Epileptic Seizure Feature Extraction using Variational Mode Decomposition

E. Swetha, Shaik.Jakeer Hussain

Abstract -Signal processing for extracting the features of biosignals needs an adaptive processing techniques. Most of the biosignals such as EEG are non stationary signals. Therefore extracting the features of these non stationary signals are the challenges faced by the researchers. Many frequency domain techniques are proposed such as Hilbert transform, DWT, EMD. The most popular recent EMD technique is to achieve the accurate denoising & interpretation, but it fails to decompose the signal effectively and also due to lack of mathematical model or proof's, choice of interpolation, and sensitivity to both sampling and noise. Hence the new emerging technique Variational mode decomposition (VMD) is used in this paper to extract the features of EEG signal. The advantage of using VMD, is lusty to sampling and noise.

Keywords: Epileptic seizure, Electro encephalogram(EEG), variational mode decomposition(VMD)

I. INTRODUCTION

According to the fact sheet details of worlds health organization 50 million people across the world have epilepsy which is the chronic neurological disorder[13]. Human brain generates an electrical signals produced by billions of nerve cells, form a pattern called brain waves. These brain waves are measured using electroencephalogram (EEG). Electro-brain electrical activities, encephalo - emitts the signals from the scalp, gram or graphy- drawing. An EEG measures the electrical signal during synaptic excitations of the dendrites of neurons in the cerebral cortex (the outer layer of the cerebrum). The electrical activity is caused by complex chemical changes (K, Na) that occur in nerve cells.

The unbalance of chemical changes inhibit the communication between the other neuron cells. The chemical changes can lead to surge of electrical activity that causes seizures. Epileptic seizures are episodes of undetectable periods to long periods of vigorous shaking, which can also result in physical injuries, can also lead to death[14]. The detection of epilepsy, from the recordings of EEG for spikes & seizures is time consuming, especially in the case of long recordings[6]. EEG signals are non stationary signals and are prone to power line electrical noise, eyes blinking, muscular activities, etc. Therefore, extracting the features of EEG plays a vital role to achieve novel characteristics of EEG signals such as delta, theta, alpha, beta, gamma.

EEG signals exhibit several patterns of rhythmic or periodic activity. The commonly used EEG frequency(F) bands are:

- Delta wave(δ) : $0.5 \leq$ (F) $<$ 4 Hz
- Theta wave(θ) : $4 \leq$ (F) $<$ 8 Hz
- Alpha wave(α) : $8 \leq$ (F) $<$ 13 Hz
- Beta wave(β) : $13 \leq$ (F) $<$ 30 Hz
- Gamma wave(γ) : $30 \leq$ (F) $<$ 100 Hz

II. METHODS

The current decomposition model i.e., EMD algorithm is limited by a) lack of mathematical proof b) requires filter bank boundaries c) sensitive to noise d) recursive shifting doesn't allow to correct the errors. In conflict, Dragomiretskiy Konstantin and Dominique Zosso proposed a non recursive variational mode decomposition model, to extract the modes concurrently[1]. To extract the EEG features variational mode decomposition technique is used in this paper.

Variational mode decomposition:

VMD is a novel technique used to decompose the input signal into different mode called as variational mode functions (VMF) . Here no.of modes 'K' is predefined and has limited bandwidth, which surrounds the center frequency(ω_k)[4]. To access the bandwidth of each mode, for a uni-dimensional signal the following scheme was proposed:

A) To obtain the unilateral frequency spectrum, compute the analytical signal by means of Hilbert transform.

B) for each modes, shift mode frequency spectrum to base band, by mixing the exponential tuned to the respective estimated center frequency[1].

C) bandwidth is estimated by using the squared L2- norm of gradient, for the smoothness of the demodulated signal.

The constrained variational problem is formulated as below:

$$\min_{\{u_k\},\{\omega_k\}} \{\sum_k \| \partial_t [(\delta(t) + \frac{j}{\pi t} * u_k(t)] e^{-j\omega_k t} \|_2^2\} \quad \text{--[1] [1]}$$

The reconstruction constraint can be resolved by using the quadratic penalty term & langrage's multiplier, they benefit from the convergence properties at finite weight & strict enforcement of the constraint respectively.

Feature Extractions:

By using variational mode decomposition, the following EEG features are extracted. The parameters used are as follows:

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1) MAD : The median absolute deviation is defined for a N no.of samples with mean distribution x, given by

$$MAD = \frac{1}{N}\sum_{i=1}^{N} |Xi - \bar{X}| \quad \text{--- (1) [6]}$$

2) Energy: Energy is defined as the square of the signal in the limited time period and is given by

$$E(i) = \sum_{k=1}^{N} X_k^2 \quad \text{---(2)[6]}$$

Where ' i' is the decomposition levels, 'N' represents the no. Of samples, X_k represents the value of the signal.

3) Inter quartile range: Inter quartile range defines the measure of variability. According to the variations the given signal is divided equally as first, second & third quartile's which are denoted as Q1, Q2 & Q3 respectively.

The IQR of each sub variation is given by

$$IQR = Q3 - Q1 \quad \text{---(3) [2]}$$

4) Weighted mean frequency: weighted mean frequency is defined as the measurement of central tendency frequency. If the frequency values occur more frequently, then the value is assigned to frequency. The assigned value is referred to as weights.

The weighted mean frequency (MF) is given by

$$MF = \frac{\sum_{i=1}^{K} A1(i) f1(i) 2}{\sum_{i=1}^{K} A1(i) f1(i)} \quad \text{---(4) [2]}$$

Where Ai = Instantaneous amplitude, fi= instantaneous frequency

5) Kurtosis: kurtosis is defined as the measure of degree of "peakedness" of a frequency distribution i.e., the combined weight of a distribution.

Kurtosis indicates the long-tailed function of the power spectral density.

$$kurtosis = \frac{f_{m4}}{(f_{m2})^2} \quad \text{---(5)}$$

where f_{m4} is the fourth order moment & (f_{m2}) is the second order moment

III. RESULTS & DISCUSSIONS

Experimental data: The experimental data is acquired from Bonn University for the study of EEG signals[12]. The recordings were done using 10-20 standard electrode placement system. The data is recorded with 128- channel amplifier system. It is sampled at 173.61 Hz and converted from analog to digital by 12-bit resolution.

The available data consists of five sets, namely Z, O, N, F, S. Each set contains 100 single channels EEG segment of 23.6 sec duration. Therefore each channel segment consists of 4096 samples. Set Z and Set O consists of EEG segments taken by external surface electrodes of a healthy subjects in an awaken state. Set Z data is acquired from the healthy subject in an awaken state with eyes open. Set O data is acquired from the healthy subject in an awaken state with eyes closed. Set N is recorded from hippocampal formation of opposite hemisphere of brain. Set F data is recorded from the epileptogenic zone. Set S data contains seizure activity[12].

Experimental Results:

The variational mode decomposition, decomposes the input signal into several modes (u_k), named as intrinsic mode function (IMF). From each mode, the statistical features such as MAD, energy, inter quartile range, mean weighted frequency, kurtosis are calculated and the average values are tabulated for each data set.

1) Mean Absolute Deviation :

The table1 shows the deviation of average values for different data sets acquired from bonn university. The below tabulated values represent the MAD average values of Z,O,N,F,S respectively. It is clearly observed from the fig 1, that the mean absolute deviation is very high during the seizure i.e., in S data set.

	Mode1	Mode2	Mode3	Mode4	Mode5
Z	18.11	13.24	13.27	11.71	5.78
O	23.01	12.91	20.37	14.04	1.17
N	25.69	24.16	18.26	15.12	8.87
F	24.98	29.95	15.53	12.99	9.03
S	112.91	140.08	81.77	90.34	89.39

Table 1: Average values of Mean absolute deviation decomposition values

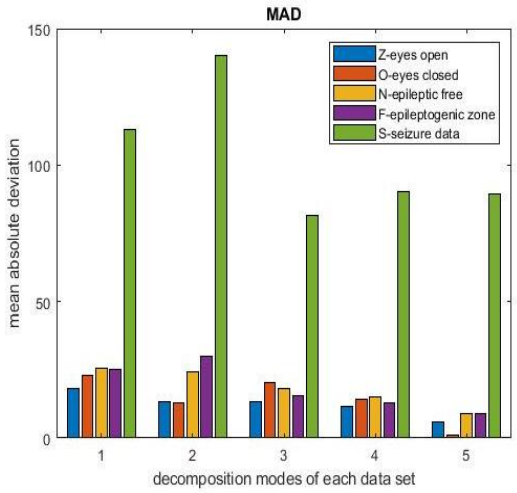

Fig1: Mean absolute deviation decomposed mode plot

2) Energy :

The below tabulated values shown in table 2 represents the average energy values of Z,O,N,F,S data sets respectively. From the graph shown in Fig 2, it is observed that the energy during the seizure period is at lofty level.

	Mode1	Mode2	Mode3	Mode4	Mode5
Z	4.82	1.16	1.25	1.03	0.33
O	3.89	1.15	2.81	1.62	0.01
N	7.79	4.39	2.52	1.71	0.60
F	10.14	7.76	2.04	1.62	0.89
S	95.58	135.96	47.89	63.33	63.85

Table 2:Average Energy decomposition values

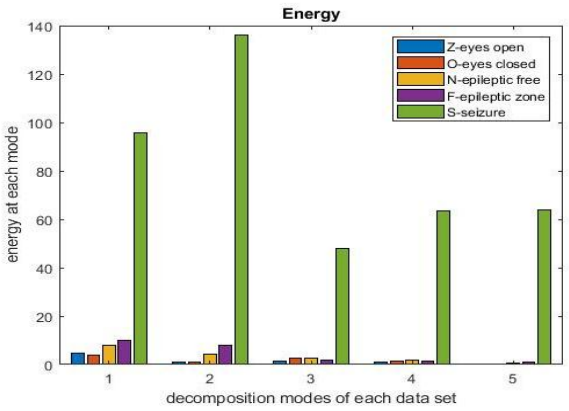

Fig 2: Energy decomposed mode plot

3) Inter Quartile Range :

The tabulated values shown in table 3, has the different data sets acquired from bonn university. The below tabulated values represent the IQR average values of Z, O, N, F, S respectively. From fig 3, in comparison with all data sets available the IQR values for seizure data is very high i.e., in S data set.

	Mode1	Mode2	Mode3	Mode4	Mode5
Z	30.90	22.01	21.19	19.37	9.72
O	36.70	20.95	33.07	22.88	2.38
N	44.53	38.83	29.91	24.35	14.42
F	42.16	47.46	23.60	19.12	12.69
S	181.09	246.76	137.66	153.26	150.79

Table 3: Inter quartile range decomposition values

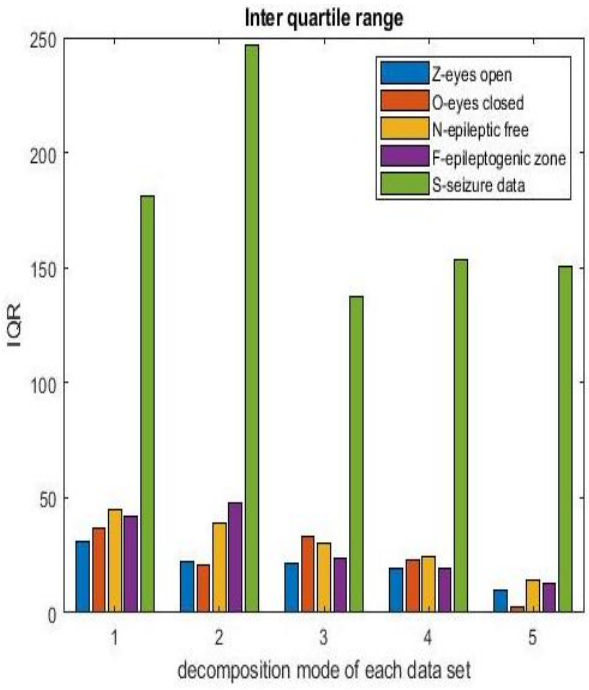

Fig 3: Inter quartile range decomposed mode plot

4) Kurtosis :

The tabulated values from table 4 shows the different data sets acquired from bonn university. The below tabulated values represent the kurtosis average values of Z, O, N, F, S respectively. Among all the data sets the average values of epileptogenic zone i.e., F is high as the no. of modes increases the F data set values also increases. This feature can be considered at the time of seizure prediction.

	Mode1	Mode2	Mode3	Mode4	Mode5
Z	3.34	3.19	3.80	3.41	3.16
O	4.36	3.60	3.45	3.45	2.63
N	2.63	3.84	3.70	3.39	3.54
F	3.09	3.21	3.81	4.39	4.98
S	3.33	2.60	3.18	2.89	2.82

Table 4: kurtosis decomposition values

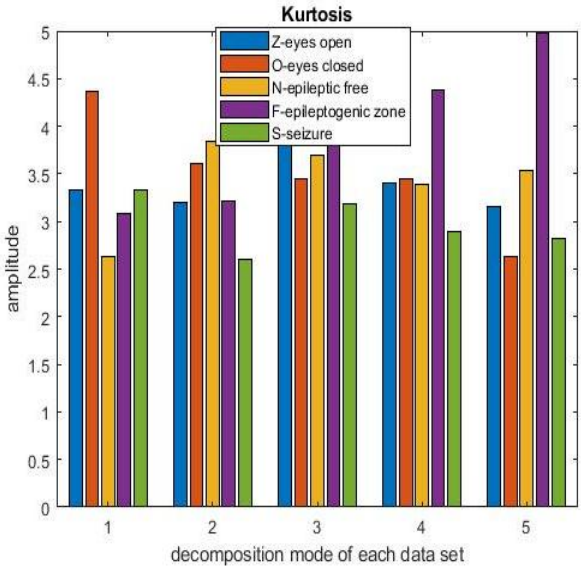

Fig 4: Kurtosis decomposed mode plot

5) Weighted Mean Frequency :

The below table 5 shows the average values of weighted mean frequency of each data set such as Z, O, N, F, S respectively. Figure 5 shows the graph plotted after the simulation of average mean weighted frequency values. The first level decomposition mode represents the delta (δ) wave of frequency ranges between 0-4 Hz.

The second level decomposition mode represents the theta (θ) wave of frequency ranges between 4-8 Hz.

The third level decomposition mode represents the alpha (α) wave of frequency ranges between 8-13 Hz.

The fourth level decomposition mode represents the beta (β) wave of frequency ranges between 13-30γ Hz.

The fifth level decomposition mode represents the gamma (γ) wave of frequency greater than 13-30 Hz.

	Mode1	Mode2	Mode3	Mode4	Mode5
Z	0.77	4.43	9.69	13.82	31.78
O	1.05	5.35	10.72	14.85	49.63
N	0.59	2.26	4.82	8.06	12.36
F	0.44	1.98	4.50	7.98	18.29
S	2.77	5.05	9.43	14.55	14.41

Table 5: Weighted mean frequency decomposition values

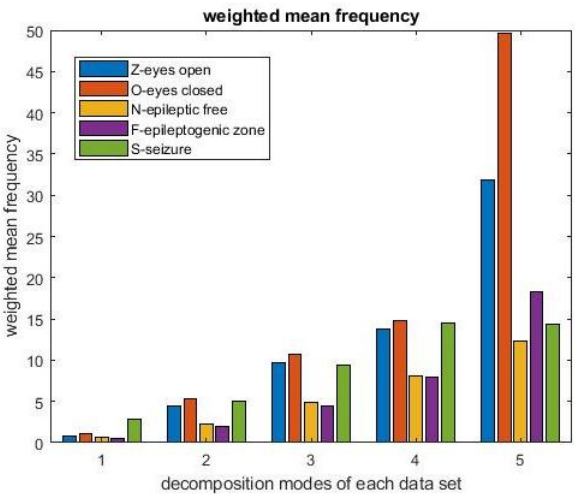

Fig 5: Decomposed weighted mean frequency plot

CONCLUSION :

In this paper, the VMD is used for extracting the EEG features, such as Delta, Theta, Alpha, Beta, Gamma waves and also calibrated the difference between healthy EEG data and the abnormal or unhealthy EEG with the measuring factors MAD, Energy and IQR . Among the experimental data taken, the measuring factors shows the impact of seizure data in EEG signal. Therefore, extracting the features plays a major role and also helps the physician's to treat the patients on time. Extracting the non-stationary signals features is resolved by using VMD which gives the benefits of modal aliasing & boundary effect. In addition, VMD is robust to sampling & noise. VMD is a novel technique for adaptive & non recursive decomposition. Decomposition of signals plays a key role as reconstruction of signals extract the signal from the noise.

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