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Automatic Classification for Neural Signals in Epilepsy Using Artificial Neural Network

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Abstract. Epilepsy is a neurological disorder which is characterized by transient and unexpected electrical disturbance of the brain. The electroencephalogram (EEG) is a commonly used signal for detection of epileptic seizures. This paper presents a compare for classification of seizure EEG signals with different method. The proposed method is based on the empirical mode decomposition (EMD), the artificial neural network (ANN) and Support Vector Machine (SVM). The EMD method decomposes an EEG signal into a set of symmetric and band-limited signals termed as intrinsic mode functions (IMFs). The Second-order difference plot (SODP) of IMFs provides elliptical structure. The 89% confidence ellipse area measured from the SODP of IMFs has been used as a feature in order to discriminate seizure-free EEG signals from the epileptic seizure EEG signals. The feature space obtained from the ellipse area parameters of two IMFs has been used for classification seizure-free EEG signals using the artificial neural network (ANN) classifier. It has been shown that the feature space formed using ellipse area parameters of first and second IMFs has given good classification performance. In ANN we check out the Training and Testing results for discriminate seizure-free EEG signals from the epileptic seizure EEG signals.

Keywords: Electroencephalogram (EEG), Artificial Neural Networks (ANN), Empirical Mode Decomposition (EMD), Intrinsic mode function (IMF), Second-order difference plot (SODP)

1. INTRODUCTION

Epilepsy is a chronic neurological disorder characterised by a recurrent tendency to have spontaneous, intermittent, abnormal electrical activity in a part of the brain, which manifest as seizures, and diagnosed as the result of a patient having a second unprovoked seizure, with at least 24 hours between the first and second seizure. This definition regards an episode of status epileptics as a single seizure. A seizure lasting more than 30 minutes or repeated seizures without intervening periods of regained function or consciousness.

However, the definition of epilepsy as a tendency to have recurrent seizures excludes seizures that are provoked by an obvious and immediate preceding cause e.g. an acute systemic or metabolic imbalance, drugs or toxins, or a recent cerebral damage from stroke, trauma or infection. Seizures occurring in children between 6 months and 6 years only within the context of a febrile illness without the evidence of intracranial aetiology or febrile seizures are also excluded, as are seizures occurring only within the neonatal period.

Seizure signal: A seizure occurs when a burst of electrical impulses in the brain escape their normal limits. They spread to neighbouring areas and create an uncontrolled storm of electrical activity. The electrical impulses can be transmitted to the muscles, causing twitches or convulsions. Seizures, abnormal movements or behaviour due to unusual electrical activity in the brain, are a symptom of epilepsy. But not all people who appear to have seizures have epilepsy, a group of related disorders characterized by a tendency for recurrent seizures.

Non-epileptic seizures are not accompanied by abnormal electrical activity in the brain and may be caused by psychological issues or stress. However, non-epileptic seizures look like true seizures, which make diagnosis more difficult. Normal EEG readings and lack of response to epileptic drugs are two clues they are not true epileptic seizures. These types of seizure may be treated with psychotherapy and psychiatric medications.

2. MATERIAL AND METHOLOGY

2.1 Data set used

Please find the original data at [1].The original dataset from the reference consists of 5 different folders, each with 100 files, with each file representing a single subject/person. Each file is a recording of brain activity for 23.6 seconds. The corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time. So we have total 500 individuals with each has 4097 data points for 23.5seconds.We divided and shuffled every 4097 data points into 21 chunks, each chunk contains 178 data points for 1 second, and each data point is the value of the EEG recording at a different point in time. So now we have 21 x 15000 pieces of information (row), each information contains 178 data points for 1 second (column),the last column represents the label y {1,2,3,4and5}.The response variable is y in column 179, the ExplanatoryvariablesX1,X2,............X178 y contains the category of the 178-dimensional input vector. Specifically y in {1, 2, 3, 4, 5}:

5 -eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open
4 - eyes closed, means when they were recording the EEG signal the patient had their eyes closed
3 - Yes they identify where the region of the tumour was in the brain and recording the EEG activity from the healthy brain area .
2-The y recorder the EEG from the area where the tumour was located
1 - Recording of seizure activity

All subjects falling in classes 2, 3, 4, and 5 are subjects who did not have epileptic seizure. Only subjects in class 1 have epileptic seizure. Our motivation for creating this version of the data was to simplify access to the data via the creation of a version of it. Although there are 5 classes most authors have done binary classification, namely class 1 (Epileptic seizure) against the rest.

2.2 Table for dataset

S.NO	**CLASSES**	**Signal Type**	**No. Of samples in each signal**	**No. of signals**
1	**5**	**Z(Healthy) Eyes open**	**4097**	**100**
2	**4**	**O(Healthy) Eyes Closed**	**4097**	**100**
3	**3**	**N (Seizure free)**	**4097**	**100**
4	**2**	**F(Seizure free)**	**4097**	**100**
5	**1**	**S(Seizure)**	**4097**	**100**

Table: 1 Dataset of seizure signal

We use in my work use classes of 1, 2, 3,4 and 5(S, N,F,O and Z)

S =409700X1
N=409700X1
F=405603X1
O =409700X1
Z =409700X1

2.3Graph of dataset

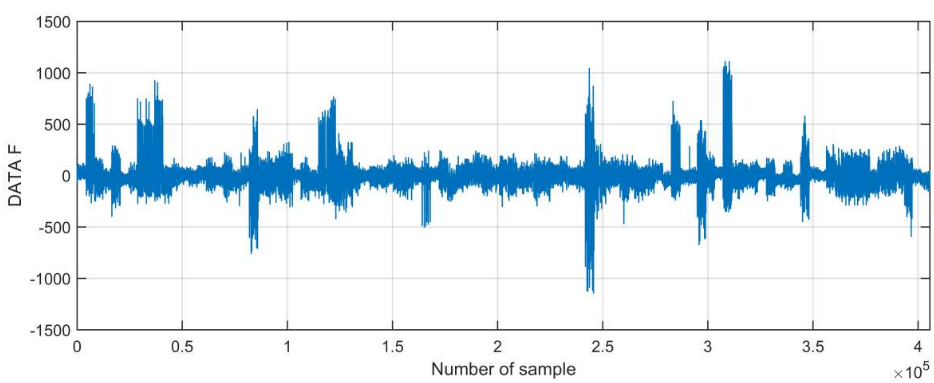


Figure: Graph of data F

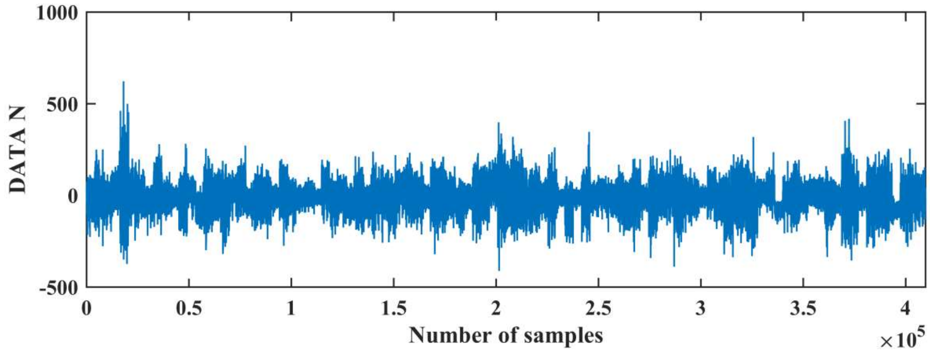


Figure: Graph of data N

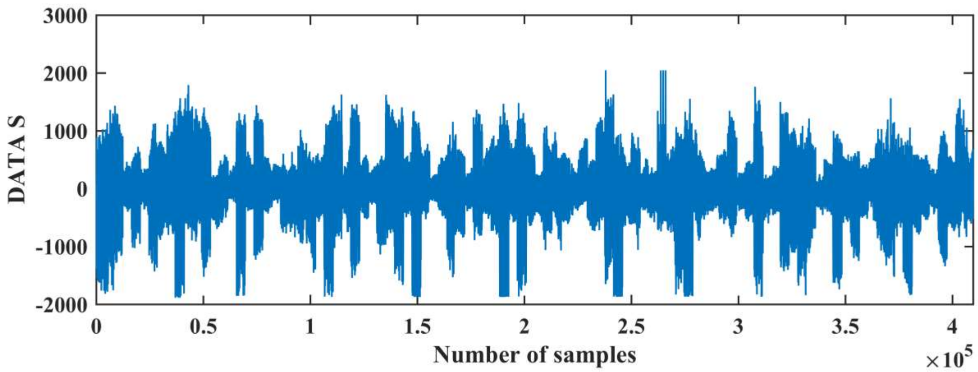


Figure: Graph of data S

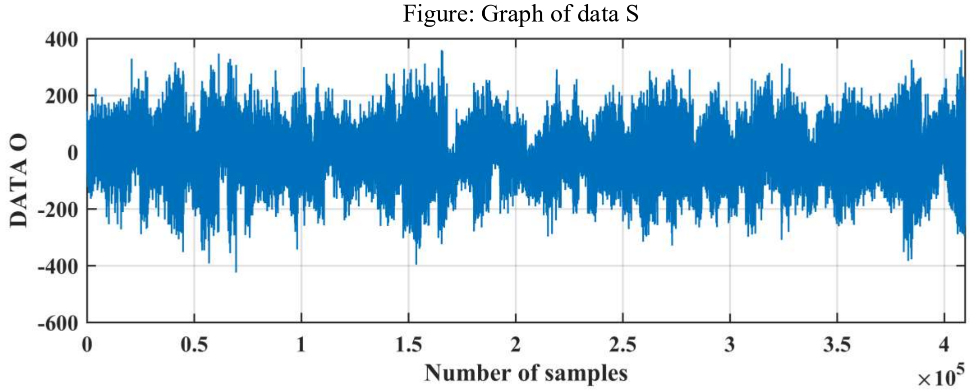


Figure: Graph of data O

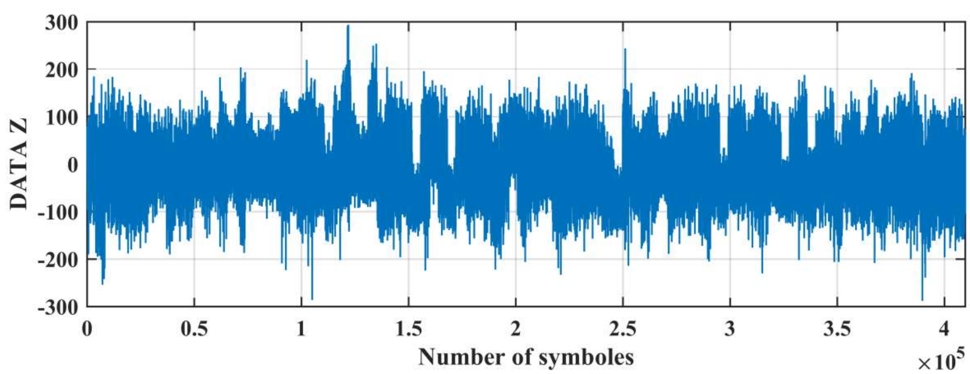


Figure: Graph of data Z

[1] http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3

Relevant Papers:

[2] Andrzejak RG, Lehnertz K, Rieke C, Mormann F, David P, Elger CE (2001) Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state, Phys. Rev. E, 64, 061907

2.2. METHOLOGY

2.2.1 EMD

Epileptic seizure detection is commonly implemented by expert clinicians with visual observation of electroencephalography (EEG) signals, which tends to be time consuming and sensitive to bias. The epileptic detection in most previous research suffers from low power and unsuitability for processing large datasets. Therefore, a computerized epileptic seizure detection method is highly required to eradicate the aforementioned problems, expedite epilepsy research and aid medical professionals. In this work, we propose an automatic epilepsy diagnosis framework based on the combination of multi-domain feature extraction and nonlinear analysis of EEG signals. Firstly, EEG signals are pre-processed by using the wavelet threshold method to remove the artefacts. We then extract representative features in the time domain, frequency domain, time-frequency domain and nonlinear analysis features based on the information theory. These features are further extracted in five frequency sub-bands based on the clinical interest, and the dimension of the original feature space is then reduced by using both a principal component analysis and an analysis of variance. Furthermore, the optimal combination of the extracted features is identified and evaluated via different classifiers for the epileptic seizure detection of EEG signals.

The foundation of this method lies on the extraction of temporal and spectral features from Empirical Mode Decomposition (EMD) of the EEG signals. The usage of EMD is motivated by the fact that EEG signals are non-stationary and EMD is a data dependent method exhibiting a better adaptability towards non-stationary in the EEG signals. The main advantage of the algorithm is

(a) The ability of the algorithm to run robustly in a clinical setting with noised EEG.

(b) Feature extraction with highly meaningful wavelet transform because hidden EEG information can be revealed and the noise effort reduced as certain data under some scales are omitted.

(c) Simplicity and low computational cost guaranteeing real clinical application.

(d) Very good sensitivity and specificity.

Empirical Mode Decomposition: Empirical Mode Decomposition (EMD) is a new and effective tool to analyze non-linear and non-stationary signals. In this method, a complicated and multi scale signal can be adaptively decomposed into a sum of finite number of zero mean oscillating components called as Intrinsic Mode Functions (IMF) whose instantaneous frequency computed by the analytic signal method process known as Hilbert Huang Transform give a physically meaningful characterization of the signal. The EMD is based on the sequential extraction of energy associated with various intrinsic time scales of the signal starting from high frequency modes to low frequency modes.

EMD is a technique which decomposes multi scale nonlinear, non-stationary signal into number of AM/FM zero mean signals, known as Intrinsic Mode Functions (IMF), in an adaptive, fully data driven. Principle of EMD is derived from the simple assumption that any signal consists of different IMFs, each of them representing an embedded characteristic oscillation on a separated time scale.

Empirical mode decomposition (EMD) adaptively decomposes a multi scale signal x (t) into a number L, of the so called, Intrinsic Mode Functions (IMFs),

$$h(i)(t),\ 1 \leq i \leq L,$$

$$x(t) = \sum_{i=1}^{L} h(i)(t) + r(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where r(t) is a remainder which is a non zero-mean slowly varying function with only few extrema. The basic concept of EMD is to identify proper time scales that reveal physical characteristics of the signal, and then decompose the signal into modes intrinsic to the function. These modes are referred to as Intrinsic Mode Functions (IMF). IMFs are signals satisfying the following conditions:

1) In the whole dataset, the number of extrema and the number of zero crossings must either be equal or differ at most by one,
2) At any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

Steps:
1. Extract all the local maxima and minima of $x(t)$.

2. Form the upper and lower envelope eu (t) and el (t) by cubic spine interpolation of the extrema point developed in step (1).

3. Calculate the mean function of the upper and lower envelop, $m_1(t)$ as

$$m_1(t) = eu(t) + el(t) / 2.$$

4. Let $d_1(t) = x(t) - m_1(t)$.

If $d_1(t)$ is a zero-mean function, then the iteration stops and $d_1(t)$ is accepted as first IMF, ie, $h_1(t) = d_1(t)$.

5. If not, use $d1(t)$ as the new data and repeat steps 1-4 until ending up with an IMF.

A stopping criteria is applied to the number of shifting iterations so that IMF component can retain amplitude and frequency modulation. Once the first IMF $h_1(t)$ is obtained, remaining IMF's are obtained by applying shifting process to the residual signal. Residual signal $r_1(t)$ can be defined as

$$r_1(t) = x(t) - h_1(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Residual signal now contains information about the lower frequency components. Shifting process will be continued until the final residue is a constant, a monotonic function or a function with only one maxima and minima from which no IMF can be obtained. At the end of decomposition process noisy signal x (t) can be represented as
a sum of IMFs plus a residue signal.
EMD procedure can be applied to decompose the time series into a set of IMFs and a residue. By applying the Hilbert transform to each IMF signal can be further analyzed to calculate the instantaneous frequency and amplitude of each IMF. The whole process is called Hilbert Huang Transform

EMD was proposed as the fundamental part of the Hilbert-Huang transform(HHT).The Hilbert-Huang transform is carried out, so to speak ,in 2 stage .first ,using the EMD algorithm, we obtain intrinsic mode function(IMF).
Then, at the second stage, the instantaneous frequency spectrum of the initial sequence is obtained by applying the Hilbert transform to the results of the above step. The HHT allows obtaining the instantaneous frequency spectrum of nonlinear and no stationary sequences. These sequences can consequently also be dealt with using the empirical mode decomposition.

However, this article is not going to cover the plotting of the instantaneous frequency spectrum using the Hilbert transform. We will focus only on the EMD algorithm.

In contrast to the previously mentioned Fourier transform and wavelet transform, the EMD decomposes any given data into intrinsic mode functions (IMF) that are not set analytically and are instead determined by an analyzed sequence alone. The basic functions are in this case derived adaptively directly from input data. An IMF resulting from the EMD shall satisfy only the following requirements:

1. The number of IMF extrema (the sum of the maxima and minima) and the number of zero-crossings must either be equal or differ at most by one;
2. At any point of an IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima shall be zero.

Decomposition results in a family of frequency ordered IMF components. Each successive IMF contains lower frequency oscillations than the preceding one. And although the term "frequency" is not quite correct when used in relation to IMFs, it is probably best suited to define their nature. The thing is that even though an IMF is of oscillatory nature, it can have variable amplitude and frequency along the time axis.

It is quite difficult to visualize the EMD algorithm performance results based on the description alone so let us proceed to its software implementation that will give us an opportunity to get to know the algorithm peculiarities.

EMD is a method of breaking down a signal without leaving the time domain. It can be compared to other analysis methods like Fourier Transforms and wavelet decomposition. The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. This parts from the assumptions of the methods we have thus far learned (namely that the systems in question be LTI, at least in approximation).

EMD filters out functions which form a complete and nearly orthogonal basis for the original signal. Completeness is based on the method of the EMD; the way it is decomposed implies completeness. The functions, known as Intrinsic Mode Functions (IMFs), are therefore sufficient to describe the signal, even though they are not necessarily orthogonal. The reasons are described in Huang et al., published in the Royal Society Proceedings on Math, Physical, and Engineering Sciences: "...the real meaning here applies only locally. For some special data, the neighbouring components could certainly have sections of data carrying the same frequency at different time durations. But locally, any two components should be orthogonal for all practical purposes" .

The fact that the functions into which a signal is decomposed are all in the time-domain and of the same length as the original signal allows for varying frequency in time to be preserved. Obtaining IMFs from real world signals is important because natural processes often have multiple causes, and each of these causes may happen at specific time intervals. This type of data is evident in an EMD analysis, but quite hidden in the Fourier domain or in wavelet coefficients.

Some examples of data to which the EMD method may be applied quite effectively are seismic readings, results of neuroscience experiments, electrocardiograms (which we will examine later), gastro electro grams, and sea-surface height (SSH) readings.

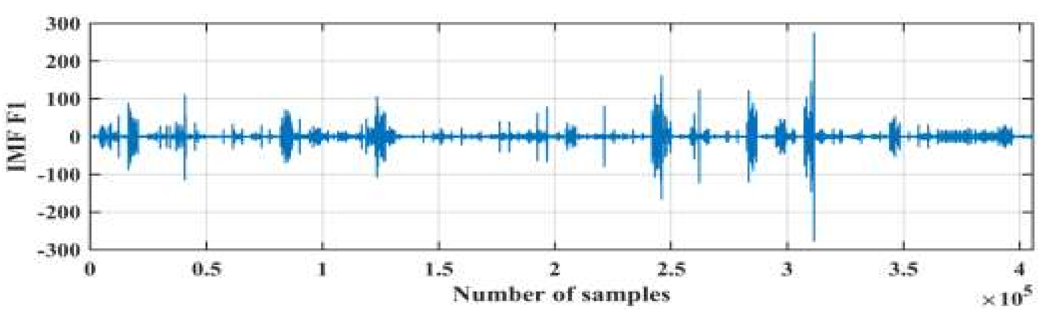
Results:- We use in my work use classes of 1, 2, and 3(S, N, and F).for finding the EMD.

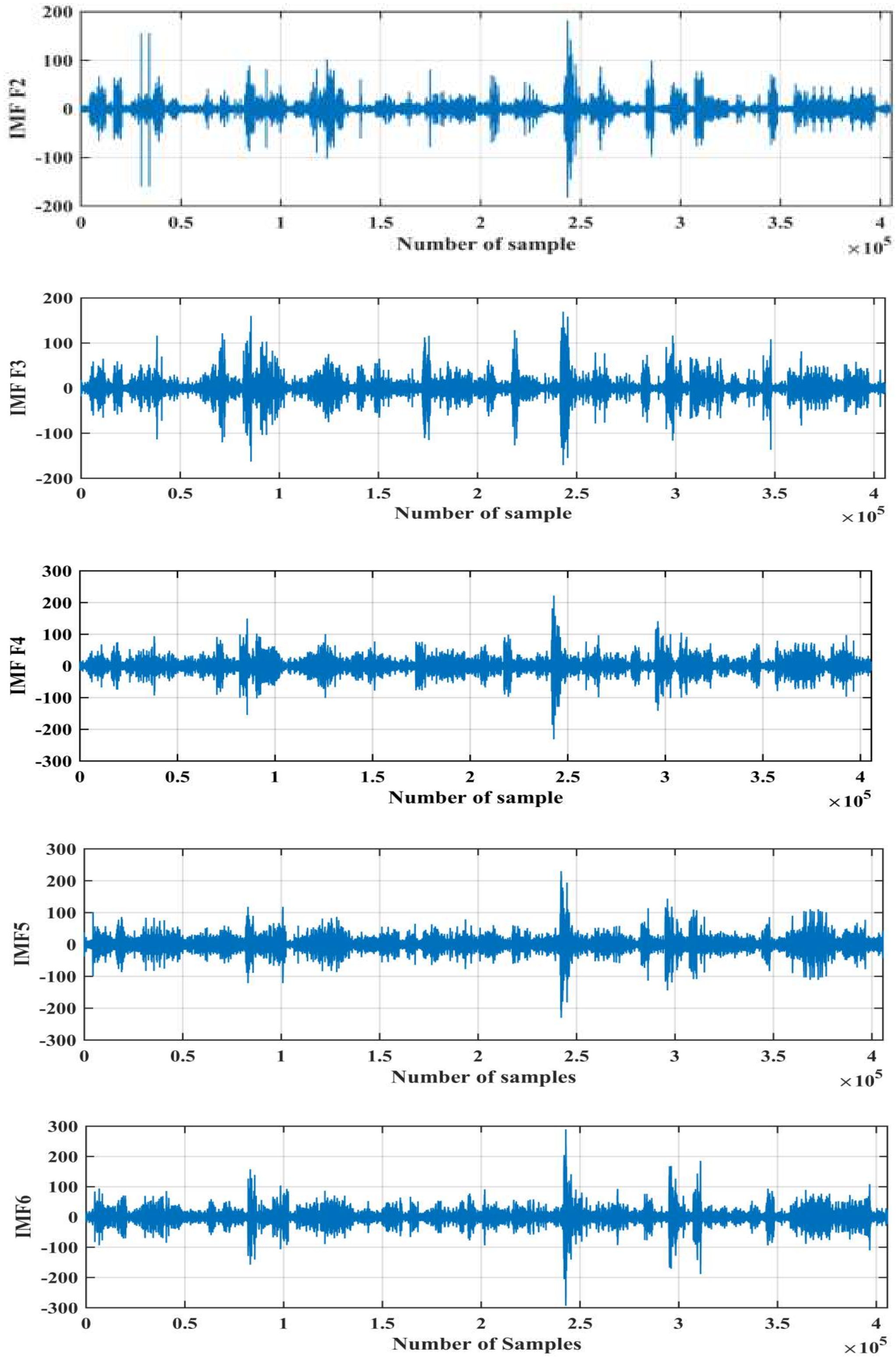
F=26x405603

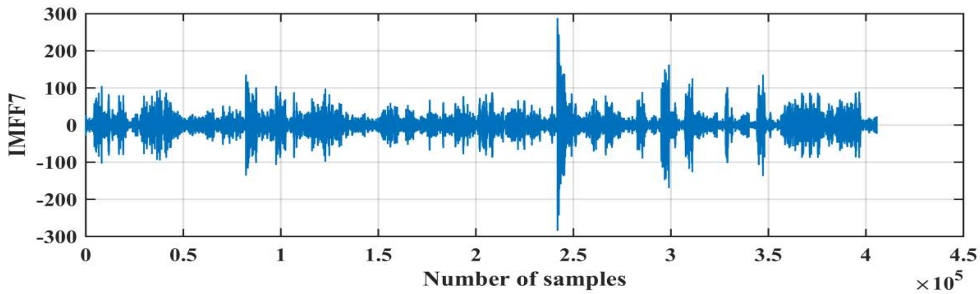
N=21x409700

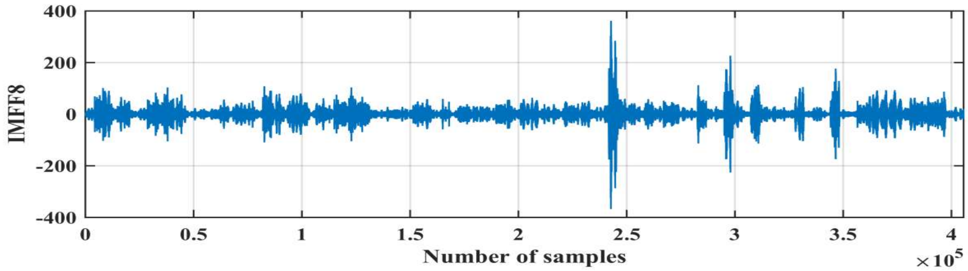
S =23x409700

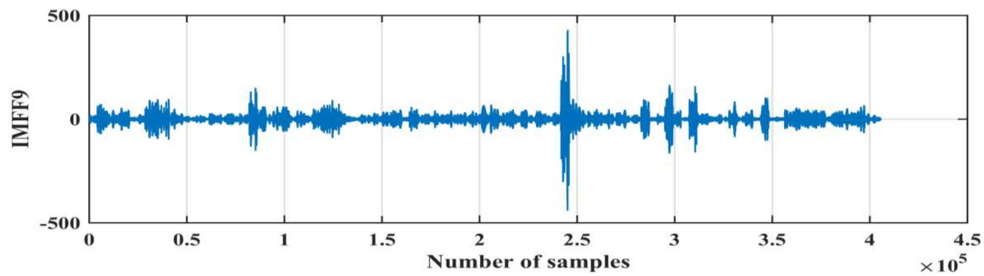
Graph of IMF_F

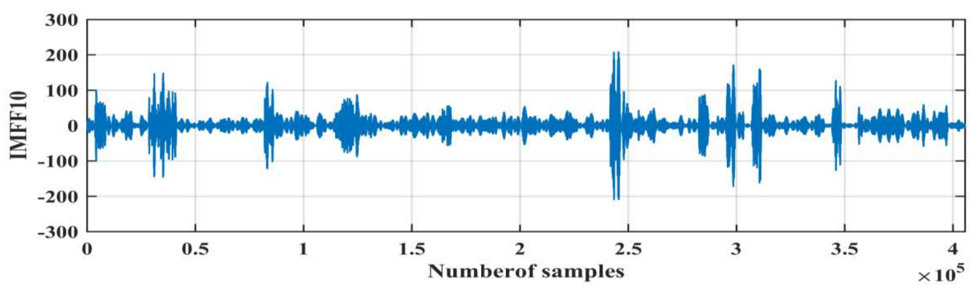


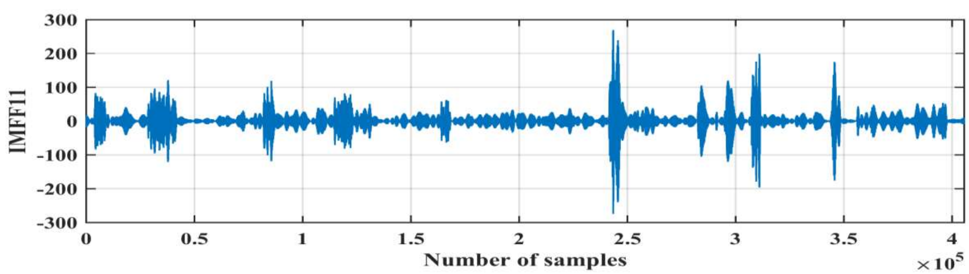

IMF F2
Number of sample
IMF F3
Number of sample
IMF F4
Number of sample
IMF5
Number of samples
IMF6
Number of Samples

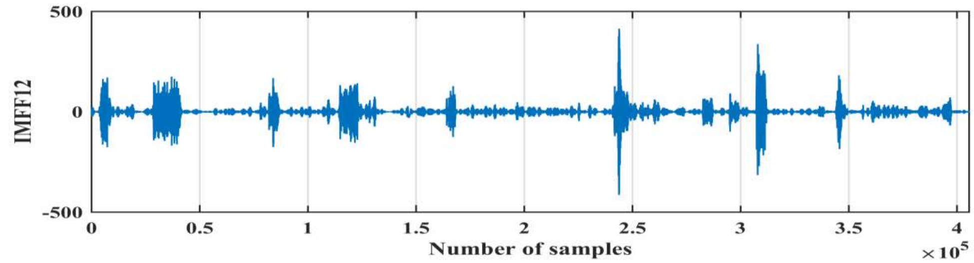

IMFF7
Number of samples
×10^5


IMFF8
Number of samples
×10^5


IMFF9
Number of samples
×10^5


IMFF10
Numberof samples
×10^5


IMFF11
Number of samples
×10^5


IMFF12
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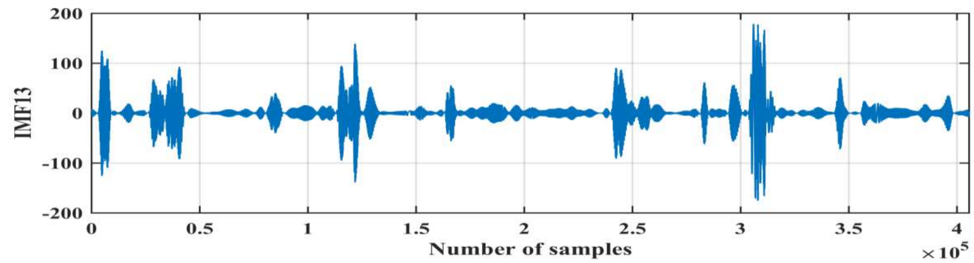
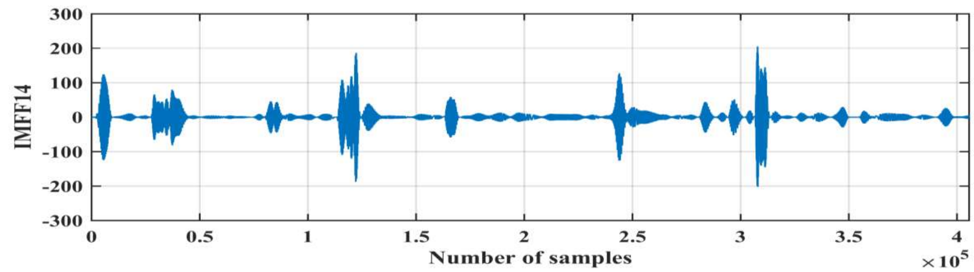
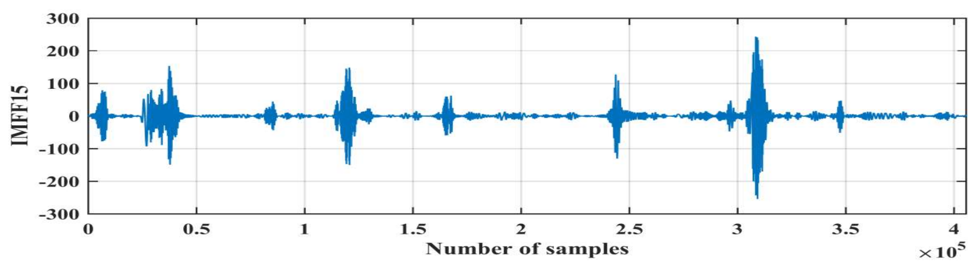
0
-500
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5


IMFF13
200
100
0
-100
-200
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5


IMFF14
300
200
100
0
-100
-200
-300
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5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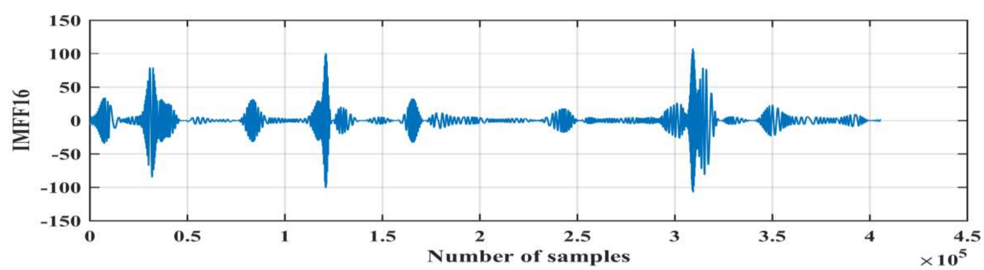
300
200
100
0
-100
-200
-300
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5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100
50
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-100
-150
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0.5
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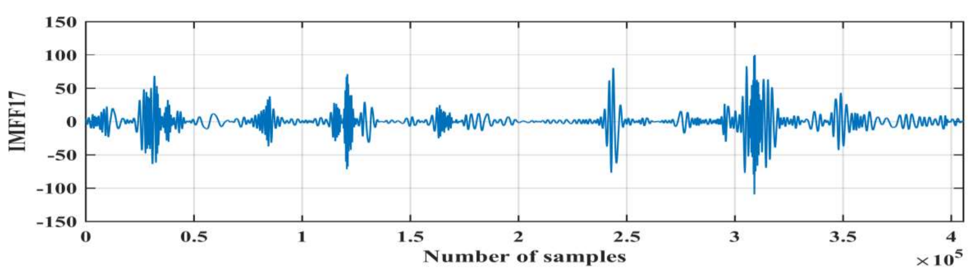
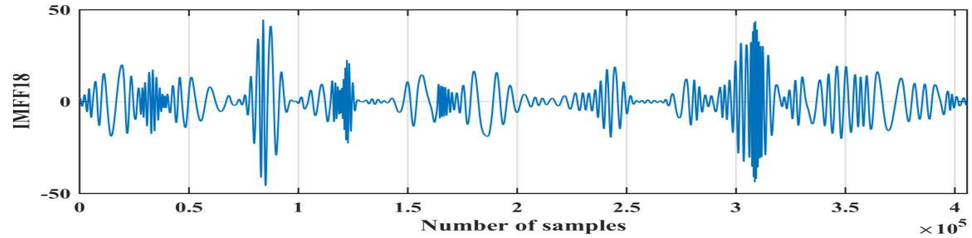
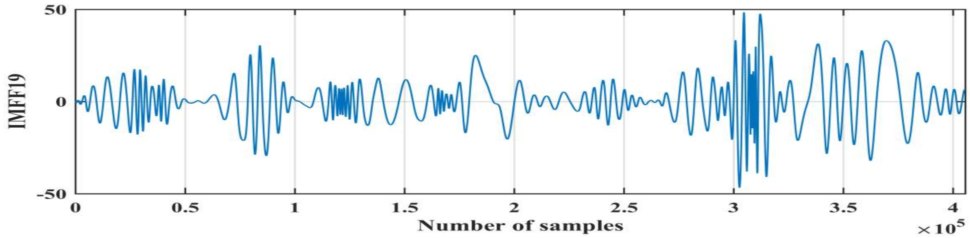
1.5
2
2.5
3
3.5
4
4.5
Number of samples
×10^5


IMFF17
150
100
50
0
-50
-100
-150
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5



IMFF18
50
0
-50
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$



IMFF19
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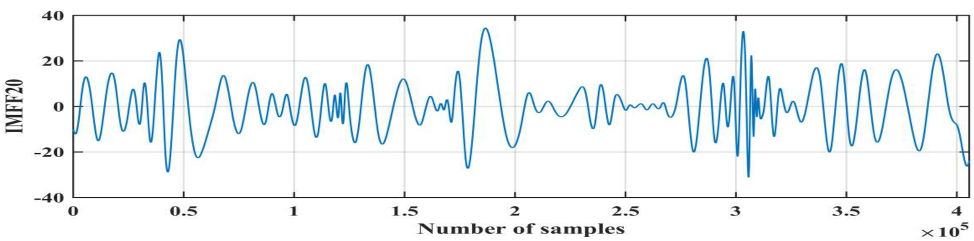
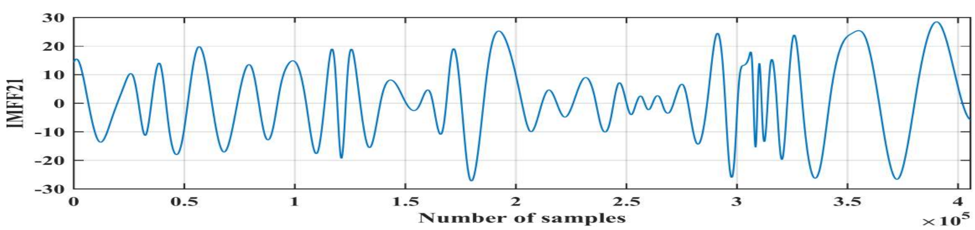
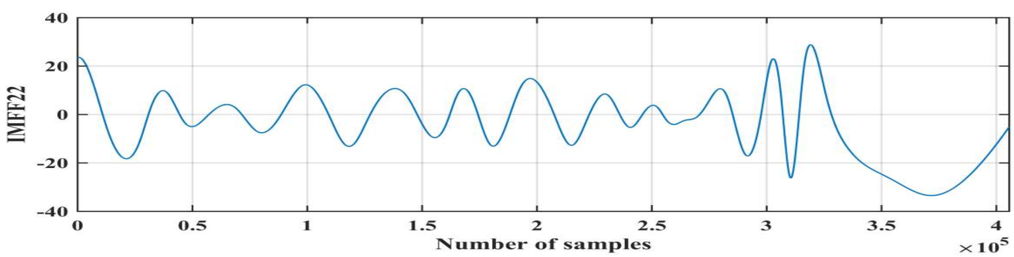
0
-50
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$



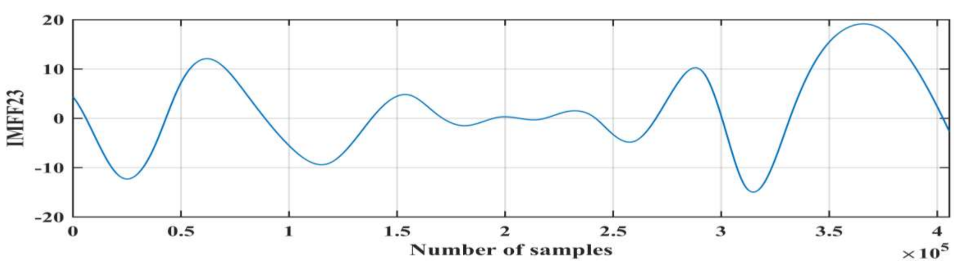
IMFF20
40
20
0
-20
-40
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$



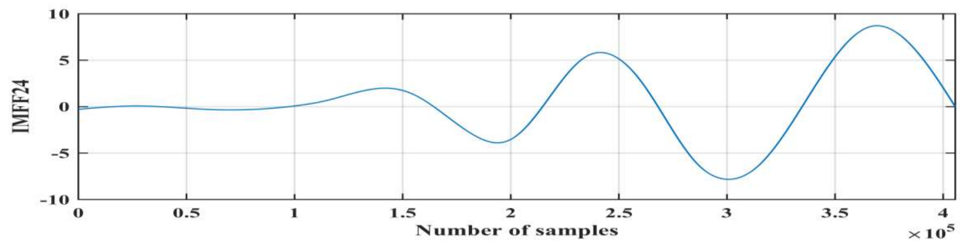
IMFF21
30
20
10
0
-10
-20
-30
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$

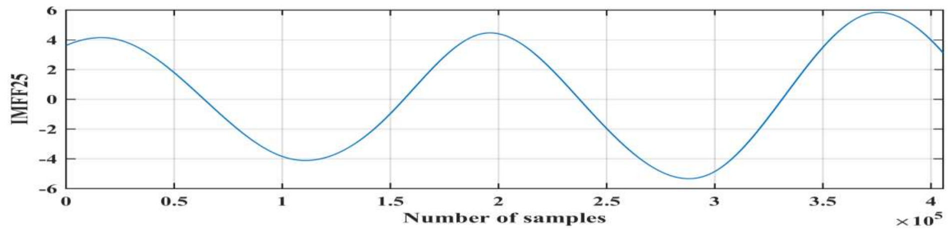


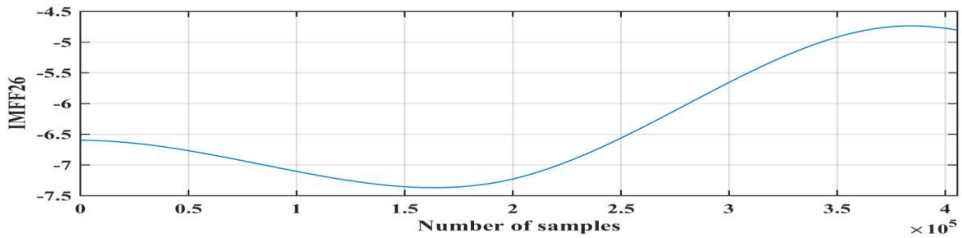
IMFF22
40
20
0
-20
-40
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$

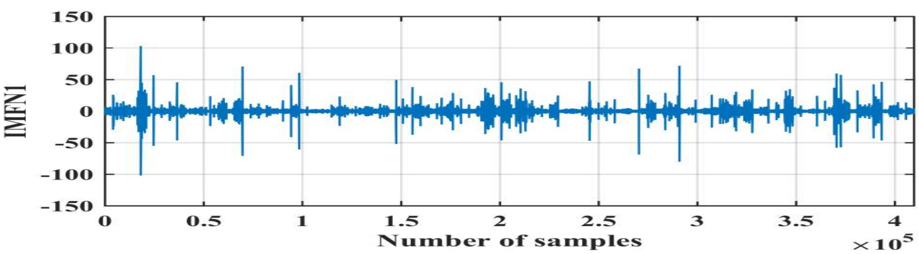


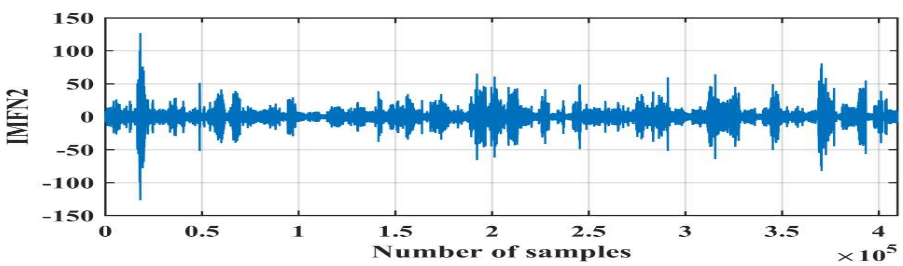
IMFF23
20
10
0
-10
-20
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
$\times 10^5$

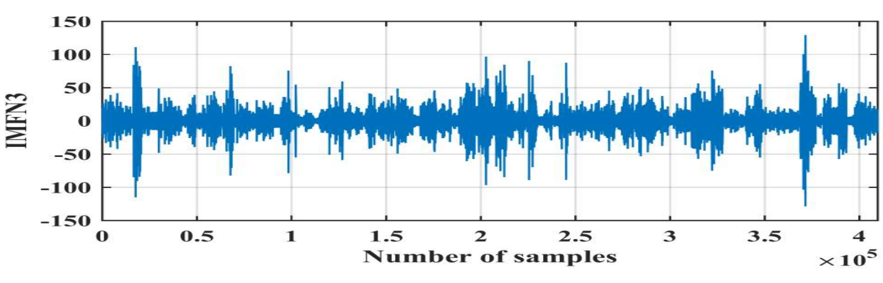

IMFF24
10
5
0
−5
−10
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5

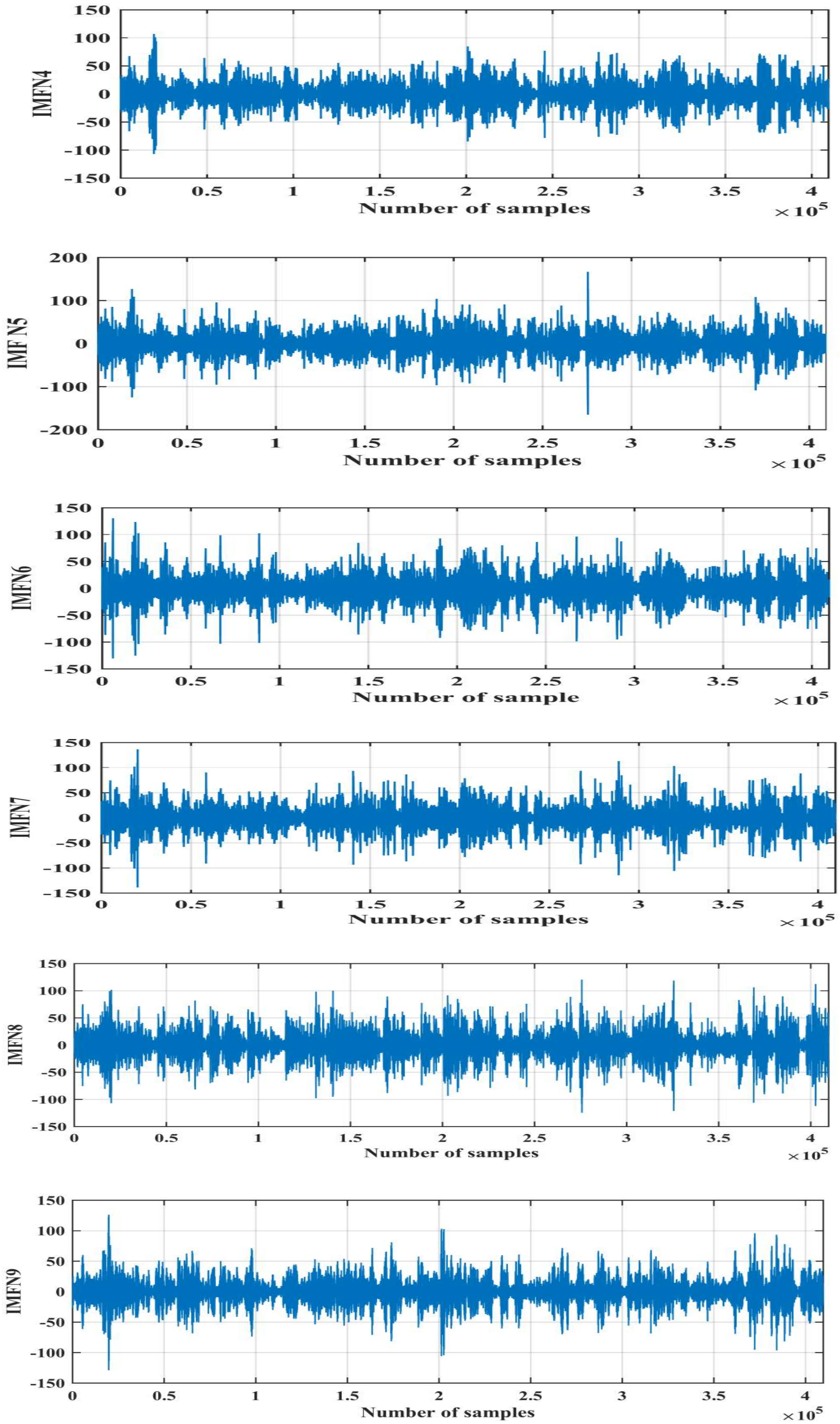

IMFF25
6
4
2
0
−2
−4
−6
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5

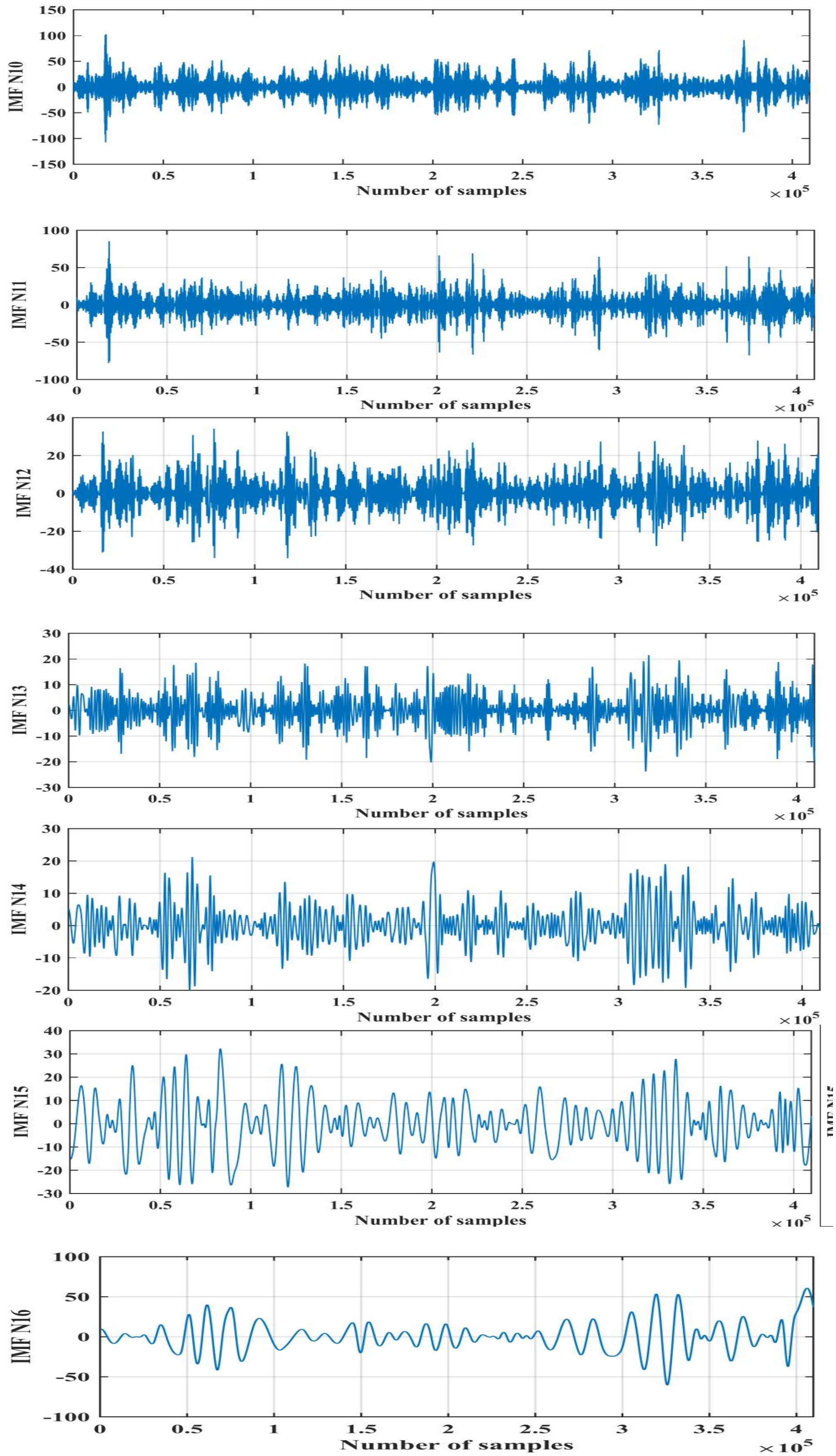

IMFF26
-4.5
-5
-5.5
-6
-6.5
-7
-7.5
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5

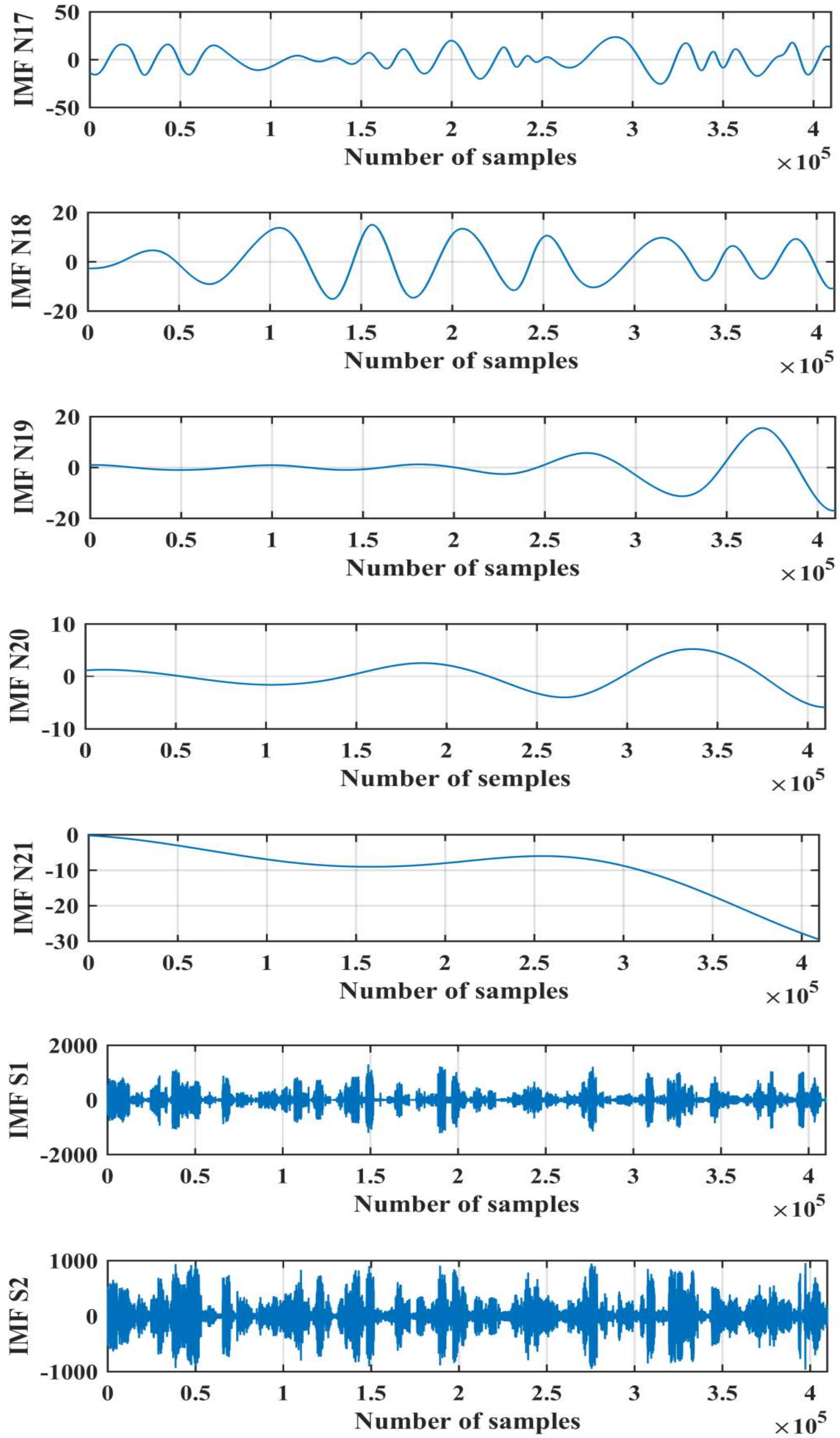

IMFN1
150
100
50
0
−50
−100
−150
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5

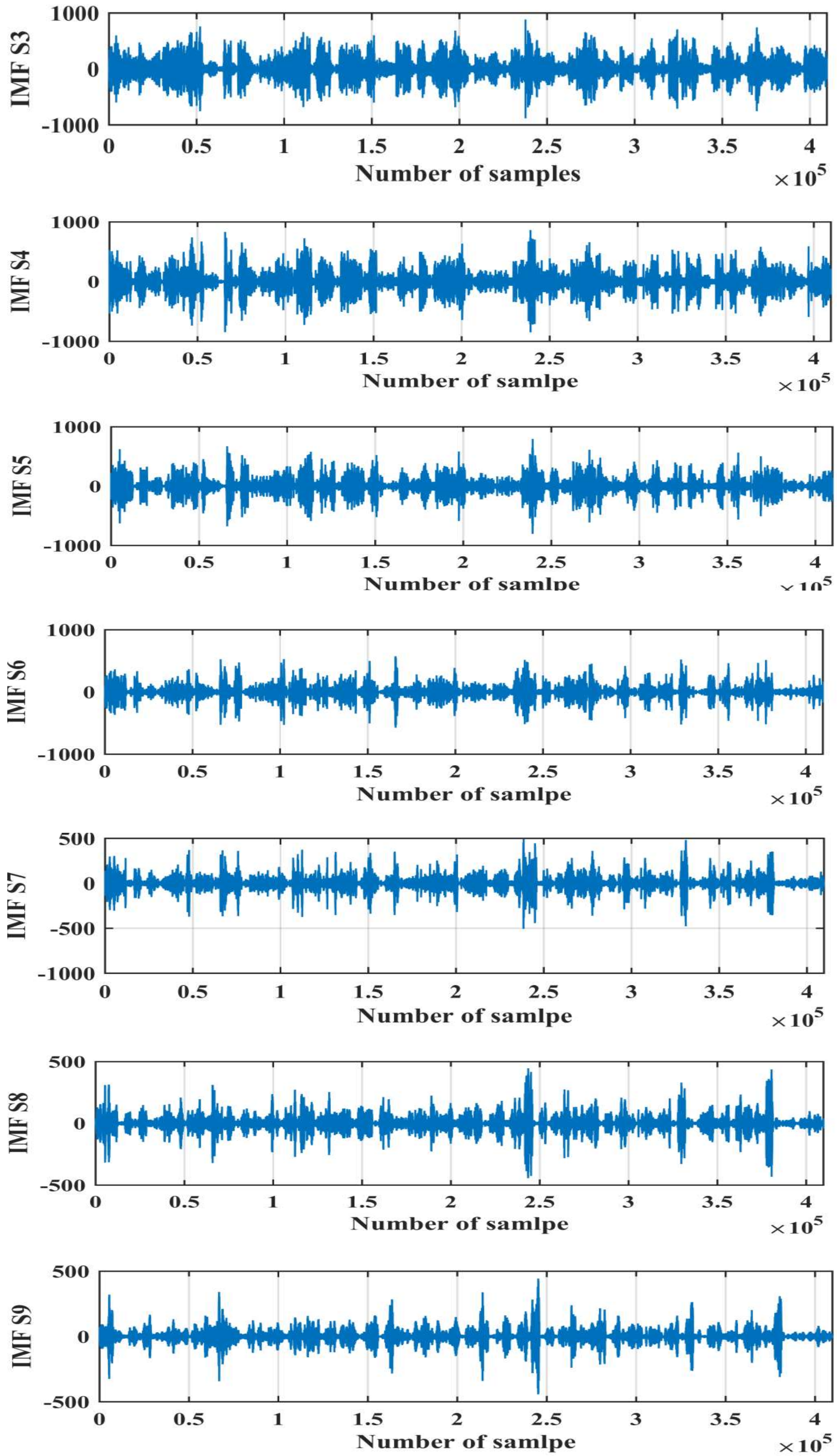

IMFN2
150
100
50
0
−50
−100
−150
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5


IMFN3
150
100
50
0
−50
−100
−150
0
0.5
1
1.5
2
2.5
3
3.5
4
Number of samples
×10^5

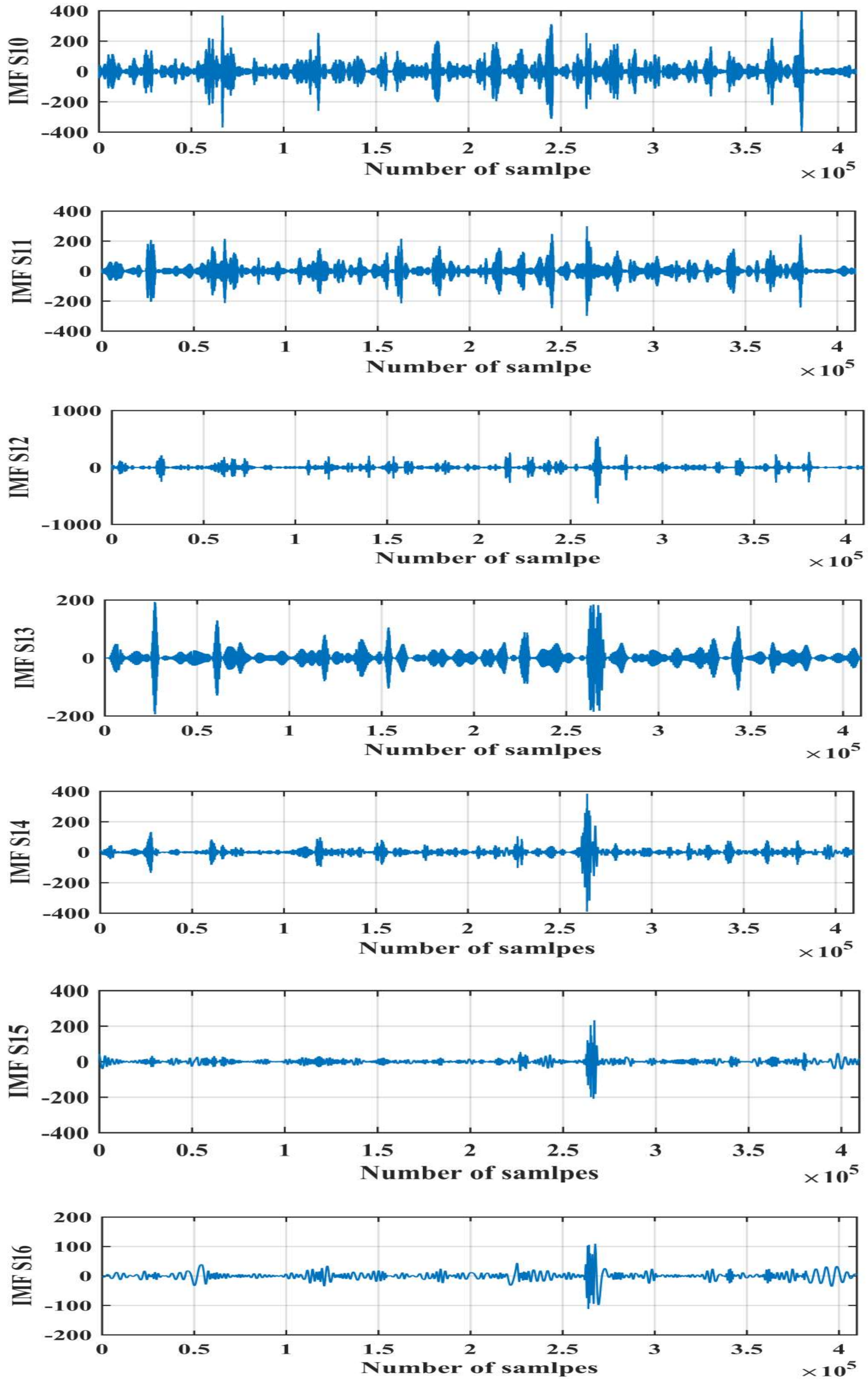

IMFN4
Number of samples
×10^5
IMF N5
Number of samples
×10^5
IMFN6
Number of sample
×10^5
IMFN7
Number of samples
×10^5
IMFN8
Number of samples
×10^5
IMFN9
Number of samples
×10^5


IMF N10
Number of samples
×10^5
IMF N11
Number of samples
×10^5
IMF N12
Number of samples
×10^5
IMF N13
Number of samples
×10^5
IMF N14
Number of samples
×10^5
IMF N15
Number of samples
×10^5
IMF N16
Number of samples
×10^5


IMF N17
Number of samples
IMF N18
Number of samples
IMF N19
Number of samples
IMF N20
Number of semples
IMF N21
Number of samples
IMF S1
Number of samples
IMF S2
Number of samples
$\times 10^5$



1000
0
-1000
IMF S3
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samples
$\times 10^5$
1000
0
-1000
IMF S4
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$
1000
0
-1000
IMF S5
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$
1000
0
-1000
IMF S6
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$
500
0
-500
-1000
IMF S7
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$
500
0
-500
IMF S8
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$
500
0
-500
IMF S9
0 0.5 1 1.5 2 2.5 3 3.5 4
Number of samlpe
$\times 10^5$


IMF S10
Number of samlpe
×10^5
IMF S11
Number of samlpe
×10^5
IMF S12
Number of samlpe
×10^5
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Number of samlpes
×10^5
IMF S14
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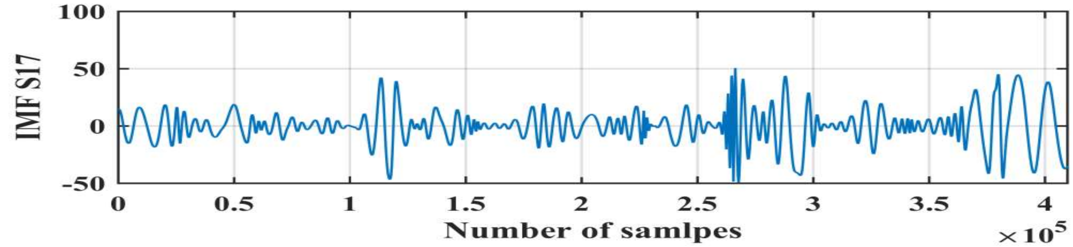
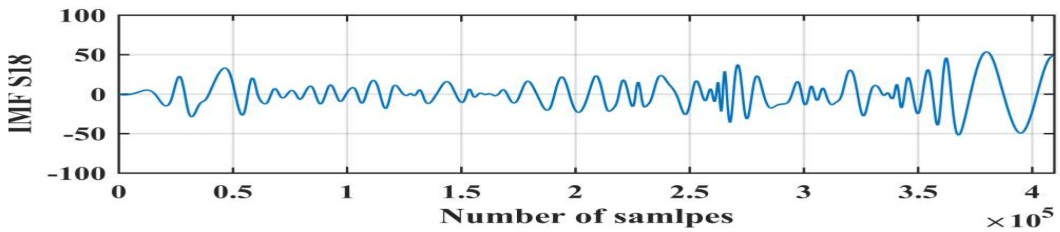
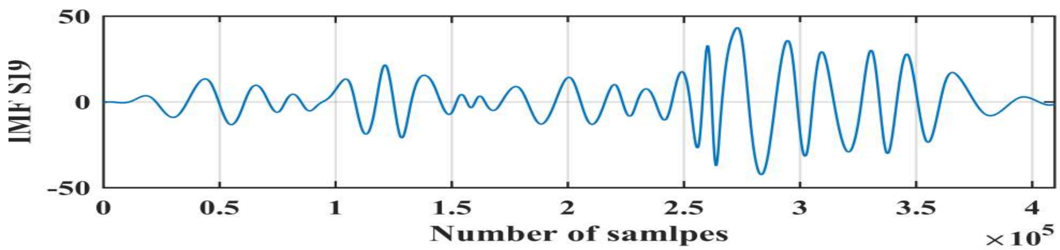
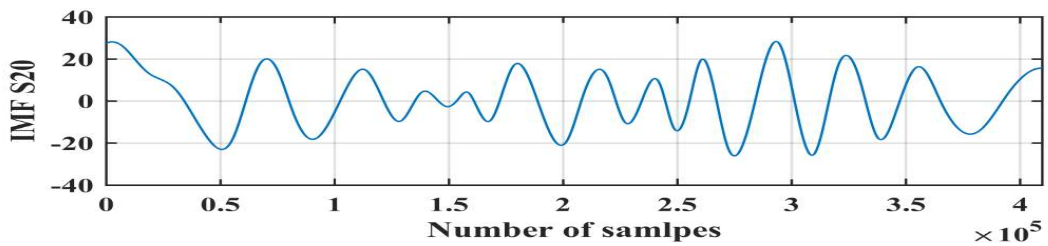
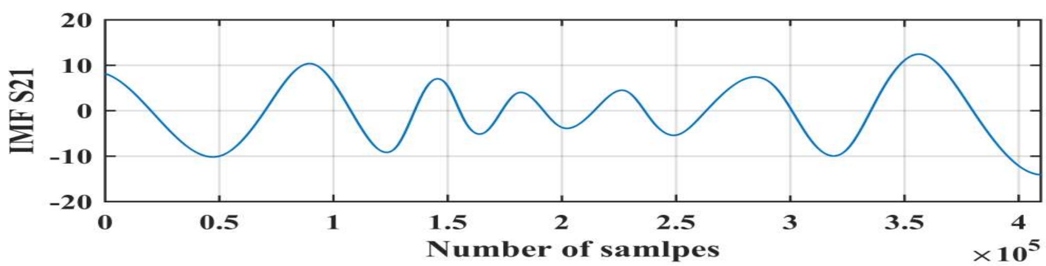
×10^5
IMF S15
Number of samlpes
×10^5
IMF S16
Number of samlpes
×10^5

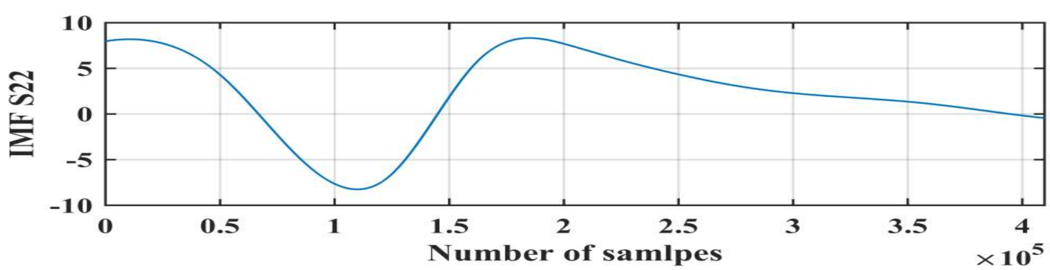

IMF S17
Number of samlpes
×10^5

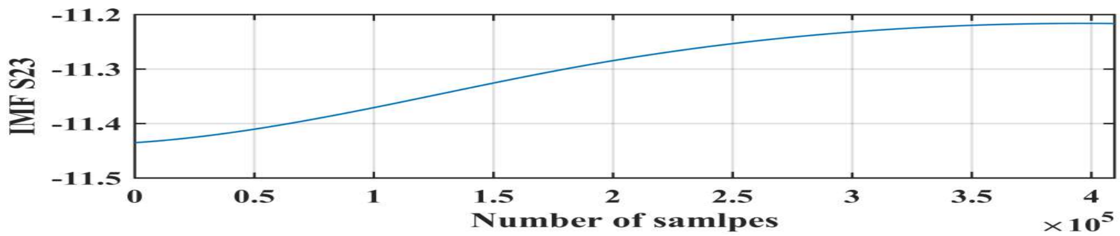

IMF S18
Number of samlpes
×10^5


IMF S19
Number of samlpes
×10^5


IMF S20
Number of samlpes
×10^5


IMF S21
Number of samlpes
×10^5


IMF S22
Number of samlpes
×10^5



2.2.2 ANN

Artificial neural networks are computing systems made up of large number of simple, highly interconnected processing elements called nodes or artificial neurons that abstractly emulate the structure and operation of the biological nervous system. Learning in ANNs is accomplished through special training algorithms developed based on learning rules presumed to mimic the learning mechanisms of biological systems. There are many different types and architectures of neural net-works varying fundamentally in the way they learn. In this paper, feed forward back propagation neural network considered The architecture of BPN may contain two or more layers. A simple two layer ANN consists only of an input layer containing the input variables to the problem, and output layer containing the solution of the problem. This type of network is a satisfactory approximate or for linear problems. However, for approximating nonlinear systems, additional intermediate or hidden processing layers are employed to handle the problem's nonlinearity and complexity. The determination of appropriate number of hidden layers is one of the most critical tasks in neural network design. Unlike the input and output layers, one starts with no prior knowledge as to the number of hidden layers. A network with too few hidden nodes would be incapable of differentiating between complex patterns leading to only a linear estimate of the actual trend. ANNs' success depends on both the quality and quantity of the data. From the decomposed EEG signal the features calculated for each sub band. Total 16 features are considered for classification. Neural network is designed with 16 input nodes and one output node. The network is trained with parameters a gradient descent algorithm with momentum factor included was used for training. The stopping criterion was specified to be 0.001 Root Mean Square Error (RMSE). The training was stopped when the RMSE between the network outputs and the targets was lesser than or equal to 0.001. The learning rate was fixed at 0.5. The number of training epochs was fixed uniformly at 1000. . The output from threshold detector value is greater than threshold value the subject considered as epileptic otherwise normal. The threshold value of 0.5 is considered. In this work. Feed Forward back propagation and Elman back propagation neural networks are used.

Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG, and gathering of additional clinical information. An artificial neural network that classifies subjects as having or not having an epileptic seizure provides a valuable diagnostic decision support tool for neurologists treating potential epilepsy, since differing etiologist of seizures result in different treatments. In this work, classification of EEG signals was examined. The features are extracted using wavelet transform technique. Four features are extracted, the features Energy, Covariance, Inter quartile range (IQR) and Median absolute deviation (MAD).The generated data from wavelet technique are given to ANN for training of normal and abnormal EEG conditions. The ANN is used to discriminate between the two tasks with a success rate of 98%. Further research is needed to find more elaborated memory architectures and its appropriate training algorithms. Neural networks as classifiers have here a high potential because they can compute in real time with a high numbers of features. This characteristic enable the development and construction of transportable devices, improving substantially the quality of life of epileptic patients intractable by medication and that must learn to live with seizures.

ARTIFICIAL NEURAL NETWORK : Neural network (artificial neural network) - the common name for mathematical structures and their software or hardware models, performing calculations or processing of signals through the rows of elements, called artificial neurons, performing a basic operation of your entrance. The original structure was inspired by the natural structure of neurons and neural systems, particularly the brain.

Definition: The neural network is a type of computer system architecture. It consists of data processing by neurons arranged in layers. The corresponding results are obtained through the learning process, which involves modifying the weights of those neurons that are responsible for the error.

ANN Use in this field:

- Signal processing: suppress line noise, with adaptive echo cancelling, blind source separation
- Control: backing up a truck: cab position, rear position, and match with the dock get converted to steering instructions. Manufacturing plants for controlling automated machines.
- Siemens successfully uses neural networks for process automation in basic industries, e.g., in rolling mill control more than 100 neural networks do their job, 24 hours a day
- Robotics - navigation, vision recognition
- Pattern recognition, i.e. recognizing handwritten characters, e.g. the current version of Apple's Newton uses a neural net
- Medicine, storing medical records based on case information
- Speech production: reading text aloud (NET talk)
- Vision: face recognition, edge detection, visual search engines
- Business, rules for mortgage decisions are extracted from past decisions made by experienced evaluators, resulting in a network that has a high level of agreement with human experts.
- Financial Applications: time series analysis, stock market prediction
- Data Compression: speech signal, image, e.g. faces
- Game Playing: chess go.

HIDDEN LAYERS NEURONS

The number of hidden layers usually counts 2. The user should decide how many hidden layers and how many neurons in each of them will be.

Input layer usually is the same as the number of input data (number of conditional attributes in data set).

The number of neurons in the output layer depends on the type of the classification problem (regression, classification to some categories).

The more neurons in hidden layer the higher the memory occupation needed from NN.

More neurons can makes the process of classification over trained and can make it too good for training set but too bad for new – unknown data.

If you noticed over trained in your neural network You should consider the decreasing of the number of neurons.

3. RESULTS and DISCUSSION

3.1. Ann Based seizure classification without EMD

RESULTS OF ANN Without EMD

HIDDEN LAYER FORMULA FOR FINDING NO.OF NEURONS FOR WITHOUT EMD

$$H.L.NO = [\left(\frac{1+2}{2}\right) + \sqrt{15000}] + 10\%$$

$$= (1.5+122.247) + 10\%$$

$$= 123.747 + 10\%$$

$$= 123.747 + 12.3747$$

$$\approx 137$$

Table Results with EMD of F_N_S

S.NO	NO OF NEURON	TRAIN %	TEST %
1	*1*	*74.6*	*74.0*
2	*2*	*74.6*	*73.9*
3	*3*	*92.4*	*82.0*
4	*4*	*92.5*	*82.2*
5	*5*	*92.3*	*82.4*
6	6	92.4	82.3
7	7	92.4	82.1
8	8	92.6	81.2
9	9	92.6	82.0
10	**10**	**92.6**	**82.8**
11	11	92.6	82.8
12	12	92.6	82.7
13	13	92.4	83.0
14	**14**	**92.6**	**83.0**
15	15	92.6	82.0
16	16	92.7	82.2
17	17	92.7	82.4
18	18	92.7	82.5
19	19	92.6	82.7
20	20	92.7	82.6
21	21	92.4	82.3
22	22	92.3	82.1
23	23	92.6	81.4
24	24	92.5	82.6
25	25	92.7	82.3
26	26	92.6	82.4
27	27	92.4	82.7
28	28	92.1	82.3
29	29	92.3	82.1
30	30	92.6	82.6
31	31	92.4	82.6
32	32	92.3	82.4
33	33	92.7	82.3
34	34	92.1	82.3
35	35	92.3	82.4
36	36	92.6	82.1
37	37	92.4	82.6
38	38	92.3	82.7
39	39	92.5	82.1
40	40	92.7	82.6
41	41	92.3	82.1
42	42	92.4	82.3
43	43	92.1	82.4
44	44	92.5	82.6
45	45	92.3	82.1
46	46	92.1	82.6
47	47	92.3	82.4
48	48	92.3	82.3
49	49	92.3	82.3
50	50	92.6	82.6
51	51	92.5	82.3
52	52	92.6	82.1
53	53	92.4	82.4
54	54	92.1	82.6
55	55	92.3	82.4

56	56	92.6	82.3
57	57	92.4	82.4
58	58	92.1	82.1
59	59	92.3	82.3
60	**60**	**92.5**	**82.8**
61	61	92.1	82.4
62	62	92.3	82.3
63	63	92.3	82.4
64	64	92.4	82.4
65	65	92.6	82.0
66	66	92.2	82.5
67	67	92.5	82.3
68	68	92.4	82.4
69	69	92.1	82.3
70	70	92.7	82.5
71	71	92.3	82.1
72	72	92.5	82.2
73	73	92.3	82.4
74	74	92.3	82.3
75	75	92.4	82.6
76	76	92.1	82.5
77	77	92.3	82.1
78	78	92.3	82.3
79	79	92.4	82.4
80	80	92.7	82.5
81	81	92.1	82.1
82	82	92.3	82.3
83	83	92.1	82.4
84	84	92.3	82.3
85	85	92.3	82.5
86	86	92.1	82.6
87	87	92.3	82.1
88	88	92.1	82.4
89	89	92.6	82.3
90	90	92.7	82.9
91	91	92.4	82.1
92	92	92.2	82.3
93	93	92.3	82.4
94	94	92.0	82.3
95	95	92.3	82.7
96	96	92.5	82.6
97	97	92.3	82.1
98	98	92.3	82.7
99	99	92.1	82.4
100	100	92.6	82.6
101	101	92.1	82.3
102	102	92.3	82.1
103	103	92.3	82.3
104	104	92.3	82.4
105	105	92.3	82.0
106	106	92.1	82.3
107	107	92.3	82.1
108	108	92.4	82.4
109	109	92.3	82.5
110	110	92.1	82.5
111	111	92.1	82.1
112	112	92.5	82.3
113	113	92.3	82.4

114	114	92.4	82.7
115	115	92.3	82.3
116	116	92.1	82.1
117	117	92.6	82.4
118	118	92.3	82.3
119	119	92.5	82.5
120	120	92.4	82.0
121	121	92.3	82.1
122	122	92.3	82.7
123	123	92.4	82.0
124	124	92.3	82.3
125	125	92.3	82.4
126	126	92.3	82.0
127	127	92.4	82.3
128	128	92.3	82.4
129	129	92.6	82.1
130	130	92.4	82.0
131	131	92.3	82.6
132	132	92.1	82.4
133	133	92.2	82.1
134	134	92.4	82.3
135	135	92.3	82.1
136	136	92.4	82.0
137	137	92.1	82.5

Table:-3- . Results: without EMD Data for S_N_F

Results: Graph

Without EMD Data for 14 neuron for S_N_F

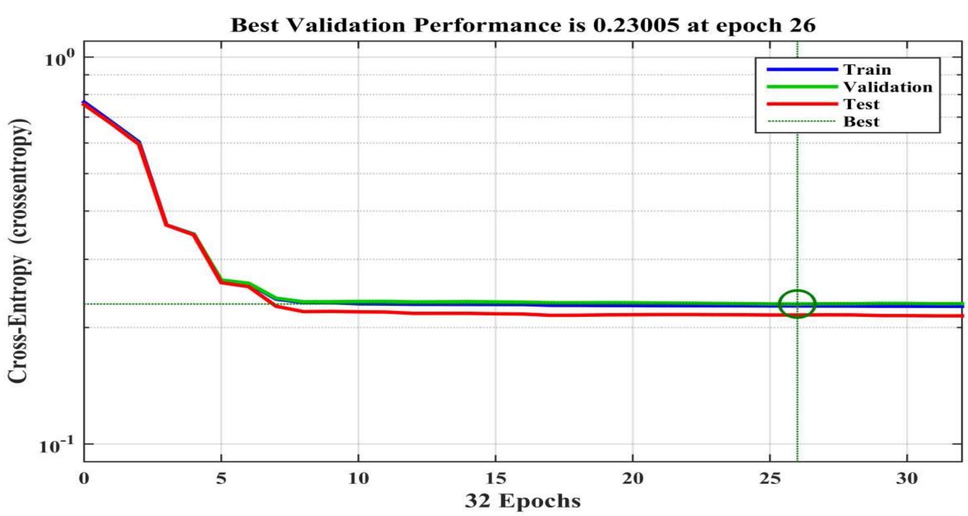


Figure: 14 -Performance Training

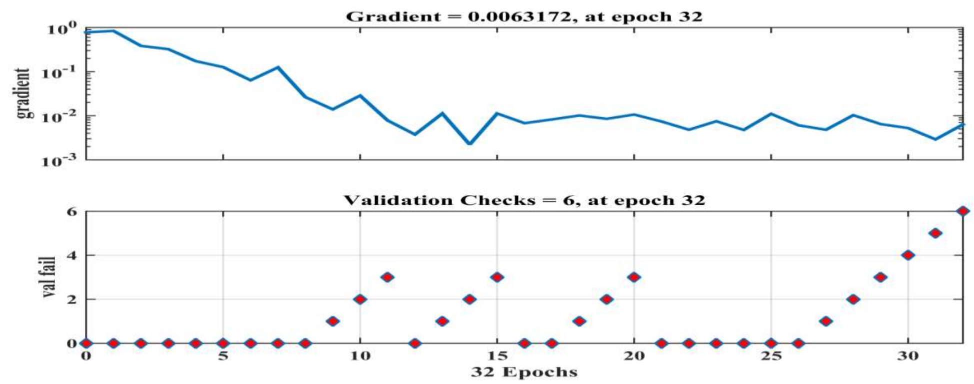


Figure: 15. -Training signal Training

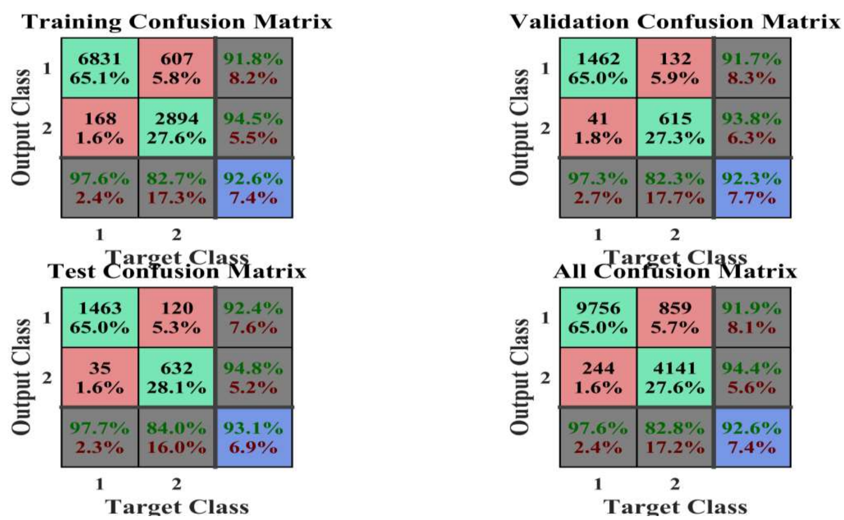


Figure: 16. -Confusion matrix Training

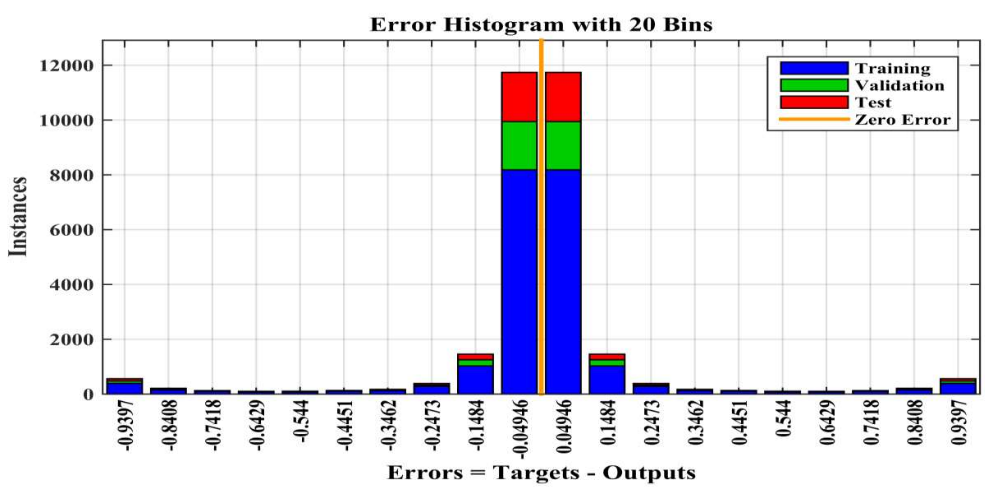


Figure: 17.-Error Histogram Training

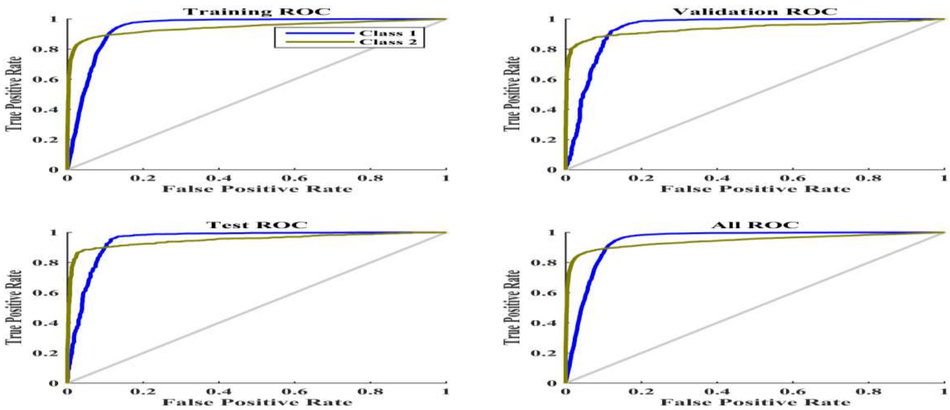


Figure: 18.-ROC Training

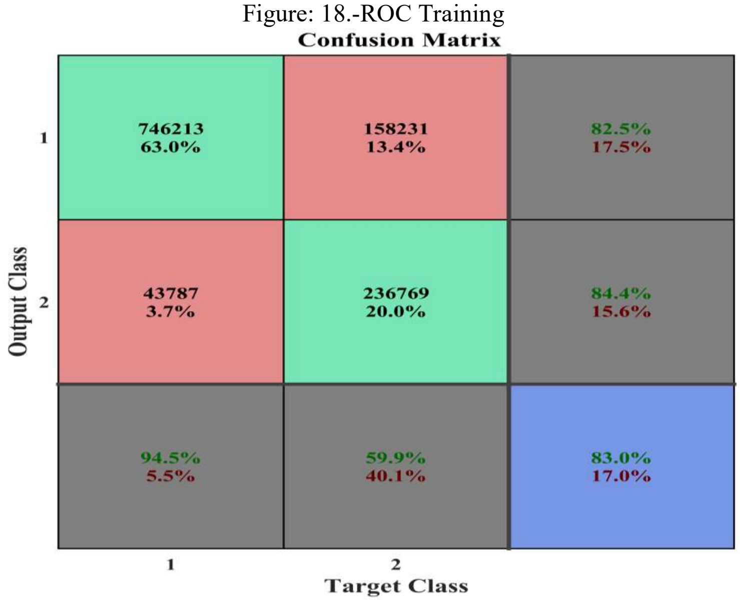


Figure: 19. - Confusion matrix Test

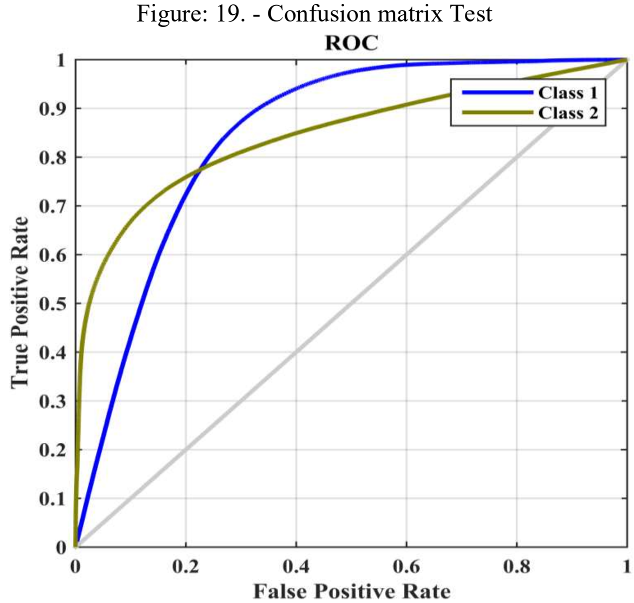


Figure: 20. -ROC Test

3.2. Ann Based seizure classification with EMD

Results with EMD of S_N_F IMF

HIDDEN LAYER FORMULA FOR FINDING NO.OF NEURONS WITH EMD

$$H.L.NO = [\left(\frac{21+2}{2}\right) + \sqrt{15000}] +10\%$$

$= (11.5+122.247) +10\%$

$=134.747+10\%$

$=134.747+13.8747$

≈ 148

Table Results with EMD of F_N_S IMF

S.NO	NO OF NEURONS	TRAIN %	TEST %
1	1	100	68
2	2	100	66.7
3	3	100	67.9
4	4	100	66.7
5	5	100	66.5
6	6	100	67.3
7	7	100	67.0
8	8	100	67.1
9	**9**	**100**	**68**
10	10	100	67.7
11	11	100	66.7
12	12	100	67.9
13	13	100	67.2
14	**14**	**100**	**68**
15	15	100	66.3
16	16	100	67.8
17	17	100	67.1
18	**18**	**100**	**68**
19	19	100	67.7
20	20	100	67.1
21	21	100	67.3
22	22	100	67.9
23	23	100	66.7
24	24	100	67.6
25	25	100	67.1
26	26	100	66.5
27	**27**	**100**	**68**
28	28	100	68.0
29	29	100	67.4
30	30	100	67.5
31	31	100	67.4
32	32	100	66.9
33	33	100	67.5
34	34	100	66.7
35	35	100	66.9
36	36	100	67.0
37	37	100	67.1
38	38	100	66.9
39	39	100	67.3
40	**40**	**100**	**68**
41	41	100	66.9
42	42	100	67.2
43	43	100	66.4

44	44	100	67.4
45	**45**	**100**	**68**
46	46	100	66.8
47	47	100	67.7
48	48	100	67.7
49	**49**	**100**	**68**
50	50	100	66.9
51	**51**	**100**	**68.0**
52	52	100	67.4
53	53	100	68.7
54	**54**	**100**	**68**
55	55	100	67.6
56	56	100	67.4
57	57	100	67.3
58	58	100	67.4
59	59	100	67.1
60	60	100	67.3
61	61	100	67.8
62	62	100	67.6
63	63	100	67.8
64	64	100	67.5
65	65	100	67.6
66	66	100	66.9
67	67	100	67.2
68	68	100	67.5
69	69	100	67.0
70	70	100	67.1
71	71	100	67.0
72	72	100	67.7
73	73	100	67.5
74	74	100	67.0
75	75	100	67.4
76	76	100	67.8
77	77	100	67.2
78	78	100	67.5
79	79	100	67.7
80	80	100	67.8
81	81	100	67.8
82	82	100	67.9
83	83	100	67.7
84	84	100	66.9
85	85	100	67.6
86	86	100	67.4
87	87	100	67.6
88	88	100	67.3
89	89	100	67.8
90	90	100	67.8
91	91	100	67.1
92	92	100	67.4
93	**93**	**100**	**68.0**
94	94	100	67.9
95	95	100	67.5
96	96	100	67.1
97	97	100	67.3
98	**98**	**100**	**68.0**
99	99	100	67.0
100	100	100	67.0
101	101	100	67.4

102	102	100	67.2
103	103	100	67.0
104	104	100	66.8
105	105	100	67.4
106	106	100	67.9
107	107	100	67.4
108	108	100	67.8
109	109	100	67.2
110	110	100	67.4
111	111	100	67.3
112	112	100	67.2
113	113	100	67.0
114	114	100	67.0
115	115	100	67.9
116	116	100	67.1
117	117	100	67.9
118	118	100	67.3
119	119	100	67.8
120	120	100	67.4
121	121	100	67.2
122	122	100	67.3
123	123	100	67.0
124	124	100	67.9
125	125	100	67.8
126	126	100	67.4
127	127	100	67.5
128	128	100	67.0
129	129	100	67.1
130	130	100	67.7
131	131	100	67.2
132	132	100	67.8
133	133	100	67.0
134	134	100	67.1
135	135	100	67.0
136	136	100	67.6
137	137	100	67.4
138	138	100	67.3
139	139	100	67.0
140	140	100	67.7
141	141	100	67.0
142	142	100	67.8
143	143	100	67.0
144	144	100	67.4
145	145	100	67.5
146	146	100	66.9
147	147	100	67.1
148	148	100	67.8

Table: 4. - Results: with EMD of F_N_S IMF

Figure Results: with EMD Data for 14 neuron for S_N_F IMF

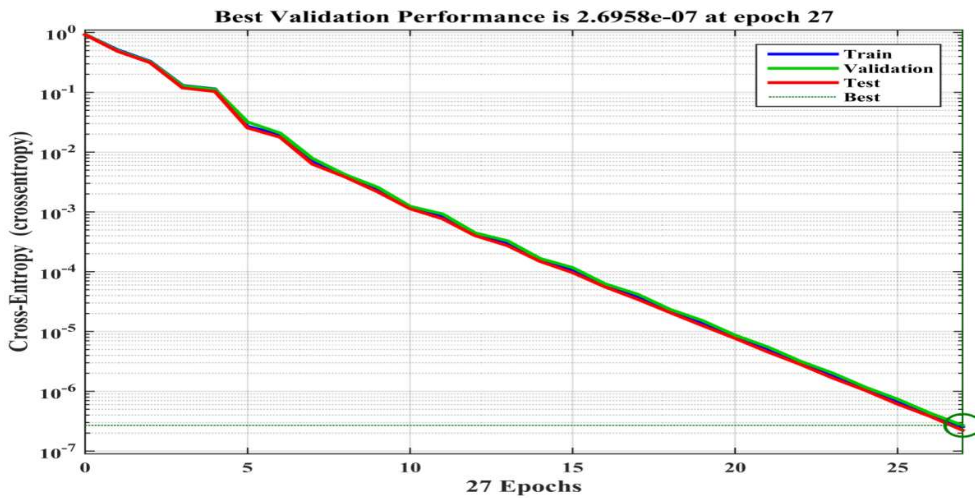


Figure: 21 performances Training IMF

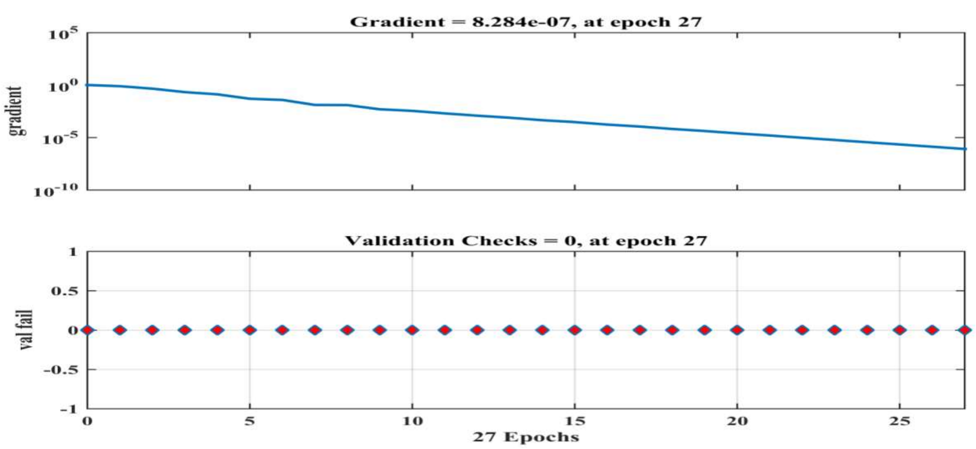


Figure: 22.-Training signal IMF

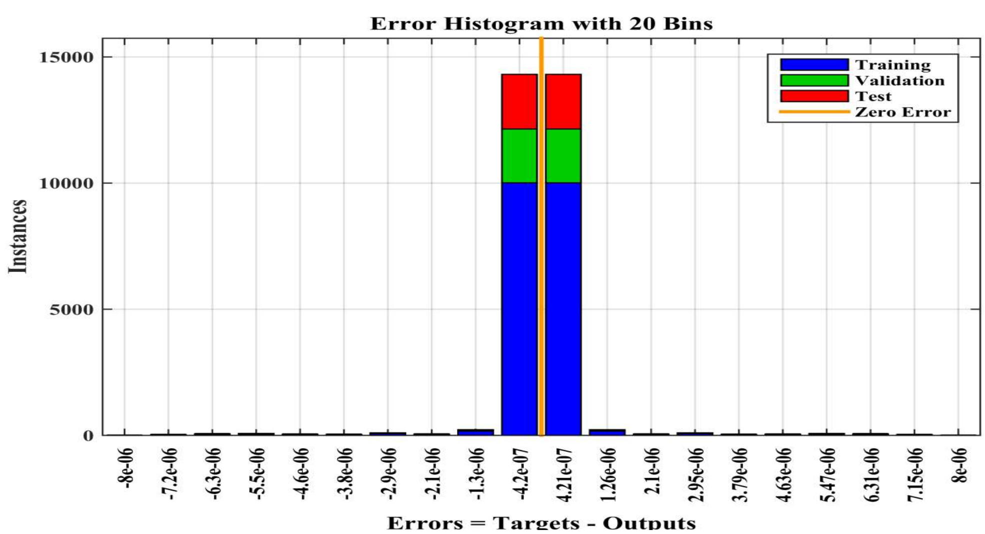


Figure: 23. -Error Histogram IMF

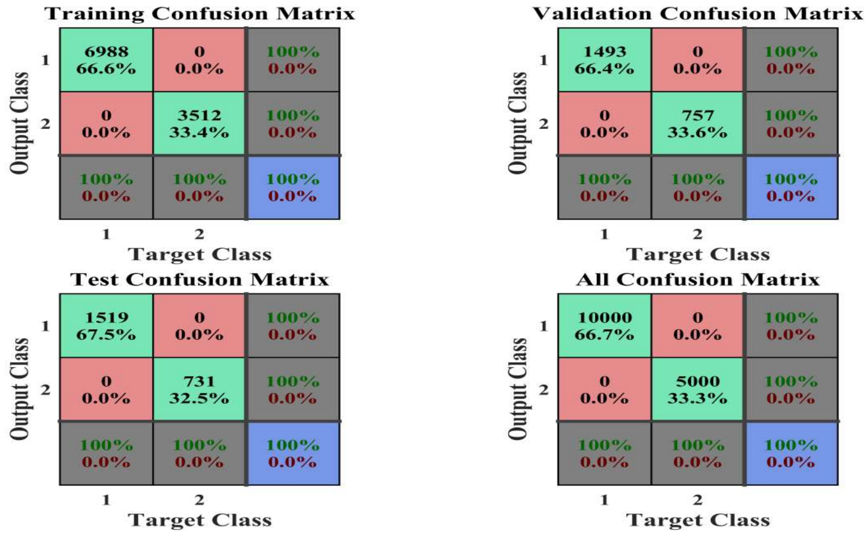


Figure: 24. - Confusion matrix IMF

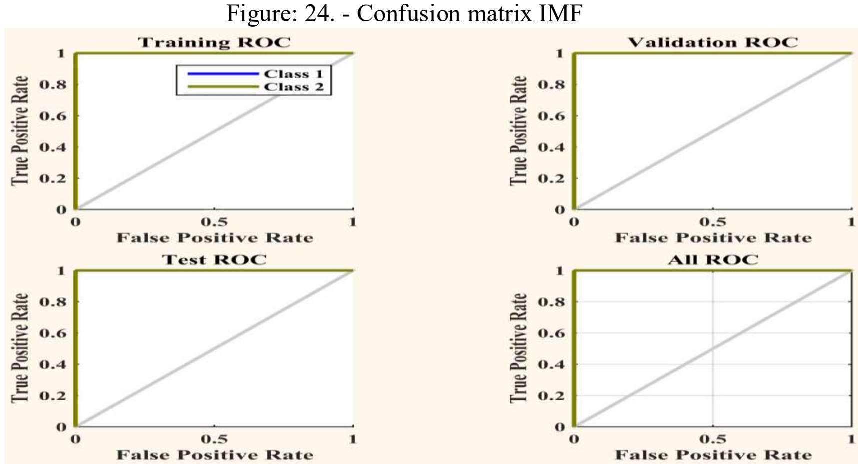


Figure: 25. -ROC Training IMF

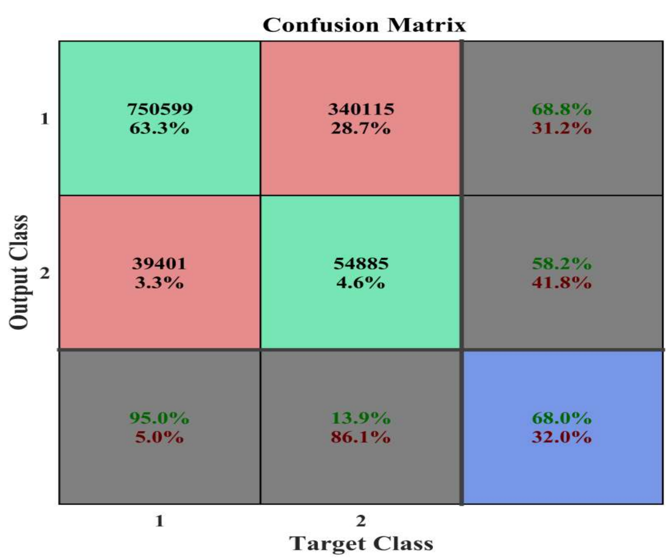


Figure: 26. -Confusion matrix Test IMF

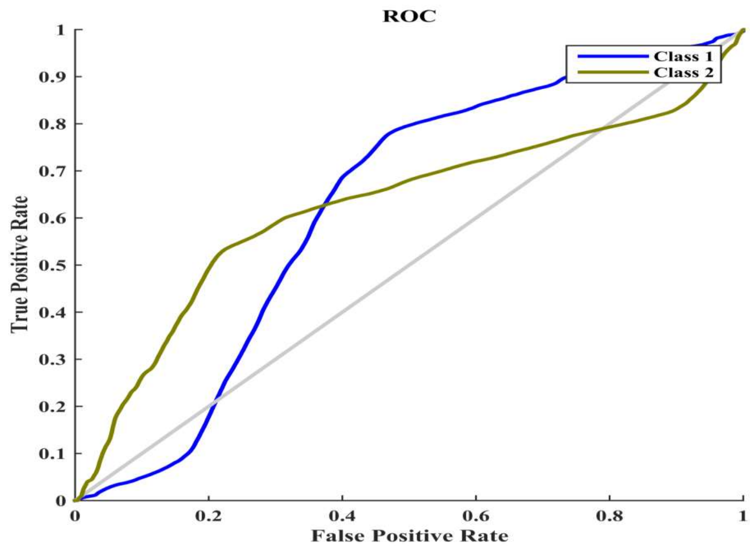


Figure: 27. -ROC Test IMF

3.3 comparative studied

In EMD with and without we observe that the variation of results are present in without results from 66%-89 %.But in case of EMD approx minimum variation comes out 66%-68%.

4 **Conclusion**:

The EMD process is a useful and powerful method to decompose EEG signal into a set of IMFs. These IMFs can be represented by the amplitude and frequency modulated (AM–FM) signal model, which makes it possible to compute AM and FM bandwidths of the IMFs. These bandwidth parameters B_{AM} and B_{FM} of the IMFs of EEG signals have been used as a feature in order to classify seizure and nonseizure EEG signals. The proposed method may be applied for analysis and classification of other no stationary signals. Future directions of this research include the effect of sampling frequency of EEG signals on the classification accuracy, and determine automatically parameters of the kernel functions for perfect classification of seizure and nonseizure EEG signals.

REFERENCES

[1] E. I. Zacharaki, S. Wang, S. Chawla, and D. Soo,“Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme,” *Magn. Reson. Med.*, vol. 62, no. 6, pp. 1609–1618, 2009.

[2] A. M. Lal, M. Balaji, and D. Aju, “Multi-Level Fusion of CT and MRI Brain Images for Classifying Tumor,” *Int. J. Enhanc. Res. Manag. Comput. Appl.*, vol. 3, no. 8, pp. 34-40, 2014.

[3] H. H. Manap, N. M. Tahir, and R. Abdullah, “Performance comparison of parkinsonian gait based on Principal Component Analysis,” *2013 IEEE Symp. Ind. Electron. Appl.*, pp. 216–221,2013.

[4] A. A. Kathalkar, “Artificial Neural Network based Brain Cancer Analysis and Classification,” *Int. J. Comput. Appl.*, vol. 66, no. 10, pp. 40–43, 2013.

[5] R. Karthik, R. Menaka, and C. Chellamuthu, “A comprehensive framework for classification of brain tumour images using SVM and curvelet transform,” *Int. J. Biomed. Eng. Technol.*, vol. 17, no. 2, pp. 168–177, 2015.

[6] C. H. C. Huang, B. Y. Bin Yan, H. J. H. Jiang, and D. W. D. Wang, "Combining Voxel-based Morphometry with Artifical Neural Network Theory in the Application Research of Diagnosing Alzheimer's Disease," *2008 Int. Conf. Biomed. Eng. Informatics*, vol. 1, pp. 250–254, 2008.

[7] J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, "A package-SFERCB-Segmentation, feature extraction, reduction and classification analysis by both SVM and ANN for brain tumors," *Appl. Soft Comput. J.*, vol. 47, pp. 151–167, 2016.

[8] X. Pan and B. Lee, "A Comparison of Support Vector Machines and Artificial Neural Networks for Mid-Term Load Forecasting," in *Industrial Technology (ICIT), 2012 IEEE International Conference on*, 2012, pp. 95–101.

[9] W. H. Ibrahim, A. A. A. Osman, and Y. I. Mohamed, "MRI Brain Image Classification Using Neural Networks," *Comput. Electr. Electron. Eng. (ICCEEE), 2013 Int. Conf. IEEE.*, pp. 253–258, 2013.

[10] Y. Zhang and L. Wu, "An MR brain images classifier via principal component analysis and kernel support vector machine," *Prog. Electromagn. Res.*, vol. 130, no. July, pp. 369–388, 2012.

[11] Z. Shi, L. He, T. Nakamura, K. Suzuki, and H. Itoh, "Survey on Neural Networks Used for Medical Image Processing Survey on Neural Networks Used for Medical Image Processing," *Int. J. Comput. Sci.*, vol. 3, no. 1, pp. 86–100, 2009.

[12] http://www.med.harvard.edu/annlib/home.html

[13] ;http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3

[14] http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3

[15]Small dataset, Epilepsy dataset (text format), http://epileptologie bonn.de/cms/front_ content.php?idcat=193&lang=3&changelang=3, Visited Date: April 28, 2012

[16] Large dataset, EEG Data set from Epilepsy Centre of the University Hospital of Freiburg http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database, Visited Date: June 10, 2012.

[17] Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P and Elger CE 2001 Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state Phys .Rev. E 64 061907

[18] F. Mormann, R.G. Andrzejak, C.E. Elger, K. Lehnertz, Seizure prediction: the long and winding road, Brain 130 (2) (2007)314–333.

[19] G.C. Ray, An algorithm to separate non stationary part of a signal using mid-prediction filter, IEEE Transactions on Signal Processing 42 (9) (1994) 2276–2279, September.

[20] S. Mukhopadhyay, G.C. Ray, A new interpretation of nonlinear energy operator and its efficacy in spike detection, IEEE Transactions on Biomedical Engineering 45 (2) (1998)180–187, February.

[21] K. Polat, S. Günes, Classification of epileptic form EEG using a hybrid system based on decision tree classifier and fast Fourier transform, Applied Mathematics and Computation187 (2) (2007) 1017–1026, April.

[22] S. Altunay, Z. Telatar, O. Erogul, Epileptic EEG detection usingthe linear prediction error energy, Expert System withApplications 37 (2) (2010) 5661–5665, August.

[23] V. Joshi, R.B. Pachori, A. Vijesh, Classification of ictal andseizure-free EEG signals using fractional linear prediction,Biomedical Signal Processing and Control 9 (2014) 1–5,January.

[24] A.T. Tzallas, M.G. Tsipouras, D.I. Fotiadis, Automatic seizuredetection based on time–frequency analysis and artificialneural networks, Computational Intelligence andNeuroscience (2007), vol. 2007, Article ID 80510, 13 pages.

[25] A.T. Tzallas, M.G. Tsipouras, D.I. Fotiadis, Epileptic seizuredetection in EEGs using time–frequency analysis, IEEETransactions on Information Technology in Biomedicine 13(5) (2009) 703–710, September.

[26] H. Adeli, Z. Zhou, N. Dadmehr, Analysis of EEG records in anepileptic patient using wavelet transform, Journal ofNeuroscience Methods 123 (1) (2003) 69–87,February.

[27] R. Uthayakumar, D. Easwaramoorthy, Epileptic seizuredetection in EEG signals using multifractal analysis andwavelet transform, Fractals 21 (2) (2013), June.

[28] L. Guo, D. Rivero, A. Pazos, Epileptic seizure detection usingmultiwavelet transform based approximate entropy andartificial neural networks, Journal of Neuroscience Methods193 (1) (2010) 156–163, October.

[29] N.F. Güler, E.D. Übeyli, I. Güler, Recurrent neural networksemploying Lyapunov exponents for EEG signal classification,Expert Systems with Applications 29 (3) (2005) 506–514,October.

[30] E.D. Übeyli, Lyapunov exponents/probabilistic neuralnetworks for analysis of EEG signals, Expert Systems withApplications 37 (2) (2010) 985–992, March.

[31] K. Lehnertz, C.E. Elger, Spatio-temporal dynamics of theprimary epileptogenic area in temporal lobe epilepsycharacterized by neuronal complexity loss,Electroencephalography and Clinical Neurophysiology 95 (2)(1995) 108–117, August.