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Development of EEG Brain-Computer Interface System for Control of Shoulder-Elbow Rehabilitation Robot

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Keywords: stroke, rehabilitation robot, electroencephalogram, brain-computer-interface.

ABSTRACT

In our previous work a shoulder-elbow rehabilitation robot was developed and applied for the rehabilitation of chronic stroke patients. The goal of this study is to integrate an EEG-based brain-computer-interface (BCI) and the rehabilitation robot to build a system by which patients can use imagery movement of arm to control the robot to assist forward reach movement of the arm. Two personal computers were employed, one for EEG processing and the other for controlling the robot. An optimal filter was realized to reduce noise in EEG and the algorithms to translate mu waves of C3 and C4 of human brain into robot command were proposed. Eight healthy and five chronic stroke subjects were recruited to test functions of the system. Two indices, namely accuracy and trigger time were utilized to evaluate performance of all subjects. The training lasted for eight weeks with two days per week. The results show the healthy subjects had no side difference on weekly accuracies. However, for the affected arm of stroke patients accuracy of the fourth week is significantly higher than that of the first week. Trigger time of the intact arm of the stroke group at eighth week is smaller than that of third week. The separation of EEG processing and robot command generation does improve quality of EEG and the EEG controlled rehabilitation robot might be used in future neuro-rehabilitation of patients.

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INTRODUCTION

Strokes are the third cause of death in Taiwan and the survivors often suffer loss of motor functions, speech impairment and even sensation. Four kinds of physical therapy methods have been developed, namely, muscle re-education, neural-facilitation and task-oriented training, and proprioceptive neuromuscular facilitation (Seitz and Carey, 2013). In our previous work, a shoulder-elbow robot was developed for the rehabilitation of the upper limbs of stroke patients (Ju et al, 2005; Lin, 2001). Equipped with torque sensors and joint position sensors, the robot could repeatedly guide the patient to perform various kinds of exercises that required coordination of the shoulder and elbow joints. The robot could provide assistive or resistive force to improve motor controllability of the patients. Recently, a module for pronation and supination of the forearm was integrated into the robot to quantify abnormal extension/flexion synergy of upper limbs, and to quantify the spasticity of pronator muscles (Kung et al, 2012; Kung et al, 2015). A review suggests that integrating EEG brain-computer-interface and existing rehabilitation methods can provide effective therapy for stroke patients (Daly & Wolpaw, 2008). Feedback control is employed to train the stroke patients to perform rotation, extension of upper extremity and grasping using the affected hands (Muller-Putz et al, 2010). An EEG brain-computer-interface integrated with functional electrical stimulation of the hand can provide higher sensory feedback and enhance effects of rehabilitation (Daly et al, 2009). In another study, the imaginary elbow extension movements were used to drive an EEG brain-computer-interface to control an upper limb rehabilitation robot (Gomez-Rodriguez, 2011). New voluntary electromyogram activity can be regained in the affected finger extensors among 4 out of 8 chronic stroke patients after 4-7 months of brain-computer-interface aided training (Shindo et al, 2011). These results demonstrate that real-time visual feedback combined with mechanical orthosis for extending the affected fingers may be beneficial for the stroke patients. In another study, the visual and somatosensory feedback given to the patients during brain-computer-interface aided rehabilitation were compared and the authors suggested that somatosensory feedback was more effective than visual feedback (Ono et al, 2014). A randomized controlled study showed that the efficacy of EEG-based motor imaginary BCI system coupled with a commercial shoulder-elbow robotic feedback was effective and safe for arm rehabilitation of chronic stroke patients and using the system the number of exercise repetitions could be reduced (Ang et al, 2015). They suggest that the revised brain symmetry index (van Putten, 2007) had a high correlation with motor improvement for BCI-based stroke rehabilitation. In a recent study, three-dimensional robotic assistance for reaching movements with an upper limb exoskeleton during motor imaginary-related de-synchronization in the beta band of EEG was tested in 9 healthy and 2 stroke subjects. They also suggested that combining visual and somatosensory feedback could enhance performance of the robot (Brauchle et al, 2015). The brain-robot interface may link three-dimensional robotic training to the subjects' efforts and allows for task-oriented practice of daily activity such as the reach movement. Besides EEG, magnetoencephalography (MEG) can also be utilized to build a brain-computer-interface. A recent study demonstrated that a MEG-based BCI system provided realistic, efficient and focused neurofeedback to the spinal cord injured patients to induce neuroplasticity (Foldes et al, 2015). In our previous study, based on mu wave, an EEG brain-computer-interface was developed to control an orthotic hand for the rehabilitation of stroke patients. In particular, a hybrid controller that could realize both position and force control was developed (Chen et al, 2009). Recently, the EEG brain-computer-interface was also integrated with a shoulder-elbow rehabilitation robot for movement training of stroke patients. However, three technical problems in that integration were found (Huang, 2012). First, EEG was severely interfered by the computer that controlled the rehabilitation robot and, second, most of the treatment movements in existing studies were not related to daily activities of the upper limb. Last, accuracy of using the BCI system was too low and it reduced the interests of the users. The goals of this study were twofold. First was to improve hardware and software of our BCI-rehabilitation robot system and second was to test functions of the improved system via human testing. In particular, the criterion of successful trial was modified and forward reach movement was utilized to guide movement of the subject's wrist and upper limb.

METHODS AND EXPERIMENTS

Modification of the EEG BCI-controlled robot

The setup of our BCI-rehabilitation robot system is shown in **Figure 1**(a). Three EEG electrodes were placed on C3, C4 and Cz of scalp of a subject whose wrist was clamped on the end module of the rehabilitation robot. In a previous study a single personal computer was employed to acquire EEG data and control the rehabilitation robot. Since the analog-to-digital conversion board for EEGs and digital-to-analog conversion board for controlling the robot shared the same DC power supply, so the acquired EEG data were severely contaminated with noises from the powerline and the AC motors of the robot. In this study, two personal computers were employed, with one for the acquisition and processing of EEG data and the other for the control of the robot (**Fig.1** (b)). The mu waves of C3, C4 and Cz were acquired, processed and translated into control command in the first personal computer, PC1. The command was then transmitted to the second personal computer, PC2, to control the robot for moving the upper limb of the subject. The shoulder-elbow robot consisted of a parallel five-link mechanism and a rotational module for supination/rotation of forearms of subjects. A hybrid fuzzy controller was realized on the robot system for both passive and active movement treatments of stroke patients. Detailed technical information about the robot can be found in (Ju et al, 2005; Lin, 2001).

(a)

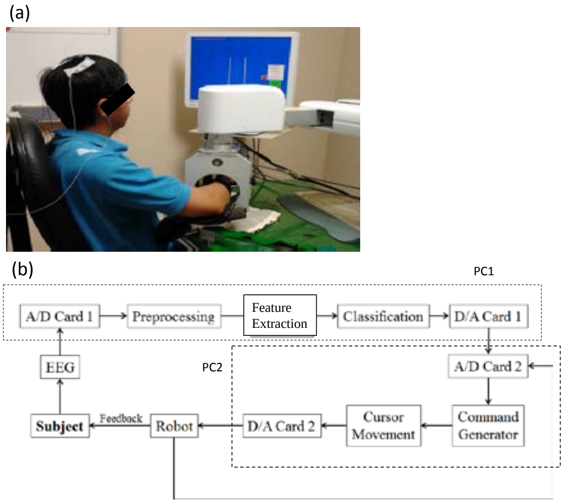

Figure 1. Setup of the BCI-controlled rehabilitation robot: (a) EEG electrodes placed at C3, C4 and Cz of the subject, (b) two personal computers PC1 and PC2 were employed to realize the rehabilitation system.

In the brain-computer-interface system, the EEG data were acquired using an EEG machine (Model 1A97, Sanei NEC Co.) with a gain of 10,000. The electrodes were disk type with a diameter of 0.4 cm and the placement of electrodes followed the ISO10-20 system guideline, which was the standard of clinical routines. On the personal computer PC1, a control development system (DS1104, dSPACE Co.) and a 16-bit analog-to-digital converter were installed to acquire the EEG data with a sampling rate of 512 Hz/

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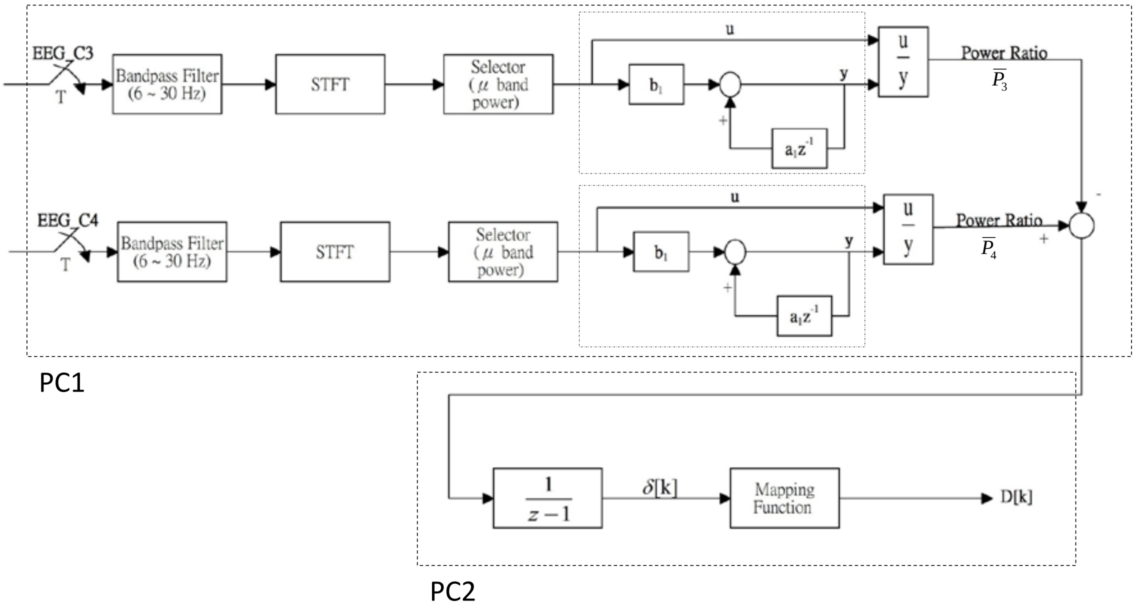

Figure 2. Block diagram of the real-time processing of EEG for generating command for the shoulder-elbow rehabilitation robot.

channel. A Parks-McClellan optimal FIR filter (Lawrence et al, 1975) with a passing band between 8 and 28 Hz was employed to reduce the noises originating from the AC servomotors of the robot and the power line. The filter was optimal in the sense that the maximum error between the desired frequency response and the actual frequency response was minimized. The filter has a lower stop band with amplitude of -90dB between 0 Hz and 6 Hz, a pass band with amplitude of 0 dB between 8 Hz and 28 Hz (with a fluctuation range of 1 dB), and an upper stop band with amplitude of -80 dB between 30 Hz and half of the sampling frequency. Under these specifications, the order of the filter was 719. **Figure 2** shows the block diagram of the real-time processing of the EEG data for generating the command for the robot. Short-time Fourier transforms of the EEG data with a window length of 1 second and shifting of 0.5 second were performed to compute the band power of the mu wave. The mu wave was defined as the components of EEG between 8–14 Hz at the Rolandic area. To obtain better estimates of the event-related desynchronization (**ERD**) power ratios of C3 and C4, an adaptation of mu wave power at the resting state was adopted where the parameters of the filter were $a_1 = 0.9$ and $b_1 = 0.1$ (see Fig. 2). The differential power ratio was further integrated to yield $\delta[k]$ with

$$\delta[k] = \sum_{i=1}^{k} (\overline{P}_4[i] - \overline{P}_3[i]) \qquad (1)$$

where

$$\overline{P}_3[i] = \frac{P_{3A}[i]}{P_{3R}[i]} \quad \text{and} \quad \overline{P}_4[i] = \frac{P_{4A}[i]}{P_{4R}[i]} \quad (2).$$

$P_{3R}[i]$ and $P_{4R}[i]$ were the power of the mu wave of i^{th} window at the resting state for C3 and C4 electrodes, respectively, and $P_{3A}[i]$ and $P_{4A}[i]$ were the power for the active state, i.e., when the subject did an imagery movement of either right hand or left hand, respectively. The final command signal, $D[k]$, for cursor movement or to trigger the robot to extend the subject's upper arm was transformed from $\delta[k]$ by a modified saturation function (or mapping function) given by

$$D[k] = \begin{cases} 2.5 & if\ \delta[k] > 2.5 \\ K \cdot \delta[k] & if\ 1 \le |\delta[k]| \le 2.5 \\ K \cdot \tan(\frac{\pi}{4} \cdot \delta[k]) & if\ |\delta[k]| < 1 \\ -2.5 & if\ \delta[k] < -2.5 \end{cases} \qquad (3).$$

The gain K was used to adjust the speed of the cursor and thus the degree of difficulty for using the brain-computer-interface. In this study it was set to *1* for all subjects. The tangent function was employed to dampen the oscillation of the command around zero. $|D[k]| \ge 1.6$ was defined as the target zone for right (positive) and left (negative) hand movements, respectively.

Experiment design and clinical trials

Eight healthy subjects and five stroke patients were recruited in this study (**Table 1**). Among the healthy subjects only one was left-handed (5 males and 2 females, mean age 25.6 ± 4.3 years old). Three stroke patients were left hemiparesis, and the other two were right hemiparesis (2 males, 3 females, mean age: 46.6 ± 11.5 years old). Inclusion criteria of the stroke patients includes a stable medical condition, an interval of at least 5 months since stroke onset, intact cognition, and having a Bruunstrom's stage greater or equal to 3. The study protocol was approved by the institutional review board of National Cheng Kung

University Hospital. Before the experiment, the purpose, potential hazards, and procedure were explained to the subjects and written consent forms were signed.

All subjects were trained bilaterally and alternatingly with five trials as a session and an inter-session time of 30 seconds. The training lasts for 8 weeks, two days per week, 10 trials per side each day. Each subject received a total of 320 trials of EEG BCI-controlled robot-assisted reach movements. The stroke patients usually had abnormal flexor synergy patterns which retarded extension of the affected upper limb by the robot. Before using the BCI-controlled robot, extension of the affected upper limb was performed by a physical therapist for several trials to reduce the abnormal synergy. The bilateral training was suggested to improve inter-limb coupling and bilateral coordination of upper limbs via inter-hemispheric crosstalk (Daly and Wolpaw, 2008).

The training procedures as depicted in Figure 3 are following.

(1) Subjects were seated in front of the robot with the trunk fastened to the back of the chair by a strap and the hand to be tested fastened to the pronation/supination module of the robot. The gravity of the upper limb was supported by a two-link passive mechanism. The robot could be stopped at any time by cutting off the power supply with an emergency button which could be pushed by either the subject or the physical therapist.

(2) Three electrodes were adhered to C3, C4 and Cz of the sensorimotor area after cleaning the cranial skin. Before BCI training, the movement parameters such as distance, speed, frequency and trajectory were programmed based on the muscle tone of each subject. To avoid inducing spasticity or antagonist activation, the speed of the wrist point was limited to 5 cm/s.

(3) Ten seconds of resting EEGs were acquired after the subject was instructed to relax mentally.

(4) Then a text 'starting imaginary movement' was shown on the computer video screen and a right or left LED light was turned on to instruct the subject to imagine moving the hand corresponding to the side of LED light. If the command D[k] entered the target zone three times within 15 seconds then the trial was marked as successful, otherwise it was a failed one. At the moment of success or the end of each trial (15 seconds) the robot would guide the subject's upper limb to perform the reach movement and back to the starting position. The command D[k] and the outcome of a trial were not shown on the video screen to reduce mental stress on the subject. However, the subject could still judge the outcome based on the relative length of trigger time.

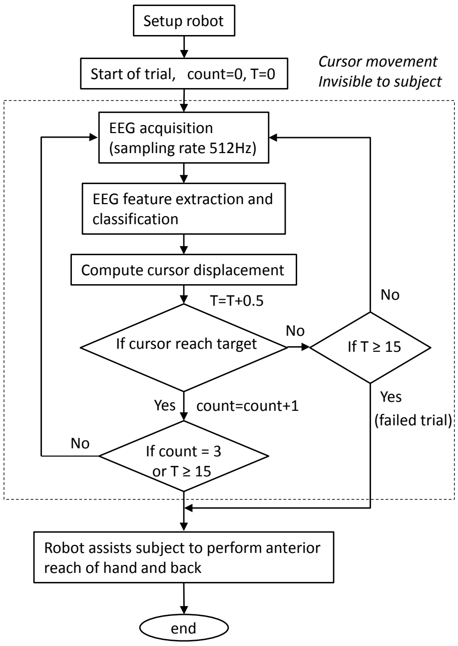

Figure 3. Block diagram of the EEG-based brain-computer interface for triggering the robot to assist subjects to perform forward reach of the hand.

Data Analysis

Two indices were employed to evaluate the performance of all subjects, namely, median trigger time ($\bar{T}_R, \bar{T}_L$) and accuracy (a_R and a_L) given by:

$$a_R = \frac{n_R}{n_T^R} \times 100\% \qquad (4).$$
$$a_L = \frac{n_L}{n_T^L} \times 100\%$$

$\bar{T}_R$ and $\bar{T}_L$ were the median values of weekly trigger time of right hand and left hand imaginary movement, respectively. a_R and a_L were accuracies of the right and left hand imaginary movements, n_R and n_L are the total number of success trials for right and left hands, respectively. n_T^R and n_T^L were total trials of right and left hand imaginations of each week respectively. The definition of the trigger time for a successful trial is shown in Figure 4(a).

Statistical analysis

Following analyses were performed for the healthy group and the stroke group using the paired t-test, namely, the differences of accuracy and median trigger time between first and consecutive weeks, bilateral side difference of accuracy and median trigger time of each week. The significance level was set as $p < 0.05$.

RESULTS

Figure 4(a)&(b) show typical trajectories of power ratios of mu waves of C3 and C4 and Fig. 4 (c) &(d) the command D[k] of the non-dominant hand of a typical healthy subject N1 at first and eighth weeks. The trigger time was reduced from 11.5s to

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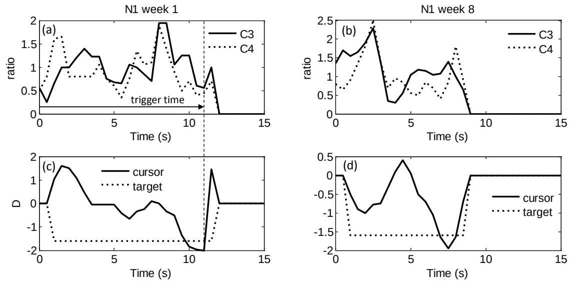

Figure 4. Non-dominant hand of healthy subject N1: (a)1st week power ratio of mu waves of C3 (dashed) and C4 (solid), (b) at 8th week, (c) computed (solid) and target (dashed) cursor trajectories at 1st week, (d) at 8th week.

8.3s after eight weeks of training. The trigger time is defined as the instant when the command is sent to the robot to perform forward reach movement. After the training the cursor resides on the left region (0, -2) more often than the first week. Figure **5**(a) & (b) show the corresponding trajectories of the affected hand of a typical stroke patient **S1** at first and eighth weeks, respectively. Similarly, the trigger time was reduced from 9.0 s to 5.5 s after same amount of training. The under-shoot of the command was highly improved after eight weeks of training (Fig. 5(c) & Fig. 5(d)) and similarly the cursor resides on the left region more often thus reduces the trigger time. In **Table 2** list the weekly accuracies of BCI control of the rehabilitation robot by all subjects and **Table 3** the weekly median trigger times. **Figure 6**(a) shows the weekly accuracies of BCI control via imaginary movements of dominant and non-dominant hands for all healthy subjects and Fig. 6(b) the median trigger times of dominant and non-dominant hands of

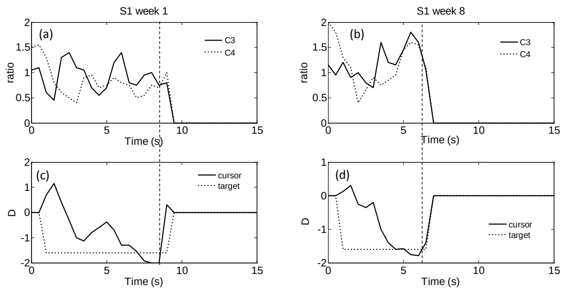

Figure 5. Affected hand of stroke subject S1: (a) 1st week power ratio of mu waves of C3 (dashed) and C4 (solid), (b) at 8th week, (c) computed (solid) and target (dashed) cursor trajectories at 1st week, (d) at 8th week.

all healthy subjects. Fig. 6(c) shows the weekly accuracies of BCI control via imaginary movements of affected and intact hands for all stroke patients and Fig. 6(d) the weekly median trigger times for all stroke patients. Weekly variations of averaged accuracies and averaged median trigger times for the healthy and the stroke groups are compared in **Figure 7**. In general, the accuracy of the healthy group is slightly higher than that of the stroke group (Fig. 7 (a)(c)). The paired-t tests show that there are no significant differences between accuracy of 1st week

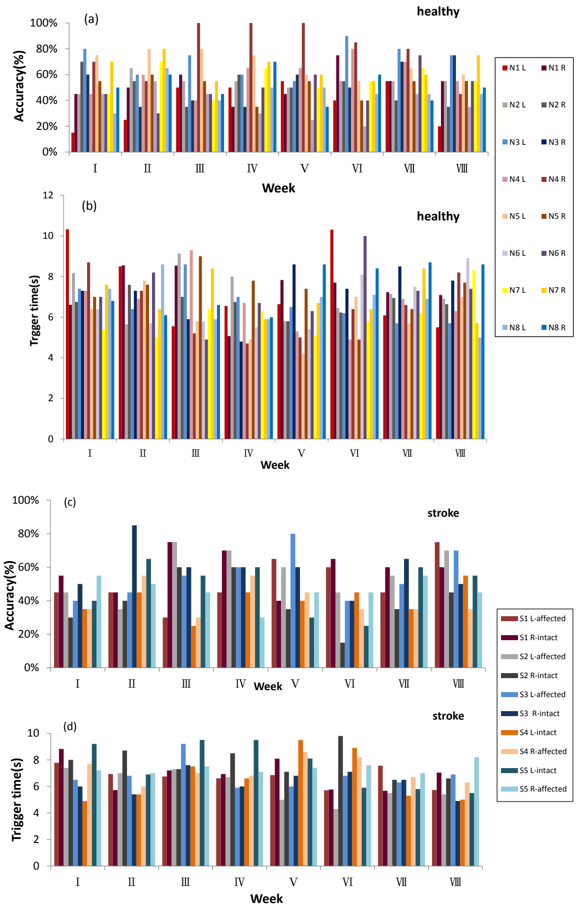

Figure 6. Weekly performances of all subjects: (a) accuracies and (b) median trigger times of the healthy, (c) accuracies and (d) median trigger times of the stroke.

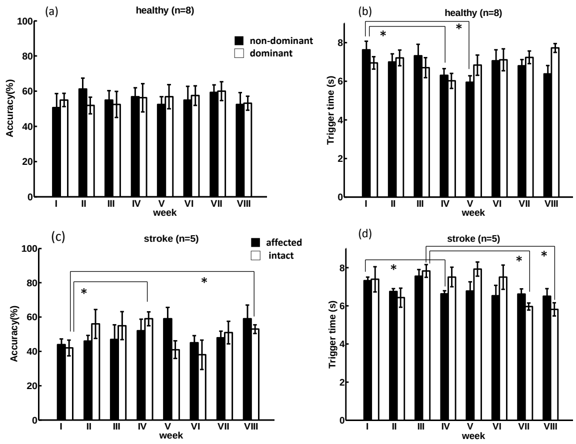

Figure 7. Comparison of performances: (a) weekly averaged accuracies (±SE) and (b) averaged median trigger times (±SE) of non-dominant vs. dominant hands of healthy group, (c) weekly averaged accuracies (± SE) and (d) weekly averaged median trigger times (±SE) of affected vs. intact hands of stroke group. (* $p<0.025$), SE: standard error.

and latter weeks for both dominant and non-dominant sides of the healthy group although the side difference is decreased after eight weeks of BCI training. For the stroke group, accuracies of both intact and affected arm control increase with week number for the first four weeks. Significant increases of accuracies are found for the fourth week ($p<0.02$) and the eighth week ($p<0.05$) for the affected arm control. On the contrary, the trigger time of the stroke group is slightly smaller than that of the healthy group (Fig.7 (b)(d)). Paired-t tests show that significant reduction of trigger times can be found for fourth week ($p<0.02$) and fifth week ($p<0.01$) for the non-dominant arm control by the healthy group. Similarly, significant reduction of trigger time at the fourth week ($p<0.02$) for the affected arm control is found for the stroke group. Although the averaged median trigger time of the eighth week is smaller than that of the first week but not statistically significant ($p=0.063$). On the other hand, median trigger times of the intact arm control at the seventh week ($p<0.03$) and the eighth week ($p<0.05$) are reduced significantly when compared with that of the third week. Significant side difference on trigger time is found at the fifth week ($p<0.02$).

Table 1 Basic data of all subjects

Subject	Age	Sex	dominant /affected	Time after stroke
N1	23	M	R	NA
N2	24	M	R	NA
N3	23	M	R	NA
N4	34	M	R	NA
N5	28	F	R	NA
N6	29	F	R	NA
N7	22	M	L	NA
N8	22	M	R	NA
S1	41	F	L	1yr 4 mo
S2	35	M	L	2yr 9 mo
S3	40	M	L	9 mo
S4	54	F	R	6 mo
S5	63	F	R	6 yr

M: male, F: female, R: right, L: left, NA: not available, yr: years and mo: month.

DISCUSSION

Although the healthy subjects could easily perform voluntary movements of both dominant and non-dominant hands, however, when instructed to perform imaginary movements, they had to inhibit the real hand movement, and this inhibition might interfere with the event-related desynchronization of the mu wave, especially for the dominant hand. But it might have less effect on the non-dominant hand that may explain why the accuracies of dominant and non-dominant sides became similar on week 8. On the contrary, the stroke patients could not perform voluntary movements of the affected hand so the averaged accuracies of the affected side were lower than that of the intact side during week 2 and week 4. However, on week 5 the averaged accuracy of the affected side exceeded that of the intact side, indicating the sensorimotor cortex of the patients might start to re-organize and on week 6 accuracies of both sides decreased. The process of learning to operate a BCI is similar to that for a conventional learning process. At the beginning, imaginary hand movement may be utilized, however, after one month of learning the patients may modulate their brain waves directly (Daly and Wolpaw, 2008). It is speculated that week 5 may be the plateau of learning for the patients and learning between week 6 and week 8 increased the accuracies of both sides. Further functional magnetic resonance image studies of the cortex may help to elucidate the progress of brain reorganization. From accuracy of using the BCI-controlled rehabilitation robot, the training is more efficient for the affected side of the stroke patients. Since the stroke patients could not move their affected hands and unlike the healthy they may be more concentrated, i.e. only single mental task was performed when performing the imaginary movement.

In general, the trigger time of the stroke group was slightly smaller than that of the healthy group, which may due to the imbalance of the mu waves of the brain causing oscillation of the command and the success criterion is entering the target zone three times within 15 seconds. For the stroke group, the side difference for trigger time was quite small at the start of training and the difference increased at week 8. On the contrary, the intact side had a longer trigger time. The results show that the actual movement of the affected hand was extremely slow or even none and the imagery movement could be faster. It might indicate that the control center in the brain did not lose its capability after the stroke, and when BCI is implemented in the future, the execution of movement may not be inferior to the intact side.

After modification of the EEG BCI system, we found that the quality of EEGs was highly improved and the accuracies of all subjects were increased when compared with our previous study. The separation of EEG processing and robot command computation onto two personal computers worked very well. The Parks-McClellan optimal filter could reject the environmental noise and resulted in cleaner EEG and thus enhanced the event-related desynchronization of the mu wave. In our previous work, the weekly accuracies for a stroke patient are ranged between 10% and 80% for the intact arm and between 0% and 60% for the affected arm (Huang, 2012). The large variation of accuracy may due to the high level of environmental noises that affect the detection of event-related desynchronization of mu wave. The other is the definition of a successful trial was modified that signal D[k] (Eq.(3)) has to remain in the target zone for three consecutive sampled times instead of one. By this the number of false positive trials was decreased. Another is that the movements of cursor were not displayed on the video screen to

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Table 2 Accuracies (%) of all subjects: healthy N1-N8, stroke S1-S5

	N1		N2		N3		N4		N5		N6		N7+		N8	
week	L	R	L	R	L	R	L	R	L	R	L	R	L	R	L	R
Ⅰ	15	45	45	70	80	60	45	70	75	55	45	45	45	70	30	50
Ⅱ	25	50	65	55	60	35	60	55	80	60	55	30	70	80	65	60
Ⅲ	50	60	55	35	75	40	40	100	80	55	45	45	40	55	40	45
Ⅳ	50	35	55	60	60	35	65	100	75	35	30	50	65	70	50	70
Ⅴ	55	45	50	50	55	60	65	100	60	55	25	60	50	60	50	35
Ⅵ	40	75	55	55	90	50	80	85	55	40	20	40	55	55	45	60
Ⅶ	55	55	55	40	80	70	70	80	65	55	45	75	65	60	45	40
Ⅷ	20	55	55	35	75	75	55	45	60	55	35	55	55	75	45	50

	S1		S2		S3		S4		S5	
week	L*	R	L*	R	L*	R	L	R*	L	R*
Ⅰ	45	55	45	30	40	50	35	35	40	55
Ⅱ	45	45	35	40	45	85	45	55	65	50
Ⅲ	30	75	75	60	55	60	25	30	55	45
Ⅳ	45	70	70	60	60	60	45	55	60	30
Ⅴ	65	40	60	35	80	60	40	45	30	45
Ⅵ	60	65	**45**	15	**40**	40	45	**35**	25	45
Ⅶ	45	60	55	35	50	65	35	35	60	55
Ⅷ	75	60	70	45	70	50	55	35	55	45

R: right hand imagery, L: left hand imagery, * affected side,
+ all healthy subjects except N7 are right-handed

Table 3 Median trigger times (s) of all subjects: healthy N1-N8, stroke S1-S5

	N1		N2		N3		N4		N5		N6		N7+		N8	
week	L	R	L	R	L	R	L	R	L	R	L	R	L	R	L	R
Ⅰ	10.3	6.6	8.2	6.8	7.4	7.3	7.3	8.7	6.4	7.0	6.4	7.0	5.4	7.6	7.4	6.8
Ⅱ	8.5	8.6	5.7	7.6	6.4	7.3	6.9	7.3	7.8	7.6	5.7	8.2	5.0	6.4	8.6	6.1
Ⅲ	5.6	8.5	9.1	7.0	8.6	5.9	9.3	5.2	5.8	9.0	5.8	4.9	6.4	8.4	5.9	6.6
Ⅳ	6.6	5.1	8.0	6.8	7.0	4.8	6.7	4.7	4.9	7.8	5.5	6.7	6.3	5.9	5.9	6.0
Ⅴ	6.6	7.8	5.8	5.8	6.5	8.6	5.3	5.0	4.2	7.4	5.4	6.3	5.1	6.7	7.0	8.6
Ⅵ	10.3	7.7	6.5	6.2	6.2	7.4	4.9	6.4	7.0	4.9	8.1	10.0	5.8	6.4	7.1	8.4
Ⅶ	6.1	7.2	7.1	6.9	5.7	8.5	6.9	6.6	5.7	6.4	7.5	7.3	6.2	8.4	6.9	8.7
Ⅷ	5.5	7.1	6.9	6.6	5.7	7.8	6.3	8.2	7.0	7.7	8.9	7.4	8.3	5.7	5.0	8.6

	S1		S2		S3		S4		S5	
week	L*	R	L*	R	L*	R	L	R*	L	R*
Ⅰ	7.8	8.8	7.4	8.0	6.5	6.0	4.9	7.7	9.2	7.2
Ⅱ	6.9	5.7	7.0	8.7	6.8	5.4	5.4	6.0	6.9	7.0
Ⅲ	6.8	7.2	7.3	7.3	9.2	7.6	7.5	7.0	9.5	7.5
Ⅳ	6.6	6.9	6.7	8.5	5.9	6.0	6.6	6.8	9.5	7.1
Ⅴ	6.9	8.1	5.0	7.1	6.0	6.8	9.5	8.6	8.1	7.4
Ⅵ	5.7	5.8	4.3	9.8	6.8	7.1	8.9	8.2	5.9	7.6
Ⅶ	7.6	5.7	5.5	6.5	6.3	6.5	5.3	6.7	5.8	7.0
Ⅷ	5.7	7.0	5.4	6.6	6.9	4.9	5.0	6.3	5.5	8.2

R: right hand imagery, L: left hand imagery, *: affected side
+ all healthy subjects except N7 are right-handed.

help the subject concentrated on the imaginary movement and also reduce the mental stress particular when successive failed trials occurred. Among the two robotic indices, the trigger time is a measure of how quickly the subject can drive the cursor into the target zone. The results show that the healthy group can achieve a mean value of around 6 seconds after four week training and eight week training for the stroke group. Compared with the total time of 15 seconds it meant the subjects can quickly drive the 'virtual' cursor into the target zone within 2/5 of the allowable time. It meant, after the training, the subject can quickly control their mu waves and for the patients it might indicate that the neurons surrounding C3 and C4 have been trained and reorganized and the trigger time may serve as a suitable index for quantifying the performance of using our BCI-controlled robot. Further validation of the training effects for the patients may need evaluations such as functional magnetic resonant imaging of the sensorimotor area of the brain cortex and biomechanical indices such as range of motion of the fingers and muscle power (Ono et al, 2015). These tests have to be performed before the BCI training, right after the training and one month after the training to examine plasticity of the brain. Clinical scales such as the Fugl-Meyer Assessment and Action Research Arm Test may have to be used to evaluate the functions of upper extremities particular for the chronic stroke patients.

CONCLUSION

An EEG-based BCI integrated with a shoulder-elbow rehabilitation robot was modified and tested on healthy and stroke subjects. The separation of EEG processing and robot command generation does improve quality of EEG and the developed EEG controlled rehabilitation robot might be used in neuro-rehabilitation of patients. The trigger time may be suitable for evaluating performance of the stroke patients when trained by the BCI-controlled robot. Further work will be more subject testing and assessment of the training effects using clinical assessment scales and biomechanics indices.

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腦波腦機介面控制肩肘復健機器人之發展

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中文摘要

本團隊曾發展肩肘復健機器人並用於慢性期中風病人復健，本研究目的為整合腦波腦機介面系統和此復健機器人，發展以想像動作控制機器人以帶動病人上臂進行復健。本研究利用兩部個人電腦和最佳化濾波器降低腦波雜訊並提出由大腦 C3，C4 的μ波將受測者想像轉為驅動機器人的演算法。以 8 名常人和 5 名慢性中風病患測試系統功能。為評估受測者的表現定義了兩種性能指標：準確率和啟動時間。每位受測者共接受每周兩天共 8 周的訓練，實驗結果顯示：常人訓練期間周間準確率差異不大，而中風病人患側第 4 周平均準確率明顯比第 1 周高，雖然第 5 周起有學習高原現象，但第 8 周平均準確率仍高於第 1 周。常人非慣用側和病人健側第 4 周啟動時間均明顯低於第 1 周，且病人患側第 8 周啟動時間小於第 3 周。本研究提出的方法的確能改善腦波的品質且系統具有神經復健的功能。