Chapter

Empirical Mode Decomposition of EEG Signals for the Effectual Classification of Seizures

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Abstract

Empirical mode decomposition (EMD) is a remarkable method for the analysis of nonlinear and non-stationary data. EMD will breakdown the given signal into intrinsic mode functions (IMFs), which can represent natural signals effectively. In this work, the competence of EMD with traditional features to classify the seizure and non-seizure EEG signals is studied. Due to the complex nature of human brain, the EEG signals which are recorded from different regions of brain are non-stationary in nature. Different features such as entropy features (approximate entropy (ApEn), sample entropy (SmEn), Shannon entropy (ShEn), Rényi entropy (RnEn)), fractal dimension features (Petrosian fractal dimension, Higuchi fractal dimension, Katz fractal dimension), statistical features (mean, standard deviation and energy) and exponential energy features are extracted from IMFs and fed to a SVM classifier. The performances of extracted features are studied independently. The result shows that, the EMD method is well suited for complex seizure EEG signal classification.

Keywords: seizures, EEG, empirical mode decomposition, intrinsic mode functions

1. Introduction

Seizures are characterized as unexpected, unprovoked and uncontrolled explosion of electrical impulses in brain [1]. During the seizure, the patient may experiences changes in behavior, loss of consciousness, unusual movements and unusual feelings [2, 3]. The recurrent and unprovoked seizure leads to epilepsy disorder which is a prevalent neurological disorder. Epilepsy disorder will tamper the patients way of life with social stigma, work productivity lose and premature death [4].

Electroencephalogram (EEG) is one of the traditional and easiest tool for the identification and diagnosis of seizures [5]. The availability of EEG for common people within their budgetary limits made it a typical method. Due to the sophisticated nature of brain system, the EEG signals acquired from the brain are also complicated. Automated analysis of EEG signals using modern signal processing techniques might be effortless and precise for the diagnosis of seizures rather than manual approach [6].

Out of modern signal processing techniques, empirical mode decomposition (EMD) is one of the widely used techniques for the efficient interpretation of signals and images. After the introduction of EMD by Huang [7] in 1998, several

studies utilized the EMD for various applications. In Nunes et al. [8] used the EMD for texture analysis and image filtering. They have used bi-dimensional EMD in their method. In another work Zeng et al. [9] applied EMD for the effective classification of gait patterns between patients with Parkinson disease and healthy subjects. In another work Hasan et al. [10] combined the deep learning methods with EMD to classify cardiovascular disease. Xiwei et al. [11] utilized the advantages of EMD in a wind speed prediction model, in which, authors used EMD for the extraction of fluctuation features of wind speed data. Another important study by Thilagaraj et al. [12] also used EMD for the identification of alcoholism.

The usefulness of the empirical mode composition for the effective understanding of the EEG signal is proven in many works in the literature. In [13], authors classified the level of autism severity from EEG with the help of EMD. They have used artificial neural network for the classification of extracted feature from intrinsic mode functions (IMFs). Two-class motor imagery EEG signals are classified in another important study based on EMD [14]. Similarly Gaur et al. [15] used multivariate empirical mode decomposition for the effective classification of multi-class BCI by analyzing EEG signals.

In this work, we have studied the effectiveness of empirical mode decomposition for the classification of seizures by analyzing EEG signals. The filtered EEG signals are segmented into 10 non-overlapping segments and decomposed into IMFs using EMD. First four IMFs are used for the feature extraction. Various features such as approximate entropy, sample entropy, Shannon entropy, Rényi entropy, exponential energy, fractal dimensional features and statistical features (mean, standard deviation and energy) are extracted from the IMFs. Support vector machine (SVM) with RBF kernel is used for classifying the seizure.

The remaining sections of the paper are as follows. A short description of EMD and algorithm is explained in Section 2. Section 3 explains the details of the dataset used in this study and in Section 4; various feature extraction methods are mentioned. In Section 5 experimental setup and results are explained. A detailed discussion of achieved results is given in Section 6 and Section 7 concludes the paper.

2. Empirical mode decomposition (EMD)

Empirical mode decomposition is a data-driven decomposition method proposed by Huang et al. for the analysis of nonlinear and non-stationary data [7], which will decomposes the signal into finite and smaller number of intrinsic mode functions (IMFs). A non-stationary signal can be represented as sum of IMFs and each IMFs should follow two conditions: (1) the number of extrema and number of zero crossing of the IMFs should be equal or differ at most by one and (2) the mean value of two envelopes defined by local maxima and local minima should be zero [16].

IMFs can be extracted from a signal through a iterative method known as shifting process as follows:

1. Use cubic spline interpolation method to construct upper (e_{max}) and lower (e_{min}) envelops by connecting detected maxima and minima individually from the signal $x(t)$.

2. Calculate the mean $m(t) = \frac{(e_{\max}+e_{\min})}{2}$.

3. Extract the difference $d(t)$ between signal $x(t)$ and calculated $m_1(t)$, $d(t) = x(t) - m(t)$.

4. Check whether $d(t)$ is satisfying the IMFs basic conditions. Repeat step 1 to 3 until $d(t)$ satisfying the IMFs conditions.

5. if $d(t)$ satisfies IMFs condition once, define the first IMF as $IMF_1 = d(t)$.

6. The next IMFs can be obtained by generating residue $r(t)$ as $r(t) = x(t) - IMF_1$ and use these residue as the original data for the next iteration.

7. Iteration will stop when final residue is a function which cannot produce any more IMFs or final residue is constant/monotonic function.

The original signal can be represented as the sum of all IMFs and final residual.

$$x(t) = \sum_{i=1}^{K} IMF_i + r_K(t) \tag{1}$$

where IMF_i is the ith IMF, K is the number of IMF and $r_K(t)$ is the final residual.

3. Dataset

A benchmark data set named as Bern-Barcelona EEG dataset is used in this study. The dataset includes two class EEG signals such as focal and non-focal. Each class contains 3750 pairs of signals. EEG signals in the focal class are collected from the epileptic area of the brain and non-focal signals are collected from non-epileptic area of the brain. The signals are 20 s duration with 10,240 samples in each. The signals are sampled at 512 Hz sampling rate. In our study we have used 50 signals from each class as did in many other studies [17–19].

4. Feature extraction

Feature extraction is one of the important tasks in any machine learning application. An effective and unbiased feature will provide the best results. There are several features, which are traditionally used for various EEG related studies.

Entropy features are widely used for the analysis of various non-stationary biosignals [20–22]. Different verities of entropy are introduced in past years. In this work we have used four verities of entropy features, namely approximate entropy (ApEn), sample entropy (SmEn), Shannon entropy (ShEn) and Rényi entropy (RnEn). Among considered entropy features, approximate entropy introduced by Pincus [23] is a good measure of complexity for non-stationary signals. One of the study proposed by Hozinger et al. [24], extracted approximate entropy from ECG time-series for better understanding of electrocardiogram (ECG) signals. Another study by Ahmed et al. [25] utilized approximate entropy for surface electromyogram (EMG) signal classification. Similar to [24], they also extracted approximate entropy from direct signals with no transformation. Also, other entropy measures such as sample entropy [27–29], Shannon entropy [30, 31] and Rényi entropy [32, 33] are used in many studies.

Fractal dimension based feature are also got wide attention of researchers in recent years. The fractal dimensions are better measures of complexity of a nonlinear or non-stationary data [35]. In this work we extracted three different fractal dimension features such as Petrosian fractal dimension, Higuchi fractal dimension and Katz fractal dimension. These measures are used in various EEG related studies

in the literature. In a study of drowsiness detection [36], authors extracted Petrosian and Higuchi fractal dimensions from EEG time domain signals. Similarly in another work, Acharya et al. [37] extracted Katz fractal dimension with other features for the classification of various sleep stages. We have also extracted one of the newly introduced feature, namely exponential energy by Fasil and Rajesh [26]. Some of the statistical features (mean, standard deviation and energy) are also tested in this work.

5. Experiments and results

In this work, seizure EEG signals and non-seizure EEG signals are classified by decomposing the EEG signal into IMFs using empirical mode decomposition. The frequencies beyond 60 Hz are irrelevant in the EEG analysis due to the non-availability of proper information in higher frequencies [34]. A sixth order butter-worth filter is used to remove frequencies beyond 60 Hz. The signals are further segmented into 10 non-overlapping segments. Empirical mode decomposition is applied on the segmented EEG signals and first four IMFs are obtained. Feature are extracted from four IMFs and averaged across the segments. Support vector

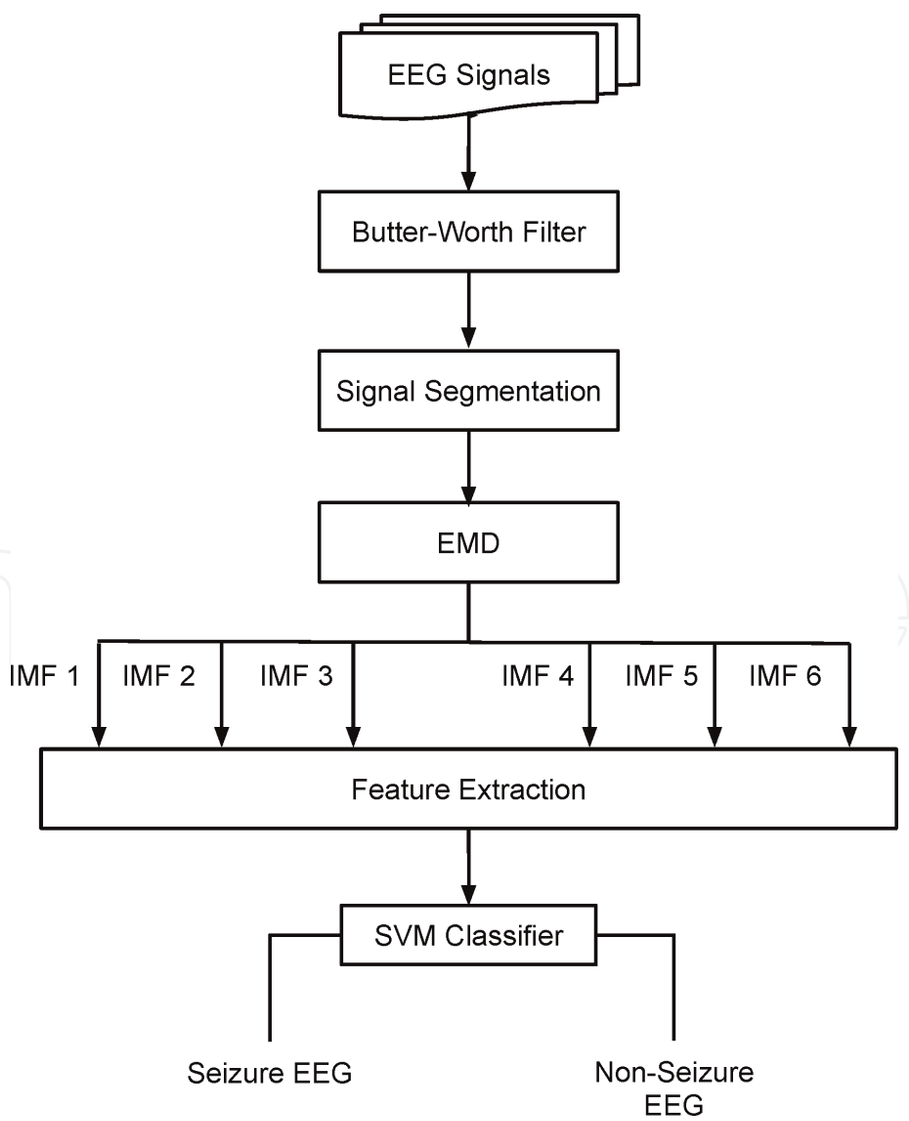

Figure 1.
Block diagram of the proposed seizure classification method.

machine with RBF kernel is used for the classification task. An overall diagram of the work is given in **Figure 1**.

The empirical mode decomposition produces six IMFs in total, though we have considered only first four IMFs. The reason behind this selection procedure is the non-availability of useful information in last IMFs. In this work we have extracted various features such as approximate entropy (ApEn), sample entropy (SmEn), Shannon entropy (ShEn), Rényi entropy (RnEn), Petrosian fractal dimension, Higuchi fractal dimension, Katz fractal dimension, exponential energy from four IMFs and statistical feature (mean, standard deviation and energy).

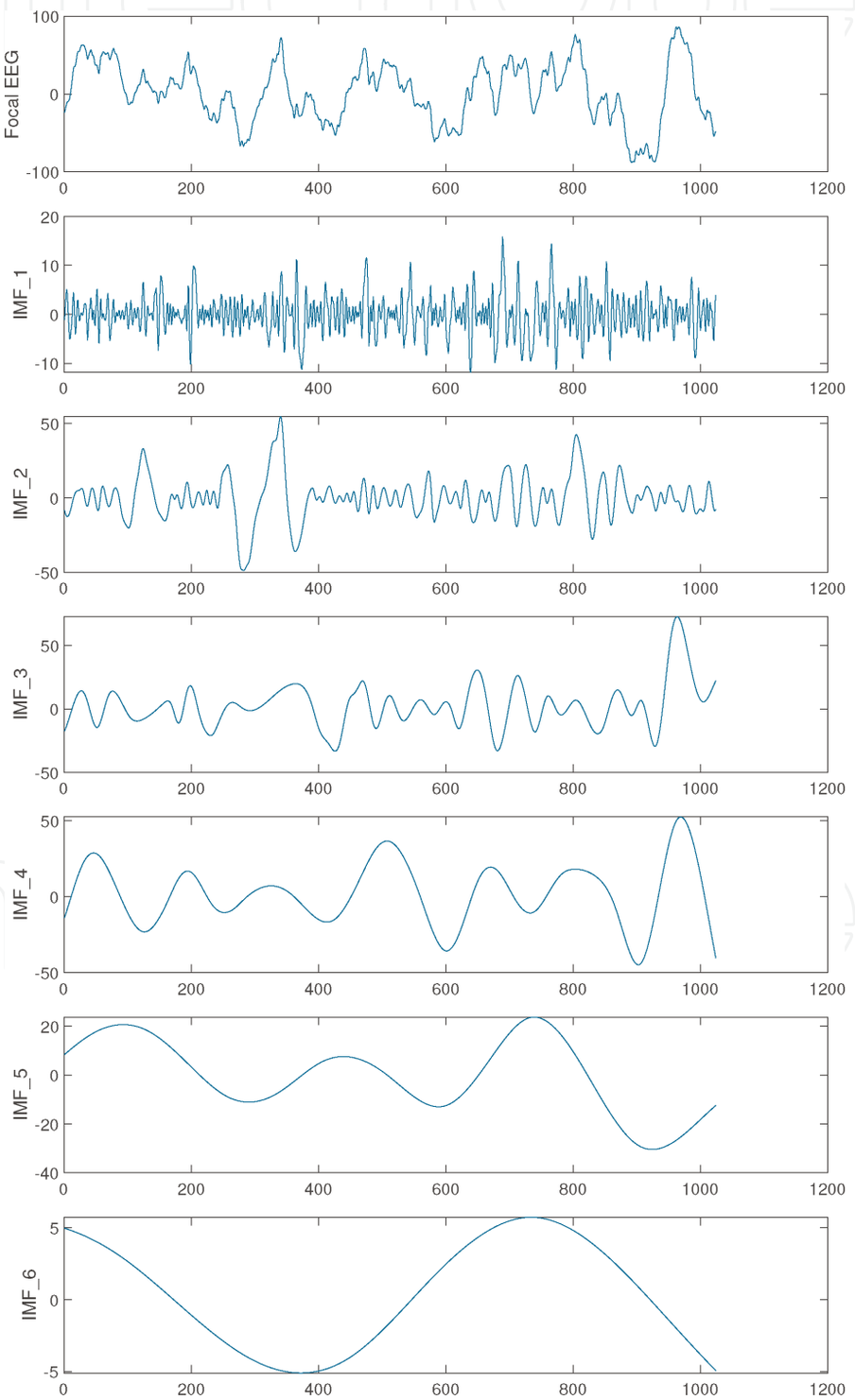

Figure 2.
Focal EEG signals and six IMFs obtained from focal EEG signal.

Sample focal EEG signal and IMFs obtained from focal EEG signals are shown in **Figure 2**. Similarly sample non-focal EEG signal and IMFs obtained from non-focal EEG signals are shown in **Figure 3**.

Each record in the dataset contains a pair of signals denoted as '*x*' and '*y*'. EMD applied on both signal separately and total 8 IMFs are obtained (4 from '*x*' and 4 from '*y*'). To investigate the ability of each feature to classify seizures, experiments are conducted on all features individually. In classification task, the capacity of RBF kernel in support vector machine is already proved in various seizure studies [26, 34]. In this work we have used RBF kernel in support vector machine for the classification task.

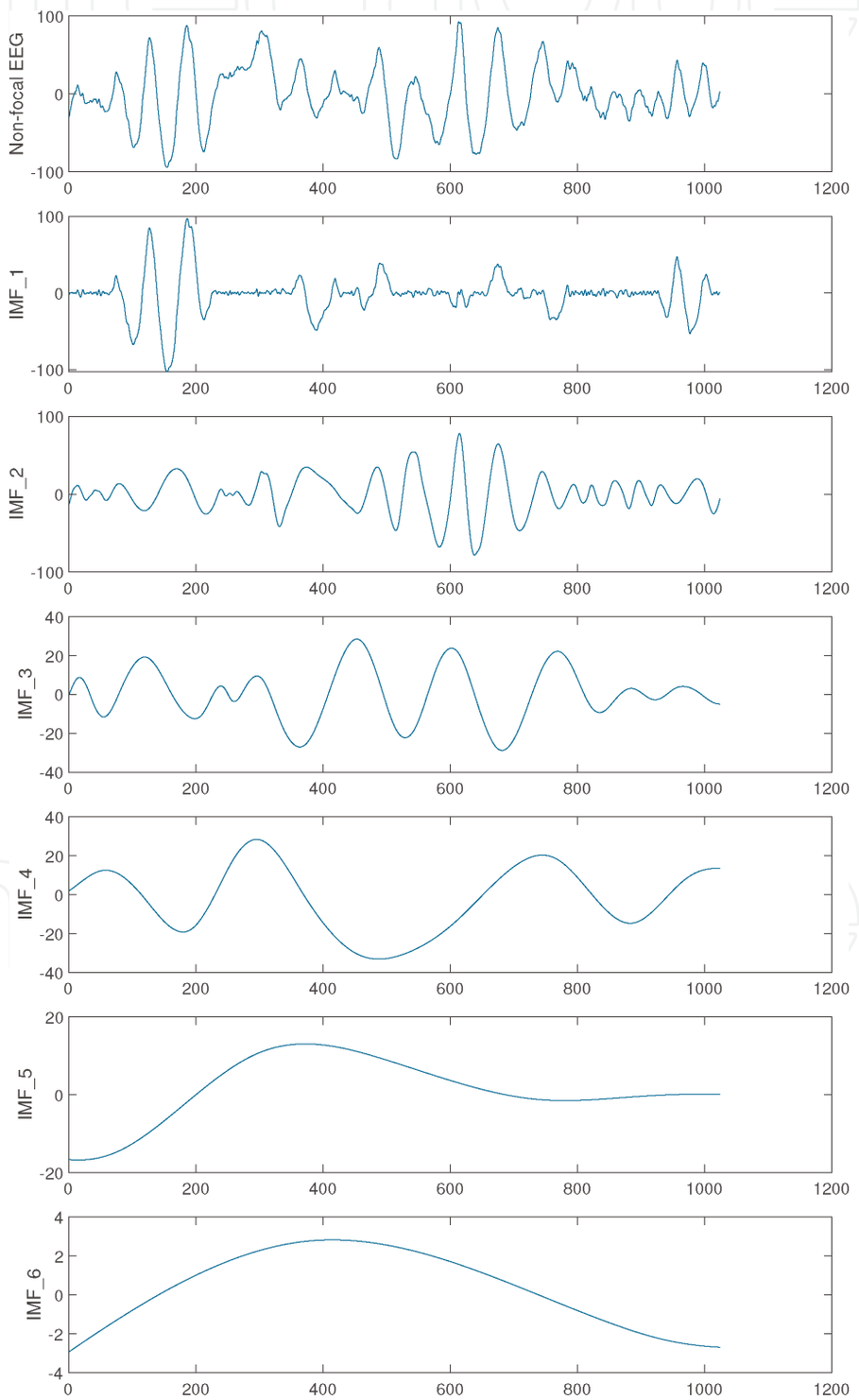

Figure 3.
Non-focal EEG signals and six IMFs obtained from non-focal EEG signal.

Feature	Accuracy (%)	Sensitivity (%)	Specificity (%)
Shannon entropy	58	26	90
Statistical features	68	54	82
Higuchi fractal dimension	71	72	70
Sample entropy	73	83	60
Approximate entropy	75	82	68
Petrosian fractal dimension	75	68	82
Rényi entropy	79	82	76
Katz fractal dimension	80	88	72
Exponential energy	84	84	84

Table 1.
Results of various features extracted from the IMFs.

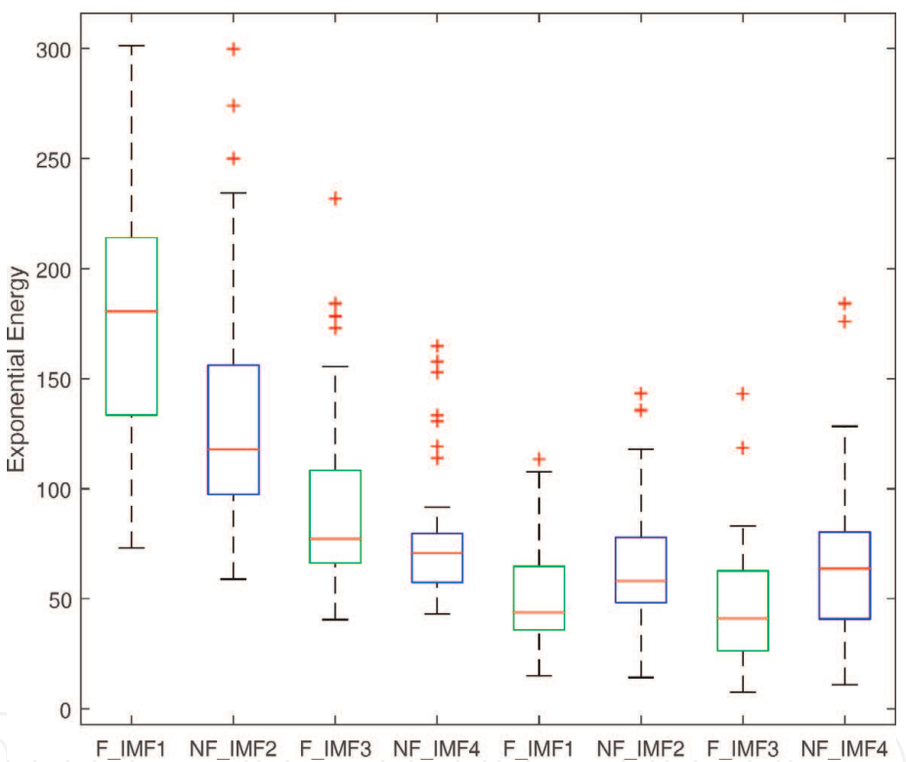

Figure 4.
Boxplot of the extracted exponential energy feature of four IMFs of focal (green color box, labeled as F_IMF) and non-focal (blue color box, labeled as NF_IMF) EEG signals.

We have used k-fold cross-validation with $k = 5$ for testing the ability of extracted features from IMFs. The results of the experiments are calculated with three benchmark measures, such as accuracy, sensitivity and specificity. The measured results are tabulated in **Table 1**.

The results in **Table 1** indicates that the features extracted from the IMFs of empirical mode decomposition gives promising results. Among the tested features, exponential energy feature provided better accuracy with 84%. A box-plot of extracted exponential energy is shown in **Figure 4**. Katz Fractal Dimension also provides better accuracy of 80% followed by Rényi entropy with 79%. Statistical features and Shannon entropy gives less accuracy out of all. It is noted that Shannon entropy giving very low sensitivity value and very high specificity, which indicates that more number of seizure signals are miss-classified as non-seizure signals.

6. Discussion

The study of EEG signals using empirical mode decomposition (EMD) gives an insight into the effectiveness of EMD method to analyze EEG signal for seizure classification. The features (includes four types of entropy features, three types of fractal dimensions, statistical features and exponential energy) considered in this work, produces better classification accuracy when it is extracted from decomposed IMFs.

Empirical mode decomposition method decomposes the signals into various intrinsic mode functions (IMFs). Since, IMFs carries more detailed information of a signal, the features extracted from these IMFs leads to better classification.

Similar to EMD, discrete wavelet transformation (DWT) is a method, which decomposes the signal into various sub-bands [38–40, 42]. Many EEG related studies used DWT method for various analysis. Li et al. [41] combined DWT method with envelope analysis for the effective feature extraction to classify epileptic signal. In another work, Kumar et al. [42] extracted fuzzy entropy from the sub-bands of DWT for seizure detection. Similarly Liu et al. [43], Mohammadi et al. [44] and Silveira et al. [45] also used DWT method to analyze EEG signals for various purposes. Though, EMD is more better than the DWT method.

A comparison of EMD method with DWT is also carried out in this work. The same features which are extracted from the IMFs are also extracted from the DWT sub-bands and classified with same classifier. A bar chart of the comparison of classification accuracy is given in **Figure 5**. The comparison results show that the EMD based feature produces better classification results than DWT based features. EMD based method produced an average accuracy of 73.66%. In case of DWT the average accuracy is 68%. Although, DWT methods shows a slight improvements in results for approximate entropy and Shannon entropy features.

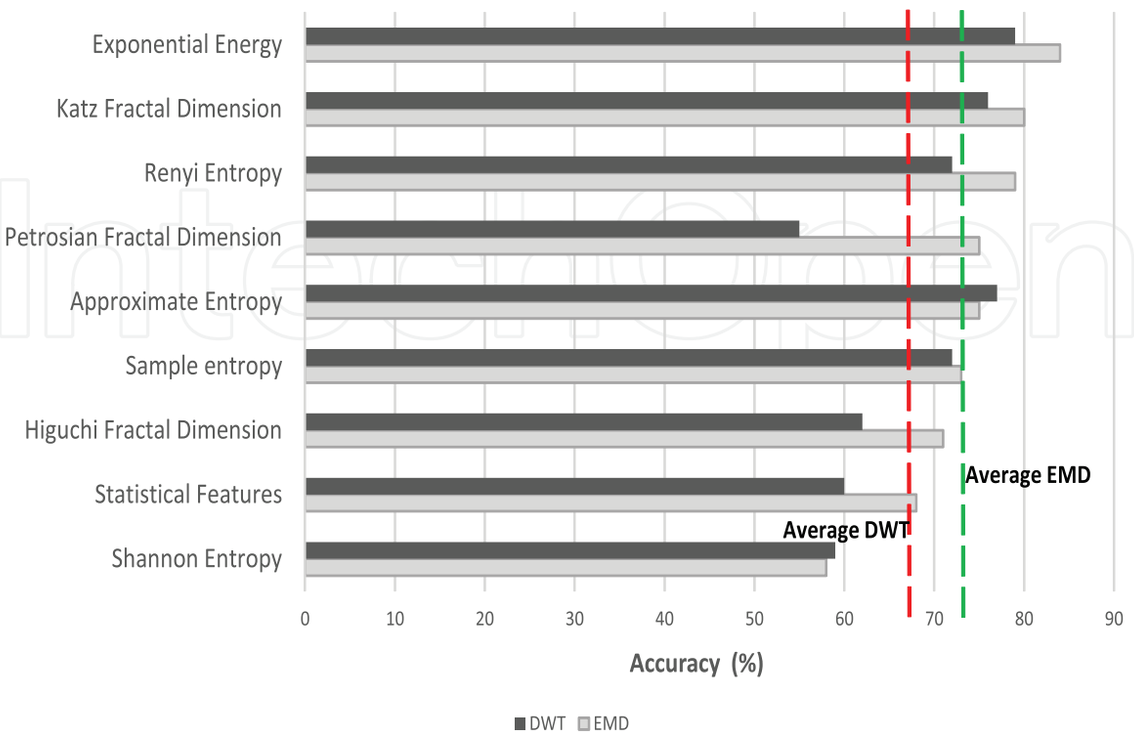

Figure 5.
A comparison of classification accuracy between empirical mode decomposition (EMD) and discrete wavelet transform (DWT). Red dashed vertical line indicates the average accuracy of all DWT features and green dashed vertical line indicates the average accuracy of all EMD features.

Among various entropy features, EMD-Rényi combination (79% accuracy) provides higher classification accuracy. Approximate entropy extracted from IMFs produced an accuracy of 75%. Shannon entropy with EMD is not a good choice of feature for epileptic seizure detection. The classification accuracy produced by Shannon entropy is only 58%. Complexity of EEG data is the reason for less percentage of accuracy.

Three fractal dimensions (Petrosian fractal dimension, Higuchi fractal dimension, Katz fractal dimension) used in this work also produce promising results when they are extracted from IMFs. In this study, EMD based Katz fractal dimension produces higher (80%) classification accuracy than Petrosian (75%) fractal dimension and Higuchi (71%) fractal dimension.

EMD based statistical features did not produce promising results for classification of epileptic EEG signals. But the results are comparatively better than the features from time domain and DWT domain. The highest classification accuracy (84%) reported in this study is with newly introduced exponential energy feature by Fasil and Rajesh [26]. Exponential energy feature utilizes the detailed information available in IMFs to classify epileptic EEG signals effectively. The achieved results show the effectiveness of empirical mode decomposition (EMD) as major step in epilepsy classification.

7. Conclusions

The scope of the empirical mode decomposition of EEG signals in effectual classification of seizure is studied in this work. Four intrinsic mode functions (IMFs) are obtained by applying EMD on filtered EEG signals. Widely used features such as entropy features, fractal dimension features, statistical features and exponential energy features are extracted and its discriminating power is studied. SVM with RBF kernel is used for the classification task. Exponential energy feature provided better results for the seizure classification.

Seizure identification is a challenging and risk bearing activity, which require better accuracy. In future, authors will concentrate on improving the results by incorporating other signal transformation methods with EMD.

Conflict of interest

Authors declare no conflict of interest.

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