A Large Clinical Study on the Ability of Stroke Patients to Use an EEG-Based Motor Imagery Brain-Computer Interface

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Key Words

Brain-Computer Interface
Electoencephalography
Motor Imagery
Stroke Rehabilitation

ABSTRACT

Brain-computer interface (BCI) technology has the prospects of helping stroke survivors by enabling the interaction with their environment through brain signals rather than through muscles, and restoring motor function by inducing activity-dependent brain plasticity. This paper presents a clinical study on the extent of detectable brain signals from a large population of stroke patients in using EEG-based motor imagery BCI.

EEG data were collected from 54 stroke patients whereby finger tapping and motor imagery of the stroke-affected hand were performed by 8 and 46 patients, respectively. EEG data from 11 patients who gave further consent to perform motor imagery were also collected for second calibration and third independent test sessions conducted on separate days. Off-line accuracies of classifying the two classes of EEG from finger tapping or motor imagery of the stroke-affected hand versus the EEG from background rest were then assessed and compared to 16 healthy subjects.

The mean off-line accuracy of detecting motor imagery by the 46 patients (μ=0.74) was significantly lower than finger tapping by 8 patients (μ=0.87, p=0.008), but not significantly lower than motor imagery by healthy subjects (μ=0.78, p=0.23). Six stroke patients performed motor imagery at chance level, and no correlation was found between the accuracies of detecting motor imagery and their motor impairment in terms of Fugl-Meyer Assessment (p=0.29). The off-line accuracies of the 11 patients in the second session (μ=0.76) were not significantly different from the first session (μ=0.72, p=0.16), or from the on-line accuracies of the third independent test session (μ=0.82, p=0.14). Hence this study showed that the majority of stroke patients could use EEG-based motor imagery BCI.

INTRODUCTION

Stroke is the third leading cause of death and the leading cause of severe disabilities in the developed world.[1] Stroke affects the quality of life of the survivors in their daily functioning in the workplace, home, and community. However, with effective rehabilitation, stroke patients can partially regain their motor control and continue their activities of daily living. A recent review has explicated some future prospects of brain-computer interface (BCI) technology in helping stroke survivors, such as to interact with their environment through brain signals rather than through muscles, and to restore motor function by inducing activity-dependent brain plasticity.[2] Current researches in the latter include: using BCI to module specific EEG rhythms,[3] using BCI to trigger functional electrical stimulation (FES) to assist movement practice,[4] and using BCI to drive an orthosis and a robot to assist movement.[5] Hence research in the use of BCI to restore motor function by inducing activity-dependent brain plasticity has just begun and several issues need to be resolved. These include the extent of detectable brain signals in stroke patients, how these brain signals can be used, and the potential of BCI in improving motor functions.[2]

Since physical movements by stroke patients are often not possible, alternate strategies are needed. Motor imagery, which is the mental rehearsal of physical movement tasks, represents an alternate approach to access the motor system for rehabilitation at all stages of stroke recovery.[6] Motor imagery is not dependent on residual motor performance, and direct cellular recordings of primates had shown that the primary motor cortex (M1) is involved during motor imagery.[7] Evidence also revealed a shared neural substrate between motor imagery and motor execution in healthy subjects.[8] Furthermore, a functional imaging study in subcortical stroke had shown that the motor system is activated during motor imagery despite the lesion.[9] Since the capacity to perform motor imagery is not impaired by stroke,[10,11] it may be substituted for motor execution with the aim to activate the motor network in stroke.[6] Unlike motor execution which can be checked by observation, motor imagery is concealed within the patient. Thus it is difficult to assess the performance of motor imagery without involving functional magnetic resonance imaging (fMRI), positron-emission tomography (PET), scalp-recorded magnetoencephalography (MEG) or electroencephalography (EEG).[6] Nevertheless, studies have shown that distinct phenomena such as event-related desynchronization or synchronization (ERD/ERS)[12,13] are detectable from EEG during motor imagery in healthy subjects.[8,14-16] Hence, EEG-based motor imagery brain-computer interface (MI-BCI),[17-20] which translates motor imagery into commands, can be used to objectively assess the performance of motor imagery.[2]

At present, studies have investigated the use of BCI to detect motor imagery on a large healthy subject population[21] and on BCI-naïve healthy subjects.[17] However, there is relatively scanty information available on stroke patients.[6] To the best of the authors' knowledge, available studies include: MEG-based BCI on 8 stroke patients,[3] and EEG-based BCI on 5 or less stroke patients.[22-25] As stroke patients suffer neurological damage to their brain, the portion of their brain that

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Table 1

Demographic of stroke patients recruited for the first part (n = 54)

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)	FMA (Range)
30 M (55.6)	49 R (90.7)	25 I (46.3)	30 R (55.6)	14 C (25.9)	51.8±9.1 (23-66)	105±143 (12-589)	14.9±11.7 (2-45)

M indicates Male; F, Female; R, Right; L, Left; N, None; I, Infarction; H, Hemorrhagic; C, Cortical; S, Subcortical.; CVA, Cerebrovascular accident; FMA, Fugl-Meyer Assessment.

is responsible for generating ERD/ERS can be compromised. Hence a study on the extent of detectable brain signals on a larger population of stroke patients is desired.[6]

This report is of the ability of stroke patients to use EEG-based motor imagery BCI. Firstly, EEG data were collected from 54 stroke patients recruited from a neurorehabilitation facility linked to a local hospital. The stroke patients' ability to use EEG-based motor imagery BCI was assessed from the accuracy of classifying the EEG from finger tapping or motor imagery of the stroke-affected hand versus the background EEG during rest, using the Filter Bank Common Spatial Pattern algorithm.[26,27] The off-line accuracies of detecting motor imagery of the stroke-affected hand from 46 stroke patients were reported and compared to the off-line accuracies of detecting finger tapping from 8 stroke patients, and motor imagery from 16 healthy subjects. Subsequently, EEG data were collected from 11 of the stroke patients who gave further consent to perform motor imagery of the stroke-affected hand on separate days. The off-line and on-line accuracies of detecting the motor imagery were also compared to the results in the first part of the study.

METHODS

The study (refer NCT00955838 in ClinicalTrials.gov) was conducted in 2 parts carried out over two and a half years.

Participants

Ethics approval was obtained from the hospital institutional review board and informed consent was obtained from the participants before recruitment into the study. The participants included healthy research staff and students recruited from the research institute, and stroke patients admitted to a neurorehabilitation facility which was linked to a local hospital. For the recruitment of patients, the following inclusion criteria were applied: (1) 21 to 65 years old; (2) single clinical stroke (ischemic or hemorrhagic); (3) moderate to severe upper extremity (UE) weakness post-stroke; (4) able to give own consent, understand simple instructions and learn through practice. The following exclusion criteria were applied: (1) patients suffering from recurrent stroke, underwent brain surgery, spasticity of Modified Ashworth scale greater than 2; (2) fixed contracture of any upper limb joint; (3) ataxia, dystonia or tremor of the involved upper limb or previous cervical myelopathy; (4) upper limb pain or painful joints in upper limb; (5) severe cognitive impairment (Abbreviated Mental Test <7/10), or (6) severe aphasia or history of seizures in the past 12 months.

A total of 16 healthy subjects (14 males, age 17-44, 14 right-handed), and 54 BCI naïve hemiparetic stroke patients were recruited. The demographic variables of the patients included the type of stroke (ischemic or hemorrhagic), side of stroke (right or left) from neuroimaging, nature of the stroke (cortical or subcortical), and 66-point upper extremity section of the Fugl-Meyer Assessment of Motor Recovery After Stroke (FMA). The FMA assesses several impairment dimensions using a 3-point ordinal scale (0=cannot perform; 1=can perform partially; 2=can perform fully).[28] Table 1 shows the demographic of the 54 stroke patients recruited.

Experimental paradigm

In the first part, EEG data were collected from subjects who performed single-trial motor imagery or finger tapping of the left and right hand in the screening session. Figure 1(a) shows the timing scheme of the screening session, which consists of four runs of 40 trials each for a total of 160 trials and an inter-run break of at least 2 minutes was given after each run. The subjects performed finger tapping or motor imagery tasks depending on the degree of motor deficit. They were instructed to perform finger tapping on the left and right hand. However, if they were too weak to perform finger tapping using the stroke-affected arm, they were instructed to perform kinesthetic motor imagery of the stroke-affected arm instead. EEG data were collected from 8 stroke patients who performed finger tapping using the stroke-affected hand, and 46 stroke patients who performed motor imagery of the stroke-affected hand. EEG data from 16 healthy subjects who performed motor imagery of the left and right hand were also collected to assess their ability to use EEG-based MI-BCI. No feedback was provided for the first screening session and the EEG data were analyzed off-line.

In the second part, EEG data were collected from stroke patients who performed motor imagery of the stroke-affected hand on separate days for the second and third sessions. Figure 1(b) shows the timing for the calibration session, which consists of four runs of 40 trials each for a total of 160 trials and an inter-run break of at least 2 minutes was also given after each run. Each subject also performed single-trial motor imagery or background rest with on-line robotic feedback in the third independent test session. Figure 1(c) shows the timing for the independent test session, which consists of 40 trials. EEG data were collected from 11 out of the 54 stroke patients because the remaining patients could not commit the time required for the study. The average time lapse between the screening session in the first part and the calibration session in the second part of the study was about two months. The second session collected EEG data for calibration purpose and thus no feedback was provided. The EEG data of the second calibration session were also analyzed off-line. Subsequently, the detection model was computed using EEG data from the second session, and was then used in the third session to provide on-line feedback using the Immotion2 MIT-Manus robotic arm.[29]

On-line BCI robotic feedback

The Inmotion[2] MIT-Manus planar shoulder and elbow robotic arm was used to provide the on-line BCI robotic feedback to the stroke patients in the second part of the study. The MIT-Manus is a robotic

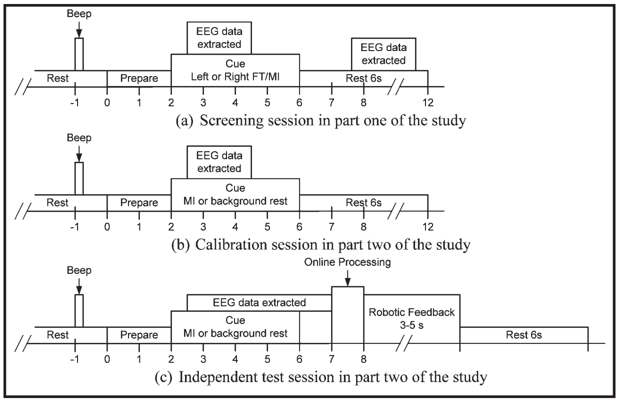

Figure 1(a).
Timing of the motor imagery or finger tapping of left and right hand tasks for the screening session in the first part of the study; (b) timing of the motor imagery of the stroke-affected hand or background rest tasks for the calibration session in the second part of the study; and (c) timing of the motor imagery of the stroke-affected hand or background tasks with on-line robotic feedback for the independent test session in the second part of the study.

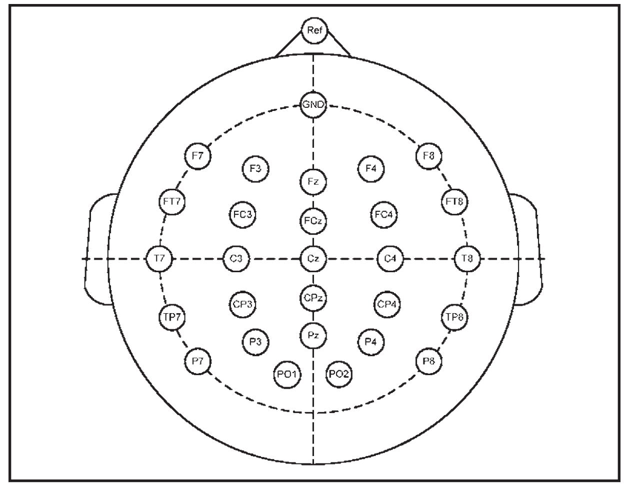

Figure 2.
Positions of EEG channel locations. The reference electrode is located on the Naison.

system that provides unrestricted unilateral passive and active shoulder and elbow movements in the horizontal plane for stroke rehabilitation.[29] In this system, the patient's stroke-affected forearm was fixed to the end-effector of the robot by means of a splint, and a computer screen provided visual feedback to indicate the target location and movement of the robot's end-effector. For both the background rest and the motor imagery tasks, visual feedback was provided on the screen to indicate the success or failure of the trial. For the motor imagery task, an additional passive movement feedback was provided by the MIT-Manus robot when a successful motor imagery trial was completed.

The visual and movement feedbacks were provided according to the clock exercise therapy of the MIT-Manus robot by passively moving the stroke-affected limb from the center position towards a target displayed on the screen and then back to the center position.[30] The clock exercise therapy of the MIT-Manus is comprised of eight peripheral targets that are equally spaced around a center position. The clock exercise allows the stroke patients to draw the hands of a clock by moving from the center to the peripheral targets and back. In this study, the clock exercise therapy of the MIT-Manus robot was only used to provide passive movement feedback, and the stroke patients were instructed not to move their stroke-affected arm.

Experimental setup

EEG measurements from 27 channels shown in Figure 2 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 instructions were presented in the form of visual cues displayed on the computer screen in each trial with a rest period between trials. The subjects were instructed to minimize physical movement and eye blinking throughout the EEG recording process.

EEG signal processing

The challenge in the analysis of the EEG recordings was the huge inter-subject variability with respect to the brain signal characteristics.[17] Literature suggests that the common spatial pattern (CSP) algorithm[17,31] is effective in constructing optimal spatial filters that discriminates two classes of EEG measurements in MI-BCI.[31-34] However, due to huge inter-subject variability, the performance of this algorithm depends on its operational frequency band.[33] Hence this study employed the filter bank common spatial pattern (FBCSP) algorithm to address this issue by performing autonomous selection of key temporal-spatial discriminative EEG characteristics.[26,27]

The FBCSP algorithm comprises four 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.[33] Each pair of band-pass and spatial filter computes the CSP features that are specific to the band-pass frequency range by linearly transforming the EEG using

$$Z_{b,i} = W_b^T E_{b,i}, \qquad 1)$$

where $E_{b,i} \in \Re^{c \times t}$ denotes the single trial EEG from the b^{th} band-pass filter of the i^{th} trial; $W_b \in \Re^{c \times c}$ denotes the CSP projection matrix; c is the number of channels; t is the number of EEG samples per channel; and ^{T} denotes transpose operator.

The spatial filtered signal $Z_{b,i}$ in equation (1) using W_b maximizes the differences in the variance of the 2 classes of band-pass filtered EEG. The m pairs of CSP features for the b^{th} band-pass filtered EEG is given by

$$v_{b,i} = \log\left(diag\left(\bar{W}_b^T E_{b,i} E_{b,i}^T \bar{W}_b\right) / \mathrm{tr}[\bar{W}_b^T E_{b,i} E_{b,i}^T \bar{W}_b]\right), \qquad 2)$$

where $v_{b,i} \in \Re^{2m}$; $\bar{W}_b$ represents the first and last m columns of W_b; $diag(\bullet)$ gets the diagonal elements of the square matrix; $\mathrm{tr}[\bullet]$ gets the sum of the diagonal elements in the square matrix.

The FBCSP feature vector for the i^{th} trial is formed using $v_i = [v_{1,i}, v_{2,i}, \ldots, v_{9,i}]$ such that the FBCSP feature matrix from training data is $V = [v_1^T \; v_2^T \; \ldots \; v_n^T]^T$ whereby n denotes the total number of trials in the training data, and $V \in \Re^{n \times (9*2m)}$.

The third stage selects discriminative CSP features from V for the subject's task using the Mutual Information-based Best Individual Feature (MIBIF) algorithm to select k=4 best features from a total of

9*2m features.[26,27] Since CSP features are paired, the corresponding features that are paired with the selected k features are included. The training data after feature selection is denoted as $\bar{X} \in \Re^{nxd}$ where d ranges from 4 to 8. For example, d=4 if all 4 features selected are from 2 pairs of CSP features; d=8 if all 4 features selected are from 4 pairs of CSP features, since their corresponding pair is included.

The fourth stage employs the Naïve Bayesian Parzen Window (NBPW) classification algorithm[26,27] to model and classify the selected CSP features. Given that x =[x_1, x_2, … x_d] denotes a random evaluation trial, the NBPW classifier estimates $p(x|\omega)$ and $P(\omega)$ from training data samples and predicts the class ω with the highest posterior probability $p(\omega|x)$ using

$$\omega = \arg\max_{\omega=1,2} p(\omega|x). \qquad 3)$$

Data analysis

In the first part of the study, the EEG data of stroke patients that comprised 80 trials of motor imagery or finger tapping on the stroke-affected upper limb and 80 single-trials of background rest were analyzed. The EEG data of healthy subjects that comprised 80 trials of motor imagery of the left hand and 80 single-trials of background rest were also analyzed. The analysis on the motor imagery of the left hand by the healthy subjects was arbitrarily chosen to compare with the motor imagery or finger tapping of the stroke-affected hand by the patients. The analysis was performed without any removal of artifacts such as Electrooculogram (EOG). The EEG data of motor imagery or finger tapping were extracted 0.5 to 2.5 s after the visual cue was shown to the subject. The EEG data of the background rest were extracted 0.5 to 2.5 s before the visual cue was shown to the subject. The performance of each subject in the first screening session was evaluated by performing single-trial classification of the temporal-spatial filtered EEG data using the FBCSP algorithm. The performance was objectively evaluated from 10 runs of 10-fold cross-validated EEG data. In each run, the EEG data extracted from all the 160 trials were randomly split into 10 equal portions in which 9 portions were used as training data and the remaining portion as test data by the FBCSP algorithm. The classification accuracy over 10-folds was noted (mean±standard deviation). This process was then repeated for a total of 10 runs by randomizing the manner in which the data were divided into 10 equal portions. The objective performance of the subject in using the EEG-based MI-BCI was then computed from the averaged accuracy of all 10 runs.

In the second part of the study, since the subjects were instructed to perform either motor imagery or background rest, the EEG data of both the motor imagery and background rest were extracted 0.5 to 2.5 s after the visual cue was shown to the subject. The performance of each subject in the second calibration session was evaluated in the same way as the first screening session. The third session conducted on a separate day was treated as an independent test session where the performance of each subject was evaluated on-line using the motor imagery detection model trained from the second calibration session.

RESULTS

Figure 3 shows the 10×10-fold cross-validation off-line accuracies of detecting motor imagery of the stroke-affected hand by 46 patients, finger tapping of the stroke-affected hand by 8 patients and motor imagery of left hand by 16 healthy subjects whereby standard deviations are plotted as vertical bars. The 95% confidence estimate of the accuracy on the respective action at chance level is approximately 0.43 to 0.58 using the inverse of binomial cumulative distribution function. Hence any subject whose accuracy falls between 43% and

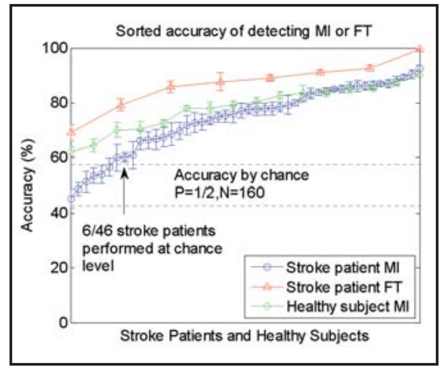

Figure 3.
Plot on the off-line accuracies of classifying motor imagery (MI) of the stroke-affected hand versus the background rest (BR) by 46 patients, the off-line accuracies of classifying finger tapping (FT) of the stroke-affected hand versus BR by 8 patients and the off-line accuracies of classifying MI of the left hand versus BR by 16 healthy subjects. The vertical axis represents the accuracies of detecting MI or FT computed from 10×10-fold cross-validations. The horizontal axis represents the subjects sorted by increasing accuracy of detecting MI or FT, and the subjects' labels were omitted for clarity.

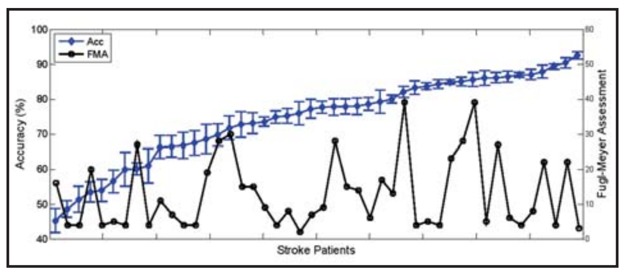

Figure 4.
Plot on the sorted off-line accuracies of classifying motor imagery (MI) of the stroke-affected hand versus the background rest (BR) by 46 patients and the Fugl-Meyer Assessment (FMA) of the patient. The left vertical axis represents the accuracies of detecting MI computed from 10×10-fold cross-validations. The horizontal axis represents the patients sorted by increasing accuracy of detecting MI, and the patients' labels were omitted for clarity. The right vertical axis represents the FMA of the correspondingly sorted patients.

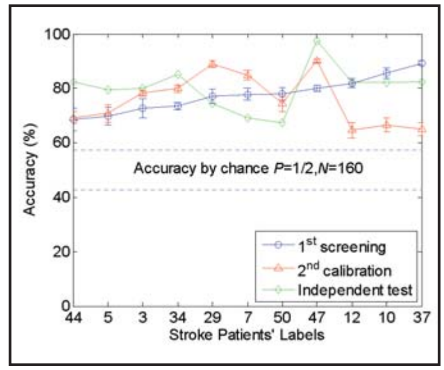

Figure 5.
Plot on the off-line accuracies of detecting motor imagery (MI) of the stroke-affected hand versus background rest (BR) by 11 patients in the first screening session, off-line accuracies of detecting MI versus BR by the patients in the second calibration session, and on-line accuracies of a third independent test session. The vertical axis represents the accuracies of detecting MI whereby the off-line accuracies computed from 10×10-fold cross-validations. The horizontal axis represents the patients' labels.

58% can be deemed as performing at chance level. The results showed that 6/46 stroke patients performed motor imagery at chance level.

Two hypotheses on the results in Figure 3 were tested: (1) Off-line accuracies of detecting motor imagery are different from finger tapping of the stroke-affected hand by the patients. (2) Off-line accuracies of detecting motor imagery of the stroke-affected hand by patients are different from motor imagery by healthy subjects. To test these two hypotheses, two-sample t-tests with a significance level of 0.05 were performed. The accuracies of detecting motor imagery by the stroke patients (μ=0.74) were significantly lower than finger tapping by the stroke patients (μ=0.87, p=0.008), but not significantly lower than motor imagery by the healthy subjects (μ=0.78, p=0.23).

Figure 4 shows a plot of the off-line accuracies of detecting motor imagery of the stroke-affected hand by 46 patients sorted in ascending accuracy with a plot of the Fugl-Meyer Assessment score of each patient. The hypothesis that the accuracies of detecting motor imagery by the stroke patients are related to their Fugl-Meyer Assessment was tested using Pearson correlation coefficient with a significance level of 0.05. The results showed that the accuracies of detecting motor imagery was not linearly correlated to stroke patients' Fugl-Meyer Assessment (r=0.16, p=0.29).

Figure 5 shows a plot of the off-line and on-line accuracies of detecting motor imagery of the stroke-affected hand by 11 patients who gave further consent to perform motor imagery for the second and third sessions. The off-line accuracies of detecting motor imagery of the stroke-affected hand in the second calibration session and the on-line accuracies of the third independent test session are also plotted. The results showed that all the 11 patients performed motor imagery of the stroke-affected hand better than chance level.

Two hypotheses on the results in Figure 5 were tested: (1) Off-line accuracies of detecting motor imagery in the second calibration session are different from the first screening session. (2) Off-line accuracies of detecting motor imagery in the second session are different from the on-line accuracies in the third independent test session. To test these two hypotheses, two-sample t-tests with a significance level of 0.05 were performed. The results showed that the off-line accuracies of detecting motor imagery of the stroke-affected hand by the 11 patients in the second calibration session (μ=0.76) were not significantly different from the first screening session (μ=0.78, p=0.62), and the on-line accuracies in the independent test session (μ=0.80, p=0.25).

DISCUSSION

The first part of this study showed that averaged off-line accuracy in classifying the EEG from motor imagery of stroke-affected hand versus the EEG from background rest of 46 patients was 74%. This was significantly lower than the accuracy of 87% in detecting the finger tapping of the stroke-affected hand of 8 patients, but was not significantly lower than the accuracy of 78% in detecting the motor imagery of the left hand by 16 healthy subjects. Off-line accuracies of detecting motor imagery of the stroke-affected hand from 6 out of 46 patients were at chance level. Analysis on the off-line accuracies and the motor deficit in terms of Fugl-Meyer Assessment of the upper extremity did not show any correlation.

The second part of this study on 11 patients showed that the off-line accuracies of the second calibration session were not significantly different from those of the third independent session and those of the first screening session. All of the 11 patients performed motor imagery of the stroke-affected hand better than chance for the second session and the third session.

While it is apparent that the accuracy of detecting motor imagery is dependent on the method of EEG signal processing used in this study, the accuracies reported may be improved by using a more advanced method. Therefore, the significance of this clinical study is limited to the use of the particular classifier to distinguish motor imagery from background rest condition in a stroke population. Nevertheless, this study has demonstrated that motor imagery and background rest condition can be adequately discriminated on a large clinical population of stroke patients, and a group of this population is able to use EEG-based BCI over time. The results showed that a majority of stroke patients (87%) could use MI-BCI; their accuracies were better than chance level, and no correlation was found between the classification accuracies and their motor impairment in terms of Fugl-Meyer Assessment of the upper extremity. Finally, the analysis of the functional effects from the use of BCI with robotic feedback is beyond the scope of this paper. Ongoing research is currently being conducted to evaluate the effectiveness of BCI-based robotic rehabilitation compared to mechanical robotic based rehabilitation, and the details will be reported in a separate paper.

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DISCLOSURE AND CONFLICT OF INTEREST

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