2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

Towards a Brain Computer Interface Driven Exoskeleton for Upper Extremity Rehabilitation

Zhen Gang Xiao, Ahmed M. Elnady, Jacob Webb, Carlo Menon, *Member, IEEE*

Abstract—**Stroke impairs individuals to perform activities of daily living. Intense rehabilitation programs offer hope for recovery, but are labor intensive and costly. Robotic rehabilitation technology plays a key role to solve such a problem. Current robotic systems along with brain computer interface (BCI) allow patients to participate in rehabilitation exercises, which require their own mental inputs. Studies have shown such active rehabilitation exercise can induce neuroplasticity and help towards recovery. However, even though BCI-driven robotic systems do exist, they are large complex systems and expensive to set up. These drawbacks limit a wide distribution of these technologies. Currently, the BCI robotic systems only used in large hospitals or research settings, not community level facilities. To facilitate the accessibility of stroke patients to such technologies, we propose a novel BCI-driven exoskeleton rehabilitation system. The exoskeleton has four degrees of freedom (DOF) for assisting the movement of the upper extremities. It is integrated with an affordable and wireless EEG headset for enabling the patients to control the movement of the exoskeleton with their brain activity. The developed exoskeleton is portable and easy to set up. A sequential control scheme is proposed to allow the user to control one movement at a time. An experiment was designed to assess if a healthy individual was able to control the movement of the exoskeleton correctly under a predefined sequence. One volunteer participated in the exploratory study and the volunteer was able to correctly control the exoskeleton in each step.**

I. INTRODUCTION

Stroke impairs individuals to perform activities of daily living [1]. Intense rehabilitation exercise offers hope to regain full or partial motor skill activities. However, the rehabilitation is often expensive primarily due to the cost of the required human resources. According to the 2013 update from the American Heart Association: "the mean expense per person for stroke care in the United States in 2009 was estimated at $6018.164 … the cost includes inpatient care, rehabilitation, and follow-up care necessary for lasting deficits" [2].

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) and the Canadian Institutes of Health Research (CIHR).

Z.G. Xiao and A.M. Elnady are PhD students with the MENRVA Group, School of Engineering Science, Simon Fraser University, Burnaby, BC V5A 1S6 Canada. (e-mail: zgx@sfu.ca, aelnady@sfu.ca).

J.Webb was a research assistant with the MENVRA Group, School of Engineering Science, Simon Fraser University, Burnaby, BC V5A 1S6 Canada. (e-mail: jacob.webb22@gmail.com).

C. Menon is an Associate Professor with the MENRVA Group, School of Engineering Science, Simon Fraser University, Burnaby, BC V5A 1S6 Canada. (Phone: 1-778-782-6860; fax: 1-778-782-4951; e-mail: cmenon@sfu.ca).

Contact author: C. Menon (e-mail: cmenon@sfu.ca).

In order to reduce the cost and enhance the quality of stroke rehabilitation, researchers around the world have been focusing on robotic rehabilitation [3]. Robotic rehabilitation systems that perform passive repetitive training can in fact reduce the cost of rehabilitation. However, they often do not actively engage the patients. Studies have shown that the exercises requiring the patient's own effort to initiate the motion have better outcomes than the passive robot assisted exercises [4, 5].

Towards this goal, robotic systems driven by surface electromyography (sEMG) signals have been proposed for active rehabilitation exercise [6-10]. However, such method is difficult to be used by patients with severe stroke, as either muscle co-contraction or atrophy can be present.

The use of brain-computer interface (BCI) [11] could potentially overcome this difficulty. Using a BCI, an individual can communicate with the outside environment without passing through the neuromuscular system. Recent research suggests that mental exercises using BCI can induce neuroplasticity, which is particularly important for individuals with stroke [12, 13].

Electroencephalography (EEG) is the most commonly used method for BCI due to its non-invasive nature. However, because EEG has low signal to noise ratio (SNR), sophisticated hardware is needed for signal extraction. The EEG acquisition equipment is usually expensive, which limits its usage in hospitals and research labs.

In the field of BCI and robotic research, projects like MIT-MANUS [14], BRAVO [15] and MUNDUS [16] are some of the comprehensive examples. However, these robotic rehabilitation systems are sizable and complex. Generally, they are inherently expensive and used for research purpose only. To accelerate the spread of BCI-driven robotic systems and make the technology available to stroke patients, a portable, easy-to-setup and potentially affordable exoskeleton-BCI system is needed.

In recent years, there has been a rapid advance in EEG technology. Portable EEG headsets are becoming more and more popular. Some examples are the Emotiv EEG Neuroheadset [17], the NeuroSky headset [18], the MindFlex [19] and the Brain Sensing Headband from Muse [20]. These off-the-shelf EEG headsets are relatively affordable and easy to setup for the users. They usually come with open source or proprietary software libraries that allow third-party developers to develop custom applications. From the application point of view, the BCI technology has become more and more mature.

In order to spread the usage of BCI and robotic technologies for rehabilitation, the development of a portable, easy-to-setup exoskeleton is one of the remaining challenges.

In this paper we propose a portable 4 DOF upper limb exoskeleton system that can be driven by the user's conscious thought using the Emotiv EEG headset.

This paper is organized as follows. The design of the exoskeleton is presented in Section II. The utilization of the EEG headset is described in the Section III. The control scheme of the BCI-exoskeleton system is described in Section IV. The experiment that was designed to show the performance of the system is presented in Section V. The experimental results are presented in Section VI. The conclusion and future work are discussed in Section VII.

II. UPPER LIMB EXOSKELETON WITH 4 DOF

The proposed exoskeleton consists of 4 DOFs. It allows independent control of the following movements: elbow flexion/extension (is actuated by Joint 1 in Fig. 1), forearm pronation/supination (is actuated by Joint 2 in Fig. 1), wrist flexion/extension and ulna/radial deviation (are actuated by Joint 3 & 4 in Fig. 1).

.

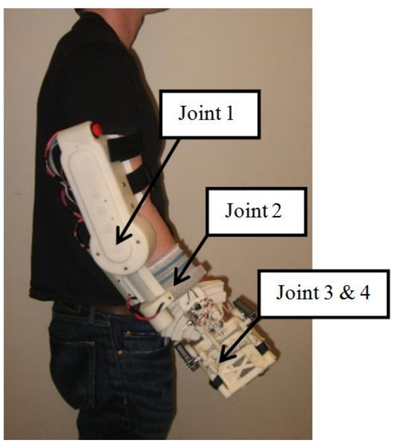

Figure 1. Exoskeleton prototype

As shown in Fig. 1, the proposed exoskeleton is a portable device. With 4 DOF of control, the exoskeleton is capable of assisting different complex functional movements for rehabilitation or assistive purposes. And to maximize its practicality for different rehabilitation tasks, it was designed in a modular fashion. It consists of two modules, the elbow-forearm module and the wrist module. Each module can be used independently.

The elbow-forearm exoskeleton module (see Fig. 2) has 2 DOFs to control elbow flexion/extension and forearm pronation/supination. The elbow movement is actuated using an efficient brushless DC (BLDC) motor with customized gearbox. The mechanism for the forearm pronation and supination consists of two interlocking semi-cylindrical components. The proximal semi-cylinder (colored in red in Fig. 2) is attached to the elbow joint while the distal semi-cylinder (colored in green in Fig. 2) is connected to the extension connector for the wrist module. A brushed DC motor, which is enclosed in the proximal semi-cylinder, is used to actuate forearm supination/pronation.

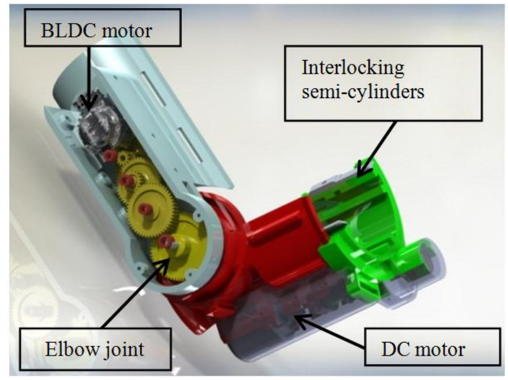

Figure 2. CAD of the elbow-forearm module

The wrist exoskeleton module (see Fig. 3) has 2 DOFs to control wrist ulnar/radial deviation and flexion/extension. The exoskeleton consists of 3 main components. They are the forearm brace (colored in light blue in Fig. 3), the hand brace (colored in green in Fig. 3) and the actuation base (colored in red in Fig. 3).

The forearm brace can be attached to the user's forearm with straps or attached to the elbow module, while the hand is secured to the hand brace with pads and straps. The 2 DOF of movements are separately actuated by two micro geared motors that are mounted on the actuation base. For the ulnar/radial deviation, the motor is mounted at the end of the base. When the motor actuates, the torque is applied to the forearm brace, and then the reaction torque drives the actuation base. For the flexion/extension, the motor is mounted on the middle of the actuation base. The torque is transferred to the hand brace using a set of sprocket and a chain.

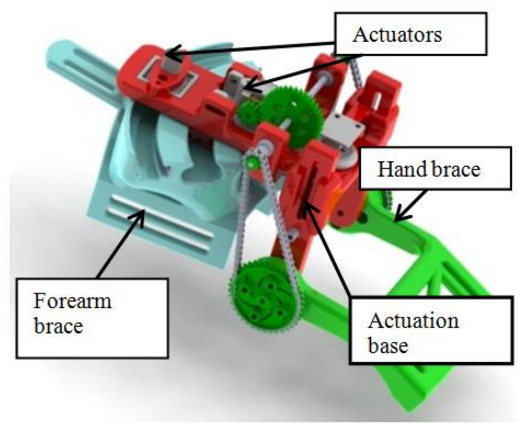

Figure 3. CAD of the wrist module

The exoskeleton are designed to provide sufficient torque to assist functional movement for the users who have mild spasticity in their muscles. And to prevent possible injuries due to movements outside the range of motion (ROM) of the users, mechanical stoppers are implemented to constrain the ROM of each joint. The maximum applied torque and the ROM of each joint of the exoskeleton are shown in Table I.

TABLE I. Maximum applied torque and ROM of the exoskeleton

Joint	Maximum applied torque	ROM
1	10 N.m.	$\pm 60^o$
2	4.4 N.m.	$\pm 75^o$
3	2 N.m.	$\pm 60^o$
4	2 N.m.	$\pm 30^o$

III. Brain control interface using Emotiv EEG headset

Among different headsets, the Emotiv EEG headset probably is the most suitable for controlling our exoskeleton because of its multichannel configuration. The Emotiv EEG headset has 14 electrodes, which are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 according to the International 10-20 system [21]. Fig. 4 shows the EEG headset and the accompanied Emotiv Cognitiv™ Suite control panel [17].

The control panel allows the user to perform mental training to control the movement of a cube in the center of a computer screen (see Fig. 4).

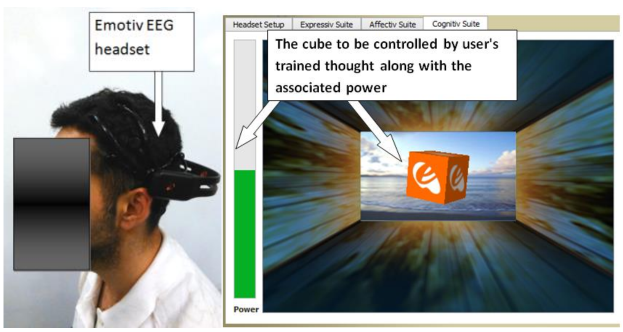

Figure 4. Emotiv EEG headset and Cognitiv™ Suite control panel

As a commercial system for gaming, the EEG signals are classified within the Cognitiv™ Suite using a supervised learning approach. The user has to train the system with one or more conscious thought. After collecting the training samples, the classification results in a control command is provided instantly with the corresponding activation power. The activation power indicates the user's concentration intensity of the trained thought.

These data can be extracted by utilizing the provided software library. However, due to the complexity of the user's mental state, artifacts or other external interference, the instant classification result does not always reflect the true conscious thought. For instance, when the user is in a non-control (i.e. neutral) state, he/she may notice the cube in the control panel bounce momentarily even though he/she has not initiated the trained thought. In the situation in which feedback is present, the user may attempt to actively "clam down", which increases the instability of the output. This situation may worsen when the user attempts to control two or more actions with different conscious thoughts. Thus, the instant classification result is not suitable for directly controlling the robotic device for rehabilitation or assistive tasks through a multi-class classification scheme.

In order to utilize the Emotive system for BCI robotic rehabilitation in practice, we adopted a simple strategy to filter the instant prediction result. In this way, the BCI system could better reflect the user's true conscious thoughts and could allow the user to control the robotic device. This strategy requires the user to maintain a conscious thought for a short period when sending a control command. The average mental activation power of this period is used instead of the instant activation power that is obtained directly from the Emotiv system.

IV. Control of BCI-Exoskeleton System

The proposed exoskeleton has 4 joints corresponding to 8 different movements that could be classified. These movements are elbow flexion/extension, forearm pronation/supination, wrist flexion/extension and wrist ulna/radial deviation. Ideally, we would like the BCI system to be able to classify 8 different thoughts, plus the user's neutral mental state. However, it is difficult for the BCI system to accurately classify more than two conscious thoughts.

In order to minimize the mental and physical fatigue of the user, we only trained the user to use one conscious thought to activate the different movements of the exoskeleton by using a sequential control scheme. Under the proposed scheme, the user can control one movement at a time and with one trained thought.

To control the different movements, a motion enabled panel is shown to the user during the operation of the system. The panel was constructed under the LabView environment as shown in Fig. 5. It consists of 8 indicators which are arranged in a 2 by 4 matrix. The columns of the matrix represent the exoskeleton joints; rows of the matrix represent the available movements of the joints.

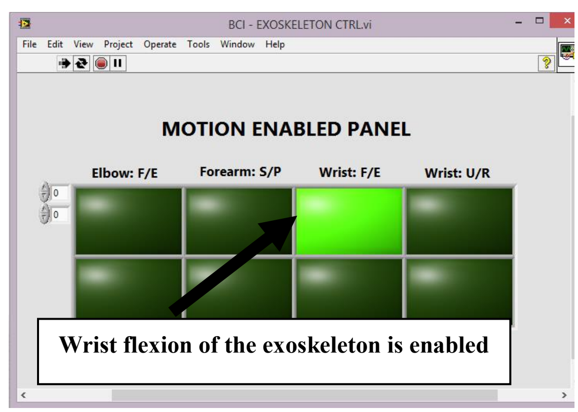

Figure 5. Motion enabled panel: F/E - flexion/extension, S/P - supination/pronation, U/R - ulna/radial deviation

When a movement of the exoskeleton is enabled, the corresponding indicator lights up as shown in Fig. 5, which signifies the user to decide whether to activate the movement or not. If the user decides to active, then the user needs to hold the trained thought for a minimum of 7 seconds; if the user decides not to active, then the user needs to maintain in the neutral state for a minimum of 7 seconds. As shown in Fig. 6, the first 3 seconds are considered to be the transition period, no data is registered. This period is followed by the decision period that lasts 4 seconds. During the decision period, the instant activation power extracted from the Emotiv library is registered. Once this period is over, it is followed by the post-decision period, which last 3 seconds. In this period, the registered instant activation power is averaged. If the averaged activation power exceeds a defined threshold, then the movement of the exoskeleton is activated; otherwise, it remains idle. This period also allows the user to return to the neutral state and get ready to give the next command. A total of 10 seconds are needed for each command given by the user. To note, the exact timing in the decision procedure is determined empirically such that the user does not feel mental fatigue while allowing the system to register enough instant activation power samples.

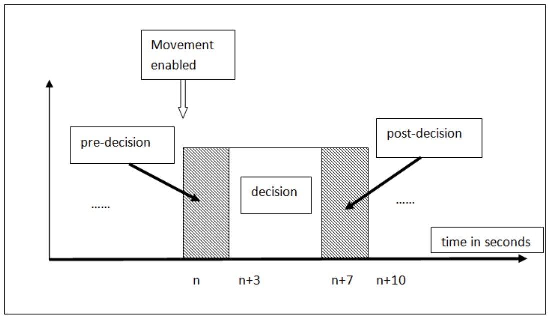

Figure 6. Decision making scheme

V. EXPERIMENTAL PROTOCOL

An experiment was designed to assess if a healthy volunteer was able to control the movements of the exoskeleton correctly under a predefined motion sequence. This sequence involves the control of all 8 different movements which the exoskeleton can assist with. However, in a real rehabilitation scenario, it is not necessary to have all 8 movements in the sequence. The operator such as the physiotherapist can specify a preferred sequence for the patients. In our experiment, the overall protocol consists of three stages: the training stage, the assessment stage, and the control stage.

During the training stage, the volunteer was given time to get familiar with the Emotiv system, spending 10 to 15 minutes to train the Emotive software for one conscious thought, which was preferred to be associated with movements. After the training stage was completed, the software would give a score based on the accuracy of the training data set. Based on prior experience, a score above 20 generally showed that the volunteer had sufficient skill to control one trained thought in the Cognitiv™ Suite (see Fig. 4). Once the training is completed, the volunteer can proceed to the assessment stage.

During the assessment stage, the volunteer follows the instructions on the screen, which prompts the volunteer to alternate the mental state between active thinking and neutral state. The purpose of this stage is to identify the optimum mental activation threshold for controlling the exoskeleton in the next stage. The exact procedure during this stage is described in the following paragraph (see Fig. 7).

Our software gives the "neural" command and the volunteer is supposed to maintain a cognitive neural state (relaxing). After 10 seconds, the software instructs the volunteer to actively think a specific thought related to the functional movement and maintain that thought for 7 seconds. After that, the volunteer returns to the neural state. The volunteer repeats this procedure for 16 times for the assessment. After the assessment stage is completed, our software captures the average activation power for both active and neutral states. Based on the information collected, a Gaussian classifier [22] is used to automatically detect the optimum mental activation threshold.

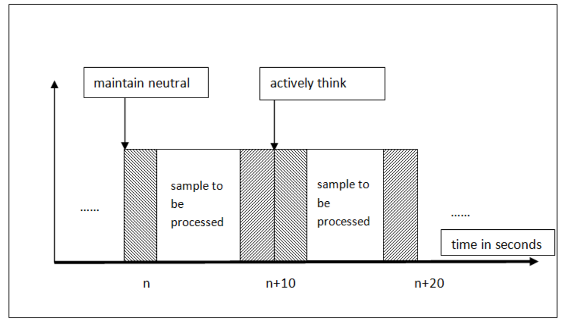

Figure 7. Command sequence in the assessment stage

During the final control stage, the volunteer is asked to drive the 4 DOF exoskeleton with only active and neutral thoughts. The indicator on the screen (see Fig. 5) shows which movement is currently enabled. The volunteer performs the active thinking when he/she intends to do so, and the timing is not prompted by the action panel. If the average activation power is higher than the threshold found in pervious stage, then the enabled movement is activated; otherwise, no movement is assisted.

For testing purpose, two predefined sequence was given to the volunteer and the system's motion enabled panel as shown in TABLE II. Under this arrangement, the volunteer could correctly complete the action sequence only if he/she performed the active thinking at the right moment; otherwise, a wrong exoskeleton movement would be triggered.

TABLE II. Action Sequence

Time (seconds)	Action sequence for volunteer	Enabled motion
10	**Think of an action**	**Elbow flexion (EF)**
20	(neutral)	Elbow extension (EE)
30	**Think of an action**	**Forearm supination (FS)**
40	(neutral)	Forearm pronation (FP)
50	**Think of an action**	**Wrist flexion (WF)**
60	(neutral)	Wrist extension (WE)
70	**Think of an action**	**Wrist ulna deviation (WU)**
80	(neutral)	Wrist radial deviation (WR)
90	(neutral)	Elbow flexion (EF)
100	**Think of an action**	**Elbow extension (EE)**
110	(neutral)	Forearm supination (FS)
120	**Think of an action**	**Forearm pronation (FP)**
130	(neutral)	Wrist flexion (WF)
140	**Think of an action**	**Wrist extension (WE)**
150	(neutral)	Wrist ulna deviation (WU)
160	**Think of an action**	**Wrist radial deviation (WR)**

VI. RESULT AND DISCUSSION

As a preliminary study, a healthy volunteer participated in the experiment. The result during the assessment stage for the volunteer is shown in Fig. 8. The y-axis shows the "thought intensity" and the x-axis is the time in seconds. The yellow region indicates the active thinking state and the white region indicates the neutral state. The black stem shows the thought intensity in each state, which was evaluated by averaging the accumulated instant thought power. After the task was completed, our software calculated the average activation intensity for the entire session (blue line in Fig. 8), as well as the average non-activation intensity (green line in Fig. 8) automatically.

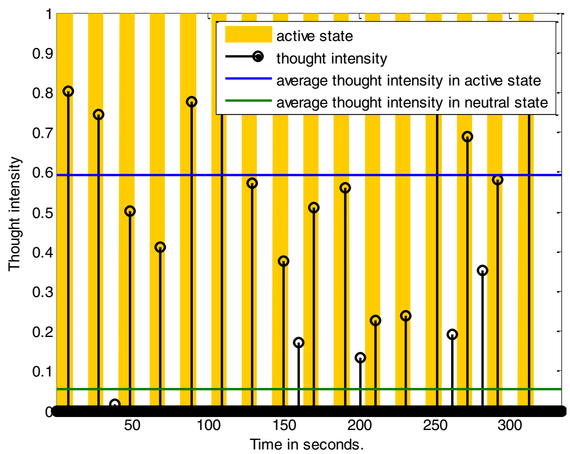

Figure 8. Thought intensity during the assessment stage

The thought intensity for active thinking has a larger variance than that for the non-active thinking. Gaussian classifier was used to decide the optimum decision boundary. Our software modeled the two sets of active and non-active thinking data using the Gaussian model, which is shown in Fig. 9. The y-axis is the probability of the thought intensity, and the x-axis is the value of the intensity. For the non-active thinking data, the mean value is 0.0319 and the standard deviation is 0.067; for the active thinking data, the mean value is 0.579 and the standard deviation is 0.211. The decision boundary was identified at the cross point between the two distributions, which was 0.195 for volunteer who participated in this study. The difference between active and non-active states can be clearly identified, which shows the volunteer can operate the BCI with ease.

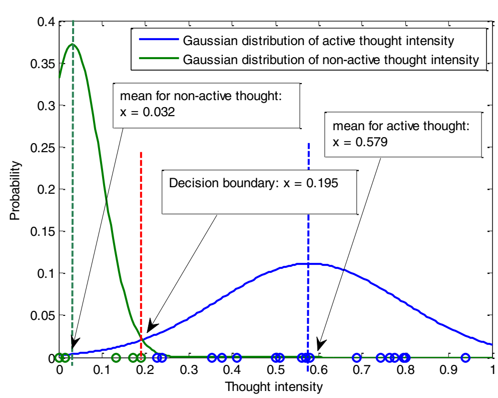

Figure 9. Gaussian model of the thought intensity of the volunteer.

The result data from the control stage for the volunteer is shown in Fig. 10. In the both plots, the background colors shows the different enabled movements of the exoskeleton as shown in the 3rd column of Table II; the red rectangles indicates the volunteer's activation sequence as shown in the 2nd column of Table II. In the upper plot, the black stems indicate the thought intensity; and in the lower plot, the colored solid lines show the angular positions of each of the four exoskeleton joints. Whenever the thought intensity was above the threshold, the exoskeleton moved to the predefined position. From this plot we can see the volunteer's thought intensity was well above the defined threshold when the desired movement was enabled, which illustrates the volunteer's ability to use the BCI system for correctly driving the exoskeleton device under the defined sequence.

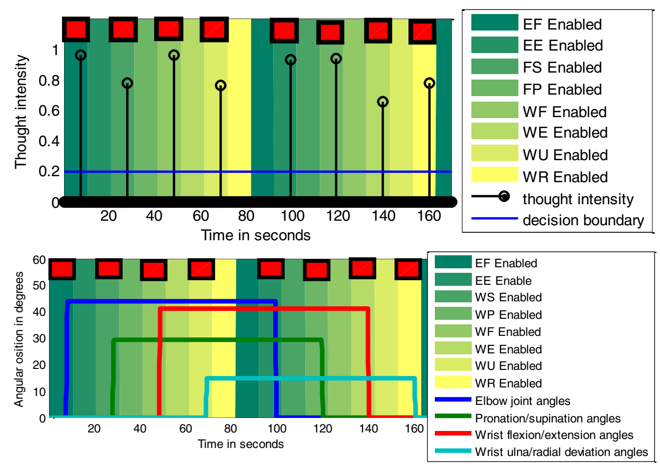

Figure 10. Test result during the control stage: EF - elbow flexion; EE - elbow extension; FS - forearm supination; FP - forearm pronation; WF - wrist flexion; WE - wrist extension; WU - wrist ulna deviation; WR - wrist radial deviation

VII. CONCLUSION

In this paper, we proposed a novel BCI-driven upper limb exoskeleton system for rehabilitation application. The exoskeleton has 4 DOF of control. Each movement can be driven by user's own thought at one instance. An experiment was designed to assess if a healthy volunteer can operate the system with ease. The result of the experiment shows the system can correctly distinguish between a conscious thought and the volunteer's neutral state and the system can use this information to drive different movements of the exoskeleton.

ACKNOWLEDGMENT

We would like to thank Xin Yi Yong, Xin Zhang, Gil Herrnstadt and Nezam Alavi for providing suggestions in various aspects in the project.

REFERENCES

[1] B. D. Capistrant, Q. Wang, S. Y. Liu, and M. M. Glymour, “Stroke-associated differences in rates of activity of daily living loss emerge years before stroke onset.,” J. Am. Geriatr. Soc., vol. 61, no. 6, pp. 931–8, Jun. 2013.

[2] A. S. Go, D. Mozaffarian, V. L. Roger, E. J. Benjamin, J. D. Berry, W. B. Borden, D. M. Bravata, S. Dai, E. S. Ford, C. S. Fox, S. Franco, H. J. Fullerton, C. Gillespie, S. M. Hailpern, J. A. Heit, V. J. Howard, M. D. Huffman, B. M. Kissela, S. J. Kittner, D. T. Lackland, J. H. Lichtman, L. D. Lisabeth, D. Magid, G. M. Marcus, A. Marelli, D. B. Matchar, D.

K. McGuire, E. R. Mohler, C. S. Moy, M. E. Mussolino, G. Nichol, N. P. Paynter, P. J. Schreiner, P. D. Sorlie, J. Stein, T. N. Turan, S. S. Virani, N. D. Wong, D. Woo, and M. B. Turner, “Heart disease and stroke statistics--2013 update: a report from the American Heart Association.,” Circulation, vol. 127, no. 1, pp. e6–e245, Jan. 2013.

[3] P. Poli, G. Morone, G. Rosati, and S. Masiero, “Robotic technologies and rehabilitation: new tools for stroke patients’ therapy.,” *Biomed Res. Int.*, vol. 2013, p. 153872, Jan. 2013.

[4] H. S. Lo and S. Q. Xie, “Exoskeleton robots for upper-limb rehabilitation: state of the art and future prospects.,” Med. Eng. Phys., vol. 34, no. 3, pp. 261–8, Apr. 2012.

[5] E. Formaggio, S. F. Storti, I. Boscolo Galazzo, M. Gandolfi, C. Geroin, N. Smania, L. Spezia, A. Waldner, A. Fiaschi, and P. Manganotti, “Modulation of event-related desynchronization in robot-assisted hand performance: brain oscillatory changes in active, passive and imagined movements.,” J. Neuroeng. Rehabil., vol. 10, p. 24, Jan. 2013.

[6] L. Bonzano, A. Tacchino, G. Brichetto, L. Roccatagliata, A. Dessypris, P. Feraco, M. L. Lopes De Carvalho, M. A. Battaglia, G. L. Mancardi, and M. Bove, “Upper limb motor rehabilitation impacts white matter microstructure in multiple sclerosis.,” Neuroimage, vol. 90C, pp. 107–116, Dec. 2013.

[7] H. I. Krebs, B. T. Volpe, D. Williams, J. Celestino, S. K. Charles, D. Lynch, and N. Hogan, “Robot-aided neurorehabilitation: a robot for wrist rehabilitation.,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 15, no. 3, pp. 327–35, Sep. 2007.

[8] R. Song, K. Tong, X. Hu, and W. Zhou, “Myoelectrically controlled wrist robot for stroke rehabilitation.,” J. Neuroeng. Rehabil., vol. 10, p. 52, Jan. 2013.

[9] Henrey, M.; Sheridan, C.; Khokhar, Z.O.; Menon, C., "Towards the development of a wearable rehabilitation device for stroke survivors," Science and Technology for Humanity (TIC-STH), 2009 IEEE Toronto International Conference , vol., no., pp.12,17, 26-27 Sept. 2009

[10] Z. O. Khokhar, Z. G. Xiao, and C. Menon, “Surface EMG pattern recognition for real-time control of a wrist exoskeleton.,” Biomed. Eng. Online, vol. 9, p. 41, Jan. 2010.

[11] J. Webb, Z. G. Xiao, P. Katharina, K. P. Aschenbrenner, G. Herrnstadt, and C. Menon, “Towards a Portable Assistive Arm Exoskeleton for Stroke Patient Rehabilitation Controlled Through a Brain Computer Interface,” in *The Fourth IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, 2012, pp. 1299–1304.

[12] J. J. Vidal, “Toward direct brain-computer communication.,” Annu. Rev. Biophys. Bioeng., vol. 2, pp. 157–80, Jan. 1973.

[13] W. Wang, J. L. Collinger, M. A. Perez, E. C. Tyler-Kabara, L. G. Cohen, N. Birbaumer, S. W. Brose, A. B. Schwartz, M. L. Boninger, and D. J. Weber, “Neural interface technology for rehabilitation: exploiting and promoting neuroplasticity.,” Phys. Med. Rehabil. Clin. N. Am., vol. 21, no. 1, pp. 157–78, Feb. 2010.

[14] Grosse-Wentrup, D. Mattia, and K. Oweiss, “Using brain-computer interfaces to induce neural plasticity and restore function.,” J. Neural Eng., vol. 8, no. 2, p. 025004, Apr. 2011.

[15] M. Bergamasco, A. Frisoli, M. Fontana, C. Loconsole, D. Leonardis, M. Troncossi, M. M. Foumashi, and V. Parenti-Castelli, “Preliminary results of BRAVO project: brain computer interfaces for Robotic enhanced Action in Visuo-motOr tasks.,” IEEE Int. Conf. Rehabil. Robot., vol. 2011, p. 5975377, Jan. 2011.

[16] A. Pedrocchi, S. Ferrante, E. Ambrosini, M. Gandolla, C. Casellato, T. Schauer, C. Klauer, J. Pascual, C. Vidaurre, M. Gfoehler, W. Reichenfelser, J. Karner, S. Micera, A. Crema, F. Molteni, M. Rossini, G. Palumbo, E. Guanziroli, A. Jedlitschka, M. Hack, M. Bulgheroni, E. D Amico, P. Schenk, S. Zwicker, A. Duschau-Wicke, J. Miseikis, L. Graber, and G. Ferrigno, “MUNDUS project: MUltimodal Neuroprosthesis for daily Upper limb Support.,” J. Neuroeng. Rehabil., vol. 10, no. 1, p. 66, Jul. 2013.

[17] “EEG neuroheadset,” [Online]. Available: https://emotiv.com/store/hardware/epoc-bci-eeg/developer-neuroheadset/. Accessed on: Feb. 2014

[18] “EEG Biosensor Solutions.” [Online]. Available: http://neurosky.com/products-markets/eeg-biosensors/. Accessed on: Feb. 2014

[19] “MindFlex.” [Online]. Available: http://mindflexgames.com/what_is_mindflex.php. Accessed on: Feb. 2014

[20] “MUSE - the brain sensing headband.” [Online]. Available: http://www.interaxon.ca/muse/.

[21] V. Jurcak, D. Tsuzuki, and I. Dan, “10/20, 10/10, and 10/5 Systems Revisited: Their Validity As Relative Head-Surface-Based Positioning Systems.,” *Neuroimage*, vol. 34, no. 4, pp. 1600–11, Feb. 2007.

[22] F. Smith, “Design of minimum-error optimal classifiers for patterns from distributions with Gaussian tails,” IEEE Trans. Inf. Theory, vol. 17, no. 6, pp. 701–707, Nov. 1971.