Seizure Detection from the Time-Frequency Based Multichannel Newborn EEG Signal through the Application of Advanced Noise Filtering and Classification Methods

Author

MOIZ YUSAF

NUST201362496MCEME35513F

Supervisor

Brig Javaid Iqbal

DEPARTMENT OF MECHATRONICS ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY

ISLAMABAD

April, 2016

Seizure Detection from the Time-Frequency Based Multichannel Newborn EEG Signal through the Application of Advanced Noise Filtering and Classification Methods

Author

MOIZ YUSAF

NUST201362496MCEME35513F

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

MS Mechatronics Engineering

Thesis Supervisor:

Brig Javaid Iqbal

Thesis Supervisor's Signature:____

DEPARTMENT OF MECHATRONICS ENGINEERING

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY, ISLAMABAD

April, 2016

Declaration

I certify that this research work titled "*Seizure Detection from the Time-Frequency Based Multichannel Newborn EEG Signal through the Application of Advanced Noise Filtering and Classification Methods"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

Moiz Yusaf

2013-NUST-Ms-Mts-078

Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

Moiz Yusaf

NUST201362496MCEME35513F

Brig. Javaid Iqbal

(Supervisor)

Acknowledgements

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout in every department of my life.

I would also like to express special thanks to my supervisor Brig Javed Iqbal and co-supervisor Dr Rabnawaz for their help throughout my thesis and also for Machine Vision course which Dr Rabnawaz has taught me. I can safely say that I haven't learned any other engineering subject in such depth than the ones which he has taught.

I would also like to pay special thanks to Dr. Mohsin Islam Tiwana and Dr. Umar Shahbaz for their tremendous support and cooperation. Each time I got stuck in something, they came up with the solution. Without their help I wouldn’t have been able to complete my thesis. I appreciate their patience and guidance throughout the whole thesis.

I would also like to thank Dr Mobeen Ghafuur for being on my thesis guidance and evaluation committee. I am also thankful to all my degree-fellows for their support and cooperation.

Finally, I would like to express my gratitude to all the individuals who have rendered valuable assistance to my study.

Dedicated to my exceptional parents and adored siblings whose tremendous support and cooperation led me to this wonderful accomplishment

Abstract

Worldwide survey from health department indicates that approximately 50 million people are currently affected with epilepsy, which is caused due to seizure. Among the top four common neurological diseases in the United States after migraine, stoke and Alzheimer's disease is epilepsy. Internationally, a vague count of average epilepsy patient's each year is 2.4 million.

Electroencephalogram (EEG) monitors the electrical activity inside our brain, which is due to the movement of neurons. It is used for the in time detection of various diseases in neonatal and adults, such as a seizure. EEG displays the signals received by our brain from all body parts. Any sort of seizure that is likely to occur in our body or brain can be seen through EEG. As only time or frequency analysis is not sufficient to clearly depict the non-stationery electrical activity. Time-frequency (TF) analysis is helpful for the dynamic property of EEG signals. The signal is affected by different artefacts, which produce false detections.

Distinct research has been carried out in this field. Various methods have been tested for extracting features of the EEG signal; also classifiers, such as Neural Networks and support vector machine (SVM), were applied for the detection purpose. TF representation provides a wealth of information about the underlying EEG in temporal as well as spectral domains. This work will use novel image-processing methods and machine learning procedures for the feature extraction stages to improve the accuracy (in terms of both sensitivity and specificity) of existing methods. The understanding and assessment about epilepsy is still a long way ahead. Epilepsy awareness and its care among the masses are below a considerate level. This work will assist the doctors in the field of neurology to improve the timely detection of seizures.

Key Words:*Electroencephalogram (EEG) , Time-frequency distribution , Feature extraction, Machine learning, 2-D Discrete Wavelet Transform (DWT),Support Vector Machine (SVM).*

Table of Contents

Declaration i
Language Correctness Certificate ii
Copyright Statement iii
Acknowledgements iv
Abstract vi
Table of Contents vii
List of Figures ix
List of Tables x
CHAPTER 1: INTRODUCTION AND MOTIVATION 1
1.1 Background, Scope and Motivation 1
1.2 Research Objectives 5
1.3 Thesis Organization 5
CHAPTER 2: LITERATURE REVIEW 6
2.1 Wavelet Transform (WT) as a Feature Extractor 6
2.2 Classification through Neural Network (NN) 12
2.3 Classification using Support Vector Machine (SVM) 14
CHAPTER 3: TIME-FREQUENCY REPRESENTATION OF NON-STATIONERY SIGNALS 17
3.1 Introduction 17
3.2 Time Domain 17
3.3 Frequency Domain 18
3.4 Joint Time-Frequency Domain 19
3.4.1 Time-Frequency Distribution (TFD) Formulation 20
3.5 Discussion 22
CHAPTER 4: PROPOSED METHOD 23
4.1 Introduction 23
4.2 EEG Signal Classifications 23
4.3 Feature Selection 25
4.3.1 Time-Frequency (t-f) Flux 25
4.3.2 Time-Frequency (t-f) Flatness 26
4.3.3 Renyi Normalized Entropy 26
4.4 Discrete Wavelet Transform (DWT) 27
4.5 Proposed Methodology 29
4.5.1 Time Representation of EEG Signal 29
4.5.2 Time-Frequency Image Representation of EEG Signal 30
4.5.3 Feature Extraction thorugh DWT 33
4.6 Discussion 34

CHAPTER 5: PARAMETERS AND CLASSIFICATION **35**
5.1 Introduction 35
5.2 ROC Analysis 35
5.2.1 Area Under Curve (AUC) 37
5.3 Classification 40
5.3.1 Classifier Results 40
5.4 Discussion 43
CHAPTER 6: CONCLUSION AND FUTURE WORK **44**
APPENDIX A **45**
REFERENCES **53**

List of Figures

Figure 1.1: EEG Signal of Single Channel 3
Figure 1.2: Fourier Transform of a Sinusoidal Time Signal 4
Figure 1.3: Joint Time-Frequency (TF) Representation 4
Figure 3.1: Time Dominion Representation of EEG 17
Figure 3.2: Frequency Dominion Representation of EEG 18
Figure 3.3: EEG's Time-Frequency (T-F) Image 19
Figure 4.1: EEG Electrodes 10-20 System 23
Figure 4.2: EEG Frequency Bands 24
Figure 4.3: Haar Wavelet Filter Function 28
Figure 4.4: EEG Test Sample of a Seizure Signal 29
Figure 4.5: EEG Sample of Non-Seizure Signal 30
Figure 4.6: Representation of Seizure Signal in Both Time & Frequency domains 31
Figure 4.7: Representation of Non-Seizure Signal in Both Time & Frequency domains 32
Figure 4.8: Methodology for Seizure Detection 33
Figure 4.9: Examples of DWT level-4 approximation coefficients of seizure (left column) and non-seizure (right column) samples. 34
Figure 5.1: Methodology for calculating Area Under Curve (AUC) 35
Figure 5.2: Area Under Curve (AUC) for Spectral Flu**x** T-F Domain using MBD 36
Figure 5.3: Area Under Curve (AUC) for Spectral Flatness T-F Domain using CW distribution 37
Figure 5.4: Area Under Curve (AUC) for Renyi Normalized Entropy using CW distribution 38
Figure 5.5: Area Under Curve (AUC) for Discrete Wavelet Transform (DWT) 39
Figure 5.6: Classifier Output for Discrete Wavelet Transform (DWT) 41

List of Tables

Table 3-1: Time-lag Kernels of the TFD’s 21
Table 5-1: Area Under Curve (AUC) values for various Features using QTFD’s..39
Table 5-2: Comparison ofEEG seizure Detection Results of 2-D DWT using SVM 42

CHAPTER 1: INTRODUCTION AND MOTIVATION

Seizure is a type of disease which needs continuous monitoring of EEG for hours by the doctors, which is physically impractical. With the increased number of patients there is a need for correct and speedy detection of seizure activity. Mainly in neonatal case it can be a life-time disability if left un-noticed. Sole objective of this effort is to provide a solution that is robust and swift.

1.1 Background, Scope and Motivation

Epilepsy came into existence centuries ago but it has become eminent in field of medical in only past hundred years or so. The only known indicator of epilepsy is the epileptic seizure and the person who has gone through it or even witnessed someone knows how fearsome it is especially without prior knowledge of modern science. Seizure recordings take us back to the first days of history. These were considered to be highly superstitious, though medically sound minded people provided more experimental findings. An extensive solution for the cure of this has been attempted by all of them.

With the passage of time epilepsy was taken as to be a likely disease and later on it was extensively acknowledged. Although modern science helped in developing mixed theories about seizure but still it wasn't believed to be a brain dysfunction. Due to which seizure was taken as a contagious disease and affected patients were restricted to specific areas of a mental hospitals. Although it started to deal seizures as a disease and scientific research started to begin in a broader perspective.

The earliest electrical theory of seizure was described by Robert Bentely Todd in 1849 at the Royal College of Physicians. But the initial findings were done by John Hughlings Jackson in 1873. Seizure was known as the irregular electric expulsions within the human body although brain was never considered as the basis of it lately. Jackson could not fully understand the reason behind seizure activity but defined his findings as an electrical abnormality.

Electroencephalography (EEG) came into existence less than a century, when first testing of electrical theory for epilepsy was discovered by Hans Berger in 1930's. The main foundations which lead to the finding about brain, being the core of epilepsy and also confirmed it to be an electric disorder inside human body were the peculiar electric markings. The unsymmetrical electrical movement that was being produced inside brain throughout an epileptic seizure proved to be the main cause of the problem, confirming the brain as its origin. In a ten years time the primary animal model for epilepsy was developed for verification of experimental methods. Afterwards multiple drugs were created and different treatment methods were suggested for this disease. Later it refined to the current range of treatments available.

Even after enormous findings and knowledge about the seizure was widespread, the disease was not considered as a same type of illness until 1990's.Although nothing superstitious was believed about seizure attacks but still there was a discriminating behavior with these patients. Disabilities Acts in 1990's mentioned epileptics and they were refrained from being discriminated. Despite significant knowledge of the seizure still there is room for research in dealing with this mysterious disease. Some fifteen years back from now a mass level conference was conducted by the Epilepsy Foundation of America to quest cure for epilepsy [1].

Seizure is an uncontrolled electrical activity inside human brain. It is found in Pakistan that about 9.99 per 1000 population is affected from epilepsy, which is caused by the seizure. Most of them are below the age of 30 years. But a very small number of epileptic persons are treated in urban and rural areas; just below twenty eight and two percents in both areas respectively. Yet there's a huge gap among the people to fully understand the affliction of epilepsy.

It has been assessed by the doctors that neonatal and youngsters those are being assumed to have seizure must be immediately taken to a physician with two weeks. If there is a neurological discrepancy, it will be detected through brain imaging. 50% of patients diagnosed with a seizure for the very first time, are expected to have other minor seizures. 25-30% of primary stage seizure patients were mainly caused by fever, head injury, excessive alcohol intake, electrolyte disturbance and brain infections [2]. Significant abnormalities can be observed in about 70% of cases, if EEG is performed within 2 days of a first seizure. Otherwise if it is delayed that outcome will be lower. Observing EEG data for a longer period of time can be a tedious task for any specialist. There is also a possibility of leaving out a potential seizure activity. For this purpose a system that can analyze hours of EEG, identify the correct time and area of brain affected by seizure will be of great assistance for the doctors. With the increasing number of seizure affected people globally, there needs to be a diagnosing method which shall not only provide correct identification but also an in-time cure of the disease.

EEG produces results in a single domain i.e. the time domain, as shown in figure 1.1 [3]. The changes that are occurring concurrently in the frequency domain cannot be seen by using only single area. To analyze the frequency part, Fourier Transform (FT) of time signal will be needed, as in figure 1.2 [3]. By this conversion the problem remains to be there, as in this part there will be no indication of time.

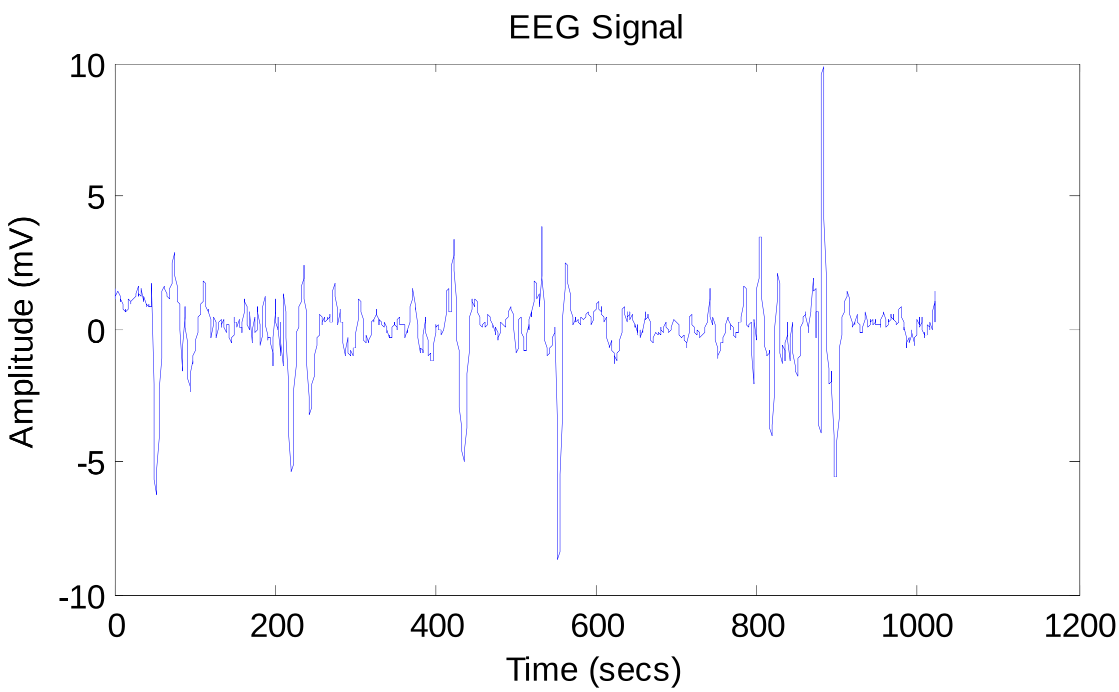


Figure 1.1: EEG Signal of Single Channel [3]

(Figure taken from TFSA toolbox by B.Boashash)

The requirement aroused for a type of representation that can simultaneously present a joint time and frequency domain. This need was fulfilled by the joint time-frequency representation of the EEG signal. As shown in figure 1.3 [3]. Along the horizontal axis (x-axis), frequency changes can be observed, while signal variation along the time can be viewed along vertical axis (y-axis).

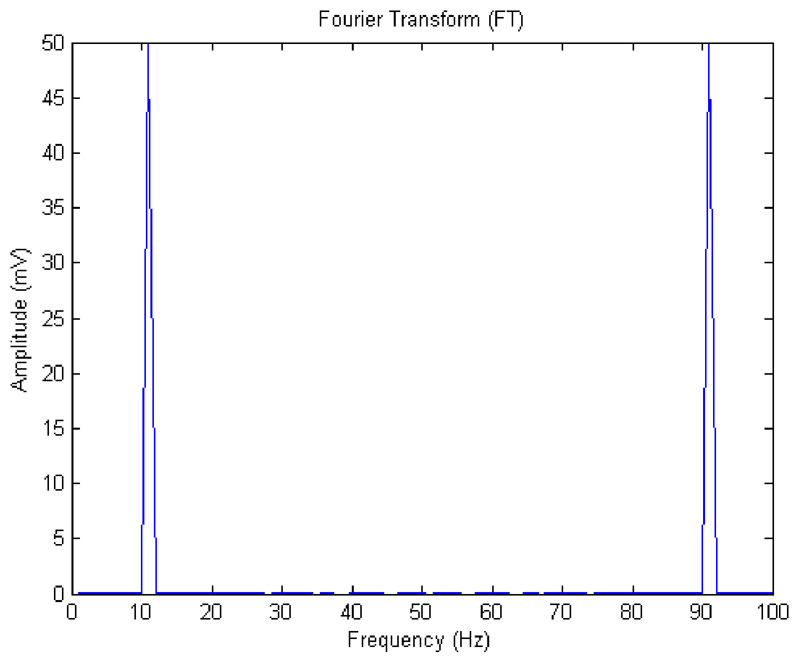


Figure 1.2: Fourier Transform of a Sinusoidal Time Signal [3]
(Figure taken from TFSA toolbox by B.Boashash)

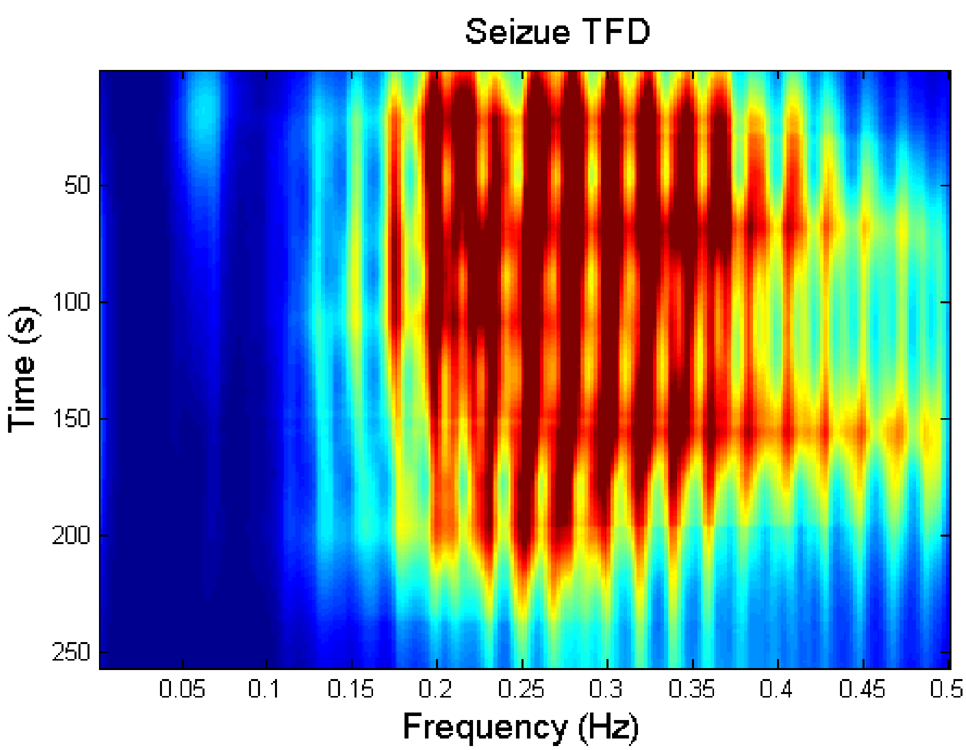


Figure 1.3: Joint Time-Frequency (TF) Representation [3]

1.2 Research Objectives

This thesis explores the objective of seizure detection by merging image processing feature and time-frequency analysis. These efforts extend previously published models for classification of the disease. In light of the contemporary researches being carried on there is a swift advancement in this field of study. Multiple methods are available for seizure detection and classification. One of the targets of this undertaking is to improve the precision of the seizure classification, which includes the imaging technique of electroencephalography (EEG) signals, further inherent time-frequency feature extractor will be assessed and then performance evaluation of the classifier will be matched with other researches.

1.3 Thesis Organization

Previously carried out studies are discussed in chapter 2. Time domain, frequency domain and joint time-frequency domain are elaborated in chapter 3. Different features that can be used for seizure detection is discussed in chapter 4.Also the mathematical derivation of time-frequency image formation is explained. Afterwards electroencephalography (EEG) signal is elaborated with different frequency components that exist in EEG signals. Further in chapter 5, performance evaluation methods and the results obtained through application of distinct features are compared. Such as area under curve (AUC) is assessed as a receiver operating characteristic (ROC) requirement. For the classification part, support vector machine (SVM) is considered. Results obtained by SVM are presented. Chapter 6 concludes the contribution of current research thesis along with the suggestions for future work in this field of study.

CHAPTER 2: Literature Review

Time-Frequency domain analysis may be new to some, but initial work in this particular area is found almost six decades ago. Eugene Wigner and Denis Gabor are the pioneers of this field of research. Wigner introduced the Wigner-Ville distribution and Gabor came up with the idea of Gabor transform. Both worked in the Quantum mechanics. Later down the road numerous advancements took place in the TF analysis. Some of the work produced in biomedical engineering is discussed herewith, although it spreads out in other areas also.

2.1 Wavelet Transform (WT) as a Feature Extractor

H. R. Mohseni et al (2006) compared different methods for seizure detection. The dataset contained three sub-sets. Set one consists of healthy persons with their eyes open. Second set contains samples with epileptogenic zone, while the third set comprises of seizure activity. For detection of seizure various features have been tested. First one is the nonlinear based features. In this method Lyapunov exponent is estimated, which can further be done in two ways. Primary is by using the time series and secondary is performed by the motion equations of any dynamic system. But this only provides the largest Lyapunov exponents. Other method is calculation of local Jacobi matrices and results in all Lyapunov exponents. Jacobi-based method is used in this study. Second is the entropy based features. Entropy consists of calculating the amplitudes of components. It detects the spectral intricacy of the time domain. Third feature detection method is the Wavelet based features. Wavelet transform are the upgraded form of short term Fourier transform. It analyses the signal at multiple frequency groups. It has scaling and dilation functions, which are the outputs of low-pass and high-pass filters. The energy of the output coefficients were taken as the input for classifier. Fourth are the time-frequency based features. It can represent the changes that are occurring simultaneously in time and frequency domain. A single representation of a time signal in both domains allows for detection of variations in both spectral and temporal domains. Further there can be numerous methods of analyzing an EEG signal in time-frequency domain using multiple distributions. After signal is converted to joint time-frequency domain, maximum frequency is checked at each instant of time. Least mean square (LMS) is used for cubic curve. Further these extracted features are input to feed-forward back propagation neural networks (FBNN). The last approach is power spectrum. It takes integration of all the frequency components that are above zero. The results show that variance based features show maximum accuracy in seizure classification of 100 percent. While time-frequency, Lyapunov exponent, entropy, logistic regression and discrete wavelet transform follow in seizure detection with accuracies of 98.25 percent, 97.38 percent, 93.7 percent, 93 percent and 86.25 percent. The variance based features show best results, which did not use any classifier, while other features were input to classifiers mostly based on neural networks. The limitation in these methods is there should be an unknown dataset for testing purpose [4].

Nasser Sadati et al (2006) compared different classifiers for the epileptic seizure detection problem. Previously Fourier transform were mostly applied for automatic EEG processes. As EEG contains four frequency bands, so it was considered that these bands have some characteristic waveforms. This study has come up with the idea of using wavelet transforms for feature extraction of the EEG signals. The database used for the evaluation contained 100 single-channel EEG recordings. Total of five sets are discussed. First and second sets were taken from five healthy persons with a 10-20 electrode placement. Third and fourth set were taken of epileptic patients, but in seizure-free interval. Fifth dataset was taken in duration of seizure activity. In this study out of five sets available, three sets have been used. The signals were shortened into parts of 256 points (5.9s). Further these were given as an input to the discrete wavelet transform. The main purpose of using discrete wavelet transform is its transient nature, as it provides localization of variations in both temporal and spectral domain. The Daubechies 4 wavelet filter has been applied in this research. The decomposition level achieved is up to fifth level. First the support vector machine (SVM) has been discussed for performance evaluation. It is an approach for a supervised classification. It places the training dataset as far as mathematically possible from the hyper plane. Further for increased distance for placement of testing and training dataset it uses radial basis function as the Kernel. After support vector machine the other classifier discussed is adaptive-network-based-fuzzy interference systems. The structure for the neuro-fuzzy network in this research uses a system of six inputs and one output. Further these inputs have a couple of Gaussian membership function and the rule base contains 144 rules. Twenty epochs were used for the training purpose of adaptive neural fuzzy interference system. Least square and gradient descent methods were applied for fuzzy structure. Another classifier used was adaptive neural fuzzy network. This works along with the adaptive neural fuzzy interference system. This is activated by the activation functions of the adaptive neural fuzzy interference system. The positive aspect of this classifier is that it has an adaptive neuron firing. For training purpose back propagation and gradient descent has been used. But there is a limitation with the back-propagation, as it can be trapped for an indefinite period in local minima. Also it requires long training time. The ratio between testing and training dataset is 1:1. A total of two hundred samples were used for training purpose and the same number for testing. The results show that adaptive neural fuzzy network has the highest accuracy rate of 85.9 percent followed by support vector machine with 83.1 percent. The adaptive neural fuzzy network provides the solution which carries the joint effect of both neural network and fuzzy systems [5].

A. Subasi (2007) presented epileptic classification model through EEG. A mixture of expert (ME) model and Multi-layer Perception Neural Network (MLPNN) are compared via discrete wavelet transform (DWT) as a feature extractor. Dataset used contained 100 single-channel EEG recordings. Total of five sets are discussed. First and second sets were taken from five healthy persons with a 10-20 electrode placement. Third and fourth set were taken of epileptic patients, but in seizure-free interval. Fifth dataset was taken in duration of seizure activity. For evaluation first and fifth sets are taken. First level of discrete wavelet transform (DWT) has been used. Daubechies filter of order 4 is being used for construction of approximation and detail coefficients. After these coefficients are constructed four statistical parameters are taken as main feature extractors. First parameter is taken as the mean of absolute values of wavelet coefficients in each sub-band. Second parameter is the average power of the wavelet coefficients in each sub-band. Third is the standard deviation of the coefficients in each sub-band. Last one is the absolute mean of adjacent sub bands. First and second feature represents the signal's distribution of frequency. Third and fourth feature will depict the total change produced in frequency distribution. Mixture of experts (ME) is used as a classification algorithm. The output from feature extractors is input for the multi-layer perception neural network (MLPNN). For classification testing 1000 random samples have been taken for training neural networks and rest of the samples have been used for testing. Mixture of expert (ME) achieved an accuracy of 94.5 percent while multi-layer perception neural network (MLPNN) had an accuracy of 93.2 percent. The cumulative of training and testing samples used are 1600, as the length of dataset increases, it requires more computational time. Best suited algorithm will train in a much less number of samples and provide better approximation results [6].

Abdul hamit Subasi (2006) came up with a methodology for epileptic seizure detection using fuzzy neural networks. In this study, epileptic discharges that are produced in brain are recorded for seizure activity. As an input to the classifier discrete wavelet transform (DWT) is used. To acquire the dataset for the study, three males and two females who only had epileptic disorder were used. Four channel data was used. 500 EEG samples have been taken. Also data was taken of subjects who were not having any seizure. Discrete wavelet transform has been used for feature extraction. As it provide better temporal and spectral analysis. They allow for multi-resolution decomposition of the input signal. A combination of high-pass and low-pass filter is applied to the input signal which can further be decomposed at a different frequency sub-band. The type of wavelet filter to be chosen depends upon the nature of signal. As there can be a signal which minimal noise or artifacts or on the contrary it can be of high noise. In this study the decomposition is taken up to the fifth level. While the Daubechies 4 filter of the wavelet family was used for decomposition. The discrete wavelet transform coefficients are then taken as an input by the dynamic fuzzy neural network. Fuzzy network has neuron as its main entity, which actually is a representation of biological neuron. When it reaches the maximum level of excitation it fires up. Fuzzy system has used Gaussian membership and center average de-fuzzifier for the activation. There were two datasets of six and five subjects for training and testing purposes respectively. A total of 300 samples were taken from training subjects and 200 samples from the testing subjects. Normal subject accuracy achieved by this method is 92.8 percent while epileptic subjects detection had 92 percent accuracy. Overall accuracy of the dynamic fuzzy neural network is rated at 93 percent [7].

Hojjat Adeli et al (2007) anticipated a wavelet chaos method for the seizure classification of epilepsy patients. A wavelet filter is applied for the feature detection. Discrete wavelet transform (DWT) has an added advantage over Fourier transform that it produces multi-resolution output. Daubechies filter 4 has been used among various wavelet family filter. The decomposition is taken up to fourth level. Online available dataset has been used. It contained 100 single-channel EEG recordings. Total of five sets are discussed. First and second sets were taken from five healthy persons with a 10-20 electrode placement. Third and fourth set were taken of epileptic patients, but in seizure-free interval. Fifth dataset was taken in duration of seizure activity. Total of 300 EEG samples are taken. Average values and standard deviation are calculated for the EEG sub-bands. Correlation dimension (CD) and largest Lyapunov exponent (LLE) has been calculated for all the sub-bands. It is concluded that alpha sub-band shows the maximum variations in LLE values among the three sets used for evaluation. Each band has its own chaotic performance. So it is suggested that dynamics are not equally shared among all the sub-bands after the decomposition, rather it limits itself to a certain band. Increasing the number of parameters will alter the accuracy of EEG classification [8].

Ling Guo et al (2010) proposed a way out for self-activating seizure detection through EEG, which has it findings on extracting line length features from Wavelet Transform (WT). Dataset consists of five subsets. It contains single channel EEG of 100 subjects. Each sample has duration of 23.6 s and sampling rate of 173.6 Hz. Discrete wavelet transform (DWT) was then applied to each sample with a cut-off frequency of ¼ of sampling frequency. Down sampling of the signal is performed till the fourth level of signal decomposition. In each decomposition level the frequency component is doubled whereas time sampling is reduced to half. The decomposition level is taken up to fourth. Daubechies (dB4) has been used as the wavelet filter as it provides better smoothing of the signal. Line length feature is then applied to the decomposed signal. This feature is responsive to amplitude and frequency changes. The output of line length feature of each subset sample is then fed to artificial neural network (ANN) for classification. Sensitivity, specificity and accuracy have been tested as performance evaluation metrics. Accuracy of up to 99.77 percent has been achieved by this method. The limitation in this work is the database used has been pre-processed for artifact removal through visual inspection, whereas in actual clinical situations artifacts can cause a change in classification [9].

Deng Wang et al (2011) proposed an epilepsy classification based on wavelet packet entropy features. It contained 100 single-channel EEG recordings. Total of five sets are discussed. First and second sets were taken from five healthy persons with a 10-20 electrode placement. Third and fourth set were taken of epileptic patients, but in seizure-free interval. Fifth dataset was taken in duration of seizure activity. The feature extraction method used in this study is the wavelet packet transform (WPT), which is derived from the wavelet transform. Disintegration of the input is produced by wavelet transform by high and low pass filter. At each stage multi stage decomposition is performed. Wavelet transform has the ability to show transients in both temporal and frequency domain. The features derived of the wavelet transform to make up a wavelet packet transform (WPT) are maximum, minimum and mean of the absolute values of the coefficients and standard deviation in each sub-band. Further a best based wavelet decomposition packet is measured. For this entropy feature is selected, after decomposition of signal at each level above mentioned values is calculated. Those wavelet coefficients which provide maximum values are considered to be most complex in computations, while those with relatively lower entropy parameter values are considered for the feature extraction. After the feature extraction a number of classifiers are also discussed. First is the k-NN classifier. It searches a test sample with the nearest training sample for classification. Next considered is the hierarchical classification system. It adds on another aspect to the k-NN classifier, with input of reference or background behavior to classify a test sample. For the classification 100 EEG samples were used. M-fold cross-validation was used. All of the five wavelet family filters were run over for best possible accuracy. 2-, 5- and 10-fold cross validation achieved accuracy of 99.355, 99.420 and 99.449 percent. The limitation in this study is setting the value for the minimal confidence level (MCL), which assures the completeness of the training dataset. Its value varies from 0<MCL<1. Also other classifiers such as support vector machine (SVM) and neural networks can add on to another dimension [10].

Yusuf U Khan (2012) with associates proposed a seizure detection approach in neonatal case. The dataset used in this study available online that was collected at Children's Hospital Boston. 23 subjects were used for EEG recordings. 10-20 electrode system has been used consisting of 23 channels. Out of 23 subjects only 10 subjects recording were used in this research. High frequency component of 60Hz is removed from this dataset. For feature extraction first histogram of the samples are taken. Histogram is taken to extract three features, first is the ratio of variance, second is ratio of absolute mean and third is kurtosis and skewness. As seizure activity is mostly present in lower frequency components, so wavelet transform is used to disintegrate the signal in low frequency. Daubechies 4 wavelet filter was used up to the fifth level. The feature vectors were given input to the support vector machine (SVM). The training to testing ratio was 4:1. The average number of false detection per hour was 1.1 and latency was 3.2 seconds. Improvement in accuracy can be attained by escalating the number of features [11].

2.2 Classification through Neural Network (NN)

Hamid Hassanpour et al (2004) discussed seizure detection of neonates using time-frequency domain. Dataset for this research was collected at the Royal Women’s Hospital, Brisbane, Australia. 10-20 electrode placement method was used over neonatal aged between two days to two weeks. Twenty channel EEG recordings were taken at 256Hz. Seizure activities were visually marked by a neurology specialist. First the signal is converted into time-frequency domain for further processing. To reduce the effect of cross-terms and acquiring low frequency components behavior B-distribution has been considered as the time-frequency distribution. For feature extraction singular value decomposition (SVD) has been used. At the start filtering is performed to extract the low-frequency components. Signals below 10Hz have been drawn out. Then the signal is divided into 30 s epochs. The third step was to reduce the no of samples per second. From 256 samples it was reduced to 20 samples. Then time-frequency representation of the above mentioned epochs are taken. Afterwards singular value decomposition has been applied for computing left and right singular values that correspond to the time frequency domain. Distribution functions are being assessed through the density functions. Next step was to figure out the histogram that related to the distribution function. The output of the four singular value matrices that were computed from histogram was taken as an input by the neural network classifier. The feed-forward neural network was used as a classifier. For training purpose of the classifier, 200 samples of both seizure and non-seizure were being used. The aggregate of iterations performed to train the classifier was 800. The remaining dataset of 100 seizure and 600 non-seizure samples was being tested. The accuracy achieved by this method was 90 percent. The limitations of this work is that it only contained features that are applicable on low frequency components, while there can only be indication of seizure in high-frequency components which will result in reduction of accuracy [12].

A. T. Tzallas et al (2007) proposed a method for the automated seizure detection. Dataset has been tested which include both epileptic and normal subjects. Single-channel EEG was taken of 100 patients. Each of which had a 23.6-second duration. Smoothed pseudo-Wigner-Ville distribution (SPWVD) is used as the Time-frequency distribution. The proposed distribution helps in cross-term reduction. Smoothing window of 64-point length was used. Frequency resolution of (64, 128, 256, or 512) was varied. Different time windows of (3 or 5) and frequency sub-bands of (4, 5, 7, or 13) have been taken as feature set. Advanced Neural Networks (ANN) has been tested for the functional evaluation of projected method. Accuracy achieved is between (97.72-100) percent. The limitations in the above study are that multiple artifacts in the dataset were removed beforehand after visual inspection. So the evaluation under real clinical environment is required. Also in the dataset frequency components above 40Hz were not taken into consideration. Only half of dataset was used for testing while other half was used for training neural network. Furthermore different feature reduction methods and alternate classifier can be tested for evaluation [13].

Alexandros T. Tzallas et al (2007) provided the importance of time-frequency distributions for the seizure detection in EEG. Dataset used in this study is publicly available. It contains of five sets. Out of which three sets have been used in this research. Set one consists of healthy persons with their eyes open. Second set contains samples with epileptogenic zone, while the third set comprises of seizure activity. Three different types of classes have been used for this study. In the first process only two classes have been tested, i.e. seizure and normal. In the second process one class is added on that is of seizure free samples. In the third process all five classes have been tested. The number of samples in each of three classes is 200,300 and 500 respectively. Thirteen various time-frequency distributions have been used independently. The smoothing window in all of the distributions was of 64-point length. For feature extraction power spectral density has been used. Further the signal was decomposed in different frequency sub-bands of 0-2.5Hz, 2.5-5.5Hz, 5.5-10.5Hz, 10.5Hz-21.5Hz and 21.5Hz-43.5Hz. This feature signifies the division of energy over the time frequency domain. Each feature vector contained 16 features. For the classification purpose feed-forward ANN was used. Input is equivalent to the size of feature vector with an additional hidden layer 5*N neurons and the number of classes equals the outputs. Among the thirteen various time frequency distributions reduced interference produced the maximum accuracy of 89 percent. The least was 54.6 percent by Margenau-hill. The limitations in this study are the less number of parameters, if increased than it can produce better approximation of the seizure activity. Also the EEG recordings are of longer duration, so there needs to be a modification to cope up with this also [14].

Varun Bajaj and Ram Bilas Pachori (2013) presented a theory for seizure detection through the area if instantaneous mode functions (IMF). The dataset used in this research is publicly available. It is taken from 21 patients that are suffering from fractious central epilepsy. The data was recorded using 6 channels EEG equipment at the epilepsy centre of the University Hospital of Freiburg, Germany. The samples were taken at a frequency of 256 Hz. Out of the 21 patient's data, only 9 of them are used for this work, which makes a total of 90 EEG signals per channel, out of which 51 samples are having ictal activity while rest of 39 are ictal free. Empirical mode decomposition (EMD) transforms the signal into a defined set of amplitude and frequency modulated components and known as the intrinsic mode functions (IMFs). The signal's Hilbert transform is taken for the analytic representation, further modified central tendency measure (CTM) is used for visual information. The area of each IMF is calculated through the CTM in imaginary plane. A set of three rules have been defined for the detection of seizure through the area calculation. After the decision rules are met it has been drawn out that first three IMF's of the EEG signal are helpful in seizure detection. Error rate detection (ERD) is computed with other performance parameters, which resulted in a reduced percentage of 40 percent as compared to 79 percent in other studies performed on same dataset. The limitations in this research is that noise reduction is not catered for which may produce false detection [15].

2.3 Classification using Support Vector Machine (SVM)

Bruno Gonzalez-Vellon et al (2004) gave a methodology for seizure detection through support vector machine (SVM). For feature extraction a window function is used, which is run over the EEG signal. Windows is over-lapped for better resolution. As there is a variation in the signal's energy during ictal activity, so energy is taken as the first feature. As window function is used so each frame's energy is calculated. The second feature used is the damping of the frequency during ictal activity. Dominant frequency of each window is calculated. The third feature used is the cyclostationarity of the signal. It calculates the energy spread over the frequency components before the seizure arrival. At the seizure activity all the frequency components drastically lose their sketch. SVM using radial basis function Kernal has been applied. 40 samples were tested over the classifier. Sensitivity of 100 percent was achieved, with no false positives. The specificity was reported to be 80 percent [16].

Thasneem Fathima et al proposed a wavelet based detection for seizure activity. The seizure detection problem involves three stages. First is the pre-processing stage, next is the feature extraction and third is the classification. As EEG signals contain artifacts due to movement of eyes and their blinking. Also A/C supplies also have an effect on EEG recordings. So pre-processing is applied to remove these major artifacts. Next is the feature extraction stage. Here wavelet transform (WT) have been applied to the signal. Because of the non-stationary property of the EEG signals it provides better representation. Also it provides varying windows for different frequency components. Wavelet transform is an advanced form of Fourier transform. As in Fourier the window is chosen once, whereas in wavelets it changes in each level. In this study two datasets have been used, first is from the five healthy persons, showing no seizure activity, whereas the other one is having seizure activity. The number of decomposition level is taken up to fourth. The Daubechies 2 wavelet filter family was used. The four features taken from the wavelet coefficients are the maximum, minimum, mean and standard deviation of the wavelet coefficients in each sub band. The output of these feature vectors was provided to a classifier for evaluation. A training set of 40000 elements and testing of 24000 elements was input to the classifier. It provides an accuracy of 99.5 percent [17].

Ram Bilas Pachori (2008) proposed a method for distinguishing ictal and non-ictal signals. Empirical mode decomposition (EMD) has been proposed for feature extraction. The decomposed signals make up a set of band-limited functions known as intrinsic mode functions (IMF). Mean frequency is computed using Fourier-Bessel expansion. The coefficients produced of this expansion are unique for every signal. Calculation of empirical mode decomposition (EMD) prior to mean frequency is essential for non-stationery signal type. In this study mean frequency (MF) estimation of the intrinsic mode function (IMF) is taken as feature extractor. Dataset contains 100 EEG recordings taken of a single channel. Out of these five sets, two sets are combined to form a single class while one is taken as another class. The two sets that were taken from subjects in seizure-free sections are combined to form one set. The other set is of seizure containing samples. The mean frequency values have been calculated for both types of datasets by using IMF. The difference in values of mean frequency for ictal and non-ictal samples is that it will be small for former and large for later mentioned samples. The classifier used is Kruskal-Wallis test. The limitations in this study are that the intrinsic mode function values are different for each decomposed sample. As these values are relying on frequency content of each signal. So when comparison is made between any two samples it might relate to different frequency bands. Also for clinical practice it should be tested on out-of-sample dataset [18].

Boualem Boashash and Ghasem Azemi (2014) presented a time-frequency based filter design for the seizure detection. The filter will remove the additive noise of the EEG recordings. Design is based on the multi-channel EEG equipment with a 10-20 electrode placement technique. As there are a numerous quadratic time-frequency distributions (QTFD) that can be used, this approach has proposed Wigner-Ville distribution (WVD) and cross Wigner-Ville distribution. Also another QTFD that has its basis on signal ambiguity domain representation, also named as

Radon-ambiguity detector is approached. The proposed methodology is tested over newborn EEG signals for seizure detection. Also different t-f kernels are also tested for evaluation. The cross Wigner-Ville distribution outperforms other QTFDs with an area under curve (AUC) value of 0.95. The performance of these can be improved using data-dependant TFD's and more efficient methodology for implementing TFDs [19].

Boualem Boashash et al (2014) discussed various quadratic time-frequency distributions (QTFDs) for the seizure detection in neonatal case. It uses two different databases, one for artifact detection and other for seizure detection. First database consists of EEG samples taken of 5 subjects at the Royal Brisbane and Women's Hospital, Brisbane, Australia. The recordings were taken for 28 minutes with a sampling frequency of 256 Hz. Second database consisted of sixty minutes of EEG recordings from 39 newborn at the Cork University Maternity Hospital, Ireland for Qatar University as part of a Qatar National Research Fund (QNRF) funded NPRP project. A total of fifteen features were being run over for the categorization of seizure containing signals. Three features were inherently from frequency domain and five from time domain, which were transformed to be applied on the joint time-frequency domain. Rests of the eight features were taken from inherent time-frequency domain. Further area under curve (AUC) was calculated for each feature using six different quadratic time frequency distributions. AUC for each dataset was calculated in the same way. Further these features were given to support vector machine (SVM) for the artifact detection and seizure classification. For seizure classification smoothed Wigner-Ville distribution (SWVD) gave maximum accuracy of 93.75 percent. Leave one-out cross validation method was used for the classification. The limitation is that the features are necessarily extended from time only and frequency only features [20].

The literature survey shows that EEG classification using TFDs as images is a new area of research where further work needs to be done. Furthermore, 2-D DWT has not been optimally utilized for EEG signal analysis in spite of its popularity in biomedical image processing [21].

CHAPTER 3: Time-Frequency Representation of Non-Stationery Signals

3.1 Introduction

Mostly in real world applications we are dealing with non-stationery signals. Stationery signals are considered those where frequency content remains same over a period of time. On the contrary if the frequency component is varying rapidly, then it will be taken as a non-stationery signal.

3.2 Time Domain

Time representation can be defined as s(t). In time domain analysis, frequency component is averaged over all time. Such as if we have a signal of the form given in equation 3.1:

$$s(t) = A \sin(2\pi f_o t) \tag{3.1}$$

In above mentioned equation if s (t) is plotted against time (t), then visualization of oscillating frequency component (f_o) will be a complex task. So only temporal domain is unable to show what is happening in frequency domain.

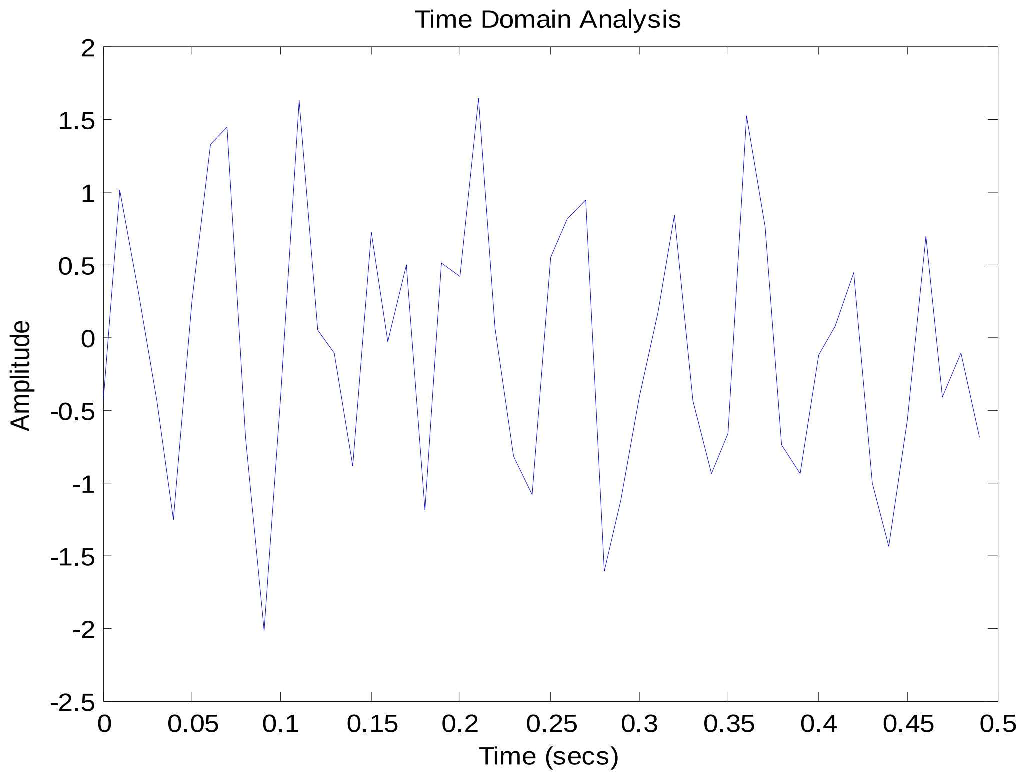


Figure 3.1: Time Dominion Representation of EEG [3]

(Figure taken from B.Boashash TFSA toolbox)

3.3 Frequency Domain

Any time signal can be transformed into frequency domain by simply taking its Fourier Transform. The transformation is represented as:

$$s\,(t)_t \leftrightarrow_f S(f)$$

Frequency domain has two parts. One is the real and other is the imaginary part. In spectral domain time is averaged over all frequencies. But it only shows the frequencies existing in the signal, there isn't any indication of what time these frequencies were present. As shown in figure 3.1, a time varying signal that consists of one or more than one frequency component can be shown by taking its Fourier transform. As displayed in figure 3.2. Along the abscissa is the frequency part and along the ordinate is the power spectral density (PSD), which is the squared magnitude spectrum.

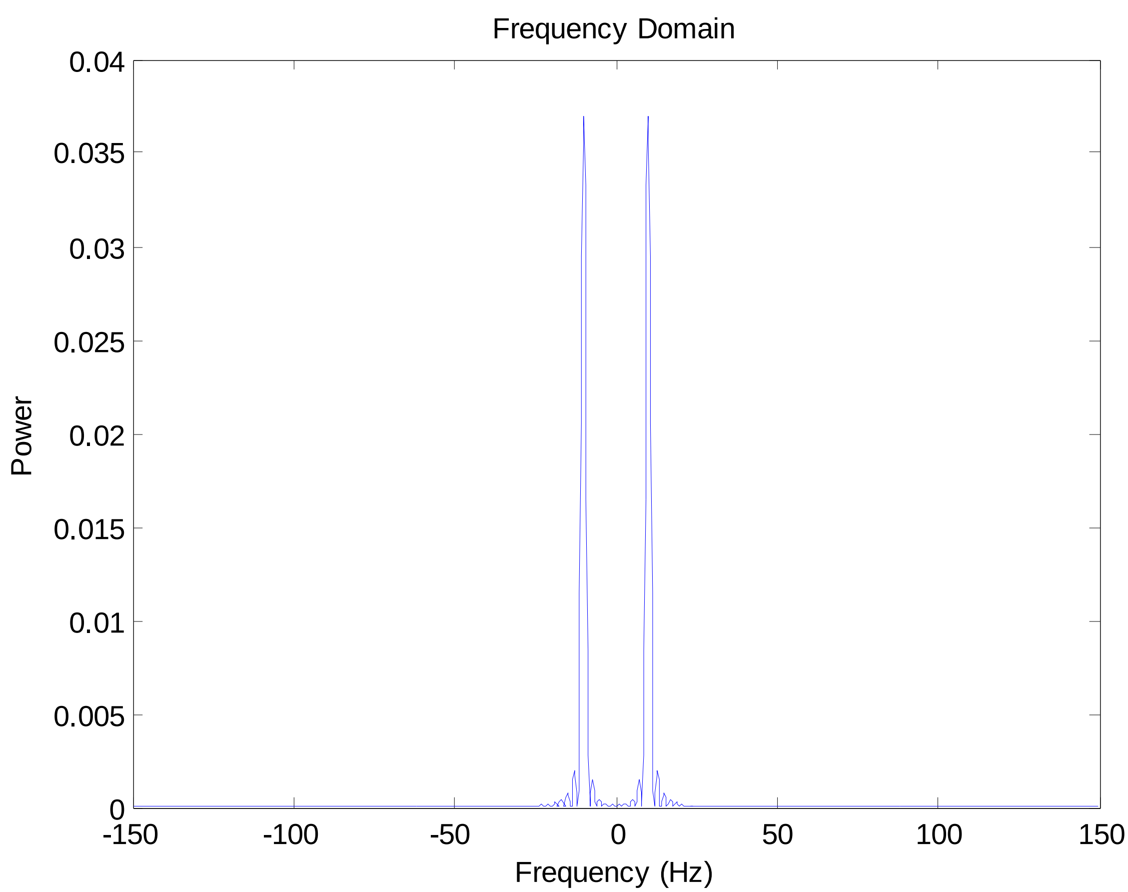


Figure 3.2: Frequency Dominion Representation of EEG [3]

(Figure taken from B.Boashash TFSA toolbox)

To observe the time observations of any particular frequency, the signal has to be converted back into time domain. This can be achieved by taking the Inverse Fourier Transform. But if the signal is non-stationery than this will be a tedious task to simultaneously observe changing in both domains.

3.4 Joint Time-Frequency Domain

As discussed in the previous two sections, only time or frequency representation of a non-stationery signal is insufficient to describe the complete nature. To accomplish this there has to be a way that can simultaneously provide bi-domain observation. One axis will represent time while other will show frequency. Constant-t will tell what frequencies are present in any particular time, while constant-f will depict the times at which any frequency is present. So moving out of the conventional time and frequency representations, bi-dimensional domain will be a convenient mode of analyzing a non-stationery signal. As a result of which a time-frequency (t-f) space will be developed. To better understand the concept of this, we will see a simple illustration of t-f domain.

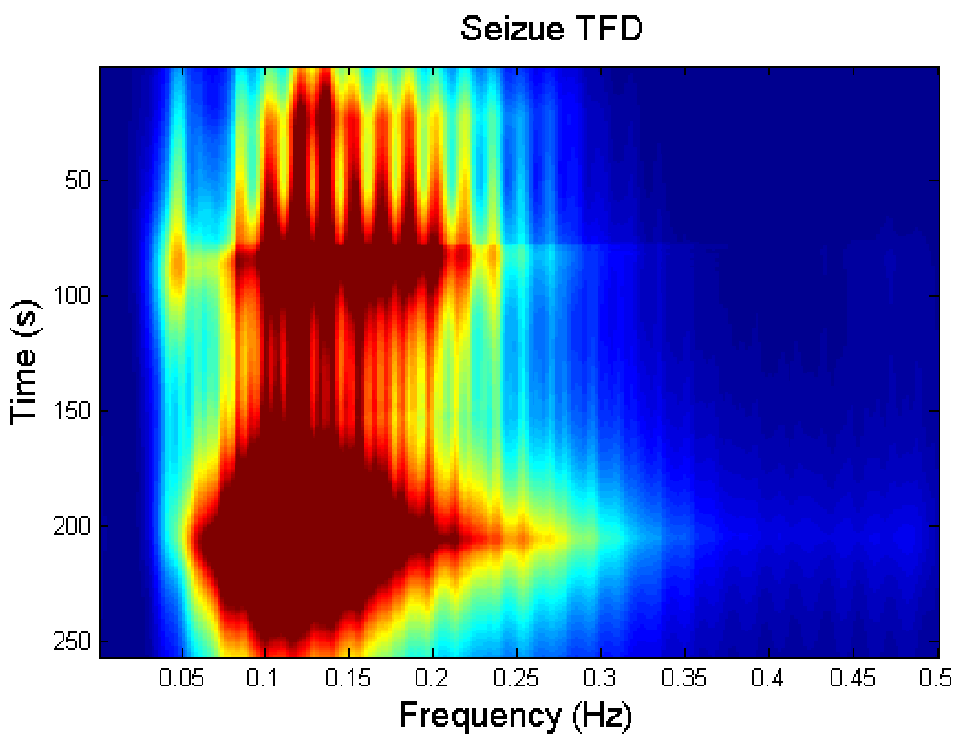


Figure 3.3: Time-Frequency (T-F) Image Representation of a Seizure Signal

The figure illustrates the t-f distribution. The input is a linear time domain signal. While time length of the input signal is 256 seconds. Quadratic time-frequency distribution of extended modified B, applied on the input signal, to attain a t-f image. As obvious from the figure 3.3, the constant-t depicts the frequencies present at any particular instant, while visualization of constant-f along the time axis gives the occurrence of a frequency at any given time.

3.4.1 Time-Frequency Distribution (TFD) Formulation

Quadratic TFD's (QTFD) will be considered for this study. As these are the type of TFD which produce images in TF domain that assist in detection and classification, through various feature applications. Further insight of QTFD's is discussed in later part.

Quadratic time-frequency distributions are considered to be most fitted approach for the non-stationery signal analysis in various applications. Mathematically they can be devised as [22]:

$$\rho(t,f) = W_z\,(t,f) **_{(t,f)}\ \gamma(t,f) \qquad (3.2)$$

In the equation 3.2, $\rho(t,f)$ indicate the time-frequency distribution, $W_z\,(t,f)$ represents the Winger-Ville distribution (WVD), $\gamma(t,f)$ is the T-F kernel of the distribution, and $**_{(t,f)}$ denotes 2D convolution function in time and frequency. With reference to equation 3.2,$\gamma(t,f)$ is 2D smoothing filter, applied to get a smoothed version of Wigner-Ville distribution (WVD). Different quadratic distributions will emerge by changing the Kernal. Each class of distribution has its own merits and de-merits. It depends upon the requirement for choosing the appropriate Kernal. WVD is the centre class described by a T-F Kernal as$\gamma(t,f) = \delta(t)\delta(f)$, where δ is the Dirac delta function. For a real-valued signal$s(t)$, the WVD is defined as:

$$W_z(t,f) = \int_{-\infty}^{+\infty} z\left(t+\frac{\tau}{2}\right) z^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau}\, d\tau \qquad (3.3)$$

In the equation 3.3 $z(t) = s(t)$ is the analytic associate of $s(t)$ and $z^*(t)$ its complex conjugate. Among different quadratic TFD's, WVD is a better option for the joint T-F image formation. But there are artifacts produced in a multi-component input signal case. As it's the case in the EEG signals. With the introduction of cross-terms the true image representation will become a difficult task. To overcome this reduced interference TFD's can be applied. Using equation 3.3, equation 3.2 can be expressed as [23]:

$$\rho(t,f) = \mathcal{F}_{\tau\to f} G(t,\tau) *_t z\left(t+\frac{\tau}{2}\right) z^*\left(t-\frac{\tau}{2}\right)$$

$$= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} G(u,\tau) z\left(t-u+\frac{\tau}{2}\right) z^*\left(t-u-\frac{\tau}{2}\right) du e^{-j2\pi f\tau} d\tau \qquad (3.4)$$

In the above expression $G(t,\tau) = \mathcal{F}_{f\to\tau}^{-1}\{\gamma(t,f)\}$ shows the time-lag Kernal of the time-frequency distribution. Among the various distributions, Extended Modified B Distribution (EMBD) is considered as the prime suitable for representation of EEG signals.

For any given analytic signal $z[n]$ associated with the real discrete time signal $x[n]$,$n = 0,1,\dots,N-1$ while the discrete side of equation 3.4 is given by equation 3.5 [23]:

$$\rho_z[n,k] = 2\, DFT_{n\to k}\{G[n,m] *_n (z[n+m]z^*[n-m])\} \qquad (3.5)$$

For an N-point real signal $x[n]$, $\rho[n.k]$ is represented by a $N \times M$ matrix of ρ_z, where $M (M \geq N)$ is the number of FFT points used in calculating the TFD. Note that $n = t$ and $k = \frac{2M}{f_s} f$ where t and f are the continuous time and frequency variables, and f_s is the sampling frequency of the signal. $G[n,m]$ is the Time-lag Kernal.Table 3-1 shows various time-lag kernels that can be used to define time-frequency distribution for image formation [23].

Table 3-1: Time-lag Kernels of the TFD's [23]

Distribution	$G[n,m]$	Parameters
WVD	$\delta[n]$	N/A
CWD	$\frac{\sqrt{\pi\sigma}}{2\lvert m\rvert} exp\left(\frac{-\pi^2\sigma n^2}{4m^2}\right)$	$\sigma = 5$
MBD	$\frac{cosh^{-2\beta} n}{\sum_n cosh^{-2\beta} n}$	$\beta = 0.01$
EMBD	$\frac{cosh^{-2\beta} n}{\sum_n cosh^{-2\beta} n}\frac{cosh^{-2\alpha} m}{\sum_n cosh^{-2\alpha} m}$	$\alpha = 0.01, \beta = 0.19$
SPEC	$w[n+m]w[n-m]$	$w[n]$: Hamming, $\frac{N}{4}$ samples long

The parameters α, β and σ are positive and real, $w[n]$ represents the windowed function used in SPEC, while N is the length of the signal under analysis in Table 3-1.

3.5 Discussion

In daily life mostly we are dealing with the non-stationery signals. EEG is one of the examples of it. Multiple frequency components are present in a single EEG waveform. Acquiring of various channel signals and simultaneously converting them into image to extract information requires a swift technique. The joint Time-Frequency distribution that has been considered in the current chapter shows a possible way out to accomplish the task. Furthermore Quadratic Time-Frequency Distribution (QTFD's) have been discussed, which are considered as a viable option among the TFD's for our case, i.e. EEG.

CHAPTER 4: PROPOSED METHOD

4.1 Introduction

Our body is continuously producing potential through chemical reactions taking place inside. The human brain senses these signals as they are occurring. Electroencephalography (EEG) is a non-invasive method of measuring these potential. Previously, a trained neurophysiologist used to visually monitor EEG for the abnormality detection. The advancement in technology has eased the way of analyzing EEG. In this chapter we will discuss four features. T-F flux, T-F flatness and Renyi normalized entropy features are used in B. Boashash research, while Discrete Wavelet Transform (DWT) has been proposed in this study.

4.2 EEG Signal Classifications

Apart from numerous biomedical signals, EEG is considered as one of the complicated signal to correctly understand. An inexperienced observer won't be able to extract the correct information, as different regions of our brain represent a unique part of human body and electrodes are placed accordingly for measurements.

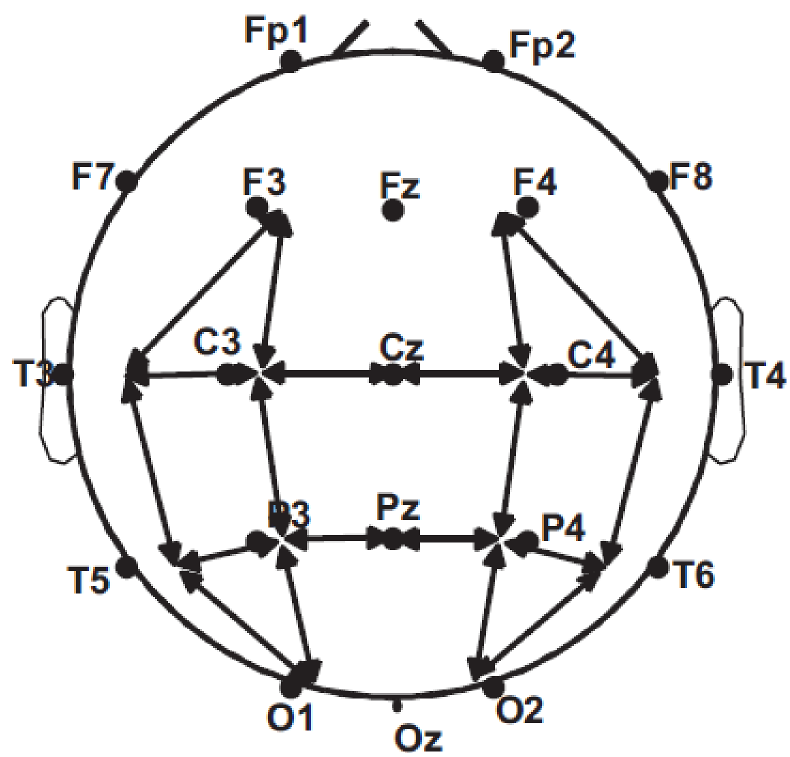


Figure 4.1: EEG Electrodes 10-20 System [20]

EEG signals are acquired through electrodes placed over the human head. International placement of EEG electrodes is known as 10/20 system. The numbers 10 and 20 represent the percentage distance between any two adjacent electrodes, right to left and front to back. Figure 4.1 depicts the electrodes placement over the head [20].

The recorded waveforms imitate the brain electrical activity. EEG signal have very minimal power amplitude, in milivolts (mV). The frequency components that are present in EEG are:

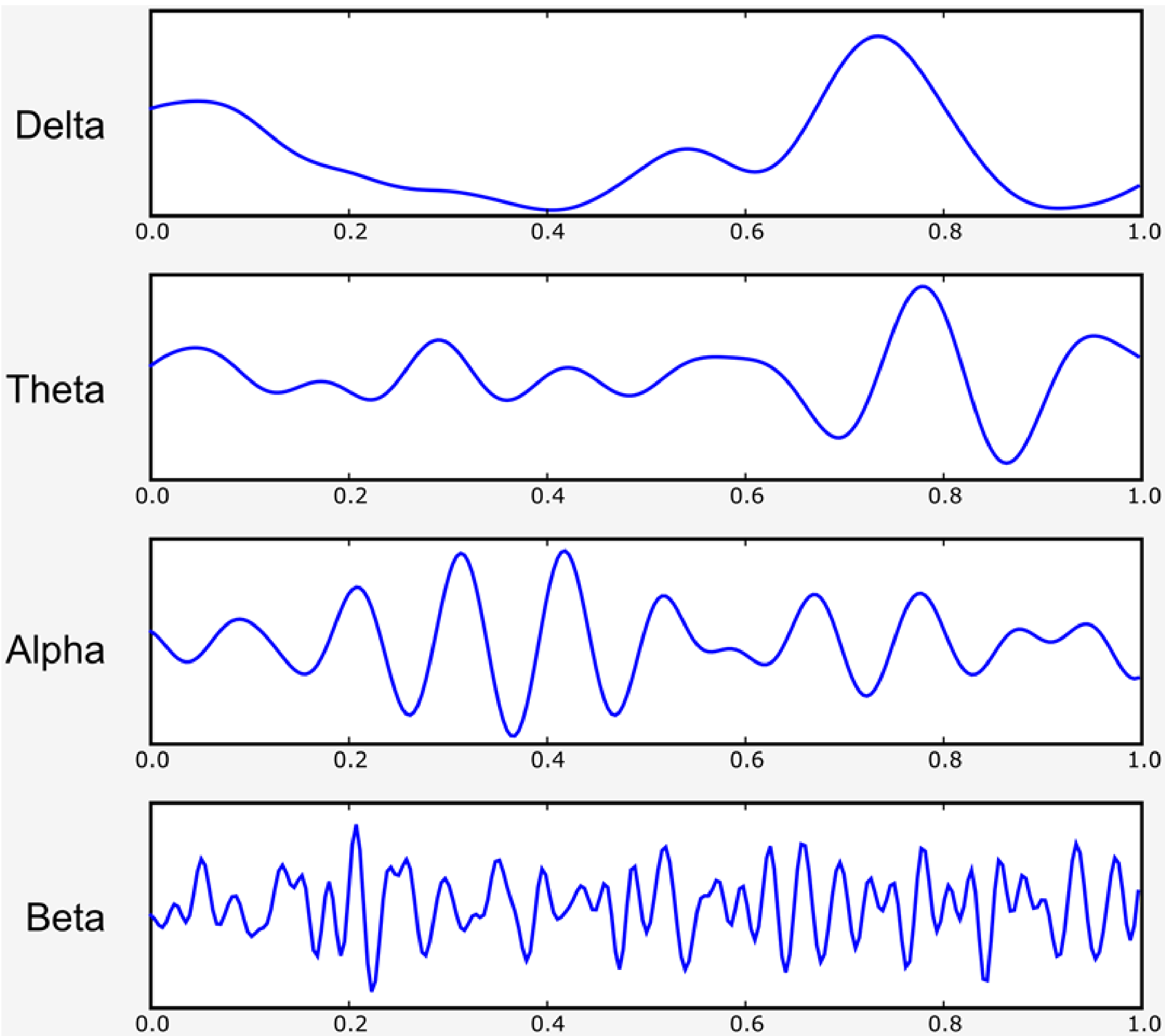


Figure 4.2: EEG Frequency Bands [24]

- **Up to 3Hz:** The frequency range of up to 3Hz is known as *Delta*. These waves are slow but high in amplitude. It is found in multiple sleep stages of up to 1 year neonatal.
- **3.5 to 7.5 Hz:** This range is considered relatively a slow activity and named as *Theta* frequency band. Children that are up to 13 years of age are found to have these waves, but are not acceptable for adults in awake condition.
- **7.5 to 13Hz:** Categorized as *Alpha*, are mostly observed in back side of the head on either part. These waveforms are elevated in magnitude on prevailing region. Alpha band is obvious during eyes closed and relaxation mode, and vanishes while eyes are open or thinking operation of brain. It is a main band observed in normal relaxed adults of age above 13 years.
- **Greater than 14Hz:** It is a relatively fast movement, known as *Beta* waves. These are commonly seen on each side and distributed proportionally. It is considered as a normal rhythm. It is prevailing in patients who are watchful, restless or having their eyes open.

Figure 4.2 shows the electroencephalography (EEG) frequency bands of Delta, Theta, Alpha and Beta [24].

4.3 Feature Selection

Extraction of features always remains a key factor of any overall system for recognition and classification, moreover for any algorithm that requires automatic detection of particular incident that is occurring in an uncontrolled manner. Dealing with the EEG signals for seizure detection, we require features that can distinguish any un-natural behavior in any of the above mentioned waveforms. There are numerous temporal and spectral features that can be applied for our system. But using too many features is not always a favorable option. Also if there is a need for a swift operation, along with the rate of incoming data is high, increasing number of features will never be a viable option. Although on the contrary if there are less numbers of feature, there is a possibility of a false detection or may be even overlooking a potential risk. Some of the features applied in this study are discussed herewith.

4.4.1 Time-Frequency (t-f) Flux

Spectral flux is the measure of only frequency change in a signal, dealing with the stationery signals. T-F flux is the modified form of spectral flux for signal's energy change detection in both temporal and frequency domain. It deals with the non-stationery signals such as the EEG signals. The mathematical form of which is shown in equation 4.1 [22]:

$$TF_{FLUX} = \sum_{n=1}^{N-l} \sum_{k=1}^{M-q} |\rho[n+l,k+q] - \rho[n,k] \quad (4.1)$$

The parameters l and q are dependent on the rate of t-f flux change. The values used are l=1,$q = 1, N = 256\ and\ M = 256$. t-f image is of dimension 256x256, so both the parameters N and M are choosen accordingly.

As EEG seizure signals change their energy slowly along both time and frequency, so t-f flux is used to identify these variations. EEG normal activity in 'awake' condition can also show an arbitrary pattern like seizure signals. While taking the (t, f) flux of EEG signals, we can distinguish between both normal and seizure states. (t,f) flux will have a lower value for seizure activity and high value for normal activity.

4.4.2 Time-Frequency (t-f) Flatness

Spectral flatness is a measure of distinction between a pure noise and a no-noise signal. The time-frequency (t,f) flatness feature will distinguish between the noises or no-noise in an EEG image. Also it determines whether EEG signal energy is widespread on concentrated in specific regions. If the t-f flatness has an increased value than it depicts that the signal's energy is equally distributed, whereas if we get a decreased value this means that the energy is concentrated in some parts of the over the EEG image. In addition to the above, the t-f flatness also assists to distinguish between TFD's having signal components entrenched in noise and those having pure noise.

Time-frequency flatness is the ratio of geometric mean and arithmetic mean of a TFD image. The transformed function from spectral flatness to t-f flatness can be mathematically expressed as [22]:

$$TF_{Flatness} = \frac{(\Pi_{n=1}^{N} \Pi_{k=1}^{M} \rho[n,k])^{\frac{1}{NM}}}{\frac{1}{NM} \sum_{n=1}^{N} \sum_{k=1}^{M} \rho[n,k]} \quad (4.2)$$

The parameters N and M both have values of 256 in the above equation (4.2). While $\rho[n,k]$ is the TFD image.

4.4.3 Renyi Normalized Entropy

The spectral entropy (SE) is the amount of irregularity in the proportion of the signal energy in the frequency domain. It can be expressed as [22]:

$$SE_{(f)} = -\sum_{k=1}^{M} Z_x[k] \log_2 Z_x[k] \quad (4.3)$$

Where $Z_x[k]$ is defined as [22]:

$$Z_x[k] = |Z_x[k]|^2 / \left(\sum_k |Z_x[k]|^2\right) \quad (4.4)$$

In time-frequency domain, spectral entropy expression will be changed. Shannon Entropy (SE) will be expressed as [22]:

$$SE_{(t,f)} = -\sum_{n=1}^{N} \sum_{k=1}^{M} \frac{\rho_{z_x}[n,k]}{\sum n \sum k \rho_{z_x}[n,k]} \log_2 \left(\frac{\rho_{z_x}[n,k]}{\sum n \sum k \rho_{z_x}[n,k]} \right) \quad (4.5)$$

Raised SE $_{(t,f)}$ value depicts that signal energy is homogeneously extended in the (t,f) plane. Low SE $_{(t,f)}$value depicts that signal energy in clustered in particular regions in the (t,f) plane. Shannon entropy has restrictions, that it can’t be used for TFD’s which assume negative values. To overcome this, normalized Renyi Entropy is introduced. The mathematical form of which is written in equation 4.6 [22]:

$$RE_{(t,f)} = \frac{1}{1-\alpha} \log_2 \sum_{n=1}^{N} \sum_{k=1}^{M} \left(\frac{\rho_{z_x}[n,k]}{\sum_n \sum_k \rho_{z_x}[n,k]} \right)^{\alpha} \quad (4.6)$$

Where in above equation α is an odd integer and $\alpha > 2$.

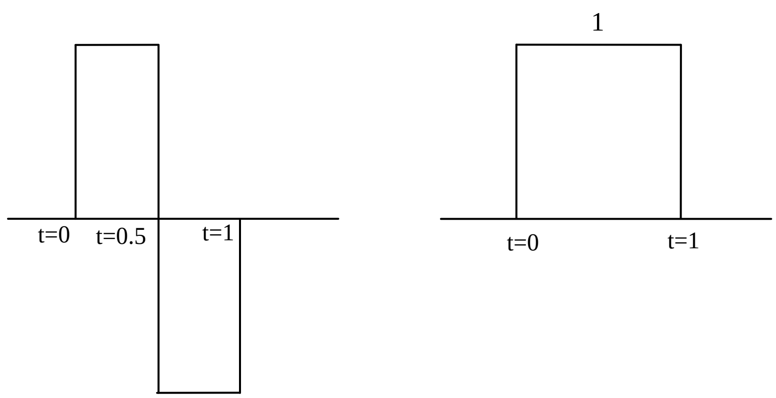
4.4 Discrete Wavelet Transform (DWT)

Wavelets provide simultaneous spatial and frequency representations of the images. The methods based on wavelets divide the images into sub bands in terms of space and frequency; hence encourage their use for feature extraction. Furthermore, the coefficients representation allows for data reduction, making it easy to handle and process the data. A considerable set of wavelet families are available, derived from their respective mother wavelet. We based DWT on the Haar Wavelet Transform. Wavelets provide multi resolution representation which keeps intact the global as well as local information.

Wavelets are categorized as Continuous wavelet transforms (CWT) and discrete wavelets transform (DWT). Mostly in real life problems we are facing non-stationery signals, wavelets are highly recommended for these sorts of situation because of their finite oscillator motions. Wavelet transform offer joint “time-frequency” resolution in contrast to only Fourier transform which present only frequency analysis.

Mother wavelet is used as a function for further analysis. Different methods are applied over temporal and frequency domain. Time analysis is undertaken with a tapered, high-frequency transformation of the mother wavelet, whereas frequency analysis is accomplished with a widened, low-frequency transformation of the mother wavelet. Basic function can be represented in a number of wavelet forms, with multiple linear combinations of wavelet coefficients. These different combinations allow for data processing with these coefficients. Furthermore optimal wavelets can be chosen that best adapts to a particular problem. In addition to this, the coefficients representation in this manner allow for data reduction, making it easy to handle and process the data.

Wavelets are decomposed as Haar, Daubechies and Symmlets. Haar wavelet is the simplest form of decomposition. It consists of a mother wavelet (Ψ) and a scaling function (Φ). The two functions can be defined as shown in figure 4.3.



Mother Wavelet Ψ (t) Scaling Function Φ (t)

Figure 4.3: Haar Wavelet Filter Function

The Haar scaling function is defined as in equation 4.7 [25]:

$$\emptyset(t) = \begin{cases} 1, & 0 \leq t < 1 \\ 0, & otherwise \end{cases} \tag{4.7}$$

The Haar wavelet mother function is expressed as in equation 4.8 [25]:

$$\psi(t) = \begin{cases} 1, & 0 \leq t < \frac{1}{2}, \\ -1, & \frac{1}{2} \leq t < 1, \\ 0, & otherwise \end{cases} \tag{4.8}$$

Daubechies wavelets in comparison to Haar wavelets are defined in a different manner. Mainly the difference is the mother wavelet and the scaling function. There are a number of Daubechies wavelet transforms but all are mostly alike. The scaling numbers are represented as [25]:

$$\alpha_1 = \frac{1+\sqrt{3}}{4\sqrt{2}}, \quad \alpha_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, \quad \alpha_3 = \frac{3-\sqrt{3}}{4\sqrt{2}}, \quad \alpha_4 = \frac{1-\sqrt{3}}{4\sqrt{2}} \tag{4.9}$$

While the Daubechies mother wavelet will be expressed as [25]:

$$\psi(t) = -\alpha_4(2t) + \alpha_3(2t-1) - \alpha_2(2t-2) + \alpha_1(2t-3) \tag{4.10}$$

Discrete Wavelet Transform (DWT) has been used in both signal analysis and image processing, for feature extraction and noise reduction applications. We will look into the details in our work in forthcoming documentation. Type of wavelet family filter and level of decomposition to reach is also important in image analysis [25].

4.5 Proposed Methodology

The proposed technique will commence from the time-frequency image representation, followed by the feature extraction by discrete wavelet transform (DWT).Extracted features will be evaluated for performance by the support vector machine (SVM) classifier. The methods that will be used for seizure detection and classification are discussed in forthcoming sections.

4.5.1 Time Representation of EEG Signal

As discussed in previous chapter the EEG signals are 1-D, with amplitude changing over a time scale. Figure 4.4 shows the EEG sample of a seizure signal.

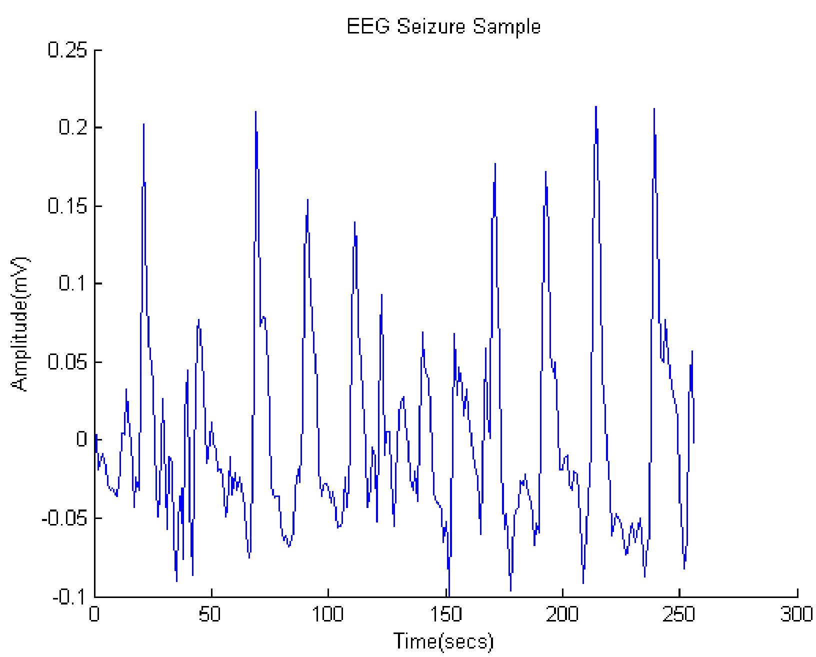


Figure 4.4: EEG Test Sample of a Seizure Signal

The sample is taken from the same dataset that was used by Boaleum Boashash in his research work. This is a one dimensional signal, with time in seconds along the abscissa and amplitude in milivolts (mV) along the ordinate. The figure 4.5 shows the EEG test sample of a non-seizure signal. Further these signals will be taken to have a joint time-frequency representation of the signals.

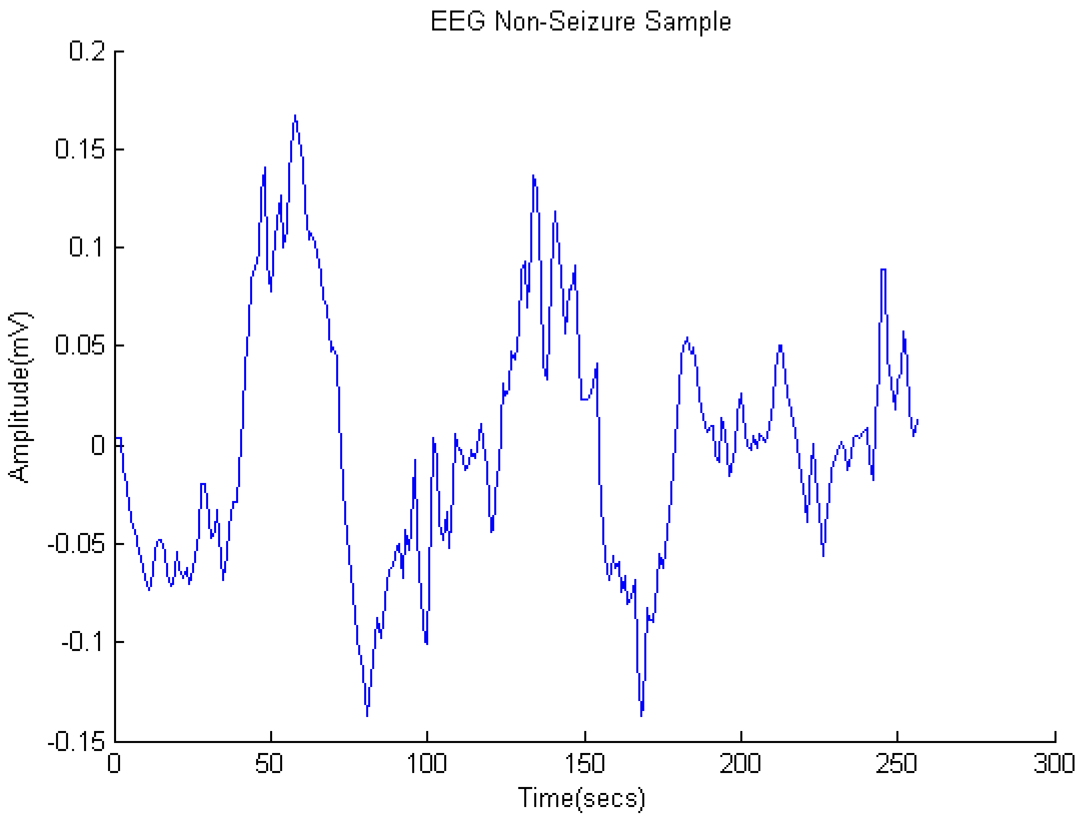


Figure 4.5: EEG Sample of a Non-Seizure Signal

4.5.2 Time-frequency Image Representation of EEG Signal

To signal represented in the above figure is taken as:

$$y(t) = s(t) \tag{4.11}$$

This signal of equation 4.11 is then given as an input to the time-frequency signal analysis toolbox (TFSA6.2) for joint time-frequency image representation. The toolbox applies different quadratic time frequency distribution (QTFD) Kernal, as per user's choice. Also the specific process used is called discrete convolution is also performed. The quadratic time-frequency distribution used in this study is extended modified B (EMB) distribution Kernal. The general equation that works to generate the time-frequency image is [23]:

tf_image =quadtfd(signal,lag_win_length,time_res,kernel[,kernel_options],[fft_length])(4.13)

In the above mentioned equation inputs to the respective quadratic time-frequency distributionare:

1) Signal, is the one dimensional input signal after computation of the real and imaginary part product.
2) Lag_window_length, is the size of the Kernal.
3) Time_res, is the successive values over the time scale that is to be taken.
4) Kernal, is the type of quadratic time-frequency distribution (QTFD) that is to be used.
5) kernel_options, are different for each QTFD. In our case two parameter values are set α=0.01 and β=0.19.
6) fft_length, is the length of the Fourier transformed signal.

Figure 4.6 and 4.7 represent the time-frequency images of the seizure and non-seizure signal respectively.

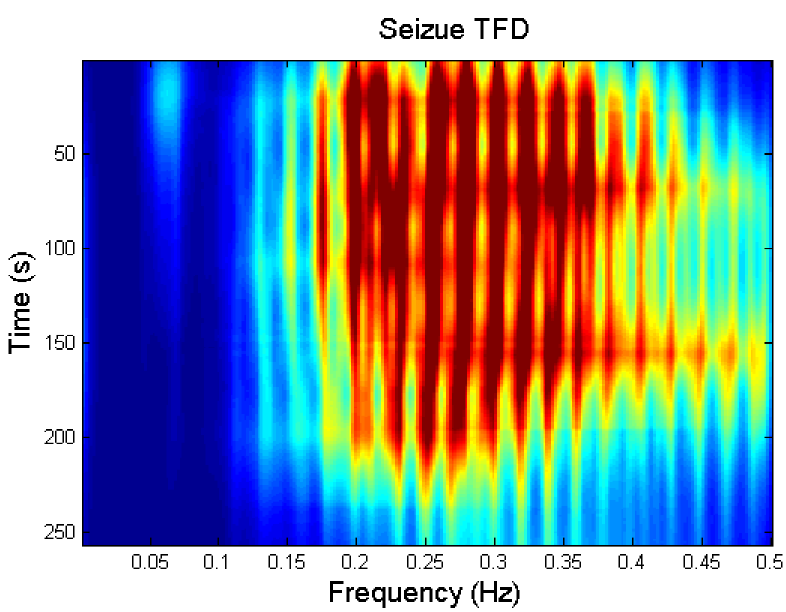
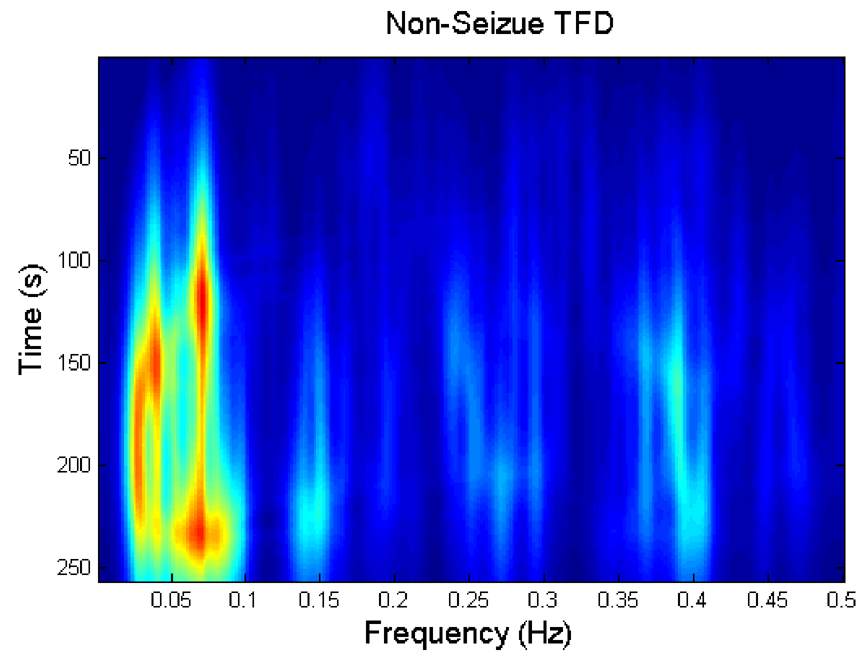


Figure 4.6: Representation of Seizure Signal in Time-Frequency Domain

Two properties of the time-frequency image are:

1) Integral of the time-frequency distribution (TFD) along the frequency axis gives us the instantaneous power $|z(t)|^2$.
2) Integral of the time-frequency distribution (TFD) along the time axis gives us the energy spectrum $|Z(f)^2|$.



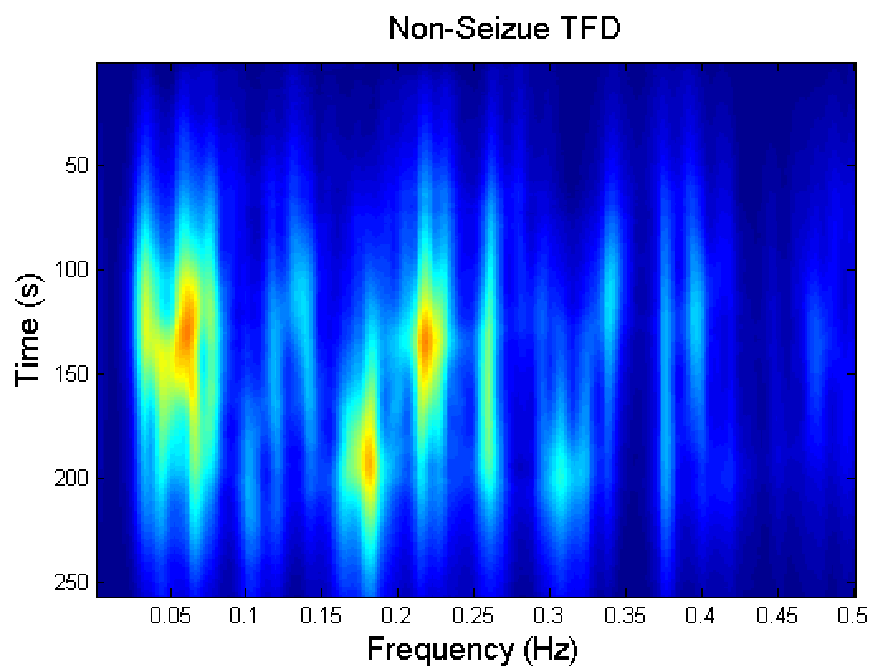


Figure 4.7: Representations of Non-Seizure Signal in Time-Frequency Domain

The mathematical form of the time-frequency image representation used in this study is expressed below [23]:

$$\rho_z[n,k] = 2\mathrm{DFT}_{n\rightarrow k}\{G[n,m] *_n (z[n+m]z^*[n-m])\} \qquad (4.13)$$

Note that $n = t$ and $k = \frac{2M}{f_s} f$ here t and f are the continuous time and frequency variables, and f_s is the sampling frequency of the signal. $G[n,m]$ is the time-lag Kernal given by Table 3-1.

4.5.3 Feature Extraction through DWT

Discrete Wavelet transform (DWT) is preferred for the feature extraction due to a number of reasons. It allows for variable window size as compared to short term Fourier transform (STFT) which doesn't allow this. As for higher frequency components a smaller window can be used, whereas for lower frequency component a larger window can be applied. In this study 2-D discrete wavelet transform has been applied. The figure 4.8 shows the methodology applied for the seizure detection. Figure 4.9 and 4.10 represents the output for seizure and non-seizure samples respectively.

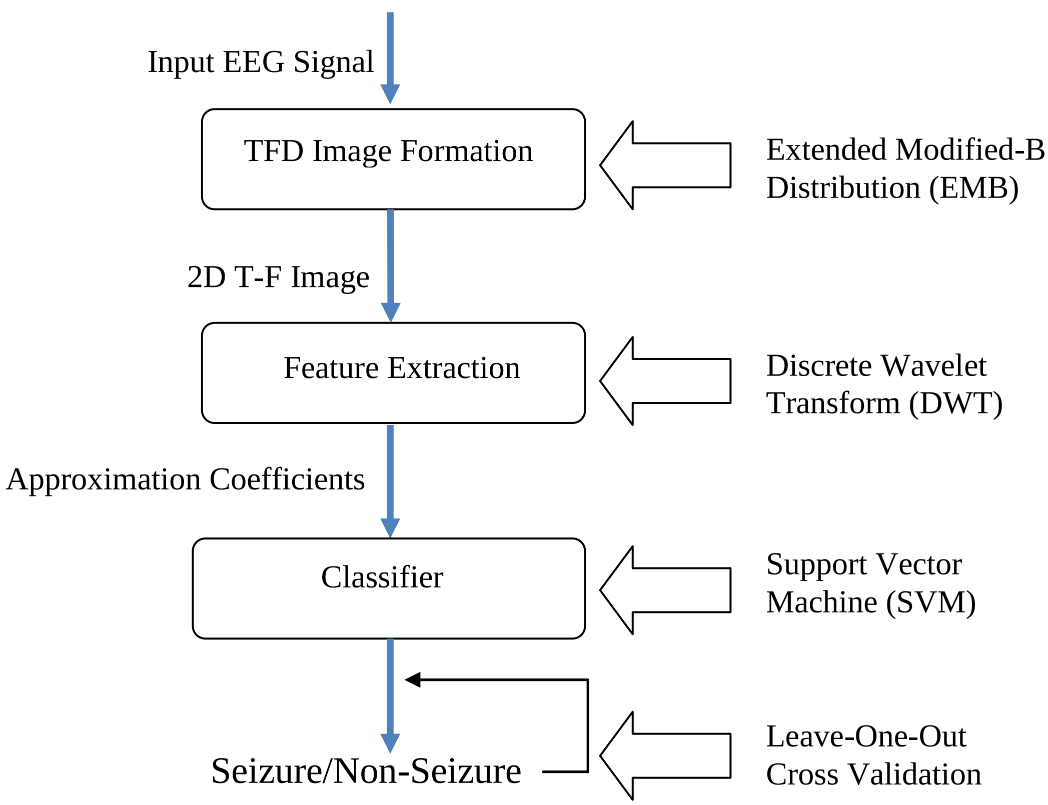


Figure 4.8: Methodology for Seizure Detection

4.6 Discussion

Time-frequency representation of non-stationery signal is presented in this chapter. It provides the transients present in both temporal and spectral domains. Constant-t shows the number of frequency components present at a particular time. Constant-f shows the power density at that frequency. In contrast to this representation, only time domain cannot show what frequency changes are occurring at each time instant and only frequency domain cannot predict the time at which any particular frequency was present in the signal. In next chapter we will discuss the classification of seizure on the basis of proposed DWT feature.

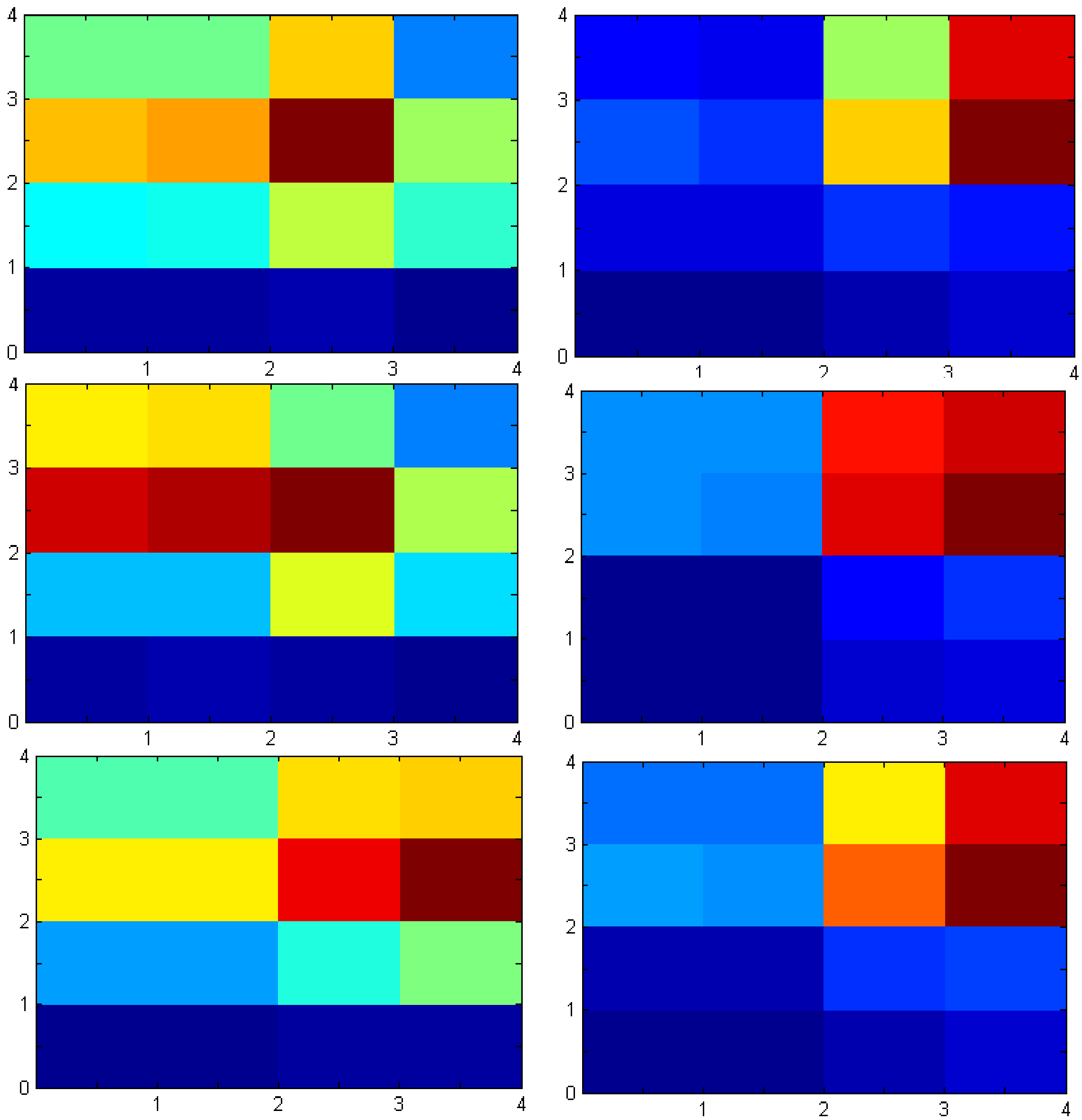


Figure 4.9: Examples of DWT level-4 approximation coefficients of seizure (left column) and non-seizure (right column) samples.

CHAPTER 5: PARAMETERS AND CLASSIFICATION

5.1 Introduction

Performance of any algorithm always remains a major factor for acceptance or rejection of a particular method. In this section the parameters that are considered as a prime technique for evaluation of a method are discussed. Results produced by various features are compared.

5.2 ROC Analysis

The features discussed in the previous chapter were tested for Receiver Operating Characteristics (ROC). Each feature is analyzed for the Area Under Curve (AUC) for seizure detection. All the modeling was executed in MATLAB. Each feature was tested by giving hundred samples of EEG. The signal values from the twenty EEG channels were averaged to give a single value. The sampling frequency of the signal is 256 Hz and length of the EEG signal is 255 s. the averaging of EEG signal over multiple channels is given by [22]:

$$x[n] = \frac{1}{20}\sum_{i=1}^{20} eeg_i[n] \tag{5.1}$$

The methodology for the seizure detection through EEG signals is presented in the following figure.

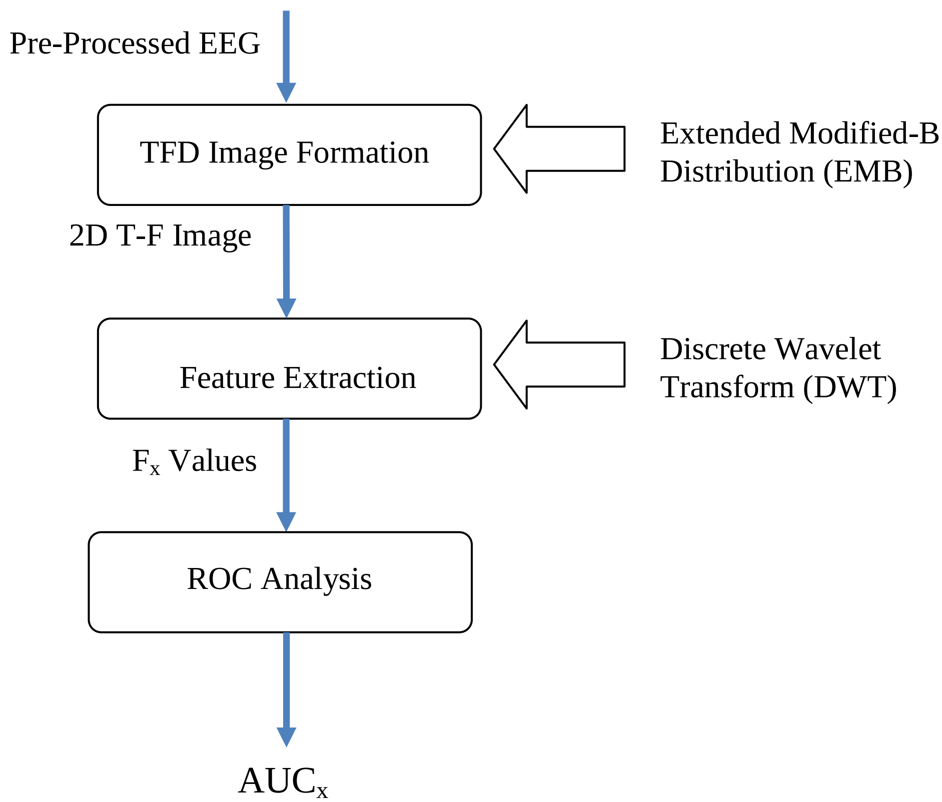


Figure 5.1: Methodology for calculating Area Under Curve (AUC)

Figure 5.1 depicts the evaluation of area under curve of each feature. Pre-processed EEG signal is averaged over twenty channels and band-passed filtered. 2-D image formation is attained by applying the TFSA toolbox available on the website link:www.timefrequency.net [22]. Afterwards this image is tested over the applied feature. The resultant vector of a feature F_x is provided to the performance evaluation parameter of Area Under Curve (AUC). After complex computations, we are provided with the resultant AUC value of respective feature.

A number of features used in this study are analyzed for best possible results. Each feature is further studied for different quadratic time-frequency domain representation. Depending upon the nature of our problem, a single feature can perform differently over various time-frequency distributions. The feature that gives maximum area under curve is considered to be best suited. There can be a number of features that to be tested over the algorithm, but here in this work we have chosen four features. Applying too many of them will increase the complexity and computational time.

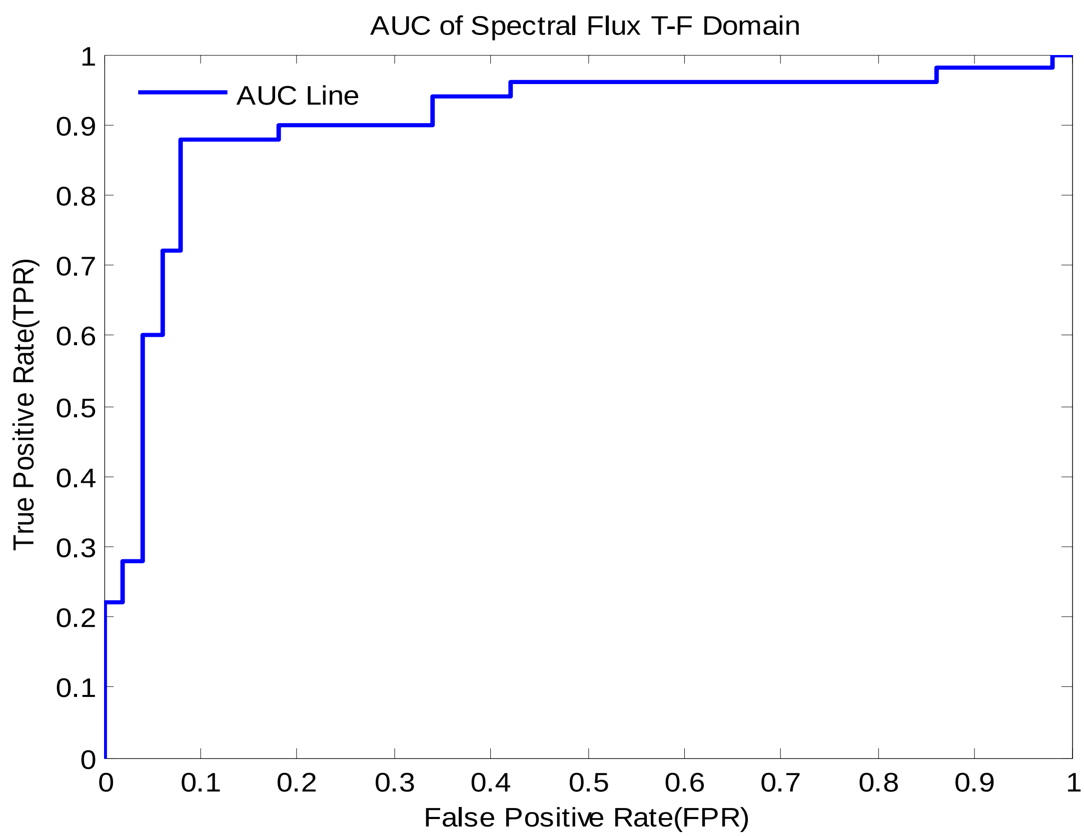


Figure 5.2: Area Under Curve (AUC) for Spectral Flux T-F Domain using MBD

5.2.1 Area Under Curve (AUC)

The area under curve (AUC) value is taken by using the perf-curve operation of MATLAB. It takes three arguments. First is *labels* values, these are the standards which are to be maintained by the algorithm. Second is the *scores*, these are the values which are obtained through the data processed by the feature set. Third is the *pos-class*, which will define the class in which the output will lie.

The first feature that has been taken is time-frequency Spectral flux (T-F Flux). The figure 5.2 shows the area under curve for the feature using Modified-B quadratic distribution. The same feature is considered for other quadratic time-frequency distributions (QTFD). The AUC value for spectral flux t-f is 0.90 in the above given figure. This is the maximum AUC value achieved by this feature for any quadratic time-frequency distribution (QTFD). The results from other QTFD's will be provided further in tabular form.

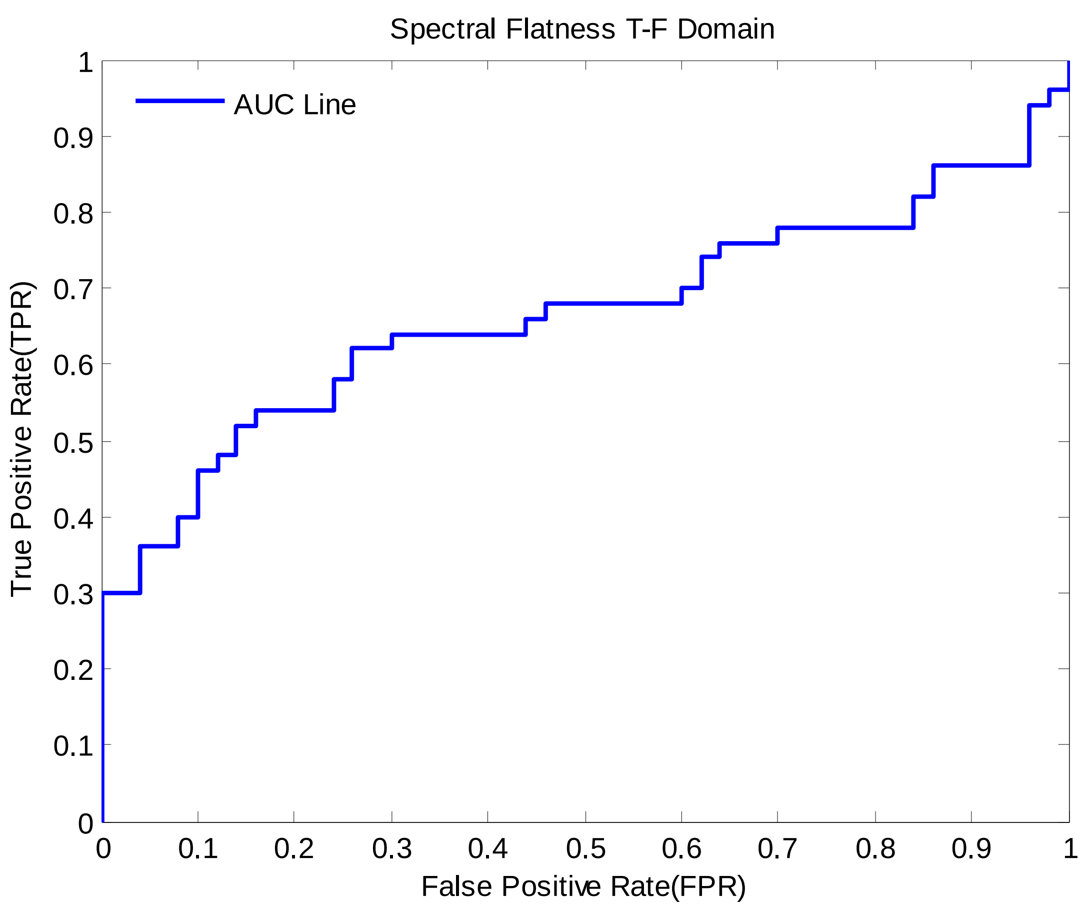


Figure 5.3: Area Under Curve (AUC) for Spectral Flatness T-F Domain using CW distribution

Second feature used is the time-frequency flatness (T-F Flatness). The highest AUC value achieved by this feature is 0.67, by using the Choi-Williams (CW) distribution. Figure 5.3 shows the area under curve.

Renyi normalized entropy is considered as another feature for the seizure detection. The best outcome from this feature is obtained through the Choi-Williams quadratic distribution. The area under curve value attained by this is 0.74. Figure 5.4 represents the AUC curve for this feature. The Renyi normalized entropy also provided better results than time-frequency flatness in other QTFD's but less than time-frequency flux. The values achieved by other TFD's will be provided in table.

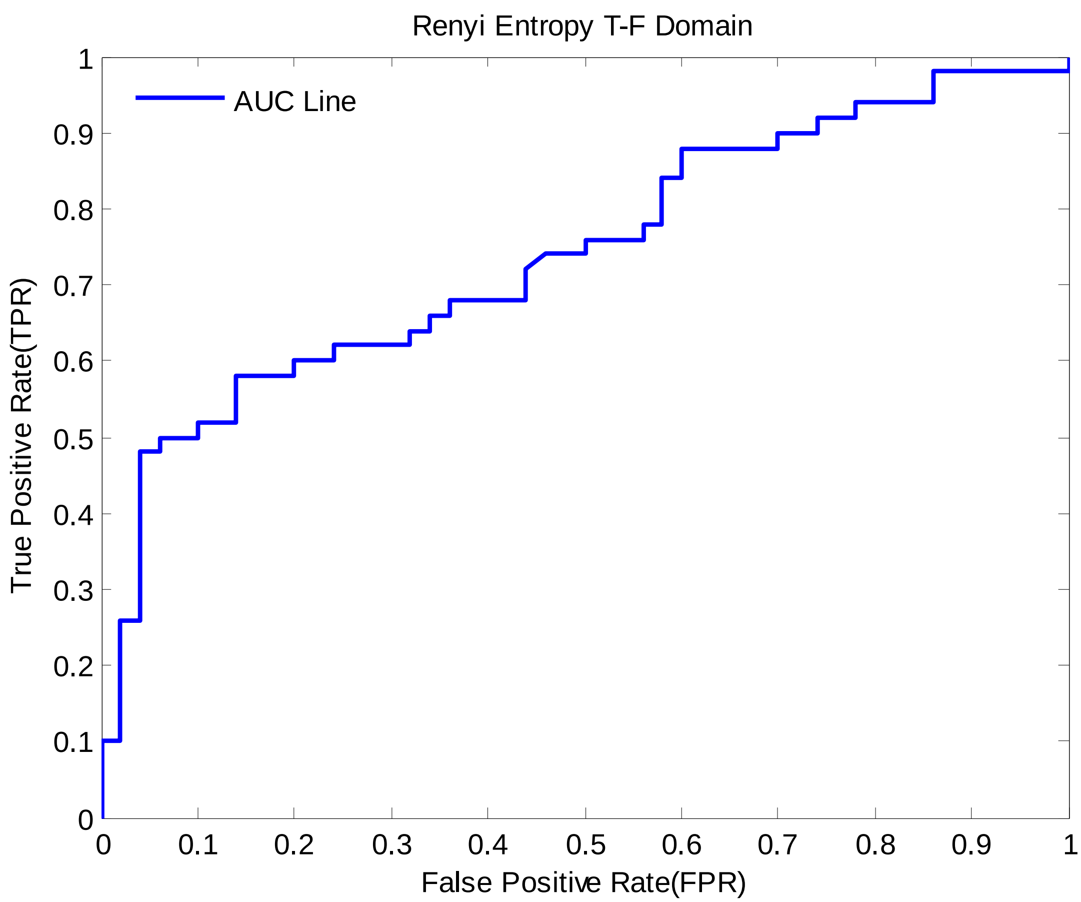


Figure 5.4: Area Under Curve (AUC) for Renyi Normalized Entropy using CW distribution

Discrete wavelet transform (DWT) is also analyzed for calculating ROC curve. This feature is run over the EEG dataset for multiple time-frequency distributions. The AUC's achieved by

DWT will be presented further in the table. Extended Modified B distribution (EMB) provided the maximum value of 0.90. While Modified B distribution (MB), Short Time Fourier Transform (STFT) and Spectrogram (SPEC) followed respectively. In this study DWT is considered for seizure classification, as AUC values for DWT is higher in three QTFD's, which is higher than any other feature.

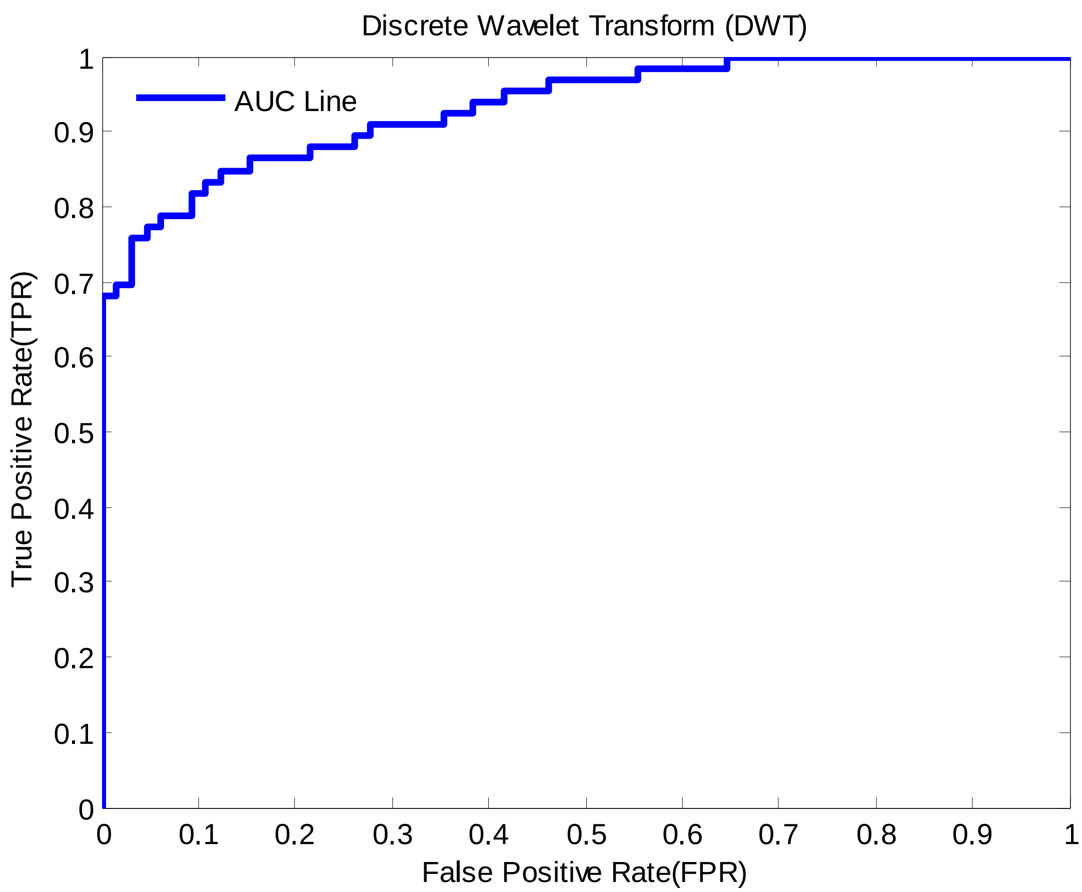


Figure 5.5: Area Under Curve (AUC) for Discrete Wavelet Transform (DWT) using EMB

Table 5-1: Area Under Curve (AUC) values for various Features using QTFD's

T-F Features	Quadratic Time-Frequency Distribution (QTFD) (%)					
	EMB	MB	SPEC	STFT	CW	WVD
DWT	90	79	72	71	55	52
Spec Flux	64	90	59	66	70	64
Spec Flatness	57	61	51	67	54	57
Renyi Entropy	65	63	65	74	51	65

Table 5-1 provides the detailed area under curve values for respective feature set using different QTFD's. Among the time-frequency distributions, extended modified B distribution gives the maximum value of AUC for variance of 16 DWT features. The same will be considered for the classification of seizure detection.

5.3 Classification

Classifying the data is a major part of evaluation. The classifier used in this work is support vector machine (SVM). It is an administered stereotype algorithm [26]. It creates a hyper plane between the data [27]. SVM is a binary classifier, which distinguishes between the classes. First the data is set for training the SVM. Afterwards data is provided for testing. For training the classifier a number of name-value pair arguments are taken by the MATLAB function. Kernel function uses to map the data. According to research the most accurate is the *Gaussian radial basis function* 'rbf' kernel. Sigma value can be set as per requirement. A value of three is selected for rbf-sigma. Also there can be a linear method, as it varies with the dataset that is to be tested. As *linear approximation* produced better accuracy in this study, so it is used. Another argument is the method for construction of hyper plane. Quadratic programming (QP) is selected here. The box-constraint is set at 2.5. After the training of the classifier, it is provided to the testing part for grouping of the data.

5.3.1 Classifier Results

To check the performance of the methodology, parameters provided by the support vector machine (SVM) are used [28]. Parameters which are sensitivity [29], specificity [30], positive predictive value (PPV) [31] and negative predictive value (NPV) [31] are checked. These will be defined in forthcoming documentation.

Support vector machine (SVM) based classification for seizure detection has been carried out through MATLAB. The results previously obtained for seizure detection through EEG are compared. The figure 5.6 below represents the classifier output. As the plot can only be 2-D, so the figure displayed will only be representing results of 2 features out of a total of 16 DWT features.

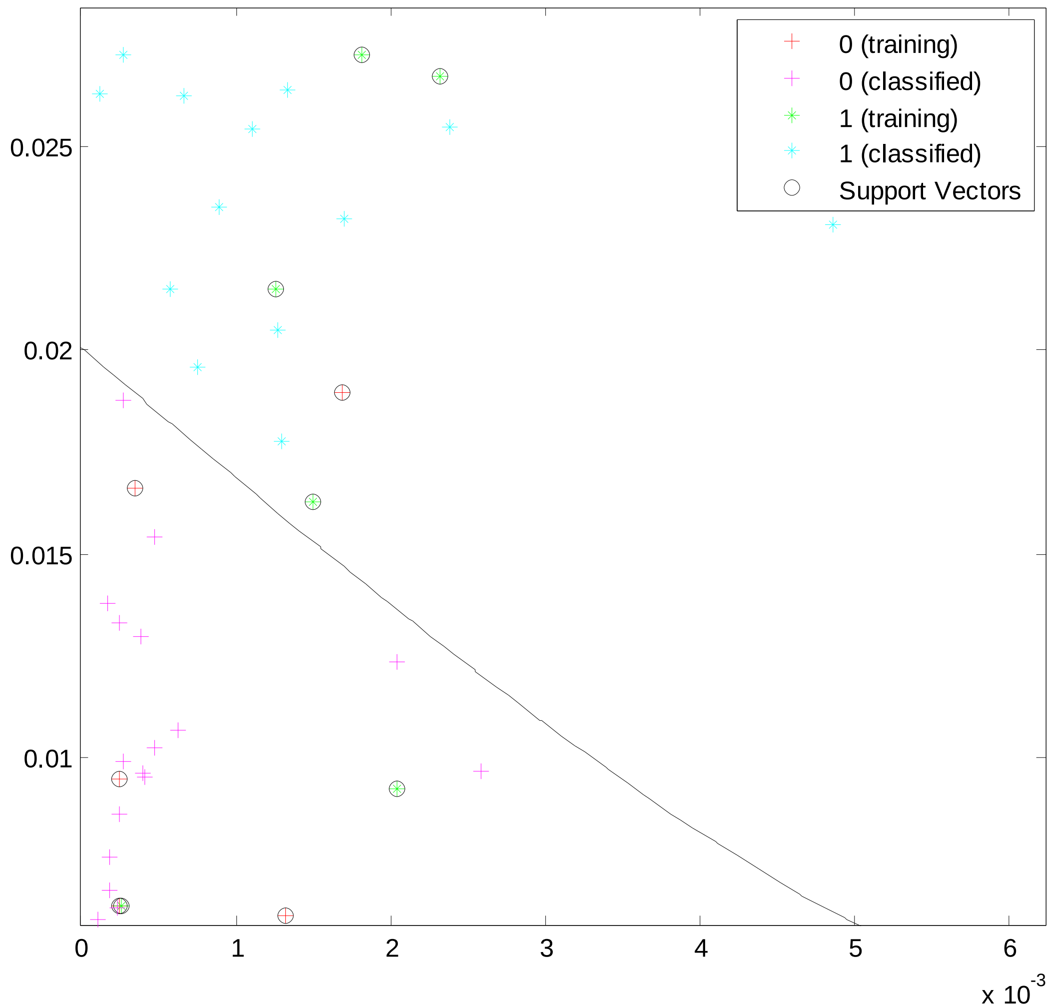


Figure 5.6: Classifier Output for 2-D Discrete Wavelet Transform (DWT)

There has been improvement in detection using the 2-D Discrete Wavelet Transform (DWT). The classifier's performance for the other three features was less than DWT. With t-f spectral flux, t-f flatness and Renyi normalized entropy resulting with 50 percent accuracy. Also comparing the results with the same features in other research study, it is examined that discrete wavelet transform (DWT) alone performs a better classification for seizure. The results from other works are also tabulated for comparison in table 5-2 [20]. Performance parameters for the classification are defined as under.

$$\text{Sensitivity} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}} \tag{5.2}$$

$$\text{Specificity} = \frac{\text{number of true negatives}}{\text{number of true positives} + \text{number of false negatives}} \tag{5.3}$$

$$\text{PPV} = \frac{\text{number of true positives}}{\text{number of true negatives} + \text{number of false positives}} \tag{5.4}$$

$$\text{NPV} = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false negatives}} \tag{5.5}$$

$$\text{Accuracy} = \frac{\text{number of true positives} + \text{number of true negatives}}{\text{number of positives} + \text{number of negatives}} \tag{5.6}$$

Table 5-2: Comparison of EEG seizure Detection Results of 2-D DWT using SVM

Feature	**TFD**	**SVM Statistical Parameter (%)**				
		SEN	SPE	PPV	NPV	ACC
DWT	EMB	98.75	100	100	98.76	**99.37**
$FV_{i=1\text{-}8}$	SWVD	95.00	92.50	93.24	95.19	93.75
$FV_{i=1\text{-}8}$	WVD	83.75	92.50	92.50	86.35	88.13
$FV_{i=1\text{-}8}$	MB	91.25	91.25	92.09	92.06	91.25
$FV_{i=9\text{-}17}$	CWD	95.00	90.00	91.46	95.67	92.50
$FV_{i=9\text{-}17}$	SPEC	93.75	92.50	92.92	94.09	93.13
$FV_{i=9\text{-}17}$	EMB	98.75	76.25	82.02	98.33	87.50

The table above represents the results achieved by this research in comparison to other work for seizure detection. Discrete Wavelet Transform (DWT) achieved an accuracy of 99.37 percent with extended modified B (EMB) as the quadratic time-frequency distribution (QTFD). Whereas in the previous study discussed here, which applies the same QTFD using eight features provided an accuracy of 87.5 percent. While a maximum of 93.75 percent of accuracy was achieved by using a feature set of eight with Smoothed Wigner-Ville Distribution (SWVD). For classifier evaluation a dataset of 80 seizures affected and 80 background signals were used, with leave-one-out cross validation. $FV_{i=1\text{-}8}$ in the table represents eight features that include (t, f) flux, (t, f) flatness, Renyi entropy, mean, variance, skewness, kurtosis and coefficient of variation. While $FV_{i=9\text{-}17}$ include mean of the IF, deviation of the IF, Complexity measure, Maximum of singular values, Mean of S_{wr}, Standard deviation of S_{wr}, Mean of S_{hr}, Standard deviation of S_{hr} and TFD concentration measure.

For the seizure detection and classification, these parameters were cross validated. The results were obtained using the random permutation of the data. As both seizure and non-seizure data was randomly distributed ten times and iterated for training and testing. Conclusive findings are achieved by taking the average of ten successive repetition of algorithm.

5.4 Discussion

Seizure detection through time-frequency imaging has achieved a considerable attention over past years. There are a number of methodologies that has been proposed and tested for accuracy. This research provides another insight for the classification of seizure activity inside human brain. Time-frequency domain proves to be a new dimension for advancement in this field of research. Also joint time-frequency domain is seems to be more suitable for the non-stationary natured signal as of electroencephalography (EEG) [21].

CHAPTER 6: Conclusion and Future Work

This thesis summarizes the quest carried out in the seizure detection through electroencephalography (EEG). It started with a broad revision of the field which made possible to decide the methodology. Multiple researches have been carried out for the same using different techniques. Each of which having it's pros and cons. The findings and observations stated in this work can serve as a guide for future research projects.

The time-frequency domain is an emerging area, awakening the interest of the researchers in biomedical engineering. It also comes up with new challenges and at the same time an opportunity to develop an improved approach. Feature extraction performed through 2-D discrete wavelet transform (DWT) provided a better approximation as compared to other features. For classification support vector machine (SVM) is used, as it produces better accuracy for binary classifier problem. Furthermore Leave-one-out cross validation (LOO) is used, as an assurance of the algorithms correct recurring decisions.

There is always room for improvements to be made in any form of research. The performance degrades, as the number of training to testing sample's ratio decreases. We plan to use detail coefficients of DWT at different decomposition levels in addition to the approximation coefficients to address this issue. Robustness of our approach will also be validated by using the available full database of 400 samples. Other datasets mentioned in the literature survey chapter will also be tried when available.

The current research used twenty channels EEG data, which can be taken up to twenty four channel. With the increased number of channels there will be excess of incoming data, to achieve the same accuracy with increased data and reduced timing can be another way forward. Further increased number of channels will have higher artifacts than lower channels. Artifact detection and removal at pre-processing stage will add on to another dimension. There has to be an algorithm which can work on any dataset that is provided to it. As different datasets will have respective artifacts and variations, so a robust algorithm that works on any dataset provided will be much more efficient. Different age group's EEG signals have distinct energy representation in respective bands. So a system that provides accurate results for any age group will be more effective than compared to the one which is applicable to only a limited set of age group.

APPENDIX A

MATLAB Code

Following are the codes that were implemented in MATLAB to achieve the results of AUC and SVM.

ROC Analysis

```
clear all
close all
clc
load('seizure_samples.mat');
load('non_seizure_samples.mat');
%Spec_flux_variance_tf_mat = zeros(100,1);
%Spectral_flatness_mat_tf = zeros(100,1);      %  Matrix for calculating Spectral flatness in
TFD
%Approximation_coefficients = zeros(131,1);
%dwt_label_mat = ones(132,1);
%Area_under_curve = zeros(100,1);
test_auc = zeros(100,256);
 row_count =1;
for samples = 151:200
        test_auc(row_count,:) = seizure_samples(samples,:);   %  Add 50 Seizure Samples for AUC
Test
    row_count = row_count+1;
end
 row_count = 51;
 for samples = 151:200
    test_auc(row_count,:) = non_seizure_samples(samples,:);   %  Add 50 Non-Seizure Samples
for AUC Test
    row_count = row_count+1;
end
 for rows = 67:131
    dwt_label_mat(rows,1)=0;
end
for patients_data = 1:100
row_1=test_auc(patients_data,:);          %    x[n],extracting EEG Data of a SINGLE Patient
figure
hold on;
plot(row_1)
title('Single Patients EEG')
label('Time')
ylabel('Value')
hold off;
```

```
%tfrep = quadtfd(signal,lag_win_length,time_res,kernel[,kernel_options],[fft_length])
tfrep = quadtfd(prod_real_imag_1,255,1,'wvd',252);          % WVD
tfrep = quadtfd(prod_real_imag_1,255,1,'cw',10,256);        % Choi-Williams
tfrep = quadtfd(prod_real_imag_1,255,1,'mb',0.01,256);      % MBD
tfrep = quadtfd(prod_real_imag_1,255,1,'emb',0.01,0.19,256); % EMBD
tfrep = spec(prod_real_imag_1,128,11,'hann',257,1);         %SPEC=0(STFT=1)

figure
%tfsapl(prod_real_imag_1,tfrep,'TimePlot','on','FreqPlot','on','title','Time-Frequency
Plot','TimeGrid','on','FreqGrid','on');  % Time-Frequency 2-D Plot
 tfrep_scaled= abs(tfrep);

 %--------------------Spectral Flux Content T-F Domain--------------------%

 k_=0;
 n_=0;
 Spectral_flux_tf = zeros(256,256);
 %Spectral_flux_tf = zeros(257,2);
 for n_= 1:255
 %    for n_ = 1:256
  for k_= 1:255
  %     for k_ = 1:1
    Spec_flux_tf = tfrep_scaled(n_+1,k_+1)-tfrep_scaled(n_,k_);
   Spectral_flux_tf(n_,k_) = Spec_flux_tf;                    %saving values of spectral content
  end
 end
 %Spec_flux_variance_tf_mat([1 patients_data])= var(Spectral_flux_tf(:));
   % Calculates Variance of each patient's Spectral Flux
 var_mat = var(Spectral_flux_tf(:));
 Spec_flux_variance_tf_mat(patients_data,:)= var_mat;
     % Calculates Variance of each patient's Spectral Flux

 %----------------------Spectral Flux Content T-F Domain------------------%

 %-------------------Spectral Flatness T-F Domain-------------------------%

 geo_mean_row_tf = geomean(tfrep_scaled,2);      % Geometric mean of rows
 geo_mean_col_tf = geomean(tfrep_scaled,1);      % Geometric mean of columns
 Spectral_flatness_num_tf = geo_mean_col_tf*geo_mean_row_tf;
 Spectral_flatness_den_tf = mean2(tfrep_scaled);% Arithmetic mean of numerator
 Spectral_flatness_mat_tf(patients_data,1) =65536*(Spectral_flatness_num_
tf/Spectral_flatness_den_tf);  % Saving Spectral flatness value in matrix

%---------------------Spectral Flatness T-F Domain----------------------%
 %------------------Spectral Flatness T-F Domain STFT/SPEC---------------%
```

```
geo_mean_row_tf = geomean(tfrep_scaled,2); % Geometric mean of rows
geo_mean_col_tf = geomean(tfrep_scaled,1); % Geometric mean of columns
Spectral_flatness_num_tf = geo_mean_row_tf*geo_mean_col_tf;
Spectral_flatness_den_tf = mean2(tfrep_scaled);% Arithmetic mean numerator
expression_1 = 65536*(Spectral_flatness_num_tf./Spectral_flatness_den_tf);
  % Saving Spectral flatness value in matrix
average_value = mean(expression_1,2);
Spectral_flatness_mat_tf(:,patients_data) = average_value;

%------------------Spectral Flatness T-F Domain STFT/SPEC----------------%

%---------------------Renyi Normalised Entropy T-F Domain----------------%
Ren_entropy_exp=0;
double(Ren_entropy_exp);
Ren_entropy_den = sum(sum(tfrep_scaled));                    % Renyi Entropy Denominator
%for ren_n = 1:256
 for ren_n = 1:256
   for ren_k = 1:256
   %for ren_k = 1:1
      Ren_entropy_exp = Ren_entropy_exp+(tfrep_scaled(ren_n,ren_k)/Ren_entropy_den)^3;
   end
end
Ren_entropy_value([1 patients_data])= Ren_entropy_exp;
%---------------------Renyi Normalised Entropy T-F Domain----------------%

%---------------------Discrete Wavelet Transform-------------------------%
  [cA,cD] = dwt(tfrep,'db4');

   [X,Y,T,AUC] = perfcurve(dwt_label_mat,cA,1);
   Area_under_curve(patients_data,1) = AUC;

%---------------------Discrete Wavelet Transform-------------------------%
end

mean(Area_under_curve);
%---------------------Spectral Flux Content T-F Domain--------------------%
spec_flux_input_mat = ones(1,100);

for columns = 51:100
   spec_flux_input_mat(1,columns)=0;
end

[X,Y,T,AUC] = perfcurve(spec_flux_input_mat,Spec_flux_variance_tf_mat,1);
plot (X,Y)    % X = Falsely +ive  Rate, Y = Truly +ive Rate
```

```
xlabel('(FPR)');
ylabel('(TPR)');
title('AUC of Spectral Flux T-F Domain');
%---------------------Spectral Flux Content T-F Domain--------------------%
%-------------------Spectral Flatness T-F Domain-------------------------%
  spec_flatness_input_mat = ones(100,1);
  for rows = 51:100
   spec_flatness_input_mat(rows,1)=0;
  end
  %label_mat = mean(Spectral_flatness_mat_tf);
[X,Y,T,AUC] = perfcurve(spec_flatness_input_mat,Spectral_flatness_mat_tf,1);
plot (X,Y,'linewidth',2)    % X = False Positive Rate, Y = Truely+ive Rate
xlabel('(FPR)');
ylabel('(TPR)');
title('Spectral Flatness T-F Domain');
legend('AUC Line','location','northwest');
legend('boxoff');
 %------------------Spectral Flatness T-F Domain-------------------------%
 %-----------------------Renyi Entropy T-F Domain------------------------%
 Renyi_entropy_input_mat = zeros(100,1);
  for rows = 1:50
   Renyi_entropy_input_mat(rows,1)=1;
  end
 Renyi_entropy_mat = (-0.5)*log2(Ren_entropy_value);     % Calculates Renyi Entropy Value
[X,Y,T,AUC] = perfcurve(Renyi_entropy_input_mat,Renyi_entropy_mat,1);
plot (X,Y,'linewidth',2)    % X = False Positive Rate, Y = Truly+ive Rate
xlabel('(FPR)');
ylabel('(TPR)');
title('Renyi Entropy T-F Domain');
legend('AUC Line','location','northwest');
legend('boxoff');
 %-----------------------Renyi Entropy T-F Domain------------------------%
```

SVM Classifier

```
clear all
close all
clc
load('seizure_samples.mat');
load('non_seizure_samples.mat');

testing_svm = zeros(50,256);
% SVM training matrix with 150 Seizure & Non-Seizure samples each
training = zeros(20,2);
```

```
% The rows of this matrix represent the sample taken and column of this matrix is the feature that
is used for distinguishing the two types
group = zeros(20,1);
% Grouping logical vector matrix
box_constraint = zeros(20,1);
% Soft margin array for SVM Struct, of same size as Training data
training_svm = zeros(20,256);
testing =zeros(50,2);
% SVM testing matrix with 25 Seizure & Non-Seizure samples each

%--------------------------EEG Training Samples---------------------------%

for rows = 1:10
   group(rows,1) = 1;%character matrix with each row representing a class
end
   %-------------------Seizure Training Samples-------------%
row_count =1;
for samples = 31:40
      training_svm(row_count,:) = seizure_samples(samples,:);
 % Add 10 Seizure Samples for AUC Test
   row_count = row_count+1;
end

row_count = 11;

for samples = 30:39
   training_svm(row_count,:) = non_seizure_samples(samples,:);
% Add 10 Non-Seizure Samples for AUC Test
   row_count = row_count+1;
end

%----------------------Box-Constraint-------------------------%

for box_rows = 1:20          % Box_constraint name-value pair rows & columns
         box_constraint(box_rows,:)= 2.5;
end

%--------------------------EEG Training Samples--------------------------%

%--------------------------EEG Testing Samples----------------------------%
row_count =1;
for samples = 1:25
      testing_svm(row_count,:) = seizure_samples(samples,:);
% Add 25 Seizure Samples for AUC Test
   row_count = row_count+1;
```

```
end

row_count = 26;

for samples = 151:175
   testing_svm(row_count,:) = non_seizure_samples(samples,:);
% Add 25 Non-Seizure Samples for AUC Test
   row_count = row_count+1;
end

%--------------------------EEG Testing Samples----------------------------%
 s = RandStream('mt19937ar','Seed',0);    % Create a scheme for RandPERM
 for k_fold = 1:10
 patients_data_1 = randperm(s,20);

%--------------------------SVMstruct Training-----------------------------%
for patients_data = 1:20
row_1=training_svm(patients_data,:);%x[n], EEG Data of a SINGLE Patient
figure
hold on;
plot(row_1)
title('Single Patients EEG')
xlabel('Time')
ylabel('Value')
hold off;



tfrep=quadtfd(signal,lag_win_length,time_res,kernel[,kernel_options],[fft_length])

tfrep = quadtfd(prod_real_imag_1,255,1,'wvd',252);          % WVD

tfrep = quadtfd(prod_real_imag_1,255,1,'cw',10,256);         % Choi-Williams

tfrep = quadtfd(prod_real_imag_1,255,1,'mb',0.09,256);       % MBD

tfrep = quadtfd(prod_real_imag_1,255,1,'emb',0.01,0.19,256); % EMBD

tfrep = spec(prod_real_imag_1,128,11,'hann',257,1);         % SPEC=0(STFT=1)

 figure

tfsapl(prod_real_imag_1,tfrep,'TimePlot','on','FreqPlot','on','title','Time-Frequency

Plot','TimeGrid','on','FreqGrid','on'); %Time-Frequency 2-D Plot
```

```
 %---------------------Discrete Wavelet Transform-------------------------%
   [cA1,cD1] = dwt(tfrep,'db8');

   approximation_coefficient_1 = cA1(10,1);      % Selected Feature Vector
   approximation_coefficient_2 = cA1(20,1);      % Selected Feature Vector
 %---------------------Discrete Wavelet Transform-------------------------%
 %--------------------------SVMstruct Training----------------------------%
training(patients_data,:) = [approximation_coefficient_1 approximation_coefficient_2];
%training data for SVMstruct

SVMStruct =
svmtrain(training,group,'kernel_function','rbf','boxconstraint',box_constraint,'method','QP');
SVMStruct =
svmtrain(training,group,'kernel_function','rbf','rbf_sigma',3,'method','QP','boxconstraint',box_co
nstraint,'showplot',true);

 %--------------------------SVMstruct Training----------------------------%
 end
 %-----------------------------SVM Testing---------------------------------%
for patients_data = 1:50
row_1=testing_svm(patients_data,:);%x[n], EEG Data of SINGLE Patient


tfrep = quadtfd(prod_real_imag_1,255,1,'mb',0.09,256);       % MBD

tfrep = quadtfd(prod_real_imag_1,255,1,'emb',0.01,0.19,256); % EMBD

tfrep = quadtfd(prod_real_imag_1,255,1,'cw',10,256);        % Choi-Williams

tfrep = spec(prod_real_imag_1,128,11,'hann',257,1);         % SPEC=0(STFT=1)

%---------------------Discrete Wavelet Transform--------------------------%
   [cA2,cD2] = dwt(tfrep,'db8');

   approximation_coefficient_3 = cA2(10,1);       % Selected Feature Vector
   approximation_coefficient_4 = cA2(20,1);       % Selected Feature Vector
%----------------------Discrete Wavelet Transform-------------------------%

%-----------------------------SVM Testing---------------------------------%
  testing(patients_data,:) = [approximation_coefficient_3 approximation_coefficient_4];   %
testing data for SVM_Classify

  %approximation_coefficients = cA2.';
  %approximation_coefficients_mean = mean(cA2,1);
```

```
 %testing(patients_data,:) = approximation_coefficients;   % testing data for SVM_Classify

%-----------------------------SVM Testing---------------------------------%

End

%--------------------------SVM CLASSIFIER--------------------------------%

 Group = svmclassify(SVMStruct,testing,'showplot',true);

 %--------------------------SVM CLASSIFIER---------------------------------%
%-------------------------Classifier Performance-------------------------------%
grouping=zeros(50,1);
for rows=1:25
   grouping(rows,1)=1;
end
cp = classperf(grouping,Group);
cp.CorrectRate

cp.Sensitivity
cp.Specificity
cp.PositivePredictiveValue
cp.NegativePredictiveValue
 %-------------------------Classifier Performance--------------------------%
```

REFERENCES

[1] "History of Epilepsy" [Online] Available: http://nawrot.psych.ndsu.nodak.edu/courses/465 Projects05/epilepsy/History.htm.

[2] Pohlmann-Eden B, Beghi E, Camfield C, et al; "The first seizure and its management in adults and children". BMJ. 2006 Feb 11; 332(7537):339-42. [Online] Available: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1363913/.

[3] "Time-frequency Signal Analysis Toolbox (TFSA) 6.2" by Boualem Boashash. Signal Processing Research Concentration, UQ Centre for Clinical Research. The University of Queensland Australia.

[4] H. R. Mohseni, A. Maghsoudi, M. B. Shamsollahi, "Seizure Detection in EEG signals: A Comparison of Different Approaches", *Annual International Conference of the IEEE Engineering In medicine and Biology Society*. IEEE Engineering in Medicine and Biology Society. Conference · FEBRUARY 2006, DOI: 10.1109/IEMBS.2006.260931

[5] N. Sadati, *Member, IEEE*, H. R. Mohseni, A. Maghsoudi, "Epileptic Seizure Detection Using Neural Fuzzy Networks", *Conference paper in IEEE international conference on fuzzy systems* ·JANUARY 2006 DOI: 10.1109/FUZZY.2006.1681772 · Source: IEEE Xplore

[6] A. Subasi, "EEG signal classification using wavelet feature extraction and a mixture of expert model", *Journal on Expert Systems with Applications* 32 (2007) 1084–1093. DOI: 10.1016/j.eswa.2006.02.005

[7] A. Subasi, "Automatic Detection Of Epileptic Seizure Using Dynamic Fuzzy Neural Networks", *Journal on Expert Systems with Applications* 31 (2006) 320–328

[8] H. Adeli, Member, *IEEE*, S.G-Dastidar, N. Dadmehr, “A Wavelet-Chaos Methodology for analysis of EEGs and EEG Sub-bands to Detect Seizure and Epilepsy”, *IEEE Transactions On Biomedical Engineering*, Vol. 54, No. 2, February 2007

[9] L Guo, D. Rivero, J Dorado, J. R. Rabu˜nal, A. Pazos, “Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks”, *Journal of Neuroscience Methods* 191 (2010) 101–109.

[10] D. Wang, D. Miao, C. Xie, “Best basis-based wavelet packet entropy feature extraction and hierarchical EEG classification for epileptic detection”, Article In *Journal of Expert Systems with applications* · June 2011, Impact Factor: 2.24 · DOI: 10.1016/j.eswa.2011.05.096 · Source: DBLP. Elsevier.

[11] Y. U. Khan, O. Farooq, P. Sharma, “Automatic Detection of Seizure Onset In Pediatric EEG”, *International Journal of Embedded Systems and Applications* (IJESA) Vol.2, No.3, September 2012.

[12] H. Hassanpour, M. Mesbah, B.Boashash, “Time-Frequency Feature Extraction of Newborn EEG Seizure Using SVD-Based Techniques”, *EURASIP Journal on Applied Signal Processing* 2004:16, 2544–2554.

[13] A**.** T. Tzallas, M. G. Tsipouras, D. I. Fotiadis, “Automatic Seizure Detection Based on Time-Frequency Analysis and Artificial Neural Networks”, *Journal of Computational Intelligence and Neuroscience* Volume 2007, Article ID 80510, 13 pages.doi:10.1155/2007/80510.

[14] A. T. Tzallas, M. G. Tsipouras, D. I. Fotiadis, “The Use of Time-Frequency Distributions for Epileptic Seizure Detection in EEG Recordings*”, Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France,* August 23-26, 2007.

[15] V. Bajaj, R. B. Pachori, “Epileptic Seizure Detection Based on the Instantaneous Area of Analytic Intrinsic Mode Functions of EEG Signals”, *Biomed Eng Letter* (2013) 3:17-21, DOI:10.1007/s13534-013-0084-0.

[16] B. Gonzalez- Velldn, S. Sanei, J. A. Chambers, “Support Vector Machines for Seizure Detection”, *Conference Paper* · January 2004, DOI: 10.1109/ISSPIT.2003.1341076 · Source: IEEE Xplore.

[17] T. Fathima, M. Bedeeuzzaman, O. Farooq, Y. U Khan, "Wavelet Based Features for Epileptic Seizure Detection", *MES Journal of Technology and Management*.

[18] R. B. Pachori, "Discrimination between Ictal and Seizure-Free EEG Signals Using Empirical Mode Decomposition", *Research Letters in Journal of Signal Processing* Volume 2008, Article ID 293056, 5 pages. DOI:10.1155/2008/293056.

[19] B. Boashash, G. Azemi, "A review of time–frequency matched filter design with application to seizure detection in multichannel newborn EEG", *Journal on Digital Signal Processing* 28 (2014) 28–38. Elsevier.

[20] B. Boashash, G. Azemi, N. A. Khan, "Principles of time–frequency features extraction for change detection in non-stationary signals: Applications to newborn EEG abnormality detection", *Journal on Pattern Recognition* 48 (2015) 616–627. Elsevier.

[21] O. Faust, U. R. Acharya, H. Adeli, A. Adeli, "Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis", *European Journal of Epilepsy* Seizure 26 (2015) 56–64.

[22] B. Boashash, N. A. Khan, T. Ben-Jabeur, "Time–frequency features for pattern recognition using high-resolution TFDs: A tutorial review", *Journal on Digital Signal Processing* 40 (2015) 1–30. Elsevier.

[23] B. Boashash, Time-Frequency Signal Analysis and Processing: A Comprehensive Reference, (Elsevier, Oxford, UK, 2003).

[24] Miguel Oritz, A brief history of bio-signal driven art. Available [Online]: http//econtact.ca/14_2/Ortiz_ biofeedback.html.

[25] "Daubechies wavelets" , Digital Signal Processing, Chapter 2, 1999 CRC Press LLC

[26] U. R. Acharya, F. Molinari, S. V. Sree, S. Chattopadhyay, Kwan-Hoong Ng, J.S. Suri, "Automated Diagnosis of Epileptic EEG Using Entropies", *Journal on Biomedical Signal Processing and Control* 7 (2012) 401– 408. Elsevier.

[27] R. Acharya U, Vinitha S. S, S. Chattopadhyay, Wenwei Yu, A. P. C.Alvin, "Application Of Recurrence Quantification Analysis For The Automated Identification Of Epileptic EEG Signals", Article In *International Journal Of Neural Systems* , June 2011, DOI: 10.1142/S0129065711002808.

[28] Kai Fu, Jianfeng Qu, Yi Chai, Yong Dong, “Classification of seizure based on the time-frequency image of EEG signals using HHT and SVM”, *Journal on Biomedical Signal Processing and Control* 13 (2014) 15–22.

[29] A. Subasi, M.I. Gursoy, “EEG Signal Classification Using PCA, ICA, LDA and Support Vector Machines”, *Journal on Expert Systems with Applications* 37 (2010) 8659–8666.B.

[30] M. Fani, G.Azemi, B. Boashash, “EEG-Based Automatic Epilepsy Diagnosis Using the Instantaneous Frequency with Sub-Band Energies”, 2011 *7th International Workshop on Systems, Signal Processing and their Applications.IEEE*.

[31] Boashash, L. Boubchir, G. Azemi, “A methodology for time–frequency image processing applied to the classification of non-stationary multichannel signals using instantaneous frequency descriptors with application to newborn EEG signals”, EURASIP J. Adv. Signal Process.2012 (2012)1–21. EURASIP *Journal on Advances in Signal Processing* 2012, 2012:117.

Completion Certificate

It is to certify that the thesis titled "Seizure Detection from the Time-Frequency Based Multichannel Newborn EEG Signal through the Application of Advanced Noise Filtering and Classification Methods" submitted by registration no. NUST201362496MCEME35513F, NS Moiz Yusaf of MS-78 Mechatronics Engineering is completed in all respects as per the requirements of Main Office, NUST (Exam branch).

Supervisor: ___________

Brig Javaid Iqbal

Date: ____ Apr, 2016