ABSTRACT

Elliptic seizure is identified and analyzed on Electroencephalogram (EEG) signals using different methods. EEG is a flexible (data-driven) time-frequency signal used to investigate non-stationary signals in brain. Different studies proposed different solutions for EEG signals in order to analyze and detect epileptic seizure in it. One of them is (EMD)Empirical Mode Decomposition. The EMD has core problem which is obtained when original signal is decomposed called “mode mixing". To solve and lessen noise-assisted problem.(ICEEMDAN) Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise, which is one of the latest methods on this era can be used to retrieve the total features of the original signal. In this research, EMD and ICEEMDAN are decomposed into some modes called intrinsic mode function (IMF). In addition, ICEEMDAN is an innovative method that is used to reduce that noises which is remained in the process in order to obtain optimal modes.

Those modes are used to detect healthy seizure and elliptic seizure. Two sets been taken for simulation, first set indicate healthy (non-seizures) as well as the second set indicate elliptic seizures. EMD and ICEENDAN methods are applied for analysis of EEG signals and extraction for their features. After feature extraction classification of EEG signals are performed. In the process of classification, (L-SVM)Linear Support Vector Machine which works on analyzing and identifying these signals. (L-SVM) were used to classify the data signals that is the modes. This research compares the ability of both method, first one via evaluating IMFs by using (RMSE)Root Mean Squire Error and(PCC) Pearson Correlation Coefficient. ICEEMDAN detects correct number of IMFs with less remaining noise. In the second one all extracted features based on EMD and ICEEMDAN were classified so as to obtain acceptable classification for detecting accuracy of the features and related methods to detect seizures and non-seizures.

Keywords:empirical mode decomposition (emd); imf; improved complete ensemble empirical mode decomposition with adaptive nosie (iceemdan); l-svm

ÖZET

Eliptiknöbet, farklıyöntemlerkullanılarakElektroensefalogram (EEG) sinyallerindetanımlanırveanalizedilir. EEG, beyindekidurağanolmayansinyalleriaraştırmakiçinkullanılanesnek (veriyedayalı) bir zaman frekansısinyalidir. Farklıçalışmalar, içindeepileptiknöbetianalizetmekvetespitetmekiçin EEG sinyalleriiçinfarklıçözümlerönerdi. Bunlardanbiriampirik mod ayrışmasıanlamınagelenEMD'dir. EMD, orijinalsinyal “mod karıştırma” olarakadlandırıldığındaayrıştırıldığındaeldeedilentemelsorunasahiptir.Gürültüdesteklipro blemiçözmekveazaltmakiçinGeliştirilmiş tam toplulukampirik mod ayrıştırması Bu çağdakienyeniyöntemlerdenbiriolanadaptifgürültü (ICEEMDAN) ileorijinalsinyalintoplamözelliklerinialmakiçinkullanılabilir.Buçalışmada, EMD ve ICEEMDAN intrinsic mod fonksiyonu (IMF) denilenbazımodlaraayrıştırılır.Ayrıca, ICEEMDAN olanbugürültüyüazaltmakiçinkullanılanyenilikçibiryöntemdir Optimal modlarıeldeetmekiçinsüreçtekaldı.

Bu modlar, sağlıklınöbetveeliptiknöbettespitetmekiçinkullanılır. Simülasyoniçiniki set alınmıştır, ilk set sağlıklı (nöbetlerhariç) veikincisettekieliptiknöbetlerigöstermektedir. EEG sinyallerininanaliziveözelliklerininçıkarılmasıiçin EMD ve ICEENDAN yöntemleriuygulanmaktadır. Özellikçıkarıldıktansonra EEG sinyallerininsınıflandırılmasıgerçekleştirilir. Sınıflandırmasürecinde, businyallerianalizetmekvetanımlamakiçinçalışanDoğrusalDestekVektörMakinesi (L-SVM). Modlarolanverisinyallerinisınıflandırmakiçinbir (doğrusal SVM) kullanılmıştır. Bu araştırma, her ikiyöntemin, ilk olarak, IMF'lerinKökOrtalama Squire Hatası (RMSE) ve Pearson KorelasyonKatsayısı (PCC) kullanılarakdeğerlendirilebilmeyeteneğinikarşılaştırmaktadır. ICEEMDAN, dahaazgürültüiledoğrusayıda IMF algılar. İkincisi, EMD veICEEMDAN'adayanantümözütlenmişözellikler, nöbetlerinvenöbetlerinsaptanmasıiçinözelliklerinveilgiliyöntemlerindoğruluğunusaptamakiçinkabuledilebilirbirsınıflandırmaeldeedecekşekildesınıflandırılmıştır.

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ARAM ISMAEL
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DETECTION OF EPILEPTIC SEIZURE USING
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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire CAVUS

We certify this thesis is a satisfactory for the award of degree of Master of Science in Computer Engineering

Examining Committee in Charge:

Assist. Prof. Dr. Boran Sekeroglu	Committee Member, Information Systems Engineering Department, NEU
Assist. Prof. Dr. Besime Erin	Committee Member, Department of Computer Engineering, NEU
Prof. Dr. Rahib H.Abiyev	Supervisor, Department of Computer Engineerin

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Aram Ismael Hamid
Signature:
Date:

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I dedicate this thesis to my beloved parents, my dearest father and my lovely mother, my lovely brothers and sisters, for their unconditional support and love. I love you all.

Among the people, I would like to thanks; Muhammed Kemal, Karzan Rashad, Bilal Ismael and Besran Aziz.

To my Mother...

ABSTRACT

Elliptic seizure is identified and analyzed on Electroencephalogram (EEG) signals using different methods. EEG is a flexible (data-driven) time-frequency signal used to investigate non-stationary signals in brain. Different studies proposed different solutions for EEG signals in order to analyze and detect epileptic seizure in it. One of them is (EMD) Empirical Mode Decomposition. The EMD has core problem which is obtained when original signal is decomposed called “mode mixing". To solve and lessen noise-assisted problem. (ICEEMDAN) Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise, which is one of the latest methods on this era can be used to retrieve the total features of the original signal. In this research, EMD and ICEEMDAN are decomposed into some modes called intrinsic mode function (IMF). In addition, ICEEMDAN is an innovative method that is used to reduce that noises which is remained in the process in order to obtain optimal modes.

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Keywords: empirical mode decomposition (emd); imf; improved complete ensemble empirical mode decomposition with adaptive nosie (iceemdan); l-svm

ÖZET

Eliptik nöbet, farklı yöntemler kullanılarak Elektroensefalogram (EEG) sinyallerinde tanımlanır ve analiz edilir. EEG, beyindeki durağan olmayan sinyalleri araştırmak için kullanılan esnek (veriye dayalı) bir zaman frekansı sinyalidir. Farklı çalışmalar, içinde epileptik nöbeti analiz etmek ve tespit etmek için EEG sinyalleri için farklı çözümler önerdi. Bunlardan biri ampirik mod ayrışması anlamına gelen EMD'dir. EMD, orijinal sinyal "mod karıştırma" olarak adlandırıldığında ayrıştırıldığında elde edilen temel soruna sahiptir.Gürültü destekli problemi çözmek ve azaltmak için Geliştirilmiş tam topluluk ampirik mod ayrıştırması Bu çağdaki en yeni yöntemlerden biri olan adaptif gürültü (ICEEMDAN) ile orijinal sinyalin toplam özelliklerini almak için kullanılabilir.Bu çalışmada, EMD ve ICEEMDAN intrinsic mod fonksiyonu (IMF) denilen bazı modlara ayrıştırılır.Ayrıca, ICEEMDAN olan bu gürültüyü azaltmak için kullanılan yenilikçi bir yöntemdir Optimal modları elde etmek için süreçte kaldı.

Bu modlar, sağlıklı nöbet ve eliptik nöbet tespit etmek için kullanılır. Simülasyon için iki set alınmıştır, ilk set sağlıklı (nöbetler hariç) ve ikinci setteki eliptik nöbetleri göstermektedir. EEG sinyallerinin analizi ve özelliklerinin çıkarılması için EMD ve ICEENDAN yöntemleri uygulanmaktadır. Özellik çıkarıldıktan sonra EEG sinyallerinin sınıflandırılması gerçekleştirilir. Sınıflandırma sürecinde, bu sinyalleri analiz etmek ve tanımlamak için çalışan Doğrusal Destek Vektör Makinesi (L-SVM). Modlar olan veri sinyallerini sınıflandırmak için bir (doğrusal SVM) kullanılmıştır. Bu araştırma, her iki yöntemin, ilk olarak, IMF'lerin Kök Ortalama Squire Hatası (RMSE) ve Pearson Korelasyon Katsayısı (PCC) kullanılarak değerlendirilebilme yeteneğini karşılaştırmaktadır. ICEEMDAN, daha az gürültü ile doğru sayıda IMF algılar. İkincisi, EMD ve ICEEMDAN'a dayanan tüm özütlenmiş özellikler, nöbetlerin ve nöbetlerin saptanması için özelliklerin ve ilgili yöntemlerin doğruluğunu saptamak için kabul edilebilir bir sınıflandırma elde edecek şekilde sınıflandırılmıştır.

Anahtar Kelimeler: ampirik mod ayrıştırma (emd); ımf; geliştirilmiş komple topluluk adaptif nosie (ıceemdan) ile ampirik mod ayrışımı; l-svm

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LIST OF ABBREVIATIONS

EMD:	Empirical Mode Decomposition
IMF:	Intrinsic Mode function
AM:	Amplitude Modulation
FM:	Frequency Modulation
EEMD:	Ensemble Empirical Mode Decomposition
CEEMD:	Complementary Ensemble Empirical Mode Decomposition
ICEEM:	Improved Ensemble Empirical Mode Decomposition
CEEMDAN:	Complete Ensemble Empirical Mode Decomposition
ICEEMDAN:	Improve Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
PCC:	Pearson’s correlation coefficients
RMSE:	Root Mean Square Error
SVM:	Support Vector Machine
L-SVM:	Linear Support Vector Machine
EEG:	Electroencephalogram
ECG:	Electrocardiogram

CHAPTER 1
INTRODUCTION

1.1. Overview

Seizure is one of the brain disorders that results from sudden movement of electrical activity in the neurons of the brain due to abnormalities in the structure of the brain, lack in the oxygen supply, encephalitis, injury in the head, having tumors, and other dysfunctionalities of the brain (Sanai & Chambers, 2013).

Frequently and recurrent seizure is known to be Epilepsy. As it's recorded, more than 1% of the world population which is 65 million people are diagnosed as epilepsy (Santaniello et al., 2011) and in Australia 225,000 are recorded with epilepsy as well (Zoghi, 2014). It's also worth mentioning that 5% of people in the world experiencing seizure during their life (Netoff, Park, & Parhi, 2009). During seizure people cannot do their daily normal movement and tasks, normal daily performance cannot be shown. Other than that, many injuries, fractures, accidents and even deaths are caused during seizure (Mormann, Andrzejak, Elger, & Lehnertz, 2007). The medication for this abnormality works well most of the times, it's about 70% of all the cases can be diagnosed and controlled by medication. It's prevented by timely and correct detection of the epilepsy signals just before the seizure onset.

Inside our brain, electricity is generated and formed due to neurons which use chemical reactions and turn them into body actions and movements. Ongoing electrical signals in the brain can be detected and recorded through EEG which stands for (Electroencephalogram), in the result it creates a graph for the recorded signals. By capturing and measuring the voltage fluctuation in the brain EEG detects epileptic seizure (Esteller et al., Dorr et al., 2007; 2004; Rosso et.al, 2003; Guttinger et al., 2005) and (Durand &Tang, 2012). Dependent on the medical stages to detect non-seizure and seizure signals, an EEG is segmented and classified in to different types. As usual, we have to know some knowledge about the human brain, data set signals, seizures and EEG. We will have the explanation of the basic steps for EEG signal detection which composed of pre-processing, feature extraction, classification. Feature-extraction and classification are the two crucial steps for seizure detection that are more important than the others steps. The database we have used in this thesis is from Bonn

University (EEG data set from Bonn University, 2012) which is a well-known modern data set composed of signals from seizure and non-seizure signals is shown in Figure 1.1 in this thesis an old EMD method is used and compared with the new proposed method ICEEMDAN for the detection of abnormal (non-seizure) and normal (seizure) using EEG. Also the ICEEMDAN are focused on. Accuracy, sensitivity and specificity.

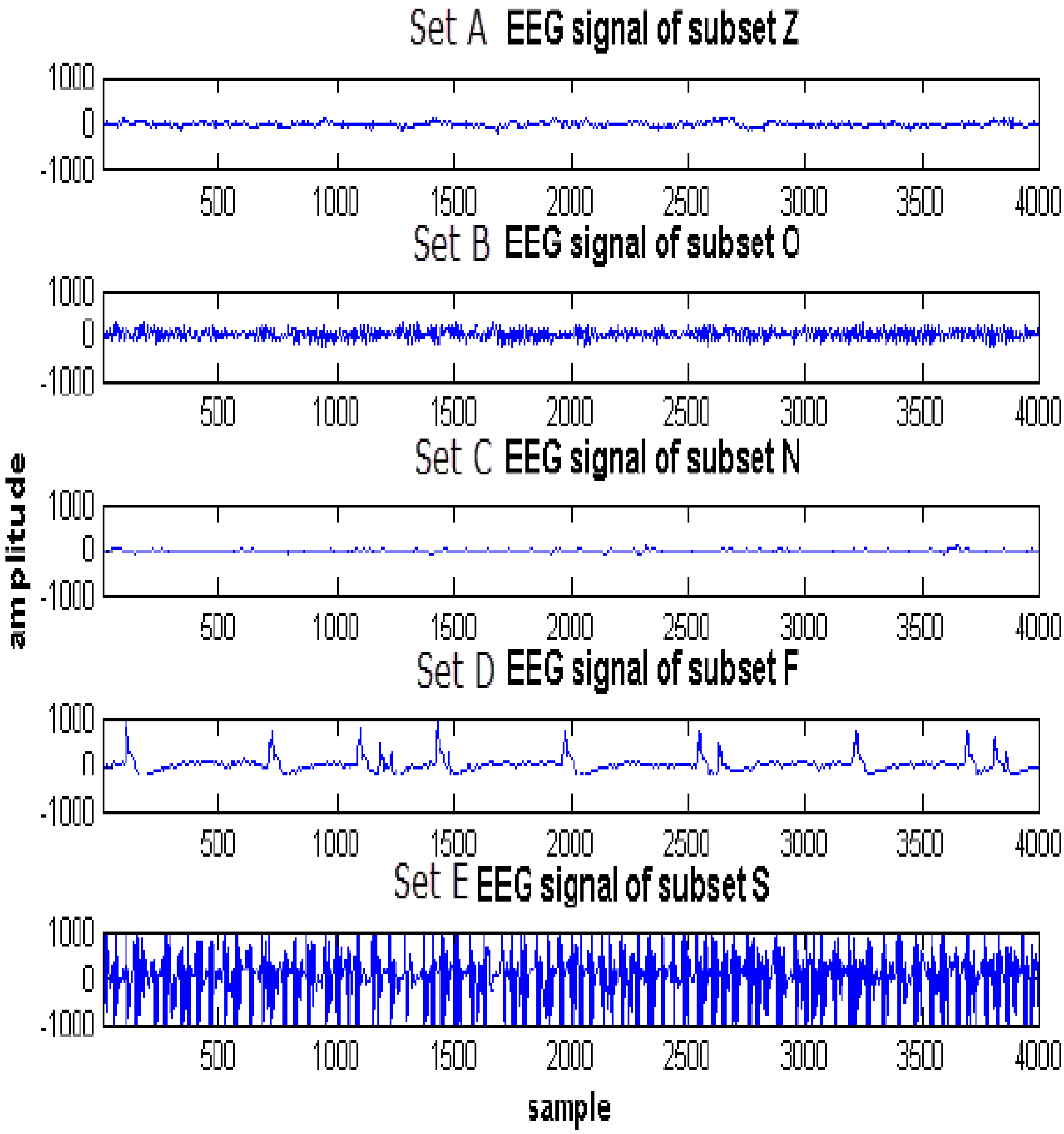


Figure 1.1: Non-seizure and Seizure signals from the data set of Bonn University, 2012

1.2. Epileptic Seizures

Seizures is one of the main property for this abnormality, which happens by sudden, brief, excessive electrical reaction which are discharging from a group of brain cells. Thus, the epileptic seizure clinical therapy usually based on the treatment for this identification, (Hamad et al., 2016).

1.3. Human Brain

The human brain is not just a part of central nervous system alone, but it is one of the most important organs that is responsible for controlling and monitoring how the human body functions. The human brain together with other organs such as a nervous system and the spinal cord are responsible for controlling involuntary activities such as digestion and breathing, and voluntary activities such as running and talking, also the flow of information in the body (Jessy, 2009).

The human brain is made up of four parts, Brain stem, Cerebellum, Diencephalon (Hypothalamus and Thalamus), and the Cerebrum which contains two large paired cerebral hemispheres. It can also be said to be consisting of four lobes; the occipital lobe, temporal lobe which is located behind the temples and is the bottom middle part of the brain which deals with auditory information, the parietal lobe which handles all activities relating to realization of stimuli, diagnoses, sense and movement, and for problem solving the frontal lobe is responsible, it also has the properties of movement, emotions, and part of speech.

In addition, the brain can be said to be composed of a lot of cells which include glial cells and neurons which transmit electro-chemical signals to and from the brain and also serve as the building blocks of the nervous system. Active neurons of the brain tend to produce local current flows which can be detected and measured an electroencephalography (EEG).

1.4. Electroencephalography (EEG)

It is widely known that the brain is the most delicate and highly active part of the human body that regulates all the activities that take place in a human body (Jessy, 2009). Also asserts that one of the notable activities that take place in the human brain is function analysis which involves the observation and recording of an amount of time period of electrical signals produced by the brain to complete a certain activity (Parvez & Paul, 2012). As it stands, there are a lot of innovative biomedical systems such as the Brain-computer interface (BCI) which are responsible for bringing the information from the brain, and enables the equivalent for bringing information from the brain which targets the influencing perceptions or the equivalent of sensation or perception, such as controlling of an artificial limb. Figure 1.2 is showing the BCI system in below, (Arman et al., 2012).

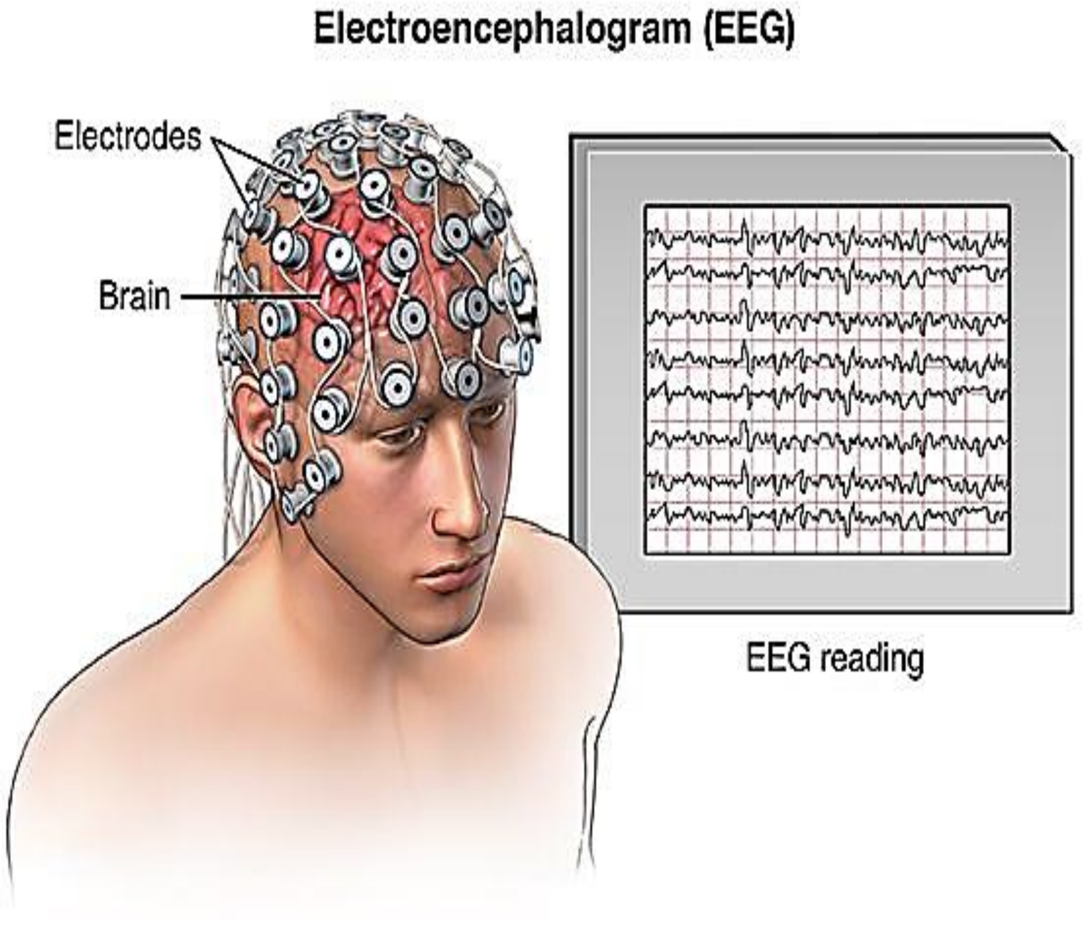


Figure 1.2: Brain Computer Interface system. (Todd, 1998)

Electrodes and sensors are used so as to obtain the EEG signals which are collected and prepared using specific filters and the Crude EEG signal forms an input into the components extraction process. The extraction process also helps in extracting appropriate features from each EEG signal which includes numerous samples in it. Comparisons will be made based on attributes of each input signal so as to identify problems posed by mental illness (Rambabu & Murthy, 2014).

1.4.1. EEG sub-waves (Sub-bands)

EEG signal is composed of many sub-waves which are known as gamma, beta, alpha, theta, and theta. In the Figure 1.3 and after it, we have briefly explained each of them.

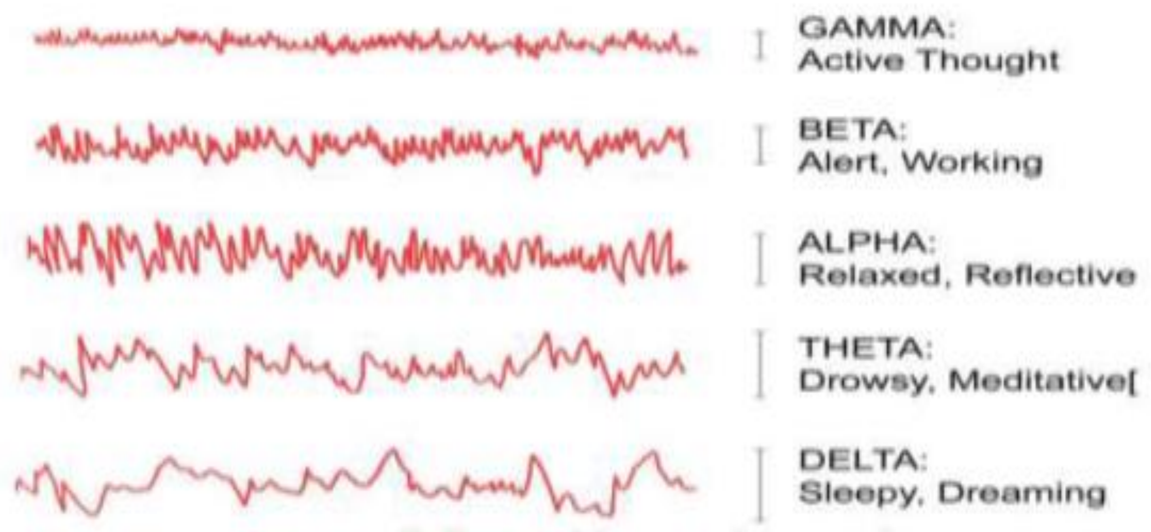


Figure 1.3: EEG signal bands (Klimesch et al., 1998)

a) Delta waves: Normally this wave occurs in infancy, when having a deep sleep and when having a serious organic brain disease (He, 2013). The method for recording this wave changes from children to adult. In adult, it's recorded frontally while in children it's done posteriorly. Usually the range of its amplitude changes in the range 20-200 μv.

b) Theta waves: Normally this wave occurs during stress, emotional situation, arousal in both adults and children and during prominent sleep. The parietal and temporal regions from the scalp are responsible for the wave. Usually the range of its amplitude changes in the range of 5-10 μv (He, 2013) and the frequency is between 4 to 7.

c) Alpha waves: Normally this wave is a rhythmic wave occurs in relax, wakefulness and eye closed in healthy adults. The voltage of this wave is between 20-200 μv and the frequency of it is 8 to 13 Hz. This wave disappears in coma or sleep disorders.

d) Beta waves: Normally this wave occurs in increasing situation of attention and vigilance. This wave replaces alpha waves during impairment in cognition system. It's recorded in both frontal and parietal from the scalp. Its frequency is between 13-30 and having amplitudes in between usually 5-10 μv.

e) Gamma waves: Gamma frequency lies between 30 to 100 Hz. During cross model sensory processing it is recorded and the place of the recording is somatosensory cortex. The common occurrence modes are creating short term memories.

1.4.2. Types of EEG systems

a) Scalp EEG Systems: It is a non-invasive measurement of the electrical activities occurring in human brain (Omidvarnia et al., 2014). Usually it is measured through electrodes on scalp see in Figure 1.4.

b) Intracranial EEG Systems: Like scalp, the intracranial EEG (IEEG) provides a spatial and temporal resolution of the electrical activity of the brain. It is highly invasive where electrodes are implanted in a limited numbers of brain locations at a given time see in Figure 1.4 therefore, it has higher spatial resolution (Sanqing, Stead, & Worrell, 2007).

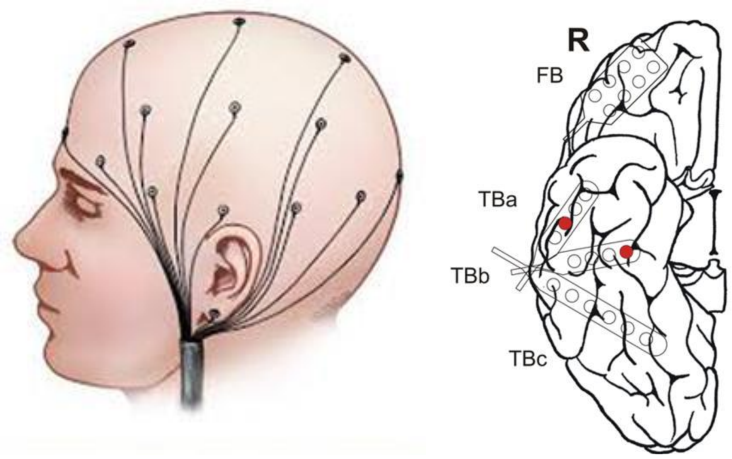


Figure 1.4: Types of EEG systems; left sub-Figure represents the scalp EEG and right sub-Figure represents the intracranial EEG. (Sanqing, et al., 2007).

1.5. Research goal

Main goals of the proposed approach is to detect and analyze the epileptic seizures using EEG signals through two methods of feature extraction applied to the original EEG signals. The first one is an EMD and the others is an ICEEMDAN which is the last study until now. We will do a classification and comparison study on both and analyze the results.

1.6. Thesis Organization

The thesis flow is parted into many chapters as following:

In chapter 2 literature review has been written. In chapter 3 (Methodology) describe both methods which are used for extracting features and classification by L-SVM.

In chapter 4 (Experimental Result) have been shown. An illustration have been made on displaying all results of analyses and detection seizures based on EMD and ICEEMDAN using EEG signals and comparison between present work and other previously mentioned methods as its been mentioned in the literature review. In chapter 5, conclusion and future works are presented.

CHAPTER 2

LITERATURE REVIEW

2.1. Overview

This chapter summarizes the review of different methods which have been applied for detection and analysis of epileptic seizure. Previous research works related to the analysis and detection of seizure using EEG signals are considered.

2.2. Related work

Recently different method have been used for the analysis and detection of the epileptic seizure. The review of some researches are described below.

Seizure detection was first applied by (Gotman, 1990). It then became widely applicable method and used for both clinical use and commercial use as well through integrating the method to commercial devices. This methods have been applied on a large number of patients in a clinical environment.

For detecting seizure from EEG signals, another good method is (Harding, 1993). But finding the performance of the method is difficult because detecting criteria for each patient were changed after recording the first seizure.

(Ocak, 2008) applied Genetic algorithm and wavelet analysis for the classification of EEG signals. In his study, he proposed fourth-level wavelet for the decomposition of the EEG signal into various frequency bands. After decomposition he has applied GA to get optimal features subset which increases the ability of Learning Vector Quantization (LVQ) classifier for detecting abnormal EEG signals and normal non-epileptic EEG signals. From the result of his study he was able to get 94.3% and 98% accuracy. Using GA was the key point to increase the performance, because without it the result wouldn't be that high.

Panda et al. (R. Panda et al., 2010) proposed method based of discrete wavelet transformation (DWT) for finding different features of signals like entropy, energy, and standard deviation

(STD), and for the case of classifier he has used support vector machine (SVM) to detect non-epileptic from epileptic using EEG signals. For his analysis, he used EEG signals which are different in properties like (condition of eye open and eye close, seizure and epileptic). EEG signals were decomposed till the 5th signals using DWT. His study results show results of classification accuracy 91.2% in seizure detection used EEG signals.

Dastidar *et al*. (Dastidar et al., 2007) decomposed EEG signal in to its frequencies through WT, and extracted correlation, STD, and Lyapunov exponent as three different features from the signal. Using them and applying many classification methods results a maximum frequency which is done by creating a feature space by nine-parameter mixed-bands. Here the importance of all three wavelet-chaos-neural network methodology key components were shown in creating the good performance. Polat *et al*. (K. Polat & Güneş, 2007) fast Fourier transform (FFT) were used to extract feature using and classified by using decision making classifier. Results of different methods which have been used give different results and conclusion. In his study (R. Panda et al., 2010) a result of 91.20% been obtained as an accuracy for his classification, (Dastidar et al., 2007) got the result of 96.70% in his study, and (K. Polat & Güneş, 2007) obtained 98.72% from their studies. There are some other methods for feature extraction and classification among them are GA, PPCA and EMD.

Liang *et al*. (S. F. Liang et al., 2010) uses two different methods Principle Component Analysis and GA for Genetic Analysis on different non-linear and linear algorithms. Applying PCA for nonlinear gives better result compared to GA which is good for linear. The maximum accuracy was 98.67%.

If we observe, we see almost excellent classification accuracy recorded by the proposed approaches of (Pachori, 2012; Birvinskas, 2012; Pachori, 2008; R. Panda, 2010) for the data sets of Bonn University data regarding non-seizure EEG and seizure EEG signals. However, if University Hospital Freiburgdata data set was used which composed of the classification for abnormal and normal EEG signal, the results performance obtained is below the expected results. As an instance, the result of the classification accuracy for Bajaj et al.'s (V. Bajaj & R. B. Pachori, 2012) method for feature extraction and feature classification is 77.90% in differentiating abnormal EEG signals and normal signal in extracting and classifying the first

IMF in data set of University Hospital of Freiburg when its applied on Frontal lobe and the result increased to 80.20% when its applied to Temporal lobe. As it’s seen, it’s much below the 98.50% accuracy which is obtained from using data set of Bonn University for non-seizure and seizure signals.

Acharya (Acharya et al., 2011) proposed the methodology for applying a testing and training parts for classifying and detecting EEG seizure and non-seizure signals by extracting Higher Order Spectra features from normal. In his study, he has used 300 segments of EEG data from the three classes to extract features and classifying the development and evaluation. The study show a near to perfect result which has the accuracy of 98.5% of detection through using Support Vector Machine (SVM).

CHAPTER 3

METHODOLOGY

3.1. Overview

In this thesis, two methods have been applied for the analysis of the EEG signals. The applied system initially uses previously recorded EEG signals then apply EMD and ICEEMDAN methods to extract IMFs. After extracting IMFs, the two extracting methods have been evaluated by RMSE and PCC procedures. L-SVM classifier has been described and used to detect seizure and non-seizure signals. The main steps of the proposed approach are preprocessing, extraction and classification. Figure 3.1 shows a block diagram of this approach.

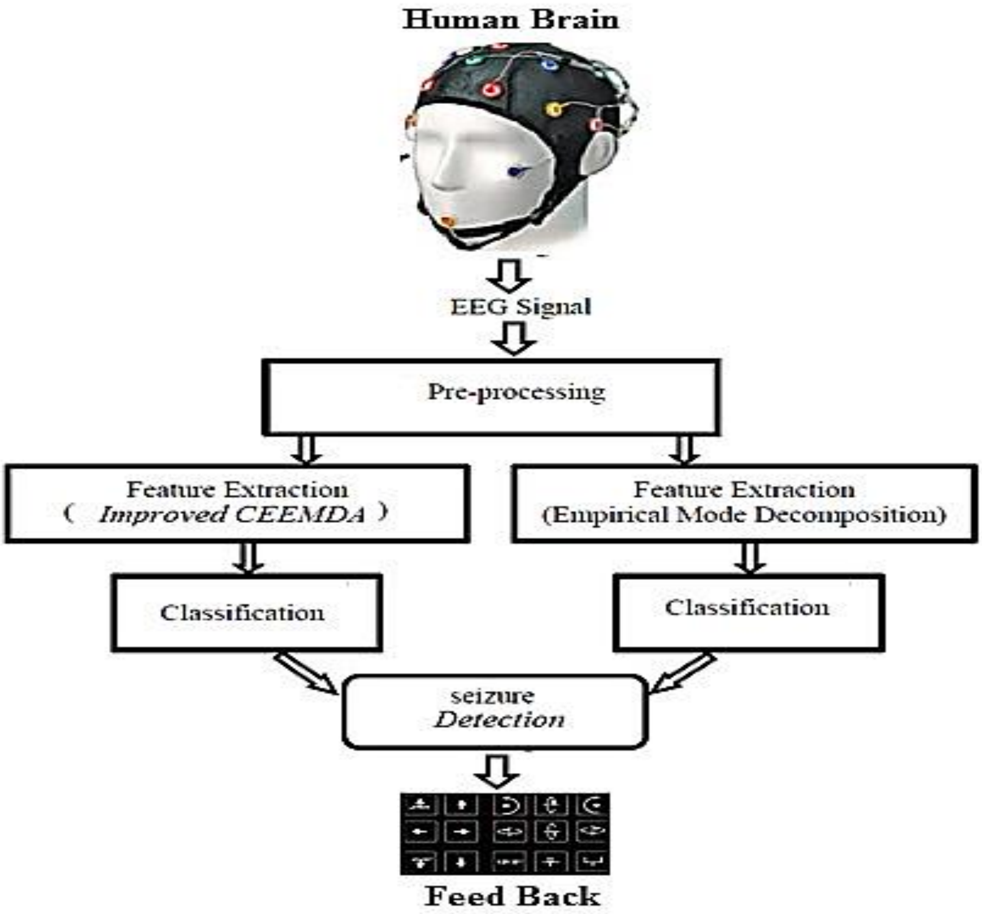


Figure 3.1: The Block diagram of the process

3.2. EEG Data Acquisition

We have used EEG data sets obtained from University of Bonn (2012) epileptologie data archives. The data was divided into five EEG sets signed by [A, B, C, D, and E]. For making comparative analysis of the results the EEG signals have been used.

In this project, two sets of EEG data signal has been selected [A and C]. The set [A] is a healthy seizures data (normal). The set [C] is time series of seizure EEG signals.. All the sets have 100 samples which composed of single EEG wave segments which lasts for 23.6 sec. Visual examinations of the artifacts were done as a result of observed eye movements and muscle activity and the affected sets or elements were separated from continuous multichannel EEG recordings. To record all EEG signals a 128-channel amplifier system have been used, which also involves the digital conversion of the 12-bit analog data. After the conversion, 173.61 Hz sampling have been used continuously to write the data on a disk for the data acquisition system. Lastly, for the pre-processing step, a band-pass filter settings of 0.5340 Hz were used to filter the EEG.

3.3. Pre-processing

In this step, the effect of noise which are signals that didn't come from the brain and known as artifacts of the EEG signals are removed. The artifacts are of two parts; the physiological artifacts is part one that arrives from the human body during the test and the non-physiological artifacts which comes from environment and other mediums. The physiological is divided into several types like eye blinking artifact, muscle artifact, eye blinking artifact and pulse artifact. The non-physiological artifacts divided into two types which are sweat artifact and power line artifact.

1. **Physiological artifacts:** in the below we have described each part in detail,
    - **Muscle activity:** They are high frequency surges coming from the muscles of face and neck during seizure (Núñez, 2010).
    - **Eye blinking artifact:** This signal affects the theta band, and generated from the moving of the eyelids vertically. This signal has a high amplitude which disrupts the produced EEG data from FP1, FP2, F3 and F4 electrodes around the eye. The

magnitude of the electrical signal for eye blink is 10 times the electrical signal produced by the cortical signal and its between 200- 400 ms. (Núñez, 2010).

2. **Physiological artifacts:** this type of artifacts are explained below,
   - **Power line artifact:** 50 Hz or 60 Hz is the A/C power supplies working in the generation of this noise. It affects the original signal due to its high amplitude and its noise is bigger than the data signal. (Núñez, 2010).
   - **Sweat artifact:** This noise originated from urea, water, mineral and lactate which are contents of sweat. It produces a changing baseline in the electrode impedance. (Núñez, 2010).

Pre-processing was done so as to separate the EEG signals based normality or abnormality, either seizure or non-seizure respectively. Both the normal and the seizure stages were divided into 5 second periods and they will be filtered by band-pass filter of 0.5-32 Hz. (Saha et al., 2016). Figure 3.2 illustrated preprocessing steps.

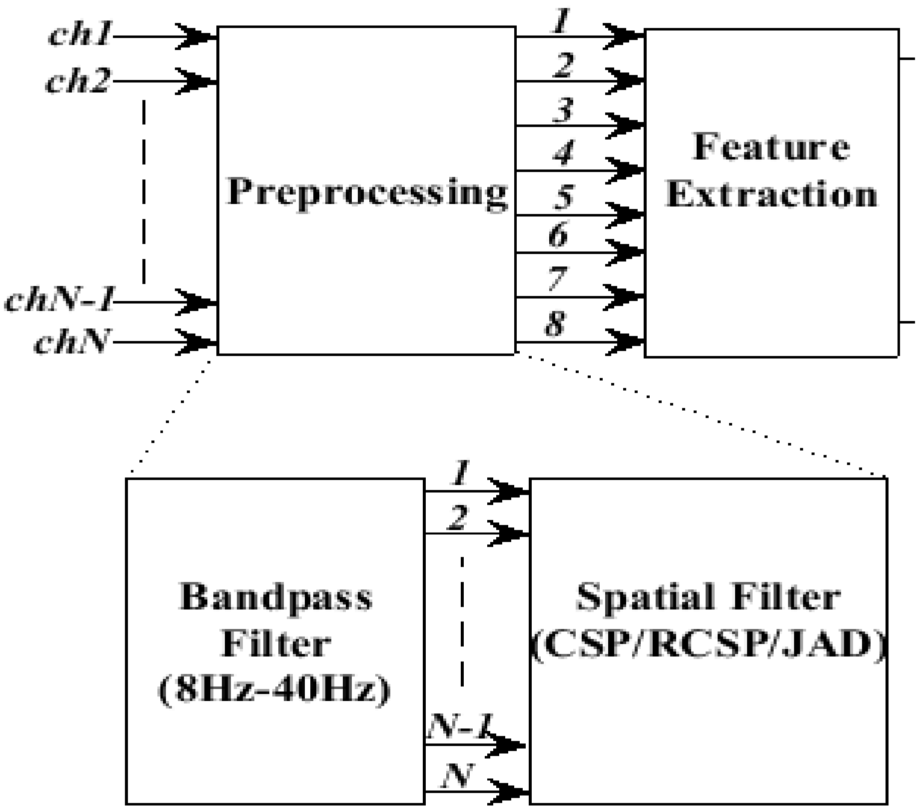


Figure 3.2: The experimental paradigm propose: in the first step the signal is pre-processed using (a) the cut off frequencies at 8Hz and 40Hz by band pass filter with and (b) spatial filtering such methods (CSP, RCSP, and JAD). 8 optimal channels and 2 channels per class by spatial filtering gives. Then, decomposed feature both algorithm EMD and ICEEMDAN.

3.3.1. Eliminate noise

A pre-processing step is sometimes needed to eliminate unwanted signals from EEG signals. After removing the unwanted signals, EEG signals can be used to be diagnosed.

3.3.2. Spatial Filtering as Preprocessing

In this thesis the preprocessing techniques are applied as Regularized Common Spatial Pattern (RCSP), Joint Approximate Diagonalizations (JAD) and Spatial Pattern (CSP). Among them, CSP method gives spatially optimal projection, a maximal discriminative features present between classes. In the RCSP, different parameters has been regularized and introduced, which show robustness to outliers.

3.4. Feature Extraction

The good point in using ICEEMDAN is its ability to analyze and identify EEG signals which are non-stationary. In applying EMD and ICEEMDAN on the signals it is possible to have an uncountable number of signals and this can be made possible by subjecting the EMD to the IMFs which follow or assume a high frequency component to low frequency component ordered pattern. But it must be noted that it is the signals local properties that determines the number of IMFs in a signal. This characteristic feature is important because it makes it possible to identify attributes of the original signal. Usually the initial IMFs can offer a sufficient number of features that is required to successfully classify seizures and non-seizures signals successfully. As the decomposition process is being done, a limited number of IMFs from the actual signals are reserved for the last feature extraction. But it is possible to keep the most essential mode functions that will be used to do the classification process. Based on the experimental results that were obtained, it was noted that all of our illustrations are true for seeing and extracting features from the first IMF to detect signals which are seizures and non-seizures.

As the decomposition process is being done, a limited number of mode functions of the actual signals are reserved for final feature extraction. But it is possible to keep the most essential mode functions that will be used to do the classification process. Based on the experimental results that were obtained, it was noted that all of our hypothesis are correct as extracted features from the first IMF successfully classify seizures and non-seizures signals. As a result, we can use the IMFs in classification applications which have original signals that have different amplitudes or frequencies and are non-stationary.

3.5. EMD

EMD is a time frequency and adaptive data driven approach that examines the presence of non-stationarity signals which is caused by nonlinear systems (Huang et al., 2012). It is also responsible for both internal and total division of signals into slow and fast oscillations. The obtained ultimate signal can either be presented as pure modes or “intrinsic mode functions” (IMF). This uses the sifting process and relies a lot on scale attributes of the main signal and are arranged in an order which starts from the smallest to the largest scale to obtain IMFs with each scale representing an IMF. The signal decomposition mechanisms often provide features of the EMD while the IMFs are transformed using the SVM. This is important because most of the time series analysis can easily be integrated with non-stationary signals. The entire methodological procedures can be seen in (Huang, et al., 1998). EMD algorithm decomposes the EEG signal into a number of IMFs. That is,

$$S(t)=\Sigma Mj+Ze=1 \qquad (3.1)$$

Where the resultant signal is shown by S(t), the remains of signal S(t) is denoted by Ze and the number of IMFs extracted from signal S(t) is denoted by e. The EMD algorithm is made up of two processes and these are IMF condition checking and sifting process.

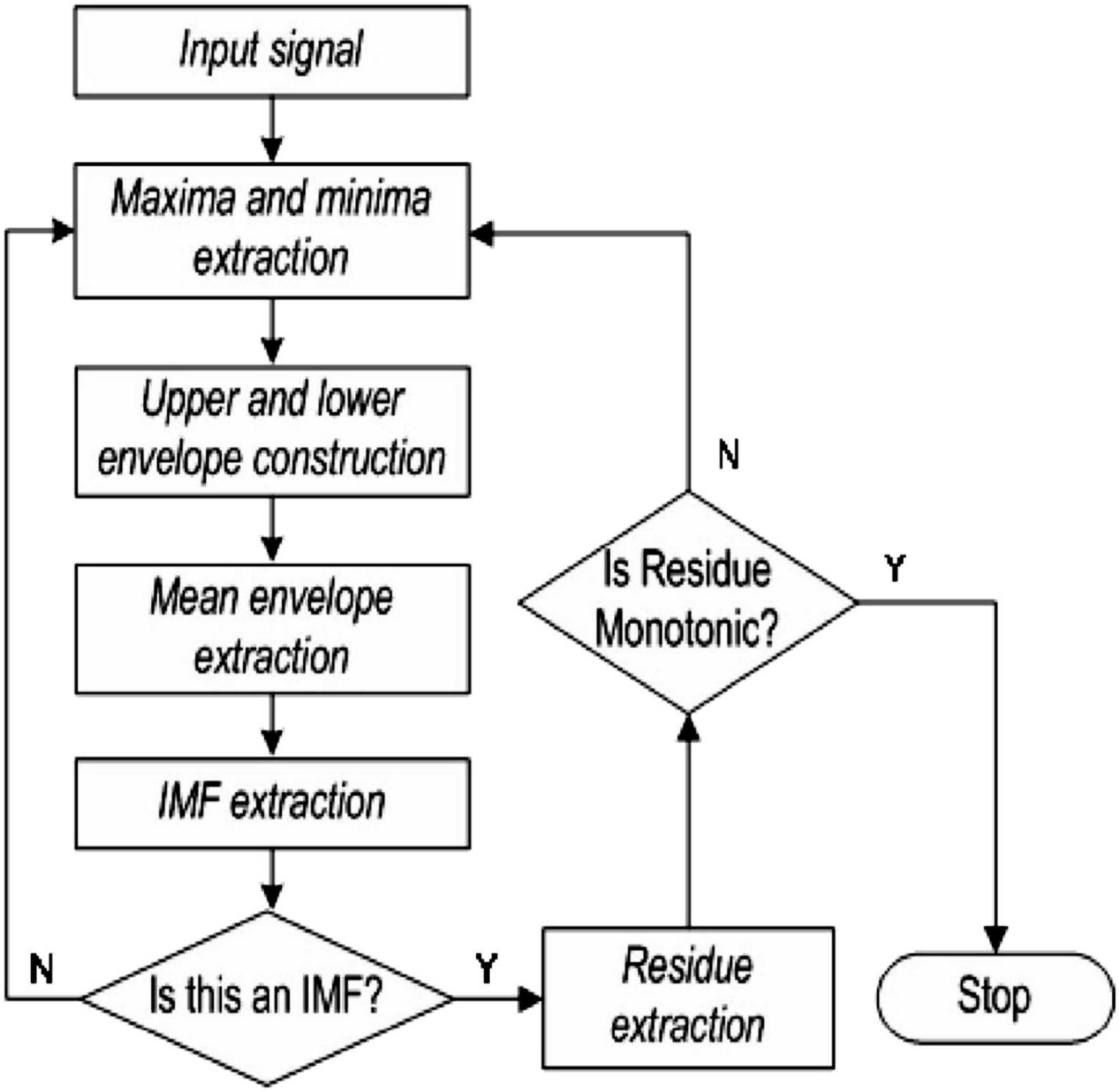


Figure 3.3: Procedure for performing the EMD (Yan & Gao, 2008).

3.5.1. Intrinsic Mode Function (IMF)

As mentioned earlier, EMD is decomposing the EEG signal into a bunch of a mono-component elements known as Intrinsic Mode Functions (IMFs). With a zero frequency-modulated, amplitude and components. An example of IMF is shown in Figure 3.4 Common harmonic functions have oscillations that are similar to the mono-component function. IMFs are therefore, a signal representation of frequency and amplitude modulated (AF-AM) signals whose order often starts with the highest frequency and ends with lowest frequency components. What distinguishes the FM and the AM is that the former relates to constant amplitude variation in frequency while the latter carries the envelope.

The computation process is done using a sifting process but this requires two conditions:

- The number of minimum and maximum values in the entire dataset that can differ must not be more than one.
- Both the lower envelope and upper envelope must have a mean value M(t) which is very near to zero irrespective of the point where it is.

Once the second condition has been fulfilled, conclusions can easily be made that the IMF has a signal which is stationary and such helps with the analysis to interpret the findings which can in most cases lead to reliable estimates (non-spurious findings). But the IMF can have both frequency and modulated amplitude is shown in Figure 3.5. The fist condition causes the production of a signal with a narrow band (Huang et al., 1998; 2009). The second condition is however caused by a global interference with lower and upper envelopes that are symmetric in size and shape and the produced signal is more suitable for Classification (Huang & Hilbert, 2005). The problem however is that is difficult to locate the envelopes because of the non-stationarity and nonlinearity elements of the data.

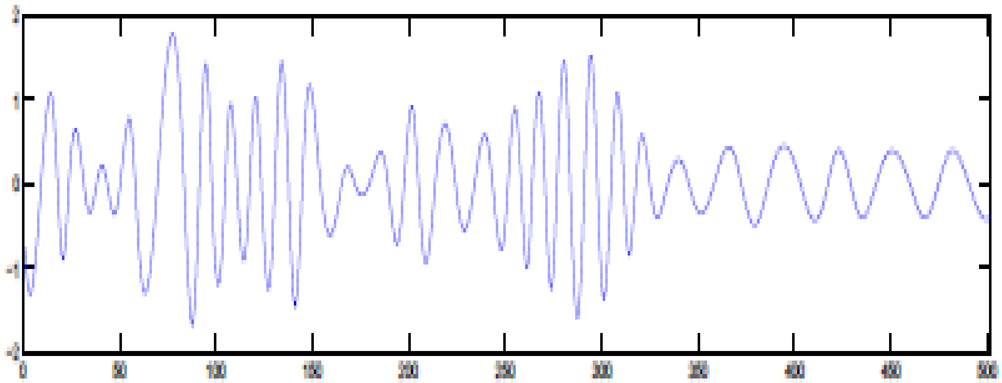


Figure 3.4: an example of Intrinsic Mode Function (IMF).

3.5.2. Sifting Process

Huang and Wu (2008) defined sifting process as a process that involves the analysis of a signal as seen in the Figure 3.4. The sifting process is summarized as below;

1) Local extrema Identification (i.e., the local minimum and local maximum)

2) Envelops the local extrema of the original signal and take the means.

   a) Deduct the means from the actual signal.

   b) Repeat the process until the IMF condition is obtained.

3) Use the output obtained from point 2 (deduction of IMF from the actual signal).

4) Iterated the residual (remaining) from point 1.

This is done with respect to the following IMF conditions:

- The number of minimum and maximum values in the entire dataset that can differ must not be more than one.
- Both the lower envelope and upper envelope must have a mean value M(t) which is very near to zero irrespective of the point where it is.

Once the EMD process was completed, it may produce an IMF that does not exist and this result in an immersed scale problem. That is, some of the scales may be immersed in other scales “Mode mixing".

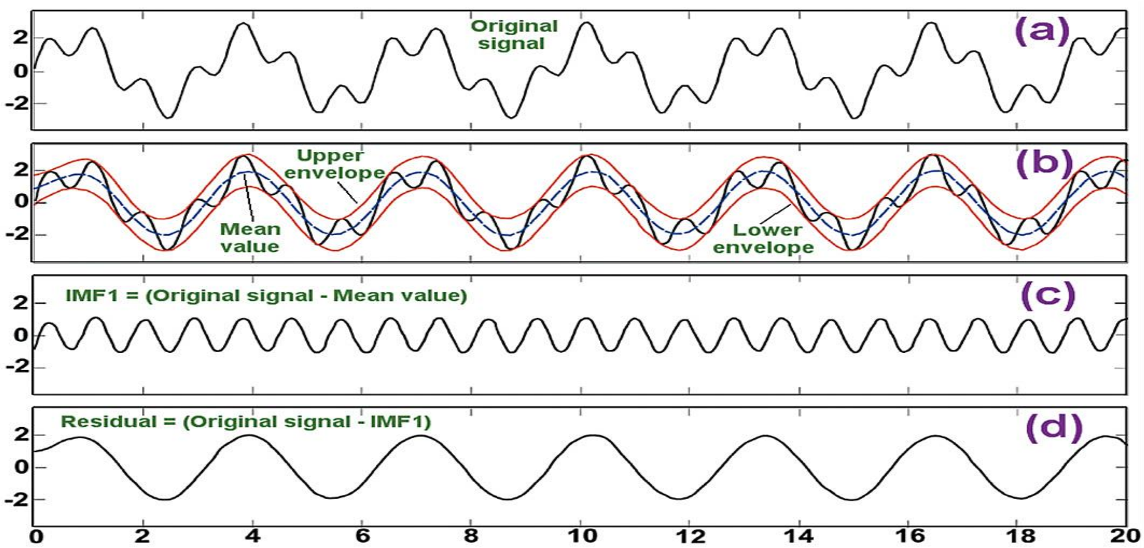


Figure 3.5: sifting process. (a) Original signal; (b) indicate local maxima; (c) envelops the extrema; and (d) the first IMF. (Hassan, 2005).

After complete EMD procedure, it may generate a number of IMFs that are not exist.

3.5.3. Mode mixing

Arguments made by (Huang et al., 1998) against the EMD procedure cited that there is a greater tendency for mode mixing to take place or occur. Thus, the sifting process of signal is criticized on the basis that it leads to an IMF that is affected by mode mixing. It is possible that a signal can produce different IMF numbers for each EMD process. The IMF may generate different results based on differences that are observed with the signal scales. That is, the other may produce scales with different IMFs while the other may be as a result of different scale. This problem can be solved by using "intermittence test" (Yang et al., 2005)The main aim to determine both the local maxima and minima during sifting process but the problem is that this procedure is not suitable when dealing with different and complex data with scales.

3.6. Ensemble empirical mode decomposition (EEMD)

The first introduction of EEMD goes back to 2005 when dealing with the mode mixing problem (Tsui et al., 2010; Murugappan et al., 2010; Todd 1998). It results in the establishment of a pseudo IMFs with true IMF components which are similar with the means of the ensemble of the tests. Once the white noise has been established, it will be added to the analyzed signal. These procedures are repeated over and over again so as to obtain a white noise that matches the signal. All the tests that are done will have an effect of producing IMFs that are noisy which is inherent in EMD method.

White noise is removed by taking all the averages that are obtained for each IMF and using the final average value to discover if the IMFs mean value and the distribution of the scale distribution of each test are within the given normal dyadic filter windows which helps to maintain the dyadic property and reduce chances of having mode mixing (Tsuen et al., 2010).

The principle of EEMD is based on the following steps;

a) First of all a white noise series is introduced as a targeted Introduce.
b) Then the signal is decomposed through adding white noise to IMFs.

c) The repetition of the first and second steps happens using various white noise series.
d) Gain the ensemble by taking the average of the related IMFs that resulted from last decomposition.

The EMD is improved to become EEMD. In EEMD, the introduced level of the noise is not of huge importance, because its amplitude is limited which reduces chances of obtaining the right ensemble. For treating the problem of mode mixing, EEMD gives a really adaptive data analysis technique. For removing the drawback of mode mixing, this technique gives a group of IMFs which include the complete physical meaning, and a time-frequency division without transitional hole. The addition of EMD and the ensemble process became major technique for non-stationary and nonlinear time series analysis (Tang at al., 2006). It must however, be noted that there will still be traces of noise that will be visible even after the reconstruction has been done and such is in the form of residue noise. This can only be reduced by using ensemble tests but the challenges is that these methods will result in an increase in costs and often require more time to compute them.

3.7. A complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)

It is established to fix major problems that are associated with EEMD. In order to overcome the EEMD drawbacks:

- Using residual noise for reconstructing the signal
- Generation of different number of IMFs form realizations of noisy signals (Torres et al., 2011)

Complete ensemble empirical mode decomposition method (CEEMDAN) calculates the residual by adding a certain noise at each and every step and with this technique, a specific noise is added for each step and after each intrinsic mode function extraction. The (CEEMDAN) algorithm can be illustrated using the below steps;

1) For the targeted signal append a white noise series.
2) Decompose all realizations noisy signal to obtain first IMFs by using EMD and take the average to gain first IMF.

$$\mathrm{IMF}_1=1/\mathrm{I}(\sum_{j=1}^{I} E_1(s(t)+ßw_j(t)). \quad (3.2)$$

Where I= number of tests, ß= ratio coefficient, and Ej =compute the jth IMF.

1. Calculate the residual

$$z_1(t)=s(t)\text{-}\mathrm{IMF}_1 \quad (3.3)$$

2. Calculate the second IMF component IMF_2

$$\mathrm{IMF2}=1/\mathrm{I}(\sum_{j=1}^{I} E_1(s(t)+ßE_1(w_j(t))) \quad (3.4)$$

3. All steps above repeated until gain the (n+1) the IMF component IMF_{n+1}.

Despite, all these procedures being done, the complete ensemble EMD is still considered to be having problems in itself. This is because it still needs improvements because of the following challenges;

- It contains residue noise.
- The signal information does not appear in the Ensemble EMD with some "pseudo" IMFs but only shows up "later" with some "pseudo" IMFs in the first stages of decomposition. But a lot of identical signal scales and noise can be found to be high in the first two or three IMFs.

3.8. Improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN)

One of the notable biomedical signal processing algorithm is the ICEEMDAN algorithm which is a suitable for biomedical processing the main idea of improved CEEMDAN is an improved, more pronounced method which can offer IMFs with less noise (Torres et al., 2011). Thus, it can be said to have been developed so as to deal with problems that are associated with the use of ICEEMDAN (pseudo IMFs and noise in IMFs). (Marcelo et al, 2014). The first problem can be deal with applying the EMD on Gaussian white noise for the first IMF while the second problem of noise can be dealt with by using average local means of the signals. The improved ICEEMDAN algorithm can be illustrated using the steps below;

1) Append a Gaussian noise series to the actual signal.

$$s^i(\mathrm{t})=\mathrm{s}(\mathrm{t})+\beta_0 E_1(w^i(\mathrm{t}))| \tag{3.5}$$

2) Use EMD to gain the first remains to compute the local mean of I tests:

$$z_1=\langle M(s^i(\mathrm{t}))\rangle \tag{3.6}$$

Where M (.) is the local mean operation and $E_k(.)$ is the average operation.

3) For j=1, compute first IMF:

$$IMF_1=\mathrm{s}(\mathrm{t})\text{- } z_1 \tag{3.7}$$

4) Calculate the second remains

$$z_2(\mathrm{t})= \langle M\ (z_1(t) + \beta_1 E_2(w^i(\mathrm{t}))\ \rangle. \tag{3.8}$$

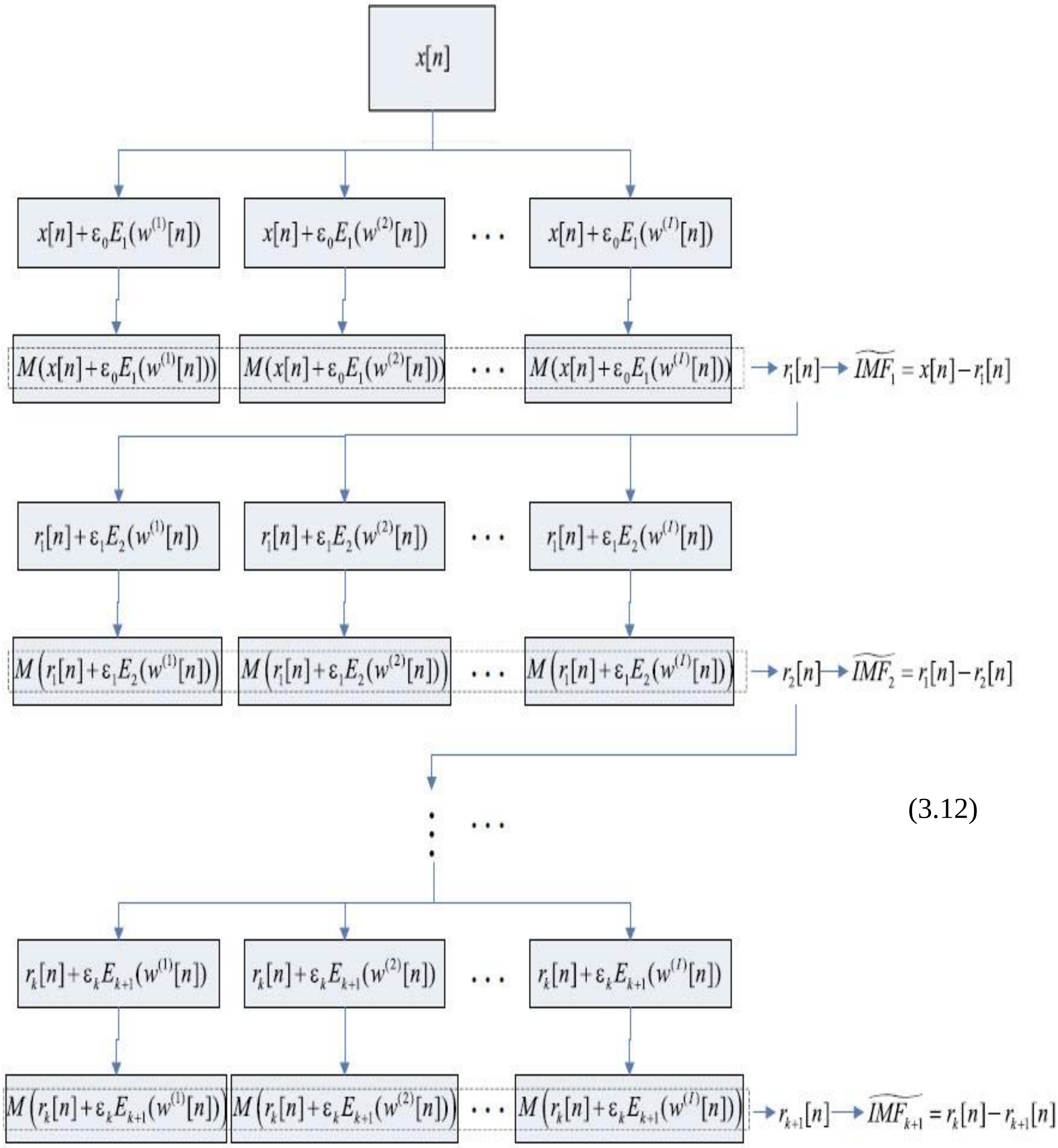
Then second IMF computed:

$$IMF_2(t)= z_1\text{- } z_2 \tag{3.9}$$

5) Calculate the j-th remains and j-th IMF

$$\begin{gathered} z_j(\mathrm{t})= \langle M\ (z_{j-1}(t) + \beta_{j-1} E_j(w^i(\mathrm{t}))\ \rangle. \\ IMF_j(t)= z_{j-1}\text{- } z_j \end{gathered} \tag{3.11}$$

6) Repeat (5) for the next j.



(3.12)

Figure 3.6: Flowchart describing the improved version of CEEMDAN. (Colominas et al., 2014).

All data signals (200 sample) Decomposed by EMD and ICEEMDAN. For each signal we get 9 to 12 modes. We take all IMFs and reconstruction signal from both techniques for comparative. Reconstruction signal gained by summation of all IMFs for each signal. We use RMSE and PCC for comparison.

3.9. Root Mean Square Error(RMSE)

The root-mean-square error (RMSE) is a frequently used measure of the differences between population and sample values obtained from an estimated model. RMSE can be said to indicate how much predicted values vary or differ from the observed values. The differences are what are called residual values which measures errors that have been made either in entering or computing data. The main use of RMSE is to offer an indication on which model minimizes these residuals or error terms. It can thus be said to be measure of the reliability of the estimated model to offer robust (Tang, 2006).

In order to determine which method is efficient, reconstruction IMFs and signal and RMSE values for the initial IMF and the signal are compiled and compared against each other. The main idea is obtained a model which minimizes the residuals, that is, a model with a low RMSE mean. The RMSE is computed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}(A-B)^2}{k}} \tag{3.13}$$

Where A refer to IMF or reconstruction signal and B refer to the original signal.

3.10. Pearson correlation coefficient

It is used to determinate the nature of correlation that exist between two variables or more variables (Rambabu & Murthy, 2014). Computing the PCC between $X(t)$ and IMFs is important because it allows us to determine the required mode which can be used to manage the IMF using a signal on behalf of the noise. The PCC is determined using the following formula:

$$\mathrm{PCC} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\left[\sum_{i=1}^{n}(x_i - \bar{x})^2\right]\left[\sum_{i=1}^{n}(y_i - \bar{y})^2\right]}} \tag{3.14}$$

Where x_i and y_i are the two variables, whereas x^{-} and y^{-} are the arithmetic mean of the two variables. n is the length of the variables.

3.11. Classification and Seizure Detection

It is from decompositions or transformations of EEG signals we extract some features. These features are classified to non-seizure and seizure signals. The major reason behind the use of classifiers is to determine the condition of the patient which in this case to determine whether the patient has got seizures or not. The classification of non-seizure and ictal is made possible by extracting different features from EMD and ICEEMDAN. The study used SVM classifier because of its high potential to yield good results when compared to other classifiers when classifying EEG signal analysis. This can be supported by ideas given by (Shigeo, 2010), which showed that SVM is a possible beneficial approach that can be used to solve kernel-based learning methods, linear and nonlinear classification, function estimation. Also showed strong support of SVM citing that it can offer a better margin hyperplane and has got an ability to reduce operational errors. This in turn leads to an improvement in classification performance. On the other hand, propositions were made by (Bra banter et al. 2011) to use an improved version of SVM which contains primal-dual interpretations and is similar to Gaussian and the regularization of networks processes which is known as the LS-SVM. Thus, LS-SVM is also a classifier which uses training set features Xm=1¡KnT, learn nonlinear mapping of training features into the patients state, Seizure and non-seizures and this is denoted by nT. This study followed similar steps which were proposed by (Xing et al. 2009), which based on the argument that in order to obtain unbiased classification results for a large number of trials such as 1000 trials it is important to separate them into four subsets. From each subset, 80% of the signals subjects are randomly chosen for the validation of training and 20% for the testing validation.

3.12. Support vector machine (SVM)

SVM is classification method that maximizes the marginal hyperplane and minimize the operational error. Hence, its use contributes towards improving classification performance. SVM can thus be said to be a better classifier for EEG signal classification. Thus, its use in the medical field is presumed to contribute towards disease diagnosis in computational biology (Pal & Mather, 2005).

SVMs is also an important analytical method which helps in dealing with data classification issues. Though SVM has been established to be easy to use, it has been noted that individuals who are not well versed with the use of SVM tend to fail to get satisfactory results (Hsu, Chang & Lin, 2003). This study does not try to solve complex SVM problems but seeks to establish the best SVM procedure that can be used to obtain the best and acceptable results.

SVM approaches classification tend to rely on the categorizing data into testing and training testing sets in which each training sets contains several “attributes" (that is, observed variables or features) and class labels (target value). Thus, an SVM can be said to be a technique that produces a model that uses train data attributes to suggest the target values of the test data (Hsu, Chang & Lin, 2003).

3.12.1. Linear Support Vector Machine (LSVM)

As a result of decompositions or transformations we extract some features, but it is important to have classifiers for identification non-seizure and seizure signals. The major reason behind the use of classifiers is to determine the condition of the patient which in this case to determine whether the patient has got seizures or not. The classification of non-seizure and seizure is made possible by extracting different features from EMD and ICEEMDAN. The study used SVM classifier because of its high potential to yield good results when compared to other classifiers when classifying EEG signal analysis. This can be supported by ideas given by Shigeo (2010), which showed that SVM is a possible beneficial approach that can be used to solve kernel-based learning methods, linear and nonlinear classification, function estimation. Further ideas obtained from Shigeo, 2010). Shigeo (2010), also showed strong support of SVM citing that it can offer a better margin hyperplane and has got an ability to reduce operational errors. This in turn leads to an improvement in classification performance. On the other hand, propositions were made by (Brabanter et al., 2011) to use an improved version of SVM which contains primal-dual interpretations and is similar to Gaussian and the regularization of networks processes which is known as the LS-SVM. Thus, LS-SVM is also a classifier which uses training set features Xm=1¡KnT, learn nonlinear mapping of training features into the patient¡¦s state, Seizure and non-seizures and this is denoted by nT. This study followed similar steps which were proposed by (Xing et al., 2009), which based on the argument that in order to obtain unbiased classification results for a large number of trials such as 100 trials it is important to separate them into four subsets.

CHAPTER 4

REXPERIMENTAL RESULT

4.1. Overview

In this chapter, a design of seizure detection system using EEG signals are described. This thesis uses two different sets, each one including 100 seizure and 100 non-seizure data. To process those data, first EMD and ICEEMDAN has been applied separately to extract features (i.e., IMFs). A flow chart diagram of the whole method is shown in Figure 4.3 Both methods have been compared using RMSE and PCC for evaluation IMFs.

For classification and analyzing of the data, the first and the second IMFs from each sample has been taken and merged together (Noran, et al., 2014) to form a new data set. For the classification, L-SVM classifier have been used. First of all an %80 of training data is inserted into the program, after that a test will be done for the %20 of the data sets which are unknown if its seizure or non-seizure. A flow chart of the whole classification process is shown in Figure 4.12.

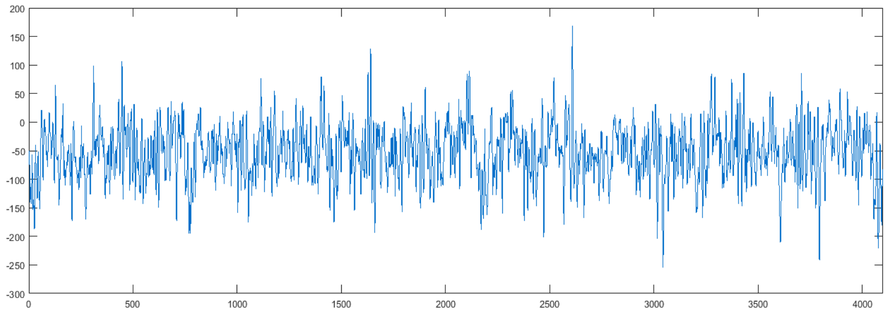


Figure 4.1: Signal sample of Set (A)

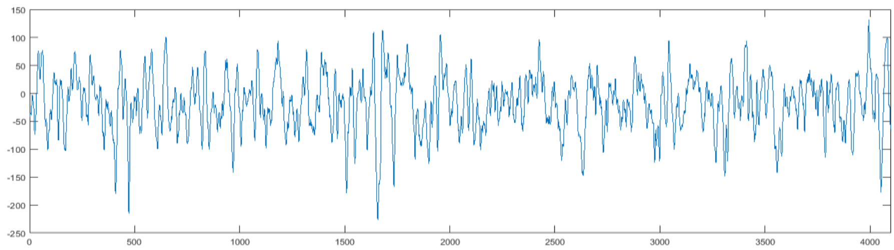


Figure 4.2: Signal sample of Set (C)

4.2. Evaluation performance

The evaluation performance of IMFs for EMD and ICEEMDAN has been compared by: Number of IMFs, RMSE and PCC.

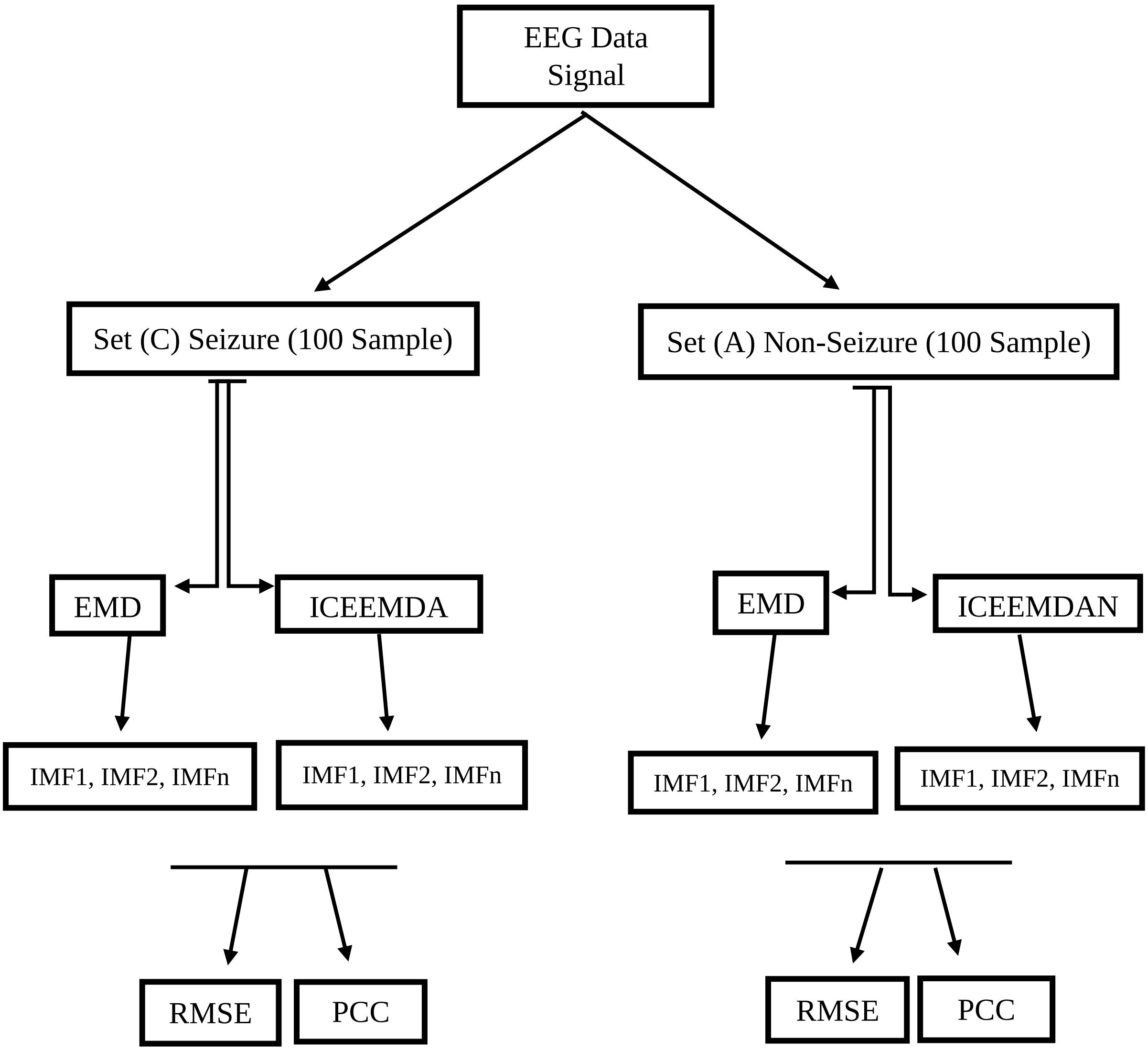


Figure 4.3: Flow Char of Evaluation Performance

4.2.1. Result for Number of IMFs

The first comparison between EMD and ICEEMDAN is in number of IMFs. We have decomposed a signal from each sets are shown in Figures 4.4 and 4.5 in both methods. Number of IMFs for each method represented in Table 4.1, from the Table 4.1 the result shows the ICEEMDAN gives the right number of IMFs. While EMD gives spurious IMFs.

Table 4.1: Number of IMFs obtained from decomposed sample of each set by EMD and ICEEMDAN using EEG signal.

Method	Set A	Set C
EMD	11	11
ICEEMDAN	9	10

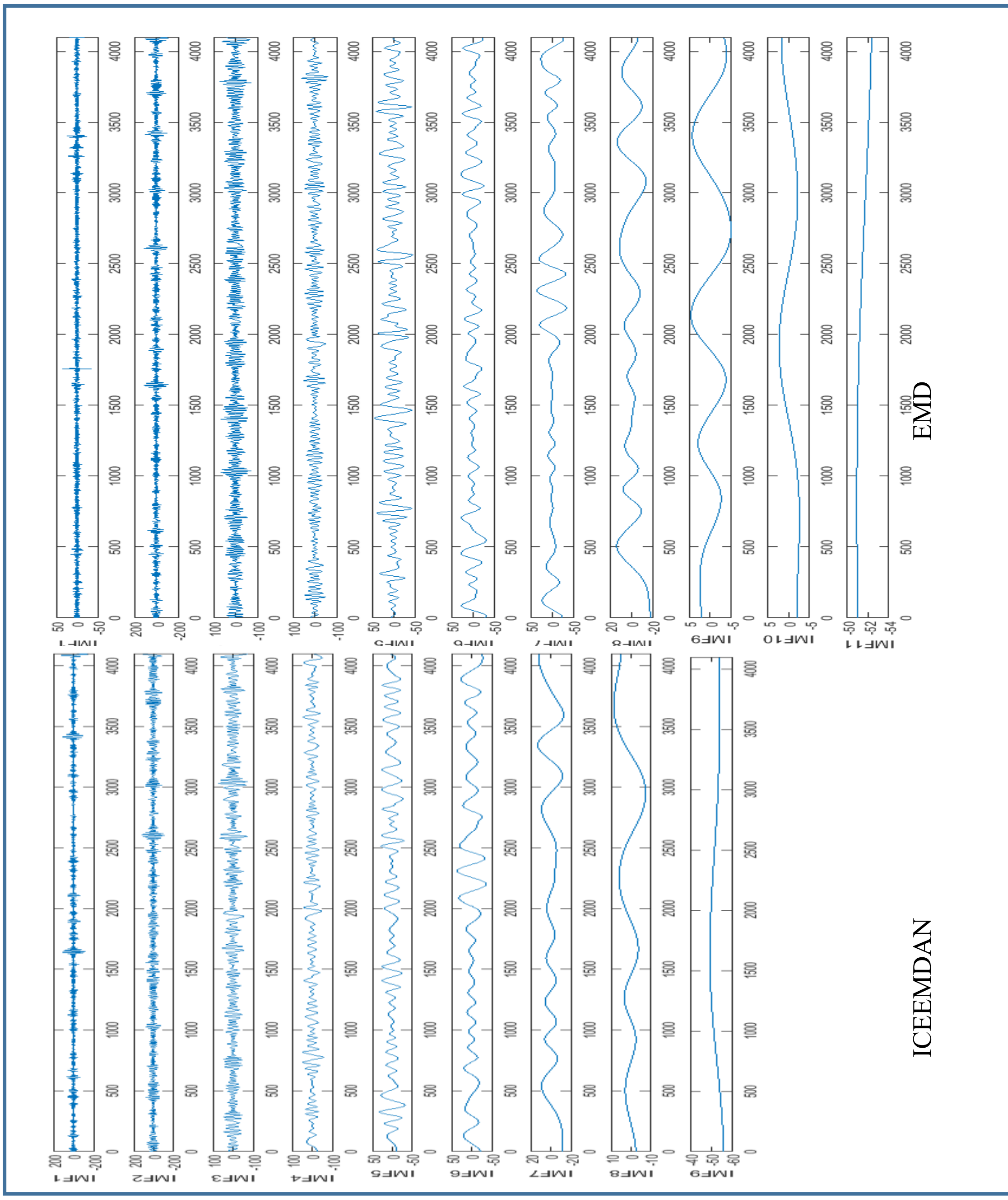


Figure 4.4: Decomposition signal of set (A) using ICEEMDAN and EMD

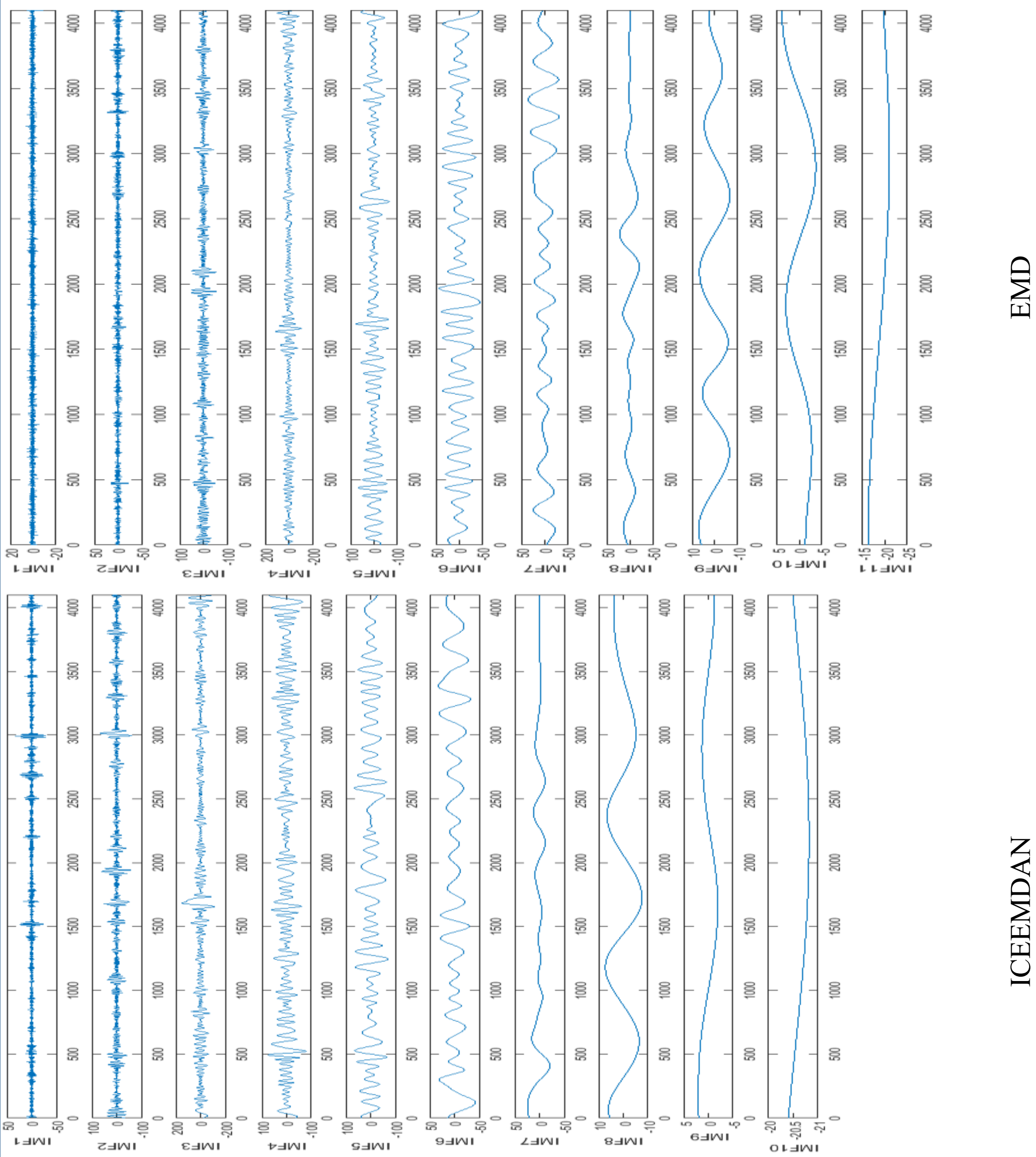


Figure 4.5: Decomposition signal of set (C) using ICEEMDAN and EMD

4.2.2. Result using RMSE.

The performance is evaluated by RMSE for both methods after decomposition process. There are 100 sample of both sets that is decomposed by EMD and ICEEMDAN. After that, the first IMF is calculated by RMSE with the original signal. By taking standard average for RMSEs. For there more, there is a same process for IMF reconstruction,

The RMSE value in ICEEMDAN is less than the RMSE value in EMD for the first IMF with the original signal are shown in Table 4.2 and Figures (4.6 and 4.7). The result of both sets (A and C) are (37.134 and 50.533) for ICEEMDAN as well as (44.773 and 68.099) for EMD respectively.

Table 4.2: RMSE of first IMF of EEG signals Decomposed by EMD and ICEEMDAN.

RMSEs	Set A	Set C
RMSE for First IMF in EMD	44.773	57.061
RMSE for First IMF in ICEEMDAN	37.134	50.533

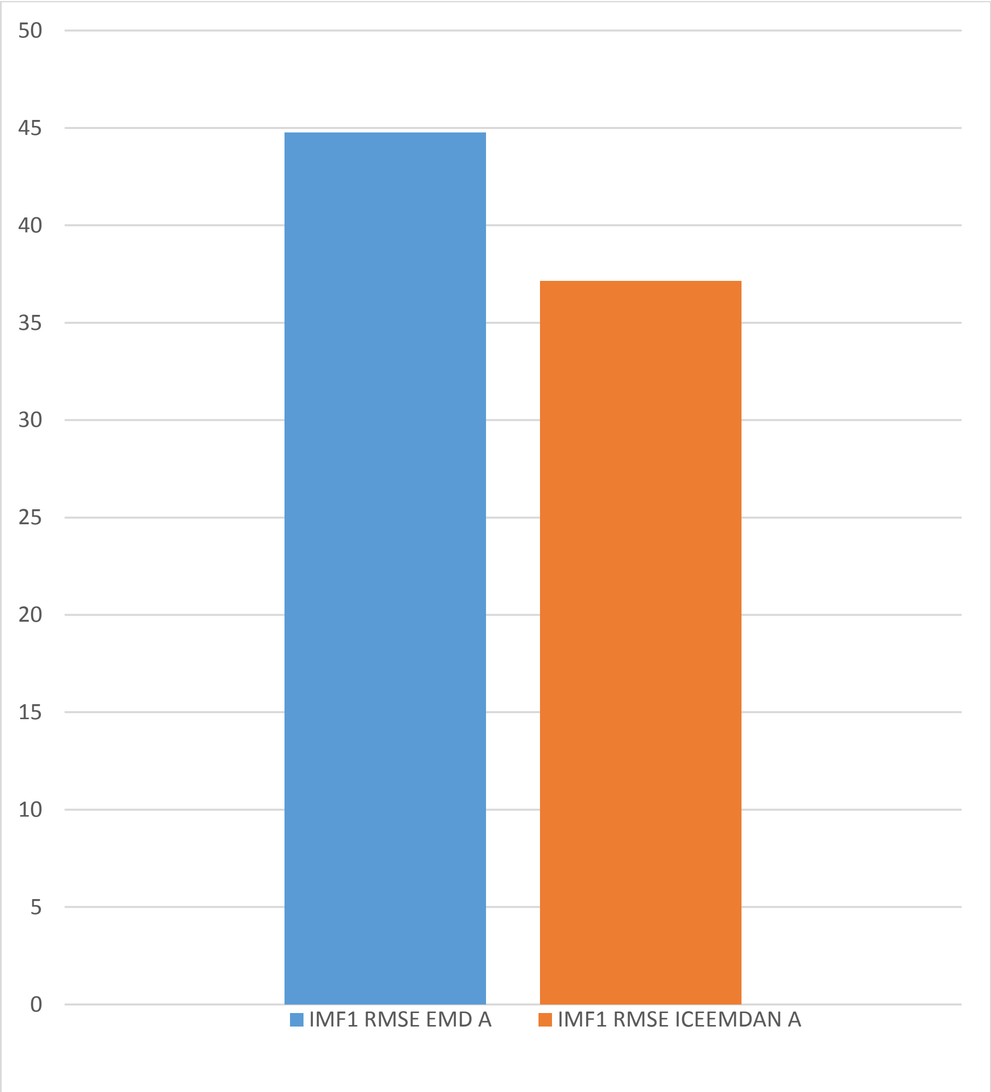


Figure 4.6: RMSE first IMF and Set A for EMD and ICEEMDAN.

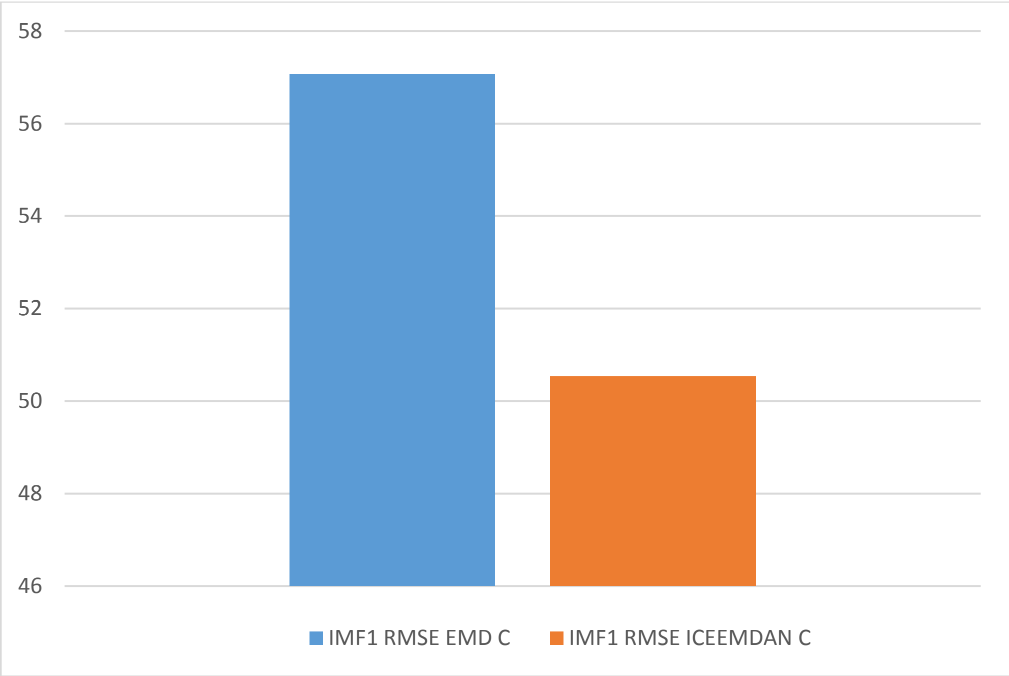


Figure 4.7: RMSE first IMF and Set C for EMD and ICEEMDAN.

Through the Table 4.3 and Figures (4.8 and 4.9) for reconstruction IMFs also shown that the ICEEMDAN has a superiority value than EMD in both sets.

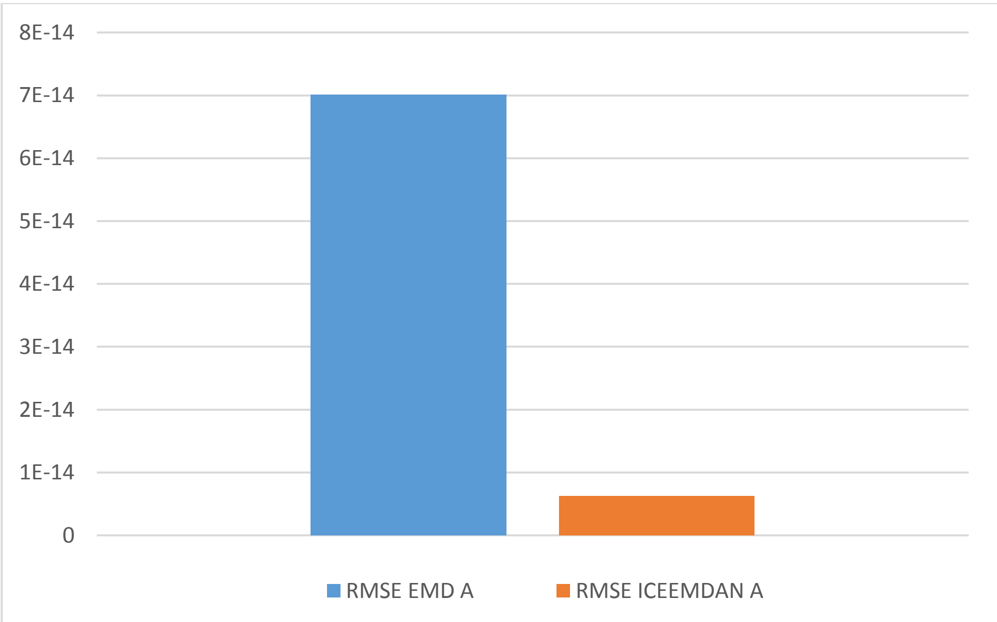


Figure 4.8: RMSE Reconstructiono IMFs in Set A for EMD and ICEEMDAN.

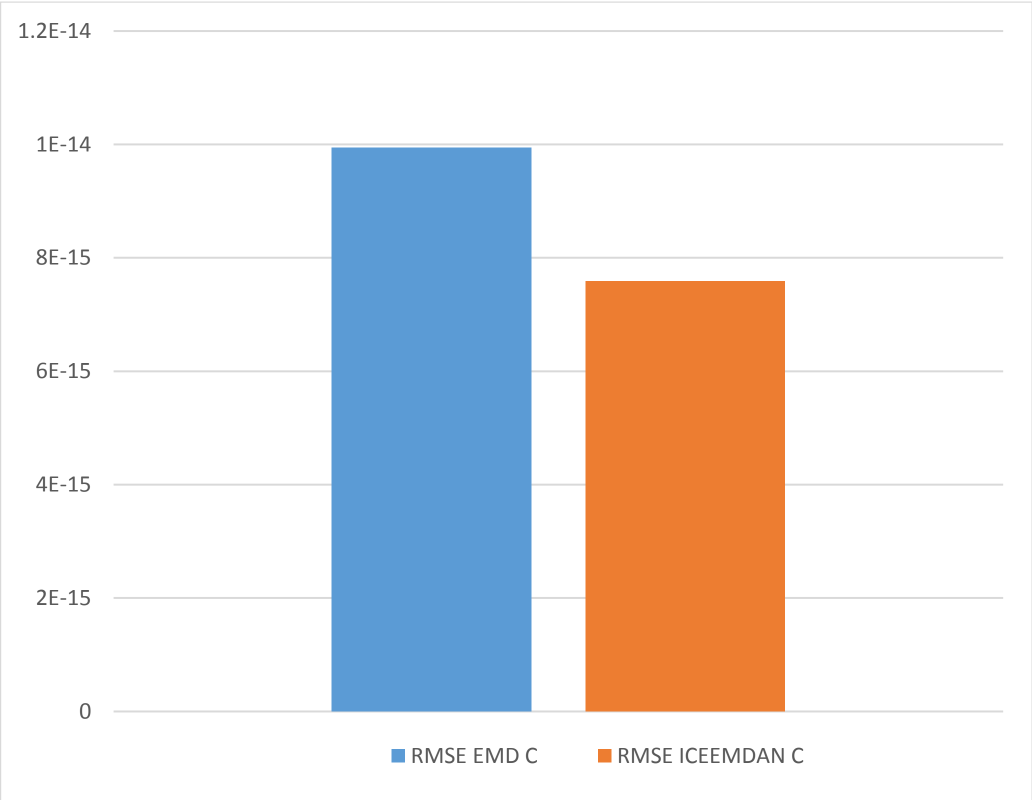


Figure 4.9: RMSE Reconstruction IMFs and Set C for EMD and ICEEMDAN.

Table 4.3: RMSE of Reconstruction IMFs of EEG signals Decomposed by EMD and ICEEMDAN.

	Set A	**Set C**
RMSE for Reconstruction IMFs in EMD	7.01014E-14	9.94262E-15
RMSE for Reconstruction IMFs in ICEEMDAN	6.29199E-15	7.58273E-15

4.2.3. Result using PCC.

To support the capability of two methods, we compute the correlation coefficients for all IMFs (sample of each set). In set (A) an ICEEMDAN have a highest correlation coefficients for all IMFs especially for third one (IMF 0.586) and decreased respectively for other IMFs are shown in Figure 4.10 and Table 4.4 And for other set and are shown in Table 4.5 and Figure 4.11.

Table 4.4: Pearson correlation coefficient signal sample of set (A) with IMFs.

Methods	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7	IMF 8	IMF 9	IMF 10	IMF 11
EMD	0.17	0.51	0.57	0.47	0.39	0.34	0.31	0.12	0.09	-0.01	-0.03
ICEEMDAN	0.35	0.54	0.58	0.48	0.4	0.37	0.32	0.13	0.09		

Table 4.5: Pearson correlation coefficient signal sample of set C with IMFs.

Methods	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7	IMF 8	IMF 9	IMF 10	IMF 11
EMD	0.06	0.19	0.45	0.64	0.59	0.4	0.29	0.16	0.09	0.03	0.02
ICEEMDAN	0.07	0.27	0.57	0.64	0.61	0.51	0.39	0.25	0.18	0.03	

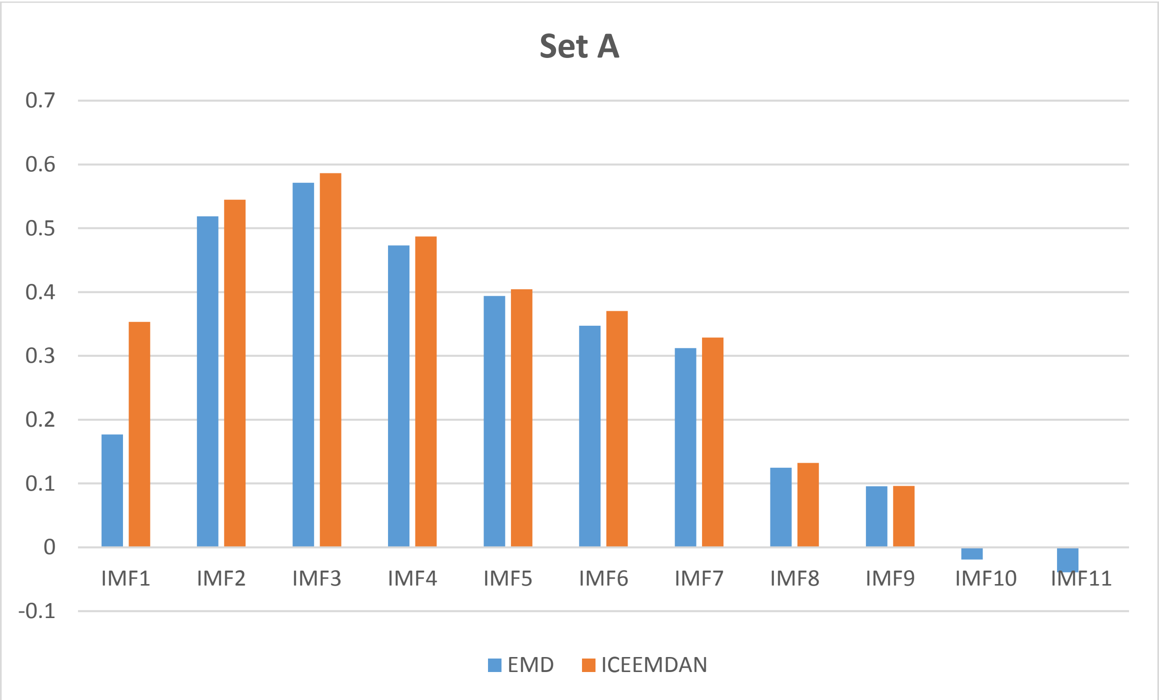


Figure 4.10: PCC signal sample of set A for EMD and ICEEMDAN with IMFs.

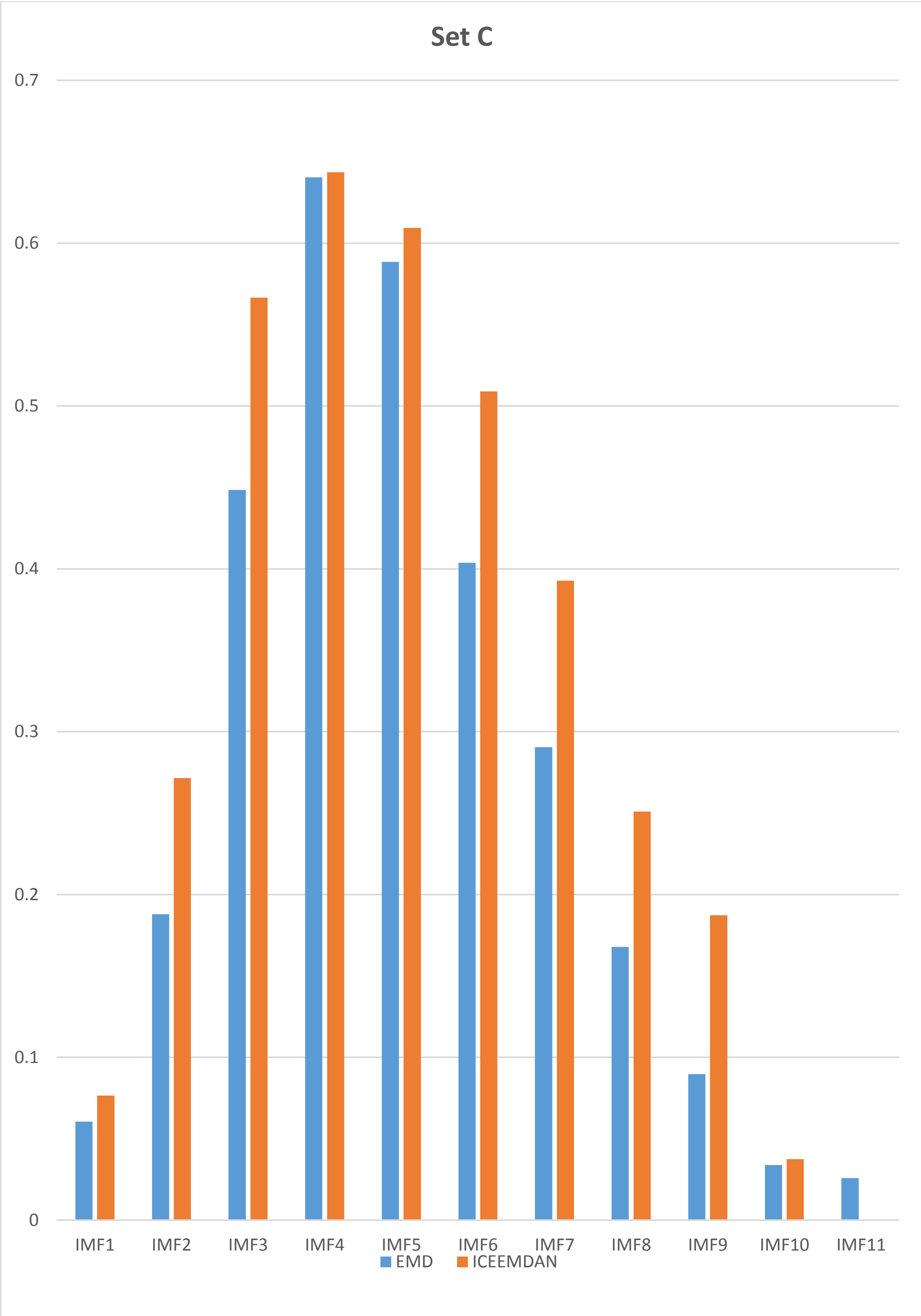


Figure 4.11: PCC signal sample of set C for EMD and ICEEMDAN with IMFs.

4.3. Classification Result

A design of seizure detection system using EEG signals is shown in Figure 4.12, this program takes data from two different sets, and in addition, this data input contains 100 samples for each sets to process this data, first EMD and ICEEMDAN has been applied separately to extract features (i.e., IMFs),

For classification and analyzing the data, the first and the second IMFs from each sample has been taken and merged together (Noran, et al., 2014) to form a new data set. For the classification, L-SVM classifier have been used. First of all an %80 of training data is inserted into the program, after that a test will be done for the %20 of the data sets which are unknown if its seizure or non-seizure.

The classifier (L-SVM) is detecting sensitivity of the computations, the accuracy and specificity. The rules for accuracy, sensitivity and specificity are described below.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TN+FP+TP+FN}} \text{ x } 100 \tag{4.1}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TP+FN}} \text{ x } 100 \tag{4.2}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \text{ x } 10 \tag{4.3}$$

The number of abnormal (seizure) epochs detected the true positive (TP) in feature vector, by two methods and professional physicians, the number of seizure epoch is a false positive (FN) which are missed by both methods, but have been detected by professional physicians, the number of non-seizure epoch is the (TN) true negative are recognized by both methods and professional physicians, and the number of non-seizure (normal) is the (FP) false positive, are recognized as seizure by both the methods.

As a result of classification for IMFs of EMD and ICEEMDAN we get different numbers of trails in accuracy are shown in Tables (4.6, 4.7, 4.8, 4.9, 4.10 and 4.11). In all trails ICEEMDAN is a better method than EMD.

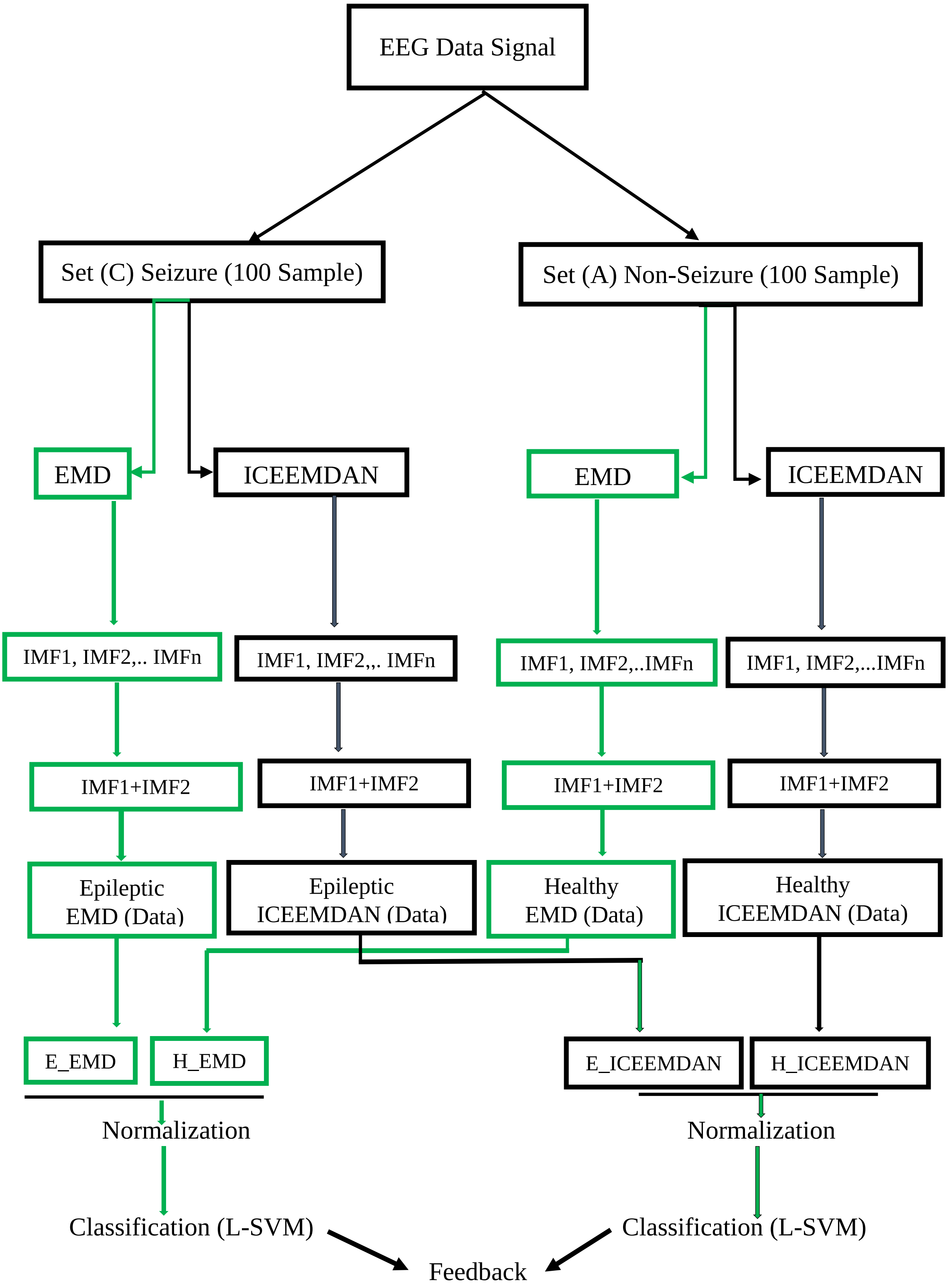


Figure 4.12: Program Seizure detection flow chart

Table 4.6: The result of using various combinations of instinct mode function of EMD using Linear SVM. 80 by 20 tests

Trial	TP	FN	TN	FP	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	20	0	20	0	100	100	100
2	19	1	20	0	95	100	97.5
3	19	1	20	0	95	100	97.5
4	20	0	20	0	100	100	100
5	20	0	20	0	100	100	100
6	19	1	20	0	95	100	97.5
7	20	0	20	0	100	100	100
8	20	0	20	0	100	100	100
9	19	1	20	0	95	100	97.5
10	20	0	20	0	100	100	100
11	20	0	20	0	100	100	100
12	19	1	20	0	95	100	97.5
13	20	0	20	0	100	100	100
14	20	0	20	0	100	100	100
15	19	1	20	0	95	100	97.5
16	19	1	20	0	95	100	97.5
17	20	0	20	0	100	100	100
18	19	1	20	0	95	100	97.5
19	20	0	20	0	100	100	100
20	20	0	20	0	100	100	100

Table 4.7: The result of using various combinations of instinct mode function of EMD using Linear SVM. 50 by 50 tests

Trial	TP	FN	TN	FP	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	49	1	50	0	98	100	99
2	49	1	50	0	98	100	99

3	49	1	50	0	98	100	99
4	49	1	50	0	98	100	99
5	50	0	50	0	100	100	100
6	49	1	50	0	98	100	99
7	49	1	50	0	98	100	99
8	50	0	50	0	100	100	100
9	49	1	50	0	98	100	99
10	49	1	50	0	98	100	99
11	49	1	50	0	98	100	99
12	49	1	50	0	98	100	99
13	49	1	50	0	98	100	99
14	50	0	50	0	100	100	100
15	49	1	50	0	98	100	99
16	49	1	50	0	98	100	99
17	50	0	50	0	100	100	100
18	49	1	50	0	98	100	99
19	49	1	50	0	98	100	99
1	49	1	50	0	98	100	99

Table 4.8: The result of using various combinations of instinct mode function of EMD using Linear SVM. 20 by 80 tests

Trial	**TP**	**FN**	**TN**	**FP**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
1	79	1	80	0	98.75	100	99.375
2	79	1	80	0	98.75	100	99.375
3	79	1	80	0	98.75	100	99.375
4	79	1	80	0	98.75	100	99.375
5	79	1	80	0	98.75	100	99.375
6	79	1	80	0	98.75	100	99.375
7	79	1	80	0	98.75	100	99.375

8	79	1	80	0	98.75	100	99.375
9	79	1	80	0	98.75	100	99.375
10	79	1	80	0	98.75	100	99.375
11	79	1	80	0	98.75	100	99.375
12	79	1	80	0	98.75	100	99.375
13	79	1	80	0	98.75	100	99.375
14	80	0	80	0	100	100	100
15	79	1	80	0	98.75	100	99.375
16	79	1	80	0	98.75	100	99.375
17	79	1	80	0	98.75	100	99.375
18	79	1	80	0	98.75	100	99.375
19	79	1	80	0	98.75	100	99.375
1	79	1	80	0	98.75	100	99.375

Table 4.9: The result of using various combinations of instinct mode function of ICEEMDAN using Linear SVM. 80 by 20

Trial	TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
1	20	0	20	0	100	100	100
2	19	1	20	0	95	100	97.5
3	20	0	20	0	100	100	100
4	20	0	20	0	100	100	100
5	20	0	20	0	100	100	100
6	20	0	20	0	100	100	100
7	20	0	20	0	100	100	100
8	20	0	20	0	100	100	100
9	19	1	20	0	95	100	97.5
10	20	0	20	0	100	100	100
11	20	0	20	0	100	100	100

12	20	0	20	0	100	100	100
13	20	0	20	0	100	100	100
14	20	0	20	0	100	100	100
15	20	0	20	0	100	100	100
16	19	1	20	0	95	100	97.5
17	20	0	20	0	100	100	100
18	20	0	20	0	100	100	100
19	20	0	20	0	100	100	100
20	20	0	20	0	100	100	100

Table 4.10: The result of using various combinations of instinct mode function of ICEEMDAN using Linear SVM. 50 by 50

Trial	TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
1	49	1	50	0	98	100	99
2	49	1	50	0	98	100	99
3	50	0	50	0	100	100	100
4	49	1	50	0	98	100	99
5	50	0	50	0	100	100	100
6	49	1	50	0	98	100	99
7	50	0	50	0	100	100	100
8	50	0	50	0	100	100	100
9	49	1	50	0	98	100	99
10	50	0	50	0	100	100	100
11	49	1	50	0	98	100	99
12	50	0	50	0	100	100	100
13	49	1	50	0	98	100	99
14	50	0	50	0	100	100	100
15	49	1	50	0	98	100	99

16	49	1	50	0	98	100	99
17	50	0	50	0	100	100	100
18	49	1	50	0	98	100	99
19	50	0	50	0	100	100	100
1	49	1	50	0	98	100	99

Table 4.11: The result of using various combinations of instinct mode function of ICEEMDAN using Linear SVM. 20 by 80

Trial	TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
1	79	1	80	0	98.75	100	99.375
2	79	1	80	0	98.75	100	99.375
3	79	1	80	0	98.75	100	99.375
4	79	1	80	0	98.75	100	99.375
5	79	1	80	0	98.75	100	99.375
6	79	1	80	0	98.75	100	99.375
7	80	0	80	0	100	100	100
8	79	1	80	0	98.75	100	99.375
9	79	1	80	0	98.75	100	99.375
10	79	1	80	0	98.75	100	99.375
11	79	1	80	0	98.75	100	99.375
12	79	1	80	0	98.75	100	99.375
13	79	1	80	0	98.75	100	99.375
14	80	0	80	0	100	100	100
15	79	1	80	0	98.75	100	99.375
16	79	1	80	0	98.75	100	99.375
17	79	1	80	0	98.75	100	99.375
18	79	1	80	0	98.75	100	99.375
19	79	1	80	0	98.75	100	99.375

1	79	1	80	0	98.75	100	99.375

Also by taking average for sensitivity and accuracy. ICEEMDAN is better than EMD by getting 99.55% in accuracy and 99.1% sensitivity while EMD is 99.1% in accuracy and 98.2% in sensitivity respectively.

Table 4.12: Average of performance measures using various combinations of features of EMD using Linear SVM. Average 80 by 20

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
19.65	0.35	20	0	98.25	100	99.1

Table 4.13: Average of performance measures using various combinations of features of EMD using Linear SVM. Average 50 by 50

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
49.24	0.76	50	0	98.48	100	99.24

Table 4.14: Average of performance measures using various combinations of features of EMD using Linear SVM. Average 20 by 80

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
79.09	0.91	80	0	98.8625	100	99.43125

Table 4.15: Average of performance measures using various combinations of features of ICEEMDAN using Linear SVM. 80 by 20

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
19.82	0.18	20	0	99.1	100	99.55

Table 4.16: Average of performance measures using various combinations of features of ICEEMDAN using Linear SVM. 50 by 50

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
49.51	0.49	50	0	99.02	100	99.51

Table 4.17: Average of performance measures using various combinations of features of ICEEMDAN using Linear SVM. 20 by 80

TP	FN	TN	FP	Sensitivity %	Specificity %	Accuracy %
79.16	0.84	80	0	98.95	100	99.475

Table 4.18: Summary of studies reporting automated detection of three classes using same database are used in this work.

Authors	Features	Classifier	Accuracy (%)
Guler et al., 2005[42]	Lyapujnov exponents	Recurrent neural - network	96.7
Dastidar et al., 2007[43]	Band-eature space	propagation neural-network	96.7
Dastidar and Adeli, 2007[44]	Mixed-band feature-space	Spiking neural - network	92.5
Chua et al., 2009[47]	Bisgpectrum entropies-Magnitude	GMM	93.1
Acharya et al., 2012[14]	Nonlinear parameters	GMM	95
Faust et al., 2010[28]	Four pectral local-maxima and minima	SVM	93.3

Acharya et al., 2011[34]	Recurrence quantification Analysis-features	SVM	95.6
(Martis et al. 2012)	EMD-features	C4.5	95.33
Present Work	EMD features	L-SVM	99.1
Present Work	ICEEMDAN features	L-SVM	99.55

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1. Conclusion

Elliptic seizure is identified and analyzed on Electroencephalogram (EEG) signals using different methods. EEG is a flexible (data-driven) time-frequency signal used to investigate non-stationary signals in brain. Different studies proposed different solutions for EEG signals in order to analyze and detect epileptic seizure in it. One of them is EMD which stands for empirical mode decomposition. The EMD has core problem which is obtained when original signal is decomposed called “mode mixing". To solve and lessen noise-assisted problem. Improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) which is one of the latest methods on this era can be used to retrieve the total features of the original signal.

The EMD is a one method that used for extracting features from the EEG signals however, in the time of decomposition, some problems occur such as remaining noise and mode mixing. The ICEEMDAN is one of the new studies that is used for feature extraction to obtain optimal IMFs by reducing remaining noise in this modes to analyze and identify the seizures.

The database used in this research stand for two case: the first one is an ecliptic seizure means abnormal that contain 100 samples. The second one includes 100 samples that denotes the healthy seizures means normal. After applied the EMD and ICEEMDAN to decomposed features means IMFs. In this research, the performance evaluation of both methods compared with each other according to number of IMFs which ICEEMDAN gave the right number of IMFs but EMD gave us incorrect IMFs. And also by using RMSE and Pearson Correlation Coefficient where first one gives a right number of IMFs and less remaining noise.

To analyses and identify seizures linear support vector machine have been used, the L-SVM

Was used to classify the recorded data signals based on EMD and ICEEMDAN, First of all an %80 of training data is inserted into the program, after that a test will be done for the %20 of the data sets which are unknown if its seizure or non-seizure.

After applied EMD and ICEEMDAN methods we come to the conclusion that, the classification accuracy obtained by the proposed method achieved 99.95%, the maximum accuracy to identify seizures. While the classification accuracy obtained by EMD shows 99.91% accuracy and compare to related work ICEEMDAN has a maximum accuracy. As a result the ICEEMDAN is a better method for detection epileptic seizure in EEG records.

5.2. Future Work

- As we can see from our results of ICEEMDAN method, it is very suitable for biological signals, but this is also can be used to detect and predicate other signals such as Speech recognition and ECG
- ICEEMDAN can be applied to different databases and results can be observed with those we have in our approach.

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APPENDICES

APPENDIX 1
SOURCE CODE

Here we have put the code for the process of getting signals from the database we have and processing them according. As it's mentioned two main ways have been mentioned here in decomposing the EEG signals in to its properties which are IMFs which are EMD and ICEEMDAN.

EMD

```
function [imf,ort,nbits] = emd(varargin)
[x,t,sd,sd2,tol,MODE_COMPLEX,ndirs,display_sifting,sdt,sd2t,r,imf,k,nbit,NbIt,MAXITERATIONS,FIXE,FIXE_H,MAXMODES,INTERP,mask] = init(varargin{:});
if display_sifting
  fig_h = figure;
end
%main loop : requires at least 3 extrema to proceed
while (~stop_EMD(r,MODE_COMPLEX,ndirs) && (k < MAXMODES+1 || MAXMODES == 0) && ~any(mask))
  % current mode
  m = r;
  % mode at previous iteration
  mp = m;
  %computation of mean and stopping criterion
  if FIXE
    [stop_sift,moyenne] = stop_sifting_fixe(t,m,INTERP,MODE_COMPLEX,ndirs);
```

```
  elseif FIXE_H
    stop_count = 0;
    [stop_sift,moyenne] = stop_sifting_fixe_h(t,m,INTERP,stop_count,FIXE_H,MODE_COMPLEX,ndirs);
  else
    [stop_sift,moyenne] = stop_sifting(m,t,sd,sd2,tol,INTERP,MODE_COMPLEX,ndirs);
  end
  if (max(abs(m))) < (1e-10)*(max(abs(x)))
    if ~stop_sift
      warning('emd:warning','forced stop of EMD : too small amplitude')
    else
      disp('forced stop of EMD : too small amplitude')
    end
    break
  end
  % sifting loop
  while ~stop_sift && nbit<MAXITERATIONS
    if(~MODE_COMPLEX && nbit>MAXITERATIONS/5 && mod(nbit,floor(MAXITERATIONS/10))==0 && ~FIXE && nbit > 100)
      disp(['mode ',int2str(k),', iteration ',int2str(nbit)])
      if exist('s','var')
        disp(['stop parameter mean value : ',num2str(s)])
      end
      [im,iM] = extr(m);
      disp([int2str(sum(m(im) > 0)),' minima > 0; ',int2str(sum(m(iM) < 0)),' maxima < 0.'])
```

```
    end

   %sifting
   m = m - moyenne;
```

ICEEMDAN

```
function [modes,its]=iceemdan(x,Nstd,NR,MaxIter,SNRFlag)
x=x(:)';
desvio_x=std(x);
x=x/desvio_x;

modes=zeros(size(x));
temp=zeros(size(x));
aux=zeros(size(x));
iter=zeros(NR,round(log2(length(x))+5));

for i=1:NR
   white_noise{i}=randn(size(x));
end;

for i=1:NR
   modes_white_noise{i}=emd(white_noise{i})
end;
```

```
for i=1:NR %calculates the first mode
    xi=x+Nstd*modes_white_noise{i}(1,:)/std(modes_white_noise{i}(1,:));
    [temp, o, it]=emd(xi,'MAXMODES',1,'MAXITERATIONS',MaxIter);
    temp=temp(1,:);
    aux=aux+(xi-temp)/NR;
    iter(i,1)=it;
end;

modes= x-aux; %saves the first mode
medias = aux;
k=1;
aux=zeros(size(x));
es_imf = min(size(emd(medias(end,:),'MAXMODES',1,'MAXITERATIONS',MaxIter)));

while es_imf>1 %calculates the rest of the modes
    for i=1:NR
        tamanio=size(modes_white_noise{i});
        if tamanio(1)>=k+1
            noise=modes_white_noise{i}(k+1,:);
            if SNRFlag == 2
                noise=noise/std(noise); %adjust the std of the noise
            end;
            noise=Nstd*noise;
            try
```

```
[temp,o,it]=emd(medias(end,:)+std(medias(end,:))*noise,'MAXMODES',1,'MAXITERAT
IONS',MaxIter);
            catch
                it=0; disp('catch 1 '); disp(num2str(k))

temp=emd(medias(end,:)+std(medias(end,:))*noise,'MAXMODES',1,'MAXITERATIONS
',MaxIter);
            end;
            temp=temp(end,:);
        else
            try
                [temp, o,
it]=emd(medias(end,:),'MAXMODES',1,'MAXITERATIONS',MaxIter);
            catch
                temp=emd(medias(end,:),'MAXMODES',1,'MAXITERATIONS',MaxIter);
                it=0; disp('catch 2 sin ruido')
            end;
            temp=temp(end,:);
        end;
        aux=aux+temp/NR;
    iter(i,k+1)=it;
    end;
    modes=[modes;medias(end,:)-aux];
    medias = [medias;aux];
    aux=zeros(size(x));
```

```
    k=k+1;
    es_imf =
min(size(emd(medias(end,:),'MAXMODES',1,'MAXITERATIONS',MaxIter)));
end;
modes = [modes;medias(end,:)];
modes=modes*desvio_x;
its=iter;
```

Normalization

```
function Norm=Normalize2(x)
[~, n]=size(x);
for i=1:n
mx=max(x(:,i));
mn=min(x(:,i));
x(:,i)=(x(:,i)-mn)/(mx-mn);
end
Norm=x;
End
```

Classification

```
for i=1:HN
      training(i,:)=Normal(randindex_N(i),:);
end
for j=1:HAb
      training(i+j,:)=AbNormal(randindex_Ab(j),:);
```

```
end
for ii=1:N-HN
    testing(ii,:)=Normal(randindex_N(HN+ii),:);
end
for jj=1:Ab-HAb
    testing(ii+jj,:)=AbNormal(randindex_Ab(HAb+jj),:); end
SVMStruct = svmtrain(training, group,'Autoscale',0 );
    class(:,trial)=svmclassify(SVMStruct,testing);
```