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# Mel Frequency Cepstral Coefficients Based Pattern Recognition for Limb Motor Action

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**ABSTRACT:** This paper proposes a Mel Frequency Cepstral Coefficient (MFCC) based **hybrid** algorithm for motor imagery classification of Electroencephalogram (EEG) signal for Brain Computer Interface (BCI). The proposed hybrid algorithm contains MFCC with Hjorth Parameter. Regression coefficient method was used for eye artifacts cancellation. The feature extraction method based on the difference of the different hjorth parameters taken from the cepstral coefficients. The extracted features from the cepstral coefficients were classified using two linear classifiers.

**KEYWORDS:** Brain-computer interface (BCI), Electroencephalogram (EEG), Mel Frequency Cepstral Coefficient (MFCC), and Movement Imagery (MI).

## I. INTRODUCTION

Brain Computer Interface (BCI) is the Emerging area of human-computer interaction.The BCItechnology is used for communication between physically disabled people with external world. The objective behind this to control assistive external devices like wheelchair control [1], prosthesis [2] etc. using electric, magnetic or hemodynamic brain signals. BCI systemcan be classified as an invasive or non-invasive according to the measurement of brain activity. When the electrodes used for measurement of brain signal are placed within the brain, is saidto be invasive. On the hand, when the electrodes are placed outside the head, is said to be non-invasive [2]. The non-invasive measurement avoids health hazards. A common non-invasive BCI system includes signal recording, pre-processing, feature extraction, feature classification, device control and feedback [3]. BCI can be evaluated by some parameters like Cohen's kappa coefficient, Mutual Information, Classification accuracy etc. Minimum and maximum value of kappa coefficient and mutual information are 0 and 1. Classification accuracy having Minimum value 0 % andmaximum value are 100 %. Achieving highest classification accuracy is a great challenge for the researchers, those who are working in the BCI area. To resolve this problem the authors propose a novel technique of EEG signal feature extraction.

The EEG signals is a slowly timevarying signal for asufficiently short period of time, i.e. between 5 and 100 ms, it behaves like stationary signal [4]. Over a longer period of time, the signal behaves like non-stationary signal. The signal changes to reflect the sequence of the brain activities. These types of signal characteristics are called quasi-stationary, which is also observed in the speech signals. Based on this quasi-stationary nature, a popular feature extraction method i.e. currently used for extractingthe speech features canbe applied to extract the brain wave features from the EEG signals. Authors consider mel-frequency cepstral coefficients(MFCCs) [11-13], the most popular feature extraction method for speech signal was applied to extract the feature of the EEG signal.

Regression coefficient method used for the artifacts cancellation purpose [7-10]. Butterworth band pass filter used as preprocessing technique. MFCC with different Hjorth parameters are used as feature extraction method [14-15]. Differences of the feature information are taken as final feature matrix. Extracted features are classified by two well-known linear classifiers Support Vector Matching (SVM) [16-17] and Fisher Linear Discriminant Analysis (FLDA) [18]. Identification of thinking pattern in human brain is done through the movement imagery classification methods and the final stage of the brain pattern identification is to control external machine by the decision [19-22].
This paper is organized as Section II describes the experimental paradigm of BCI competition dataset [5-6] Section III describes the proposed methodology, and Section IV describes the result and discussions followed by the conclusion.Experimental results showthe performance level of proposed method.

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## II.EXPERIMENTAL PARADIGM OF BCI COMPETITION DATA SET

BCI competition IV data set 2b was used for this experimental analysis. The data set was provided by the Institute for Knowledge Discovery, Graz University of Technology,Austria. This data set contains the EEG data,recorded from 9 subjects[5].
Subjects are right-handed, sitting in an armchair and watching at a screen monitor 1 m away at eye level. 5 sessions are provided for every subject, first two sessions consists training data without feedback andthe last three sessions were consists with feedback.

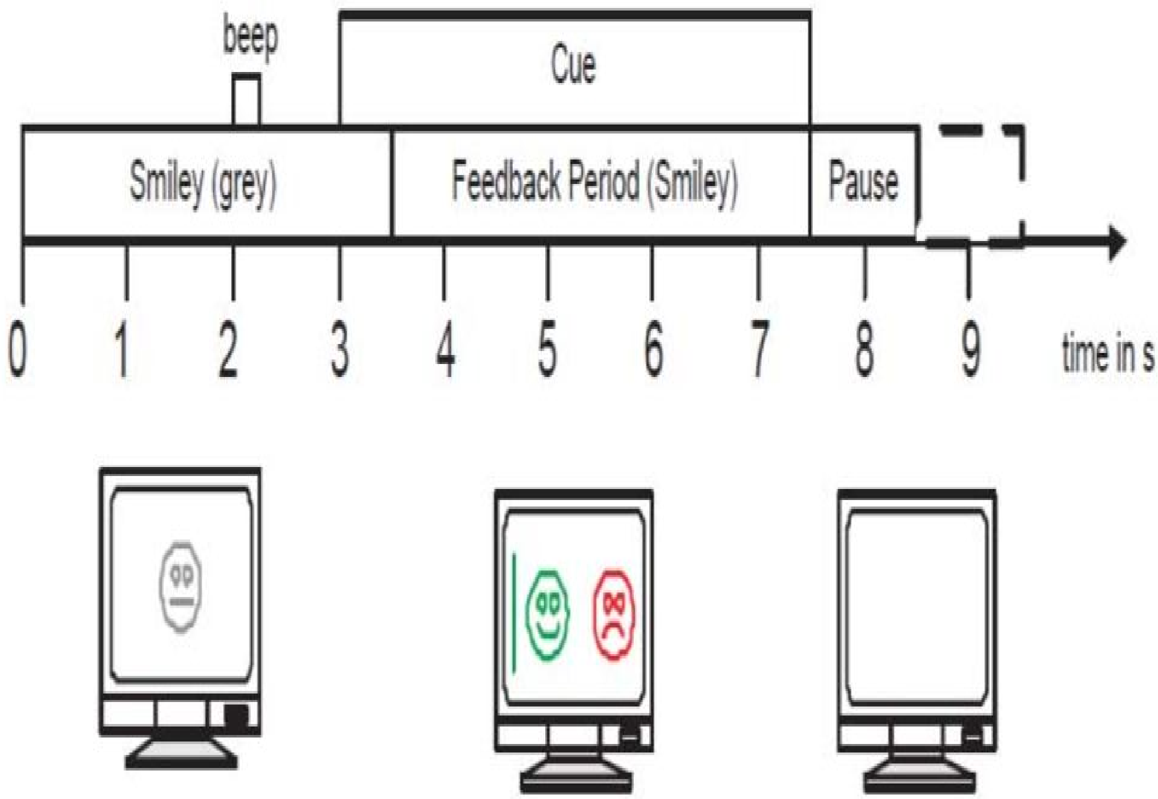


Figure 1. Timing scheme of the paradigm

Several runs are performed for each session and every subject contributinga single session of *03T for the training and *04E for the evaluation Analysis. The data set consists of two classes, namely MI of left hand movement as class 1 and right hand movement as class 2. Three bipolar EEG channels C3, Cz, and C4 were recorded in a sampling frequency of 250 Hz and the recorded signal band-passfiltered between 0.5 Hz and100 Hz, and a notch filter was used at 50 Hz for power line noise cancelation. For movement imagery investigation, only C3 and C4 are utilized. The beginning of each trial started at 0 second in the Figure 1 with a gray smiley was centered on the screen. A shortwarning beep of 1 kHz, 70 mswas givenat 2ndsecond [5].

A cue was started from 3 to 7.5 second and the subjects were accordingly performed the specific imagination. At the 7.5 second, the screen went blank and to avoid user adaptationa random interval was added between 1.0 and 2.0 second to the trials. The details of the experimental paradigm are available in [5-6].

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## III. PROPOSED METHODOLOGY

The Proposed method of the EEG signal preprocessing is shown in the Figure.2.

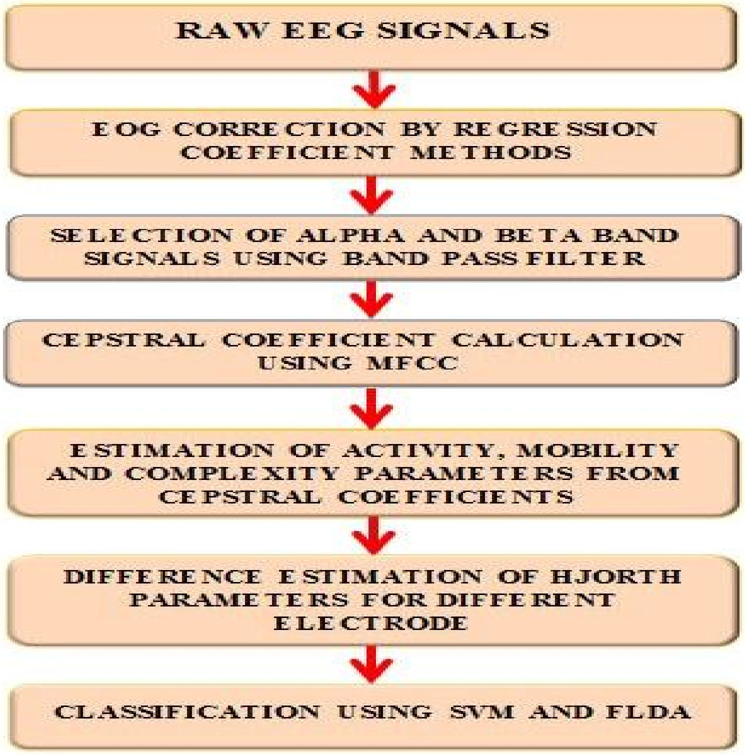


Figure 2. Proposed Methodology

***A. Artifact Removal –***

The EEG signals are prone to contaminate with various kinds of artifacts like eye blinking, eye movement etc. The electrooculogram (EOG) signal are the most common artifacts present in the recorded EEG signal. Regression coefficient based method was used as artifact canceller [7-8]. Data set contains 6 channel signals three of the are EOG channel and other three are C3, Cz and C4 channels. Authors removed the artifacts of the C3, Cz and C4 channels using three EOG signals through the regression coefficient method [7-10].

The artifact removed EEG signals are $E_C^i(n)$ where C $\in$ [C3, C4] and i $\in$ [left, right]

***B. Preprocessing using Band Pass Filter-***

Band pass FIR filter was used for filtering the alpha and beta band signal concurrently i.e. 8 to 30 Hz frequency band signal.

$$X_C^i(n) = h(n) * E_C^i(n) \qquad (1)$$

***C. Feature Extraction***

***C.1 Mel-Frequency Cepstral Coefficients (MFCC)***

The MFCC was usedon basis of the behavior of mel-frequency that follows below 1 kHz linear spacing andabove 1 kHz logarithmic spacing. In our case the samplingfrequency of the data set was 250Hz, so that a linearity assumption can be applied. [11-13]

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The MFCC process has following steps:

1. Windowing
2. Calculating First Fourier Transformation (FFT) on the windowed signal
3. Calculating the log amplitudes of the spectrum into the Melscale, using triangular filter bank
4. Calculating Discrete Cosine Transformation (DCT) of the Mel log amplitudes
5. The resulting amplitudes of the spectrum are the Cepstral Coefficient in Mel scale

Data set was divided in 7 frames of 50% overlap; ten linearly spaced Mel filter-bankswere computed per channel and twelve number of cepstral coefficientsselected per frame.

$$[\mathrm{C}_{\mathrm{C}}^{\mathrm{i}}]_r = \sqrt{\frac{2}{N}}\sum_{j=1}^{n} m_j \cos(r(j-0.5)\frac{\pi}{N}) \qquad (2)$$

Where $m_j$ are the log filterbank amplitudes, r is the number of cepstral coefficient, N is the number of filter bank channels.

### *C.2 Hjorth Parameter (Activity, Mobility and Complexity)*

Estimation ofstatistical properties of any time domain or frequency domain signals can be possible by using Hjorth method. It has three parameters (Activity, Mobility, and Complexity) [14-15]. Here we have used the all three parameters individually.

***Activity:***
The activity parameter is estimated by means of the amplitudevariance

$$[H_C^i]_r = [ACT_C^i]_r = Var[C_C^i]_r \qquad (3)$$

***Mobility:***
The mobility parameter is defined as the ratio of square root of the variance of the first order derivative of the signal with the variance for the time domain signal.

$$[H_C^i]_r = [MOB_C^i]_r = \sqrt{\frac{Var[C_C^i]_r^{'}}{Var[C_C^i]_r}} \qquad (4)$$

***Complexity:***
Complexity parameter for time domain signal is estimated as the ratio of mobility of the first order derivative of the signal with the mobility of the zero order derivative of the signal

$$[H_C^i]_r = [COM_C^i]_r = \frac{Mobility([C_C^i]_r^{'})}{Mobility([C_C^i]_r)} \qquad (5)$$

### *C.3 Difference Estimation of Hjorth Parameters*

$$F^i = ([H_{C3}^i]_r - [H_{C4}^i]_r) \qquad (6)$$

$F^i$ has taken as feature matrix and it was further processed for classification.

### *D.Feature Classification*

We experimented with both the radial and thelinear basis functions.

*Support Vector Machine (SVM):*SVM is one of the most widely used linear classifier [16]. It is a standard machine learning tool. It models the decision boundary for the separation of class as a hyper plane. It involves a high dimensional feature mapping of space based on a kernel. The two popular kernels are linear basis function and radial basis functions.

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SVM was derived from the Vapnik's statistical learning theory [1 6]. The SVM is specifically used to solve the binary classification problems. Learning problems of the SVM are framed as a quadratic optimization problem. Here the error surface has global optimum and it is free of any local minimum. The primary objective for binary classification by SVM is to build an optimal separating hyper-plane (OSH) where the margin of separation between two nearest data points of two different classes is maximized. The SVM achieves this characteristics principle of on the basis of Structural Risk Minimization (SRM). The SRM principle is to reduce the upper bound of the universal error containing the sum of the training error [17].

*Fisher Linear Discriminant Analysis (FLDA)*:FLDA is a well-known linear classifier based on the Fisher criterion. The dimensionality reduction is the most important property for characterizing the statistical data. Linear classifier projects multidimensional data into one dimension and we take decision for classification of its belonging as per some defined measure [18].

## IV. EXPERIMENT AND RESULT

To validate the performance of the MFCC based proposed method, we apply it to a publicly available data sets BCI competition IV [5-6] data set.

Table 1. Classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Activity parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation Analysis

| Subject | FLDA Classifier | | | | SVM Classifier | | | |
|---|---|---|---|---|---|---|---|---|
| | Training | | Testing | | Training | | Testing | |
| | ACC % | MI | ACC % | MI | ACC % | MI | ACC % | MI |
| B01 | 76. 25 | 0.22 | 59.38 | 0.056 | 86.88 | 0.49 | 58.13 | 0.056 |
| B02 | 55.83 | 0.009 | 50.83 | 0.002 | 66.67 | 0.083 | 51.67 | 0.008 |
| B03 | 48.13 | 0.001 | 53.75 | 0.004 | 69.37 | 0.11 | 53.13 | 0.003 |
| B04 | 98.12 | 0.867 | 98.12 | 0.867 | 98.75 | 0.903 | 98.12 | 0.867 |
| B05 | 83.75 | 0.363 | 67.50 | 0.140 | 90.00 | 0.553 | 66.25 | 0.125 |
| B06 | 81.87 | 0.317 | 76.88 | 0.230 | 87.50 | 0.457 | 77.50 | 0.248 |
| B07 | 81.25 | 0.305 | 53.13 | 0.003 | 90.00 | 0.544 | 70.21 | 0.004 |
| B08 | 87.50 | 0.458 | 85.00 | 0.401 | 93.75 | 0.668 | 86.25 | 0.430 |
| B09 | 89.38 | 0.516 | 90.63 | 0.597 | 93.13 | 0.670 | 88.12 | 0.534 |
| **Average** | **78** | **0.34** | **61.58** | **0.26** | **86.22** | **0.50** | **72.15** | **0.005** |

Table 1 displays the classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Activity parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation analysis.

Table 2. Classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Mobility parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation Analysis

| **Subject** | **FLDA Classifier** | | | | **SVM Classifier** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Training** | | **Testing** | | **Training** | | **Testing** | |
| | **ACC %** | **MI** | **ACC %** | **MI** | **ACC %** | **MI** | **ACC %** | **MI** |
| **B01** | 58.13 | 0.019 | 56.87 | 0.013 | 73.75 | 0.170 | 56.87 | 0.013 |
| **B02** | 54.17 | 0.005 | 59.17 | 0.026 | 65.00 | 0.066 | 59.17 | 0.026 |
| **B03** | 56.25 | 0.011 | 50.00 | 00 | 71.88 | 0.143 | 50.00 | 00 |
| **B04** | 85.62 | 0.406 | 89.38 | 0.537 | 94.37 | 0.688 | 90.00 | 0.565 |
| **B05** | 65.63 | 0.073 | 64.38 | 0.061 | 73.75 | 0.170 | 64.38 | 0.061 |
| **B06** | 48.75 | 0.004 | 57.50 | 0.016 | 66.87 | 0.085 | 57.50 | 0.016 |
| **B07** | 62.50 | 0.046 | 53.13 | 0.003 | 76.25 | 0.209 | 53.13 | 0.003 |
| **B08** | 83.13 | 0.345 | 85.00 | 0.391 | 88.75 | 0.493 | 83.75 | 0.363 |
| **B09** | 58.13 | 0.019 | 57.50 | 0.018 | 71.25 | 0.135 | 56.25 | 0.012 |
| **Average** | **63.59** | **0.103** | **63.65** | **0.118** | **75.76** | **0.238** | **63.45** | **0.118** |

Table 2 displays the classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Mobility parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation analysis.

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Table 3. Classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Complexity parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation Analysis

| Subject | FLDA Classifier | | | | SVM Classifier | | | |
|---|---|---|---|---|---|---|---|---|
| | Training | | Testing | | Training | | Testing | |
| | ACC % | MI | ACC % | MI | ACC % | MI | ACC % | MI |
| **B01** | 55.00 | 0.007 | 53.13 | 0.003 | 74.38 | 0.179 | 53.13 | 0.003 |
| **B02** | 47.50 | 0.002 | 58.33 | 0.021 | 65.83 | 0.074 | 58.33 | 0.021 |
| **B03** | 40.00 | 0.029 | 50.00 | 00 | 68.75 | 0.104 | 50.00 | 00 |
| **B04** | 90.00 | 0.531 | 91.87 | 0.633 | 94.37 | 0.688 | 92.50 | 0.651 |
| **B05** | 50.00 | 00 | 50.62 | 0.001 | 67.50 | 0.091 | 50.62 | 0.001 |
| **B06** | 58.75 | 0.022 | 56.87 | 0.014 | 72.50 | 0.151 | 56.25 | 0.012 |
| **B07** | 60.62 | 0.033 | 56.87 | 0.014 | 72.50 | 0.152 | 56.25 | 0.012 |
| **B08** | 85.00 | 0.392 | 85.00 | 0.390 | 92.50 | 0.616 | 85.62 | 0.412 |
| **B09** | 45.62 | 0.006 | 56.87 | 0.014 | 71.25 | 0.136 | 56.87 | 0.014 |
| **Average** | **59.17** | **0.114** | **62.17** | **0.121** | **75.51** | **0.243** | **62.17** | **0.125** |

## V.CONCLUSION

Table 3 displays the classification performance in terms of accuracy (%), the validation results of our proposed algorithm using Complexity parameter for BCI competition IV data set of *03T for the training and *04E for the evaluation analysis. After analyzing the result we can conclude that the performance of BCI system depends on the subject, i.e. for every subject performance is not equal. Performance of three different algorithm shows that the subject 4is excellent and subject three is poor. By comparing three different algorithms, we can conclude that the algorithm with activity parameter is shows good performance and performance of the proposed algorithm with the SVM classifier is better than the FLDA classifier.

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