# Transcranial direct current stimulation and EEG-based motor imagery BCI for upper limb stroke rehabilitation

Kai Keng Ang, Cuntai Guan, Kok Soon Phua, Chuanchu Wang, Irvin Teh, Chang Wu Chen, Effie Chew

Abstract—Clinical studies had shown that EEG-based motor imagery Brain-Computer Interface (MI-BCI) combined with robotic feedback is effective in upper limb stroke rehabilitation, and transcranial Direct Current Stimulation (tDCS) combined with other rehabilitation techniques further enhanced the facilitating effect of tDCS. This motivated the current clinical study to investigate the effects of combining tDCS with MI-BCI and robotic feedback compared to sham-tDCS for upper limb stroke rehabilitation. The stroke patients recruited were randomized to receive 20 minutes of tDCS or sham-tDCS prior to 10 sessions of 1-hour MI-BCI with robotic feedback for 2 weeks. The online accuracies of detecting motor imagery from idle condition were assessed and offline accuracies of classifying motor imagery from background rest condition were assessed from the EEG of the evaluation and therapy parts of the 10 rehabilitation sessions respectively. The results showed no evident differences between the online accuracies on the evaluation part from both groups, but the offline analysis on the therapy part yielded higher averaged accuracies for subjects who received tDCS (n=3) compared to sham-tDCS (n=2). The results suggest towards tDCS effect in modulating motor imagery in stroke, but a more conclusive result can be drawn when more data are collected in the ongoing study.

## I. INTRODUCTION

Stroke is the third leading cause of death and the leading cause of severe disabilities in the developed world [1]. With effective rehabilitation, stroke survivors can partially regain their motor control and continue their activities of daily living. Brain—computer interface (BCI) technology has the prospects of helping stroke survivors to interact with the environment through brain signals rather than through muscles, and to restore motor function by inducing activity-dependent brain plasticity [2]. Current researches of BCI in this area 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].

Since physical movements by stroke patients are often not

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

possible due to paralysis, 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]. Since the capacity to perform motor imagery is not impaired by stroke [7], [8], it may be substituted for motor execution with the aim to activate the motor network in stroke [6]. However, motor execution can be checked by observation, but motor imagery is concealed within the patient. Thus it is difficult to assess the performance of motor imagery. Nevertheless, studies have shown that distinct phenomena such as eventrelated desynchronization or synchronization (ERD/ERS) [9] are detectable from EEG during motor imagery in healthy subjects [10]. Hence, EEG-based motor imagery braincomputer interface (MI-BCI) [11], which translates motor imagery into commands, can be used to objectively assess the performance of motor imagery [2]. However, as stroke patients suffer neurological damage to their brain, the portion of their brain that is responsible for generating ERD/ERS can be compromised. Nevertheless, a large recent clinical study had showed evidence that majority of stroke patients could operate EEG-based MI-BCI [12], and preliminary results had shown that EEG-based MI-BCI with robotic feedback rehabilitation is effective in restoring upper extremities motor function in stroke [13].

Transcranial Direct Current Stimulation (tDCS) is a noninvasive, safe, and relatively painless brain stimulation technique for modulating cortical activity, and is also used to facilitate treatments of various neurologic disorders [14]. tDCS delivers a weak polarizing electric current to the cortex through a pair of electrodes, and the increase or decrease in brain excitability depends on anodal or cathodal stimulation that is based on the polarity of the current flow [15]. Study had also shown that reducing excitability in the contra-lesional hemisphere by cathodal tDCS and enhancing excitability in the ipsi-lesional hemisphere by anodal tDCS improved motor performance in stroke [16]. Although studies had shown motor improvements using tDCS, recent studies using tDCS combined with other rehabilitation techniques suggested enhanced facilitating effect from tDCS [14]. Specifically, a study on the use of transcranial Direct Current Stimulation (tDCS) with robot-assisted arm training was shown to improve motor function in stroke [17]. Although a study had shown that EEG-based MI-BCI with robotic feedback was effective in restoring upper extremities motor function in stroke [13], to the best of the authors'

K. K. Ang, C. Guan, K. S. Phua, C. Wang 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}@i2r.a-star.edu.sg).

C. W. Chen and E. Chew are with National University Hospital, 5 Lower Kent Ridge Road, Singapore 119074. (email: {Changwu\_CHEN, Effie\_CHEW}@nuhs.edu.sg).

I. Teh is with A\*STAR-NUS Clinical Imaging Research Centre, 14 Medical Drive #B1-01, Singapore 117599 (email: medv820@nus.edu.sg).

knowledge, there is currently no clinical study that investigated the effects of combining tDCS with EEG-based MI-BCI and robotic feedback rehabilitation in stroke.

#### II. TDCS AND MI-BCI WITH ROBOTIC FEEDBACK

Although studies had demonstrated the efficacy of tDCS [18], [19], and EEG-based MI-BCI with robotic feedback in post-stroke motor recovery [13], to the best of the author's knowledge, the combination of both modalities for poststroke motor recovery is not investigated. Since a study using transcranial magnetic stimulation had shown that motor cortical excitability increased for up to 90 minutes in subjects who received tDCS [20], the feasibility of coupling both modalities by first inducing long-lasting excitability modulation using tDCS followed by EEG-based MI-BCI with robotic feedback stroke rehabilitation is thus potentially feasible. However, the mechanisms of tDCS in facilitating motor imagery and subsequently the efficacy in post-stroke motor recovery remains to be investigated. This motivated the study on the effects of tDCS on the EEG data collected while subjects performed MI-based MI-BCI with robotic feedback compared to sham-tDCS as shown in Figure 1.



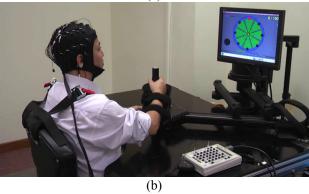


Figure 1. Setup of (a) transcranial Direct Current Stimulation (tDCS) and (b) EEG-based Motor Imagery Brain-Computer Interface (MI-BCI) with robotic feedback rehabilitation for stroke in a local hospital. The same setup is employed for sham-tDCS.

## III. EXPERIMENTAL STUDY

This section describes the clinical study, with approval from the Ethics Approval Board, to investigate the effects of tDCS on hemiparetic stroke patients while undergoing EEG-based MI-BCI with robotic feedback rehabilitation compared to sham-tDCS.

## A. Analysis on EEG from screening session

To-date, 19 BCI naïve hemiparetic stroke patients were recruited from a neurorehabilitation facility linked to the local hospital with an acute stroke unit. Since a study had shown that not all BCI naïve stroke patients could operate EEG-based MI-BCI [12], the patients recruited first underwent a MI-BCI screening session. 27 channels of EEG data were collected from each subject using Nuamps acquisition hardware (http://www.neuroscan.com) with unipolar Ag/AgCl electrodes sampled at 250 Hz. A total of 160 trials of EEG that randomly comprised 80 motor imagery of the stroke-affected upper limb and 80 idle condition were collected. Each trial lasted approximately 12 s. For each trial, the subject was first prepared with a visual cue for 2 s on the screen, and another visual cue then instructed the subject to perform motor imagery or idle for 4 s, followed by 6 s of rest. The subjects were advised to minimize any body movement throughout the process. 10 minutes of rest were given in between every 40 trials. The 160 trials of data were then analyzed offline without any removal of artifacts such as Electrooculogram (EOG).

Figure 2 shows the results of performing 10×10-fold cross-validations using the Filter Bank Common Spatial Pattern (FBCSP) algorithm [21], [22] on the EEG data extracted 0.5 to 2.5 s after the visual cue from the screening session. The accuracies in classifying motor imagery from the idle condition from the EEG for each subject were sorted in ascending accuracy. The results showed that 13 subjects (68%) operated the MI-BCI better than chance level.

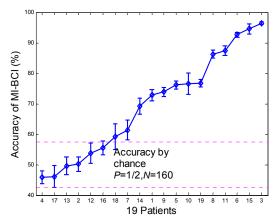


Figure 2. Plot on the off-line accuracies of classifying motor imagery (MI) of the stroke-affected hand versus the idle condition by 19 patients. The left vertical axis represents the accuracies of classifying MI and idle computed from  $10\times10$ -fold cross-validations. The horizontal axis represents the patients sorted by increasing accuracy.

#### B. Analysis of EEG from rehabilitation sessions

5 out of the 13 recruited subjects who passed the screening sessions gave further consent and completed the subsequent 10 rehabilitation sessions to investigate the efficacy of tDCS and EEG-based MI-BCI with robotic feedback stroke rehabilitation compared to sham-tDCS. The remaining 8 recruited subjects were either currently undergoing the clinical trial, or did not give further consent

for further study. Each subject enrolled for the study was randomized into either the tDCS or the sham-tDCS group.

Subjects in both groups first underwent a calibration session whereby the stroke affected-limb of the subject was strapped to the MIT-Manus robot. The EEG data were collected using 27 channels using Nuamps acquisition hardware similar to section III.A. 160 trials of EEG were collected from a total of 4 sessions that comprised 80 MI of stroke-affected upper limb and 80 idle condition using the 12-second protocol similar to section III.A.

Subsequently, the subjects in both groups underwent 10 rehabilitation sessions for 2 weeks, 5 times a week. Each rehabilitation session comprised of 20 minutes of tDCS or sham-tDCS, followed by 8 minutes of evaluation and 1 hour of therapy using EEG-based MI-BCI with robotic feedback. For subjects in the tDCS group, direct current was transferred to the subjects using a saline-soaked pair of surface sponge electrode from a battery-operated constant current stimulator with a maximum output of 10 mA through a non-metallic conductor rubber electrode. Stimulation was conducted at an intensity of 1 mA with the anode placed over the M1 motor cortex of the ipsi-lesional hemisphere and the cathode placed over the contra-lesional M1. For subjects in the sham-tDCS group, the current was only applied for 30 s to give the sensation of the stimulation [23].

During the evaluation part of each rehabilitation session, the online accuracy of detecting motor imagery was first evaluated by collecting 40 trials that comprised 20 MI of the stroke-affected upper limb and 20 idle condition. The online accuracy was computed by using the FBCSP algorithm [21], [22] on the EEG data extracted 0.5 to 2.5 s after the visual cue from the calibration session of the same subject, and evaluated online during the evaluation part of the rehabilitation session.

To-date, 3 and 2 subjects from the tDCS and sham-tDCS group have completed the 10 rehabilitation sessions of the ongoing clinical trial. Preliminary analyses on the data from these 5 subjects are then presented as follows:

Figure 3 shows the averaged online accuracies of detecting motor imagery versus the idle condition across the evaluation part of the 10 rehabilitation sessions. The results showed deviation of online accuracies across subjects and sessions. The results also showed that the average online accuracy is approximately 67% from both groups, and there is no evidence that one group yielded higher online detection accuracy across the sessions than the other group.

The therapy part of each rehabilitation session involved a total of 160 trials of EEG that comprised entirely of motor imagery of the stroke-affected upper limb. 10 minutes of rest were given in between every 40 trials. If MI was detected, a movement feedback was provided by the MIT-Manus robot in moving the stroke-affected limb towards the goal display on the screen, and back to the origin of the clock game interface similar to the study performed in [13]. The EEG data from the therapy part of each rehabilitation session were collected for offline analysis.

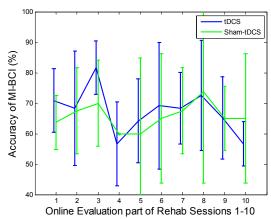


Figure 3. Plot on the average online accuracies of detecting motor imagery (MI) of the stroke-affected hand versus the idle condition for the tDCS and the sham-tDCS group. The left vertical axis represents the accuracies of detecting MI and idle condition computed during online evaluation part of the rehabilitation sessions using the FBCSP algorithm trained on data from the calibration session. The horizontal axis represents the 10 rehabilitation sessions that the patients underwent.

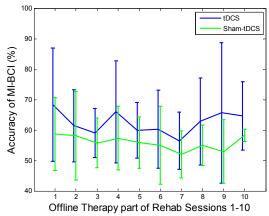


Figure 4. Plot on the average off-line accuracies of classifying motor imagery (MI) of the stroke-affected hand versus the background rest (BR) condition for the tDCS and the sham-tDCS group. The left vertical axis represents the accuracies of classifying MI and BR computed by performing session-to-session transfer using the FBCSP algorithm trained on data from the calibration session to the therapy part of each of the 10 rehabilitation sessions. The horizontal axis represents the 10 rehabilitation sessions that the patients underwent.

Offline analysis of classifying motor imagery from the background rest condition was then performed on the therapy part of each rehabilitation session. The EEG data of motor imagery were extracted 0.5 to 2.5 s after the visual cue was shown to the subject, and the EEG data of the background rest were extracted 0.5 to 2.5 s before the visual cue was shown to the subject.

Figure 4 shows the averaged accuracies of the session-to-session transfer of the calibration session to the therapy part of each of the 10 rehabilitation sessions. The results showed that the averaged accuracies of the subjects from the tDCS group across the 10 rehabilitation sessions are higher than the averaged accuracies of the subjects from the sham-tDCS group. However, the results are not statistically significant due to the large deviations of the accuracies across subjects and due to the small number of subjects in each group.

#### IV. CONCLUSIONS

This paper presented the preliminary results from an ongoing clinical study that investigates the effects of transcranial Direct Current Stimulation (tDCS) and EEG-based Motor Imagery Brain-Computer Interface (MI-BCI) with robotic feedback compared to sham-tDCS for upper limb stroke rehabilitation. Since a study had shown that motor cortical excitability increased for up to 90 minutes in subjects who received tDCS [20], this study investigates whether the application of tDCS will increase the cortical excitability to facilitate motor imagery leading to improved functional outcomes of motor recovery when combined with MI-BCI and robotic feedback stroke rehabilitation.

The subjects recruited first underwent MI-BCI screening session, and the results showed that 68% of stroke subjects operated the MI-BCI better than chance level. This is lower than the 89% reported for a larger study [12], probably due to differences in the screening protocol and lower number of patients screened. Furthermore, the ongoing clinical study has not yet recruited sufficient stroke patients to yield conclusive functional outcomes between the tDCS and sham-tDCS group. Nevertheless, the results of online and offline accuracies in detecting and classifying motor imagery for 3 and 2 patients from the tDCS and sham-tDCS group who completed the 10 rehabilitation sessions are presented.

The results on the evaluation part of each rehabilitation sessions showed that the average online accuracy of detecting motor imagery versus the idle condition was approximately 67% from both groups, and there were no evident differences between the accuracies from both groups. Since the therapy part of the rehabilitation session only involved the performance of motor imagery for all the trials, the result showed that the FBCSP algorithm [21], [22] used was effective in detecting motor imagery, and the performance was almost the same for both groups.

The offline analysis on classifying the MI and background rest of the EEG data from the therapy part of the rehabilitation session showed that the averaged accuracies of the subjects from the tDCS group across the 10 rehabilitation sessions were higher than the sham-tDCS group. Although the results were currently not statistically significant, due to the large deviations across subjects and the small number of subjects in each group, the results suggest towards tDCS facilitating effect in modulating motor imagery. Nevertheless, a more conclusive result could be drawn when data from more patients are available in the ongoing study.

## REFERENCES

- M. H. Beers and R. Berkow, "The Merck Manual of Geriatrics," 3rd ed New Jersey: Merck Research Laboratories, 2000.
- [2] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *The Lancet Neurology*, vol. 7, no. 11, pp. 1032-1043, 2008.
- [3] E. Buch, C. Weber, L. G. Cohen, C. Braun, M. A. Dimyan, T. Ard, J. Mellinger, A. Caria, S. Soekadar, A. Fourkas, and N. Birbaumer, "Think to Move: a Neuromagnetic Brain-Computer Interface (BCI) System for Chronic Stroke," *Stroke*, vol. 39, no. 3, pp. 910-917, Mar. 2008

- [4] J. J. Daly, R. Cheng, J. Rogers, K. Litinas, K. Hrovat, and M. Dohring, "Feasibility of a New Application of Noninvasive Brain Computer Interface (BCI): A Case Study of Training for Recovery of Volitional Motor Control After Stroke," J. Neurol. Phys. Ther., vol. 33, no. 4, pp. 203-211, 2009.
- [5] D. Broetz, C. Braun, C. Weber, S. R. Soekadar, A. Caria, and N. Birbaumer, "Combination of Brain-Computer Interface Training and Goal-Directed Physical Therapy in Chronic Stroke: A Case Report," *Neurorehab. Neural Re.*, vol. 24, no. 7, pp. 674-679, Sep. 2010.
- [6] N. Sharma, V. M. Pomeroy, and J.-C. Baron, "Motor Imagery: A Backdoor to the Motor System After Stroke?," *Stroke*, vol. 37, no. 7, pp. 1941-1952, Jul. 2006.
- [7] S. H. Johnson, "Imagining the impossible: intact motor representations in hemiplegics," *Neuroreport*, vol. 11, no. 4, pp. 729-732, 2000.
- [8] S. H. Johnson, G. Sprehn, and A. J. Saykin, "Intact Motor Imagery in Chronic Upper Limb Hemiplegics: Evidence for Activity-Independent Action Representations," *J. Cog. Neurosci.*, vol. 14, no. 6, pp. 841-852, 2002.
- [9] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842-1857, Nov. 1999.
- [10] G. Pfurtscheller, C. Brunner, A. Schlogl, and F. H. Lopes da Silva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, no. 1, pp. 153-159, Feb. 2006.
- [11] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767-791, Jun. 2002.
- [12] K. K. Ang, C. Guan, K. S. G. Chua, B. T. Ang, C. W. K. Kuah, C. Wang, K. S. Phua, Z. Y. Chin, and H. Zhang, "A large clinical study on the ability of stroke patients to use EEG-based motor imagery brain-computer interface," *Clin. EEG Neurosci.*, vol. 42, no. 4, pp. 253-258, 2011.
- [13] K. K. Ang, C. Guan, K. S. G. Chua, B. T. Ang, C. W. K. Kuah, C. Wang, K. S. Phua, Z. Y. Chin, and H. Zhang, "Clinical study of neurorehabilitation in stroke using EEG-based motor imagery brain-computer interface with robotic feedback," in *Proc. 32nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2010, pp. 5549-5552.
- [14] G. Schlaug, V. Renga, and D. Nair, "Transcranial Direct Current Stimulation in Stroke Recovery," *Archives of Neurology*, vol. 65, no. 12, pp. 1571-1576, Dec. 2008.
- [15] M. A. Nitsche and W. Paulus, "Excitability changes induced in the human motor cortex by weak transcranial direct current stimulation," *The Journal of Physiology*, vol. 527, no. 3, pp. 633-639, 2000.
- [16] F. Fregni, P. S. Boggio, C. G. Mansur, T. Wagner, M. J. L. Ferreira, M. C. Lima, S. P. Rigonatti, M. A. Marcolin, S. D. Freedman, M. A. Nitsche, and A. Pascual-Leone, "Transcranial direct current stimulation of the unaffected hemisphere in stroke patients," *Neuroreport*, vol. 16, no. 14, pp. 1551-1555, 2005.
- [17] S. Hesse, C. Werner, E. M. Schonhardt, A. Bardeleben, W. Jenrich, and S. G. B. Kirker, "Combined transcranial direct current stimulation and robot-assisted arm training in subacute stroke patients: A pilot study," *Restor. Neurol. Neurosci.*, vol. 25, no. 1, pp. 9-15, 2007.
- [18] P. Celnik, N.-J. Paik, Y. Vandermeeren, M. Dimyan, and L. G. Cohen, "Effects of Combined Peripheral Nerve Stimulation and Brain Polarization on Performance of a Motor Sequence Task After Chronic Stroke," Stroke, vol. 40, no. 5, pp. 1764-1771, May 2009.
- [19] F. Hummel, P. Celnik, P. Giraux, A. Floel, W.-H. Wu, C. Gerloff, and L. G. Cohen, "Effects of non-invasive cortical stimulation on skilled motor function in chronic stroke," *Brain*, vol. 128, no. 3, pp. 490-499, Mar. 2005.
- [20] M. A. Nitsche and W. Paulus, "Sustained excitability elevations induced by transcranial DC motor cortex stimulation in humans," *Neurology*, vol. 57, no. 10, pp. 1899-1901, 2001.
- [21] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, 2008, pp. 2391-2398.
- [22] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter Bank Common Spatial Pattern algorithm on BCI Competition IV Datasets 2a and 2b," *Frontiers in Neuroscience*, vol. 6, 2012.
- [23] P. C. Gandiga, F. C. Hummel, and L. G. Cohen, "Transcranial DC stimulation (tDCS): A tool for double-blind sham-controlled clinical studies in brain stimulation," *Clin. Neurophysiol.*, vol. 117, no. 4, pp. 845-850, 2006.