechies wavelet) is chosen for decomposition, db4 wavelet is known for its orthogonality property and its smoothing features and it is useful for detecting the changes in EEG signals. The raw EEG signal

$x(n)$ is decomposed by a sampling frequency of 500Hz is shown in Figure 4, where each stage output provides a detailed co-efficient and a approximation co-efficient. The filters are low pass filter and high pass filter which is decomposed into different scales. The low pass filter is the approximation coefficient. The multi-resolution analysis is decomposed using “db4” for eight levels of decomposition, which yields five separate EEG sub-bands. The main objective of the proposed method is the division of the original EEG signals into different frequency bands. Table 1, shows the decomposed EEG bands lying at their frequencies after decomposition.

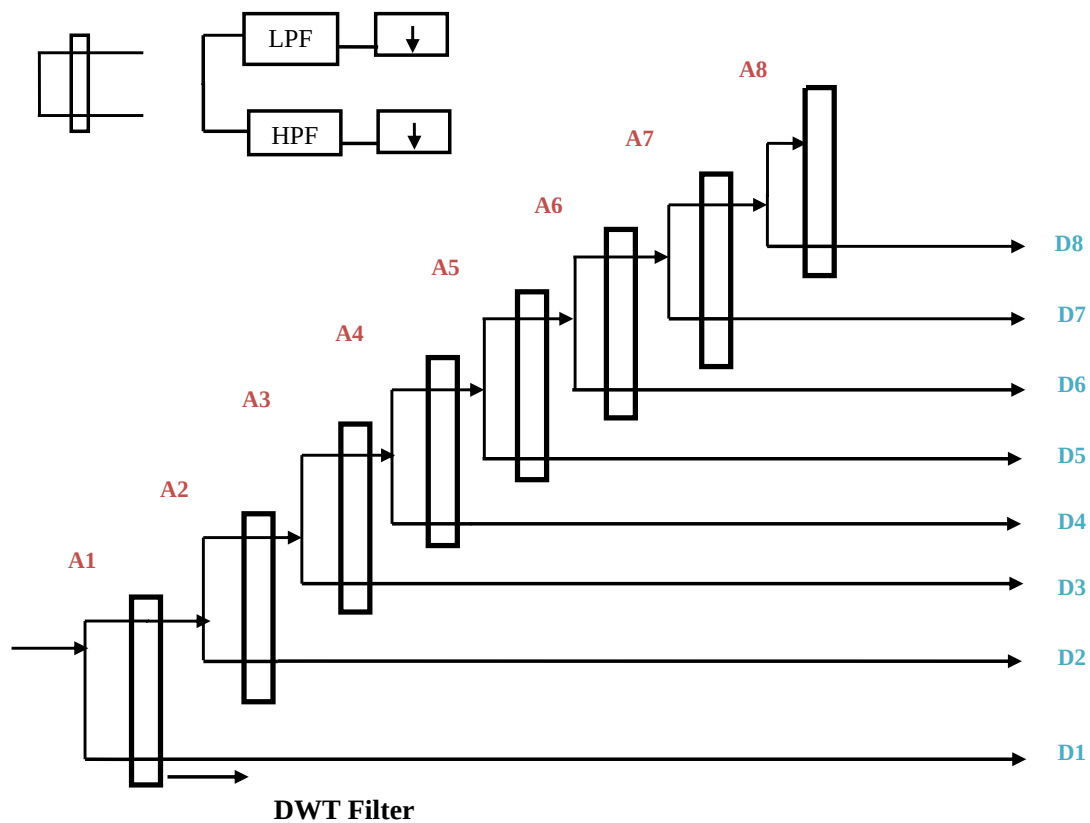


Figure 4. Decomposition of input signal into its Detailed and Approximation Co-efficient for 8 levels

Decomposition Levels	EEG Bands	Frequency Range (Hz)
D5	Gamma	37-56 Hz
D6	Beta	11-37 Hz
D7	Alpha	6-11 Hz
D8	Theta	4-6 Hz
A8	Delta	0-4 Hz

Table 1. Decomposition of EEG Signals and their frequency range in Hz

The following flowchart shown in Figure 5, represents the decomposition of EEG data using Matlab which is decomposed to 8 levels and further reduced to 3, 2 and 1 levels and the energy computation is performed.

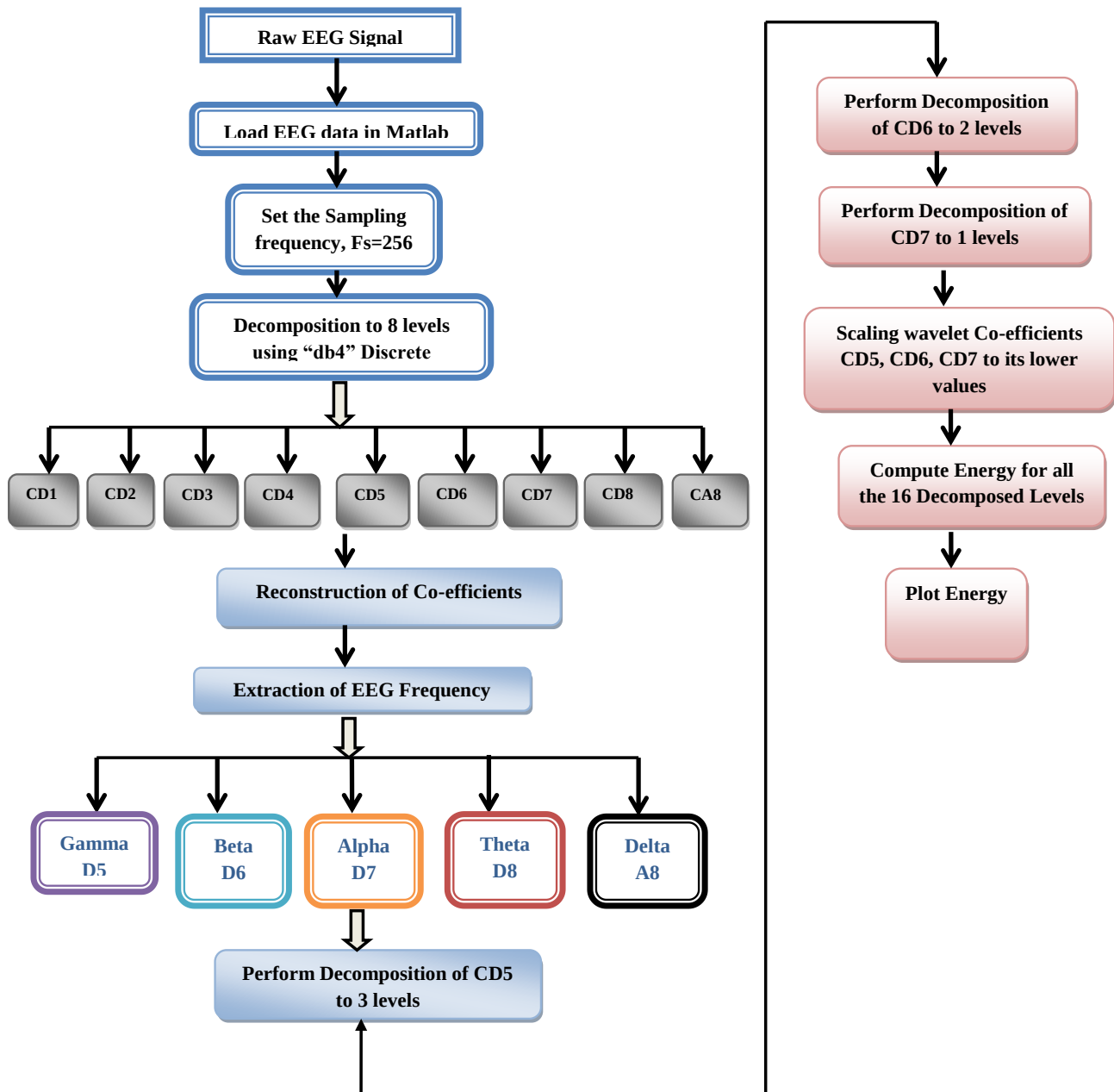


Figure 5. Flowchart of Feature Extraction using Matlab

6. Neural Network Classification

Neural Network is an information processing paradigm that is inspired by the way biological nervous systems, such as brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (Neurons) working in union to solve specific problems. Artificial neural networks (ANN) have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that a typical ANN consists of large number of neurons, units, cells (or) nodes that are organized according to a particular arrangement. Each neuron is connected to other neuron by means of directed communication links, each with an associated weight. The weights represent information being used by the net to solve the problem. Each neuron has an internal state, called its activation (or) activity level, which is a function of the inputs it has received. Typically a neuron sends its activation as a signal to several other neurons. Feedforward Back Propagation Neural Network (FFBPNN) are appropriate for solving problems that involve learning the relationships between a set of inputs and known outputs. Classification of emotions is performed using FFBPNN training algorithm is implemented using neural network Toolbox. In this work, training is opted for considering two subjects namely normal and abnormal subjects. The performance of neural network is analyzed by considering the input values and the target values which are set. In this work, a topology of 16-10-16 is considered as the network topology. The performance graph, regression plot is achieved, which gives an optimal solution for better classification accuracy in terms of efficiency. The MATLAB software enables training with different convergence criteria, tolerance level, activation functions and number of epochs. The neural network models studied in this investigation uses transfer function = 'TANSIG' as activation function. After this the network model is ready for prediction of desired output. The plots namely Plot Performance, Plot Regression are shown in Figure 6. The Plot Performance shows the best validation performance with 16 epochs. The plot train state shows the system state after training based on the Plot regression which shows the plot between and training samples, between output data and validation samples and between output data and test samples (R value shows the correlation between output and target values).

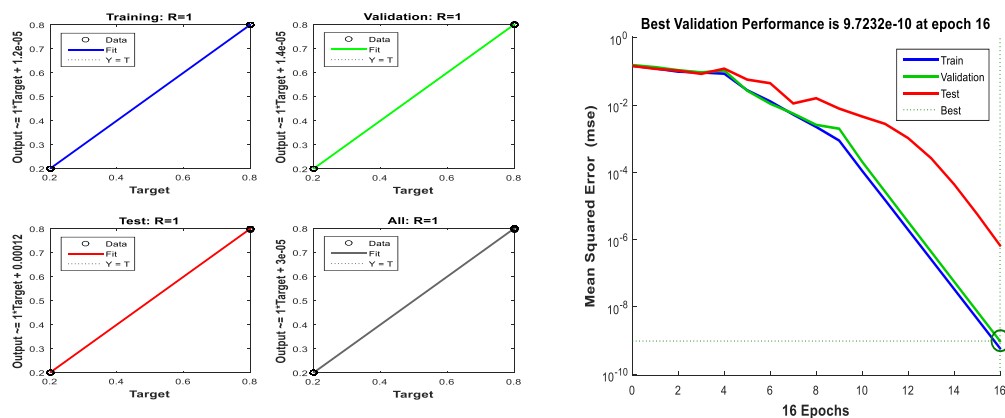


Figure 6. Snapshots of Best Validation Performance and Training States

7. Results and Discussion

Energy Graph of six different electrodes is shown in Figure 7, which represents the varying energy values of all the five EEG bands taken from a normal subject. From the analysis, P4-O2 is having a higher Energy Density, compared to other Electrodes. P4-O2 is a region which lies the Parietal and Occipital lobes of the brain. The emotions pertaining to these lobes generate signals which are in a relaxed state of mind and are active in the frontal regions of the brain. The comparison of Energy values is represented in the graph which shows the decomposition levels of six electrodes.

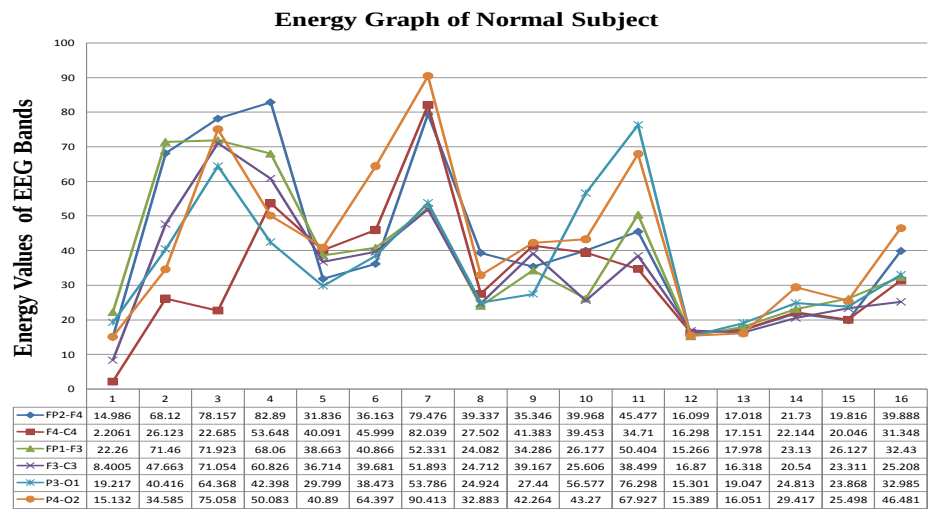


Figure 7. Energy Plot of Normal Subject considering six Electrodes

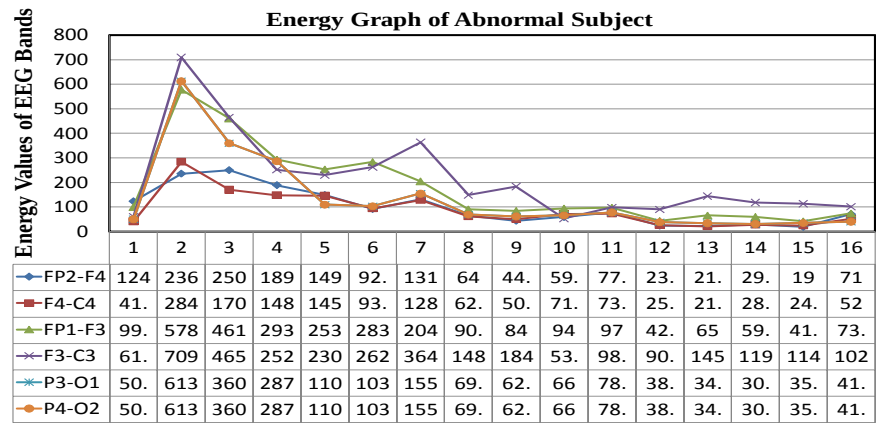


Figure 8. Energy Plot of Abnormal Subject considering six Electrodes

Figure 8, represents the varying energy values of abnormal subject. From the energy graph, F3-C3, shows a greater energy density value compared to other electrodes. F3-C3 is a region which lies in the Frontal and Central parts of the brain lobes. The frontal lobe is located at the front of each cerebral hemisphere and positioned in front of the parietal lobe and above and in front of the lobe. The emotions pertaining to frontal lobe experience frontal lobe trauma where an appropriate response to a situation is exhibited but displays an inappropriate response to those same situations in "real life", they experience unwarranted displays of emotion. The energy density of these two subjects is calculated and fed to the NN toolbox for classification to analyze its performance

In the Neural network training stage, input data and sample data are fed to the neural network Classifier, where the targets are set as 0.2 for normal and 0.8 for abnormal subjects. A network topology of 16-10-16 is considered. The performance graph, regression plot is achieved, which gives an optimal solution for better classification accuracy in terms of efficiency. Table 2, represents the performance value, the number errors and the number of epochs for two different networks. The classification accuracy for each type of network is achieved which can be compared with one another. Network 1, gives an optimal accuracy of 88% compared to network 2

Network Type	Performance	Epochs	Gradient	Mu	Errors	Classification Accuracy (%)	
						Normal Subject	Abnormal Subject
Network 1	0.00044	16	0.00096	8.3×10^{-7}	4	100%	88%
Network 2	0.00069	31	7.4×10^{-8}	1.1×10^{-7}	5	100%	86%

Table 2. Training and Simulated output results

8. Conclusion

The proposed method in this paper highlights the performance of ANN Classification. A novel method is implemented by choosing a better wavelet for feature extraction. The classification performance is performed by achieving an optimal accuracy of 88% for network 1 for abnormal subject and network 2 achieves an accuracy of 86%. In the future more number of emotional states can be implemented with different classification algorithms.

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