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Motor Imagery Recognition of EEG Signal using Cuckoo-Search Masking Empirical Mode Decomposition

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ABSTRACT

Brain Computer Interface (BCI) aims at providing an alternate means of communication and control to people with severe cognitive or sensory-motor disabilities. Brain Computer Interface in electroencephalogram (EEG) is of great important but it is challenging to manage the non-stationary EEG. EEG signals are more vulnerable to contamination due to noise and artifacts. In our proposed work, we used Cuckoo-Search Masking Empirical Mode decomposition to ignore such vulnerable things. Initially, the features of EEG signals are taken such as Energy, AR Coefficients, Morphological features and Fuzzy Approximate Entropy. Then, for Feature extraction method, Masking Empirical Mode Decomposition (MEMD) is applied to deal with motor imagery (MI) recognition tasks. The EEG signal is decomposed by MEMD and hybrid features are then extracted from the first two intrinsic mode functions (IMFs). After the extracted features, Cuckoo Search algorithm is used to select the significant features. Different weights for the relevance and redundancy in the fitness function of the proposed algorithm are used to further improve their performance in terms of the number of features and the classification accuracy and finally they are fed into Linear Discriminant Analysis for classification. This analysis produces models whose accuracy is as good as more complex method. The results show that our proposed method can achieve the highest accuracy, maximal MI, recall as well as precision for Motor Imagery Recognition tasks. Our proposed method is comparable or superior than existing method.

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KEYWORDs: Brain Computer Interface, Motor Imagery (MI) Recognition, Empirical Mode Decomposition

I. INRODUCTION

Brain-computer interfaces (BCIs) are systems which enables a user to control a device using only his or her brain neural activity. BCIs are proposed as a communication tool for the paralyzed, but also have a wide range of other applications including neural prosthetics, wheel chairs, video games and virtual reality, creative expression, access to the internet etc. Although some of the BCI applications can also be useful for healthy people, the main focus in BCI research is put on providing a means of communication and control to the disabled users, who otherwise would have limited—or no — means of communication with the outer world[2]. BCI applications utilize the brain and its nervous system functions where the human's central nervous system consists of the spinal cord and the brain. Forming a BCI system requires following three main steps are signal acquisition, signal processing, data manipulation. In motor imagery (MI), when people imagining an action without execution, the corresponding brain sensorimotor areas are activated and the same electroencephalogram (EEG) generates, sas if the action is done [3].

Imagining left or right hand movement, an obvious ERD from the mu (8~12Hz) and beta (13–30 Hz) rhythms of EEG which gathered from the contralateral sensorimotor area of cerebral cortex [5]. These characters lay the foundation of MI-based BCI.

In feature extraction phase, the problem is to choose the appropriate features from the EEG signal to extract the features of the EEG Dataset. And another major problem is to select the suitable feature selection methods because the signal features should be taken into account in order to make the system with greater accuracy. In training phase, the problem is to train the databases created in the server. Because of the Kruskal-Wallis test and Linear Discriminant Analysis, the training is difficult to make the system with high performances. In testing phase, the difficulty identified is to extract the features of the EEG Dataset with less accuracy and maximal MI in real time with the less number of databases. [5]

The solution of this problem is that: In feature selection, the features which gives the exact features of the EEG signal in Dataset such as Energy, AR coefficients, morphological characteristics and fuzzy approximate entropy are selected In training and testing phase, Cuckoo-Search algorithm and Linear Discriminant Analysis classifiers are used to increase the accuracy, maximal MI and include the precision and recall which are not in the existing method i.e. MEMD, LDA+AFAPS, HSF, SVM. To recognize the Motor Imagery Tasks (direction of left hand and right hand movement) by using classifier stage. To extract EEG features such as Energy, AR Coefficients, Morphological features and Fuzzy Approximate Entropy using Masking Empirical Mode

Decomposition, and to select the particular features using Cuckoo-Search Algorithm to EEG data of performing motor imagery on another day.

The remainder of this paper is organized as follows: Section II describes the experimental methodology for this study. Section III presents the experimental results. Finally, section IV concludes the paper.

II. SUBJECTS AND METHODS

A. Subjects

This study recruited 12 healthy subjects. Ethics approval and informed consent were obtained. Two subjects chose to perform motor imagery and passive movement of the left hand while the remaining 10 subjects chose to perform on the right hand.

B. EEG data collection

The recording was made using Brain Amp MR plus amplifiers and an Ag/AgCl electrode cap. Signals from 59 EEG positions were measured that were most densely distributed over sensorimotor areas. Signals were band-pass filtered between 0.05 and 200 Hz and then digitized at 1000 Hz with 16 bit (0.1 μV) accuracy. We provide also a version of the data that is down sampled at 100 Hz (first low-pass filtering the original data (Chebyshev Type II filter of order 10 with stop band ripple 50dB down and stop band edge frequency 49Hz) and then calculating the mean of blocks of 10 samples). Here, the motor imagery tasks were cued by soft acoustic stimuli (words left, right, and foot) for periods of varying length between 1.5 and 8 seconds. The end of the motor imagery period was indicated by the word stop. Intermitting periods had also a varying duration of 1.5 to 8s. Note that in the evaluation data, there are not necessarily equally many trials from each condition.

Fig.1. Experimental setup to collect EEG data from passive movement of the left hand

There are four spectral features extracted such as Energy, AR coefficients, Morphological features and Fuzzy approximate entropy in the proposed classification

Energy

Energy is a crucial parameter for the identification of left-right MI EEG. The expression is given by,

$$E = \sum_{n=0}^{N-1} |H_1(n)|^2 \qquad \ldots\ldots\ldots\ldots..(1)$$

Where N is the length of the signal.
AR coefficients, Morphological features and Fuzzy approximate entropy are also extracted.

C. Least mean square algorithm:

LMS algorithm is relatively simple; it does not require correlation function calculation. LMS algorithms are a class of adaptive filter used for adaptive noise cancellation by varying its step size parameter μ for different filter order and number of iteration. It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time.

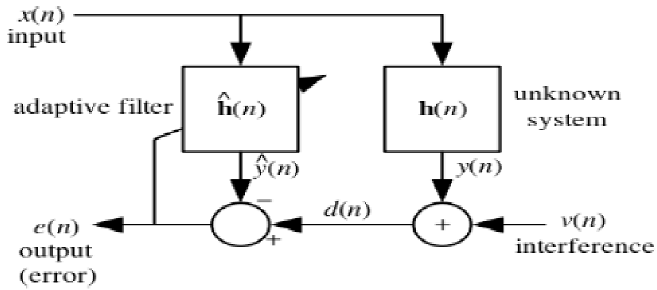


Fig.2 LMS Methodology

1. Masking Empirical Mode Decomposition:

Empirical mode decomposition (EMD) is one such adaptive signal processing technique for decomposing a signal. The signal decomposition aims at revealing intrinsic mode functions (IMFs) having meaningful instantaneous frequency.

A masking signal of frequency higher than the highest frequency component present in the original non-stationary signal is added and subtracted to obtain two new signals. EMD is performed on these two signals to extract the first IMFs from these two signals. The average of these two is computed to yield IMF of the original signal. The main idea of this method is to insert a row of sine wave s (t) (masking signal) into the original signal to prevent the mode mixing phenomenon which is caused by the low frequency components mixing into the IMF in the process of the EMD.

2. Cuckoo-Search Algorithm

Cuckoo Search (CS) is heuristic search algorithm which is inspired by the reproduction strategy of cuckoos. Cuckoo bird or something like water drops but also provides some principles which can help in providing solutions to real world applications .These algorithms work on the basis of random search in some suitable search region depending on the problem.

CSA is one of the modern nature inspired meta-heuristic algorithms. CS algorithm is based on the obligate brood parasitic behavior of some cuckoo species in combination with the Levy flight behavior of some birds and fruit flies.

3. Linear Discriminant Analysis

(LDA) is aclassification method based upon the concept of searching for a linear combination of variables (predictors) that best separate two best separate two classes.. LDA works when the measurements made on each observation are continuous quantities. The objective of LDA is to perform dimensionality reduction while preserving as much of the class Discriminatory information as possible.

Technique for CSMEMD is proposed in this paper, Motor *Precision* Imagery Recognition of EEG signal using Cuckoo Search Masking Empirical Mode Decomposition has various stages to get the classified output. Different stages are LMS, MEMD, CS-Algorithm and LDA. And also the output of the proposed method is compared to LDA+AFAPS, HSF, MEMD, SVM.

III. EXPERIMENTAL RESULTS

Visual studio coding to evaluate performance of MEMD and CSMEMD by calculated the basic parameters like Accuracy, Precision, Recall, MaximalMI. The performance Evolution of the proposed Algorithm shows the analysis of accuracy, precision, recall and maximal MI for Number of Training data sets.

Accuracy

The accuracy of a measurement system is how close it gets to a quantity's actual (true) value. It increases the performance of the system.

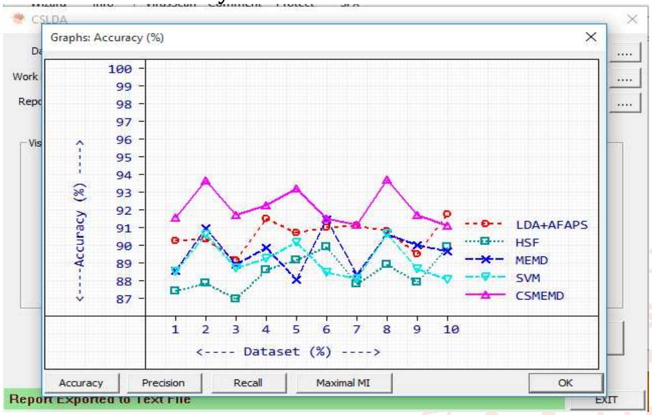


Fig3 Accuracy Vs No of Training Data

The performance evolution of the proposed algorithm shows the analysis of accuracy for number of training datasets.When the Number of Training data set is seven, the accuracy is attained for LDA+AFAPS be 90.6%, HSF will be 88.5%,MEMD will be 89.7% and our proposed Algorithm will achieve a accuracy of 92% which is maximum than other three methods. As the Number of training Data set is increased, there is a gradual increase, decrease in accuracy. But our proposed algorithm (CSMEMD) maintains a slow increase in accuracy as the number of training set is increased. This means our proposed method gives a better accuracy as the number of training data set is increasing.

The performance evolution of the proposed algorithm for Precision, Recall and Maximal MI shown in Fig3,Fig 4, Fig5.

Accuracy, Precision, Recall and Maximal MI for CSMEMD, Precision, Recall and Maximal MI for CSMEMD is more when compared with LDA+AFAPS, HSF, MEMD, SVM. In CSMEMD the four parameters were increased.

Precision

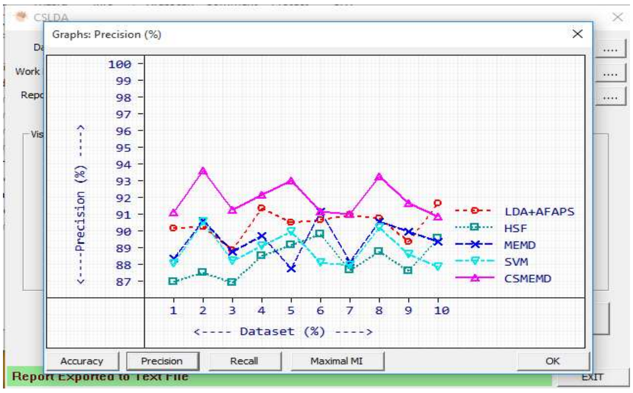


Fig4 Precision Vs No of Training Data

Recall

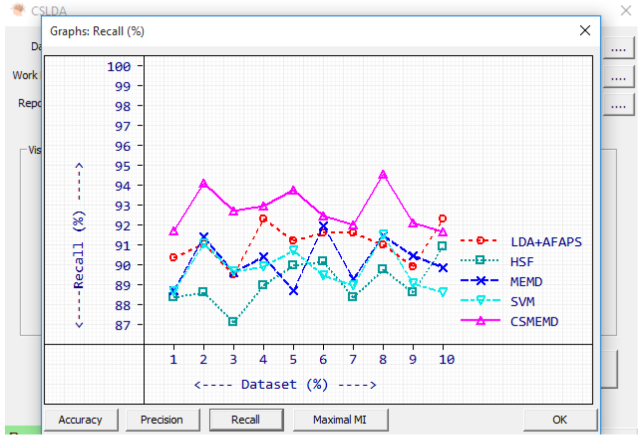


Fig.5 Recall Vs No. of training data

Maximal MI

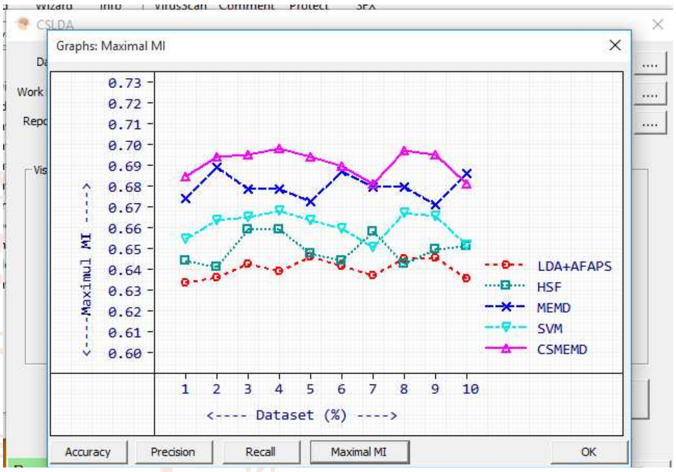
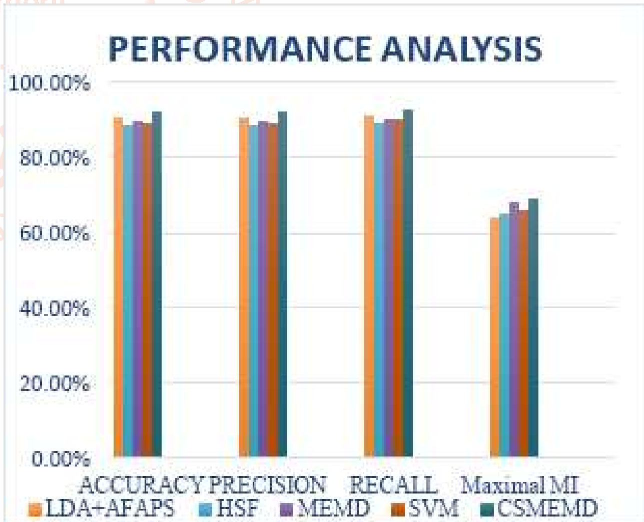


Fig 5 Maximal MI Vs No of Training Data



IV. CONCLUSIONS

Finally the objective mentioned has been achieved successfully. The experiment was conducted by using seven EEG datasets from BCI competition. To analyze the performance of LDA+AFAPS, HSF, MEMD, SVM and CSMEMD the feature vectors namely energy, AR coefficients, morphological features and fuzzy approximate entropy were extracted from the motor imagery EEG dataset to measure the performance metrics like Accuracy, Recall, Precision and Maximal MI. From the analysis the accuracy of the CSMEMD is higher when compared to other classifiers. Similarly the precision and recall metrics also gives the higher performance compare to others. To show the great accuracy and precision of our proposed methodology, we compared the performance results obtained in this work with results obtained in other works. Our proposed methodology is an efficient to recognize the motor imagery tasks.

After the recognition of motor imagery tasks, the obtained result is given to the specific application, which is considered to be our future work.

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