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# Distinguishing two Different Mental States with Application of Non-Linear Parameters

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## ABSTRACT

Electroencephalograph (EEG) is useful modality nowadays which is utilized to capture cognitive activities in the form of a signal representing the potential for a given period. Brain Computer Interface (BCI) systems are one of the practical application of EEG signal. Response to mental task is a well-known type of BCI systems which augments the life of disabled persons to communicate their core needs to machines that can able to distinguish among mental states corresponding to thought responses to the EEG. The success of classification of these mental tasks depends on the pertinent set formation of features (analysis, extraction and selection) of the EEG signals for the classification process. In the recent past, a filter based heuristic technique, Empirical Mode Decomposition (EMD), is employed to analyse EEG signal. EMD is a mathematical technique which is suitable to analyze a non-stationary and non-linear signal such as EEG. In this work, three stage feature set formation from EEG signal for building classification model is suggested to distinguish different mental states. In the first stage, the signal is broken into a number of oscillatory functions through EMD algorithm. The second stage involves compact representation in terms of four different features obtained from the each oscillatory function. It has also observed that not all features are relevant therefore there is need to select most relevant features from the pool of the formed features which is carried out in the third stage. Two well-known multi-variate feature selection algorithms are investigated in combination with EMD algorithm for forming the feature vectors for further classification. Classification is carried out with help of learning the Support Vector Machine (SVM) classification model. Experimental result on a publicly available dataset shows the superior performance of the proposed approach

**Keywords:** Brain Computer Interface, Response to Mental Tasks, Feature Extraction, Empirical Mode Decomposition, Electroencephalograph.

## I. INTRODUCTION

The Brain-Computer Interface (BCI) is one of the regions which has sponsored up in developing techniques for assisting neurotechnologies for ailment prediction and manage motion [1, 2, 13]. BCIs are rudimentary geared toward availing, augmenting or rehabilitating human cognitive or motor-sensory characteristic [12, 16]. To capture brain activities, EEG is one of the prevalent technology as it provides signal with high temporal resolution in a non-invasive way [12, 13]. Mental task classification (MTC) based BCI is one of the famed categories of BCI technology which does no longer involve any muscular activities [3] i.e. EEG responses to mental tasks.

In literature, the EEG signals have been analyzed especially in 3 domain names specifically temporal, spectral and hybrid domain. In hybrid domain, both the frequency and temporal information is utilized for analysis of the EEG signals simultaneously. Empirical mode decomposition (EMD) is this sort of heuristic hybrid approach that can examine the signal in both domains by decomposing the signal in distinctive frequency components termed as Intrinsic Mode Function (IMF) [9]. In literature, EMD has been incorporated for data analysis followed by using these decomposed signals for parametric feature vector formation for building classification model [5, 7].

In this work, final set of feature vectors for the classification process is obtained in three stages. In first stage the raw EEG signal is analysed using EMD algorithms which results into number of IMFs. A compact representation of these IMFs with the parametric feature coding has been introduced with the help of four well-known parameters namely Hurst exponent, Lampelziv Complexity, Approximate entropy and Lyapunov exponent. Further to select only relevant features, two multi-variate feature selection methods are investigated which is the third stage of the proposed method for obtaining the final feature vectors for classification.

Outline of this article is as follows: Section 2 contains overview of feature extraction and parametric feature formation. Feature selection approach is discussed in Section 3. In section 2, a brief description of dataset and Experimental result are discussed. The conclusion is discussed in Section 5.

## II. FEATURE EXTRACTION

In this work, feature extraction from EEG signal has been carried out in two stages: First stage involves the decomposition of EEG signal from each channel into $k$ number of intrinsic mode functions (IMFs) using Empirical Mode Decomposition (EMD) algorithm (discussed in Subsection 2.1). Later in second stage, these decomposed IMFs obtained from each channel were used to calculate four parametric features. Hence, each signal can be transformed to more compact form. A brief description of EMD and parametric Feature vector construction are described in the following subsection.

### A. Empirical Mode Decomposition (EMD)

EMD is a mathematical technique which is utilized to analyze a non-stationary and non-linear signal. EMD assumes that a signal is composed of a series of different IMFs and decompose the signal into these continuous functions. Each IMFs have the following properties [9]:

1. Number of zero crossings and number of extrema are either equal or differ at most by one.
2. Local maxima and local minima produces the envelope whose mean value is equal to zero at a given point.

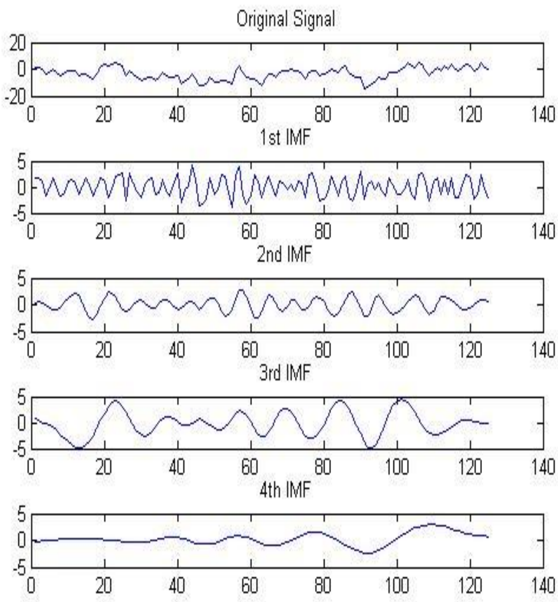


**Figure 1:** IMF plot obtained for a given EEG signal.

Figure 1 showed the plot of first four IMFs of an EEG segment using EMD algorithm. More details of this algorithm can be found in [9].

B. Parametric Feature vector construction

For constructing feature vector from the decomposed EEG signal, we have calculated four parameters using complexity measure and dynamical values of the decomposed signal. The complexity measure shows repetitive nature in the time series signal of decomposed signal and the uncertainty value denotes how much information contained by the signal. These parameters are Hurst exponent, Lampleziv Complexity, Approximate entropy and Lyaponov exponent of the signal.

**B1. Lempel-Ziv Complexity**

This complexity was first introduced by [15]. It quantifies the characteristics of degree of order or disorder and development of spatio-temporal patterns of the signal. It gives number of distinct patterns in a given finite sequence and reflects the rate of occurrence of new symbols in the pattern. Its value lies between 0 and 1, 0 indicates pure static and 1 represents randomness. If $L(n)$ is the length of encoded $n$ observations then $LZ$ complexity is given by:

$$C_{LZ} = \frac{L(n)}{n} \quad (1)$$

**B2. Lyapunov exponent**

It denotes the rate of separation of infinitesimally close trajectory of a dynamically system [11]. If two trajectory of the dynamical system having phase spaces with initial phase separation $\delta Z_0$ divergence at the rate $t$, is given by:

$$|\delta Z(t)| \approx e^{\lambda t} |\delta Z_0| \quad (2)$$

here, $\lambda$ is Lyapunov Exponent

**B3. Hurst Exponent**

In financial time series data analysis, it has been seen that the presence of long memory dependence in asset returns has been fascinating academicians as well as financial market professionals [4]. The existence of long memory behavior in asset returns was observed by Mandelbrot and many researchers have supported his findings [4, 18] . These long-range memory dependence can be measured in terms of Hurst Exponent [10]. Extracting this parametric property from EEG signals can be a highly discriminating feature to represent long-range memory dependence for two different mental task. To the best of our knowledge, this parameter has not been explored for mental task classification. Hurst Exponent $H$ is defined as:

$$H = \frac{\log \frac{E\left[\frac{R(n)}{S(n)}\right]}{C}}{\log n} \quad as \ n \to \infty \quad (3)$$

where $R(n)$ and $S(n)$ denotes range and standard deviation for $n$ observation of a given time series respectively. $E[\cdot]$ is the expected value and $C$ is constant.

**B4. Approximate Entropy**

It quantifies the amount of regularity and fluctuation of time series data [17]. For a $u(1), u(2), \ldots u(N)$, $N$ equally spaced time series data, having $m$ and $r$, fix integer for the length fixed pattern and real number for criterion. There would be a sequence of vectors $x(1), x(2), \ldots, x(N-m+1)$ , where each $x(i) = [u(i), u(i+1), \ldots, u(i+m-1)]$ . Fraction of pattern $C_i^m(r)$ length $m$ that resemble the pattern of the same length that begins at interval $i$.

$$C_i^m = \text{numberof } x(j) \text{suchthat} \quad d[x(i), x(j)] \le \frac{r}{(N-m+1)} \quad (4)$$

where

$$d[x, x^*] = max[u(a) - u^*(a)] \quad (5)$$

$$\phi^m(r) = (N-m+1)^{-1} \sum_{i=1}^{N-m+1} log(C_i^m(r) \quad (6)$$

Approximate entropy can be defined as:

$$Apen = \phi^{m}(r) - \phi^{m+1}(r) \tag{7}$$

## III. FEATURE SELECTION

Feature selection [14, 8] is one of the approach to determine relevant features. Inspite of available rich research works on feature selection, not much work has been done in the area of mental task classification. The feature selection can be done using two methods. First method is classifier independent and relevance of the feature is measured by the its inherent statistical properties such as distance measure, correlation etc.This approach is also known as filter method of feature selection. The second is wrapper method, where feature selection is classifier dependent and choose optimal subset of features to enhance accuracy of classifier. The wrapper based methods [14] find optimal or relevant subset of features from all possible combination of subsets of features and require classifier to evaluate the performance of the subset. Therefore, the computational cost of wrapper methods is much higher than filter methods. In this work, two distance based multi-variate feature selection methods, namely Bhattacharaya Distance and Kullback Divergence.

The problem under consideration has $n$ samples of EEG signal, $d$ features and $m$ distinct classes for mental task problem. Letâ€™s assume that matrix **X** represents available EEG data of dimension $n \times d$, where n is total number of samples and d represents total number of features. Here, each row xi in matrix represents sample from class label $c_i$ where i = 1,2,3,….,m and each column fj in matrix represents feature vector. Thus, the matrix **X** is represented as:

$$
\mathbf{X} = \begin{array}{c|c|c|c|c|c|c|}
 & \mathbf{f_1} & \mathbf{f_2} & \mathbf{f_3} & \cdots & \mathbf{f_d} & \text{Class}(\mathbf{c}) \\
\hline
\mathbf{x_1} & X_{11} & X_{12} & X_{13} & \cdots & X_{1d} & c_1 \\
\hline
\mathbf{x_2} & X_{21} & X_{22} & X_{23} & \cdots & X_{2d} & c_2 \\
\hline
\mathbf{x_3} & X_{31} & X_{32} & X_{33} & \cdots & X_{3d} & c_3 \\
\hline
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
\hline
\mathbf{x_n} & X_{n1} & X_{n2} & X_{n3} & \cdots & X_{nd} & c_n \\
\hline
\end{array}
$$

A. Bhattacharaya Distance

It is a one kind of distance between two data points based on their probability distributions. In the domain x, for the two data p and q, Battacharaya distance is defined as:

$$D_B(p,q) = -ln(BC(p,q)) \tag{8}$$

where BC is Bhattacharaya coefficient,defined as

$$BC(p,q) = \sum_{x \in p,q} \sqrt{p(x)q(x)} \tag{9}$$

B. Kulback Divergence

It is another probability distribution based divergence between two data. For two data, P and Q, over same probability space, the Kullback Divergence is defined as:

$$D_{KL}(P||Q) = -\sum_i P(i) log \frac{P(i)}{Q(i)} \tag{10}$$

## IV. EXPERIMENT SETUP AND RESULT

### A. Dataset and constructing feature vector

In order to check the effectiveness of the proposed method, experiments have been performed on a publicly available dataset [1] [13] which consists of recordings of EEG signals using six electrode channels from seven subjects with the recording protocols. Each subject was asked to perform 5 different mental tasks as namely Baseline task relax (B), Letter Composing task (L), Non trivial Mathematical task (M), Visualizing Counting (C) of numbers written on a blackboard and Geometric Figure Rotation (R) task. For conducting the experiment, data from all the subjects are utilized except Subject 4; as data recorded for Subject 4 is incomplete [6].

The EEG signal corresponding to each mental task of a particular subject is formed into half-second segments which yields into 20 segments (signal) per trial per channel. Thus, for every channel, each of 20 segments are decomposed using EMD algorithm into 4 IMFs. The four parameters are extracted for each of these IMFs per segment per channel per trial for a given subject. A set of aforementioned eight statistical parameters is obtained for each of the six channels of the signal and these sets were concatenated to form a feature vector. Hence, the final feature vector is of 96 dimensions (4 IMFs × 4 parameters × 6 channels) after applying the parametric feature vector formation step. As the dimension of feature vector are still high and not all features are relevant for classification so feature selection methods are utilized for selecting only relevant features for classification which results in lowering the time for building the classification model. Figure 2 shows complete pipeline for constructing the feature vector from each subject using all trial corresponding to each mental tasks labels (B, L, M, C and R) for further classification using SVM classifier.

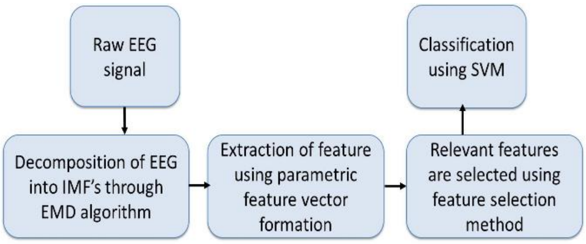


**Figure 2:** Flow diagram of the proposed method.

### B. Results and Discussion

As discussed in the previous subsection, a set of feature vectors have been obtained corresponding to every mental task labels (B, L, M, C and R). Binary mental task classification problem has been formulated to distinguish the different mental state of different subjects. The optimal value of SVM regularization parameters i.e., gamma and cost, were obtained with the help of grid search algorithm. The average classification accuracy of 10 runs of 10 cross-validations has been reported. Figure 3 shows average classification accuracy of different binary combination of mental tasks averaged over all subjects corresponding to different feature selection techniques. Number of relevant features selected corresponding to given feature selection method is summarized in Figure 5. From these figures it can be noted that incorporating the feature selection techniques will leads to better accuracy in comparison to without feature selection.

Hence, our model can be beneficial for the differently abled persons to communicate with the machine more efficiently i.e., quickly and accurately.

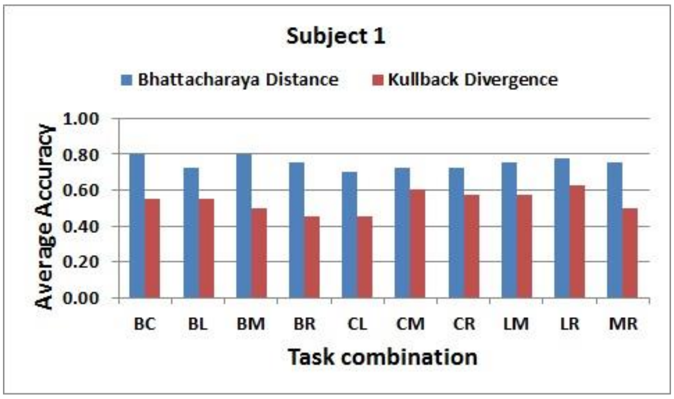


**Figure 3** : Average classification accuracy for different binary mental task combinations for Subject 1.

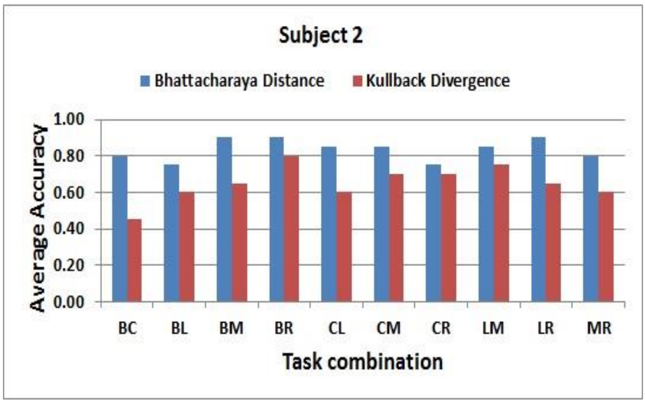


**Figure 4:** Average classification accuracy for different binary mental task combinations for Subject 2.

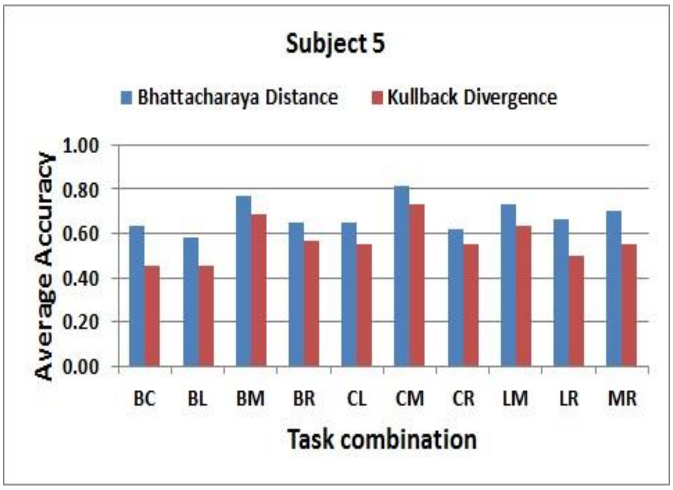


**Figure 5:** Average classification accuracy for different binary mental task combinations for Subject 5.

## V. CONCLUSION

The EEG signals are used to capture the cognitive activities and each activity had embedded hidden patterns. Our study employed effective machine learning strategy to capture the hidden patterns from the EEG signal of different mental tasks and make prediction about the unknown mental task from the given signal. In this work EMD algorithm is used to decomposed EEG signal into IMFs and parametric features are calculated for forming the feature vectors. Further for selecting only relevant features, four well known univariate feature selection techniques are investigated which reduces the dimension of feature vectors which results into reduction of time in building the classification model. The experiment has been performed on a publicly available EEG dataset which contains the responses to different mental thought regarding some task. The experimental results shows the performance of the proposed approached for binary mental task classification problem is improved after incorporating the feature selection in conjunction with EMD algorithm.

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