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Investigate the Features for Analysis of EEG Signals Using Multivariate Empirical Mode Decomposition

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Abstract: BCI (Brain Computer Interface) is collaboration between neural activity of the brain and an external device. These are the control and communication systems which converts human brain signals into commands and messages in order to control application such as moving a pointer on a computer, typing letters using a virtual keyboard. The neural activity of the brain can be interpreted by EEG signal. In this paper, the performance of feed forward backpropagation classifier for classification of three different mental tasks such as baseline, mental arithmetic and letter composing were investigated. Multivariate Empirical Mode Decomposition (MEMD) was used for features extraction of the raw EEG signal. The new features have been investigated for three mental tasks for classifying a small set of non-motor cognitive task. The discriminatory power of features has been investigated using paired t-test. The neural network were trained and tested for all three mental tasks. The classification accuracy during combination of three mental tasks was found near about 80% to 90%.
Keywords- Electroencephalogram (EEG), Multivariate Empirical Mode Decomposition (MEMD), Brain Computer Interface (BCI), intrinsic mode function (IMF).

I. INTRODUCTION

Brain Computer Interface (BCI) is collaboration between human brain and external device that enables neural signals from the brain to direct some external activity. BCI systems play a crucial role for those people who suffer from neurodegenerative diseases such as cerebral palsy and neuro-muscular disorders. These are the control and communication systems which converts human brain signals into commands and messages in order to control application such as moving a pointer on a computer, typing letters using a virtual keyboard. The neural activity of the brain can be interpreted by EEG signal. BCIs systems can be invasive type or non-invasive type. Development of electrodes devices that are minimally invasive is the biggest challenges in developing BCI system. Among the two, non-invasive BCIs are most commonly used and EEG signals are recorded by various electrodes placed on the scalp to record the neural activity of the brain. No BCI system can be developed that works for all users because brain development and learning are unique to each individual user. Hence achieving high level of accuracy in a BCI system includes a process of integration and requires training of neural activity in a predetermined method. Human brain signals are highly complex and rich in information process. The signals generated by the brain have very high temporal resolution and decoding such small changes is a difficult task. The central challenges for EEG analysis are to extracting important features for accurate identification of such small changes in neural activity. Abnormalities in brain and many neurological disorders in the brain can be recognized with the help of EEG signal. Signal acquisition, preprocessing of EEG signal, features extraction and classification of EEG signal is basically some stages of BCI system. At the first stage the EEG data is collected and represented using special filters by method of signal acquisition. After that the acquired signal is preprocessed and then features are extracted. These features should capture the valuable information embedded in the EEG signals. The last stages of the BCI system is classification of EEG signals to obtained accuracy.

II. MATERIALS AND METHOD

This section describes the data set used in this research and presents the methodology for features extraction and classification purpose.

A. Experimental Data Set

EEG data set used in this study comes from the experimental data set of Keirn and Aunon, from Purdue University. The electrodes are used to record the data of the dataset. The dataset consist the EEG signals from seven subjects performing different five mental tasks. An Electro-Cap elastic electrode namely C3, C4, P3, P4, O1 and O2 is used to record neural activity of the subjects and 10-20 standard system of electrodes placement was used. Two electrodes names A1 and A2 were used as reference electrodes. The five mental task were-

Baseline mental task-In this task the subject was made to relax with their eyes closed and no mental task is performed in this stage.

Multiplication task- In this task the subjects was asked to solve mathematical problem such as multiplication, addition is given to subject and the subject was instructed solves it mentally without making any physical movement.

Letter-composing task- In this task the subject is asked to compose a letter to other friend mentally.

Geometric figure rotation task- The subjects requiring to visualize a three dimensional object and perform geometrical figures rotating mentally about an axis.

Counting task- In this task the subjects are asked to imagine a blackboard and counts the numbers being written on it mentally.

The EEG data were sampled at 250 samples per second and EEG signal were recorded for duration of 10 seconds for each mental task. Total number of trials for each mental task was ten with 2500 samples per trials. All subjects attended two sessions and the each task was repeated five times in each session.

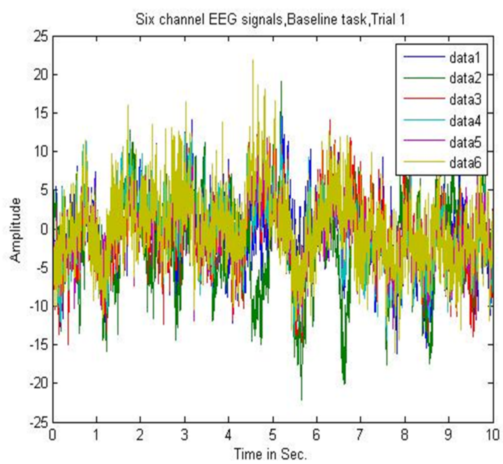

Fig.1. Multi-channel EEG Signal

B. Methodology

This section describes the method's which had been adopted for features extraction and classification of EEG signals.

1) Empirical Mode Decomposition (EMD): Empirical mode decomposition is a technique which is used for nonlinear and non stationary signals. EMD is adaptive and does not require any a-priori basis function. Any nonlinear and non stationary complicated data can be decomposed into a finite number of components with the help of Empirical mode decomposition. These mono-components are known as intrinsic mode functions (IMFs) and each mono-component represents a simple oscillatory harmonic function with variable amplitude and frequency along the time axis. Each IMF satisfies two basic conditions: (i) the number of extrema and the number of zero crossings must be the same or differ at most by one in the complete data set (ii) at any point, the mean value of the envelope defined by local maxima and the envelope defined by local minima is zero. The EMD algorithm (Huang et al., 1998) is summarized as follows:

Determine the extrema (maxima and minima) of the data set $x(t)$;

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;

Determine the local mean $m_1(t)$ by averaging the upper and lower signal envelopes;

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 decomposition of the signal $x(t)$ can be written as:

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

2) Multivariate Empirical Mode Decomposition (MEMD): EMD gives good results for non-stationary and nonlinear data (Diez et al., 2009, Molla et al., 2010). But for analysis of multichannel EEG data EMD presents several limitations. Generic extension of the standard EMD is Multivariate EMD.

The IMFs comes from different channel having a different number of IMFs, means they do not have the same frequency. To achieve the same number of IMFs for different channels is very difficult task. Multivariate EMD is needed to overcome this problem. The multivariate EMD is recently introduced by Rehman and Mandic. The local mean is computed in this algorithm, by taking an average of upper and lower envelopes, which in turn are obtained by interpolating between the local maxima and minima.

The algorithm by (Rehman and Mandic, 2010) is summarized as follows:

Choose a suitable point set for sampling on an (n−1) sphere.

Calculate a projection, denoted by p^{θ_k} (t)}$_{t=1}^{T}$, of the input signal {v(t)}$_{t=1}^{T}$ Along the direction vector x^{θ_k}, for all k (the whole set of direction vectors),), giving p^{θ_k}(t)}$_{k=1}^{K}$as the set of projections.

Find the time instants { $t_i^{\theta_k}$} corresponding to the maxima of the set of projected signals $p^{\theta_k}(t)\}_{k=1}^{K}$.

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

For a set of K direction vectors, the mean m (t) of the envelope curves is calculated as

$$m(t)= \frac{1}{K}\sum_{k=1}^{K} e^{\theta_k}(t)$$

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).*

3) Proposed Analysis Method Based On MEMD:

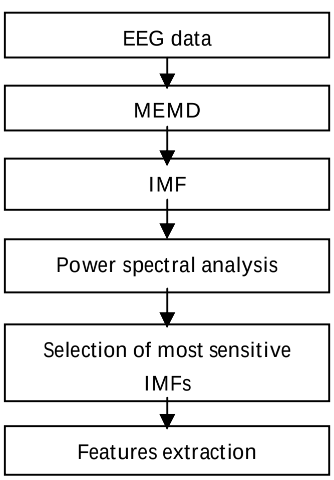

Fig.2:Flow chart of the proposed method

III. RESULTS

In this section, we present the results of six channel EEG data corresponding to three different mental tasks such as baseline, mental arithmetic and letter-composing task based on multivariate empirical mode decomposition. Thirteen mono-component oscillatory modes are generated after MEMD based decomposition. These mono-components are mode-aligned and have common frequency oscillation for all the channels. Out of these thirteen mono-components oscillatory modes, first twelve are IMFs and last one is residue. Higher order IMFs represents low frequency components and high frequency components are represented by lower order IMFs. All of IMFs does not contain important information related to a particular task so all these IMFs are not important. So the most sensitive IMF to a specific mental task can be identified through power spectral analysis and the IMF showing highest power spectral density in their power spectrum. The most sensitive IMF for mental arithmetic task is IMF8 and IMF9 is most sensitive IMF corresponding to baseline and letter-composing mental task. Then local features are extracted from most sensitive IMF corresponding to each mental task. Finally we apply paired t-test.

A. MEMD Based Decomposition

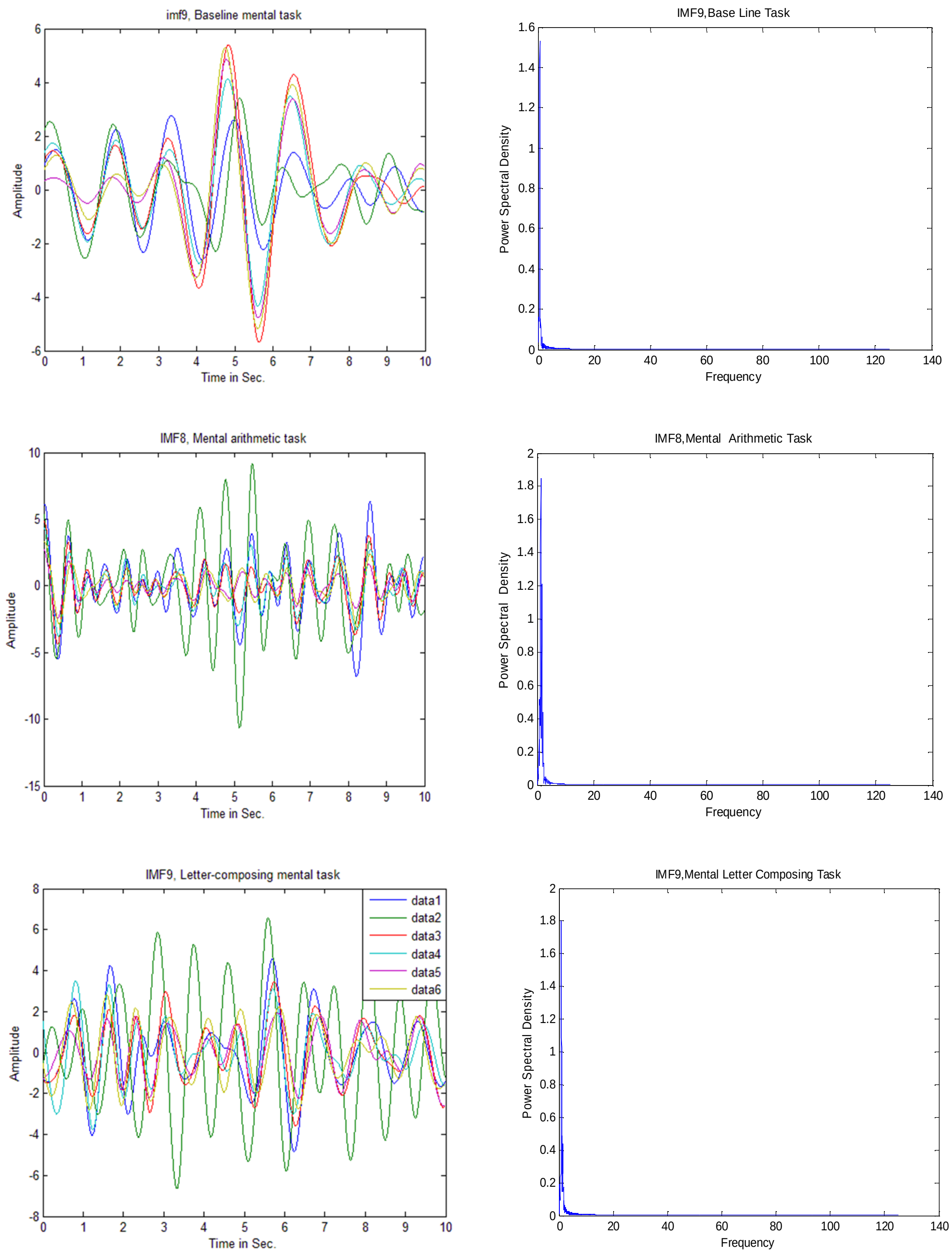

Fig3. Waveforms and its associate power spectral density of the most sensitive IMF corresponding to three mental task for single trial of six channel EEG signals

All the six channels EEG data is decomposed by multivariate empirical mode decomposition instead of standard EMD. Mode mixing and mode alignment problems are removed by MEMD. The application of MEMD algorithm on multi-channel EEG data corresponding to each mental task resulted in twelve intrinsic mode functions and one residue. These mono-component oscillatory modes are mode aligned. Power spectral density of all IMFs is obtained using Welch method. A particular IMF has highest power spectral density corresponding to each mental task. IMF8 is found the most sensitive IMF for each and every trial of mental arithmetic task whereas IMF9 is most sensitive IMF for both baseline and letter-composing mental task. Fig3. Shows the waveforms and power spectral density of the most sensitive IMF corresponding to each mental task for single trial of six channel EEG data obtained from MEMD based decomposition. From power spectral density figure it is observed that for each mental task, a particular IMF is having highest power spectral density. After analysis of IMFs we extract the local statistical features from most sensitive IMF corresponding to each mental task. For baseline and letter-composing mental task we extract local features form IMF9 which is most sensitive IMF for both baseline and letter-composing task. For mental arithmetic the features are extracted from IMF8. We extract the local features like mean, maximum, minimum, standard deviation and kurtosis. The local statistical features extracted from MEMD based decomposition is shown in table 1. (See table 1 in Appendix)

IV. DISCUSSIONS

EEG signals are nonlinear and non-stationary in nature so their decomposition gives better localization in joint time-frequency domain as compare to frequency or time alone. So MEMD is a time-frequency domain method which gives better results as compare to FFT (Fast Fourier Transform) and wavelet transform. In this method the signals does not decomposed onto fixed basis; rather it adjusts basis function adaptively based on signal envelopes. MEMD based decomposition gives finite number of mono-component intrinsic mode functions corresponding to three different mental tasks having common frequency of oscillation across the six channels. So the application of MEMD algorithm equal number of mode aligned IMFs is generated per channel. The local statistical features from the MEMD based on multi-channel analysis are presented in Table 1 and class discrimination ability of these features is investigated by applying paired t-test. The main motive of our research comes from the use of MEMD based decomposition for multi-channel EEG signals.

V. CONCLUSIONS

In this research paper, the authors investigate the applicability of MEMD based features from the most sensitive IMF corresponding to each mental task and using paired t-test, authors assessed their class discrimination power. MEMD based analyses of multi-channel EEG signals provides the correlation among the channels and help to identify different brain states under different mental tasks. So the local features are extracted from most sensitive IMF having highest power spectral density. From result and discussion, it has been concluded that IMF8 is the most sensitive IMF for mental arithmetic task and IMF9 is most sensitive for both letter composing and baseline task. The class discrimination power of these features was tested using paired t-test. After paired t-test the features vector can be used for any classification application. In future scope, this research open up a number of directions for further analysis of multi-channel EEG signals in diverse application domain. Also non linear features such as entropy, correlation dimension, fractal dimension etc. can be extracted for further research.

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APPENDIX

Table1. MEMD based local features from the most sensitive IMF of each trial of a mental task

MEMD based local features						
mental tasks	Trial	Mean	Max	Min	Std	kurtosis
	1	0.0744	2.7589	-2.6193	1.3470	2.2507
	2	0.0269	4.5262	-4.1778	2.0478	2.5599
	3	-0.0027	3.8823	-4.4107	1.5364	3.8971
	4	-0.0447	2.0551	-2.1751	0.8825	2.6142
Base line	5	-0.0109	1.7507	-1.6299	0.6935	2.7564
	6	0.1372	4.0849	-4.1079	1.8656	2.1786
	7	0.0295	3.8301	-3.8142	1.7021	3.7081
	8	0.0048	4.4686	-4.0156	1.6586	2.1586
	9	0.0491	2.1624	-2.1624	0.9575	2.2654
	10	0.0093	7.6000	-6.5885	2.9510	2.3508
	1	-0.0568	6.3342	-6.7925	2.2825	3.6126
	2	-0.0385	9.0445	-7.8579	2.6676	4.4185
	3	-0.0225	4.9048	-5.4254	2.0408	2.8011
	4	-0.0628	6.2974	-7.2898	2.3322	3.5611
Mental arithmetic	5	-0.0558	5.5108	-5.7596	2.5269	2.2673
	6	-0.0797	4.1280	-3.8647	1.8636	2.6524
	7	0.0326	4.3246	-4.2827	1.4952	4.0231
	8	-0.0294	5.9558	-6.4880	2.3066	3.4657
	9	-0.0237	4.1776	-4.3379	1.7005	2.1294
	10	0.2653	7.5987	-6.5499	2.9101	2.0236
	1	-0.0566	4.5684	-4.8218	1.8194	3.2217
	2	-0.0343	2.6770	-2.5671	1.4815	1.7495
	3	0.0271	2.5495	-2.5734	1.1919	2.2787
	4	-0.0723	2.6847	-2.7087	1.1637	2.9613
Letter-composing	5	0.2429	4.5755	-4.0267	2.2025	2.0620
	6	0.0752	6.1052	-5.7717	2.0549	1.6354
	7	-0.1802	3.7465	-3.9961	2.1353	2.4358
	8	-0.0627	2.7569	-2.7262	1.1849	3.1324
	9	0.1536	4.7334	-4.7600	2.3067	2.3874
	10	-0.0596	2.9481	-3.1669	1.1312	2.6239