FEATURE EXTRACTION AND CLASSIFICATION OF EEG SIGNALS

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(With Specialization in Instrumentation and Signal Processing)

By

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CANDIDATE'S DECLARATION

I hereby declare that this thesis report entitled "**Feature Extraction and Classification of EEG signals** ", submitted to the Department of Electrical Engineering, Indian Institute of Technology, Roorkee, India, in partial fulfilment of the requirements for the award of the Degree of **Master of Technology in Electrical Engineering** with specialization in **Instrumentation and Signal Processing** is an authentic record of the work carried out by me during the period from July 2012 to June 2013 under the supervision of **Dr. R.S.Anand**, Department of Electrical Engineering, Indian Institute of Technology, Roorkee. The matter presented in this thesis report has not been submitted by me for the award of any other degree of this institute or any other institute.

Date : 17/06/2013

Place : Roorkee

(NIKHIL M)

CERTIFICATE

This is to certify that the above statement made by the candidate is correct to best of my knowledge.

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I dedicate this thesis to my family and friends who unremittingly supported me during my years of study. They made this work possible.

Nikhil M

ABSTRACT

The EEG biometric system will be superior in performance and much reliable. In the case of EEG based security system, the mere presence of a person is not enough to bypass the system. EEG of same person will differ with the state of the person and conditions under which it is recorded. The biometric security system will have a sample of EEG recorded under some standard condition. So if a person is forcefully asked to bypass the system, he will not be able to bypass it. This is not the case with most conventional security systems like fingerprinting. Here we may be able to bypass the system, by forceful placement of finger printing or using some fake finger print.

The challenging part in this will be to identify and calculate the features of EEG which will give best results. This is a case dependent problem, and hence we cannot say for certain that a particular set of features will give best result. Further the classification efficiency will also depend up on the type of classifier used.

In my thesis work I tried to classify EEG belonging to different persons and thereby there by trying to classify different person. If this classification works well for a large number of persons of whom some may be intruders i.e., their EEG is not in the list of EEG patterns of persons whom we have to identify, then we will be able to make a biometric security system.

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ABBREVIATIONS

EEG	ElectroEncephaloGram
MSE	Mean Squared Error
EOG	Electrooculography
EMG	Electromyogram
VEOG	Vertical Electrooculography
HEOG	Horizontal Electrooculography
ECG	Electrocardiography
VEP	Visual Evoked Potential

CHAPTER 1 INTRODUCTION

EEG is one of the prominent medical signals used nowadays. EEG records the activity of brain over time. The activity is measured by measuring the electric potential occurring at a point in brain. The potential is created by the random firing of millions of neurons present in the brain. This electric field is created by the exchange of ions taking place when a neuron is exited. The EEG is a complicated signal, hence it can be considered as a random process. Also it is a non-Gaussian, non-stationary signal. Further the non-linear characteristics make it a complex signal. Brain is the central part of a human body which decides what actions should be taken at a particular place for a particular time. So by measuring the activity of brain we will be able to access the condition of body [1,2].

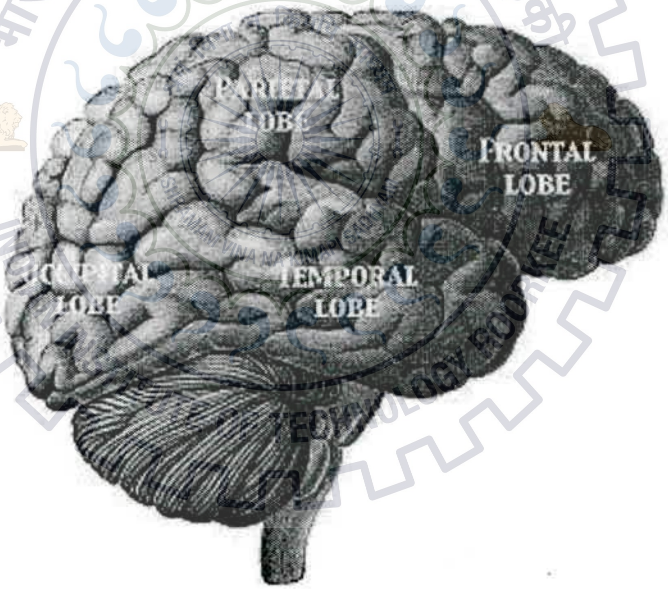

Figure 1.1 Various lobes of brain[1]

This property make EEG most widely studied subject. For analysis purpose the brain is divided into five lobes- frontal (F), temporal (T), occipital (O), central (C) and parietal (P).

Frontal lobe accounts for the conscious thinking process of a person. Since thinking process is largely different for different person, it shows the maximum uniqueness for a person. Damage to this region can result in mood changes, social differences, etc. Parietal lobe helps in integration of information from various sensory organs, manipulation of objects and in visual-spatial integration. Occipital lobe plays important role in vision. Abnormality in this region can cause hallucinations. Temporal lobe helps in detecting smell and sound. Further it helps in the facial and scene recognition [4].

The electrical signal is produced by a neuron is very small, so that we will not be able the measure such a value. What we will be measuring will be the electric field which is occurring due to the combined effect of a particular set of neurons which will be having some similar properties. The electric field thus produced will be largely attenuated by the skull, which will absorb most of the electrical energy. Further the conductivity will be affected by the dryness of the skin and presence of hair, which will not conduct electric field. The EEG signal recorded will be a function of positions x, y, z of brain from where it is recorded and also time of recording t. So roughly we can write EEG signal as

$$EEG = \phi(x, y, z, t)$$

If we fix the positions from where we are recording EEG, then we a function which is depending on only the time when it is recorded. The resolution with which we will be able to record the signal depends on the number of electrodes used. Normally for high resolution we have to use more number of electrodes. But the drawback is that as the number of channels increases, the data recorded will increase drastically. So to record such data a lot of memory space will be consumed. Further the processing time required to analyse it will become large. To limit this we have to reduce the number of channels used. So some trade off should be done so that the EEG recorded is having sufficient resolution at the same time analysis is less troublesome [5, 6].

1.1 The 10-20 electrode arrangement

10-20 electrode system is such a solution. It is most commonly used and most popular EEG recording system. It consists of total 22 electrodes. Out of this, two electrodes are used as reference and the remaining twenty for recording EEG. The reference electrodes are placed at the ear lobes. From the remaining twenty electrodes we form 10 channels of EEG, each channel recording the difference in potential between two electrodes.

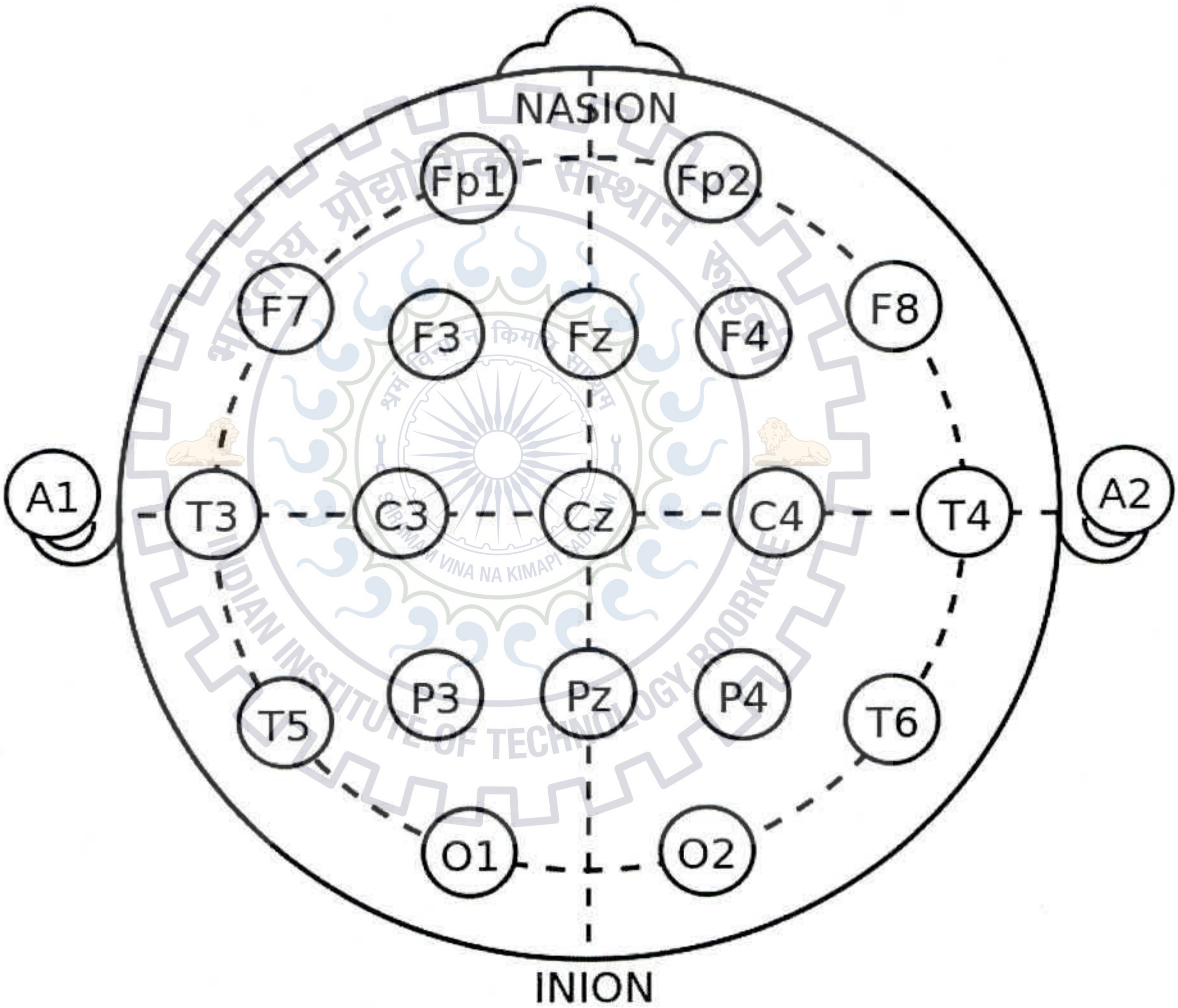

Figure 1.2 Arrangement of electrodes in 10-20 system [7]

The distance between adjacent electrodes are either 10 or 20 percent of total front to back or left to right distance and thus name 10-20 electrode system. The electrodes in the left hand side are given odd number and right hand side even numbers. Normally the adjacent electrodes are having similar data, and hence the data will be highly correlated. This can be used for data compression of EEG signals.

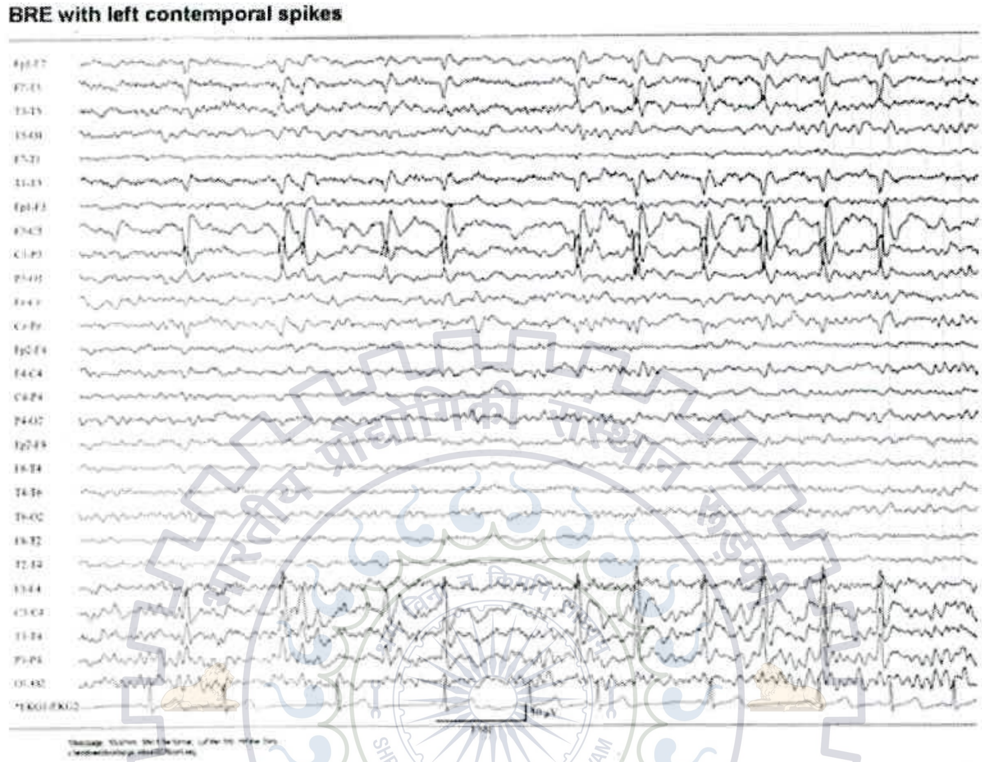

Figure 1.3 EEG of a person [7]

1.2 EEG sub-bands

The EEG signals consist of five major sub-bands for each channel. They are delta, theta, alpha, beta, and gamma. Delta wave has frequency range from 0.5-4Hz. Its amplitude ranges from 20-200 micro-volts. It predominantly occurs during deep sleep stages. The location of occurrence varies. It is reduced in wakeful state. Theta wave occurs during various stages of sleep. Frequency of this signal varies from 4-8Hz. Amplitude of this signal ranges from 5-100 micro-volts. This wave is also suppressed during wakeful states. Frontal and temporal region are the most prominent regions where it occurs. Alpha band has frequency range 8-13Hz. It is prominent during the relaxed state of body. It occurs mainly in occipital and temporal region. Alpha wave is suppressed during eye open condition. Further alpha wave recorded at the occipital region with eyes closed is one of the strongest EEG signal. Beta wave has frequency component range 13-30Hz. It is predominant during exited state, rigorous thinking, etc. Amplitude ranges from 2-20 micro-volts. It occurs mainly in the frontal lobes. Gamma wave ranges from 30-45Hz. It is having very low amplitude. It is normally present in infants, and the presence of it in adults may be an abnormality. But it can be present in adults during rigorous metal activities, extreme emotion, etc.

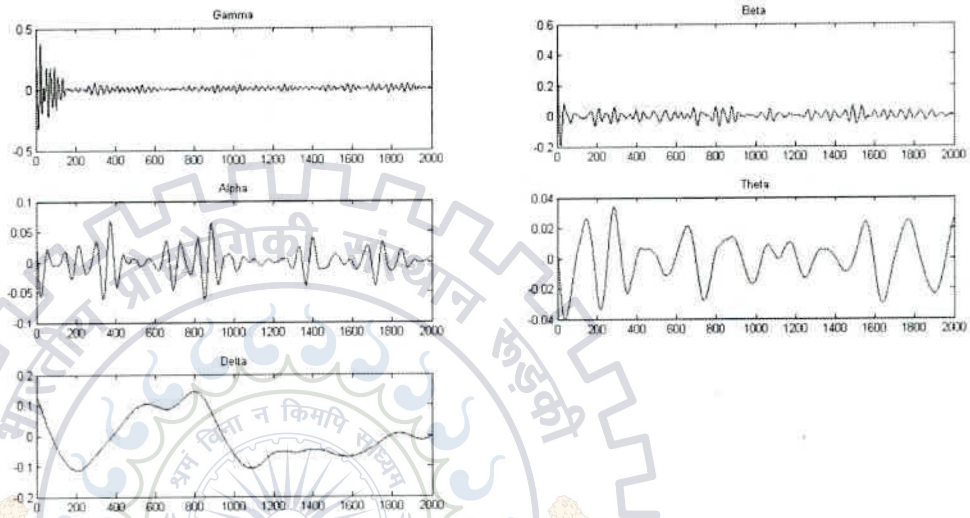

Figure 1.4 Different sub-bands of EEG

The above figure shows the various frequency bands and their corresponding amplitudes. As we can see, the amplitude of signal decreases as the frequency increases.

1.3 Effect of artifacts and noise

The recorded EEG will be affected by various artifacts and noises from surrounding like power supply noise. Artifacts are defined as the signals which are recorded in the EEG channels but are not the part of EEG.

The various artifacts include EOG, EMG, etc. EOG signal is produced due to the rapid eye movement. Since they are close to EEG electrodes they regularly corrode the useful data. Eye movement can be either vertical which produced VEOG or horizontal which produces HEOG. They mainly corrode the theta and alpha band. Next one is EMG. They are produced due to the muscle movement. Other common artifacts are produced due to breathing, body movement, etc. some of the artifacts like EOG,EMG, etc are high frequency artifacts (>35Hz) as compared to normal EEG, whereas artifacts due to breathing, etc are low frequency artifacts (<0.5Hz).

Noise induced in the channel is predominantly due to power supply noise. The channels are corrupted by signals from power supply which are having peaks values at 50Hz and its harmonics. Another noise is induced due to the non-linear characteristics of high gain amplifiers which are used to amplify raw EEG data.

1.4 Literature Survey

EEG signal being both non-stationary and non-Gaussian, analysis of the signal become complex. Due to the complexity of these signals, a variety of research has been happening using EEG. But only a few researches have taken to use EEG as a biometric security system. For classification and analysis of EEG, various statistical parameters were used. Some of them are calculated for single channel like linear complexity, auto regression, entropy, skewness, Fourier transform, etc. while others are calculated using relationship between different channels like mutual information, correlation ratio, etc.

Shedeed H A was able to classify 3 different people from a group people. He used a wavelet packet transform, to obtain alpha and beta band from recorded EEG for two channels C3-C4 and P3-P4. For the selected band, mean, variance and entropy were calculated. The neural network with standard back propagation algorithm was used to trained and classify people. He was able to attain very good classification while using three different people [25].

Rieria used two channel data of EEG for authentication. Data were recorded with person in sitting position with eyes closed. Features used for classification were auto regression, Fourier transform, and coherence and cross correlation. They were able to obtain true acceptance of 96.6% [10]. Hema recorded three channels EEG of six different people, and was able to authenticate people with an acceptance of 97% [11]. Jiang Feng Hu recorded a six channel EEG. Classification based on the feature variation when person thinks about hand, tongue and leg movement. Acceptance rate varied from 75-80% for authentication and 75-78.3% for identification [12]. Ravi and Palaniappan measured VEP EEG using 61 channels. They used for person authentication and obtained at max 95% acceptance [13].

Poulus recorded single channel EEG under eye closed state. DFT were calculated for feature extraction. Classification is done using Learning Vector Quantization (LVQ). Classification was case dependent and ranged from 80-100% [14]. The result thus obtained here is degrades if we increase number of persons. Paranjape was able to classify up to forty different persons using eight different channels with AR model with a classification rate of 82% [15]. Energy of brain potential during visual stimulus (VEPs) is used in biometry. The normalized energy from each channels were the classification features, and a standard back propagation algorithm was used for classification. 98.6 was the maximum correct classification obtained. But this method suffers from many drawbacks. The eye movement artifact will be predominant. This artifact will not be automatically removed. Another problem is that, since eye is open, the person may get distracted easily.

The energy of brain potentials evoked during processing of visual stimuli (Visual Evoked Potentials (VEP)) is considered as a new biometric in [16]. To form the EEG features, the energy of the EEG signal from each channel was computed and normalized according to the total energy from all 61 channels. These 61 EEG features were then classified by a multi-layer Perceptron Neural Network trained by a standard back propagation algorithm. The proposed method achieved a maximum recognition rate of 98.56, thus validates the ability of the proposed method to identify individuals. However, the VEP method is hardly to be practical in security check. Firstly, the eye-blink artifact will be abundant during picture evoking and it hardly automatically removed. Without automation, security check cannot be promoted in real world. Secondly, 61 channel signal collection will gravely distract subjects' activities and emotions, as well as complexity of the operation, which makes this method obtrusive. At last, the requirement of visual evoking is a limitation to wide application because it is inappropriate to blind one and distracted one [17, 25].

A kind of event related potential P300, was employed as the input of the identification system in [17] and Learning Vector Quantization (LVQ) neural network was used as a classifier. The average correct ratio of 7 subjects was 82.72%. After adopting a voting scheme, the average correct ratio was significantly increased to 92.14%. The main drawback of this method is also the use of visual evoking which is impractical to wide application [18, 25].

From the literature review it is clear that there is lot of potential in developing a biometric system based on EEG. But in most of these works the classification rate is very low considering other biometric systems. My aim is to develop a EEG biometric security system which will be more accurate.

1.5 Problem statement

Certain feature of EEG signals can be unique for a person under certain conditions. If we can identify these features, we can make a biometric security system based on EEG just like we have based on finger print, face recognition, etc. If such a system is possible, then we will be able to make a security system which is much more powerful, reliable and impossible to fool the system. This is because, unlike the conventional security system like finger print, the EEG is almost impossible to create artificially. Moreover the finger print can be taken from a cut out finger, which will make the person present at that place even if he is not there. Same is the case if we use face recognition software.

This is not the case if we use EEG. EEG signal is present only when a person is alive. Further the same persons EEG will differ under different emotions like fear, calm, etc. Under calm condition the beta band is having minimum power, but at an exited state beta band will have considerable power. So even if a person is forcefully asked to bypass the system, he will not be able to do it.

Due to the complexity, randomness and non-linearity of signal, it is very difficult to find out a set of features which will be able to accurately classify a person from the rest of person. Further the number of features cannot be high, as it increases the processing time and dimensionality. This make the training by a neural network give good training, but poor generalization. But if the number of features selected is less than required, then accurate classification is not possible.

The features extracted under different conditions (e.g. Eyes closed and eyes open) will give entirely different values. So we have to fix under what conditions the recording happens. Some of them will be relatively easy to analyse, but for the person it will be difficult. The selection of classification tool used will be another important factor. A neural network will need at least one hidden layer to classify the data as the boundary will not be a linear hyper plane. The type neural network used will also have an effect on the end result. The results obtained will be considerably improved if we provide some methodology for effective artefact removal.

1.6 Organisation of thesis

In the first chapter of my thesis, basics of EEG are discussed. This includes a brief description of the 10-20 system of recording of EEG. Next the various sub-bands present in EEG are discussed. Further various artifacts affecting the EEG are mentioned. Next sub-section discusses the various works done. Finally the problem statement is given. In chapter two, the various methodologies used are discussed. It started with a discussion on BIOPACK MP150 EEG measuring system and AcKnowledge software. Then brief discussion of sampling theorem and back-propagation neural network is given. In chapter three the procedure followed to get my result is discussed. In chapter four, the various results obtained are given. In chapter five, the conclusion obtained and future works possible are looked into.

The recording of EEG is done in Biomedical Lab, Electrical Engineering Lab, IIT Roorkee using BIOPACK instrument. I recorded EEG of 6 different people one female and five male. During the time of recording the person is asked to sit in a chair, their eyes closed. Person is asked to remain still i.e. with minimum body movement, and remain calm throughout the recording process. The recording is done in a quiet place so that the EEG signal is not corrupted by the unwanted attention due to any disturbance.

The recording is done through BIOPACK instrument, and it is done for approximately five minutes. The sampling rate used is 1000 samples/s. The signal obtained is amplified with a high gain, low noise amplifier so that the signal which is initially in micro-volt range is converted into milli-volt range. Each sample is encoded using 32bit s. The recorded file thus obtained will be in name.acq format, which we cannot directly load into MATLAB. For this we have used AcqKNowldge software.

The recorded EEG thus obtained was loaded into AcqKNowldge software, and name.acq format file was converted into name.txt format. The text document is now used for further processing. From the text document corresponding to EEG of each person, we take a sample EEG data of two second duration. For each sampled EEG, having ten different channels we calculate the different sub-bands present in it- alpha, beta, gamma, delta and theta. For each sub-band of each channel we have calculated different features like mean, variance, etc. The selected features which is having desired characteristics are used to train the neural network. After fully trained neural network, we will check the validity of our process by giving testing data set to neural network and check whether we were able to obtain the desired result.

2.1 BIOPACK MP150

BIOPACK MP150 instrument was used for recording EEG. The instrument consists of a total of fifteen channels. Out of this, first ten were the channels of 10-20 system, and they came along with a cap which was put on top the head. Remaining electrodes were used to measure the ECG signal at different positions. This is because, the ECG signal is assumed to be affected by EEG signal. The position of remaining electrodes is one near the heart, two electrodes positioned at two legs and two electrodes at each hand. For our purpose the data from channels 11-15 are of no importance.

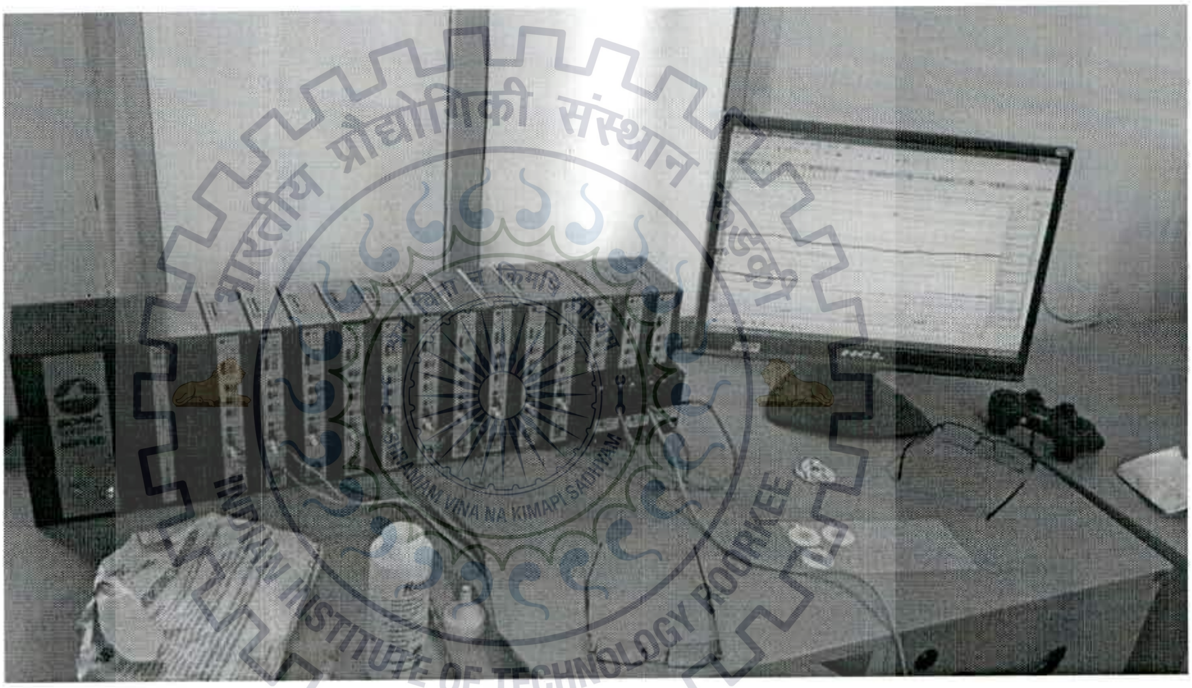

Figure 2.1 EEG recording instrument

The EEG recording system has both hardware part and software part. With the help of software AcqKnowledge 4, we will be record and display the recorded EEG. This software is compactable with Windows Vista and Mac OSX.

The main features are listed below

Function	MP150
Aggregate sampling rate	400kHz
To Cpt Memory or disk	300kHz
Internal buffer size	6MB
SNR of ADC	86dB (typical)
DAC resolution	16bits
DAC output rate	Independent of ADC rate
Communication to computer	Ethernet (10 base T, UDP and DLC Type2)

At initial stage, the measured EEG signal is amplified using a high gain, low noise amplifier. Then it is sampled at 1000samples/s. Each sample is encoded using 32 bits. For reducing the effect of miss-conduction due to air gap between the sensor and the skin, a water gel is put which is having similar conductivity as the skin.

MP150 provides 10 channels of EEG signal, using 21 electrodes. These electrodes are placed in a cap cover so that the positions of recording are fixed, and error due to the misplacement is minimised. The electrodes record EEG data from all the five lobes as shown in the table below.

POSITION	ELECTRODES
FRONTAL	FP_1, FP_2, F_3, F_4, F_8, F_Z
CENTRAL	C_3, C_4, C_Z
TEMPORAL	T_3, T_4, T_5, T_6
OCCIPITAL	O_1,O_2
PARIETAL	P_3, P_4, P_Z

Of the 21 electrodes, we form 10 channels of EEG data. Differential value between two electrode is measured which is of micro-volts and it is subsequently amplified to milli-volt range. The various channels thus formed is shown below.

COLOUR	CHANNEL
Brown	CH-1
Red	CH-2
Orange	CH-3
Yellow	CH-4
Green	CH-5
Blue	CH-6
Indigo	CH-7
Gray	CH-8
White	CH-9
Black	CH-10

MP150 has Universal Interfacing Module, UIM100C to connect with external devices. With the help of it we connect signals like chart recorder, pre-amplifier, triggers, event counters and recorders.

2.2 AcqKnowledge software

This software can perform four basic operations. Controlling of data acquisition process, real-time calculations like filtering, processing of acquired data like DFT calculations, and file management. I used only this software for saving the document in text format, which is a file management function. The data obtained from BIOPACK software is in *.acq format. This format is not possible to be directly loaded into MATLAB. For the data to be able to be loaded into MATLAB, the format should be changed to a text format *.txt. This is done through AcqKnowledge software.

After loading the required data in the software we will select the channel 1-10, which is the one we are interested in. Further at a stretch we will not use all the data of five minutes duration. This is because, it takes a lot of memory space and loading that document in MATLAB might not be possible. For my experiment, I have taken data of 1 minute duration.

2.3 Sampling theorem

Sampling theorem states that for proper reconstruction of a band limited signal having a maximum frequency component of f_{max}, the sampling frequency should be at least twice of f_{max}. This sampling rate is called Nyquist sampling rate.

$$F_s > 2f_m$$

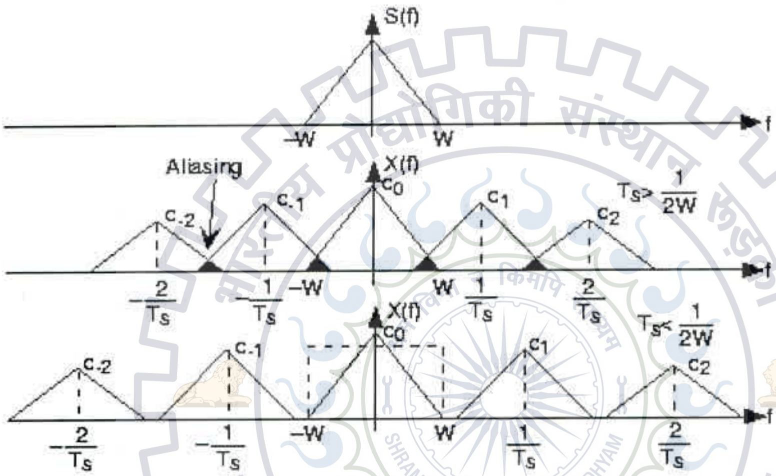

Figure 2.2 Signal sampled at different sampling rate.

In the figure.6, when the continuous time signal is sampled at a sampling rate less than Nyquist rate, reconstructed signal was different signal. But when we sampled the signal at a sampling rate greater than the sampling rate, we were able to reconstruct back the original signal. The EEG signal is having a frequency component of maximum up to 50Hz. So Nyquist sampling rate is 100samples/s. But the signal is sampled at a sampling rate ten times it. So the signal is oversampled. While oversampling will not cause any problem in reconstructing back the original signal, but it will take more processing time and more memory. In order to avoid these practical considerations we have to limit the sampling rate.

IEEE 745 standard is used to represent floating point numbers in binary format. It is used in MATLAB to encode data of each sample of EEG signal. A simplified version contains 32 bit for representing each floating point number. First bit is sign bit, which is used to represent whether the number is positive or negative. Next eight bits are used for exponents. The decimal equivalent of this number formed from the eight bits is subtracted from 127 to obtain the actual exponent term. The remaining twenty three bits are used to represent the fraction term.

For EEG signal the sign bit will always be zero, as difference between two electrodes will always be a positive quantity. Further the exponent term will be having a negative number, as the amplitude of the recorded signal will be of the order of micro-volts.

2.4 Back propagation algorithm

The back propagation algorithm is one of the classification method using neural networks. In this method both forward and backward movement of information take place. Forward information is produced due to the output generation to the input pattern presented. Backward propagation of data happens in the form of error, which assumes that error produced at the output is the combined effect of preceding neurons.

Learning of neural network take place by updating the initial weights as a function of error produced at the output. The classification problem is non-linear and hence the decision boundary will not be a hyper plane, but a complex boundary.

The weight updating is done based on gradient at that instant. General equation is given by

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}, \text{ where}$$

$$\Delta w_{ij} = \eta \delta_j x_{ji}$$

Delta value is calculated by different formula for output neuron and hidden neuron

$\delta_k = o_k(1-o_k)(t_k - o_k)$, for output neuron

And $\delta_h = o_h(1-o_h) \sum_{k \in downstrem(k)} w_{kh}\delta_k$, for hidden neurons

For getting good classification, the inputs given to the neurons should be normalised. This is because; decision boundaries may not be able to classify every class properly. This is a practical limitation.

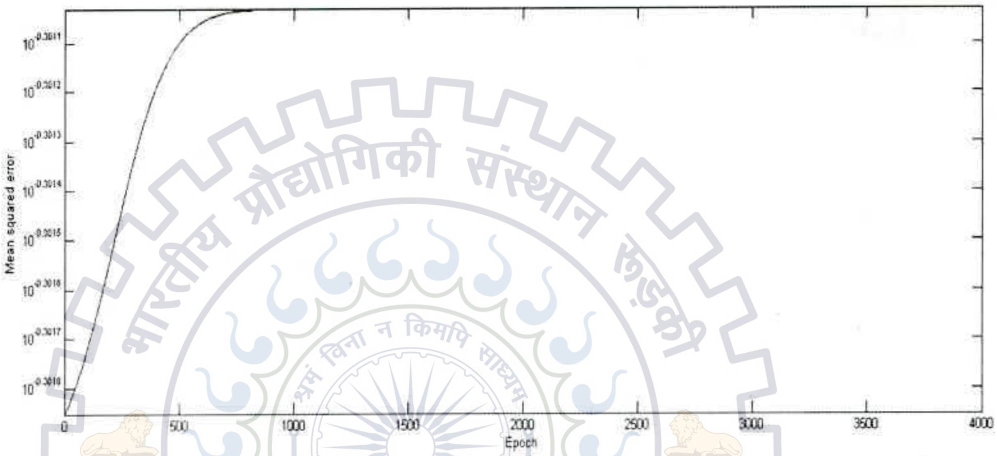

Figure 2.3 MSE without normalisation

The above figure shows that, the neural network fails to provide a good classification, when input are not normalised. The mean square value gets saturated at a high value, which gives a large number of miss-classifications.

The below figure shows the mean square plot when the inputs are normalised. As can be seen from the graph the mean square reaches a minimum value, which is sufficiently small so that a good classification can be possible.

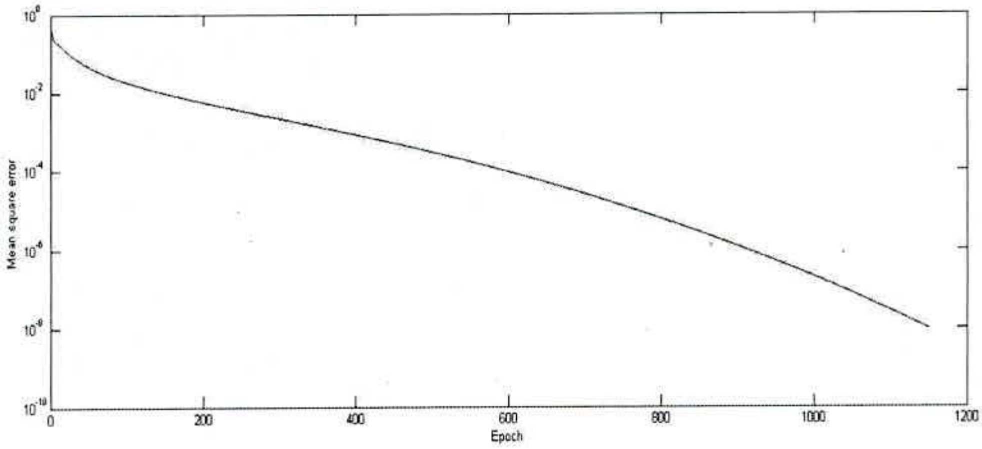

Figure 2.4 MSE with normalisation

When we calculated features like mean, variance, entropy and energy, mean was of the order of 10e-4, standard deviation of order 10e-3, entropy of order 1 and energy of order 1e-6. So for normalisation of inputs, we multiply mean value with 1e4, standard deviation with 1e3 and energy with 1e6.

A neural network cannot be trained to make error absolutely zero. So if we don't give some stop criteria, the neural network will go on updating weights without ever stopping. To avoid such a condition, we define two stop criterions- one is stop training if MSE is less than 1e-20, and other is maximum number of epoch is limited to 4000. If either one of this condition is met, neural network stops training.

The EEG data analysed in my project was recorded in Biomedical lab, Electrical Engineering Dept., IIT Roorkee. The data was recorded from different persons, who were asked to sit in a chair in relaxed position with eye closed position in a quiet place. Eyes are closed so that the EEG is not corrupted by EOG signals which are caused due to the horizontal and vertical movement of eye.

Eye closed state also ensures that the alpha band is not suppressed. Further person is asked to remain in cam position so that the movement of body is minimised, so that corruption of EEG signal by EMG is minimized. The EEG was recorded by BIOPACK 10-20 electrode system. This system has total 22 electrodes. Out of which two electrodes are placed above earlobe and they act as the reference points. With the remaining 20 electrodes, we measure the difference in potential of two electrodes. Thus we get 10 different channels. The database consists of EEG recorded from 10 persons for about five minutes. The sampling rate was 1000samples/s. Each sample is encoded by 32bits.

3.1 Proposed Procedure for EEG Classification

The proposed method has following steps- data acquisition, pre-processing, sub-band splitting, feature extraction and neural network classifier.

3.1.1 EEG acquisition

EEG was recorded using a standard 10-20 electrode system, where the person is asked to sit in a chair with his eyes closed while in a relaxed state. The EEG was recorded for about 5 minutes. The sampling frequency was 1000 samples/s. The EEG data consists of a 10 columns, each representing data from each channel.

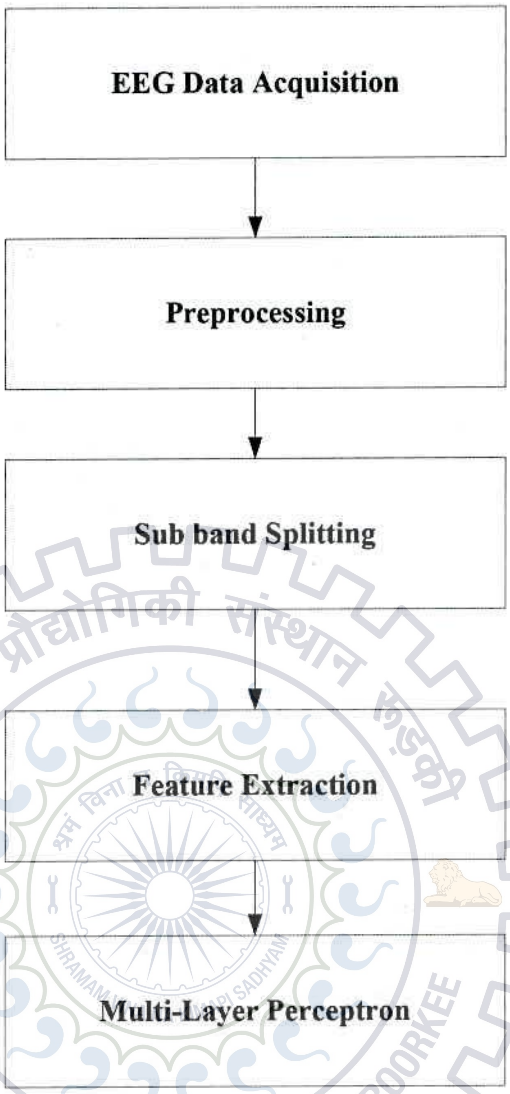

Figure 3.1 Flowchart of proposed method

3.1.2 Pre-processing

The sampling frequency used for recording EEG is 1000 samples/s. But EEG signal has maximum frequency component of less than 50Hz. So ideal sampling frequency required for sampling is 100 samples/s. Considering the non-ideal characteristics of reconstruction filter (a low pass filter) sampling frequency should be slightly greater than 100samples/s. The recorded EEG is oversampled. Practically oversampling is not preferred. This is because it increases the processing time required, and also the memory space required will also increase. To reduce this effects the sampling frequency is reduced by a factor of 5, i.e. the new sampling frequency is 200samples/s.

Figure 3.2 EEG measurements for proposed method

The recorded EEG is of very small amplitude. So it is heavily affected by various artifacts and noise. It consists of both high frequency and low frequency artifacts. Low frequency artifacts include movement, breathing etc. High frequency artifacts include vertical and horizontal EOG signals. Further it is affected by power supply noise which is having predominant effect at and around 50Hz.

To remove 50Hz power supply noise we use a notch filter of 50Hz notch frequency. The stop band is assumed to be from 45Hz to 55Hz. Further similar notch filters are also designed to filter out the harmonics of 50Hz supply like 100Hz, 150Hz, etc.

For removing low frequency artifacts we use a third order Butterworth high pass filter with cut-off frequency of 0.5Hz. Butterworth filter is chosen because we don't want any change in amplitude, which is the case if we use any other filter like Chebyshev filter. Similarly for removing high frequency artifacts we use a third order Butterworth low pass filter with a cut-off of 40Hz.

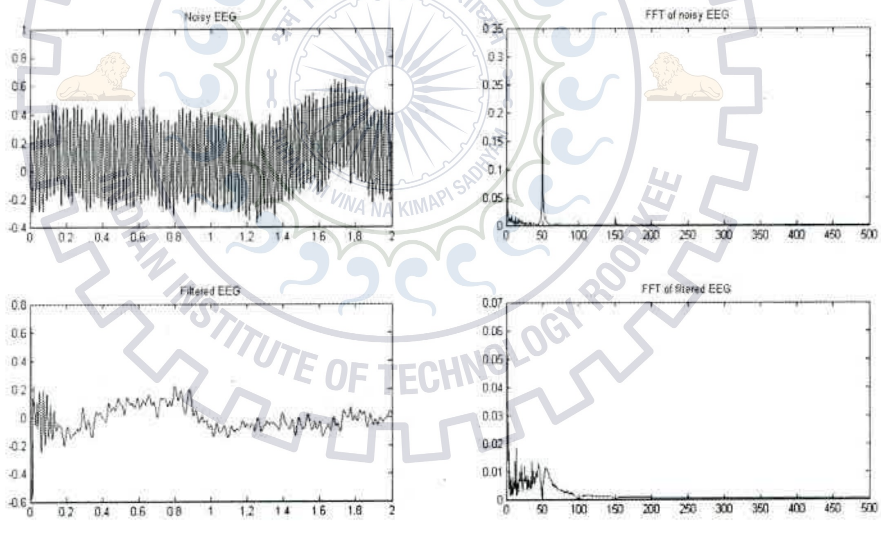

Figure 3.3 Noisy and filtered EEG and its frequency spectrum

From the above figure we can see that the recorded EEG was initially heavily affected by noise and other high frequency artifacts. This is justified by the frequency spectrum which is showing a 50Hz peak. After the various pre-processing steps, the resulting EEG is less affected by it. This is conformed from frequency spectrum of processed signal.

3.1.3 Sub-band splitting

The EEG has mainly five frequency components delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (14–30Hz) and gamma (>30Hz). For getting these sub-bands from original data, I have used a parallel connection of band-pass filters. The cut-off frequency was designed as 0.5-4Hz for delta band, 4-8Hz for theta band, 8-13Hz for alpha band, 13-30Hz for beta band and 30-45Hz for gamma band.

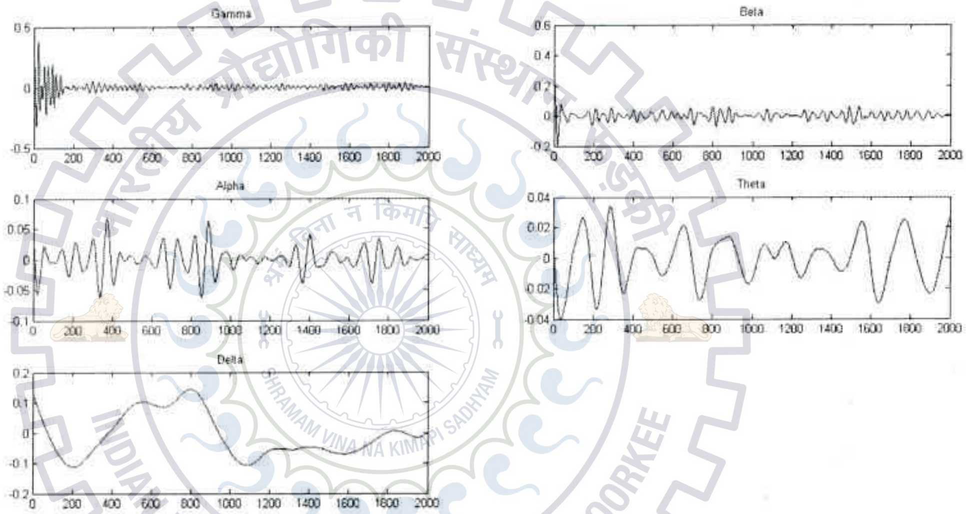

Figure 3.4 Various sub-bands of a channel of EEG

The filters used are FIR filters with appropriate coefficients. FIR filters are chosen because they are guaranteed to be stable. The transition region should be small and stop-band should have very good attenuation. This is because the various bands are having overlapping frequency regions and our aim is to minimize the effect of one on other. Further the amplitude in pass-band will be small value i.e. of the order of milli-volts. So a even a small change in their amplitudes can vary the characteristics drastically. For avoiding these effects we use a Butterworth band-pass filters of appropriate bandwidth and cut-off frequencies. Butterworth filter is characterised by a ripple less pass and stop-bands, and a maximally flat response. The order of filter is chosen to be third order.

The below figure shows the various sub-bands extracted from one of the EEG signals. As we can see the frequency of signal goes on increasing from delta to theta to delta to beta to gamma.

The practical filter design of this sub-band extraction is affected by the difficulty in getting filter coefficients which can serve this purpose.

3.1.4 Feature selection

EEG signal is essentially a random signal. So the value of this signal at a particular instant will be impossible to tell before recording them. So we have to use some statistical parameters for the analysis of this signal. Some of the commonly used parameters are mean, standard deviation, entropy, energy, correlation, covariance, frequency spectrum, maximum amplitude, etc.

Mean is calculated as

$$\mu_x = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Mean of a signal gives the dc component present in the signal. Its value will be slightly more than or equal to zero.

Standard deviation is calculated as

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)^2}$$

The standard deviation represents the ac component present in the signal. Its value will always be greater than zero.

Entropy as

$$\varepsilon(x) = -\sum_{i=1}^{n} x^2(t)\log(x^2(t))$$

Entropy is a measure of dis-order in the signal. For discrete time system it is always a positive quantity. Another definition for entropy is

$$\varepsilon(x) = -\sum_{i=1}^{n} p_i \log(p_i)$$

The maximum value of such a signal occurs when all the signals are equally likely. For example if the signal can have take two symbols s1 and s2, then entropy will be

$$\varepsilon(x) = -p_1 \log_2 p_1 - p_2 \log_2 p_2$$

This will take a maximum value at p1=p2=0.5.

Energy as

$$E(x) = \sum_{i=1}^{n} x^2(n)$$

Where n is the length of the sample and x(n) is the value of sample at that instant. Energy of a signal gives the total strength present in the signal. It also represents the total power (ac and dc) present in the signal.

Kurtosis as

$$\beta_2 = \frac{E[X-\mu]^4}{(E[(X-\mu)^2])^2}$$

And excess kurtosis as

$$\beta_2 = \frac{E[X-\mu]^4}{(E[(X-\mu)^2])^2} - 3$$

Kurtosis gives an approximate estimate of peak value of a distribution. Mathematically it is a scaled version of fourth moment of the distribution. Kurtosis lies between 0 and 3. For making it a comparable with a standard normal distribution we subtract the above equation from 3, so that we get excess kurtosis. A larger value of kurtosis represents that the variance is large and is caused due to the infrequent large variations and not due to the frequent small variations.

Skewness as

$$\gamma_1 = E[\frac{X-\mu}{\sigma}]^3 = \frac{E[X-\mu]^3}{E[(X-\mu)^2]^{\frac{3}{2}}}$$

It is a measure of symmetry of a distribution. It value can be negative, zero, positive or undefined. A positive value of skewness represents that there is a right shift in distribution about the mean as compared with normal distribution with same mean. Similarly for negative skewness we are having a left tilt as compared to normal distribution of same mean. A zero skewness represents symmetric distribution.

Maximum value defined as

$$\max = \max imum(x(i)), wherei = 1, 2, .., n$$

This gives the maximum strength which it can provide.

Correlation is defined as the similarity between two signals or the same signal at different time instants. If the correlation is taken for different channels, we get cross correlation and if we take same channel at different time we get cross correlation.

Mathematically autocorrelation is given as

$$R(s,t) = \frac{E[(X_t-\mu_t)(X_s-\mu_s)]}{\sigma_t\sigma_s}$$

And cross-correlation is given as

$$R_{xy}(n) = \frac{1}{n}\sum_{x.y}\frac{(f(x,y)-\bar{f})(t(x,y)-\bar{t})}{\sigma_f\sigma_t}$$

Pearson's correlation ratio as

$$\rho_{x,y} = \frac{\mathrm{cov}(X,Y)}{\sigma_x\sigma_y} = \frac{E[(X-\mu_x)(Y-\mu_y)]}{\sigma_x\sigma_y}$$

Its value lies between -1 and 1. Value 0 represents that the two variables are uncorrelated, while a positive value represents increasing linear relationship, while negative value represents a decreasing relationship.

Of the above statistical parameters not all the parameters measured for each channel and each sub band will be useful for classification. The selection of features should be such that these features have high inter-subject variability i.e., features have very high difference when selected from different person, low intra-subject variability i.e. features having very low difference when selected from same person, uniqueness for each person, and feature should not change over time. Further feature selection also depends on application as condition for each application will be different. For example under eye open condition, the alpha band will be suppressed, so under such conditions features extracted for alpha band will not give any convenient results.

3.1.5 Multi-layer perceptron

This is the last stage. Here the features extracted in the previous stage will be used for classification. The total training data is divided into two classes- training data and testing data. Training data is used to train the neural network so that when the neural network is presented with a new patter it will correctly classify them. We use the test data formed from the samples to test whether we are getting correctly classified output. The number of data for training should be chosen such that it is large which will give poor generalisation but not very small which will not train neural network properly. The learning rate is so chosen that it is not so large that it fails to reach the desired result, but also not so small so that it takes large time to reach stable value. The inputs should be properly normalised, otherwise there are chances that the neural network will wrongly classify.

From the 5 minute data of different persons, I have extracted 30 samples of data, each having 2 second duration for each person. We are having six persons, so the total number of input patterns available is 180. I have calculated four feature mean, standard deviation, entropy and energy of signal. I have calculated this for alpha and beta sub bands of two channels C3-C4 and P3-P4. Thus my total input patters become 2 channels * 2 sub bands * 4 features = 16 input features.

	Alpha mean		Alpha variance		Alpha Entropy		Alpha energy	
	C3-C4	P3-P4	C3-C4	P3-P4	C3-C4	P3-P4	C3-C4	P3-P4
P1	-0.0395	-0.1100	7.22951	2.20094	2.62445	1.49712	3.66758	3.94931
P2	0.02899	-0.3632	10.4066	2.74396	3.73475	3.62203	3.12419	3.35992
P3	0.19294	0.15545	9.44496	5.93112	4.90017	3.44581	8.12973	3.22817
P4	-0.2194	-0.0250	11.0575	4.25021	8.38048	5.06683	5.74087	1.83065
P5	-0.1463	-0.2179	17.8082	2.82939	1.70876	3.87147	3.53585	1.64894
P6	0.0068	0.2664	6.4965	3.2825	8.9020	3.1150	2.5361	2.8237

Table no: 1 mean value of alpha band features

Before giving these input patterns for a neural network, the input patterns should be normalised for better classification. For normalisation mean and variance value was multiplied by a factor of 1e4, entropy remain unchanged and energy multiplied by a factor of 1e4. The normalised value of input is given below.

	Beta mean		Beta variance		Beta Entropy		Beta energy	
	C3-C4	P3-P4	C3-C4	P3-P4	C3-C4	P3-P4	C3-C4	P3-P4
P1	0.09458	0.03774	8.15312	2.56949	2.65823	2.31285	3.47640	4.32514
P2	-0.1602	0.28718	7.04856	2.50475	3.30692	5.55641	3.22733	3.84581
P3	0.01839	-0.2112	4.80362	4.24651	3.89354	3.97173	8.40309	2.46614
P4	0.06729	0.190966	10.3265	2.79103	6.44605	3.35924	3.52938	3.17143
P5	0.117999	-0.0293	18.6580	3.39599	1.71148	4.67611	4.17107	1.79276
Per 6	-0.4180	-0.1158	6.406328	3.496331	10.09433	3.427509	2.540419	2.290914

Table no: 2 mean value of different beta band features

It is evident from the above data; there is significant change in values of parameters of each person. So a classification is possible. Of these thirty samples per person, fifteen samples were used to train the multilayer perception with standard back propagation algorithm and remaining fifteen were used to test the result.

In my work I was able to classify up to four different persons. For training I have used a multi layer perceptron using standard back propagation algorithm. I have used log-sigmoid activation function for hidden and output neuron and a learning rate of 0.1. The number of inputs was sixteen and number of outputs was four. Number of hidden neurons was fixed at twenty. The target data is fixed as [1 0 0 0] for person 1, [0 1 0 0] for person 2, [0 0 1 0] for person 3 and [0 0 0 1] for person 4.

Error is said to have occurs in neural network generalisation, if there is a miss-classification i.e. the EEG belongs to person 1, but classified as person 2, etc. When EEG samples 30 from each person and four people at a time are given as test samples, we are able to classify correctly more than 115 samples per 120 samples which convert to an accuracy of more than 95 %.

Further when an intruder EEG data is given, that is a person whose EEG is not present in the neural network, it is able to detect the intruder in a convincing way. For practical considerations we have to define some stopping criteria which when met, the neural network should cease training. The stopping criteria are MSE is less than 1e-20 and maximum number of epoch as 4000.

5.1 Conclusions

The aim of my thesis was to identify a person based on the person's EEG. If we are able to achieve this goal, we will be able to make a biometric security system just like finger print, face recognition but with a higher rate of integrity, i.e. the system is impossible to fool.

In my work I was able to classify four different people with an accuracy of more than 95%, and it also was able to detect two intruder EEG signals with considerable accuracy. This is achieved by selection of some selected features from different channels of processed EEG. These features are assumed to be different for, each person and different for different person. Further these features are assumed to be constant over time for a person. These selected features are used to train a neural network with standard back propagation algorithm. The results obtained are impressive.

For a Biometric security system, the number of person needed to be classified is much greater than 4. So much work has to be done on this field to get such a number, and that too without much degradation in the accuracy. This can be done by measuring more number of statistical parameters that will act as unique feature of a person. But the selection of features should not be unnecessarily large, as it may result in poor generalisation. Further the number of channels used can also be increased to give better resolution to recorded EEG.

5.2 Future scope

Up until now we have assumed that the feature selected from a recorded EEG under similar conditions of a person will remain over time. But it might slightly vary with time. To take that into consideration, each time a person is identified update the features of the person now, so that we are regularly in track with the changes in EEG of a person.

The condition under which the recording is done like eye closed, etc. is generally uncomfortable for the person whose EEG is taken. So in future work we should be able to classify a person who is in normal, standing relaxed position. For this we should be able to take into effect the various artifacts like EOG, EEG, and EMG which in such a case will become more prominent. This can be done with adaptive cancellation of these artifacts. But in order to do it we need more channels which record there artifacts. Further under normal condition, most of the features extracted with restricted condition might have changed drastically and some may no longer be used for classification purpose. One such example will be the alpha band under eye open condition. At this condition this band will be suppressed, which make features of alpha band selected useless.

When the EEG is recorded under normal conditions, it will be greatly affected by feelings and state of mind of the person. For the same person who is under relaxed and tensed state will have entirely different. So new algorithms and features should be calculated, which can analyse these feelings and thus make proper correction and estimate the EEG of person under normal condition. One of the methods might be to include other signals like ECG, EOG, etc to estimate the feelings.

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