

A Novel Approach for the Analysis of Multi-Channel EEG Signal using Advance Technique

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Abstract

Objectives: In this research paper, Electroencephalogram (EEG) is recorded by placing electrodes on the scalp for different mental task. The significant features are extracted for three different mental tasks as mental arithmetic, baseline and letter composing. **Methods/Statistical analysis:** In the EEG signals, there are many features which having some significant information and some having false. The significant features are extracted by using advance techniques as Multivariate Empirical Mode Decomposition (MEMD) and Hilbert-Huang Transform (HHT). The t-paired test is used for determining the discrimination power of extracted features. **Findings:** After applying MEMD techniques we have achieved twelve multivariate Intrinsic Mode Functions (IMFs) and one residue. Most sensitive IMFs are selected by calculating Power Spectral Density (PSD) of each IMFs functions by Welch method. The Instantaneous Amplitude (IA) and Instantaneous Phase (IP) from most sensitive IMF are investigated by using Hilbert Huang transform (HHT) and features such as min., max., Skewness and kurtosis are extracted from IA and IP. The feature values are tested for their class discrimination power ($p < .05$) using paired t test. The results of paired t test support their applicability to be used as feature vector for any classification application. Accuracy nearby 80% to 90% is procured for different mental task EEG signals by using these extracted features. **Application/Improvements:** The investigated results are applicable for Brain Computer Interface. If a handicapped person (his hands and legs are not working/living) wants to write some letters on the screen of a desktop, so by putting the electrode on scalp and by measuring the electrical signals of his/her brain through EEG, we can apply these significant features for converting the electrical signals in to letters with the help of computer. In this research, we have investigated only linear feature, so further research area is open for investigating of Non-linear features of EEG signals.

Keywords: Brain Computer Interface (BCI), Electroencephalogram (EEG), Hilbert-Huang Transform (HHT), Intrinsic Mode Function, Multivariate Empirical Mode Decomposition (MEMD)

1. Introduction

Different activities of our body are controlled by active part of brain and the functions of this active part can be examined by neural activity of neuron. With the help of EEG signal these neural activity of brain is measured in terms of voltage or current within very small period

of time with the help of electrodes. Brain signals are composite and fully abundant in information. The information about functionality of brain is dynamics in nature. The EEG signals have very high temporal resolution. Due to brain cognitive function and any neurological disorders change also occurs in EEG signal because these signals are non linear, non stationary

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and non Gaussian in nature. So extracting crucial features of such precise changes in the activity of brain is the central challenges for researcher. EEG spectrum contain some characteristics waveforms within five frequency bands like-delta (0.5-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz) and gamma (>30 Hz). The amplitude as well as frequency undergoes changes during different cognitive mental task .Brain abnormalities and various neurological disorders have been recognized with the help of EEG signal analysis and brain computer interface is used for this purpose. BCI connects the brain activities of the user to the computer and control various devices with the brain signal, without using any muscular activities. BCI system basically consist some stages such as signal acquisition, preprocessing of EEG signal, features extraction and classification. For non-stationary types of signal analysis HHT has been investigated in diverse domain². Another tool for non-stationary signal analysis Teager–Kaiser Energy Operator (TEO) also investigated⁷. It is a non linear energy operator used for non linear signal such as surface electromyography signal representation in terms of energy estimation of Amplitude–Frequency (AM-FM) modulated signal¹⁴. EEG signals are also nonlinear, non-stationary, noisy and random in nature and due to complex nature of EEG signals there is a need to investigate more essential features that have more discriminatory power for their joint time-frequency localization. A large numbers of joint time–frequency techniques like Wavelet transform (WT), S-transform, Empirical Mode Decomposition (EMD) and Hilbert transform etc. are available. For a particular application, finding best time–frequency techniques also become an open research problem of researcher. By using time-frequency based WT many research has been done but this transform give better results only for stationary and linear signal. So the performance becomes insufficient for non-stationary and non-linear signal by using Wavelet transform. A new flexible method called EMD has been investigated that give sufficient results for non-linear and non-stationary signals.

EEG signals are firstly collected and represented using special filters by the method of signal acquisition. Then acquired signal is preprocessed where raw EEG data is translated into the estimated mental state and artifacts are removed. Features extraction describes the EEG signals by a few relevant values called features. Such

features should represent the information placed in EEG signals. All extracted features are arranged into a vector called features vector. Classification allocate a class to a set of features extracted from the signals and different algorithm and classifier are used to obtain accuracy to the system and different algorithm and classifier are used to obtain accuracy to the system.

2. Materials and Method

This section describes the data set used in this research and presents the methodology to be used.

2.1 EEG Data Set

EEG data set used in this research comes from the experimental data set of Keirn and Aunon, from Purdue University. The data of the dataset are recorded from the electrodes. Data is a cell array and each individual cell array is made up of a subject string, task string, trials string and data array. A 10-20 system of electrode placement was used and an Electro-Cap elastic electrode namely C3, C4, P3, P4, O1 and O2 recorded the neural activity of the subjects and A1 and A2 were reference electrodes. EEG signals were recorded on seven subjects and five different tasks were performed by the seven subjects. The five task were¹

- i. Baseline task-In this task the subject was made to relax and think of nothing in particular.
- ii. Multiplication task-This task involves any mathematical problem such as multiplication is given to subject and he solves it mentally without making any physical movement
- iii. Letter-composing task- in which subjects composed a letter mentally without any written action.
- iv. Geometric figure rotation task perform rotation mentally about an axis.
- v. Number counting task-This task involves the subjects imagined a blackboard and mentally count the numbers being written on it.

EEG data was recorded from six electrodes for duration of 10 seconds for each task and total number of 2500 samples per trials. The subject completed the tasks in ten trials and attended two sessions, the task was repeated five times in each session. Sampling rate 250 Hz was selected for the dataset³.

2.2 Methodology

This section describes the method's which had been adopted for the multi-scale analysis of EEG data set.

2.2.1 Empirical Mode Decomposition

EMD is a signal processing algorithm used for adaptive and multiscale decomposition of nonlinear and non-stationary time series data. A dataset can be decomposed into a finite number of mono-components known as IMFs. IMFs represent a simple oscillatory harmonic function. The IMFs which are modulated in amplitude, phase and frequency are used as the bases of the decomposition. This decomposition is intuitive and adaptive i.e. signal – dependent decomposition. This decomposition does not require conditions about the linearity and stationarity of the signal. The principle of this technique is to decompose complicated nonlinear signal $x(t)$ iteratively into a set of band-limited functions known as IMFs. Each IMF satisfies two basic conditions: (i) the number of extrema and the number of zero crossings in the complete data set must be the same or differ at most by one, (ii) at any point, the mean value of the envelope defined by local maxima and the envelope defined by local minima is zero⁴⁻⁶. The EMD algorithm is summarized as follows^{8,9}:

- i. Determine the extrema (maxima and minima) of the data set $x(t)$;
- ii. Generate the upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$, respectively by connecting the maxima and minima separately with cubic spline interpolation;
- 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).
- v. Then the decomposition of the signal $x(t)$ can be written as:

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

2.2.2 MEMD

The multivariate EMD is advanced methods of the standard EMD. EMD has achieved good results for non-stationary and nonlinear signals¹⁰. But in processing of multichannel EEG data this method presents several limitations. The IMFs from different time series having

a different number of IMFs, means they do not have the same frequency. So it is very difficult task to achieve the same number of IMFs for different channels. To overcome this problem multivariate EMD is required. The algorithm is summarized as follows¹²⁻¹⁹:

1. Select an appropriate point set on an $(n-1)$ sphere for sampling purpose.
2. p^{θ_k} is projection $(t)_{t=1}^T$, of the input signal $\{v(t)\}_{t=1}^T$ with direction vector x^{θ_k} , for all k (the whole set of direction vectors), giving $p^{\theta_k}(t)_{k=1}^K$ a particular set of projections.
3. Find the time instants $\{t_i^{\theta_k}\}$ corresponding to the maxima of the set of projected signals $p^{\theta_k}(t)_{k=1}^K$.
4. Interpolate $[t_i^{\theta_k}, v(t_i^{\theta_k})]$ to obtain multivariate envelope curves $e^{\theta_k}(t)_{k=1}^K$.
5. For a set of K direction vectors, the mean $m(t)$ of the envelope curves is calculated as

$$m(t) = \frac{1}{K} \sum_{k=1}^K e^{\theta_k}(t)$$
6. Extract the 'detail $d(t)$ ' using $d(t) = x(t) - m(t)$. If the 'detail $d(t)$ ' fulfills the stoppage criterion for a multivariate IMF, apply the above procedure to $x(t) - d(t)$, otherwise apply it to $d(t)$.

2.2.3 Hilbert Huang Transform

This method was developed by Huang E for time-frequency analysis of nonlinear and non-stationary signals. HHT is adaptive and does not require any a-priori basis function. HHT basically consists of two parts: first part is EMD and second part is Hilbert transform. The instantaneous frequency is physically meaningful for this system which is calculated with the help of Hilbert transform. An analytic signal is defined by using Hilbert transform which consists the imaginary part its amplitude and phase is time dependent. Due to this, three concepts were introduced, the IA, the phase functions and the instantaneous frequency. Instantaneous frequency is obtained from the time derivative of phase function.

$x(t)$ is a real signal. The analytic signal can be obtained from⁹⁻¹¹:

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

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

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

Where $\phi(t)$ and $a(t)$ are the IP and amplitude of $z(t)$. The instantaneous frequency $\omega(t)$ of $z(t)$ is expressed as
$$\omega(t) = \frac{d\phi(t)}{dt} \quad \omega(t) = \frac{d\phi(t)}{dt}$$

3. Result and Discussion

In this study, we present the results of FFT, MEMD and HHT based decomposition of six channel (C3, C4, P3, P4, O1, O2) EEG data (per subject per task over multiple trial) corresponding to three different tasks such as base line, mental arithmetic and mental letter composing. MEMD based adaptive decomposition provides the IMFs which are modulated in amplitude and frequency. Due to MEMD based decomposition resulted in the production of thirteen mono-components oscillatory modes which are mode-aligned and represent common frequency oscillations embedded in all the channels. First twelve are IMFs and the last one is residue representing the trend out of these thirteen components. Higher order IMFs represents low frequency components and the lower order IMFs correspond to high frequency components.

All these IMFs are not useful. The useful IMFs hold unique characteristics such as they are of higher power. Due to this specific characteristic, with the help of the analysis of their power spectrum, most sensitive IMF can be identified. Out of these thirteen IMF, the IMF showing highest PSD in their power spectrum is considered as most sensitive to a specific mental task. With the help of analysis of power spectrum, IMF9 is the most sensitive IMF corresponding to mental letter composing and base line task and IMF8 is the most sensitive corresponding to mental arithmetic task¹. After MEMD decomposition, Hilbert transform is applied to the most sensitive IMF and the local features i.e. IA and IP are estimated from their analytical representations.

3.1 Decomposition Based on MEMD

At the first stage, MEMD algorithm is employed instead of standard EMD algorithm to decompose all the six EEG channels simultaneously. MEMD avoids the problems of mode mixing and mode alignment. The generated IMFs which are modulated in both amplitude and phase are mode aligned and represent an oscillatory mode having single frequency or a very

narrow frequency band common to all the six channels. The principle of first stage was to extract the common intrinsic oscillatory modes from each and every trial of a six channel EEG signal.

When MEMD algorithm is employed on six channel EEG data resulted in twelve multivariate IMFs and one residue. These IMFs are mode aligned and represent mono-component oscillatory modes common across the six EEG channels have been analyzed through their obtained. PSD of all the twelve IMFs is obtained by using Welch method. After analysis of power spectrum, it is observed that for each trial of a mental task, a particular IMF is having highest value of PSD. For each trial of mental task this particular IMF may be considered as the most sensitive IMF. IMF9 is most sensitive for each and every trial of baseline task and letter composing and IMF8 is most sensitive for mental arithmetic task.

The statistical descriptors such as max, min, skewness and kurtosis of IA and IP of the most sensitive IMF and at last, we 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.

3.2 Hilbert Transform

At the second stage, Hilbert transform was applied to the most sensitive IMF of each trial of a particular mental task. The aim was to extract their local features i.e. IP and IAs. Finally, the statistical descriptors i.e. mean second maximum, minimum and standard deviation of both IP and IA were calculated as class representative features. Using paired t-test the statistical significance of these features was tested. The t-test results support their discriminatory power for separating two different classes of mental tasks. This EEG signal obtained a time series and after decomposition we obtained 12 IMF and a residual. The Figure 1 (as shown in appendix) represents the characteristics of most sensitive IMF corresponding to each trial of a mental task EEG signal for IA and Figure 2 (as shown in appendix) shows the characteristics of most sensitive IMF corresponding to each trial of a mental task EEG signal for IP as shown in appendix.

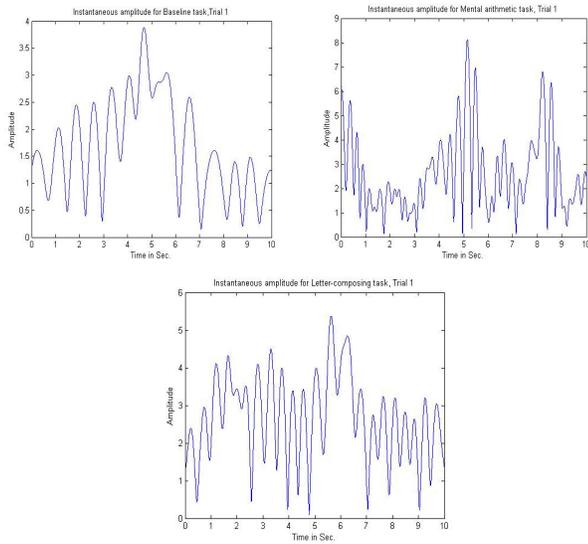


Figure 1. Characteristics of most sensitive IMF corresponding to each trial of a mental task EEG signal of IA.

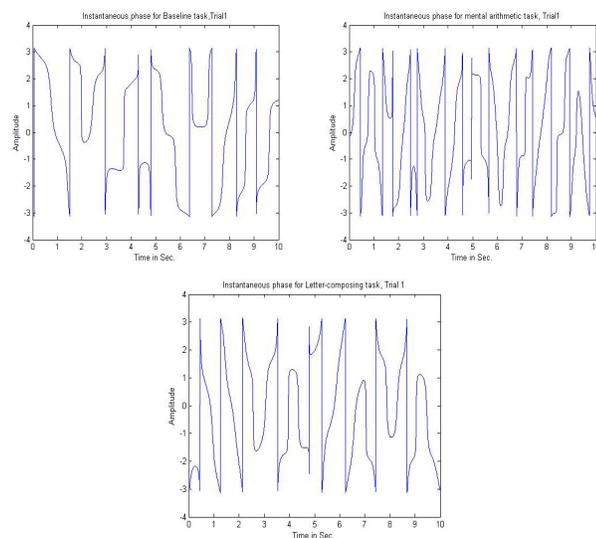


Figure 2. Characteristics of most sensitive IMF corresponding to each trial of a mental task EEG signal of IP.

Table 1(as shown in appendix) represents the local features for HHT based using Instantaneous amplitude and IP from the most sensitive IMFs. In this table, the readings were noted down for 10 trials in each mental task.

4. Discussions

The signals which are generated by brain are complicated nonlinear and non-stationary, due to this reason analysis

method for their decomposition giving better result in joint time-frequency domain as compare to time domain or frequency domain alone. Hilbert-Huang is a time-frequency method and has been investigated for nonlinear and non-stationary process. HHT offers several advantages over FFT (Fast Fourier transform) or wavelet transform. First this method provides more accurate estimates because the time and frequency resolutions of HHT are also adaptive. Second, it adjusts the frequency band adaptively based on the signal envelopes. The application of MEMD on the six channels EEG signal corresponding to three different mental tasks provides finite number of aligned IMFs. Each IMF represents one mono oscillatory component having common frequency of oscillation across the channel. With the help of MEMD algorithm, equal number of mode aligned IMFs are generated per channel. These IMFs provide information on amplitude, frequency, phase, energy etc. Applying HHT local features extracted from multichannel analysis of three different mental tasks are presented in Table 1 as shown in appendix. At last with the help of paired t-test on HHT based local features based on skewness, maximum, minimum and kurtosis of instantaneous amplitude and instantaneous phase, we investigated the class discrimination ability. The p-value represents difference between the data of any pair of mental tasks. The main contribution of our research comes from application of MEMD for multi channel EEG signals decompositions and application of MEMD provides the additional information on cross-channel interdependence.

5. Conclusions

In this paper, the authors investigate the applicability of HHT based new features extracted from multi channel EEG data. With the help of HHT the local features i.e. IA and IP of the most sensitive IMF corresponding to a mental task EEG signal assessed their class discrimination power using paired t-test. Analysis of multichannel signals based on HHT enabled us to represents the correlation among the channels and opened up the possibility to identify different states of brain under different cognitive tasks. The features i.e. skewness, maximum, minimum and kurtosis of both IP and IA were calculated from the analytic representation of IMF having highest PSD.

Using paired t-test, we investigated the class discrimination ability. The results of paired t test support their applicability to be used as feature vector for any classification application.

6. References

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7. Appendix

Table 1. HHT based local features of IA and IP from the most sensitive IMF

Class of mental task	Trial	IA_skewness	IA_Max	IA_Min	IA_kurtosis	IP_skewness	IP_Max	IP_Min	IP_kurtosis
Base line	1	0.3372	3.8799	0.1430	2.2785	-0.0121	3.1289	-3.1395	1.8004
	2	0.5848	4.8197	0.1297	2.3017	0.0063	3.1387	-3.1394	1.9102
	3	1.3763	4.6293	0.0238	3.9838	0.1794	3.1393	-3.1415	1.9605
	4	0.6102	2.8722	0.0132	3.0520	0.0297	3.1398	-3.1390	1.7197
	5	0.4783	1.7586	0.0426	2.5741	0.0087	3.1392	-3.1400	1.7741
	6	0.6931	4.2848	1.1489	2.5318	-0.0476	3.1412	-3.1395	2.0668
	7	0.4505	8.7846	0.4200	2.3518	-0.1474	3.1371	-3.1390	1.8542
	8	0.9715	4.5185	0.2624	3.0930	-0.2175	3.1409	-3.1412	1.8890
	9	0.5867	2.1957	0.2237	2.4537	0.0175	3.1376	-3.1413	1.8882
	10	0.7648	12.6031	1.1188	2.7159	-0.1318	3.1381	-3.1366	1.6713
Mental arithmetic	1	1.1285	8.1315	0.1174	3.9377	-0.0497	3.1389	-3.1402	1.7851
	2	1.2937	10.4497	0.0255	4.8124	-0.0397	3.1413	-3.1413	1.8127
	3	0.7255	6.6421	0.0117	3.5951	0.0299	3.1342	-3.1413	1.6689
	4	1.1501	9.2036	0.0938	4.4334	-0.0380	3.1412	-3.1377	1.6959
	5	0.1129	6.6088	0.0374	2.4795	-0.0069	3.1370	-3.1360	1.7877
	6	0.6324	4.1282	0.0710	2.4614	-0.1933	3.1409	-3.1398	1.8138
	7	1.1594	4.9267	0.0700	4.0803	-0.0411	3.1383	-3.1389	1.9891
	8	0.8556	10.6994	0.0653	3.1772	-0.1309	3.1407	-3.1412	1.7631
	9	1.3348	7.4998	0.4813	4.8481	-0.1493	3.1411	-3.1346	1.8949
	10	0.7471	6.1533	0.3412	2.8840	-0.0923	3.1400	-3.1399	2.0041
Letter-composing	1	0.0121	5.3729	0.0951	2.5665	0.1016	3.1412	-3.1388	1.6753
	2	0.1042	3.3192	0.0269	2.0491	-0.1628	3.1414	-3.1392	1.8305
	3	0.9742	3.4803	0.0380	3.5134	-0.0399	3.1396	-3.1384	1.9387
	4	0.3291	2.9120	0.0492	2.2005	-0.0896	3.1415	-3.1383	1.8111
	5	0.4391	5.1310	0.5056	2.6315	0.0557	3.1375	-3.1399	1.8597
	6	1.6041	11.3500	0.1423	4.9848	-0.0234	3.1403	-3.1410	1.8661
	7	0.3999	4.2946	1.7900	2.5795	-0.2593	3.1343	-3.1339	1.7541
	8	0.6282	4.6812	0.0064	2.4015	-0.1614	3.1369	-3.1403	1.7055
	9	0.3346	7.6620	1.2311	2.2846	-0.0210	3.1389	-3.1401	1.7546
	10	1.3469	3.1717	0.1488	4.1263	-0.1398	3.1410	-3.1360	1.7808