EMPIRICAL MODE DECOMPOSITION FOR EEG SIGNAL ANALYSIS

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Abstract— Electroencephalogram (EEG) is used to record electrical activity of brain. Human brain is fascinated by the different idea of thoughts and feelings generated from external and internal stimuli. Feature extraction and classification of EEG signal plays an important role in diagnosis of various brain diseases and mental tasks. In this paper, powerful technique of empirical mode decomposition (EMD) for the EEG signal is proposed. For extracting data from nonlinear and nonstationary process EMD is used in wide variety of applications. Intrinsic mode functions (IMFs) resulting from EMD process are considered as set of amplitude modulation (AM) and frequency modulation (FM) signals. Hilbert Huang transform is used for analytic representation of IMF. Features obtained from IMF can be applied to classifier to show effectiveness of EMD process.

Keywords— EEG signal analysis, Electroencephalogram (EEG), intrinsic mode function, Hilbert huang transform (HHT)

I) INTRODUCTION

Brain controls various activities of our body and it is very active part. Brain functions are analyzed by an observing electrical signals generated by neurons. EEG signal measures changes of these signals in terms of voltage fluctuations of brain within very short time period [1]. In modern biomedical applications EEG signal is investigated as function of human- computer communication. Computers help in recognition of abnormalities in brain from EEG signal. Many neurological disorders can be easily diagnosis with the help of brain rhythms which can be easily recognized by visual inspection of the EEG signal. EEG signal occurs in frequency ranges of delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta greater than 13 Hz.

To record electrical signals, electrodes are arranged on the surface of scalp using 10-20 system of an electrode placement. As name indicates that distance between the adjacent electrodes are either 10% or 20% from total front-back or left-right portion of skull. It uses letters and numbers for placement of electrodes. The electrode site is labeled with a letter which corresponds to the area of the brain, and the number which indicates the right hemisphere even, or the left hemisphere – odd.

Nasion and Inion are the anatomical landmarks. 10-20 system is shown in given in Fig.1.

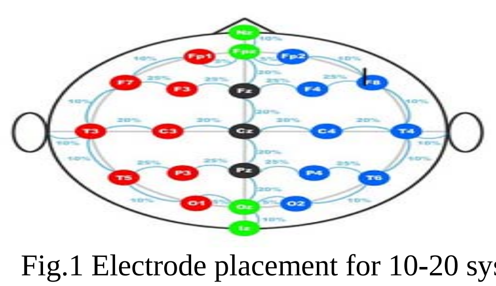


Fig.1 Electrode placement for 10-20 system

Brain Computer Interface (BCI) is an advanced technology that acquires and analyzes signal for achieving communication between brain thoughts, messages and computer [2] [3]. Basic BCI System is shown in Fig.2.

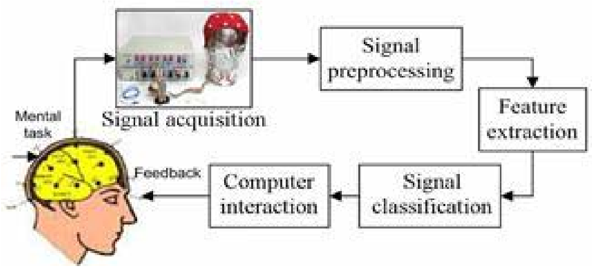


Fig.2.BCI system

EEG signal is acquired by electrodes and sensors. These signals are collected and preprocessed using special filters. Raw EEG signal is input to the feature extraction.EEG features are extracted using several methods. Suitable features characterizing each signal are extracted from each signal. Each EEG signal consists of huge number of samples in it. The feature extraction method employs some characteristic quantities from each input signal. Comparison of different features can be used to identify mental disorder problems [4].

Empirical mode decomposition (EMD) is process of extracting amplitude and frequency related oscillatory pattern from time series of data.EMD decomposes EEG signal into intrinsic mode functions (IMFs).They are based upon local characteristics of time scale data.EMD is particularly well suited for analyzing nonstationary signal such as EEG. It is data adaptive decomposition method. Huang, et al. (1998) has introduced the concept of Empirical Mode Decomposition and application of Hilbert transform, which is called Hilbert-Huang Transform, to extract time-frequency information data from a nonlinear and nonstationary signal. R. Oweis et al. has proposed [5] EMD method for recognition of seizure and Nonseizure detection using Hilbert huang transform. From this intrinsic mode functions are extracted to obtain amplitude and frequency components. In this case EMD method provides fast diagnosis of abnormal activities of brain and high accuracy to classifier about 94%. C.Park et al. [6] describes bivariate extension of EMD facilitates enhanced spectrum estimation for multichannel recordings. Amplitude and frequency components are analyzed locally. BEMD provides stability to the system also BEMD based asymmetry calculation provides higher accuracy over EMD based asymmetry. S.M.Shafiul [7] has proposed EMD-chaos based approach for analysis of healthy and epileptic patients during seizure attacks. EEG signals are discriminated using Lyapunov exponent and correlation dimension. Parameters obtained from this method are able to distinguish EEGs of seizure attacks from other tasks. Bajaj et al. [8] has introduced EMD method for classification of ictal and Interictal part. Amplitude and frequency modulated bandwidth features resulting from IMFs are used along with least square support vector machine (LS-SVM) which increases performance and accuracy of classifier.

II) METHODOLOGY

A. Dataset

An EEG dataset used here is available at http://www.cs.colostate.edu/eeg.[9]. This dataset consist of data recorded from electrodes. Data is a cell array and each individual cell array is made up of a subject string, task string, trial string, and data array. Each data array is 7 rows by 2500 columns. The 7 rows correspond to channels c3, c4, p3, p4, o1, o2, and EOG. Across columns are samples taken at 250 Hz for 10 seconds, for 2500 samples. Data consists of five tasks such as-

(1) Baseline Task- The subjects are asked to relax in this task means they are not performing any mental task.

(2) Multiplication task-In this task subjects are required to solve a multiplication problem without any vocalizing or making any other physical movement.

(3) Letter Composition- The subjects are instructed to mentally compose some letter to other friend or relative without making any vocalizing.

(4) Number Counting-In this task subjects are asked to imagine a blackboard and to visualize numbers which are written on board.

(5) Geometric Figure Rotation- The subjects are asked to visualize a given drawing of complex three dimensional block figure to study and after some particular period it will removed and instructed to visualize box is being rotated about an axis [10].

B. Empirical Mode Decomposition

EMD is data dependent process. IMFs are derived using basis obtained from EEG data itself. There are two basic conditions for each IMF that (1) the number of extrema and number of zero crossings of signal must be same or they are at most differ by one. (2) at any point mean value of envelope of signal defined by local maxima and envelope of signal defined by local minima is zero [11]. 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 maxima and minima separately with cubic spline interpolation.

3. Determine the local mean as,

$$a(t) = [e_m(t) + e_l(t)]/2$$

4. Extract the detail

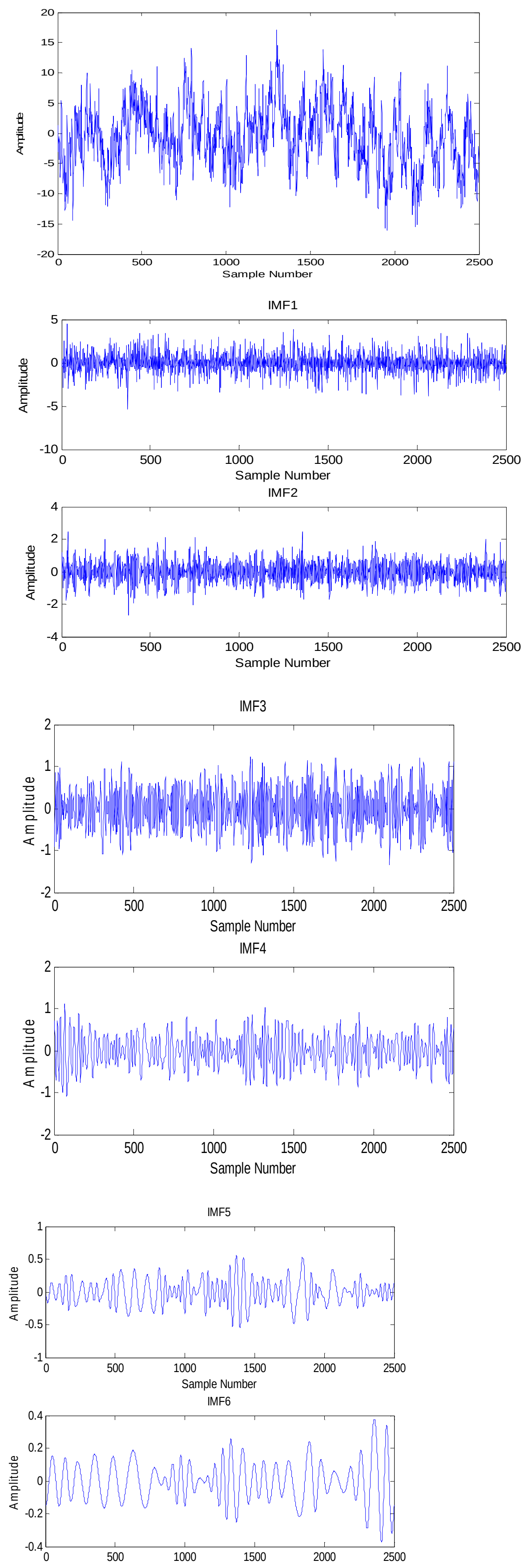
$$h_1(t) = x(t) - a(t)$$

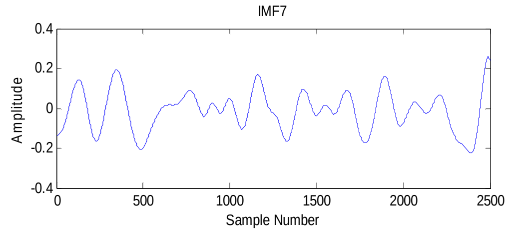
5. Decide whether $h_1(t)$ is an IMF or not by checking the two basic conditions as described above. Repeat the steps (1) to (4) and end when an IMF $h_1(t)$ is obtained .Once the first IMF is derived, define $c_1(t) = h_1(t)$ which is the smallest temporal scale in x(t). To determine the rest of the IMFs, generate the residue $h_1(t) = x(t) - c_1(t)$ 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 given in Eq.1,

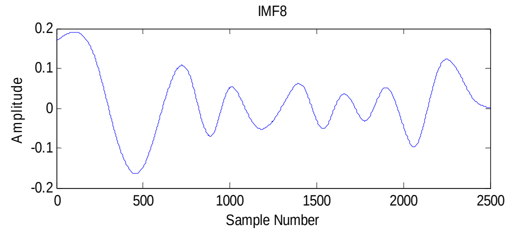
$$x(t) = \sum_{m=1}^{M} Cm(t) + rM(t) \qquad (1)$$

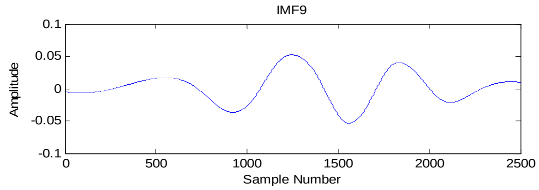
Where M is the number of IMFs, $c_m(t)$ is the m^{th} IMF and $r_M(t)$ is the final residue [12] [13].

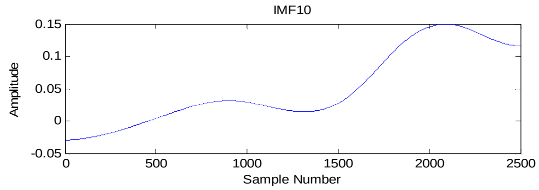
IMFs generated by the EMD process are shown in Fig.3











As the number of IMF increases, the corresponding data become smoother. The EMD algorithm is however very sensitive to noise in the recorded signal.

C. Analytic Signal Representation

Hilbert transform is used for each of the IMF obtained by EMD method. HHT mainly consists of EMD technique along with Hilbert spectral analysis. HHT provides local description of oscillating components and computes an instantaneous frequency and amplitude [14] [15]. The analytic signal amplitude by applying Hilbert transform is denoted by,

$$A(t) = \sqrt{\left(C^2(t) + C_H{}^2(t)\right)}$$

(2)

Where $c(t)$ represents IMF of signal and $c_H(t)$ for Hilbert transform of IMF. For each IMF instantaneous phase $\Phi(t)$ is given by Eq.3

$$\phi(t) = \arctan\left[C_H(t) / C(t)\right]$$

(3)

The important conditions for a meaningful definition of instantaneous frequency is based upon the analytic representation of the signal and that signal is symmetric with respect to the local zero mean, and has the same number of extrema and zero crossings[16]. Each order of IMF component contains different energy when the bearing works in different conditions. Energy of IMFs at some orders will decrease and that of the others it will increase. Hence IMF energies are combined as feature vector to realize some disorders in brain.

Energy feature of analytic signal is calculated as in Eq.4

$$Ej = \sum_{i=1}^{N} \left|C_j(t)\right|^2$$

(4)

where E_j represents the energy of the j^{th} IMF component, $c_j(i)$ denotes the i^{th} data point of the

j^{th} IMF component and N denotes the total number of samples present in each IMF [17] [18].

The feature vector gives sum of all energies of IMFs designated in Eq.5

$$E = \left(E_1 + E_2 + E_3 + ... + E_n\right)$$

(5)

IMF feature energy is used to separate normal and disturbed condition of mental tasks. Combining these IMF features and applied to proper classifier may help to increase accuracy.

III)RESULTS AND DISCUSSION

EMD method decomposes nonlinear and nonstationary data of EEG signal into limited set of narrow band AM-FM components which indicates computation of bandwidth due to amplitude and frequency modulation.

The IMFs are arraged from higher to lower frequency components. The complex demodulation decomposes raw EEG signal into 3 designated delta, theta, and alpha bands with complex EEG signal representation at sampled time instant, which enables the extraction of amplitude envelope and phase information.

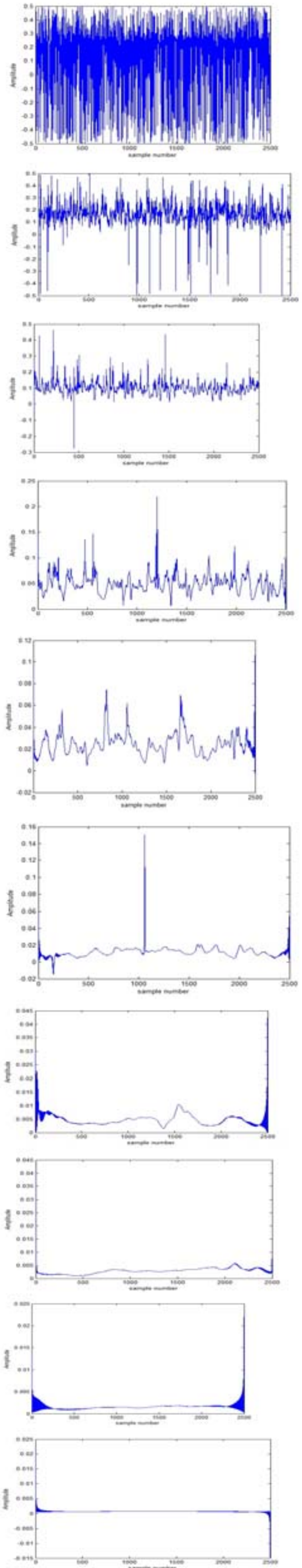


Fig.4A.Instantaneous frequencies of ten IMFs of Baseline data

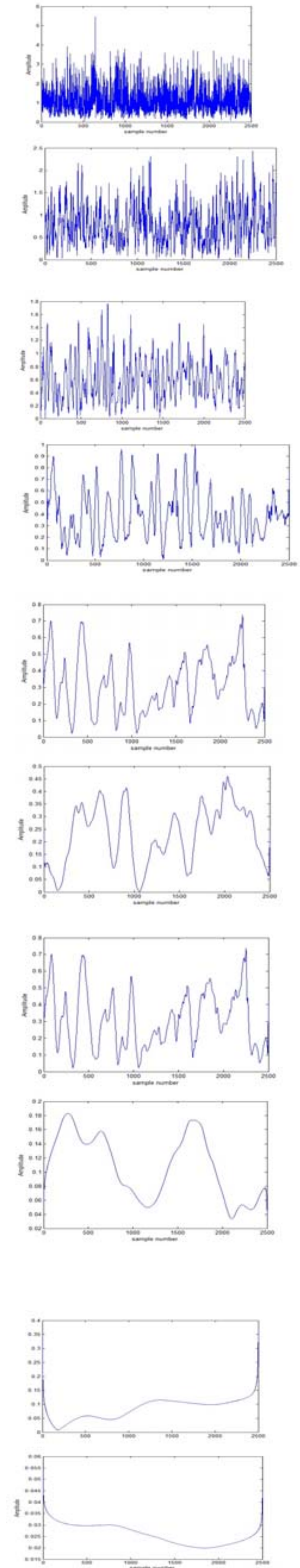


Fig.4.B.Instantaneous amplitudes of ten IMFs of Baseline data

The IMFs are arraged from higher to lower frequency components. The complex demodulation decomposes raw EEG signal into

3 designated delta, theta, and alpha bands with complex EEG signal representation at sampled time instant, which enables the extraction of amplitude envelope and phase information [19].

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