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Epileptic seizure detection in EEG signals using normalized IMFs in CEEMDAN domain and quadratic discriminant classifier

Md. Faizul Bari*, Shaikh Anowarul Fattah

Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh

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ABSTRACT

Epilepsy is the fourth most common neurological disorder that manifests itself through unprovoked seizures, detection of which is the very first step of proper diagnosis and treatment of this severe disease. In this paper, an automated seizure detection method has been proposed based on the statistical and spectral features of max normalized intrinsic mode functions or IMFs that were extracted using complete ensemble empirical mode decomposition with adaptive noise method. First, a publicly available dataset of EEG signals was used to generate the IMFs and noise or outliers were discarded. Then IMFs were max normalized which was shown to improve the separability of features. Statistical and spectral features were extracted from the normalized IMFs which offered better separation of seizure and seizure-free data. Finally, Quadratic Discriminant classifier was used for the classification purpose and 10-fold cross validation was performed to validate the trained model. The proposed scheme is numerically efficient and shows a maximum of 100% accuracy which is the highest reported on this data set.

1. Introduction

1.1. Motivation

The International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE) have defined the terms *epileptic seizure* and *epilepsy* as follows: an epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain and epilepsy is a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures and by the neurobiologic, cognitive, psychological, and social consequences of this condition [1]. The definition of epilepsy requires the occurrence of at least one epileptic seizure. According to World Health Organization (WHO), approximately 50 million people have epilepsy worldwide. Around 80% of epilepsy patients are either from low or middle-income countries, of which around 75% fail to get proper treatment. Epilepsy has severe socioeconomic consequences, including high treatment cost, low employment rate, and low salary among epileptic patients [2]. Epilepsy remains resistant to drug therapy in about one-third of patients and people with pharmacoresistant epilepsy are about 2–10 times more likely to die compared to the general population [3].

To ensure proper treatment of epileptic patients, the very first step is to diagnose the disease accurately. EEG (electroencephalogram) signals, first recorded by Hans Berger, are used to detect epileptic seizures. The traditional way of the analysis of the recorded EEG data performed primarily by neurologists through visual inspection is costly, time-consuming and prone to human errors [4]. Thus, we need an automated seizure detection algorithm which can analyze EEG data and detect epileptic seizures with high accuracy. Another point is that traditionally proposed methods are computationally heavy. We need simpler method that can run on even resource limited cheaper devices. Also simpler, computationally less heavy methods can provide real-time epileptic seizure detection. This is extremely important as seizure attacks are unpredictable and put the life of the patient in a vulnerable state. If smart devices can detect the epileptic seizure in real-time (assuming real time EEG signal also available, which is not the focus of our work) and notify emergency services, valuable lives can be saved. To sum up, we are motivated to work on a computationally simple, automated epileptic seizure detection method that can identify seizure attack with high accuracy.

1.2. Related work

Researchers have developed different algorithms with different accuracy and sensitivity. Most popular techniques use wavelet transform for domain transformation of EEG signal and extract various features from it, which are used further to classify and detect

* Corresponding author.
E-mail address: faizul.eee.buet@gmail.com (Md.F. Bari).

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epileptic seizures. Ocak [5] used approximate entropy (ApEn) and discrete wavelet transform (DWT) analysis of EEG signals. At first, he decomposed EEG signals into approximation and detail coefficients using DWT and later computed ApEn values of the approximation and detail coefficients. The differences of the ApEn values between the epileptic and the normal EEG were used to detect seizures. Swami et al. [4] used dual-tree complex wavelet transformation to generate feature sets which were used in general regression neural network to detect epileptic seizures. Sharma et al. [6] used analytic time-frequency flexible wavelet transform (ATFFWT) to decompose EEG signals in desired sub-bands and calculated fractal dimension (FD) for each sub-band which were fed to least-squares support vector machine (LS-SVM) classifier. They achieved a perfect 100% sensitivity. Tzimourta et al. [7] used discrete wavelet transform (DWT) along with support vector machine (SVM) classifier and achieved a high specificity (99%). Wang et al. [8] used wavelet-based directed transfer functions and achieved remarkable 99.4% accuracy. Similar method of using directed transfer function was reported by Wang et al.[9] They used sliding window technique to segment EEG recordings and calculated cerebral functional connectivity using directed transfer functions. Later, they calculated information outflow based on the connectivity by adding up the information flow from a single EEG channel to other channels, which were used as features in SVM classifier. Their reported average accuracy is 98.45%.

Other than wavelet transform and its variants, different methods were also used to detect epileptic seizures including deep convolutional neural network [10], principal component analysis (PCA) [11], independent component analysis (ICA), and fuzzy systems [12]. Another method for time-frequency transformation is empirical mode decomposition (EMD). EMD decomposes nonstable nonlinear signals into intrinsic mode functions (IMF) to obtain instantaneous frequency data. EMDs are used with different classifiers like LS-SVM, artificial neural network, etc. to detect epileptic seizures [13]. These EMD based methods have mode-mixing problems (mixed frequencies). To overcome this issue Hassan and Subasi [14] used complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). Six IMFs were extracted from the CEEMDAN mode functions and train and test matrices were formed which were later fed into the linear programming boosting (LPBoost) classifier to identify epileptic seizures. Jia et al. [15] used CEEMDAN to generate IMFs which were used to generate two dimensional and three dimensional phase space representations (PSR). Phase space data were transformed to form growth curve from which various features were extracted. These features along with normal inverse Gaussian (NIG) modeling parameters were fed into random forest (RF) classifier to classify epileptic seizure and seizure-free EEG data.

In our proposed method, we have calculated IMFs using CEEMDAN method instead of EMD method, because the later has mode mixing problem where the former one provides better mode separation. Then, we have max normalized each set of IMFs. Later we extracted some basic statistical features as well as spectral features which are typically used in the field of physiological signal classification. These feature sets were fed into quadratic discriminant classifier and 10-fold cross validation was used to train and test our model. This method provided less computational burden with very high accuracy in seizure detection. The effect of using less number of IMFs was investigated. We compared the performances of other popular classifiers for this method as well. Also, performance comparison with others' work has been shown.

1.3. Our contribution

1. We proposed a simple method of using max normalization to better separate features from IMFs. To our best knowledge, no one has proposed a similar method for epilepsy detection from EEG signal.
2. In our method, accuracy can be as high as 100% which, to our best knowledge, is the highest reported accuracy on this data set.
3. Our proposed method is computationally much simpler compared to many other methods reported in the literature. This can pave the way for real-time epilepsy detection. Real-time detection can be incorporated in smart devices (like smartwatch) and can save the life of many patients suffering from epileptic seizures.

2. Methodology

2.1. Database

A publicly available database [16] from University of Bonn was used for our work. The full database consists of five sets (denoted A–E). Each set has 100 single channel EEG segments of 23.6 s duration. The sampling rate was 173.61 Hz. So each segment has 4097 samples. These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts like muscle activity or eye movements. Surface EEG recordings which were carried out on five healthy volunteers when they were awake and relaxed are in set A and set B, where set A contains recordings when eyes were open and set B contains recordings when eyes were closed. Sets C, D, and E were taken from the EEG archive of pre-surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of the detected epileptogenic zone-one of the hippocampal formations. Both set C and set D contain segments recorded from the hippocampal formation of opposite brain hemispheres (set D from epileptogenic zone). Unlike set C and set D which contain seizure free data, set E contains EEG segments that are recorded during seizure activity. Set A–E were written to the disk as different compressed files denoted by Z.zip, O.zip, N.zip, F.zip, and S.zip respectively. For rest of the paper, we will use these file names to refer to corresponding data.

In this work, we have used only set N, F and S. In our classifier, we have used two classes, namely seizure and seizure-free classes. EEG segments from set S represent data during seizure activity and set N and set F represent data during seizure-free activity.

2.2. IMF generation

Intrinsic mode function (IMF) is defined as a function that satisfies two conditions: (1) in the whole data set, the number of peaks/troughs and the number of zero crossings must not differ by more than one and (2) at any point, the mean value of the envelopes defined by the local maxima and the local minima is zero. The name was given because each intrinsic mode function represent only one mode in the data without any complex riding wave. According to the definition, IMFs need not be narrow band signals. They can be both frequency and amplitude modulated. IMFs can be generated by empirical mode decomposition (EMD) method [17,18]. The EMD algorithm [19] to decompose N-point EEG signal X is as follows:

1. Set $h_1 = X$.
2. Identify the local maxima and minima of h_1.
3. Use cubic spline interpolation to get the envelope of local maxima $e_{\max}$ and that of local minima $e_{\min}$.
4. Generate the local mean curve m by generating the upper and lower envelopes:

$$m = \frac{e_{\max} + e_{\min}}{2}$$

5. Compute h_2 by subtracting the local mean curve from:

$$h_2 = h_1 - m$$

6. Repeat steps 2–5 until the difference between h_{k+1} and $h_k(SD(k))$ defined as follows reaches a predefined value ϵ

$$SD(k) = \frac{||h_{k+1} - h_k||^2}{||h_k||^2} < \epsilon$$

   where $||.||$ is the Euclidean norm.
7. Set $i_1 = h_k$ as the first mode.
8. Find the residue $r_1 = X - i_1$
9. Substitute X in step 1 with r. Repeat steps 1–7 to find the rest of the IMFs $i_2, i_3, \ldots, i_I$.

This process can continue until the residue function r becomes a monotonic and no further IMF extraction is possible. EMD exhibits mode mixing problem [20]. A better approach is to use ensemble empirical mode decomposition. CEEMDAN method uses EMD as a sub-step and provides better mode separation. Let us begin with a white Gaussian noise $w^i(n)(i = 1, 2, \ldots, I)$ with zero mean and unit variance. Let, standard deviation be ϵ_0. The operator $E_j()$ is defined as producing the jth mode. CEEMDAN algorithm [21] can be described as follows:

1. Calculate $x(n) + \epsilon_0 w^i(n)$.
2. Utilize the EMD method to decompose the mentioned I signals and obtain their first modes.
3. Calculate the first mode:

$$IMF_1(n) = \frac{1}{I}\sum_{i=1}^{I} imf_1^i(n)$$

4. Find the first residue

$$r_1(n) = x(n) - IMF_1(n)$$

5. Decompose realization $r_1(n) + \epsilon_1 E_1(w^i(n))$ with $i = 1, 2, \ldots, I$ up to its first EMD mode. ϵ_k (in this case, $k = 1$) is the standard deviation of the white Gaussian noise of the kth stage. $IMF_2(n)$ is given by

$$IMF_2(n) = \frac{1}{I}\sum_{i=1}^{I} E_1(r_1(n) + \epsilon_1 E_1(w^i(n)))$$

6. Compute the kth residue for $k = 2, 3, \ldots, K$ as

$$r_k(n) = r_{k-1}(n) - IMF_k(n)$$

7. Decompose realization $r_1(n) + \epsilon_1 E_1(w^i(n))$ with $i = 1, 2, \ldots, I$ up to its first EMD mode and define the $(k+1)$th mode as

$$IMF_{k+1}(n) = \frac{1}{I}\sum_{i=1}^{I} E_1(r_k(n) + \epsilon_k E_k(w^i(n)))$$

8. Go to step 6 for next k.

Steps 6–8 are looped to extract every IMF until the residue becomes a monotonic function. Finally, the original signal $x(n)$ can be written as

$$x(n) = \sum_{k=1}^{K} IMF_k(n) + r_k(n)$$

where K is the total number of modes and $r_k(n)$ is the final residue. We have used CEEMDAN to generate our IMFs. At the beginning, first six IMFs were used and later, variation in result due to variation in IMF number has been shown in the result section. A plot of first eight *IMFs* is shown in Fig. 1.

We want to put a brief discussion here on the value of I. In CEEMDAN method, main signal x is added with a white Gaussian noise to produce a noisy signal and extract IMFs from there, which are averaged finally to produce the final IMFs. When I is sufficiently large, noise pattern does not affect the ultimate IMF values, except that it provides better separation among modes. Due to random generation, multiple realization and averaging, final IMFs are independent of noise pattern when I is sufficiently large. For our simulation purpose, we took $I = 500$. This is high enough value and increasing I does not change our IMF values significantly. Since IMFs remain same, our classification result will also remain same.

2.3. Max normalization

IMFs of seizure and seizure-free signal show some important characteristics. To demonstrate them, we have plotted first six IMFs from both seizure (S) and seizure-free (F,N) signals in Fig. 2. The first thing to notice is that maxima and minima of the IMFs are more or less similar except for a few outliers. These can be regarded as sudden spikes and can be ignored from main data. So, 5% of the highest value points from all the IMFs are sorted and discarded. Secondly, we can see that for any particular IMF, the values of the data points in the seizure data are relatively higher than that of seizure-free data. But, the relative relation is not maintained when different IMFs of the same signal are compared. The reason is the range or maxima/minima values differ highly among IMFs. Also peak value varies among set S, F, and N data. Since IMFs are generated from a single EEG data, we need to bring them to a general scale for comparison. We propose to use scale factors for different IMFs. For example, let us consider IMF_1. In our case, we have taken a constant value and divided by the max of the IMF signal. We have called the resultant as scale factor of that IMF. Now all the data for IMF_1 (set S, F and N) are multiplied by that scale factor. So, each data point in IMF_1 gets multiplied by the same factor. Again, we take IMF_2 and do the same sort of scaling. This max normalization was done to each IMF so that they can be compared without losing their relative amplitude variation. This simple step provides better separation of feature values and makes the classification of seizure and seizure-free data much easier.

To justify this claim and demonstrate that feature values indeed get improved, we have shown the boxplots for two features in Figs. 3 and 4 . One spectral feature (spectral spread) and one statistical feature (kurtosis) were used that were chosen randomly. From the figures, it is obvious that after max normalization feature values have improved and overlapping becomes negligible. So the separability increases which ensures better classification.

2.4. Features

Spectral features are widely used in speech signal processing, physiological signal classification, etc. [15,22]. We have used five spectral moment based features namely spectral decrease (SD), spectral flatness (SF), spectral centroid (SC), spectral spread (SS), and spectral slope (SL).

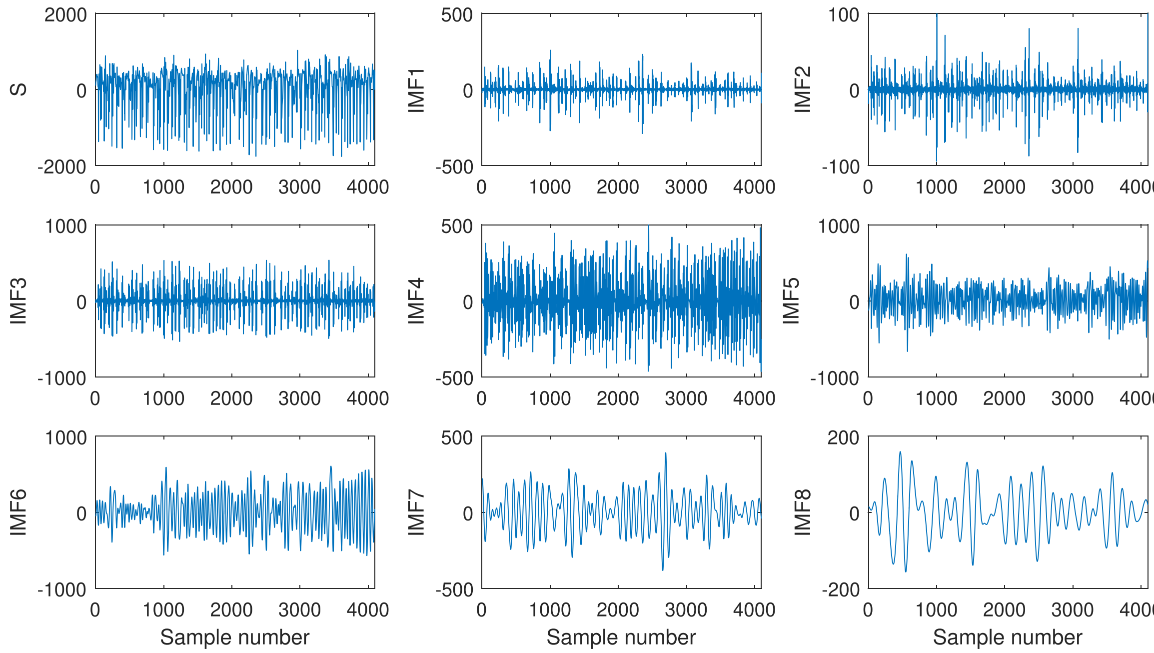

Fig. 1. A sample signal and its first eight IMFs are shown.

Let us assume $x(i)$ is I-point IMF, $i = 1, 2, \ldots, I-1$. $X(f)$ is the discrete Fourier transform of $x(i)$ and $f_m = \frac{f}{I}$. Definition of each feature is given below:

$$SD = \frac{\sum_{f=1}^{I-1} \frac{1}{f}(|X(f)| - |X(0)|)}{\sum_{f=1}^{I-1} \frac{1}{f}(|X(f)|)}$$

$$SC = \frac{\sum_{f=0}^{I-1} f(|X(f)|)}{\sum_{f=0}^{I-1}(|X(f)|)}$$

$$SS = \frac{\sum_{f=0}^{I-1}(f - SC)^2(|X(f)|)}{\sum_{f=0}^{I-1}(|X(f)|)}$$

$$SF = \frac{\prod_{f=0}^{I-1}(|X(f)|)^{1/I}}{(1/I)\sum_{f=0}^{I-1}(|X(f)|)}$$

$$SL = \frac{I\sum_{f=0}^{I-1} f_m|X(f)| - \sum_{f=0}^{I-1} f_m \sum_{f=0}^{I-1}|X(f)|}{I\sum_{f=0}^{I-1} f_m^2 - \sum_{f=0}^{I-1}|X(f)|}$$

Other than spectral features, three common statistical features namely mean, skewness, and kurtosis were also used.

2.5. Classifier and validation

We have primarily used quadratic discriminant analysis (QDA) classifier. Performance comparison with some other popular classifiers has been shown at the result section. We have used k-fold cross validation method to deal with overestimation and more accurate classification. In our case we did 10-fold cross validation. Data were divided into 10 subsets. Each time nine subsets were used to train the model and the last one was used to test the model. By this way all ten subsets were used respectively to test data and finally the performance parameters were calculated from the mean of their performance.

2.6. Performance parameters

There are different performance parameters which are popularly used to measure classification performance, e.g., accuracy (ACC), sensitivity (SEN), specificity (SPF), positive predictive value (PPV), negative predictive value (NPV), and Matthews correlation coefficient (MCC). The equations of these performance parameters are given in Table 1. Here, TP or true positive represents the number of seizure-free data distinguished as seizure-free data. Similarly, TN or true negative means the number of epileptic seizure data recognized as epileptic seizure data, FP or false positive is the number of epileptic seizure data classified as seizure-free signals, and FN or false negative is the number of seizure-free signals detected as epileptic seizure signals.

Table 1
Performance parameters.

Parameter name	Equation
Accuracy (ACC)	$ACC = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$
Sensitivity (SEN)	$SEN = \frac{TP}{TP+FN} \times 100\%$
Specificity (SPF)	$SPF = \frac{TN}{TN+FP} \times 100\%$
Positive predictive value (PPV)	$PPV = \frac{TP}{TP+FP} \times 100\%$
Negative predictive value (NPV)	$NPV = \frac{TN}{TN+FN} \times 100\%$
Matthews correlation coefficient (MCC)	$MCC = \frac{(TP.TN-FP.FN)\times 100\%}{\sqrt{\prod(TP/TN+FP/FN)}}$

3. Results and discussion

As mentioned in the methodology section, we have decomposed the signals in IMFs using CEEMDAN method. Later features were extracted from scaled and normalized IMFs. We show our result in four parts. At first we compare various performance parameters when individual feature values are used versus their average is used. Then we show the effect of IMF Number on performance. Later comparison with other classifiers show that our choice of classifier is valid. Finally awe compare our work with recently published other works.

3.1. Mean feature value

We have taken first six IMFs and eight features from each IMFs. So, our feature set consists of 48 features for each signal. Later each feature from six IMFs were averaged and used to classify data. To

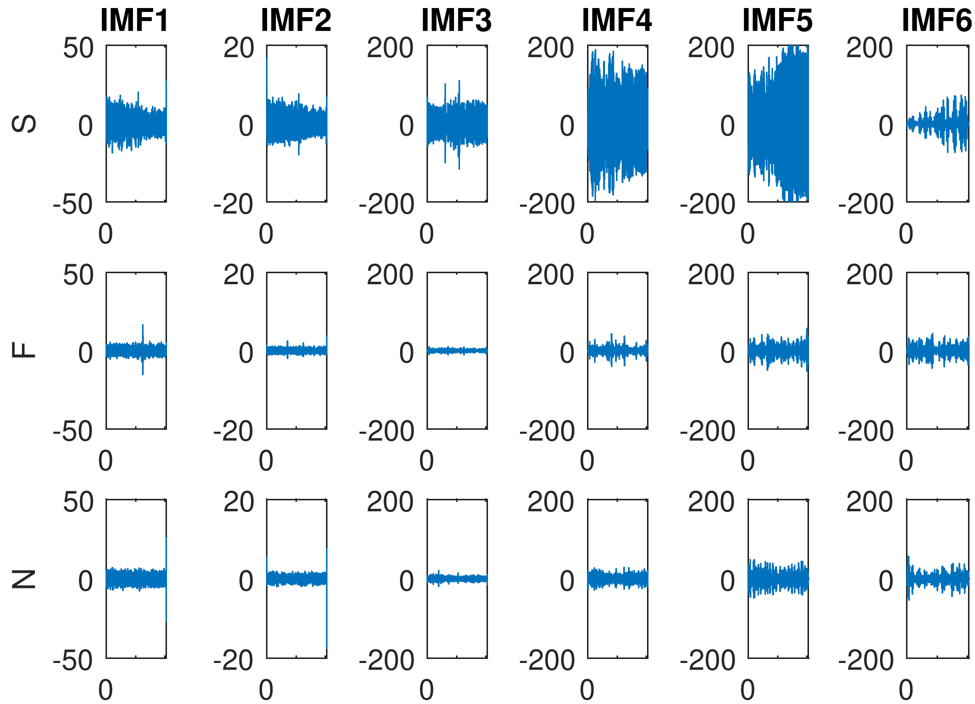

Fig. 2. First six IMFs of three signals are shown. S is the signal containing seizure data and F, N are the seizure-free signals.

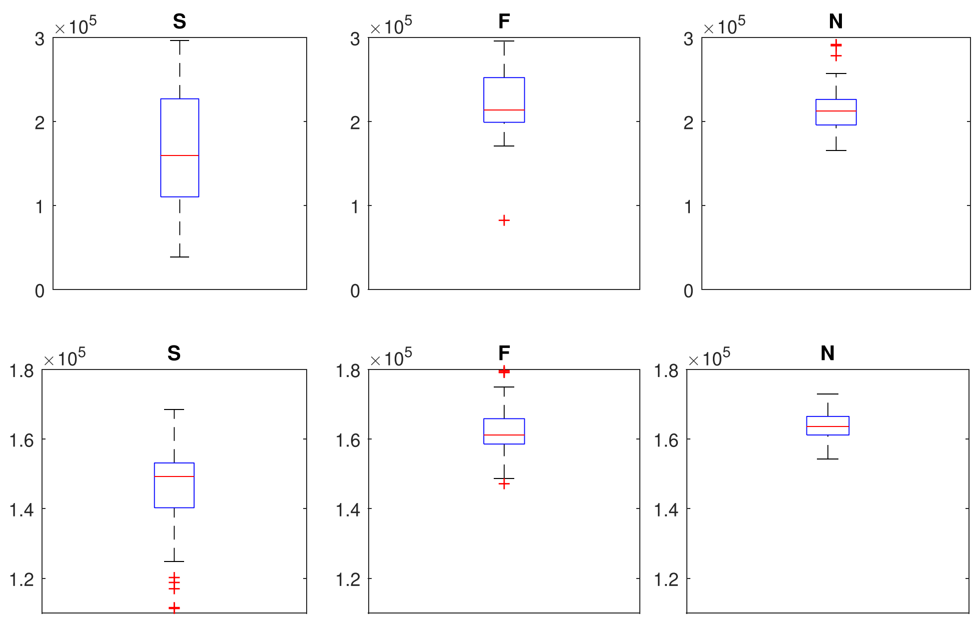

Fig. 3. A spectral feature, spectral spread, has been shown to improve with max normalization. Top row shows feature values extracted before normalization and bottom row shows after normalization.

Table 2
Performance comparison between individual and mean feature set.

Performance parameter	Individual feature	Mean feature
ACC	99.1%	100%
SEN	98.8%	100%
SPF	99.7%	100%
PPV	99.8%	100%
NPV	97.6%	100%
MCC	97.9%	100%

compare the change in performance parameters for both cases, we have listed them in Table 2.

It is obvious that averaging features from six IMFs boosts the overall performance greatly. This is because some features from a certain IMF can be outliers. That is they can be either too small or too large compared to others. This reduces classification efficiency. When we average a particular feature value from six IMFs for each signal, weight on outliers decreases and the performance gets better. The rest of the result section is shown with mean features.

3.2. IMF number

So far we have used first six IMFs and achieved high accuracy, sensitivity and specificity. We know that, frequency of IMFs

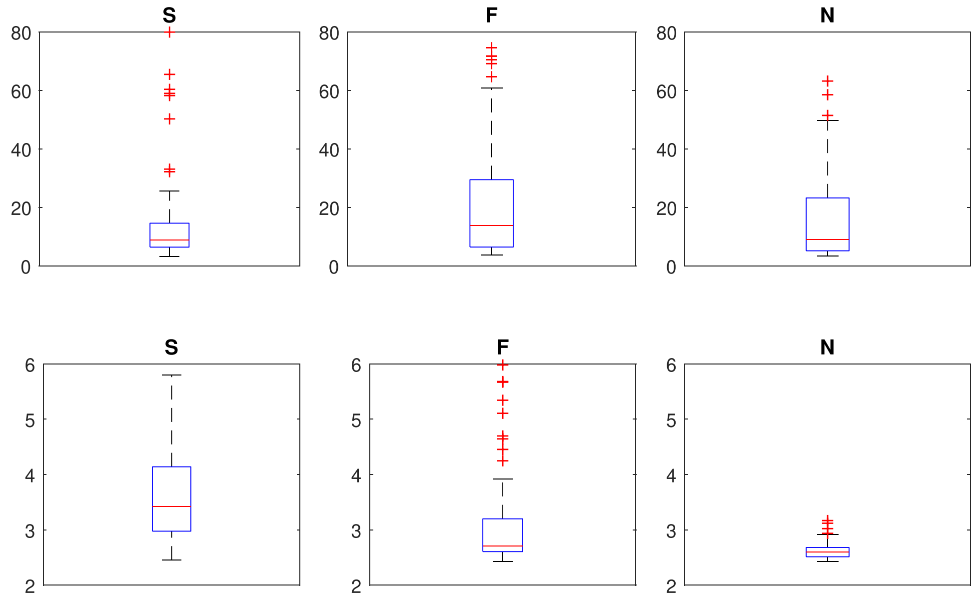

Fig. 4. A statistical feature, kurtosis, has been shown to improve with max normalization. Top row shows feature values extracted before normalization and bottom row shows after normalization.

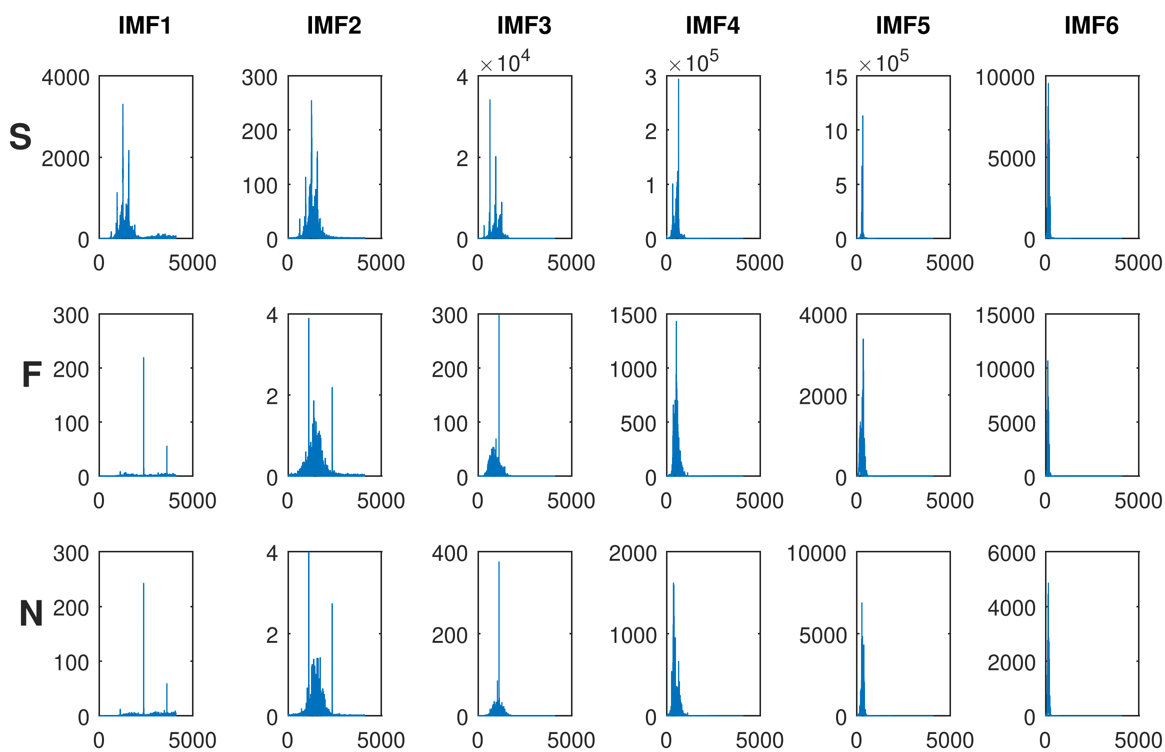

Fig. 5. Periodogram of first six IMFs of a randomly selected patient's data. Changes are prominent for the first IMF and declines gradually for later IMFs.

decreases gradually from first being the highest frequency IMF and the last being the lowest frequency IMF, a trend which is also obvious from Fig. 1. To choose optimum number of IMFs, we need to check what changes happen in IMFs when epileptic seizure takes place. Previously we have seen that in time domain, amplitude of the IMFs changes relatively from seizure-free to seizure data. Now we will examine the changes in frequency domain. To demonstrate the variation in frequency domain, in Figs. 5 and 6 , we have plotted the periodogram of first six IMFs for two cases which were chosen randomly. If we compare seizure data (S) with seizure-free data (F, N), we can see that seizure basically manifests itself in the contents of the first IMF. The second and third IMFs are slightly changed. Changes in later IMFs are almost indiscernible.

This effect can be shown to reflect in the performance of classifiers when we vary IMF numbers. Table 3 shows a comparison of performance parameters using only the first IMF, first three IMFs and first six IMFs for the purpose of feature generation and classification.

IMF generation is an iterative process and requires higher computational power and time. In our method, using only the first IMF, we can still get high enough accuracy, specificity and sensitivity. This can be useful for low power mobile devices for constant mon-

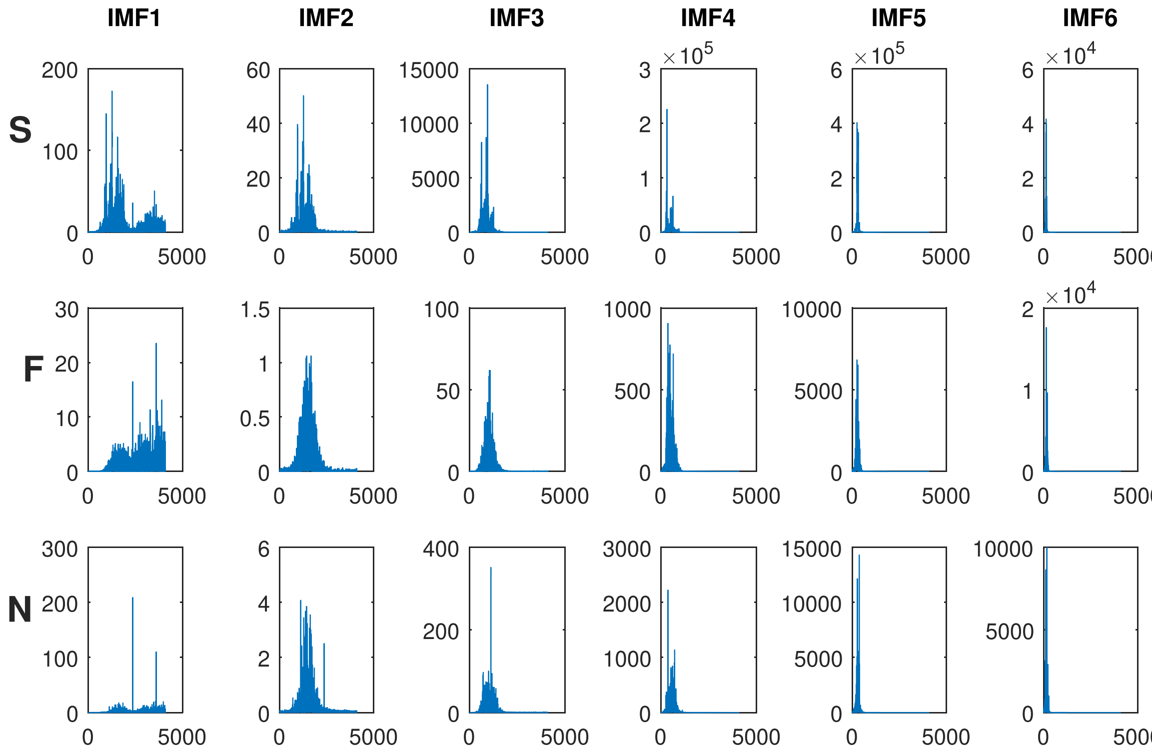

Fig. 6. Periodogram of first six IMFs of another randomly selected patient's data. Changes are prominent for the first IMF and declines gradually for later IMFs.

Table 3
Performance comparison between feature sets from only the first IMF, first three IMFs and first six IMFs.

Performance parameter	Only one IMF	Three IMFs	Six IMFs
ACC	99%	99.7%	100%
SEN	98.5%	99.5%	100%
SPF	100%	100%	100%
PPV	100%	100%	100%
NPV	97.1%	99%	100%
MCC	97.8%	99.3%	100%

Table 4
Comparison of different classifiers.

Classifier name	First IMF only			First six IMFs		
	ACC	SEN	SPF	ACC	SEN	SPF
QDC	99%	98.5%	100%	100%	100%	100%
Linear SVM	97.3%	96.5%	99%	98.3%	97.5%	100%
Weighted KNN	97.3%	97.5%	97%	98.7%	98%	100%

itoring of the patient. Also, computationally less heavy device will be cheaper and accessible to more people.

3.3. Comparison of different classifiers

We have compared the performance of different commonly used classifiers namely quadratic discriminant classifier, linear support vector machine (SVM), and weighted K-nearest neighbors (KNN) for both the cases of feature from first IMF and mean feature from all six IMFs. Table 4 shows the comparison data. It is obvious that although all of them perform pretty well, the Quadratic Discriminant Classifier outperforms the other two in terms of accuracy, sensitivity and specificity. So, our choice of classifier was justified.

Table 5
Comparison with previous works.

Author and reference of the work	ACC	SEN	SPF
Sharma et al. [6]	98.67%	100%	96%
Tzimourta et al. [7]	99.26%	93.77%	99.86%
Acharya et al. [10]	88.67%	95%	90%
Patidar and Panigrahi [23]	97.75%	97%	99%
Jia et al. [15]	99%	99.5%	100%
Wang et al. [8]	99.4%	92.1%	99.5%
Wang et al. [9]	98.45%	93.36%	98.42%
Wang et al. [24]	98.3%	91.44%	99.34%
Our proposed work (best result shown)	100%	100%	100%

3.4. Comparison with other works

At the very beginning of this article, we have mentioned earlier works on automated detection of epileptic seizure using EEG signals. At this point we would like to compare the performance of our proposed method with others' works based on three performance parameters namely accuracy (ACC), sensitivity (SEN), and specificity (SPF). It should be noted that the mentioned works and data have used different methods for classification and verification purpose. Table 5 shows this comparison data.

It can be seen from this comparison that our proposed method shows better or at least the same level of performance as others. For example: Jia et al. [15] have used CEEMDAN method and we want to discuss and compare both works. They converted their decomposed IMFs to two and three dimensional Phase Space Representations (PSR). Then PSR was converted to form growth curve by averaging the paired distances. Features were extracted from growth. Along with statistical and spectral features, normal inverse Gaussian (NIG) parameters were also used. Finally, Random Forest classifier was used for classification and 10-k cross validation was used to validate the trained model. Compared to this method, our proposed work presents simpler solution. Instead of converting IMF to PSR to growth curve, we have directly used IMFs. Max or peak normalization was used to improve separability of features. Then classification and validation were done. We have also shown that we can use only one IMF without sacrificing much accuracy. So, our proposed method is computationally less heavy and less time consuming. Specially, IMF generation using CEEMDAN is an iterative and highly time consuming process. Using less IMFs cuts off huge numerical burden and provides an efficient method that can be implemented in computationally less heavy, cheaper and low power instruments. As we have mentioned at the introduction section of this article, 80% of epilepsy patients are either from low or middle-income countries, of which around three fourth cannot afford treatment. A cheap diagnostic device will be a part of the cheap treatment process for epilepsy.

4. Conclusions

In this work, we have used a publicly available database of EEG signals from University of Bonn and CEEMDAN method to decompose IMFs. Although CEEMDAN is data driven like EMD, it has better separation of modes and original signal can be fully reconstructed from decomposed IMFs and residue. Later IMFs were max normalized to make them comparable on similar range. Improvement of separability in feature value due to normalization was shown for two features, one spectral and one statistical. A bunch of spectral features along with some common statistical features were extracted from the scaled IMFs. For better performance, features from each IMF of a particular segment were taken and their mean was used. Feature set was fed into quadratic discriminant classifier. For validation, 10-fold cross validation method was used to hinder over-fitting. We obtained high accuracy, sensitivity, specificity and other performance parameters using our proposed method. We have also shown that most important IMF is the first one and features can be extracted only using this first IMF without losing much accuracy, sensitivity or specificity. This reduces huge numerical burden. Finally, a comparison was shown with other state-of-the art methods of automated epileptic seizure detection. Our proposed method is numerically less burdensome and has also very high accuracy, sensitivity and specificity.

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Conflict of interest: None declared.

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