"EMPIRICAL MODE DECOMPOSITION (EMD) FOR NON LINEAR SIGNAL PROCESSING"

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ABSTRACT

Empirical Mode Decomposition (EMD) is a decomposition technique for the complex signals like EEG, ECG etc, with the help of Hung transformation. EMD consists of breaking down a signal without leaving the time domain. EMD filters out functions which form a complete and nearly orthogonal basis for the original signal. Completeness is based on the method of the EMD; the way it is decomposed implies completeness.

It can be compared to other analysis methods like Fourier Transforms and wavelet decomposition. The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. EMD obtain the functions, known as Intrinsic Mode Functions (IMFs), are therefore sufficient to describe the signal, even though they are not necessarily orthogonal.

The technique of Empirical Mode Decomposition (EMD) is presented, and issues related to its effective implementation are discussed in this paper. Also how EMD is better than popular Wavelet decomposition is discussed.

KEYWORDS: EEG, EMD, IMF, HHT etc

I. INTRODUCTION

In general there are many natural signals which are complex and most often non-linear and non-stationary. For our discussion we will consider EEG signals among them throughout this paper. EEG contains a set of electric potential differences developed as a result of volume currents spreading from an active neural tissue throughout the conductive media of the brain. These measurements can be obtained either using sensors on the scalp or by placing special intracranial electrodes. EEG has been considered a successful tool in neuroscience to diagnose diseases and disorders. Epilepsy is one of the most serious neurological disorders.

Various algorithms have been introduced for detecting seizure from EEG records. A multidimensional probability evolution-based technique is introduced by McSharry et al., which gives fewer false positives as compared to using variances [1]. However, the difference is quite small and, thus, does not negate the significance of linear statistics such as variance in identifying seizures. In [2], seizures are detected by threshold variances calculated from local windows using an arbitrary threshold for classifying normal and seizure activities. In [3], chaotic features that include largest Lyapunov exponent (LLE) and correlation dimension (CD) obtained from the wavelet sub bands of the

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EEG signals are shown to be effective in differentiating the signals of various classes including those of seizures. Concurrently, Lyapunov spectra have been used in [4] to make a multi way classification using multiclass support vector machines (SVMs). The approximate entropy in conjunction with autoregressive model parameters extracted from the Fourier transforms of the EEG signals is employed in linear and nonlinear classifiers by Liang et al. [5].

A two-way classification using fractal dimension and artificial neural networks (ANN) is carried out in [6]. In [7] and [8], linear statistical measures obtained from the EEG signals are used as features, later employed in a linear classifier to distinguish normal and seizure activities. Various time–frequency analysis (TFA) techniques such as smoothed pseudo-Wigner–Ville and reduced interference are used in conjunction with an ANN in [9] and [10] and a high accuracy in detection is reported. Recently, the empirical mode decomposition (EMD) has drawn the attention of researchers in nonlinear signal analysis for being intuitive and adaptive to signals, while requiring no assumption in regard to stationarity and linearity [11].

Since the EEG signals exhibit non stationary behavior, a number of methods have been developed to detect seizures in the EMD domain. The mean frequencies of the intrinsic mode function (IMF) obtained by the EMD of an EEG signal are shown to be effective in discriminating the ictal periods from the non ictal ones, that is, seizure activities from the non seizure ones. The energy of an IMF and minimum distance duration are used in [12] for seizure detection. In [13], features are extracted from the IMFs using Mann–Whitney Test and Lambda of Wilks criterion and used in a linear discriminate analyzer for classifying the EEG signals. In [14], chaotic features such as the LLE and CD computed from the various IMFs are shown to be effective in distinguishing the EEG signals of various classes.

II. EMD

The EMD is a process of extracting amplitude and frequency modulated oscillatory patterns from a time series data. These patterns, called IMFs, are derived using from the data itself [15].

For an N-point data, $Y\ \{y1,\ y2.\ \ .\ .\ yN\}$, the decomposition is carried out as follows [16].

1) Set input as $h = Y$ and $ho = h$.

2) The local maxima and minima of ho are identified.

3) Envelops of local maxima $emax$ and that of local minima $emin$ are obtained. In this cubic spline interpolation is used.

4) The values of the mean of $e$max and $e$min are calculated as $Mean = (emax + emin)/2$ and subsequently subtracted from

ho as

$$h1 = h\text{old} - Mean. \ldots\ldots\ldots\ldots\ldots (1)$$

5) Set ho = $h1$.

Go to step 2. Steps 2–5 are repeated until

$$SD = \frac{\sum |h1 - h0|^2}{\sum h0^2} < \alpha \ldots\ldots\ldots (2)$$

Where α is an arbitrary value preset in the range of 0.2–0.3. The jth sample of ho is considered to be local maxima if it is greater than both the (j + 1)th and (j − 1)th sample and minima if it is less than both the (j + 1)th and (j − 1)th sample. When (2) is satisfied, $h1$ becomes the IMF ci and a residue ri is obtained as $ri = h - ci$, where i represents the decomposition level. The residue ri is assigned to h and the entire process is repeated from Step 2. Thus, the input signal can be decomposed into M IMFs until the residue becomes a monotonic function such that further extraction of an IMF is not possible. The input Y can be reconstructed from all the IMFs as

$$Y = \sum_{i=1}^{M} Ci + rM \ \ldots\ldots\ldots\ldots. (3)$$

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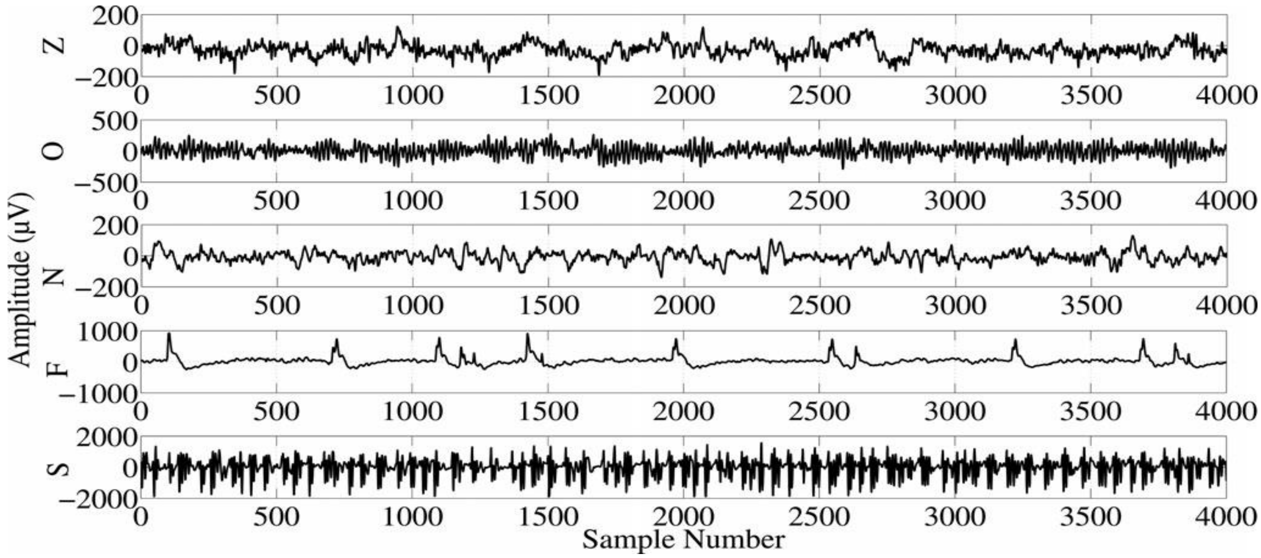

Fig. 1. Example of EEG signals

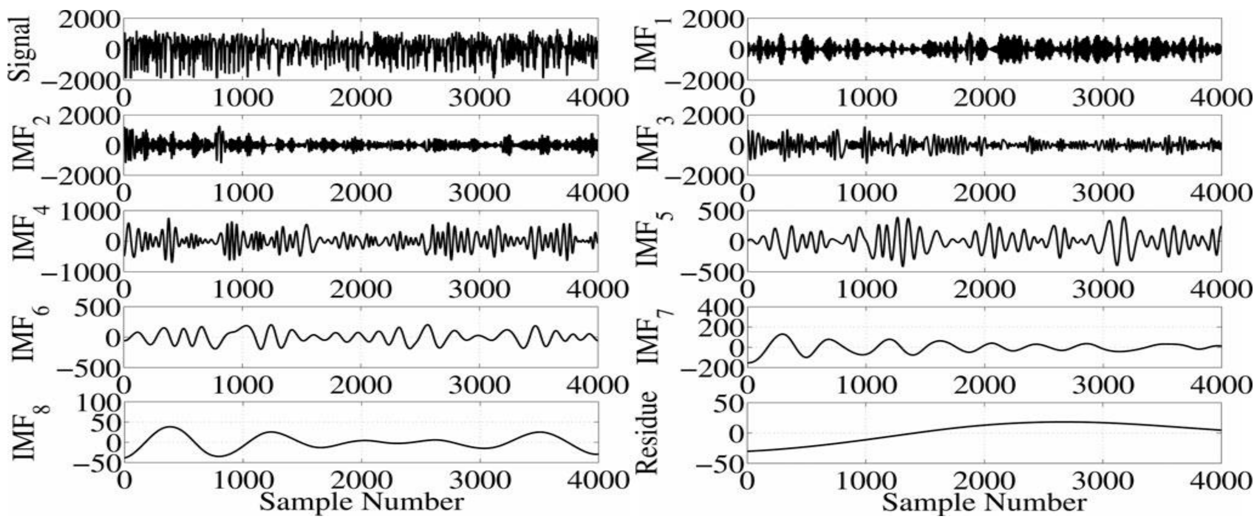

Fig. 2. Empirical mode decomposition of EEG signal.

The above database is easily available on internet, so that we can easily analyze the EMD process on EEG signals [17].

III. HHT

Hilbert Transform is Applying to every intrinsic mode with the aim of tracking instantaneous frequencies and amplitudes.

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The weighted frequencies of counterpart intrinsic modes will statistically compare using the t-test. The t-test assesses whether the distribution means of the two groups are statistically different from each other. The weighted frequency index of the proposed approach, when it provides a significant difference, made it possible to discriminate between healthy and seizure activities.

IV. DISCUSSION

The EMD method decomposes the nonlinear and non stationary signal into a set of narrow-band AM–FM components or IMFs, which facilitates computation of the bandwidth due to amplitude modulation (*BAM*) and bandwidth due to frequency modulation (*BFM*). Above Figs. show the plots of IMFs obtained by applying EMD method on seizure and non seizure EEG signals, respectively. It is evident from these figures that the first IMF contains higher frequency components than the second and other IMFs. The IMFs of EEG signals are ordered from highest frequency component to the lowest frequency component.

The bandwidth features (*BAM* and *BFM)* of first four IMFs of EEG signals were used as an input features to the LS-SVM classifier with the polynomial kernel, RBF kernel, Mexican hat wavelet kernel, and Morlet wavelet kernel functions. The optimal kernel parameters can be selected by using trial and error approach. The classification test performance of the LS-SVM classifier can be determined by the computation of sensitivity, specificity, and accuracy.

V. CONCLUSION

The EMD process is a useful and powerful method to decompose EEG signal into a set of IMFs. These IMFs can be represented by the amplitude and frequency modulated (AM–FM) signal model, which makes it possible to compute AM and FM BWs of the IMFs. These bandwidth parameters BAM and BFM of the IMFs of EEG signals have been used as a feature in order to classify seizure and non seizure EEG signals.

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