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Detection of Epileptic Seizure using Radius Measurement and Higher Order Moments in The EMD Domain

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Abstract*: This paper presents a method for the detection of epileptic seizure from EEG signal using empirical mode decomposition (EMD). The intrinsic mode functions (IMFs) which is generated by the EMD method can be considered as a set of amplitude and frequency modulated (AM-FM) signals. The Hilbert transformations of these IMFs which is circular form in the complex plane can be used as a feature for radius calculation and the higher order moments like variance, skewness and kurtosis are applied on the output values of Short-time Fourier transform (STFT) of the IMFs, the proposed method shows better classification result than simply applying higher order moments. The effectiveness of the proposed method is tested using the dataset which is available online. It is found that the result obtained from radius measurement and higher order statistical moments provide good discrimination performance for the detection of epileptic seizure.

Index Terms*: Electroencephalogram (EEG), intrinsic mode functions (IMFs), empirical mode decomposition (EMD), Epileptic Seizure.

I. INTRODUCTION

EEG is an electrophysiological monitoring method that contains the information about the human brain activity. It exhibits the data regarding the volume currents that spread from a neural tissue throughout the conductive media of the brain. These EEG signals can be obtained using sensors placed on the scalp or using the intracranial electrodes. The EEG signals can be effectively used for various applications such as emotion recognition [1], brain–computer interfaces (BCIs) [2], etc. One of the most important applications of the analysis of EEG signals is its use in neuroscience to diagnose diseases and brain disorders. Epileptic seizure is one of the most common neurological disorders worldwide [3], [4]. Its detection is typically done by the physicians using a visual scanning of the EEG signals which is a time consuming process and may be inaccurate. These inaccuracies are particularly significant for long time duration EEG signals [5]. There are lots of methods developed in the literature for EEG signal analysis and classification are based on time domain, frequency domain, and time-frequency domain. The spikes detection methods for EEG signal analysis have been proposed in [6]. The measures namely, dominant frequency, average power in the main energy zone, normalized spectral entropy, spike rhythm city, and relative spike amplitude together with artificial neural network (ANN) have been used for normal and epileptic EEG signal analysis [7]. Earlier studies have shown that the EEG signal is a non-stationary signal. The nonlinear measures like correlation dimension, Lyapunov exponent and fractal dimension quantify the degree of complexity of a EEG signal [8-9]. The correlation integral measure is sensitive to wide variety of non-linearity and has been used to characterize the epileptogenic regions of the brain during the interictal period.

More recently, new techniques for the analysis of nonstationary and nonlinear signals have been proposed which are mainly based on empirical mode decomposition (EMD) [10]. The EMD is a time-frequency based method which decomposes a signals into a number of intrinsic mode functions (IMF) which are oscillatory components. This is an empirical method and thus is effective for a time-frequency analysis of the nonstationary signals. This characteristic of EMD has motivated the researchers to use it for the analysis of EEG signals. Oweis *et al.* [11] have used the analytic IMFs [Hilbert-Huang transform (HHT)] for seizure classification in EEG signals.

In this paper we will first perform EMD on EEG signal which will give us the IMFs. After that we will perform Hilbert transform on the original EEG signals (seizure and seizure free EEG signals) and as well as on their IMFs also, which is circular form in the complex plane and using central tendency measure (CTM) on that analytic IMFs we can calculate the radius. For the second case we will perform STFT on these IMFs and on that STFT result we will calculate variance, skewness and kurtosis, which generally shows better classification results than simply applying these on the IMFs. The rest of the paper is organized as follows: The EEG dataset in section II, methods in section III, which includes EMD, analytic signal representation of IMFs and central tendency measure of analytic IMFs , STFT and higher order statistical moments of IMFs, the results and discussion is in section IV and finally section V concludes the paper.

II. DATASET

In this paper the dataset we have used is available online in [12]. The dataset consists of five subsets (namely Z, O, N, F, and S), each containing 100 single-channel EEG signals, each one having 23.6 s duration. These signals have been selected from continuous multichannel EEG recording after visual inspection for artifacts.

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The subsets Z and O have been recorded extra cranially, whereas the subsets N, F, and S have been recorded intracranial. The subsets Z and O have been acquired from surface EEG recordings of five healthy volunteers with eyes open and closed, respectively. The signals in two subsets have been measured in seizure-free intervals from five patients in the epileptogenic zone (subset F) and from the hippocampal formation of the opposite hemisphere of the brain (subset N). The subset S contains seizure activity, selected from all recording sites exhibiting ictal activity. These are partial seizures, probably complex partial, which may then have developed to secondary generalized tonic clonic seizures. The sampling frequency of EEG signals in the dataset is 173.61 Hz.

In this paper we have selected subsets Z and S for experimental purpose which is shown in fig. 2.

III. METHODS

A. Empirical Mode Decomposition

The EMD is a data dependent method of decomposing a signal into a number of oscillatory components, known as intrinsic mode functions (IMFs) [13]. The EMD method does not require any condition about the stationary and linearity of the signal. The aim of the EMD method is to decompose the nonlinear and nonstationary signal *x(t)* into a sum of intrinsic mode functions (IMFs). Each IMF satisfies two basic conditions: 1) the number of extrema and the number of zero crossings must be the same or differ at most by one; 2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD algorithm for the signal $x(t)$ can be summarized as follows :

1) Detect the extrema (maxima and minima) of the dataset *x(t).*

2) Generate the upper and lower envelopes $e_m(t)$ and $e_l(t)$ respectively, by connecting the maxima and minima separately with cubic spline interpolation.

3) Determine the local mean as $a(t)=\dfrac{e_m(t)+e_l(t)}{2}$

4) Extract the detail $h_1(t)=x(t)-a(t)$

5) Decide whether $h_1(t)$ is an IMF or not by checking the two basic conditions as described above.

6) Repeat steps (1) to (4) and end when an IMF $h_1(t)$ is obtained.

Once the first IMF is derived, define $c_1(t)=h_1(t)$, which is the smallest temporal scale in $x(t)$. To determine the the rest of the IMFs, generate the residue $r_1(t)=x(t)-c_1(t)$ the residue can be treated as the new signal and repeat the above illustrated process until the final residue is a constant or a function from which no more IMFs can be derived. At the end of the decomposition, the original signal $x(t)$ is represented as

$$x(t)=\sum_{m=1}^{M} c_m(t)+r_M(t) \qquad \textbf{(1)}$$

where M is the number of IMFs, $c_m(t)$ is the *mth* IMF, and $r_M(t)$ is the final residue. Each IMF in (1) is assumed to yield a meaningful local frequency, and different IMFs do not exhibit the same frequency at the same time. Then, (1) can be written as

$$x(t)=\sum_{m=1}^{M} A_m(t)\cos\left[\varphi_m(t)\right] \qquad \textbf{(2)}$$

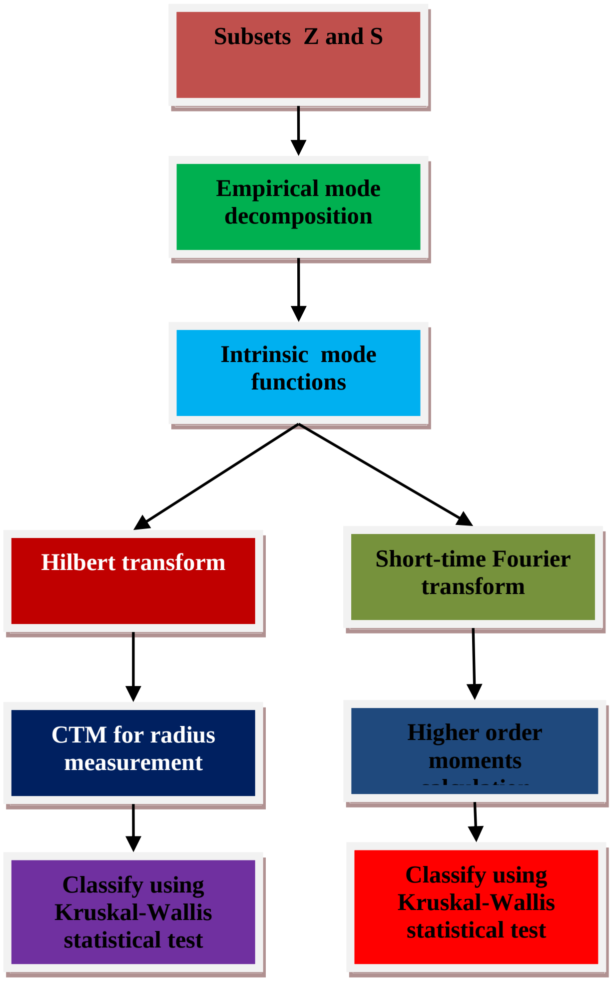

Fig. 1. Block diagram of the proposed method.

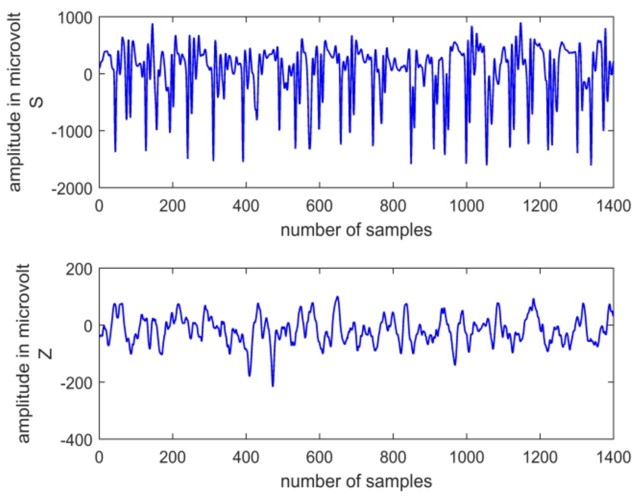

Fig. 2. Seizure (S) and normal (Z) EEG signals (window length=1400 samples)

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B. Analytic Representation of IMFs

The Hilbert transform should be applied to all the IMFs to get the analytic representation of IMFs [13]. The analytic Signal representation of any IMF $c(t)$ is defined as

$$z(t) = c(t) + jcH(t) \quad (3)$$

where the Hilbert transform of $c(t)$ is given by $cH(t)=c(t)*\frac{1}{\pi t}$ Equation (3) can be written as

$$z(t) = A(t)e^{j\varphi(t)} \quad (4)$$

The analytic signal amplitude $A(t)$ and instantaneous phase $\varphi(t)$ can be defined as follows:

$$A(t) = \sqrt{c^2(t) + c_H^2(t)} \qquad \varphi(t) = \arctan\left[\frac{c_H(t)}{c(t)}\right] \quad (5)$$

The instantaneous frequency of the analytic IMF $z(t)$ is given By

$$w(t) = \frac{d\varphi(t)}{dt} \quad (6)$$

The signal $x(t)$ given in (2) can be expressed in a Fourier-like representation as

$$x(t) = \mathbb{R}\left\{\sum_{m=1}^{M} A_m(t)e^{j\varphi_m(t)}\right\} \quad (7)$$

where the index m refers to mth IMF and $\mathbb{R}\{.\}$ denotes the real part of a complex quantity.

C. Central Tendency Measure of Analytic IMFs

The CTM has been used to quantify the degree of variability from a second-order difference plot of signals like EEG and center of pressure signals . In this work, we have used a CTM to determine the radius of the circle of the analytic signal representation of intrinsic mode functions in the complex plane. The radius corresponding to 95% CTM has been used in this work and we can also able to compute the area of analytic IMF in the complex plane.

The CTM is computed by selecting a circular region of radius r, around the origin, counting the number of points that fall within the radius, and dividing by the total number of points [14]. Let K be the total number of points and r the radius of the central area. Then, the modified CTM for analytic signal $x[n]$ is given by the following expression:

$$\text{CTM} = \frac{\sum_{n=1}^{K} \delta(l)}{K} \quad (8)$$

Where

$$\delta(l) = \begin{cases} 1, if \left([\mathbb{R}\{x[n]\}]^2 + [\Im\{x[n]\}]^2\right)^{0.5} < r \\ 0, otherwise \end{cases} \quad (9)$$

Analytic representation of IMFs is shown in fig. 5. And fig. 6. Which is generally circular form in complex plane.

D. Short-Time Fourier Transform and Higher Order Statistical Moments of IMFs.

In this paper, STFT is used before computing higher order statistical moments such as variance, skewness, and kurtosis for classifying the EEG signals in the EMD domain which

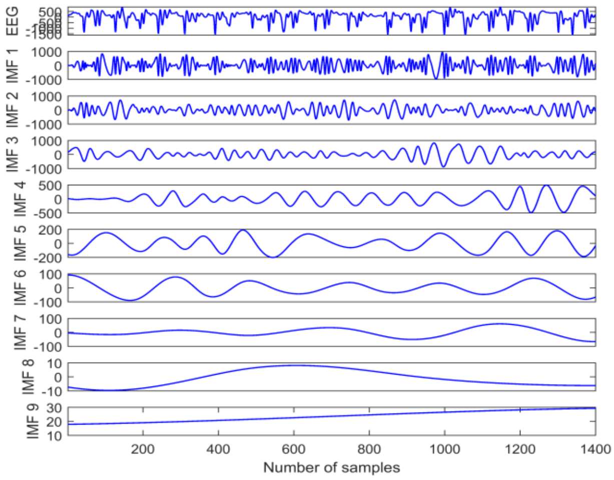

Fig. 3. Empirical mode decomposition of seizure EEG signal for 1400 samples.

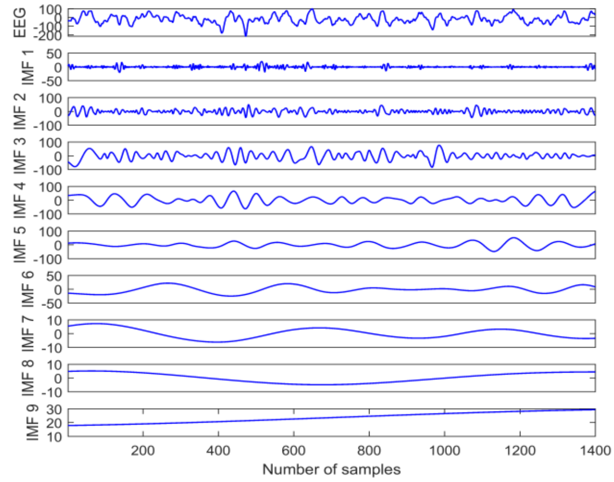

Fig. 4. Empirical mode decomposition of normal EEG signal for 1400 samples.

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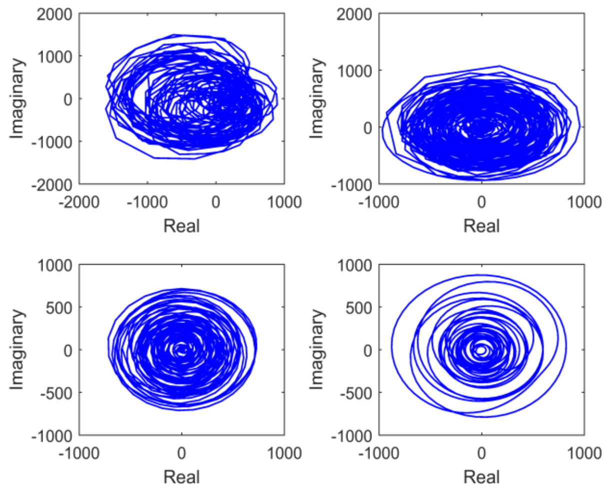

Fig. 5. Analytic signal representation of seizure EEG signal and its first three IMFs.

shows better classification result than simply applying higher order statistics on IMFs. The STFT of a signal is given by

$$\mathrm{STFT}\{x(t)\}(\tau,\omega) \equiv X(\tau,\omega) = \int_{\infty}^{-\infty} x(t)w(t-\tau)e^{-j\omega t}dt \quad (10)$$

where $w(t)$ is the window function, $x(t)$ is the signal to be transformed. $X(\tau,\omega)$ is essentially the Fourier Transform of $x(t)w(t-\tau)$, a complex function which represents the phase and magnitude of the signal over time and frequency.

For an N-point data, the corresponding variance σ^2, skewness β_1, and kurtosis β_2 are calculated as

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2 \quad (11)$$

$$\beta_1 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3 \quad (12)$$

$$\beta_2 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4 \quad (13)$$

Where μ denotes the sample mean of the N-point data

IV. RESULTS AND DISCUSSION

At the beginning from the data set, we have selected only subsets Z and S. We have considered subset Z to form one class (normal EEG signals) and subset S forms the other class (epileptic seizure EEG signals) and out of 4097 samples we have selected 1400 samples for each and considered for validation. In this paper we have used two methods for the detection of epileptic seizure from EEG signals, First one is using radius measurement of both the normal and epileptic seizure EEG signals for that we have used Hilbert transform on the IMFs obtained by EMD method, which is circular form in the complex plane. Which motivates us to calculate the radius of the circle in the complex plane. If we simply apply Hilbert transform in the original signal it is not possible for us to calculate the radius as we can see from the fig. 5 and fig. 6, as it do not have a specific centre of rotation for that only we need EMD which generally represents any signal into sum of proper rotations. Here we have used Central Tendency Measure to calculate the radius, the radius corresponding to 95% CTM is considered for the proposed method. To classify the seizure EEG signals and normal EEG signals using radius measurement we have used Kruskal–Wallis statistical test. The radius values for all the IMFs are significantly different among the two classes of EEG signals ($p < 0.01$). The results are shown in fig. 7 in case of first three IMFs having p-value is 0. In the second method we have used STFT on the IMFs and on that STFT output values we have used higher order statistical moments such as variance, skewness and kurtosis [15],[16].Which showed a better classification result than simply applying higher order statistical moments on the IMFs. The class of discrimination ability of seizure signal from the normal signal using higher order statistical moments is performed using Kruskal–Wallis statistical test and the results are shown in fig. 8, 9 and 10. Table I shows the p-values obtained as a result of Kruskal–Wallis statistical test for variance, skewness and kurtosis of first eight IMFs.

From the table it is clear that kurtosis of IMF1 to IMF6 provides smaller p-values gives rise to a better discrimination performance between seizure and normal EEG signals.

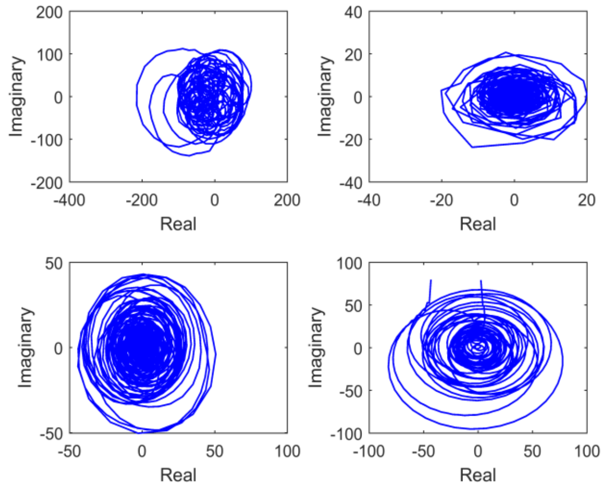

Fig. 6. Analytic signal representation of normal EEG signal and its first three IMFs.

TABLE I *p*-values obtained as a result of Kruskal–Wallis statistical test.

Signals	*P*- for variance	*p*-for skewness	*p*-for kurtosis
IMF1	**0**	**0**	**0**
IMF2	**0**	**2.32e-8**	**0**
IMF3	**0**	**0**	**0**
IMF4	**0**	0.01207213	**0**
IMF5	**0**	**3.12e-11**	**0**
IMF6	**0**	0.90123471	**4.41e-5**
IMF7	**1.17e-17**	0.61189341	0.00218832
IMF8	**0**	**9.41e-4**	0.08114256

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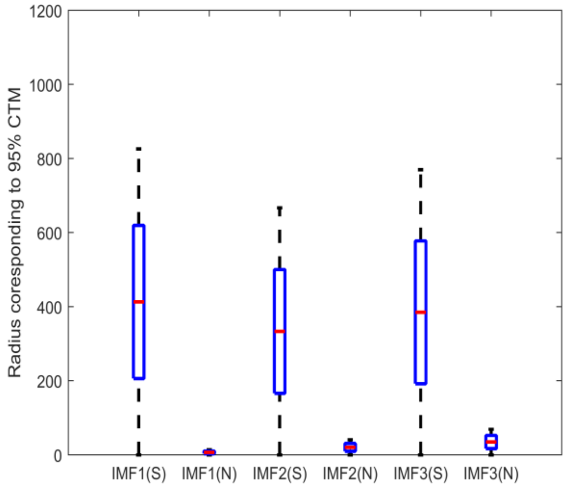

Fig. 7. Box-plot for the comparison seizure and normal EEG signals using radius measurement for the first three IMFs.

Similarly variance of IMF1 to IMF8 and skewness of IMF1, IMF2, IMF3, IMF5, IMF8 shows smaller *p*-values means better classification between the IMFs.

V. CONCLUSION

In this paper we have used radius measurement and higher order statistical moments in the EMD domain in order to detect epileptic seizure in EEG signal. The class of discrimination ability between seizure signal and the normal signal is performed using Kruskal–Wallis statistical test. We have performed the same test on the other numbers of samples like 500, 1000, 2000 and 4097 samples. It shows a satisfactory discrimination performance in almost all the cases.

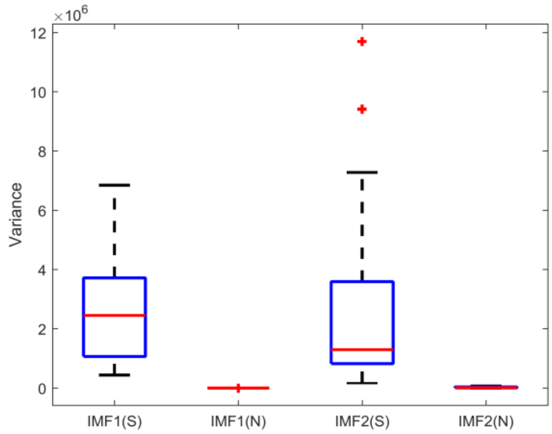

Fig. 8. Box-plot for the comparison of seizure and normal EEG signals using variance values for the first two IMFs.

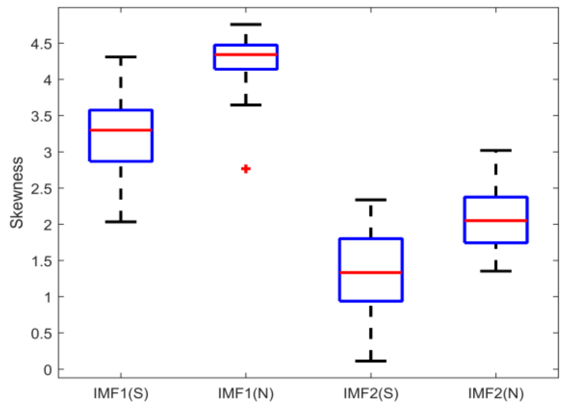

Fig. 9. Box-plot for the comparison of seizure and normal EEG signals using skewness values for the first two IMFs.

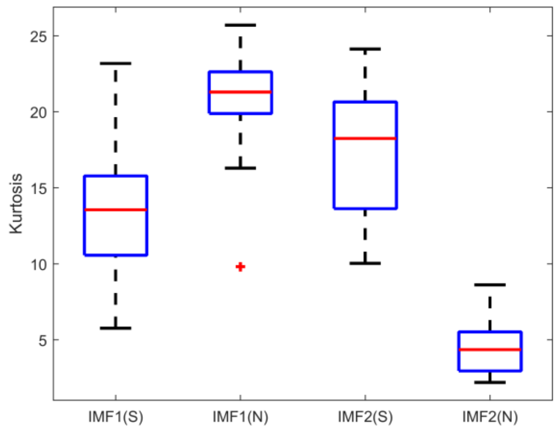

Fig. 10. Box-plot for the comparison of seizure and normal EEG signals using kurtosis values for the first two IMFs.

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