33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Calibrating EEG-based motor imagery brain-computer interface from passive movement

Kai Keng Ang, Cuntai Guan, Chuanchu Wang, Kok Soon Phua,
Adrian Hock Guan Tan, Zheng Yang Chin

***Abstract*—EEG data from performing motor imagery are usually collected to calibrate a subject-specific model for classifying the EEG data during the evaluation phase of motor imagery Brain-Computer Interface (BCI). However, there is no direct objective measure to determine if a subject is performing motor imagery correctly for proper calibration. Studies have shown that passive movement, which is directly observable, induces Event-Related Synchronization patterns that are similar to those induced from motor imagery. Hence, this paper investigates the feasibility of calibrating EEG-based motor imagery BCI from passive movement. EEG data of 12 healthy subjects were collected during motor imagery and passive movement of the hand by a haptic knob robot. The calibration models using the Filter Bank Common Spatial Pattern algorithm on the EEG data from motor imagery were compared against using the EEG data from passive movement. The performances were compared based on the 10×10-fold cross-validation accuracies of the calibration data, and off-line session-to-session transfer kappa values to other sessions of motor imagery performed on another day. The results showed that the calibration performed using passive movement yielded higher model accuracy and off-line session-to-session transfer (73.6% and 0.354) than the calibration performed using motor imagery (71.3% and 0.311), and no significant differences were observed between the two groups (*p*=0.20, 0.23). Hence, this study shows that it is feasible to calibrate EEG-based motor imagery BCI from passive movement.**

I. Introduction

Brain–computer interface (BCI) provides a channel for using brain signals to communicate or control external devices without using the normal output pathways of peripheral nerves [1]. A motor imagery BCI, which translates the imagination of movements into commands, provides a promising approach for neurological rehabilitation [2]. BCIs generally adopt the subject learning approach [3], the machine learning approach [4], or the co-adaptive approach using both subject and machine learning [5]. In motor imagery BCIs that adopt the machine learning approach, the system generally operates in two phases, namely, the calibration phase and the evaluation or feedback phase [6]. Typically, EEG data are collected from a subject while performing motor imagery to train a subject-specific model in the calibration phase. The subject-specific model may include the subject-specific temporal filters, spatial filters computed using the Common Spatial Pattern algorithm [7], and parameters of a classifier. This subject-specific model is then used to classify the EEG data from the subject in the evaluation phase and translate the classifier output into control signals.

However, the performance of motor imagery is internal to the subject and is thus not directly observable. Hence, there is no direct objective measure as to whether the subject is performing motor imagery correctly for proper calibration. An indirect measure is to compute the cross-validation accuracy of the subject-specific model using the EEG data collected in the calibration phase. This can be performed by using part of the EEG data to calibrate the model and classifying the remaining part using the calibrated model.

Nevertheless, studies had shown that the performance of voluntary movement, passive movement [8], [9] and motor imagery [10] of the hand revealed similar Event-Related Desynchronization/Synchronization (ERD/ERS) patterns [11] in the primary sensorimotor areas. Further studies on EEG [12] and MEG data [13] were also reported on voluntary and passive movement of the foot. These studies also revealed that the performance of motor imagery induced both ERD and ERS patterns in the mu rhythms [14] whereas passive movement induced ERS patterns in the beta rhythms [8], [9], [12].

Since passive movement is directly observable, this paper investigates the feasibility of calibrating EEG-based motor imagery BCI from passive movement. EEG data from performing motor imagery and passive movement were collected from 12 healthy subjects for this study. The subject-specific models calibrated using the Filter Bank Common Spatial Pattern (FBCSP) algorithm [15], [16] on the EEG data collected from performing motor imagery were compared against the subject-specific models calibrated using the EEG data collected from performing passive movement. The performances were analyzed on the cross-validation accuracies of the calibration data and off-line session-to-session transfer of both the subject-specific calibration models to EEG data of performing motor imagery on another day.

The remainder of this paper is organized as follows: Section II describes the experimental methodology for this study. Section III presents the experimental results. Finally, section VI concludes the paper.

This work was supported by the Science and Engineering Research Council of A*STAR (Agency for Science, Technology and Research), Singapore.

K. K. Ang, C. Guan, C. Wang, K. S. Phua, A. H. G. Tan and Z. Y. Chin are with Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way, #21-01, Connexis, Singapore 138632. (email: {kkang, ctguan, ccwang, ksphua, hgatan, zychin}@i2r.a-star.edu.sg).

II. Subjects and Methods

A. Subjects

This study recruited 12 healthy subjects. Ethics approval and informed consent were obtained. Two subjects chose to perform motor imagery and passive movement of the left hand while the remaining 10 subjects chose to perform on the right hand.

B. EEG data collection

EEG from 27 channels were collected using the Nuamps EEG acquisition hardware (http://www.neuroscan.com) with unipolar Ag/AgCl electrodes channels, digitally sampled at 250 Hz with a resolution of 22 bits for voltage ranges of ±130 mV. EEG recordings from all channels are bandpass filtered from 0.05 to 40 Hz by the acquisition hardware. The subjects were instructed to minimize physical movement and eye blinking throughout the EEG recording process.

EEG data were collected without feedback in two parts for this study from each subject on separate days. In the first part, four sessions of EEG data were collected. The first two sessions collected EEG from a subject while performing motor imagery of the chosen hand and background rest condition. The next two sessions collected EEG data from the subject while passive movement of the chosen hand was performed using the haptic knob robot [17] and background rest condition. Fig. 1 shows the experimental setup to collect EEG data as the haptic knob robot is used to move the subject's right hand.

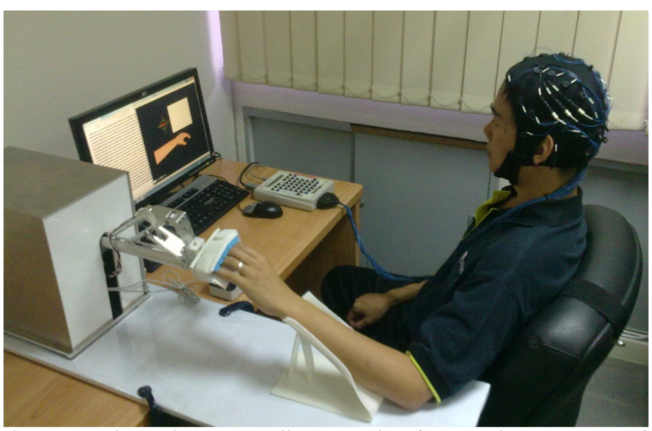

Fig. 1. Experimental setup to collect EEG data from passive movement of the left hand using the haptic knob robot [17] for calibrating EEG-based motor imagery BCI.

The subjects were instructed to perform kinaesthetic motor imagery of the chosen hand in the first two sessions. The instructions were presented in the form of visual cues displayed on the computer screen in each trial. The subjects were instructed to perform mental counting during the background rest condition. This instruction was given to define the background rest condition to the subject. In the subsequent two sessions, the subjects were instructed to relax while the movement of the chosen hand was performed using the haptic knob robot [17]. The subjects were also instructed to perform mental counting during the background rest condition for these two sessions.

Each session lasted about for approximately 16 minutes that comprised of 40 trials of either motor imagery or passive movement, and 40 trials of background rest condition. Each trial comprised a preparatory segment of 2 s, the presentation of the visual cue for 4 s, and a rest segment of at least 6 s. Each trial lasted approximately 12 s, and a break period of at least 2 minutes was given after each session of EEG recording. The EEG data from the first and second sessions were used to calibrate the subject-specific model from performing motor imagery, and the EEG data from the third and fourth sessions were used to calibrate the subject-specific model from passive movement.

In the second part of this study, three sessions of EEG data were collected without feedback on another day from the subject while performing motor imagery of the chosen hand and background rest condition. Each session again lasted about for approximately 16 minutes that comprised of 40 trials of motor imagery and 40 trials of background rest condition.

C. EEG data analysis

The challenge in the analysis of the EEG recordings is the huge inter-subject variability with respect to the brain signal characteristics [18]. Studies had shown that the common spatial pattern (CSP) algorithm [10], [18] is effective in constructing optimal spatial filters that discriminates two classes of EEG measurements in motor imagery BCI [7], [10], [19]. However, due to huge inter-subject variability, the performance of this algorithm depends on its operational frequency band [7]. Hence, this study used the filter bank common spatial pattern (FBCSP) algorithm to address this issue by performing autonomous selection of key temporal-spatial discriminative EEG characteristics [15], [16].

The FBCSP algorithm comprises 4 progressive stages of EEG processing to construct a subject-specific motor imagery detection model. The first stage employs a filter bank that decomposes the EEG into multiple frequency pass bands using Chebyshev Type II filters. A total of 9 band-pass filters are used, namely, 4-8 Hz, 8-12 Hz,…, 36-40 Hz. The second stage performs CSP spatial filtering [7]. Each pair of band-pass and spatial filter computes the CSP features that are specific to the band-pass frequency range. The third stage selects discriminative CSP features for the subject's task using the Mutual Information-based Best Individual Feature (MIBIF) algorithm to select k=4 best features. Finally, the fourth stage employs the Naïve Bayesian Parzen Window (NBPW) classification algorithm to model and classify the selected CSP features. The reader is referred to [15], [16] for more details on the FBCSP algorithm.

Two EEG data analysis was performed on the data collected. The first analysis was performed to evaluate on the cross-validation accuracies of the calibration data from the first part of this study. The second analysis was performed to evaluate the off-line session-to-session transfer of both calibration models to the EEG data from performing motor imagery collected in the second part of this study.

For the first analysis, the EEG data from the first and second sessions of the first part that comprised 80 single-trials of motor imagery and 80 single-trials of background rest condition were used to evaluate the subject-specific models calibrated using motor imagery. The EEG data from the third and fourth sessions of the first part that comprised 80 single-trials of passive movement and 80 single-trials of background rest condition were used to evaluate the subject-specific models calibrated using passive movement. The EEG data were extracted 0.5 to 2.5 s after the visual cue was shown to the subject, and the performance of the subject-specific models for each subject was evaluated by performing single-trial classification of the EEG data using 10×10-fold cross-validations with the FBCSP algorithm.

For the second analysis, off-line session-to-session transfers were performed using the subject-specific models calibrated using motor imagery versus passive movement to the EEG collected from the second part in performing motor imagery. The Kappa coefficient was used in this analysis to evaluate the maximum Kappa value on the entire single-trial EEG from the onset of the fixation cross. The Kappa values and the standard error were computed using the *bci4eval* function from the BioSig Toolbox [20]. The Kappa value was computed from the onset of the fixation cross to 2 s after the presentation of the cue for every point in time across all the trials of the evaluation data.

III. Experimental Results

Fig. 2 shows the 10×10-fold cross-validation accuracies of detecting motor imagery the background rest condition versus detecting passive movement from the background rest condition for the first analysis.

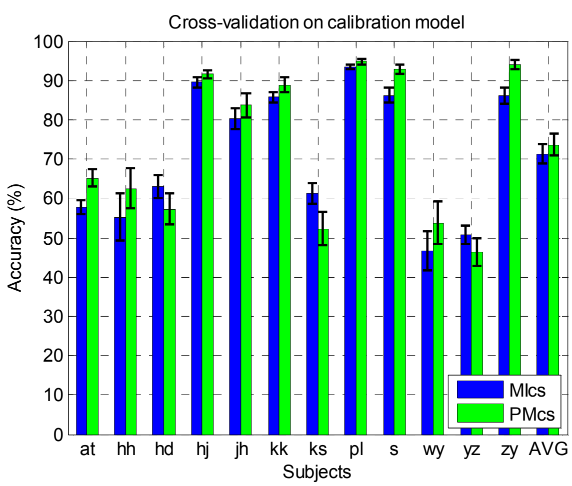

Fig. 2. 10×10-fold cross-validation accuracies of the motor imagery calibration sessions (denoted MIcs) and the passive movement calibration sessions (denoted PMcs) collected from 12 healthy subjects in the first part of the study. The standard deviations are plotted as vertical bars.

The results in Fig. 2 showed that the averaged accuracy of detecting passive movement from the background rest condition (73.6%) was higher than the averaged accuracy of detecting motor imagery from the background rest condition (71.3%), but no significant difference was found (p=0.20) using paired sample t-test.

Five of the subjects labeled *hh*, *kk*, *ks*, *s* and *zy* had prior experience in operating EEG-based motor imagery BCI. The remaining seven were BCI-naïve subjects. Based on this prior information, the results showed that the averaged accuracies of detecting motor imagery from background rest condition for the experienced subjects (76.5%) was higher than the BCI naïve subjects (67.7%). Nevertheless, the results also showed that there were three BCI-naïve subjects *hj*, *jh* and *pl* who demonstrated greater than 80% accuracies and one BCI-experienced subject *hh* who demonstrated less than 60% accuracy.

Fig. 3 shows the maximum kappa value of the off-line session-to-session transfers of the calibration sessions collected from motor imagery and passive movement in the first part of the study to the EEG data collected from motor imagery in the second part of the study for the second analysis.

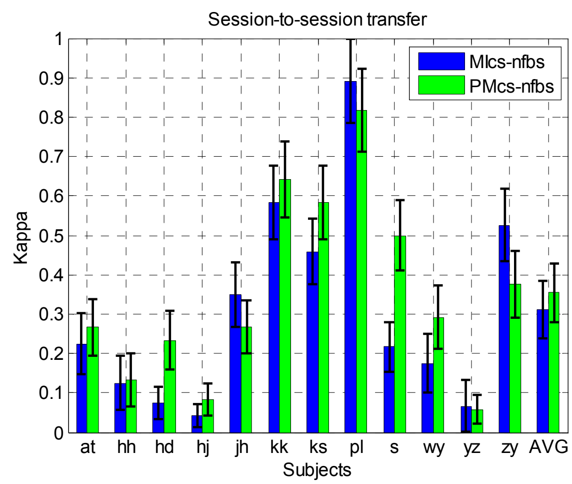

Fig. 3. The maximum Kappa values of the off-line session-to-session transfers of the motor imagery calibration sessions (denoted MIcs-nfbs) and the passive movement calibration sessions (denoted PMcs-nfbs) collected in the first part of the study from 12 healthy subjects to the motor imagery sessions collected without feedback in the second part of the study. The standard errors of the Kappa values are plotted as vertical bars.

The results in Fig. 3 showed that the calibration performed using passive movement yielded higher off-line session-to-session transfer maximum kappa value (0.354) than the calibration performed using motor imagery (0.311), but no significant difference was found (p=0.23) using paired sample t-test.

Since the brain signals of the subjects can change substantially from the training data collected in the first part of this study to the data collected on a separate day in the second part of this study [21], the results in Fig. 3 showed that the averaged kappa values for the off-line session-to-session transfer were rather low. Comparing the results in Fig. 2 with Fig. 3, the former was based on accuracy and the latter on maximum kappa value. Hence, a way to compare these results is to note that the kappa value for an accuracy of 50% in a two-class problem is equivalent to zero indicating random performance.

Examining the subjects *at*, *hd*, *ks*, *wy* who demonstrated about 60% in cross-validation accuracy in Fig. 2, the results in Fig. 3 showed that these subjects yielded an averaged improvement of 0.08 in kappa value when the subject-specific models were calibrated using passive movement instead of motor imagery. The exception was subject *yz* who showed no improvement. Nevertheless, these results showed that calibrating the subject-specific models using passive movement could potentially improve the detection of motor imagery on subjects who demonstrated low accuracies in the calibration sessions.

On the other hand, examining the subject *zy* who demonstrated 86.2% accuracy in Fig. 2, the results in Fig. 3 showed that this subject yielded a deterioration of 0.15 in kappa value when the subject-specific models were calibrated using passive movement instead of motor imagery. Hence, this result showed a potential mismatch between the subject-specific model calibrated using passive movement for the detection of motor imagery from the background rest condition.

IV. Conclusions

This study investigated the feasibility of calibrating EEG-based motor imagery BCI from passive movement on 12 healthy subjects. The study collected EEG data in performing motor imagery or passive movement of the chosen hand and the background rest condition instead of the right and the left hand. The design of this study is based on the use of EEG-based motor imagery brain-computer interface for neurorehabilitation in stroke [22].

The results showed that the calibration performed using passive movement yielded slightly higher cross-validation accuracy and off-line session-to-session transfer than the calibration performed using motor imagery, but there is no statistical evidence to suggest that the passive movement scheme is better. It is apparent that the results reported is dependent on the method of the EEG analysis used, thus the results reported may be improved upon using more advanced methods. Nevertheless, this study showed that it is feasible to calibrate EEG-based motor imagery BCI from passive movement.

Since the performance of passive movement is relatively easier and directly observable compared to the performance of motor imagery, the results suggest a promising direction to first calibrate the subject-specific model using passive movement followed by a feedback to the subject in performing motor imagery in a form of co-adaptive learning.

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