Performance Evaluation of Empirical Mode Decomposition Algorithms for Mental Task Classification

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Abstract

The electroencephalograph (EEG) signal is the one of the monitoring techniques to observe brain functionality. EEG is most preferable technology not just because of its non-invasive and cost effective quality, but also it can detect the cognitive activity of human. Brain Computer Interface (BCI), a direct pathway between the human brain and computer, is one of the most pragmatic applications of EEG signal. Mental Task Classification (MTC) is a demanding BCI as it does not involve any muscular activity. Empirical Mode Decomposition (EMD) is a filter based heuristic technique to analyze non-linear and non-stationary signal like EEG. There are several variants of EMD algorithms which have their own merits and demerits. In this paper, we have explored three different EMD algorithms on EEG data for MTC-based BCI named as Empirical Mode Decomposition (EMD),Ensemble Empirical Mode Decomposition (EEMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). Features are extracted from EEG signal in two phases; in the first phase, the signal is decomposed into different oscillatory functions with the help of different EMD algorithm and in the second phase, eight different parameters (features) are calculated for the each function for compact representation. In this paper a new feature known as Hurst Exponent along with other feature have been investigated for mental task classification. These features are fed up into Support Vector Machine (SVM) classifier to classify the different mental tasks. We have formulated two different typs of MTC, the first one is binary and second one is multi-MTC. The proposed work outperforms the existing work for both binary and multi mental tasks classification.

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Index terms— Brain Computer Interface, Mental Tasks Classification, Feature Extraction.

1 Introduction

Human brain has the capability to distinguish two or more different tasks without much effort. In literature, most of the research works have been suggested to distinguish between two different tasks at a given instant of time; a few research works deal with multitask classification (Donoghue, 2002; Li et al., 2014; Palaniappan et al., 2002; Wang et al., 2012; Zhang et al., 2010) . There is a need of a multiple mental task classification system that can distinguish more than two mental tasks at a given instance of time. Such a BCI system is known as the multi-class mental task classification system.

As the number of chosen classes grows, it becomes more difficult to classify a test sample correctly. The computational complexity of the multi-class problem is much higher in comparison to a binary class problem with comparable amount of data. The amplitude of the captured EEG signals is low. Hence, the signal in its raw form is not helpful to distinguish multiple mental tasks at a given time. Given these facts, classification of multiple mental tasks is considered to be a challenging problem. However, limited BCI models (Li et al., 2014; Palaniappan et al., 2002; Zhang et al., 2010) have been proposed to distinguish more than two tasks at a given instance of time. Therefore in this study, we have formulated problem for the multi mental task as well as binary mental task classification. One versus rest approach based support vector machine (SVM) is used as a multi mental class classifier to build the decision model. The overall flow chart of proposed model has been shown in Figure 1.

Rest of the paper is organized as follows: In section 2, the state of art of feature extraction for BCI as well as multi-class BCI is given. Section 3 contains the brief description of feature extraction. Support Vector Machine is discussed in section 4. Experimental data and the related discussion are given in section 5, and finally section 6 draws the conclusion.

2 Related Works

Various feature extraction techniques have been studied and suggested for BCI. These feature extraction techniques can be grouped into three major categories: (i) Temporal methods (ii) Frequency domain methods and (iii) hybrid of temporal and frequency domain methods. The temporal methods are predominantly adaptive to describe neurophysiological signals with an accurate and specific time information. The temporal variations of the signal are characterized by the features in temporal method. In
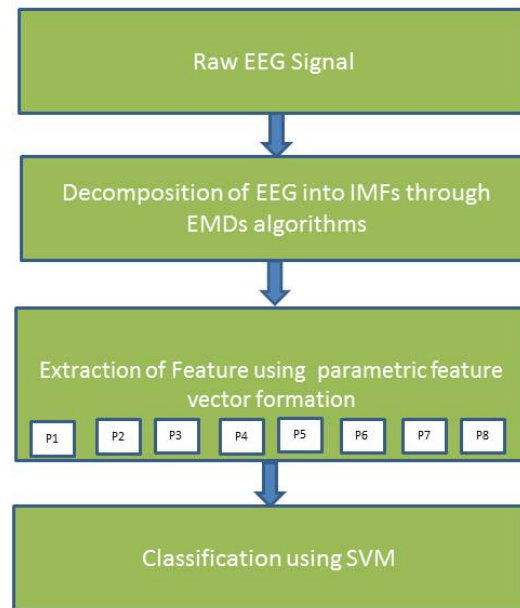
Figure 1: Schematic flow chart of the proposed model for Mental Task Classification

time domain, amplitude of the signal or statistics measures like absolute mean, standard deviation and kurtosis of the signal are used to characterize EEG signal. But these statistics do not consider correlation between two samples (Motamedi-Fakhr et al., 2014). On the basis of temporal dynamics of EEG signal, a collection of three measures (Activity, Mobility and Complexity) known as Hjorth parameters (Hjorth, 1970) have been used to extract features from EEG signal (Bostanov, 2004; Vidaurre et al., 2009). Another temporal property of EEG signal is Detrended Fluctuation Analysis (DFA), which is used to measure long range correlation in EEG time series signal (Peng et al., 1994; Shen et al., 2003).

It is known that EEG signals consist of a set of explicit oscillations, which are known as rhythms. Corresponding to the different mental tasks, rhythms associated with these signals are different. There is a need to utilize frequency information embedded in the signal to represent the signal more accurately. Power spectral analysis (density) has been used in literature to extract accurate frequency content features and produce high frequency resolution.

Power spectral density (PSD) method broadly falls into three categories: (i) Non-Parametric method, (ii) Parametric method and (iii) Sub-Space method. In non-parametric method of PSD, there is no assumption of the nature of the data, i.e.,

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how the data are generated (Proakis, 1995). The popular techniques in this category are Bertlett, Blackman and Tukky, and Welch (Welch, 1967). These methods are simple to compute. However, non-parametric methods require long data record in order to achieve high frequency resolution. The popular feature extraction methods used to extract spectral features in parametric method in the BCI systems are Auto-Regressive (AR) techniques (Anderson et al., 1998; Palaniappan et al., 2002) and its two popular variants, Adaptive Auto-Regressive (AAR) (Penny et al., 2000; Pfurtscheller et al., 1998) and Auto-Regressive with exogenous output (ARX) technique (Palaniappan et al., 2002). However, the primary issue with AR modelling is that the accuracy of the spectral estimate is highly dependent on the selected model order. An insufficient model order tends to blur the spectrum, whereas an overly large order may create artificial peaks in the spectrum. These methods also assume linearity, Gaussian behaviour and minimum-phase within EEG (Anderson et al., 1998; Basseville and Benveniste, 1983; Freeman, 1999; Graimann et al., 2003; Pfurtscheller et al., 1998). The research work (Diez, Torres, Avila, Laciar and Mut, 2009) has used parametric and non-parametric methods for math-imagine and motor imagery data. The research work (Anderson et al., 1998) and (Palaniappan et al., 2002) have employed parametric approach for estimating PSD values on Keirn & Aunon dataset for mental task classification. Sub-space methods are often used when signal to noise ratio (SNR) is low. In this method, the PSD values are obtained in terms of Eigenvalue-decomposition of autocorrelation matrix. Sub-space methods are well suited for line spectra or spectra having sinusoidal signals and also effective in the recognition of sinusoidal mixed in noise. However, the sub-space method suffers from the following drawbacks, such as, it may not yield true PSD estimates; it does not preserve power required for processing between the time and frequency domains, and fails in recovering the autocorrelation series by calculating inverse Fourier transform of the frequency estimate. The sub-space method has been applied on epilepsy dataset for estimating PSDs (Übeyli, 2008).

However, the neurophysiological signal used in BCI have generally specific properties in both the temporal and frequential domain. Also, the frequency spectrum of the EEG signal is observed to vary over time, indicating that the EEG signal is a non-stationary signal. Hence, a feature extraction method should be used to model the non-stationary nature of the signal for better representation. Hence, short-time Fourier transform or wavelet transform are suggested methods extract both frequency and time information based features from the signal. The main benefit of these time-frequency representation of the signal is that they can determine sudden temporal variations in the EEG signal, while still keeping frequency information. The Wavelet Transform (WT) (Daubechies, 1990; Mallat, 1989) is an effective technique that can be used, which allows analysis of both time and frequency contents of the signal simultaneously. EEG signals have been analyzed with the WT in the fields of motor imagery and epileptic seizures, (Bostanov, 2004; Cvetkovic et al., 2008; Hsu and Sun, 2009; Ocak, 2009), brain disorders, (Hazarika et al., 1997), classification of hu-

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man emotions (Murugappan et al., 2010), and non-motor imagery (Cabrera et al., 2010).However, WT uses some fixed basis independent of the processed signal, which makes it non-adaptive. Another successful heuristic method for feature extraction is Empirical Mode Decomposition (EMD)(Huang et al., 1998),which is a data driven approach. This method does not use a fixed set of basis functions but the method is self-adaptive according to the signal to be processed. It decomposes a signal into finite, well defined, low frequency and high frequency components known as Intrinsic Mode Functions (IMFs) or modes. The EMD method has been used to extract representative data for BCI (Diez, Mut, Laciar, Torres and Avila, 2009; Kaleem et al., 2010) to classify mental task.

For multi-class BCI, most of the research works have been suggested for two categories: sensory motor activity (Donoghue, 2002; Wang et al., 2012)and response to the mental task (Li et al., 2014; Palaniappan et al., 2002; Zhang et al., 2010). One of the most efficient method for the recognition of sensory motor rhythms is the method of common spatial patterns (CSPs) suggested by Müller-Gerking et al. (1999). CSP has been extended to multi-class CSP, which is based on pairwise classification and voting (Ramoser et al., 2000). Donoghue (2002) has also suggested two new methods based on CSP method for multi-class classification, which improved the classification accuracy. In the category of response to mental task, Palaniappan et al. (2002) has used three type of power of spectral density methods namely Wiener-Khinchine (WK) with Parzen smoothing window, WK with Tuky window smoothing and 6th order auto-regressive model to extract features for 3-class mental task classification. They have used Fuzzy ARTMAP classifier for three class mental task classification. The Welch periodogram algorithm to estimate the power spectrum of the EEG signal and asymmetric ratio was adjusted for calculation of different number of frequency band powers of multi-class data in Zhang et al. (2010). Fisher Discriminant Analysis (FDA) and Mahalanobis distance based classifier was used in their work. Li et al. (2014) extracted features using two methods: wavelet packet entropy and Granger causality. The extracted features were used to build learning model using multiple kernels support vector machine.

This work explore the usefulness of variants of EMD for binary as well as multi mental tasks classification. A new parameter associated with data i.e. Hurst Exponent is incorporated which produced the good classification model along with the other parameter. A comparative study of variant of EMD has been done. A non-parametric statistical test is also carried out to validate the experimental findings.

3   Feature Extraction

Features are extracted from the EEG signal in two steps: In the first phase, EEG signal is decomposed by various forms of Empirical Mode Decomposition (EMDs) and in the second phase statistical and uncertainty parameters are calculated from

each decomposed signal to represent the signal more compactly. Brief description of EMDs, and the parameters are discussed below.

3.1 Empirical Mode Decomposition (EMD)

EMD is a mathematical tool that analyses a non-stationary and non-linear signal with the help of dynamic basis. Under the assumption that any signal contains a series of different intrinsic oscillation modes, the EMD is used to decompose an incoming signal into its different Intrinsic Mode Functions (IMF). An IMF is a continuous function that satisfies the following conditions (Huang et al., 1998):

1. The number of extrema and the number of zero crossings are either equal, or differ at most by one.

2. The mean value of the envelope defined by the local maxima and the envelop; defined by local minima is zero.

The first condition implies that there is need of a narrow band requirement for a signal to be a stationary Guassian process (Huang et al., 1998). The second condition is needed for abstaining instantaneous frequency from unwanted fluctuations induced by asymmetric waveforms (Huang et al., 1998). The basic steps of EMD are given in algorithm 1.

Algorithm 1: Algorithm for EMD

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1 **Input:** Signal $x(m)$;
2 For a given signal, $x(m)$, identify all local maxima and minima;
3 Calculate the upper envelope by connecting all the local maxima points of the signal using a cubic spline;
4 Repeat the same for the local minima points of the signal to find the lower envelope;
5 Calculate the mean value of both envelopes, say m_1;
6 Update the signal, $x(m) = x(m) - m_1$;
7 Continue the steps 1 to 5, and consider $x(m)$ as the input signal, until it can be considered as an IMF as per the definition stated above;
8 The residue r_1 is obtained by subtracting the first $IMF(IMF_1)$ from $x(m)$ i.e. $r_1 = x(m) - IMF_1$. The residual of this step becomes the signal $x(m)$ for the next iteration;
9 Iterate steps 2 to 8 on the residual r_j; $j = 1, 2, 3, \ldots, m$ in order to find all the IMFs of the signal;

The procedure terminates when the residual r_j is either a constant value or a function with a single optima value.

Thus, a signal $x(m)$, can be represented as:

$$x(m) = \sum_{j=1}^{m} IMF_j + r_m \tag{1}$$

According to Huang et al. (1998), there is one stopping criteria in T steps to further produce IMFs based on standard deviation, can be defined as

$$SD_i = \sum_{t=0}^{T} \frac{|IMF_{i+1}(t) - IMF_i(t)|^2}{IMF_i(t)^2} \tag{2}$$

The decomposition process stops when the value of SD is smaller than predefined value.

3.2 Ensemble Empirical Mode Decomposition (EEMD)

One of the major problems with EMD method is that frequent mode mixing, which can be defined as single IMF, contains signal of widely different scale or a signal of same scale that is obtained from different IMFs (Wu and Huang, 2009). To alleviate the problem of scale separation, Wu and Huang (2009) have proposed a noise-assisted data analysis (NADA) method, called Ensemble Empirical Mode Decomposition (EEMD). EEMD define true IMF components as the mean of an ensemble of the trails which consists of signal plus white noise with finite amplitude (Wu and Huang, 2009). Thus the signal $x(m)$ in i^{th} trial can be represented as

$$x^i(m) = x(m) + a_0 w^i(n), \text{ for } i = 1, \dots l \tag{3}$$

where $w^i(n)$ is the white noise in i^{th} trial with unit variance and a_0 amplitude. The average k^{th} $I\bar{M}F_k$ can be defined as

$$I\bar{M}F_k = \frac{1}{l} \sum_{i=1}^{l} IMF_k^i \tag{4}$$

The pragmatic concepts of EEMD are as follows:

1. The added collection of white noise cancels each other with the help of ensemble mean, thus only signal can be one ingredient of the mixture of the signal and white noise.

2. To search all possible solution, it is necessary to ensemble white noise of finite amplitude with signal.

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3. To obtain true and physically meaning full answer of the EMD, it is necessary to add noise to the signal.

3.3 Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)

The problem of mode mixing in original EMD algorithm is successfully addressed by EEMD by adding white noise into the signal, but this also leads to a problem that noise is not fully segregated from the signal and the resultant different IMFs may contain mixture of noise and signal. To resolve this problem, Yeh et al. (2010), have proposed complementary ensemble EMD (CEEMD) algorithm in which positive and negative white noise are added to the signal, so that these positive and negative noises become complementary to each other and IMFs become free from noise.

The first residue can be calculated as:

$$r_1(m) = x(m) - I\bar{M}F_1, \tag{5}$$

where $I\bar{M}F_1$ is the first average IMF obtained by EEMD. The second average IMF can be found as:

$$I\bar{M}F = \frac{1}{l}\sum_{i=1}^{l} E_1\left(r_1(m) + a_0 E_1\left(w^i(m)\right)\right). \tag{6}$$

After finding k^{th} residue, for $k = 2, \ldots, K$, the $k+1$ average IMF can be defined as:

$$I\bar{M}F_{k+1} = \frac{1}{l}\sum_{i=1}^{l} E_1\left(r_k(m) + a_k E_k\left(w^i(m)\right)\right), \tag{7}$$

where $E_k(.)$ is an operator to extract k^{th} IMF from given signal by EMD algorithm.

3.4 Statistical Parametric Feature Vector Formulation

For the compact representation of the EEG signal, the following statistical measures or parameters were used to represent the IMF. Some of these parameters represent linear characteristics of the EEG signal and other represent non-linear properties of EEG (Diez, Torres, Avila, Laciar and Mut, 2009; Gupta and Agrawal, 2012; Gupta et al., 2015). These features are chosen in this work empirically as every signal or data has the distinguishable property in terms of a certain set of statistical parameters associated with the signal or data as shown in Figure 2. The brief description of these parameters (features) are given below.
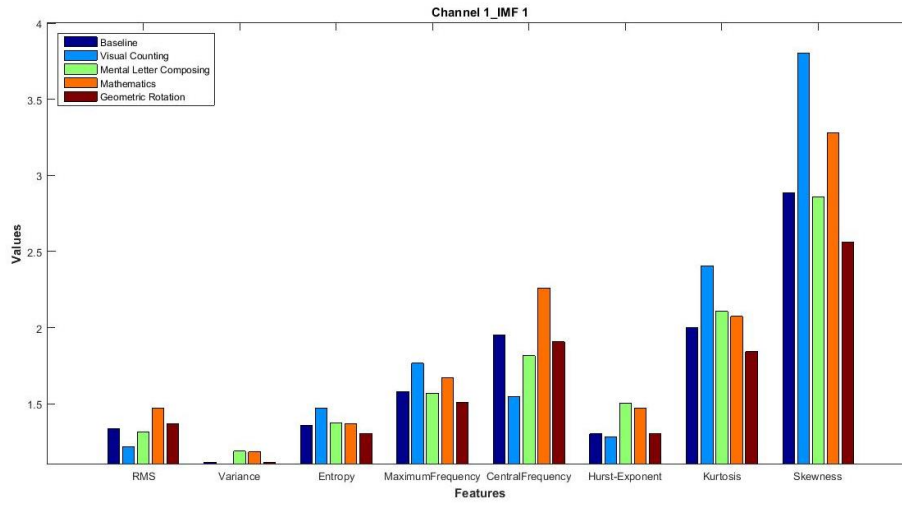
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Figure 2: Eight features obtained corresponding to all five mental tasks for channel 1 from IMF 1 using EEMD method for Subject 1.

Mean

This is one of the central tendency measures, also known as first order moment. If there are n observations $(x_1, x_2 \ldots, x_n)$ then mean is given by:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i. \tag{8}$$

Root Mean Square (RMS)

This is a statistical measure of the magnitude of variable, useful when variable has more positive and negative peaks, i.e. follows sinusoidal nature. The value of RMS is considered most significant because it depicts power of the signal. It is given by:

$$rms\,(x_1, x_2, \ldots x_n) = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \ldots + x_n^2)}. \tag{9}$$

Variance

This is the second order moment and measures spread or variability of the data around mean value. The variance of the data is given by:

$$var(x_1, x_2, \ldots, x_n) = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2. \tag{10}$$

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The square root of variance is known as standard deviation which is given by:

$$\sigma = \sqrt{var(x_1, x_2, \ldots x_n)}. \tag{11}$$

Skewness

This is the third order moment. The value of skewness depicts degree of asymmetry of distribution around mean value of the signal. The mean and the variance are the dimensional quantities where skewness is a pure number which depicts bending nature of the signal around mean value of the signal on either side. It is defined as:

$$skew(x_1, x_2, \ldots, x_n) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x - \bar{x}}{\sigma}\right)^3. \tag{12}$$

Kurtosis

This is fourth order moment and is a non-dimensional quantity. The value of kurtosis describes relative spikeness or flatness of signal with respect to the signal which follows normal distribution. It can be calculated as

$$Kur(x_1, x_2, \ldots, x_n) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x - \bar{x}}{\sigma}\right)^4. \tag{13}$$

Hurst Exponent

The long term memory of given time series is calculated by Hurst Exponent, denoted by H, given by Edwin Hurst (Hurst, 1951). Auto-correlation of the time series can be calculated with the help of Hurst Exponent and decreases as lag of the the time series increases. It is also referred as index of independence or long range of independence. The Hurst Exponent H, can be defined as:

$$E\left[\frac{R(n)}{S(n)}\right] = Cn^H \text{ as } n \to \infty, \tag{14}$$

where E denotes statistical expected value of given quantity, $R(n)$ and $S(n)$ are the range and standard deviation of the given n observation of time series respectively, C is the constant.

Central and Maximum frequency

These values depict how much frequency content is centralized over the signal and the maximum frequency present in the signal. The frequency content can be calculated

by discrete Fourier transform of the signal, and is given as

$$X\left(f\right) = \sum_{n=-\infty}^{\infty} x\left[n\right] e^{-j2\pi fn}. \tag{15}$$

Shannon Entropy

It measures how much uncertainty is possessed by the signal, i.e. randomness of signal. Higher entropy means more randomness is present in the signal. If p_i is the probability associated with variable x_i in a set of n observations then entropy is defined as:

$$H\left(x\right) = -\sum_i p_i \log_2\left(p_i\right). \tag{16}$$

4   Experimental Setup and Result

4.1   Dataset

For our experiment, we have used publicly available data for mental task classification (Keirn and Aunon, 1990). The original EEG dataset consists of recordings from seven subjects; we have utilized data of all subjects except Subject 4, due to its some missing and incomplete information. Similar kind of observation has been made by Faradji et al. (2009). Each subject has performed five different mental tasks as: the **Baseline task** (relax: **B**); the mental **Letter Composing task** (**L**); the Non trivial **Mathematical task** (**M**); the **Visualizing Counting** (**C**) of numbers written on a blackboard task, and the **Geometric Figure Rotation** (**R**) task. Detailed explanation can be found in the work of Keirn and Aunon (1990) [1].

For feature construction, the data of each task of each subject is decomposed into half-second segments, yielding 20 segments (signal) per trial for each subject.The feature vector corresponding to a given signal is constructed in two phase. In the first phase, four level decomposition of signal is carried out with three EMDs algorithms. In the second phase, signal is represented in terms of eight statistical parameters, estimated from each decomposed signal.

4.2   Result

The performance of the EMD and its variant has been evaluated in terms of classification accuracy achieved with SVM classifier with one versus all approach by Gaussian Kernel. Grid search is used to find optimal choice of regularization constant C and gamma. The average classification accuracy of 10 runs of 10 cross-validations is

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[1] http://www.cs.colostate.edu/eeg/main/data/1989_Keirn_and_Aunon

quoted. To check the efficacy of the proposed method, we have formulated three type of multi-mental task classification problems viz. three class, four class and five class as well as binary mental task classification.

Binary Class Problem We have used binary combination of these tasks as BC, BL, BM, BR, CL, CM, CR, LM, LR and MR in this work.

Three Class Problem In this problem, we have formed three-class mental tasks problems by choosing three different mental tasks at a time from given five mental tasks. There are ten different triplet mental task combinations for forming three class problem given as: BCL, BCM, BCR, BLM, BLR, BMR,CLM, CLR, CMR and LMR.

Four Class Problem Construction of four mental task classification problems has been done by choosing four tasks at a time from the given five tasks. There are five different four class problems namely BCLM, BCLR, BCMR, BLMR and CLMR.

Five Class Problem For the formation of the five mental task classification problem we have taken all five mental tasks at a time. Thus, we have the five-class mental tasks classification problem as: BCLMR.

Table 1: Classification accuracy of EMD for binary mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BC	92.33	77.74	72.35	63.18	86.80	84.47	79.48
BL	84.35	65.85	77.50	61.47	67.33	77.00	72.25
BM	92.93	87.40	76.45	70.85	89.25	92.10	84.83
BR	96.78	**98.35**	66.05	75.92	88.60	99.05	87.46
CL	68.45	77.79	**84.15**	67.02	78.03	92.16	77.93
CM	96.50	83.05	66.85	77.50	**98.78**	93.26	85.99
CR	74.65	90.21	58.35	**80.38**	87.18	99.32	81.68
LM	98.25	92.15	81.58	74.32	87.25	98.95	**88.75**
LR	86.98	97.65	75.60	75.27	81.13	**99.45**	86.01
MR	**97.75**	88.35	67.50	79.40	84.55	82.25	83.30
Average	**88.90**	**85.85**	**72.64**	**72.53**	**84.89**	**91.80**	**82.77**

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Table 2: Classification accuracy of EEMD for binary mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BC	93.75	90.85	72.33	94.42	89.85	91.65	88.81
BL	86.48	71.55	79.53	82.65	71.03	82.70	78.99
BM	93.23	88.95	80.33	**97.15**	94.23	96.80	91.78
BR	96.83	98.20	68.70	96.70	93.98	98.80	**92.20**
CL	71.30	88.50	**85.03**	69.92	82.45	91.90	81.52
CM	96.63	86.90	65.63	76.35	**99.43**	96.40	86.89
CR	76.60	95.35	60.60	81.35	92.00	98.55	84.08
LM	**98.25**	94.30	82.88	73.52	91.75	98.30	89.83
LR	87.00	**98.95**	77.50	76.13	89.03	**100.00**	88.10
MR	97.73	90.15	62.58	80.37	87.73	87.50	84.34
Average	**89.78**	**90.37**	**73.51**	**82.86**	**89.15**	**94.26**	**86.65**

Table 3: Classification accuracy of CEEMDAN for binary mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BC	93.13	90.05	72.73	66.08	90.63	88.30	83.48
BL	86.20	71.30	78.93	62.85	73.10	81.00	75.56
BM	92.25	90.50	80.63	73.83	94.35	91.90	87.24
BR	97.60	99.20	67.73	78.40	94.08	98.25	89.21
CL	72.53	83.80	**85.23**	71.03	85.03	91.40	81.50
CM	97.03	87.20	67.63	75.47	**99.68**	95.30	87.05
CR	78.10	95.15	61.70	81.20	90.58	98.50	84.20
LM	97.43	93.45	81.38	73.70	92.10	98.75	**89.47**
LR	87.48	**99.70**	73.83	76.13	89.95	**99.50**	87.76
MR	**98.18**	90.60	64.50	**81.38**	88.80	84.30	84.63
Average	**89.99**	**90.10**	**73.43**	**74.01**	**89.83**	**92.72**	**85.01**

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Table 4: Classification accuracy of EMD for three class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCL	61.67	59.34	66.72	51.50	64.35	70.24	62.30
BCM	87.38	72.41	56.80	56.83	**82.02**	83.41	73.14
BCR	76.82	74.21	51.05	57.93	76.30	83.48	69.96
BLM	81.22	66.87	**66.87**	54.50	66.72	78.63	69.13
BLR	74.67	71.17	61.98	58.62	66.28	82.53	69.21
BMR	**92.53**	82.90	56.07	64.66	76.32	80.97	**75.57**
CLM	75.00	74.03	62.60	61.64	75.00	86.00	72.38
CLR	62.25	73.83	56.62	63.90	71.02	**86.83**	69.07
CMR	80.07	79.45	49.07	**66.76**	78.67	80.93	72.49
LMR	87.92	**84.07**	60.15	63.83	72.12	83.83	75.32
Average	**77.95**	**73.83**	**58.79**	**60.02**	**72.88**	**81.69**	**70.86**

Table 5: Classification accuracy of EEMD for three class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCL	65.15	68.57	69.17	76.24	69.20	78.50	71.14
BCM	87.75	82.30	57.98	79.78	**87.88**	88.00	80.62
BCR	80.70	83.63	53.93	82.77	83.62	90.17	79.14
BLM	84.05	68.27	**71.07**	77.84	75.72	83.47	76.74
BLR	77.85	76.07	64.98	80.04	73.28	85.47	76.28
BMR	**93.00**	83.17	56.18	**83.92**	85.15	84.10	**80.92**
CLM	77.78	81.27	62.50	62.77	81.62	**92.00**	76.32
CLR	66.65	81.53	59.57	65.49	80.47	90.80	74.08
CMR	82.65	81.87	46.88	66.51	86.02	86.03	74.99
LMR	88.32	**88.37**	58.18	64.90	81.60	86.00	77.89
Average	**80.39**	**79.50**	**60.05**	**74.03**	**80.46**	**86.45**	**76.81**

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Table 6: Classification accuracy of CEEMDAN for three class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCL	64.58	67.77	69.38	51.84	69.30	77.50	66.73
BCM	86.63	82.87	58.27	56.71	**87.22**	84.93	76.10
BCR	80.90	81.20	52.65	60.24	84.35	88.53	74.65
BLM	83.42	68.67	**69.95**	54.79	76.30	82.93	72.68
BLR	77.63	75.00	64.45	57.57	72.83	87.43	72.49
BMR	**92.60**	85.97	57.18	67.00	84.53	80.33	**77.94**
CLM	77.62	78.73	62.13	62.84	82.30	89.37	75.50
CLR	66.42	76.30	58.85	66.56	79.57	**90.63**	73.05
CMR	83.32	84.90	49.27	**67.38**	85.75	85.43	76.01
LMR	88.32	**87.70**	57.52	64.70	82.88	85.23	77.73
Average	**80.14**	**78.91**	**59.97**	**60.96**	**80.50**	**85.23**	**74.29**

Table 7: Classification accuracy of EMD for four class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCLM	65.03	57.28	**55.18**	49.81	63.00	70.92	60.20
BCLR	66.80	**68.21**	48.19	**56.21**	64.46	**76.97**	63.47
BCMR	74.96	65.08	53.36	53.33	60.95	72.00	63.28
BLMR	**76.48**	67.72	45.76	54.80	**71.01**	74.64	**65.07**
CLMR	56.50	58.59	48.64	52.48	60.90	71.13	58.04
Average	**67.95**	**63.37**	**50.23**	**53.33**	**64.07**	**73.13**	**62.01**

Table 8: Classification accuracy of EEMD for four class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCLM	69.54	65.05	**57.11**	67.96	71.08	78.55	68.21
BCLR	71.40	**75.95**	46.85	57.10	75.93	**83.63**	68.48
BCMR	77.36	68.73	54.25	69.86	71.28	78.20	69.95
BLMR	**78.60**	75.80	45.16	**70.50**	**79.00**	79.70	**71.46**
CLMR	61.66	65.60	52.76	69.70	68.40	80.53	66.44
Average	**71.71**	**70.23**	**51.23**	**67.02**	**73.14**	**80.12**	**68.91**

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Table 9: Classification accuracy of CEEMDAN for four class mental task classification.

Task-Combination	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
BCLM	67.63	63.73	**55.36**	49.09	70.66	74.90	63.56
BCLR	69.23	74.13	47.91	**57.83**	75.98	**80.98**	67.67
BCMR	77.48	69.70	54.48	52.44	72.05	76.53	67.11
BLMR	**78.05**	**76.90**	45.64	55.27	**79.16**	76.65	**68.61**
CLMR	60.55	64.25	53.00	50.52	67.28	79.40	62.50
Average	**70.59**	**69.74**	**51.28**	**53.03**	**73.03**	**77.69**	**65.89**

Table 10: Classification accuracy for all five class mental task classification of all feature extraction method.

Task-Combination	Feature Extraction methods	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
	EMD	59.60	56.71	44.53	53.26	57.47	66.41	56.33
BCLMR	EEMD	**65.23**	**63.00**	44.69	**62.04**	67.47	**74.26**	**62.78**
	CEEMDAN	63.85	62.92	**46.93**	48.45	**67.81**	71.40	60.23

Table 1 to Table 3 show the classification accuracy for the binary mental tasks classification problem of three different EMDs algorithms. The bold values show the best and average classification accuracy for different subjects. From these tables, it is clear that among three EMDs algorithms, CEEMDAN performs best for binary MTC. Similar kind of observation can be seen for three class, four class and five class of MTC, which have been shown from Table 4 to Table 10 respectively.

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4.3 Comparison with some recent works

In this subsection, we have discussed and compared the proposed approach with some current works. Table 11, and 12 shows the comparison of the work of Gupta and Kirar (2015), Gupta et al. (2015), and Zhang et al. (2010) with the proposed work respectively. In the work of Gupta and Kirar (2015), features were extracted from the EEG signal for binary mental task classification in the single step, i.e. with the help of parametric approach using eight different parameters.

In our study features has been extracted, as stated earlier, in two steps, in the first step, the signal is decomposed into different IMFs with the help of any three EMD algorithms, and the second step consists extraction of the eight parameters from each IMF as calculated in the work of Gupta and Kirar (2015) except we have incorporated Hurst exponent instead of Lampel Ziv complexity as this new feature give the good discriminative. It can be observed from Table 11 that the average classification accuracy for the binary mental task classification is drastically increased which shows the usefulness of the EMD methods for the classification.

In the work of Gupta et al. (2015), EMD and Wavelets methods are used to extract the features. They have used the same parameters to represent the feature vector for further classification as Gupta and Kirar (2015). Table 11 shows the average classification accuracy of the work of Gupta et al. (2015) for binary mental tasks classification for all the subjects. It is observed that the proposed methods outperformed and this shows the introduction of new parameter in our study i.e. Hurst exponent instead of Lampel Ziv complexity is playing a significant role for creating good discriminating feature which is good for building the classification model.

Table 11: Comparison table of the proposed approach with some recent works for binary mental task classification.

Work	Sub 1	Sub 2	Sub 3	Sub 5	Sub 6	Sub 7	Average
Gupta and Kirar (2015)	75.20	64.50	52.70	59.50	67.80	65.00	64.30
Gupta et al. (2015)_EMD	61.75	61.50	53.00	54.50	57.00	62.00	58.29
Gupta et al. (2015)_Wavelets	59.75	62.50	53.00	55.17	54.25	60.50	57.53
Proposed EMD approach	**88.90**	**85.85**	**72.64**	**72.53**	**84.89**	**91.80**	**82.77**
Proposed EEMD approach	**89.78**	**90.37**	**73.51**	**82.86**	**89.15**	**94.26**	**86.65**
Proposed CEEMDAD approach	**89.99**	**90.10**	**73.43**	**74.01**	**89.83**	**92.72**	**85.01**

In the Table 12, methods A, B and C are the schemes used by Zhang et al. (2010) based on asymmetry ratio for calculation of different number of frequency band powers using 75-dimensional, 90-dimensional and 42-dimensional feature vector, respectively. From this table, it is clear that our approach outperforms for all the three subject for all the multi mental tasks classification problem.

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Table 12: Comparison table of classification accuracy achieved for multi mental task classification of the work of Zhang et al. (2010) with proposed approach.

	Two class classification			Three class classification			Four class classification			Five class classification		
Zhang et al. (2010)	A	B	C	A	B	C	A	B	C	A	B	C
Sub1	77.60	**85.90**	83.80	63.90	**75.30**	70.90	54.40	**66.60**	60.50	47.60	**60.40**	55.40
Sub2	62.90	**67.50**	66.20	46.50	**53.80**	47.90	37.90	**45.40**	38.30	31.90	**39.90**	33.60
Sub3	69.40	**72.50**	71.50	54.10	**59.40**	57.00	45.30	**52.10**	49.80	39.30	**46.30**	43.70
Proposed approach	EMD	EEMD	CEEMDAD	EMD	EEMD	CEEMDAD	EMD	EEMD	CEEMDAD	EMD	EEMD	CEEMDAD
Sub1	88.90	89.78	**89.99**	77.95	**80.39**	80.14	67.95	**71.71**	70.59	59.60	**65.23**	63.85
Sub2	85.85	**90.37**	90.10	73.83	**79.50**	78.91	63.37	**70.23**	69.74	56.71	**63.00**	62.92
Sub3	72.64	**73.51**	73.43	58.79	**60.05**	59.97	50.23	51.23	**51.28**	44.53	44.69	**46.93**

4.4 Discussion

Since EEG signal having non-linear and non-stationary property, thus there is a need of an algorithm which can capture such properties of the signal. EMD is such an algorithm which can capture tempo-spectral information of the signal. After decomposing the signal in high and low frequency components, it is important to extract some statistical and uncertainty parameters from the decomposed signal to its compact representation and to distinguish from one mental state to another. In addition, there are two improved version of EMD algorithm named as EEMD and CEMDAN algorithm, which can capture tempo-spectral information even from noise assist signal.

Figure 3 to Figure 6 represent the average classification over all tasks combination for all the possible combination of mental tasks of all subjects. From the figures, it is clear that EEMD algorithm outperforms from other two algorithm. It is also observed that for the Sub 1, Sub 2 and Sub 7, the distinguish capacity of the SVM to differentiate the two or more mental tasks simultaneously is better than other subjects, from the extracted features by the EMDs algorithms.

Although, all the EMDs algorithms are data driven approach , there is need of more data driven approach algorithm such that performance of the given learning system would be independent of the data.
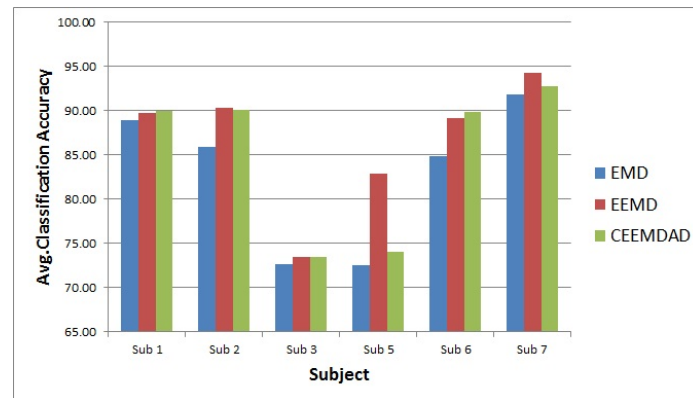
Figure 3: Bar chart for the average classification accuracy over all binary mental tasks for all six subjects.
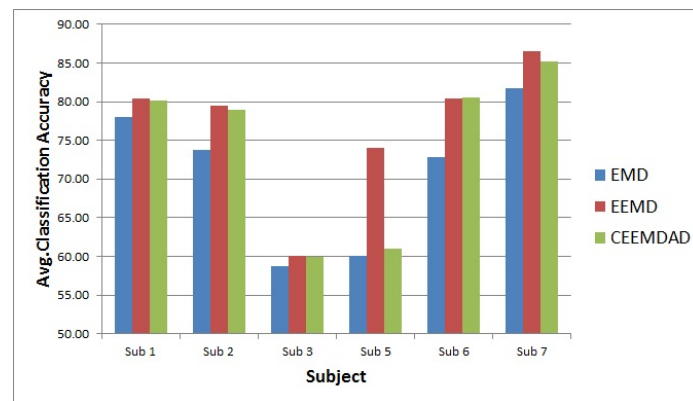

Figure 4: Bar chart for the average classification accuracy over all three class mental tasks for all six subjects.
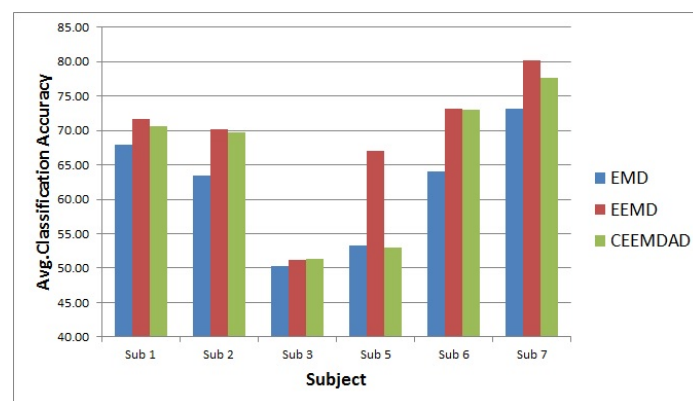

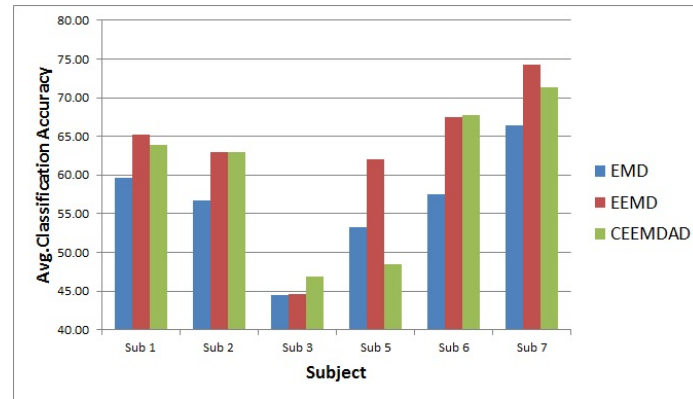Figure 5: Bar chart for the average classification accuracy over all four class mental tasks for all six subjects.

Figure 6: Bar chart for the average classification accuracy over all five class mental tasks for all six subjects.

4.5   Statistical Test

We have utilized a two way, non-parametric statistical test known as Friedman test (Derrac et al., 2011; Friedman, 1937) to find out the significant difference among these three EMD methods for EEG signal. The Table 13 shows the average Friedman ranking of the methods for different combination of metal tasks classification problem, which shows that EEMD method outperform among three methods for all the possible metal tasks classification problem.

The performance of any EMD method (in this work) is studied with respect to control method i.e. best performer from the Friedman's ranking (EEMD). The test statistics for the comparison of mth method to n^{th} method, z, is given as

$$z = \frac{R_m - R_n}{\sqrt{\frac{k(k+1)}{6N}}}, \tag{17}$$

where R_m and R_n are the average ranking of the methods, k and N are the number of methods (algorithms) and experiments respectively. However, these p values so obtained are not suitable for comparison with the control method. Instead, adjusted p values (Derrac et al., 2011) are computed that take into account the error accumulated and provide the correct correlation. For this, a set of post-hoc procedures are defined and adjusted p values are computed to be used in the analysis. For pair-wise comparisons, the widely used post hoc methods to obtain adjusted p values are (Derrac et al., 2011): Bonferroni-Dunn,Holm,Hochberg and Hommel procedures. Table 14 shows the various value of adjusted p values obtained from aforementioned methods. From this table, it is clear that there is statistical difference between EEMD and other two methods.

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Table 13: Average Rankings of the algorithms

Algorithm	Ranking			
method	Binary Class	Three Class	Four Class	Five Class
EMD	3.00	3.00	3.00	2.93
EEMD	**1.03**	**1.01**	**1.03**	**1.17**
CEEMDAN	1.97	1.99	1.97	1.90

Table 14: Adjusted p-values

Class Combinations	Algorithm	unadjusted p	p_{Bonf}	p_{Holm}	p_{Hoch}	p_{Homm}
Binary Class	EMD	4.16E-44	8.33E-44	8.33E-44	8.33E-44	8.33E-44
	CEEMDAN	2.99E-11	5.99E-11	2.99E-11	2.99E-11	2.99E-11
Three Class	EMD	5.69E-45	1.14E-44	1.14E-44	1.14E-44	1.14E-44
	CEEMDAN	4.22E-12	8.44E-12	4.22E-12	4.22E-12	4.22E-12
Four Class	EMD	4.16E-44	8.33E-44	8.33E-44	8.33E-44	8.33E-44
	CEEMDAN	2.99E-11	5.99E-11	2.99E-11	2.99E-11	2.99E-11
Five Class	EMD	1.49E-35	2.97E-35	2.97E-35	2.97E-35	2.97E-35
	CEEMDAN	2.44E-7	4.89E-7	2.44E-7	2.44E-7	2.44E-7

5   Conclusion

Classification of EEG signal for any purpose requires detail analysis of the signal, i.e. intrinsic properties of the signal. This work presented a comprehensive comparison of three different EMDs algorithms to find intrinsic characteristics of the EEG signal for mental task classification problem. After decomposing the signal through the EMDs algorithms, 8 parameters were calculated from each segment of the decomposed signal to form the feature vector of the signal. SVM was used for the classification process. Experimental results showed that EEMD algorithm perform best among three. A set of statistical analysis are also performed to investigate whether three EMDs algorithms statistically different or not.

In the future work, we would like to explore some advance decomposition methods for the EEG signal. It would be also of interest to find some new parameters which can help to identify the different mental states.

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Compliance with Ethical Standards

The article does not contain any ethical issues.

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