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A Feasibility Study of Non-Invasive Motor-Imagery BCI-based Robotic Rehabilitation for Stroke Patients

Chuanchu Wang, Kok Soon Phua, Kai Keng Ang, Cuntai Guan, Haihong Zhang, Rongsheng Lin
Institute for Infocomm Research, A*STAR
Singapore
{ccwang, ctguan, ksphua, kkang, hhzhang, rlin}
@i2r.a-star.edu.sg

Karen Sui Geok Chua*, Beng Ti Ang+, Christopher Wee Keong Kuah*
*Tan Tock Seng Hospital Rehabilitation Centre, Singapore
+National Neuroscience Institute, Singapore
Karen_chua@ttsh.com.sg, Beng_Ti_Ang@nni.com.sg, Christopher_Kuah@ttsh.com.sg

Abstract—**This paper describes an initial study of non-invasive electroencephalograph (EEG)-based Brain Computer Interface (BCI) application on Stroke patients. The purpose of this study is to combine BCI and robotic arm for after-stroke rehabilitation exercises. A clinically-proven MANUS robotic rehabilitation shell is integrated with the NeuroComm BCI platform, whereby the robotic control mechanism is complemented by the motor imagery of the patient. 8 hemiparetic stroke patients with varying degrees of paralysis on the unilateral upper extremity are recruited for this study. The results show that most BCI-naïve hemiparetic stroke patients are capable of operating the BCI effectively, hence motivates further clinical studies on the extent of how BCI-based robotic rehabilitation are comparable with the control group that uses only robotic rehabilitation.**

Keywords-non-invasive BCI; stroke rehabilitation; robot-aided rehabilitation

I. INTRODUCTION

Stroke is one of the major cause of severe disabilities in the developed world [1]. An estimated 75% of people who have had a stroke will survive for at least a year; about one third of them will have moderate to severe disabilities in movement, speech, concentration, and cognition [1]. Stroke adversely affects the daily functioning of the patients in the workplace, home, and community. With effective rehabilitation, most patients could partially regain their motor control and continue their activities of daily living (ADL).

In recent years, there is a rapid growth in the use of robots for rehabilitation treatments. As compared to the traditional manually-assisted-movement-treatment applied by therapist(s), robotic rehabilitation is less labor-intensive, allows intense repetitive exercise and can track the patient's progress and make recommendations to the human therapist whenever necessary. Studies in [2],[3] show positive results of robot-assisted rehabilitation exercises that helps to promote motor function recovery.

On the other front, we see rapid developments in Brain-Computer Interface (BCI) techniques which assist paralyzed or locked-in patients communicate with the outside world; control devices such as television and motorized wheelchair. In particular, two studies have shown the possibilities of using BCI to control Functional Electric Simulation (FES) system for assistive hand movements. In the first study [4], a tetraplegic patient will try to grasp a glass of water to drink using their BCI-FES system. The second study [5] proposes a BCI-FES system for stroke patients' arm flexion and extension exercises. Both systems employ the use of motor imagery techniques.

The adult brain is capable of reorganizing itself after suffering a stroke because the healthy parts of the brain learn and take over the functions previously carried out by the damaged regions of the brain. The brain's reorganizing capability is commonly known as Neuro-plasticity [6] which can be seen as the moving of the position of a given function from one location to another in the brain from repeated learning. Furthermore, several studies [7],[8] have shown that distinct mental processes related to movement such as Event-Related Desynchronization (ERD) / Synchronization (ERS) are detectable for both real and imagined motor activity (left hand, right hand and legs) on healthy subjects [9]. Since stroke patients suffer from neurological damage, the portion of the brain that is responsible for generating ERD/ERS could be compromised.

In this paper, we explore the possibilities of using non-invasive Brain Computer Interface (BCI) and mechanical robotic-aided rehabilitation for upper extremity (UE) weakness post-stroke rehabilitation. This technique translates the mental imagination of movements acquired by analyzing scalp-recorded electroencephalogram (EEG) from a stroke patient into commands to drive a robotic arm to manipulate the affected arm in a similar way as during a physical therapy exercise. The incorporation of BCI into robot-assisted rehabilitation exercises will guide the user to perform rehabilitation exercises effectively. It will motivate the stroke patients towards faster recovery, which is vital for effective rehabilitation.

In Section II of this paper, we will provide the system design. The implementation of this system will be discussed in detail in Section III. Section IV will discuss the results of the various experiments using the proposed system. Finally, in Section V of this paper, we will conclude our findings.

II. SYSTEM DESIGN

The system was build under the NeuroComm [10] platform which allows several BCI applications to be included into one single system using configuration files. This platform is made up of four core modules: The configuration console module that enrolls new users maintains user database and manages

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system configuration settings for BCI applications. The application interface module has an application-specific GUI, a system control component to control the process flow and a device control component to convert process result into device control signal. The DAQ module reads raw EEG and stimulus data. The signal processing module extracts features from raw EEG data and classifies them into control commands.

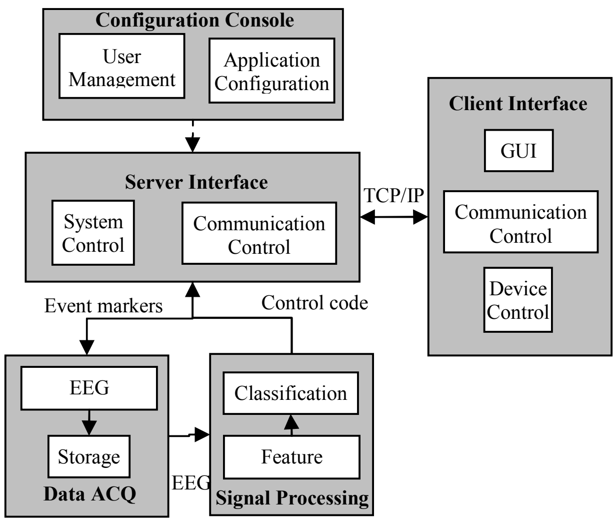


Fig. 1. Structure of NeuroComm that consists of four main modules: application configuration, application interface, data acquisition and signal processing.

Here the Application Interface and Signal Processing modules are customized for this study as described below.

A. Server and Client Interfaces

NeuroComm platform is built on Windows system. For this project, however, the graphic interface and robot control are built under a PC running Linux operating system, as discussed in the following Experiment Setup section. Therefore, the Application Interface module is separated into two parts and a TCP/IP based server/client mechanism is used for communication between them, as shown in Fig 1. The Client Interface part including application GUI and Device Control is running on Linux PC and the Server interface part is running on Windows PC.

B. Model training and Classification

The Common Spatial Pattern (CSP) algorithm [11],[12] is highly effective in constructing optimal spatial filters that discriminates two classes of EEG measurements. However, the CSP algorithm is highly dependent on the operational frequency band and requires setting a broad frequency range to manually select a subject-specific frequency range [13],[14]. Recently, the Filter Bank Common Spatial Pattern (FBCSP) algorithm [15] is developed to perform autonomous selection of operational frequency band that represents key temporal-spatial discriminative EEG characteristics and is used in this project to compute the operational frequency band for generating the spatial patterns (see Fig. 2).

Different feature selection and classification algorithms for Motor-Imagery BCI have been analysed ([15]). Based on experimenting results, the Mutual Information Best Individual Feature (MIBIF) algorithm and the Naïve Bayes Parzen Window (NBPW) are used to select and classify the CSP features respectively in this study.

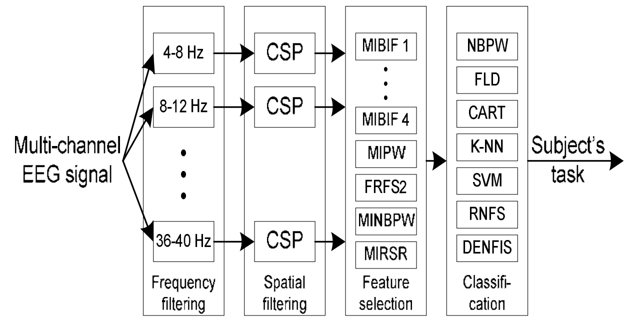


Fig. 2. Architecture of the FBCSP algorithm

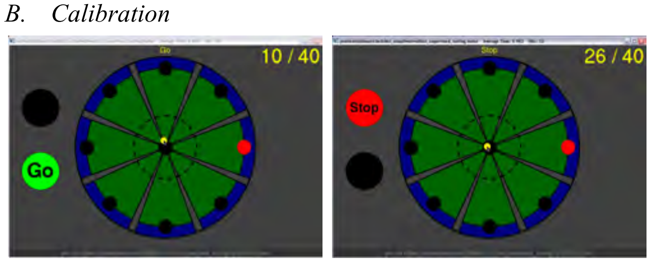
III. EXPERIMENT SETUP

The hardware configuration of the system includes an EEG amplifier, a PC running Microsoft® Windows® XP operating system, a Linux PC running Linux operating system and a robot shell for patient to operate on. The EEG amplifier used is Nuamps (http://www.neuroscan.com) with 40 unipolar Ag/AgCl electrodes channels, sampling rate of 250Hz, resolution of 22 bits, voltage ranges of ±130mv. The real-time data collection and BCI analysis system was implemented on Windows PC using the NeuroComm platform. Continuous EEG was recorded from 27 channels with hardware filtering from 0.5 to 50 Hz with the reference point on the nose.

A. Robotic shell

The MANUS was selected as the robotic shell to be used with the BCI application for upper extremity rehabilitation. MANUS [16],[17] is a two degrees-of-freedom, impedance control robotic system that provides unrestricted unilateral passive and active shoulder and elbow movements in the horizontal plane. It is control by a PC running real time Ubuntu Linux operation system.

B. Calibration



(a) 'GO' motor imageries (b) 'STOP' motor imageries

Fig. 3. Screenshot of calibration process

We have adapted the original clock-game interface used by the MANUS to provide the BCI-Manus rehabilitation process (see Fig. 3) with eight black target points on the circumference and a black center point. The system will provide the instruction for the subject to move by showing a "Go" visual stimulus and the target point will turn from black to red. The subject is instructed that if he/she sees a "Go" instruction, he/she has to imagine that he/she is moving the affected hand without actual hand movement (see Fig 3a). On the other hand, if the subject sees a "Stop" visual stimulus, he has to imagine that he is not moving the affected hand (see Fig 3b).

For each trial, the time periods of the preparation, action and rest stages are 2, 4 and 6 seconds respectively. The subjects are advised to minimize any body movement throughout the calibration process expect during the rest period indicated by the float bar in the center. The calibration process consists of 160 trials of 80 'Go' and 80 'Stop' motor imagery tasks, in a random sequence. The subjects are given 10 minutes rest after each 40 trial.

C. *BCI-Manus therapy*

Fig. 4 shows the BCI-Manus therapy in progress whereby the left hand of a subject is strapped to a harness attached to the robotic shell. The EEG signals are extracted from the scalp via the EEG cap worn by the subject.

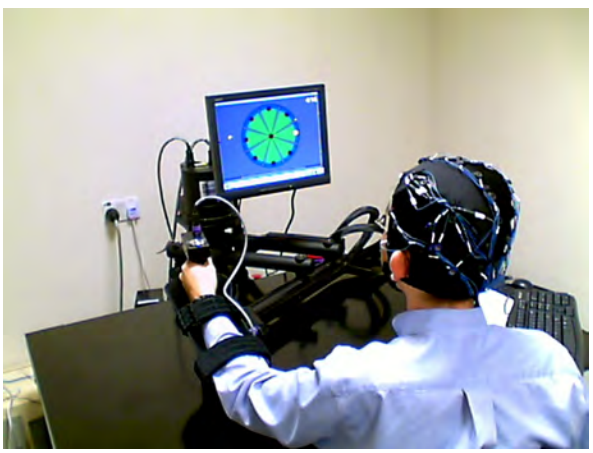
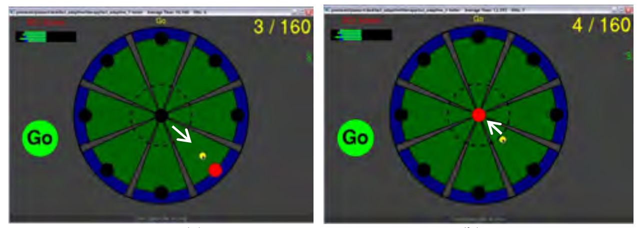


Fig. 4. The BCI Manus robotic system

In the modified therapy interface shown in Fig 5, the smaller yellow circle represents the current position of the robotic arm that holds the patient's stroke-affected arm. The clock-game interface allows the exercising of the upper extremity of the subject in eight different directions by a planar shoulder and elbow robot. One BCI-Manus therapy session consists of a series of 160 BCI-controlled clockwise repetitions to each robot target and back to the center point. So, each session consist of 320 moves, same as that used in the MANUS only therapy session.



(a) (b)

Fig. 5. The modified clock-game interface for the BCI-Manus therapy

During therapy process, if the system detects an "Intention to Move" signal, the robotic arm will move the affected arm to the respective target (Fig. 6a) and back to the center point (Fig. 6b). After each move, the patient's arm will be re-positioned to the center position and the total number of successful BCI moves will increase by one.

The system also provides a feedback to the subject through the BCI score window on the top left-hand corner of the display. The BCI score window is divided into the left and right sectors representing the left/right tasks performed by the subject. After each move, the classifier will output results through five yellow horizontal bars that represent five continuous segments of the EEG signal, the longer the bar, the higher is the score of corresponding segment. As an example provided in Fig. 4, the system correctly classified a move intention of the left arm by displaying five horizontal bars on the left-hand sector of the BCI score window. Data segmentation for the classifier is 500 to 2500 ms after visual stimulus cue.

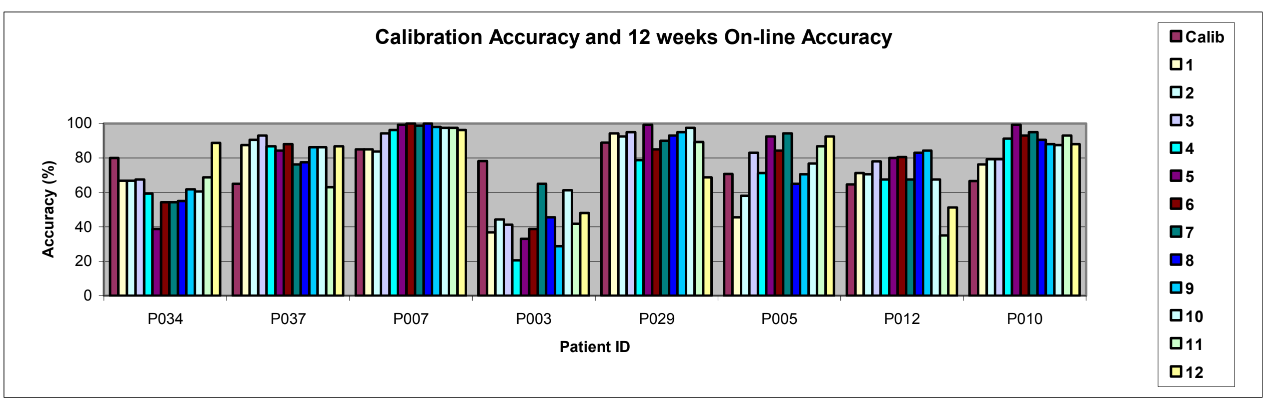


Fig. 6. Experimental results on the BCI accuracy collected from 8 hemiparetic stroke patients for Brain-Computer Interface.

IV. Results and Discussion

Fig 6 shows the accuracy for the 8 patients with each patient having 13 colored bars. The first gray ‘Calib’ bar shows the test accuracies of 10x10-fold cross-validations performed using FBCSP on the EEG data of the patients, the remain 12 bars show the on-line accuracy for the 12 therapy sessions whereby the BCI system correctly detect an “Intention to Move his left/right affected hand” signal.

Fig. 7 shows the calibration accuracy and the mean on-line accuracy of the BCI system for the 8 subjects. The result shows that six subjects (i.e. P037, P007, P029, P005, P012, and P010) achieved high mean on-line accuracies as compared to the calibration accuracies.

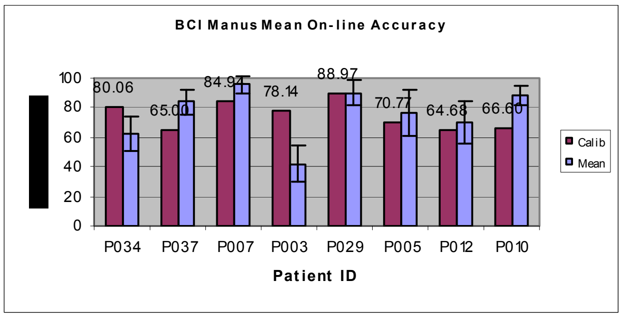


Fig. 7. Calibration accuracy and mean on-line accuracy of the 8 hemiparetic stroke patients.

The results show that the average on-line accuracy of the 8 hemiparetic stroke patients is 76.05±17.63%. Hence this indicates that the neurological damage in the hemiparetic stroke patients does not significantly affect their capability of operating BCI. This result is very encouraging and we will be recruiting more subjects for a more comprehensive study.

V. Conclusion

In this paper, we have investigated the possibility of using non-invasive BCI and mechanical robotic-aided rehabilitation for upper extremity poststroke rehabilitation. In particular, we integrated the NeuroComm BCI platform with a MANUS robotic rehabilitation shell and used the motor imagery of the patient as the control to drive the robotic arm attached with the patient’s paralyzed arm. Initial testing was performed on 8 hemiparetic stroke patients who undergo a 12 day therapy session. The results show that most BCI-naïve hemiparetic stroke patients are capable of operating the BCI effectively.

The method used here is classification of movement (imagination) vs. relaxing idle state, using the paralyzed arm. Although it is enough for hemiplegic patients to perform rehabilitation tasks described in this paper, it would be useful and can be a future direction to study multiple class classification related to different upper limb moving directions. However, our preliminary results are not very positive, only marginal differentiation when use 128-channel EEG and 1000Hz sampling rate.

Work is currently in progress to reduce the time needed for calibration using a semi-supervised machine learning approach as well as reducing the number of EEG channels necessary to provide accurate classification. We are also looking into converting the synchronization motor imagery tasks to be asynchronous whereby the subject can intuitively controlled the robotic arm without the visual stimulus cues.

References

[1] M. H. Beers and R. Berkow. *The Merck Manual of Geriatrics*, 3rd ed. New Jersey:Merck Research Laboratories, 2000.

[2] P. S. Lum, C. G. Burgar, P. C. Shor, M. Majmundar, and M. Van der Loos, "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke," *Arch. Phys. Med. Rehabil.*, vol. 83, no. 7, pp. 952-959, 2002.

[3] L. Kahn, M. Zygman, W. Z. Rymer, and D. Reinkensmeyer, "Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: a randomized controlled pilot study," *Journal of NeuroEngineering and Rehabilitation*, vol. 3, pp. 12 2006.

[4] G. Pfurtscheller, G. R. Müller-Putz, J. Pfurtscheller, and R. Rupp, "EEG-Based Asynchronous BCI Controls Functional Electrical Stimulation in a Tetraplegic Patient," *EURASIP Journal on Applied Signal Processing*, vol. 2005, no. 19, pp. 3152-3155, 2005.

[5] H. G. Tan, H. H. Zhang, C. C. Wang, C. Y. Shee, W. T. Ang, and C. T. Guan, "Arm Flexion and Extension Exercises using a Brain-Computer Interface and Functional Electrical Stimulation," *Proceedings of the Sixth IASTED International Conference on Biomedical Engineering,* pp.322-326, 2008.

[6] R. S. J. Frackowiak, "Imaging neuroscience: Lessons from studies of brain plasticity," *5th IEEE EMBS International Summer School on Biomedical Imaging,* pp.14, 2002.

[7] 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, 1999.

[8] M. Stavrinou, L. Moraru, L. Cimponeriu, S. Della Penna, and A. Bezerianos, "Evaluation of Cortical Connectivity During Real and Imagined Rhythmic Finger Tapping," *Brain Topography*, vol. 19, no. 3, pp. 137-145, 2007.

[9] 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, 2006.

[10] C. Wang, H. Zhang, K. S. Phua, T. H. Dat, and C. Guan, "Introduction to NeuroComm: a Platform for Developing Real-Time EEG-based Brain-Computer Interface Applications," *Proceedings of the IEEE Engineering in Medicine and Biology Society (EMBS '07),* pp.4703-4706, 2007.

[11] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Muller, and G. Curio, "The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, no. 2, pp. 539-550, 2007.

[12] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123-1134, 2001.

[13] Q. Novi, C. Guan, T. H. Dat, and P. Xue, "Sub-band Common Spatial Pattern (SBCSP) for Brain-Computer Interface," *Proceedings of the IEEE/EMBS Conference on Neural Engineering (CNE '07),* pp.204-207, 2007.

[14] G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio, and K.-R. Muller, "Combined Optimization of Spatial and Temporal Filters for Improving Brain-Computer Interfacing," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 11, pp. 2274-2281, 2006.

[15] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," *Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN '08),* pp 2391-2398, 2008.

[16] H. I. Krebs, N. Hogan, M. L. Aisen, and B. T. Volpe, "Robot-aided neurorehabilitation," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 1, pp. 75-87, 1998.

[17] H. I. Krebs and N. Hogan, "Therapeutic Robotics: A Technology Push, " *Proc. IEEE* , vol. 94, no. 9, pp. 1727-1738, 2006.