Hurst Exponent as a New Ingredient to Parametric Feature Set for Mental Task Classification

Akshansh Gupta, Dhirendra Kumar and Anirban Chakraborti

Abstract Electroencephalograph (EEG) is a popular modality to capture signals associated with brain activities in a given time window. One of the powerful applications of EEG signal is in developing Brain–Computer Interface (BCI) systems. Response to mental tasks is one of BCI systems which helps disabled persons to communicate their need to the machines through signals related to particular thought also known as Mental Task Classification (MTC). The success of application depends on the efficient analysis of these signals for further classification. Empirical Mode Decomposition (EMD), a filter-based heuristic technique, is utilized to analyze EEG signal in the recent past. In this work, feature extraction from the EEG signal is done in two stages. In the first stage, the signal is broken into a number of oscillatory functions by means of EMD algorithm. The second stage involves compact representation in terms of eight different statistics (features) obtained from each function. Hurst Exponent as a new ingredient to parametric feature set is investigated to check its suitability for MTC. Support Vector Machine (SVM) classifier is utilized to develop a classification model and to validate the proposed approach for feature construction for classifying the different mental tasks. Experimental result on a publicly available dataset shows the superior performance of the proposed approach in comparison to the state-of-the-art methods.

Keywords Brain–computer interface · Response to mental tasks · Feature extraction · Empirical mode decomposition · Electroencephalograph

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1 Introduction

The Brain–Computer Interface (BCI) is one of the areas which has backed up in developing techniques for assisting neurotechnologies for disease prediction and control motion [1, 2, 12]. BCIs are rudimentary and aimed at availing, augmenting or rehabilitating human cognitive or motor-sensory function [11, 13]. To acquire brain activities, EEG is one of the popular technologies as it provides signal with high temporal resolution in a noninvasive manner [11, 12]. Mental task classification (MTC) based BCI is one of the renowned categories of BCI technology which does not involve any muscular activities [3].

In the literature, the EEG signals have been analyzed mainly in three domains namely temporal, spectral, and hybrid domain. In hybrid domain both frequency and temporal information can be captured simultaneously. Empirical Mode Decomposition (EMD) is such a heuristic hybrid technique which can analyze the signal in both domains by decomposing the signals in different frequency components termed as Intrinsic Mode Function (IMF) [9, 15]. To represent these decomposed signals in a compact manner, features are extracted in terms of statistical and uncertainty parameters [5, 7]. These features can be used to classify two different mental tasks.

In this work, a new long-range memory dependence parameter known as Hurst Exponent has been investigated to represent the decomposed signal along with other statistical and uncertainty parameters [7].

Outline of this article is as follows: Sect. 2 contains the brief overview of feature extraction. In Sect. 3, the brief description of dataset and experimental results are discussed. The conclusion and future directions are discussed in Sect. 4.

2 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 Sect. 2.1). Later in the second stage, these decomposed IMFs obtained from each channel were used to calculate eight parametric features. Hence, each signal can be transformed to more compact form. A brief description of EMD and the newly incorporated parametric feature named Hurst Exponent to create feature vector are discussed in following subsections.

2.1 Empirical Mode Decomposition (EMD)

EMD is a mathematical technique which is utilized to analyze a nonstationary and nonlinear signal. EMD assumes that a signal is composed of a series of different

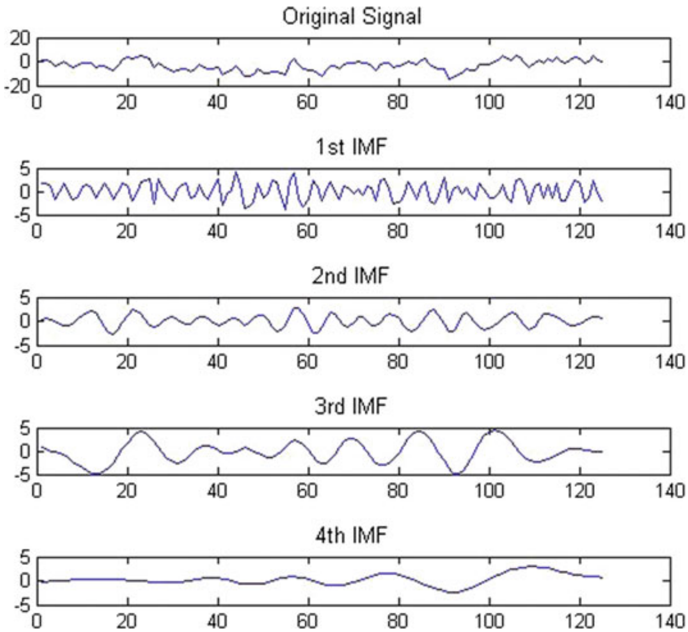


Fig. 1 IMF plot obtained for a given EEG signal

IMFs and decompose the signal into these continuous functions. Each IMF has 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 produce the envelope whose mean value is equal to zero at a given point.

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].

2.2 Parametric Feature Vector Construction

For constructing feature vector from the decomposed EEG signal, we have calculated eight parameters using moment values, long-range dependence and uncertainty values of the decomposed signal. The moments characterize the decomposed signal by certain statistical properties, a long memory dependence which indicates autocorrelation in time series of decomposed signal and the uncertainty value denotes how much information is possessed by the signal. These parameters are root mean square, variance, skewness, kurtosis, Hurst Exponent, central and maximum frequency, and Shannon entropy of the signal. All the parameters are well known, we have discussed only Hurst Exponent in the following Sect. 2.3.

2.3 Hurst Exponent as a Feature

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, 14]. These long-range memory dependences 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 tasks. To the best of our knowledge, this parameter has not been explored for mental task classification. Hurst Exponent H is defined as

$$H = \frac{\log \frac{E\left[\frac{R(n)}{S(n)}\right]}{C}}{\log n} \; as\; n \to \infty, \tag{1}$$

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.

3 Experimental Setup and Result

3.1 Dataset and Constructing Feature Vector

To check the efficacy of the proposed approach, experiments have been carried out on a publicly available dataset 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 follows:

1. *Baseline task relax* (*B*).
2. *Letter Composing task* (*L*).
3. Nontrivial *Mathematical task* (*M*).

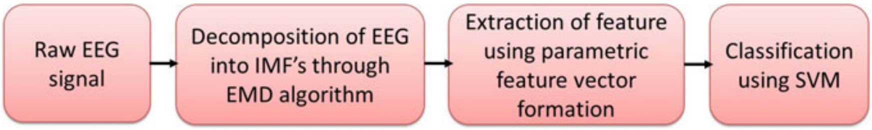


Fig. 2 Flow diagram of the proposed method

4. *Visualizing Counting* (*C*) of numbers written on a blackboard.
5. *Geometric Figure Rotation* (*R*) task.

The more details about this dataset can be found in the work of [12].[1] For conducting the experiment, data from all the subjects are utilized except Subject 4; as data recorded from Subject 4 contains some incomplete data [6]. The complete pipeline (See Fig. 2) for constructing the feature vector from each subject using all trial corresponding to each mental tasks labels (B, L, M, C, and R) is described below:

1. The EEG signal corresponding to each task of a given subject is sampled into half-second segments, which results into 20 segments (signal) per trial per channel.
2. In this way, corresponding to each channel, each of the 20 segments is used to generate the 4 IMFs using EMD algorithm.
3. Eight parameters are calculated for each of these IMFs per segment per channel per trial for a given subject.

A set of aforementioned eight parameters was obtained for each of the six channels of the signal and these sets were concatenated to form a feature vector for classification purpose. Hence, the final feature vector is of 192 dimensions (4 IMFs segments $\times$ 8 parameters $\times$ 6 channels).

3.2 Result

The performance of the proposed approach has been evaluated in terms of classification accuracy achieved using SVM classifier for binary mental task classification problem (BC, BL, BM, BR, CL, CM, CR, LM, LR, and MR), i.e., total 10 classification models for different binary mental task combinations. 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 summarizes the classification accuracy for the different binary mental task combinations for all the subjects. From Fig. 3, it can be noted that the average classification accuracy for Subject 1 outperforms for BC,

[1] http://www.cs.colostate.edu/eeg.

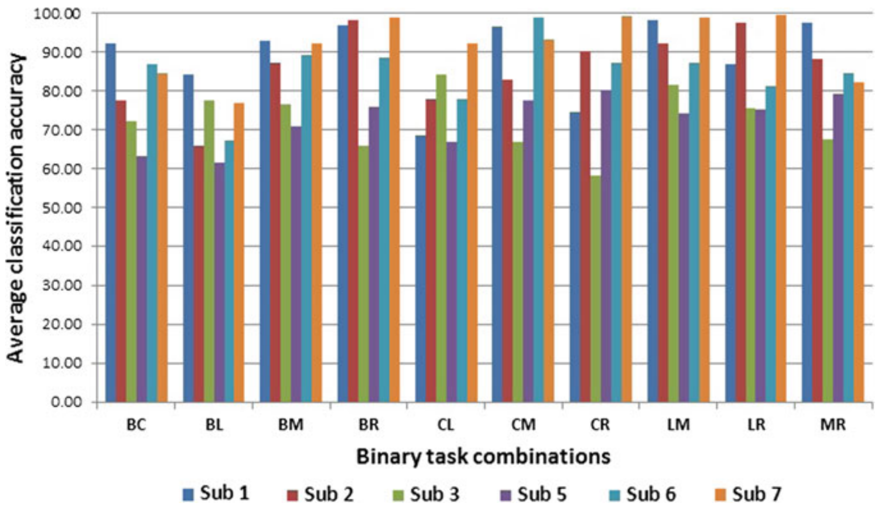
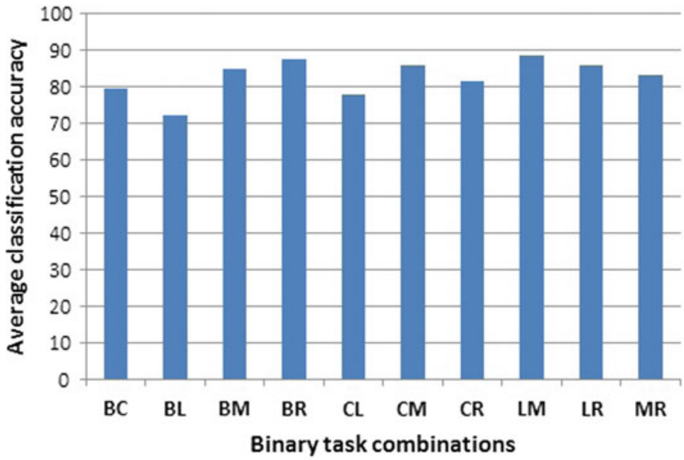


Fig. 3 Classification accuracy of the proposed method for different subjects for binary metal task classification

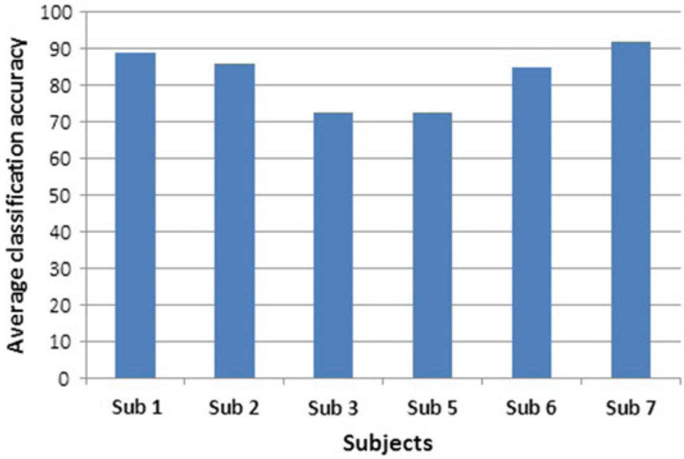
BL, BM, and MR task combinations compared to other subjects whereas the average classification accuracy for BR, CL, CR, LM, and LR binary task combination for Subject 7 is better than others. Figure 4a, b show the average classification accuracy over all the subjects and all binary mental task combinations. From this figure, it can be noted that average for all the subjects and for all binary task combinations the average classification accuracy is more than 70%.

3.3 Comparison with Some Recent Works

In this subsection, we have compared the results of the proposed method with existing approaches for binary mental task classification under the same experimental setup. Figure 5 shows the comparison of the proposed method with the work of Gupta et al. (2015) [7] (EMD and Wavelets) and Gupta and Kirar [8] for binary mental task classification in terms of average classification accuracy for each subject (average calculated over all binary mental task combinations). Figure 5 shows bar diagram of average classification accuracy for different subjects corresponding to different approaches along with the proposed approach for binary mental tasks classification. It is observed from Fig. 5 that the proposed method achieved the highest average classification accuracy for all the subject in comparison to other approaches. Hence,



(a) Average classification accuracy of the proposed method for different binary metal task combinations over all subjects



(b) Average classification accuracy of the proposed method for different subjects over all binary metal task combinations

Fig. 4 Average classification accuracy of the proposed method

this study shows that the proposed approach which investigated the new parameter, i.e., Hurst Exponent (along with other parameters) for MTC significantly improves the average classification accuracy.

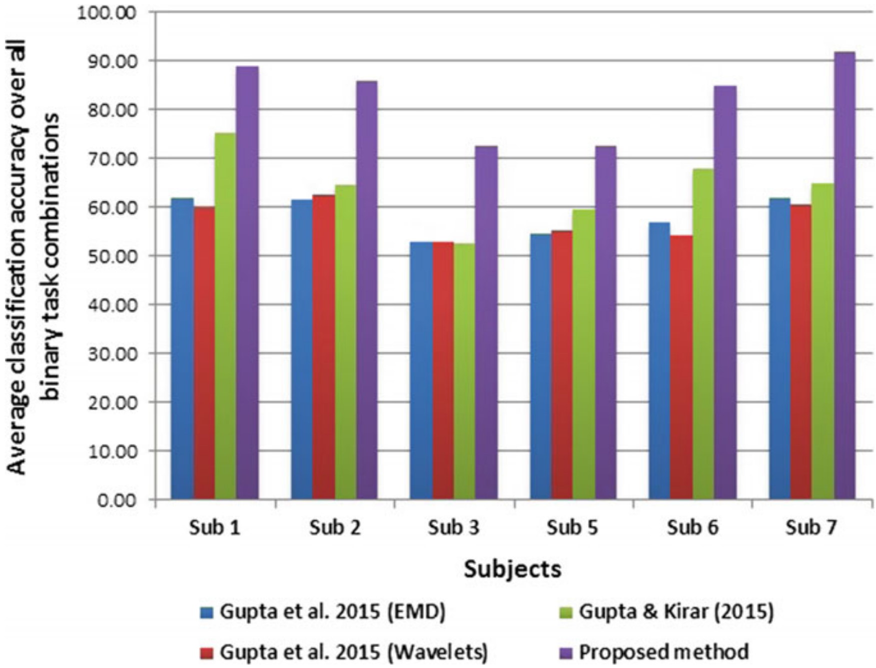


Fig. 5 Comparison of average classification accuracy of the proposed method for different subjects over binary metal task combinations

4 Conclusion

This work presented a study of new parameter Hurst Exponent as a novel feature to encode the long-range memory dependence in decomposed EEG signal along with some statistical parameters. Feature vectors obtained from EEG signal decomposition using EMD algorithm corresponding to data of each mental tasks separately. SVM has been utilized to build the classification model using feature vectors for binary mental task classification. Experimental results showed that the proposed approach outperforms the similar state-of-the-art work. In future work, it would be interesting to investigate some new set of parameters associated with the signals which can help in distinguishing different mental states more accurately. Further, the proposed approach can be extended to solve multi-mental task classification problem.

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