Feature Extraction for the Analysis of Multi-Channel EEG Signals Using Hilbert-Huang Technique

Mahipal Singh[#1], Rekha Goyat[*2]
[#]Assistant Professor, School of Electronics and Electrical Engineering,
Lovely Professional University, Jalandhar, Punjab, India.
[#]Corresponding Author: Email: mahip.lamboria@gmail.com
Ph no. +91-9779399908

***Abstract*- This research article seeks to propose a Hilbert-Huang transform (HHT) based novel feature extraction approach for the analysis of multi-channel EEG signals using its local time scale features. The applicability of this recently developed HHT based new features has been investigated in the analysis of multi-channel EEG signals for classifying a small set of non-motor cognitive task. HHT is combination of multivariate empirical mode decomposition (MEMD) and Hilbert transform (HT). At the first stage, multi-channel EEG signals (6 channels per trial per task per subject) corresponding to a small set of non-motor mental task were decomposed by using MEMD algorithm. This gives rise to adaptive i.e. data driven decomposition of the data into twelve mono component oscillatory modes known as intrinsic mode functions (IMFs) and one residue function. These generated intrinsic mode functions (IMFs) are multivariate i.e. mode aligned and narrowband. From the generated IMFs, most sensitive IMF has been chosen by analysing their power spectrum. Since IMFs are amplitude and frequency modulated, the chosen IMF has been analysed through their instantaneous amplitude (IA) and instantaneous frequency (IF) i.e. local features extracted by applying Hilbert transform on them. Finally, the discriminatory power of these local features has been investigated through statistical significance test using paired t-test. The analysis results clearly support the potential of these local features for classifying different cognitive task in EEG based Brain –Computer Interface (BCI) system.**

Keywords- Electroencephalogram (EEG) signal, Hilbert-Huang transforms (HHT), Multivariate Empirical Mode Decomposition (MEMD), Intrinsic Mode Functions (IMFs), Brain-Computer Interface (BCI)

I. INTRODUCTION

Electroencephalogram (EEG) signals represent electrical activity of brain and are measured noninvasively from the scalp using surface electrodes.These signals are highly complex and rich in information i.e. their dynamics contain a lot of information about human brain function and neurological disorders. These signals have very high temporal resolution i.e. they can reflect any subtle changes occurring in the brain activity pattern corresponding to cognitive brain function or neurological disorders. Decoding such subtle information by identifying the patterns in EEG signals is a formidable task since it is buried in the noise. Extracting representative features for accurate identification of such subtle changes in the brain activity pattern is the central challenge for any application of EEG analysis such as epilepsy detection, sleep stage monitoring, EEG based BCI system etc.

Among many techniques for non-stationary signal analysis, the suitability of the recently developed Hilbert-Huang transform has been investigated extensively for non-stationary signal analysis in diverse domains [1]. Another useful tool for non-stationary signal analysis comes in the form of the Teager–Kaiser Energy Operator (TEO) [2]. The Teager energy operator is a nonlinear operator that can be used for energy estimation of amplitude-frequency (AM-FM) modulated representations of a non-stationary signal, such as a surface electromyography signal [3]. The EEG signals are notoriously known as noisy, nonlinear and non-stationaryin nature. Besides their noisy background, these signals are non-Gaussian, nonlinear and non-stationary in nature. Due to theirvery complex nature, it is felt that there is a need to investigate more discriminatory features from their joint time-frequency localization. But, the time-frequency representation of a signal is not unique since a number of transformation methods such as Wavelet Transform (WT), Wavelet Packet transform (WPT) ,S-transform, Wigner Valley (WV) decomposition etc. are available. Due to this, finding an optimal time-frequency representation for a particular application has become an open research problem.

Till date, many research has been done using wavelet based time –frequency analysis of the EEG signals under normal and pathological conditions. The drawback of Wavelet based decomposition is that it is not adaptive to the data tobe analysed, i.e. It requires suitable a priori basis function for its decomposition. Due to this, wavelet based decomposition gives adequate performance for linear and stationary signals only. They give sub-optimal localization in the joint time- frequency representation and due to this their performance becomes inadequate for nonlinear and non-stationary signals. This has given rise to the development of anew adaptivei.e.

Data driven method called, empirical mode decomposition (EMD) whose performance has been established to be adequate in many cases of nonlinear and non-stationary real world data such as earthquake data, winds, ocean acoustic signals, mechanical vibration signals, biomedical signals etc. In contrast to wavelet based decomposition, EMD is a fully datadriven algorithm which does not require any apriori basis function for the multi scale decomposition of the signal. Consequently it has been applied toa large number of natural data sets and found to give better time-frequency localization suitable to the nature of the data to be analysed.
The main purpose of this research stems from the need of investigating new features extracted from the HHT based multi-scale analysis of the large scale dynamics reflected in the cognitive EEG signals and find their the applicability for developing pattern recognition based brain-computer interface. The proposed approach based on the combined application of multivariate EMD and Hilbert transform enabled us to decode the large scale brain dynamics at multi-scale accurately by unravelling their time-frequency structure embedded in the multichannel EEG data. Due to the use of multi-channel data, and their MEMD based decomposition, the proposed approach allows us to take into account the nonlinear, non-stationary and topographical variation of the brain signals. The novelty of our approach lies in using multichannel EEG data and analysing the same by combined application of multivariate extension of standard EMD (MEMD) and Hilbert transform (HT). Till date, analysis of large scale dynamics of brain networks at multi-scale using HHT based local features is limited. Researchers have used HHT based methods to examine sleep EEG signals. Yang et. al. proposed an HHT based spindle detection approach [4]. EMD has been used to decompose sleep EEGs intoseveral IMFs and the high resolution time-frequency Hilbert spectrum has been used to extract features of the sleep EEGs. The experiments show that the HHT based spindle detection approach is suitable for sleep EEG signals [5]. Causa et al used EMD and HHT for detecting and characterizing sleep spindles [6]. Chen et al used Hilbert-Huang spectral entropy for developing real-time EEG analysis method for use on patients under anaesthesia [7]. Zhang et al used EMD to decompose EEG signals into several IMFs and used different thresholds to treat and reconstruct the IMFs for de-noising the signals [8]. Rutkowski et al developed a new method of extending a single channel EMD approach to multichannel EEG signal analysis with steady-state responses for application to brain-computer interface (BCI). HHT based time-frequency analysis has been used to characterize ECG signals also [9]. John et.al. has been used EMD to decompose normal and various abnormal rhythms in ECG signals and then used a chaos analysis method to discuss the resulting IMFs [10]. Wu et.al. has been used EMD to decompose ventricular fibrillation (VF) ECG signals into several IMFs , and calculated the instantaneous phase of the resulting IMFs by using Hilbert transform.Multichannel EEG has necessitated the application of MEMD algorithm instead of standard EMD algorithm [11]. Standard EMD when applied to multi-channel data gives rise to two problems such as a) mode mixing and b) mode alignment. MEMD overcomes these two drawbacks of single channel EMD. Besides, the analysis of multichannel EEG on a channel by channel basis by employing standard EMD doesnot reveal the information on cross-channel interdependence of the EEG channels. This paper is organized as follows : After the introduction in section1, the dataset used and proposed methodology is presented in section 2, experimental results and discussions are presented in section 3 and finally conclusions are presented in section 4.

II. MATERIALS AND METHODS

This section describes the data set used in the current research and presents the methodology investigated.

A. EEG Dataset

The benchmark EEG data set used in this research comes from the experimental data set of Keirn and Aunon, from Purdue University.

This EEG dataset is publicly available. An Electro-Cap elastic electrode was used to record from six locations (such as C3, C4, P3, P4, O1 and O2, defined by the 10-20 system of electrode placement). EEG signals were recorded on 7 subjects, who performed five different tasks each. The tasks were

i. Base line task, which required subjects to relax and think of nothing in particular;
ii. Multiplication task, involving mental multiplication of 2 multi -digit numbers;
iii. Letter writing task, in which subjects mentally composed a letter without vocalizing;
iv. Geometric figure rotation task, requiring subjects to visualize a three dimensional object being rotated; and finally,
v. Counting task, in which subjects imagined a blackboard with numbers being written on it.The subjects performed the tasks in ten trial each over two days, and for each trial , EEG data was recorded from six electrodes at positions (C3,C4,P3,P4,O1,O2) for ten seconds at a frequency of 250 samples per second using Lab Master 12 bit A/D converter mounted on computer. Further details about the data are available in research paper mentioned in reference [2] and [8].

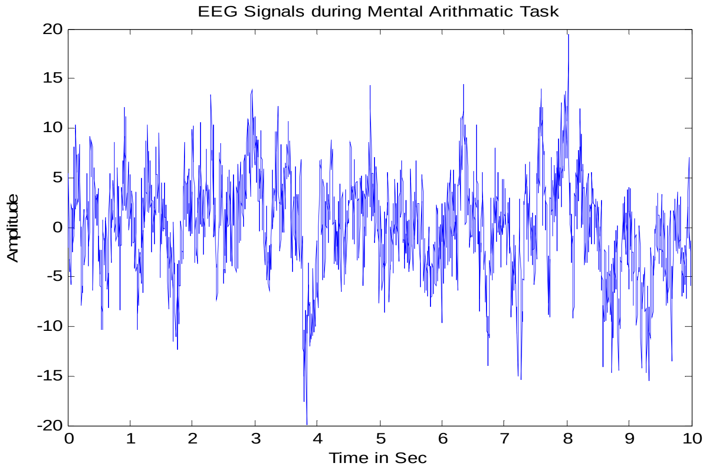


Fig.1. One Channel EEG Signal

B. Methodology

This section describes the methodology which had been adopted for the multi-scale analysis of the large scale brain dynamics contained in the multi-channel EEG data set using local features and different aspects of this methodology. The recent technology HHT is used to analyse the EEG Signals.

C. Empirical Mode Decomposition (Huang Transform)

Empirical mode decomposition (EMD) isan advanced signal processing algorithm used for multiscale and adaptive decomposition of nonlinear and non-stationary time series data. It decomposes the data set into a finite number of mono-component oscillatory modes known as intrinsic mode functions (IMFs). The IMFs which are modulated in amplitude and frequency are used as the bases of the decomposition. This decomposition is intuitive and gives adaptive i.e. signal–dependent decomposition. Moreover, the decomposition does not require any conditions about the linearity and stationarity of the signal. The principle of the EMD technique is to decompose a complicated signal x (t) iteratively into a set of band-limited functions known as intrinsic mode functions (IMFs). Each IMF satisfies two basic conditions : (i) in the complete data set , the number of extrema and the number of zero crossings must be the same or differ at most by one, ii) 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 first condition is similar to the narrow-band requirement the second condition is a local requirement induced from the global one, and necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by the asymmetric waveforms [9]. The EMD algorithm (Huang et al., 1998) for a signal x (t) can be summarized as follows:

i. Determine the local maxima and minima of x(t);
ii. Generate the upper and lower signal envelope by connecting those local maxima and minima respectively by an interpolation method;
iii. Determine the local mean $m_1(t)$, by averaging the upper and lower signal envelopes;
iv. Subtract the local mean from the data: $h_1(t) = x(t)-m_1(t)$.If $h_1(t)$ obeys the stopping criteria, then we have $d(t)=h_1(t)$ as an IMF , otherwise set $x(t) = h_1(t)$ and repeat the process from step(i).

Then, the empirical mode decomposition of a signal x (t) can be written as:

$$x(t) = \sum_{k=1}^{n} IMF_k\,(t) + \epsilon_n(t)$$

Where n is the number of extracted IMFs and the final residue ε_n (t) is the mean trend or a constant.

D. Multivariate Empirical Mode Decomposition

EMD has achieved optimal results in nonlinear and non-stationary data processing (Diez et al., 2009, Molla et al., 2010). However; this method presents several shortcomings in processing multi channel EEG data. The IMFs from different time series do not necessarily correspond to the same frequency ,and different time series may end up having a different number of IMFs .For computational purpose , it is difficult to match the different obtained IMFs from different channels (Mutlu and Aviyente,2011).

To solve these shortcomings, an extension of EMD to multivariate data is required. The multivariate EMD, recently introduced by Rehman and Mandic is a natural and generic extension of the standard EMD and BEMD. In this algorithm, the local mean iscomputed by takinganaverageofupperandlower envelopes, which in turn are obtained by interpolating between the local maxima and minima. However, in general, for multivariate signals, the local maxima and minima may not be defined directly. To deal with these problems, multiple n-dimensional envelopes are generated by taking signal projections along different direction in n-dimensional spaces (Rehman and Mandic, 2010). MEMD is the technique used in this paper tocompute all the decompositions.

The algorithm (Rehman and Mandic, 2010) can be summarized as follows:

(i) Choose a suitable point set for sampling on a $(n-1)$ sphere. (this $(n-1)$sphere resides in an n dimensional Euclidean coordinate system).

(ii) Calculate the projection , $p^{\theta_k}(t)\}_{t=1}^{T}$ of the input signal $v(t)_{t=1}^{T}$along the direction vector, x^{θ_k} for all k giving up $p^{\theta_k}(t)\}_{t=1}^{k}$

(iii) Find the time instants $t_i^{\theta_k}$ corresponding to the maxima ofthe setof projected signals $p^{\theta_k}(t)\}_{t=1}^{T}$

(iv) Interpolate$\left[t_i^{\theta_k}, v\left(t_i^{\theta_k}\right)\right]$ to obtain multivariate envelope curves $e^{\theta_k}(t)\}_{t=1}^{k}$

(v) For a set of K direction vectors, the mean of the envelope curves is calculated as $m(t) = \left(1/_K\right)\sum_{k=1}^{K} e^{\theta_k}(t)$

(vi) Extract the detail $d(t)$using $d(t) = x(t) - m(t)$.If the detail $d(t)$fulfils the stopping criterion for a multivariate IMF, apply the aboveProcedureto $x(t) - m(t)$, otherwise apply it to $d(t)$.

Then, the MEMD of a signal $x(t)$can be written as detailed in equation 1.The used stopping criterion is defined in (Rilling et al., 2003).

E. Hilbert-Huang Transform

Hilbert-Huang transform (HHT) method was put forward by Huang E in 1998 for the time frequency analysis of nonlinear and non-stationary signals. The various attempts using Spectrograms, Wavelet analysis and the neural network etc. have been made for the analysis of nonlinear and non-stationary data, but the Hilbert-Huang Transform (HHT) is unique and different from the existing methods of data analysis since its main part i.e. EMD does not require a priori functional basis. Unlike wavelet transform (WT) and fast Fourier transform (FFT), HHT can be applied to analyze both non-stationary and nonlinear signals. Both WT and FFT assumes linearity and stationarity of the data and requires a-priori basis functions which makes it difficult to present signal characteristics .On the other hand , HHT does not require any a-priori basis function, it is adaptive to the local characteristic time scales of the data to be analyzed.

The HHT consists of two parts: empirical mode decomposition (EMD) and Hilbert spectral analysis (HAS). This method is potentially viable for nonlinear and non-stationary data analysis, especially for time-frequency –energy representations. The physically meaningful way to describe such a system is in terms of the instantaneous frequency, which will reveal the intra-wave frequency modulations. The easiest way to compute the instantaneous frequency is by using the Hilbert transform. Using the Hilbert transform of a time series, it is possible to define an analytical signal, in which the Hilbert transform constitutes the imaginary part. The result of Hilbert transform of a time series is an analytical time series, a complex valued signal. Its amplitude and phase is time dependent .This introduces the concepts of instantaneous amplitude, instantaneous phase and instantaneous frequency. Instantaneous frequency is estimated from the time derivative of phase function.

The analytic signal z (t) of a real signal

x (t), can be obtained from:

$$z(t) = x(t) + iy(t) = a(t)e^{i\varphi(t)} \quad (1)$$

$$a(t) = [x^2(t) + y^2(t)]^{1/2} \quad (2)$$

$$\varphi(t) = arctan(\frac{y(t)}{x(t)}) \quad (3)$$

Where $a(t)$ and $\emptyset(t)$ are the instantaneous amplitude and phase of z(t) respectively. The instantaneous pulsation $\omega(t)$of $z(t)$ is expressed as$\omega(t) = \frac{d\omega(t)}{dt}$.

The Hilbert Transform

$$y(t) = \frac{1}{\pi}\lim_{\epsilon\to 0^+}\left(\int_{t-1/\epsilon}^{1-\epsilon}\frac{x(\tau)}{t-\tau}d\tau + \int_{t+\epsilon}^{t+1/\epsilon}\frac{x(\tau)}{t-\tau}d\tau\right)$$

F. Proposed analysis method based on Hilbert Huang Transform

Our proposed feature extraction and analysis approach based on the combined application of MEMD and Hilbert spectral analysis is shown in the flow chart given below.

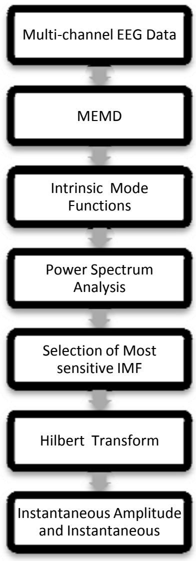


Fig. 2. Flow chart of the proposed method

III. RESULT AND DISCUSSION

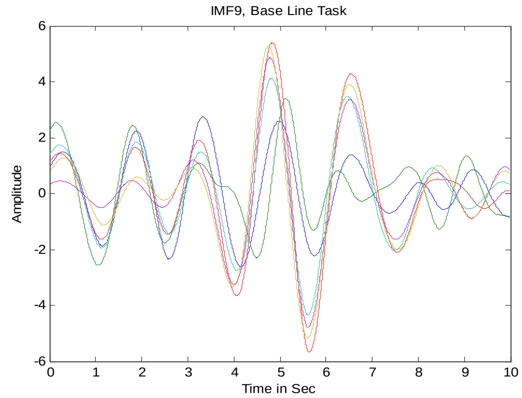
In this section , we present the results of the multivariate empirical mode decomposition (MEMD) based decomposition of the six channel (C3,C4, P3,P4,O1,O2) EEG data (per subject per task over multiple trial) corresponding to three different classes of non-motor cognitive tasks such base line, mental arithmetic and mental letter composing. MEMD based adaptive decomposition reveals the natural mono-component oscillations termed as intrinsic mode functions (IMFs) which are modulated in amplitude and frequency. Due to their AM/FM characteristics, they can reveal local characteristic timescales of the signal. The MEMD based decomposition resulted in the production of thirteen mono-component oscillatory modes which are mode-aligned and represent common frequency oscillations embedded in all the channels. Out of these thirteen components, first twelve are IMFs and the last one is residue representing the trend. The lower order IMFs correspond to high frequency componentswhereas higher order IMFs represents low frequency components. All these IMFs are not significant i.e. contain information relevant to a task. The significant IMFs usually hold unique characteristics such as they are usually of higher power. Due to this specific characteristic, most sensitive IMF can be identified through the analysis of their power spectrum. The IMF showing highest Power Spectral Density (PSD) in their power spectrum is considered asmost sensitive to a specific mental task. In Fig 3, the most sensitive IMFcorresponding to one trial of each mental task and its power spectrum has been shown. As shown in Fig3, IMF8 is the most sensitive IMF corresponding to mental arithmetic task, whereas IMF9 is the most sensitive IMF corresponding to mental letter composing and base line task. In the second stage, Hilberttransform is applied to the most sensitive IMF and the local features i.e. Instantaneous amplitude (IA) andinstantaneous frequency (IF) are estimated from their analytical representations. Feature vectors areformed from the statistical descriptors such as mean andstandard deviation of IA and IF of the most sensitive IMF.

Finally, we have performed statistical significance analysis of the extracted features for assessing their discriminatory power i.e. effectiveness in separating different classes using paired t-test. The suitability of the above mentioned features was supported by the results of the t-test with P-value approximately equals to zero indicating excellent statistical significance. The results of paired t test are displayed in TABLE II.

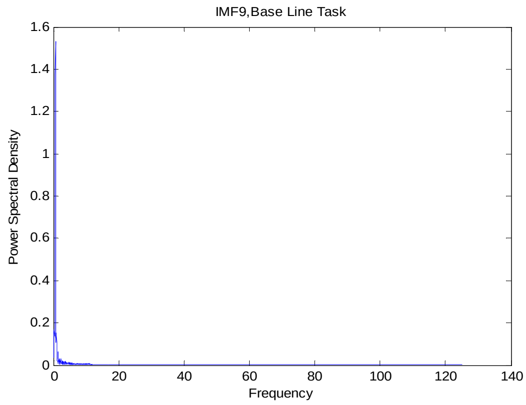
A. MEMD based Decomposition

At the first stage, we employed multivariate empirical mode decomposition (MEMD) algorithm instead of standard EMD algorithm to decompose all the six EEG channels simultaneously. This avoids the problems of mode mixing and mode alignment faced by standard EMD when applied to multi-channel data. The IMFs are produced iteratively by a procedure termed as sifting which involves projecting the signal onto basis functions adapted to the data. The generated IMFs which are modulated in both amplitude and frequency are mode aligned and represent an oscillatory mode having single frequency or a very narrow frequency band common to all the six channels. Fig 3 (a1) illustrates the result of decomposition of a six channel EEG signal corresponding to base line task (trial1, subject1) performed by MEMD. The Fig 3 (b1) shows the result of decomposition of a six channel EEG signal corresponding to mental arithmetic task (trial1, subject1). The Fig 3 (c1) illustrates the result of decomposition of a six channel EEG signal corresponding to mental letter writing task (trial1, subject1). The main goal of this first stage was to extract the common intrinsic oscillatory modes from each and every trial of a six channel EEG signal.

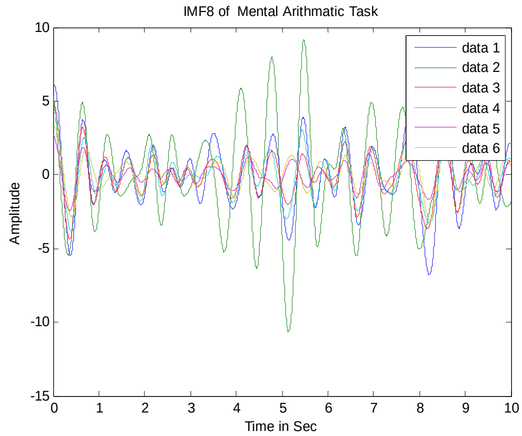
The application of multivariate EMD (MEMD) algorithm on six channel EEG data corresponding to one trial of each task resulted in twelve multivariate intrinsic mode functions (IMFs) and one residue. These IMFs are mode aligned and represent mono-component oscillatory modes common across the six EEG channels. All the twelve IMFs have been analyzed through their power spectral density (PSD) obtained using Welch method. From Fig 3 (a2, b2 and c2), it has been observed that for each trial of a mental task, a particular IMF9 is having highest value of PSD i.e. the signal power is concentrated in that oscillatory component represented by the same IMF. This particular IMF9 may be considered as the most sensitive IMF for that task. For each and every trial of mental arithmetic task, the most sensitive IMF is found to be IMF8 whereas for both mental letter composing and baseline task, the most sensitive IMF is found to be IMF9.



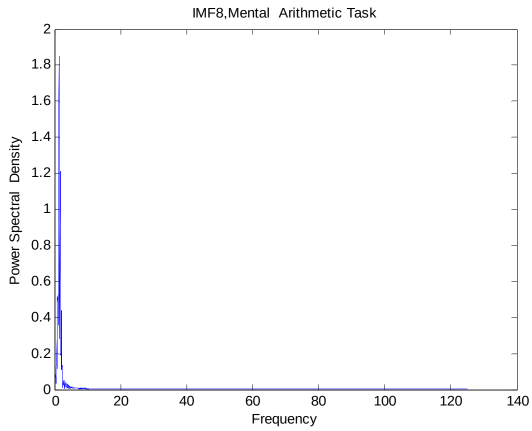
(a1)



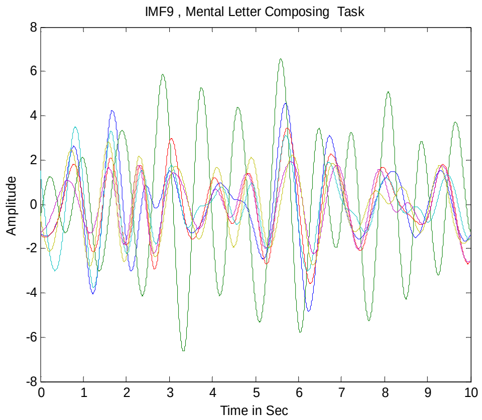
(a2)



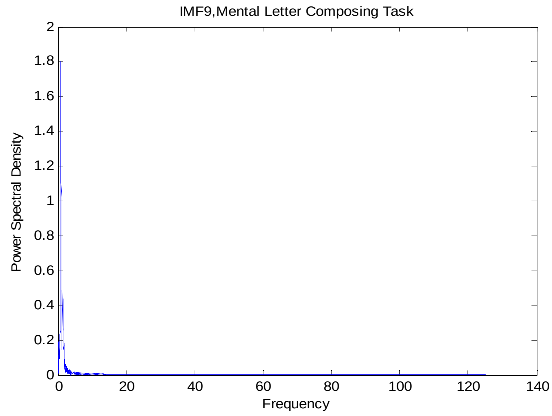
(b1)



(b2)



(c1)



(c2)

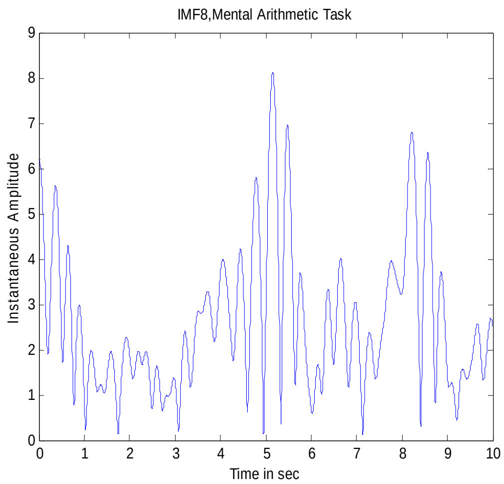
Fig.3. Illustrates the waveform and its associate power spectrum of the most sensitive IMF obtained from the MEMD base decomposition of a single trial (10 sec duration) of six channel EEG signals under three different mental tasks.

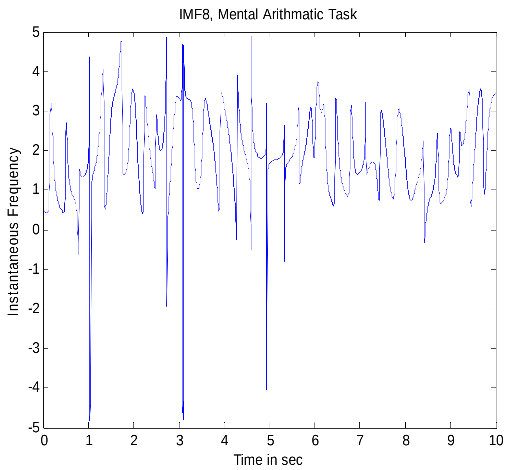
Decomposition of a six channel EEG by MEMD. The first time series is the EEG signal. The decomposition yields 12 IMF and a residual. The IMFs are the time-frequency constituents or components of the EEG signal. Frequency content is ordered in a descending order (IMF1 has the highest frequency content).

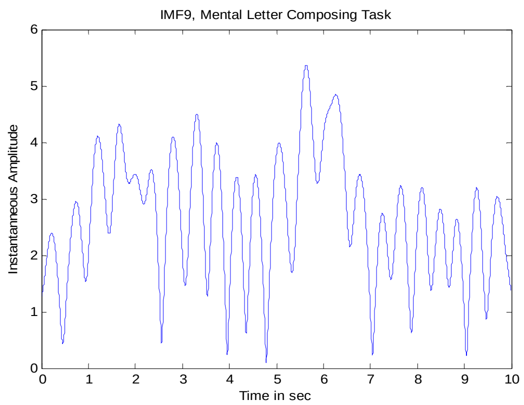
B. Analysis of IMFs.

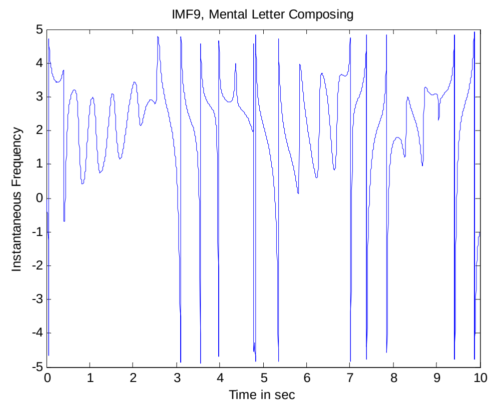
At the second stage, all mode aligned IMFs of a single trial EEG were analysed in the frequency domain through their power spectrum. The most sensitive IMF is determined from these by comparing their power spectrum and found to have the highest power spectral density.

Hilbert transform was applied to the most sensitive IMF of each trial of a particular mental task. The aim was to track their local features i.e .instantaneous frequency (IF) and instantaneous amplitudes (IA). Instantaneous frequency (IF) and Instantaneous amplitude (IA) of the most sensitive IMF is estimated from their analytic representation obtained by computing its Hilbert transform and it is shown in Fig 4 for three different mental task stated above. Finally, the statistical descriptors i.e. mean and standard deviation ofboth IF and IA were calculated as class representative features. The statistical significance of these features was tested using paired t-test. The t-test results support their discriminatory power for separating the two different classes of mental tasks.









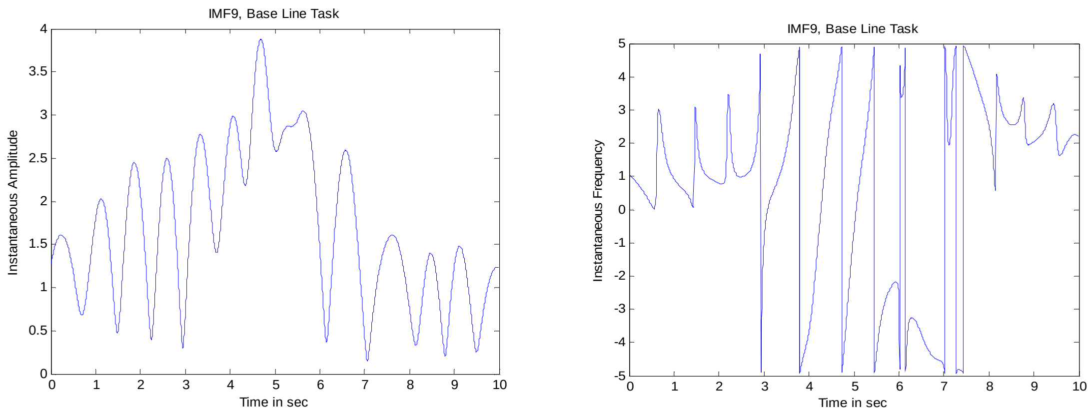


Fig: 4. Characteristics of most sensitive IMF corresponding to each trial of different mental task EEG signal.

D. Discussions

Due to the nonlinear and non-stationary nature of brain signals, their analysis method calls for their decomposition giving better localization in the joint time-frequency domain as compared to time or frequency domain alone. Though a plethora of time-frequency method is available, but the recently developed Hilbert-Huang transform has been found promising in representing many real world nonlinear and non-stationary processes . HHT offers several advantages over Short-Time Fourier transform (STFT) or Wavelet transform. First it does not project the time series data onto a fixed basis; rather, it adjusts the frequency band of interest adaptively based on the signal envelopes. Second, the time and frequency resolutions of HHT are also adaptive, so that this method potentially provides far more accurate estimates over regions of `interest. A visual comparison between Fig 1 and Fig 2 may lead to a qualitative discrimination of the signals. A quantitative discrimination based on local frequency/amplitude can be obtained from the HS spectrum by applying Hilbert-Huang transform. The application of MEMD on the six channel (c3, c4,p3,p4,o1,o2) EEG signals corresponding to three different mental task gives rise to finite number of mode aligned multivariate Intrinsic Mode Functions(IMFs) , where each IMF represents one mono or narrow band oscillatory component having frequency of oscillation common across the channels. Due to simultaneous decomposition of the multichannel data by MEMD algorithm, equal number of mode aligned IMFs are generated per channel. Applying Hilbert transform to these IMFs provides instantaneous information on amplitude, frequency, energy etc. The proposed method offers the advantage of instantaneous frequency /energy tracking which is very necessary for non-stationary signals and outperforms other methods based on only average values. Thus, it can also be used as an online technique. The local features extracted from the HHT based multichannel analysis of three different mental tasks are presented in Table1.

TABLE I. HHT based local features from the most sensitive IMF of each trial of a mental task

HHT based Local Features					
Class Of Mental Task	Trial	IA_Mean	IA_Std	IF_Mean	IF_Std
	1	1.7294	0.8017	0.0273	0.0095
	2	2.5245	1.4185	0.0275	0.0098
	3	1.7286	1.3161	0.0316	0.0221
	4	1.1439	0.5006	0.0311	0.0441
Mental Arithmetic	5	0.8911	0.4096	0.0313	0.0127
	6	2.4158	1.0683	0.0275	0.0121
	7	2.1785	1.0235	0.0275	0.0121
	8	2.7787	1.6428	0.0668	0.0271
	9	3.0339	2.2417	0.0628	0.0310
	10	2.5573	1.3372	0.0627	0.0365
	1	2.7528	1.8169	0.0548	0.0548
	2	3.3749	1.1743	0.0550	0.0208
	3	2.4141	1.0593	0.0509	0.0482
	4	1.8088	1.0950	0.0550	0.0287
Mental Letter Composing	5	2.2391	1.2681	0.0316	0.0279
	6	2.0398	0.4775	0.0312	0.0119
	7	1.5664	0.6226	0.0315	0.0073
	8	1.4003	0.8671	0.0353	0.0111
	9	2.8745	1.2225	0.0237	0.0213
	10	2.3514	1.7087	0.0273	0.0163
	1	2.9380	0.7184	0.0235	0.0102
	2	1.9946	1.2337	0.0388	0.0375
	3	1.2016	0.6257	0.0272	0.0196
	4	3.7794	1.7685	0.0273	0.0135
Base Line	5	2.8609	1.5665	0.0550	0.0255
	6	2.1968	0.9776	0.0273	0.0135
	7	3.5497	2.0982	0.0510	0.0196
	8	1.4111	0.9054	0.0194	0.0421
	9	3.0858	1.0677	0.0194	0.0164
	10	1.3144	0.9133	0.0335	0.0389

C. Significance testing of the extracted features using paired t-test

TABLE II. The P –values resulting from the statistical paired t-test between two classes

HHT based Local Features				
	IA based		IF based	
Classes	Mean	Standard Deviation	Mean	Standard Deviation
Mental Arithmetic Versus Base Line	0.0542	0.0316	0.0000	0.0197
Letter Composing Versus Base Line	0.2420	0.8559	0.9809	0.7259
Mental Arithmetic Versus Letter Composing	0.1787	0.1356	0.0000	0.0132

Finally we investigated the class discrimination ability of the HHT based local features based on the mean and standard deviation of instantaneous frequency (IF) and instantaneous amplitude(IA) by performing paired t- test on them.

The results of statistical significance test between the extracted features of a pair of mental task using paired ttest are presented in Table 2. The p value indicates the discrimination power of these instantaneous information based features. The p-values show significant differences between the data of any pair of mental tasks. The main contribution of our research comes from the useof multi-channel EEG signals and subsequent application of MEMD for their decompositions. Though standard EMD based channel by channel analysis of these EEG signals has been done, till date no research report is available in the literature presenting MEMD based simultaneous decompositions of these multichannel EEG signals. The application of MEMD enabled us to reveal the additional information on cross-channel interdependence which is missed by standard EMD algorithm. With this HHT based multichannel analysis method, we added a new spatial dimension apart from time-spectral for delving deeper into the topographical variation of the subtle dynamics hidden in the multichannel EEG signals. We demonstrated that these HHT based novel feature should better potential to be used as a tool in the arsenal of EEG analysis techniques. The test result supports in favour of its potential to be extended too many other application areas of EEG analysis such as detection of neurological disorder, brain-computer interface and understanding brain functions etc.

IV. CONCLUSIONS

In the current research, we have investigated the applicability of HHT based new features extracted from the statistical descriptors of local information i.e. IA and IF of the most sensitive IMF corresponding to a mental task EEG signal and assessed their class discrimination power using paired t test. These features capture the large scale dynamics of brain networks during a mentaltask at multi-scale. HHT based multichannel analysis of the signals enabled us to reveal the correlation among the channels and opened up the possibility to identify different brain states under different cognitive tasks. We extracted local features i.e. mean and standard deviation of instantaneous frequency (IF) and instantaneous amplitude (IA) [9] obtained from the analytic representation of the IMF having highest value of power spectral density (PSD). The feature values were tested for their class discrimination power ($p< .05$) using paired t test. The results of paired t test supporttheir applicability to be used as feature vector for any classification application. The outcome of our analysis opensup a number of directions for further analysis of EEG signal in diverseapplication domains. Besides different application domains, the selection of sensitive IMFs using different selection criterion, the number of IMFs to be used for feature extraction and many other nonlinear features such as correlation dimension, Lyapunov exponent, entropy etc provides the basis of further research .

REFERENCES

[1] N.E.Huang, Z.Shen, S,R.Long, M.C.Wu, H. H. Shoh, Q. Zhenge, N. C. Yen, C. C. Tung and H, H, Liu, The empirical mode decomposition and the Hilbert Spectrum for nonlinearandnon-ststionary time series analysis, Proceeding of the royal Society of London, Series A:Mmathematical, Physical and Engineering Sciences, Vol.454, Issue.1971, March 1998,pp.903-995.

[2] P.F.Diez, V.Mut, E.Laciar, A.Torres and E.Avila, "Application of the empirical mode decomposition to extraction of features from EEG signals for mental task classification",31st Annual international Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, September 2-6,2009,pp. 2579-2582.

[3] M.F.Kaleem, L.Sugavaneswaran, A. Guergachi, S. Krishnan, "Application of Empirical Mode Decomposition and Teager Energy Operator to EEG Signals for mental task classification", Annual International Conference of the IEEE Engineering in Medicine and Biology Society , Buenos Aires, Aug 31- sept 4, 2010,pp.4590-4593

[4] Tomasz M. Rutkowski, Danilo P. Mandic,AndrzejCichocki, and Andrzej W. Przybyszewski, "EMD Approach to Multichannel EEG Data -The Amplitude and Phase Synchrony Analysis technique", D.-s. Huang et al. (Eds.): ICIC , Springer-Verlag, Berlin Heidelberg,2008,LNCS 5226,PP.122-129

[5] CheolsooPark,DavidLooney,NaveedurRehman, AlirezaAhrabian, and Danilo P. Mandic,"Classification of Motor Imagery BCI Using Multivariate Empirical Mode Decomposition",IEEE Transactions on Neural Systems and Rehabilitation Engineering,Vol.21,Issue.1.Jan 2013,pp.10-22

[6] A. Roy, Wen Chun-Hsien J.F. Doherty, J.D. Mathews," Signal Feature Extraction from Microbarograph Observations Using the Hilbert–Huang Transform ", IEEE Transactions on Geoscience and Remote Sensing, May 2008, pp. 1442 - 1447

[7] Xie .Hongbo, Wang. Zhizhong,' "Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis",Computer Methods and Programs in Biomedicine, Volume 82, Issue 2, May 2006, Pages 114–120

[8] Lorena Orosco, Eric Laciar, AgustinaGarcesCorrea, Abel Torres, and juan P. Graffigna, "An Epileptic Seizures Detection Algorithm based on the Empirical Mode Decomposition of EEG" 31st Annual International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, September 2-6,2009,pp.2651-2654.

[9] Qin Shuren and JiZhong, "Extraction of features in EEG signal with the non-stationary signal analysis technology", 26th Annual International Conference of the IEEE EMBS, SanFrancisco, CA.USA, September 1-5, 2004, pp.349-352.

[10] C.W.Anderson and J.A. Bratman, "Translating Thoughts Into Actions by Finding Patterns in Brainwave", Fourteenth Yale Workshop on Adaptive and learning Systems, Yale University, New Haven, CT, USA, June 2008, pp.1-6.

[11] Jean-Christophe Cexus and Abdel QuahabBoudraa, "Non-Stationary Signal Analysis by Teager-Huang Transform". 14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006.

[12] Patrick Flandrin, Paulo Goncalves and Gabriel Rilling, "Detrending and denoising with empirical mode decompositions", 12th European Signal Processing Conference, Vienna, Austria, September 6-11, 2004,pp. 1581-1584.

[13] Bradley Metthew Battista, CameliaKnapp,TomMc Gee and Vaughn Goebel, Application of the empirical mode ecompostion and Hilbert huang transform to sismic reflection data, Geophysics. Vol.71, Issue.2, March-April 2007, pp.H29-H37.

[14] KonstantinosDrakakis, Empirical Mode Decomposition of Financial Data, International Mathematical Forum, Vol.3, Issue. 25, 2008, pp. 1191-1202.

[15] F. Jabloun, A.E.Cetin, E. Erzin , Teager energy based feature parameters for speech recognition in car noise, IEEE Signal Processing Letters, Vol.6, Issue. 10, October 1999, pp.259-261.

[16] P.Maragos, J.F.Kaiser, and T. F. Quatieri, On amplitude and frequency demodulation using energy operators, IEEE Transactions on Signal Processing, Vol. 41, Issue. 4, 1993, pp. 1532-1550.

[17] Richard Lauer and Laura Prosser, Use of the Teager-Kaiser Energy Operator for Muscle Activity Detection in Children, Annals of Biomedical Engineering, Vol. 37, Issue.8, 2009, pp.1584-1593.

[18] Zhidong Zhao and Chan Ma, "An Intelligent System for Noninvasive Diagnosis of Coronary Artery Disease with EMD-TEO and BP Neural Network", International Workshop on Education Technology and Training, 2008. And 2008 International Workshop on Geoscience and Remote Sensing. ETT and GRS 2008, pp. 631-635.

[19] MehrnazShokrollahi, Sridhar Krishnan, Dana Jewell and Brian Murray, "Analysis of the Electromyogram of Rapid Eye Movement Sleep using Wavelet Techniques", 31^{st} Annual International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, September 2-6,2009,pp.2659-2662.

AUTHOR PROFILE

Mahipal Singh is working as an Assistant Professor in the Department of Electronics and Electrical Engineering, Lovely Professional University, Jalandhar, Punjab, India. I did my B.Tech degree from Maharishi Dayanand University, Rohtak, Haryana and the Master in Technology degree from Lovely Professional University, Jalandhar. Currently i am pursuing Ph.D (part time) from Dr. B.R. Ambedkar National Institute of Technology, Jalandhar, Punjab, in the field of Cognitive Ergonomics.

Rekha Goyat has completed their Master in Technology degree from Punjab Technical University, Jalandhar, Punjab. I did my B.Tech degree from Maharishi Dayanand University, Rohtak, Haryana.