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# Motor Imagery based EEG Signal Classification using Electrode Optimization Methodology

Megha M. Wankhade, AISSMS Institute of Information Technology, Pune, India, wmegha13@gmail.com
Suvarna. S. Chorage, Bharati Vidyapeeth College of Engineering for Women Pune, India, sschorage@gmail.com

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***Abstract:***
This paper focuses on motor imagery Electroencephalography (EEG) signal classification based on electrode optimization. Motor imagery (MI) signals captured through EEG is the popular non-surgical way of acquiring brain signals. MI-based Brain-Computer Interface (BCI) assists motor impaired persons to link to the outside world by undertaking a series of motor functions. The BCI system commonly includes filtering of raw brain signal, extraction of significant features and classification. The electrode optimization technique is used by selecting limited electrodes attached to the brain parts related to motor functioning. Preprocessing using band pass filtering is done between 7-30 Hz as mu (μ) and beta (β) patterns responsible for imagery movements lie within this frequency range to remove artifacts. To obtain excellent classification performance, preprocessing plays a vital role. Band pass filtering applied to selected channels gives the classification accuracy of 87.27% as compared to 66.39% obtained without filtering. Hence there is a 21% increase in accuracy with filtering using Linear Discriminant Analysis (LDA) as a classifier. The proposed system is validated using test dataset IVb of BCI competition III. The findings prove that the proposed system enhances accuracy for the selected channel of interest, thus reducing computational complexity.

***Keywords:*** *Brain-Computer Interface, Classification Accuracy, Motor imagery, Electroencephalography (EEG), Linear Discriminant Analysis (LDA).*

## I. Introduction

This A brain-computer (BCI) interface is a tool that takes an input signal from the brain and decodes some kind of information to control a physical device or software interface [1]. BCIs have been analysed with the prime goal of providing assistive technologies for people with severe motor disabilities. Electroencephalography (EEG) has been extensively utilized for building a BCI system that can translate and decode users' goals without doing invasive clinical practices. Hence the system can be used in day-to-day life due to its non-invasiveness, ease of use, and low cost.[2][3]. EEG-based BCI signal classifications comprise stimuli-based potentials, slow cortical potentials, and sensorimotor rhythms (SMRs). SMRs are easily noticeable in healthy and disabled persons with neuromuscular disorders or damages. Signals related to motor movements present high grades of independence when related to actual and imagining actions of hands, limbs, feet and tongue.[4].

The brain behaviors related to motor imagery BCI are mu(7-13Hz) and/or beta(13-30Hz) patterns. These behaviors are linked with cortical areas, which are associated with the brain's normal motor output pathway. Action or planning for action results in decrease in mu and beta patterns. This decrease is called 'event-related desynchronization' or ERD. Its contrasting pattern increase or 'event-related synchronization' (ERS) occurs after the action has been executed and with a relaxed condition. Hence ERD and ERS, which do not need actual action and can happen with motor imagery are most applicable for BCI applications.

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To capture EEG signals is a tiresome procedure and requires more time. Handling EEG signals delays the process and degrades the classification accuracy. In addition to this, captured patterns vary for the same user between one day and another or between sessions. For the same user, these variations of EEG signals lead to poor classification results. Different features extracted from motor imagery EEG signals such as statistic, time domain, frequency domain, and wavelet features [8] are of great concern to users. To solve the above issues, we are trying to optimize electrodes considering the motor areas. frequency domain features are extracted to improve the overall performance of Motor imagery based BCI process.

Electrodes attached to the brain parts related to motor functioning have the more vital information of motor movements, as mentioned in [4]. Hence those electrodes are selected for pre-processing.

The organisation of this paper is as follows: Section II describes the dataset used. Section III contains the methodology of research. In section IV, the results are displayed with the discussion. Lastly, section V is the conclusion.

## II. Data Description

The dataset used is Dataset IVb [6] from BCI Competition III provided by Intelligent Data Analysis Group and Department of Neurology, Neurophysics Group (Germany). The EEG signals recorded were given in both MATLAB format and ASCII format.

This data set was recorded from one healthy subject. Two motor imagery, which is left hand and right foot, were performed in this experimentation. This data set contains information from the 7 initial sessions without feedback. The first 3 sessions were given with labels as a training set. Visual signs (letter presentation) were shown for 3.5 seconds to perform 2 motor imageries (L) left hand and (F) right foot. Training sets were provided with complete marker information, which shows where the mental task is performed. Continuous EEG signals of sessions 4 to 7 are given without any cue information (neither target class nor timing) as a test set. MI signals on 118 channels have been recorded corresponding to the worldwide 10-20 system. A total of 210 indications were provided for the left hand and the right foot for the competition. The band-pass signals have been filtered between 0.05 and 200 Hz and sampled with 16-bit precision at 1000 Hz. The study used data sampled at 100 Hz. [6].

## III. Methodology of Research

The flowchart of the suggested BCI system based on motor imagery is shown in fig.1. The working of the system is as follows:

1. EEG signals captured from the brain are used from dataset IVb of standard BCI Competition III which were given in MATLAB format as mentioned in the data description.
2. Electrodes attached to the brain parts related to motor functioning are selected for processing.
3. EEG signals from the selected electrodes are band pass filtered to remove the unwanted components or artifacts.
4. Frequency-domain features are extracted using the most effective Common Spatial Pattern (CSP) feature extraction technique.
5. Extracted features are applied to two standard classifiers, namely LDA and SVM.
6. Experimental results are compared in terms of classification accuracy by applying test dataset to the classifiers to signals captured from all electrodes (118) and for optimized electrodes (30) to decode the type of movement.

### A. *Signal Pre-processing*

Electrode Optimization: To process all EEG channels is very time-consuming. Hence channels related to the motor cortex are considered and information is extracted from this area only. The

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logic applied is to find only channels start with alphabet 'C' related motor areas of the brain. Thus, instead of considering all the electrodes, electrodes attached to the brain parts related to motor functioning are selected for further processing. Due to this, artifacts associated with eye blinking are removed and the removal of such unrelated channels increased the robustness of classification system [7].

EEG Signals captured from brain
BCI competition III, dataset IV b

↓

Electrode Selection over the motor areas

↓

Pre-Processing
Frequency Filtering (7-30Hz)

↓

Feature Extraction
Common Spatial Patterns (CSP)

↓

Classification
(LDA/ SVM)

↓

Movement Decoding
Applying test data to classifier

Fig. 1. The flowchart of the BCI system based on motor imagery.

Figure 2 shows the brain lobes and the areas responsible for motor functions, the standard 10±20 electrode positioning system of the 128 channel EEG device, and the electrodes selected for processing. The green and red circles represent the chosen channels and on the left and right side of the head, the red circle shows the C3 and C4 channels. [7].

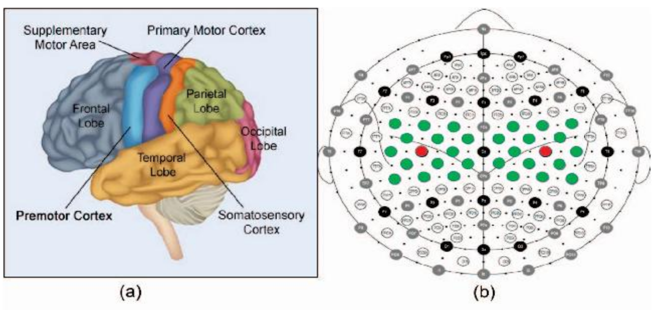


Fig. 2: (a) Brain lobes and the motor areas (b) The standard 10±20 electrode positioning system of the 128 channel EEG device. [7].

*B. Band- pass Filtering*

According to a given dataset, EEG signals are sampled at 1000 Hz since the EEG signal is a low-frequency signal, they are down sampled to 100 Hz for further processing. Selected EEG channels are retransmitted via a 7 to 30-Hz band pass filter, as mu (μ) and beta (β) patterns are in this range of frequencies. [4]. When the signal is displayed for testing, motor imagination is done for 3.5 seconds (350 samples).

*C. Feature Extraction using common Spatial Pattern (CSP)*

CSP is a most effective method for transferring multi-channel EEG signals into a space that is small in dimensions. Differences between classes are emphasized and similarities are reduced. It generates the projection matrix, which maximizes the variance of two class signal matrices [8][10].

The standardized spatial covariance S is determined by CSP from input data I, representing the raw data from a single test using:

$$S = \frac{II'}{trace(II')} \qquad (1.1)$$

where, I is an $N \times T$ matrix, in which T is the number of electrodes, and N is the number of samples per channel.

The apostrophe $'$ indicates the transpose operation and trace(I) is the sum of the diagonal elements of I.

The composite spatial covariance is calculated as:

$$\overline{Sl} + \overline{Sr} = Uc\lambda cUc'$$

(1.2)

where Uc is the matrix of eigenvectors, and λc is the diagonal matrix of eigenvalues. The full transformation matrix is then produced as follows

$$P = E'\sqrt{\lambda_c^{-1} U_c'} \qquad (1.3)$$

Where E indicates the matrix of eigenvectors for the whitening spatial covariance matrix. The eigenvalues and eigenvectors are sorts out from first to last in descending order.

$$W = P'\mathrm{I} \qquad (1.4)$$

A two-dimensional feature is then created from the variance of the rows of W. The signal variance for one group is maximized, while for the other class, it is minimized.

*D. Classification*

The classification process is the technique to identify the class of the samples in the dataset. In this paper, the classifier is used to determine the type of movements such as the left hand and right foot. The prevalent algorithms of BCI motor imaging systems are linear discriminant analysis (LDA) and support vector machine (SVM). Both use hyperplanes to differentiate between classes. In LDA, the statistics is plotted, which increases the distance between the mean of classes and reduces the variance between the classes. The SVM algorithm tries to boost the distance between the closest points of the various classes (support vectors). Classification performance of LDA and SVM does not affect though there are variations in training information [9].

## IV. RESULTS

In this section, the classification accuracy of imagery movements of the left hand and right foot using dataset IVb of BCI competition III was tabulated and illustrated in tables and graphs, respectively. The algorithms have been written in MATLAB 2018 in this research. The proposed system was implemented by considering all the 118 electrodes given in the dataset and the 30 electrodes of interest present over the motor area.

The results of the SVM and LDA classifiers are given in Table I by considering 118 and 30 electrodes with and without filtering. It was observed from the results that the accuracy achieved without filtering was considerably lower than with filtering for both electrodes. The graph showing the effect of filtering for both cases is shown in figure 3 and figure 4 respectively.

TABLE I
Effect of Electrode Optimization on Classification accuracy

| **Classifier** | **Classification Accuracy** | | | |
|---|---|---|---|---|
| | ***118 channels*** | | ***30 channels*** | |
| | Without Filtering | With Filtering | Without Filtering | With Filtering |
| **SVM** | 51.64 % | **88.36 %** | 66.72 % | **86.96%** |
| **LDA** | 51.52 % | **86.98 %** | 66.39 % | **87.27%** |

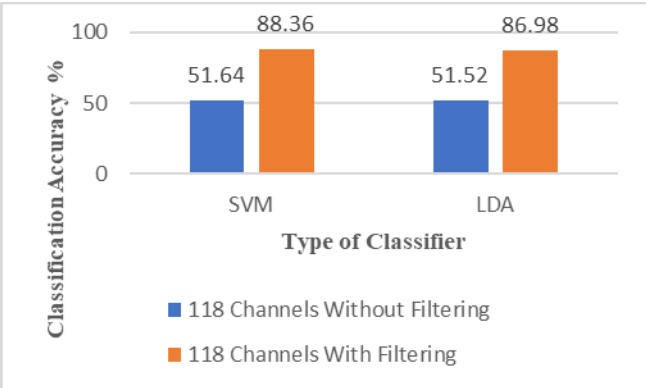


Fig. 3. Effect of Filtering on Classification accuracy for 118 Channels

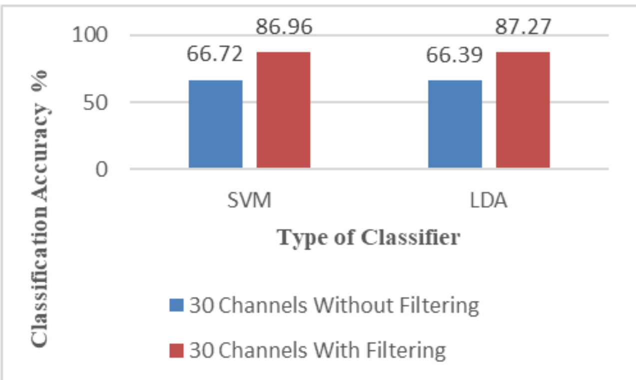


Fig. 4. Effect of Filtering on Classification accuracy for 30 Channels

From the values obtained for both 118 and 30 electrodes with filtering, it was observed that there

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was only a 14% decrease in accuracy for 30 electrodes when the SVM classifier was used whereas for LDA, accuracy was increased by 29% for same electrodes. Since there was not a significant effect on accuracy when 30 electrodes were used, computational complexity was reduced using an electrode optimization approach. This effect is shown in figure 5.

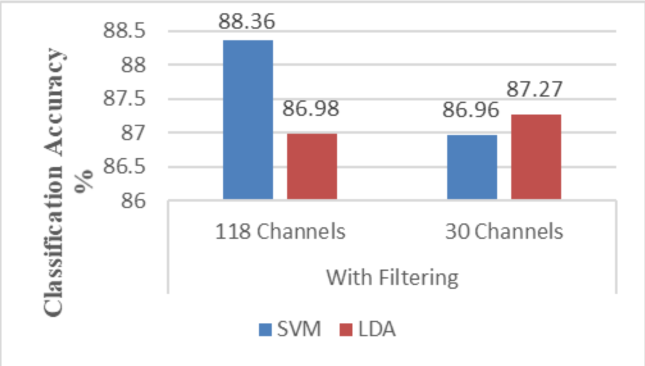


Fig. 5. Effect of Electrode Optimization on Classification Accuracy

## V. Conclusion

In this paper, a model is introduced to classify motor imagery EEG signals using electrode optimization methodology for BCI applications. Only the channels of interest concerned with the motor area are selected for processing to reduce the computational complexity. The proposed system is based on removing artifacts using band pass filtering. Optimized and useful frequency domain features are extracted using a common spatial pattern. Selected features are applied to SVM and LDA classifiers to decode the imagery movement of the left hand and right foot. With LDA as a classifier, though the number of electrodes is reduced from 118 to 30, still there is a 29% increase in accuracy for 30 electrodes as compared to considering all 118 electrodes. It is observed that the working of Motor imagery BCI can be enhanced by making use of electrodes of interest applied to the LDA classifier. Since the LDA classifier provides better performance as compared to SVM. In future work, we will explore extending the proposed system by further reducing the channels of interest and testing the performance in terms of classification accuracy and computational complexity. Also, we will examine how to modify the system in getting superior results than existing for movement classification and will try to apply the proposed methodology to classify three or four motor imagery movements.

## VI. Acknowledgment

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## AUTHOR'S PROFILE

**Megha M. Wankhade** received her B.E. degree in Electronics and Telecommunication from Amravati University and M.E. degree in Electronics and Telecommunication from Savitribai Phule Pune University, India and currently pursuing a Ph.D. in Electronics and Telecommunication engineering from All India Shri Shivaji Memorial Society's Institute of Information Technology, Pune, India. Her research areas include Biomedical signal processing, video surveillance and Brain computer Interface. She received RPS for the project "Path Finder- RFID based system for blind navigation" from AICTE, New Delhi and Research grant for the project "Tracking of Persons for Video Surveillance of Unattended environment" from BCUD, University of Pune. She has published around 20 papers in National and International Journals and Conferences.

**Suvarna S. Chorage** is graduated from Mumbai university in E&TC Engg. in 1996 and received her ME degree in E&TC Microwave engg. in 2003 from Govt college of engg. Pune. She has received her Ph. D. in electronics engg. from Bharati Vidyapeeth university, Pune in 2012. Her subject expertise include radiation and microwave techniques, Signals and systems, digital communication, Information theory and coding techniques, optical fiber communication, mobile communication, software defined radio and machine intelligence. She has published 23 research papers in renowned international journals that includes Elsevier, optical engineering, IEEE explore, national and international conferences.