

Analysis of Motor Action and Motor Imagery Signals for BCI Applications

B.Vivekananthan¹, R.Nithya², B.Divya³

Department of Biomedical Engineering,
SSN College of Engineering,
Kalavakkam-603110

Email: vivek269411@gmail.com¹, nithyar@ssn.edu.in², divyab@ssn.edu.in³

Abstract— Brain Computer Interface (BCI) is a computerized system that acquires brain signals, extracts and classifies features during different mental activities, and converts them into correct control signals, and transfers them to external devices. BCI helps people with motor disabilities. Real-time application of a BCI system needs an efficient classification of motor tasks. Motor Imagery task identification based on EEG signals is still challenging for researchers. Extraction of robust, mutual information and discriminative features which can be converted into device commands is the biggest challenge in Motor Imagery BCI system. This study aims to analyse the effectiveness of motor and motor imagery classification for left hand and right-hand movements. The motor and motor imagery of left and right-hand movements is defined using statistical features of a higher order that are fed to classifier SVM and Random Forest Classifier. Using SVM classifier, for motor action the classification accuracy of 62.5% was reached and for motor imagery classification accuracy of 45.83% was reached. Using random forest classifier, for motor action the classification accuracy of 80.2% was reached and for motor imagery classification accuracy of 64.58% was reached.

Keywords— BCI, SVM, Random forest, Motor Action, Motor Imagery

I. INTRODUCTION

The perception of brain activity plays an important role in Brain Computer Interface (BCI) systems in which a disabled person can perform actions only through thinking. BCI is an artificial intelligence device that uses EEG signals as input and generates control signals or commands for the machine at its output so that people with disabilities can use a PC without mouse or keyboard. A BCI system comprises five sequential stages: signal acquisition, pre-processing or signal enhancement, feature extraction, classification, and interface control. Figure 1 displays a block diagram of the MI-BCI system.

The essence of the BCI program is the detection of intent by a person from his / her EEG signals. This is a highly challenging task that challenges researchers who are hoping to see the day when BCI technology is becoming more open and functioning. The identification/recognition of information in most existing BCI systems is based on classification algorithms which rely on the extraction of features. To date, numerous features have been suggested for testing different classifiers to classify specific brain functions. A large number of classifiers were used to classify brain tasks,

particularly in non-invasive MI-based BCI systems, using several kinds of features. Multilayer perceptron (MLP), support vector machine (SVM) with various kernel functions, linear discriminant analysis (LDA), k-nearest neighbour (KNN), naïve Bayes, hidden Markov model (HMM) and Fuzzy classifiers have been extensively used to classify various MI tasks in these works. The classifiers work a less fairway for the same features, i.e., we offer just about the same accuracy in classification. The features are very critical and play a significant role in classification.

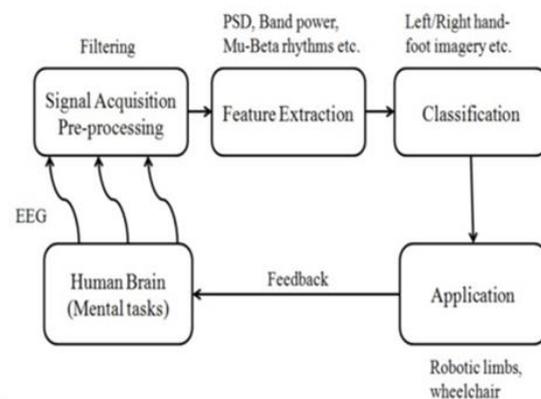


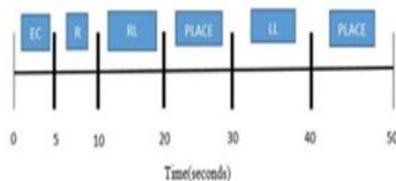
Fig. 1. Block diagram of MI-BCI system

II. EXPERIMENTAL PROTOCOL

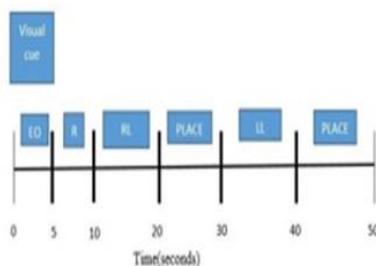
Fifteen healthy male volunteers aged between 20 and 28 had participated in the experiment. Each subject is allowed to practice and execute actual hand movements before the experiment.

Two protocols are followed in this work. Initially, motor action EEG signals are acquired by providing an auditory cue to perform for left hand and right-hand movements. For the motor action protocol, subjects are at eyes closed position (5 secs), followed by eyes opened position (5 secs), lifting of the right hand (10 secs) and placing of the right hand (10 secs) and finally lifting (10 secs) and placing of the left hand (10 secs). Then, motor imagery EEG signals are acquired by providing a visual cue of the same procedure followed in motor action protocol for 50 secs in which the subjects are explicitly instructed to imagine the kinesthetic sensation of movement and not to merely visualize the movement. The same procedure was repeated and then noted as the second trail.

Motor Action



Motor Imagery



EC-Eyes Close
R-Rest
RL-Right arm Lift
LL-Left arm Lift
EO-Eyes Open

Fig. 2. Experimental Protocol

III. METHODOLOGY

SIGNAL ACQUISITION

The EEG signals are recorded via g.tec, g. Nautilus 16 channel wireless EEG device, which is known to be one of the most accurate with high-resolution devices

available for recording. The EEG Signals are sampled at a rate of 250 Hz.

In this work, Cz, FP2, F3, Fz, F4, T7, C3, FP1, C4, T8, P3, Pz, P4, PO7, PO8, Oz channels are concentrated. Both the odd electrode numbers are on the left, and even the ones on the right hemisphere. Signals obtained from odd electrodes represent imagery of the left motor motion and even the electrodes represent the movement of the right motor signal. The signal from the C3 electrode, for example, was used for left-hand movement, and C4 was used for imagination with right-hand movement. Such electrodes are reference electrodes with the 'z' subscript.

PREPROCESSING

EEG signal is pre-processed by configuring the bandpass filter and notch filter in the g. Nautilus wireless EEG device. The bandpass filter is ranged between the frequency 0.5 and 30 Hz and the notch filter is ranged between the frequency 48 and 58 Hz. EOG artefacts with amplitude greater than 100 μ V are neglected.

EEG signal during left-hand movement and right-hand movement is separated from the acquired signal. Alpha band (8- 12Hz) is separated from each left and right-hand movement signals of all subjects and beta band (13-30 Hz) is separated from each left and right-hand movement signals of all subjects.

FEATURE EXTRACTION

Feature extraction is necessary for identifying different movements in the EEG signal. In this work, the left hand and right-hand movements will be identified. Different features such as statistical features, time-domain features, frequency domain features were extracted for both alpha band and beta band of each signal. In this work features such as mean, variance, standard deviation, skewness, kurtosis, average power, entropy, energy, moment (order-2,3,4), mean frequency, median frequency, max-amplitude, min-amplitude, coefficient of variation is used.

CLASSIFICATION

Support Vector Machine (SVM) and Random Forest are applied to data to determine the efficiency of the features described to provide a clear view of how these features are capable of separating the movement tasks of the left and right hand in motor activity and motor picture signals. 10 Validation of the cross fold was applied.

IV. RESULTS AND DISCUSSION

CHANNEL ANALYSIS

Electrodes in the motor cortex and occipital lobes were analysed for alpha and beta band for any activities during the two tasks. Cz, C3, C4 electrodes on

motor cortex region and PO7, PO8, Oz on occipital region were taken for analysis. Band power of the six channels for alpha and beta bands were computed and plotted in a graph.

The band power of Cz channel during left-hand motor action for the alpha band and the beta band is having maximum peak between 300 and 350 dB while it is between 50 and 150 dB in the case of po8 channel for alpha band respectively. The other channels did not show any noticeable peak in Figure 3.

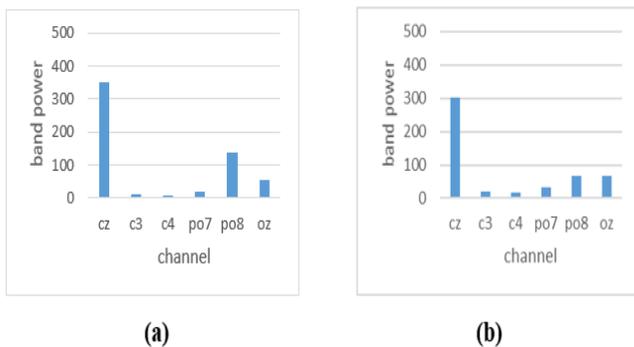


Fig. 3. (a)Band power of selected channels for alpha and (b)beta band left motor action

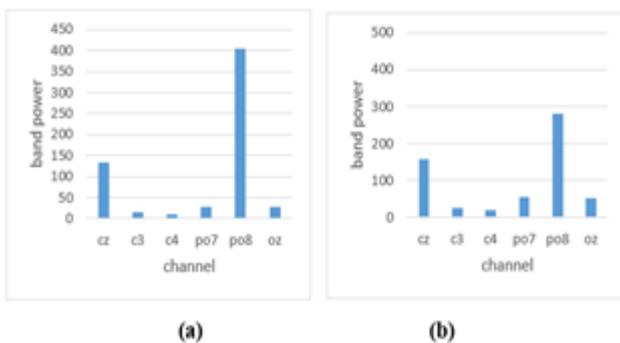


Fig. 4 (a)Band power of selected channels for alpha and (b)beta band right motor action

On the contrary, the band power of po8 during right-hand motor action of alpha-band shows maximum peak between 250 and 400 dB whereas Cz channel shows peak between 100 and 150 dB for beta-band respectively in Figure 4.

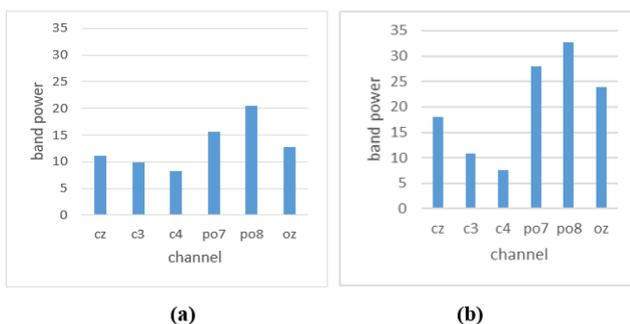


Fig. 5 (a)Band power of selected channels for alpha and (b)beta band left motor imagery

From Figure 5, it is inferred that the band power of EEG is higher in motor cortex i.e. in Cz channel and in visual cortex i.e. in Po7, P08 and Oz channels of alpha and beta bands. This higher activity is due to the hand movements imagination which influences the motor cortex channels and the visual cue which influence the visual cortex channels.

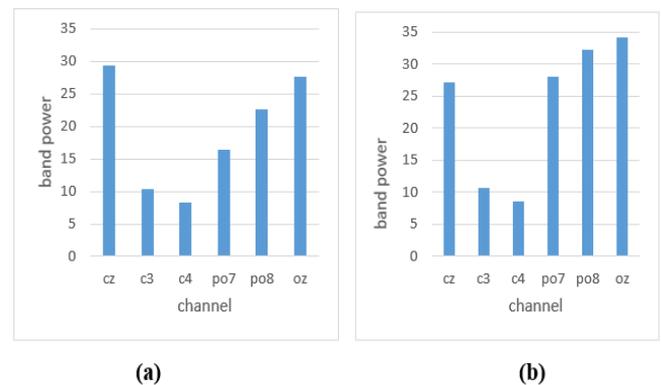


Fig. 6 (a)Band power of selected channels for alpha and (b)beta band right motor imagery

From Figure 6, it is inferred that the band power of EEG is higher in motor cortex i.e. in Cz channel and in visual cortex i.e. in Po7, P08 and Oz channels of alpha and beta bands. This higher activity is due to the hand movements imagination which influences the motor cortex channels and the visual cue which influence the visual cortex channels.

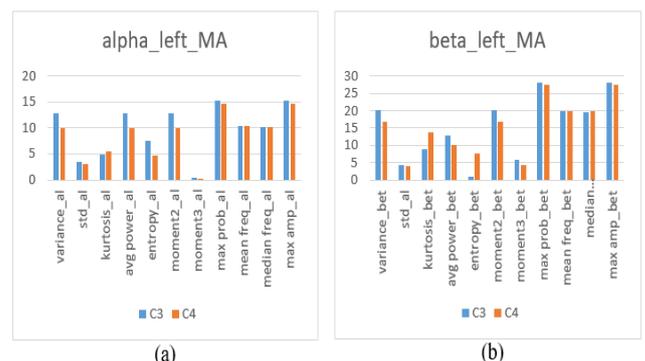


Fig. 7 Time-domain and frequency-domain features, statistical features of alpha (a) and beta (b) band during left-hand motor action EEG signal in C3 and C4 electrode.

The features are showing a maximum peak in C3 electrode during left-hand motor action in alpha wave except for entropy while in beta wave except for kurtosis, entropy and moment 3 in Figure 7.

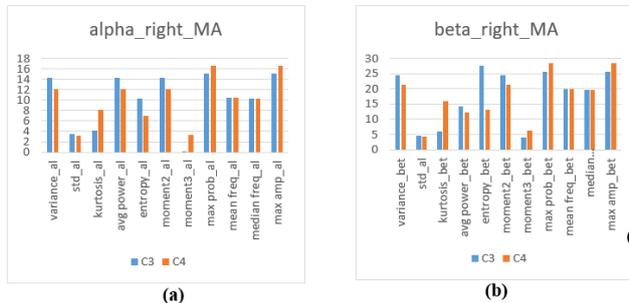


Fig. 8 Time domain and frequency domain features, statistical features of alpha (a) and beta (b) band during right-hand motor action EEG signal in C3 and C4 electrode.

In C4 electrode, the features are having maximum peak except for variance, entropy, average power and moment 2 in alpha band whereas the maximum peak are seen in beta band features except for variance and average power in Figure 8.

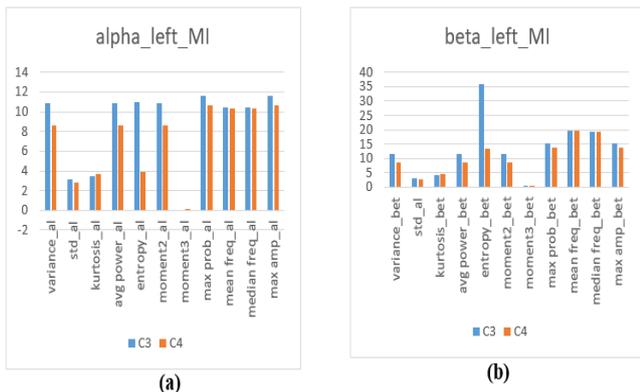


Fig. 9 Time domain and frequency domain features, statistical features of alpha (a) and beta (b) band during left-hand motor imagery EEG signal in C3 and C4 electrode.

The features are showing a maximum peak in C3 electrode during left-hand motor imagery in alpha wave except for entropy while in beta wave except for entropy in Figure 9.

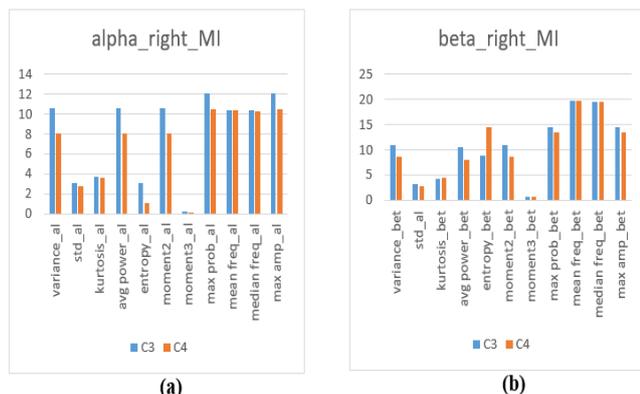


Fig.10 Time domain and frequency domain features, statistical features of alpha (a) and beta (b) band during right-hand motor imagery EEG signal in C3 and C4 electrode.

In C3 electrode, the features are having maximum peak except for entropy, in the alpha band and the beta band as illustrated in Figure 10.

CLASSIFICATION

In this segment, the classifier's result is presented. The output of the apps is evaluated for motor activity and motor imagery with two separate classifiers, SVM and Random forest. Dataset was created with the extracted features from alpha and beta bands and given to the classifiers.

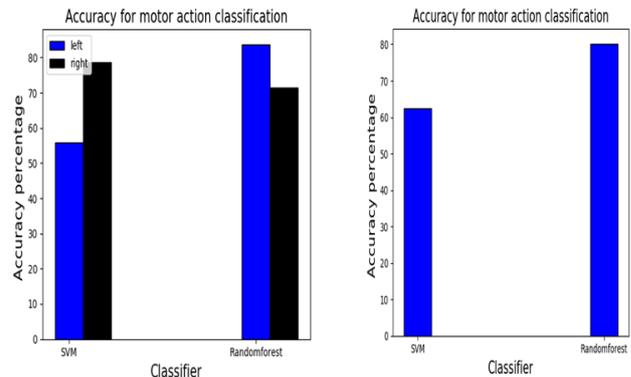


Fig.11 Comparison of classification accuracy of motor action for SVM and Random forest

Figure 11 shows that SVM classifier classified more than fifty per cent of left-hand action and more than seventy-five per cent of right-hand action accurately from the test data. Random forest classifier classified more than eighty per cent of left-hand action and more than seventy per cent of right-hand action accurately from the test data.

The overall results of motor action classification show that SVM classifier has attained 62.5% and Random forest classifier has attained comparatively the highest accuracy of 80.2%.

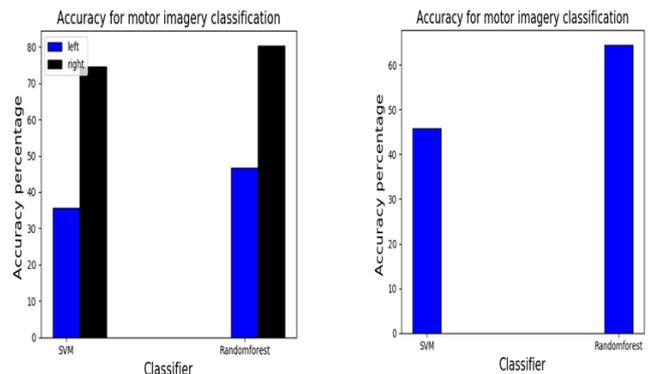


Fig.12 Comparison of classification accuracy of motor imagery for SVM and Random forest

Figure 12 shows that SVM classifier classified more than thirty-five per cent of left-hand action and more than seventy per cent of right-hand action accurately from the test data. Random forest classifier classified more than forty-five per cent of left-hand action and more than seventy-five per cent of right-hand action accurately from the test data.

The overall accuracy of motor imagery classification shows that SVM classifier has attained 45.83% and Random forest classifier attained 64.58%. The random forest has the highest classification accuracy than SVM.

V. CONCLUSION

In this work, the EEG signal for 15 subjects was acquired using 16-channel g. Nautilus EEG system and statistical features from alpha and beta bands were extracted. The channel analysis result indicates that during motor action both motor and visual areas are affected but the motor cortex region during motor action has more effects. For motor imagery with the implemented protocol of showing visual cue, the channel analysis result indicates that during motor action both motor and visual areas are affected but the visual region during motor imagery has more effects. SVM and Random forest classifiers were used to assess the ability of the statistical features for classification. In SVM classifier, for motor action, the classification accuracy of 62.5% was reached and for motor imagery classification accuracy of 45.83% was reached. In Random forest classifier, for motor action, the classification accuracy of 80.2% was reached and for motor imagery classification accuracy of 64.58% was reached. This shows that the features used for classification give less accuracy for left and right-hand motor imagery signals. In future for better classification accuracy of different tasks of motor imagery signal, features such as common spatial patterns, continuous wavelet transform can be used.

REFERENCES

- [1] Lindig-Leon, Cecilia, and Laurent Bougrain. "A multi-label classification method for detection of combined motor imageries." In *2015 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 3128-3133. IEEE, 2015.
- [2] Mebarkia, Kamel, and Aicha Reffad. "Multi optimized SVM classifiers for motor imagery left and right hand movement identification." *Australasian physical & engineering sciences in medicine* 42, no. 4 (2019): 949-958.
- [3] Leena, R., and Ashok Kumar. "Classification of Motor Imagery Based EEG Signals."
- [4] Alomari, Mohammad H., Aya Samaha, and Khaled AlKamha. "Automated classification of L/R hand movement EEG signals using advanced feature extraction and machine learning." *arXiv preprint arXiv:1312.2877* (2013).
- [5] Korhan, Nuri, Zumray Dokur, and Tamer Olmez. "Motor Imagery Based EEG Classification by Using Common Spatial Patterns and Convolutional Neural Networks." In *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, pp. 1-4. IEEE, 2019.
- [6] AYDEMİR, ÖNDER. "Common spatial pattern-based feature extraction from the best time segment of BCI data." *Turkish Journal of Electrical Engineering & Computer Sciences* 24, no. 5 (2016): 3976-3986.
- [7] Chatterjee, Rajdeep, Tathagata Bandyopadhyay, Debarshi Kumar Sanyal, and Dibyajyoti Guha. "Comparative analysis of feature extraction techniques in motor imagery EEG signal classification." In *Proceedings of First International Conference on Smart System, Innovations and Computing*, pp. 73-83. Springer, Singapore, 2018.
- [8] Chatterjee, Rajdeep, Tathagata Bandyopadhyay, and Debarshi Kumar Sanyal. "Effects of wavelets on quality of features in motor-imagery EEG signal classification." In *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pp. 1346-1350. IEEE, 2016.
- [9] Fu, Rongrong, Yongsheng Tian, Tiantian Bao, Zong Meng, and Peiming Shi. "Improvement motor imagery EEG classification based on regularized linear discriminant analysis." *Journal of medical systems* 43, no. 6 (2019): 169.
- [10] Chaudhary, Shalu, Sachin Taran, Varun Bajaj, and Abdulkadir Sengur. "Convolutional neural network based approach towards motor imagery tasks EEG signals classification." *IEEE Sensors Journal* 19, no. 12 (2019): 4494-4500.
- [11] Yu, Zhongliang, Lili Li, Jinchun Song, and Hangyuan Lv. "The Study of Visual-Auditory Interactions on Lower Limb Motor Imagery." *Frontiers in neuroscience* 12 (2018): 509.
- [12] Tang, Zhichuan, Chao Li, and Shouqian Sun. "Single-trial EEG classification of motor imagery using deep convolutional neural networks." *Optik* 130 (2017): 11-18..