ANALYSIS AND CLASSIFICATION OF ELECTROENCEPHALOGRAPHY SIGNALS

A THESIS SUBMITTED IN PARTIAL REQUIREMENTS FOR THE DEGREE OF

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS & COMMUNICATION ENGINEERING

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Rourkela

CERTIFICATE

This is to certify that the thesis entitled, "Analysis and Classification of Electroencephalography signals" submitted by Amit Kumar Verma and Anoop Kumar Mangaraj in partial fulfillment of requirements for the award of Bachelors in Technology degree in Electronics and Communication Engineering, Department of Electronics and Communication Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by them under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any university /institute for award of any degree or diploma.

Date: 10th May, 2010

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ACKNOWLEDGEMENT

We take this opportunity to thank all the individuals whose guidance, help and timely support made us to complete the project within the stipulated time. Unfortunately it isn't possible to express our thanks to all of them in a single page of acknowledgement.

First and foremost we would like to express our sincere gratitude to our project supervisor Prof. Samit Ari for his invaluable support, motivation, guidance and constant encouragement which made this project a rich and insightful experience. His timely inputs, valuable feedbacks and constructive criticism in many stages of this work were instrumental in understanding and execution of this project.

We are also grateful to Prof. S.K. Patra (Head of the Department), Department of Electronics and Communication engineering for assigning us this interesting project and providing us with various facilities of the department. His valuable suggestions and inspiring guidance were extremely helpful.

An assemblage of this nature could never have been attempted without reference to and inspiration from the works of others whose details are mentioned in reference section. We acknowledge our indebtedness to all of them.

We would also like to thank all professors and lecturers, and members of the department for their generous help in various ways for the completion of this thesis. We also extend our thanks to our dear friends for their support and cooperation.

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Contents

ABSTRACT

EEG signal processing is one of the hottest areas of research in digital signal processing applications and biomedical research. Analysis of EEG signals provides a crucial tool for diagnosis of neurobiological diseases. The problem of EEG signal classification into healthy and pathological cases is primarily a pattern recognition problem using extracted features. Many methods of feature extraction have been applied to extract the relevant characteristics from a given EEG data. The EEG data was collected from a publicly available source. Three types of cases were classified viz. signals recorded from healthy volunteers having their eyes open, epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures. The feature extraction was done by computing the discrete wavelet transform and spectral analysis using AR model. The wavelet transform coefficients compress the number of data points into few features. Various statistics were used to further reduce the dimensionality. The AR coefficients obtained from burg auto-regressive method provide important features of the EEG signals. Classification of the EEG data using committee neural network provides robust and improved performance over individual members of the committee. F-ratio based dimension reduction technique was used to reduce the number of features without affecting the accuracy much.

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

1.1 What are EEG Signals?

Electroencephalography (EEG) is the recording of spontaneous electrical activity of the brain which is obtained by firing of neurons within the brain. EEG signals are recorded in a short time, normally for 20-40 minutes. We get the recordings by placing the electrodes at various positions on the scalp. Figure.1 shows the schematic view of the scalp and dots represent the placing of the multiple electrodes on the scalp. It is believed that the EEG signals not only represents the brain signal but represents the status of the whole body. The diagnostic application in case of epilepsy gives us the prime motivation to apply the Digital Signal Processing techniques to the EEG signals.

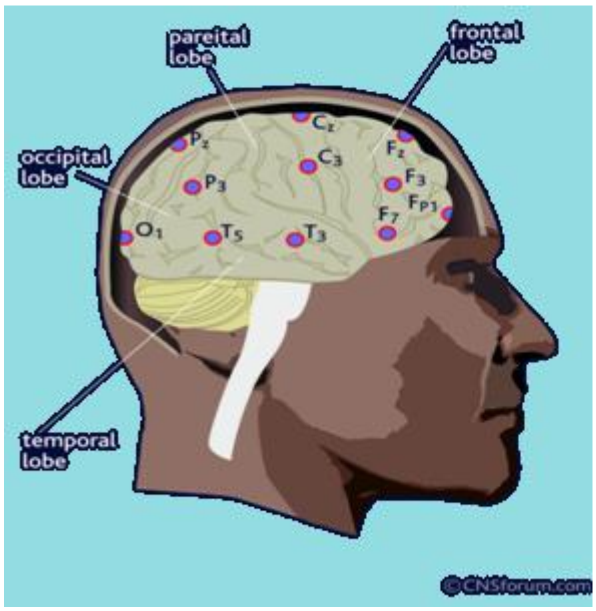


Figure 1.1: Schematic view of the scalp [20]

1.2 EEG generation

An EEG signal is generated due to the currents that flow between the brain cells in the cerebral cortex region of the brain. When the neurons are activated, current flows between dendrites due to their synaptic excitations. This current generates a magnetic field and a secondary electric field. The magnetic field is measurable by electromyogram (EMG) machines and the electric field is measured by EEG systems over the scalp [1].

The human head consists of various layers including the brain, skull, scalp and other thin layers in between. The level of attenuation due to skull is approximately hundred times greater than that of the soft tissues. While recording EEG signals noise can be internal (generated within the brain) or external (over the scalp). Hence only a large number of activated neurons can generate enough potential to have a recordable signal. These signals have to be amplified for further processing [2].

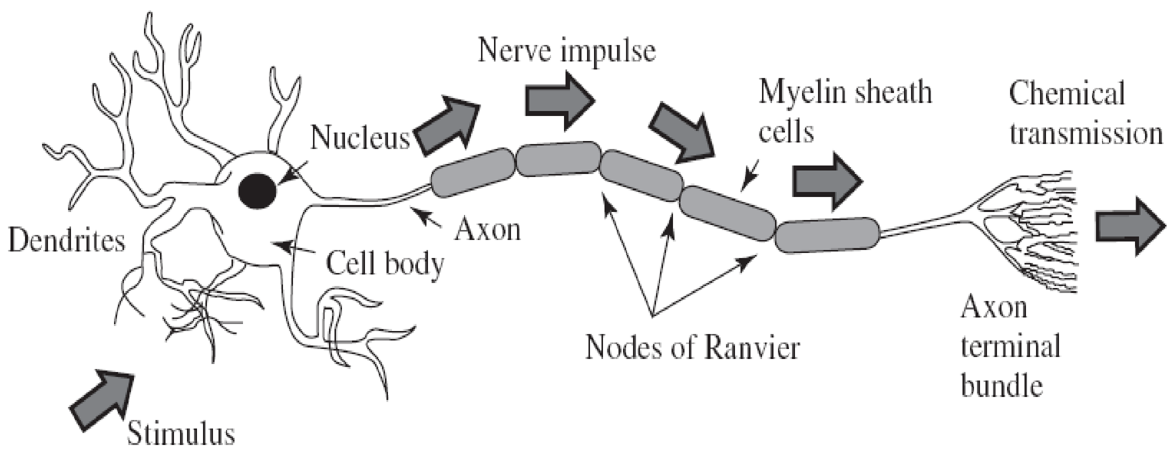


Figure 1.2: Structure of a neuron [2]

1.3 EEG recordings

EEG systems consist of a number of electrodes, differential amplifiers, filters and needle (pen)-type registers [3]. The EEG signals can be easily plotted on paper. Recent systems use computers for digitization and storing purposes. For digitization sampling, quantization and encoding is done. The effective bandwidth of the EEG signals is about 100 Hz. Thus a minimum of 200 samples per second is necessary for sampling (Nyquist criterion). For quantization representation using 16 bits is mostly used. Fig 1.3 shows the conventional electrode arrangement recommended by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology for 21 electrodes (called 10-20 electrode position) [4].

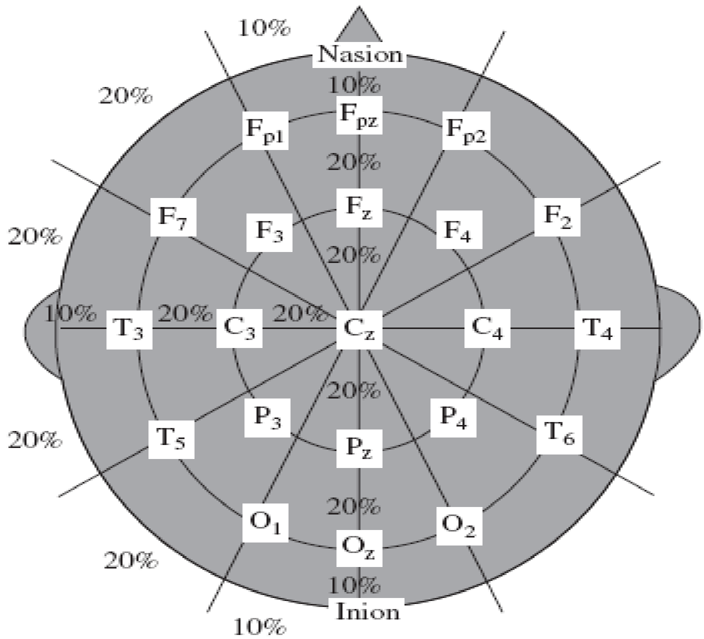


Figure 1.3: Conventional 10–20 EEG electrode positions for the placement of 21 electrodes

1.4 Brain rhythms

Brain rhythms can be easily recognized by visual inspection of the EEG signal hence many neurological disorders can be easily identified. The amplitude and frequency of these signals vary with human state (asleep or awake), age, health etc. There are five major brain waves distinguished by their frequency ranges. These are alpha (α), theta (θ), beta (β), delta (δ), and gamma (γ).

Alpha waves frequencies lie within the range of 8-13 Hz. They can be detected in the posterior lobes of the brain. In the whole realm of brain activity alpha waves are the most prominent rhythm. They are detected in a normal person when he is in a relaxed state without any attention or concentration. Closed eye state also produces some alpha waves [5].

A beta wave lies in the range 14-26 Hz. It is chiefly encountered in frontal and central regions. It is the usual waking rhythm of the brain associated with active concentration, active thinking, problem solving, focussing on things. When a person is in a panic state a high level beta wave is generated [6].

Theta waves lie within the range 4-7.5 Hz. It is assumed that it has origins in the thalamic region. When a person is slipping into a drowsy state from conscious state theta waves are observed. They play a crucial role in infants and young children. Creative thinking, deep meditation, access to unconscious material is associated with theta waves [7].

Delta waves are within the range 0.5-4 Hz. They are found frontally in adults and posteriorily in children. They are associated with deep sleep and may be present in waking state.

Gamma waves are also called fast beta waves and they have frequencies above 30 Hz. The amplitude of these waves is very low and they have rare occurrence. They are associated with certain cognitive and motor functions. Detection of these rhythms can be used to confirm certain neurological diseases. It is also a good indicator of event related synchronisation (ERS) of the brain [8].

1.5 Why do we use EEG signals?

There are various advantages of EEG signals some of them can be states as follows:

- Temporal resolution of the EEG signal is high.
- EEG measures the electrical activity directly.
- EEG is a non-invasive procedure.
- It has the ability to analyze the brain activity; it unfolds in real time at level of milliseconds, *i.e.* thousands of a second.

It is very hard to find the source of electrical activity where the electrical activity is coming from. This is the major disadvantages of EEG signals. By placing the multiple electrodes on the scalp we can get some information where the ERP is strongest.

EEG signals are used for various tasks. We can divide the uses of EEG as clinical uses and research uses [21]:

Clinical uses:

- EEG signals are used in the diagnosis of several neurological diseases.
- EEG signals are used to characterize the seizures for the purpose of treatment.
- EEG signals are used to monitor the depth of anesthesia.
- EEG signals are used to determine the wean-epileptic medication.

Research uses:

- EEG signals are used in neuroscience.
- EEG signals are used in cognitive science.
- EEG signals can be used for the psychophysiological research.
- EEG signals can be used for the study of the responses to auditory stimuli.

1.6 Objective

Our objective is to analyze the EEG signals and classify the EEG data into different classes. Our main target is to improve the accuracy of EEG signals. In our project we have also applied optimization techniques to reduce the computation complexity of the network without affecting the accuracy of the classification.

Figure. 4 shows the block diagram for the EEG signal processing. For the classification purpose we have taken the raw EEG signals available at [9]. From the five data sets available we have selected 3 sets (set A, set D, set E). In set A EEG signals were recorded from healthy volunteers. In set D recordings were taken from within epiletogenic zone but during seizure free interval while set E contained only seizure activity. For each of these data we extracted the features using discrete wavelet transform and Auto-Regressive coefficients method. After feature extraction the different data sets were classified using committee neural network trained with back propagation algorithm. To reduce the dimensionality of the features we have used Fisher's ratio based optimization technique.

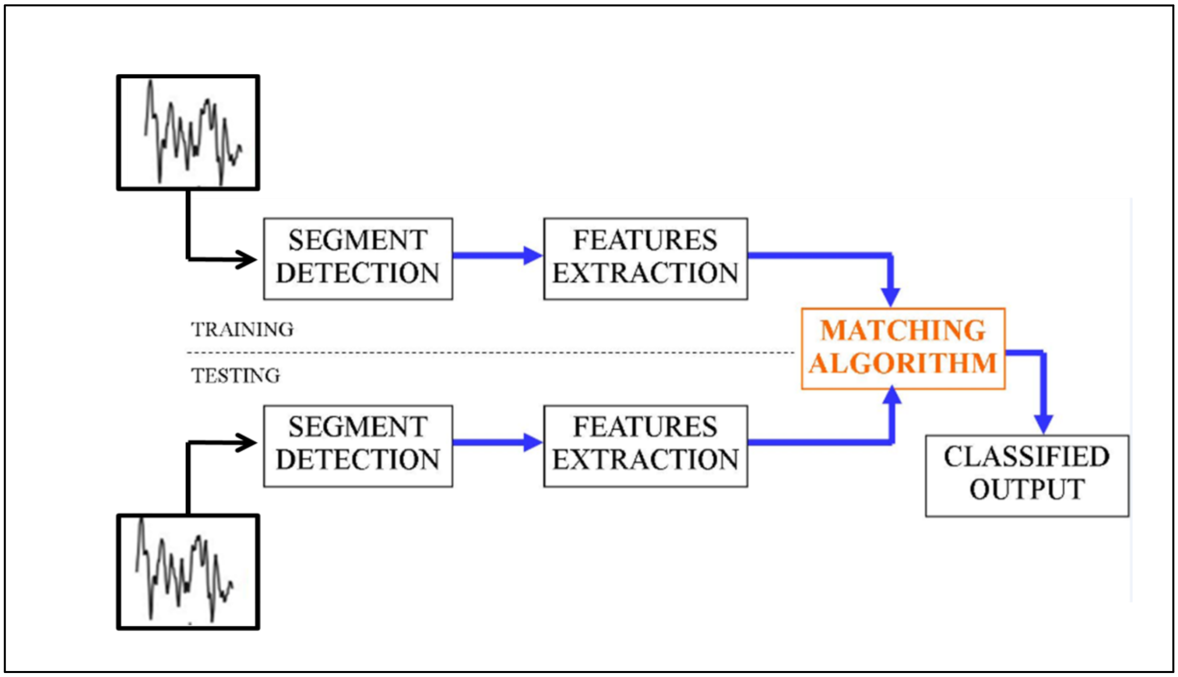


Figure 1.4: Block diagram of EEG signal classification

In chapter 2 our proposed technique for the classification purpose is discussed, then in the chapter 3 F-ratio based technique to reduce computational complexity. In chapter 4 we conclude our thesis along with future work.

1.7 Data Selection

The EEG data used in this study was obtained from the database available with the Bonn University. This data is publicly available at [9]. The complete dataset consists of five classes (A, B, C, D, E) each of which contains 100 single channel EEG segments of 23.6s duration. Each segment was selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts e.g. due to eye movement or muscle activity.

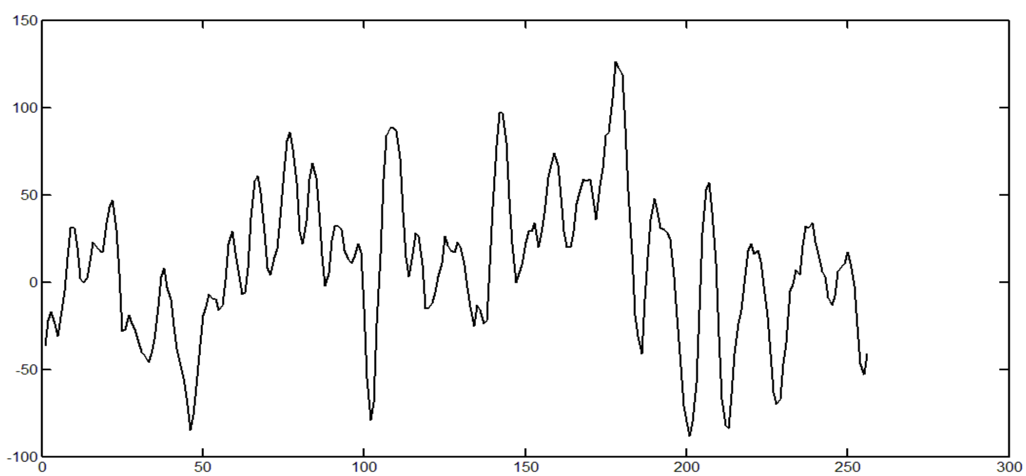
Sets A and B consisted of signals taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme (International

10–20 system). Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C–E originated from the EEG archive of presurgical 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. Signals in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure-free intervals, set E only contained seizure activity.

Using an average common reference, all EEG signals were recorded with the same 128-channel amplifier system. The data were digitized at 173.61 samples per second using 12 bit analog-to-digital converter. The settings of the band pass filter were 0.53–40 Hz (12 dB/oct.) [10]. In the present study sets A, D, E was used.

1.8 Raw EEG signal

From the data available at [9], a rectangular window of length 256 discrete data was selected to form a single EEG segment. The plot of segment of the three classes (A, D, E) is shown below



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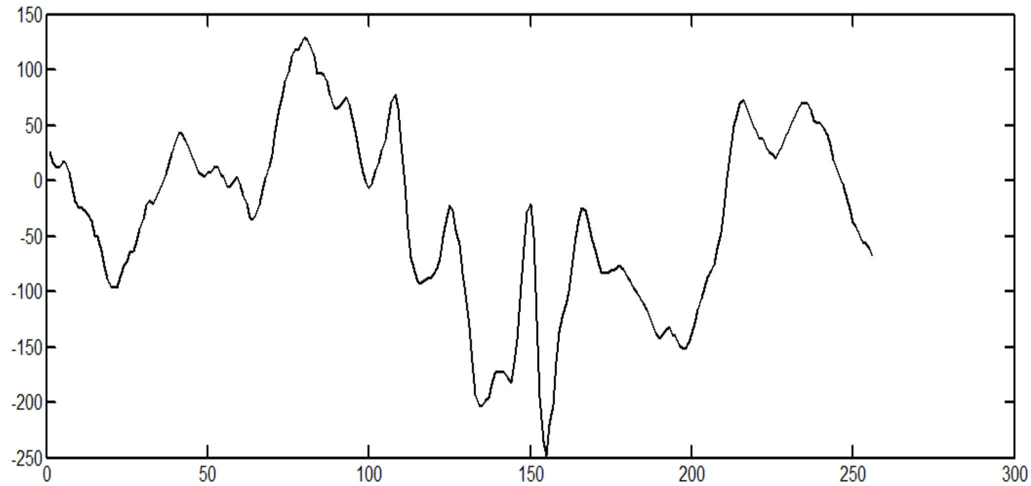

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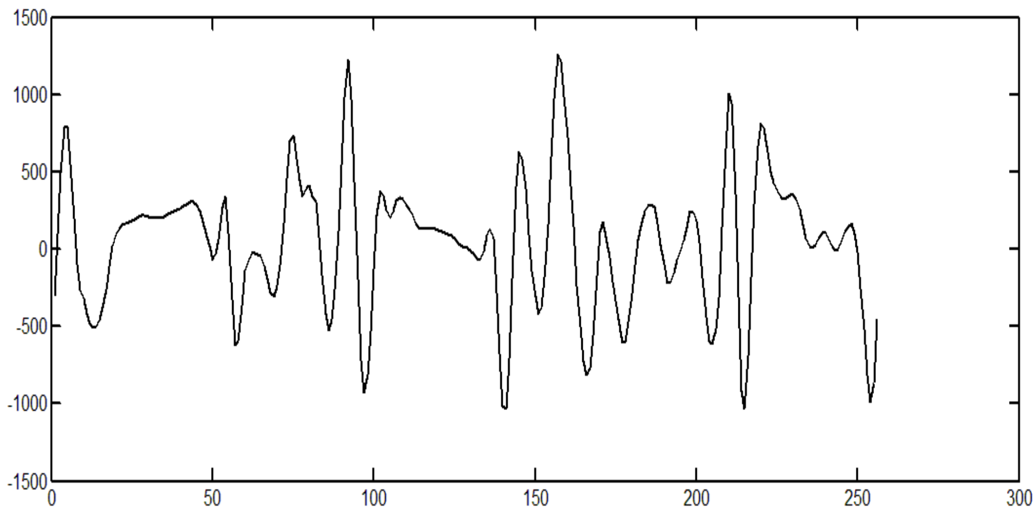


(c)

Figure 1.5 (a) EEG segment of class A (b) EEG segment of class D (c) EEG segment of class E

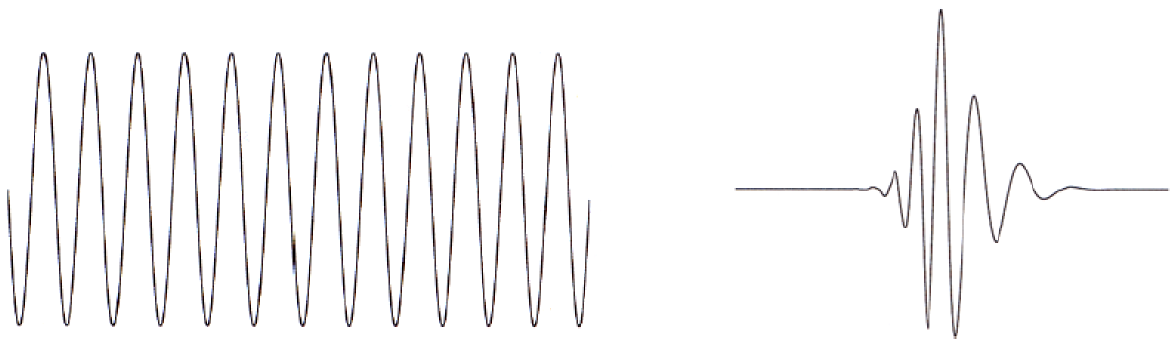
Chapter 2

Classification of EEG Signal

2.1 Wavelet Transform

The transform of a signal is just another way of representing a signal as it doesn't change any information content of a signal. Although short time Fourier transform (STFT) can be used to analyze non-stationary signals, it has a constant resolution at all frequencies. The wavelet transform gives a time-frequency representation and in this transform different frequencies are analyzed with different resolutions.

Wavelet transform uses wavelets of finite energy. Wavelets are localized waves which are suited to analyze transients since their energy is concentrated in time and space [11].



(a) (b)

Figure 2.1 Representation of (a) wave (b) wavelet

The wavelet transform gives us multi-resolution description of a signal. It addresses the problems of non-stationary signals and hence is particularly suited for feature extraction of EEG signals [12]. At high frequencies it provides a good time resolution and for low frequencies it provides better frequency resolution, this is because the transform is computed using a mother wavelet and different basis functions which are generated from the mother wavelet through scaling and translation operations. Hence it has a varying window size which is broad at low frequencies and narrow at high frequencies, thus providing optimal resolution at all frequencies.

2.1.1 Continuous wavelet transform

The continuous wavelet transform is defined as

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|\,s\,|}} \int x(t).\psi(\frac{t-\tau}{s})\,dt$$

Where *x(t)* is the signal to be analyzed , *ψ(t)* is the mother wavelet or the basis function *τ* is the translation parameter and *s* is the scale parameter.

The Continuous wavelet transform performs the convolution operation of the basis function and the signal. The mother wavelet is chosen depending upon the characteristics associated with the signal. The translation parameter *τ* relates to the time information present in the signal and it is used to shift the location of the wavelet function in the signal. The scale parameter *s* correspond to the frequency information is defined as the inverse of frequency. Scaling expands or contracts a signal, hence large scales expand the signal and give the hidden local information while small scales contract a signal and provide global information [11].

2.1.2 Discrete wavelet transform

The computation of CWT consumes a lot of time and resources and results in large amount of data, hence Discrete wavelet transform, which is based on sub-band coding is used as it gives a fast computation of wavelet transform. In DWT the time-scale representation of the signal can be achieved using digital filtering techniques. The approach for the multi-resolution decomposition of a signal *x(n)* is shown in Fig. 2.2. 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 downsamplers 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 downsampled 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 [13-14].

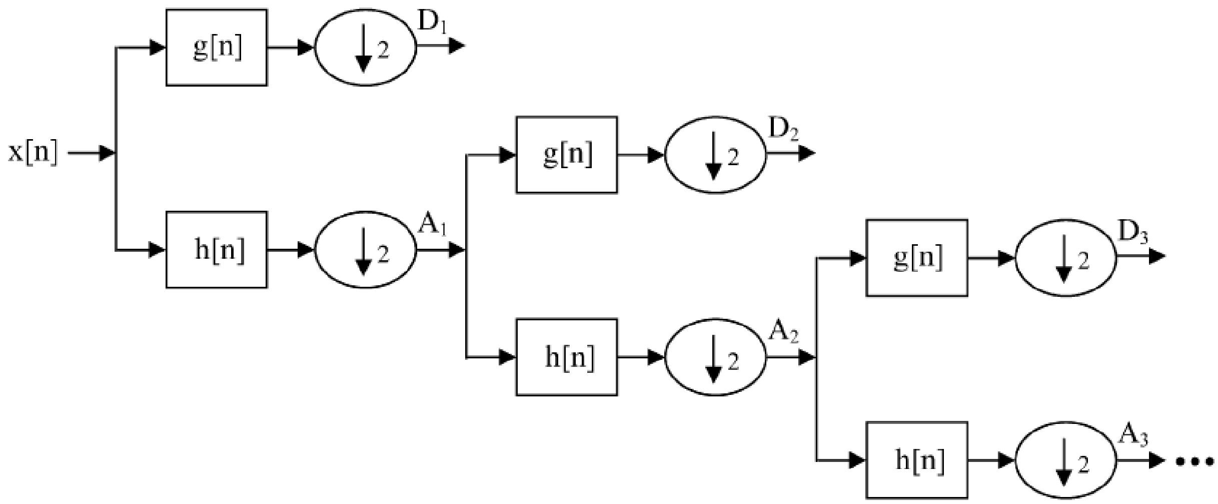


Figure: 2.2 Discrete wavelet transform block diagram [15]

The standard quadrature filter condition is

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1$$

where *H(z)* is the Z-transform the low pass filter *h*. this filter can be used to specify all wavelet transforms.

The complementary high pass filter is defined as

$$G(z) = zH(-z^{-1})$$

Now the sequence of filters can be obtained as

$$H_{k+1}(z) = H(z^{2k})H_k(z),$$

$$G_{k+1} = G(z^{2k})H_k(z), \quad k = 0,1 \dots \dots K-1$$

with the initial condition $H_0(z) = 1$. In time domain we have

$$h_{k+1}(n) = [h]_{\uparrow 2k} * h_k(n)$$

$$g_{k+1}(n) = [g]_{\uparrow 2k} * h_k(n)$$

The subscript $[.]_{\uparrow 2k}$ denotes upsampling by 2k. Here n is the discrete sampled time.

The normalized wavelet and scale basis function are defined as

$$\varphi_{k,l} = 2^{\frac{k}{2}} h_k(n - 2kl)$$

$$\psi_{k,l}(n) = 2^{\frac{k}{2}} g_k(n - 2kl)$$

where the factor $2^{k/2}$ is the inner product normalization, k and l are the scale and translation parameter respectively.

The DWT decomposition can be described as

$$a_{(k)}(l) = x(k) * \varphi_{k,l}(n)$$

$$d_{(k)}(l) = x(k) * \psi_{k,l}(n)$$

where $a_{(k)}(l)$ and $d_{(k)}(l)$ are the approximation coefficients and the detail coefficients at resolution k, respectively [13-16].

2.1.3 Wavelet families

There are a number of basic functions that can be used as the mother wavelet for Wavelet transform. While choosing the mother wavelet the characteristics of the signal should be taken into account since it produces the different wavelets through translation and dilation and hence determines the characteristics of the resulting transform. Figure 2.3 illustrates the commonly used wavelet functions. The wavelets are chosen on the basis of their shape and ability to analyze the signal for a particular application.

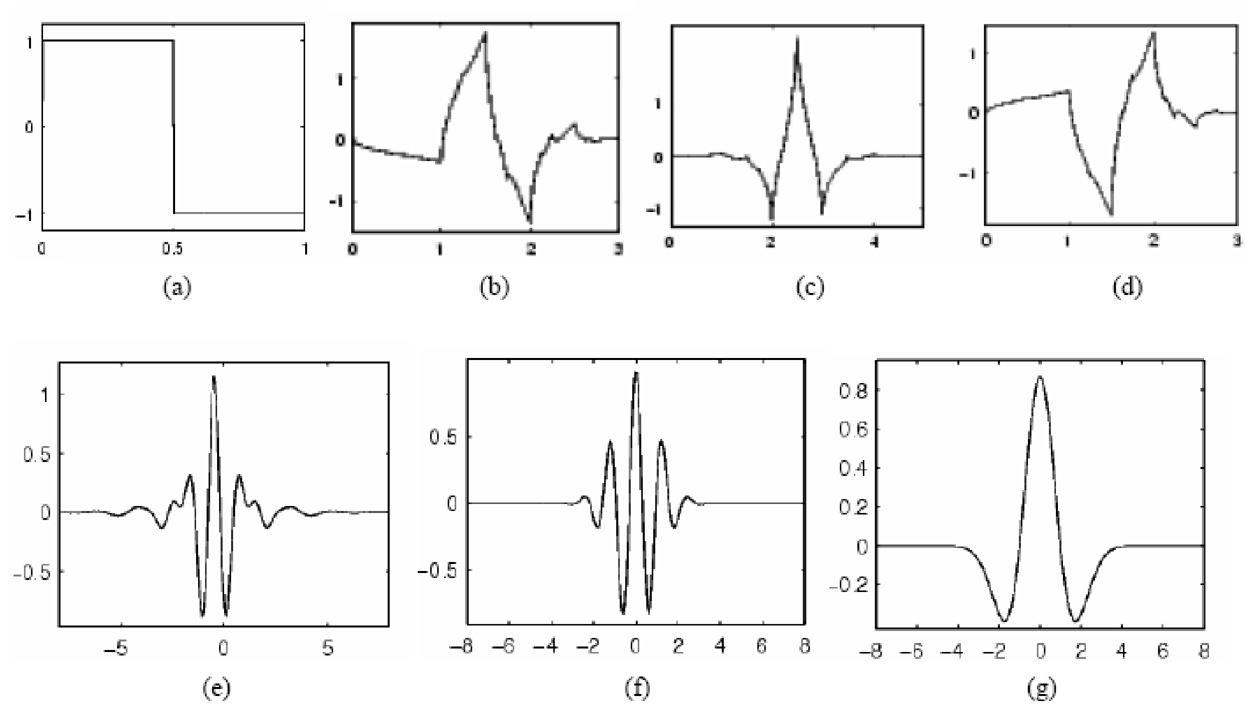


Figure 2.3: Commonly used wavelet functions (a) Haar (b) Daubechies4 (c) Coiflet1 (d) Symlet2 (e) Meyer (f) Morlet (g) Mexican Hat [11].

2.2 Feature extraction using discrete 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 tranform selection of the appropriate wavelet and number of decomposition level is of utmost importantce. 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-D4 and one approximation A4. For the four detail coefficients we get 247 coefficients (129+66+34+18) and 18 for the approximation coefficient. So a total of 265 coefficients were obtained for each segment [15].

To reduce the number of features following statistics were used:

- Maximum of wavelet coefficients in each sub band
- Minimum of wavelet coefficients in each sub band
- Mean of wavelet coefficients in each sub band
- Standard deviation of wavelet coefficients in each sub band [22]

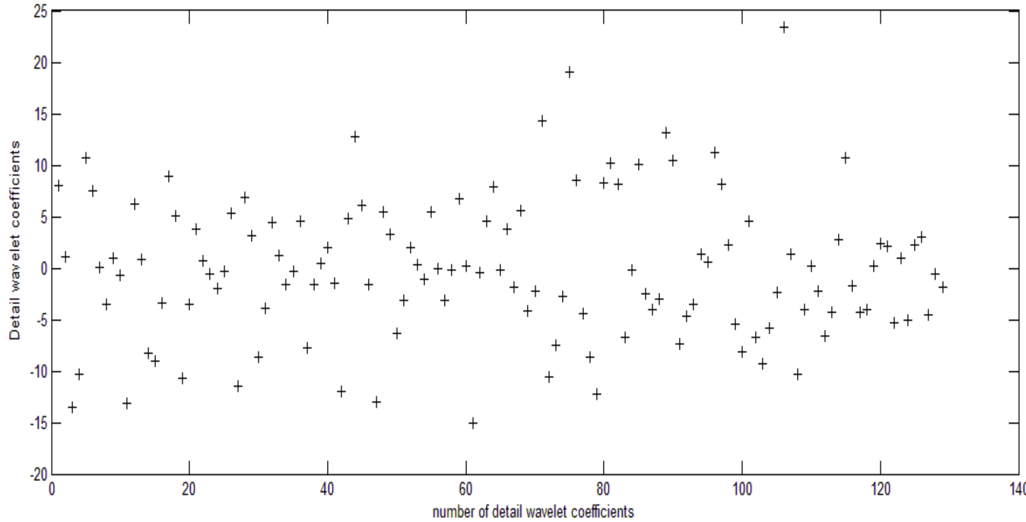
Hence the dimension of DWT coefficients is 20.

The table for DWT coefficients of an EEG segment of classes A, D, E is shown below

Table 2.1 Statistics of wavelet coefficients

Dataset	Extracted Features	Wavelet coefficients				
		Sub bands				
		D_1	D_2	D_3	D_4	A_4
Set A	Maximum	23.44104	65.70968	177.9029	83.28186	286.3614
	Minimum	-15.1013	-52.1523	-141.268	-171.945	-260.701
	Mean	-0.16537	-1.21974	-7.68956	-4.04699	-0.86361
	Std. deviation	6.86211	24.09339	61.35413	63.63968	166.1364
Set B	Maximum	9.763284	24.68172	72.32882	194.7452	401.7753
	Minimum	-8.08096	-28.8256	-84.667	-118.222	-600.716
	Mean	0.078406	0.366535	2.012951	9.170777	-31.4094
	Std. deviation	2.820835	8.466435	36.18396	84.91487	227.0395
Set C	Maximum	63.49726	309.0024	816.6531	1366.084	1055.255
	Minimum	-110.733	-317.317	-868.665	-1180.19	-1095.01
	Mean	-0.69357	2.200813	-41.2569	-99.0486	-214.138
	Std. deviation	28.63028	117.3747	479.7756	712.5626	650.2858

The detailed wavelet coefficients of set A, set D, set E EEG segments at the first decomposition level is shown in the following figures.



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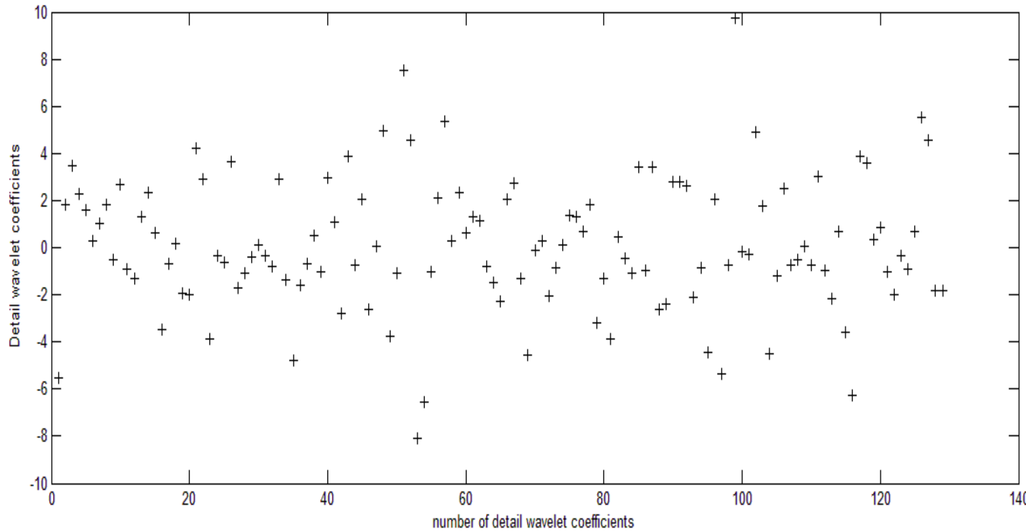

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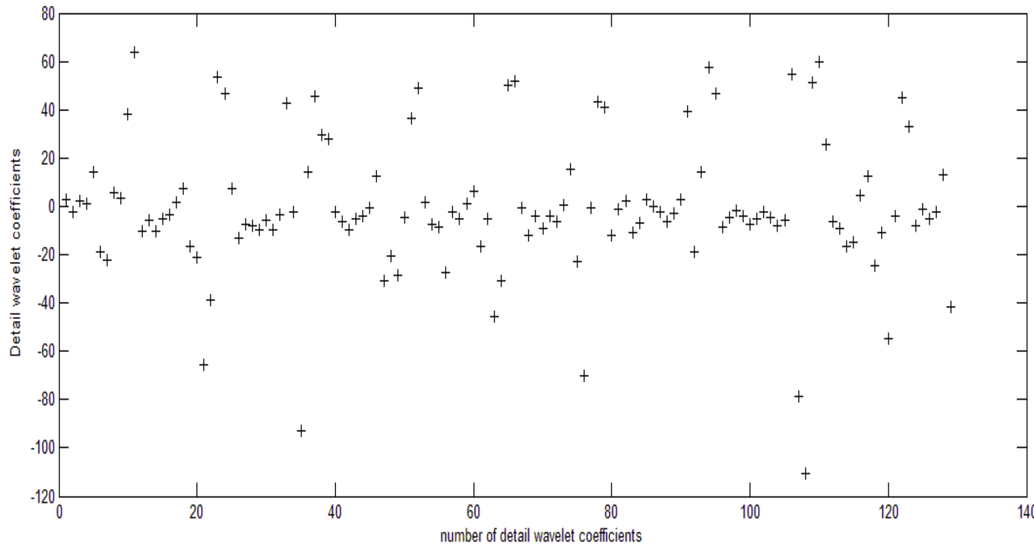


(c)

Figure 2.4 (a), (b), (c) Plot for Discrete wavelet coefficients of class A, D and E respectively

2.3 Feature Extraction using Autoregressive Coefficients

The Autoregressive (AR) Power spectral density estimation of the EEG signals of set A, set B and set C was computed. The Power spectral density is the distribution of power with respect to the frequency. Power spectral density R_{xx} of the random stationary signal can be expressed by polynomials A(z) and B(z) having roots that fall inside the unit circle in the z-plane [pr] as shown in the given formula [23]

$$Rxx(z) = \sigma_w^2 \frac{B(z)B(z^{-1})}{A(z)A(z^{-1})}, \qquad r_1 < |z| < r_2$$

where σ_w is the variance of the white Gaussian noise *w(n)*. Now the linear filter *H(z)* for generating the random process *x(n)* from the white Gaussian noise *w(n)* can be written as

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sum_{k=0}^{q} b_k z^{-k}}{1+\sum_{k=1}^{p} a_k z^{-k}}, \qquad |z| > r_1$$

Hence the output *x(n)* can be related to the input by using the following difference equation:

$$x(n) + \sum_{k=1}^{p} a_k x(n-k) = \sum_{k=0}^{q} b_k w(n-k)$$

If $b_0 = 1$, $b_k = 0$, $k > 0$ then the linear filter $H(z)$ can be written as $1/A(z)$. Now the difference equation for the AR process can be reduced to

$$x(n) + \sum_{k=1}^{p} a_k x(n-k) = w(n)$$

If $a_k = 0$, $k \geq 1$ then the linear filter $H(z) = B(z)$ and the difference equation for the moving average (MA) process can be written as follows:

$$x(n) = \sum_{k=0}^{q} b_k w(n-k)$$

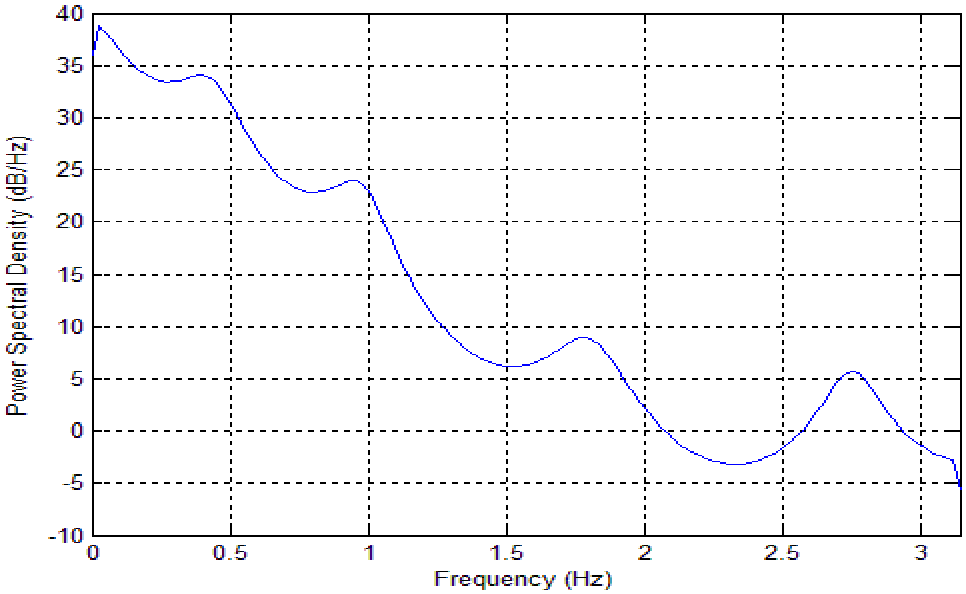
In case of Autoregressive moving average (ARMA) process linear filter $H(z) = B(z)/A(z)$ has both finite poles and zeros in the z-plane [23].

Autoregressive coefficients are very important features as they represent the PSD of the signal which is very common. Since the method characterizes the input data using an all-pole model, the correct choice of the model order *p* is important. We cannot take the value of model order too large or too small as it gives poor estimation of PSDs. We can model any stochastic process using AR model.

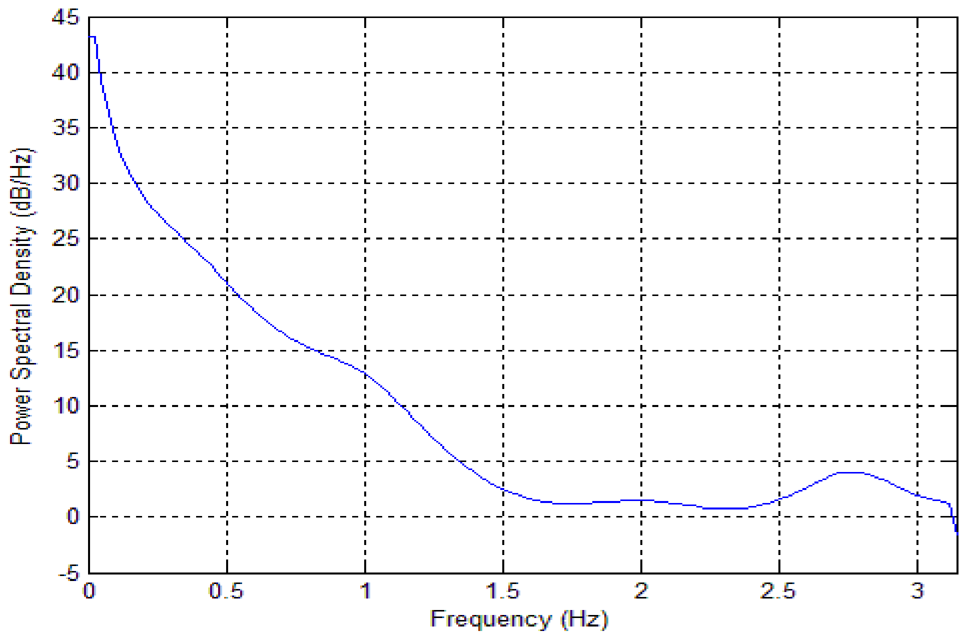
There are various methods available for AR modeling such as moving average (MA) model, autoregressive moving average (ARMA) model, Burg's algorithm [24]. ARMA method of AR model is normally used to get good accuracy. Burg algorithm estimates the reflection coefficient a_k. we can use Burg method to fit a p^{th} order autoregressive (AR) model to the input signal, *x*, by minimizing (least squares) the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion [25]. The Burg method is a recursive process.

In this paper we have followed the Burg's method to find the AR coefficients. The model order is taken to be equal to 10. We have used the Burg algorithm to find the AR coefficients using MATLAB.

AR coefficients and the Power spectral densitywere obtained by using MATLAB. Since the model order is 10 we have 11 AR coefficients. The plot for the power spectral density is shown in the following figures:



(a)



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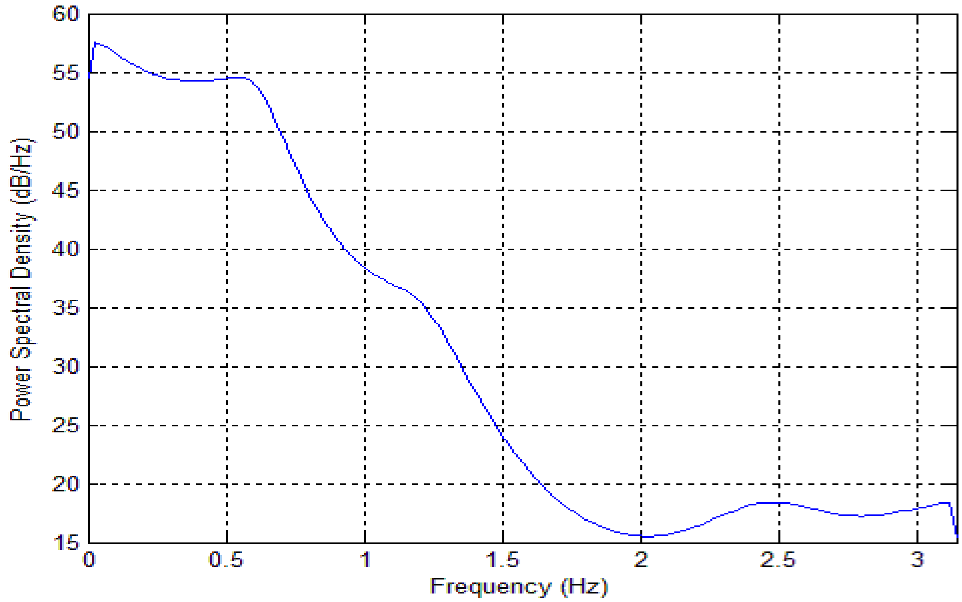
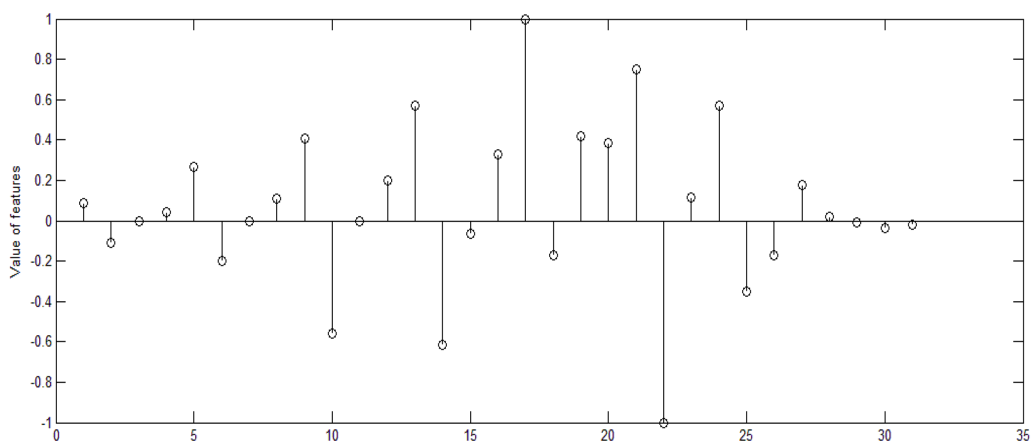


(c)

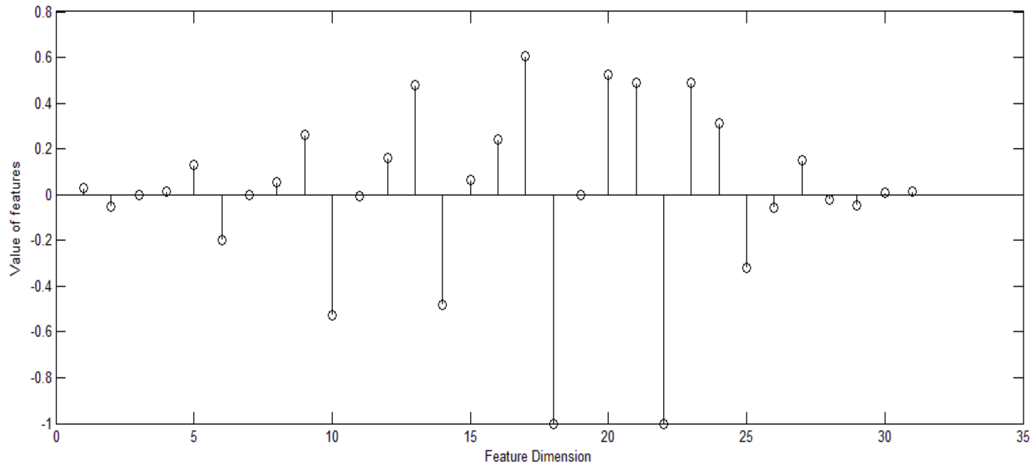
Figure 2.5 (a), (b), (c) Plot for power spectral density of class A, D and E respectively

2.4 Feature Vector

The 20 discrete wavelet coefficients and 11 Auto-regressive coefficients were appended to form feature vector of dimension 31. These feature coefficients are shown as follows:



(a)



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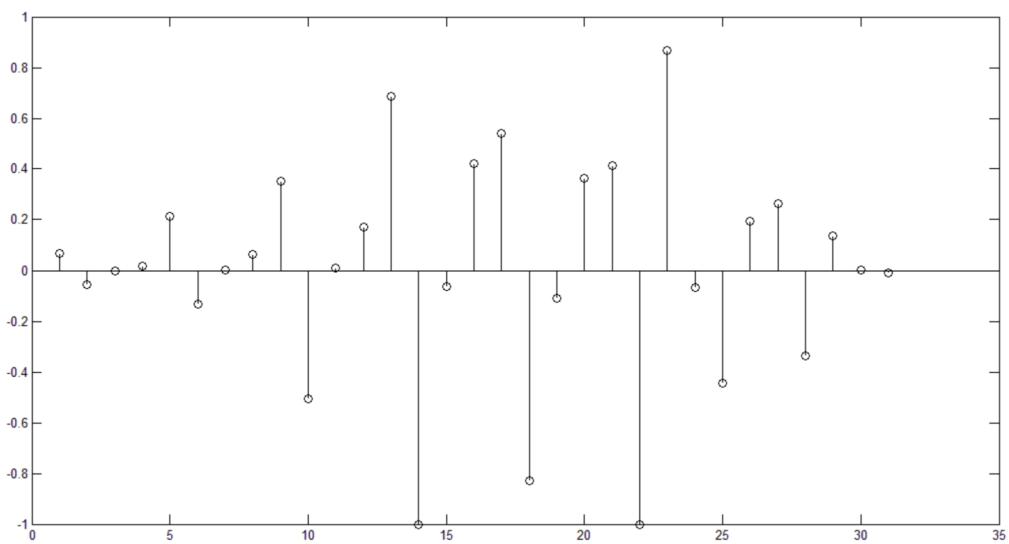

(c)

Figure 2.6 (a), (b), (c) Feature vector of dimension 31 of class A, D and E respectively

2.5 Artificial Neural Network

An artificial neural network can be defined as a machine that is modelled on a human brain. The fundamental structural constituents of the brain are neurons which are also the basic information processing units of an ANN. The neural network is formed by a massive interconnection of these neurons. The network so formed has the capability of learning i.e acquiring knowledge from the environment by performing computations. The synaptic weights which are the interneuron connection strengths are used to store this acquired knowledge. In the learning process synaptic weights can modified according to many algorithms to achieve the desired design objective. Fig 2.7 shows the model of a single neuron [18].

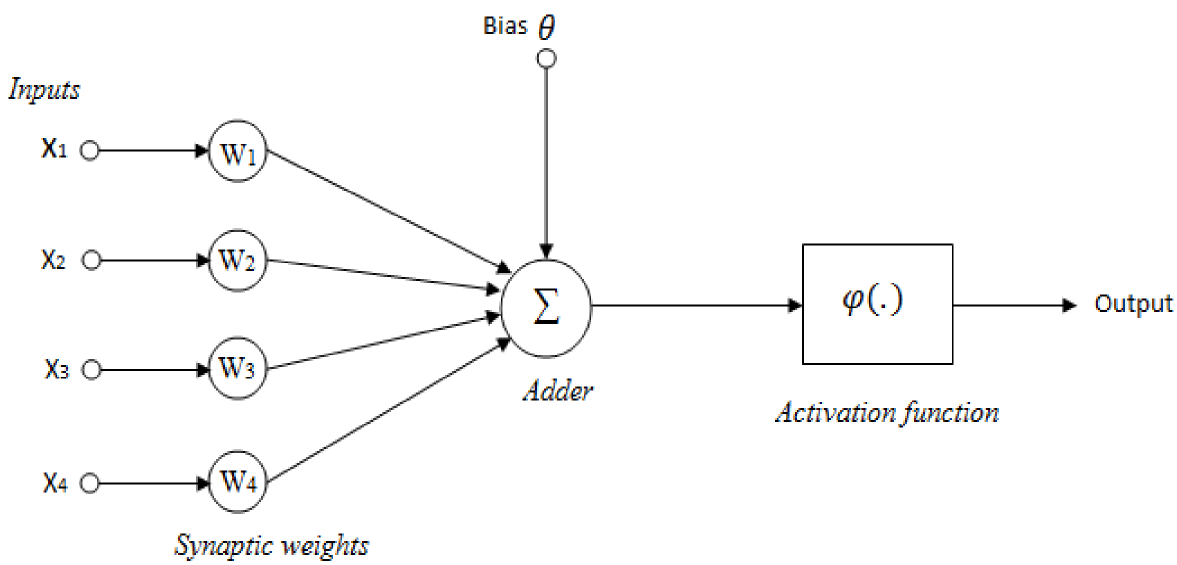

Figure 2.7: Model of a neuron

A typical neural network consists of the following layers

1. Input layer
2. Hidden layer
3. Output layer

The input layer consists of source nodes which supply the input vector (activation pattern) i.e the input signals to the next layer.

A neural network can have one or more hidden layer. This layer consists of hidden neurons. These neurons are crucial to perform certain higher order statistics and computations to perform a specific task. They intervene between the input and output layer in some useful manner. The ability of hidden neurons to extract higher order statistics is valuable when the size of the input layer is large. The output signals of a particular layer act supplied to the next layer.

The output layer is the last layer of a network structure. The set of output signals of the neurons in the output layer is gives the overall response of the network to the input vector supplied at the input layer. Fig 2.8 shows a typical network structure with one hidden layer. This network has 4 neurons in the input layer, three neurons in the hidden layer and a single out neuron. A network is said to be fully connected when each node in each layer of the network is connected to every other node in the adjacent forward layer, otherwise if some connections are missing then is said to be partially connected.

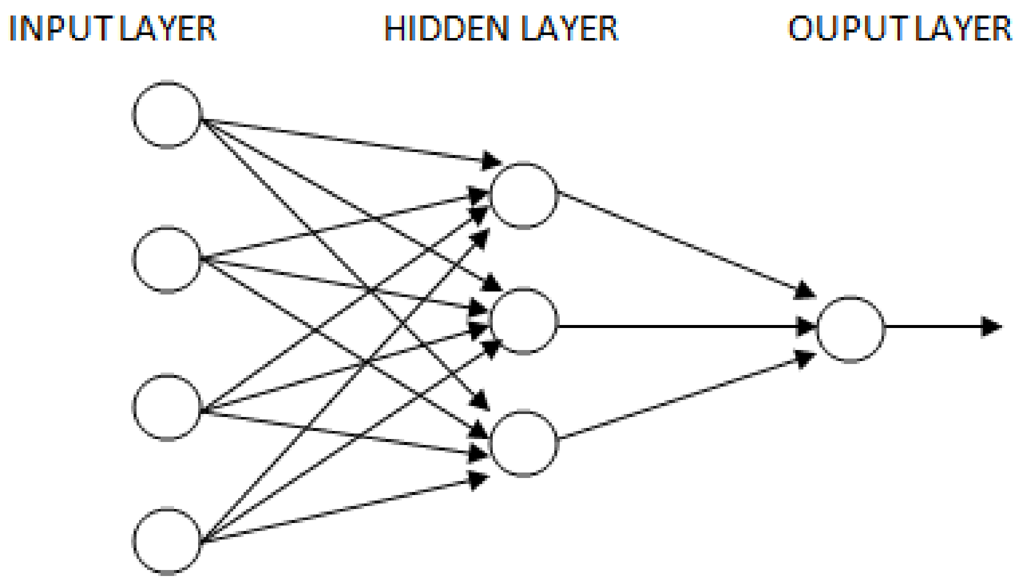

Figure 2.8: Structure of a neural network

2.6 Learning Process

Learning is a process in which the neural network undergoes changes in its free parameters when it is stimulated by the environment. As a result of this learning it structure changes and it responds in a new way to its environment. Gradually its performance improves through this process. There are many types of learning rules, some of it are mentioned below [18].

- **Error- correction learning** in which the error signal actuates a control mechanism so as to make adjustments in to the synaptic weights. These changes make the output signal come closer to the target value in a step by step manner. The error signal is the difference between the desired output and the output from the network. The objective in this type of learning is to minimize the cost function or the index of performance. The cost function is the instantaneous value of the error energy.
- **Memory based learning-** here all the past values of correctly classified input-output examples are stored. When a new test pattern is applied to the network this learning algorithm responds by retrieving and analyzing the training data in the local neighbourhood of the test pattern. Nearest neighbour rule and K-nearest classifier are two popular algorithm in this type of learning.
- **Hebbian learning-**It is the oldest and most famous of all learning rules. It is based on hebbian synapse which is defined as a synapse with time-dependent, highly local, and strongly interactive mechanism to increase synaptic efficiency as a function of the correlation between presynaptic and post synaptic activities. [Brown et al.,1990]. In other words if the neurons on either side of a synapse are simultaneously activated then the strength of that synapse is selectively increased and if activated asynchronously then the synapse is selectively weakened or eliminated [Stent,1973; Changeux and Danchin 1976].
- **Competitive learning-**As the name implies the output neurons of the network compete among themselves to get become active. At a time only one neuron is activated. The set of neurons are all same but for some randomly distributed synaptic weights, there is a mechanism in place so that for the given input pattern only one neuron is fired i.e. the neuron that wins the competition is called a winner-takes-all-neuron [Rumel Hart and Zipser 1985]. So this rule is suited for feature detection and pattern recognition purposes.

2.7 MLPNN and Back Propagation algorithm

The multilayer perceptron is the most popular and commonly used neural network structure. It is an extension of the single layer perceptron. Basically an MPLNN consists of a set of source nodes called the input layer, one or more layer of hidden neurons and an output layer. These type of networks have been used to solve many pattern recognition problems by training them in a supervised manner by using a highly popular algorithm based on error correction rule called the error back propagation algorithm.

The back propagation algorithm is based on delta rule and gradient descent of error surface in weight space. According to delta rule the synaptic weight change of a neuron is proportional to the learning rate parameter and the gradient of the cost function at the particular weight in multidimensional weight space. Basically this algorithm consists of two passes – forward and backward through different layers of the network. In the forward pass an input signal is applied to the input layer. This signal is propagated in the forward direction layer by layer by performing computations at each and every node. In this pass the synaptic weight remain unchanged. At the output layer we get a response for each activity pattern applied. In the backward pass the error signal is computed as the difference between the target value and output value. This signal is responsible for changes in weights layer by layer according to the delta rule so that the response of the network moves closer to the desired response in a statistical sense.

The steps involved in the back propagation algorithm are given below [18].

i. **Initialization**- the synaptic weights and biases are given random values which are picked from a uniform distribution with zero mean.

ii. **Presentation of input patterns**- the network is presents with input patterns which act as training vectors. These patterns are used to compute the forward pass and then the backward pass.

iii. **Forward pass**- Let the input and target of a training example is (***x****(n)*, ***d****(n)*), the induced local field $v_j^{(l)}(n)$ can be formulated as below

$$v_j^{(l)}(n) = \sum_{i=0}^{m_0} w_{ji}^{(l)}(n) y_i^{(l-1)}(n)$$

The output signal of neuron j in layer l can be given as below

$$y_j^{(l)} = \varphi_j(v_j(n))$$

If the neuron j is in the first hidden layer (i.e. l = 1)

$$y_j^{(0)}(n) = x_j(n)$$

If the neuron j is in the output layer (i.e. l = L)

$$y_j^{(L)} = o_j(n)$$

Error can be computed as

$$e_j(n) = d_j(n) - o_j(n)$$

iv. **Backward pass-** The local gradient (δs) can be computed by

$$\delta_j^{(l)}(n) = \begin{cases} e_j^{(L)}\varphi'_j\left(v_j^{(L)}(n)\right) & for\ neuron\ j\ in\ outut\ layer\ L \\ \varphi'_j\left(v_j^{(l)}(n)\right)\sum_k \delta_k^{(l+1)}(n)w_{kj}^{(l+1)}(n) & for\ neuron\ j\ in\ hidden\ layer\ l \end{cases}$$

Where φ'(.) denotes the differentiation with respect to the argument. Now adjust the synaptic weights using the generalized rule

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left[w_{ji}^{(l)}(n-1)\right] + \eta\delta_j^{(l)}(n)y_i^{(l-1)}(n)$$

v. **Iteration-** Now we can iterate the forward and backward computation.

2.8 Committee Neural Network

Committee neural network is an approach that reaps the benefits of its individual members. It has a parallel structure that produces a final output [18-19] by combining results of its member neural networks. In the present study the proposed technique consists of 3 steps (1) selection of appropriate inputs for the individual member of the committee (2) training of each member (3) decision making based on majority opinion.

The committee network consists of member neural networks which are multi layer perceptron neural network trained with back propagation algorithm. The available data is divided into training and testing data. From the training data features were extracted using wavelet transform and AR coefficients. The input feature set is divided equally among all the neural networks for training purpose. The different networks have different neurons and initial weights. After the training phase is completed the networks are tested with testing data. All the neural networks were trained using gradient descent back propagation algorithm using MATLAB software package. Out of the different networks employed for the initial training stage the best performing networks were selected to form the committee. For the classification purpose the majority decision of the committee formed the final output .Fig 2.9 shows the block diagram of the committee

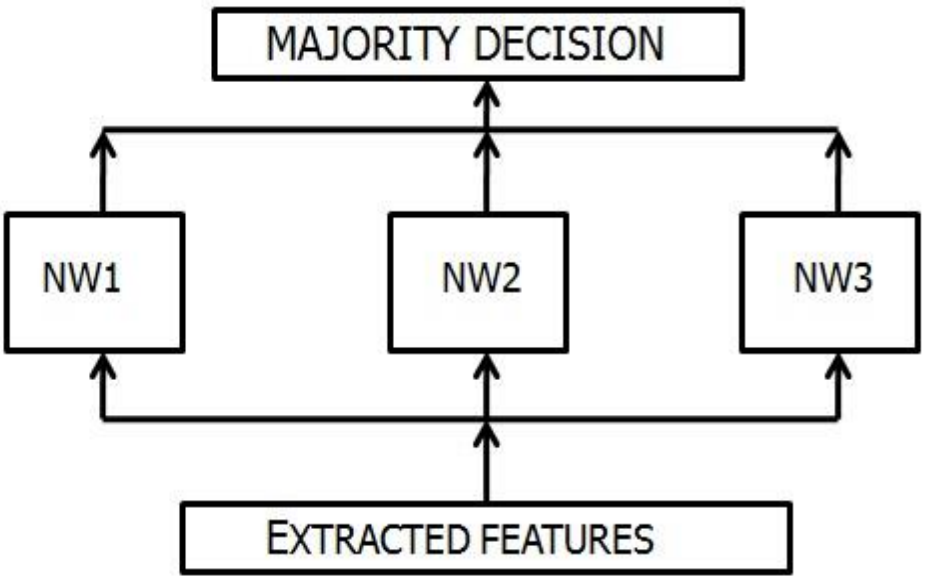

Figure 2.9: Block diagram of Committee neural network [17]

2.9 Classification using Committee Neural Network

The committee neural network was formed by three independent members each trained with different feature sets. Prior to recruitment in the committee many networks containing different hidden neurons and initial weights were trained and the best performing three were selected. The decision fusion was obtained using majority voting. In order to reach a firm majority decision odd number of networks is required. The resulting accuracy of individual and the committee is shown in table 2.9.

Table 2.2 Confusion matrix of Neural Network 1

Classifier	Desired result	Output result		
		Set A	Set D	Set E
NN 1	Set A	612	32	18
	Set D	26	577	20
	Set E	2	31	602

Table 2.3 Confusion matrix of Neural Network 2

Classifier	Desired result	Output result		
		Set A	Set D	Set E
NN 2	Set A	621	27	17
	Set D	14	586	14
	Set E	5	27	609

Table 2.4 Confusion matrix of Neural Network 3

Classifier	Desired result	Output result		
		Set A	Set D	Set E
NN 3	Set A	628	60	15
	Set D	11	538	10
	Set E	1	42	615

Table 2.5 Statistical parameters of Neural Network 1

Statistical Parameters	**Values (%)**
Specificity	95.63
Sensitivity (seizure free epileptogenic zone segments)	90.16
Sensitivity (epileptic seizure segment)	94.06
Total classification accuracy	93.28

Table 2.6 Statistical parameters of Neural Network 2

Statistical Parameters	**Values (%)**
Specificity	97.03
Sensitivity (seizure free epileptogenic zone segments)	91.56
Sensitivity (epileptic seizure segment)	95.16
Total classification accuracy	94.52

Table 2.7 Statistical parameters of Neural Network 3

Statistical Parameters	**Values (%)**
Specificity	98.13
Sensitivity (seizure free epileptogenic zone segments)	84.06
Sensitivity (epileptic seizure segment)	96.09
Total classification accuracy	92.76

Table 2.8 Statistical parameters of Committee Neural Network

Statistical Parameters	Values (%)
Specificity	98.02
Sensitivity (seizure free epileptogenic zone segments)	91.82
Sensitivity (epileptic seizure segment)	96.09
Total classification accuracy	95.31

Table 2.9 Accuracy of Committee neural network

ANN	Accuracy
NN1	93.28
NN2	94.52
NN3	92.76
CNN	95.31

The outputs of the member MLPNN of the committee were represented by unit basis vectors: i.e.

[0 0 1] = healthy segments (set A)

[0 1 0] = seizure free epileptogenic zone segments (set D)

[1 0 0] = epileptic seizure segments (set E)

The statistical parameters are defined as follows:

Specificity: Number of correctly classified healthy segments/ Total number of healthy segments.

Sensitivity (seizure free epileptogenic zone segments): Number of correctly classified seizure free epileptogenic zone segments/ Total number of seizure free epileptogenic zone segments.

Sensitivity (epileptic seizure segments): Number of correctly classified epileptic seizure segments/Total number of epileptic seizure segments.

Total classification accuracy: Number of correct classified segments/ total number of segments[22].

The committee neural network achieves better performances than individual members with accuracy of 98.02%, 91.82% and 96.09% for set A, D and E respectively and overall accuracy of 95.31%.

Chapter 3

Dimension Reduction using F-Ratio based Technique

3.1 F-Ratio

F-Ratio is a statistical measure which is used in the comparison of statistical models that have been fit to data set to identify the model that best fits the population from which the data were sampled [21]. We can see a multi cluster data as shown in fig 3.1. F-ratio can be formulated as

$$F-ratio = \frac{Variance\ of\ mean\ between\ the\ clusters}{Average\ variance\ within\ the\ cluster}$$

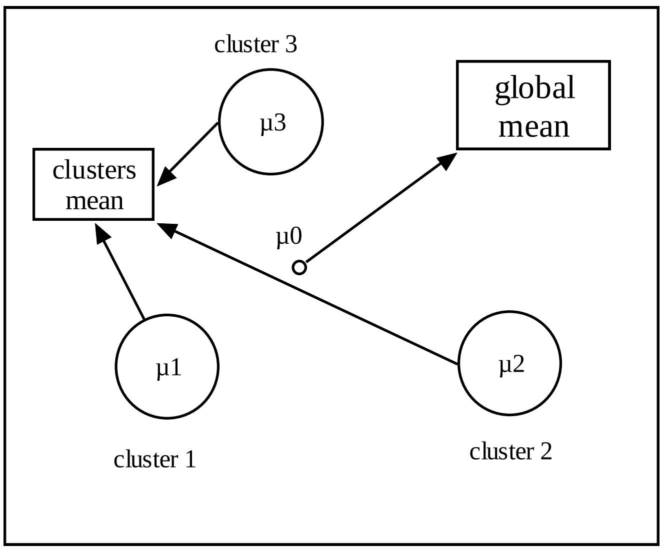

Figure 3.1: Diagram for multi-cluster data

Suppose there are k numbers of clusters each having n number of data points. If x_{ij} is an i^{th} element of the j^{th} class then the mean of the j^{th} class μ_j can be expressed as [26]

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$$

The mean of all μ_j is called the global mean of the data and can be expressed as μ_0

$$\mu_0 = \frac{1}{k}\sum_{j=1}^{k} \mu_j$$

The f-ratio can be expressed as [26]

$$F - ratio = \frac{\frac{1}{k}\sum_{j=1}^{k}(\mu_j - \mu_0)^2}{\frac{1}{k}\sum_{j=1}^{k}\frac{1}{n}\sum_{i=1}^{n}(x_{ij} - \mu_j)^2}$$

If the f-ratio increases then the clusters move away from each other or the cluster size shrinks. We can apply this f-ratio based optimization technique in case of EEG signals to reduce the dimensionality of the feature vector.

3.2 Optimization using F-Ratio

The features having low value of F-Ratio are less important as compared to the features having high value of F-Ratio. To reduce the computational complexity of the network we can delete the features having lesser values of F-ratio. By deleting these features the accuracy of classification does not decrease much. In this paper we have deleted features one by one and each time we have analyzed the classification accuracy simultaneously. If there is a large decrease in classification accuracy then we did not delete that particular feature. In this way we can reduce the feature dimension and hence we can optimize the network without affecting the classification accuracy. In some cases the accuracy was found to increase on deletion of features.

3.3 F-Ratio of the extracted features

The F-Ratio corresponding to each feature is shown in table 3.1.

Table 3.1 F-Ratio of the extracted features

Serial No.	Coefficient No.	Coefficients F-ratio	Serial No.	Coefficient No.	Coefficients F-ratio
1	21	1.082	17	1	0.226
2	22	0.9316	18	13	0.1972
3	12	0.5243	19	14	0.1958
4	8	0.4748	20	31	0.1634
5	24	0.4714	21	28	0.1555
6	9	0.4464	22	27	0.0459
7	6	0.4073	23	20	0.0444
8	10	0.401	24	26	0.0407
9	23	0.3981	25	17	0.0036
10	4	0.3915	26	18	0.0023
11	25	0.3708	27	19	0.0011
12	5	0.3699	28	11	0.0004
13	30	0.365	29	15	0.0003
14	16	0.301	30	3	0.0002
15	29	0.2875	31	7	0.0001
16	2	0.2766	x	x	x

Now in order to reduce the dimension of the feature vector features having less F-Ratio were deleted. In the table 3.2 we have shown that the accuracy after the deletion of features.

Table 3.2 dimension reduction using F-Ratio

Serial No.	No. of coefficients taken	Network structure	Accuracy %
1	31	31-93-3	95.31
2	30	30-90-3	94.91
3	29	29-87-3	95.00
4	28	28-84-3	94.71
5	27	27-81-3	94.79
6	26	26-78-3	95.03
7	25	25-75-3	95.32
8	24	24-72-3	95.02
9	23	23-69-3	95.12
10	22	22-66-3	95.37
11	21	21-63-3	94.95
12	20	20-60-3	95.16
13	19	19-57-3	95.45
14	18	18-54-3	95.29
15	17	17-51-3	95.70
16	16	16-48-3	95.83
17	15	15-45-3	95.15
18	14	14-42-3	95.04
19	13	13-39-3	94.35

Hence on the basis of F-Ratio based optimization technique 18 features were deleted. Thus computational complexity was reduced without affecting the accuracy much.

Chapter 4

Conclusions and Future Work

Conclusion

The EEG signals was collected from [9], visual inspection of the three classes does not provide much information regarding the health of individual. So we have proceeded with the following methods

- Feature extraction was done using discrete wavelet transform and the power spectral density was estimated by Burg's algorithm for AR model.
- To reduce the number of wavelet coefficients we have used the statistics, viz. maximum, minimum, mean, and standard deviation for each of the detail and the approximate coefficients.
- The AR coefficients were appended to the discrete wavelet coefficients to form the feature vector.
- We have used Committee neural network for the classification purpose. The Committee neural network consisted of three member neural networks which were trained using error back propagation algorithm.
- The Committee neural network gives robust performance as compared to the individual networks.
- We have used the F-Ratio based optimization technique to reduce the dimension of feature vector.

Finally using our proposed technique we have successfully classified the EEG signals and reduced the computational complexity of the classifier.

Future Work

- EEG signal processing promises to be a vast area of research. The technique of committee neural network is a novel approach to improve the classification accuracy. The process of combining the outputs of each member from the committee implemented in this project was based on majority decision.
- There are many new methodologies that can be implemented in this area. Further different types of classifiers can be tested using different EEG database.
- Other feature extraction techniques can be tried so that a best possible set of features can be used also to reduce the computational complexity other dimensionality reduction techniques can be applied to the feature vectors.

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