CLASSIFICATION OF ELECTROENCEPHALOGRAM (EEG) SIGNAL BASED ON FOURIER TRANSFORM AND NEURAL NETWORK

PULOMA PRAMANICK (109EE0640)

Department of Electrical Engineering
National Institute of Technology Rourkela

CLASSIFICATION OF ELECTROENCEPHALOGRAM (EEG) SIGNAL BASED ON FOURIER TRANSFORM AND NEURAL NETWORK

A Thesis submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology in "Electrical Engineering"

By

PULOMA PRAMANICK (109EE0640)

Under guidance of

Prof. SUBHOJIT GHOSH

Department of Electrical Engineering

National Institute of Technology

Rourkela-769008 (ODISHA)

May-2013

DEPARTMENT OF ELECTRICAL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

ODISHA, INDIA-769008

CERTIFICATE

This is to certify that the thesis entitled "**Classification of Electroencephalogram(EEG) signal based on Fourier transform and neural network**", submitted by **Puloma Pramanick(Roll No. 109EE0640)** in partial fulfilment of the requirements for the award of **Bachelor of Technology** in **Electrical Engineering** during session 2012-2013 at National Institute of Technology, Rourkela, is a bonafide record of research work carried out by her under my supervision and guidance.

The candidate has fulfilled all the prescribed requirements.

The Thesis which is based on candidate's own work, has not submitted elsewhere for a degree/diploma.

In my opinion, the thesis is of standard required for the award of a bachelor of technology degree in Electrical Engineering.

Place: Rourkela

Dept. of Electrical Engineering
National institute of Technology
Rourkela-769008

Prof. Subhojit Ghosh
Assistant Professor

ACKNOWLEDGEMENTS

I am very thankful to my guide Prof. Subhojit Ghosh for his valuable help. He is always there to show the right track, when needed his help. It is with the help of his valuable suggestions, guidance and encouragement, that I am able to perform this project work.

Puloma Pramanick

B.Tech (Electrical Engineering)

ABSTRACT

Human normal and epileptic electroencephalogram (EEG) signals have been analysed using Fourier Transform (FT). The area under the spectrum of both normal and epileptic EEG is calculated as feature for classification. The classification is done with the help of neural network (Levenberg - Marquardt algorithm).Our final goal of the study is the automatic detection of the epileptic disorders in the EEG in order to support the diagnosis and care of the epileptic syndromes and related seizure disorders.

CONTENTS

3.3 Back-propagation Training

3.4 Data Series Partitioning

CHAPTER 4

RESULTS

4.1 Results

CHAPTER 5

CONCLUSIONS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 INTRODUCTION

The electroencephalogram (EEG) consists of a time series data of evoked potentials resulting from the systematic neural activities in a brain. The recording data of the human EEGs are carried out by placing the electrodes [1] on the scalp, and plotted as voltage magnitude against time. The voltage of the EEG signal corresponds to its amplitude. The general voltage range of the scalp EEG lie between 10 and 100 μV**,** and in adults more frequently in the range of 10 and 50μV**.** In the frequency spectrum range of the EEG, the frequency range extends from ultraslow to ultra-fast frequency components. The extreme frequency ranges play no significant role in the clinical EEG. The general frequency range of interest lies between 0.1Hz and 100Hz for the classification purpose. The frequency range is generally classified into several frequency components, or delta rhythm (0.5 - 4Hz), theta rhythm (4 -8Hz), alpha rhythm (8 - 13Hz) and beta rhythm **(**13- 30Hz). For normal adults, the slow ranges (0.3 -7Hz) and the very fast range (>30Hz) are sparsely represented, and medium (8 - 13Hz) and fast (14 - 30Hz) components predominate [2].

Since 1970, research in the automated seizure detection began [3] and various algorithms are proposed for this problem [4]. These algorithms for automated detection of epileptic seizures depend on the identification of various patterns such as an increase in amplitude [5], sustained rhythmic activity [6], or EEG flattening [7]. Many of the algorithms have been developed based on spectral features [8-11] or wavelet features [12- 16], amplitude relative to background activity [17] and spatial context [17, 18]. Other features of chaotic [19, 20] include correlation dimension [21], entropy [22] and Lyapunov exponents [16,22] also characterize the EEG signal. These features is used to classify the EEG signal using nearest neighbor classifiers [24], decision trees [10], ANNs [16, 22], support vector machines (SVMs) [11,16] or adaptive neuro-fuzzy inference systems [14,15,22] in order to identify the occurrence of seizures.

We have analyzed the human normal and epileptic EEG signals from the waveform and periodicity using the Fourier transform (FT) in order to test their abilities to detect localized characteristic frequency component in EEG and extract features from them. Then, these features are used to classify the segments concerning the presence or absence of epileptic seizures.

1.1.1 Activities of the Neuron

There are two types of cells in the Central Nervous System (CNS), nerve cells and glia cells. The nerve cell consists of axons, dendrites and cell bodies. The cylindrical shaped axon transmits the electrical impulse. Dendrites are connected to the axons or dendrites of other inside cells and receive the electrical impulse from other nerves cells. Each nerve of human is approximately connected to 10000 other nerves [25]. The electrical activity is mainly due the current flow between the tip of dendrites and axons, dendrites and dendrites of cells. The level of these signals is in μV range and its frequency is less than 100Hz [25].

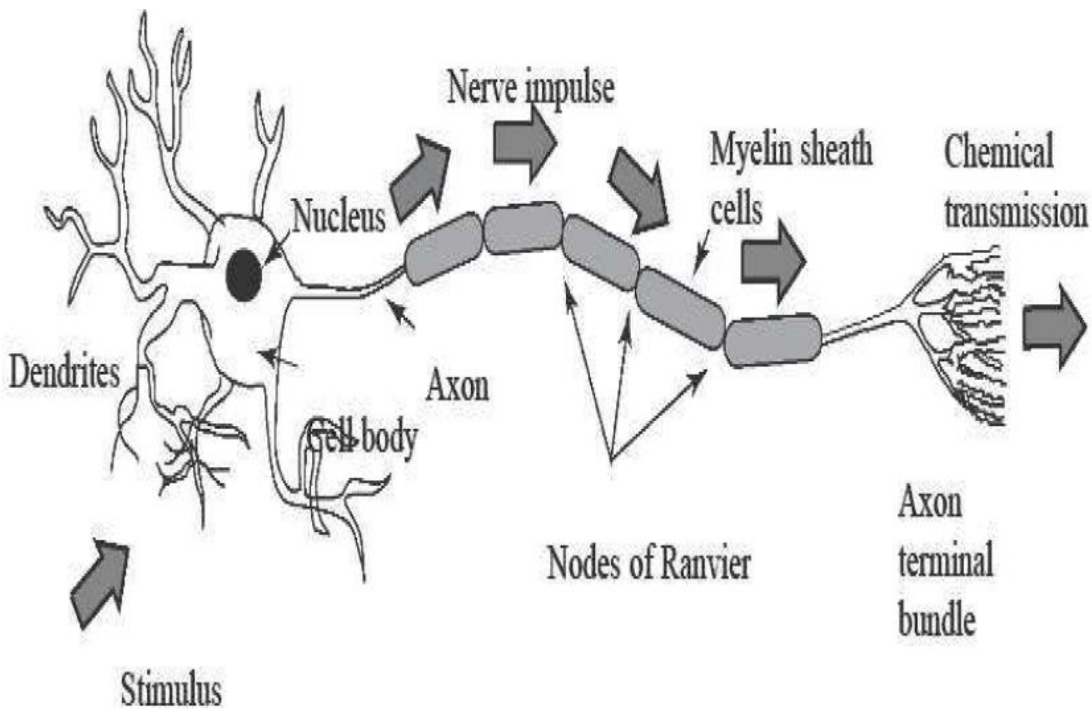

Figure 1.1 Structure of a neuron [25]

1.1.2 Recording of EEG signals

EEG is recorded from many electrodes arranged in a particular pattern or montage. A common standard called the International 10/20 System is used here. These methods are cheap and give a continuous record of brain activity with better than millisecond resolution. This tool can achieve the high temporal resolution and for this reasons the detailed discoveries of dynamic cognitive processes have been reported using EEG and ERP (Event Related Potentials) methods.

1.1.3 Frequency bands of the EEG signal

Most of EEG waves range from 0.5-500Hz, however the following four frequency bands are clinically relevant: (i) delta, (ii) theta, (iii) alpha and (iv) beta

Delta waves: Delta waves frequency is up to 3 Hz. It is slowest wave having highest amplitude. It is dominant in infants up to one year and adults in deep sleep.

Theta waves: It is a slow wave with frequency range from 4 Hz to 7 Hz. It emerges with closing of the eyes and with relaxation. It is normally seen in young children and in adults.

Alpha waves: Alpha has frequency range from 7 Hz to 12 Hz. It is most commonly seen in adults. Alpha activity occurs rhythmically on both sides of the head. Alpha wave appears with closing eyes (relaxation state) and disappears normally with opening eyes/stress. It is treated as a normal waveform.

Beta waves: Beta activity is fast with small amplitude. It has frequency range from 14 Hz to 30 Hz. It is dominant in patients who are alert or anxious or who have their eyes open. Beta waves usually seen on both sides in symmetrical distribution and is most evident frontally. It is a normal rhythm and observed in all age groups. These mostly appear in frontal and central portion of the brain. The amplitude of the beta wave is less than 30μV [25].

1.2 OBJECTIVE

The objective is to analyse the human normal and epileptic EEG signals using signal processing tools and classify them into different classes. To achieve this,

(i) Fourier analysis is done on both normal and epileptic EEG signals,

(ii) Features are extracted based on area under the spectrum,

(iii) Signals are classified with the help of Artificial Neural Network classifier.

1.3 ORGANISATION OF THESIS

Chapter 1 outlines the basic theory of the EEG signals.

Chapter 2 discusses about the data collected, pre-processing, feature extraction and classification of the EEG signals.

Chapter 3 discusses the results obtained.

Chapter 4 summarizes the conclusion and references.

CHAPTER **2**

Dataset and Feature Extraction

2.1 DATASET

We used the dataset described in reference [26]. The complete dataset consists of five sets (denoted as Z, O, N, F and S) each containing 100 single-channel EEG segments each having 23.6 sec duration. Sets Z and O have been taken from surface EEG recordings of five healthy volunteers with eye open and closed, respectively. Signals in the two sets have been measured in seizure-free intervals from five patients in the epileptogenic zone (F) and from the hippocampal formation of the opposite hemisphere of the brain (N). Set S contains seizure activity. Here, all the sets are used.

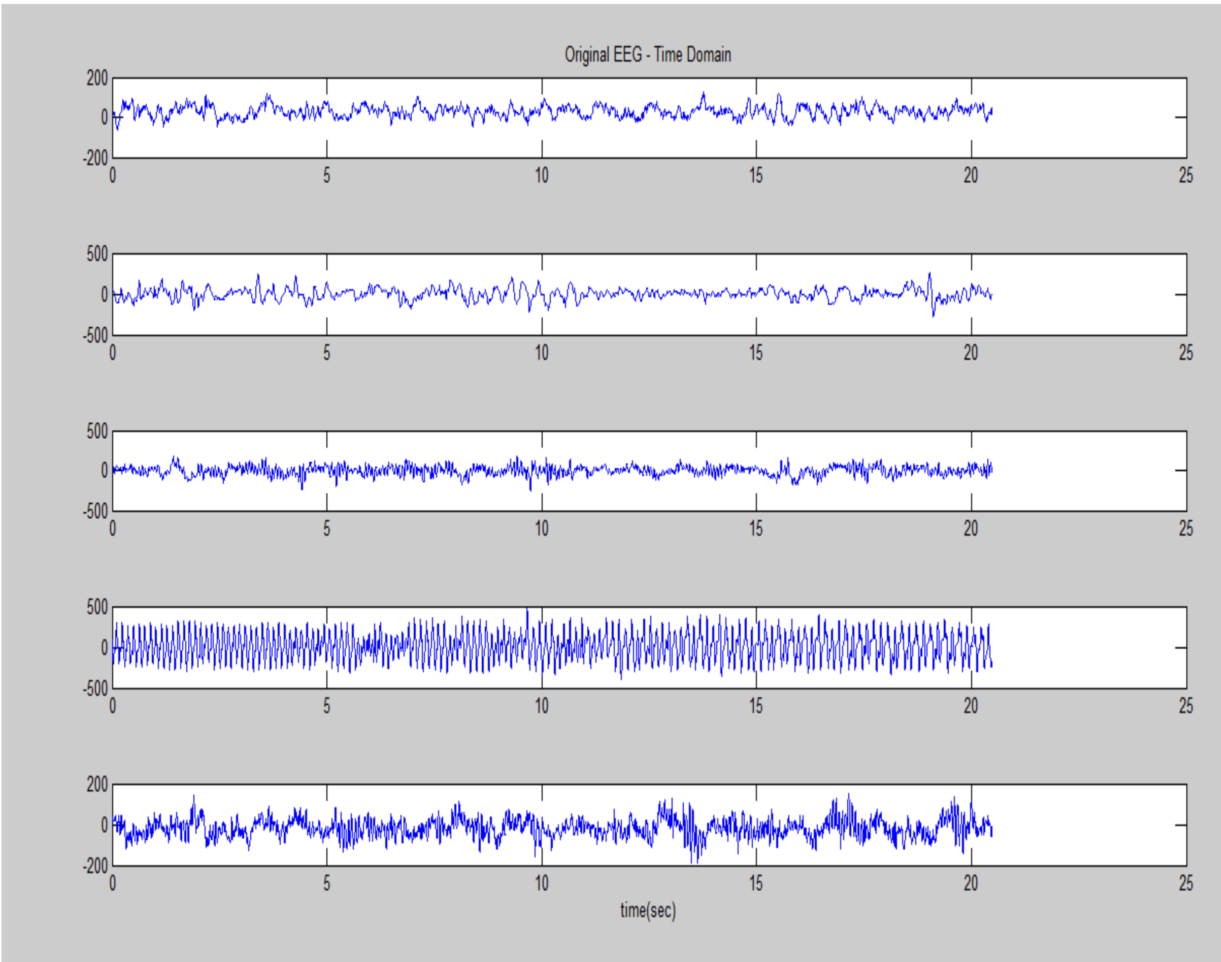

Figure 2.1: EEG signal for the sets F, N, O, S and Z [26] (magnitude in microvolts).

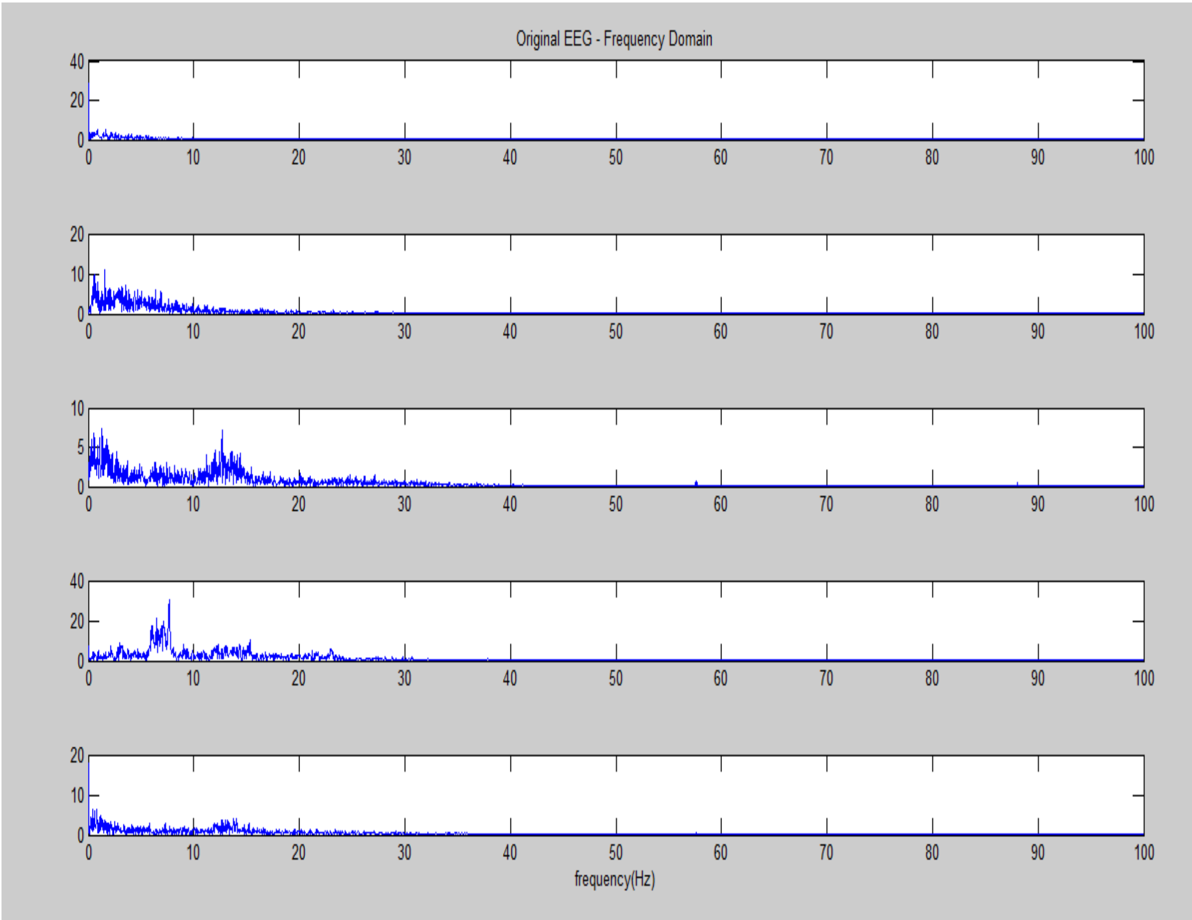

Figure 2.2: Frequency spectrum of the EEG signals for the sets F, N, O, S and Z [26].

2.2 PRE-PROCESSING

The application of a FIR [27] filter of 30 Hz, is regarded as the first step of analysis. Signal pre-processing is necessary to maximize the signal-to-noise ratio (SNR) because there are many noise sources encountered with the EEG signal. Noise sources can be non-neural (eye movements, muscular activity, 50Hz power-line noise) or neural (EEG features other than those used for control). Further pre-processing was not performed because the purpose is to be as close as possible for real-time applications and pre-processing would slowdown the process of data analysis. Moreover, data recorded outside the laboratory are likely to be noisier than those recorded inside. So it is assumed that processing noisier data would have better generalization properties.

2.3 FOURIER ANALYSIS

Discrete fourier transform:

$$X(k) = \sum_{j=1}^{N} x(j)\omega_N^{(j-1)(k-1)} \qquad (2.1)$$

$$x(j) = (1/N)\sum_{k=1}^{N} X(k)\omega_N^{-(j-1)(k-1)} \qquad (2.2)$$

where $\omega_N = e^{(-2\pi i)/N}$

is the N^{th} root of unity.

The Fast Fourier Transform (FFT) is simply a fast (computationally efficient) way to calculate the Discrete Fourier Transform (DFT) which reduces the number of computations needed for N points from $2N^2$ to 2NlgN, where lg is the base-2 logarithm.

To compute an N-point DFT when N is composite (that is, when $N=N_1N_2$), the problem is sovled using the Cooley-Tukey algorithm [28], which first computes N_1 transforms of size N_2 , and then computes N_1 transforms of size N_2 . The decomposition is to be applied recursively to both the N_1- and N_2 -point DFTs until the problem is solved using one machine-generated fixed-size "codelets". The codelets then use several algorithms in combination, such as a variation of Cooley-Tukey [30], a prime factor algorithm [31], and a split-radix algorithm [29]. The particular factorization of N is chosen heuristically.

When N is a prime number, an N-point problem is decomposed into three (N-1)-point problems using Rader's algorithm [32]. It then uses the Cooley-Tukey decomposition described above to compute the (N-1)-point DFT. For most N, real-input DFTs require roughly half the computation time of complex-input DFTs. The execution time for FFT depends on the length of the transform. It is fastest for powers of two.

2.4 FEATURES EXTRACTION

Features are extracted for different bands. The feature used here is area under the spectra. The area is calculated using the trapezoidal rule. In numerical analysis, the **trapezoidal**

rule (also known as the **trapezoid rule** or **trapezium rule**) is a technique for approximating the definite integral

$$\int_a^b f(x)dx \qquad (2.3)$$

The trapezoidal rule works by approximating the region under the graph of the function f(x) as a trapezoid and calculating its area. It follows that

$$\int_a^b f(x)dx \approx (b-a)((f(a)+f(b))/2) \qquad (2.4)$$

Area of the frequency bands (delta, theta, alpha, beta) are calculated for each EEG segments. There are 100 EEG segments in each set.

For example, only ten values for each set are shown.

Frequency Bands / Sl. No. of EEG data	δ	θ	α	β
1	1.6090	0.0968	0.0697	2.0751
2	2.1102	0.1515	0.1014	2.6351
3	1.6851	0.1152	0.0790	2.2138
4	2.1054	0.2680	0.1650	3.7274
5	1.6558	0.1632	0.1090	2.1241
6	1.8004	0.1133	0.0711	2.3644
7	2.0154	0.1357	0.0989	3.4960
8	1.3267	0.0781	0.0499	1.9388
9	1.0111	0.1119	0.0765	1.4273
10	1.2582	0.0911	0.0640	1.6643

Table 2.1: Area under different sub-bands of the frequency spectrum (Z set).

Frequency Bands / Sl. No. of EEG data	δ	θ	α	β
1	1.8023	0.1475	0.0972	2.1722
2	1.7660	0.1001	0.0659	1.9112
3	2.0737	0.1131	0.0814	2.5793
4	2.4891	0.1218	0.0889	2.8784
5	2.2747	0.0976	0.0686	2.2707
6	2.0332	0.1948	0.1274	2.3489
7	2.3861	0.1227	0.0809	1.9850
8	1.8757	0.1065	0.0786	2.3671
9	1.9817	0.1015	0.0681	1.9499
10	3.5417	0.1478	0.1005	3.6591

Table 2.2: Area under different sub-bands of the frequency spectrum (set O).

Frequency Bands / Sl. No. of EEG data	δ	θ	α	β
1	0.6675	0.0736	0.0459	0.7107
2	1.9032	0.0913	0.0590	1.5143
3	2.4944	0.0829	0.0554	1.6491
4	0.9838	0.0787	0.0479	0.6794
5	2.7019	0.1897	0.1178	3.2943
6	0.6508	0.0587	0.0351	0.5404
7	1.2585	0.1329	0.0789	1.2961
8	2.0523	0.0713	0.0460	0.9778
9	8.8239	0.4322	0.3265	3.9499
10	2.5738	0.1035	0.0742	1.9110

Table 2.3: Area under different sub bands of the frequency spectrum (set F).

Frequency Bands / Sl. No. of EEG data	δ	θ	α	β
1	1.1659	0.0640	0.0420	0.7205
2	1.5301	0.0942	0.0647	1.1614
3	1.2224	0.1034	0.0648	1.1079
4	1.1150	0.1012	0.0670	0.9082
5	4.1540	0.4466	0.2776	5.2455
6	1.2557	0.0853	0.0545	1.0953
7	0.9313	0.0872	0.0559	0.9377
8	0.8588	0.0776	0.0499	.7275
9	1.5266	0.1274	0.0829	1.3612
10	0.9322	0.0623	0.0399	0.8706

Table 2.4: Area under different sub-bands of the frequency spectrum (set N).

Frequency Bands / Sl.No. of EEG data	δ	θ	α	β
1	20.3300	0.9862	0.7205	20.6770
2	21.7060	1.2177	0.8595	21.8050
3	17.4810	0.7699	0.5015	22.6240
4	6.36170	0.1828	0.1241	4.03300
5	12.2130	0.5927	0.3809	9.32790
6	4.98120	0.1557	0.1097	4.19029
7	9.17380	1.4740	1.1305	21.8920
8	14.4450	0.4538	0.3218	7.92038
9	14.4860	0.5674	0.3932	10.9850
10	27.5000	1.6397	1.1746	43.0630

Table 2.5: Area under different sub-bands of the frequency spectrum (set S).

CHAPTER 3

Artificial Neural Network

Neural Networks (NN) are highly interconnected and simple processing units which is designed to model the way human brain performs a particular task [33]. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, the choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems. In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions [34].

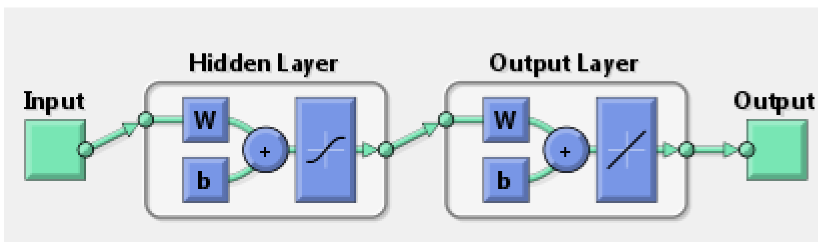

Figure 3.1: Neural network architecture

3.1 Background

A neural network is a computational model based on the neuron cell structure of the biological nervous system. With a training set of data, the neural network can learn the data by using learning algorithm; here, the most common algorithm, back-propagation, is used. Through back-propagation, the neural network forms a mapping between inputs and desired outputs from the training set by altering weighted connections within the network

3.2 Feed-Forward Neural Networks

A neural network has many *layers*, *units* per layer, *network inputs,* and *network outputs*.

When the network runs, each hidden layer unit performs the calculation in Equation (3.1) on its inputs and transfers the result (O_c) to the next layer of units.

Activation function of a hidden layer unit is given by

$$O_c = h_{hidden}(\sum_{p=1}^{P} i_{c,p} \, w_{c,p} + b_c) \qquad (3.1)$$

where

$h_{hidden}(x) = 1/(1 + e^{-x})$

O_c = the output of the current hidden layer unit c,

P = either the number of units in the previous hidden layer or number of network inputs,

$i_{c,p}$ = an input to unit c from either the previous hidden layer unit p or network input p,

$w_{c,p}$ = the weight modifying the connection from either unit p to unit c or from input p to unit c, and

b_c = the bias.

In Equation (3.1), $h_{Hidden}(x)$ is the sigmoid *activation function* of the unit and is shown in Figure 3.2. The training data must be scaled appropriately to avoid saturation which can make the training of the network difficult. Similarly, the weights and biases are initialized to appropriately scaled values before training.

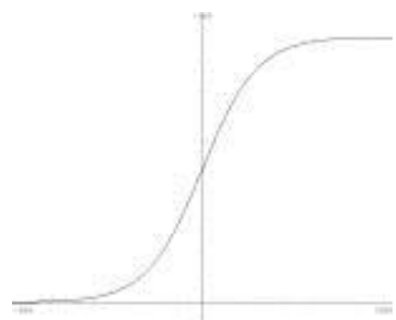

Figure 3.2: Sigmoid activation function.

3.3 Back-propagation Training

The neural network has to be trained on data series. <**input**, **output**> pairs are extracted from data series, where **input** and **output** are vectors equal in size to the number of network inputs and outputs, respectively. *Back-propagation* training has three steps:

1. Present an **input** vector to the network inputs and run the network: activation functions are sequentially computed in the forward direction from the first hidden layer to the output layer

2. Compute the difference between the desired output for that data series, **output**, and the actual network output (output of unit(s) in the output layer). The error is sequentially propagated backward from the output layer to the first hidden layer
3. For every connection, change the weight modifying that connection in proportion to the error.

3.4 Data Series Partitioning

The method for training a network is to first divide the data series into three disjoint sets: *training set*, *validation set*, and *test set*. The network is trained (e.g., with back-propagation) with training set, its *generalization ability* is monitored on the validation set, and its ability to forecast is tested on the test set. Network should avoid overfitting. Overfitting occurs when the network is blindly trained. A network that has overfit the training data is said to have poor generalization ability.

CHAPTER 4

Results

4.1 RESULTS

In the classification stage, the area under the spectrum features are applied as input to feed-forward neural network. The feed-forward back-propagation network has been implemented using Lavenberg-Marquardt optimization algorithm. The algorithm involves minimization of the error by updating the network and bias using damped least squares. It interpolates between the Gauss Newton algorithm and the method of gradient descent. The total dataset consisting of 500 patterns has been divided into training and testing set of 400 and 100 patterns respectively. In the present work, the network with four input and one output neurons is created using the *newff* command in MATLAB. The accuracy of the network trained in correctly classifying the test patterns into two groups i.e., seizure and healthy.

Different combination of network structures (hidden layer and neurons) was tested through pilot runs. Table 4.1 reports the accuracy of ANN with three different combinations of hidden layer and neurons. The vector corresponding to the structure in the first column refers to the number of hidden neurons in each hidden layer i.e. [20,5] refers to the two hidden layer each with twenty and five neurons. Since the training phase involves initialization with random weights, different execution of the training algorithm leads to different network and hence different accuracy. The results reported in Table 4.1 refer to the best accuracy obtained for five runs of algorithm. The corresponding iterative variation of the mean square error between the network and actual output is displayed in figures 4.1-4.3 respectively.

Structure of the neural network	Accuracy
[20]	98
[20,5]	99
[20,10,5]	99

Table 4.1: Structure of the neural network and accuracy achieved with the trained network

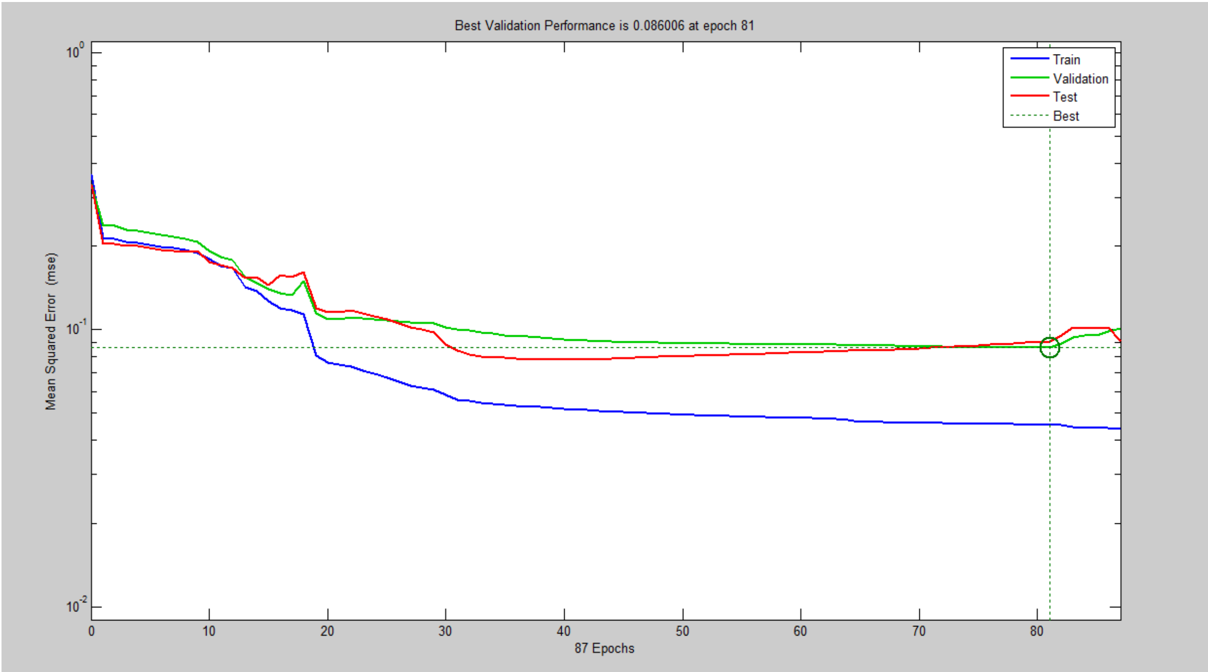

Figure 4.1 Iterative variation of the mean square error between the actual output and a trained network with a single hidden layer of 20 neurons.

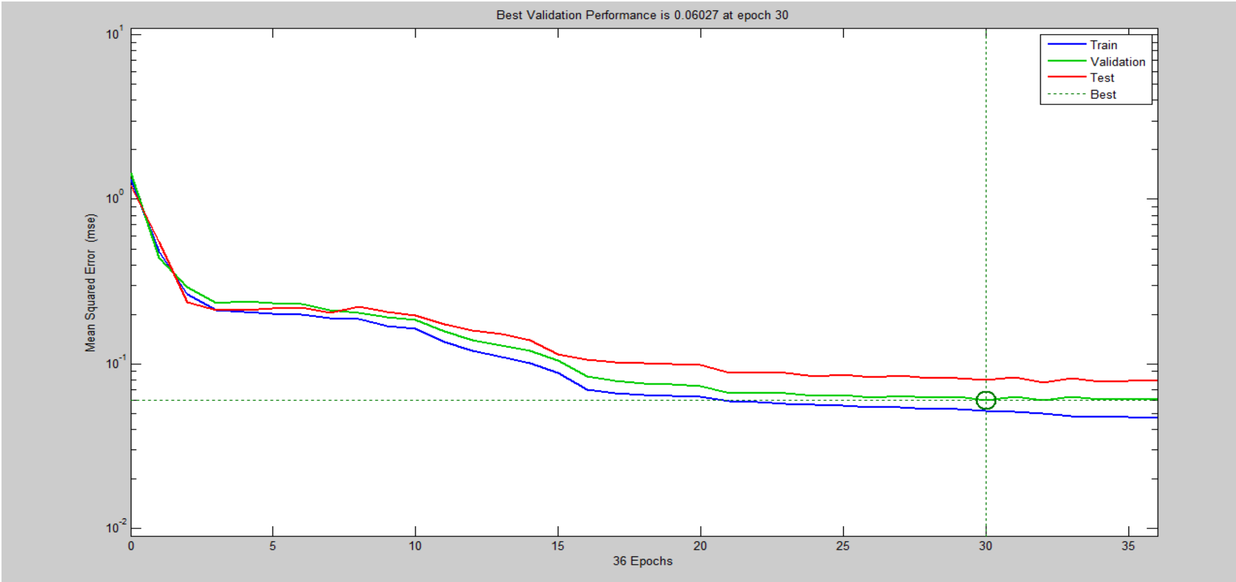

Figure 4.2 Iterative variation of the mean square error between the actual output and a trained network with two hidden layer of each of 20 and 5 neurons.

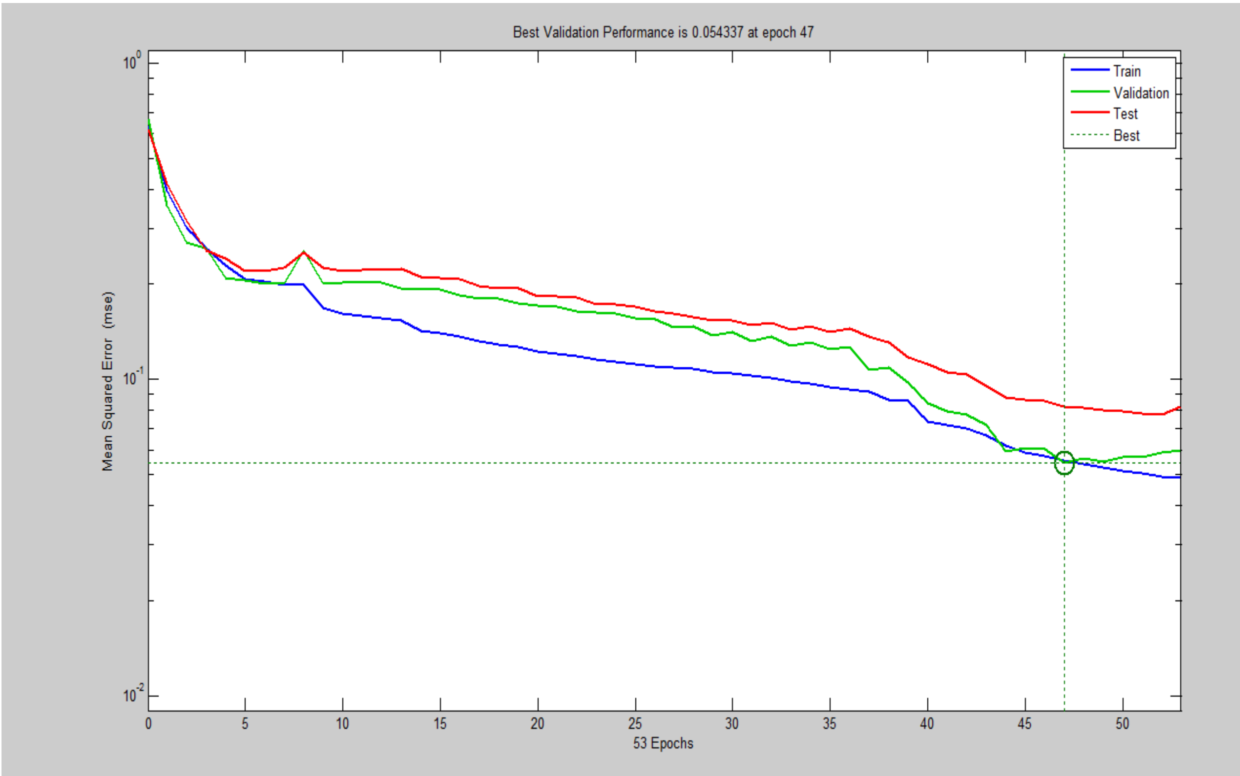

Figure 4.3 Iterative variation of the mean square error between the actual output and a trained network with three hidden layer, each of 20, 10 and 5 neurons

CHAPTER 5

Conclusion

Epileptic seizures are manifestations of epilepsy. The detection of epileptiform discharges in the EEG is an important component in the diagnosis of epilepsy. The present works aim at classifying the EEG pattern into two groups (seizure and healthy), based on the area of the frequency spectrum under different sub-bands. After feature extraction, the classification of the patterns based on the frequency spectrum features is carried out using a neural network. The network based on the back-propagation algorithm is able to achieve an accuracy of 99%. The algorithm is found to be highly sensitive to initial weight and network structure. Future work in this direction is planned on the use of optimization algorithms for determining the optimal structure of the neural and network.

REFERENCES:

[1] Sinha RK, EEG power spectrum and neural network based sleephypnogram analysis for a model of heat stress. J Clin Monit Comput 2008; 22:261–268

[2] E. Niedermeyer, “Epileptic seizure disorders” Chapter 27, in E. Niedermeyer and F.L. da Silva ed. “Electroencephalography: Basic principles, Clinical applications, and Related fields”, Fourth edition. Lippincott Willams & Wilkins, Philadelphia (1999).

[3] Alexandros T. Tzallas, Markos G. Tsipouras, Dimitrios I. Fotiadis, “A Time-Frequency Based Method for the Detection of Epileptic Seizures in EEG Recordings”, Twentieth IEEE International Symposium on Computer-Based Medical Systems (CBMS'07).

[4] J. Gotman, “Automatic detection of seizures and spikes,” J. Clin. Neurophysiol, vol. 16, 1999, pp. 130-40.

[5] P.F. Prior, R.S.M. Virden, and D.E. Maynard, “An EEG device for monitoring seizure discharges,” Epilepsia, vol. 14 (4), 1973, pp. 367-72.

[6] W.R. S. Webber, R.P. Lesser, R.T. Richardson, and K. Wilson, “An approach to seizure detection using an artificial neural network (ANN),” Electroenceph. Clin. Neurophysiol., vol. 98 (4), 1996, pp. 250-72.

[7] G.W. Harding, “An automated seizure monitoring system for patients with indwelling recording electrodes”,Electroenceph. Clin. Neurophysiol., vol. 86 (6), 1993, pp. 428-37.

[8] V. Srinivasan, C. Eswaran, and N. Sriraam, “Artificial Neural Network Based Epileptic Detection Using Time- Domain and Frequency Domain Features”, J. Med. Syst., vol.29 (6), 2005, pp. 647-60.

[9] V.P. Nigam, and D. Graupe, “A neural-network-based detection of epilepsy”, Neurol. Res., vol. 26 (6), 2004, pp. 55-60.

[10] K. Polat, and S. Güneş, “Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform”, Appl. Math. Comput., vol. 32 (2), 2007, pp 625-31.

[11] B. Gonzalez-Vellon, S. Sanei, and J.A. Chambers, “Support vector machines for seizure detection”, in Proc. Of the 3rd IEEE Intern. Symp. on Sign. Proc. and Inf. Technol., 14-17 Dec. 2003, Germany, pp. 126- 29.

[12] H. Adeli, Z. Zhou, and N. Dadmehr, “Analysis of EEG records in an epileptic patient using wavelet transform”, J. Neurosc. Meth., vol. 123 (1), 2003, pp. 69-87.

[13] A. Subasi, “Signal classification using wavelet feature extraction and a mixture of expert model”, Exp. Syst. Appl., vol. 32 (4), 2007, pp. 1084-93.

[14] N. Sadati, H.R. Mohseni, and A. Magshoudi, "Epileptic Seizure Detection Using Neural Fuzzy Networks", in Proc. of the IEEE Intern. Conf. on Fuzzy Syst., 16-21 Jul. 2006, Canada, pp. 596-600.

[15] İ. Güler and E.D. Übeyli, "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients", J. Neurosc. Meth., vol. 148 (2), 2005, pp 113-21.

[16] I. Güler, and E.D. Übeyli, "Multiclass Support Vector Machines for EEG Signals Classification", IEEE Trans. Inform. Techn. Biomed., in Press.

[17] A.A. Dingle, R.D. Jones, G.J. Caroll, and W.R. Fright, "A Multistage System to Detect Epileptiform Activity in the EEG*",* IEEE Trans. Biomed. Eng., vol. 40 (12), 1993, pp. 1260-68.

[18] F.I. Argoud, F.M. De Azevedo, J.M. Neto, and E. Grillo, "SADE3: an effective system for automated detection of epileptiform events in long-term EEG based on context information", Med. Biol. Eng. Comput., vol. 44 (6), 2006, pp. 459-70.

[19] L.D. Iasemidis, and J.C. Sackellares, "Chaos theory and epilepsy", The Neurosc., vol. 2, 1996, pp. 118-26.

[20] N. Kannathal, U.R. Acharya, C.M. Lim, and P.K. Sadasivan, "Characterization of EEG-A comparative study", Comp. Meth. Prog. Biomed., vol. 80 (1), 2005, pp. 17-23.

[21] D.E. Lerner, "Monitoring changing dynamics with correlation integrals: case study of an epileptic seizure", Physica D, vol. 97 (4), 1996, pp. 563-76.

[22] N.F. Güler, E.D. Übeyli, and İ. Güler, "Recurrent neural networks employing Lyapunov exponents for EEG signals classification", Exp. Syst. Appl., vol. 29 (3), 2005, pp. 506-14.

[23] N. Kannathal, M.L. Choo, U.R. Acharya, and P.K. Sadasivan, "Entropies for detection of epilepsy in EEG", Comput. Meth. Prog. Biomed., vol. 80 (3), 2005, pp. 187-94.

[24] H. Qu, and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device", IEEE Trans. Biomed. Eng., vol. 44 (2), 1997, pp. 115-22.

[25] Saeid Sanei and J.A. Chambers, *EEG Signal Processing*, John Wiley and Sons Ltd, England, 2007

[26] R.G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," Phys. Rev. E, vol. 64, 2001, pp. 061907 (1-8).

[27] Programs for Digital Signal Processing, IEEE Press, New York, 1979. Algorithm 5.2

[28] Cooley, J. W. and J. W. Tukey, "An Algorithm for the Machine Computation of the

Complex Fourier Series, "Mathematics of Computation, Vol. 19, April 1965, pp. 297-301.
[29] Duhamel, P. and M. Vetterli, "Fast Fourier Transforms: A Tutorial Review and a State of the Art," Signal Processing, Vol. 19, April 1990, pp. 259-299.
[30] Oppenheim, A. V. and R. W. Schafer, Discrete-Time Signal Processing, Prentice-Hall, 1989, p. 611.
[31] Oppenheim, A. V. and R. W. Schafer, Discrete-Time Signal Processing, Prentice-Hall, 1989, p. 619.
[32] Rader, C. M., "Discrete Fourier Transforms when the Number of Data Samples Is Prime," Proceedings of the IEEE, Vol. 56, June 1968, pp. 1107-1108.
[33] S. Haykin, Neural Networks: A Comprehensive Foundation, Prentice-Hall, New Jersey, 1999.
[34] Neural Network Toolbox; Users' Guide (R2011b), Mathswork,2011.