MULTICLASS EPILEPTIC SEIZURE ACTIVITY CLASSIFICATION EXPLOITING STATISTICAL MODELING OF BAND-SPECIFIC DWT COEFFICIENTS OF EEG SIGNALS

by

Tanima Tasmin Chowdhury
Student ID. 1014062117

MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY March 2019

The thesis entitled "**MULTICLASS EPILEPTIC SEIZURE ACTIVITY CLASSIFICATION EXPLOITING STATISTICAL MODELING OF BAND-SPECIFIC DWT COEFFICIENTS OF EEG SIGNALS**" submitted by Tanima Tasmin Chowdhury, Student ID. 1014062117P, Session: October, 2014 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on March 6, 2019.

BOARD OF EXAMINERS

1. Celia Shahnaz

(Dr. Celia Shahnaz)
Professor
Department of Electrical and Electronic Engineering
Bangladesh University of Science and Technology
Dhaka-1205

Chairman
(Supervisor)

2.

(Dr. Md. Shafiqul Islam)
Professor and Head
Department of Electrical and Electronic Engineering
Bangladesh University of Science and Technology
Dhaka-1205

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(Ex-officio)

3.

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Bangladesh University of Science and Technology
Dhaka-1205

Member

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(Dr. Ajay Krishno Sarker)
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Department of Electrical and Electronic Engineering
Rajshahi University of Engineering and Technology
Rajshahi-6204

Member
(External)

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Signature of the candidate

Tanima Tasmin Chowdhury

Dedication

To my parents.

Acknowledgments

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Abstract

Epileptic seizure is often interpreted by the abnormalities in the brain activity and Electroencephalogram (EEG) is a promising tool for identi cation of Epilep-tic seizure. Signal processing methods try to model visual information into few paramters, thus decision making becomes more accurate compared to the meth-ods based on visual observation of EEG where sometimes misinterpretation takes place in disease treatment. Researchers have used di erent signal processing and machine learning algorithms to extract features for seizure activity detection and classi cation. Since EEG is a non-stationary signal, Discrete Wavelet Transform (DWT) has the potential to perform better than conventional time-frequency anal-ysis method. However, detection and classi cation of multiclass EEG signals of epileptic seizure activity originated from di erent parts and state of the brain in the stringent condition is still a challenging task. DWT of the EEG signals is performed and band-speci c gamma and theta DWT coe cients have been cho-sen. A statistical model has been employed to summarize information in Discrete Wavelet Transform (DWT) coe cients and thus form e ective feature set utiliz-ing the parameters of the proposed statistical probability density function (PDF). Rather than taking discrete parameter as feature like wavelet energy or entropy, it is found more rational to use statistical modeling parameters as features since they are being taken from the shape of the entire data class and representing the class in more consistent way. Gaussian statistical model has been found t for this purpose based on visual inspection of superimposed plots of empirical and Gaussian PDFs, cumulative distribution functions (CDFs) in probability-probability (p-p) plot and K-S test result. The goodness of features has been justi ed by one way ANOVA test, Geometrical Separability Index and Bhattacharyya Distance parameters. The feature set is found e ective and e cient for detecting and classifying multi-class EEG signals of epileptic seizure activity when fed to di erent state-of-the-art clas-si ers in stringent condition random selection of training and testing dataset. The performance parameters (accuracy, sensitivity and speci city) achieved using pro-posed scheme are found almost 100% (maximum accuracy of 100% for 3-class and 93% for 5-class) for multi-class classi cation problems and outperformed the stat-of-the-art strategies.

Contents

List of Tables

List of Figures

Abbreviations

EEG	Electroencephalography
EMD	Empirical Mode Decomposition
IMF	Intrinsic Mode Functions
FFT	Fast Fourier Transform
DWT	Discrete Wavelet Transform
DT-CWT	Dual Tree Complex Wavelet Transform
ANN	Arti cial Neural Network
KNN	K-Nearest Neighbor
SVM	Support Vector Machine
PDF	Probability Density Function
GSI	Geometrical Separability Index
BD	Bhattachariyya Distance

Chapter 1

Introduction

The present world has 1% of its population su ering from epilepsy [1]. Epilepsy, the neurological disorder, is characterized by the recurrence of seizures which is an abnormal but synchronized surge of electrical activity in the brain. Many di erent things can occur during a seizure. Seizures may cause dramatic symptoms such as uncontrollable muscle movement, frothing at the mouth and violent shaking, along with blackout and confusion. However, symptoms can also be mild, with few physical symptoms. 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 the 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 di erent disorders that can a ect 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. These types of physical and mental limitations lead to profound social consequences for su erer and has greatly added to the burden of this disease. So, seizure detection and classi cation 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 epileptic seizures of Electroen-cephalography (EEG) signals. Finally, organization of the thesis is presented for a better clari cation.

1.1 Types of Seizure

There are several types of seizure including non-epileptic seizures which may arise, for example, from a head injury or illness, as well as partial or focal and generalized seizures, which are associated with epilepsy [1].

Partial seizures arise from abnormal activity in one part of the brain. Symptoms may vary according to where exactly that abnormality is, but examples include a wave-like sensation, a sense of numbness, tingling and visual disturbances such as hallucination. The term focal is used instead of partial to be more accurate when talking about where seizures begin. Focal seizures can start in one area or group of cells in one side of the brain. When a person is awake and aware during a seizure, it's called a focal aware seizure. This used to be called a simple partial seizure. When a person is confused or their awareness is a ected in some way during a focal seizure, it's called a focal impaired awareness seizure. This used to be called a complex partial seizure.

Abnormal electrical activity involving a larger portion or the whole of the brain are referred to as generalized seizures. Examples of generalized seizure include: Absence seizure where a person appears inattentive for a short period; Myoclonic seizure { which is Characterized by muscle twitching; Clonic seizure where the su erer experiences involuntary muscle spasms and Tonic-clonic seizure where the skeletal muscles sti en up causing the body to contract (tonic phase) followed by convulsions and vibration of the sti ened limbs (clonic phase). Another type of generalized seizure is atonic seizure, also called a drop seizure, which is usually noticeable as a drooping of the head as strength in the head and neck muscles is lost. Although the seizure itself is not damaging, the loss of muscle tone can cause a person to fall and hurt themselves. Warning signs that may precede a seizure include a sense of fear or anxiety, nausea, dizziness and visual disturbances.

When the beginning of a seizure is not known, it's called an unknown onset seizure. A seizure could also be called an unknown onset if it's not witnessed or seen by anyone, for example when seizures happen at night or in a person who lives alone. As more information is learned, an unknown onset seizure may later be diagnosed as a focal or generalized seizure.

1.2 Epilepsy

Epilepsy is the fourth most common neurological disorder and a ects people of all ages. Epilepsy is a chronic disorder, the hallmark of which is recurrent, unprovoked seizures. Although the symptoms of a seizure may a ect 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 a ected, and how long it lasts all have profound e ects. A person is diagnosed with epilepsy if they have two unprovoked seizures (or one unprovoked seizure with the likelihood of more) that were not caused by some known and reversible medical condition like alcohol withdrawal or extremely low blood sugar [2]. Seizures and epilepsy are not the same. An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. Epilepsy is a disease characterized by an enduring predisposition to generate epileptic seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition. A seizure is an event and epilepsy is the disease involving recurrent unprovoked seizures [2].

Therefore, the de nition of epilepsy addresses each of the following points:

At least two unprovoked (or re ex) seizures occurring greater than 24 hours apart.

One unprovoked (or re ex) seizure and a probability of further seizures simi-lar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years.

Diagnosis of an epilepsy syndrome.

1.2.1 Prevalence of Epilepsy

As mentioned earlier, epilepsy is the 4th most common neurological problem { only migraine, stroke, and Alzheimer's disease occur more frequently. The prevalence of epilepsy looks at the number of people with epilepsy at any given point in time. This includes people with new onset epilepsy as well as those who have had epilepsy for a number of years.

Approximately 50 million people currently live with epilepsy worldwide. The es-timated proportion of the general population with active epilepsy (i.e. continuing seizures or with the need for treatment) at a given time is between 4 and 10 per 1000 people. However, some studies in low- and middle-income countries suggest that the proportion is much higher, between 7 and 14 per 1000 people. Close to 80% of people with epilepsy live in low- and middle-income countries. Globally, an estimated 2.4 million people are diagnosed with epilepsy each year. In high-income countries, annual new cases are between 30 and 50 per 100,000 people in the general population. In low- and middle-income countries, this gure can be up to two times higher. Despite how common it is and major advances in di-agnosis and treatment, epilepsy is among the least understood of major chronic medical conditions, even though one in three adults knows someone with the disor-der [3]. The prevalence of epilepsy in poor regions of the world is shown in Fig. 1.1.

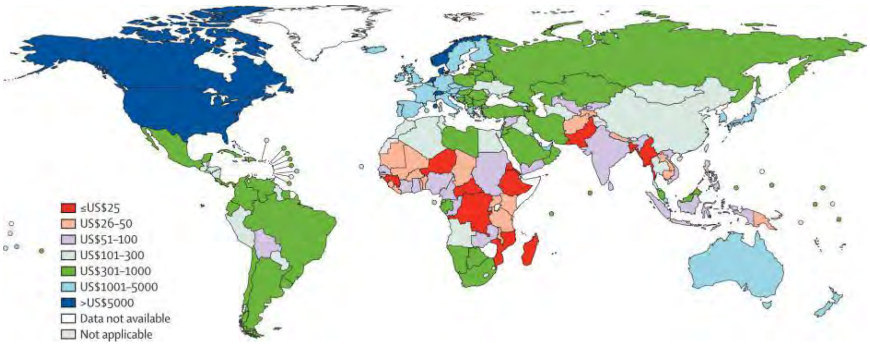


Fig. 1.1: Prevalence of Epilepsy in Poor Regions of the World

1.2.2 Cause of Epilepsy

Epilepsy is not contagious. The most common type of epilepsy, which a ects 6 out of 10 people with the disorder, is called idiopathic epilepsy and has no identi able cause. Epilepsy with a known cause is called secondary epilepsy, or symptomatic epilepsy. The causes of secondary (or symptomatic) epilepsy include [4]:

Genetic in uence: Some types of epilepsy, which are categorized by the type of seizure one experiences or the part of the brain that is a ected, run in families. In these cases, it's likely that there's a genetic in uence. Researchers have linked some types of epilepsy to speci c genes, but for most people, genes are only part of the cause of epilepsy. Certain genes may make a person more sensitive to environmental conditions that trigger seizures.

Head trauma: Head trauma as a result of a car accident or other traumatic injury can cause epilepsy.

Brain conditions: Brain conditions that cause damage to the brain, such as brain tumors or strokes, can cause epilepsy. Stroke is a leading cause of epilepsy in adults older than age 35.

Infectious diseases: Infectious diseases, such as meningitis, AIDS and viral encephalitis, can cause epilepsy.

Prenatal injury: Before birth, babies are sensitive to brain damage that could be caused by several factors, such as an infection in the mother, poor nutrition or oxygen de ciencies. This brain damage can result in epilepsy or cerebral palsy.

Developmental disorders: Epilepsy can sometimes be associated with developmental disorders, such as autism and neuro bromatosis.

1.2.3 Diagnosis of Epilepsy

Epilepsy is usually di cult to diagnose quickly. To diagnose one's condition, the doctor reviews patient's symptoms and medical history. The doctor may order sev-eral tests to diagnose epilepsy and determine the cause of seizures. The evaluation may include a neurological exam where the doctor may test patient's behavior, motor abilities, mental function and other areas to diagnose the condition and determine the type of epilepsy one may have. Doctor may take a blood sample to check for signs of infections, genetic conditions or other conditions that may be associated with seizures. A CT scan uses X-rays to obtain cross-sectional images of the brain. CT scans can reveal abnormalities in the brain that might be causing seizures, such as tumors, bleeding and cysts. An MRI uses powerful magnets and radio waves to create a detailed view of the brain. PET scans use a small amount of low-dose radioactive material that's injected into a vein to help visualize active areas of the brain and detect abnormalities.

EEG is the most common test used to diagnose epilepsy. In this test, doctors attach electrodes to patient's scalp with a paste-like substance. The electrodes record the electrical activity of the brain. If one has epilepsy, it's common to have changes in normal pattern of brain waves, even when one is not having a seizure. Doctor may monitor one on video while conducting an EEG while one is awake or asleep, to record any seizures one experience. Recording the seizures may help the doctor determine what kind of seizures one is having or rule out other conditions. Doctor may give one instructions to do something that will cause seizures, such as getting little sleep prior to the test. If they see changes in normal brain wave pattern, that's a symptom. Many people with epilepsy have abnormal EEGs. The doctor may watch the patient on video to record how body reacts during a seizure. This usually requires an overnight stay or two at the hospital.

1.3 Electroencephalography (EEG)

Electroencephalography (encephalon = brain), or EEG, is the physiological method of choice to record all of the electrical activity generated by the brain from elec-trodes placed on the scalp surface. EEG measures electrical activity generated by the synchronized activity of thousands of neurons (in voltage); provides excellent time resolution, allowing ones to analyze which brain areas are active at a certain time { even at sub-second timescales [5]. Since the voltage uctuations measured at the electrodes are very small, the recorded data is digitized and sent to an am-pli er. The ampli ed data can then be displayed as a sequence of voltage values. EEG is one of the fastest imaging techniques available as it can take thousands of snapshots per second (256 Hz or higher). 100 years ago the EEG time course was a plot on paper. Current systems display the data as continuous ow of voltages on a screen. Price di erences in EEG systems are typically due to the number of electrodes, the quality of the digitization, the quality of the ampli er, and the number of snapshots the device can take per second (this is the sampling rate in Hz).

1.3.1 Source of EEG Signal

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or \polarized") by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of similar charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbours, who push their neighbours, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal in the electrodes. Since metal conducts the push and pull of electrons easily, the di erence in push or pull voltages between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG [6].

The electric potential generated by an individual neuron is far too small to be picked up by EEG or MEG. EEG activity therefore always re ects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. Pyramidal neurons of the cortex are thought to produce the most EEG signal because they are well-aligned and re together. Because voltage eld gradients fall o with the square of distance, activity from deep sources is more di cult to detect than currents near the skull.

EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with di erent states of brain functioning (e.g., waking and the various sleep stages). These oscillations represent synchronized activity over a network of neurons.

1.3.2 EEG Signal Frequency Range

The electroencephalogram (EEG) is the depiction of the electrical activity occurring at the surface of the brain. This activity appears on the screen of the EEG machine as waveforms of varying frequency and amplitude measured in voltage (speci cally micro-voltages). EEG waveforms are generally classi ed according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classi cation uses EEG waveform frequency.

The frequencies most brain waves range from are 0.5-500 Hz. However, the follow-ing categories of frequencies are the most clinically relevant [7]:

Delta waves (4Hz or less):

These slow waves have a frequency of 4 Hz or less. They normally are seen in deep sleep in adults as well as in infants and children. Delta waves are abnormal in the awake adult. Often, they have the largest amplitude of all waves. Delta waves can be focal (local pathology) or di use (generalized dysfunction).

Theta waves (4-8 Hz):

Theta waves normally are seen in sleep at any age. In awake adults, these waves are abnormal if they occur in excess. Theta and delta waves are known collectively as slow waves.

Alpha waves (8-16 Hz):

Alpha waves generally are seen in all age groups but are most common in adults. They occur rhythmically on both sides of the head but are often slightly higher in amplitude on the non-dominant side, especially in right-handed individuals. A normal alpha variant is noted when a harmonic of alpha frequency occurs in the posterior head regions. They tend to be present posteriorly more than anteriorly and are especially prominent with closed eyes and with relaxation. Alpha activity disappears normally with attention (eg, mental arithmetic, stress, opening eyes). In most instances, it is regarded as a normal waveform. An abnormal exception is alpha coma, most often caused by hypoxic-ischemic encephalopathy of destructive processes in the pons (eg, intracerebral hemorrhage). In alpha coma, alpha waves are distributed uniformly both anteriorly and posteriorly in patients who are unresponsive to stimuli.

Beta waves (16-40 Hz):

Beta waves are observed in all age groups. They tend to be small in ampli-tude and usually are symmetric and more evident anteriorly. Drugs, such as barbiturates and benzodiazepines, augment beta waves.

Gamma waves (40-150 Hz):

These are involved in higher processing tasks as well as cognitive functioning. Gamma waves are important for learning, memory and information process-ing. It is thought that the 40 Hz gamma wave is important for the binding of our senses in regards to perception and are involved in learning new ma-terial. It has been found that individuals who are mentally challenged and have learning disabilities tend to have lower gamma activity than average.

1.3.3 EEG Recording System

In conventional scalp EEG, the recording is obtained by placing electrodes on the scalp with a conductive gel or paste, usually after preparing the scalp area by light abrasion to reduce impedance due to dead skin cells. Many systems typically use electrodes, each of which is attached to an individual wire. Some systems use caps or nets into which electrodes are embedded; this is particularly common when high-density arrays of electrodes are needed.

Electrode locations and names are speci ed by the International 10{20 system for most clinical and research applications [8]. This system ensures that the naming of electrodes is consistent across laboratories. The \10" and \20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front{back or right{left distance of the skull. Each electrode placement site has a letter to identify the lobe, or area of the brain it is reading from : Pre-frontal (Fp), Frontal (F), Temporal (T), Parietal (P), Occipital (O), and Central (C). There are also (Z) sites: A \Z" (zero) refers to an electrode placed on the midline sagittal plane of the skull, (Fpz, Fz, Cz, Oz)and is present mostly for reference/measure-ment points. Even numbered electrodes (2,4,6,8) refer to electrode placement on the right side of the head, whereas odd numbers (1,3,5,7) refer to those on the left. In most clinical applications, 19 recording electrodes (plus ground and sys-tem reference) are used. A smaller number of electrodes are typically used when recording EEG from neonates. Additional electrodes can be added to the standard set-up when a clinical or research application demands increased spatial resolution for a particular area of the brain. High-density arrays (typically via cap or net) can contain up to 256 electrodes more-or-less evenly spaced around the scalp. The \A" (sometimes referred to as \M" for mastoid process) refers to the prominent bone process usually found just behind the outer ear (less prominent in children and some adults). In basic Polysomnography, F3, F4, Fz, Cz, C3, C4, O1, O2, A1, A2 (M1, M2), are used. Cz and Fz are `ground' or `common' reference points for all EEG and EOG electrodes, and A1-A2 are used for contralateral referencing of all EEG electrodes. This EEG montage may be extended to utilize T3-T4, P3-P4, as well as others, if an extended or \seizure montage" is called for. The position of the electrode of 10-20 system is shown in Fig. 1.2.

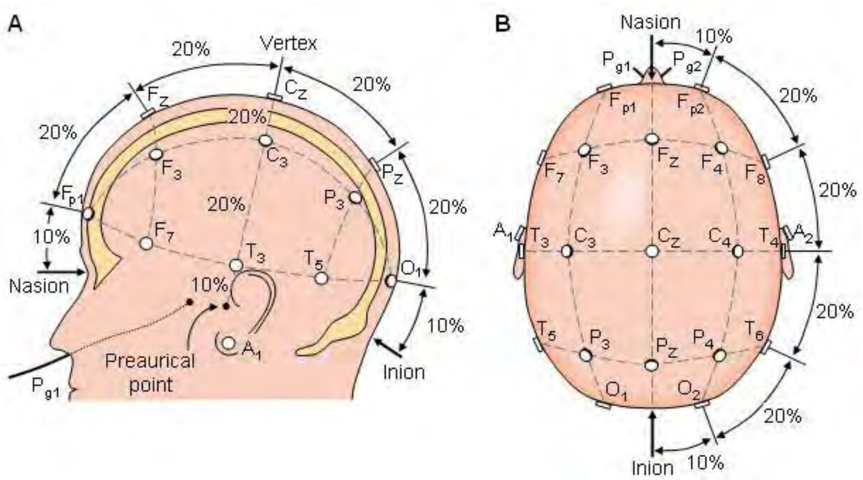


Fig. 1.2: EEG Electrodes Position on the Scalp in 10-20 EEG Recording system

During the recording, a series of activation procedures may be used. These procedures may induce normal or abnormal EEG activity that might not otherwise be seen. These procedures include hyperventilation, photic stimulation (with a strobe light), eye closure, mental activity, sleep and sleep deprivation. During (inpatient) epilepsy monitoring, a patient's typical seizure medications may be withdrawn.

As part of an evaluation for epilepsy surgery, it may be necessary to insert electrodes near the surface of the brain, under the surface of the dura mater. This is accomplished via burr hole or craniotomy. This is referred to variously as \electrocorticography (ECoG)", \intracranial EEG (IEEG)" or \subdural EEG (SD-EEG)". Depth electrodes may also be placed into brain structures, such as the amygdala or hippocampus, structures, which are common epileptic foci and may not be \seen" clearly by scalp EEG. The electrocorticographic signal is processed in the same manner as digital scalp EEG, with a couple of caveats. IEEG is typically recorded at higher sampling rates than scalp EEG because of the requirements of Nyquist theorem|the subdural signal is composed of a higher predominance of higher fre-quency components. Also, many of the artifacts that a ect scalp EEG do not impact IEEG, and therefore display ltering is often not needed [9].

1.4 Epilepsy Detection and Classi cation Methods

EEG measures voltage uctuations resulting from ionic current ows 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. Di erent techniques are exploited for detection and classi cation of the Epieptic seizures in the mul-tiple channel EEG recordings. Conventionally, physicians use visual inspection in decision making process which not only need superior expertise but also require a lot of time. With a view to easing the decision making process and time consum-ing problem, signal processing techniques introduce di erent processes to achieve expert like accuracy in both case of detection and classi cation process of such EEG signals.

1.4.1 Conventional Methods of Seizure Detection and Classi cation

Conventionally seizure is detected and classi ed by the visual inspection of EEG signals by experts. The EEG provides important information about background EEG and epileptiform discharges and is required for the diagnosis of speci c electro-clinical syndromes. Following a seizure (i.e, during the postictal period) the EEG background may be slow. However, interictal background EEG frequencies that are slower than normal for age usually suggest a symptomatic epilepsy (i.e, epilepsy secondary to brain insult). Normal background suggests primary epilepsy (idiopathic or possibly genetic epilepsy). Thus EEG background o ers important prognostic and classi cation information [10].

Lennox-Gastaut syndrome (LGS) is a type of epilepsy that a ects a child's intellectual functioning and may cause behavioral disturbances. Unfortunately, LGS usually persists through childhood and adolescence into adulthood. When diag-nosing LGS, doctors will look for di used slow spikes and slow waves of 2-2.5 cycles per second [10]. This is between seizures, and while the person is awake. An EEG during sleep is also necessary. Bursts of di use or bilateral fast rhythm patterns (10 cycles/second) or \polyspikes", also called generalized paroxysmal fast activity are recorded during sleep. These EEG patterns help di erentiate LGS from other epilepsy syndromes [11].

Generalized onset tonic seizures are epileptic seizures of mainly severe epilepsies of neonates, infants, and children with learning di culties who also su er from frequent seizures of other types [12]. Lennox-Gastaut syndrome is the prototype disorder of generalized onset tonic seizures. Generalized onset tonic seizures mani-fest with abrupt onset and termination of sustained increase in muscle contraction, usually lasting a few seconds to 1 minute. Severity varies from inconspicuous to marked clinical manifestations with falls depending on the extent and group of muscles involved and violence of the attack. The seizures predominantly occur in sleep. Interictal and ictal EEG are usually grossly abnormal.

Atypical absences are generalized epileptic seizures of mainly severe epilepsies in children with learning di culties who also su er from frequent seizures of another type. Atypical absence seizures are characterized by a slow, insidious start and end with usually mild impairment of consciousness and signi cant atonic symptoms. Ictal EEG shows di use spike and slow wave discharges with a varying range of frequencies at less than 2.5 Hz. Interictal EEG is often abnormal.

Visual seizure detection and classi cation from direct observation of EEG recording has not been proven very e ective as visual observation su ers from misinterpreta-tion frequently and needs highest level of expertise which is also time consuming. E cient automated seizure detection and classi cation systems aid the diagnosis of such epilepsy and improve the management of long term EEG recording. As a result, di erent signal processing based EEG signal detection and classi cation methods are exploited to ease expert decision with superior accuracy and fast decision making.

1.4.2 Signal Processing Based Seizure Detection and Clas-si cation

The literature shows numerous approaches to classify seizure and non-seizure ac-tivities with the intention to simplify the diagnosis procedure of epilepsy. Until recently, only visual inspection by skilled neurologist was used to identify seizures. Yet, this procedure may constitute a lengthy tedious task for long-continuous EEG tracks. Therefore, computer aided programmed algorithms have progressed to make the procedure automated and shortened while several seizure detection ap-proaches are found in the international literature in this regard.

A seizure detection system must be able to determine the presence or absence of ongoing seizures. A variety of algorithms of di erent biometric signals can do this even prior to clinical onset of a seizure. All seizure detection algorithms involve two main steps.

First, appropriate quantitative values or features must be computed from the data. 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 demonstrated in Fig. 1.3 where time domain plot of EEG signals obtained from di erent state and parts of the brain are shown.

The classi cation of seizures from di erent state and parts of the brain from this time domain plot is ambiguous and erroneous. That is why; it is inevitable to look for feature set which can represent these EEG recordings as depicted in Fig 1.3 to di erentiate these seizures originated from di erent state and parts of the brain more precisely.

Secondly, a threshold or model-based criteria must be applied to the features to determine the presence or absence of a seizure. This second step, called classi ca-tion, might be as simple as thresholding a value or might require models derived from modern machine learning algorithms.

Several state-of-the-art methods have been exploited for detection and classi ca-tion of epilepsy. Di erent types of features such as mean-squared error of estimated auto-regressive models, relative power of di erent spectral band of EEG signals, spectral edge frequency, spectral edge power, statistical moment, long term energy are used to composite di erent feature vectors in order to analyze EEG signals [13]-[19].

Assuming the input EEG signal as stationary, some work derived features with the aid of conventional signal transformation techniques like Fourier transform [14]-

[16]. 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 adopt-ing techniques in [14]-[16]. Due to this non-stationarity, perfect decision making

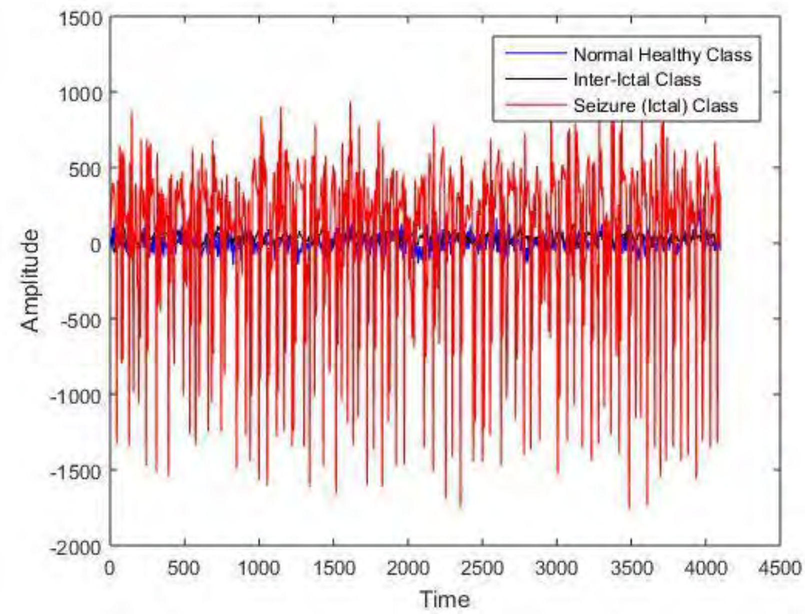


Fig. 1.3: Time Domain Plot of Di erent Classes of EEG Signals

for detection and classi cation of EEG signals is mostly dependent on accuracy of extracting feature in time and frequency domain. As distribution of energy at di erent frequency bands demonstrate the seizure activities, time-frequency distribution performs better than conventional frequency analysis methods [20], [21].

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 [22]. 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 [23]. 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.

The Correlation Dimension (CD) provides the degree of complexity in comparison with seizure and non-seizure EEG recordings [24]. 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 [25]. The Approximation Entropy (ApEn) is a statistical index for the overall complexity and predictability of a given time series. The value of ApEn reduces signi cantly during seizure attack thus quite helpful for seizure event prediction and detection [26]. These feature sets are used to represent particular patterns for di erent types of EEG recording which are fed into di erent classi ers like di erent distance based classi er (QDA, LDA, Euclidean based, k-NN etc), neural network based classi er etc. to automatically detect and classify seizures originating from di erent states and parts of the brain.

Many previous works used time-frequency analysis to detect pre-seizure chirps and multi-resolution analysis of EEG. E ectiveness of these works depends on frequency or time domain smoothing. Reduced Interference (RI) distribution and twelve kohen class kernels are used for smoothing purpose before feature extraction [27], [28]. But, due to selection of speci c 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 Mode Decomposition (EMD) and Dual-Tree Complex Wavelet Transform (DT-CWT) has been proposed in [29]-[31] for seizure detection and classi cation.

1.5 Problem De nition

The investigation, detection, and classi cation of seizure and epilepsy can be easily performed from the behavioral actions of brain recorded by Electroencephalogra-phy (EEG) signals. Conventional detection of epileptic seizure normally needs visual expertise and longer time which may be a source of misinterpretation and a problem in case of disease treatment. The objective of computer-aided digital signal processing of EEG signal is to reduce the time taken by the physicists in interpreting the results. The seizure detection algorithms found in literature in-volve extracting the features from EEG signals decomposed into time-frequency sub-bands to discriminate them between seizure (ictal) and seizure-free (non-ictal or inter-ictal) activity without mentioning any rationale behind choosing speci c time-frequency sub-band. These exploited features include wavelet energy, higher order statistical moment, Shannon entropy, root mean square amplitude, total power and so on. However, most of the algorithms have the high dimensional fea-ture set considering all bands of EEG signals and not all of them have reported their performance in stringent conditions for detecting and classifying multiclass EEG signals. Thus, development of a pro cient method capable of detecting and classifying multiclass EEG epilepsy with a reduced feature set is still a challenging task.

1.6 Motivation

In light of above discussions, it is evident that we need to propose and develop an e ective multiclass epileptic seizure activity classi cation scheme which will be capable of performing e ciently in numerous stringent conditions. Due to the non-stationarity of EEG signals, we have moved to exploit discrete wavelet transform (DWT) operation and choose band-speci c DWT coe cients for reduced feature set which will make the algorithm more e cient. For an e ective feature extraction and classi cation strategy, we have been motivated to build a statistical model of the band-speci c DWT coe cients and feed the modeling parameters to the classi ers for sorting purpose. It is found more functional to make the features from the entire shape of the data class rather than taking discrete parameters which is representing each class in more consistent way and further make the classi cation procedure e ective. Lastly, a classi cation problem involving several kinds of EEG data from numerous brain location and state is found very limitedly reported in literature. That is why; we have been motivated to propose a multiclass epileptic seizure activity classi cation exploiting statistical modeling of band-speci c DWT coe cients of EEG signals.

1.7 Objective of the Thesis

The objectives of this thesis are:

1. To analyze the given EEG signals through band-speci c Discrete Wavelet Transform (DWT) coe cients .

2. To nd out the appropriate statistical probability density function (PDF) for modeling the band-speci c DWT coe cients through visual inspection of PDFs and goodness of t tests.

3. To develop an e ective and reduced feature set to detect and classify epileptic seizure activities based on the statistical modeling parameters of the band-speci c DWT coe cients.

4. To investigate the performance of the proposed method with di erent state-of-the art comparison methods for the detection and classi cation of epileptic seizure activities using the same dataset.

The outcome of this thesis is the development of EEG based multiclass seizure activity classi cation method with e ective and reduced feature sets exploiting band-speci c DWT coe cients and its statistical modeling with greater accuracy, sensitivity and speci city.

1.8 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 classi cation methods re-ported in literature

Chapter 3 describes the proposed method of epileptic seizure detection and classi cation from EEG signals based on statistical modeling of band-speci c DWT coe cients

Simulation results and quantitative performance analysis are described 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 chaper 5, concluding remarks highlighting the contribution of the thesis and suggstions for further investigation are provided.

Chapter 2

Literature Review

A plentiful of researches is available in the literature concerned with automated detection and classi cation of epileptic seizure using EEG signals. During the seventies, EEG analysis implied interpreting the EEG waveform using descrip-tive and heuristic methods. In time, various methods have been used to analyze several subtle changes in the EEG signal. Most of the methods fall under three broad categories: (1) time domain, (2) frequency domain, and (3) time{frequency domain.

The two primary considerations for this detection system are- the type of features to be extracted from the EEG input signal (feature extraction techniques) and the type of analysis techniques to be applied on these extracted features to detect the stage (classi cation techniques).

2.1 Time Domain Methods

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 am-plitude di erence and time separation between peak values as well as minima [32]. The features used for classi cation of an epoch as a seizure or non-seizure is the estimated values of the histogram bins. The authors used a support vector ma-chine (SVM) classi er 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-speci c epileptic seizures [33]. The authors used an SVM as a classi er 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.

Another approach to deal with time-domain seizure detection is to exploit some dis-criminating statistics between seizure and non-seizure epochs. Dalton et al., 2012 developed a body sensor network (BSN) that can monitor and detect epileptic seizures based on statistics extracted from time-domain signals [34]. These statis-tics include the mean, variance, zero-crossing rate, entropy, and autocorrelation with template signals. For auto-correlation estimation, they adopted a Dynamic Time Warping (DTW) approach for best alignment between the signal segment to be tested and the template signal.

Zandi et al., 2013 used the zero-crossing rate of EEG signal segments to develop a patient-speci c seizure prediction method [35], [36]. A moving window analysis is used in this method. The histograms of the di erent window intervals are es-timated, and selected histogram bins are used for classi cation into pre-ictal and inter-ictal states based on comparison with reference histograms. A variational Bayesian Gaussian mixture model has been used for classi cation. In this method, a combined index for the decisions taken on selected bins is computed and com-pared with a pre-de ned patient-speci c threshold to raise an alarm for coming seizures.

Aarabi [37] developed a time-domain rule-based patient-speci c seizure prediction method which consists of three stages: pre-processing, feature extraction, and rule-based decision making. In the pre-processing stage, the IEEG data is ltered using a 0.5- to 100-Hz pass lter in addition to a 50-Hz notch lter. Then, the ltered signal is segmented into non-overlapping 10-s segments. Five univariate features (correlation entropy, correlation dimension, Lempel-Ziv complexity, noise level, and largest Lyapunov exponent) and one bivariate feature (non-linear inde-pendence) were extracted from each segment in the second stage.

Based on the theory of chaos, the correlation dimension (denoted by v) represents a dimensionality measure of the space having a set of random points; in our case, EEG signals. For an m-dimensional space containing a set of N points, it can be written:

$$x(i) = [x_1(i); x_2(i); ::::::; x_m(i)]; \; i = 1; 2::::::N \tag{2.1}$$

The correlation integral C( ) can be estimated as [38]:

$$C(\ ) = \lim_{N!1} \frac{g}{N^2} \tag{2.2}$$

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

$$C(\ ) = {}^{y} \tag{2.3}$$

If a large number of evenly distributed points exists, a log-log graph of the correlation integral versus can be used to estimate . 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 [38].

Correlation entropy 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 speci c patterns is an indication that the segment at hand belongs to a dataset with similar characteristics to the stored pattern [39].

The Lempel-Ziv complexity is a measure of randomness of data sequences [40]. It counts the number of data patterns with certain characteristics in data segments. For example, if we nd enough short patterns with speci c mean, variance, or higher-order statistics are found in an EEG segment, we can classify this segment 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 Z_0 will eventually diverge at a rate given by [40]

$$j\ Z(t)j = {}^{t}j\ Z_0 j \tag{2.4}$$

where is the Lyapunov exponent. This can be achieved if the divergence can be dealt with within the linearized approximation. The separation rate di ers based on the initial separation vector orientation. The maximal Lyapunov exponent can be estimated as [41]:

$$= \lim_{t!1} \lim_{Z_0!1} \frac{1}{t} \ln \frac{j\ Z(t)j}{j\ Z_0 j} \tag{2.5}$$

The limit Z_0 ! 0 ensures the validity of the linear approximation at any time.

Wang et al., 2010 proposed an adaptive learning system that interactively learns from the patient and improves its seizure predictability over time [42]. It is based on reinforcement learning and online monitoring, in addition to adaptive control theory. In this system, a sliding window size of 10 min is used to read continuous multichannel EEG data with a 50% overlap at each move. Then, k-nearest neighbor (KNN) method is adopted for the classi cation of the windowed epochs to normal or preseizure states.

Bedeeuzzaman et al., 2014 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 [43]. A linear classi er has been used to nd the seizure prediction time in pre-ictal IEEGs. The envelope of the EEG signal can be exploited to distinguish between di erent activities.

Li et al., 2013 presented a time-domain method for seizure prediction that is based on spike rate estimation [44]. Morphological operations and averaging lters 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 identi ed through comparison with a certain threshold.

Another approach to process EEG signals in the time domain in order to detect or predict seizure is to create models from the EEG signal segments corresponding to di erent 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 coe cients. Chisci et al., 2010 studied the implantation of monitoring and control units on drug-resistant epilepsy patients with AR modeling [45]. They adopted AR modeling with a least-squares parameter estimator for EEG feature extraction in addition to a binary SVM classi er to distinguish between pre-ictal, ictal, and inter-ictal states.

2.2 Frequency Domain Methods

Frequency-domain techniques have been used for EEG seizure detection. Both of the Fourier transform magnitude and phase can be exploited for this purpose. Rana et al., 2012 presented a frequency-domain epileptic seizure detection approach depending on the phase-slope index (PSI) of multi-channel EEG signals [46]. If we consider signals $z_i[n]$ and $z_j[n]$, their cross spectrum is given by:

$$S_{ij}(f) = E[Z_i(f)Z_j^*(f)]: \tag{2.6}$$

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:

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}} \tag{2.7}$$

An un-normalized PSI metric can be defined using complex coherence as follows:

$$\tilde{\Psi}_{ij} = \mathrm{Im}\left(\sum_{f \in F} C_{ij}^*(f)C_{ij}(f+\delta f)\right) \tag{2.8}$$

where δf is the frequency resolution and F is the frequency band of interest. We can deduce that $\tilde{\Psi}_{ij}$ measures a weighted sum of the slopes of the phase between $z_i[n]$ and $z_j[n]$ over the selected band F [46]. 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. The detection performance has been evaluated over five patients having different types of epilepsy with 47 seizures in 258h of recorded data. The simulation results showed that this algorithm succeeded in the detection of all seizures for four out of five patients, and it achieved a lower false detection rate than two per hour. The results also showed that the channels with strong activity can be determined for each patient.

Khamis et al., 2013 used frequency-moment signatures for building a patient-specific seizure detection method [47]. 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 T6-P4 for the right hemisphere and T5-P3 for 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.

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. 2012 presented a modi ed method for the detection of normal, pre-ictal, and ictal conditions from recorded EEG signals [48]. This method is based on four entropy features for classi cation: phase entropy 1 (S1), phase entropy 2 (S2), 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 di erent classi ers for comparison: SVM, KNN, naive Bayes classi er (NBC), Arti cial Neural Network (ANN).

2.3 Time-Frequency Domain Methods

Even though time and frequency analyses are widely used in signal processing, they have well known disadvantages when applied to signals such as EEG. Time-domain analysis can be used to assess the exact location of events but it cannot distin-guish which frequencies are involved in those events. Frequency-domain analysis di erentiates the frequencies present in a signal but not the time moment of their occurrence. Due to these limitations, time-frequency analysis techniques have been developed. Time-frequency approaches include Wigner-Ville distribution (WVD) , Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT), which are the most widely used techniques for EEG.

2.3.1 Wigner-Ville Distribution

The Wigner-Ville distribution (WVD) function used in signal processing as a transform in time-frequency analysis is one of the most studied and best understood time-frequency distributions [49]. This particular distribution has very good resolution in both the time and frequency domains, and has interesting time and frequency support properties [50]. Tzallas et al. 2008 [28] applied the WVD to selected segments of EEG signals and extracted several features for each segment that represent the energy distribution in the time-frequency plane. The calculated features are fed into a feed-forward ANN. To reduce the dimensionality of the input patterns, principal component analysis (PCA) is also employed.

2.3.2 Empirical Mode Decomposition (EMD)

The EMD is a signal decomposition process which transforms a signal into a group of intrinsic mode functions (IMFs). For EEG seizure detection, these IMFs show di erent behavior with normal and abnormal activities in the signals. Features can also be extracted from the IMFs and tested for seizure detection and prediction.

Eftekhar et al., 2008 used the EMD approach for seizure detection [51]. They adopted features such as the frequency rise at the seizure onset with the EMD in a patient-speci c 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., 2008 evaluated the performance of the EMD in discriminating epileptic seizure data from normal data using means of the absolute of the IMFs as features [52]. They compared this approach for feature extraction with wavelet features using both multi-layer perception (MLP) and self-organizing map (SOM) neural networks.

Orosco et al., 2009 presented a seizure detection approach based on the energies of IMFs as discriminating features between seizure and non-seizure activities in
[53]. In this approach, the IMF energies are compared with certain thresholds for decision making. It was tested on nine patient records from Freiburg database with invasive nature. Guarnizo and Delgado presented a modi ed EMD approach, in which mutual information is used for feature selection in the EMD domain [54]. 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 Shannon's entropy have been selected as features extracted from the en-ergy estimated with the Teager energy operator (TEO) over all EMD components. This approach adopts a linear Bayes classi er. Bajaj and Pachori presented an EMD-based seizure detection method to detect focal temporal lobe epilepsy [18]. In this method, they used Hilbert transformation of IMFs which were obtained by an EMD process. Epileptic seizures are then detected based on the instantaneous area estimated from the trace of analytic IMFs of EEG signals. The performance of this epileptic detection method was evaluated on Freiburg. Alam and Bhuiyan presented a seizure detection method depending on extracting kurtosis, skewness, largest Lyapunov exponent, variance, approximate entropy, and correlation di-mension from the IMFs of EEG signals with arti cial neural network classi ers [31], [55]. This method achieved a 100% sensitivity in seizure detection and has shown a superiority as compared to time-frequency techniques and band-limited techniques in the computational complexity. However, in the features reported in

[18], [31], [55] from the set of extracted IMFs; no automatic selection of IMF is proposed and classi cation performance is reported with respect to each individual IMF. Recently in [56], rst four IMFs have been taken into account considering the strength of IMFs in power spectral density estimation and bimodal Gaussian statistical modeling parameters have been extracted from the IMFs for multiclass epileptic seizure activity classi cation.

2.3.3 Wavelet Transform

Wavelets have been widely used in the eld of EEG signal analysis, especially for seizure detection and prediction. The wavelet transform in itself can be regarded as some sort of sub-band decomposition, but with downsampling. 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 ve-level wavelet decomposition method for seizure detection was developed by Liu et al.. 2014 [57]. This method works on multi-channel IEEG signals. Three wavelet sub-bands are selected for further processing. The extracted features from these sub-bands are the relative amplitude, relative energy, coe cient of variation (ratio between the standard deviation of a decomposed sub-band and the square of its mean), and uctuation index (a measure of the intensity of a decomposed sub-band) from the selected frequency bands. An SVM classi er is used in this approach, and some sort of post-processing is implemented to enhance the detection performance with smoothing.

Khan et al., 2012 proposed a similar approach for seizure detection, but with rel-ative energy and a normalized coe cient of variation (NCOV) as features [58]. Wang et al. used Neyman Pearson rules and an SVM classi er for seizure de-tection [59]. This method depends on the wavelet coe cients in addition to the approximate entropy in the wavelet domain as extracted features, and the detec-tion 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. 2013 investigated the use of Wavelet Neural Networks (WNNs) based on wavelet basis functions for seizure detection [60]. Firstly, the wavelet transform of EEG signals is estimated, and maximum, minimum, and standard deviation of the absolute values of the wavelet coe cients in each sub-band are extracted as features. These features are then fed to trained WNNs. The Gaus-sian, Mexican Hat, and Morlet wavelet activation functions have been investigated for classi cation. A cross-validation approach have been adopted in the simu-lation 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. 2009 presented a wavelet-based method for epileptic seizure detec-tion that adopts recurrence quanti cation analysis (RQA) on EEG recordings and their delta, theta, alpha, beta, and gamma sub-bands extracted through a four-level Daubechies wavelet transform [61]. The RQA is well-suited for non-linear data analysis. It quanti es 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 are the features corresponding to each EEG signal state. The authors adopted an error-correcting output coding (ECOC) classi er for discriminating between three states: healthy, inter-ictal, and ictal.

In [62], EEG signals were summarized by a statistical generalized Gaussian model and only onset of seizure detector was proposed on a multi-resolution wavelet scheme. Recently, a method based on Dual-Tree Complex Wavelet Transform (DT-CWT) has been applied in [30] to detect epilepsy. In this method, seizure detection is acquired after applying DT-CWT to each EEG signals to obtain sub-bands for di erent 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). Then the modeling parameters are used as feature with SVM classi er to detect epilepsy.

However, in all methods described in [30], [56]-[62], no band-speci c term or cause to select particular time-frequency sub-band is declared in DT-CWT or DWT for classi cation of seizure and non-seizure activities originated from di erent parts and state of the brain . Therefore, 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 de-tection and classi cation 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 classi cation method is needed to be capable of producing greater accuracy, sensitivity, speci city and lesser processing time even in case of stringent conditions such as speci c time-frequency band, reduced feature set as well as random selection of training and testing dataset for multiclass problem where EEG signals from di erent part and state of the brain are involved.

Chapter 3

Multiclass Seizure Activity Classi cation Exploiting Statistical Modeling of the Band-Speci c DWT Coe cients 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 di cult task. Since, EEG is a non-stationary signal, discrete wavelet transform (DWT) has the potential to perform better than the conventional time-frequency analysis method. But, selection of speci c time-frequency band resulting from DWT is also crucial in this case. In this chapter, DWT analysis of the EEG signals is performed at rst and the band-speci c DWT coe cients are taken into account. For the reduction of the dimension of the feature vector, a statistical model of the band-speci c DWT coe cients has been built and the modeling parameters are employed to form the feature vector. Rather than taking discrete parameters like total power, wavelet energy, root mean square amplitude, Hjorth parameter, higher order statistical moment, Shannon entropy and so on as feature; it is found rational to propose feature set by taking parameters attained from the statistical model since they are achieved from the shape of the entire data distribution and make the feature set more consistent for each class. The reduced feature set thus formed is found e ective for detecting and classifying multiclass EEG signals for epilepsy investigation when fed to di erent state-of-art classi ers in stringent conditions although preliminary results for 3 classes and 5 classes have been reported in [63], [64].

3.2 Proposed Method

The proposed EEG based epileptic seizure activity detection and classi cation method consist of some major steps, namely- pre-processing, discrete wavelet transform (DWT), statistical modeling of band speci c DWT coe cients, fea-ture extraction and classi cation. In the classi cation, we consider three di erent classi cation problems, namely two class, three class and ve class problem. Pre-processing manipulates the signal to be ready for DWT analysis. An appropriate statistical model of the band-speci c DWT coe cients is constructed and feature set is built with the statistical model parameters. For the purpose of detecting epileptic seizure and to classify epileptic seizure originated from di erent parts and state of the brain, a training database is needed to be prepared consisting of template EEG signals of di erent classes as well as di erent persons. The detec-tion and classi cation task is based on comparing a test EEG signal with training dataset. It is obvious that considering EEG signals themselves would require ex-tensive computations for the purpose of comparison. Thus, instead of utilizing the EEG signals, some characteristic features are extracted from the parameters of probability density function (PDF) of proposed statistical model of DWT coef-cients for preparing the training dataset. It is to be noted that the detection and classi cation accuracy strongly depends upon the quality of the extracted features. Therefore, the main focus of this work is to develop an e ective feature extraction algorithm from appropriate statistical model. The simpli ed 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 ve popular time-frequency bands namely gamma, beta, alpha, theta and delta. These bands altogether cover their signi cant energies for the frequency range up to 80 Hz. As a result, fre-quencies above 80 Hz are considered as noise. To eliminate the noise, 6th-ordder butterworth lter having a cut-o frequency to 80Hz has been used in this work. The plots of original and proposed seizure and non-seizure EEG signals are shown in Fig. 3.2
From this gure, it is quite di cult to identify any particular pattern for seizure

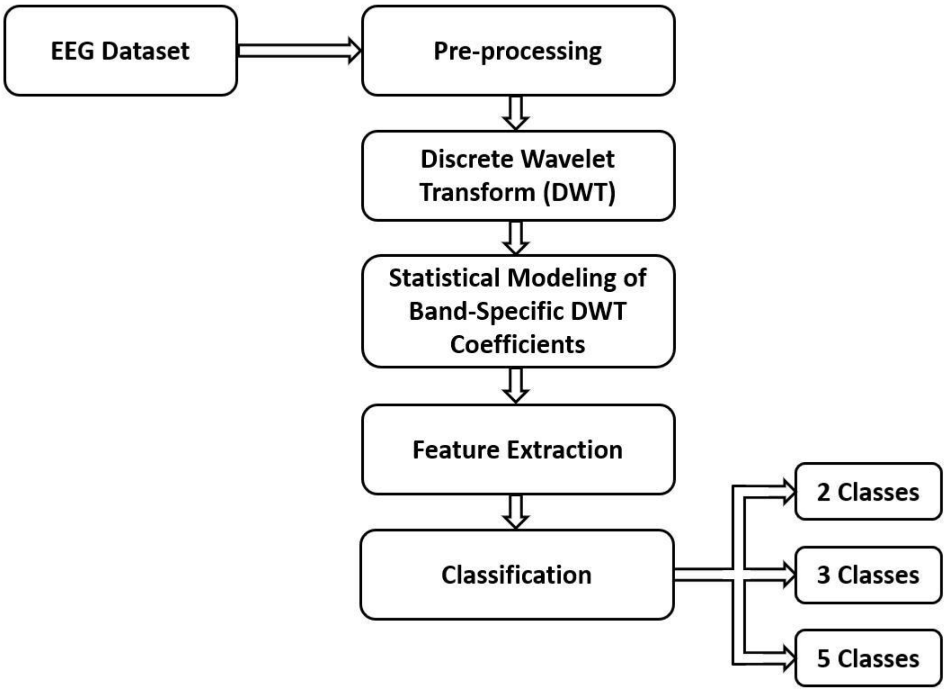


Fig. 3.1: Simpli ed Block Diagram of the Proposed Method

and non-seizure activities from time domain EEG signals. As a result, we need to transform EEG signals in another domain and capture suitable feature in that domain for seizure activity detection and classi cation.

3.2.2 Discrete Wavelet Transform (DWT)

Discrete Wavelet Transforms (DWTs) are widely applied in many engineering elds for solving various real-life problems. The Fourier transform of a signal contains the frequency content of the signal over the analysis window and, as such, lacks any time domain localization information. In order to achieve time localization information, it is necessary for the time window to be short, therefore compro-mising frequency localization. On the contrary, achieving frequency localization requires a large time analysis window and time localization is compromised. The short-time fourier transform (STFT) represents a sort of compromise between the time and frequency based views of a signal and contains both time and frequency information. STFT has a limited frequency resolution determined by the size of the analysis window. This frequency resolution is xed for the entire frequency band. Contrary to STFT, Wavelet Transform (WT) provides a more exible way of time-frequency representation of a signal by allowing the use of variable sized windows. In WT, long time windows are used to get a ner low frequency reso-lution and short time windows are used to get high frequency information. Thus,

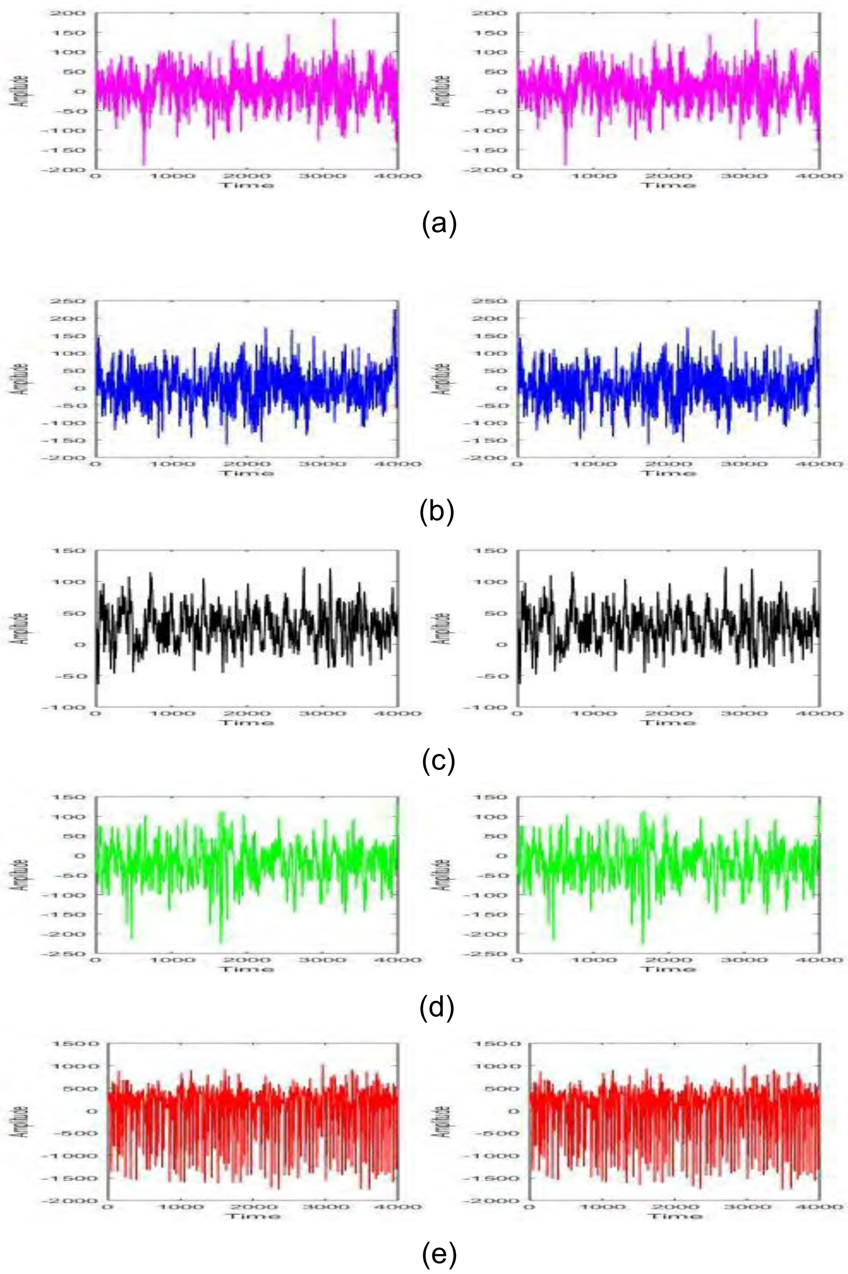


Fig. 3.2: Non-seizure [(a) to (d)] and Seizure [(e)] EEG Signals [Original(left) and Proposed (Right)]

WT gives precise frequency information at low frequencies and precise time in-formation at high frequencies. This makes the WT suitable for the analysis of irregular data patterns, such as impulses occurring at various time instances. The continuous wavelet transform (CWT) of a signal, x(t), is the integral of the signal multiplied by scaled and shifted versions of a wavelet function w and is de ned by [65],

$$CWT(a;b) = \int_{-1}^{1} x(t) \frac{1}{\sqrt{|a|}} \left(\frac{t-b}{a}\right) dt \quad (3.1)$$

where a and b are so called the scaling (reciprocal of frequency) and time localiza-tion or shifting parameters, respectively. Calculating wavelet coe cients at every possible scale is computationally a very expensive task. Instead, if the scales and shifts are selected based on powers of two, so-called dyadic scales and positions, then the wavelet analysis will be much more e cient. Such analysis is obtained from the DWT which is de ned as,

$$DW\,T\,(j;k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t)\,\psi\left(\frac{t-2^j k}{2^j}\right)dt \qquad (3.2)$$

where a and b are replaced by 2^j and $2^j k$, respectively. Mallat Mallat (1989) [65] developed an e cient way for implementing this scheme by passing the sig-nal through a series of low-pass (LP) and high-pass (HP) lter pairs named as quadrature mirror lters.

In the rst step of the DWT, the signal is simultaneously passed through a LP and HP lters with the cut-o frequency being the one fourth of the sampling frequency. The outputs from the low and high pass lters are referred to as approximation (A1) and detail (D1) coe cients of the rst level, respectively. The output signals having half the frequency bandwidth of the original signal can be downsampled by two according to Nyquist rule. The same procedure can be repeated for the rst level approximation and the detail coe cients to get the second level coe cients. At each step of this decomposition process, the frequency resolution is doubled through ltering and the time resolution is halved through down sampling. Fig. 3.3 illustrates the four level wavelet decomposition of a signal. In this representation, the coe cients A1, D1, A2, D2, A3, D3, A4 and D4 represent the frequency content of the original signal within the bands 0{fs/4, fs/4{fs/2, 0{fs/8, fs/8{fs/4, 0{fs/16, fs/16{fs/8, 0{fs/32, and fs/32{fs/16, respectively where fs is the sampling frequency of the original signal r[n].

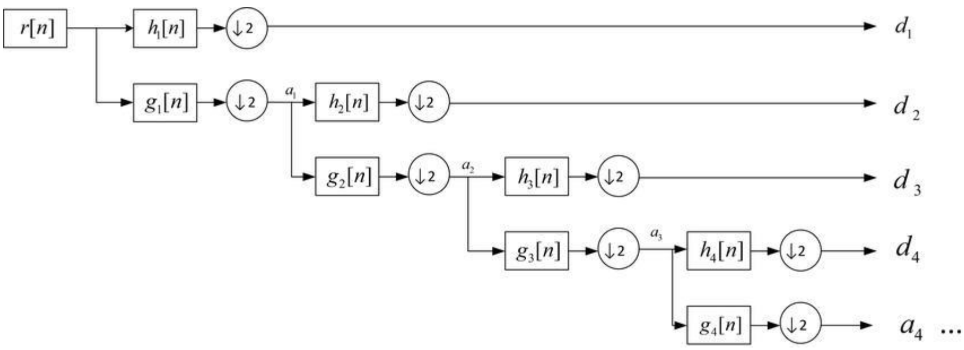


Fig. 3.3: DWT Decomposition of a Signal r[n]

3.2.2.1 Band-Speci c DWT Coe cients

Basically, extracted all band of DWT coe cients do not uniquely deceive whether the corresponding EEG signal is seizure or non-seizure. However, recent stud-ies indicate that pathologic high-frequency oscillations (HFOs) are signatures of epileptogenic brain [66]. Recent studies using presurgical intracranial EEG (IEEG) recordings report gamma ( ) oscillations (40{80 Hz) (Buzsaki, 1996, 1998; Bragin et al., 1999a; Grenier et al., 2003a) [67]-[69], and high-gamma/ripple oscillations (80{200 Hz) that may be important for learning and memory consolidation (Llinas, 1988; Lisman and Idiart, 1995; Buzsaki, 1996, 1998; Bragin et al., 1999a; Grenier et al., 2003a) [66]-[71]. In addition to their role in normal brain function, high-frequency activity has been described at seizure onset (Allen et al., 1992; Fisher et al., 1992; Alarcon et al., 1995; Bragin et al., 1999b; Grenier et al., 2003a; Worrell et al., 2004; Jirsch et al., 2006)][66], [69], [72]-[76] and in human epileptogenic foci at times temporally remote from seizure onset (Fisher et al., 1992; Bragin et al., 1999a; Worrell et al., 2004) [66], [74], [76].

Moreover, Canolty et. al. [77] observed robust coupling between the high- and low-frequency bands of ongoing electrical activity in the human brain. In partic-ular, the phase of the low-frequency theta (4-8 Hz) rhythm modulates power in the high-gamma/ripple (80-150 Hz) band of the electrocorticogram, with stronger modulation occurring at higher theta amplitudes.

Inspired from the above mentioned ndings of [66]-[77], we selected and speci ed the e ective time-frequency band gamma (40-80 Hz) and theta (4-8 Hz) for taking DWT coe cients for classi cation purpose. The ranges of di erent frequency bands are shown in Table 3.1. Therefore, the rst level and fourth level detail Haar wavelet coe cients are taken here for capturing the parts of the signal which are associated with the high-frequency oscillation in gamma and theta band required for EEG signals classi cation.

Table 3.1: Frequency Range Corresponding to Di erent Levels of DWT Analysis

Decomposed signal	Frequency range (Hz)
D1	43 - 86
D2	21.5 - 43
D3	10.75 - 21.5
D4	5.375 - 10.75
A4	0 - 5.375

3.2.3 Statistical Modeling

It is found that EEG data usually follow a normal distribution [78]. Therefore, to choose an appropriate statistical distributional model for DWT coe cients, we compared visually tting of some statistical models: Normal Inverse Gaus-sian (NIG), T-Location Scale, Cauchy and Gaussian PDFs with empirical PDF of DWT coe cients in gamma and theta band for every single-channel EEG signal of complete dataset.

3.2.3.1 T-location Scale

The t location-scale distribution is useful for modeling data distributions with heavier tails (more prone to outliers) than the normal distribution. The probability density function (PDF) of the t location-scale distribution is

$$f(x) = \frac{\left(\frac{v+1}{2}\right)}{\quad} \frac{"v + \left(\frac{x}{\quad}\right)^2 \#}{\quad}^{\left(\frac{v+1}{2}\right)} \tag{3.3}$$

where ( ) is the gamma function, is the location parameter, is the scale parameter, and v is the shape parameter. The PDF approaches the normal distri-bution as v approaches in nity, and smaller values of v yield heavier tails.

The mean of the t location-scale distribution, is the location parameter. The mean is only de ned for shape parameter values v >1. For other values of v, the mean is unde ned.

The variance of the t location-scale distribution is

$$\mathrm{var} = {}^2 \frac{v}{v\ \ 2} \tag{3.4}$$

The variance is only de ned for values of v >2. For other values of v, the variance is unde ned.

3.2.3.2 Cauchy

The Cauchy distribution has the probability density function (PDF) [83], [84]

$$f(x; x_0; \ ) = \frac{1}{[1 + (\frac{x \ x_0}{})^2]} = \frac{2}{[(x \ x_0)^2 + \ ^2]} \tag{3.5}$$

where x_0 is the location parameter, specifying the location of the peak of the distribution, and is the scale parameter which speci es the half-width at half-maximum (HWHM), alternatively 2 is full width at half maximum (FWHM). is also equal to half the interquartile range and is sometimes called the probable error. Augustin-Louis Cauchy exploited such a density function in 1827 with an in nitesimal scale parameter, de ning what would now be called a Dirac delta function.

The maximum value or amplitude of the Cauchy PDF is $\frac{1}{}$, located at $x = x_0$. It is sometimes convenient to express the PDF in terms of the complex parameter

$= x_0 + i$

$$f(x; \ ) = \frac{1}{} \mathrm{Im}(\frac{1}{x \ }) = \frac{1}{} \mathrm{Re}(\frac{i}{x \ }) \tag{3.6}$$

The special case when $x_0 = 0$ and $= 1$ is called the standard Cauchy distribution with the probability density function [85], [86]

$$f(x; 0; 1) = \frac{1}{(1 + x^2)} \tag{3.7}$$

3.2.3.3 Normal Inverse Gaussian (NIG)

The normal inverse Gaussian distribution is a variance-mean mixture of a Gaussian distribution with an inverse Gaussian. A stochastic variable X is said to be normal inverse Gaussian if it has a probability density function of the form [79]-[81]

$$f(x) = \frac{\ \exp[p(x)]}{q(x)} K_1[\ q(x)] \tag{3.8}$$

where $K_1(x)$ is the modi ed Bessel function of the second kind with index 1,

$p(x) = \sqrt{\ ^2 \ ^2} + \ (x \ )$, $q(x) = ((x \ )^2 + \ ^2)^{1=2}$. Furthermore, $0 \ j \ j < \ $, > 0, $1 \ 1$

As seen from the de nition in Eq. 3.8 , the shape of the NIG density is speci ed by a four dimensional parameter vector (; ; ;). This parameterization is very exible indeed, making it possible to model a large variety of shapes and with various decay rates of the tail.

The four parameters of the NIG-distribution have natural interpretations relating to the overall shape of the density as follows:

The -parameter controls the steepness of the density, in the sense that the steep-ness of the density increases monotonically with increasing . This has implications also for the tail behavior, by the fact that large values of implies light tails, while smaller values of implies heavier tails [82].

The parameter is a skewness parameter, in the sense that < 0 implies a density skew to the left, > 0 implies a density skew to the right, and = 0 implies a density that is symmetric around , which is obviously a centrality or translation parameter. Last, the parameter is a scale parameter in the sense that the rescaled parameters ! and ! are invariant under location-scale changes of x.

3.2.3.4 Gaussian

The Gaussian distribution is suitable for making statistical model of one dimen-sional data which has numerous uses in biomedical signal processing for its adapt-ability nature [88]. The probability density function (PDF) of this parametric distribution having 2 parameters (,) is estimated at x values by:

$$f(xj\ ;\ ) = \frac{1}{p\,\overline{2}}\, e^{\frac{(x\ \ )^2}{2^{\ 2}}} \tag{3.9}$$

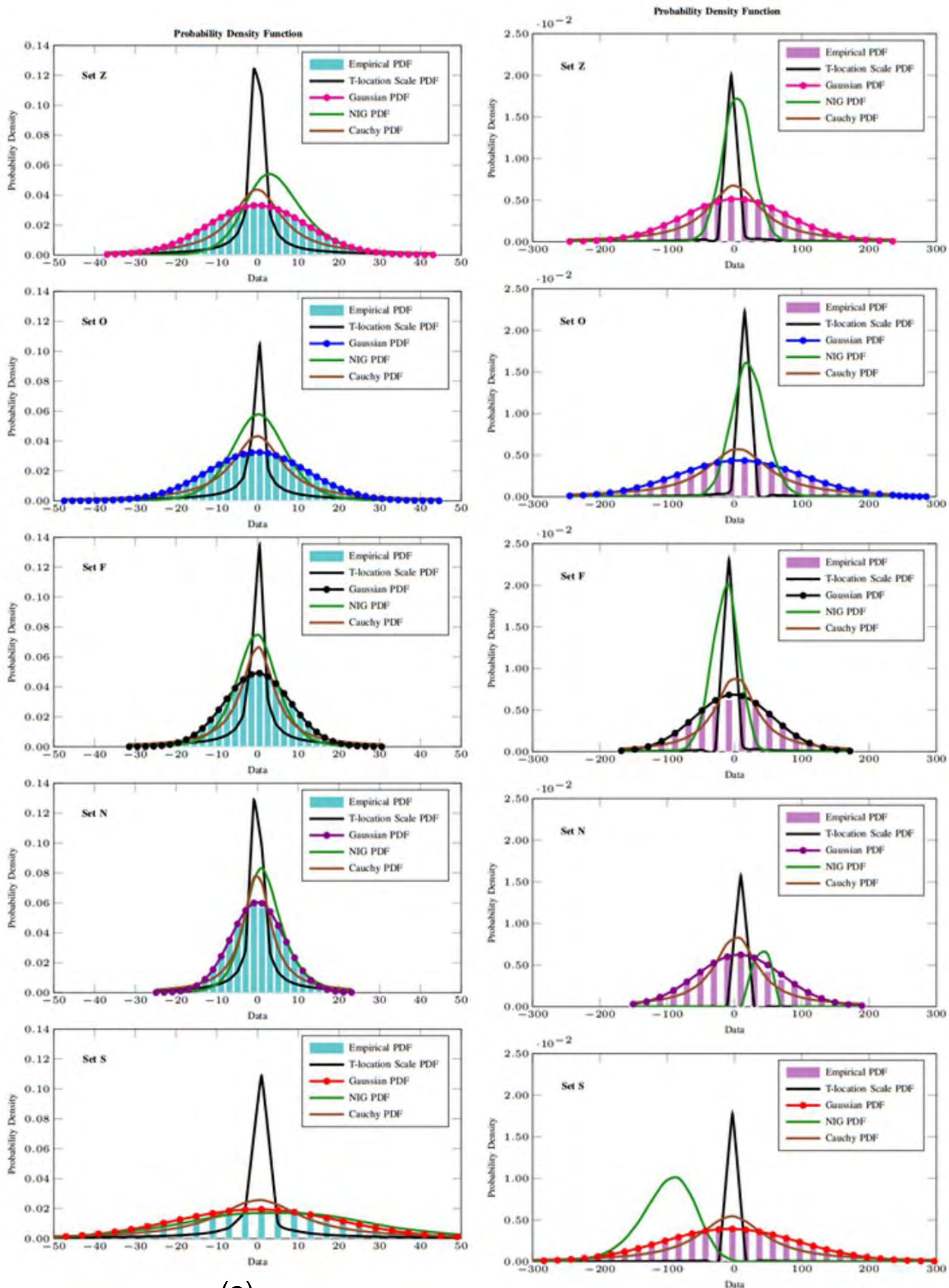
Here, mean or expectation (also its median and mode), 2 R of the distribution is a location parameter and standard deviation, 2 R+ is a scale parameter. They are established from the corresponding N number of x DWT coe cients of EEG signals utilizing:

$$= \frac{x_1 + x_2 + x_3 + \quad + x_n}{N} \tag{3.10}$$

$$= \sqrt{\frac{1}{N}\sum^{N} (x_i\ \ )^2} \tag{3.11}$$

The PDF has a few properties for exact demonstrating the insights of DWT coef-cients. A portion of these are: i) Eq. 3.9 is symmetric with respect to ii) the estimation of Eq. 3.9 tends to zero as x grades to positive and negative in nity [88].

3.2.4 Goodness of Fit to a Statistical Model



(a)

(b)

Fig. 3.4: Plots of the Empirical PDFs and Numerous Statistical Model PDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets

Fig. 3.4 illustrates the graphical t of above mentioned PDFs for gamma and theta band DWT coe cients of arbitrarily selected single-channel EEG signal from each set Z, O, F, N and S with their empirical PDFs which are also valid for almost the complete dataset. It is evident from Fig. 3.4 that only the Gaussian distribution delivers the best match with empirical PDF for displaying the DWT coe cients. Therefore, Gaussian distribution has been adopted for further investigation.

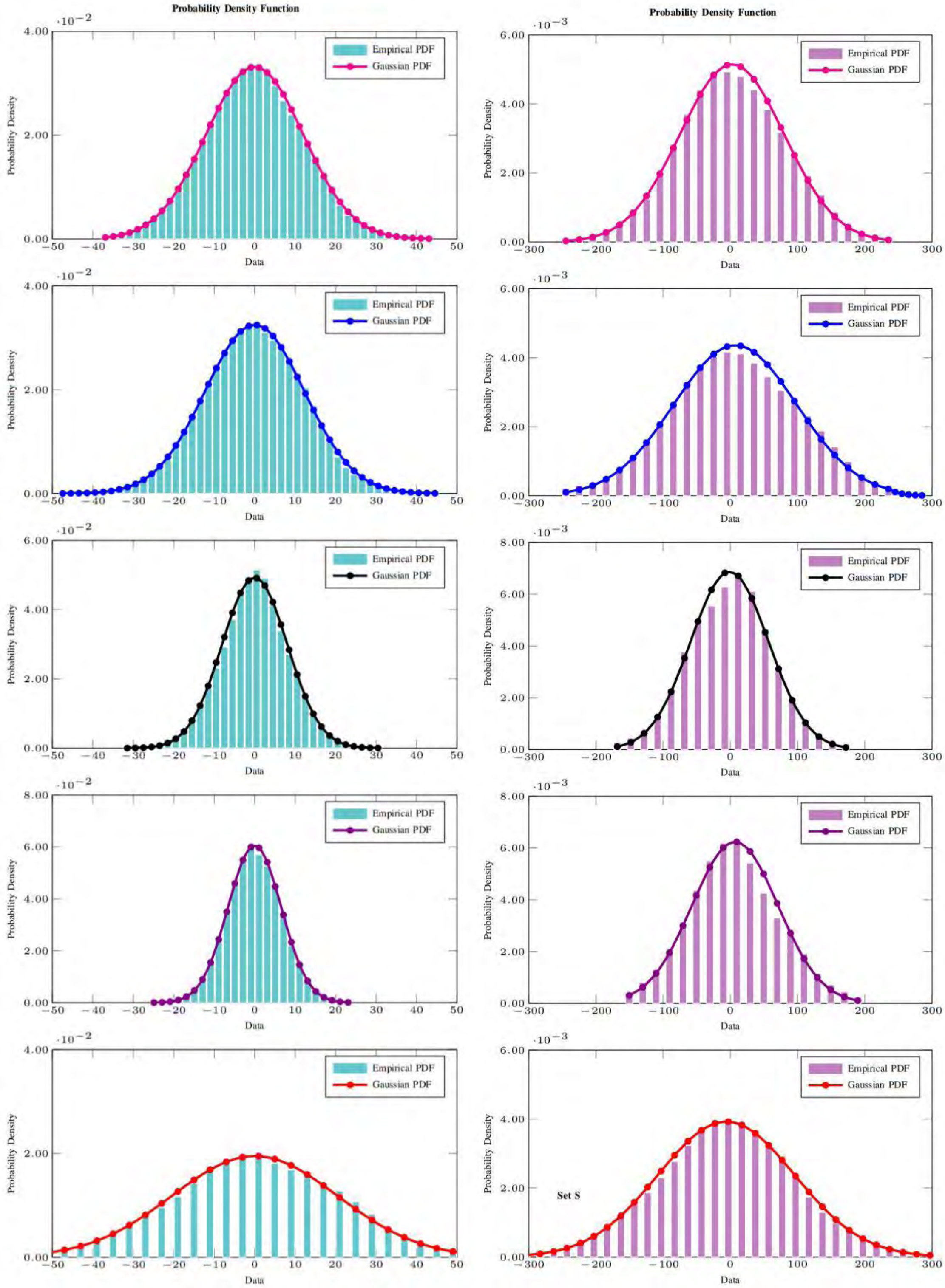
Fig. 3.5 shows the empirical PDF and adopted Gaussian PDF only for DWT coe cients of Set Z, O, F, N and S. It is seen from Fig. 3.5 that the ve groups of the classi cation problem have ve di erent Gaussian frameworks with respect to its spread. The inter-ictal group (Set F or N) has more enfolded PDF and PDF of ictal group (Set S) is more dispersed with respect to PDF of normal group (Set Z or O). The location parameter mean and scale parameter standard deviation convey these distinctions to be included in feature set for classi cation of EEG signals. In case of ve class classi cation problem when distinguishing between Set F and N or Set Z and O are required, accurate range of the PDF location is necessary where PDF is constructed.

In statistics, a P{P plot (probability{probability plot or percent{percent plot or P value plot) is a probability plot for assessing how closely two data sets agree, which plots the two cumulative distribution functions (CDF) against each other. From Fig. 3.6 to Fig. 3.9, the probability-probability (P-P) plots of T-location, Cauchy, NIG and Gaussian distributions are included which show the cumulative distribution functions (CDFs) of the randomly chosen prior PDFs against the empirical CDFs used to model the corresponding DWT coe cients of gamma and theta band from Sets Z, O, F, N and S. It is seen from the plots that Gaussian P-P plot is best matched with the reference line. This is also applicable for each single EEG signal in the entire dataset which further testi es the goodness of t for proposed Gaussian statistical model.

For a Gaussian distribution with mean and standard deviation , the cumulative distribution function is:

$$F(x) = \frac{x}{\;} = \frac{1}{2}\left(1 + \mathrm{erf}\,\frac{x}{\sqrt{2}}\right) \qquad (3.12)$$

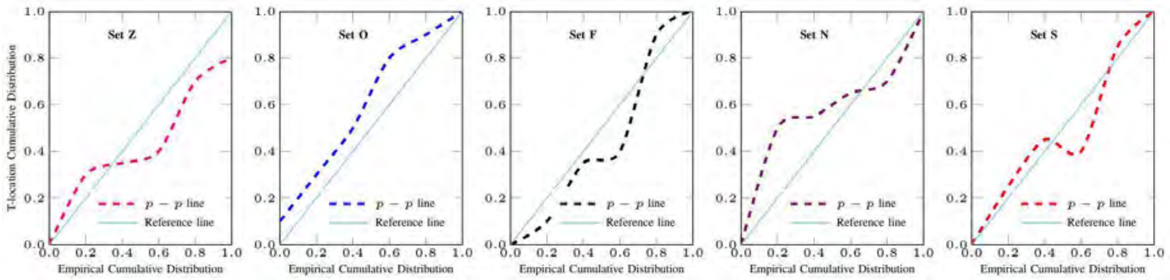
Here, (x) represents the standard Gaussian CDF and error function erf(x) shows the probability of a arbitrary variable with normal distribution of mean 0 and variance 1=2 dropping in the range [-x; x]; that is:



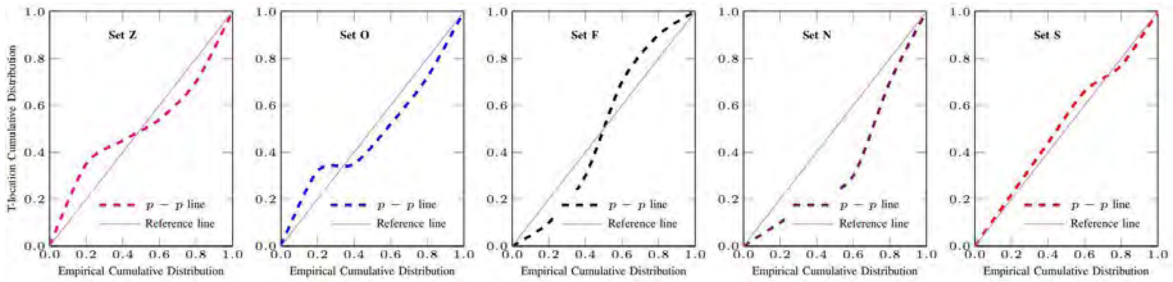
(a) (b)

Fig. 3.5: Plots of the Empirical PDFs and Gaussian Statistical Model PDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets

$$\mathrm{erf}(x) = \frac{1}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt \tag{3.13}$$

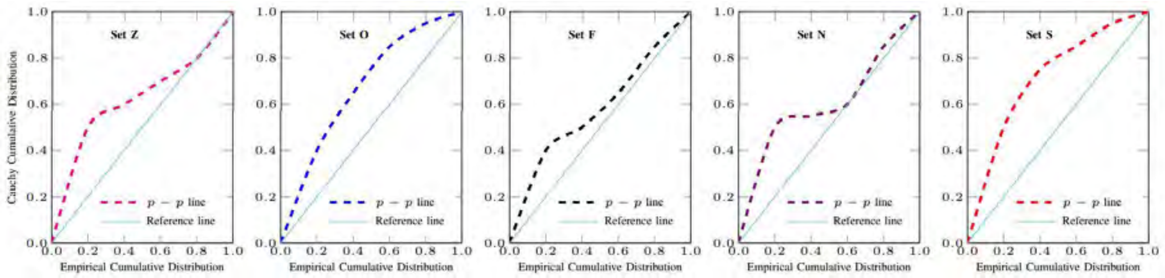


(a)

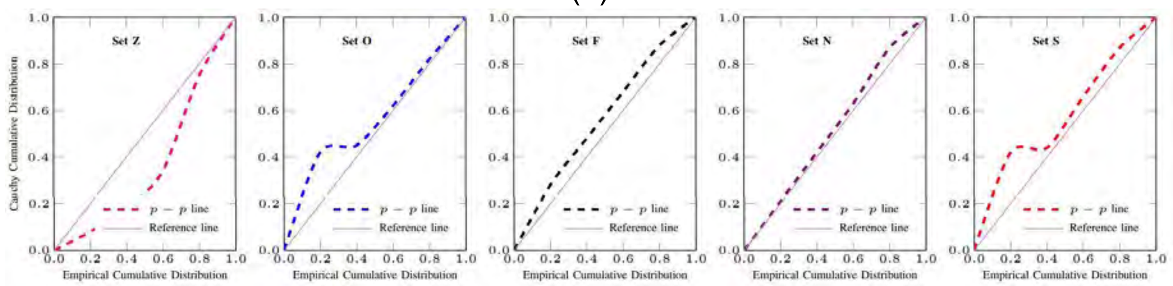


(b)

Fig. 3.6: P P Plots of the Empirical and T-location CDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets



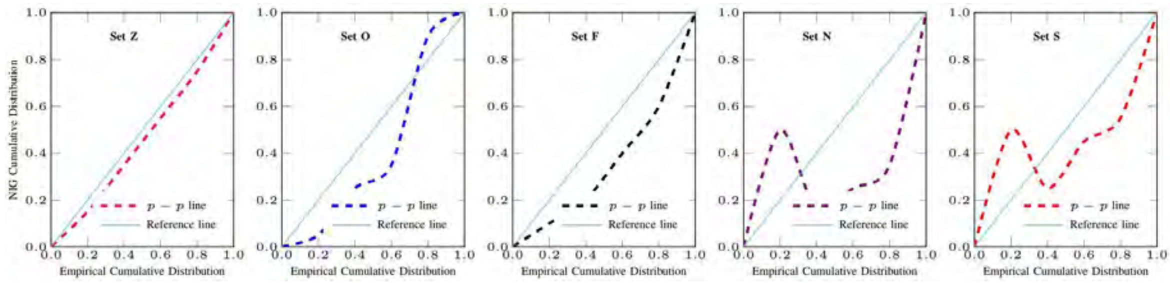
(a)



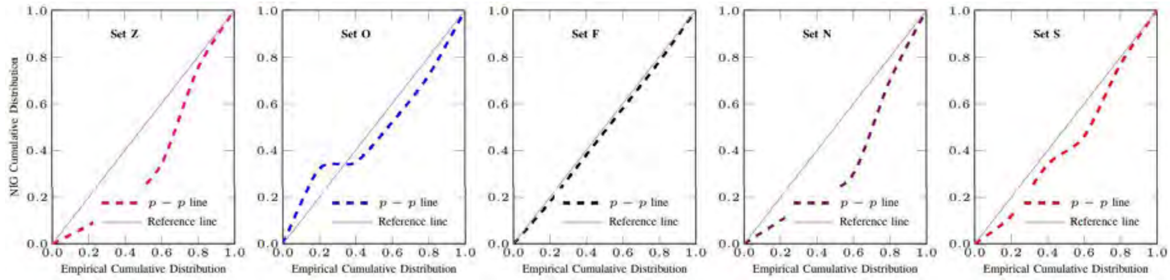
(b)

Fig. 3.7: P P Plots of the Empirical and Cauchy CDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets

Table 3.2 to Table 3.5 represents the average result of two-sample Kolmogorov-Smirnov test (K-S test) for each set Z, O, F, N and S in gamma and theta band for T-location, Cauchy, NIG and Gaussian PDF. This test result yields a trial assessment for the null hypothesis that the data in modeled and empirical PDF are from the same statistical distribution. The result `1' in the test for each sample

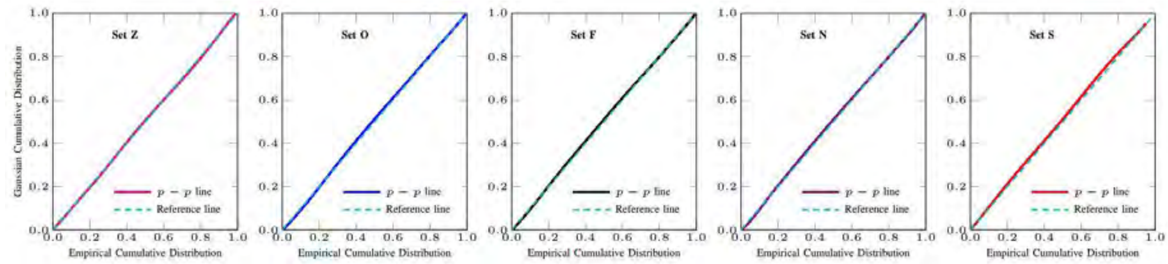


(a)

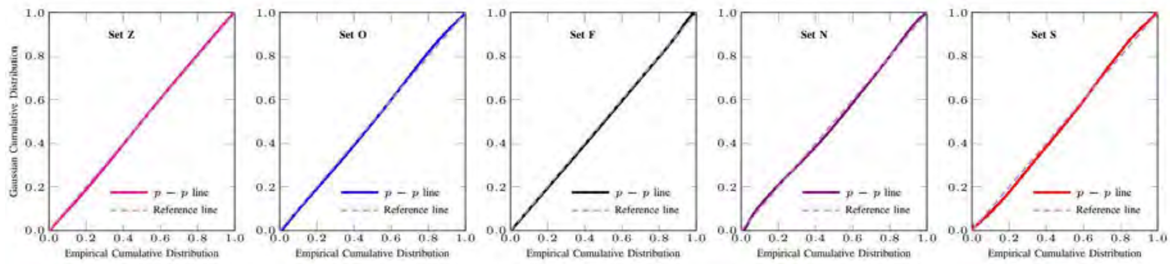


(b)

Fig. 3.8: P P Plots of the Empirical and NIG CDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets



(a)



(b)

Fig. 3.9: P P Plots of the Empirical and Gaussian CDFs in (a) Gamma Band and (b) Theta Band for the Five Subsets

rejects the null hypothesis whereas the `0' result accepts the hypothesis that the data in modeled and empirical PDF are from the same statistical distribution [89]. The average result of K-S test for each set having 100 EEG signals in Table 3.5 for only Gassian PDF is found very small which reveals that individual test result for majority EEG signals is `0' and justi es the goodness of Gaussian distribution t.

Table 3.2: K-S Test Result for Empirical and T-location Statistical Model

Sets	Gamma	Theta
Z	0.70	0.72
O	0.75	0.81
F	0.73	0.80
N	0.79	0.76
S	0.83	0.86

Table 3.3: K-S Test Result for Empirical and Cauchy Statistical Model

Sets	Gamma	Theta
Z	0.82	0.80
O	0.80	0.81
F	0.81	0.80
N	0.70	0.76
S	0.75	0.79

Table 3.4: K-S Test Result for Empirical and NIG Statistical Model

Sets	Gamma	Theta
Z	0.71	0.78
O	0.82	0.81
F	0.71	0.80
N	0.76	0.76
S	0.73	0.82

Table 3.5: K-S Test Result for Empirical and Gaussian Statistical Model

Sets	Gamma	Theta
Z	0	0
O	0	0.01
F	0.01	0
N	0	0.06
S	0.03	0.06

3.2.5 Proposed Feature Extraction

The statistical modeling parameters- location parameter (mean-) and scale parameter (standard deviation-) of the distribution have been extracted from gamma band and theta band coe cients of each EEG signals from ve groups (Set Z, O, F, N and S). As each model provides 2 features according to Eq. 3.9 for Gaussian statistical distribution, DWT coe cients from two time-frequency band (gamma and theta band) create a feature set consisting of total 4 (2*2) features (shown in Eq. 3.14) obtained from modeling parameters.

$$F\ eatureSet = [\ _{g};\ \ _{g};\ \ _{t};\ \ _{t};\ ] \quad (3.14)$$

In case of ve class classi cation problem, to include the upper and lower limit of the values at where PDF was constructed; maximum and minimum value of the gamma band and theta band coe cients of each EEG signal have been inserted in the feature set. Now, as each model provides 4 features according to Eq. 3.9 for Gaussian statistical distribution, DWT coe cients from two time-frequency band (gamma and theta band) create a feature set consisting of total 8 (4*2) features (shown in Eq. 3.15) obtained from modeling parameters.

$$F\ eatureSet = [\ _{g};\ \ _{g};\ \text{min-value}_{g};\ \text{max-value}_{g};$$
$$\ _{t};\ \ _{t};\ \text{min-value}_{t};\ \text{max-value}_{t}] \quad (3.15)$$

Here, and represent mean and standard deviation. Max-value and min-value indicate the upper and lower limit of the values where PDF was constructed. Subscript g and t represent gamma and theta band. The feature set thus obtained are now fed to classi er to classify numerous sets (Z, O, F, N and S) of EEG signals.

3.2.6 Classi cation

Once a set of features has been obtained to characterize a section of EEG, it is necessary to apply a classi cation method in order to decide whether this section of EEG is taken from an epileptic seizure or not. Just as a wide variety of features has been used, an equally varied set of classi cation methods can be found in the literature. Three di erent classi ers have been used in this work in classifying epileptic seizures originating from di erent parts and states of the brain.

3.2.6.1 k-NN Classi er

k-NN classi er was adopted in some literatures for its simplicity fact and wide ranging use in patterns categorization. k-NN classi er is based on learning by analogy. This algorithm calculates the distance function between feature set of EEG signal from test set and neighboring feature set of EEG signals from all groups of training set for this classi cation problem. The testing EEG signal is labeled as the class tag k-closer group of EEG signals [90].

Euclidean distance has been followed in this exertion and k-value has been var-ied within a large range to nd the proper value of it for consistent and better performance.

3.2.6.2 Support Vector Machine (SVM) classi er

SVM is a highly rated machine learning algorithm widely used in the eld of pattern recognition. For the binary pattern recognition problem (case k = 2), the support vector approach has been well developed [91]. The classical approach to solve k-class pattern recognition problems is to consider the problem as a collection of binary classi cation problems. In the one-versus-rest (also named as One-vs.-All) method, one constructs k classi ers, one for each class. The nth classier constructs a hyperplane between class n and the k-1 other classes. One-vs.-All (OVA) scheme has been followed in this work due to its better conceptual and computational simplicity while maintaining similar performance like One-vs.-One or other approaches [92]. For ve class classi cation problem consisting of set Z, O, F, N and S; the 1st SVM di erentiates set Z from set O, F, N, S. The 2nd SVM di ers set O from set Z, F, N and S. The 3rd SVM separates set F from set Z, O, N, S whereas set N is distinguished from set Z, O, F and S by 4th classi er. Lastly the 5th classi er classi es set S from set Z, O, F and N.

Following [30], kernel- radial basis function (RBF) and method- least square (LS) have been used for better performance in this exertion. Other hyper parameters of LS-RBF SVM were selected after su cient search and iterations. Each classi er generates a class label and a real-valued con dence score for its decision of each test sample as just a single class label may create ambiguities when multiple class labels are anticipated from multiple binary classi ers for a single test sample. The decision of class prediction is made upon the report of the highest con dence score.

3.2.6.3 ANN Classi er

Arti cial Neural Network (ANN) is one of the state-of-the-art machine learning algorithms used in pattern recognition. Arti cial neural networks are computing systems made up of large number of simple, highly interconnected processing ele-ments (called nodes or arti cial neurons) that abstractly emulate the structure and operation of the biological nervous system [93]. Learning in ANNs is accomplished through special training algorithms developed based on learning rules presumed to mimic the learning mechanisms of biological systems.

There are many di erent types and architectures of neural net-works varying fun-damentally in the way they learn. The architecture of back-propagation network

(BPN) may contain two or more layers. A simple two-layer ANN consists only of an input layer containing the input variables to the problem, and output layer containing the solution of the problem. This type of network is a satisfactory ap-proximate for linear problems. However, for approximating nonlinear systems, additional intermediate (hidden) processing layers are employed to handle the problem's nonlinearity and complexity. The determination of appropriate num-ber of hidden layers is one of the most critical tasks in neural network design. A network with too few hidden nodes would be incapable of di erentiating between complex patterns leading to only a linear estimate of the actual trend. ANNs' success depends on both the quality and quantity of the data.

In this thesis work, feature vectors have been fed to a feed-forward neural network with one hidden layer to perform the classi cation. The number of neurons in the output and hidden layers is equal to the number of classes and 20, respectively. The network is trained using a standard backpropagation algorithm with the hyperbolic tangent sigmoid transfer function used both in the hidden and output layers.

For ve class classi cation work, the ANN architecture contains two hidden layer with 8 and 16 neurons and output layer with 5 neurons equal to the number of classes. The feed-forward network is trained using a standard backpropagation algorithm with the hyperbolic tangent sigmoid and log sigmoid transfer function

[94] used in the rst and second hidden layers; respectively. Softmax transfer function is used in output layer. The hyper parameters such as number of hidden layers and their neurons and transfer function were set after su cient search and iterations.

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 described the multiclass classi cation of EEG signals for seizure activity investigation holding gamma and theta frequency oscillations only. At rst, discrete wavelet transform (DWT) was executed for acquiring the wavelet coe cients demonstrating the gamma and theta band. In the next step, a statis-tical model has been inspected for summarizing DWT coe cients of EEG signals in gamma and theta band to categorize epileptic seizure activities. Gaussian dis-tribution model has been chosen while contending with NIG of [30] or other distri-butional models for summarizing signal statistics because of the better match of its PDF with empirical PDF in visual inspection and justi cation in p-p plot and K-S test in order to classify multiclass seizure activities, a task where very limited work is reported in the literature.

Chapter 4

Simulation Results

A number of simulations are carried out to evaluate the performance of the pro-posed method. Performance is analyzed for both seizure detection and classi ca-tion cases. Performance of proposed method is compared with the few state-of-the-art methods for the evaluation purpose. A popular well-established database is utilized for simulation purpose for both detection and classi cation of multiclass epileptic seizures.

4.1 EEG Dataset

EEG segments used in this research are those collected by Andrzejak et al. [95] at Bonn University, Germany. The segments were selected from continuous mul-tichannel EEG recordings with artifacts removed via visual examination due to muscle activity and eye movements. The dataset includes ve subsets (denoted as Z, O, N, F, and S) each containing 100 single-channel EEG segments, each one having 23.6-second duration. The subsets Z and O have been acquired using surface EEG recordings of ve healthy volunteers with eyes open and closed, re-spectively. Signals in two sets have been measured in seizure-free intervals from ve patients in the epileptogenic zone (set F) and from the hippocampal formation of the opposite hemisphere of the brain (set N). Finally, subset S contains seizure activity, selected from all recording sites exhibiting ictal activity.

Subsets Z and O have been recorded extracranially, using standard electrode posi-tioning (according to the international 10{20 system), whereas subsets N, F, and S have been recorded intracranially. More speci cally, depth electrodes are im-planted symmetrically into the hippocampal formation. EEG segments of subsets N and F were taken from all contacts of the relevant depth electrode. In addition, strip electrodes are implanted onto the lateral and basal regions (middle and bottom) of the neocortex. EEG segments of the subsets S were taken from contacts of all electrodes (depth and strip). All EEG signals were recorded with the same 128-channel ampli er system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution and they have the spectral bandwidth of the acquisition system varies from 0.5 Hz to 85 Hz. Typical EEG segments (one from each category of the dataset) are shown in Fig. 4.1.

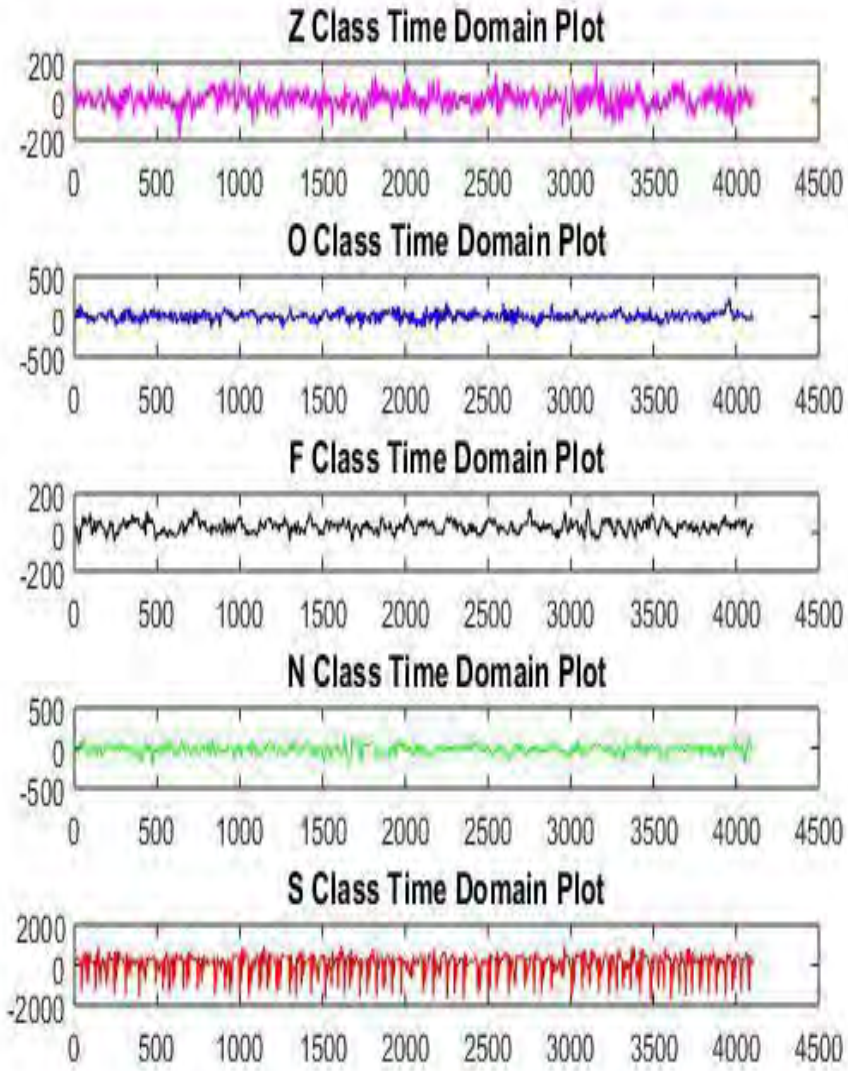


Fig. 4.1: Time Domain Plot of Di erent Classes of EEG Signals

For the evaluation of proposed method; training, testing and cross-validation assignment of data are done on two ways. Firstly 50% of feature data is used for training and the rest 50% is used for testing. Both training and testing division are selected randomly. For random data distribution, average result is presented after 10 set of performance.

Secondly, 10 fold cross validation is performed on the entire dataset for training and testing purpose.

Since pre-surgical intracranial EEG (IEEG) recordings report the substantial role of high frequency oscillations (HFO) of gamma band (40-80 Hz) in human epilepto-genic foci at seizure onset and inter-ictally at times temporally remote from seizure onset; frequencies after 80 Hz are considered here as noise and eliminated by using 6th-order butterworth lter having a cut-o frequency 80 Hz.

For accessing EEG signals at particular frequency band, Haar wavelet is used be-cause of its simplest structure in multilevel DWT decomposition. For a particular DWT band and proposed Gaussian statistical modeling parameter, the size of fea-ture vector would be 2*1; thus, to represent a particular EEG class, the proposed feature vector would be 2*2 because we are considering two time-frequency sub-band gamma and theta for each EEG recording. Theta sub-band is considered in this work as literature shows that the segment of the low-frequency theta (4-8 Hz) band modulates power of the high gamma (80-150 Hz) band of the IEEG with strong modulation happening at higher theta amplitudes.

The feature set thus obtained are now fed to di erent state-of-the-art classi ers to evaluate the e ectiveness of the proposed method in di erent simulation condi-tions. Six di erent state-of-the-art cases of classi cation problems and a ve class classi cation problem are handled to evaluate the performance of our method. The cases are chosen based on their clinical relevance and use in various papers in the literature to facilitate comparison.

Case I: In the rst problem, two classes are examined: normal and seizure. The normal class includes only the Z-type EEG segments while the seizure class includes the S type. Thus, the dataset used for the rst classi cation problem consists of 200 EEG segments.

Case II: This case deals with F and S type of EEG data which is another two class classi cation problem. Case II corresponds to the detection of the onset of seizure. Due to recording spot of epileptic zone, Set F is vastly connected to early-ictal activities and considered for seizure onset detection.

Case III: Case III is another two class classi cation problem with N and S class of EEG data. Case II corresponds to the detection of the onset of seizure, since the signals in Set F are obtained from epileptic zone. Like

Case II, Case III is related to discriminate the seizure recordings from the non-seizure activity of seizure ones.

Case IV: In this case, all the EEG segments from the dataset were used and they were classi ed into two di erent classes: Z, O, N, and F types are included in the rst class altogether as non-seizure class and type S in the second class as seizure class. This is also close to real medical applications for discriminating seizure and seizure-free EEG signals.

Case V: In this case, again all the EEG segments from the dataset were used and they were classi ed into three di erent classes: Z and O types of EEG segments were combined to a single class, N and F types were also combined to a single class, and type S was the third class. This set is the one closest to real medical applications including three categories; EEG segments from Sets Z and O are grouped together as normal healthy class. Sets F and N are grouped into the seizure free interval (inter-ictal) class of seizure patient and Set S is the seizure (ictal) class. For clinical relevancy, this case is used for discriminating healthy individuals from the epilepsy along with detection of seizures.

Case VI: The sixth case has similar classes with the previous case V, that is, normal, seizure-free and seizure, but not all the EEG segments from the dataset were employed. The normal class includes only the Z-type EEG segments, the seizure-free class includes the F-type EEG segments, and the seizure class is the S-type.

Five Class Classi cation Problem: In this case, all ve classes are used, including all EEG segments from the previously described dataset (thus 500 EEG segments). EEG segments from Set Z is denoted as normal healthy class recorded at awakening state with eyes open where Set O is noted as normal healthy class recorded at relaxed state with eyes closed. Sets F and N are assembled as seizure free classes of seizure patient (inter-ictal) recorded from an epileptogenic zone of the brain and from the hippocampal forma-tion of the opposite hemisphere of the brain; respectively. Set F is vastly connected to early-ictal activities and considered for seizure onset detection. Set S has been recorded from those seizure patients when exhibiting seizure activity and denoted as the seizure (ictal) class. This case is used in a clinical requirement for discriminating healthy individuals from the epilepsy patients as well as detection of seizures onset recorded at di erent relaxed or awaken states and brain locations altogether. As a result, this ve class classi cation problem holds importance because it can detect and classify seizure activi-ties by considering only a single case of classi cation problem to distinguish di erent activities inside the brain.

For the purpose of comparison, we have implemented the state-of-the-art methods of [28], [29], [30], [31] and compared those with the proposed method.In case of two class problem, 200 EEG signals are used while in case of three class problem, 300 EEG signals are utilized. We have also evaluated the performance of the proposed method for a 5 class classi cation problem. In case of 5 class EEG classi cation problem; total 500 EEG signals are used.

4.2 Goodness of Proposed Features

The proposed Gaussian modeling parameters along with the features of comparison methods were subjected to one way ANOVA test for the evaluation of statistical implication. Probability (p) and the Fishers discrimination index (F) accomplished from the test were used to rank the features.

Furthermore, justi cation of the goodness of features extracted from this proposed statistical Gaussian model over the other mentioned features has been performed by two statistical indices: Geometrical Separability Index and Bhattacharyya Dis-tance. These two measures show the numerical demonstration of inter class dis-tance and intra-class compactness; respectively.

4.2.1 ANOVA Test

The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically signi cant di erences between the means of two or more in-dependent (unrelated) groups. The null hypothesis for ANOVA is that the mean (average value of the dependent variable) is the same for all groups [96]. A high F value means that the data does not well support the null hypothesis.

Low p-valuesare indications of strong evidence against the null hypothesis.

Table 4.1: Results of ANOVA Test for Features of Proposed and Comparison Methods

Features	No of Features	Fisher's Discrimination Index, F	Probability, p
Autoregressive Weights [29]	42	3.85	0.0039
HOS Moments [31]	6	57.3	4.4219e-47
Normal Inverse GaussianParame-ters [30]	8	74.74	3.4906e-61
Spectral Energy [28]	6	74.93	4.7186e-59
Proposed Gaussian Parameters	4	86.79	4.7008e-68

The Gaussian modeling parameters along with the features of comparison methods-Energy on speci c time-frequency window [28], Weights of autoregressive model with approximate entropy [29], Normal Inverse Gaussian (NIG) modeling parame-ters [30], and Higher Order Statistical (HOS) moments [31] were subjected to one way ANOVA test for the evaluation of statistical implication. Probability (p) and the Fishers discrimination index (F) accomplished from the test were used to rank the features. The feature with maximum F index and lowermost p value revealed in Table 4.1 can be graded as rst to categorize input signals [97].

4.2.2 Geometrical Separability Index

Geometrical Separability Index (GSI) shows the numerical demonstration of inter class distance. Based on the nearest neighbor aptitude measurement, it reports a clue to which degree two classes can be considered as separable or inseparable.

GSI, also known as Thornton's separability index s is de ned as the fraction of a set of data points whose classi cation 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 [98]. It may be written

$$s = \sum_{i=1}^{n} \frac{(f(x_i) + f(x_i') + 1) \bmod 2}{n} \quad (4.1)$$

Where, x^0 is the nearest neighbour of x and n is the number of points.
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. A regular intermeshed grid of alternately-labelled points (as would be generated by the exclusive-OR or parity problems) would have s = 0.

GSI value of the proposed feature set and features of comparison methods are shown in Table 4.2 4.6. It is found from GSI values of stated all features in Table 4.2 4.6, each entree for same classes corresponding to Gaussian statistical modeling parameters are having a value `0', while the quantity for two di erent classes corresponding to Gaussian statistical modeling parameters are having a value closest to `1'. Thus, the pro ciency of projected scheme to o er high sepa-rability among ve classes in this work is established.

4.2.3 Bhattachariyya Distance

In statistics, the Bhattacharyya distance measures the similarity of two probability distributions. It is closely related to the Bhattacharyya coe cient which is a measure of the amount of overlap between two statistical samples or populations. The coe cient can be used to determine the relative closeness of the two samples being considered. It is used to measure the separability of classes in classi cation. The class with smaller BD value shows strong compactness of its features.

In its simplest formulation, the Bhattacharyya distance between two classes under the normal distribution can be calculated [99] by extracting the mean and variances of two separate distributions or classes:

$$D_B(p; q) = \frac{1}{4}\ln\left(\frac{1}{4}\left(\frac{\sigma_p^2}{\sigma_q^2}+\frac{\sigma_q^2}{\sigma_p^2}+2\right)\right)+\frac{1}{4}\left(\frac{(\mu_p-\mu_q)^2}{\sigma_p^2+\sigma_q^2}\right) \quad (4.2)$$

where: $D_B(p; q)$ is the Bhattacharyya distance between p and q distributions or classes,

σ_p^2 is the variance of the p-th distribution,

μ_p is the mean of the p-th distribution, and

BD value of the proposed feature set and features of comparison methods are shown in Table 4.7 4.11. It is found from the BD values of stated all features in Table 4.7 4.11, each entree corresponding to Gaussian statistical modeling parameters are having a value closing to `0' which further shows the goodness of proposed feature set.

Table 4.2: GSI Values of Energy on Time Frequency Band [28]

Classes	Z	O	F	N	S
Z	0	0.9	0.955	0.965	0.995
O	0.9	0	0.84	0.87	0.93
F	0.955	0.84	0	0.62	0.93
N	0.965	0.87	0.62	0	0.97
S	0.995	0.93	0.93	0.97	0

Table 4.3: GSI Values of Autoregressive Model Weights [29]

Classes	Z	O	F	N	S
Z	0	0.875	0.95	0.97	0.995
O	0.875	0	0.835	0.835	0.925
F	0.95	0.835	0	0.6	0.92
N	0.97	0.835	0.6	0	0.975
S	0.995	0.925	0.92	0.975	0

Table 4.4: GSI Values of NIG Parameters [30]

Classes	Z	O	F	N	S
Z	0	0.875	0.975	0.95	0.995
O	0.875	0	0.845	0.835	0.925
F	0.975	0.845	0	0.59	0.92
N	0.95	0.835	0.59	0	0.975
S	0.995	0.925	0.92	0.975	0

Table 4.5: GSI Values of HOS Moments [31]

Classes	Z	O	F	N	S
Z	0	0.86	0.85	0.865	0.995
O	0.86	0	0.725	0.82	0.94
F	0.85	0.725	0	0.63	0.92
N	0.865	0.82	0.63	0	0.97
S	0.995	0.94	0.92	0.97	0

Table 4.6: GSI Values of the Proposed Method

Classes	Z	O	F	N	S
Z	0	0.94	0.975	0.985	0.995
O	0.94	0	1	1	0.99
F	0.975	1	0	0.88	0.965
N	0.985	1	0.88	0	0.98
S	0.995	0.99	0.965	0.98	0

4.3 Performance Parameters

For the performance evaluation of the proposed method, criteria considered in our simulation study are: 1) Sensitivity 2) Speci city 3) Accuracy. These indices have been calculated from confusion matrix which is a way of showing the assessment result from a classi cation test.

The columns in the matrix stand for the actual classes to be tested and rows provide the class classi ed 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 column but classi ed as the class corresponding to the row. In Fig. 4.2, a general confusion matrix for a two, three and ve class problem is shown, where TP , FP , FN and TN are represented for class i.

In general, TP_i, true positive for any class i, denotes the number of testing cases, which are correctly classi ed as class i.

FP_i, false positive for any class i, measures the number of testing cases, which are incorrectly classi ed as class i.

FN_i, false negative for any class i, measures the number of testing cases, which are incorrectly classi ed as other than class i.

TN_i, true negative for any class i, denotes the number of testing cases, which are correctly classi ed as other than class i.

In Fig. 4.2, a general confusion matrix with respect to set Z for a two, three and ve class problem is shown.

4.3.1 Sensitivity

Sensitivity refers to the test's ability to correctly detect ill patients who do have the condition. In the example of a medical test used to identify a disease, the sensitivity of the test is the proportion of people who test positive for the disease

Table 4.7: BD Values of Energy on Time Frequency Band [28]

Z	O	F	N	S
0.0769	0.1786	0.5532	0.1824	0.4196

Table 4.8: BD Values of Autoregressive Model Weights [29]

Z	O	F	N	S
0.1160	0.1132	0.1380	0.1411	02450

Table 4.9: BD Values of NIG Parameters [30]

Z	O	F	N	S
0.0148	0.0454	0.1778	0.0501	0.1295

Table 4.10: BD Values of HOS Moments [31]

Z	O	F	N	S
0.049	0.1383	0.4873	0.1575	0.3569

Table 4.11: BD Values of the Proposed Method

Z	O	F	N	S
0.0134	0.0421	0.1683	0.0472	0.1227

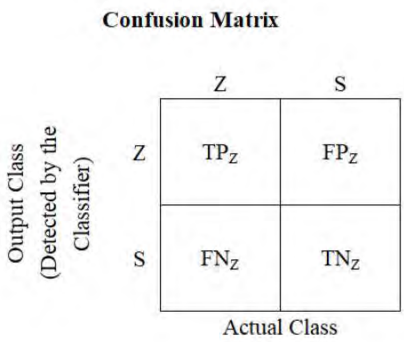
among those who have the disease. Mathematically, this can be expressed as:

$$\begin{aligned} \text{Sensitivity} &= \frac{\text{number of true positives}}{\text{numer of true positives + number of f alse negatives}} \\ &= \frac{TP}{TP + FN} \\ &= \text{probability of positive test result given that the patient has the disease} \end{aligned} \quad (4.3)$$

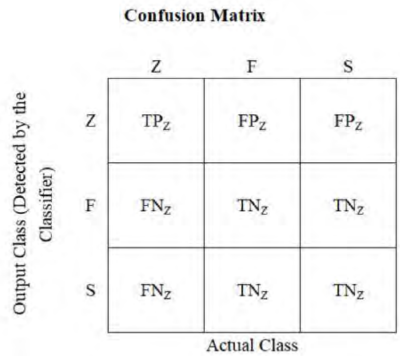
4.3.2 Speci city

Speci city relates to the test's ability to correctly reject healthy patients without a condition. In the example of a medical test used to identify a disease, Speci city of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as:

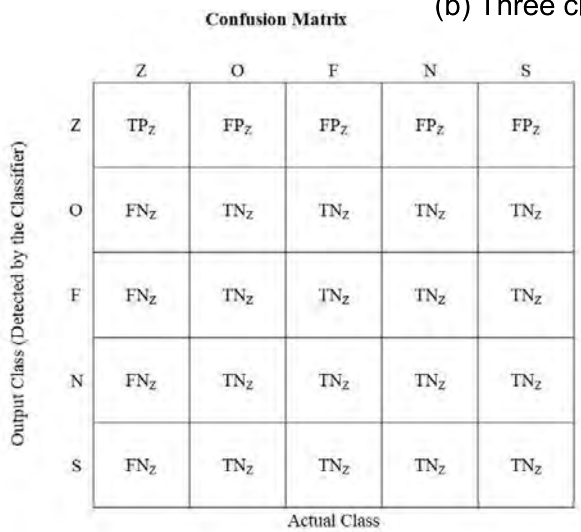
$$\begin{aligned} \text{Specif icity} &= \frac{\text{number of true negatives}}{\text{numer of true negatives + number of f alse positives}} \\ &= \frac{TN}{TN + FP} \\ &= \text{probability of negative test result given that the patient is well} \end{aligned} \quad (4.4)$$



(a) Two class with respect to Z



(b) Three class with respect to Z



(c) Five class with respect to Z

Fig. 4.2: Confusion Matrix for Two, Three and Five Class Classi cation Cases

4.3.3 Accuracy

Accuracy is one metric for evaluating classi cation models. Informally, accuracy is the fraction of predictions our model got right. Formally, accuracy has the following de nition:

$$\text{Accurracy} = \frac{\text{Number of Correct Predictions}}{\text{Number of Total Predictions}} \tag{4.5}$$

Accuracy can also be calculated in terms of positives and negatives as follows:

$$\text{Accurracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.6}$$

4.4 Simulation Results

Performance of the multiclass seizure and non-seizure activity detection and clas-si cation method based on statistical modeling of gamma and theta band DWT coe cients of EEG signals, described in chapter 3, are analyzed and compared with the state-of-the-art methods.

The methods in [30], [31] have not reported classi cation performance involving all ve classes of EEG recordings. Whereas methods in [28], [29] reported ve class classi cation result in case of seizure activity detection. Therefore, for further investigation of the e ectiveness of proposed method; we opt to report the result of ve class classi cation problem in terms of performance parameters and compare the results with state-of-the-art comparison methods of [30], [31] by implementing them for a ve class problem.

The simulation results of proposed method for six di erent cases and ve class classi cation problem as mentioned before are reported with accuracy, sensitivity and speci city from Table 4.12 to 4.25. Each simulation result is obtained in two ways. Firstly, 50% data is randomly used for training and rest 50% data is used for testing. Due to random selection of training and testing data, average result is taken resulting from ten sets of performance. Secondly, the average sensitivity, speci city and accuracy for the classi cation exercise of proposed method were taken after ten-fold cross validation evaluation approach used on the entire dataset. The comparisons of di erent cases of proposed method with some state-of-the-art methods in literature are shown in Table 4.26 4.32.

From the classi cation result in the di erent tables, it is vivid that in all seven cases with di erent classi ers, the proposed method acceptably outperformed the comparison methods with superior performance. Selection of speci ed and e ec-tive time-frequency band with reference to [65]-[77] lessens the number of features and computational burden in classi cation exercise. Though the sensitivity, speci-city and accuracy are quite high and leave behind the state-of-art methods; it is understood from sensitivity and speci city report that due to misclassi cation of inter-ictal classes set F and set N, 100% accuracy is not achieved in ve class classi cation problems. Nevertheless, almost 100% sensitivity is accomplished for seizure group- ictal (S) class which con rms the particular discernment of seizure activity from other non-seizure activities of normal and inter-ictal classes. More-over, largely misclassi ed set F and N are both taken from seizure-free interval of seizure patients at two di erent brain locations which will not create any investi-gation or treatment error.

In Table 4.33, the time required for the classi cation of the feature of a testing sample of the proposed method and that of the state-of-the-art comparison meth-ods [30], [31] are provided along with the size of the feature vector to evaluate the computational complexity of the methods. For comparison, methods of [30], [31] have been chosen as mentioned all VII cases of classi cation problems in this thesis work are shown to be solved with these methods. The whole process from feature extraction to the performance analysis is run on the MATLAB R2015 software with a core i3 processor at the speed 2.10 GHz. It is found from Table 4.33 that the comparison methods in [30], [31] require more computation time since it used windowing of EEG recordings 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.

Table 4.12: Case I [(Z, S)] (Using 50% Data Division for Training and Testing)

Method	Sensitivity		Speci city		Accuracy
	Z	S	Z	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.13: Case I [(Z, S)] (Using 10-fold Cross Validation)

Method	Sensitivity		Speci city		Accuracy
	Z	S	Z	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.14: Case II [(F, S)] (Using 50% Data Division for Training and Testing)

Method	Sensitivity		Speci city		Accuracy
	F	S	F	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.15: Case II [(F, S)] (Using 10-fold Cross Validation)

Method	Sensitivity		Speci city		Accuracy
	F	S	F	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.16: Case III [(N, S)] (Using 50% Data Division for Training and Testing)

Method	Sensitivity		Speci city		Accuracy
	N	S	N	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method	100%	100%	100%	100%	100%

Using SVM Classi er					
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.17: Case III [(N, S)] (Using 10-fold Cross Validation)

Method	Sensitivity		Speci city		Accuracy
	N	S	N	S	
Proposed Method Using K-NN Classi er	100%	100%	100%	100%	100%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.18: Case IV [(Z,O,F,N),S] (Using 50% Data Division for Training and Testing)

Method	Sensitivity		Speci city		Accuracy
	ZOFN	S	ZOFN	S	
Proposed Method Using K-NN Classi er	99%	98%	98%	99%	98.8%
Proposed Method Using SVM Classi er	99.5%	100%	100%	99.5%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%

Table 4.19: Case IV [(Z,O,F,N),S] (Using 10-fold Cross Validation)

Method	Sensitivity		Speci city		Accuracy
	ZOFN	S	ZOFN	S	
Proposed Method Using K-NN Classi er	97.75%	99%	99%	97.75%	98%
Proposed Method Using SVM Classi er	98.75%	100%	100%	98.75%	99%
Proposed Method	100%	100%	100%	100%	100%

Using ANN Classi er					

Table 4.20: Case V [(Z,O),(F,N),S] (Using 50% Data Division for Training and Testing)

Method	Sensitivity			Speci city			Accuracy
	ZO	FN	S	ZO	FN	S	
Proposed Method Using K-NN Classi er	91%	89%	98%	92.61%	93.33%	100%	91.6%
Proposed Method Using SVM Classi er	97%	96.5%	98%	98.64%	97.64%	98.97%	97%
Proposed Method Using ANN Classi er	97.5%	98%	100%	99.32%	98.33%	99.49%	98.2%

Table 4.21: Case V [(Z,O),(F,N),S] (Using 10-fold Cross Validation)

Method	Sensitivity			Speci city			Accuracy
	ZO	FN	S	ZO	FN	S	
Proposed Method Using K-NN Classi er	87.5%	92.85%	95%	95.16%	93.1%	96.55%	91%
Proposed Method Using SVM Classi er	97.5%	95.45%	95.83%	96.67%	96.87%	100%	98%
Proposed Method Using ANN Classi er	100%	95%	100%	95%	100%	100%	98%

Table 4.22: Case VI [(Z,F,S)] (Using 50% Data Division for Training and Testing)

Method	Sensitivity			Speci city			Accuracy
	Z	F	S	Z	F	S	
Proposed Method Using K-NN Classi er	98%	96%	98%	98.97%	98%	98.97%	97.33%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%	100%	100%

Table 4.23: Case VI [(Z,F,S)] (Using 10-fold Cross Validation)

Method	Sensitivity			Speci city			Accuracy
	Z	F	S	Z	F	S	
Proposed Method Using K-NN Classi er	96%	96%	99%	97.985%	97.5%	100%	97%
Proposed Method Using SVM Classi er	100%	100%	100%	100%	100%	100%	100%
Proposed Method Using ANN Classi er	100%	100%	100%	100%	100%	100%	100%

Table 4.24: Five Class Classi cation [(Z,O,F,N,S)] (Using 50% Data Division for Training and Testing)

Method	Sensitivity					Speci city					Accuracy
	Z	O	F	N	S	Z	O	F	N	S	
Proposed Method Using K-NN Classi er	86.7%	76.9%	69.8%	80.6%	93.2%	94.9%	93.7%	94.6%	91.9%	98.7%	81.2%
Proposed Method Using SVM Classi er	94.3%	89.5%	77.2%	73.2%	97.9%	100%	96.6%	90.5%	96.2%	98.8%	86.4%
Proposed Method Using ANN Classi er	98%	92%	90%	88%	97%	97.9%	97.6%	97.9%	98.2%	99.2%	93%

Table 4.25: Five Class Classi cation [(Z,O,F,N,S)] (Using 10-fold Cross Validation)

Method	Sensitivity					Speci city					Accuracy
	Z	O	F	N	S	Z	O	F	N	S	
Proposed Method Using K-NN Classi er	86.9%	73.6%	68.9%	80.7%	93.2%	94.7%	93.6%	93.5%	91.7%	98.6%	80.4%
Proposed Method Using SVM Classi er	91.7%	77.3%	95%	63.3%	100%	95.6%	97.3%	88.1%	98.6%	100%	85%
Proposed Method Using ANN Classi er	94.5%	95%	95%	75.3%	100%	98.6%	97.3%	94.8%	98.7%	100%	92%

Table 4.26: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case I

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	Z,S	100%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	Z,S	100%
Tzallas et al. [28] (2009)	Time-frequency analysis, ANN Classi er	Z,S	100%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	Z,S	100%

Table 4.27: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case II

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	F,S	100%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	F,S	100%
Liang et al. [29] (2010)	Time frequency & Autoregressive model and approximate entropy analysis, RBF-SVM Classi er	F,S	97.75%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	F,S	100%

Table 4.28: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case III

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	N,S	100%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	N,S	100%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	N,S	100%

Table 4.29: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case IV

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	ZOFN,S	100%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	ZOFN,S	100%
Liang et al. [29] (2010)	Time frequency & Autoregressive model and approximate entropy analysis, RBF-SVM Classi er	ZOFN,S	98.58%
Tzallas et al. [28] (2009)	Time-frequency analysis, ANN Classi er	ZOFN,S	97.73%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	ZOFN,S	100%

Table 4.30: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case V

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	ZO,FN,S	80%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	ZO,FN,S	96.28%
Tzallas et al. [28] (2009)	Time-frequency analysis, ANN Classi er	ZO,FN,S	97.72%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	ZO,FN,S	98.2%

Table 4.31: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Case VI

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	Z,F,S	100%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	Z,F,S	100%
Liang et al. [29] (2010)	Time frequency & Autoregressive model and approximate entropy analysis, RBF-SVM Classi er	Z,F,S	98.67%
Tzallas et al. [28] (2009)	Time-frequency analysis, ANN Classi er	Z,F,S	100%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters,	Z,F,S	100%

	ANN classi er			

Table 4.32: Comparison of Accuracy Performance of Various Methods from Liter-ature and Proposed Method for Five Class Classi cation Problem

Authors	Method	Data-Class	Accuracy
Alam et al. [31] (2013)	EMD operation, Higher order statistical moments, ANN classi er	Z,O,F,N,S	61%
Das et al. [30] (2016)	DT-CWT, NIG parameters, SVM multiclass classi er	Z,O,F,N,S	72%
Liang et al. [29] (2010)	Time frequency & Autoregressive model and approximate entropy analysis, RBF-SVM Classi er	Z,O,F,N,S	85.9%
Tzallas et al. [28] (2009)	Time-frequency analysis, ANN Classi er	Z,O,F,N,S	89%
Proposed Method	Gamma & theta band WT coe cients, Gaussian parameters, ANN classi er	Z,O,F,N,S	93%

Table 4.33: Time Requirements for the Proposed and Comparison Methods

Methods	Size of Feature Vector to test an EEG Data	Required Time (in sec)
Method in [30]	16 4	1.5470
Method in [31]	16 3	1.3956
Proposed Method	4	0.89

4.5 Conclusion

The Gaussian modeling parameters based feature set derived from gamma and theta band DWT coe cients of EEG signals is found most e ective for seizure activity detection and classi cation from the standard EEG dataset. Selection of speci ed and e ective time-frequency band lessens the number of features and computational burden in classi cation exercise. Such feature set is more compact in intra-class and separable in inter-class than the feature sets used for the com-parison methods. As a result, proposed feature set is superior in terms of accuracy, speci city and sensitivity in seizure activity detection and classi cation in stringent conditions such as speci c time-frequency band, reduced feature set, random selection of training and testing data than the state-of-the-art methods. Apart from classifying di erent state-of-the-art clinical cases which are used for detec-tion of epileptic seizures, the proposed feature set also exhibits its e ectiveness in handling ve class classi cation problem which is limitedly reported. Due to re-duced dimension of the proposed feature set, the proposed feature set works faster to detect and classify multiclass EEG signals than the state-of-the-art comparison methods.

Chapter 5

Conclusion

5.1 Concluding Remarks

In this thesis, investigation of epilepsy has been performed with respect to seizure activity, seizure onset and brain signal recording location exploiting time-frequency domain operation wavelet analysis on the gamma (40-80 Hz) and theta (4-8 Hz) band oscillations of EEG signals. Gaussian statistical model has been employed from several normal distributions to summarize information in Discrete Wavelet Transform (DWT) coe cients and propose feature set utilizing the modeling pa-rameters of Gaussian probability density function (PDF). This model has been pro-posed after visual inspection of plotting together empirical and Gaussian PDF in addition to their cumulative distribution function (CDF) in probability-probability (p-p) plot and goodness of t K-S test result and found most e ective to feed modeling parameters of Gaussian PDF to numerous classi ers as feature set. The goodness of features has been justi ed by one way ANOVA test, Geometrical Separability Index and Bhattacharyya Distance parameter. Extensive varieties of simulations are completed using an established dataset. The proposed strategy is found competent for making higher values of sensitivity, speci city and accu-racy compared to that made by some front line techniques utilizing the same EEG dataset in stringent conditions, such as band-speci c DWT coe cients, reduced feature set, random selection of training and testing data with less computation time.

5.2 Contribution of this Thesis

The major contributions of this thesis are,

Introducing band-speci c (gamma and theta) DWT coe cients of EEG signals for detecting and classifying multiclass seizure activity. It is found in literature that pre-surgical intracranial EEG (IEEG) recordings show the substantial role of high frequency oscillations (HFO) of gamma band (40-80 Hz) and high gamma/ripple band (80-150 Hz) in human epileptogenic foci at seizure onset and inter-ictally at times temporally remote from seizure onset. Moreover, it is also found in literature that there is a strong connection regarding the high and low-frequency bands of frequent electrical action in the human brain. More speci cally, the segment of the low-frequency theta (4-8 Hz) band modulates power of the high gamma (80-150 Hz) band of the IEEG with strong modulation happening at higher theta amplitudes. Such band speci c time-frequency representations of signals are helpful and less computationally expensive than conventional time-frequency analysis using di erent kernels for seizure activity detection and classi cation.

The detailed information of DWT coe cients has been summarized to a statistical model and modeling parameters of that statistical distribution PDF have been evaluated to minimize the dimensions of gathered feature vectors. Use of statistical modeling parameters as feature set is more rational as shape of the entire dataset is included here with less number of features. Moreover, statistical model is able of give a more consistent class representation.

The proposed feature vector is used in seven state-of-the-art classi cation problems. These classi cation problems include two, three and ve classes. The performance of the proposed method on such classi cation problem has been investigated based on two simulation condition for training, cross-validation and testing data of EEG signals and compared with the state-of-the-art comparison methods. In all classi cation cases, proposed method has the superior accuracy, sensitivity and speci city than the state-of-the-art comparison methods. Such performance show the e ectiveness of the proposed method in detection and classi cation of multiclass epileptic seizures in stringent conditions as mentioned before.

This thesis work has developed an EEG based multiclass seizure activity clas-si cation method with e ective and reduced feature sets exploiting gamma and theta band DWT coe cients and its statistical modeling with greater accuracy, sensitivity and speci city.

5.3 Scopes for Future Work

In this thesis, e ective and e cient statistical model of band-speci c DWT co-e cients of EEG signal has been built for multiclass epileptic seizure activity classi cation. However, there are some scopes for future research as mentioned below:

- In this thesis, we use a popular EEG database which consists of ve class EEG data. The proposed method can classify those with superior accuracy using statistical modeling of band-speci c DWT coe cients. In future, ef-fectiveness of the proposed method using di erent EEG databases can be veri ed.

- Since the proposed method uses only time-frequency domain DWT approach to extract gamma and theta frequency, other time-frequency domain ap-proaches can be investigated to extract gamma and theta frequencies.

- A statistical model has been built with the band-speci c DWT coe cients for e ective and e cient feature set. Instead of manual formation of feature set, extracted gamma and theta band EEG signal can be sent to convolu-tional neural network architecture for automated feature set selection and classi cation.

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