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Classification of Electroencephalogram (EEG) Signals Using Linear Discriminant Analysis

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ABSTRACT

The cognitive behavior of brain can be analyzed using EEG signals. Nowadays, EEG signals are widely used to study brain related activities and various disorders. Artificial intelligence tools are widely used to analyze these signals which are captured using network of electrodes fixed on the human scalp and transferred on mobile device for further analysis. In the present study, EEG signal analysis is performed on the online data set containing motor imagery information. Various parameters of EEG signals are pre-processed before analyzing. EEG signal pre-processing is done using Independent Component Analysis (ICA). For filtering purpose, FIR filter is used, as it shows linear phase response. Eigenvalues as features are selected. Morlet wavelet transform is used to perform time-frequency analysis and to compute average power present in signals. Principal Component Analysis (PCA) is done for dimensionality reduction. Further, EEG signals are classified using Linear Discriminant Analysis (LDA).

KEYWORDS

EEG signals; Pre-processing; ICA; Artifacts; Down-sampling; Filtering; FIR; ERP; Feature extraction; Eigenvalues; TFR; Morlet wavelet; Average Power; PCA; Classification by LDA.

1. INTRODUCTION

This is a qualitative experimental type of research. It uses an inductive method which has bottom-up, specific to general approach. This paper uses LDA technique for classification of EEG signals for Motor Imagery (MI) and Motor Execution (ME) tasks analysis. LDA is one of the most prominent techniques in classification used for supervised machine learning algorithms. In this paper, online MNE data set is used [1]. The data set contains EEG signal recording for motor imagery and motor execution tasks performed by 109 subjects. These tasks are i.e., left vs. right hand movement, hands vs. feet movement, eyes movement, etc. A total of 64 channels or electrodes are used. Channel names are Fc5, Fc3, Fc1, Fcz, Fc2, Fc4, Fc6, C5, C3, C1, etc. Sampling frequency is 160 Hz. The range between high pass and low pass frequencies is 0.01-80 Hz. The computer program in Python is used for EEG signal analysis. In this paper, the EEG signal analysis involves pre-processing, filtering, features extraction, dimensionality reduction and classification which are discussed in the methodology section. Highest accuracy obtained using LDA classification, is discussed in results and discussion section and it is compared with motor imagery decoding from EEG data using the Common Spatial Pattern [30].

2. LITERATURE REVIEW

Lisha Sun et.al. (2005) presented the modeling of clinical electroencephalography (EEG) signals which is an important problem in clinical diagnosis of brain diseases. It is shown that the method using support vector machine (SVM) based on the structure risk minimization provides an effective kind of learning machine [2]. Hasminda Hassan et al. (2012) found that music is known to have positive effects on humans, enhances learning and aids the healing process. They presented the outcomes of preliminary research that investigates a subject's reaction when exposed to live violin music [3]. Xu Huang et al. (2012) discussed various techniques of EEG signal processing [4]. J. Satheesh Kumar et al. (2012) presented the cognitive behavior of brain by analyzing either signals or images from the brain. They have visualized human behavior can be in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. These states are related with specific signal frequency which helps to understand functional behavior of complex brain structure. They found that Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponding to various states from the scalp surface area [5]. Amjed S. Al-Fahoum et al. (2014) discussed different methods to extract the features from EEG signals, among these methods are time frequency distributions (TFD), Fast Fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT), and auto regressive method (ARM) [6]. Jasjeet Kaur et al. (2015) developed the Electroencephalography (EEG) which enlightens about the state of the brain i.e., about the electrical bustle going on in the brain. In this method the electrical activity measured as voltage at different points of brain act as basis of EEG [7]. Rab Nawaz et al. (2018) presented the effect of music stimuli on human brain using electroencephalogram [9]. Jaehoon Cha et al. (2019) carried out EEG signal analysis using machine learning [11]. Sho Nakagome et al. (2019) decoded EEG signals using neural network and machine learning algorithms [13]. Sheng Li et.al. (2019) focused on use of prosthetic limbs to compensate for the function of normal upper limbs, so the demand for the upper limb movement recognition has increased. They have analyzed upper limb movements through EEG signals by the EEG signal classification method to identify the upper limb movements [14]. Pengcheng Ma et al. (2020) analyzed the EEG signal for the by building a depth factorization machine model, so that based on analyzing the characteristics of user interaction the EEG data can be generated to predict the binomial state of eyes (open eyes and closed eyes) [18]. Zheng Li (2020) used deep learning algorithms for EEG analysis and classification [19]. Vikrant Doma et al. (2020) found that emotion recognition using brain signals has the potential to change the way we identify and treat some health conditions. Brainwave EEG signals can reflect the changes in electrical potential resulting from communications networks between neurons. They analyzed the epoch data from EEG sensor channels and performed comparative analysis of multiple machine learning techniques, namely Support Vector Machine (SVM), K-nearest neighbor, Linear Discriminant Analysis, Logistic Regression and Decision Trees [20]. Xiongliang Xiao et al. (2021) discussed motor imagery EEG signal recognition using deep convolution neural network [21]. Indurani P. et al. (2021) used EEG signal processing in E-health care applications [23]. Min Wu et al. (2022) found that Brain computer interface and EEG signal recognition are not only used in the field of human-computer interaction, but also in advanced military technologies. They have divided EEG signals into two categories: evoked EEG signals and spontaneous EEG signals [26]. Prakash Chandra Sharma et al. (2022) used EEG signal processing for real time signal enhancement [28]. Anupreet Kaur Singh et al. (2022) discussed various methods for EEG signal features extraction [29].

3. METHODOLOGY

This paper presents the study of EEG signal by performing various machine learning steps which are given below. The flow chart of EEG signal analysis and classification is shown in Fig.1.

EEG Data Acquisition

↓

Signal pre-processing using ICA Technique

↓

FIR Filtering

↓

Features Extraction using TFR Analysis

↓

Dimensionality Reduction using PCA

↓

Classification using LDA

Fig. 1 Block Diagram used in EEG signal analysis

3.1 Data Acquisition

The data acquisition involves the use of Magnetometer which consists of the sensors connected to EEG electrodes. The data set contains EEG signals obtained from 109 subjects for 14 different event related tasks performed by those subjects. Frequency Ranges from 0.01 to 80 Hertz. The sampling frequency is 160 Hertz. Total 64 n-channels are used. Channel names are Fc5, Fc3, Fc1, Fcz, Fc2, Fc4, Fc6, C5, C3, C1, etc. The placement of electrodes on scalp is used to display position of channels which is also called as montage. The sensors or electrodes placement on the human scalp is shown in Fig. 2.

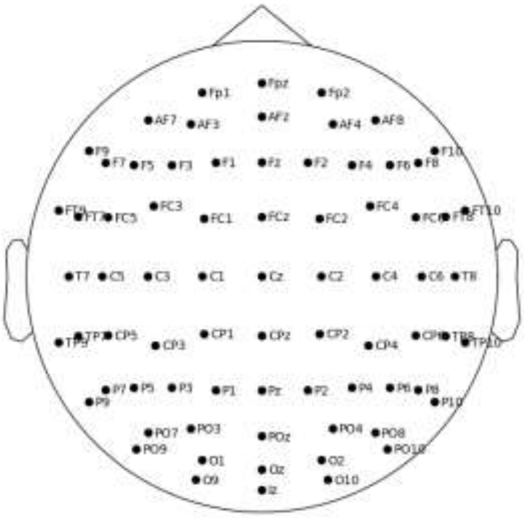

Fig. 2 Sensors or Electrodes placement on the scalp

The Raw plot for subject-1 and run-1 is obtained using acquired data.

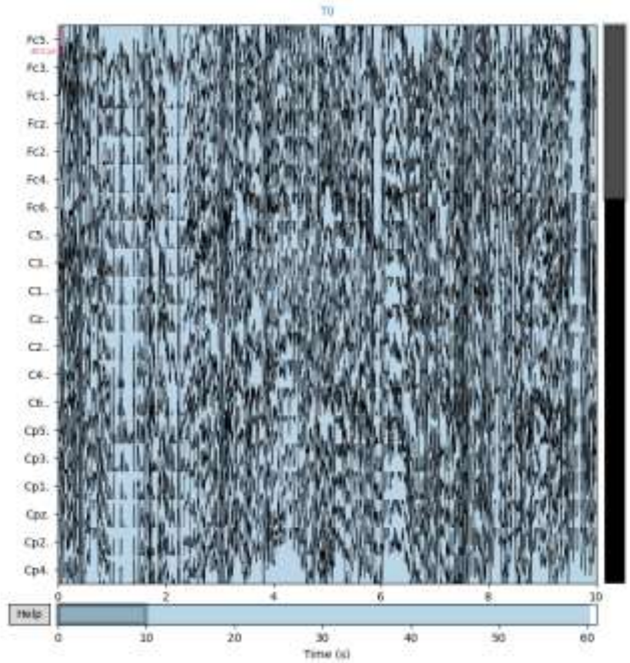

Fig. 3 Raw plot (Sub-01, Run-1)

3.2 Signal Pre-processing

3.2.1 Pre-processing using ICA Technique

The EEG signals are pre-processed from Independent Component Analysis (ICA). Independent Component Analysis (ICA) is often used at the signal pre-processing stage in EEG analysis because of its ability to remove unwanted components from the signal. In the following graph, ICA Components (Topomaps) upto 20 channels are displayed. Topomap is the graph which contains brain activity. Matching events are 448. Maximum Iterations are 50. Zero projection items activated. ICA 0 to 19 are obtained as shown in Fig. 3.

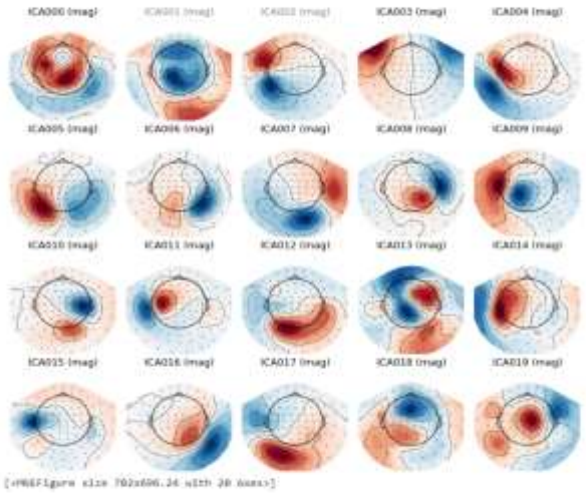

Fig. 3 ICA Components (0 to 19)

Fig. 4 (a) to (e) show the topomaps of ICA component, segment images, spectrum and dropped segments of ICA 000 to ICA 004.

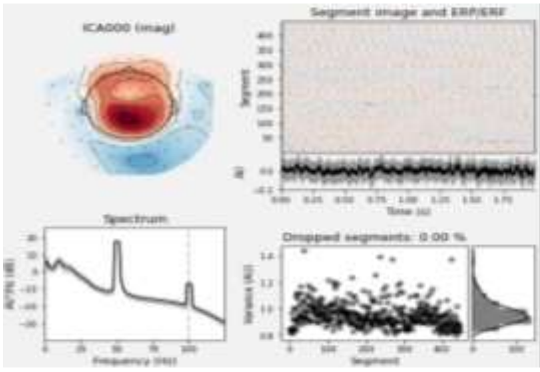

Fig. 4 (a) ICA000 Topomap, Segment Image, Spectrum, Dropped segments

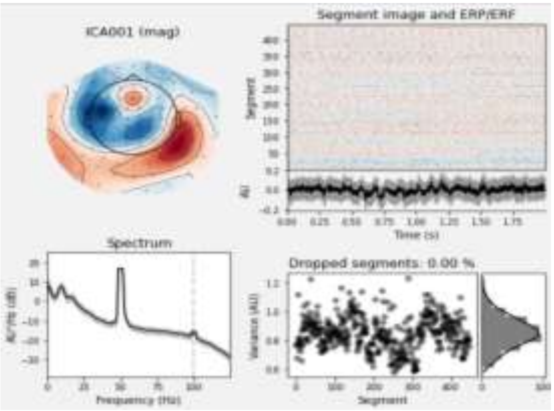

Fig. 4 (b) ICA001 Topomap, Segment Image, Spectrum, Dropped segments

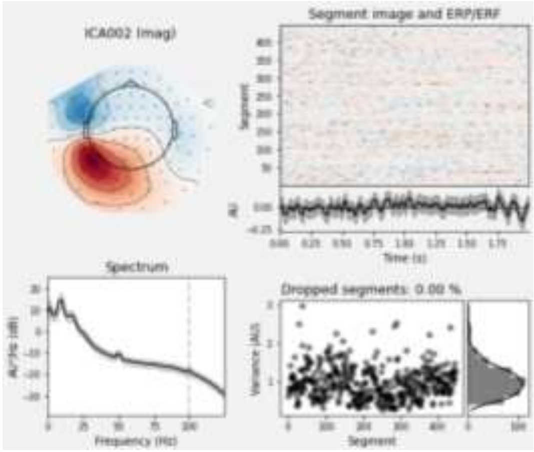

Fig. 4 (c) ICA002 Topomap, Segment Image, Spectrum, Dropped segments

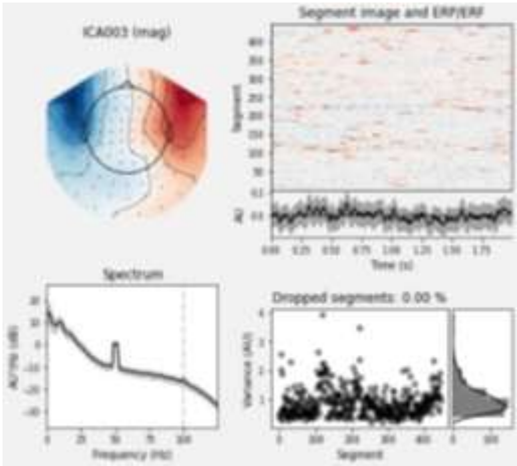

Fig. 4 (d) ICA003 Topomap, Segment Image, Spectrum, Dropped segments

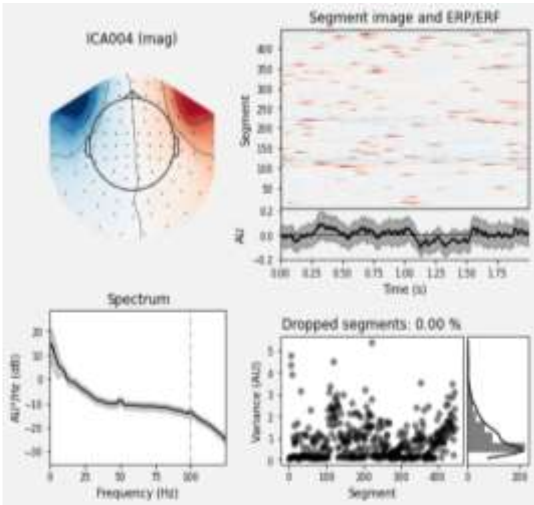

Fig. 4 (e) ICA004 Topomap, Segment Image, Spectrum, Dropped segments

Fig. 5 shows the ICA sources plot of time (seconds) vs ICA, excluding ICA 004 due to its spiked waveform. ICA technique is an efficient method used for pre-processing.

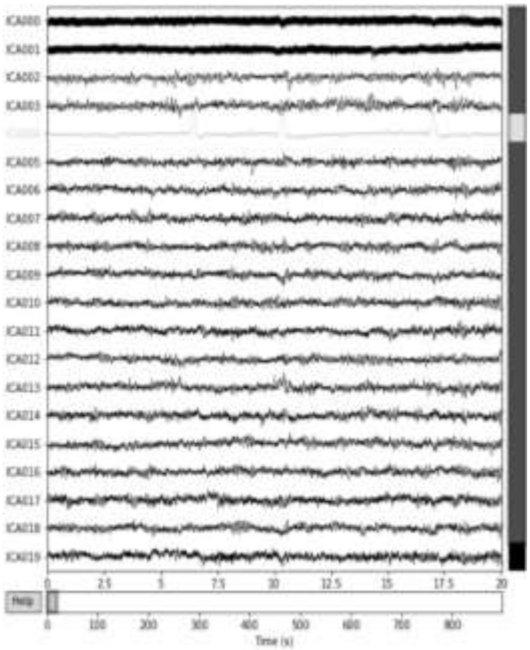

Fig. 5 ICA Sources Plot

3.2.2 Artifacts detection and downsampling

Artifacts detection and removal is also an important aspect in signal pre-processing. The EEGBCI dataset is very large, so processing on EEG signal may be a time-consuming task. To reduce signal processing time, down sampling of EEG signal is done at specific sampling rate. Here sampling rate is taken 200 Hertz. Fig. 6 shows plots for original and down sampled data. Frequency of 1 to 200 Hertz where an appreciable artifact at 60 Hertz of 10 µV is observed. Other minor artifacts can be neglected.

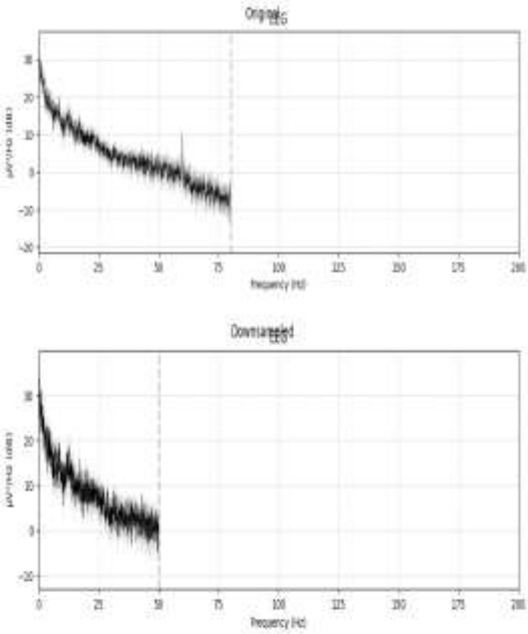

Fig. 6 Downsampling and Artifacts Removal

Fig. 7 shows downsampled waveform for the same Subject.

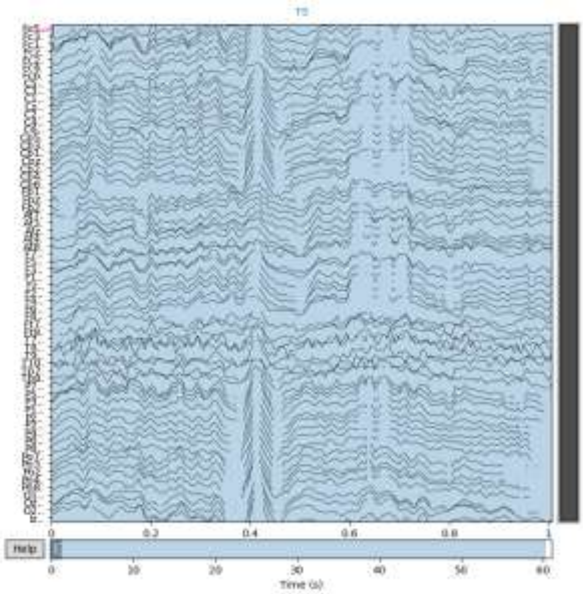

Fig. 7 Downsampled waveform

3.3 FIR Filtering

To process the EEG signal the FIR filter is the best suited option. The noise in the EEG signal can reduced by using FIR filter. It gives linear phase response of signal. It is a non-recursive filter. Fig. 8 is a plot of FIR filtering response. FIR filtering parameters are viz. non-causal, butterworth, zero-phase, bandpass filter. Hamming window method is used. EEG signals of frequency ranging from 1 to 60 Hertz are filtered. It is found that the passband ripple and stopband attenuation of signals is 0.0194 and 53 decibels respectively. The lower cut-off frequency is 0.5 Hertz while upper cut-off frequency is 67.5 Hertz. Filter length is taken for 529 samples (3.306 s). The following subplot (1) shows Time in seconds vs. Amplitude in Volts response of FIR filter. Subplot (2) shows Frequency in Hertz vs. Amplitude in decibels response. Subplot (3) shows Frequency in Hertz vs. Delay in seconds response.

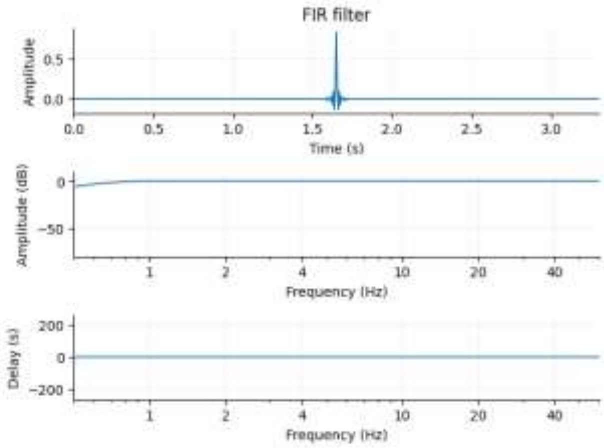

Fig. 8 FIR Filtering

Fig. 9 shows FIR filtered waveform of EEG signal for Sub-1.

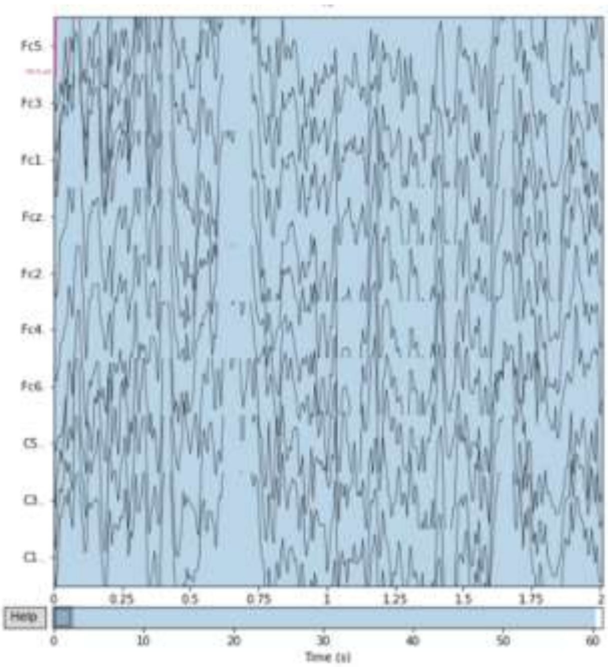

Fig. 9 FIR filtered waveform

3.4 Features Extraction using TFR Analysis

3.4.1 Time Frequency Representation (TFR) Analysis

Feature Extraction technique is used to minimize the number of features in a data set. This technique creates new features which are derived from the existing ones. Then original features are discarded. The new reduced set of features is having significant information of the original features. This method helps to establish the model with less efforts and it increases the speed of machine learning process. The Wavelet transform is used to perform the time vs. frequency analysis of EEG signal. Morlet wavelets (or Gabor wavelets) are mostly used in time-frequency analysis of time series data, such as electrical signals recorded from the brain. It is a wavelet composed of a complex exponential carrier multiplied by a Gaussian window also called as envelope. Following eq.1 shows Morlet Wavelet Transform.

$$c_\sigma = \left(1 + e^{-\sigma^2} - 2e^{-\frac{3}{4}\sigma^2}\right)^{-\frac{1}{2}} \tag{1}$$

Central frequency is obtained by following eq.2.

$$\omega_\Psi = \sigma \frac{1}{1 - e^{-\sigma\omega_\Psi}} \tag{2}$$

This wavelet is taken in this research, as it is closely related to human vision and hearing. In this research, Eigen values and Eigen vectors are used as features. Different numbers of cycle per frequency (N-cycles) are calculated as n_cycles = frequency / 4 for TFR analysis. Different frequencies used for TFR Morlet wavelet are taken as 3 Hz, 6 Hz, 30 Hz. Fig. 10 shows heatmap of EEG covariance matrix to EEG signals. Covariance is used to measure the relationship between two variables. In the following graph, 20 matching events were found. 1 bad epoch dropped. 0 projection items activated. Intensity changes from red to blue color.

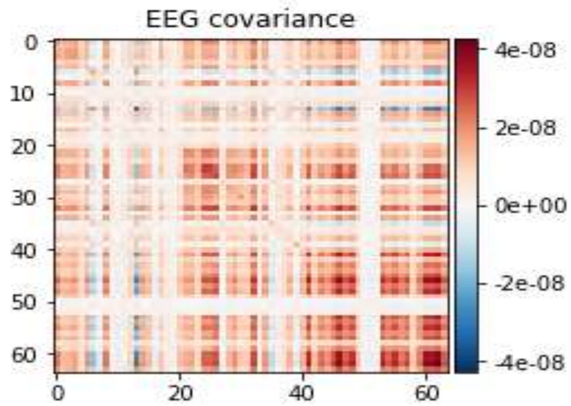

Fig. 10 EEG Covariance plot

Eigen values as features are extracted and plotted in Fig. 11. This plot shows Eigen values index vs. noise. Rank is 14. As Eigen value index increases the noise reduces.

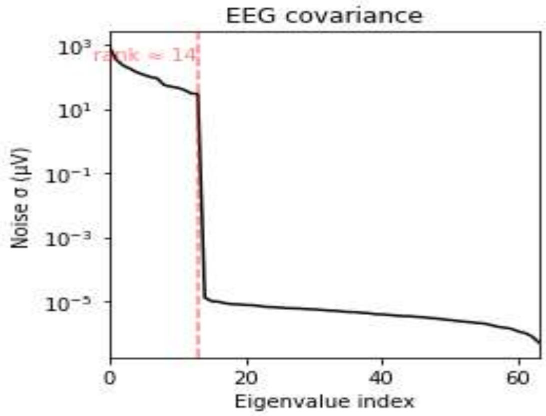

Fig. 11 Eigen values vs. Noise

3.4.2 Average power calculation using TFR Analysis

In this research, average power in EEG Signal is calculated using Time-Frequency Analysis. The average power of EEG signal is governed by its frequency. The confusion matrix in the form of heatmap for average power is plotted in the graph below. Time (0 to 1s) is on X-axis and Frequency (0 to 80 Hz) is on Y-axis. Minimum to maximum power is indicated from Red to Blue color. Fig. 12 shows a time-frequency plot of average power of EEG signals which is computed using Morlet wavlet.

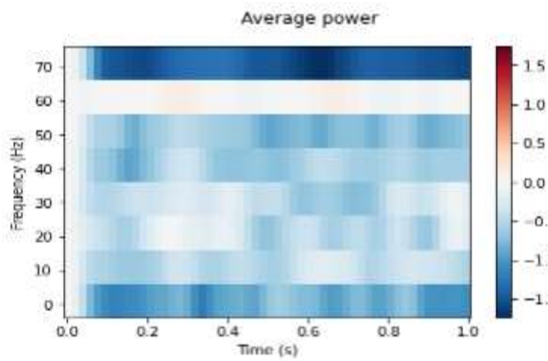

Fig. 12 Average Power vs. Frequency using Morlet Wavelet

Fig. 13 shows topomaps for average power.

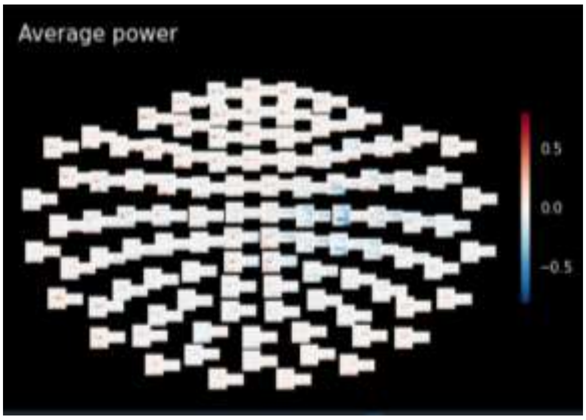

Fig. 13 Average Power Topomap

3.5 Dimensionality reduction using PCA

Dimensionality reduction using PCA technique is prudent technique for feature selection. Fig. 14 shows the plot of time vs amplitude. In the following graph, PCA for 20 channels is being plotted. Time(s) is on X-axis and amplitude in µV is on Y-axis. A principal component is observed at time instant of 0.2s.

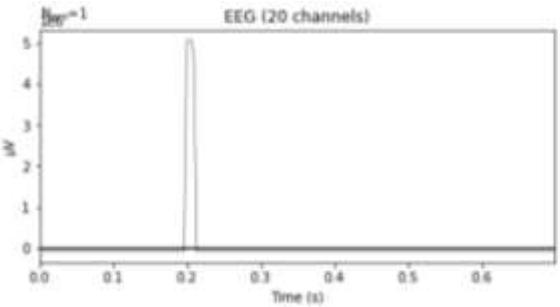

Fig. 14 Dimensionality reduction using PCA

3.6 Classification using LDA

Linear Discriminant Analysis (LDA) is a linear method used for classification techniques. It is supervised algorithm. LDA is an effective method for classification, because it minimizes the dimensionality of the data set by maximizing separability. Thus, to draw decision boundaries for the given data with maximum class separability becomes easier, as, LDA includes all important features. Various tasks are performed by subject are discussed in the following table 1.

Table. 1Task Description

Run	Task
1	Baseline, eyes open
2	Baseline, eyes closed
3, 7, 11	Motor Execution : Left vs. Right Hand
4, 8, 12	Motor Imagery : Left vs. Right Hand
5, 9, 13	Motor Execution : Hands vs. Feet
6, 10, 14	Motor Imagery : Hands vs. Feet

Confusion matrix is an important parameter while doing classification. The heatmap of confusion matrix using LDA is obtained by using LDA classification is shown in Fig. 15.

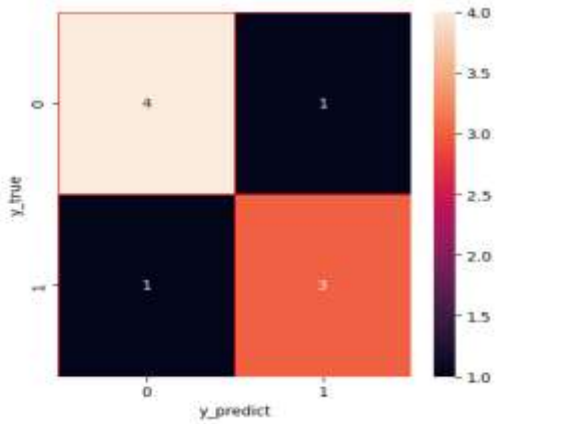

Fig. 15 Confusion Matrix for LDA Classification

Further, Topomaps for common spatial patterns (CSP) are obtained by applying LDA. CSP 0 to 7 are shown in Fig. 16.

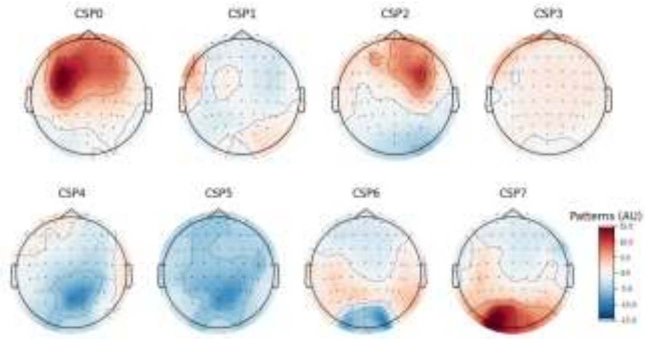

Fig. 16 Common Spatial Patterns (CSP 0 to 3)

Blue color indicates active state of brain while red color indicates relaxed state. Remaining area indicates resting state of mind. It is observed that CSP 5 shows completely blue color which indicates that person is completely active for performing given task. Beta brain waves ranges from 12 to 30 Hz are responsible for active state of brain.

4. RESULTS AND DISCUSSION

Table 2 gives accuracies obtained for different tasks performed by subject-1. Classification of task is done using Linear Discriminant Analysis (LDA). Frequency range is taken from 12 to 30 Hertz for beta band, as this band indicates active state of brain waves.

Table. 2 Tasks vs. Accuracy

Sr. No	Task runs	Description of tasks	Accuracy
1	5, 9, 13	Motor Execution (Hands vs. Feet)	93.33 %
2	6, 10, 14	Motor Imagery (Hands vs. Feet)	97.77 %
3	3, 7, 11	Motor Execution (Left vs. Right Hand)	68.88 %
4	4, 8, 12	Motor Imagery (Left vs. Right Hand)	65.55 %

From Table 2, it is found that, highest accuracy is 97.77 % for the motor imagery task (6, 10, 14).

Fig. 17 shows a plot of highest accuracy obtained.

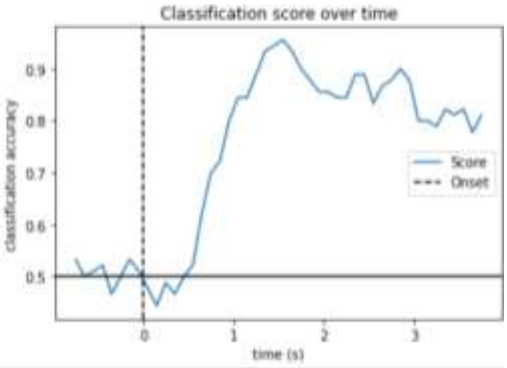

Fig. 15 Highest Accuracy Plot

Table. 3 Validation of Result with reported results

Basis of comparison	Result of the present study	Result of Reference [30]
Highest accuracy	97.77%	93.33%

From Table 3, it is discerned that, the highest accuracy of classification using LDA for chosen task is 97.77% which is in close agreement with the accuracy of 93.33% of the reported results.

5. CONCLUSIONS

The present study is a novel attempt of qualitative experimental type of research in which bottom-up approach for inductive method is used. This study is unique in the aspect of use of MNE Motor Imagery (MI) data set to perform both movement analysis and tasks classification. The movement analysis involves total 109 subjects and 14 runs for each subject. Total six tasks in the movement analysis are Eyes open, Eyes closed, Motor execution left vs. right hand, Motor imagery left vs. right hand, Motor execution hand vs. feet and Motor imagery hand vs. Feet. Pre-processing is done using ICA and Down sampling technique. FIR filtering is done using Butterworth, band-pass filter for frequency range 1 to 60 Hz. Eigenvalues as features are extracted. Further a plot of Eigen value vs. Noise is obtained. An EEG covariance matrix of size M x M is obtained where M indicates number of channels used. This matrix represents a spatial distribution of signal along with spatial correlation of EEG channel recordings. It shows changes in variance between different regions of the brain. The present study also includes Average power Time-Frequency Representation (TFR) analysis. The prominent conclusions of the present study are:

1. From dimensionality reduction using PCA , the principal component is noticed at early time instant of 0.2 s.
2. By the classification using LDA for the tasks (6, 10, 14) highest accuracy is found to be 97.77 % for the frequency range 12 to 30 Hertz. Hence, it is concluded that, beta waves are more active for the chosen task.

Future Scope: Authors are working on analysis on EEG signals by statistical techniques i.e. Chi-square test, ANOVA test, Z- test, etc. *Authors will perform **classification of*** EEG signals using classification techniques such as KNN, SVM, Logistic Regression, Decision Tree, and Random Forest. Enhancement of mental activities of mankind using Analysis of Sentiments and Behavior through artificial intelligence algorithms techniques is emerging as cutting edge technology of the future.

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