ITERATIVE FILTERING BASED AUTOMATED DETECTION OF EPILEPTIC SEIZURE EEG SIGNALS

M.Tech. Thesis

By

PIYUSH VARSHNEY

DISCIPLINE OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

JULY 2018

ITERATIVE FILTERING BASED AUTOMATED DETECTION OF EPILEPTIC SEIZURE EEG SIGNALS

A THESIS

Submitted in partial fulfillment of the requirements for the award of the degree
of
Master of Technology
in
Electrical Engineering
with specialization in
Communication and Signal Processing

by
PIYUSH VARSHNEY

DISCIPLINE OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE
JULY 2018

INDIAN INSTITUTE OF TECHNOLOGY INDORE

CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **"ITERATIVE FILTERING BASED AUTOMATED DETECTION OF EPILEPTIC SEIZURE EEG SIGNALS"** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DISCIPLINE OF ELECTRICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July 2017 to July 2018 under the supervision of Prof. Ram Bilas Pachori, Professor, Discipline of Electrical Engineering and Dr. Santosh Kumar Vishvakarma, Associate Professor, Discipline of Electrical Engineering, IIT Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student with date
(PIYUSH VARSHNEY)

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

Signature of the Supervisor of
M.Tech. thesis #1 (with date)
(Prof. Ram Bilas Pachori)

Signature of the Supervisor of
M.Tech. thesis #2 (with date)
(Dr. Santosh Kumar Vishvakarma)

PIYUSH VARSHNEY has successfully given his M.Tech. Oral Examination held on **10-07-2018**

Signature(s) of Supervisor(s) of M.Tech. thesis
Date:

Convener, DPGC
Date:

Signature of PSPC Member #1
Date:

Signature of PSPC Member #2
Date:

Acknowledgements

First of all, I would like to express my sincere gratitude to my thesis supervisors, **Prof. Ram Bilas Pachori** and **Dr. Santosh Kumar Vishvakarma** for their constant support and guidance through the learning process of this master thesis. Furthermore, I would also like to express my gratitude to my PSPC committee members Dr. Vivek Kanhangad and Prof. Anand Parey for their valuable suggestions.

I would also like to thank all the faculty members and the staff at IIT Indore for their cooperation throughout my study and thesis work. I would like to thank the Discipline of Electrical Engineering for providing all the facilities, resources, and research environment required for the completion of this work.

I would like to thank all the members of Signal Analysis Research Lab for their assistance during this work. In particular, I would like to thank Mr. Rishi Raj Sharma and Mr. Mohit Kumar for their assistance at various levels of this work.

I am grateful to my batchmates Ugrasen Singh, Avinash Kalyani, Puneet Jain, Prathishta Chandra, and Lokesh Singh for their support and making my stay at the institute enjoyable.

I am especially grateful to my family members for their invaluable support and strong belief in me. I dedicate my Master's thesis to my great parents for their countless sacrifices.

PIYUSH VARSHNEY

(mt1602102006)

M.Tech. (Communication and Signal Processing)

Discipline of Electrical Engineering, IIT Indore

Dedicated to my family

Abstract

The analysis of non-stationary characteristics present in electroencephalogram (EEG) signal requires a crucial analysis which can reveal a method for diagnosis of neurological abnormalities, especially epilepsy. This thesis presents a new technique for automated classification of epileptic EEG signals into two classes and three classes based on iterative filtering of EEG signals. In this work EEG epochs are decomposed into their intrinsic mode functions (IMFs) using iterative filtering. Amplitude envelope (AE) and instantaneous frequency (IF) functions are extracted from these modes, using discrete separation energy algorithm (DESA). The features are extracted from these IMFs and AE-IF functions. Our feature set includes K-nearest neighbor entropy estimator (KNNE), log energy entropy (LEE), Shannon entropy (SE), Poincaré plot parameters (width, length, and area of plot) of extracted AE functions and IMFs. These features are tested for their discriminative strength, on the basis of their p-values, for classification of EEG signals into seizure, seizure-free, and normal. Our proposed method has given a classification accuracy (ACC) of 98% with random forest classifier and 97% with C4.5 decision tree for three class classification and ACC of 99.5% for a two class classification problem, using mentioned feature set. This proposed methodology has obtained a high ACC in the classification of seizure, seizure-free, and normal EEG epochs, which can be useful in more accurate diagnosis of epilepsy.

Contents

List of Figures

List of Abbreviations

ACC	Accuracy
AE	Amplitude envelope
AM	Amplitude modulation
ANOVA	Analysis of variance
CAD	Computer aided diagonistics
CT	Computerized tomography
DESA	Discrete energy separation algorithm
ECG	Electrocardiogram
EEG	Electroencephalogram
EEMD	Ensemble empirical mode decomposition
EMD	Empirical mode decomposition
EMU	Epilepsy monitoring unit
EMG	Electromyogram
ERS	Event-related synchronization
FMRI	Functional magnetic resonance imaging
FLP	Fraction linear prediction
FM	Frequency modulation
FN	False negative
FP	False positive
FT	Fourier transform
HOS	Higher order spectra
HHT	Hilbert-Huang transform
IF	Instantaneous frequency
IMF	Intrinsic mode function
KNN	K-nearest neighbor
KNNE	K-nearest neighbor entropy
KW	Kruskal-Wallis
LBP	Local binary pattern
LEE	Log energy entropy
LP	Linear prediction
LTM	Long term monitoring

LS-SVM	Least square support vector machine
MF	Margin function
MLPNN	Multilayer perceptron neural network
PCA	Principal component analysis
PET	Positron emission tomography
PSR	Phase space representation
PWVD	Pseudo Wigner-Ville distribution
RBF	Radial basis function
ROC	Receiver operating characterstics
RQA	Recurrence qualification analysis
SE	Shannon entropy
SEEG	Stereo electroencephalogram
STFT	Short-time Fourier transform
SUDEP	Sudden unexplained death in epilepsy
SVM	Support vector machine
TN	True negative
TP	True positive

Chapter 1

Introduction

Electroencephalogram (EEG) monitoring helps in identifying the exact location of brain regions involved in epilepsy. This observation enhances the success rate of epilepsy treatment. EEG, a record of brain activity, is a highly nonlinear and dynamic signal that has a lot of information content about functioning of brain and disorders related to it. A neurological disorder defined by the recurrence of seizures is labeled as epilepsy. EEG segments are studied for three classes namely seizure, seizure-free, and normal [1]. Methods for automatic monitoring of epileptic activities have been adopted, as visual inspection of EEG signals for diagnosis is strenuous and time consuming for long recordings of data. Development of computer aided diagnostic (CAD) techniques can address these issues. An easier, faster, more effective, and affordable way to study epileptic activity is offered by these automated techniques. This way of diagnosis mainly involves epileptic seizure detection in EEG signals [2].

In this chapter, we present some basic details about EEG signal and epileptic seizure, problem background, and motivation behind our research. Finally, an organization of the thesis has been presented.

1.1 Electroencephalogram and epilepsy

EEG is an extensively used electrophysiological assessment technique for clinically recognizing and managing various neurological disorders, including epilepsy. In

order to measure neurophysiological activity of brain, electrodes are placed on the scalp or intracranially on the cerebral cortex or in special case on deeper brain tissues. Measured activity in the form of traces is known as EEG or brain waves [2, 3]. Based on the position of electrode used for measuring the activity, EEG are of two types: Non-invasive EEG, in which electrodes are placed on the scalp and other type is intracranial EEG, in which electrodes are implanted on deep brain. Subdural EEG electrodes are used as scalp electrodes and intracranial EEG electrodes are inserted in the brain [4].
Epilepsy is one of the chronic and common neurological ailment known to mankind. Different causes may lead to variety of disorders and malfunctioning of brain, giving reflections as ailments. Epilepsy is one collective term for such disorders [4]. Abnormal discharges in large group of brain neurons are observed during an epileptic seizure [4]. Diminished consciousness, motor activity loss, loss of senses, behavioral changes, are some of the clinical symptoms of a person suffering with epilepsy. In many cases epilepsy may cause sudden death due to unknown reason, clinically termed as sudden unexplained death in epilepsy (SUDEP) [5, 6]. Medically intractable seizures usually require a surgical resection (removal of epileptic foci in brain), which need a better seizure localization technique. As surgical removal of epilepsy is not an easy task to be performed, nor all epilepsy affected persons benefit from surgery, a prolonged monitoring of EEG signal from such patients can give an insight in providing a cure through neuroimaging and electrophysiological assessment.

Activity monitoring during epilepsy and determining exact information about the time of occurrence, nature, and the center of neural discharge, all can be done with ease using EEG [7]-[9]. Positron emission tomography (PET), functional magnetic resonance imaging (FMRI), and computerized tomography (CT) scans are some advanced imaging techniques useful in providing anatomical information about the abnormal growth in the brain, but these techniques are discontinuous in nature i.e scanning cannot be done during an on going seizure, thereby fail in continuous scanning of patient [10, 11]. Only practical solution is EEG recordings for long durations. EEG has helped in detecting seizure and aborting their progression by triggering focal treatment (drug release, electrical stimulation or focal cooling) [12, 13].

1.2 Amplitude and spectral characteristics of EEG signal

Signals from both cerebral and non-cerebral origins are present in EEG. Depending on the vicinity of electrodes to neurons, as in case of subdural electrodes, the amplitude of depth electrodes is usually larger than that of scalp electrode [14]-[16]. It has been observed that the amplitude of scalp electrode signals varies from 20 μV to 100 μV, while depth electrode amplitude varies from 100 μV to 2 mV. Frequency range of EEG (seizure and seizure free) is from 0.5 Hz to about 500 Hz. Five frequency bands out of this spectral bandwidth are of clinical importance: (a) delta, (b) theta, (c) alpha, (d) beta, and (e) gamma, which are explained below [17].

1. **Delta waves**: These waves have a spectral content of about 3 Hz. It is a wave with least frequency and highest amplitude [17].

2. **Theta waves**: These slow waves have a frequency content ranging from 4 Hz to 7 Hz. Closing of eyes with relaxation emerges these waves. This is normally found in EEG signals of young children and adults [17].

3. **Alpha waves**: Commonly found in adults with a spectral range from 7 Hz to 12 Hz. These waves arise in rhythms on both sides of the head. On non-dominant side it has slightly higher amplitude. They disappear with stress/opening of eyes and are regarded as normal waveform [17].

4. **Beta waves**: Characterized by small amplitude and fast activity, these waves have a frequency range of 14 Hz to 30 Hz. These dominant rhythms are present in patients, who are alert or anxious with their eyes open. These are usually seen on both the sides with symmetrical distribution, dominant in frontal area.

In areas of cortical damage, it may be absent or diminished. These waves are mostly dominant in frontal and central portion of brain. Amplitude of beta waves is less than 30 μV [17].

5. **Gamma waves**: Fastest of all brain waves, these waves have a spectral content in the range of 30-45 Hz. These are also known as fast beta waves. These waves are rarely present and have very small amplitude. these rhythms play a crucial role in neurological disease diagnosis. These waves usually occur in central part of brain. Event-related synchronization (ERS) of the brain is suggested by these waves [17].

1.3 Clinical approach for EEG classification

Epileptic activities are visually inspected by an expert by looking at prolonged recordings. In prolonged recordings, time between normal and epileptic seizure, is known as seizure-free period. Normal rhythmic discharges like alpha rhythms as well as abnormal (high frequency oscillations, spikes, etc.) patterns are present in this recording [18]-[20].

EEG from a patient is generally characterized by rhythmic discharge of large amplitude or a low amplitude unsynchronized signal at the onset of seizure and also with repetitive spikes. A general definition for seizures is that, during an epileptic seizure, a new type of random EEG signal appears in an unsure manner and soon it becomes prominent in the entire EEG trace. EEG trace tends to become slower with an increasing amplitude and with more distinct spiky phases of the rhythmical waves [21]. Figure 1.1 shows one example of such seizure and different epochs from a prolonged recording showing separately seizure, seizure-free, and normal activities.

A clinically significant information about epileptic focus is provided by early stages of an epileptic seizure. Depending on the clinical significance of epileptic seizures, they are divided into two distinct categories; (a) clinical and (b) sub-clinical. Certain behavioral changes are associated with clinical seizures. In case of sub-clinical seizures, there are minimal or no behavioral changes visible. In

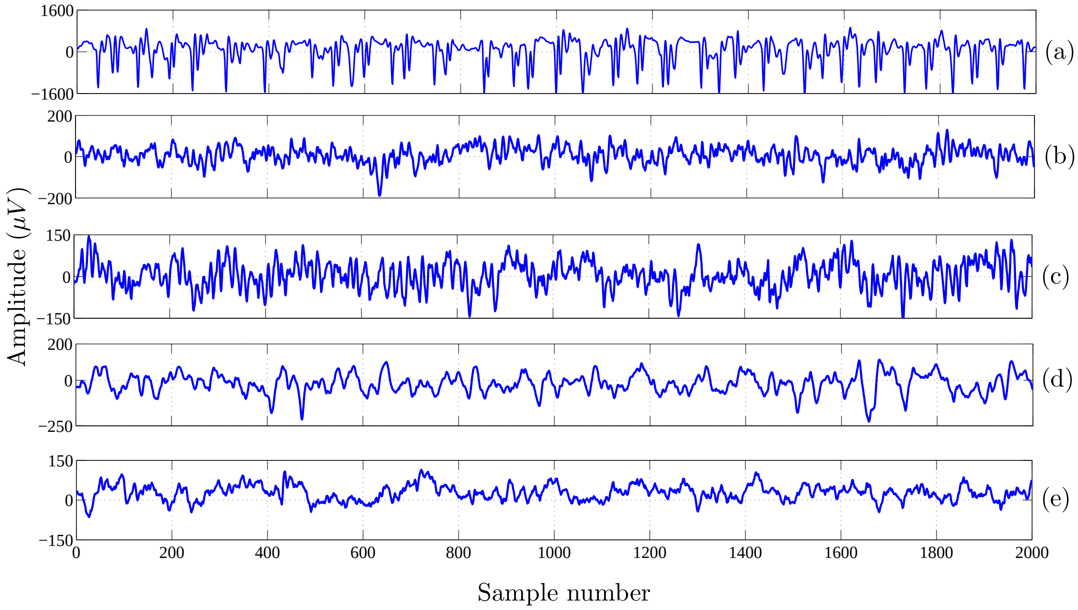


Figure 1.1: Plots of EEG epochs for: (a) Seizure activity; (b) Normal EEG with eyes open; (c) Normal EEG with eyes closed; (d) Seizure-free activity EEG taken from epileptic zone; (e) Seizure-free activity EEG taken from hippocampal formation from opposite hemisphere of the brain.

both the types of seizures, abnormal activity is captured by EEG. In order to come up with a medical cure for preventing irreversible secondary brain damages, patients are monitored on a long term basis (continuous long term monitoring (LTM)) [22, 23]. Time frame chosen for this LTM ranges from days to weeks in the epilepsy monitoring unit (EMU). A neurologist or brain expert tags EEG recording during the period of epileptic attack. As the procedure is tedious and prone to errors in prediction, an automated detection of epileptic event on EEG recording and classification of various EEG segments into seizure, seizure-free, and normal is needed [24, 25].

1.4 Literature review

Signal processing techniques are useful in EEG signal analysis before any surgical operation of brain. In automated diagnostic techniques, significant features from EEG signals are extracted using time-based, frequency-based or time-frequency based methods for developing classification models. These models provide a best possible combination of classifier and feature sub-set, that will yield the highest possible accuracy (ACC).

Many time-domain based methods for detection and classification of the epileptic seizures from EEG signals have been proposed. Methods using linear prediction (LP) error energy for epileptic EEG detection has been proposed in [25]. Fractional linear prediction (FLP) error as features for EEG classification have been proposed in [26]. In this work FLP based features with support vector machine (SVM) as classifier using linear, radial basis function (RBF), and polynomial kernels, ACC of 88.67%, 95.33%, and 94.67% respectively are obtained for three classes (seizure, seizure-free, and normal) classification. FLP coefficients with SVM, trained using RBF, have given ACC of 95.33% for classification of seizure and seizure-free classes [26]. Authors in [27] have developed a methodology based on principal component analysis (PCA) with enhanced cosine radial basis function neural network, for seizure detection.

Discrimination between seizure and seizure-free EEG signals has been done on the basis of Lyapunov exponent in [28]. EEG classification into normal, seizure-free, and seizure classes has been done using recurrence quantification analysis (RQA) based features in [29]. Multi-level local pattern based seizure and seizure- free classification has been performed in [30]. ACC of 98.67% has been obtained using these extracted features with nearest neighbor classifier.

Empirical mode decomposition (EMD) has been proposed to analyze non-stationary signals [31]. Mean frequency, obtained using Fourier-Bessel series expansion, of intrinsic mode functions (IMFs), has been used as a feature to discriminate between seizure and seizure-free EEG signals [32]. Amplitude modulation (AM) and frequency modulation (FM) bandwidths of IMFs, obtained using EMD, have been calculated and used as a feature for classification of seizure and non-seizure EEG signals [33]. Also in [34], 95% confidence area of ellipse fitted in second order difference plots of calculated IMFs is used as a discriminatory feature for seizure and seizure-free classification. Using this 95% area feature with multilayer perceptron neural network (MLPNN) as classifier, a maximum ACC of 100% has been achieved in [34]. Descriptors from 3-D and 2-D phase space representation of IMFs have been used as feature for classification of EEG signals in [35]. Using Hilbert-Huang transform (HHT), time-frequency images of EEG signals have been obtained and histogram based features are used for classification of signals. A combination scheme of k-means clustering with ensemble empirical mode decomposition (EEMD) has resulted in 98% ACC for seizure and normal EEG signals classification case [36].

Fourier transform (FT) has been used to extract features from spectral components of EEG signals [37]. Spectral representation of higher order statistics i.e. moments and cumulants of third and higher orders, is called higher order spectra (HOS). Features extracted from HOS have been employed for classification of the normal, seizure-free, and seizure EEG signals. ACC of 98.5% has been achieved using HOS features with SVM in [38]. However, assumption associated with FT analysis is that the signal is stationary i.e invariant in amplitude, phase or frequency with time. Earlier studies have shown that frequency components of EEG signal change with time i.e. EEG signal is a non-stationary process [39]-[42].

Time-frequency based methods like short-time Fourier transform (STFT) [42], wavelet transform (WT) [43], the multiwavelet transform [44] and the smoothed pseudo-Wigner-Ville distribution (PWVD) [45], have been proposed for epileptic seizure detection from EEG signals. EEG signal is decomposed into sub-band signals and sub-band frequencies of these sub-band signals are used as features for classification of normal and seizure EEG signals. Using mixture of experts (ME) model, classifier ACC of 94.5% has been achieved for seizure and normal EEG signals classification. This method with MLPNN based classifier has yielded ACC as 93.2% [46]. The line length feature, of discrete wavelet transform (DWT) coefficients, has been used for classification of normal and epileptic seizure EEG signals. In this work, with MLPNN as classifier, ACC of 99.6% for two classes (seizure and normal) and ACC of 97.5% for three classes (seizure, seizure-free, and normal) have been achieved [47]. Eigenvalue decomposition of Hankel matrix along with Hilbert transform [48, 49] is used as a time-frequency technique for classification of seizure and seizure-free EEG signals. In this method, the extracted features with least square SVM (LS-SVM), has given a ACC of 100% for seizure and seizure-free classes [48].

1.5 Motivation

The EEG can be used for the following purposes in epilepsy studies:

- Clinical diagnosis of epilepsy.
- Classification of epileptic and normal durations of EEG recordings.
- Identification of epileptic zone for pre-surgical patients.
- To deduce the absence of epileptic seizure.

A large storage space is needed for storing EEG data for a single patient. Therefore, automated signal analysis, classification, and prediction methods are needed to be explored. A good insight into neurophysiological state just prior to an epileptic seizure, is needed to devise a reliable prediction algorithm for epilepsy detection. So testing and training of automated learning system, which perform EEG signal analysis and classification is very important.

Many studies have been proposed for gaining insight to EEG signal analysis by visual inspection but these studies require a prolonged inspection time and are many times prone to come up with false detection. Therefore, some more refined and better techniques for automated classification of EEG signals are still required. It is clear for section 1.4 that many time-series based, frequency domain based, and time-frequency based detection and classification techniques have been proposed. Time-frequency domain based proposed methodologies are complex in their implementation. There is a need for a time-series based technique, which when applied to EEG signal, will yield maximum information about the signal in time-domain itself. EMD is one such attempt for non-stationary signal analysis [50]. Shortcoming of EMD is its convergence analysis. Unavailability of proper convergence criteria may lead to over sifting or under sifting of data which leads to extraction of improper IMFs. Iterative filtering replaces the mean of upper and lower envelope obtained by using cubic-spline interpolation, as used in traditional EMD, by some moving average of the signal to solve this convergence issue. In this method, mean is calculated by convolving the signal with a perfectly weighted variant of signal itself [51]. Our work emphasizes on decomposition of EEG signal segments using iterative filtering and then extracting features from the obtained IMFs for classification of EEG signals. Iterative filtering has been applied on EEG signals for automated sleep stages classification in [52]. This thesis presents an application of iterative filtering on classification of EEG signals. As EEG signals can be used for multiple other purposes, the focus of the thesis will be classification of EEG signals into seizure, seizure-free, and normal classes.

1.6 Objectives

Main objective of our work is to analyze the acquired raw data set using signal processing tools and extract features from them for their classification into different classes. Our work focuses on decomposition of EEG signal using iterative filtering and then extracting some non-linear highly discriminative features from the decomposed signal, so that maximum ACC can be obtained. In order to achieve this: (i) EEG signals are decomposed into IMFs using iterative filtering, (ii) Discrete energy separation algorithm (DESA) is applied to obtained IMFs for obtaining amplitude envelope (AE) and instantaneous frequency (IF) functions from them, and finally, (iii) non-linear entropy based features are extracted from these AE-IF functions and given to artificial neural network (ANN) for classification.

Time series based features like area of Poincaré plots, length of Poincaré plots, width of Poincaré plots along with some nonlinear entropy features, namely

K-nearest neighbor entropy estimator (KNNE), log energy entropy (LEE), and Shannon entropy (SE) are computed from these IMFs and AE-IF functions, which reveal the complexity present in various IMFs of seizure, normal, and seizure-free EEG signals.

1.7 Thesis organization

The rest of the thesis is organized as follows:

Chapter 2 deals with detailed description of iterative filtering algorithm and DESA, where signal decomposition using these algorithms is discussed.

Chapter 3 contains the description of database used and proposed approach.

Chapter 4 contains results and discussion of the proposed approach and comparison of obtained results with other existing methodologies.

Chapter 5 discusses the conclusions drawn and scope of future work.

1.8 Summary

Epilepsy is a neurological disorder characterized by abnormal neurological discharges leading to loss of consciousness, behavioral changes, and even death under some chronic conditions. Therefore, detection of epileptic seizure before the occurrence of epileptic event is of clinical importance. Automated seizure detection through EEG recordings and their classification is one solution in this direction.

In literature, many techniques for EEG signal classification are presented but still a better technique is needed. In this work we have studied the acquired raw EEG signals and proposed a technique for their classification.

Chapter 2

Iterative filtering and DESA methods

In the proposed methodology, acquired EEG signals are first decomposed into their IMFs using iterative filtering algorithm. Then, DESA is used to extract AE-IF functions from these obtained IMFs and features from these functions are used for signal classification. In this chapter, a detailed description about iterative filtering and AE-IF functions extraction using DESA is given.

2.1 Empirical mode decomposition method and need for iterative filtering

Practical research applications essentially require signal and data analysis. As data gathered today from numerous sources is chaotic in nature and large in volume, understanding of collected data is important and challenging. Estimation of parameters or confirming a certain model for extracting hidden information from large volumes of data is one of the potent challenge before any data analyst. Difficulties faced during analysis of large data include short span of data, non-linearity and non-stationarity present in data, and mingling of essential information with noise or other irrelevant information.

Spectral analysis using FT, is an earlier attempt in this direction, providing a general method of analysis of signals and data. Limitation of Fourier analysis is that it does not work well with for non-stationary data or data from non-linear systems. Also information about spatial and temporal localization, which may be useful for some applications in signal processing is absent in Fourier analysis. To extract spatial-temporal localization information, WT was proposed. This method captures discontinuities in data, but suffers from leakage of data due to limited length of wavelets used [50].

Also in case of wavelets, a locally occurring change has to be looked into high frequency range, as time resolution has to be high and if the change is of higher frequency range, basic wavelet will be more localized. But if the event is occurring in low frequency range, then also one has to look for change in higher frequency range. This is the basic drawback of wavelets.

The EMD, proposed in [50], is a data adaptive complement to existing methodologies. Motivation behind the study of EMD is a requirement of an effective way for extracting the IF of signals for an in-depth analysis of data. Hilbert transform of a signal defines its IF. Hilbert transform of a signal $g(t)$ is defined as [50]

$$G^H(t) = \frac{1}{\Pi}\mathrm{PV}\int \frac{G(s)}{t-s}ds \tag{2.1}$$

where PV is the principal value of the integral. FT of Hilbert transform of signal also gives useful information about Hilbert transform [50]. Taking Fourier transform of (2.1) yields

$$\widehat{G^H(\beta)} = -j\mathrm{sign}(\beta)\widehat{G(\beta)} \tag{2.2}$$

where sign(β) is the standard signum function. Defining

$$Q(t) = G(t) + jG^H(t) = a(t)\exp(j\theta(t)) \tag{2.3}$$

where $a(t)$ is the magnitude of Q(t). The IF at time t is given as: $\omega(t)=\dfrac{\mathrm{d}\theta(t)}{\mathrm{d}t}$.

EMD decomposes data set into a finite, often small, number of components called IMFs, satisfying following two conditions [50]:

- The number of the zero-crossings and the number of extrema of an IMF must be equal or differ at most by one.

- The mean value of the envelopes defined by the local extrema is zero, at any point of IMF.

In HHT, Hilbert transform of the obtained IMFs is computed for meaningful estimation of IF from data. EMD and HHT are useful for analyzing a very wide range of data sets in astronomy, medical sciences, engineering, geology, and other fields dealing with large data sets [53]-[56].

EMD is orginally an algorithm known as the sifting process. Cubic splines are used to connect local minima and maxima in the process are connected to form lower and upper envelopes. The average of the two envelopes is then subtracted from the original data. Iteratively applying this process yields EMD [50]. Due to highly data adaptive nature, sifting algorithm is subjected to instability, as any small change in data often lead to different IMFs. Fundamental mathematical issues related to EMD, like convergence of sifting algorithm, definition of suitable stopping criteria have not been established. This is due to highly adaptive nature of sifting algorithm and only using cubic splines for envelope development. One such attempt was made by replacing cubic splines by B-splines, giving another way for EMD, but certain issues remained unresolved [57].

Iterative filtering is another such attempt of replacing mean of envelopes by certain moving average in the sifting algorithm. Moving average can be adaptive as it is data dependent. An added advantage of iterative filtering over traditional EMD is that it can be generalized to higher dimensions [58].

2.1.1 Iterative filtering algorithm

Defining an operator $\Psi(p)$ which calculates the moving average of any signal $p(t)$, where $t \in \Re$, using a double averaging filter $d(t)$. Moving average of the signal $p(t)$

is given by the convolution defined as [58] :

$$\Psi(p)(t) = \int_{-m}^{m} p(\tau + t)d(\tau)d\tau \tag{2.4}$$

Defining p_1 and the operator $\Theta_{1,n}$=p_n - $\Psi_n^{(1)}(p_n)$ = p_{n+1} which captures the fluctuating parts of p_n, then first IMF is given by $I_1 = \lim_{n\to\infty} \Theta_{1,n}(p_n)$, where operator $\Psi_n^{(1)}$ depends on mask length (m_n) of the filter at n^{th} step of sifting algorithm, superscript refers to the first IMF. Applying the operator Θ to the remainder of signal $(p - I_1)$, second IMF I_2. Iterating the process we get the k^{th} IMF as $I_k = \lim_{n\to\infty} \Theta_{k,n}(r_n) = r_{n+1}$, where $r = p - (I_1 + I_2 + ... + I_k)$.
Iterative method stops when the remainder signal is a trend signal .i.e having at most one maximum or minimum. Finally signal can be represented as follows [58]:

$$p(t) = \sum_{j=1}^{k} I_j(t) + r(t) \tag{2.5}$$

where k represents number of IMFs into which signal is decomposed. $r(t)$ is the remainder trend signal. There are two methods by which the moving average can be calculated for iterative algorithm. One way of calculating it is by taking the average function of the lower and upper envelope, given by cubic splines connecting local minima and maxima of $p(t)$. This method is similar as EMD process and suffers from instability under perturbation. Other method is to calculate the average derived by the convolution of signal $p(t)$ with a double averaging filter $d(t)$, given by [59]:

$$d(t) = \frac{m + 1 - |t|)}{(m + 1)^2} \tag{2.6}$$

Discrete version of double averaging filter with mask coefficients c_j can be expressed as [58]:

$$c_j = \frac{m + 1 - j}{(m + 1)^2} \tag{2.7}$$

where m is the mask length and j is the sample about which filtering is done.

Iterative filtering algorithm [59] can be summarized in a below mentioned stepwise manner, which consists of two nested 'while' loops: an inner 'while' loop, in which each single IMF is calculated, and an 'while' outer loop, which derive all the IMFs. Pseudo code for iterative filterng algorithm for any discrete signal $p[n]$ is given below [58].

Algorithm 1 Iterative filtering [59]

IMFs to be calculated **IMF** $= \{\}$
intialize the remaining signal $r{=}p$
outer while loop
while Number of maximas of $f \geq 2$ **do check for condition**
calculation of data dependent filter coefficients of filter h_x.
inner while loop for extracting IMF
while stopping criteria not satisfied **do**
set $p_{nj} = 0$ for $j \neq 0, ...m-1$, m is the filter length.
compute the moving average l_m of p_n
$l_m = \frac{1}{m-1}\sum_j (p_{mj}) h_x(x_i - x_j)$, i=0,......m-1
$p_{m+1} = p - l_m$
$m = m+1$
inner while loop ends
IMF $=$ **IMF** $\cup\, \boldsymbol{f}$
extracted IMF **IMF** $=$ **IMF** $\cup\, p_m$
residue signal left after first IMF$r = p - p_m$
outer while loop ends

We can compute mask length (m_n) using the formula [58]: $m_n = 2\lfloor(\lambda\frac{N}{i})\rfloor$, where λ is the parameter with value 1.5-3.5; N is number of sample points in signal; i represents number of its extreme points. $\lfloor(.)\rfloor$ rounds a positive integer close to zero.

In iterative filtering algorithm updating of mask length (m_n) is done at each step of inner loop, but in the presented algorithm we calculated the mask length in the first step and then used the same value throughout. Same mask length at all steps of inner loop is used to ensure that the IMFs produced by this method should contain a well-defined set of IMFs. To make this happen, operators θ and Ψ are made independent of step number n. 'h_x', which is used in the algorithm is a suitable discrete double averaging filter same as $d(t)$, as discussed earlier.

Also in the implemented algorithm, some stopping criteria is used for stopping the inner loop instead of letting n to go to infinity. One such stopping criteria can be defined as [58]:

$$\delta := \frac{||I_{1,n} - I_{1,n-1}||_2}{||I_{1,n-1}||_2} \tag{2.8}$$

.

Certain threshold value of δ can be used as a stopping criteria [59] or maximum number of iterations can be set in the inner loop for stopping the algorithm. Convergence of inner loop of algorithm is guaranteed for periodic signals and studied for l^∞ functions in [59].

Example

Here is one illustration on working of iterative filtering for signal decomposition. A synthetic sequence $s(n) = 4y(n)+3z(n)+7u(n)$ is generated as a linear combination of three linear frequency modulated signals, with $y(n) = \cos[2\pi(f_1\frac{n}{F_s} + 0.4(\frac{n}{F_s})^2)]$, $z(n) = \cos[2\pi(f_2\frac{n}{F_s}+0.4(\frac{n}{F_s})^2)]$, and $u(n) = \cos[2\pi(f_3\frac{n}{F_s}+0.4(\frac{n}{F_s})^2)]$, where $f_1 = 40$ Hz, $f_2 = 10$ Hz, $f_3 = 180$ Hz, and $F_s = 1000$ Hz. Figure 2.1 shows the generated signal. Iterative filtering is applied on the generated signal $s(n)$ to decompose it into its IMFs, which are shown in Figure 2.2. In this experiment, value of δ is chosen as 0.01 and mask length m_n of each iteration is calculated using $m_n = 2\lfloor(\lambda\frac{N}{i})\rfloor$, where value of λ is taken as 3. Value of λ can be varied for generating a different set of IMFs for the same generated signal $s(n)$. MATLAB codes used here for implementation of the algorithm using double averaging filters are available at `http://www.mathworks.com/matlabcentral/fileexchange/53405-iterative-filters`.

Better separation of IMFs can be obtained by further lowering the value of δ, but limitation of lowering is that it will produce more number of IMFs if noise in data is present. Also tuning of mask length by changing value of λ affects the separation of IMFs. This method of signal decomposition has been used for sleep stage classification in [52].

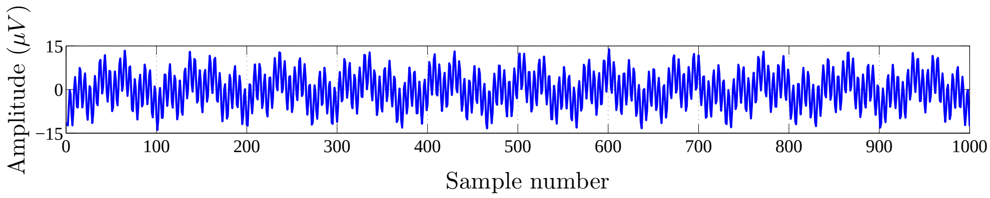


Figure 2.1: Generated signal $s(n)$

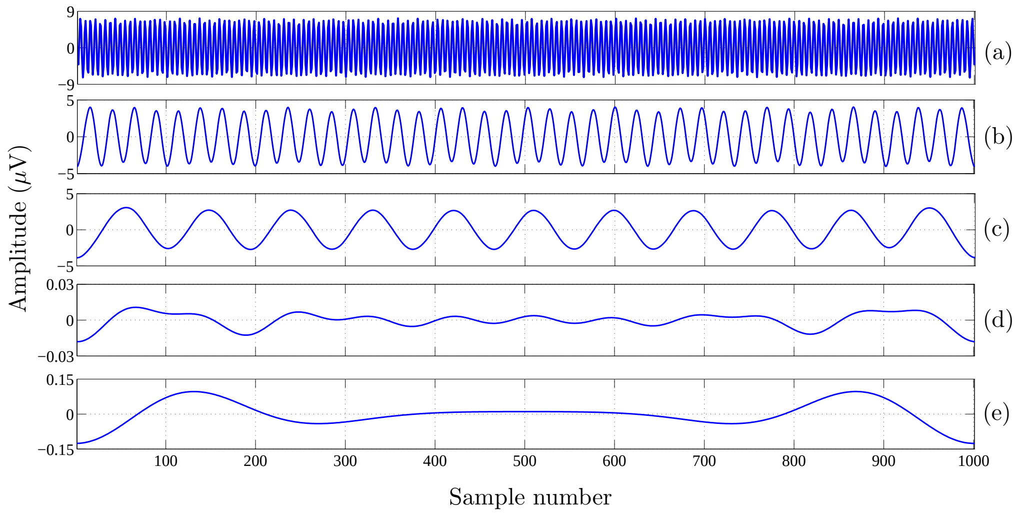


Figure 2.2: Plots of IMFs of generated signal $s(n)$: (a) IMF1; (b) IMF2; (c) IMF3; (d) IMF4; (e) IMF5

2.1.2 AE and IF functions estimation using DESA

Amplitude and frequency modulations of sine wave are frequently used in communication systems. Basic knowledge of AM and FM systems can be used in modeling many of the naturally occurring signals like speech [60]. Time varying amplitude and frequency patterns present in the signal can be represented by these AM-FM models. Non-linear modelling of speech has been done in [61]-[65].

As variations in AE function of signal is due the AM component of signal, so extracting AE from signal can give information about the AM component. Similarly, IF function extraction provides information about FM component of signal. Extraction of AM and FM components can be done using Teager operator which estimates the AE and IF functions of AM-FM based on “energy-tracking ”. Kaiser first introduced these operators [66, 67] for tracking energy of simple oscillators. Teager further developed these operators for non-linear speech processing both in continuous and discrete domains [68]. For continuous domain this energy operator is given by :

$$\Upsilon_c[x(t)] = [x\dot{(t)}]^2 - x(t)x\ddot{(t)} \tag{2.9}$$

where $x(t)$ is a continuous-time signal and $\dot{x} = \frac{dx(t)}{dt}$ and for discrete-domain it is given as :

$$\Upsilon[x(n)] = x^2(n) - x(n-1)x(n+1) \tag{2.10}$$

with $x(n)$ as discrete-time sequence where $n = 0, \pm 1, \pm 2, ...$

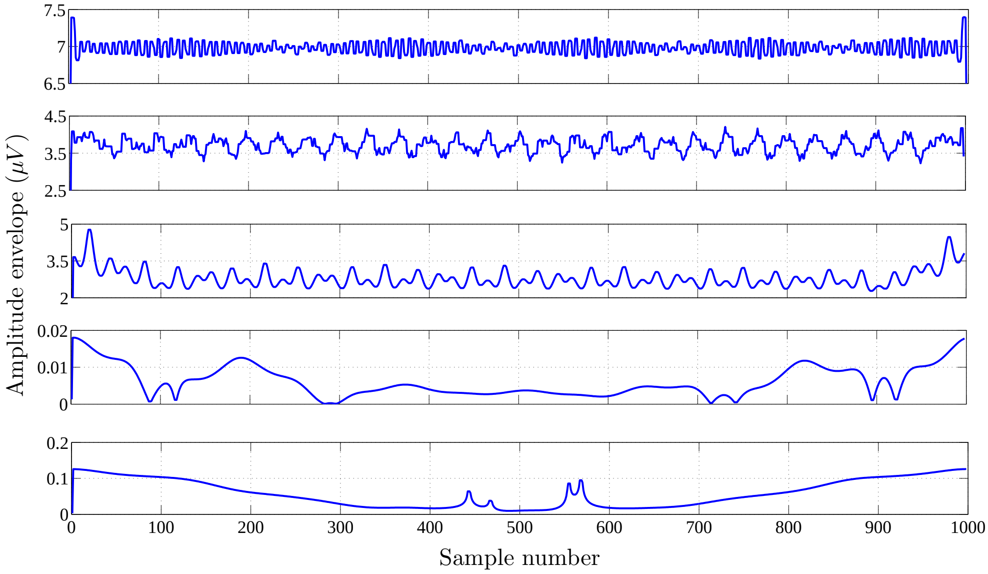
The AE and IF functions of the IMFs, obtained using iterative filtering, can be given as follows [68]:

$$\text{AE} \approx \sqrt{\frac{\Upsilon[I(n)]}{[1 - (\frac{\Upsilon[H(n)]+\Upsilon[H(n+1)]}{4\Upsilon[I(n)]})^2]}} \tag{2.11}$$

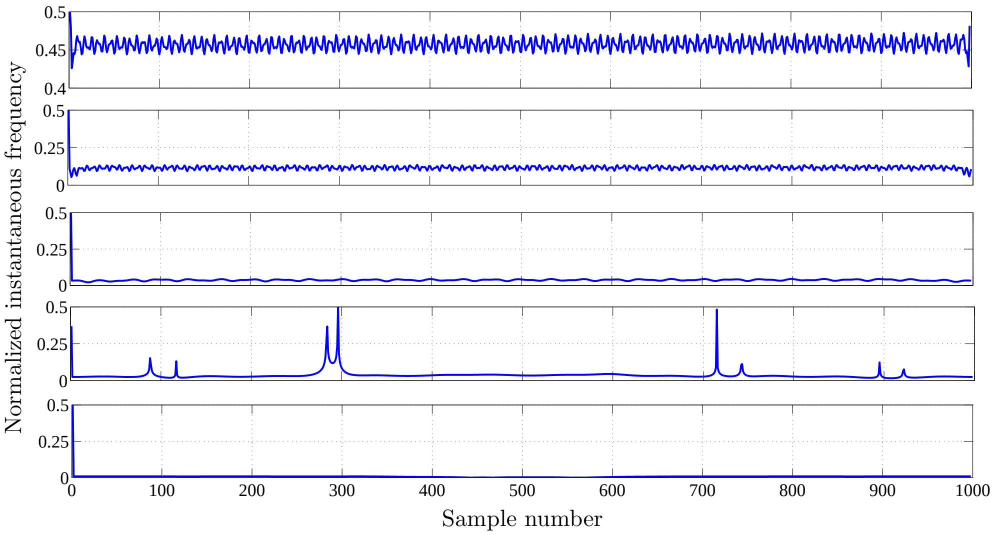
$$\text{IF} \approx \arccos(1 - \frac{\Upsilon[H(n)] + \Upsilon[H(n+1)]}{4\Upsilon[I(n)]}) \tag{2.12}$$

where $H(n)$ is the time-domain difference signal of IMF $I(n)$ given as $H(n) = I(n) - I(n-1)$, $I(n)$ is the IMF [68].

An illustration of DESA on extraction of AE-IF functions of signal is presented here. DESA is applied on IMFs of the signal $s(n)$ which are shown in Figure 2.2. The extracted AE and IF functions of each IMF are shown in Figure 2.3. The AE functions are shown in Figure 2.3(a) and Figure 2.3(b) contains the normalized IF of signal $s(n)$.



(a)



(b)

Figure 2.3: Plots of (a) AE functions; (b) IF functions of first five IMFs of generated signal $s(n)$.

2.2 Summary

Iterative filtering can be used as a variant of EMD by replacing the cubic spline interpolation technique with moving average double filter. Spurious nature present in data can be dealt effectively by using this technique. Iterative filtering can better handle issues of horizontal comparison, which means IMFs of different signals with same index contain almost equal information content [52]. AE and IF functions of the signal can be extracted using DESA. AE and IF functions are an indicator of AM and FM components of signal respectively. DESA has been used for modeling of non-stationary signals in [61].

Chapter 3

Database and methodology

This chapter presents the methodology used for designing an automated technique for classification of EEG signals into different classes. Chapter also contains the information of database used in our work. Block diagram representing the steps involved in methodology is shown in Figure 3.1. Initially, the EEG signals are collected from the database, as mentioned in the next section. Then acquired EEG signals are decomposed into IMFs using iterative filtering, a detailed description of which is given in chapter 2. After obtaining IMFs, their AE and IF functions are obtained using DESA. Obtained AE and IF functions are used for extracting features from them for classification of EEG signals. In our work, we have conducted experiments on clinically significant classification cases, which involves two-class and three-class classification problems, which are discussed in upcoming sections. We have used 3 different classifiers namely; Random forest, C4.5 decision tree, and Naïve Bayes, in our classification task and compared the performance of the three classifiers on the basis of performance parameters [69] like ACC, sensitivity (SEN), receiver operating characteristics (ROC) area, and specificity (SPF). The tabulated values of all these parameters with different classification cases are presented in next chapter.

Table 3.1: Description of dataset used with number of signals

	A and B	C and D	E
Subject	5 normal	5 epileptic	5 epileptic
Electrode type	surface	intracranial	intracranial
State	Eyes open and eyes closed	Seizure-free	Seizure
Epoch duration	23.6 sec	23.6 sec	23.6 sec
Number of epochs	200	200	100

3.1 Database

In the present work, we have used publicly available database which consists of clinically recorded EEG time series data (consists of five sets A, B, C, D and E) at the Bonn University and is publicly available at [70] and its details are given in [71]. EEG epochs, each 23.6 sec long, are taken from five healthy and five epileptic patients. A total of 500 EEG epochs belonging to three categories: normal, seizure and seizure-free are present in the database. Each segment was treated as separate EEG signal accounting to 500 EEG signals in total. EEG data used here is recorded using standard 10-20 electrode placement scheme. Sampling rate of signals is 173.61 Hz, resulting 4097 samples in single channel recording.

Detail information about different sets in database can be given as: A (Recorded from healthy persons in awake state with their eyes open) and B (Recorded from healthy persons in awake state with their eyes closed) subsets were captured extra cranially. Sets C (epochs were recorded during seizure-free duration using from the intracranial electrodes that were implanted into the hippocampal formations of opposite hemisphere of brain), D (epochs were recorded during seizure-free duration using intracranial electrodes in the epileptic zone), and E (seizure epochs were recorded from all cerebral locations displaying seizure activity using intracranial and strip electrodes by implanting them into the lateral and basal regions of the neocortex) were captured using in depth electrodes. Table 3.1 gives a description of database used in this work.

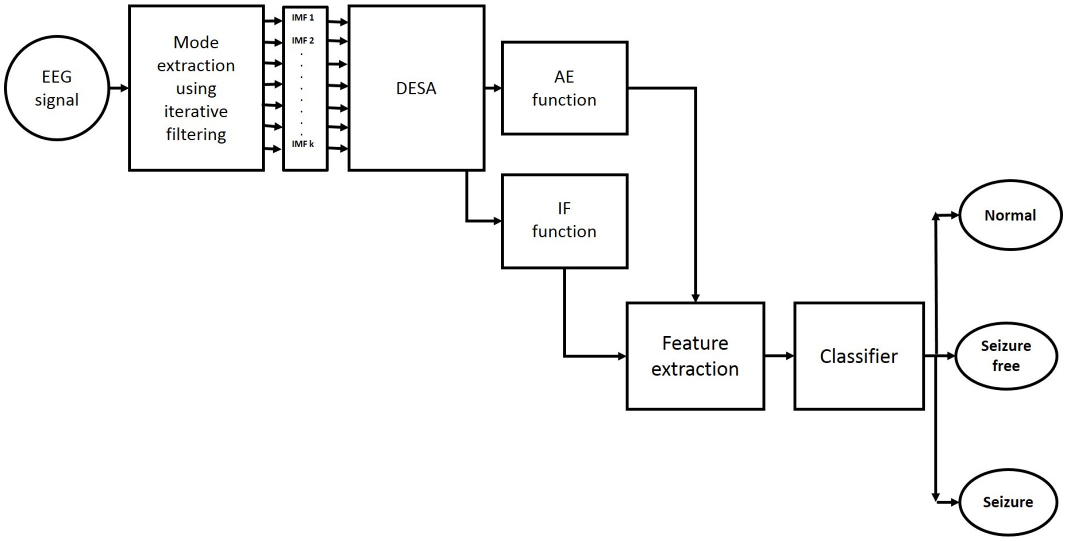


Figure 3.1: Block diagram for the proposed methodology.

3.2 Proposed methodology

Figure 3.1 shows the block diagram of the proposed methodology. In the methodology, iterative filtering is adapted as a variant of EMD for signal decomposition. Steps involved in extracting the IMFs from any signal have been discussed in iterative filtering algorithm in the previous chapter. Using low pass filters with a revised sifting algorithm, iterative filtering decomposes a signal into its corresponding IMFs. Mask length after completion of each while loop is calculated using parameter λ using the formula $m_n = 2\lfloor(\lambda\frac{N}{i})\rfloor$. Values of λ used in our work are in 1.5-3.5 range. Five IMFs of each epoch taken from data set are computed. As first IMF has more information content than other higher index IMFs, we have used only 3 out of 5 IMFs for further processing. These chosen 3 IMFs are decomposed into their AE and IF functions using DESA, which is discussed in chapter 2. Obtained AE-IF functions are used for extracting the feature set.

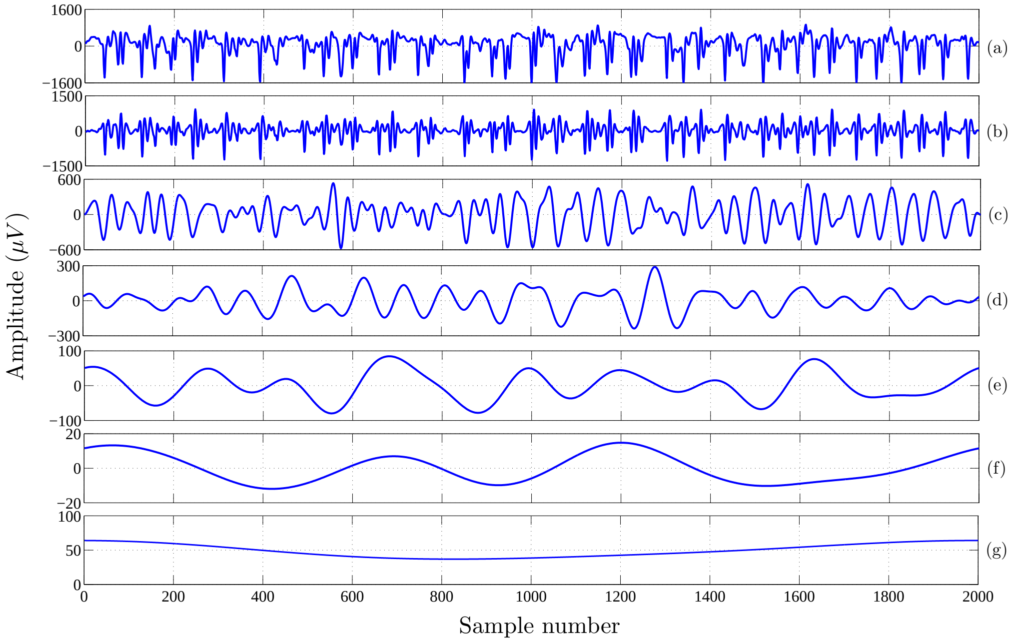


Figure 3.2: Plots of seizure activity EEG epoch and its IMFs: (a) Seizure activity epoch; (b) IMF1; (c) IMF2; (d) IMF3; (e) IMF4; (f) IMF5; (g) Residual signal.

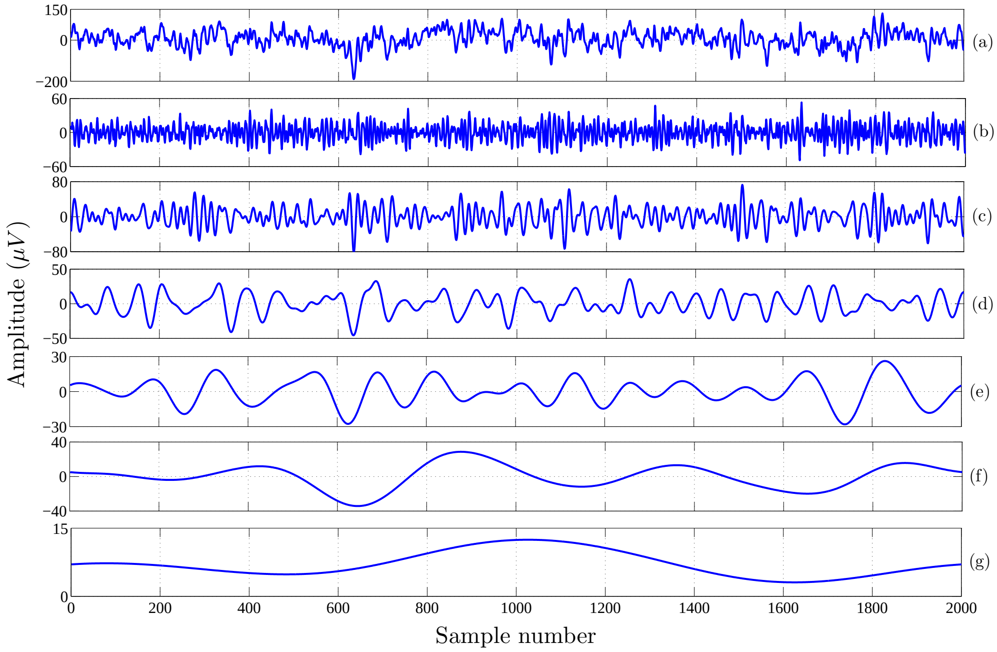


Figure 3.3: Plots of normal EEG with eyes open epoch and its IMFs: (a) Normal EEG epoch; (b) IMF1; (c) IMF2; (d) IMF3; (e) IMF4; (f) IMF5; (g) Residual signal.

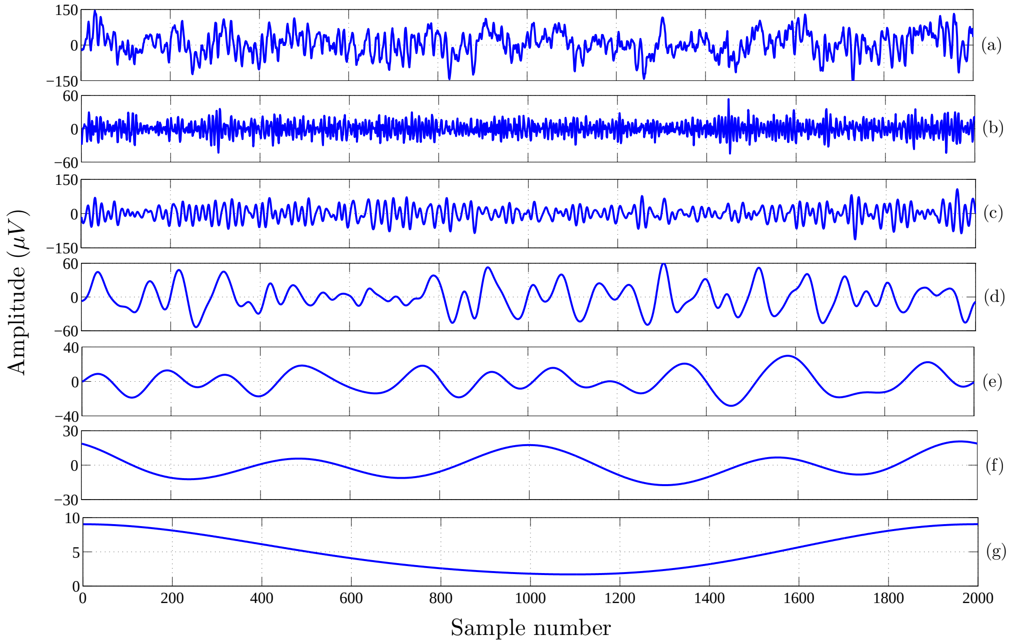


Figure 3.4: Plots of normal EEG with eyes closed epoch and its IMFs: (a) Normal EEG epoch; (b) IMF1; (c) IMF2; (d) IMF3; (e) IMF4; (f) IMF5; (g) Residual signal.

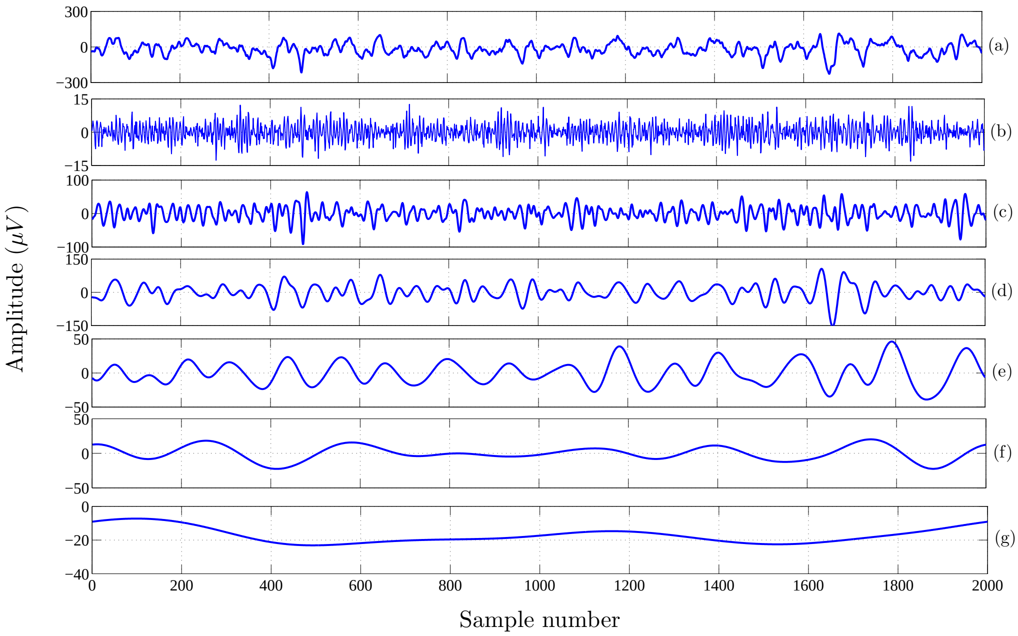


Figure 3.5: Plots of seizure-free EEG epoch taken from hippocampal formation from opposite hemisphere of the brain and its IMFs: (a) seizure-free EEG epoch; (b) IMF1; (c) IMF2; (d) IMF3; (e) IMF4; (f) IMF5; (g) residual signal.

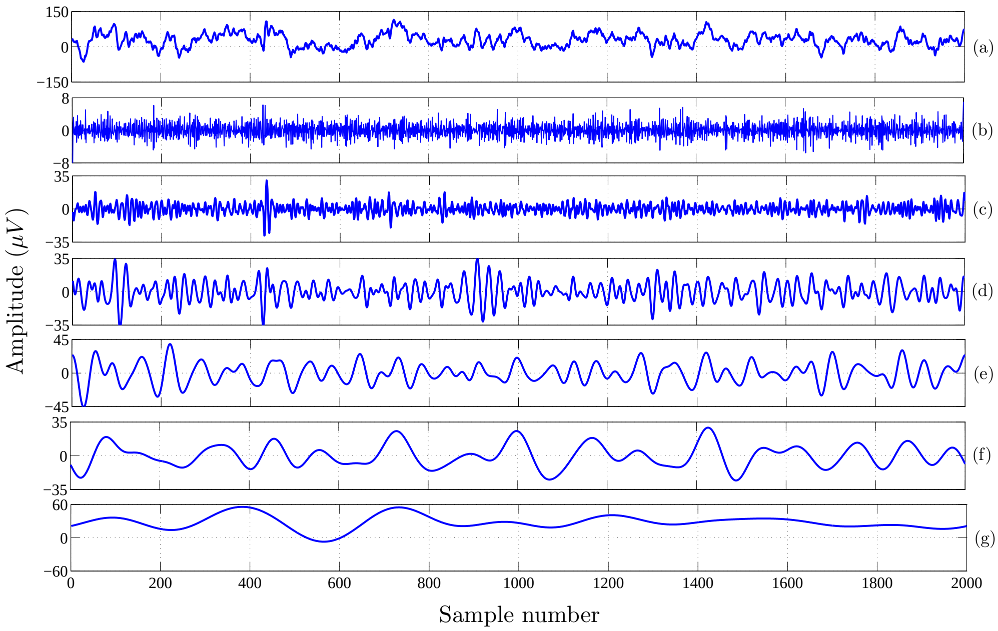
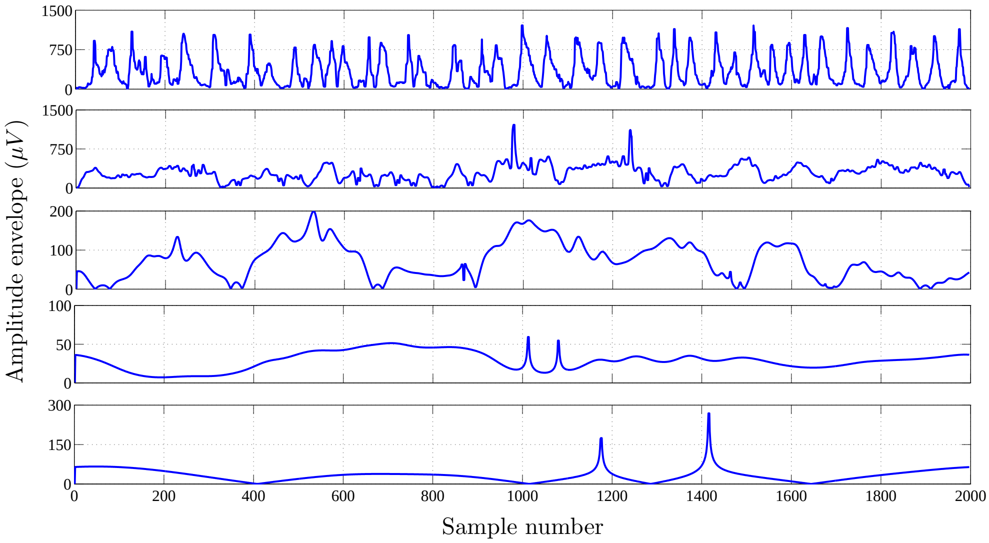
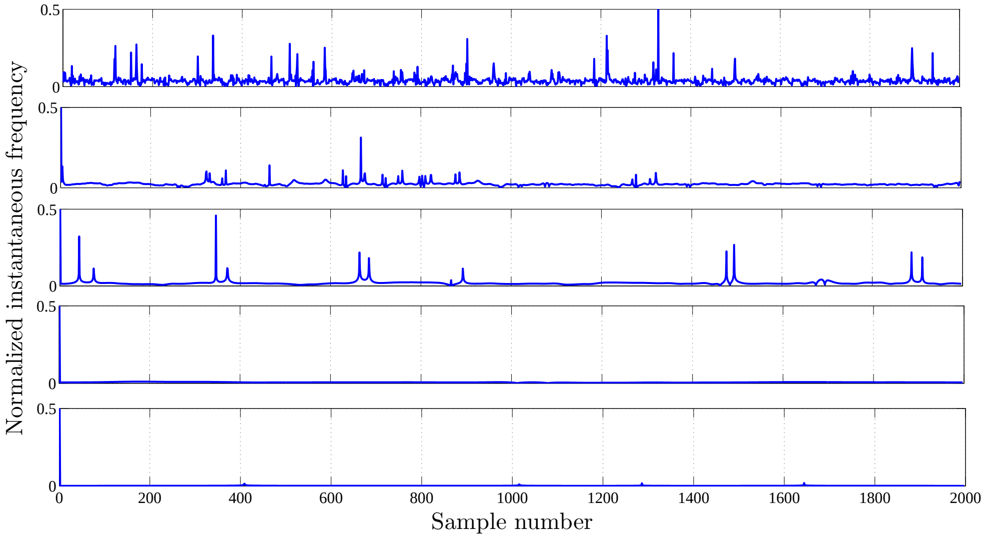


Figure 3.6: Plots of seizure-free EEG epoch taken from epileptic zone and its IMFs: (a) seizure-free EEG epoch; (b) IMF1; (c) IMF2; (d) IMF3; (e) IMF4; (f) IMF5; (g) residual signal.

Figure 3.2-Figure 3.6 show IMFs obtained from EEG epochs for the signals of each sub-set from (A, B, C, D, and E) using iterative filtering. Figure 3.7-Figure 3.11 represent AE and IF functions of obtained IMFs respectively. The (a) parts of Figure 3.7-Figure 3.11 represent the corresponding AE functions of IMFs and (b) parts of Figure 3.7-Figure 3.11 show IF functions of the obtained IMFs.

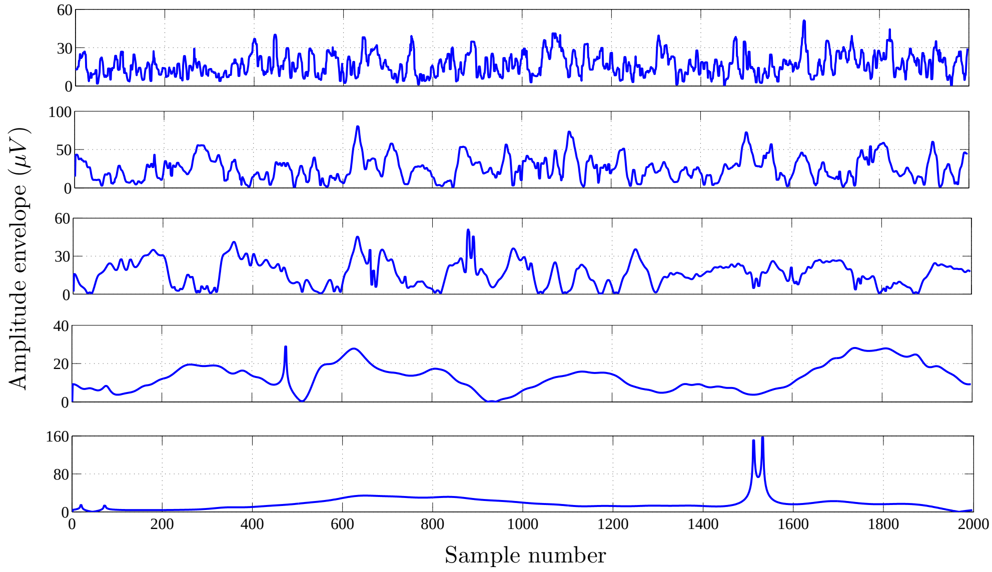


(a)

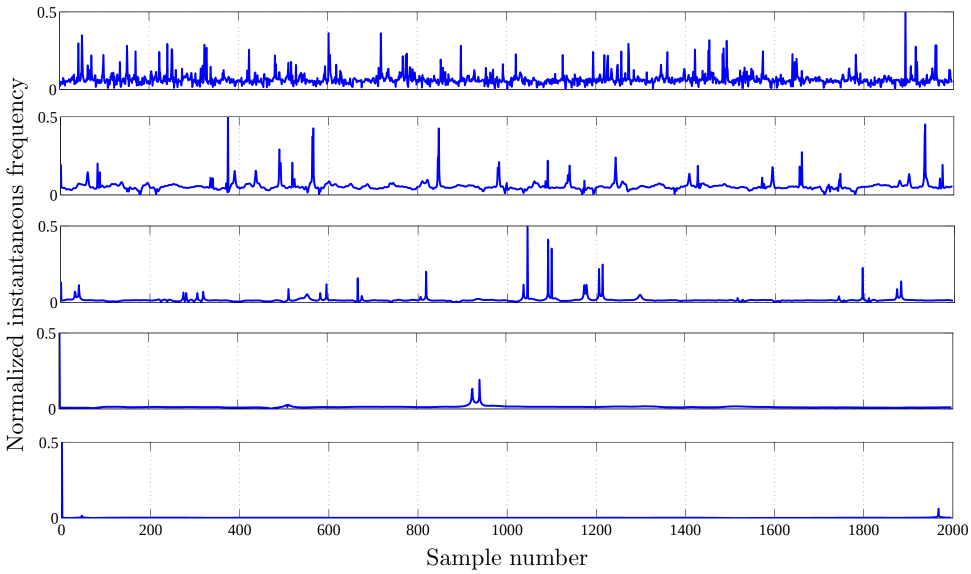


(b)

Figure 3.7: Plots of (a) AE functions; (b) IF functions of first five IMFs of seizure EEG epoch.

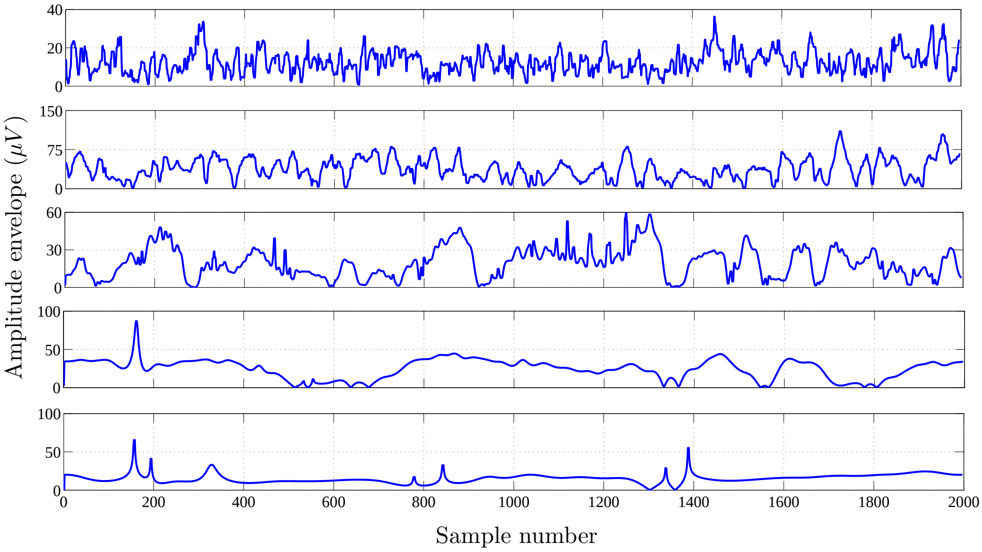


(a)

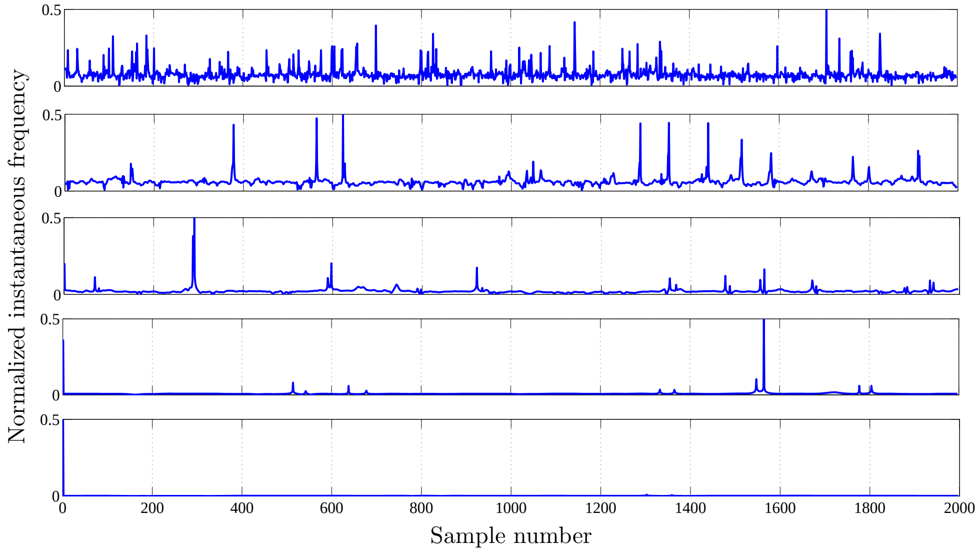


(b)

Figure 3.8: Plots of (a) AE functions; (b) IF functions of first five IMFs of Normal EEG epoch taken with eyes open.

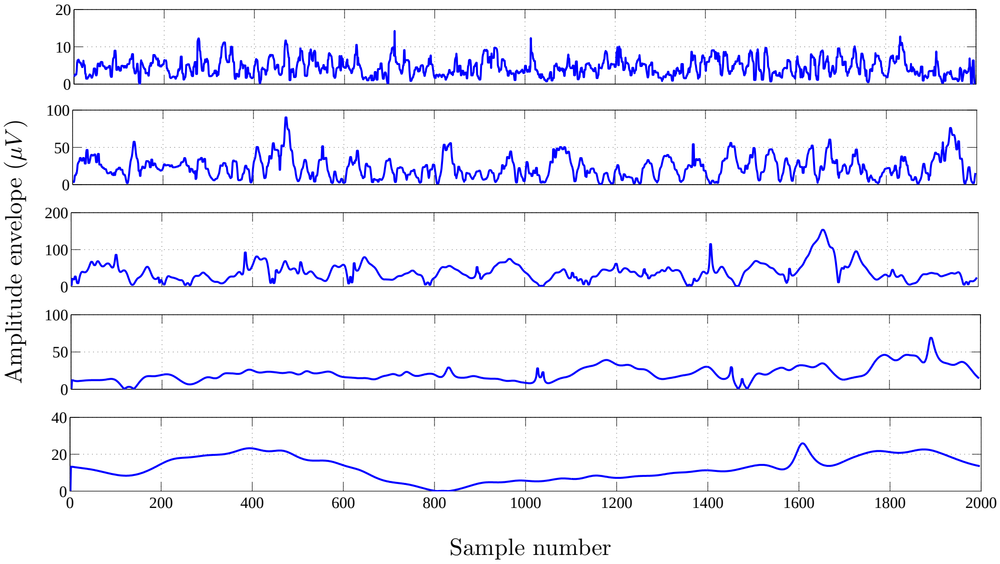


(a)

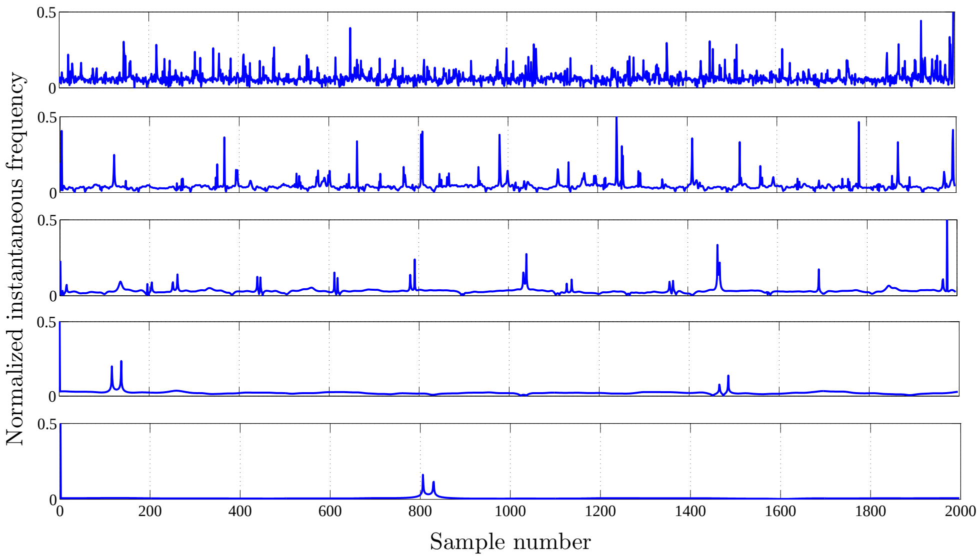


(b)

Figure 3.9: Plots of (a) AE functions; (b) IF functions of first five IMFs of normal EEG epoch taken with eyes closed.

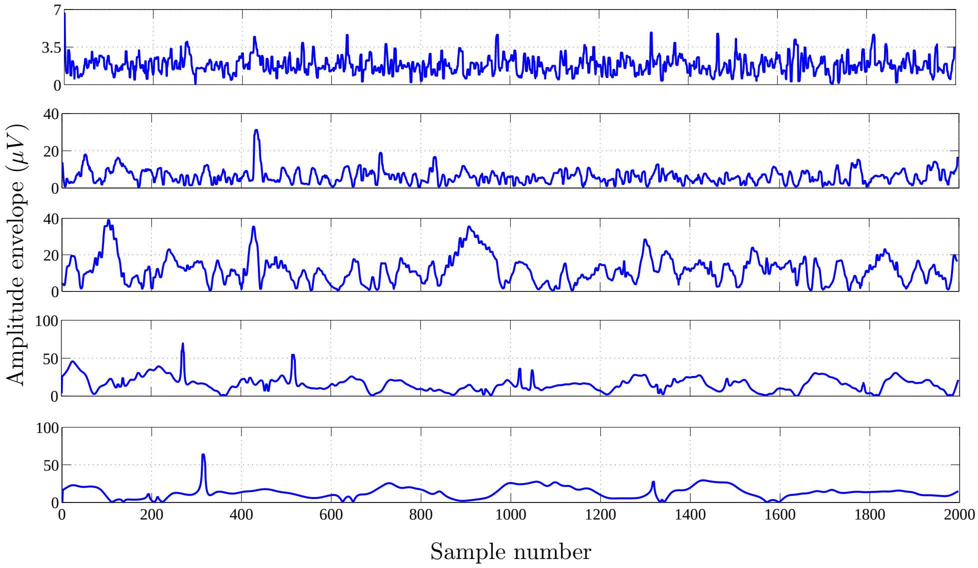


(a)

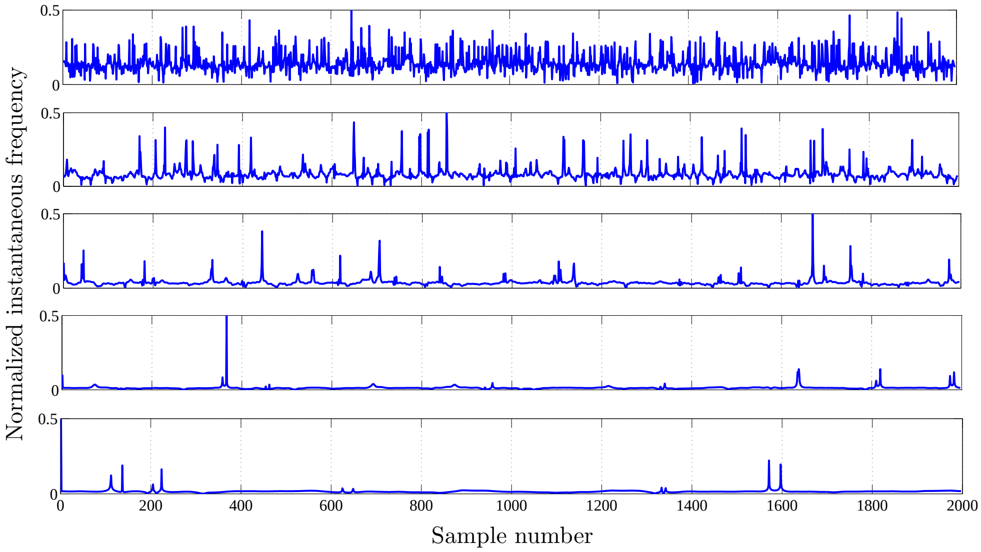


(b)

Figure 3.10: Plots of (a) AE functions; (b) IF functions of first five IMFs of seizure-free EEG epoch taken from hippocampal formation from opposite hemisphere of the brain.



(a)



(b)

Figure 3.11: Plots of (a) AE functions; (b) IF functions of first five IMFs of seizure-free EEG Epoch taken from epileptic zone.

3.2.1 Classification objective

In our thesis proposed methodology is studied on the EEG signals obtained from publicly database available at [70] to determine the efficiency of it in terms of classification parameters [69]. Number of epochs used in this thesis are mentioned in Table 3.1. Performance parameters using proposed methodology are evaluated for each multi-class classification case and compared with the other existing methods. The earlier mentioned features namely KNNE [75], SE [76], LEE [77], width of Poincaré plot [78], length of Poincaré plot [78], and area of Poincaré plot [78], are computed from first three modes obtained using iterative filtering decomposition. For the five sets of EEG recordings described in section 3.1, we have considered five different cases of classification problems in this work.

Based on their clinical relevance as well as their wide usage by various researchers these cases are formulated for EEG signal classification [72, 73, 74]. The **Case 1** corresponds to classifying the EEG signals into three different categories. The EEG segments from sets A and B are grouped together forming normal class, sets C and D are grouped as seizure-free class, and set E signals belong to seizure class. In **Case 2**, the signals in sets A, D, and E are classified as healthy, seizure-free, and seizure classes respectively. In **Case 3**, the signals from sets A and E are used in classification between healthy and seizure classes respectively. **Case 4**, contains sets A, B, C, and D grouped together as the non-seizure class whereas the set E is considered as seizure class and classification among the two classes has been done. **Case 5**, contains sets D and E, which are classified as seizure-free and seizure classes respectively. All cases discussed here are tabulated in Table 3.2.

Table 3.2: Cases based on different clinical purposes for classification

Cases	Grouping of sets	Classifications
Case 1	Sets A,B	Normal
	Sets C,D	Seizure-free
	Set E	Seizure
Case 2	Set A	Normal
	Set D	Seizure-free
	Set E	Seizure
Case 3	Set A	Normal
	Set E	Seizure
Case 4	Sets A,B,C,D	Non-seizure
	Set E	Seizure
Case 5	Set D	Seizure-free
	Set E	Seizure

3.3 Feature set

Feature extraction from EEG signal is a crucial task for classification. In this work, we have used KNNE [75], SE [76], LEE [77], and Poincaré plot descriptors [78] as features. These features are summarized as follows:

3.3.1 Entropies

Coifman and Wicker Hauser [79] presented entropy-based wavelet packet decomposition used to compute the SE and LEE. Information content of signal is computed by entropy. In other words, degree of randomness present in a signal is represented by entropy of signal. For a finite length discrete random variable $X = [x(0), x(1), x(2), ...x(N-1)]$, with probability distribution function denoted by $p(x)$ entropy is defined by following equation:

$$H(X) = -\sum_{i=1}^{\infty} p_i(x)\log_2[p_i(x)] \tag{3.1}$$

.

where i indicates one of the discrete states.

The KNNE is a measure of scattering of the signal [79]. The central idea in

KNEE estimator is to estimate the probability mass around each sample point by a local Gaussian approximation. Its computation is based on the distances of a sample from its k nearest neighbors [79]. The value of $k = 5, 11, 15$ are considered in this work. In our work, maximum value of ACC is obtained for $k = 11$. The SE, introduced by Shannon [79], is an functional of $p(x)$ in the sense of expectation in the following form:

$$H_{\mathrm{SE}}(X) = -E[\log_2(p(x)] \tag{3.2}$$

where E denotes expectation operator. The SE is the average information content of any random variable X. The SE is used as a measure of uncertainty in the system and can be given as follows [76]:

$$H_{\mathrm{SE}}(X) = -\sum_{i=1}^{\infty}[p_i(x)]^2[\log_2 p_i(x)]^2 \tag{3.3}$$

. Similarly LEE [77] is defined as:

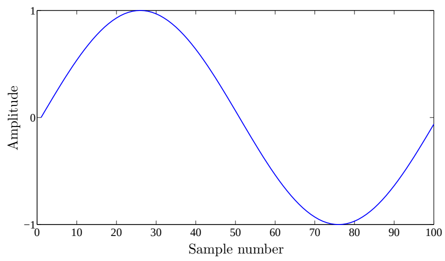
$$H_{\mathrm{LEE}}(X) = -\sum_{i=1}^{\infty}(\log_2 p_i(x))^2 \tag{3.4}$$

In this work, entropies namely LE, SE and KNNE are computed to analyze the regularities in EEG signals. The more regular the data, lower is the calculated SE.

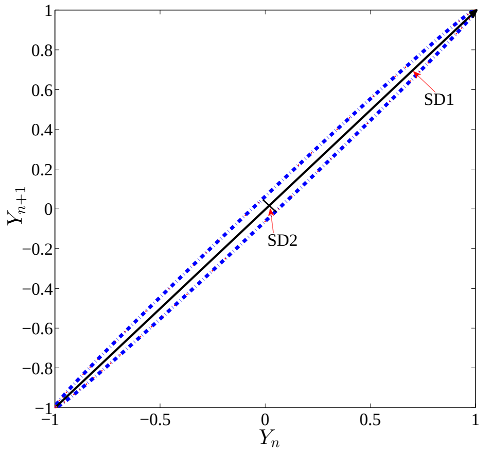
3.3.2 Poincaré plot

Poincaré plot is a return map depicting each measured value as a function of previous value. It is a simple method that describes the evolution of a system and helps in finding out the variability measure of any time series [78]. Idea of return map can be given as follows [80]: for a given time series $y(n)$ represented as $y(n) = y(0), y(1), y(2), ...$ then its return map can be given as map of points $(y(0), y(1))$, $(y(1), y(2))$, $(y(2), y(3))$ and so on. Poincaré plot gives an idea of how much repeatability is present in the time series, so that some recurring property of time series, especially non-stationary time series like electrocardiogram (ECG), electromyogram (EMG) signal, can be tracked. By fitting an ellipse on the

Poincaré plot, two standard descriptors of plot, namely length of ellipse (SD1) and width of ellipse (SD2) , can be used to quantify the plot. Also these parameters can be used as discriminative factor for classifying the two time series with different characteristics.



(a)

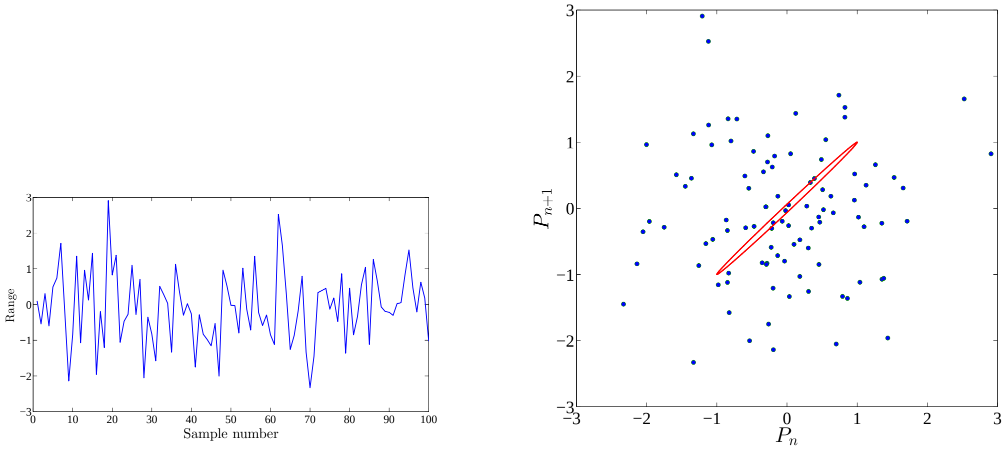


(b)

Figure 3.12: (a) Sinusoidal signal $y(n)$; (b) Poincaré of $y(n)$ and ellipse fitting in plot

Figure 3.12(a) shows a generated sinusoidal $y(n)$ of 1 Hz with sampling frequency $F_s = 100$ Hz and its Poincaré plot is shown in Figure 3.12(b). Poincaré plot generated here is by plotting one sampled advanced time series $y(n+1)$ with respect to $y(n)$. A perfect ellipse can be fitted if the data series(original series and its time shifted version) is well correlated. Larger the area of Poincaré, higher is the repeatability present in the time series. Figure 3.13(a) shows a plot of normally distributed random noise, with amplitude range [-3,3] and Figure 3.13(b) shows its Poincaré plot. Ellipse fitting on Poincaré plot is shown in Figure 3.12(b) and in Figure 3.13(b). As random noise is highly uncorrelated, no ellipse can be fitted to plot and the area of ellipse is nearly zero.

In our work, we have used length of Poincaré plot SD1, its width SD2 and area of the fitted ellipse given as, Area=$\pi \times$ SD1 $\times$ SD2 [78], as features for classification between seizure, normal and seizure-free EEG classes.



(a) (b)

Figure 3.13: (a) Generated random noise $p(n)$ (b) Poincaré plot of $p(n)$ and ellipse fitting in plot

3.4 Kruskal-Wallis test

The Kruskal-Wallis (KW) [81, 82] test is similar to classical one-way analysis of variance (ANOVA) except that it is non-parametric in nature. In this method, medians of the groups of given data, are compared to determine if the samples come from same population or populations who have similar distributions. This process results in probability p-value for the hypothesis. Lower the p-value, better will be the discriminative property available in data columns. In our work, all suggested features are found to be significant, with lower p-values ($p<0.05$), indicating their suitability for good discrimination of seizure, seizure-free, and normal EEG signals. KW test has been used for feature analysis in [83].

3.5 Classifiers

Features extracted from EEG signals (seizure, seizure-free, and seizure) are given to various classifiers for classification. The performance of the classifier is measured in terms of ACC, SEN, SPF, and area under ROC [84]. The classifiers employed in this work are briefly discussed in this section.

3.5.1 Naïve Bayes

Naïve Bayes [85] uses Bayes theorem approach for classification. Simpler approach for accurate prediction of test instances based on probabilistic information is used in Naïve Bayes classifier. Conditional independence of predictive attributes and absence of unknown attributes, which can affect the prediction process, are the assumptions used with this classification algorithm [85].

3.5.2 C4.5 decision tree classifier

This is a most commonly used, logically inductive, and interpretive classification method [86]. A top-down approach is followed for tree construction, which starts from a tuple [87]. Collection of attributes and a class value is called a tuple. An attribute may have continuous as well as discrete values but only discrete values must be present in a class. A tree consists of nodes and leaves. Classification ability of an attribute is tested by specifying a node to it. Whole training set is initially connected to root node and each weight value is set to unity. This algorithm employs a divide and conquer approach to construct a decision tree [88]. At any node, highest information gain attribute is selected for test and for each possible outcome of particular class, a child node is created. Selection of best attribute for the node is done by repeating the process for each attribute.

3.5.3 Random forest

Different classification trees make collective decision to perform a classification in random forest classifier [89]. A decision about a particular class is done by each individual tree and final decision about any class is done by assigning a weight to each tree. Overall classification decision output about a class is done by taking each tree into consideration. A random tree is employed for constructing a tree [90]. In this algorithm, n^{th} tree is assigned a random vector. This random vector ρ_n is generated without disturbing the previous distribution of vectors and is created independently of other vectors. A decision tree is grown based on the input vector$h$ and vector ρ_n, resulting in a tree classifier $T(h, \rho_n)$ [89]. On the basis of the margin function (MF), a class is determined, which can be defined for training through two randomly selected vector distribution U, Z as [89]:

$$\mathrm{MF}(U,Z) = \mu\beta_n I[T_n(U) = Z] - \max_{j \neq Q} \mu\beta_n I[T_n(U) = j] \tag{3.5}$$

where $T_n(U) = T(h, \rho_n)$ and $I(:)$ denotes indicator function[89]. The operator $\mu\beta_n$ indicates the average value. Higher confidence in classification is obtained by large margin value of a particular class. The generalization error (GE) is obtained as :

$$GE = P_{u,z}[\mathrm{MF}(U,Z) < 0] \tag{3.6}$$

where $P_{u,z}$ indicates probability over U, Z space. Accuracy of individual classifier and dependency are determined by two parameters namely, strength and correlation. In this work, Waikato environment for knowledge analysis (WEKA) software implementation [91] of Naïve Bayes, C4.5 decision tree, and random forest classifier for classification of seizure, seizure-free, and normal EEG signals is used. WEKA has been used for classification task in coronary artery disease diagnosis in [92]. Evaluation of a classifier can be done using some performance parameters. With test data set having TP number of correctly identified samples, TN number of true negative samples, FP number false positive samples, and FN number of false negative samples, some parameters can be defined as follows :

- **SEN**: This parameter measures ratio of correctly identified positive samples present in test set to the total number of positive samples [69] in the data set that can be given as follows:

$$SEN = \frac{TP}{TP + FN} \times 100(\%) \tag{3.7}$$

- **SPF**:Parameter evaluates classifier on the basis of ratio of ratio of correctly identified negative samples present in test set to the total number of negative samples [69] in the data set which can formulated as follows:

$$SPF = \frac{TN}{TN + FP} \times 100(\%) \tag{3.8}$$

- **ACC**: It is the ratio of correctly identified samples by the classifier to total number of samples [69] in test set. It can be formulated as follows:

$$ACC = \frac{TN + TP}{TP + FN + TN + FP} \times 100(\%) \tag{3.9}$$

ROC area, along with above mentioned parameters, has been taken into consideration for performance evaluation of classifiers.

Development of robust classifiers, which perform well with new data sample, is done by using ten-fold cross validation, a data re-sampling technique for training and testing purposes. In this re-sampling technique, ten-part splitting of data is done with approximately same proportion of data in each part. Training of the classifier is done using nine parts and left one part is used for testing. This procedure is repeated nine more times. Results obtained in each fold are used for calculating SEN, SPF, area under ROC curve and classification ACC. Performance of classifier is estimated by averaging the values of performance measures over these ten folds.

3.6 Summary

Proposed methodology of this work can be used for efficient EEG signal classification. Nonlinear entropy based feature set as well as Poincaré plot descriptors are used as attributes for classification. A brief description, about each of the feature and classifier used in this work has been given in this chapter. Ten-fold data re-sampling technique is used for a robust classification scheme.

Chapter 4

Results and discussion

4.0.1 Results

A total 500 EEG epochs (100 from each set) are used in this work. Significant features (mentioned in earlier section) have been selected from these data to form classification data set. Classification algorithms are selected on the basis of this data set. Suggested features from AE and IF fucntions of IMFs are extracted and their discriminative strength is obtained by performing KW statistical test [81] on the feature set. This test results in the p-values. All suggested features are found to be significant with less p-values ($p<0.05$) indicating their suitability for good discrimination of seizure, seizure-free, and normal EEG signals. Obtained p-values are mentioned in Table 4.1. Box plots for the suggested features using first three IMFs of epochs are shown in Figures 4.1-4.3. In these figures, S denotes seizure, N denotes normal, and SF denotes seizure-free class. Features obtained by suggested descriptors are used for classification using random forest classifier, C4.5 decision tree, and Näive Bayes classifier. Through experiments, we have observed that classification done using suggested features has outperformed many other existing methods in terms of ACC. All the calculated values are tabulated in Table 4.2. The best performance has been achieved using random forest classifier. For three class classification KNNE yielded best results with random forest classifier.

Table 4.1: Range (Mean $\pm$ standard deviation) and p-value of various features computed using first three IMFs.

Feature		Range (Mean $\pm$ standard deviation)			p-value
		Seizure	Normal	Seizure-free	
SE	IMF1	$(-2.7213\pm 3.7306) \times 10^{+9}$	$(-4.2725\pm 8.2127) \times 10^{+7}$	$(-2.234\pm 7.6115) \times 10^{+6}$	6.5805×10^{-66}
	IMF2	$(-1.7162\pm 2.0847) \times 10^{+9}$	$(-1.6934\pm 0.20094) \times 10^{+8}$	$(-2.5305\pm 5.9304) \times 10^{+7}$	7.5805×10^{-81}
	IMF3	$(-2.5016\pm 0.57471)\times10^{+9}$	$(-6.6048\pm 5.0067)\times10^{+6}$	$(-0.6203\pm 2.2358)\times10^{+8}$	3.065×10^{-81}
KNNE (11 neighbors)	IMF1	-7.6857 ± 9.7687	-26.8364 ± 7.2272	(-44.5745 ± 7.2514)	$(3.1172) \times 10^{-69}$
	IMF2	-8.0289 ± 8.0539	-27.5663 ± 4.0156	(-29.0277 ± 6.4891)	$(2.1672) \times 10^{-19}$
	IMF3	-20.1595 ± 8.6436	-31.3310 ± 3.0717	-24.8416 ± 5.4583	4.027×10^{-16}
KNEE (15 neighbors)	IMF1	-8.7431 ± 13.3217	-34.8596 ± 9.8555	-59.0511 ± 9.8876	3.046×10^{-69}
	IMF2	-9.2102 ± 10.9832	-35.8559 ± 5.4747	-37.8478 ± 8.8496	2.18×10^{-19}
	IMF3	-25.7512 ± 11.7846	-40.9843 ± 4.1850	-32.1317 ± 7.4455	3.776×10^{-16}
KNNE (5 neighbors)	IMF1	-2.7093 ± 4.4404	-11.4134 ± 3.2856	-19.4768 ± 3.2979	3.2280×10^{-69}
	IMF2	-12.2564 ± 3.0870	-14.2166 ± 1.8762	-11.9294 ± 3.1311	8.8980×10^{-16}
	IMF3	-11.7093 ± 5.4504	-13.4134 ± 2.2866	-18.4768 ± 5.2679	4.2280×10^{-13}
LEE	IMF1	$(3.2301 \pm 0.7942) \times 10^{+4}$	$(1.9427 \pm 0.5307) \times 10^{+4}$	$(6.3172\pm 5.308) \times 10^{+3}$	6.504×10^{-66}
	IMF2	$(3.4298 \pm 0.6858)\times10^{+4}$	$(1.9665 \pm 0.2922)\times10^{+4}$	$(15.03\pm 5.0046)\times10^{+3}$	7.504×10^{-18}
	IMF3	$(2.6274 \pm 0.70521)\times10^{+4}$	$(1.5664 \pm 0.2200)\times10^{+4}$	$(1.9794\pm 0.3930)\times10^{+3}$	3.065×10^{-16}
Plot length SD1	IMF1	$(5.2629 \pm 7.7318) \times 10^{+4}$	$(0.7596 \pm 1.5589) \times 10^{+3}$	$(0.6693\pm 2.6401)\times10^{+2}$	2.3940×10^{-79}
	IMF2	$(2.6282 \pm 2.8371)\times10^{+4}$	$(0.6448 \pm 0.5549)\times10^{+3}$	$(0.64238\pm 1.8502)\times10^{+3}$	1.8126×10^{-58}
	IMF3	$(7.4453 \pm 10.088)\times10^{+3}$	$(0.2094 \pm 0.1126)\times10^{+3}$	$(1.7047\pm 6.6259)\times10^{+3}$	1.6575×10^{-54}
Plot width SD2	IMF1	$(1.0664 \pm 1.4873) \times 10^{+3}$	(19.7086 ± 33.4019)	(1.5699 ± 4.7586)	2.0047×10^{-81}
	IMF2	(285.6918 ± 362.5319)	(5.1938 ± 4.7312)	(6.3746 ± 13.4310)	1.8824×10^{-44}
	IMF3	(46.3996 ± 111.1172)	(1.0620 ± 0.7355)	(10.4421 ± 54.0776)	1.5908×10^{-46}
Plot area ($\pi \times$ SD1 $\times$ SD2))	IMF1	$(4.7645 \pm 10.088) \times 10^{+8}$	$(2.0558 \pm 6.2735) \times 10^{+5}$	$(0.3872\pm 2.6329) \times 10^{+4}$	1.2014×10^{-80}
	IMF2	$(5.2482 \pm 11.528)\times10^{+7}$	$(1.7117 \pm 4.5973)\times10^{+4}$	$(0.8727\pm 5.8601)\times10^{+5}$	1.3977×10^{-51}
	IMF3	$(3.8431 \pm 12.891)\times10^{+6}$	$(1.5664 \pm 0.2200)\times10^{+4}$	$(0.8348\pm 7.6244)\times10^{+6}$	8.8736×10^{-53}

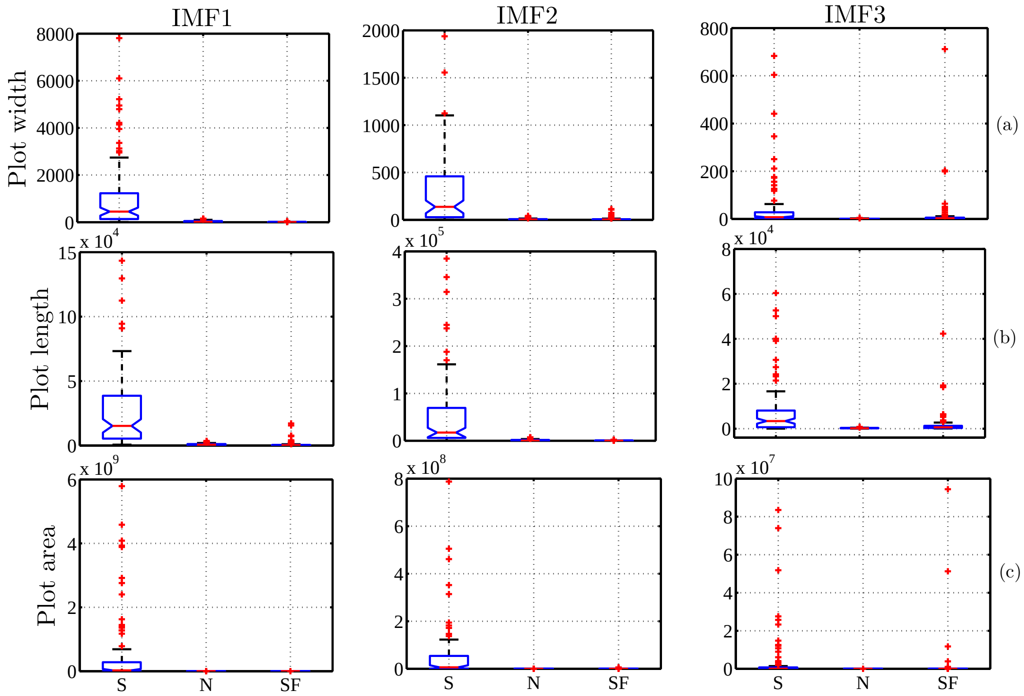


Figure 4.1: Box plots for first three IMFs for features obtained from Poincaré plots; (a) Plot width SD2; (b) Plot length SD1; (c) Plot area.

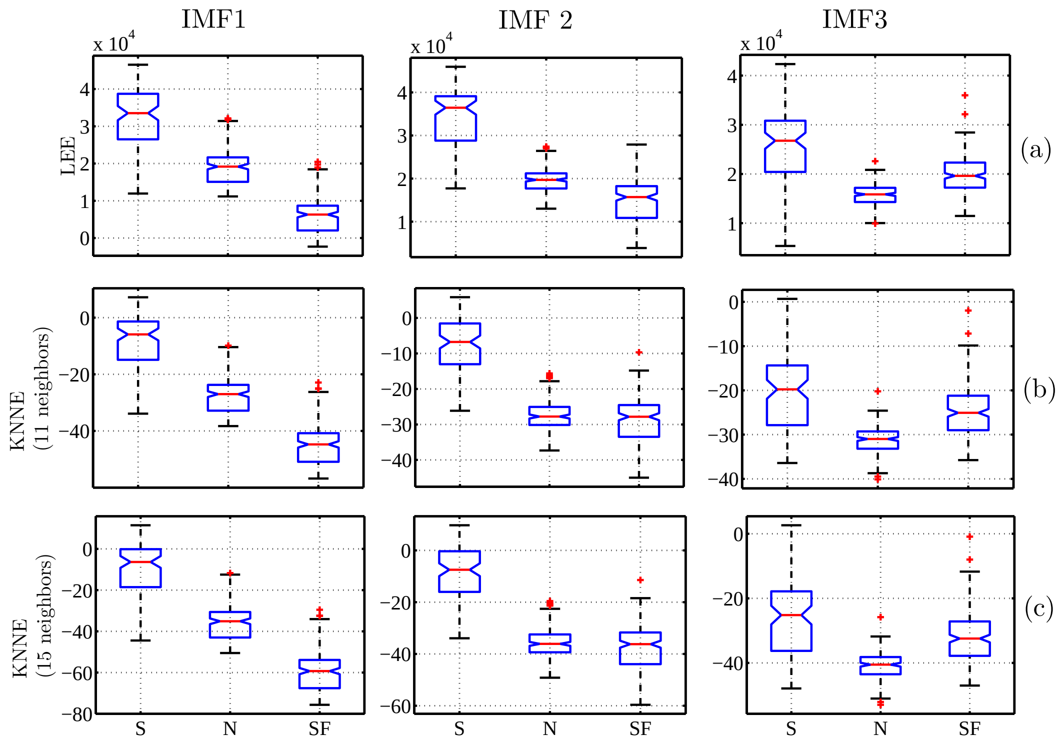


Figure 4.2: Box plots for first three IMFs for obtained features (a) LEE; (b) KNNE with 11 neighbors; (c) KNNE with 15 neighbors.

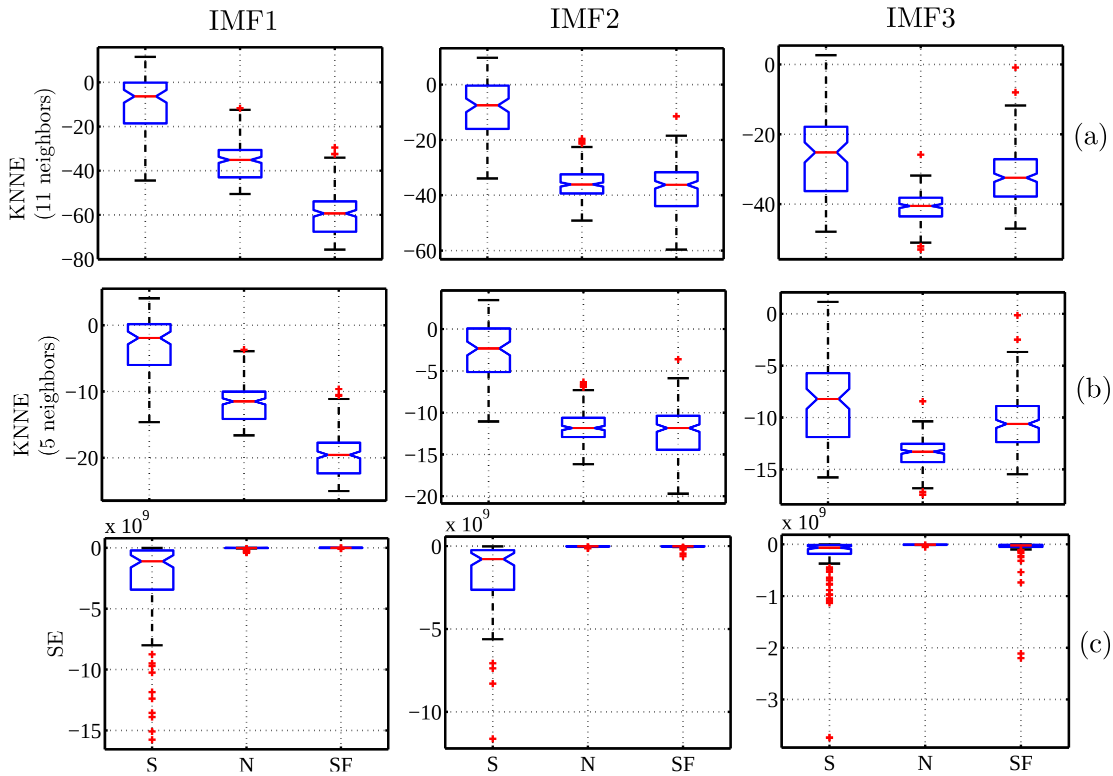
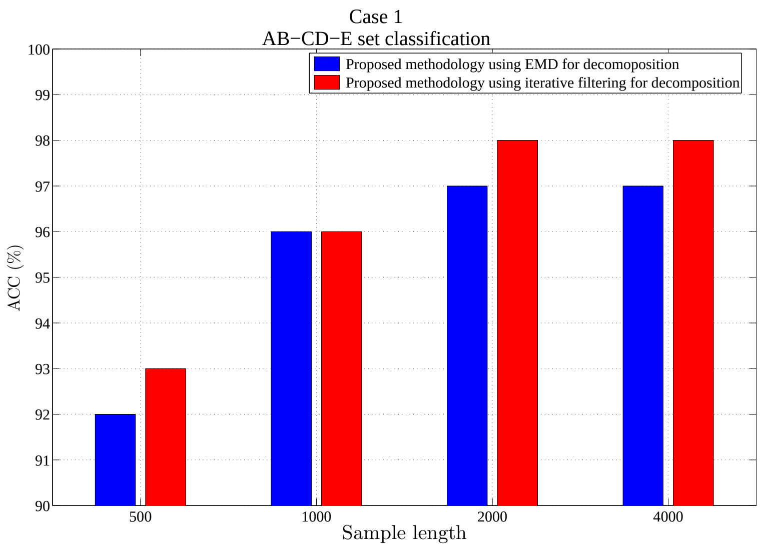


Figure 4.3: Box plots for first three IMFs for obtained features (a) KNNE with 15 neighbors; (b) KNNE with 5 neighbors; (c) SE.

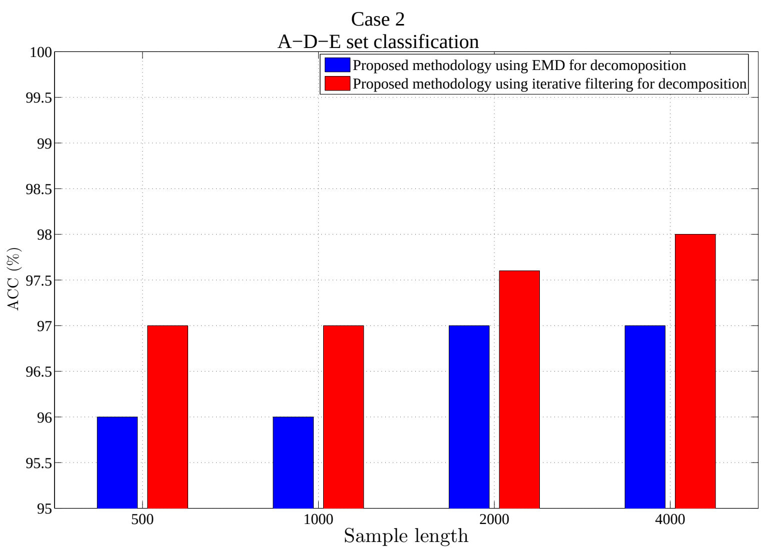
Table 4.2: Classification results for studied cases on the basis of classifier efficiency parameters with five different epoch lengths.

Sample length	Case	ACC (%)	SEN (%)	SPF (%)	ROC area
4000 samples	Case 1	98.0	97.8	99.0	0.998
	Case 2	98.0	97.8	99.0	0.990
	Case 3	99.5	99.5	99.5	1.000
	Case 4	98.6	98.6	96.4	0.992
	Case 5	96.0	96.0	96.0	0.969
2000 samples	Case 1	98.0	97.8	99.0	0.998
	Case 2	97.6	97.6	96.8	0.997
	Case 3	99.5	99.5	99.5	1.000
	Case 4	98.4	98.4	95.0	0.997
	Case 5	96.0	96.0	96.0	0.969
1000 samples	Case 1	96.0	95.8	97.5	0.995
	Case 2	97.0	97.0	98.5	0.997
	Case 3	99.5	99.5	99.5	1.000
	Case 4	98.4	98.4	95.1	0.997
	Case 5	96.0	96.0	96.0	0.969
500 samples	Case 1	93.2	93.2	96.0	0.991
	Case 2	97.0	97.0	98.5	0.997
	Case 3	98.0	98.0	98.0	1.000
	Case 4	96.8	96.8	91.7	0.995
	Case 5	93.5	93.5	93.5	0.991

Figures 4.4(a), 4.5(a), 4.6(a) represent the performance on the basis of ACC of proposed methodology and EMD using random forest classifier for all five cases of clinical imporatnce as discussed in earlier chapter. Figure 4.6(b) represents a comparison of performance between random forest classifier and C4.5 decision tree classifier on the basis of ACC for case 1. Figure 4.7 represents a comparison of performance between random forest classifier and Naïve Bayes classifier on the basis of ACC for case 1. Figure 4.8(a) and (b) shows the variation of ACC with the number of trees used for classification in random forest classifier for case 1 and case 3, respectively.

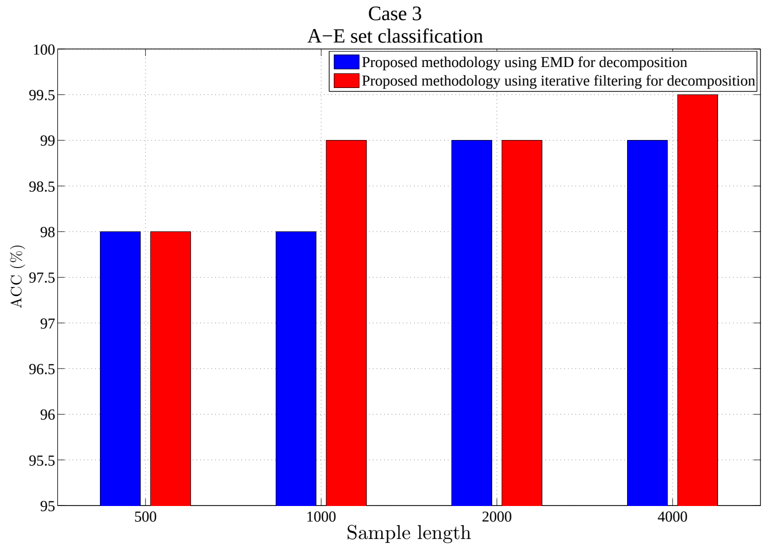


(a)

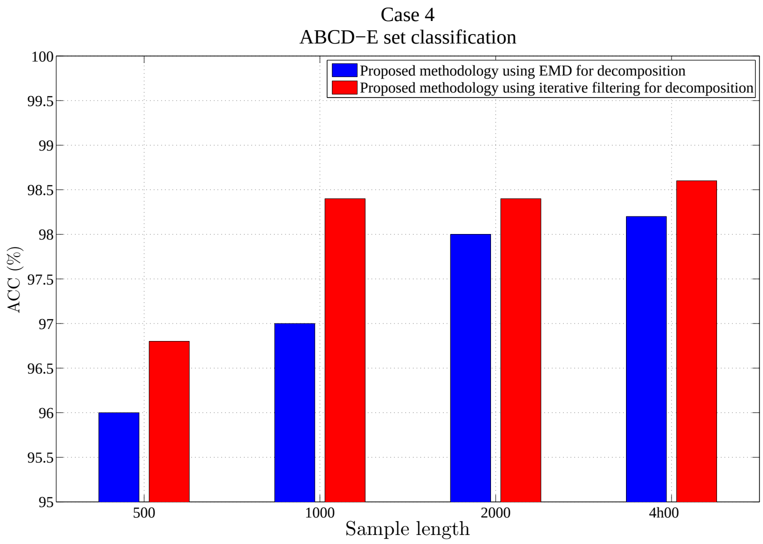


(b)

Figure 4.4: Plot of results obtained (a) ACC comparison of iterative filtering and EMD based proposed methodology for case 1; (b) ACC comparison of iterative filtering and EMD based proposed methodology for case 2.

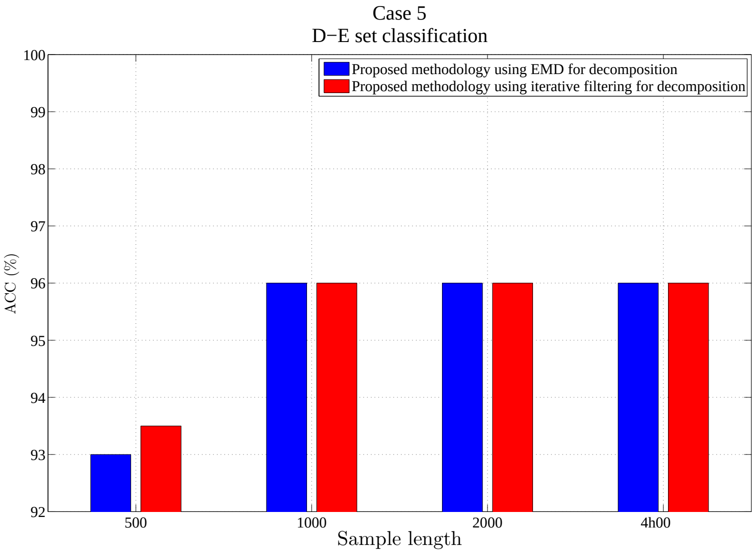


(a)

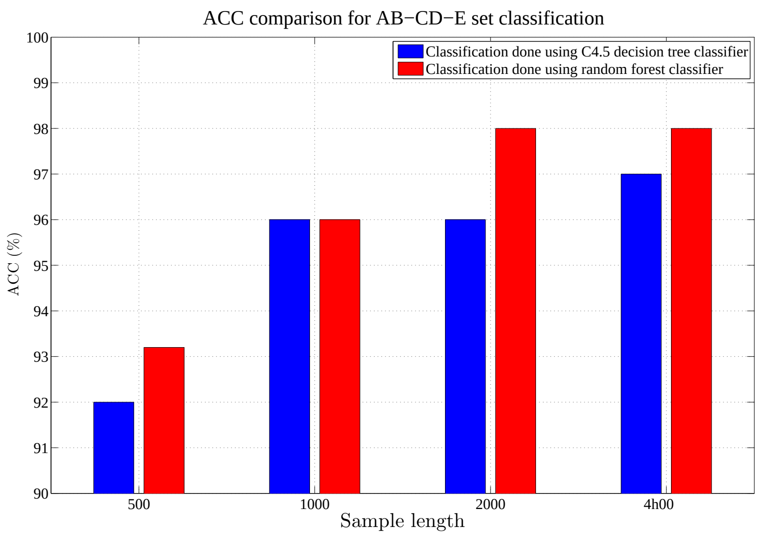


(b)

Figure 4.5: Plot of results obtained (a) ACC comparison of iterative filtering and EMD based proposed methodology for case 3; (b) ACC comparison of iterative filtering and EMD based proposed methodology for case 4.

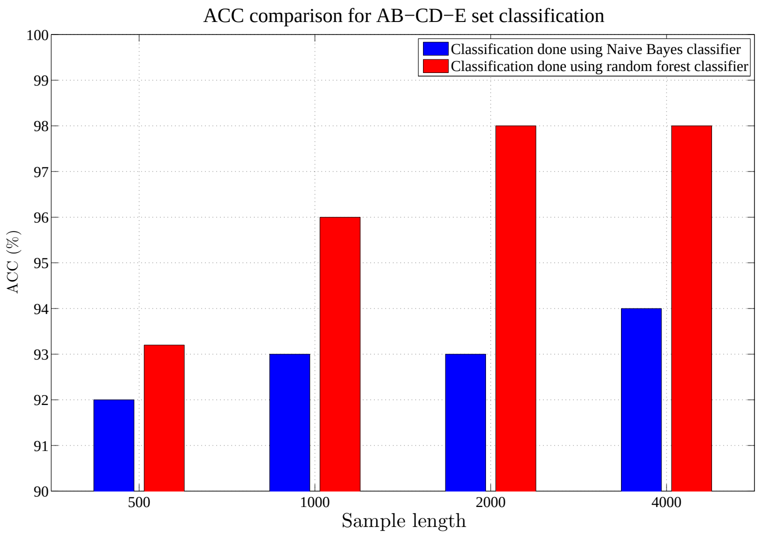


(a)



(b)

Figure 4.6: Plot of results obtained: (a) ACC comparison of iterative filtering and EMD based proposed methodology for case 5; (b)Comparison of ACC using RF and C4.5 classifiers for seizure, seizure-free, and normal classes.



(a)

Figure 4.7: Plot of results obtained: Comparison of ACC using random forest and Naïve Bayes classifiers for seizure, seizure-free, and normal classes.

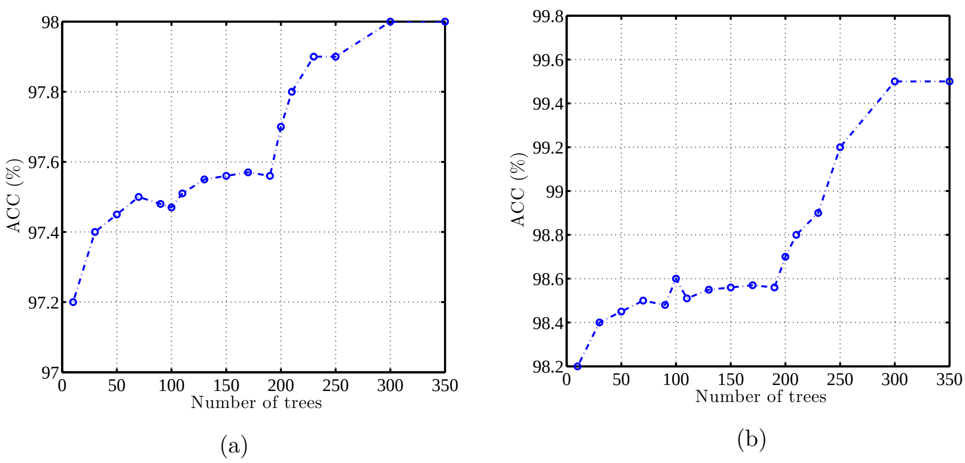


Figure 4.8: Plot of results obtained: Variation of ACC with varying number of trees in random forest classifier (a) 3-class classification for sets (AB-CD-E); (b) 2-class classification for sets (A-E).

Performance comparison of our proposed methodology with other existing methods for three class classification for set (AB-CD-E) and two class classification for sets (ABCD-E) and (A-E), is tabulated in Table 4.3. Comparison between different methods has been done on the basis of ACC.

Table 4.3: Performance comparison of our proposed methodology with other existing methods for sets (A-E), (ABCD-E) and (AB-CD-E) classification. Epoch sample length = 4000 samples.

Authors	**Techniques used**	**Experiment type**	**ACC (%)**
Tzallas et al. [42] (2007)	Time frequency analysis and ANN	A-E ABCD-E AB-CD-E	100 97.73 97.72
Orhan et al. [94] (2011)	K-means clustering and multilayer perceptron (MLP) neural network model	A-E ABCD-E AB-CD-E	100 99.60 95.60
Tiwari et al. [93] (2017)	Key-point-based local binary pattern (LBP) and SVM	A-E ABCD-E AB-CD-E	100 99.30 98.80
This work	Iterative filtering with SE, LEE, KNNE, and Poincaré plot features with random forest classifier	A-E ABCD-E AB-CD-E	99.50 98.40 98.00

Table 4.4: Performance comparison of our proposed methodology with other existing methods for sets (D-E) and (A-D-E) classification. Epoch sample length = 4000 samples.

Authors	**Technique used**	**Experiment type**	**ACC (%)**
Kaya et al. [95] (2014)	1D-LBP and Bayes Net	D-E A-D-E	95.50 95.67
Twafik et al. [96] (2016)	Weighted permutation entropy and SVM	D-E A-D-E	97.50 97.70
This work	Iterative filtering with SE, LEE, KNNE, and Poincaré plot features random forest classifier	D-E A-D-E	96.00 98.00

4.0.2 Discussion

A comparative study of proposed methodology with other existing methods, on the basis of ACC obtained for various cases, on same database is shown in Table 4.3 and Table 4.4. In [42] time-frequency based methods with ANN are used for EEG signal analysis and have achieved ACC of 100% for seizure and normal classes classification problem, 97.7% for seizure and non-seizure classes classification with epochs taken from sets (A, B, C, D) for non-seizure epoch and set (E) for seizure epoch. The methodology proposed in [42] has achieved ACC of 97.7% for normal, seizure-free, and seizure classification i.e. sets (AB-CD-E) classification case. A DWT based methodology has been proposed in [94] and features from decomposed coefficients are used for EEG signal classification. With k-means clustering and multilayer perceptron (MLP) classifier ACC of 100%, 99.6% and 95.6% has been achieved for epoch sets (A-E), (ABCD-E) and (AB-CD-E) classification cases respectively. Methodology in [93] resulted in a ACC of 99.31% and 98.8% for (ABCD- E) and (AB-CD-E) sets classification cases respectively. Our proposed method has achieved a highest ACC of 99.5% for seizure and seizure-free with epochs taken from (A and E) and sample length of 4000 samples. With a epoch length of 4000 samples, ACC of 98.4% has been achieved for seizure, seizure-free, and normal classes classification with epochs taken from sets (A and B) for normal, (C and D) for seizure-free, and from set (E) for seizure. The proposed method has achieved 98.00% ACC for sets (AB-CD-E), which is better as compared to the methods proposed in [94] and [42]. However, the proposed method achieved comparable ACC in comparison to the method proposed in [93] for sets (AB-CD-E). Similarly, the proposed method achieved 98.00% ACC for sets (A-D-E) which is superior to the methods presented in [95] and [96]. Therefore, it can be stated that the proposed method is suitable for epileptic seizure EEG signal classification for different combination of sets.

4.1 Summary

Iterative filtering, a variant of EMD, is used for signal decomposition in this work. Features extracted from AE-IF functions of signal IMFs are used for classification of EEG signals. Two and three classes classification, for various cases of clinical importance, have been done. Values of parameters obtained using classifiers with ten-fold cross validation are tabulated in Table 4.2. The obtained p-values of the features, by performing KW test on feature set, are tabulated in Table 4.1. A comparative study of our methodology and other proposed works on same database is tabulated in Table 4.3 and Table 4.4 for different classification cases. Our proposed method has proved to be quite efficient for the studied cases. On comparison of ACC obtained using random forest classifier, Nave Bayes, and C4.5 decision tree, random forest has given best results.

Chapter 5

Conclusions and future work

5.1 Conclusions

Non-stationary nature of EEG signal requires an efficient signal analysis technique for gaining a key insight to brain functioning, classification of epileptic and normal durations of EEG recordings, identification of epileptic zone for pre-surgical patients, and to deduce the absence of epileptic seizure. In our work we have used an online available EEG data set. Iterative filtering is used for decomposition of EEG epochs into their respective IMFs. From these obtained IMFs, features with good discriminative strength are selected on the basis of p-values obtained using KW test. Obtained features are given to classifiers for classification of EEG epochs. In our work we have used three classifiers namely, random forest classifier, J48 classifier, and Naïve Bayes classifier. We have obtained highest ACC of 99.5% for a two class problem, normal and seizure classes (sets (A-E)), and 98% for a three class problem normal, seizure-free, and seizure classes (sets (AB-CD-E)) using random forest classifier with epoch lengths of 4000 samples. All the mentioned cases are also tested for different epoch lengths of 2000, 1000, and 500 samples and results obtained in terms of classifier parameters have been tabulated. It is observed that with decreasing the sample length ACC also decreases. Also we have compared random forest classifier and Nave Bayes classifiers on the basis of ACC. Comparison result shows that random forest classifier has a better classification ability than Naïve Bayes classifier for the feature set obtained in our work. Variation of ACC using different number of trees in random forest classification has also been reported in this thesis. ACC obtained using EMD and our methodology on same database have also been compared. The comparison of ACC, obtained by using proposed methodology with EMD and iterative filtering for decomposition, has been reported. A slightly higher ACC has been obtained using iterative filtering. Therefore, iterative filtering can be further explored for better results. Several other features can be extracted using AE and IF functions.

5.2 Future work

Classification accuracy for 3 class problem, sets (AB-CD-E), can be further increased by combining our feature set with other non-linear features. Changing of mask length by tuning the length parameter λ affects the nature of decomposed modes. So, iterative filtering can be explored for better decomposition of signal, which can be used for extraction of more discriminative features. This can increase the ACC for smaller epoch length, which will help in automated epileptic seizure prediction with small number of samples available. Tuning of mask length can also provide a method to use iterative filtering for real time non-stationary signal processing. Adapted methodology can also be used for classification of long duration EEG signals, which will be helpful in long term monitoring. Other biomedical signals like speech, ECG, EMG etc. can be analysed using proposed methodology. Hardware implementation of methodology can also be done for real time EEG classification.

References

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

[2] L.D. Iasemidis, D.S. Shiau, W. Chaovalitwongse, J.C. Sackellares, P.M. Pardalos, J.C. Principe, P.R. Carney, A. Prasad, B. Veeramani, and K. Tsakalis, "Adaptive epileptic seizure prediction system," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 616-627, 2003.

[3] R.S. Fisher, G. Harding, G. Erba, G.L. Barkley, and A. Wilkins, "Photic and pattern-induced seizures: a review for the epilepsy foundation of America working group," *Epilepsia*, vol. 46, no. 9, pp. 1426-41, 2005.

[4] F. Mormann, R.G. Andrzejak, T. Kreuz, C. Rieke, P. David, C.E. Elger, and K. Lehnertz, "Automated detection of a pre-seizure state based on a decrease in synchronization in intracranial electroencephalogram recordings from epilepsy patients," *Physical Review Edition*, vol. 67, no. 2 , pp. 21912, 2003.

[5] X.F. Yang and S.M. Rothman, "Focal cooling rapidly terminates experimental neocortical seizures," *Annals of Neurology*, vol. 49, no. 6, pp. 1875-1888, 2010.

[6] X.F. Yang, D.W. Duffy, R.E. Morley, and S.M. Rothman, "Neocortical seizure termination by focal cooling: temperature dependence and automated seizure detection," *Epilepsia*, vol. 43, no. 3, pp. 240-245, 2002.

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

[8] W.S. Anderson, E.H. Kossoff, G.K. Bergey and G.I. Jallo, "Implantation of a responsive neurostimulator device in patients with refractory epilepsy," *Neurosurgical Focus*, vol. 25, no. 3, pp. E12, 2008.

[9] T.L. Skarpaas and M.J. Morrell, "Intracranial stimulation therapy for epilepsy," *Neurotherapeutics*, vol. 6, no. 2, pp. 238-243, 2009.

[10] S. Wong, G.H. Baltuch, J.L. Jaggi, and S.F. Danish, "Functional localization and visualization of the subthalamic nucleus from microelectrode recordings acquired during DBS surgery with unsupervised machine learning," *Journal of Neural Engineering*, vol. 6, no. 2, pp. 026006, 2009.

[11] K.B. Baker, B.H. Kopell, D. Malone, C. Horenstein, M. Lowe, M.D. Phillips, and A. R. Rezai, "Deep brain stimulation for obsessive-compulsive disorder: using functional magnetic resonance imaging and electrophysiological techniques: technical case report," *Neurosurgery*, vol. 61, no. 5, pp. 367-368, 2007.

[12] S.M. Rothman, "The therapeutic potential of focal cooling for neocortical epilepsy," *Neurotherapeutics*, vol. 6, no. 2, pp. 251-257, 2015.

[13] S. Raghunathan, S.K. Gupta, M.P. Ward, R.M. Worth, K. Roy, and P.P. Irazoqui, "The design and hardware implementation of a low-power real-time seizure detection algorithm," *Journal of Neural Engineering.*, vol. 6, no. 5, pp. 56005, 2009.

[14] H. Qu and J. Gotman, "Improvement in seizure detection performance by automatic adaptation to the EEG of each patient," *Electroencephalography and Clinical Neurophysiology.*, vol. 86, no. 2, pp. 79-87, 1993.

[15] H. Qu, "Self-adapting algorithms for seizure detection during EEG monitoring," *PhD thesis.*, Department of Biomedical Engineering, McGill University, 1994.

[16] H. Qu and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 2, pp. 115-122, 1997.

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

[18] E. Niedermeyer and F.L.D. Silva, *Electroencephalography: Basic Principles, Clinical Applications and Related Fields,* Lippincott Williams and Wilkins, 2004.

[19] J. Gotman, "Automatic recognition of interseizure spikes," *Electroencephalography and Clinical Neurophysiology*, vol. 37, pp. 93-114, 1985.

[20] D. Zumsteg, D.M. Andrade and R.A. Wennberg, "Source localization of small sharp spikes: low resolution electromagnetic tomography (LORETA) reveals two distinct cortical sources," *Clinical Neurophysiology*, vol. 117, no. 6, pp. 1380-1387, 2006.

[21] E. Niedermeyer, "The clinical relevance of EEG interpretation," *Clinical Electroencephalography*, vol. 34, no. 3, pp. 93-98, 2003.

[22] E. Niedermeyer, "Ultrafast EEG activities and their significance," *Journal of Clinical EEG and Neuroscience*, vol. 36, no. 4, pp. 257-262, 2005.

[23] T. Yu, Y. Wang, G. Zhang, L. Cai, W. Du, and Y. Li, "Posterior cortex epilepsy: Diagnostic considerations and surgical outcome," *Seizure*, 2009.

[24] M. Zijlmans, J. Jacobs, Y.U. Kahn, R. Zelmann, F. Dubeau, and J. Gotman, "Seizure and interseizure high frequency oscillations in patients with focal epilepsy," *Clinical Neurophysiology*, vol. 122, no. 4, pp. 664-671, 2011.

[25] S. Altunay, Z. Telatar, and O. Erogul, "Altunay, Semih, Ziya Telatar, and Osman Erogul. "Epileptic EEG detection using the linear prediction error energy," *Expert Systems with Applications*, vol. 37, no. 8, pp. 5661-5665, 2010.

[26] V. Joshi, R.B. Pachori, and A. Vijesh, "Classification of seizure and seizure-free EEG signals using fractional linear prediction," *Biomed. Signal Process and Control*, vol. 9, pp. 1-5, 2014.

[27] S.G. Dastidar, H. Adeli and N. Dadmehr, "Principal component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 2, pp. 512-518, 2008.

[28] N.F. Guler, E.D. Ubeyli, and I. Guler ,"Recurrent neural networks employing Lyapunov exponents for EEG signals classification," *Expert Systems with Applications*, vol. 29, no. 3, pp. 506-514, 2005.

[29] U.R. Acharya, S.V. Sree, S. Chattopadhyay, W. Yu, and P.C.A. Ang, "Application of recurrence quantification analysis for the automated identification of epileptic EEG signals," *International Journal of Neural Systems*, vol. 21, no. 3, pp. 199-211, 2011.

[30] T.S. Kumar, V. Kanhangad, and R.B. Pachori, "Classification of seizure and seizure-free EEG signals using multi-level local patterns," *Conf. Proc. Int. Conf. Digit. Signal Process.*, pp. 646-650, 2014.

[31] H. Huang and J. Pan, "Speech pitch determination based on Hilbert-Huang transform," *IEEE Transactions on Signal Processing*, vol. 86, no. 4, pp. 792-803, 2006.

[32] R.B. Pachori, "Discrimination between seizure and seizure-free EEG signals using empirical mode decomposition," *Research Letters in Signal Processing* , 2008 .

[33] V. Bajaj and R.B. Pachori, "Classification of seizure and non-seizure EEG signals using empirical mode decomposition," *IEEE Transactions on Information Technology in Biomedicine*,vol. 16, no. 2, pp. 1135-1142, 2012.

[34] R.B. Pachori and S. Patidar, "Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions," *Comput. Methods Programs Biomed.*, vol. 113, no.2, pp. 494-502, 2014.

[35] R. Sharma and R. B. Pachori, Classification of epileptic seizures in EEG signals

based on phase space representation of intrinsic mode functions," *Expert System Application*, vol. 42, no. 3, pp. 1106-1117, 2015.

[36] P.A. Bizopoulos, D.G. Tsalikakis, A.T. Tzallas, D.D. Koutsouris, and D.I. Fotiadis, "EEG epileptic seizure detection using k-means clustering and marginal spectrum based on ensemble empirical mode decomposition," *IEEE 13th International Conference on Bioinformatics and Bioengineering (BIBE)*, pp. 1-4, 2013.

[37] V. Srinivasan, C. Eswaran, and N. Sriraam, "Artificial neural network based epileptic detection using time-domain and frequency-domain features," *Journal of Medical Systems*, vol. 29, no. 6, pp. 647-660, 2005.

[38] U.R. Acharya, S.V. Sree, and J.S. Suri, "Automatic detection of epileptic EEG signals using higher order cumulant features," *International Journal of Neural Systems*, vol. 21, no. 5, pp. 403-414, 2011 .

[39] B. Boashash, M. Mesbah, and P. Colditz, *Time-Frequency Signal Analysis and Processing,* Elsevier, 2003.

[40] R.B. Pachori and P. Sircar, "EEG signal analysis using FB expansion and second-order linear TVAR process," *Signal Processing*, vol. 88, no. 2, pp. 415-420, 2008.

[41] Y.U. Khan and J. Gotman, "Wavelet based automatic seizure detection in intracerebral electroencephalogram," *Clinical Neurophysiology*, vol. 114, no. 5, pp. 898-908, 2003.

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

[43] H. Ocak, "Optimal classification of epileptic seizures in EEG using wavelet analysis and genetic algorithm," *Signal processing*, vol. 88, no. 7, pp. 1858-1867, 2008.

[44] L. Guo, D. Rivero, and A. Pazos, "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks," *Journal of Neuroscience Methods*, vol. 193, no. 4, pp. 156-163, 2010.

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

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

[47] L. Guo, D. Rivero, J. Dorado, J.R. Rabual and A. Pazos , "Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks," *Journal of Neuroscience Methods*, vol. 191, no. 1, pp. 101-109, 2010.

[48] R.R. Sharma and R.B. Pachori, "Time-frequency representation using IEVDHM-HT with application to classification of epileptic EEG signals," *IET Science, Measurement and Technology*, vol. 12, no. 1, pp. 72-82, 2017.

[49] R.R. Sharma and R.B. Pachori, "A new method for non-stationary signal analysis using eigenvalue decomposition of the Hankel matrix and Hilbert transform," *4th International Conference on Signal Processing and Integrated Networks (SPIN)*, pp. 484-488, 2017.

[50] N. Huang et. al, "The empirical mode decomposition and the Hilbert spectrum for nonlinear non-stationary time series analysis," *Proceedings of Royal Society of London*, vol. 454, no. 1971, pp. 903-995, 1998.

[51] L. Lin, Y. Wang and H. Zhou, "Iterative filtering as an alternative algorithm for empirical mode decomposition," *Adv. Adaptive Data Analysis*, vol. 1, no. 4, pp. 543-560, 2009.

[52] R. Sharma, R.B. Pachori, A. Upadhyay, "Automatic sleep stages classification based on iterative filtering of electroencephalogram signals," *Neural Computing and Applications.*, vol. 28, no. 10, pp. 1-20, 2017.

[53] J.C. Echeverria, J.A. Crowe, M.S. Woolfson and B.R. Hayes-Gill, "Application of empirical mode decomposition to heart rate variability analysis," *Medical and Biological Engineering and Computing*, vol. 39, no. 4, pp. 471-479, 2001.

[54] N. Huang, Z. Shen and S. Long, "A new view of nonlinear water waves: the Hilbert spectrum," *Annual Rev. Fluid Mech.*, vol. 31, no. 1, pp. 417-457, 1999.

[55] B. Liu, S. Riemenschneider and Y. Xu, "Gearbox fault diagnosis using empirical mode decomposition and Hilbert spectrum," *Medical and Biological Engineering and Computing*, vol. 20, no. 3, pp. 718-734, 2006.

[56] D. Pines and L. Salvino, "Health monitoring of one dimensional structures using empirical mode decomposition and the Hilbert-Huang transform," *Proceedings of Society of Photographic Instrumentation Engineers*, vol. 4701, no. 1, pp. 127-143, 2002.

[57] Q. Chen, N. Huang, S. Riemenschneider and Y. Xu, "B-spline approach for empirical mode decomposition,". *Adv. Comput. Math*, vol. 1, no. 1-4, pp. 171-195, 2006.

[58] A. Cicone, J. Liu and H. Zhou, "Adaptive local iterative filtering for signal decomposition and instantaneous frequency analysis," *Applied Computer Harmonic Analysis*, vol. 41, no. 2, pp. 384-411, 2016.

[59] Y. Wang and Z. Zhou, "On the convergence of iterative filtering empirical mode decomposition," *Excursions in Harmonic Analysis*, vol. 2, pp. 157-172, 2013.

[60] P. Maragos, T.F. Quatieri and J.F. Kaiser, "Speech non-linearities, modulations, and energy operators,". *IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp. 421-424, 1991.

[61] H.M. Teager, "Screening for vocal tract neoplasms," *Proposal*, 1976.

[62] H.M. Teager, "Some observations on oral air flow during phonation," *IEEE Trans. Acoust. Speech Signal Processing*, vol. 28, no. 5, pp. 599-601, 1991.

[63] H.M. Teager, "Physiology of speech phoneme production," *3rd Tech. Rep.*, 1981.

[64] H.M. Teager and S.M. Teager, "A phenomenological model for vowel production in the vocal tract," *Speech Science: Recent Advances*, pp.73-109, 1983.

[65] W.J. Hardcastle and A. Marchal, Evidence for nonlinear sound production in the vocal tract: Speech Production and Speech Modeling, Springer, pp.241-261, 1990.

[66] J.F. Kaiser, "On a simple algorithm to calculate the energy of a signal," *Proc. Int. Conf. Acoustic Speech Signal Processing*, pp. 381-384, 1990.

[67] J.F. Kaiser, "On Teager$'s$ algorithm and its generalization to continuous signals," *Proc. 4th IEEE Digital Signal Processing Workshop*, 1990.

[68] P. Maragos, J.F. Kaiser, and T.F. Quatieri, "On amplitude and frequency demodulation using energy operators,". *IEEE Trans. Signal Processing*, vol. 41, pp. 1532-1550, 1993.

[69] A.T. Azar and S.A. El-Said, "Performance analysis of support vector machines classifiers in breast cancer mammography recognition," *Neural Computing and Applications*, vol. 24, no. 5, pp. 1163-1177, 2014.

[70] EEG time series data (Department of Epileptology, University of Bonn) `http://www.meb.uni-bonn.de/epileptologie/science/physik/eegdata.html`.

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

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

[73] H. Adeli, S.G. Dastidar, and N. Dadmehr, "A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 2, pp. 205-211, 2007.

[74] I. Guler and E.D. Ubeyli , "Multi-class support vector machines for EEG-signals classification," *IEEE Transactions on Information Technology in Biomedicine*, vol. 11, no. 2, pp. 117-126, 2007.

[75] A. Kraskov, H. Stögbauer, and P. Grassberger, "Estimating mutual information," *Physical Review E* , vol. 69, no. 6, pp. 066138, 2004.

[76] D. Phung, D. Tran, W. Ma, P. Nguyen, and T. Pham, "Investigating the impacts of epilepsy on EEG-based person identification systems," *International Joint Conference on Neural Networks (IJCNN)*, pp. 3644-3648, 2014.

[77] J. Han, F. Dong, and Y.Y. Xu, "Entropy feature extraction on flow pattern of gas/liquid two-phase flow based on cross-section measurement," *Journal of Physics: Conference Series*, vol. 147, pp. 012041, 2009.

[78] J. Piskorski and P. Guzik, "Geometry of the Poincaré plot of RR intervals and its asymmetry in healthy adults" *Physiological Measurement*, vol. 28, no. 3, pp. 287-300, 2007.

[79] R.R. Coifman and M.V. Wickerhauser, "Entropy-based algorithms for best basis selection," *IEEE Transactions on Information Theory*, vol. 38, no. 2, pp. 713-718, 1992.

[80] M. Brennan, M. Palaniswami, and P. Kamen, "Do existing measures of Poincaré plot geometry reflect nonlinear features of heart rate variability?," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 11, pp. 1342-1347, 2011.

[81] Rudolf J. Freund and William J. Wilson, "Statistical Methods, Academic Press, San Diego, CA, USA, 1993.

[82] P. E. McKnight and J. Najab, Mann-Whitney U test: Corsini Encyclopedia of Psychology, John Wiley and Sons, vol. 2, 2010.

[83] R.R. Sharma, P. Chandra and R.B. Pachori, "Electromyogram signal analysis using eigenvalue decomposition of the Hankel matrix," *Proceedings of the International Conference on Machine Intelligence and Signal Processing*, 2017.

[84] A.P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognition*, vol. 30, no. 7, pp. 1145-1159, 1997.

[85] G.H. John and P. Langley, "Estimating continuous distributions in Bayesian classifiers," *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, pp. 338-345, 1995.

[86] D. Md Farid, Li. Zhang, C.M. Rahman, M.A. Hossain, and R. Strachan, "Hybrid decision tree and Naive Bayes classifiers for multi-class classification tasks," *Expert Systems with Applications*, vol. 41, no. 4, pp. 1937-1946, 2014.

[87] S. Ruggieri, "Efficient C4. 5 [classification algorithm]" *IEEE Transactions on Knowledge and Data Engineering*, vol. 14, no. 2, pp. 438-444, 2002.

[88] J.R. Quinlan, "Induction of decision trees," *Machine Learning*, vol. 1, no. 1, pp. 81-106, 1986.

[89] L. Breiman, "Random forests,"., *Machine Learning*, vol. 45, no. 1, pp.5-32, 2001.

[90] L. Fraiwan, K. Lweesy, N. Khasawneh, H. Wenz and H. Dickhaus, "Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier," *Computer Methods and Programs in Biomedicine*, vol. 108, no. 1, pp. 10-19, 2012.

[91] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I.H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD Explorations Newsletter*, vol. 11, no. 1, pp. 10-18, 2009.

[92] R.R. Sharma, M. Kumar, and R.B. Pachori, "Automated CAD identification system using time-frequency representation based on eigenvalue decomposition of ECG signals," *International Conference on Machine Intelligence and Signal Processing*, pp. 22-24, 2017.

[93] A.K. Tiwari, R.B. Pachori, V. Kanhangad, and B.K. Panigrahi, Automated diagnosis of epilepsy using key-point based local binary pattern of EEG signals,"

IEEE Journal Biomedical and Health Informatics, vol. 21, no. 4, pp. 888-896, 2017.

[94] U. Orhan, M. Hekim and M. Ozer, "EEG signals classification using the K-means clustering and a multilayer perceptron neural network model," *Expert Syst. Appl*, vol. 38, no. 10, pp. 13475-13481, 2011.

[95] Y. Kaya, M. Uyar, R. Tekin and S. Yldrm, "1D-local binary pattern based feature extraction for classification of epileptic EEG signals," *Appl. Math. Comput.*, vol. 243, pp. 209-219, 2014.

[96] N.S. Tawfik, S.M. Youssef and M. Kholief, "A hybrid automated detection of epileptic seizures in EEG records," *Comput. Electr. Eng.*, vol. 53, pp. 177-190, 2016.