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A clinical study of motor imagery-based brain-computer interface for upper limb robotic rehabilitation

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Abstract—**Non-invasive EEG-based motor imagery brain-computer interface (MI-BCI) holds promise to effectively restore motor control to stroke survivors. This clinical study investigates the effects of MI-BCI for upper limb robotic rehabilitation compared to standard robotic rehabilitation. The subjects are hemiparetic stroke patients with mean age of 50.2 and baseline Fugl-Meyer (FM) score 29.7 (out of 66, higher = better) randomly assigned to each group respectively (N=8 and 10). Each subject underwent 12 sessions of 1-hour rehabilitation for 4 weeks. Significant gains in FM scores were observed in both groups at post-rehabilitation (4.9, p=0.001) and 2-month post-rehabilitation (4.9, p=0.002). The experimental group yielded higher 2-month post-rehabilitation gain than the control (6.0 versus 4.0) but no significance was found (p=0.475). However, among subjects with positive gain (N=6 and 7), the initial difference of 2.8 between the two groups was increased to a significant 6.5 (p=0.019) after adjustment for age and gender. Hence this study provides evidence that BCI-driven robotic rehabilitation is effective in restoring motor control for stroke.**

I. 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 could partially regain their motor control and continue their activities of daily living. Presently, physical therapy approaches are the most widely used treatment for stroke [2], which involves human therapists to assist the stroke patients in recovering their stroke-affected side of the body. Robotic rehabilitation augments the physical rehabilitation by human therapists and enables novel exercises that are not otherwise available [3]. Studies have shown that robotic rehabilitation helps to improve impairment of hemiparetic upper extremity after chronic stroke [4].

Recent advances in the analysis of brain signals have enabled patients with motor disabilities to use their brain signals for communication and control [5]. The emergent non-invasive Brain-Computer Interface (BCI) technology is capable of bypassing the normal motor output neural pathways and directly translate brain signals into commands for controlling external devices [6-9]. This technology could restore motor control to stroke patients by showing the patient's current state of brain activity, or supplement the patient's impaired muscle control by detecting their motor intentions [5].

The neurophysiological background behind the BCI technology in decoding motor intents is that motor activity [10], motor imagery [11] or somatosensory stimulation [12] modulates the relevant spatial localization of the sensori motor rhythm [13]. The localizations can be conceptualized using cortical homunculus (See Fig. 3 in [13]), which describes the topographical localization of the brain that is directly responsibly for specific motor and somatosensori activity. Studies have shown that distinct phenomena such as event-related desynchronization or synchronization (ERD/ERS) [14] are detectable from EEG for both real and imagined motor movements in healthy subjects [11], [15], [16]. Thus motor imagery-based BCI (MI-BCI) holds promise to recruit the motor system for stroke recovery [17].

However, one of the challenges in MI-BCI is the huge inter-subject variability with respect to the characteristics of the brain signals [6]. In addition, since stroke patients suffer from neurological damage, the portion of the brain that is responsible for generating ERD/ERS in MI-BCI could be compromised. Nevertheless, a former study on BCI-naïve stroke patients revealed that they are capable of operating MI-BCI as effectively as healthy subjects, and their performance is not correlated with level of motor impairment [18]. This motivated the current study on the effectiveness of the synergy of non-invasive EEG-based MI-BCI with the clinically proven MIT-Manus robotic rehabilitation [4], [19]. The objective of this mind robot synergy is to capitalize on the motor intent detected from the MI-BCI for driving the stroke rehabilitation of paretic or plegic upper extremities.

II. MI-BCI UPPER LIMB ROBOTIC REHABILITATION

Motor network reorganization after stroke is known to be influenced by motor training [20], and studies have shown that effective movement therapy can be delivered from robots [21]. Active motor training using robots requires the

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stroke patient to initiate movement whereby the movement is detected from the speed of moving the robot by the patient or through electromyography (EMG) [22]. This involves the voluntary drive from the stroke patient, but plegic patients with no moment in the hand cannot initiate movement.

On the other hand, motor imagery incorporates the voluntary drive and directly involves the primary motor cortex [23]. Thus motor imagery opens up a novel backdoor to recruit the motor system at all stages of stroke recovery [17]. This motivates the development of a Motor Imagery-based Brain-Computer Interface (MI-BCI) robotic rehabilitation in this work (refer to [24] for more implementation details). The architecture of the proposed MI-BCI upper limb robotic rehabilitation is illustrated in Fig. 1, which synergizes MI-BCI with the clinically-proven MIT-Manus robot [19] so that the voluntary drive from the stroke patient is captured as motor intent to drive the rehabilitation of paretic or plegic upper extremities.

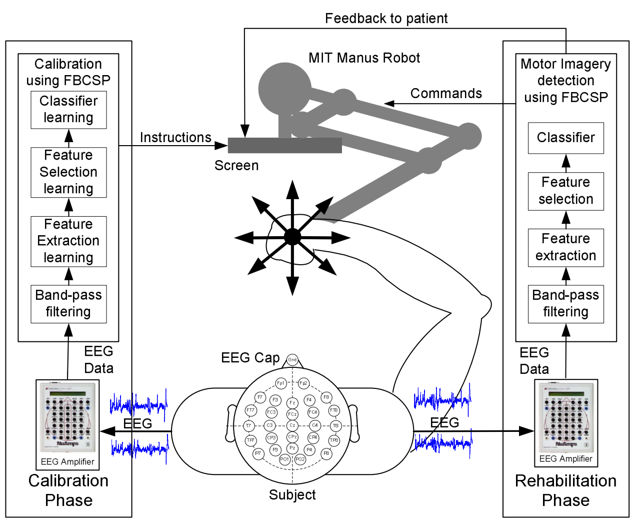


Fig. 1. Architecture of Motor Imagery-based Brain-Computer Interface (MI-BCI) for upper limb robotic rehabilitation

The upper limb rehabilitation using the MIT-Manus robot employs motor training in the form of a video game whereby the subject is required to move the impaired limb towards the goal displayed on the video screen [19]. The subject's impaired limb is strapped to the robot end-effector. If the subject cannot perform the motor task after a pre-defined period of 2 s after the onset of the visual cue, the robot will assist and guide the subject's impaired limb towards the goal [22].

In the proposed MI-BCI robotic rehabilitation, the MIT-Manus robot is coupled with a non-invasive EEG-based MI-BCI. There are two phases illustrated in Fig. 1, namely, a calibration phase and a rehabilitation phase. In the calibration phase, the subject is presented with a "go" or "stop" cue on the video screen. For the "go" cue, the subject is instructed to imagine moving the impaired limb without performing actual movement. For the "stop" cue, the subject is instructed not to imagine moving the stroke-affected limb. The purpose of this calibration phase is to address the inter-subject variability with respect to the characteristics of the brain signals [6]. This is addressed by employing the Filter Bank Common Spatial Pattern (FBCSP) algorithm [25] to perform brain signal processing and machine learning on the EEG measurements acquired. The FBCSP algorithm comprises 4 progressive stages of EEG measurements processing: multiple bandpass filters using zero-phase Chebyshev Type II filters, spatial filtering using the Common Spatial Pattern (CSP) algorithm, feature selection of the CSP features, and classification of the selected CSP features. These 4 stages collectively construct a subject-specific motor imagery detection model.

As illustrated in the rehabilitation phase in Fig. 1, the FBCSP algorithm detects motor intent in the EEG measurements using the subject-specific model constructed in the calibration phase. If motor intent is detected, the MIT-Manus robot directly assists the subject in moving the impaired limb towards the goal. The main difference between this proposed MI-BCI based robotic rehabilitation and the standard MIT-Manus robotic rehabilitation is that the former initiates robot-assisted movement if voluntary motor intent is detected whereas the latter initiates robot-assisted movement if no movement is detected after a pre-defined period of 2 s.

III. EXPERIMENTAL STUDY

This section describes the clinical study performed to investigate the effects of the proposed MI-BCI robotic rehabilitation compared to standard robotic rehabilitation. Fig. 2 shows the setup of the proposed MI-BCI robotic rehabilitation in a local hospital. The subject's brain signals are acquired using non-invasive EEG and the affected limb is strapped to the MIT-Manus end-effector. The screen shows the current position of the end-effector, the goal, and the intensity of the voluntary motor intent detected.

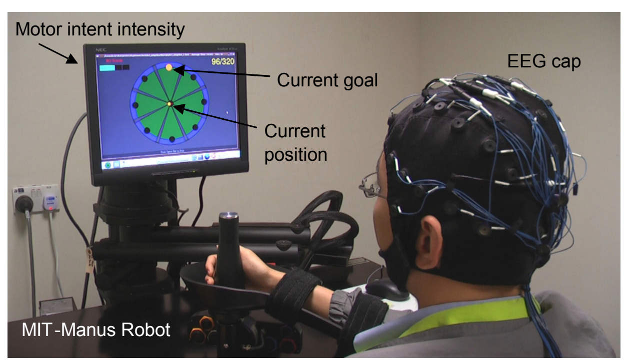


Fig. 2 The setup of the proposed Motor Imagery-based Brain-Computer Interface (MI-BCI) robotic rehabilitation in a local hospital.

As to-date, 47 hemiparetic subjects were recruited from stroke patients admitted to a neurorehabilitation facility linked to the local hospital with an acute stroke unit. A screening session was first performed on these stroke subjects to determine if they could operate MI-BCI effectively on the impaired limb (refer [18], [26] for details on the screening). 18 of these subjects were recruited for this study. Ethics approval was obtained from the hospital institutional review board and informed consent was obtained from the subjects before recruitment into the study. Most of the subjects could not commit the time for 12 sessions of rehabilitation and were thus not recruited.

TABLE I

DEMOGRAPHIC AND CLINICAL VARIABLES FOR STROKE SUBJECTS (N=18)

Gender M/F (%)	Handedness R/L (%)	Stroke Type I/H (%)	Stroke Side R/L (%)	Nature C/S (%)	Mean age (Range)	Days to trial (Range)	FM (Range)	MI-BCI Performance (% Range)
10 M (55.6)	10 R (55.6)	6 I (33.3)	10 R (54.3)	5 C (20.0)	50.2 ±12.4 (23-65)	385.5 ±293.5 (57-1053)	29.7 ±17.7 (4-61)	80.1 ±7.1 (71.0-92.5)

M indicates Male; F, Female; R, Right; L, Left; N, None; I, Infarction; H, Haemorrhagic; C, Cortical; S, Subcortical.; MI-BCI for Motor Imagery-based Brain-Computer Interface; FM, Fugl-Meyer Assessment.

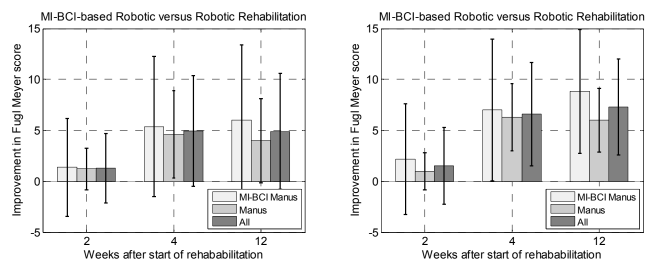
Table I shows the demographic and clinical variables of these stroke subjects. The demographic variables are gender, handedness, age and duration from stroke admission to the clinical study. The clinical variables are type of stroke (ischaemic or hemorrhagic), side of stroke (right or left) from neuroimaging, nature of the stroke (cortical or subcortical), baseline Fugl-Meyer (FM) motor assessment before rehabilitation, and the accuracy of performing MI-BCI from the screening session. The subjects were randomly assigned to the experimental group or the control group. The experimental group underwent the proposed MI-BCI robotic rehabilitation and the control group underwent standard robotic rehabilitation using the MIT-Manus. Each patient in either group underwent 12 sessions of 1-hour rehabilitation on the impaired upper limb for 4 weeks.

27 channels of EEG measurements were acquired using Nuamps 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 measurements from all channels were band-pass filtered from 0.05 to 40 Hz by the acquisition hardware. The control group did not involve any EEG measurements. The calibration phase of the experimental group acquired a total of 160 trials of EEG measurements that randomly comprised 80 trials of motor imagery and 80 trials of non-motor imagery. Each trial lasted for approximately 12 s. For each trial, the subject was first prepared with a visual cue for 2 s on the screen. Another visual cue then instructed the subject to perform motor imagery or non-motor imagery for 4 s, followed by 6 s of rest. The subjects were advised to minimize any body movement throughout the process expect during the rest period. 10 mins of rest were given in between every 40 trials.

In the rehabilitation phase of the experiment group, the subject's impaired limb was strapped to the MIT-Manus robot. The subject was then instructed to perform motor imagery of the impaired limb. The subject was first prepared with a visual cue for 2 s, then a "go" cue would instruct the patient to perform motor imagery for 4 s followed by 6 s of rest. If the voluntary motor intent was detected within the 4 s action period, the MIT-Manus robot would assist the subject in moving the impaired limb towards the goal. Since the movement of the robot was recorded, motor imagery and subject's motion is discernable if motion was recorded during the action period before the robot-assisted motion.

The 12-second trial protocol of the MI-BCI robotic rehabilitation limits the number of movements that stroke patient could perform within a certain time frame. In addition, motor intent could not be detected in some trials. Since each rehabilitation session from both groups was constrained to be within 1 hour, the number of movements performed by the subjects from each group differed significantly. On the average, the experimental group performed 122 robot-assisted movements whereas the control group performed 960 movements.

The baseline and outcome measure were performed using the FM upper extremity scale, which is a 66 point ordinal scale that measures motor impairment of the affected upper limb [27]. A baseline measure was performed prior rehabilitation, and outcome measures were performed mid-rehabilitation at the 2^{nd} week, post-rehabilitation at the 4^{th} week, and 2-month post-rehabilitation at the 12^{th} week. The last outcome measure was performed to assess sustained post-rehabilitation motor improvements.



(a) (b)

Fig. 3. Improvements in Fugl-Meyer score at the 3 endpoints for the experimental group (MI-BCI Manus), and control group (Manus) and combined group (All). (a) shows the results of 8, 10 and 18 stroke subjects for each group, (b) shows the results of 6. 7 and 13 stroke subjects for each group with positive improvements.

Fig. 3(a) shows the outcome measures of the 3 endpoints of the experimental group, the control group, as well as the combined group. Statistical analysis was performed using Matlab. Statistical *t*-test on the combined group showed insignificant improvement in terms of FM scores at mid-rehabilitation (1.5, p=0.132); but significant improvement were observed at post-rehabilitation (4.9, p=0.001) and 2-month post-rehabilitation (4.9, p=0.002). The experimental group showed 2-month post-rehabilitation improvement of 6.0 versus 4.0 from the control group, but no significant difference was found (p=0.475).

The results in Fig. 3(a) showed a large deviation in the improvements in FM score of the upper extremity among the stroke subjects recruited for this clinical study. There are 2 and 3 stroke subjects in the experimental and control groups respectively that showed no positive improvements in terms of FM scores relative to the baseline FM score (Δ FM ≤ 0).

For analysis purposes, Fig. 3(b) shows the results that excluded these stroke subjects whereby the initial difference of 2.0 between the experimental and control in Fig. 3(a) is now increased to 2.8, but still no significant difference was found (p=0.302). This difference of 2.8 between the two groups is increased to a significant 6.5 after adjustment for age and gender (p=0.019). This adjustment is performed on clinical studies in stroke so that the analysis is independent of age and gender in both groups [28]. This is performed by multi-linear regression using Matlab on the improvements in FM score with the group label, age and gender followed by analyzing the regression coefficient β and the p-value of the group label predictor.

IV. CONCLUSIONS

This clinical study showed evidence that the proposed MI-BCI robotic rehabilitation is as effective as standard robotic rehabilitation in restoring motor control of upper limb for hemiparetic stroke, despite the significantly less motor activity performed in the former. Among the stroke patients with positive motor improvement, evidence suggests that MI-BCI robotic rehabilitation resulted in greater motor improvements than standard robotic rehabilitation. However, the results are currently inconclusive due to the large variations in motor improvements in both groups and the limited number of stroke patients recruited for the study. Since the recruitment of stroke patients for this study is still ongoing, a final conclusive result could be drawn from a larger scale study. Nevertheless, the outcome of this preliminary clinical study is promising as it demonstrated the role of BCI in neurorehabilitation.

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