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A clinical study of motor imagery BCI performance in stroke by including calibration data from passive movement

Kai Keng Ang, Cuntai Guan, Karen Sui Geok Chua, Kok Soon Phua, Chuanchu Wang, Zheng Yang Chin, Longjiang Zhou, Ka Yin Tang, Gopal Joseph Ephraim Joseph, Christopher Kuah

***Abstract*—Electroencephalogram (EEG) data from performing motor imagery are usually used to calibrate a subject-specific model in Motor Imagery Brain-Computer Interface (MI-BCI). However, the performance of MI is not directly observable by another person. Studies that attempted to address this issue in order to improve subjects with low MI performance had shown that it is feasible to use calibration data from Passive Movement (PM) to detect MI in healthy subjects. This study investigates the feasibility of using calibration data from PM of stroke patients to detect MI. EEG data from 2 calibration runs of MI and PM by a robotic haptic knob, and 1 evaluation run of MI were collected in one session of recording from 34 hemiparetic stroke patients recruited in the clinical study. In each run, 40 trials of MI or PM and 40 trials of the background rest were collected. The off-line run-to-run transfer kappa values from the calibration runs of MI, PM, and combined MI and PM, to the evaluation run of MI were then evaluated and compared. The results showed that calibration using PM (0.392) yielded significantly lower kappa value than the calibration using MI (0.457, p=4.40e-14). The results may be due to a significant disparity between the EEG data from PM and MI in stroke subjects. Nevertheless, the results showed that the calibration using both MI and PM (0.506) yielded significantly higher kappa value than the calibration using MI (0.457, p=9.54e-14). Hence, the results of this study suggest a promising direction to combine calibration data from PM and MI to improve MI detection on stroke.**

I. Introduction

Motor Imagery Brain-Computer Interface (MI-BCI) is a emergent technology that translates the imagination of movements into commands [1], and has the prospects of restoring motor control in stroke [2]. MI-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]. MI-BCIs that adopt the machine learning approach generally operates in two phases: the calibration phase, and the evaluation or feedback phase [6]. Electroencephalogram (EEG) data are usually collected from a subject in performing motor imagery to train a subject-specific model in the calibration phase [7]. The subject-specific model may include the subject-specific time segment, temporal filters, spatial filters computed using the Common Spatial Pattern algorithm [8], 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 the classifier output is translated into control signals.

However, when the subject is performing MI, the process is inherently internal to the subject and is not directly observable by another person. For example, the subject may have other thoughts instead of imagining the motor movement as instructed. Thus there is no direct measure to indicate that the subject is performing MI properly for calibration. An indirect measure is to evaluate the cross-validation accuracy of the subject-specific model using the calibration data. 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, there are evidences that performing Active Movement (AM), Passive Movement (PM) [9], [10] and MI [11] of the hand yielded similar Event-Related Desynchronization/Synchronization (ERD/ERS) patterns [12] in the primary sensorimotor areas. Studies of EEG [13] and MEG [14] on performing AM and PM of the foot also showed similar findings. There are also studies that showed MI induced both ERD and ERS patterns in the mu rhythms [15] whereas PM induced ERS patterns in the beta rhythms [9], [10], [13].

Since AM or PM are directly observable compared to MI, existing studies had investigated the feasibility of calibrating EEG-based motor imagery BCI using AM or PM on healthy subjects. The study in [16] on 3 Laplacian channel EEG data collected from 19 elderly healthy subjects showed that the performance of MI of the hand did not differ significantly from calibration from AM or PM by a hand robot Tyromotion. Furthermore, the study in [17] on 27-channel EEG data from 12 healthy subjects showed that the performance of MI of the hand from the calibration using PM yielded slightly higher session-to-session transfer than the calibration using MI, but no significant differences were observed.

Stroke often results in hemiparesis or hemiplegia that is contralateral to the affected side of the brain. Motor imagery is appealing to stroke patients because they can perform imagined movements or even attempt to move their plegic hand in the absence of any motor function. Although studies had shown that it is feasible to calibrate EEG-based MI-BCI from AM or PM on healthy subjects [16], [17], AM by stroke patients is often not possible. Hence one of the objectives in this clinical trial is to investigate the feasibility of using calibration data from PM of stroke patients to detect MI. Furthermore, since stroke patients suffer neurological

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K. K. Ang, C. Guan, K. S. Phua, C. Wang, Z. Y. Chin, L. Zhou, K.Y Tang 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, ksphua, ccwang, zychin, zhoul, kytang}@i2r.a-star.edu.sg).

K. S. G. Chua, G. J. E. Joseph, and C Kuah are with Tan Tock Seng Hospital, 11 Jalan Tan Tock Seng, Singapore 308433. (email: {Karen_Chua, gopal_joseph_ephraim, Christopher_Kuah}@ttsh.com.sg).

damage to their brain, the portion of their brain that is responsible for generating ERD/ERS can be compromised. This motivates the investigation on the performance of calibrating MI-BCI using PM of the hand from stroke patients to detect MI compared to calibrating data from MI of stroke patients.

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.

II. Subjects and Methods

A. Subjects

As to-date, 34 BCI naïve hemiparetic subjects were recruited from stroke patients admitted to a neurorehabilitation facility linked to the local hospital with an acute stroke unit. Ethics approval and informed consent were obtained. Table I shows the demographic and clinical variables of these stroke subjects, which include type of stroke (ischaemic or hemorrhagic), side of stroke (right or left) from neuroimaging, nature of the stroke (cortical or subcortical), and baseline Fugl-Meyer Assessment (FMA).

TABLE I
DEMOGRAPHIC AND CLINICAL VARIABLES FOR STROKE SUBJECTS (N=34)

Gender M/F (%)	Handedness R/L (%)	Stroke Type I/H (%)	Stroke Side R/L (%)	Stroke Nature C/S (%)	Mean age (Range)	CVA to screen days (Range)
23 M (69.7)	32 R (94.1)	18 I (52.9)	19 R (55.9)	10 C (29.4)	56.4 ±12.6 (30-79)	409.5 ±195.4 (183-1106)

M INDICATES MALE; F, FEMALE; R, RIGHT; L, LEFT; N, NONE; I, INFARCTION; H, HAEMORRHAGIC; C, CORTICAL; S, SUBCORTICAL; CVA, CEREBROVASCULAR ACCIDENT

B. EEG data collection

EEG from 27 channels were collected using the Nuamps EEG acquisition hardware with unipolar Ag/AgCl electrodes channels, digitally sampled at 250 Hz. 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. Two calibration runs and one evaluation run of EEG data were collected from one session on the same day. The first calibration run collected EEG from the subject while performing MI, the second calibration run collected EEG from the subject while performing PM. Fig. 1 shows the experimental setup to collect EEG data whereby PM was performed by the haptic knob robot by opening and closing the subject's hand. The third evaluation run collected EEG data from the subject while performing MI.

The subjects were instructed to perform kinaesthetic motor imagery of the stroke-affected hand in the first MI calibration run. The instructions were presented in the form of visual cues displayed on the computer screen in each trial. The subjects were instructed to rest during the background rest condition. In the second PM calibration run, the subjects were instructed to relax while PM was performed using the haptic knob robot [18] to open and close the stroke-affected hand of the subject. In the third MI evaluation run, the subjects were instructed as per the first MI calibration run.

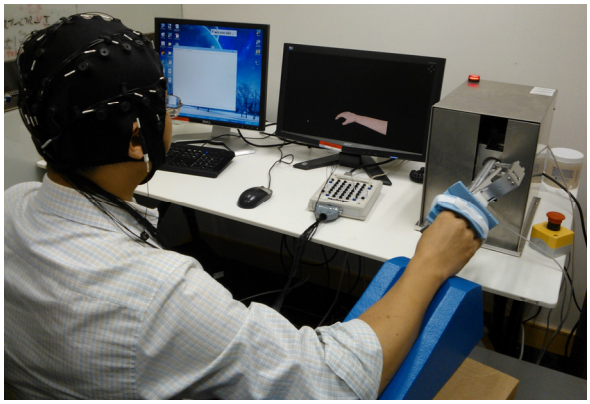

Fig. 1. Experimental setup to collect EEG data from Motor Imagery (MI), Passive Movement (PM) of the right hand using the haptic knob robot for calibrating EEG-based MI-BCI

Each run lasted about for approximately 16 minutes that comprised of 40 trials of either MI or PM, 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 run. The EEG data from the first and second calibration runs were used to calibrate the subject-specific model from performing motor imagery, and the EEG data from the third run were used to evaluation the performance of the subject-specific model.

C. Evaluating the subject-specific model

The Filter Bank Common Spatial Pattern (FBCSP) [19] algorithm was used to evaluate the performance of the subject-specific model. The FBCSP algorithm comprises 4 progressive stages of EEG processing to construct the subject-specific model. The first stage employs a filter bank that decomposes the EEG into multiple frequency pass bands filters. The second stage performs CSP spatial filtering. Each pair of band-pass and spatial filter then computes the CSP features that are specific to the band-pass frequency range. The third stage selects discriminative CSP features based on the mutual information between the CSP features and the subject's performed task to select 4 best features. Finally, the fourth stage employs the Fisher Linear Discriminant classification algorithm to model and classify the selected CSP features. The reader is referred to [19] for more details on the FBCSP algorithm.

Two analyses was performed: first to evaluate on the cross-validation accuracies of the calibration data from MI and PM, and second to evaluate the off-line run-to-run transfer of the data from the calibration models to the data from the third evaluation run.

For the first analysis, the EEG data from the first MI calibration run that comprised 40 trials of MI and 40 trials of background rest, and second PM calibration run that comprised 40 trials of PM and 40 trials of background rest condition were used to evaluate the subject-specific models calibrated. 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.

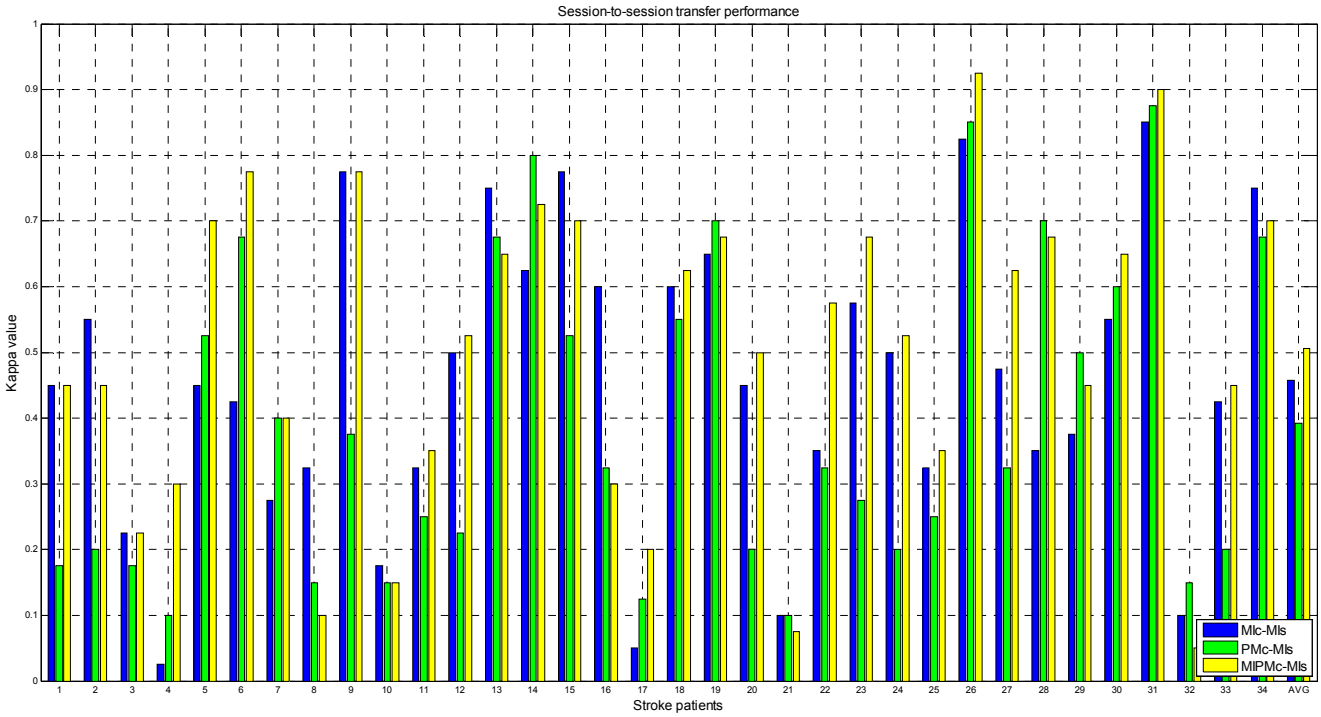

Fig. 2. The maximum Kappa values of the off-line run-to-run transfers of the MI calibration run (denoted MIc-MIs), the PM calibration run (denoted PMc-MIs), and combined MI and PM calibration runs (denoted MIPMc-MIs) from 34 stroke patients to the MI evaluation run.

For the second analysis, the performance of calibrating MI-BCI was evaluated on the Kappa coefficient from the off-line run-to-run transfer from the FBCSP algorithm using three calibration models to the MI evaluation run. The EEG data used to train the FBCSP algorithm were extracted 0.5 to 2.5 s after the visual cue was shown to the subject in the calibration data. The 3 calibration models are:

- *MI calibration model* – EEG data from the first calibration run that comprised 40 trials of MI and 40 trials of background rest condition.
- *PM calibration model* – EEG data from the second calibration run that comprised 40 trials of PM and 40 trials of background rest condition.
- *MI and PM calibration model*. – EEG data from the first and second calibration run that comprised of 40 trials of MI, 40 trials of PM and 80 trials of background rest condition.

The Kappa coefficient was used to evaluate the maximum Kappa value based on the entire timecourse of the single-trial EEG from the onset of the visual cue. It was computed using the bci4eval function of the BioSig Toolbox [20] from the results of the FBCSP algorithm after the presentation of the cue for every point in time across all the trials on the evaluation data.

III. Experimental Results

The results of the 10×10-fold cross-validation accuracies from the first analysis on the calibration runs showed that the averaged accuracy of detecting PM from the background rest condition (74.0%) was significantly higher than the averaged accuracy of detecting MI from the background rest condition (72.6%, p=0.005) using paired sample t-test. This result is consistent with the results on healthy subjects presented in [17] where it was shown that the averaged accuracy of detecting PM of the chosen hand from the background rest condition from healthy subjects (73.6%) was higher than detecting MI (71.3%). However, the study on 12 healthy subjects in [17] did not reveal significant differences, which may be due to the smaller number subjects involved.

The results of the maximum kappa value from the off-line run-to-run transfers of the calibration runs collected from MI, PM, and combined MI and PM to the EEG data collected from MI are shown in Fig. 2. The results showed that the calibration performed using PM yielded lower off-line run-to-run transfer kappa value (0.392) than the calibration performed using MI (0.457, p=4.40e-14) using paired sample t-test. This result is in contrast with the results on healthy subjects presented in [17] where it was shown that calibration performed using PM yielded higher off-line run-to-run transfer kappa value (0.354) than the calibration performed using MI (0.311). However, the study on 12 healthy subjects in [17] did not reveal significant differences, which may be due to the smaller number of subjects involved again. The contrast in the results may also be due a significant disparity between the EEG data from PM and MI in stroke subjects. Although the performance of PM is relatively easier and directly observable compared to the performance of MI, the results of this study showed that it may not be that promising to first calibrate the subject-specific model using PM to detect the performance of MI in stroke.

Nevertheless, the results showed that the calibration performed using both MI and PM yielded significantly higher

off-line run-to-run transfer kappa value (0.506) than the calibration performed using MI (0.457, p=9.54e-14). Hence, the results of this study suggest a very promising direction to combine calibration data from PM and MI to improve MI detection on stroke.

IV. Conclusion

This clinical trial investigates the feasibility of using calibration data on PM from stroke patients to detect MI. The study collected EEG data from 35 BCI naïve hemiparetic stroke patients in performing MI or PM of the stroke-affected hand and the background rest condition. The design of this clinical study is based on the use of EEG-based MI-BCI for neurorehabilitation in stroke [1].

Contrary to the findings presented in the previous study on healthy subjects [17], the results of this clinical trial showed that the calibration performed using PM yielded significantly lower off-line run-to-run transfer averaged kappa value than the calibration performed using MI. Thus the results showed that it may not be feasible to first calibrate the subject-specific model using PM to detect the performance of MI in stroke. The results may be due to a significant disparity between the EEG data from PM and MI in stroke subjects in contrast to healthy subjects, and this requires further analysis.

Nevertheless, the results showed that the calibration performed using both MI and PM yielded significantly higher off-line run-to-run transfer kappa value than the calibration performed using MI. Since the performance of PM is easier and observable compared to MI, the results showed that it is feasible to combine calibration data from PM and MI to improve MI detection on stroke.

However, one limitation of this study is that the results of using both the PM and MI calibration runs involved double the amount of training data compared to the results of using only the PM or MI calibration run. Thus the results may be due to an inherent increase in available training data and further analysis is required. Another limitation is that the results reported are dependent on the method of the EEG analysis used. Thus the results reported may be improved upon using more advanced methods such as Mutual information-based selection of optimal spatial-temporal patterns in [7]. Lastly, the study is very preliminary as it is limited to the run-to-run transfer from one session collected on the same day. Further analysis on the session-to-session transfer performance is required for a more conclusive study.

As-to-date, the clinical trial is still ongoing. Stroke patients are first screened on their ability to use EEG-based MI-BCI similar to the clinical trial conducted in [1]. Patients who passed the screen are then asked to give consent to be recruited into three groups: BCI-based robotic rehabilitation using the haptic knob, robotic based rehabilitation using the haptic knob, and conventional therapy. The results on the functional improvements of these three groups will be analyzed and reported once the clinical trial is completed.

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