

Comparison of Area Measured by Second Order Difference Plot and Circular Tendency Measured of EEG Signal of Epileptic Seizure

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ABSTRACT: Epilepsy is one of the most common neurological diseases which disturbed the electrical activity of the brain. The Electroencephalography is a commonly used technique for measuring the electrical activity which contains information relating to the different physiological states of the brain. This paper presents the application of Empirical mode decomposition (EMD) and Hilbert transform for analyzing the epileptic signal. EMD decomposes an EEG signal into symmetrical and band limited signals termed as Intrinsic Mode Function (IMF). Hilbert transform of IMFs gives the analytic representation of the signal, which has circular form in the complex plane. Paper also represents the comparison of the area measured by second order difference plot (SODP) and central tendency measure (CTM) to discriminate ictal and normal EEG signal.

KEYWORDS: Epilepsy; Electroencephalogram (EEG); Empirical Mode Decomposition (EMD); Second Order Difference plot (SODP); Central Tendency Measure (CTM).

I. INTRODUCTION

Our brain is one of the most critical parts of our body. A small change in it creates not only neurological problems but also physical and mental problems [1]. An epileptic seizure is one of them. It is a chronic disorder of the human brain that affects people of all age group. According to World Health Organisation (WHO) nearly 50 million people worldwide have epilepsy [2]. This leads the risk of premature death of person having epilepsy is three times higher than that of a normal person.

Electroencephalography (EEG) is the important method in the diagnosis of epilepsy [3]. Parameters extracted from EEG signals are very useful for detection and discrimination of epileptic seizures. Spectrum analysis is a very common technique used for analysis of EEG signals, as it extracted the frequency present in the signal being analyzed must be stationary (i.e. the mean value, variance and frequency content of the signal do not change over time) Previous studies shows that the EEG signal is a non-stationary process [4-6].

Many nonlinear methods such as wavelet transform, multi-wavelet transform have been proposed to extract the new parameter from the EEG signal of the brain. Among these parameter Lyapunov exponents can be detected electroencephalographic changes [7], the correlation dimension technique can contain information about the different neurological states of the brain, the fractal dimension and entropy measure the complexity or the degree of disorder of the EEG signal, while correlation integral, measures the variety of nonlinearity [8]. During the epileptic seizure, the value of approximate entropy (ApEn) has been found to exhibit a strong relationship with the synchronous discharge of a large group of neurons.

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Recently new methods have been developed for analysis of nonlinear and nonstationary signals, which are based on the empirical mode decomposition (EMD) [9]. The mean frequency (MF) measure of intrinsic mode function (IMF) has been proposed to discriminate well between ictal and seizure free EEG signals.

The proposed method in this paper is based on EMD and Hilbert-Huang transform (HHT) [10]. HHT consist of extracting the intrinsic mode functions (IMFs) by using EMD [11]. Remaining paper organized as follows: section 2 describes methodology, section 3 results and discussion, in section 4 conclusion and at last references.

II. RELATED WORK

A. Dataset

EEG data sets used is consisting of both healthy and epileptic subjects, provided by University of Bonn [13]. These data set available for public used. The datasets consist of five sets of data. Each consist 100 single channel EEG segments of 23.6 seconds. A sampling rate of 173.61Hz is used. The sample Z and O were recorded using surface EEG recording of healthy volunteers with eyes open and closed respectively. In this work data of standard electrode placement scheme used. According to the international standard of 10-20 system [13]. Sample N is the data of an epileptic patient in seizure-free interval recorded from a hippocampal formation of the opposite hemisphere of the brain. Data F is the data of an epileptic patient in seizure-free interval recorded within an epileptic zone and the last one data S shows the seizure activity of the patients. In this work, samples Z and S have been used, which are the data of EEG signal of the healthy volunteer and the person having epilepsy.

B. Empirical Mode Decomposition (EMD)

The Empirical mode decomposition [14] is the method of breaking down a signal into a finite set of amplitude and frequency modulated oscillating signals. This is the basis of decomposition furthermore decomposition does not require any condition about linearity and stationarity. The process is useful for analyzing natural signals which are most often non-linear and non-stationary in nature.

EMD filters out the functions which forms nearly orthogonal basis for the signal. Completeness of the method is based on the process the way it decomposed. The functions known as intrinsic mode functions (IMFs) are significant to describe the signal. The fact that the functions into which signal is decomposed are all in the time domain and of the same length as original signal allows for varying frequency in time to be preserved.

Obtaining intrinsic mode function from real world signal is very important because process often has multiple causes and each of them may happen at specific time intervals. This type of data is evident in EMD analysis but quite hidden in the Fourier domain or in wavelet coefficients.

EMD provides finite sets of amplitude and frequency modulated (AM-FM) oscillating components which are bases of the decomposition termed as intrinsic mode functions (IMFs). An EMD technique doesn't required any condition of linearity or stationarity of the signal. The principle of the EMD is to decompose a complex signal into set of band limited function $D_m(t)$ which is called intrinsic mode function.

Each IMF has to satisfy the following conditions.

In complete set of data, the number of extremes and number of zero crossing must be same or differ by at most one.

At any point, the mean value define by the envelope of local maxima and local minima should be zero.

Steps to be follow while performing EMD.

1. Set $g_I(t) = x(t)$.
2. Detect the extrema (both maxima and minima) of $g_I(t)$.
3. 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.

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4. Determine the local mean as: $m(t) = \frac{e_m(t) + e_l(t)}{2}$
5. IMF must have zero local mean; subtract $m(t)$ from the original signal as $g_l(t) = g_l(t) - m(t)$.
6. Decide whether $g_l(t)$ is an IMF or not by checking the two basic condition as mentioned above.
7. Repeat steps 2-6 and ends when an IMF $g_l(t)$ is obtained.

When the first IMF is derived, define $D_1(t) = g_l(t)$, which is the smallest temporal scale in $x(t)$. To find out the rest of the IMF components, generate the residue $r_1(t)$ of the data by subtracting $D_1(t)$ from the signal.

$$r_1(t) = x(t) - D_1(t)$$

The shifting process will be continued until the final residue is a constant a monotonic function with only maxima one minima and no further IMF can be derived. Then the subsequent basis functions and the residues are computed as:

$$r_1(t) - D_2(t) = r_2(t), \dots, r_{m-1}(t) - D_m(t) = r_M(t)$$

Where $r_M(t)$ is the final residue at the end of the decomposition the signal $x(t)$ is define as follows:

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

Where M is the no. of IMFs. Each IMF is assumed to yield a meaningful local frequency and different IMFs do not exhibit the same frequency at the same time. Then above equation can be written as:

$$x(t) = \sum_{m=1}^M A_m(t) \cos(\phi_m(t))$$

C. Analytical Signal Representation

It has been proposed that the Hilbert transform should be applied on all IMFs obtained by EMD method. The analytic signal of any real IMF is defined as:

$$Z(t) = x(t) + jy(t)$$

Where $x(t)$ is the real signal and the Hilbert transform of $x(t)$ is given by: $y(t) = x(t) * \frac{1}{\pi t}$

The analytic signal can be further expressed as: $Z(t) = A(t)e^{j\phi(t)}$

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Vol. 6, Issue 7, July 2017

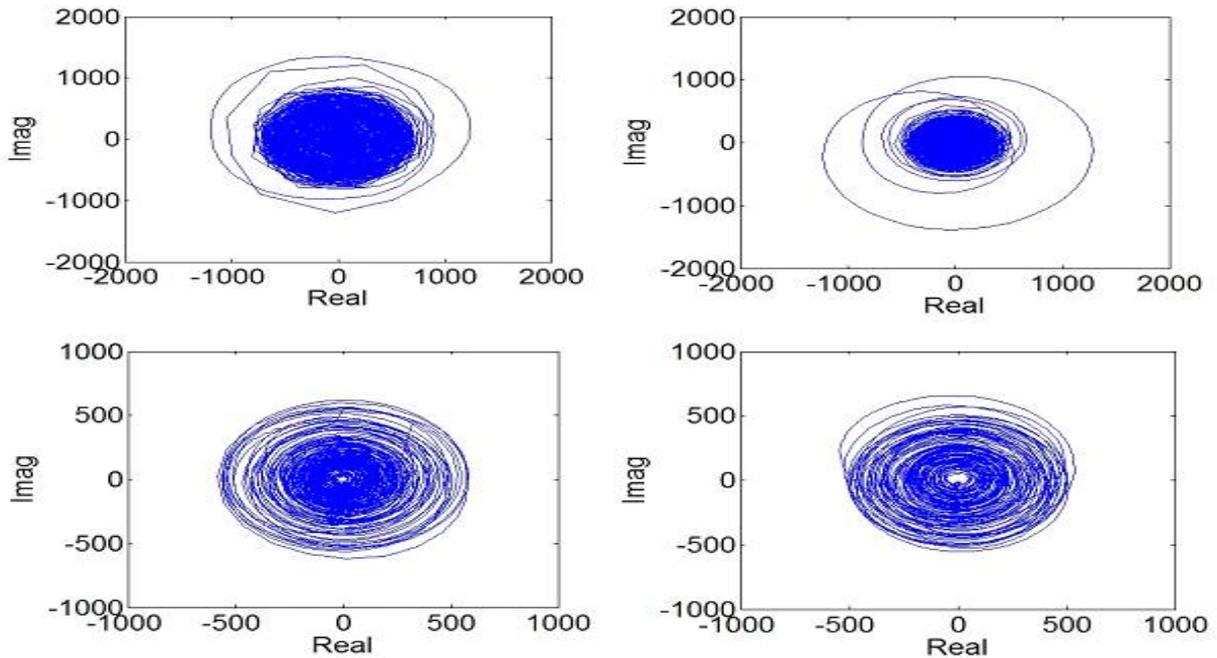


Fig. 1. Analytic signal representation of seizure signal

Where $A(t) = \sqrt{x^2(t) + y^2(t)}$ is the modulus (amplitude) of $Z(t)$ and $\phi(t) = \arctan(y(t)/x(t))$ is the instantaneous phase. From which instantaneous frequency $w(t)$ is obtained by differentiation:

$$w(t) = \frac{d\phi(t)}{dt}$$

$$= \frac{x(t)\dot{y}(t) - \dot{x}(t)y(t)}{A^2(t)}$$

Fig.1 shows the analytic signal representation of each IMF of the person having epileptic seizure. First figure is for IMF 1, second is for IMF 2 third is for IMF 3 and last one is representing IMF 4.

III. PROPOSED METHODOLOGY

A. Second Order Difference

Second order difference plot of intrinsic mode function of EEG signal can provide us valuable diagnosis feature for classification of ictal and seizure free EEG signals [15]. The SODP can be obtained by plot $x(n)$ against $y(n)$ which can be defined as:

$$x(n) = x(n+1) - x(n)$$

$$y(n) = x(n+2) - x(n+1)$$

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Website: www.ijirset.com

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The second order difference plot is a geographical representation of successive rates against each other and provides a rate of variability of data. Variability measured from the SODP has been used for analysis of EEG [16].

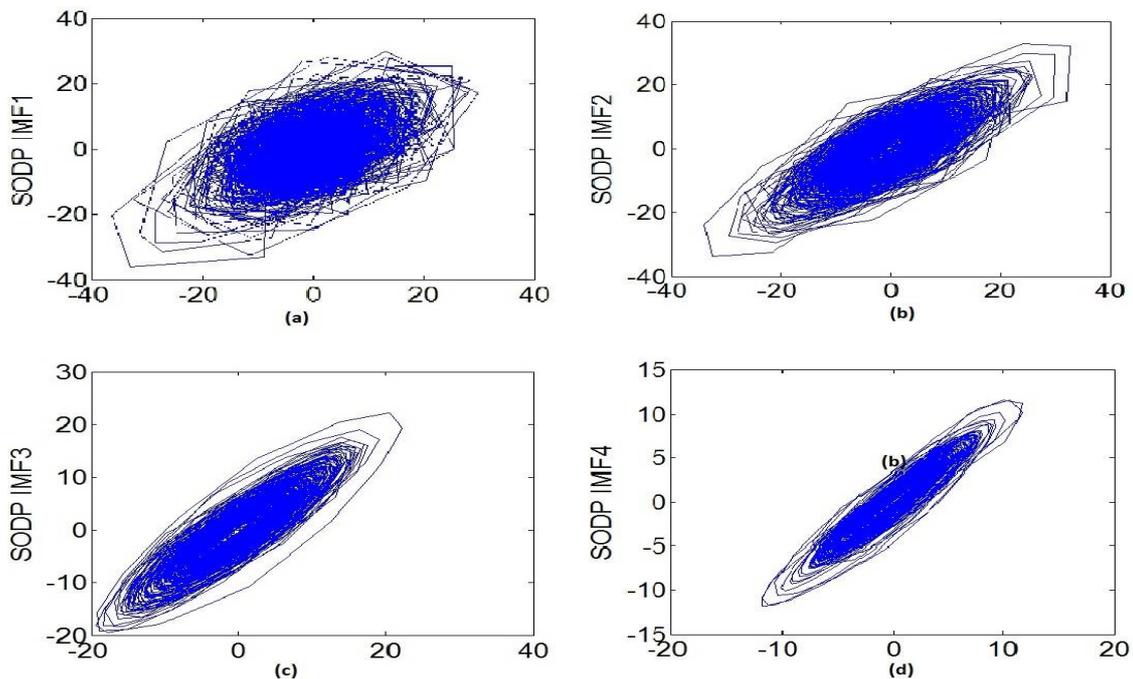


Fig. 2. Second Order difference plot of normal EEG signal,
(a) IMF 1, (b) IMF 2, (c) IMF 3, (d) IMF 4

Above mention fig. 2 represents the second order difference plot of normal signal. In which part (a) shows the IMF1, part (b) shows the IMF2, part (c) represents the IMF3 and part (d) represents IMF4.

B. Central Tendency Measure (CTM)

The process of central tendency measure starts with second order difference. The central tendency measure is the ratio of the number of points that fall within the radius, to the total number of points [17]. For computing, the circular tendency measure selects a circular region of radius r around the origin, count the number of points that fall within the radius r and dividing it by the total number of points.

Let N be the radius of the points and r the radius of the central area. Then the modified CTM for analytic signal $Z(n)$ can be given by the following expression:

$$CTM = \frac{\sum_{n=1}^N \delta(d_n)}{N}$$

Where

$$\delta(d_n) = \begin{cases} 1 & \text{if } (|x(i+2) - x(i+1)|^2 + |x(i+1) - x(i)|^2)^{1/2} < r \\ 0 & \text{otherwise} \end{cases}$$

For each radius r , CTM provides the fraction of the total number of points lies within it. CTM plot of first four IMF of an epileptic seizure and a normal signal EEG signal shown in fig. 2 and 3 respectively.

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Vol. 6, Issue 7, July 2017

C. Area measured by SODP and CTM

Area of second order difference plot can be computed as follows:

$$S_x = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} x^2(n)}$$

$$S_y = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} y^2(n)}$$

$$S_{xy} = \frac{1}{N} \sum x(n)y(n) \quad D = \sqrt{(S_x^2 + S_y^2) - 4(S_x^2 S_y^2 - S_{xy}^2)}$$

Now,

$$a = 1.7321 \sqrt{S_x^2 + S_y^2 + D} \quad b = 1.7321 \sqrt{S_x^2 + S_y^2 - D}$$

Area of ellipse can be calculated by: $A = \pi ab$

Area of circular analytic signal is: $A = \pi(\text{radius})^2$

IV. EXPERIMENTAL RESULTS

In this paper, EMD has done before computing the Hilbert transform of EEG signal, which provides us greater insight than simply applying the Hilbert transform to the signal. It is also detected into the difference between the surface area of normal and epileptic seizure EEG signals. Fig.2 and Fig.3 clearly indicate the analytic signal representation of EEG signal in a complex plane, do not have a specific geometry, and thus makes it difficult to find out the surface area.

In this paper area estimation is considered as an important parameter for discriminating between normal and seizure EEG signal. From the dataset, the data only from the subset Z and subset S have been considered. Subset Z is normal EEG signal data and subset S is epileptic seizure EEG data.

Second order difference plot of EEG signal have epileptic shape and thus the area can be measured by the above defined formulas.

Central tendency measure defines the circle that encloses 95% of the total data points. It defines the number of data points that lies inside the circle of particular radius. The decomposition based on EMD makes us possible to cover more than 95% of data points lie within the circle. The form of analytic trace differs between the EEG signals. Such a tracing is an indication of multiple centers of rotation possibly due to the presence of several different rhythms (or frequency component) in EEG signals. In contrast, the trace of the analytic signals of each IMF has a circular form. Then the surface area of which can be estimated in the complex plane.

The area parameter has been estimated for both sets of data using an analytic signal representation of IMF. Table 1 shows area of ellipse of second order difference plot of EEG signal (min for minimum, mean for average and max for maximum) for normal and seizure signal whereas Table 2 shows surface area of analytic signal representation for each of the classes. The mean value of the surface area is small in the case of normal signal whereas it is higher in the case of seizure signal. The higher value of the surface area in signal is possibly due to the higher value of amplitude in seizure signal. In case of SODP 25 results found positive whereas in case of CTM we found 29 results positive which lie in this range.

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 6, Issue 7, July 2017

TABLE I. AREA OF ELLIPSE OF SECOND ORDER DIFFERENCE PLOT OF NORMAL AND SEIZURE EEG SIGNAL

Value	Normal Subject			
	IMF1	IMF2	IMF3	IMF4
Min	9.60×10^5	1.60×10^6	1.12×10^5	4.0×10^5
Mean	3.51×10^6	4.53×10^6	2.69×10^6	9.54×10^5
Max	1.40×10^7	1.0×10^7	7.0×10^6	2.40×10^6
Seizure Subject				
Min	2.79×10^6	2.41×10^6	1.68×10^6	1.6×10^6
Mean	8.85×10^8	4.19×10^8	1.25×10^8	5.04×10^7
Max	5.59×10^9	1.26×10^9	2.60×10^8	1.80×10^8

TABLE II. AREA OF CIRCLE OF NORMAL AND SEIZURE EEG SIGNAL

Value	Normal Subject			
	IMF1	IMF2	IMF3	IMF4
Min	0.3142	0.616	0.5309	0.201
Mean	1.4908	2.1302	1.4567	0.5961
Max	5.027	5.0265	3.217	1.963
Seizure Subject				
Min	1.96	1.9633	1.2566	1.0179
Mean	465.062	199.4665	67.675	32.4938
Max	2544.7	865.9015	166.1903	101.79

V. CONCLUSION

In this paper, we explored the ability of the analytic signal representation of intrinsic mode function to differentiate EEG signal which contains epileptic seizure and normal EEG signals. The use of EMD to decompose EEG signals into IMFs is a promising method, which provides a set of proper rotation which makes possible to accurately identify the center and estimating surface areas in the complex plane. The area parameter provides a significant difference between epileptic signal and normal signal. The ellipse area parameter of first four IMFs have provide better classification, accuracy for ictal and normal EEG signal. In future, the proposed method can be used for classification of other brain condition like sleep stage classification, hyper classification and human emotion classification using EEG signals.

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Vol. 6, Issue 7, July 2017

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