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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) is a collaboration between a brain and device that enables the signals from the brain to done the external activity, i.e. Cursor, Prosthetic control or Wheel chair movement. The brain and object have the direct communication control by using BCI systems. Mostly the current research should be focused on non-invasive method. The array of neurons should be read by using the computer chips and programs then translate the signals in to action i.e., Motor Imagery (MI). The main objective is used to help the disable person without someone help. Mainly the BCI System should be very helpful for the people those who are affect from paralysis to write something and control the motorized wheel chair through thought alone. In Brain Computer Interfacing BCI) the Electroencephalogram (EEG) is a very challenging non-stationary signal. In this paper the preprocessing should be done by Least Mean Square (LMS) algorithm and Empirical mode decomposition (EMD) is a new method to extract the non-stationary signal should be apply on motor imagery recognition task. The features of EEG such as energy, fuzzy approximate entropy, Morphological features and AR coefficients are extracted using Masking empirical mode decomposition. The extracted features are selected by using the cuckoo search algorithm (CSA). In this paper the extracted features should be compare, with cuckoo search or without cuckoo search algorithm analyzed. After the feature selection features are classified by using the linear discriminant analysis (LDA) with respect to some parameters like Accuracy, Precision, Recall, Maximal (MI).***

Keywords: ***Brain Computer Interface (BCI), linear discriminant analysis (LDA), Empirical mode decomposition (EMD), Cuckoo Search Algorithm (CSA), Motor imagery (MI), Least Mean Square (LMS).***

I. INTRODUCTION

The interface between the brain activity and electronic device are enable by the brain computer system (BCI).The bio signal is taken as a input to the BCI system and predicts the action is suggested in [1].The corresponding brain sensorimotor areas are activated when the people imagining an action without execution and the same EEG should be generates as if the action is done in motor imagery [2,3].The main challenge in the EEG classification,the brain signals should be small in amplitude. Therefore, some events like eye movement, muscular movements, etc. should have the lower SNR value. The various techniques have been proposed to prevent the decoding system to correctly decode the user's thoughts such as temporal filtering methods, [4], feature extraction and feature selection techniques [5], and classification algorithm [6]. The several feature extraction techniques such as common spatial pattern (CSP) [7], power spectral density (PSD) [8], have been studied. Classifiers such as k-nearest neighbor (KNN) [9], support vector machine (SVM) [10], etc. have been explored for Classification of MI-EEG signals. Actually, the EEG signal is almost invariably non -linear and non-stationary [11]. To overcome this the empirical mode decomposition should be analyzed (EMD) [11]. The mode mixing and edge effect should be hardly avoided by the EMD and also it makes a sub-signal being a lower signal-to-noise ratio. The EMD is used to rectify the problem such as mode mixing and edge effect. It is also given the better classification to given the higher accuracy. In Masking empirical mode decomposition [12], the original signal should be added first and secondly it should be subtracted to get the frequency masking signal. Initially filtered the EEG using Linear mean square(LMS) algorithm and then the Intrinsic mode function (IMF)extraction should be done using MEMD technique. The required signals are selected as a mu and beta subcomponents, from these components the Energy, morphological features, and fuzzy approximate entropy auto-regressive (AR)coefficients are extracted [2]. The extracted features are selected by the cuckoo search algorithm and finally applied to the linear discriminant analysis (LDA) for classification purpose.

II. MATERIALS AND METHODS

A. *EEG Data*

In this work , the Brain Computer Interfacing competition IV data set I was given by Berlin institute of technology is used to verify the motor imagery movements of left or right hand/foot. BCI Competition is an open competition which aims at evaluating various approaches used in brain computer interfaces and comparing them on the same data set in order to obtain a reliable measurement of performance for each algorithm. It is an attempt to solve the problem of comparing BCI-related signal processing. Methods that are published, but their accuracy was verified on different data sets or they use different performance measures, which makes the relative comparison between any two of the selected methods impossible [13].

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Four editions of the BCI Competition were organized and each edition consisted of 3–5 data sets for which a different classification task. The recording was done by using Ag/AgCl electrode cap and Brain Amp MR plus amplifiers.

The EEG Signals were measured from 59 channels and it should be distributed fully on the sensorimotor areas. For detailed information please refer to [14].

B. *Preprocessing*

The quality of EEG signals is enhanced by pre-processing. The signal to noise ratio and data dimensionality should be reduced by means LMS Algorithm and it also used to remove the data artefacts.

- ***LMS Algorithm***

By varying the step size parameter µ and number of iterations in adaptive noise cancellation and it is also quite simple when compared
to another algorithm by using equation (1). The LMS Methodology is shown in the fig1.It is calculated as,

$$\underline{W}(n+1) = \underline{W}(n) - \mu\frac{\partial e^2(n)}{\partial \underline{W}(n)}$$

$$= \underline{W}(n) + 2\mu e(n)X(n) \qquad (1)$$

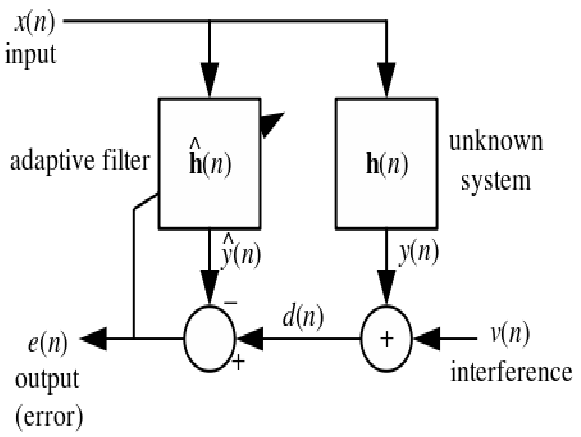

Fig.1. LMS Methodology

C. *Feature extraction*

The Empirical mode decomposition method were represented by the EEG signals.

- ***MEMD***

The Empirical mode decomposition has been included with Hilbert-Huang method. It is a good tool for non-stationary signal. The resolution power of EMD is limited. The frequency cannot separate the signals and is should be very close. To overwhelmed the issue of mode mixing problem, the M-EMD technique should be taken [2]. This method is MM performed by adding and subtracted original non-stationary signals to obtain the new signals. The first IMF function should be extract from these two signals and finally average the signal. The instantaneous amplitude and instantaneous frequency are calculated by using the equation (2) & (3).

$$a_z = \frac{1.6}{N}\sum_{i=1}^{N} a_{IMF1} \qquad (2)$$

$$f_z = \sum_{i=1}^{N} a_{IMF1}(i) f^2{}_{IMF1} \qquad (3)$$

The flow diagram of an Empirical mode decomposition is shown in the Fig 2.

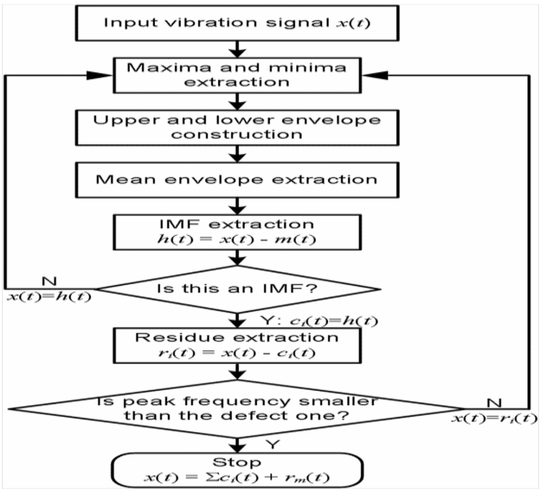

Fig.2.Flow diagram of EMD

There are four spectral features are extracted they are Fuzzy approximate entropy, Morphological process, Energy and AR coefficients,

The energy is calculated as,

$$E = \sum^{N-1}|H_1(n)|^2 \qquad (4)$$

The single channel for an auto regressive model of order p can be written as,

$$X(t) = \sum^{p}{}_{i=1} a(i)X(t-i) + e(t) \qquad (5)$$

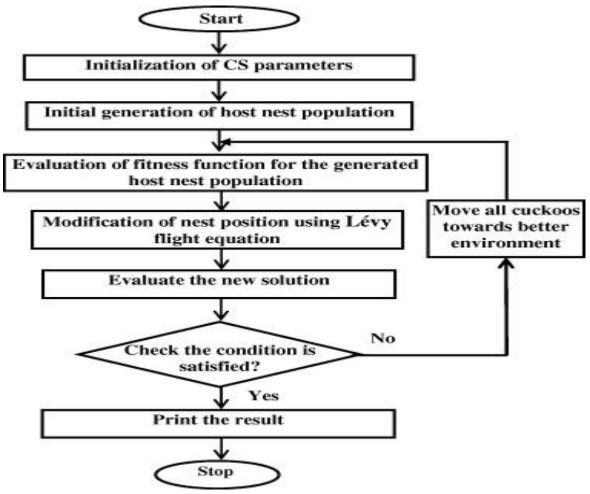

Fig 3. Cuckoo search Algorithm

Five Morphological features are calculated as,

Adaptive AR = max$|x(t)|$

Positive $AR = \sum_t 0.5 * [x(t) + |x(t)|]$

Negative $AR = \sum_t 0.5 * [x(t) - x(t)|]$

Total $AR = PA + NA$

Total Absolute $AR = PA + |NA|$

Fuzzy approximate entropy should be calculated as

$$x^m = \{x(i), x(i+1), \ldots, x(i+m-1)\} - x_0(i) \qquad (6)$$

D. *Feature Extraction*

- ***Cuckoo search Algorithm***

The extracted features are selected by means of cuckoo search algorithm. This proposed method of this approach should be done by with cuckoo search and without cuckoo search.

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This type of algorithm is inspired by the reproduction tactics of cuckoo. The flow chart of cuckoo search was shown in the Fig 3.

Flow diagram steps:

1.First we initialize the cuckoo search parameters
2.Initialise the host nest population.
3.Calculate the fitness calculation.
4.Calculate the Levy flight behavior function
5.By using that evaluate the new solution.
6.Check the condition satisfied otherwise once again calculate the fitness equation.
7.Finally stop the program

E. Classifications

- ***Linear Discriminant Analysis***

The dimensionality reduction is done by linear discriminant analysis. After the process of feature selection, the classes should be identified by LDA. The Flow chart of proposed classifier using EMD method shown in the Fig4.The two classes should be identified by using this algorithm with seven subject’s data. The Flow chart of proposed classifier using EMD method shown in the Fig4.The two classes should be identified by using this algorithm with seven subject’s data. The LDA classifier obtained by the scalar values and vector determined by,

$$y = w^T x$$

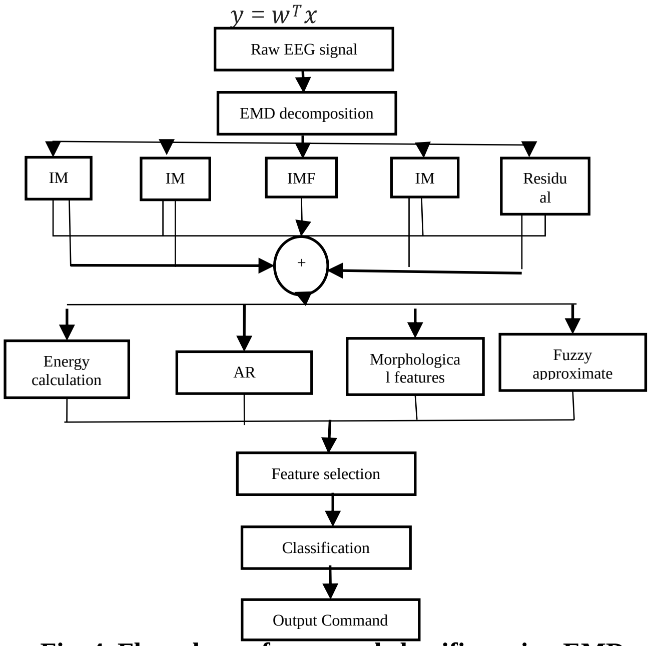

Fig .4. Flow chart of proposed classifier using EMD method

III. PARAMETER ANALYSIS:

Table 1: Comparison of parameters between our work and other classification

PARAMETER	LDA+ AFAPS	HSF	MEMD	SVM	CS MEMD
Accuracy	90.60%	88.50%	89.70%	89%	92%
Precision	90.50%	88.3%.	89.50%	88.90%	91.90%
Recall	91.10%	89%	90.20%	89.80%	92.80%
Maximal MI	0.64%	0.65%	0.68%	0.66%	0.69%

IV. PERFORMANCE ANALYSIS

The parameters are classified with different classification methods as shown in fig 5 -fig 8 .The better classification results should be taken place in cuckoo search algorithm with MEMD

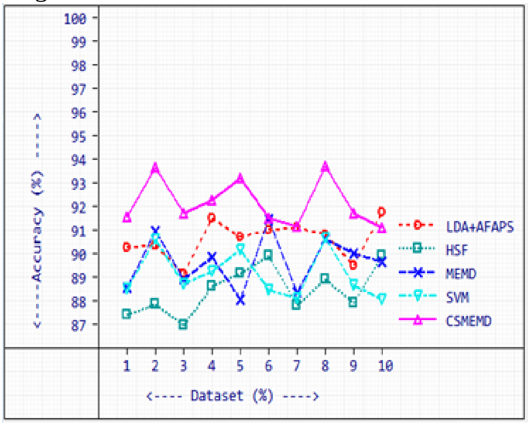

Fig 5.Performance analysis of Accuracy

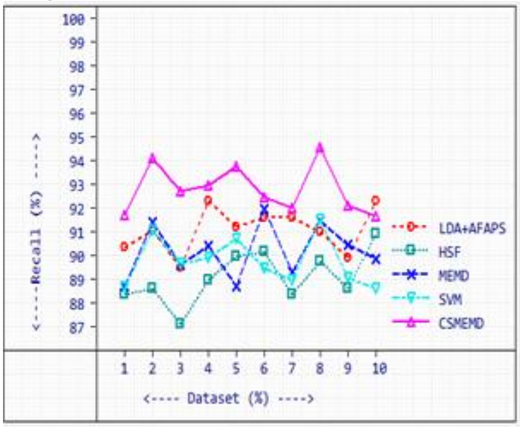

Fig 6. Performance Analysis of Recall

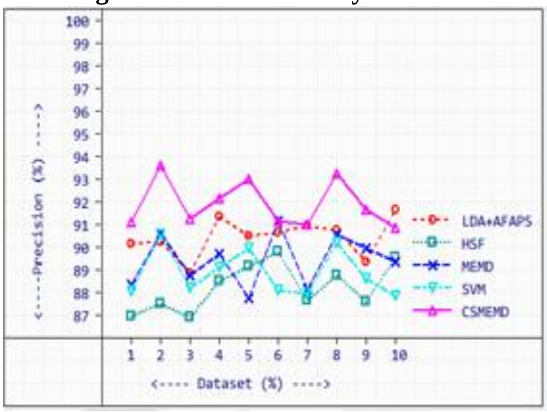

Fig 7. Performance analysis of Precision

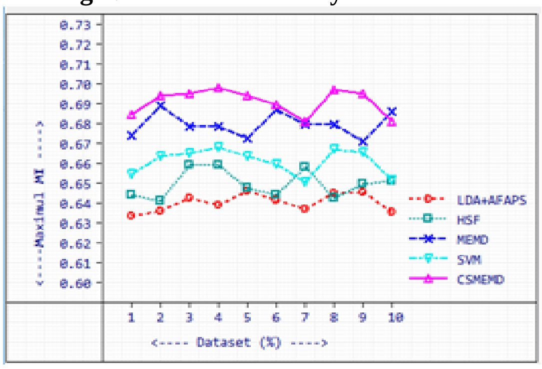

Fig 8. Performance Analysis of Recall

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The Comparative analysis of parameters with different classifications is shown in the Fig 9. When compare to other methods 92% of accuracy should be come over through this MEMD technique.

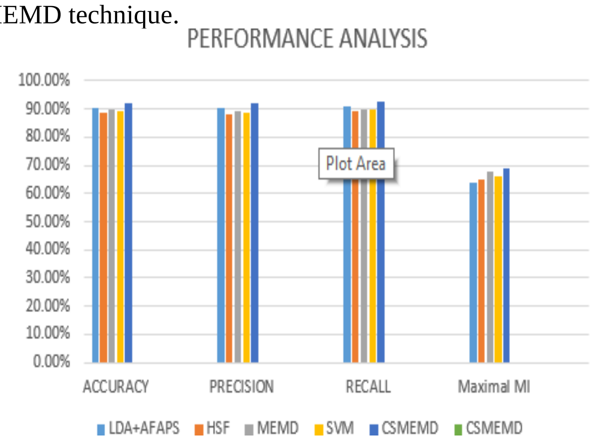

Fig 9. Comparative analysis of parameters with different classifications

V. CONCLUSION

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, morphological features, and fuzzy approximate entropy auto-regressive (AR)coefficients 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 and other parameters values 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 mot or imagery tasks, the obtained result is given to the specific application, which is considered to be our future work.

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