DETECTION AND CLASSIFICATION OF MULTICLASS EPILEPTIC SEIZURES EXPLOITING EMD-WAVELET ANALYSIS OF EEG SIGNALS

by

Robiul Hossain Md. Rafi

MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering
BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

July 2016

The thesis entitled '**DETECTION AND CLASSIFICATION OF MULTI-CLASS EPILEPTIC SEIZURES EXPLOITING EMD-WAVELET ANALYSIS OF EEG SIGNALS** " submitted by Robiul Hossain Md. Rafi, Student No.: 0411062231F, Session: April, 2011 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on July 17, 2016.

BOARD OF EXAMINERS

1. Celia Shahnaz ________________________

(Dr. Celia Shahnaz) **Chairman**
Professor (Supervisor)
Department of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka - 1000, Bangladesh.

2. ________________________

(Dr. Quazi Deen Mohd Khosru) **Member**
Professor and Head (Ex-officio)
Department of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka - 1000, Bangladesh.

3. ________________________

(Dr. Mohammed Imamul Hassan Bhuiyan) **Member**
Professor
Department of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka - 1000, Bangladesh.

4. ________________________

(Dr. Mohammad Shorif Uddin) **Member**
Professor and Chairman (External)
Department of Computer Science and Engineering
Jahangirnagar University
Savar, Dhaka-1342, Bangladesh.

CANDIDATE'S DECLARATION

I, do, hereby declare that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

Signature of the Candidate

Robiul Hossain

Robiul Hossain Md. Rafi

Dedication

To my parents.

Acknowledgments

This dissertation would not have been possible without the guidance and the help of several individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study. First and foremost, I would like to express my deepest gratitude and indebtedness to my advisor, Dr. Celia Shahnaz, for her excellent guidance, caring, patience, encouragement, constructive suggestions and providing me with an excellent atmosphere for doing research. Dr. Shahnaz has been guiding my research for the past few years and helping me to develop my background in digital signal processing, EEG and biomedical instrumentation. I also want to thank her for spending so many hours with me in exploring new areas of research and new ideas and improving the writing of this dissertation. I would also like to thank the rest of the members of my thesis committee: Prof. Dr. Quazi Deen Mohd Khosru, Prof. Dr. Mohammed Imamul Hassan Bhuiyan, and Prof. Dr. Mohammad Shorif Uddin, for their steadfast encouragement and insightful comments. I would like to thank the head of the department of Electrical and Electronic Engineering for allowing me to use the lab facilities and all sorts of the financial, academic and technical support, which contributed greatly in completing the work in time. I would like to thank Prof. Dr. Shaikh Anowarul Fattah, who as an academic advisor, was always willing to help and give his best suggestions and thoughtful comments. Special note of thanks goes to the research group for their continuous moral support, accompany and friendly cooperation.

Abstract

Epileptic seizure is often interpreted by the abnormalities in the brain activity and Electroencephalogram (EEG) is a promising tool for identification of Epileptic seizure. Signal processing methods try to model visual information into few parameters, thus decision making becomes more accurate compared to the method based on visual observation of EEG, a source of misinterpretation in disease treatment. Researchers have used different signal processing and machine learning algorithms to extract features for seizure detection and classification . Since, EEG is a non-stationary signal, empirical mode decomposition (EMD), and discrete wavelet transform (DWT) have the potential to perform better than the conventional time-frequency analysis method. However, detection and classification of multiclass EEG epilepsy originated from different parts and state of the brain in the stringent conditions is still a challenging task. EMD analysis of the EEG signals is performed and the temporal energy contents of the IMFs is analyzed to select the dominant IMF. Since the dominant IMF vary for different EEG recordings, a mismatch may be produced between training and testing data even for the same class. Therefore, histogram analysis of the dominant IMFs of all classes is performed to develop a criterion for selecting appropriate number of IMFs for each EEG class. For a better time-frequency resolution and more discriminatory behavior, DWT analysis is carried out on the selected IMFs. Analyzing the parameters, namely normalized energy, Fourier spectrum and cross-correlation coefficient, only the 4th Level DWT coefficients of selected IMFs are found reasonable for feature computation. Finally, HOS, such as variance, skewness amd kurtosis of these coefficients are proposed to constitute the feature vector. The reduced feature vector is found effective for detecting and classifying multi-class EEG epilepsy when fed to diferent state-of-the art classifiers, in stringent conditions, such as reduced training data as well as random selection of training and testing dataset.

Contents

List of Tables

List of Figures

List of abbreviations

EEG	Electroenchapelogram
EMD	Empirical Mode Decomposition
IMF	Intrinsic Mode Function
FFT	Fast Fourier Transform
DWT	Discrete Wavelet Transform
DT-CWT	Dual Tree Complex Wavelet Transform
ANN	Artificial Neural Network
KNN	K-nearest neighbor
SVM	Support Vector Machine
LDA	Linear Discriminant Analysis
QDA	Quadratic Discriminant Analysis
LS-SVM	Least Square Support Vector Machine

Chapter 1

Introduction

A seizure is a sudden surge of electrical activity in the brain. It usually affects how a person appears or acts for a short time. Many different things can occur during a seizure. Whatever the brain and body can do normally can also occur during a seizure. Normally brain cells either excite or inhibit other brain cells from sending messages. Usually there is a balance of cells that excite and those that can stop these messages. However, when a seizure occurs, there may be too much or too little activity, causing an imbalance between exciting and stopping activity. These chemical changes can lead to surges of electrical activity that cause seizures. Seizures lead to symptoms of many different disorders that can affect the brain. Some seizures can hardly be noticed, while others are totally disabling. These symptoms of seizures are dramatic and alarming and frequently elicit fear and misunderstanding. This type of physical and mental limitation led to profound social consequences for sufferers and has greatly added to the burden of this disease. So, seizure detection and classification methods utilizing the signal processing technique can make the diagnosis process more accurate and faster.

In this chapter, we describe about epilepsy and diagnosis methods, motivation and objective of the thesis to detect and classify the epileptic seizures of Electroencephalogram (EEG) signals. Finally organization of the thesis is presented for a better clarification.

1.0.1 Types of Seizure

Seizures are generally described in two major groups of seizures, generalized seizures and partial seizures. The difference between the types of seizures is in how and where they begin in the brain. A new way of naming seizures has been developed by epilepsy specialists, but most often these common names are still used.

Generalized seizures begin with a widespread electrical discharge that involves both sides of the brain at once. Hereditary factors are important in many of these seizures. The main types of generalized seizures are tonic-clonic, absence, myoclonic, tonic and atonic. During a generalized tonic-clonic (formerly grand mal) seizure, electric discharges instantaneously involve the entire brain. The person loses consciousness right from the beginning of the seizure. A tonic-clonic seizure usually lasts one to three minutes, but may last up to five minutes. If seizures last more than five minutes, or occur one after another without recovering between seizures is a life-threatening medical emergency and requires immediate medical help. An absence seizure is a milder type of activity that causes unconsciousness without convulsions. After the seizure, the person has no memory of it. An absence seizure begins and ends abruptly and without warning. It consists of a period of unconsciousness with a blank stare. It may look like the person is daydreaming. The person may lose muscle control and make repetitive movements. Myoclonic seizures occur in several different types of childhood epilepsy. They involve abrupt muscle jerks in parts or all of the body. A hand may suddenly fling out, a shoulder may shrug, a foot may kick, or the entire body may jerk. Myoclonic seizures can occur as a single event or in series. Consciousness and memory are not impaired. A myoclonic seizure may cause a child to spill or drop what s/he is holding, or to fall from his/her chair. Tonic seizures are characterized by facial and truncal muscle spasms, flexion or extension of the upper and lower extremities, and impaired consciousness.Atonic seizures consist of a sudden and general loss of muscle tone, particularly in the arms and legs, which often results in a fall.

Partial seizures begin with an electrical discharge in one limited area of the brain. Many different things can cause partial seizures, for example head injury, brain infection, stroke, tumor, or changes in the way an area of the brain was formed before birth (called cortical dysplasias). Many times, no known cause is found, but genetic factors may be important in some partial seizures. Partial seizures can be broken down further, depending on whether a person's awareness or consciousness (the ability to respond and remember) is affected. Partial seizures are mostly categorized according to the starting position of the seizure in the brain. Different parts of the brain are shown in Fig. 1.1. These parts of the brain are used to categorize the partial seizure. Temporal lobe epilepsy occurs in the section of the brain located on the sides of the head behind the temples and cheekbones. Compared to other lobes in the brain, the temporal lobes seem to have a tendency to have seizures. There are so many diverse functions like hearing, speech, memory and emotions either in or closely related to the temporal lobe. The features of seizures beginning in the temporal lobe can be extremely varied, but certain patterns are common. There may be a mixture of different feelings, emotions, thoughts and experiences, which may be familiar or completely foreign. In some cases, a series of old memories resurfaces. In others, the person may feel as if everything appears strange. Hallucinations of voices, music, people, smells, or tastes may occur. They may last for just a few seconds, or may continue as long as a minute or two. Frontal lobe epilepsy is the term for recurring seizures beginning in the area of the brain located behind the forehead. Because the frontal lobe is responsible for planning and execution of movements and personality, frontal lobe epilepsy can have a dramatic affect on a patients quality of life. Because there are so many connections between the frontal and temporal lobes, it can be difficult to determine which section of the brain is being affected. Frontal lobe seizures may produce unusual symptoms that can appear to be related to a psychiatric problem or a sleep disorder. Frontal lobe seizures often occur during sleep and may feature bicycle pedaling motions and pelvic thrusting. Some people scream profanities or laugh during frontal lobe seizures. Focal seizures which involve the parietal lobes are uncommon. The parietal lobes integrate sensory information and construct a spatial coordinate system so that perceptions of objects around us can be made to understand the world around us. Seizures with ictal onset in the parietal lobe may be difficult to diagnose, especially in children, because of the subjective nature of these seizures. Complex visual hallucinations, vertiginous , visual illusions and disturbance of body image can occur. Receptive language impairment can occur with dominant hemisphere involvement. Ipsilateral or contralateral rotatory body movements can also occur.Focal seizures beginning in the occipital lobe are not common. Occipital lobe is the section of the brain located in the back of the head primarily responsible for vision. When a seizure begins in the occipital lobe, flashing bright lights or other visual changes may be experienced off to the left side

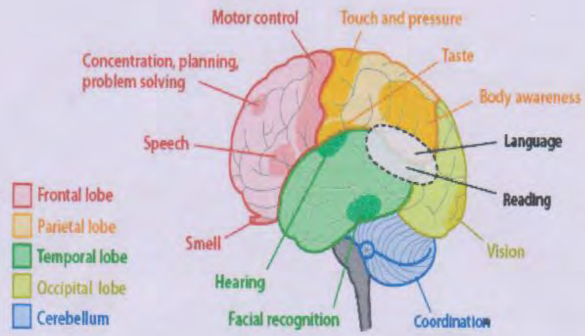


Fig. 1.1: Different parts of the brain and functions of those parts

(if occurring in the right cortex), or the right side (if occurring in the left cortex).

1.1 Epilepsy

Epilepsy is a chronic disorder, the hallmark of which is recurrent, unprovoked seizures caused by a synchronized electrical discharge of a group of neuron. Many people with epilepsy have more than one type of seizure and may have other symptoms of neurological problems as well. The human brain is the source of human epilepsy. Although the symptoms of a seizure may affect any part of the body, the electrical events that produce the symptoms occur in the brain. The location of that event, how it spreads and how much of the brain is affected, and how long it lasts all have profound effects. These factors determine the character of a seizure and its impact on the individual. As of 2013, about 22 million people in the world have epilepsy [1]. Nearly 80% of cases occur in the developing world [2]. In 2013, it is resulted in 116,000 deaths up from 112,000 deaths in 1990 [3]. The prevalence of active epilepsy tends to increase with age. More than 300,000 persons older than 65 years of age have epilepsy. Antiepileptic drug (AED) therapy, the mainstay of treatment for epilepsy, has four goals: to eliminate seizures or reduce their frequency to the maximum degree possible, to evade the adverse effects associated with long-term treatment, to aid patients in maintaining or restoring their usual psychosocial and vocational activities, and in maintaining a normal lifestyle. The decision to start

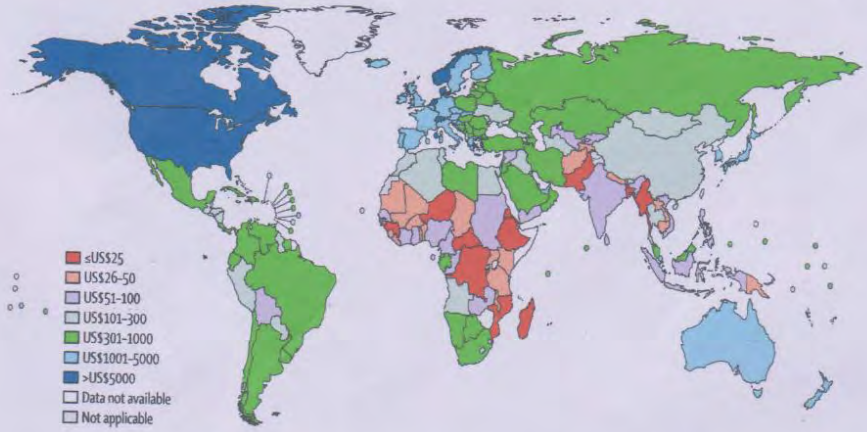


Fig. 1.2: Prevalence of Epilepsy in poor regions of the world

AED therapy should be based on an informed analysis of the likelihood of seizure recurrence, the consequences of continuing seizures for patients, and the beneficial and adverse effects of the pharmacological agent chosen. Medication can control seizures in most people with epilepsy, but for about 30% of patients, they aren't effective or are intolerable. In some cases, brain surgery may be an option. Despite how common it is and major advances in diagnosis and treatment, epilepsy is among the least understood of major chronic medical conditions, even though one in three adults knows someone with the disorder. The prevalence of Epilepsy in poor regions of the world is shown in Fig. 1.2.

1.1.1 Diagnosis of Epilepsy

Epilepsy is usually difficult to diagnose quickly. In most cases, it cannot be confirmed until anybody has had more than one seizure. It can be difficult to diagnose because many other congruent medical conditions, such as migraines and panic attacks which cause similar symptoms. Moreover, many people with seizures or epilepsy have abnormal electrical recordings, many do not. Apart from medical history of patients there are a number of additional tests that help doctors identify the type of seizure and its effects. The doctor may perform a thorough physical examination, especially of the nervous system, as well as analysis of blood and other bodily fluids. Imaging methods such as CT (computerized tomography) or MRI (magnetic resonance imaging) scans may be used to search for any growths, scars or other physical conditions in the brain that may be causing the seizures. In a few research centers, positron emission tomography (PET) imaging is used to identify areas of the brain which are producing seizures. Blood tests are used to check general health, and to look for any medical conditions that might be causing epilepsy.

A second battery of diagnostic tools includes an electroencephalograph (EEG). An EEG test tells doctors about the electrical activity happening in the brain. An EEG only shows what is happening in the brain at the time the test is being done. Its not able to show what has already happened or what is going to happen in the future. Despite this, an EEG can sometimes be very helpful to doctors when they are diagnosing epilepsy.

1.2 EEG

An electroencephalogram (EEG) is a test used to evaluate the electrical activity in the brain. Brain cells communicate with each other through electrical impulses. An EEG can be used to help detect potential problems associated with this activity. During the test, small sensors are attached to the scalp to pick up the electrical signals produced when brain cells send messages to each other. These signals are recorded by a machine and are looked at by a doctor later to see if they're unusual. Since this recording process is non-invasive i.e. the electrode only picks up electric signal from the brain and does not affect the brain. So this process is totally painless and harmless. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution is required.

1.2.1 Source of EEG Signal

EEG is a graphic representation of the difference in voltage between two different cerebral locations plotted over time. The scalp EEG signal generated by cerebral neurons is modified by electrical conductive properties of the tissues between the electrical source and the recording electrode on the scalp, conductive properties of the electrode itself, as well as the orientation of the cortical generator to the recording electrode. Because of the process of current flow through the tissues between the electrical generator and the recording electrode which is known as volume conduction, EEG provides a two-dimensional projection of our brain. It detects the summed ionic currents of thousands of pyramidal neurons beneath each of the 16 and 25 individual macro electrodes, and reports them as voltage differences across low resistance extracellular space. Specifically, the potentials recorded by the macro-electrodes on the skin of the skull are primarily generated by extracellular current flow of synaptic potentials in pyramidal cells. Action potentials of the neurons are usually asynchronous and too fast-moving to generate detectable potentials on the skin's surface. As a result brain cells other than pyramidal neurons such as interneurons and glial cells make relatively little contribution to skin potentials because, unlike pyramidal neurons, these cells are neither oriented in parallel to one another nor do their dendrites run perpendicular to the cortical surface. In contrast, pyramidal neurons run parallel to one another with large dendritic branches that run perpendicular to the cortical surface. Since voltage fields fall off with the square of distance, activity from deep sources is more difficult to detect than currents near the skull. The EEG waves obtained from the scalp electrodes show oscillations at different frequencies. Such oscillations at a variety of frequencies are associated with different states of brain functioning involving different parts of our brain. As a result, such oscillations depict synchronized activity over different networks of neurons which are known as neuronal networks. From such neuronal networks some of these oscillations are understood, while many others are not.

1.2.2 Types of EEG recording

For the diagnosis of epileptic seizure, several types of EEG including Routine EEG, Ambulatory EEG, and Video-EEG are used. Routine EEG is normally used in clinical circumstances where short measurement is sufficient like distinguishing epileptic seizure from other types of seizures or to evaluate coma. A routine EEG recording lasts for about 20 to 40 minutes. During the test, the patient is asked to rest quietly and open or close his/her eyes from time to time. In most cases, the patient is also be asked to breathe in and out deeply (known as hyperventilation) for a few minutes. At the end of the procedure a flashing light may be placed nearby to see if this affects his/her brain activity. Since seizure is a random event this types of standard test may not fulfill the requirement. Ambulatory test is done to observe the brain activity more deeply. An ambulatory EEG is where brain activity is recorded throughout the day and night over a period of one or more days. The electrodes will be attached to a small portable EEG recorder that can be clipped on to the patient clothing so that s/he can continue with most of his/her normal daily activities while the recording is being taken. Patient does not usually stay in hospital while the test is being done. Sometimes patients may be asked to have an EEG test while they are asleep. This could be because sometimes seizures happen when patients are asleep or when patients are tired. A sleep EEG is carried out while the patient is asleep. A clinical suspicion of epilepsy can be confirmed by recording a seizure on Ambulatory EEG. This is most likely to occur when the patient is experiencing daily or almost daily spells. In patients with intractable epilepsy, Ambulatory EEG has been used to localize seizure onset as part of pre-surgical evaluation [4]. Video telemetry, also known as video EEG, is a special type of EEG where the patients are filmed while a recording is taken. This can help provide more information about patients brain activity. The test is usually carried out over a few days while staying in a purpose-built hospital suite. The EEG signals are transmitted wirelessly to a computer. The video is also recorded by the computer and kept under regular surveillance by trained staff. Patient would usually only has a video-telemetry test if they have already been diagnosed with epilepsy. However, due to the relatively infrequent nature of epileptic seizures, the long-term video-EEG monitoring is mandatory. Thus, ambulatory EEG can be integrated with video recording which correlates the patient behavior with EEG data.

Inter-ictal findings from electroencephalography (EEG) offer the most specific test for diagnosing epileptic seizure. A short period EEG recording can be used to identify the inter-ictal indications of epilepsy. Generally inter-ictal events are characterized by isolated spikes, sharp waves and spike-wave-complex, whereas ictal period is manifested by rhythmic waveforms and poly-spikes. However, visual seizure detection has not been proven very effective as visual observation suffers from misinterpretation frequently and needs highest level of expertise. Detecting dominance of different frequency components from visual observation does not correlate with few parameters only. For confident decision, involvements of few mathemati-

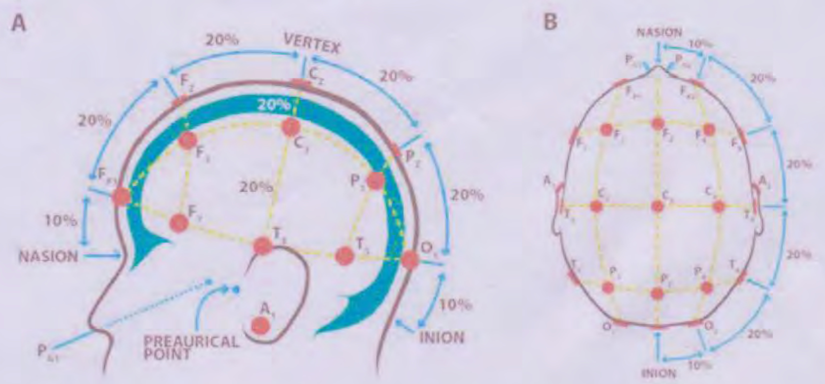


Fig. 1.3: EEG electrodes position on the scalp in 10-20 EEG recording system

cal features are mandatory. Efficient automated seizure detection and classification schemes facilitate the diagnosis of epilepsy and enhance the management of long-term EEG recordings. But for influent seizures long term monitoring is mandatory where automatic detection of seizure will be very helpful for the physician [5].

1.2.3 10-20 Standard EEG System

The International 10-20 System of Electrode Placement is the most widely used method to describe the location of scalp electrodes during an EEG recording or experiment. The 10-20 system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. Each site has a letter (to identify the lobe) and a number or another letter to identify the hemisphere location. The position of the electrode of the 10-20 system are shown in Fig. 1.3 [6]. This method was developed to ensure standardized reproducibility so that a subjects studies could be compared over time and subjects could be compared to each other. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. Note that there exists no central lobe; the C letter is only used for identification purposes only. Even numbers (2, 4, 6, and 8) refer to the right hemisphere and odd numbers (1, 3, 5 and 7) refer to the left hemisphere. "Z" refers to an electrode placed on the mid line. The smaller the number, the closer the position to the mid line. "Fp" stands for Front polar.

Two anatomical land marks are used for the essential positioning of the EEG

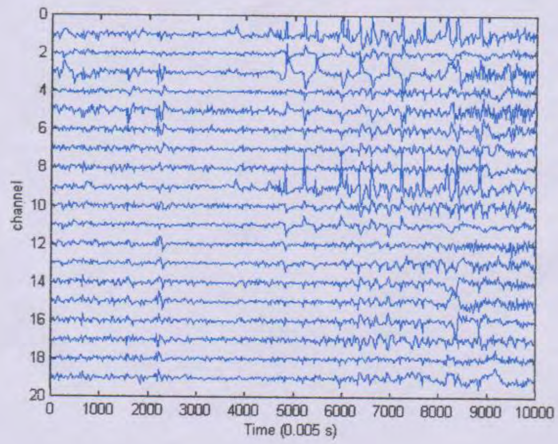


Fig. 1.4: Multichannel EEG signal example with seizure

electrodes: first, the nasion which is the point between the forehead and the nose; second, the inion which is the lowest point of the skull from the back of the head and is normally indicated by a prominent bump. The "10" and "20" (10-20 system) refer to the 10% and 20% inter electrode distance. When recording a more detailed EEG with more electrodes, extra electrodes are added utilizing the spaces in-between the existing 10-20 system. This new electrode-naming-system is more complicated giving rise to the Modified Combinatorial Nomenclature (MCN). This MCN system uses 1, 3, 5, 7, 9 for the left hemisphere which represents 10%, 20%, 30%, 40%, 50% of the inion-to-nasion distance respectively. 2, 4, 6, 8, 10 are used to represent the right hemisphere. The introduction of extra letters allows the naming of extra electrode sites. These new letters do not necessarily refer to an area on the underlying cerebral cortex. Multichannel EEG measures the voltage difference in two different electrodes. A multichannel EEG signal example is shown in Fig. 1.4.

1.3 Epilepsy Detection and Classification Methods

EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brains spontaneous electrical activity over a short period of time. Different techniques are exploited for detection and classification of the Epileptic seizures in multiple channel EEG recordings. Conventionally, physicians use visual observation in decision making process for the detection and classification of epilepsy which not only needs superior expertise but also requires a lots of time. With a view to easing the decision making process and time consuming problem, Signal processing techniques introduce different methods to achieve expert like accuracy in case of both detection and classification process of such EEG signals.

1.3.1 Conventional Methods of Seizure Detection and Classification

Conventionally seizure is detected and classified by the visual observation of EEG signals by experts. The EEG provides important information about background EEG and epileptiform discharges and is required for the diagnosis of specific electroclinical syndromes. Following a seizure (ie, during the postictal period) the EEG recording may be slow. However, interictal recording of EEG frequencies that are slower than normal recording for age usually suggest a symptomatic epilepsy (i.e., epilepsy secondary to brain insult) in normal recording suggests primary epilepsy (i.e., idiopathic or possibly genetic epilepsy). Thus, EEG offers important detection and classification information [7].

Lennox Gastaut syndrome (LGS) is a type of epilepsy that usually develops before the age of seven [8]. When diagnosing LGS, experts will look for diffused slow spikes and slow waves of 2-2.5 cycles per second. This is between seizures, and while the person is awake. An EEG during sleep is also necessary. Bursts of diffuse or bilateral fast rhythm patterns (10 cycles/second) or "polyspikes," are recorded during sleep. These EEG patterns help differentiate LGS from other epilepsy syndromes.

During tonic seizure EEG always shows bilateral, symmetrical, and synchronous discharges. Generalized onset tonic seizures manifest with abrupt onset and termination of sustained increase in muscle contraction, usually lasting a few seconds to 1 minute. Rapid desynchronization with or without subsequent rapid synchronization, pure hypersynchronization at 10 Hz (the epileptic recruiting rhythm), termination by added slow wave activity appearing as spike-waves, or other patterns may also be seen during tonic seizure EEG recording.

An atypical absence seizure has less abrupt onset and offset of loss of awareness than typical absence seizures. A Slow (less than 2.5 Hz) generalized spike-and-wave discharges accompany atypical absences. These seizures can be difficult to detect in a patient with ongoing slow (less than 2.5 Hz) generalized spike-and-wave on EEG.

Myoclonic-atonic seizures are a particular type of brief and abrupt generalized epileptic seizure. These seizures are brief (approximately 1 second), abrupt and manifest with a myoclonic symptom followed by an atonic symptom in continuity. The seizure recording manifests with a high-amplitude, 1 to 3 Hz generalized spikes and poly-spikes discharge associated with the myoclonic jerk followed by a slow wave associated with the loss of muscle tone.

Visual seizure detection and classification from direct observation of EEG recordings has not been proven very effective as visual observation suffers from misinterpretation frequently and needs highest level of expertise which is also time consuming. Efficient automated seizure detection and classification systems aid the diagnosis of such epilepsy and improve the management of long-term EEG recordings. As a result, different signal processing based EEG signal detection and classification methods are exploited to ease expert decision with superior accuracy and fast decision making.

1.3.2 Signal processing for seizure detection

Different Signal processing approaches facilitate the mathematical representations of scattered visual information by different feature sets. These feature sets precise all information and model the whole EEG recording into few parameters from where decision making is easier, more accurate and less time consuming than the conventional manual methods. Such facts are in demonstrated in Fig. 1.5 where time domain plot of EEG signals obtained from different state and parts of the brain are shown. The classification of seizures from different state and parts of the brain from this time domain plot is ambiguous and erroneous. Thats why it is inevitable to look for feature sets which can represent these EEG recordings as depicted in Fig. 1.5 to differentiate these seizures originated from different state and parts of the brain more precisely.

Different types of Features such as mean-squared error of estimated auto regressive models, relative power of different spectral bands of EEG signals, spectral edge

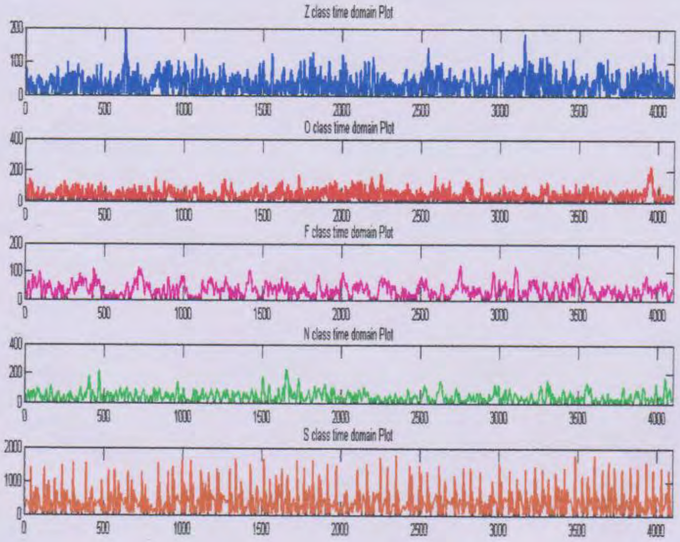


Fig. 1.5: Time domain plot of different classes of EEG Signals

frequency, spectral edge power, decorrelation time, statistical moment, long-term energy [9–19] are used to composite different feature vectors in order to analyze EEG signals.

Assuming the input EEG signal as stationary, some work derived features with the aid of conventional signal transformation techniques like Fourier, Wavelet Transform etc. [20–22]. But due to change in frequency component over the time EEG is always considered as a non-stationary process. As a result minor variation in frequency domain may not be detected by adopting techniques in [20–22]. Due to this non-stationarity taking perfect decision for detection and classification of EEG signals is mostly dependent on the accuracy of extracting feature in time and frequency domain.

As distribution of energy at different frequency bands demonstrate the seizure activities, time frequency distribution performs better than conventional frequency analysis methods [23, 24].

However, despite good results have been obtained with these techniques, they only provide a limited amount of information about the electrical activity of the brain because they ignore the underlying nonlinear EEG Dynamics. As it is widely accepted, the underlying subsystems of the nervous system that generates the EEG signals are considered nonlinear or with nonlinear counterparts [25]. Even in healthy subjects, the EEG signals show the chaotic behavior of the nervous system. Therefore, due to this nonlinear nature of EEGs, additional information provided by techniques from nonlinear dynamics has been progressively incorporated in order to reveal aspects that cannot be measured from linear methods [26]. Nonlinear dynamic measures of complexity (e.g., the correlation dimension) and stability (e.g., the Lyapunov exponent and Kolmogorov entropy) quantify critical aspects of the brain dynamics to derive features for EEG epilepsy detection and classification. The Correlation Dimension (CD) provides the degree of complexity in comparison with seizure and non-seizure EEG recordings [27]. The Fractal Dimension (FD) parameter depicts the complexity, irregularity and the chaotic nature of the EEG signals which is helpful for proper discrimination of Epileptic and normal EEG [28]. The Approximation Entropy (ApEn) is a statistical index for the overall complexity and predictability of a given time series. The value of ApEn reduces significantly during seizure attack thus quite helpful for seizure event prediction and detection [29]. These feature sets are used to represent particular patterns for different types of EEG recordings which are fed into different classifiers like different distance based classifier (QDA, LDA, Euclidean based, kNN etc.), neural network based classifier etc. to automatically detect and classify seizures originating from different states and parts of the brain.

Spike detection during inter-ictal period is investigated through several methods, like wavelet, frequency domain analysis, ICA, ANN, SVM, data mining and template matching etc. [30–35].

Many previous works used time frequency analysis to detect preseizure chirps and multi-resolution analysis of EEG [36,37]. Effectiveness of these works depends on frequency or time domain smoothing. RI distribution and twelve kohen class kernels are used for smoothing purpose before feature extraction [38–40]. But due to selection of specific kernels among a set of kernels and complex feature extraction process make time frequency analysis computationally expensive. To encounter this problem of kernel selection and cost complexity recent method based on Empirical Method Decomposition (EMD) and Dual Tree Complex Wavelet Transform (DT-

CWT) has been proposed in [41–43] for seizure detection and classification.

1.4 Problem Definition

Long time EEG recording is needed to capture a seizure event which can be used for further diagnosis. From EEG recording, types and source of the seizure can be identified. But random signal type, involvement of multiple node and long time of recording make it difficult to detect and classify EEG signals accurately and quickly. EEG signal vary in time and frequency domain simultaneously, so only time and only frequency domain feature is not sufficient for multi class EEG signal classification problem. Besides, time-frequency analysis can extract time-frequency information more precisely than conventional frequency analysis method but inherently introduces some interference which requires some time and frequency domain smoothing function to reduce these interferences. So selection of smoothing functions also affect the performance of the classification problem and make the analysis computationally expensive [44]. Similarly, selection of simple feature set which can extract necessary information from the processed EEG signals is another major criteria for good and fast classification results. Since, EEG is a non-stationary signal, empirical mode decomposition (EMD), and discrete wavelet transform (DWT) have the potential to perform better than the conventional time-frequency analysis method [38–40, 44]. However, detection and classification of multiclass EEG epilepsy originated from different parts and state of the brain in the stringent conditions is still a challenging task.

1.5 Objective of the Thesis

The objectives of this thesis are:

- To analyze the given EEG signals through different Intrinsic Mode Functions (IMFs) obtained from the EMD analysis.
- To develop a criterion for selecting the appropriate number of IMFs based on histogram analysis of the resulting IMFs.
- To propose a Higher order statistics (HOS) based feature set by analyzing the selected IMFs in the DWT domain.

- To evaluate the performance of the proposed feature set using different classifiers and to compare the performance with different state-of-the art methods.

The outcome of this thesis is the development of an effective method based on EMD-Wavelet analysis of EEG signals, which is able to detect and classify multiclass epilepsy originated from different parts and state of the brain. The proposed method provides greater accuracy, sensitivity and specificity and lesser processing time even in case of reduction training data and random selection training and testing dataset.

1.6 Organization of the Thesis

The thesis is organized as follows:

- Chapter 1 provides the introduction of the overall thesis.
- Chapter 2 presents popular seizure detection and classification methods reported in literature.
- Chapter 3 describes the proposed method of epileptic seizure detection and detection from EEG signals based on EMD-Wavelet Analysis.
- Simulation results and quantitative performance analysis is discussed in Chapter 4 for the proposed method described in Chapter 3. Performance of the proposed method is also compared with the state-of-the-art methods.
- Finally, in Chapter 5, concluding remarks highlighting the contributions of the thesis and suggestions for further investigation are provided.

Chapter 2

Literature Review

2.1 Introduction

Epileptic seizures are classified as a neurological disorder that affects the brain, impacts about 2% of the world population leading to a reduction in their productivity and imposing restrictions on their daily life. Diagnosis of epilepsy is done by analyzing electroencephalogram (EEG) signals, as well as patient behavior. The seizure detection and classification process can be made on a single or multi-channel basis. Single-channel seizure detection and classification requires selecting the channel containing the strongest EEG signal collected from the closest point to the seizure spot. This selection process depends mainly on activity measures evaluated for the different channels instantaneously such as the local variance. A better treatment to the seizure detection issue depends on incorporating the information from all EEG signals available into the seizure detection process through data fusion, or multi-channel processing techniques. These processing techniques involve multiple channel and frequency variation in different parts and state of the brain. A plentiful of researches is available in the literature concerned with automated detection and classification of epileptic seizures using EEG signals. All those researches try to extract feature from EEG signals and then use different classifier for detection and classification purpose. Some of those use time domain analysis, few use frequency domain analysis, few incorporate both time-frequency domain, few use Empirical Mode Decomposition and Wavelet analysis to extract feature from the EEG signals.

2.1.1 Time Domain Approaches

To detect EEG seizures in time domain, there is a need to analyze discrete time sequences of EEG epochs. This analysis can be accomplished through histograms of the epochs. Runarsson and Sigurdsson presented a simple time-domain seizure detection method that is based on tracing consecutive peaks and minima in the signal segment at hand and estimating the histograms for two variables: the amplitude difference and time separation between peak values as well as minima [45]. The features used for classification of an epoch as a seizure or non-seizure are the estimated values of the histogram bins. The authors in [45] used a support vector machine (SVM) classifier for this task and achieved an average sensitivity of about 90% on self-recorded data.

Another approach to deal with the EEG seizure detection method in time domain is to compute the signal energy during seizure and non-seizure periods. A better treatment to the energy estimation approach is to estimate the energies of the signal sub-bands not the signal as a whole in order to build a more discriminative feature vector. Yoo et al. adopted this approach and presented an eight-channel EEG acquisition system-on-chip (SoC) that can detect and record patient-specific epileptic seizures [46]. The authors in [46] used an SVM as a classifier with a gain and bandwidth (GBW) controller to perform real-time gain and bandwidth adaptation to analog front end (AFE) in order to keep a high accuracy.

In [47] some discriminating statistics between seizure and non-seizure epochs are exploited for seizure detection. Here, Dalton et al. developed a body senor network (BSN) that can monitor and detect epileptic seizures based on statistics extracted from time-domain signals [47]. These statistics include the mean, variance, zero-crossing rate, entropy, and autocorrelation with template signals. For autocorrelation estimation, authors in [47] adopted a dynamic time warping (DTW) approach for best alignment between the signal segment to be tested and the template signal.

Zandi et al. used the zerocrossing rate of EEG signal segments to develop a patient-specific seizure prediction method [48,49]. A moving window analysis is used in this method. The histograms of the different window intervals are estimated, and selected histogram bins are used for classification into pre-ictal and inter-ictal states based on comparison with reference histograms.

A variational Bayesian Gaussian mixture model has been used for classification. In this method, a combined index for the decisions taken on selected bins is computed and compared with a pre-defined patient-specific threshold to raise an alarm for coming seizures.

Aarabi [50] developed a time-domain rule based patient-specific seizure prediction method which consists of three stages: pre-processing, feature extraction, and rule-based decision making. Five univariate features (correlation entropy, correlation dimension, Lempel-Ziv complexity, noise level, and largest Lyapunov exponent) and one bivariate feature (non-linear independence) were extracted from each segment in the feature extraction stage.

Based on the theory of chaos, the correlation dimension (denoted by ν) represents a dimensionality measure of the space having a set of EEG signals. For an m-dimensional space containing a set of N points, we have:

$$\vec{x}(i) = [x_1(i), x_2(i), ., x_m(i)], i = 1, 2, ., N \tag{2.1}$$

The correlation integral $C(\epsilon)$ can be estimated as [51]:

$$C(\epsilon) = \lim_{N\to\infty} \frac{g}{N^2} \tag{2.2}$$

where g represents the total number of pairs of signals or points having a distance less than ϵ. As the number of points increases and tends to infinity and the distance tends to be shorter or close to zero, the correlation integral, in turn, for small values of ϵ becomes:

$$C(\epsilon) \approx \epsilon^{\nu} \tag{2.3}$$

If a large number of evenly distributed points exists, a log-log graph of the correlation integral versus ϵ can be used to estimate ν. For objects with higher dimensions, several ways exist for points to be close to each other, and hence, the number of pairs which are close to each other jumps rapidly for higher dimensions [51]. In preictal states, drops in correlation dimension were observed making this measure able to identify states preceding seizures [52].

Correlation entropy (CE) is a Kolmogorov entropy variant, which is similar to the mutual information between two sequences of data. Large mutual information between an available data segment and stored segments with specific patterns is an indication that the segment at hand belongs to a dataset with similar characteristics to the stored pattern [53]. Higher positive values of CE suggest a chaotic behavior of the system, whereas lower values suggest a more ordered system to distinguish seizure and non-seizure activities. The

Lempel-Ziv complexity is a measure of randomness of data sequences [54]. It counts the number of data patterns with certain characteristics in data segments. For example, if anyone finds enough short patterns with specific mean, variance, or higher-order statistics in an EEG segment, then this segment can be classified as a seizure segment.

The Lyapunov exponent of a dynamical system determines the separation rate of very closely related trajectories. Hence, two signal vectors in the phase space with an initial separation of δZ_0 will eventually diverge at a rate given by:

$$|\delta Z(t)| \approx e^{\lambda t}|\delta Z_0| \tag{2.4}$$

where λ is the Lyapunov exponent. This can be achieved if the divergence can be dealt with within the linearized approximation. The separation rate differs based on the initial separation vector orientation. The maximal Lyapunov exponent can be estimated as [55] :

$$\lambda = \lim_{t\to\infty} \lim_{\delta Z_0 \to \infty} \frac{1}{t} \ln \frac{|\delta Z(t)|}{|\delta Z_0|} \tag{2.5}$$

The limit $\delta Z_0 \to 0$ ensures the validity of the linear approximation at any time. The idea behind this approach is that the transition from normal to epileptic EEG is reflected by a transition from chaotic to a more ordered state, and therefore, the spatiotemporal dynamical properties of the epileptic brain are different for different clinical states.

Co Wang et al. proposed an adaptive learning system that interactively learns from the patient and improves its seizure predictability over time [56]. It is based on reinforcement learning and online monitoring, in addition to adaptive control theory. In this system, a sliding window is used to read EEG data with a 50% overlap at each move. Then, k-nearest neighbor (kNN) method is adopted for the classification of the windowed epochs for normal and preseizure states.

Researchers have proved that symptoms like sleep problems or headaches are observable from the analysis of the EEG. These symptoms can be utilized as a major tool for seizure detection and classification.

Bedeeuzzaman et al. have presented a seizure prediction algorithm with a statistical feature set consisting of mean absolute deviation (MAD) and inter-quartile range (IQR) to predict epileptic seizures [57]. A linear classifier has been used to find the seizure prediction time in pre-ictal EEGs. The envelope of the EEG signal can be exploited to distinguish between different activities. Li et al. presented a time-domain method for seizure prediction that is based on spike rate estimation [58].

Morphological operations and averaging filters are applied to transform each signal segment to a train of spikes in a way similar to the process of envelope detection. Based on the spike rate, ictal, inter-ictal, and pre-ictal states can be identified through comparison with a certain threshold.

Another approach to process EEG signals in the time domain in order to detect or classify seizures is to create models from the EEG signal segments corresponding to different activities. One of such models is the autoregressive (AR) model, which can be thought of as a data reduction model that transforms the EEG signal segment into few coefficients. Chisci et al. studied the implantation of monitoring and control units on drug-resistant epilepsy patients with AR modeling [59]. They adopted AR modeling with a least-squares parameter estimator for EEG feature extraction in addition to a binary SVM classifier to distinguish between pre-ictal, ictal, and inter-ictal states.

Such Time domain based analysis provide effective information about magnitude and dynamics of the EEG recordings. Due to random nature of EEG signals frequency is extracted from variation of magnitude with respect to time. As a result, minor and frequent change in different frequency band are overlooked during time domain analysis which in turn limit the performance in case of detecting and classifying different types of EEG signals. So frequency domain analysis is introduced to make a deeper look at the variation of frequency in EEG signals.

2.1.2 EMD Domain Approaches

The EMD is a signal decomposition method which transforms a signal into a group of intrinsic mode functions (IMFs). For EEG seizure detection, these IMFs show different behavior with normal and abnormal activities in the signals. Features can also be extracted from the IMFs and tested for seizure detection and classification. Eftekhar et al. used the EMD approach for seizure detection [60]. They adopted features such as the frequency rise at the seizure onset with the EMD in a patient-specific manner. Their simulation results have shown that the Hilbert transform can be used to decompose EEG signals into components, from which features can be extracted for seizure onset detection. Tafreshi et al. evaluated the performance of the EMD in discriminating epileptic seizure data from normal data using means of the absolute of the IMFs as features [61].

Orosco et al. presented a seizure detection approach based on the energies of IMFs as discriminating features between seizure and non-seizure activities in [62]. In this approach, the IMF energies are compared with certain thresholds for decision making.

Guarnizo and Delgado presented a modified EMD approach, in which mutual information is used for feature selection in the EMD domain [63]. These features include the average or instantaneous frequency and amplitude for all EMD components. Higher-order statistics such as the skewness and kurtosis in addition to Shannons entropy have been selected as features extracted from the energy estimated with the Teager energy operator (TEO) over all EMD components. This approach adopts a linear Bayes classifier.

Bajaj and Pachori presented an EMD-based two class seizure classificaton method in [41]. In this method seizure classification is achieved after using EMD algorithm on each EEG signal and considering individual IMF as an approximation of modulated AM-FM waves. Then computed AM-FM bandwidth is extracted as feature and then fed into LS-SVM classifier for classification purpose.

Alam and Bhuiyan presented a seizure detection method to handle two to three class classification problems based on extracting variance, kurtosis, skewness from the EMD of EEG signals with artificial neural network classifier [42]. This method achieved a superior sensitivity in seizure detection and has shown a superiority as compared to time-frequency techniques and band-limited techniques in terms of computational complexity.

However, In both the methods reported in [41, 42],from the set of extracted

IMFs no automatic selection of IMF is proposed and classification performance is reported with respect to each individual IMF. Furthermore, the classification problem involving all classes of EEG recordings such as five class are not reported in [41, 42].

2.2 Frequency Domain Approaches

Frequency-domain techniques have been used for EEG seizure detection and classification. Characteristic of the frequency domain variation are also reported as useful features for EEG classification. The EEG signal has usually been described in terms of main frequency bands, δ (less than 4 Hz), θ (4-8 Hz), α (8-12 Hz), β (13-30 Hz), and γ (greater than 30 Hz). Relative power in any frequency band is defined as the area under the curve of the power spectrum within the bandwidth under consideration divided by total power for all bands. So the relative power contained in these bands can be defined as

$$\delta = \frac{1}{P}\sum_{f=0.5Hz}^{4Hz} P_f; \theta = \frac{1}{P}\sum_{f=4Hz}^{8Hz} P_f; \alpha = \frac{1}{P}\sum_{f=8Hz}^{12Hz} P_f; \beta = \frac{1}{P}\sum_{f=13Hz}^{30Hz} P_f; \gamma = \frac{1}{P}\sum_{f=30Hz}^{100Hz} P_f \tag{2.6}$$

here, P is the total power of the signal. In [64], it have been shown that for the preictal period in comparison with the interictal period, there is a relative decrease of power in the delta band that is accompanied by a relative increase in the remaining bands. This variation can classify only preictal and interictal events but it is not capable of classifying EEG signal of different state in the interictal period. The analysis shown in [65] is based upon extraction of relevant information and learning of object parameter values such as power distribution in various phases of EEG time series, seizure time and spectral power in various frequency bands of EEG. The averaged spectral power in EEG epochs of pre seizure, seizure, post seizure and non seizure is calculated. The power distribution, particularly in alpha band and delta band is computed, thereby alpha band delta band ratio (ADR) has been calculated to detect seizure. Only involving alpha and delta band frequencies limits the performance of the detection and classification. Variation in other frequency band should be monitored also for classification of broader range EEG classification problem. In a typical EEG signal, most of the power is contained within the frequency band from 0 Hz up to 60 Hz: $P_{60Hz} \approx P$. As a characterizing measure for the power distribution, the so-called spectral edge frequency can be used [66], which is defined as the minimum frequency up to which 50% the spectral power up to 60 Hz is contained in the signal:

$$f_{50} = min\{f^*|p_f > (P_{60} \times 0.5)\} \tag{2.7}$$

Moreover, both of the Fourier transform magnitude and phase are also exploited for the detection and classification purpose. Rana et al. presented a frequency-domain epileptic seizure detection approach depending on the phase-slope index (PSI) of multi-channel EEG signals [67]. If we consider signals $z_i[n]$ and $z_j[n]$, their cross spectrum is given by:

$$S_{ij}(f) = E[Z_i(f)Z_j^*(f)] \tag{2.8}$$

where $Z_i(f)$ and $Z_j(f)$ are the Fourier transforms of $z_i[n]$and $z_j[n]$. Hence, the complex coherence is given by:

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}} \tag{2.9}$$

An unnormalized PSI metric can be defined using complex coherence as follows:

$$\tilde{\Psi_{ij}} = \sum_{f \epsilon F} C_{ij}^*(f)C_{ij}(f + \delta f) \tag{2.10}$$

where δf is the frequency resolution and F is the frequency band of interest. $\tilde{\Psi_{ij}}$ measures a weighted sum of the slopes of the phase between $z_i[n]$and $z_j[n]$ over the selected band F [67]. Normalization with the standard deviation is used to determine whether causal influence from $z_i[n]$ to $z_j[n]$ is of significant extent or not. The PSI computes the measure of interaction between two channels. The authors used the PSI metric to distinguish between seizure and normal activities.

Khamis et al. used frequency-moment signatures for building a patient-specific seizure detection method [68]. Firstly, experienced electroencephalographs have marked the collected scalp EEG data with seizure events. After that, a filtering process has been performed on the windowed EEG data from electrode differences for the right hemisphere and the left hemisphere. Power spectral densities of the signals on both hemispheres have been computed and a background removal technique has been used. Moments of these spectra have been used as features for signal classification as seizure or non-seizure.

Since EEG signals are in general non-linear and non-stationary. So, there is a difficulty to characterize different activities of EEG signals with certain mathematical models. To tackle this problem, Acharya et al. presented a modified method for the detection of normal, pre-ictal, and ictal conditions from recorded EEG signals [69]. This method is based on four entropy features for classification: phase entropy 1 (S_1), phase entropy 2 (S_2), approximate entropy (ApEn), and sample entropy (SampEn). The phase entropies are estimated from the higher-order spectra of EEG signal epochs as discriminating features for ictal, pre-ictal, and inter-ictal activities. The approximate and sample entropies are logarithmic metrics that determine the closeness and matching between the incoming EEG signal pattern and the recorded templates. These features are extracted from EEG signals and fed to seven different classifiers for comparison: SVM, fuzzy Sugeno classifier (FSC), probabilistic neural network (PNN), KNN, naive Bayes classifier (NBC), decision tree (DT), and Gaussian mixture model (GMM).

But epileptic EEG signal during an epileptic seizure activity exhibits different temporal characteristics between different frequency bands as compared to the epileptic EEG signal during a non-seizure period thus making frequency domain analysis problematic to classify different types of seizure activities.

2.3 Time-frequency Domain Approaches

Time-frequency based feature extraction methods provides the variation of signals with respect to both time and frequency. Various studies that employ time-frequency approaches have been used in the area of seizure detection and classification [70].

Hassanpour et al. [71] has used time-frequency patterns as signatures in order to detect seizures.

Rankine et al. [72] proposed a related methodology analyzing changes in preictal, ictal, and postictal states. Moreover, an improved time-frequency dictionary in terms of reconstruction accuracy and discrimination between seizure and non-seizure states is presented in [73].

In [40, 74, 75] an extensive investigation of well-known time–frequency distributions are performed, extracting features from the Power Spectral Density (PSD) time-frequency grid followed by artificial neural network (ANN) classification. With this methodology, the accuracy for three different classification (two, three and five class) problems has been reported using reduced interference time-frequency distribution and ANNs. A time-frequency matched filter was introduced in [23, 76] in order to reveal seizure patterns.

2.3.1 Wavelet Domain Approaches

Wavelets have been widely used in the field of EEG signal analysis, especially for seizure detection and classification. The wavelet transform in itself can be regarded as some sort of sub-band decomposition, but with down-sampling. The main challenge in wavelet-based EEG seizure detection is the determination of the appropriate wavelet decomposition level and the selection of the features from certain sub-bands for discrimination between seizure and non-seizure periods.

A five-level wavelet decomposition method for seizure detection was developed by Liu et al. [77]. This method works on multi-channel EEG signals. Three wavelet sub-bands are selected for further processing. The extracted features from these sub-bands are the relative amplitude, relative energy, coefficient of variation, and fluctuation index from the selected frequency bands. The coefficient of variation is the ratio between the standard deviation of a decomposed sub-band and the square of its mean. The fluctuation index is a measure of the intensity of a decomposed sub-band. An SVM classifier is used in this approach, and some sort of post-processing is implemented to enhance the detection performance with smoothing.

The five-level wavelet decomposition was also adopted by Panda et al. with an SVM classifier for seizure detection from background EEGs [78]. This classifier was tested on a healthy subject with open eyes, a healthy subject with closed eyes, and an epilepsy patient. The extracted features for signal classification are energy, standard deviation, and entropy.

Khan et al. proposed a similar approach for seizure detection, but with relative energy and a normalized coefficient of variation (NCOV) as features [79]. Wang et al. used Neyman-Pearson rules and an SVM classifier for seizure detection in [80]. This method depends on the wavelet coefficients in addition to the Approximate entropy (ApEn) in the wavelet domain as extracted features, and the detection is performed using Neyman-Pearson rules with an SVM. The approximate entropy is an entropy metric that takes into consideration the ordering of the points of the discrete time sequence at hand, and hence, it is a good measure for the regularity of the data sequence.

Zainuddin et al. investigated the use of wavelet neural networks (WNNs) based on wavelet basis functions for seizure detection [81]. Firstly, the wavelet transform of EEG signals is estimated, and maximum, minimum, and standard deviation of the absolute values of the wavelet coefficients in each sub-band are extracted as features. These features are then fed to train WNNs. The Gaussian, Mexican Hat, and Morlet wavelet activation functions have been investigated for classification. A cross-validation approach have been adopted in the simulation experiments. Simulation results revealed that the best performance was obtained with WNNs employing a Morlet wavelet activation function with order 4 Daubechies wavelet for feature extraction.

Niknazar et al. presented a wavelet-based method for epileptic seizure detection that adopts recurrence quantification analysis (RQA) on EEG recordings and their delta, theta, alpha, beta, and gamma sub-bands extracted through a four-level Daubechies wavelet transform [82]. The RQA is well-suited for non-linear data analysis. It quantifies the number and duration of recurrences of the EEG signals based on phase space trajectories. The phase space is built on estimating a time delay and an embedding dimension, which the features are corresponding to each EEG signal state. The authors adopted an error-correcting output coding (ECOG) classifier for discriminating between three states: healthy, inter-ictal, and ictal.

The methods depicted in [21, 83] decompose the raw EEG signal into five dominant frequency bands like $\alpha, \beta, \gamma, \theta$ and δ by using Discrete Wavelet (DWT) analysis. Then the obtained Detail And Approximate Coefficients from DWT analysis along with different statistical measures like mean, average, standard deviation of powers at different frequency bands are used as feature for the detection and classification of epileptic seizure in [21, 83].

Since Wavelet transform has some limitations like lack of adaptivity, shift variance etc. Dual Tree Complex Wavelet Transform (DT-CWT) is exploited to overcome the problems encountered by using the conventional wavelet transform technique in [84]. Recently a method based on DT-CWT has been proposed in [43] to detect epilepsy. In this method seizure detection is acquired after applying DTCWT to each EEG signals to obtain sub bands for different classes of EEG signals. Then modeling of these sub bands of EEG signals is done via using Normal Inverse Gaussian (NIG) Probability density function (Pdf). This modeling has also been verified by using different statistical measures such that the NIG parameters are used to obtain these Pdfs for different classes are used as feature with SVM classifier to detect epilepsy.

However, all methods mentioned in [21, 43, 77–84] do not show its effectiveness for classifying epileptic seizure originated from different parts and state of the brain, thus classifying multiclass EEG signals in stringent conditions is still remain challenging.

2.4 Conclusion

In this chapter, a brief literature survey of the recent state-of-the-art seizure detection and classification methods are provided. All the methods have their advantages and limitations. In order to handle the practical situations of real life applications, a seizure detection and classification method, is needed to be capable of producing greater accuracy, sensitivity and specificity and lesser processing time even in case of stringent conditions, such as reduced training data as well as random selection of training and testing dataset for multiclass problem, where EEG signals from different part and state of the brain are involved.

Chapter 3

Detection and Classification of Multiclass Epileptic Seizures exploiting EMD-Wavelet analysis of EEG Signals

3.1 Introduction

Designing a feature set which is capable of extracting distinguishable information to detect and classify seizure data from mixture of normal and seizure EEG signals is a difficult task. Since, EEG is a non-stationary signal, empirical mode decomposition (EMD), and discrete wavelet transform (DWT) have the potential to perform better than the conventional time-frequency analysis method. But selection of intrinsic mode function (IMF) resulting from EMD analysis is also crucial in this case. In this chapter, first EMD analysis of the EEG signals is performed and the temporal energy contents of the different IMFs are analyzed to select dominant IMFs. After histogram analysis of the dominant IMFs of all classes of EEG signals it is found reasonable to select the first four IMFs as dominant IMFs for each EEG class. In order to obtain more discriminatory behavior, DWT analysis is carried out on the selected IMFs. Considering the parameters like normalized energy, Fourier spectrum and cross-correlation coefficient, only the 4th Level DWT coefficients of the selected dominant IMFs are found suitable for feature computation. For the reduction of the dimension of the feature vector, Higher order statistics of these coefficients are employed to form the feature vector. The reduced feature vector thus formed is found effective for detecting and classifying multi-class EEG epilepsy when fed to different state-of-the art classifiers, in stringent conditions, such as reduced training data as well as random selection of training and testing dataset [85].

3.2 Proposed Method

The proposed EEG based epileptic seizure detection and classification Method consists of some major steps, namely, pre-processing, EMD and Wavelet analysis, feature extraction and classification. In the classification, we consider three different classification problems, namely two class, three class and five class problem. Pre-processing manipulates the signal to be ready for EMD and Wavelet analysis and for feature extraction. For the purpose of detecting epileptic seizure and to classify epileptic seizures originated from different parts and state of the brain, a training database is needed to be prepared consisting of template EEG signals of different classes as well as different persons. The detection and classification task is based on comparing a test EEG signal with training dataset. It is obvious that considering EEG signals themselves would require extensive computations for the purpose of comparison. Thus, instead of utilizing the EEG signals, some characteristic features are extracted for preparing the training dataset. It is to be noted that the detection and classification accuracy strongly depends upon the quality of the extracted features. Therefore, the main focus of this work is to develop an effective feature extraction algorithm. The simplified block diagram of the proposed method is shown in Fig. 3.1.

3.2.1 Pre-processing

All the activities of an EEG signal can be divided into five popular frequency bands, namely $\alpha, \beta, \gamma, \theta$ and δ. These bands altogether covers their significant energies for the frequency range up to 60 Hz [42]. As a result, frequencies above 60 Hz are considered as noise. To eliminate the noise, 6th-order butterworth filter having a cut-off frequency of 60 Hz has been used in this work. The plots of original and preprocessed seizure and non-seizure EEG signals are shown in Fig. 3.2.

From this figure, it is quite difficult to identify any particular pattern for seizure and non-seizure activities from time domain EEG signals. As a result, we need to transform EEG signals in another domain for capturing suitable feature in another domain for detection and classification.

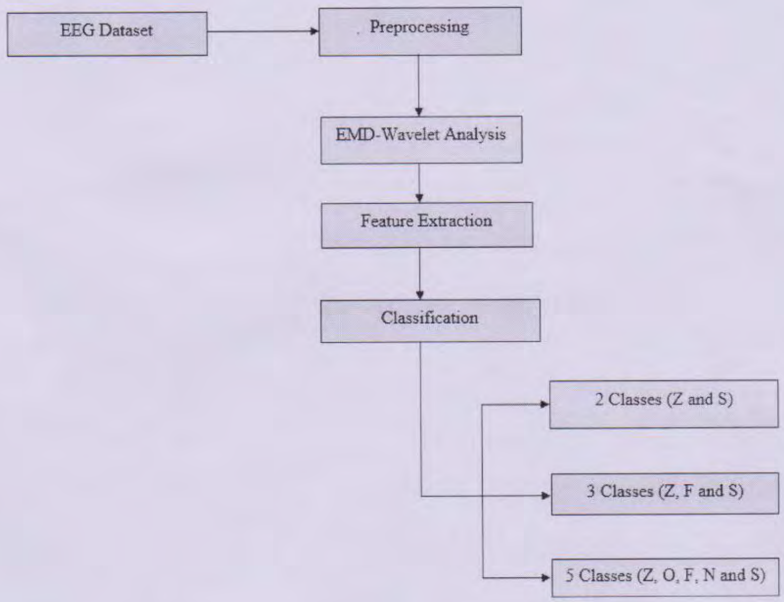


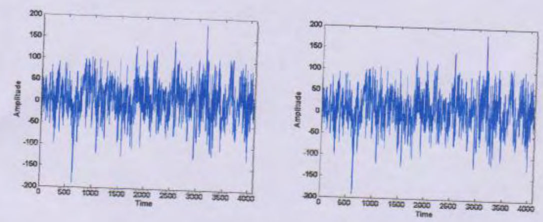
Fig. 3.1: Simplified Block diagram of the proposed method

3.2.2 EMD Analysis

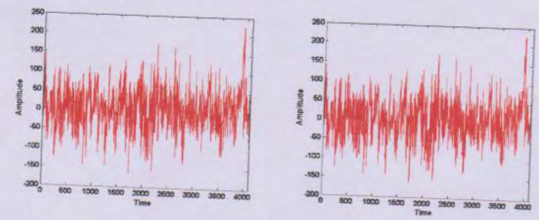
EMD is one of the recently emerged signal processing algorithms for decomposition, where basic functions can be deduced fully form the data itself. Due to adaptive and intuitive nature of the algorithm, it has been used quite largely in non-stationary signal environment, like EEG [86].

The main purpose is to turn a signal into several oscillatory signals, known as Intrinsic Mode Functions (IMFs) after decomposing the signal via sifting process. If a function can satisfy two conditions then it should be called an IMF, firstly the number of local extrema and that of zero crossings of a whole data set must be equal to each other or differ by at most one and in the end, at any point, the mean value of the envelope defined by the local extrema (both minima and maxima) should be zero. The sifting process of an EEG signal $y[n]$ can be stated as follows:

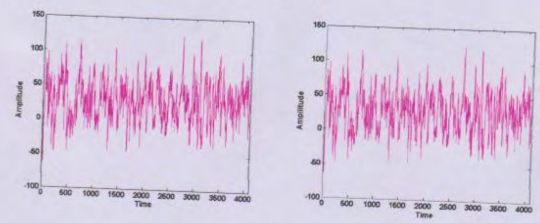
i All the local extrema i.e. maxima and minima of an EEG recording are dictated and interpolated by cubic spline line thus constructing an upper envelope and a lower envelope respectively for maxima and minima.



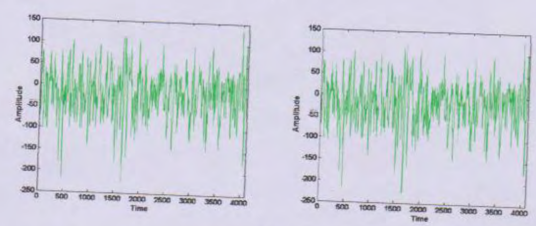
(a)



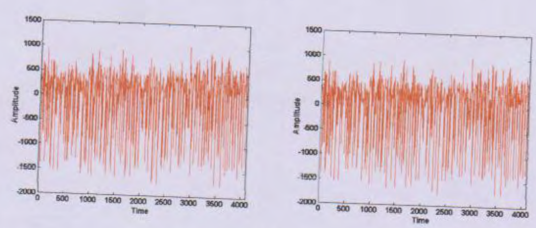
(b)



(c)



(d)



(e)

Fig. 3.2: Non-seizure [(a) to (d)] and Seizure [(e)] EEG signals [Original (Left) and Preprocessed (Right)].

ii After constructing both envelopes their mean m_1 are calculated to determine the difference between the given signal $y[n]$ and m_1 which is denoted as $p_1[n]$:

$$p_1[n] = y[n] - m_1 \tag{3.1}$$

iii If $p_1[n]$ satisfies the above stated conditions to be an IMF,then it is the first FM and AM approximated oscillatory mode i.e. IMF of $y[n]$.

iv If $p_1[n]$ does not become an IMF, it is regarded as the input data in the second sifting process, where steps i, ii are repeated where second component $p_2[n]$ can be derived as:

$$p_2[n] = p_1[n] - m_2 \tag{3.2}$$

in which m_2 is the mean of extrema envelopes of $p_1[n]$.

v If this process continues up to t times and thus we will get the following equation:

$$p_t[n] = p_{t-1}[n] - m_t \tag{3.3}$$

where $p_t[n]$ becomes an IMF which is then denoted as $i_1[n]$ $=p_t[n]$, the first IMF of the input signal.

vi After obtaining first IMF $i_1[n]$ the difference between $y[n]$ and $i_1[n]$ is denoted as

$$r_1[n] = y[n] - i_1[n] \tag{3.4}$$

which is treated as the original data for further operation for calculating the next IMF.

vii If this operation is repeated for M times, M no. of IMFs are obtained. For the stopping of sifting process following popular stopping criteria for which a standard difference (SD) within a threshold is given as:

$$SD = \sum_{n=1}^{L} \frac{|(p_{t-1}[n] - p_t[n])|^2}{p_t[n]^2} \tag{3.5}$$

Here, t and $t-1$ are indices which indicate two consecutive sifting processes. The decomposition process is stopped when the resultant signal becomes a monotonic function from which no more IMF can be extracted. This signal $r_M[n]$ is known as residue. After obtaining M no. of IMFs the input signal

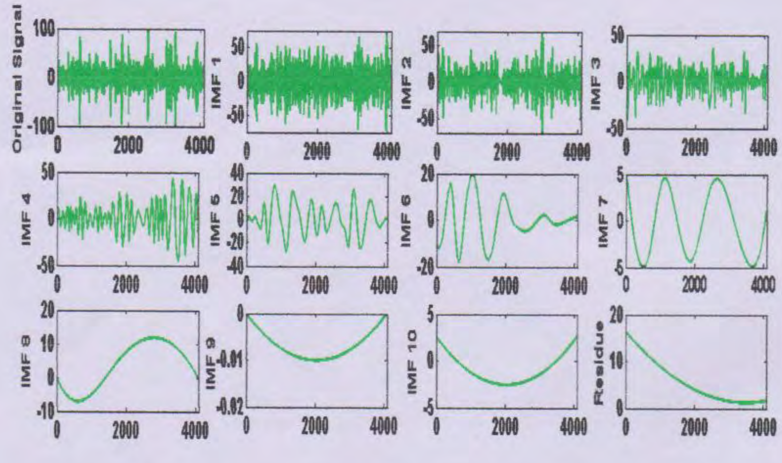


Fig. 3.3: An EEG signal along its IMFs and residue

$y[n]$ can also be reconstructed using these IMFs and its residue which is given by the following formula:

$$y[n] = \sum_{j=1}^{M} i_j[n] + r_M[n] \tag{3.6}$$

In above equation i_1,i_2,i_3,..... represent the IMFs.

For a particular type of EEG signal, its IMFs and residue are shown in Fig. 3.3.

3.2.3 Dominant IMF Selection and Analysis

Basically extracted IMFs do not uniquely describe whether the corresponding EEG signal is seizure or non-seizure. However it is to be mentioned that as expected the energy content of IMFs of non-seizure group usually lower than that of the seizure one. As a result, based on temporal energy content of IMFs, the selection criteria for the dominant IMF has been proposed. Among the extracted IMFs for a particular EEG recording, the dominant IMF has been selected via the maximum temporal energy content of all the IMFs. The temporal energy of the dominant IMF is given by ,

$$E_d = \sum_{n=1}^{L} i_d[n]^2 \tag{3.7}$$

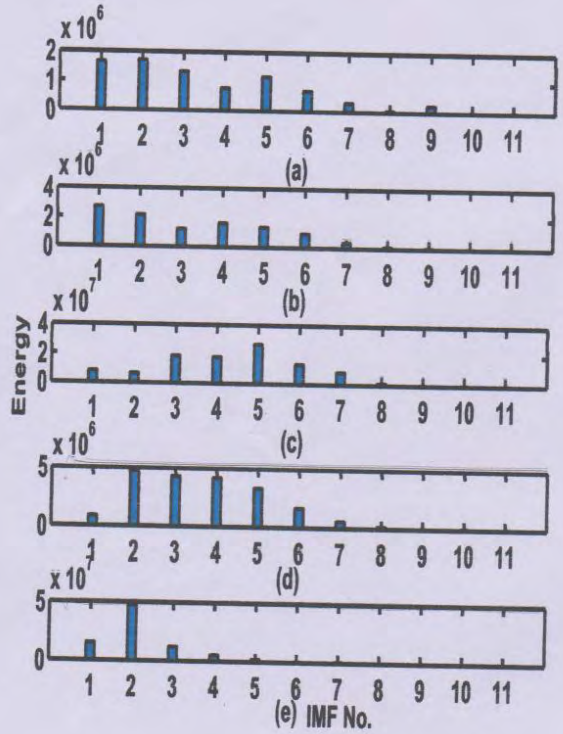


Fig. 3.4: Temporal Energy Pattern of IMFs of Non-seizure (a to d) and seizure (e) EEG signals of a particular channel.

Here L is the length of the IMF and E_d represents the temporal energy of the dominant IMF $i_d[n]$.

Temporal energy patterns of all the IMFs of the multi-class EEG recordings of a particular channel are shown in Fig. 3.4, where (a) to (d) correspond to non-seizure data and (e) corresponds to the seizure data. It is observed from non-seizure classes presented in (a) to (d) in Fig. 3.4 that the second, first, fifth and second IMFs contain the maximum temporal energy for the corresponding classes respectively and hence can be identified as the dominant IMFs for the non-seizure classes. It is seen from Fig. 3.4 (e) that since the second IMF has the highest temporal energy, it is identified as the dominant IMF for the seizure EEG recording. However, due to random nature of different EEG recordings, the dominant IMFs obtained from

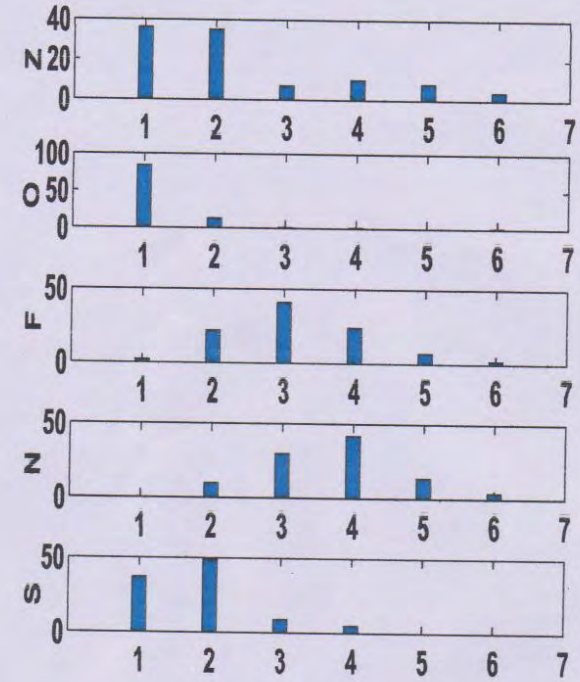


Fig. 3.5: Histogram of the Dominant IMFs obtained for all channels of Each class of the EEG signal

those recordings will also vary. As a result, in case of multiclass classification problem which involves different parts and states of the brain, a mismatch may be produced between training and testing data even for the same class. Therefore, adopting such method as presented in [87] in case of multiclass classification problem would provide classification error.

In order to overcome such problem, an analysis of the dominant IMFs via histogram is performed. In Fig. 3.5, histogram of the dominant IMFs obtained from all channels of each class of EEG signal is plotted. From histogram analysis a criterion has been developed for selecting the appropriate number of IMFs for each EEG class. From the figure it is evident that the dominant IMF varies from channel to channel for each EEG class and there is no unique dominant IMF that can be selected for all channels. Therefore, from the histogram analysis according to the proposed criterion the dominant IMFs that have occurred in at least 50% of the channels for an EEG class have been considered as the dominant IMFs for that class. In case of healthy EEG signal (Z) channels, first and second IMF have been found as the most dominant for at least 50% of the recordings. In case of other Non-Seizure EEG signals (O,F,N), first and second, third and fourth, third and fourth IMFs are found mostly dominant over 50% of the channels. In case of Seizure EEG signals (S), first and second IMFs are found as the most dominant. Therefore, considering only the two most dominant IMFs (first and second) of a class such as Z,O,S will also vary compared that of(third and fourth IMFs) other classes such as F and N, which may cause mismatch between the training and testing data in case of detection and classification. To avoid this mismatch, we consider to select the two most dominant IMFs from all classes. As a result, for representation of any class we will consider four IMFs (one and two for Z,O,S ,three and four for F,N class)for generalization of the dominant IMFs during training and testing phase. In order to obtain better discriminatory behaviour and improved time-frequency resolution mong the EEG recordings for all classes, DWT analysis is carried out on the selected IMFs [88].

3.2.4 Discrete Wavelet Transform Analysis of the Selected IMF

The wavelet transform is a better time-frequency multi-resolution technique usually adopted for analyzing non-stationary signals, where conventional signal processing methods are not useful. Like EMD it is also preferred for EEG signal analysis [89–91]. The Discrete Wavelet Transform (DWT) is a multi-resolution technique that provides localization in both time and frequency [92]. It exhibits good frequency resolution at low frequencies and good time resolution at high frequencies. The DWT of a signal $x[n]$ can be obtained as,

$$D(p,q) = \sum_{n \epsilon Z} x[n]\phi_{p,q}[n] \tag{3.8}$$

where p is the dilation or scale, q the translation and $\phi_{p,q}[n]$ is the discrete wavelet which is expressed as,

$$\phi_{p,q}[n] = (\frac{1}{\sqrt{p}}) \times \phi(\frac{n-q}{p}) \tag{3.9}$$

For dyadic wavelet transform, $p = 2^{-a}$, $q = b \times 2^{-a}$, $\phi_{p,q}[n] = 2^{\frac{a}{2}} \times \phi[2^a n - b]$ with $b \in Z$, $j \in N$. The DWT analyzes decomposing the signal into a coarse approximation and detail information. The original signal $x[n]$ being filtered via high-pass filter $h[n]$ and a low-pass $g[n]$ produces output of the first level decomposition, which can be respectively expressed as:

$$c_{high}(m) = \sum_n x[n].h[2m - n] \tag{3.10}$$

$$c_{low}(m) = \sum_n x[n].g[2m - n] \tag{3.11}$$

It is to be mentioned that $c_{high}(m)$ and $c_{low}(m)$ are obtained after performing a down-sampling by 2 operation. The above procedure can be repeated for further decomposition. At every level of decomposition, the filtering and down-sampling will result in half the number of samples and half the frequency band spanned. The obtained approximate DWT coefficients nearly depict the magnitude of the signal at that time point, which corresponds to the peak of the wavelet function. The detail DWT coefficients depict subsequently higher frequency information that is missing from the approximation. Such decomposition process for a signal $x[n]$ is illustrated in Fig. 3.6.

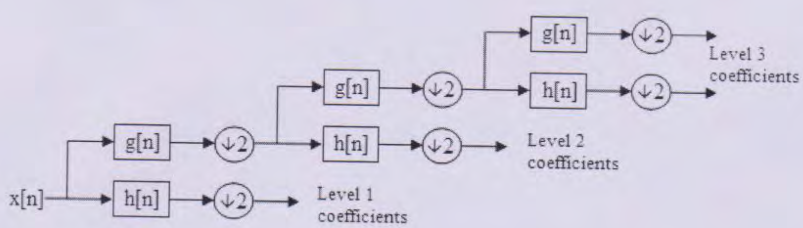


Fig. 3.6: DWT decomposition of a signal $x[n]$

In this proposed method, a mulilevel DWT analysis is performed on the selected dominant IMFs. But the main challenge in DWT decomposition is the determination of the appropriate wavelet decomposition level and the selection of the features from certain sub-bands for discrimination between seizure and non-seizure activities. That's why, for a selected IMF, all coefficients at different levels of DWT decomposition have been analyzed in terms of normalized average energy of, normalized average sum of fourier contents and normalized cross-correlation coefficient of approximate and detail coefficients.

The average energy of approximate and detail coefficients of the selected IMF at a given level P is given by,

$$E_{avg} = \frac{1}{L}\sum_{n=1}^{L}(A_P[n]^2 + D_P[n]^2) \tag{3.12}$$

Here $A_P[n]$ and $D_P[n]$ are the approximate and detail coefficients at a given level P where P = 1,2,3 etc. and L = Length of the signal.

The average of sum of fourier contents of approximate and detail coefficients of the selected IMF at a given level P is given by ,

$$F_{avg} = \frac{1}{N}\sum_{f=1}^{N}(A_P[f]^2 + D_P[f]^2) \tag{3.13}$$

Here $A_P[f]$ and $D_P[f]$ are the fourier transforms of $A_P[n]$ and $D_P[n]$ respectively at a given level P and N = The no. of frequency points in the Signal.

The coss-correlation coefficient of approximate and detail coefficients of the selected IMF of length N at a given level P is given by ,

$$r_{A_P D_P} = \frac{\sum_{n=1}^{L}(A_P[n] - \bar{A_P}[n])(D_P[n] - \bar{D_P}[n])}{\sqrt{\sum_{n=1}^{L}(A_P[n] - \bar{A_P}[n])^2 \sum_{n=1}^{L}(D_P[n] - \bar{D_P}[n])^2}} \tag{3.14}$$

Here $\bar{A_P}[n]$ and $\bar{D_P}[n]$ are the mean of $A_P[n]$ and $D_P[n]$ respectively.

The average energy is plotted for determining the maximum energy of the coefficients among different decomposition levels as seen in Fig. 3.7. The average of sum of fourier contents of approximate and detail coefficients is presented for different decomposition levels in Fig. 3.8 to find the level corresponds to the maximum appropriate frequency content in the Fourier domain. The maximum cross correlation co-efficient for different level in Fig. 3.9 is to determine level that has higher correlation than any other decomposition levels.

From these figures, it is evident that 4th level DWT coefficients of the selected IMF has the maximum normalized average energy , the maximum average sum of fourier contents of the coefficients, the maximum cross correlation co-efficient. Moreover, excluding any one of the approximate or detail coefficients of the 4th

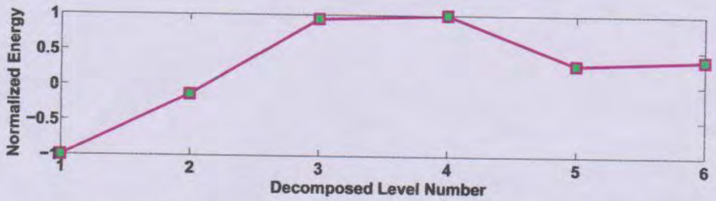


Fig. 3.7: Normalized Energy Analysis at different decomposition level for the DWT analysis of a selected dominant IMF

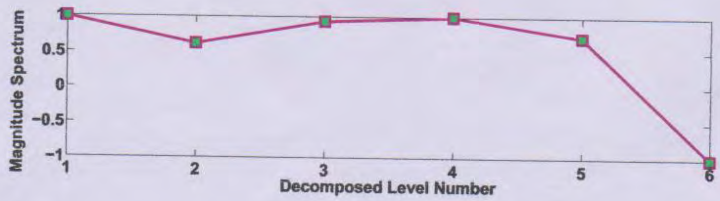


Fig. 3.8: Normalized Fourier Spectrum Analysis at different decomposition level for the DWT analysis of a selected dominant IMF

level would cause loss of information about peak of the wavelet function or the higher frequency information which is very important in case of seizure detection. Therefore, we opt to consider both approximate and detail coefficients only from the 4th level for feature extraction. These selected approximate (A4) and detail (D4) coefficients of the selected dominant IMFs are shown in Fig. 3.10-3.14 for all classes of EEG signals.

From the figures it is evident that these classes show their distinguishing characteristic more accurately in the DWT domain compared to that of the selected IMFs. However, using all DWT coefficients even from the selected 4th level as feature would

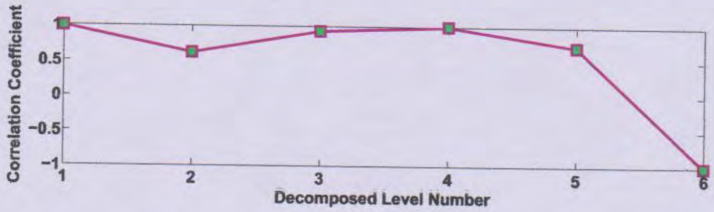


Fig. 3.9: Cross-Correlation Analysis at different decomposition level for the DWT analysis of a selected dominant IMF

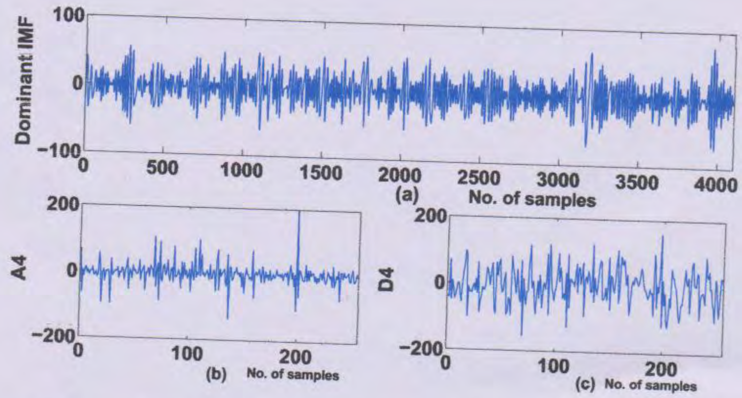


Fig. 3.10: Non-seizure EEG signal(With Eyes Open): (a) dominant IMF waveform, (b) level-4 approximate DWT coefficients of the dominant IMF (c) level-4 detail DWT coefficients of the dominant IMF.

increase the dimensionality of the feature vector in training and testing phase. Thus for reducing the feature vector dimensionality the higher order statistics (HOS) of the DWT coefficients are suggested to be exploited to form the feature vector.

3.2.5 Higher Order Statistics of the DWT Coefficients

The higher order statistics such as variance, skewness and kurtosis of the level 4 DWT coefficients of the selected IMFs are calculated and utilized as a feature set for classifying the multi-class EEG signals. The distribution of the samples of a data set can be often described in terms of dispersion, asymmetry and concentration around the mean. These attributes can be easily utilized by using these measures. For N point vector of approximate or detail coefficients, namely like $A4$ or $D4$, the corresponding variance (σ^2) will be,

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(A4[i]-\mu)^2, \mu = \frac{1}{N}\sum_{i=1}^{N}A4[i] \tag{3.15}$$

Here, μ denote the mean of the data.

The skewness(β_1) is computed as:

$$\beta_1 = \frac{1}{N}\sum_{i=1}^{N}\frac{(A4[i]-\mu)^3}{s^3} \tag{3.16}$$

Here, s denote the standard deviation of the data.

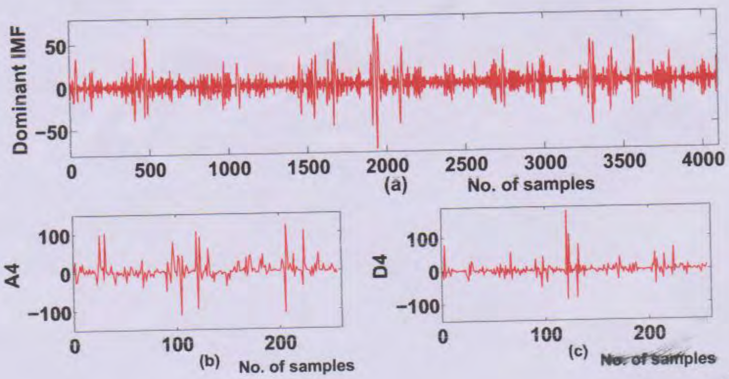


Fig. 3.11: Non-seizure EEG signal(With Eyes Closed): (a) dominant IMF waveform, (b) level-4 approximate DWT coefficients of the dominant IMF (c) level-4 detail DWT coefficients of the dominant IMF.

The kurtosis(β_2) can be computed as:

$$\beta_2 = \frac{1}{N}\sum_{i=1}^{N}\frac{(A4[i]-\mu)^4}{s^4} \tag{3.17}$$

These quantities represent the dispersion, asymmetry and peakedness of a data. Since the distinguishing characteristic of different EEG recordings are more prominent in the DWT domain rather than EMD domain,one may expect that these statistical measures would be more effective if computed in the DWT domain rather than in EMD domain alone for classifying the EEG signals. As a result feature vector, F representing a particular IMF will be denoted as:

$$F = [\sigma^2_{A4} \quad \sigma^2_{D4} \quad \beta_{1A4} \quad \beta_{1D4} \quad \beta_{2A4} \quad \beta_{2D4}]$$

The selection of such higher order statistics can also be justified by observing the boxplots of HOS, such as variance, skewness and kurtosis in case of all the preprocessed EEG recordings, for their dominant IMFs and finally for the detail and approximate coefficients of the 4th level for a particular IMF, which are shown in Fig. 3.15, Fig. 3.16, Fig. 3.17 and Fig. 3.18, respectively.

Normally the boxpolts with different median for each class of EEG signal notably represent the significant statistical difference among the data of all classes. As a result, the boxplots with different median for each class of EEG signal will show

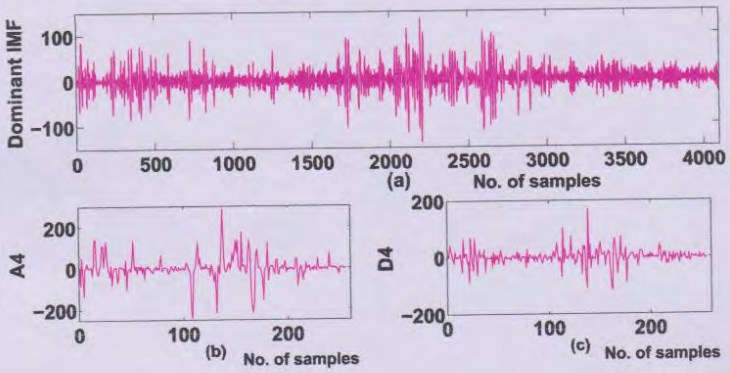


Fig. 3.12: Non-seizure EEG signal(Seizure Free Activity For Seizure Patient recorded in epileptogenic zone): (a) dominant IMF waveform, (b) level-4 approximate DWT coefficients of the dominant IMF (c) level-4 detail DWT coefficients of the dominant IMF.

better discriminatory attribute in case of detection and classification of multiclass EEG signals. The outliers in the boxplot for a class of EEG signals tend to overlap with the data of other classes of EEG signals. Therefore, the outliers of a box plot would normally limit the accuracy in case of discrimination of multiclass EEG signals. If boxplots of multiclass EEG signals show this overlapping attribute of outliers it indicate that the desired level of accuracy can not be achieved in case of detection and classification of multiclass EEG signals. Such facts are evident in the boxplots for the mentioned feature in Figs. 3.15 and 3.16. From Fig. 3.15, it is seen that apart from the outliers, the median of such HOS for the preprocessed EEG signals are heavily overlapping (especially in class F) which would cause less accurate detection of multiclass EEG signals when these features are fed to different state-of-the art classifiers. Whereas, the boxplots for HOS computed from the Dominant IMFs for the EEG signals as shown in Fig. 3.16, there are also highly overlapping median with overlapping outliers among the classes but they are relatively less in number (especially in class F). Therefore, as shown in Figs. 3.15 and 3.16, such overlapping nature in the boxplots of the features mentioned before clearly indicate their less effectiveness in detection and classification of multiclass seizure signals.

In Figs. 3.17 and 3.18, show the boxplots of HOS of the 4th level Detail and Approximate DWT coefficients for a particular dominant IMF are presented, respec-

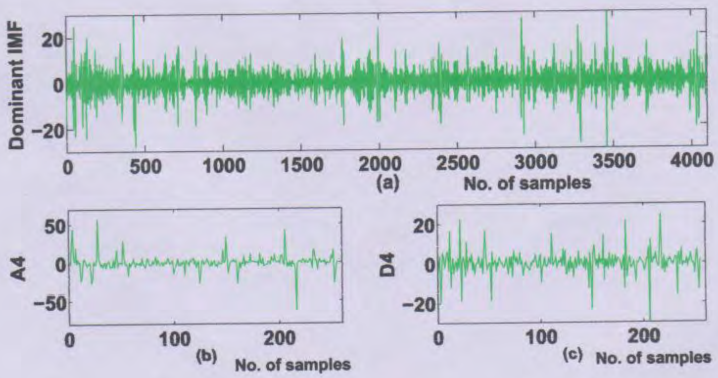


Fig. 3.13: Non-seizure EEG signal(Seizure Free Activity For Seizure Patient recorded in opposite hemosphere in the brain): (a) dominant IMF waveform, (b) level-4 approximate DWT coefficients of the dominant IMF (c) level-4 detail DWT coefficients of the dominant IMF.

tively. These boxplots show better variability in case of median with less number of outliers among the classes than that seen in Figs. 3.15 and 3.16. It is an attestation that using the HOS of such DWT coefficients of the selected IMFs would yield more discriminatory attribute than that obtained from the HOS of the preprocessed EEG signals and the HOS of the dominant IMF.

Since the resultant feature vector will contain the information from 1st to 4th IMF thus the giving the size of feature vector 24×1. Further reduction of feature set for training and testing purpose is done by using Principal Component Analysis (PCA) algorithm. PCA is a widely used dimensionality reduction algorithm of feature set which uses mapping of feature set from the original space to a new space with highly uncorrelated data giving less no. of principal components to reduce the dimension of the feature set [93].

3.2.6 Classification

After obtaining the HOS of the 4th level detail and approximate coefficients of the selected dominant IMFs as features;they are then fed to different state-of-the art classifiers. Four different classifiers have been used to determine the efficacy of the feature vector in classifying epileptic seizures originating from different parts and states of the brain.

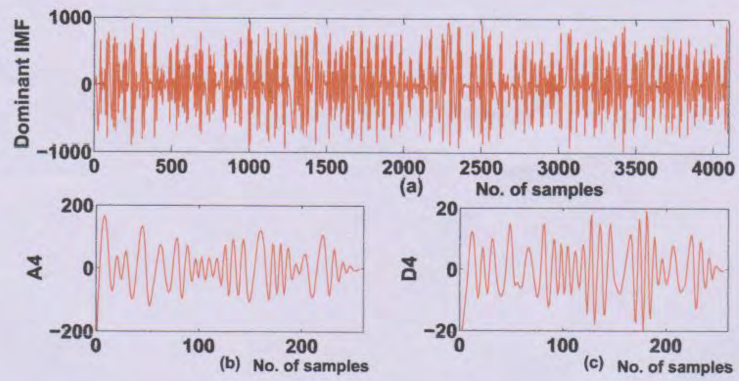


Fig. 3.14: Seizure EEG signal: (a) dominant IMF waveform, (b) level-4 approximate DWT coefficients of the dominant IMF (c) level-4 detail DWT coefficients of the dominant IMF.

k-Nearest Neighbors

The k nearest neighborhood (k-NN) is simple in nature but pretty efficient in classifying many complex patterns [94]. It exploits a distance function which is calculated between the features from the EEG pattern in test set and k neighboring EEG patterns from EEG recordings in the training set. In k-nearest neighbor learning the number of neighbouring samples in can be a constant defined by the user or vary based on the local density of points. The distance can be any metric measure. For obtaining accurate classification performance it is necessary to find a suitable value of k. In the proposed method the value of k is varied such a way that consistent performance is achieved. These methods are also known as non-generalizing machine learning methods, since they simply remember all of its training data. Despite its simplicity, nearest neighbors has been successful in a large number of classification and regression problems, including handwritten digits or satellite image scenes [95,96]. Being a non-parametric method, it is often successful in classification situations where the decision boundary is very irregular [97].

Discriminant Analysis

Like k-NN classifier, discriminant analysis is also another simple classifier [98]. It assumes each feature set from each EEG pattern from each class is normally dis-

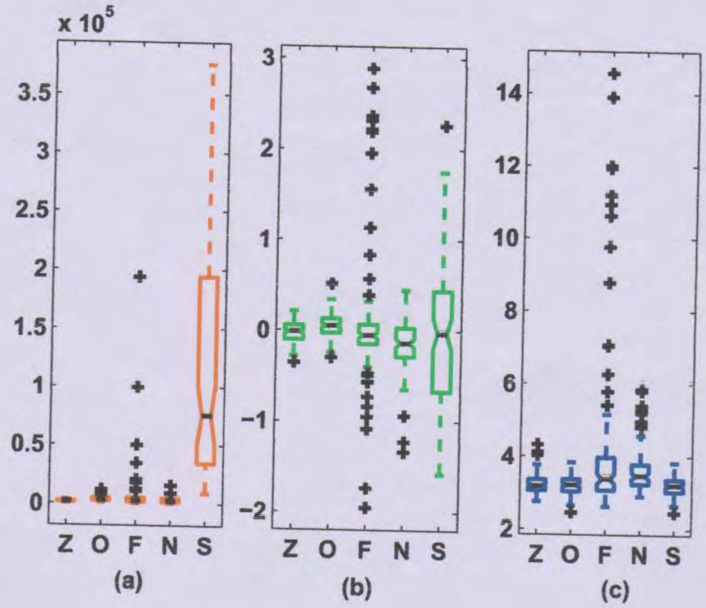


Fig. 3.15: Box plots of using HOS of preprocessed EEG signals of all classes [(a) Variance, (b) Skewness and (c) Kurtosis]

tributed. It is basically of two kinds: linear (LDA) and quadratic (QDA). LDA assumes same covariance for each class of EEG pattern while means are varied. While in case of QDA both covariance and means vary. Moreover, in LDA only linear combination of features is used while in QDA quadtaric combination of features are used in both training and testing phase. In this work, we used QDA classifier to report the classification performance since the proposed features are highly non-linear.

Support Vector Machine

Support Vector Machine (SVM) is also another highly rated machine learning algorithm widely used in the field of pattern recognition [99]. SVM basically builds a classification model by assigning the training EEG patterns into two categories. The model will also assign the testing EEG pattern on one of two categories based on the hypothesis of the built model. In case of non-linear classification, it utilizes different kernel function approach which enables different types of decision boundaries in or-

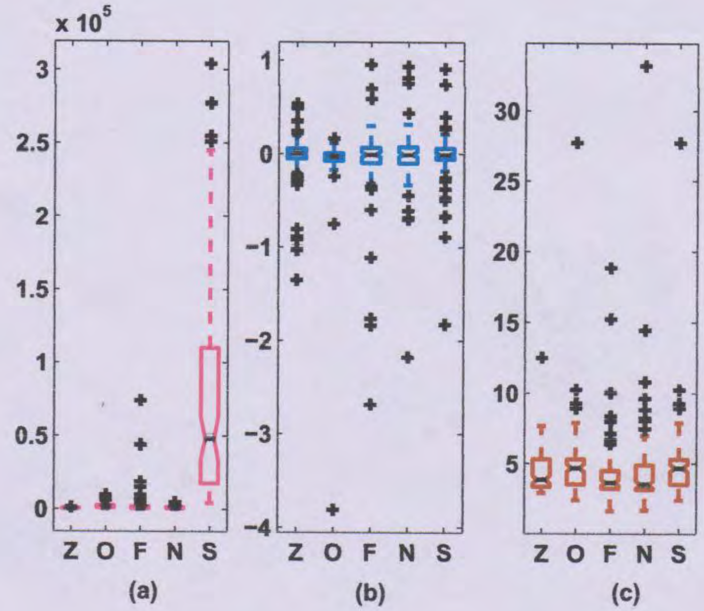


Fig. 3.16: Box plots of using HOS of the Dominant IMF of all classes [(a) Variance, (b) Skewness and (c) Kurtosis]

der to ensure efficient classification. Since SVM methodology supports only two class classification approach, in case of multi-class classification one vs. all classification scheme is used. In one vs all classification scheme multiple two class classification schemes are used where all possible combinations of two class EEG patterns from all EEG classes data are taken. Different SVM schemes are used widely in different literatures [41, 43] including LS-SVM. LS-SVM, is least squares version of support vector machine (SVM), which is a set of related supervised learning method that analyze different EEG patterns and are used for classification and regression analysis. In LS-SVM, the optimal solution is found by solving a set of linear equations instead of a convex quadratic programming (QP) optimization problem which is used for SVM. It is one kind of kernel-based learning methods.

Artificial Neural Network

Artificial Neural Network (ANN) is one of the state-of-the-art machine learning algorithms used in pattern recognition [100]. It is inspired by the biological structure

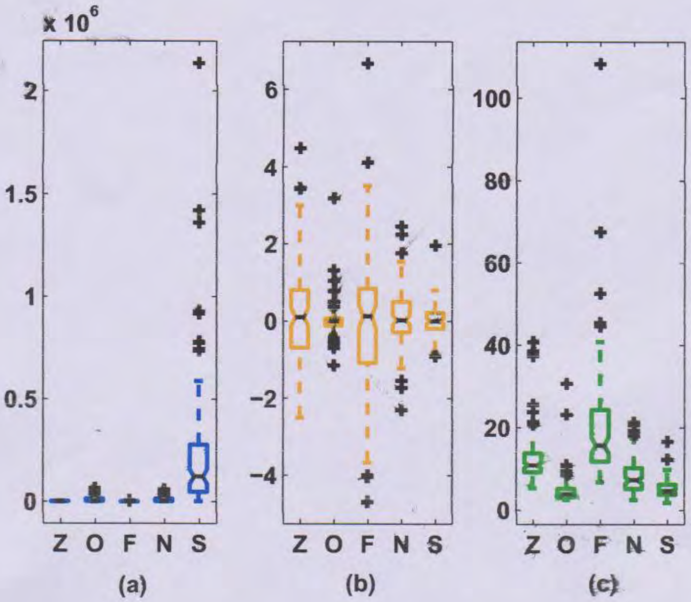


Fig. 3.17: Box plots of using HOS of the 4th level Detail DWT coefficients for a particular dominant IMF of all classes [(a) Variance, (b) Skewness and (c) Kurtosis]

or function of neurons [101]. The complexity of real neurons is highly visualized during modeling of artificial neurons. It has been developed as a mathematical or computational model which can mimic the activity of neurons. The model basically consists of inputs like synapses which are multiplied by weights and then a mathematical function which computes the activation of the neuron by different mathematical activation function. As a result it processes information using a connectionist approach to computation since it consists of an interconnected group of artificial neurons. Due to variability of the weights, the computation of the neuron will be different. Thorough adjustment of the weights of an artificial neuron one can obtain the output for specific inputs. This process of adjusting the weights is called learning or training. Therefore, it can be treated as adaptive system since it can change structure while learning the patterns during training and testing phase. Modern neural networks employs non-linear statistical data modeling tools that are normally exploited to recognize multi-class EEG signals.

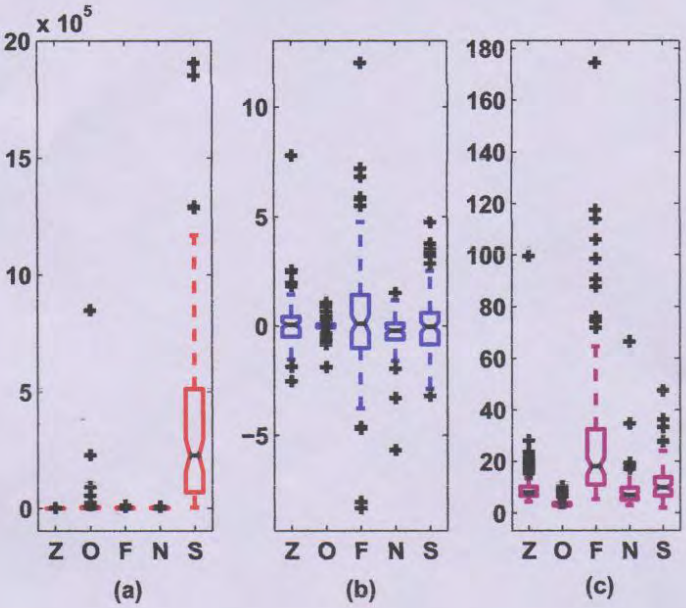


Fig. 3.18: Box plots of using HOS of the 4th level Approximate DWT coefficients for a particular dominant IMF of all classes [(a) Variance, (b) Skewness and (c) Kurtosis]

3.3 Conclusion

Conventional time or frequency domain analysis is found inadequate to describe the characteristics of a non-stationary signal such as, EEG. Moreover, conventional time-frequency analysis has the limitation of being computationally expensive. In this chapter, we opt for EMD analysis to determine the dominant IMFs for the EEG recordings. Then histogram analysis is performed on the obtained dominant IMFs to select a set of IMFs. To overcome the problem of random nature of the selected dominant IMFs and for obtaining better time-frequency resolution, the selected IMFs are used for DWT analysis. The higher order statistics of the selected 4th level DWT coefficients of the selected dominant IMFs particular IMF can be used as a feature set which can detect and classify epileptic seizures originating from different parts and states of the brain. The justification of using such features is also verified from the box plots of the obtained features. Then these features are fed to K-NN, QDA, SVM, LS-SVM and ANN classifiers in order to classify multiclass epileptic seizures, a task where very limited work is reported in the literature.

Chapter 4

Simulation Results

4.1 Introduction

A number of simulations is carried out to evaluate the performance of the proposed method. Performance is analyzed for both seizure detection and classification cases. Performance of proposed method is compared with the few state-of-art methods for the evaluation purpose. A popular EEG database which consists five class EEG data is utilized for simulation purpose for both detection and classification of multiclass epileptic seizures.

4.2 EEG Dataset

For the effectiveness of the proposed method the EEG dataset described in [102,103] is used for training and testing purpose. Here all the EEG recordings are acquired with the same 128-channel amplifier system using an average common reference. The sampling rate of these recordings is 173.61 Hz. As a result according to Nyquist theorem the bandwidth of these data varies from 0.5 to 85 Hz. These recordings are divided into 5 sets of data where each set represents 100 single channel EEG data containing an interval of 23.6s. These sets can be denoted as Z,O,F,N,S. The recordings from set Z comprise the data for five non-seizure healthy volunteers with eyes open. The set O comprises same recordings like Z but with eyes are closed. The set F is recorded in epileptogenic zone contains the recording of seizure free EEG data from seizure patient, while set N contains recordings like F but recorded in the opposite hemisphere of the brain in hippocampal formation. S is the only recording of seizure EEG data i.e. only contains recordings from five seizure patients. So the recordings form Z,O contain the healthy non-seizure EEG data where F,N contain the seizure free EEG data during seizure EEG recording and finally set S contain the seizure EEG data.

Since the frequency range of an EEG signal spans up to 60 Hz,so frequencies above 60 Hz are considered as noise. This noise is eliminated by using 6th-order butterworth filter which has a cut-off frequency of 60 Hz. For multilevel DWT decomposition Haar wavelet is used because of its simplest structure. For a particular IMF the size of feature vector would be 6×1; thus to represent a signal of a particular EEG class, the proposed feature vector size would be 24×1 because we are considering the four IMFs for a particular EEG recording. After using PCA on the size of the proposed feature vector reduces from 24×1 to 6×1. The reduced feature vector is then fed into different state-of-the art classifiers to evaluate the effectiveness of the proposed method in different simulation conditions.

For the evaluation of proposed method training,testing and cross-validation assignment of data are done in following three ways.

- Simulation Condition I: 50% of feature data are used for training and rest of the 50% are used for testing where 10% of training data are used for cross-validation purpose. First case of division of data is considered in our work for the fact to test the effectiveness of the proposed feature set using less training data than the state-of-the-art comparison methods [43,42].
- Simulation Condition II: 50% of data are used for training and rest of the data are used for testing [43].
- Simulation Condition III: 60% of the data are used for training, 5% of the data are used for cross validation and 35% of the data are used for testing [42]. Simulation Condition II and III are used to have a fair platform of comparison with the methods in [43,42]. The splitting of data are done randomly in all simulation conditions.

For the purpose of comparison, we have implemented the the state-of-the art method in [43,42] that handle 2 and 3 class problem and compared them with the proposed method. In [43,42] two and three class classification problems are considered. We have also evaluated the performance of the proposed method for a 5 class problem and compared with that reported in [40,42,43].

Six different state-of-the art cases of classification problems and a five class classification problem are handled to evaluate the performance of our method. also considered . The six classification cases are chosen based on their clinical relevance which are used in case of detection of epilepsy.

- Case I and II are defined as three class classification problem. Where in Case I, Z and O type of EEG data are grouped as one class, F and N type of EEG data are grouped as another class where S type of data are assigned in another class. Z and S type EEG data. Whereas in Case II is designed as three class problem where Z,F and S class data are used. Here, Z and O is normal, F and N is seizure free interval data of seizure patient and S is seizure data. As for clinical relevance, Cases I and II are used for discriminating healthy persons from the epilepsy patients as well as occurrence of seizures.

- Case III and IV are denoted as two class classification problem. In case III, Z and S type of EEG data are used for classification. In case IV, the features from Z,O,F,N are grouped as one class of EEG data and S type of data are assigned into another class. Cases III and IV are used for detection of seizure and in addition, may be related to the discrimination of surface EEGs from the intra-cranial ones since Sets Z,O and F,N,S are acquired from surface and intra-cranial electrodes, respectively.

- Case V deals with F and S type of EEG data which is a two class classification problem.Case V corresponds to the detection of the onset of seizure, since the signals in Set F are obtained from epileptogenic zone and thus, highly related to the early-seizure activities.

- Case VI is a two class classification problem with N and S class of EEG data. Case V corresponds to the detection of the onset of seizure, since the signals in Set F are obtained from epileptogenic zone and thus, highly related to the early-seizure activities. Like Case V, Case VI is related to discriminating the seizure recordings from the nonseizure activity for seizure ones.

- The final problem is a five class classification problem where all data (Z,O,F,N,S) as mentioned above are used. Here, data for each type of EEG are considered as individual group for classification purpose. Considering different types of EEG data such as Z,O,F,N,S as different classes in the classification problem can be a case for handling seizure detection, seizure onset detection, inter-ictal activity classification and mental state classification altogether. As a result, the five class classification problem holds importance because it can detect and classify seizures activities by only considering a case of classification problem to distinguish different activities inside the brain.

For the purpose of comparison, we have implemented the the state-of-the art method in [42, 43] and compared it with the proposed method. In [42, 43] two and three class classification problems are considered. In case of two class problem 200 EEG signals are used while in case of three class problem 300 EEG signals are utilized in [42, 43]. We have also evaluate the performance of the proposed method for a 5 class problem and compared with that reported in [40]. In case of 5 class EEG classification problem depicted in [40] total 500 EEG signals are used.

In case of k-NN classification Euclidean distance has been used. In case of ANN classification two layer feed forward neural network has been used. The transfer function, no.of neurons in the hidden and the output layer, training algorithm has been used as same as described in [42]. In [42] the hyperbolic tangent sigmoid transfer function is used in both the hidden and output layers. The number of neurons in the hidden and output layers is 20 and equal to the number of classes used for classification purpose, respectively. In case of SVM, LS-SVM radial basis function has been used as kernel function having width of 0.4.

4.2.1 Goodness of Feature

For proper justification of proposed feature set in case of multi-class classification and detection of EEG signals among different statistical parameters, we utilize Geometrical Separability Index (GSI) and Bhattacharya Distance (BD) of feature sets. GSI quantitatively show the class-to-class distance while class dispersion is quantitatively shown by BD.

4.2.2 Geometrical Separability Index (GSI)

Geometrical Separability Index (GSI) also known as Thorntons separability index is useful to understand the separability of clusters. Thorntons separability index s is defined as the fraction of a set of data points whose classification labels are the same as those of their nearest neighbours. Thus it is a measure of the degree to which inputs associated with the same output tend to cluster together. It gives an index which can quantify the degree to which classes are separable. The GSI index varies from zero to one where the GSI value close to zero declares the two classes are merely separable and value approximates to one will declare the two classes are mostly separable. It may be written as:

$$s = \frac{\sum_{i=1}^{N}(f(x_i)) + f(x_i') + 1)\ mod\ 2}{N} \tag{4.1}$$

where x' is the nearest neighbour of x and n is the number of points.

From the above equation It is intuitively obvious that s will be close to 1 for a set of points in which those with opposite labels exist in tight, well-separated clusters. As the clusters move closer together and points from opposing classes begin to overlap, the index will begin to fall. If the centroids of the clusters coincide, or the points are uniformly distributed in the space without clustering, the nearest neighbour of a point will have no more than a 50% probability of having the same class label as its neighbour, and the separability index will be close to 0.5 [104].

The GSI indices for the feature set of the given EEG recordings implemented by using the proposed and that for the comparison methods in [42, 43] are depicted in Tables 4.1 to 4.6. In [42], the authors used the features with respect to the first four individual IMFs for detection of epilepsy. Therefore, we have reported the GSI indices of these IMFs individually in the Table 4.1 to 4.6 of the feature set of the method described in [42]. In all the tables Z,O denote the healthy people activity , F,N represent Non-seizure activity for Seizure patients and S represents seizure activity of seizure patient.

It is evident from Table 4.1 to 4.6 that for both proposed and comparison methods each diagonal entry representing the same class has a value of zero. In table 4.1, the non-diagonal entries showing higher GSI value close to one except for Z and O classes showing 0.88 which may occur due to same nature of EEG recording for both classes since they both represent healthy people data. While in table 4.2 to 4.6 for the comparison methods, these non-diagonal entries exhibit lower GSI indices in most cases than that presented in Table I. Such representation of GSI values indicate that the proposed method has the more capability to provide the higher class separability between any two different classes of EEG signals.

Table 4.1: GSI of the proposed method

Classes	S	Z	O	F	N
S	0	1	0.99	0.97	0.98
Z	1	0	0.88	1	0.96
O	0.99	0.88	0	0.99	0.98
F	0.97	1	0.99	0	0.99
N	0.98	0.96	0.98	0.99	0

Table 4.2: GSI of the comparison method in [43]

Classes	S	Z	O	F	N
S	0	0.85	0.89	0.99	0.99
Z	0.85	0	0.75	0.99	0.99
O	0.89	0.75	0	0.99	0.99
F	0.99	0.99	0.99	0	0.99
N	0.99	0.99	0.99	0.99	0

Table 4.3: GSI of the comparison method in [42] using the 1st IMF

Classes	S	Z	O	F	N
S	0	0.98	0.83	0.92	0.96
Z	0.98	0	0.73	0.82	0.75
O	0.83	0.73	0	0.80	0.84
F	0.92	0.82	0.80	0	0.55
N	0.96	0.75	0.84	0.55	0

4.2.3 Bhattacharya Distance (BD)

Bhattacharyya distance measures the similarity of two discrete or continuous probability distributions. BD is another statistical parameter which reflects the ability to signify the intra-class compactness of a single class. Basically it indicates the intra-class compactness of the given feature set.

Table 4.4: GSI of the comparison method in [42] using the 2nd IMF

Classes	S	Z	O	F	N
S	0	0.98	0.89	0.90	0.94
Z	0.98	0	0.70	0.86	0.63
O	0.89	0.70	0	0.71	0.76
F	0.90	0.86	0.71	0	0.57
N	0.94	0.63	0.76	0.57	0

Table 4.5: GSI of the comparison method in [42] using the 3rd IMF

Classes	S	Z	O	F	N
S	0	0.93	0.89	0.95	0.96
Z	0.93	0	0.75	0.90	0.70
O	0.89	0.75	0	0.77	0.87
F	0.95	0.90	0.77	0	0.58
N	0.96	0.70	0.87	0.58	0

The equation of Bhattacharya Distance of two independent Gaussian data clusters is given below:

$$BD = \tfrac{1}{8}(\mu_2 - \mu_1)^T[\tfrac{1}{2}(\delta)_1 + \delta)_2]^{-1}(\mu_2 - \mu_1) + \tfrac{1}{2}\ln\left(\frac{det(\frac{\delta_1+\delta_2}{2})}{\sqrt{det(\delta_1))} * \sqrt{det(\delta_2))}}\right) \quad (4.2)$$

Here, δ_1 and δ_2 are the covariance matrices of clusters 1 and 2 respectively; μ_1 and μ_2 are mean vectors of clusters 1 and 2 respectively, det denotes the determinant of the matrices.

In Table 4.7, the BD values of feature set obtained by using both the proposed and the comparison methods in [42, 43] have been shown. Each EEG class yields less average BD values will ensure the better intra-class compactness. Here in the proposed method, BD values are competitive in case of seizure (S) and non-seizure activity of seizure patient (F) classes than the comparison method in [43]. However, in most of the cases, BD values of proposed method are less than that of comparison methods, which show better intraclass compactness.

As a result, having a better GSI indices and less BD values in maximum cases of the feature set in proposed method will ensure the better class separability and intraclass compactness than the comparison methods.

Table 4.6: GSI of the comparison method in [42] using the 4th IMF

Classes	S	Z	O	F	N
S	0	0.81	0.82	0.66	0.68
Z	0.81	0	0.53	0.65	0.60
O	0.82	0.53	0	0.59	0.56
F	0.66	0.65	0.59	0	0.52
N	0.68	0.60	0.56	0.52	0

Table 4.7: Intraclass BD values for the proposed and comparison methods

Methods	S	Z	O	F	N
Proposed Method	0.67	0.05	0.13	0.38	0.19
Method in [43]	0.44	0.122	0.17	0.34	0.21
Method in [42] (The 1st IMF)	0.72	0.33	0.26	0.49	0.35
Method in [42] (The 2nd IMF)	0.56	0.20	0.15	0.42	0.26
Method in [42] (The 3rd IMF)	0.78	0.23	0.20	0.34	0.27
Method in [42] (The 4th IMF)	0.67	0.25	0.56	0.40	0.50

4.3 Performance Parameters

For the performance evaluation of the proposed method, criteria considered in our simulation study are: 1) Sensitivity 2) Selectivity 3) Accuracy.

All the criteria as mentioned above can be derived from the confusion matrix, which is a form of representing the result from a classification exercise. The rows in the matrix stand for the actual classes to be tested and columns provide the class classified by a method. In particular, any [*row*, *column*] entry in the confusion matrix indicates the number of cases from the test database that belongs to the class corresponding to the row but classified as the class corresponding to the column.

In Fig. 4.1, a general confusion matrix for a two, three and five class problem is shown, where TP, FP, FN and TN are represented for Z class. In general, TP_i, true positive for any class i, measures the number of testing cases, which are correctly classified as class i. FP_i, false positive for any class i, denotes the number of testing cases i, which are incorrectly classified as class i. FN_i, false negative for any class i, indicates the number of testing cases, which are incorrectly classified as other than class i. TN_i, true negative for any class i, means the number of testing cases, which are correctly classified as other than class i.

<table>
<tr><td></td><td></td><td colspan="2">Classified by the classifier</td></tr>
<tr><td></td><td></td><td>Z</td><td>S</td></tr>
<tr><td rowspan="2">Actual Class</td><td>Z</td><td>TP_Z</td><td>FN_Z</td></tr>
<tr><td>S</td><td>FP_Z</td><td>TN_Z</td></tr>
</table>

(a) Two class with respect to Z

<table>
<tr><td></td><td></td><td colspan="3">Detected by the classifier</td></tr>
<tr><td></td><td></td><td>Z</td><td>F</td><td>S</td></tr>
<tr><td rowspan="3">Actual Class</td><td>Z</td><td colspan="2" rowspan="2">TN_S</td><td rowspan="2">FP_S</td></tr>
<tr><td>F</td></tr>
<tr><td>S</td><td colspan="2">FN_S</td><td>TP_S</td></tr>
</table>

(b) Three class with respect to S

<table>
<tr><td></td><td></td><td colspan="5">Detected by the classifier</td></tr>
<tr><td></td><td></td><td>Z</td><td>O</td><td>N</td><td>F</td><td>S</td></tr>
<tr><td rowspan="5">Actual Class</td><td>Z</td><td colspan="2" rowspan="2">TN_N</td><td rowspan="2">FP_N</td><td colspan="2" rowspan="2">TN_N</td></tr>
<tr><td>O</td></tr>
<tr><td>N</td><td colspan="2">FN_N</td><td>TP_N</td><td colspan="2">FN_N</td></tr>
<tr><td>F</td><td colspan="2" rowspan="2">TN_N</td><td rowspan="2">FP_N</td><td colspan="2" rowspan="2">TN_N</td></tr>
<tr><td>S</td></tr>
</table>

(c) Five class with respect to N

Fig. 4.1: Confusion matrix for two, three and five class classification cases

Sensitivity of a class relates the number of positive testing cases which are correctly classified to the number of testing cases of that particular class. Thus, sensitivity, for a particular class i, can be defined as

$$Sensitivity_i = \frac{TP_i}{TP_i + FN_i} \tag{4.3}$$

A classifier, which always indicates positive, regardless of the class of the testing case, provides 100% sensitivity for that class. Therefore the sensitivity alone cannot be used to determine the usefulness of the classifier in practice. Selectivity of a class relates the number of positive testing cases, which are correctly classified to the number of classified cases in that particular class. Therefore, selectivity, for a particular class i, can be expressed as

$$Selectivity_i = \frac{TP_i}{TP_i + FP_i} \tag{4.4}$$

Accuracy of a class relates the number of testing cases, which are correctly classified to the number of total testing cases. Therefore, accuracy, for a particular class i, can be written as

$$Accuracy_i = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \tag{4.5}$$

4.4 Simulation Results

Performance of the multiclass epilectical seizures detection and classification method based on EMD-Wavelet analysis of EEG signals, described in Chapter.3,are analyzed and compared with the state-of-art methods.

4.4.1 Performance Analysis and Comparison

The simulation results for six different cases as mentioned before are mentioned with accuracy, specificity and sensitivity from Table 4.8 to 4.10. Due to random selection of training and testing data, the maximum result is taken from 100 iterations of training and testing of the feature set. Here in the tables (from Table 4.8 to 4.10) the results are obtained by using 40% data for training , 10% data for cross-validation and 50% data for testing purpose for the proposed method with different classifiers. While the partition of training, testing and cross validation data is kept the same for the comparison methods in [42, 43] for a fair evaluation.

From the classification result in the different tables, it is vivid that in all six cases with different classifiers, the proposed method produces greater accuracy,specificity and sensitivity in most classification cases even with less complicated classifier (k-NN) and less amount of training data (40%) than with the training data reported in [42] (60%), and [43](50%). Thus the effectiveness of the proposed method in case of seizure detection is attested. In some case, the result of the proposed method is competitive compared to the methods in [42, 43] due to randomness of training and testing samples among the proposed and comparison methods.

The methods in [43,42] have not reported classification performances involving all five classes of EEG recordings. Therefore, for further investigation of the effectiveness of the proposed method, we opt to report the result of five class classification

Table 4.8: Performance Comparison of Case I and II

Case I [(Z,O),(F,N),S]				
Methods	**Classifier**	**Accuracy**	**Specificity**	**Sensitivity**
Method in [43]	SVM	96%	96%	97%
Method in [42]	ANN	80%	96%	83%
Proposed Method	SVM	92%	94%	94%
Proposed Method	LS-SVM	96%	98%	98%
Proposed Method	QDA	95%	97%	96%
Proposed Method	k-NN	96%	98%	99%
Proposed Method	ANN	100%	100%	100%
Case II [(Z,F,S]				
Methods	**Classifier**	**Accuracy**	**Specificity**	**Sensitivity**
Method in [43]	SVM	100%	100%	100%
Method in [42]	ANN	100%	100%	100%
Proposed Method	SVM	98%	98%	98%
Proposed Method	LS-SVM	98%	98%	98%
Proposed Method	QDA	100%	100%	100%
Proposed Method	k-NN	100%	100%	100%
Proposed Method	ANN	100%	100%	100%

problem in terms of accuracy, specificity and sensitivity and compare the results with respect to the state-of-the-art comparison methods like [43,42] by implementing them for a five class problem.

In Table 4.10 to Table 4.13, accuracy, specificity and sensitivity using the proposed method and comparison methods are presented for five class classification problem using Simulation Condition I, II and III respectively for different classifiers. From these tables, for different classifiers at different simulations conditions it is vivid that the proposed method is capable of producing much higher values of accuracy, specificity and sensitivity in comparison with the methods in [43,42] in 5 class classification problem using all classifiers.

Moreover, in case of 5 class EEG classification problem, the accuracy is also reported on Table 4.14 where the result of another state-of-the-art method [40] is included for our comparison. It is seen from this table that proposed method is able to classify multi-class EEG signals more accurately than the state-of-the-art comparison methods in [40, 42, 43] even with a simple classifier such as k-NN. Here the maximum accuracy for the proposed method is reported (from Table 4.10 to Table 4.13) for all classifiers.

In Table 4.15, the time required for the classification of the feature of a testing

Table 4.9: Performance Comparison of Case III and IV

Case III [(Z,S]				
Methods	Classifier	Accuracy	Specificity	Sensitivity
Method in [43]	SVM	100%	100%	100%
Method in [42]	ANN	100%	100%	100%
Proposed Method	SVM	100%	100%	100%
Proposed Method	LS-SVM	100%	100%	100%
Proposed Method	QDA	100%	100%	100%
Proposed Method	k-NN	100%	100%	100%
Proposed Method	ANN	100%	100%	100%
Case IV [(Z,O,F,N),S]				
Methods	Classifier	Accuracy	Specificity	Sensitivity
Method in [43]	SVM	100%	100%	100%
Method in [42]	ANN	100%	100%	100%
Proposed Method	SVM	98%	97%	96%
Proposed Method	LS-SVM	98%	95%	98%
Proposed Method	QDA	98%	98%	98%
Proposed Method	k-NN	100%	100%	100%
Proposed Method	ANN	100%	100%	100%

sample of the proposed method and that of the state-of-the-art comparison methods is provided along with the size of the feature vector to evaluate the computational complexity of the methods. The whole process from feature extraction to the performance analysis is run on the MATLAB R2014 software with a core i3 processor at the speed 2.10 GHz. It is found from Table 4.30, that the comparison methods in [42, 43] requires more computation time since it used windowing of EEG recordings and IMFs prior to feature extraction by dividing the given EEG recordings into 16 non-overlapping blocks. Less computational requirement is another attractive potential of the proposed method.

4.5 Conclusion

The higher order statistics based feature set derived from EMD-Wavelet analysis of EEG signals is found most effective for seizure detection and classification from the standard EEG dataset. Such feature set is more compact and separable than the feature sets used for the comparison methods. As a result proposed feature set is superior in terms of accuracy, specificity and sensitivity in seizure detection and classification in stringent conditions, such as less training data, simple classifier and random selection of training and testing data than the state-of-the art methods.

Table 4.10: Performance Comparison of Case V and VI

Case V [(F,S)]				
Methods	**Classifier**	**Accuracy**	**Specificity**	**Sensitivity**
Method in [43]	SVM	100%	100%	100%
Method in [42]	ANN	100%	100%	100%
Proposed Method	SVM	97%	94%	97%
Proposed Method	LS-SVM	96%	95%	98%
Proposed Method	QDA	99%	98%	99%
Proposed Method	k-NN	100%	100%	100%
Proposed Method	ANN	100%	100%	100%
Case VI [(N,S)]				
Methods	**Classifier**	**Accuracy**	**Specificity**	**Sensitivity**
Method in [43]	SVM	100%	100%	100%
Method in [42]	ANN	100%	100%	100%
Proposed Method	SVM	100%	100%	100%
Proposed Method	LS-SVM	100%	100%	100%
Proposed Method	QDA	100%	100%	100%
Proposed Method	k-NN	100%	100%	100%
Proposed Method	ANN	100%	100%	100%

Apart from classifying different state-of-the-art clinical cases, which are used for detection of epileptic seizures, the proposed feature set also exhibits its effectiveness in handling five class problem which is limitedly reported. Due to reduced dimension of the proposed feature set, the proposed method works faster to detect and classify multiclass EEG signals than the state-of-the art comparison methods.

Table 4.11: Performance of 5 class Problem Using Simulation Condition I

SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	71%	75%	93%
Method in [42] using the 1st IMF	45%	75%	77%
Method in [42] using the 2nd IMF	41%	74%	65%
Method in [42] using the 3rd IMF	48%	80%	64%
Method in [42] using the 4th IMF	35%	68%	69%
Proposed Method	89%	92%	93%
LS-SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	67%	74%	92%
Method in [42] using the 1st IMF	49%	84%	77%
Method in [42] using the 2nd IMF	45%	78%	70%
Method in [42] using the 3rd IMF	50%	84%	69%
Method in [42] using the 4th IMF	42%	73%	68%
Proposed Method	91%	95%	97%
QDA Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	56%	87%	93%
Method in [42] using the 1st IMF	47%	80%	78%
Method in [42] using the 2nd IMF	42%	78%	72%
Method in [42] using the 3rd IMF	49%	84%	73%
Method in [42] using the 4th IMF	38%	73%	71%
Proposed Method	91%	96%	96%
k-NN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	66%	93%	81%
Method in [42] using the 1st IMF	47%	81%	80%
Method in [42]using the 2nd IMF	45%	77%	70%
Method in [42] using the 3rd IMF	51%	83%	71%
Method in [42] using the 4th IMF	41%	72%	70%
Proposed Method	92%	98%	97%
ANN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	72%	75%	92%
Method in [42] using the 1st IMF	54%	88%	65%
Method in [42] using the 2nd IMF	49%	75%	61%
Method in [42] using the 3rd IMF	57%	86%	66%
Method in [422] using the 4th IMF	45%	76%	58%
Proposed Method	95%	98%	96%

Table 4.12: Performance of 5 class Problem Using Simulation Condition II

SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	72%	72%	93%
Method in [42] using the 1st IMF	45%	77%	77%
Method in [42] using the 2nd IMF	42%	75%	66%
Method in [42] using the 3rd IMF	48%	82%	63%
Method in [42] using the 4th IMF	37%	70%	69%
Proposed Method	90%	94%	94%
LS-SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	67%	74%	92%
Method in [42] using the 1st IMF	51%	86%	79%
Method in [42] using the 2nd IMF	47%	78%	73%
Method in [42] using the 3rd IMF	52%	86%	71%
Method in [42] using the 4th IMF	44%	75%	68%
Proposed Method	93%	97%	97%
QDA Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	59%	89%	84%
Method in [42] using the 1st IMF	47%	80%	80%
Method in [42]using the 2nd IMF	44%	79%	73%
Method in [42] using the 3rd IMF	49%	86%	75%
Method in [42] using the 4th IMF	39%	74%	72%
Proposed Method	91%	96%	96%
k-NN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	67%	92%	82%
Method in [42] using the 1st IMF	49%	85%	81%
Method in [42] using the 2nd IMF	48%	77%	70%
Method in [42] using the 3rd IMF	53%	83%	71%
Method in [42] using the 4th IMF	44%	74%	70%
Proposed Method	93%	97%	98%
ANN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [8]	72%	74%	93%
Method in [10] using the 1st IMF	55%	89%	67%
Method in [10] using the 2nd IMF	51%	76%	65%
Method in [10] using the 3rd IMF	57%	88%	67%
Method in [10] using the 4th IMF	47%	78%	57%
Proposed Method	95%	98%	96%

Table 4.13: Performance of 5 class Problem Using Simulation Condition III

SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	72%	76%	94%
Method in [42] using the 1st IMF	49%	79%	80%
Method in [42] using the 2nd IMF	46%	76%	68%
Method in [42] using the 3rd IMF	51%	84%	67%
Method in [42] using the 4th IMF	36%	70%	68%
Proposed Method	91%	95%	97%
LS-SVM Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	69%	77%	94%
Method in [42] using the 1st IMF	52%	88%	80%
Method in [42] using the 2nd IMF	49%	81%	73%
Method in [42] using the 3rd IMF	54%	86%	74%
Method in [42] using the 4th IMF	45%	76%	75%
Proposed Method	94%	97%	98%
QDA Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	61%	92%	88%
Method in [42] using the 1st IMF	50%	84%	80%
Method in [42] using the 2nd IMF	46%	83%	76%
Method in [42] using the 3rd IMF	51%	86%	76%
Method in [42] using the 4th IMF	40%	78%	76%
Proposed Method	93%	98%	97%
k-NN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	68%	89%	85%
Method in [42] using the 1st IMF	52%	88%	80%
Method in [42] using the 2nd IMF	49%	81%	73%
Method in [42] using the 3rd IMF	54%	86%	74%
Method in [42] using the 4th IMF	45%	76%	75%
Proposed Method	95%	99%	98%
ANN Classifier			
Methods	Accuracy	Specificity	Sensitivity
Method in [43]	72%	72%	94%
Method in [42] using the 1st IMF	58%	91%	68%
Method in [42] using the 2nd IMF	53%	79%	65%
Method in [42] using the 3rd IMF	61%	88%	70%
Method in [42] using the 4th IMF	48%	78%	60%
Proposed Method	98%	99%	98%

Table 4.14: 5 Class Problem Performances

Methods	Classifier	Accuracy
Method in [43]	SVM	72%
Method in [42]	ANN	61%
Method in [40]	ANN	89%
Proposed Method	SVM	91%
Proposed Method	LS-SVM	94%
Proposed Method	QDA	93%
Proposed Method	k-NN	95%
Proposed Method	ANN	98%

Table 4.15: Time Requiremnets for the Proposed and Comparison Methods

Methods	Size of Feature Vector to test an EEG Data	Required Time (in sec)
Method in [13]	16×3	1.3946
Method in [11]	16×12	1.5470
Proposed Method	6×1	1.3390

Chapter 5

Conclusion

5.1 Concluding Remarks

In this thesis, an EMD-wavelet based approach to solve the seizure detection and classification problem has been presented. The IMFs of the EEG signals resulted from EMD analysis are analyzed to select the dominant IMF. A criterion for selecting the appropriate number of IMFs for each EEG class has been developed via histogram analysis of the dominant IMFs of all EEG classes. DWT analysis is carried out on these selected IMFs to obtain a better time-frequency resolution and more discriminatory behavior for each EEG class. For feature computation the 4th Level DWT coefficients of selected IMFs are found reasonable after analyzing the parameters, like normalized energy, Fourier spectrum and cross-correlation coefficient among different decomposition levels. The reduction of the feature vector is done by using the higher order statistics such as variance,skewness and kurtosis of the selected DWT coefficients. The further reduced proposed feature vector obtained after using PCA vector with faster processing time is found effective for detecting and classifying multi-class EEG epilepsy when fed to different state-of-the art classifiers, in stringent conditions, such as reduced training data as well as random selection of training and testing dataset .

5.2 Contributions of this Thesis

The major contribution of the thesis are,

- Introducing EMD and Wavelet analysis of EEG signals altogether for detecting and classifying multiclass epileptic seizures. EMD analysis is used due to its usefulness in analyzing non-stationary signals. DWT analysis is used for obtaining better distinguishing behaviour of IMFs among different classes. Such time-frequency representations of signals are helpful and less computationally expensive than conventional time-frequency analysis using different kernels for seizure detection and classification.

- Automatic selection of dominant IMF from a set of IMFs is done by using temporal energy analysis of the IMFs. Due to varying nature of dominant IMFs of different EEG recordings, histogram analysis of these dominant IMFs are done for the purpose of obtaining better discriminatory behaviour among the EEG signals. By utilizing Histogram analysis of the dominant IMFs of all classes, appropriate number of IMFs for each EEG class have been selected for both seizure detection and classification cases.

- Effect of using DWT analysis on the selected IMFs are also analyzed. The parameters, namely normalized energy, Fourier spectrum and cross-correlation coefficient of DWT coefficients of the selected dominant IMFs at different decomposition levels are analyzed to select a suitable decomposition level for feature computation. Moreover, the discriminatory attribute of EEG signals are also found prominent on that selected decomposition level.

- Higher Order Statistics, such as variance, skewness and kurtosis of the selected DWT coefficients are proposed to constitute feature vector. These features are easy to compute and can be used for the detection for the abnormalities within the data quite quickly. As a result, the reduction of feature dimension and reduced processing time are achieved in the proposed method.

- The proposed feature vector is used in seven types of state-of-the art classification problems. These classification problems include two, three and five classes. The performance of the proposed method on such classification problems has been investigated based on three simulation conditions for training, cross validation and testing data of EEG signals along and compared with the state-of-the art comparison methods. In all classification cases, proposed method has the superior accuracy, sensitivity and specificity with the state-of-the art comparison methods. Such performance show the effectiveness of the proposed method in detection and classification of multiclass epileptic seizures in stringent conditions as mentioned before.

- Five types of classifiers have been used for detection and classification purpose. In all simulation conditions, Euclidean distance based kNN and ANN have shown better performance in terms of all performance criteria.

5.3 Scopes for Future Work

In this thesis, effective EMD-Wavelet based method for seizure detection and classification is developed. However, there are some scopes for future research, as mentioned below:

- In this thesis, we use a popular EEG database which consists of five class EEG data. The proposed method can classify those with superior accuracy using EMD-Wavelet analysis. In future, effectiveness of the proposed method using different EEG databases with larger recordings can be verified.

- Further effectiveness of the proposed method can also be tested Scalp EEG recordings where data is more challenging to extract.

- Since the proposed method uses only Higher Order Statistics as feature, other feature set utilizing different statistical parameters, nonlinear features from EEG dynamics can be investigated.

Bibliography

[1] T. Vos, R. M. Barber, B. Bell, A. Bertozzi-Villa, S. Biryukov, I. Bolliger, F. Charlson, A. Davis, L. Degenhardt, D. Dicker *et al.*, "Global, regional, and national incidence, prevalence, and years lived with disability for 301 acute and chronic diseases and injuries in 188 countries, 1990–2013: a systematic analysis for the global burden of disease study 2013," *The Lancet*, vol. 386, no. 9995, pp. 743–800, 2015.

[2] I. Megiddo, A. Colson, D. Chisholm, T. Dua, A. Nandi, and R. Laxminarayan, "Health and economic benefits of public financing of epilepsy treatment in india: An agent-based simulation model," *Epilepsia*, vol. 57, no. 3, pp. 464–474.

[3] M. Naghavi, H. Wang, R. Lozano, A. Davis, X. Liang, M. Zhou, S. E. Vollset, A. A. Ozgoren, S. Abdalla, F. Abd-Allah *et al.*, "Global, regional, and national age-sex specific all-cause and cause-specific mortality for 240 causes of death, 1990-2013: a systematic analysis for the global burden of disease study 2013," *Lancet*, vol. 385, no. 9963, pp. 117–171, 2015.

[4] E. Goodwin, R. H. Kandler, and J. J. Alix, "The value of home video with ambulatory EEG: a prospective service review," *Seizure*, vol. 23, no. 6, pp. 480–482, 2014.

[5] D. P. Subha, P. K. Joseph, R. Acharya U, and C. M. Lim, "EEG signal analysis: A survey," *Journal of Medical Systems*, vol. 34, no. 2, pp. 195–212, 2010.

[6] J. Malmivuo and R. Plonsey, *"Bioelectromagnetism: principles and applications of bioelectric and biomagnetic fields"*. Oxford University Press, USA, 1995.

[7] N. Pendse, M. Wissmeyer, S. Altrichter, M. Vargas, J. Delavelle, M. Viallon, A. Federspiel, M. Seeck, K. Schaller, and K.-O. Lövblad, "Interictal arterial spin-labeling MRI perfusion in intractable epilepsy," *Journal of neuroradiology*, vol. 37, no. 1, pp. 60–63, 2010.

[8] E. Caulder, "Metabotropic glutamate receptors as targets for antiepileptic drug therapy: a behavioral and electroencephalographic analysis," 2013.

[9] W. H. Theodore and R. S. Fisher, "Brain stimulation for epilepsy," *The Lancet Neurology*, vol. 3, no. 2, pp. 111–118, 2004.

[10] S. Rothman and X.-F. Yang, "Local cooling: a therapy for intractable neocortical epilepsy," *Epilepsy Currents*, vol. 3, no. 5, pp. 153–156, 2003.

[11] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186–197, 2010.

[12] S. B. Wilson, M. L. Scheuer, R. G. Emerson, and A. J. Gabor, "Seizure detection: evaluation of the reveal algorithm," *Clinical Neurophysiology*, vol. 115, no. 10, pp. 2280–2291, 2004.

[13] A. Shoeb, A. Kharbouch, J. Soegaard, S. Schachter, and J. Guttag, "An algorithm for detecting seizure termination in scalp EEG," in *Annual International Conference of the IEEE in Engineering , Medicine and Biology Society, EMBC*, 2011, pp. 1443–1446.

[14] S. Nasehi and H. Pourghassem, "Online mental task classification based on dwt-pca features and probabilistic neural network," *International Journal of Imaging and Robotics*, vol. 7, no. 1, pp. 110–118, 2012.

[15] A. Aarabi, R. Grebe, and F. Wallois, "A multistage knowledge-based system for EEG seizure detection in newborn infants," *Clinical Neurophysiology*, vol. 118, no. 12, pp. 2781–2797, 2007.

[16] A. J. Casson, D. C. Yates, J. S. Duncan, E. Rodriguez-Villegas *et al.*, "Wearable electroencephalography," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 29, no. 3, pp. 44–56, 2010.

[17] B. Litt and J. Echauz, "Prediction of epileptic seizures," *The Lancet Neurology*, vol. 1, no. 1, pp. 22–30, 2002.

[18] P. Celka and P. Colditz, "A computer-aided detection of EEG seizures in infants: a singular-spectrum approach and performance comparison," *IEEE Transactions on Biomedical Engineering*, vol. 49, no. 5, pp. 455–462, 2002.

[19] S. Nasehi and H. Pourghassem, "Patient-specific epileptic seizure onset detection algorithm based on spectral features and ipsonn classifier," in *IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, 2013, pp. 186–190.

[20] M. Bedeeuzzaman, O. Farooq, and Y. U. Khan, "Dispersion measures and entropy for seizure detection," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2011, pp. 673–676.

[21] D. Najumnissa and T. Rangaswamy, "Detection and classification of epileptic seizures using wavelet feature extraction and adaptive neuro-fuzzy inference system," *International Journal of Computational Engineering Research*, vol. 2, pp. 755–761, 2012.

[22] T. N. Thieu and H.-J. Yang, *Current Approaches in Applied Artificial Intelligence: 28th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2015, Seoul, South Korea, June 10-12, 2015, Proceedings.* Springer International Publishing, 2015, ch. Diagnosis of Epilepsy in Patients Based on the Classification of EEG Signals Using Fast Fourier Transform, pp. 493–500.

[23] B. Boashash, M. Mesbah, and P. Coldtiz, "Time-frequency detection of EEG abnormalities, chapter 15, article 15.5 in [8]," 2003.

[24] A. Temko, C. Nadeu, W. Marnane, G. B. Boylan, and G. Lightbody, "EEG signal description with spectral-envelope-based speech recognition features for detection of neonatal seizures," *Information Technology in Biomedicine,*, vol. 15, no. 6, pp. 839–847, 2011.

[25] J. Wright, R. Kydd, and D. Liley, "EEG models: Chaotic and linear," *Psycoloquy*, vol. 4, no. 60, 1993.

[26] C. J. Stam, "Nonlinear dynamical analysis of EEG and MEG: review of an emerging field," *Clinical Neurophysiology*, vol. 116, no. 10, pp. 2266–2301, 2005.

[27] S. Geng and W. Zhou, "Nonlinear feature comparision of EEG using correlation dimension and approximate entropy," in *3rd IEEE International Conference on Biomedical Engineering and Informatics (BMEI)*, vol. 3, 2010, pp. 978–981.

[28] G. Polychronaki, P. Ktonas, S. Gatzonis, A. Siatouni, P. Asvestas, H. Tsekou, D. Sakas, and K. Nikita, "Comparison of fractal dimension estimation algorithms for epileptic seizure onset detection," *Journal of neural engineering*, vol. 7, no. 4, p. 046007, 2010.

[29] C. Wang, J. Zou, J. Zhang, M. Wang, and R. Wang, "Feature extraction and recognition of epileptiform activity in EEG by combining PCA with apen," *Cognitive neurodynamics*, vol. 4, no. 3, pp. 233–240, 2010.

[30] S. B. Wilson and R. Emerson, "Spike detection: a review and comparison of algorithms," *Clinical Neurophysiology*, vol. 113, no. 12, pp. 1873–1881, 2002.

[31] J. Gotman and P. Gloor, "Automatic recognition and quantification of interictal epileptic activity in the human scalp EEG," *Electroencephalography and clinical neurophysiology*, vol. 41, no. 5, pp. 513–529, 1976.

[32] M. Dümpelmann and C. Elger, "Automatic detection of epileptiform spikes in the electrocorticogram: a comparison of two algorithms," *Seizure*, vol. 7, no. 2, pp. 145–152, 1998.

[33] S. B. Wilson, C. A. Turner, R. G. Emerson, and M. L. Scheuer, "Spike detection ii: automatic, perception-based detection and clustering," *Clinical neurophysiology*, vol. 110, no. 3, pp. 404–411, 1999.

[34] A. Tzallas, P. Karvelis, C. Katsis, D. Fotiadis, S. Giannopoulos, S. Konitsiotis *et al.*, "A method for classification of transient events in EEG recordings: application to epilepsy diagnosis," *Methods of Information in Medicine*, vol. 45, no. 6, pp. 610–621, 2006.

[35] N. Acır and C. Güzeliş, "Automatic spike detection in EEG by a two-stage procedure based on support vector machines," *Computers in Biology and Medicine*, vol. 34, no. 7, pp. 561–575, 2004.

[36] J. J. Benedetto and D. Colella, "Wavelet analysis of spectrogram seizure chirps," in *SPIE's 1995 International Symposium on Optical Science, Engineering, and Instrumentation.* International Society for Optics and Photonics, 1995, pp. 512–521.

[37] S. J. Schiff, J. Heller, S. L. Weinstein, and J. G. Milton, "Controlled wavelet transforms for EEG spike and seizure localization," in *SPIE's International Symposium on Optical Engineering and Photonics in Aerospace Sensing.* International Society for Optics and Photonics, 1994, pp. 762–775.

[38] W. J. Williams, H. P. Zaveri, and J. C. Sackellares, "Time-frequency analysis of electrophysiology signals in epilepsy," *Engineering in Medicine and Biology Magazine*, vol. 14, no. 2, pp. 133–143, 1995.

[39] H. P. Zaveri, R. B. Duckrow, N. C. De Lanerolle, and S. S. Spencer, "Distinguishing subtypes of temporal lobe epilepsy with background hippocampal activity," *Epilepsia*, vol. 42, no. 6, pp. 725–730, 2001.

[40] A. T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, "Epileptic seizure detection in EEGs using time–frequency analysis," *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 703–710, 2009.

[41] V. Bajaj and R. B. Pachori, "Classification of seizure and nonseizure EEG signals using empirical mode decomposition," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 6, pp. 1135–1142, 2012.

[42] S. Alam and M. I. H. Bhuiyan, "Detection of seizure and epilepsy using higher order statistics in the EMD domain," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 2, pp. 312–318, 2013.

[43] A. B. Das, M. I. H. Bhuiyan, and S. M. Alam, "Classification of EEG signals using normal inverse gaussian parameters in the dual-tree complex wavelet transform domain for seizure detection," *Signal, Image and Video Processing*, vol. 10, no. 2, pp. 259–266, 2016.

[44] P. P. Acharjee and C. Shahnaz, "Multiclass epileptic seizure classification using time-frequency analysis of EEG signals," in *7th International Conference on Electrical & Computer Engineering (ICECE)*, 2012, pp. 260–263.

[45] T. P. Runarsson and S. Sigurdsson, "On-line detection of patient specific neonatal seizures using support vector machines and half-wave attribute histograms," in *null*, 2005, pp. 673–677.

[46] J. Yoo, L. Yan, D. El-Damak, M. A. B. Altaf, A. H. Shoeb, and A. P. Chandrakasan, "An 8-channel scalable EEG acquisition soc with patient-specific seizure classification and recording processor," *IEEE Journal of Solid-State Circuits*, vol. 48, no. 1, pp. 214–228, 2013.

[47] A. Dalton, S. Patel, A. R. Chowdhury, M. Welsh, T. Pang, S. C. Schachter, G. OLaighin, and P. Bonato, "Development of a body sensor network to detect motor patterns of epileptic seizures," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 11, pp. 3204–3211, 2012.

[48] A. S. Zandi, R. Tafreshi, M. Javidan, and G. A. Dumont, "Predicting temporal lobe epileptic seizures based on zero-crossing interval analysis in scalp EEG," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2010, pp. 5537–5540.

[49] A. Shahidi Zandi, R. Tafreshi, M. Javidan, and G. A. Dumont, "Predicting epileptic seizures in scalp EEG based on a variational bayesian gaussian mixture model of zero-crossing intervals," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 5, pp. 1401–1413, 2013.

[50] A. Aarabi and B. He, "A rule-based seizure prediction method for focal neocortical epilepsy," *Clinical Neurophysiology*, vol. 123, no. 6, pp. 1111–1122, 2012.

[51] J. C. Sprott and G. Rowlands, "Improved correlation dimension calculation," *International Journal of Bifurcation and Chaos*, vol. 11, no. 07, pp. 1865–1880, 2001.

[52] R. Aschenbrenner-Scheibe, T. Maiwald, M. Winterhalder, H. Voss, J. Timmer, and A. Schulze-Bonhage, "How well can epileptic seizures be predicted? an evaluation of a nonlinear method," *Brain*, vol. 126, no. 12, pp. 2616–2626, 2003.

[53] S.-J. Gu, C.-P. Sun, and H.-Q. Lin, "Universal role of correlation entropy in critical phenomena," *Journal of Physics A: Mathematical and Theoretical*, vol. 41, no. 2, p. 025002, 2007.

[54] A. Doğanaksoy and F. Göloğlu, "On lempel-ziv complexity of sequences," in *Sequences and Their Applications–SETA 2006*. Springer, 2006, pp. 180–189.

[55] J. B. Dingwell, "Lyapunov exponents," *Wiley Encyclopedia of Biomedical Engineering*, 2006.

[56] S. Wang, W. A. Chaovalitwongse, and S. Wong, "A novel reinforcement learning framework for online adaptive seizure prediction," in *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2010, pp. 499–504.

[57] M. Bedeeuzzaman, T. Fathima, Y. U. Khan, and O. Farooq, "Seizure prediction using statistical dispersion measures of intracranial EEG," *Biomedical Signal Processing and Control*, vol. 10, pp. 338–341, 2014.

[58] S. Li, W. Zhou, Q. Yuan, and Y. Liu, "Seizure prediction using spike rate of intracranial EEG," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 21, no. 6, pp. 880–886, 2013.

[59] L. Chisci, A. Mavino, G. Perferi, M. Sciandrone, C. Anile, G. Colicchio, and F. Fuggetta, "Real-time epileptic seizure prediction using AR models and sup-

[68] H. Khamis, A. Mohamed, and S. Simpson, "Frequency–moment signatures: a method for automated seizure detection from scalp EEG," *Clinical Neurophysiology*, vol. 124, no. 12, pp. 2317–2327, 2013.

[69] U. R. Acharya, F. Molinari, S. V. Sree, S. Chattopadhyay, K.-H. Ng, and J. S. Suri, "Automated diagnosis of epileptic EEG using entropies," *Biomedical Signal Processing and Control*, vol. 7, no. 4, pp. 401–408, 2012.

[70] M. Musselman and D. Djurdjanovic, "Time–frequency distributions in the classification of epilepsy from EEG signals," *Expert Systems with Applications*, vol. 39, no. 13, pp. 11 413–11 422, 2012.

[71] H. Hassanpour, M. Mesbah, and B. Boashash, "Time–frequency based newborn EEG seizure detection using low and high frequency signatures," *Physiological Measurement*, vol. 25, no. 4, p. 935, 2004.

[72] L. Rankine, M. Mesbah, and B. Boashash, "A matching pursuit-based signal complexity measure for the analysis of newborn EEG," *Medical & biological engineering & computing*, vol. 45, no. 3, pp. 251–260, 2007.

[73] S. B. Nagaraj, N. Stevenson, W. Marnane, G. Boylan, and G. Lightbody, "A novel dictionary for neonatal EEG seizure detection using atomic decomposition," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 1073–1076.

[74] A. Tzallas, M. Tsipouras, and D. Fotiadis, "Automatic seizure detection based on time-frequency analysis and artificial neural networks," *Computational Intelligence and Neuroscience*, vol. 2007, 2007.

[75] A. T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, "The use of time-frequency distributions for epileptic seizure detection in EEG recordings," in *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2007, pp. 3–6.

[76] M. S. Khlif, M. Mesbah, B. Boashash, and P. Colditz, "Multichannel-based newborn EEG seizure detection using time-frequency matched filter," in *29th*

Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007, pp. 1265–1268.

[77] Y. Liu, W. Zhou, Q. Yuan, and S. Chen, "Automatic seizure detection using wavelet transform and svm in long-term intracranial EEG," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 20, no. 6, pp. 749–755, 2012.

[78] R. Panda, P. Khobragade, P. Jambhule, S. Jengthe, P. Pal, and T. Gandhi, "Classification of EEG signal using wavelet transform and support vector machine for epileptic seizure diction," in *International Conference on Systems in Medicine and Biology (ICSMB)*, 2010, pp. 405–408.

[79] Y. U. Khan, N. Rafiuddin, and O. Farooq, "Automated seizure detection in scalp EEG using multiple wavelet scales," in *IEEE International Conference on Signal Processing, Computing and Control (ISPCC)*. IEEE, 2012, pp. 1–5.

[80] C.-m. Wang, C.-m. Zhang, J.-z. Zou, and J. Zhang, "Performance evaluation for epileptic electroencephalogram (EEG) detection by using neyman–pearson criteria and a support vector machine," *Physica A: Statistical Mechanics and its Applications*, vol. 391, no. 4, pp. 1602–1609, 2012.

[81] Z. Zainuddin, L. K. Huong, and O. Pauline, "On the use of wavelet neural networks in the task of epileptic seizure detection from electroencephalography signals," *Procedia Computer Science*, vol. 11, pp. 149–159, 2012.

[82] M. Niknazar, S. Mousavi, B. V. Vahdat, and M. Sayyah, "A new framework based on recurrence quantification analysis for epileptic seizure detection," *IEEE journal of biomedical and health informatics*, vol. 17, no. 3, pp. 572–578, 2013.

[83] A. Subasi, "EEG signal classification using wavelet feature extraction and a mixture of expert model," *Expert Systems with Applications*, vol. 32, no. 4, pp. 1084–1093, 2007.

[84] I. W. Selesnick, R. G. Baraniuk, and N. G. Kingsbury, "The dual-tree complex wavelet transform," *IEEE Signal Processing Magazine*, vol. 22, no. 6, pp. 123–151, 2005.

[85] C. Shahnaz, R. Rafi, S. Fattah, W. ZHU, and M. Ahmad, "Detection and classification of multiclass epileptic seizures exploiting EMD-Wavelet analysis of EEG signals," *Submitted to IEEE Journal of Biomedical and Health Informatics*.

[86] M. A. Kabir and C. Shahnaz, "Denoising of ECG signals based on noise reduction algorithms in EMD and wavelet domains," *Biomedical Signal Processing and Control*, vol. 7, no. 5, pp. 481–489, 2012.

[87] C. Shahnaz, R. Md Rafi, and S. Fattah, "Classification of seizure and non-seizure EEG signals exploiting higher order statistics of the dominant intrinsic mode function," in *17th International Conference on Computer and Information Technology (ICCIT)*, 2014, pp. 350–353.

[88] C. Shahnaz, R. Rafi, S. Fattah, W. ZHU, and M. Ahmad, "Seizure detection exploiting EMD-wavelet analysis of EEG signals," in *IEEE International Symposium on Circuits and Systems (ISCAS)*, 2015, pp. 57–60.

[89] "A wavelet methodology for EEG time-frequency analysis in a time discrimination task."

[90] N. Hazarika, J. Z. Chen, A. C. Tsoi, and A. Sergejew, "Classification of EEG signals using the wavelet transform," in *13th International Conference on Digital Signal Processing*, vol. 1, 1997, pp. 89–92.

[91] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," *Journal of neuroscience methods*, vol. 123, no. 1, pp. 69–87, 2003.

[92] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, and K. Dizdarevic, "Energy distribution of EEG signals: Eeg signal wavelet-neural network classifier," *arXiv preprint arXiv:1307.7897*, 2013.

[93] I. Jolliffe, *Principal component analysis*. Wiley Online Library, 2002.

[94] D. Bremner, E. Demaine, J. Erickson, J. Iacono, S. Langerman, P. Morin, and G. Toussaint, "Output-sensitive algorithms for computing nearest-neighbour decision boundaries," *Discrete & Computational Geometry*, vol. 33, no. 4, pp. 593–604, 2005.

[95] Y. Lee, "Handwritten digit recognition using k nearest-neighbor, radial-basis function, and backpropagation neural networks," *Neural computation*, vol. 3, no. 3, pp. 440–449, 1991.

[96] D. Dai and W. Yang, "Satellite image classification via two-layer sparse coding with biased image representation," *IEEE Geoscience and Remote Sensing Letters*, vol. 8, no. 1, pp. 173–176, 2011.

[97] K. Fukunaga, *Introduction to statistical pattern recognition.* Academic press, 2013.

[98] C. C. Aggarwal and C. Zhai, *Mining text data.* Springer Science & Business Media, 2012.

[99] C. J. Burges, "A tutorial on support vector machines for pattern recognition," *Data mining and knowledge discovery*, vol. 2, no. 2, pp. 121–167, 1998.

[100] Y. Pao, "Adaptive pattern recognition and neural networks," 1989.

[101] C. G. Looney, *Pattern recognition using neural networks: theory and algorithms for engineers and scientists.* Oxford University Press, Inc., 1997.

[102] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, p. 061907, 2001.

[103] http://epileptologiebonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3.

[104] J. Greene, "Feature subset selection using thorntons separability index and its applicability to a number of sparse proximity-based classifiers," in *Proceedings*

of Annual Symposium of the Pattern Recognition Association of South Africa, 2001.