2018 15th International Conference on
Control, Automation, Robotics and Vision (ICARCV)
Singapore, November 18-21, 2018

EEG-based Discriminative Features During Hand Movement Execution and Imagination

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***Abstract*— Electroencephalogram (EEG) is one the most commonly used brain activity measurement tools in Brain-Computer Interface (BCI) framework to establish "thought' based human-machine interaction. On account of the fact that mental rehearsal of motor movement termed motor imagery, is a robust candidate for developing BCI systems, it is of great importance to find the distinction between the neural correlates of executed motor movement and its imagination, to enhance command signal generation and utilization in BCI-based communication and control. This paper investigates the EEG-based parameters associated with execution and imagination of left and right hand movement from a set of 10 healthy subjects. The study explores the distinguishable power and phase features in theta (4-8 Hz), alpha/mu (8-12 Hz), lower beta (12-20 Hz), higher beta (20-30 Hz) and gamma (30-40 Hz) bands of EEG. It is observed that the most informative channels that effectively discriminates motor execution and imagination varies across bands and tasks. Frontal and parietal channels are found to be more discriminative compared to those in central region in both tasks. Combining the task-specific discriminative features along with Common Spatial Pattern (CSP) based spatial features, an average classification accuracy of 81 % is achieved in 5 x 5 –fold cross validation, over 10 subjects. Further study is essential to investigate the temporal structure of the distinguishable features, to generalize the discriminative spectral and spatial characteristics and to improve the classification accuracy.**

Keywords—Electroencephalogram (EEG), Brain-computer interface, band power, phase, discrimination and classification accuracy.

I. INTRODUCTION

Brain-Computer Interface (BCI) technology aims to allow a person to communicate through thoughts to the external world [1]. Its huge potential can be utilized for the disabled as well as for the healthy population. Literature reports more than three decades of BCI research exploring its promising capabilities to help the locked-in patients by establishing a new mode of communication from human to the external world that offers novel assistive devices, neuroenhancement techniques, robotic rehabilitation programme etc. [2]. BCI can also provide unique and interesting modes of communication between human and machine for the healthy population, offering novel entertainment methodologies, namely neurofeedback games [3]. Success of any BCI application depends on its efficacy of communication that can be assessed by the classification accuracy or information transfer rate in performance [4]. Quality of signal recorded, signal processing methods and classification are of great importance to obtain higher BCI performance rates [5]. Using robust signal processing and machine learning techniques, a brain pattern associated with an imagined or executed activity can be accurately transformed into appropriate command signals for many applications. The higher the accuracy of mental task detection, the higher the performance of any BCI application. Tasks that a person performs to generate control signal in BCI is expected to generate unique brain patterns which in turn helps in proper detection and translation of control signals [6]. Hence, finding out unique tasks and extracting accurate task-specific features are of great importance in the success of any BCI system.

Most of the current BCI systems rely on the Electroencephalogram (EEG) technique, as it is the least expensive and most comfortable technique among the available brain activity recorders [7]. Among the EEG-based BCI systems, EEG modulation associated with motor movements of the user is one of the commonly explored features for various kinds of applications, from developing games to BCI based rehabilitation for stroke patients [8]. The Event Related De-/Synchronization (ERD/ERS) found in EEG, accompanied with an executed or imagined motor movement has unique topographic features. The distinguishable ERD/ERS patterns mostly appear in *mu* (8-12 Hz) or beta (12-30 Hz) bands, especially in the motor cortex [7].

Though the neurophysiological correlates of execution and imagination are having cortical similarities, a number of studies in literature investigate on the differences between the modes of activity using fNIRS [9], ECoG [10] and EEG [11-13]. These reports indicate that the activation/suppression of certain EEG sub bands in contralateral and ipsilateral hemispheres do have similarities, but the intensity of modulations in execution is higher than that in imagery. EEG-based study in [11-13] also shows that EEG patterns during executed and imagined motor movements can be classified effectively through the use of sophisticated machine learning techniques, despite the close similarities between the two signals. The similarities and variations can be subject-specific. However, if the distinct features of execution and imagination distributed over different lobes and bands have been determined properly, it would be beneficial in generating precise command signals for BCI applications such as neuroprosthetic rehabilitation and to add the number of control inputs for brain-activated

Research supported by Ministry of Education, Singapore, AcRF Tier 2 grant MOE2015-T2-2-011.

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device/application control [11]. Motivated by these facts, this paper investigates the discriminative features for separating EEG patterns during hand movement execution and imagination. At first, we examine the separability of EEG signals using band power and phase based features, in theta (4-8 Hz), alpha (8-12 Hz), lower beta (12-20 Hz), higher beta (20-30 Hz) and gamma (30-40 Hz) bands. Later, discriminative band power/phase based features from chosen bands and channels are used to frame the feature vector for classification. In addition to these features, Common Spatial Pattern (CSP) based spatial features are also concatenated, to examine the effect of fusion of parameters in classification accuracy. It is found that concatenation of CSP features with power/phase features helps to enhance classification accuracy of motor execution (ME) and motor imagery (MI) of both left hand and right hand tasks.

The remainder of this paper is organized as follows. Section II presents the experimental details. Section III introduces the details of the proposed methodology. Section IV presents the results of the data analysis. Finally, Section V summarizes the of the paper.

II. EXPERIMENTAL DETAILS

An experiment has been designed to record EEG when a subject performs right and left hand motor tasks. The BCI paradigm used in this study is similar to the widely used Graz BCI paradigm. Ten subjects (7 male, 3 female, age 26.6±5.5 years, all right-handed) participated in this study. The participants were seated comfortably in a chair with arms placed on the armrest. EEG was recorded using BrainAmp ActiCHamp amplifier from 31 electrodes placed on the scalp according to 10-20 system. The signals were sampled at 500Hz, and filtered with a band pass filter of 0.05 to 200 Hz. Twenty channels from the sensorimotor (SM) area were used in further analysis thereby excluding spurious interactions of physical limb/eye muscle artefacts in occipital and temporal electrodes. Each experiment started with a 20 seconds period in which subject was instructed to relax with eyes open. This was followed by the calibration session, which included 1 run of motor execution and 2 runs of MI. The sequence of visual cues for data acquisition is as shown in Fig.1.

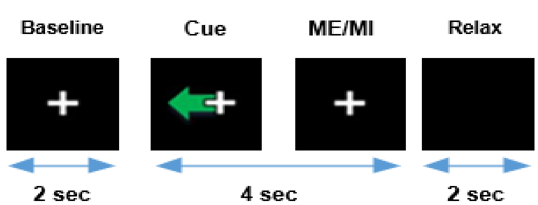


Fig. 1 Timing protocol for the experiment done.

Each trial started with a 2-second interval in which a white cross appeared in the center of the black screen, which served as the visual fixation point. Following this, a green arrow pointing toward right or left appeared for one second which indicates the subject to perform right or left hand movement task respectively until the cross disappears. The cross disappears after 4 seconds, and the subject was instructed to relax. This rest period lasts for 2 seconds which is the end of the trial. This timeline is repeated for the entire run with task cues presented in random order. The MI calibration session consisted of 2 runs of 50 trials each, resulting in 100 trials of bilateral MI, and single run with 50 trials per class. The data from ME and MI runs of calibration session are used in this study. This research was approved by the Institutional Review Board of Nanyang Technological University, Singapore (IRB-2016-07-019).

III. METHODOLOGY

The aim of the study is to investigate the differences in neural correlates of ME and MI of each hand movement. In order to accomplish the same, the discriminative intensities of the band power and phase features of the EEG signals within the 5 EEG sub bands mentioned in Section I, for all subjects for each of the tasks have been analyzed. The separability of ME and MI features for each hand activity in each band is assessed using a Fisher ratio based Discriminative Index (FDI), for each channel [14]. This ratio has been computed for band power and phase based features. Both of these features are estimated using the spectrogram method, which computes the power spectral density (PSD) and phase value of every frequency component of the signal received. FDI on band power values in c^{th} channel on f^{th} frequency component denoted as $PoFDI_f^c$ in equation (1) represents the ratio of sum of inter-class variance (*ICV*) of band power values across the whole set of trials, to the sum of the within-class variance (*WCV*) of band power values for each task, for the respective channel and frequency point. Similarly, the FDI of phase feature, $PhFDI_f^c$ is also computed as in equation (2).

$$PoFDI_f^c = \frac{ICV_f^c(Power)}{WCV_f^c(Power)} \tag{1}$$

$$PhFDI_f^c = \frac{ICV_f^c(Phase)}{WCV_f^c(Phase)} \tag{2}$$

As given in equations, these values exist at every frequency point of the spectrogram output which can then be utilized to represent the FDI of each band. Mean values of FDI values across all the 5 bands are computed from $PoFDI_f^c$ and $PhFDI_f^c$ values for each type of activity (left hand or right hand), for every subject. Plotting the channel-specific FDI values and topographic maps of these values across each band will be able to show the discriminative indices of all channels and features. The analysis of whole data, individually for left hand and right hand motor activity has been performed and the observations are shown in Section IV.

Motivated by the observations in the discriminative analysis, a BCI system has been proposed to classify the ME and MI activations of EEG patterns, as shown in Fig. 2. The main modules in the system are data acquisition, baseline filtering (to remove the baseline shift of the EEG data), band pass filtering using Chebyshev Type 2 Infinite Impulse Response (IIR) filters, feature extraction, feature selection and classification. Literature shows that one of the most robust methods to extract discriminative features for motor activity in EEG is CSP technique [15]. The goal of the CSP algorithm is to design spatial filters whose variances are optimal for the discrimination of two-classes of EEG measurements. CSP algorithm is based on the simultaneous diagonalization of two covariance matrices [15], and variance of spatially projected EEG is considered as robust information carriers for classification too. Hence, we propose to combine the band power and phase values computed from each channel along with the CSP features in most discriminative band. From the combined set of features, only the most informative features are selected based on mutual information based feature selection algorithm. It helps to improve the robustness of the classifier. Among the wrapper and filter based approaches of feature selection algorithms available in literature, we used Mutual Information based best individual feature selection in filter approach as in [16, 17] i.e. from an initial set *F* with d features, find the subset with a fixed pairs of features that maximizes musual iinformation. This algorithm requires a user defined parameter to select the number of best features, which is fixed as 20 in our work. Then the selected features are given to the Support Vector Machine (SVM) classification algorithm which is a linear discriminant that maximizes the separation between two classes based on the assumption that it improves the classifier's generalization capability.

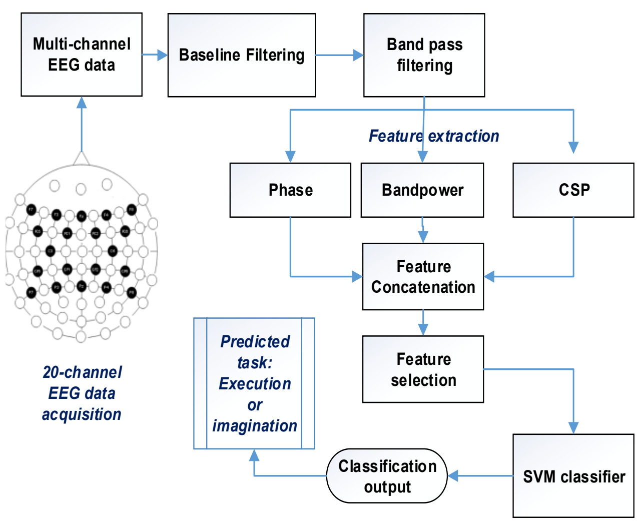


Fig. 2 Schematic of the BCI methodology used.

Data analysis is performed using EEG from 20 channels (F7, F3, Fz, FC5, FC1, C3, CP5, CP1, P7, P3, F4, F8, FC2, FC6, C4, CP2, CP6, P4, P8 and Pz). A 5 x 5 fold cross validation procedure is adopted to estimate the classification accuracy of the proposed system shown in Fig. 2. Classification accuracies of motor execution and imagination are noted, for each hand activity. Classification results and performance analysis are explained in the following section.

IV. Results

Results of our study are given in this section, presenting the discriminative FDI values and ME/ME classification results/analysis.

A. Evaluation of FDI values

As mentioned in Section III, we have estimated $PoFDI_f^c$ and $PhFDI_f^c$ values for theta, alpha, lower beta, upper beta and gamma bands, in order to examine the discrimination during execution and imagination, for left hand and right hand individually. Fig. 3 provides the difference in PSD values of all frequency components for channel F8, C4 and FC6 for left tasks whereas Fig. 4 provides similar plots for right tasks in channels FC5, C4 and CP6. Absolute difference of phase values of all frequency components for 3 channels in Subject-4 for left ME/MI tasks are given in Fig. 5 whereas Fig. 6 provides the same plot for right ME/MI tasks for channels F8, CP1 and P4.

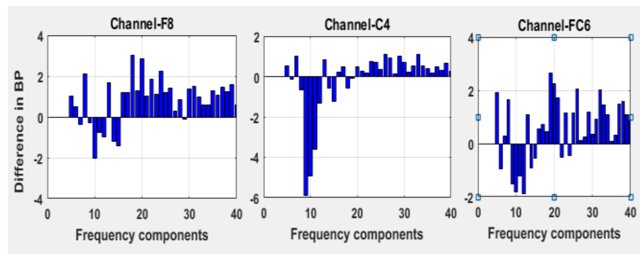


Fig. 3 Difference of PSD values of all frequency components for 3 channels in Subject-1 for left ME/MI.

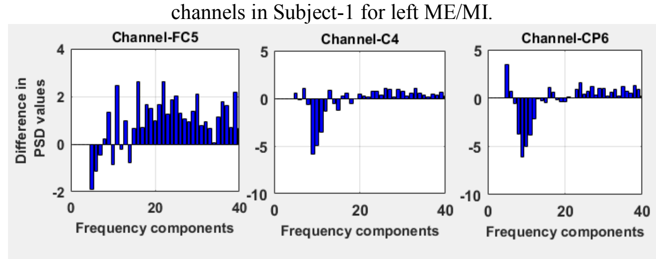


Fig. 4 Difference of PSD values of all frequency components for 3 channels in Subject-1 for right ME/MI.

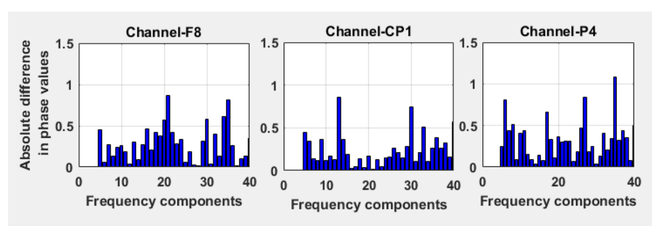


Fig. 5 Absolute difference of phase values of all frequency components for 3 channels in Subject-4 for left ME/MI.

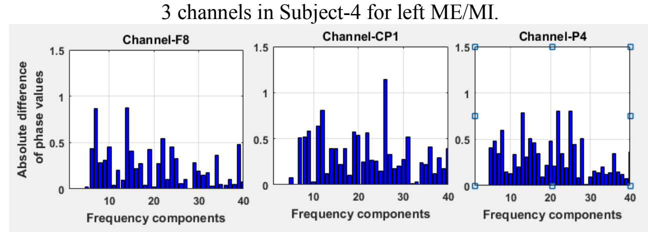


Fig. 6 Absolute difference of phase values of all frequency components for 3 channels in Subject-4 for right ME/MI.

Similar characteristics of PSD and phase values have been observed for all subjects. Analyzing the PSD and phase value of all subjects for both type of tasks, it is found that there exists distinguishable characteristics for PSD and phase values, but their intensities and spatial/spectral locations vary between subjects and tasks. In order to show discriminative weights of all channels, the topographic maps

Theta alpha lower beta higher beta gamma

are plotted. Figures 7 and 8 show the topographic maps of $PoFDI_f^c$ and $PhFDI_f^c$ respectively for left hand. Figures 9 and 10 show the topographic maps of $PoFDI_f^c$ and $PhFDI_f^c$ respectively for right hand. In Figs. 7-10, the five columns stand for theta, alpha, lower beta, higher beta and gamma bands respectively.

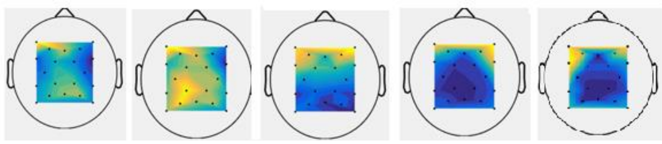


Fig. 7 Topographic maps of mean $PoFDI_f^c$ values in left hand task.

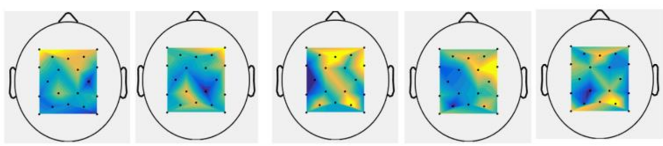


Fig. 8 Topographic maps of mean $PhFDI_f^c$ values in left hand task.

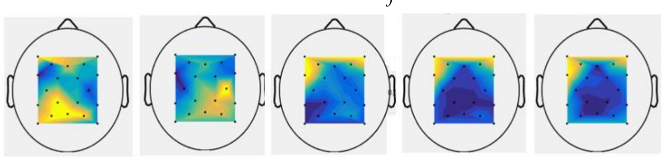


Fig. 9 Topographic maps of mean $PoFDI_f^c$ values in right hand task.

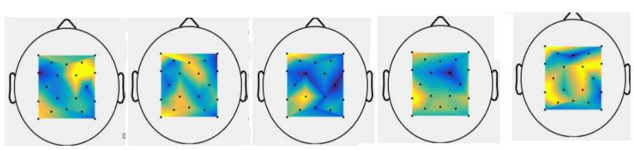
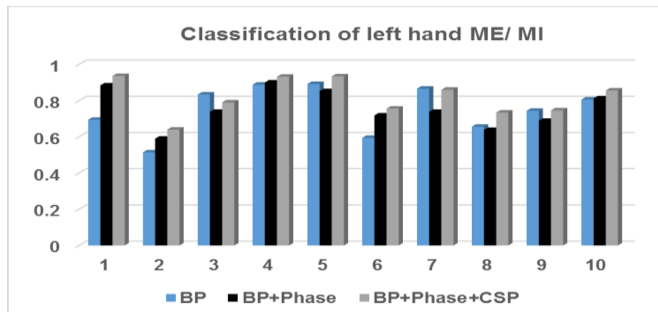


Fig. 10 Topographic maps of mean $PhFDI_f^c$ values in right hand task.

It can be found that the cortical regions that offer higher separation from execution and imagination tasks are mainly the frontal and parietal regions. Also comparing the left hand and right hand topographic maps, the beta and gamma band FDI map seems to have similarities, especially in $PoFDI_f^c$. Motivated by this observation, the classification analysis presented here will be using the beta and gamma band from frontal regions to classify execution and imagination patterns, for the left hand and right hand.

B. Classification Performance

Based on the similarity of beta and gamma band activity in left and right hand motor tasks, this study reports the classification performance using the same bands. In order to classify the motor activity related EEG patterns in beta and gamma bands, the extracted features from training trials in the 5 x 5-fold cross validation are fed to SVM classifier to build the subject-specific classifier model, which are then used to predict the labels of test feature vectors. As there are 100 trials for each subject, training model is based on 80 trials which are then used to predict test data consisting of 20 trials. The average classification accuracy in all the test folds is considered as the performance index of the proposed system. Figures 11 (a) and (b) show the classification accuracy of the execution and imagination of left hand and right hand respectively for the ten subjects, using band power features in lower beta, upper beta and gamma bands, from 5 channels from frontal region alone, namely F7, F3, Fz, F4 and F8. These channels are selected based on their higher discriminative indices in 20-30 Hz (as in Fig. 7 and 9). Table I provides the average classification accuracy of the 3 methods employed in the framework. The method that combines CSP, band power and phase features (BP+Phase+CSP) provides higher accuracy than others, with an average accuracy of 81%.



Figs. 11 (a) Classification results of left hand ME/MI.

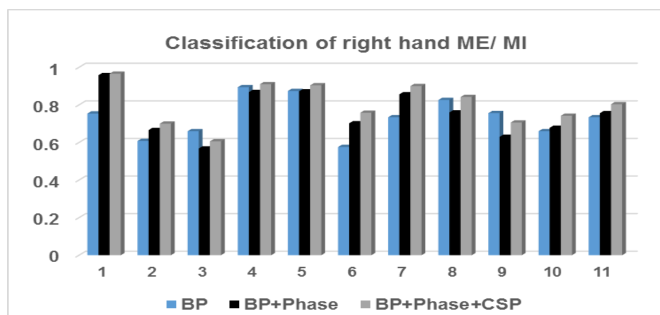


Fig. 11 (b) Classification results of right hand ME/MI.

Table I Average classification performance

Method	BP	BP+Phase	BP+Phase+CSP
Left hand	74.88±13.12	75.58±10.42	81.84± 10.12
Right hand	73.42± 10.87	75.58± 12.70	80.34± 11.72
Average	**74.15 ±11.99**	**75.58± 11.56**	**81.09±10.92**

C. Discussion

The investigation on the separability of ME/MI indicates that it is possible to utilize band power, phase and CSP features in the classification of imagery and execution EEG patterns, related to hand movement. The choice of beta and gamma bands of frontal lobe EEG in classification are based on the inference found on the topographical maps of FDI values, as shown in Figures 7-10 (columns 3 to 5). However, as the maps explicitly show, the FDI values of power and phase features vary across bands and channels. Hence, incorporating the knowledge of band-specific discriminative channels is expected to improve the classification performance. Also the literature reports that the central region electrodes are comparatively more activated during motor movements than during motor imagery. The intensity of cortical activity in motor cortex during execution of a task is reported to be higher than imagined task [12, 13], which is mostly reflected in *mu* band. In line with this report, central electrodes also show some discrimination between execution and imagination in mu band, as seen in second column of Fig. 7 and 9.

Also the phase values show discrimination mostly in the frontal and parietal regions, which might be representing the higher level of planning and co-ordination of thinking strategies accompanied with motor imagery, than execution task. These activations in frontal and parietal regions might be markers of cognitive and visual excitations respectively of brain during imagination (than real execution), which can be seen in Figs. 8 and 10.

These preliminary observations in the discriminative analysis give more insights to separability of band power and phase features between execution and imagination, and incites further study to understand neurophysiological correlates of these distinct parameters. To compute the phase and power in every frequency bin of the signal, the spectrogram tool in matlab has been utilized. The hamming window used in the spectrogram technique covers the whole 2.5 seconds for the data to estimate PSD, and hence temporal variations of PSD/phase values have not been counted for this work for both ME or MI. Acquiring more knowledge about the separability of various EEG patterns in temporal, spectral and spatial domains will help to enhance the EEG-based control paradigms and performance of numerous BCI applications. In future, we will examine the degree of overlap or discrimination of cortical activations, their temporal variations during execution and imagination of motor tasks more precisely, and develop robust and optimized BCI models for improving system performance and user experience.

V. Conclusion

Execution and imagination of motor movements are reported to share similar neural activations and is reflected in *mu*-band (8-12 Hz) of EEG signals, mainly in the central motor cortex. However extensive discriminative analysis comparing various EEG sub hands and cortical regions are rarely investigated for the left hand and right hand movement tasks individually. This paper investigates the distinct features during imagination and execution, using band power and phase information across various electrodes, in five EEG-sub bands, namely theta, alpha/mu, lower beta, upper beta and gamma. The discriminative indices using power and phase values are found to vary across bands and tasks. However, it is observed that frontal and parietal regions offer more discriminative information in both power and phase analysis, which might be on account of the additional involvement of cognitive and visual cortical networks in motor imagery, compared motor execution. Based on the similar FDI values of frontal regions in beta and gamma bands observed for both left and right motor activity, a BCI model is developed to classify two-class motor tasks. Preliminary investigation provides a classification accuracy of 81% over 10 subjects, showing the separability of band power, phase and CSP based features during ME and MI. Further study is required to examine the temporal variations of these distinct parameters and to optimize the BCI model to enhance classification performance.

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