Using SSVEP based Brain-Computer Interface to Control Functional Electrical Stimulation Training System

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Abstract— **In this work, a functional electrical stimulation (FES) training system using steady-state visual evoked potential (SSVEP) based brain-computer interface (BCI) was designed to realize the control of upper limb movements. Subjects were required to initiatively focus on one of five flickering lights with different frequencies on the computer screen, while the electroencephalogram (EEG) signal was acquired from the channels at the visual cortex region. The five primary flickering frequencies and their harmonic components were extracted as classification features from the EEG channels at the visual cortex region, and then linear discriminant analysis (LDA) classifier in pairwise strategy was used to decode the subject's intention corresponding to the flickering light that the subject was focusing on. Thereafter the user's intention was transformed into a command to trigger the FES system to generate the desired stimulation pattern. The experimental results showed that the feature extraction and classification methods were efficient in on-line classification. Moreover an energy bar was applied to the human-machine interaction interface to enhance the performance of the system as a dynamic feedback to the user. The results indicated that the subjects could control the FES training system to realize the predefined action sequences with their own intention.**

I. Introduction

FUNCTIONAL electrical stimulation (FES) is a fairly advanced technology in rehabilitation engineering, which activates muscles to contract by stimulation of the motor neurons with low-level electrical current, so as to restore or recover patient's impaired motor function. Nowadays, FES has been widely used, and its application is no longer restricted to simple physical therapy [1]. The extended FES applications include hand grasping and opening, extension and flexion of upper extremity, standing, walking, and riding. It could also be used to assist the patients with severe respiration difficulty [2]. In a word, highly developed FES technology gives hope to people who lose their body control ability.

A typical FES system consists of four parts: controller, stimulation device, sensor, and musculoskeletal system. Among them the core part is the controller, which looks like a substitution of impaired central nervous system to produce proper electric pulse. In traditional FES controller design, artificial algorithms are adopted to realize the desired trajectory tracking of joints of the paralyzed limb. The controllers work independently while the patient's subjective consciousness has not participated. To some extent, the functionality of FES system was constrained. Therefore, brain-computer interface (BCI) technology would be introduced into FES system as a subjective controlling resource. BCI enables the user to send information or command to a communication system not through the brain's peripheral neuromuscular pathway as conventional output pathway [3]. The main purpose is to help paralyzed patients restore communication and control ability when human's conventional output pathways are obstructed. So BCI might be used as a substitution of conventional neuromuscular pathways to offer patients who lost motor ability with a new communication and control channel.

Electroencephalogram (EEG) is a noninvasive method to record weak electrical signals produced by a large amount of brain neurons activity. As one of the most important technologies in BCI, EEG is widely adopted by researchers because of its useful features of noninvasive interface, economy, convenience, and high time resolution etc. According to different types of neurological phenomena, EEG based BCI could mainly be classified to four categories: steady-state visual evoked potential (SSVEP), slow cortical potential (SCP), P300, and mu and beta rhythm of motor imagery.

Integration of BCI and FES is an interesting and promising research direction [4]. Actually some research teams have already brought EEG based BCI into FES system. In 2003, Pfurtscheller et al. did a groundbreaking experiment [5], helping patients with upper limb hemiplegia to conduct hand grasping by triggering FES system through motor imagery based BCI. Similarly, using motor imagery based BCI, other research teams developed BCI-FES systems for rehabilitation on stroke patients, which showed the feasibility for stroke patients to accomplish the BCI triggered FES rehabilitation training [6, 7]. Differently, Bentley et al. proposed a P300 based BCI [8] and Gollee et al. proposed an SSVEP based BCI [2] for FES application, respectively.

Analyzing the current status on the combination research of BCI and FES, we find that the motor imagery based BCI should be preferable in nature, but it is prevalently considered not to be efficient. There are some fatal shortcomings

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including apparently lower recognition accuracy, relatively longer training cycle, and individual discrepancy and so on. Moreover, all these problems would not be easily solved in a short term.

For purpose of urgent practical application at present, we considered SSVEP based BCI which has a much higher information transfer rate, a much shorter training cycle, and relatively less individual discrepancy. These advantages are desired in the BCI-FES training systems.

A. System Overview

The schematic diagram of the proposed system is given as follows. There are several flickering lights with different frequencies indicating different motions. When a subject stares at a specific flickering light, the EEG signals are acquired from the scalp. After feature extraction and pattern recognition, the intention about which light is being focused on could be detected, i.e. the patient's intention is understood by the system. Then a command is generated, which triggers FES to produce the corresponding muscle activation, so that the patient could do some movements such as hand grasping and opening, elbow extending and flexing according to his or her own willingness (reference to Fig.1).

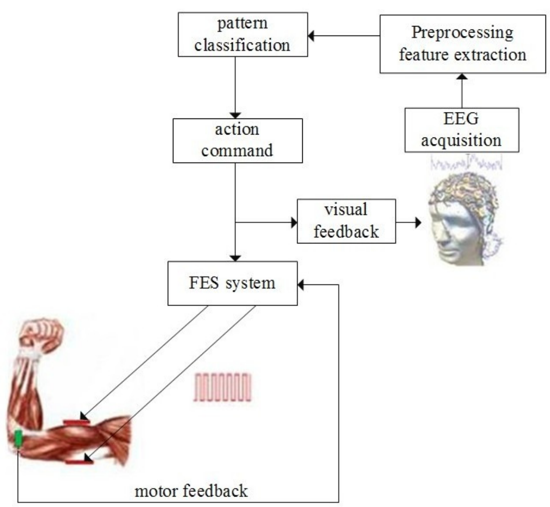


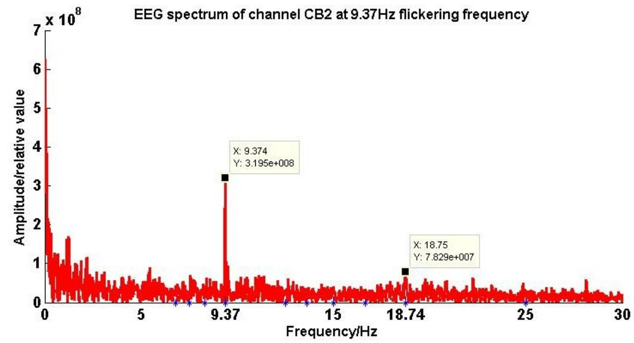
Fig. 1. Schematic diagram of BCI-FES system

B. Methodology

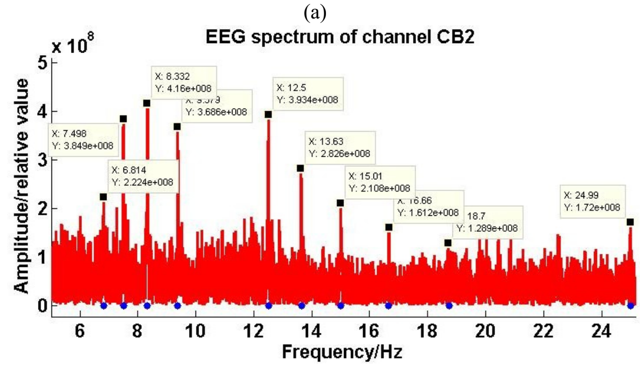
When the human continuously focuses on instantaneous visual stimulus with constant time interval, steady state visual evoked potential will occur in primary visual cortex of the brain. EEG signals show that the corresponding stimulus frequency and its harmonic wave components will be obvious in frequency domain, i.e. the EEG signal is modulated with the stimulus frequency in aspect to signal modulation theory. The signal processing technique is used to obtain the features related to stimulus frequency from the complex modulated EEG signals.

1) Feature Extraction

According to previous researches, stimulus frequency and its first harmonic wave component should be extracted as the classification features in SSVEP [9, 10]. Fig. 2 (a) shows the EEG spectrum of channel CB2 on primary visual cortex when the subject is staring at the flickering light of 9.37Hz. It is clear that the 9.37Hz flickering frequency and its harmonic components are sticking out in frequency domain. Furthermore, Fig. 2(b) shows the EEG spectrum of channel CB2 when the subject consequently stares at five different stimuli lights each lasting about 30 seconds. It's found that the five stimuli frequencies and their harmonic wave components all stick out in the spectrum, and these prominent features are used for classification.



(a)



(b)

Fig.2. EEG spectrum at channel CB2

Suppose $S_i(t)$ is the EEG signal from channel i with $i=1...N$, and f_j is the j th stimuli frequency with $j=1...M$, and $W(t-c)$ is the window function with the center at c. We apply inner product to extract the specified frequency as projecting the signal to sine and cosine space. The continuous forms of feature extractions are given as

$$A_{ij}(c) = sqrt(\left|\langle S_i(t)W(t-c), \cos(2\pi f_j t)\rangle\right|^2 + \left|\langle S_i(t)W(t-c), \sin(2\pi f_j t)\rangle\right|^2) \quad (1)$$

$$B_{ij}(c) = sqrt(\left|\langle S_i(t)W(t-c), \cos(2\pi \bullet 2 f_j t)\rangle\right|^2 + \left|\langle S_i(t)W(t-c), \sin(2\pi \bullet 2 f_j t)\rangle\right|^2) \quad (2)$$

where $A_{ij}(c)$ is the j th frequency component from EEG channel i at time point c; $B_{ij}(c)$ is the harmonic wave component of j th frequency from EEG channel i at time point c.

Referred to the experiment setup in section 3, with the sampling interval $\Delta T = 1/f_s$ and sliding window length $p = 100*\Delta T$, the continuous form could be converted to the discrete form:

$$A_{ij}(n) = \sqrt{L_1(n) + L_2(n)} \quad (3)$$

$$B_{ij}(n) = \sqrt{H_1(n) + H_2(n)} \quad (4)$$

where

$$L_1(n) = \left| \left\langle S_i(m\Delta T) W(m\Delta T - np), \cos(2\pi f_j m\Delta T) \right\rangle \right|^2$$

$$L_2(n) = \left| \left\langle S_i(m\Delta T) W(m\Delta T - np), \sin(2\pi f_j m\Delta T) \right\rangle \right|^2$$

$$H_1(n) = \left| \left\langle S_i(m\Delta T) W(m\Delta T - np), \cos(2\pi \bullet 2 f_j m\Delta T) \right\rangle \right|^2$$

$$H_2(n) = \left| \left\langle S_i(m\Delta T) W(m\Delta T - np), \sin(2\pi \bullet 2 f_j m\Delta T) \right\rangle \right|^2$$

So the feature vector for the classification could be of the form:

$$\begin{aligned} F = (&A_{11}, A_{12}, ..., A_{1M}, B_{11}, B_{12}, ..., B_{1M}, \\ &A_{21}, A_{22}, ..., A_{2M}, B_{21}, B_{22}, ..., B_{2M}, \\ &..., A_{N1}, A_{N2}, ..., A_{NM}, B_{N1}, B_{N2}, ..., B_{NM})^T \end{aligned} \quad (5)$$

2) Classification

There are five classes to be classified. we apply LDA in pairwise strategy based on the considerations that the features in different categories are quite discriminable and the training samples are relatively much more than that in other BCI systems.

Regarding i th and j th categories classification problem, for example, suppose F^i and F^j be i th and j th training feature sets, the average features of the two sets are

$$\mu_i = E(F^i) \quad (6)$$

$$\mu_j = E(F^j) \quad (7)$$

E denotes the expectation operator, and the within class covariance is defined as

$$\begin{aligned} S_w^{ij} = &E\left[(F^i - \mu_i)(F^i - \mu_i)^T\right] \\ &+ E\left[(F^j - \mu_j)(F^j - \mu_j)^T\right] \end{aligned} \quad (8)$$

The parameters of the LDA classifier could be derived by Fisher method which tries to find an optimal projection direction that maximizes the difference between the two classes while minimize the difference within the class.

The discriminant plane can be expressed in the linear formulation as

$$y = w^T x + b \quad (9)$$

where

$$w = S_w^{ij-1}(\mu_1 - \mu_1)$$

$$b = -w^T \frac{\mu_1 + \mu_1}{2}$$

II. EXPERIMENTAL WORK

A. Experiment setup

The stimulator(Compex Motion II, Switzerland) with four channels was adopted, which stimulated muscles via surface electrodes. EEG signals were recorded using a SynAmps system (Neuroscan, U.S.A.) in a shielded room which could reduce interference from the noise and electromagnetic in open environment. BCI and FES interface circuit was designed as follows. In the upper level, the singlechip communicated with PC through standard RS232 serial port, with the purpose to receive BCI commands. In the lower level, the singlechip produced voltage signal with specified amplitude and duration in accordance with FES input detection-trigger criteria. After receiving action command from BCI, a signal with specified amplitude and duration was produced by singlechip to trigger FES device, then certain intensity of electrical impulse was produced to activate the concerned muscle to contract. The experiment system was shown in Fig.3.

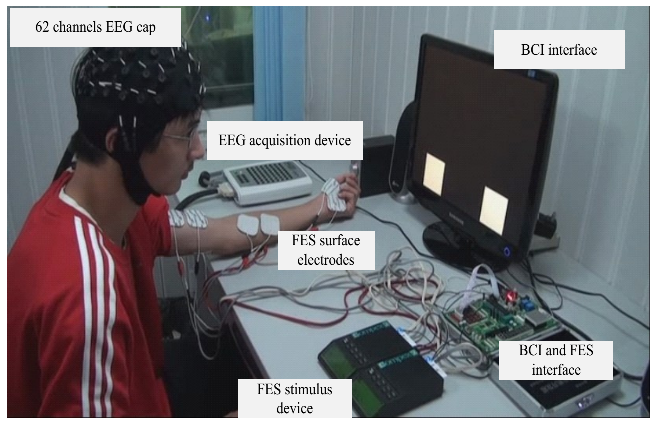


Fig. 3. Framework of experiment system

All channels of FES device are set to generate bipolar current impulse with pulse width of 125us and pulse frequency of 25Hz. As muscles in different locations needed different current intensity to activate, according to practical test the current parameters were set as: current intensity was 9mA for M. ext. digitorum communis (EDC) and M. ext. pollicis longus (EPL); 10 mA for M. flex. digitorum superficialis (FDS) and M. flex. pollicis longus (FPL); 14mA for biceps brachii; 11mA for triceps brachii. The stimulation electrodes were distributed as shown in Fig. 4.

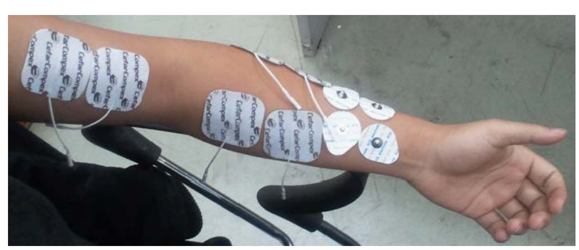


Fig. 4. Distribution of stimulation electrodes

Eight channels in EEG cap located on occipital region were used to collect brain potential signals, which were PO3, POz, PO4, O1, Oz, O2, CB1, CB2 according to international 10/20 system. The reference electrode was located between Cz and CPz, and ground electrode was located on forehead. An analog bandwidth filter with 0.5~30Hz and a notch filter with 50Hz to diminish power line interference were applied to the original signals, and sampled at 1000Hz. The flickering frequencies of five white blocks from left to right and up to down were 12.5Hz, 7.5Hz, 9.37Hz, 8.33Hz, and 6.82Hz respectively as shown in Fig. 5. So, M standing for number of visual stimulation frequencies mentioned above equaled to 5, and N standing for EEG channel number equaled to 8.

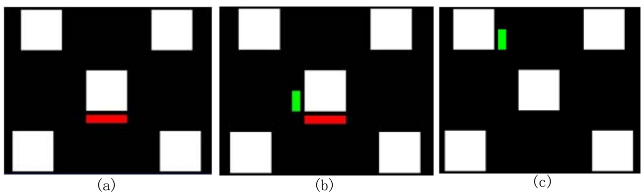


Fig. 5. User interface at different stages

B. Experiment protocol

Five different flickering frequencies in SSVEP were mapped respectively to different stimulus modes in FES. The 12.5Hz flickering frequency corresponded to hand grasp action while 8.33Hz corresponded to hand open action. The 6.82Hz flickering frequency corresponded to elbow flex action while 7.5Hz corresponded to elbow extend action. Finally the 9.37Hz corresponded to idle state without any stimulation of muscles. When the subject closed eyes for about one to two seconds, the alpha rhythm was obvious. Thus idle state was easy to attain since 9.37Hz was within that range. When the subject stared at light of specific flickering frequency on the screen, subject's intention would be acquired through processing of EEG signals, and then the corresponding action would be carried out by stimulation of related muscle groups. The single stimulation process was divided into two steps. In step 1, the first 1~3 seconds were for interaction between subject and BCI, and the subject was required to focus on staring one of the five flickering lights according to his own willingness. In step 2, the next 8 seconds were for electrical stimulation. During that time, FES device stimulated the targeted muscle groups to contract. Every subject took part in two sessions, and each session has the following action sequences:

1). hand open: simultaneously stimulate EDC and EPL
2). hand grasp: stimulate FDS for four finger closing first, and then FPL for thumb closing
3). elbow flex: stimulate biceps brachii
4). elbow extent: stimulate triceps brachii
5). hand open: stimulate EDC and EPL
6). idle state: no stimuli

C. Experiment paradigm

The experiment was carried out as shown in Fig 6, and divided into four stages. The solid line arrow indicated the normal experimental process, and the dashed line arrow indicated "back to previous state" when certain conditions were not met as mentioned below.

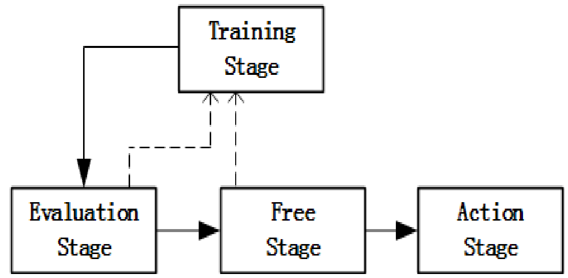


Fig. 6. Experiment flowchart

Training stage: The training stage was so important that it might influence all the following stages. So, subjects should fully relax themselves not to be nervous, and sit still focusing his attention on the screen, meanwhile trying not to blink as possible. The stage's training time was about 150 seconds. Every five seconds there would randomly appear a red bar, as shown in Fig. 5 (a), indicating subject to stare at the white flickering block pointed by the red bar with 5 seconds. After about 30 times of repeating, the training stage ended, and then experiment process came to the next stage.

Evaluation stage: The main purpose of this stage was to evaluate the performance of training stage. At this stage, five red bars would sequentially appear on the screen, at the same time subject was required to focus on the corresponding white flickering block pointed by the red bar. Meanwhile an energy bar which reflected user's intention would appear beside the white flickering block, as shown in Fig. 5 (b). The dynamic changing of the energy bar was designed to reflect user's intention and used as evaluation of the training effect. Experimenter should adjust the parameters of the experiment according to the subject's performance, or return back to the training stage.

Free stage: The main purpose of this stage was to make subject gradually adapt to the BCI system. At this stage, subject could stare at any one of the five flickering blocks on his or her own intention, and self evaluate whether the dynamical changing of the energy bar was in accordance with his or her intention, as shown in Fig 5 (c). The time length of this stage should be decided by the subjects themselves. If the subject felt whether the system was either too quick or too slow, or the system could not fully express his or her intention, the subject should return back to training stage or the experimenter should adjust the parameter of the experiment.

Action stage: Subjects should sequentially gaze at the certain white flickering block according to the experimental paradigm. When the subject focused on one block persistently, the corresponding energy bar length would change, which worked as a feedback to the subject about which frequency he was focusing on at that time. When the length of the energy bar exceeded the predefined threshold, FES device would be triggered, and the corresponding action mode would be performed. At this action stage, some procedure statuses were defined by variables that reflected the experimental performance including True Positive (TP), False Negative (FN), and Back to Previous (BP) [10]. If the desired motion was performed, TP value would be added by 1. Otherwise, FN value would be added by 1. BP equaled to the counting number of action steps back to the previous state when undesired action mode was performed.

III. Experiment result and analysis

The experiment is carried out in a soundproof room. Using extracted feature vector as in (5) and pairwise LDA classifier as in (9), some results are obtained. Table 1 shows the on-line performance of four participants from S1 to S4. Within one session, recognition accuracies are obviously different for five flickering frequencies on each subject. And it is mainly caused by the characteristics of individual response intensity to each stimulus as can be seen from reaction spectrum of scalp EEG in Fig. 2(b), where EEG is contaminated by background brain activity. Moreover, the recognition accuracy of the same frequency varied greatly among different subjects, as the primary visual structure differs slightly from subject to subject. Generally, accuracy of the second session is greater than that of the first session. This is easily understood since the first session looks like a training stage for the subject in this case.

Table 1.On-line classification accuracy of SSVEP of the four subjects

subject	session	12.5Hz (%)	9.37Hz (%)	8.33Hz (%)	7.5Hz (%)	6.82Hz (%)	Average (%)
S1	No.1	78.61	85.72	88.74	90.11	85.88	83.76
	No.2	89.24	86.24	83.42	89.83	92.09	87.35
S2	No.1	75.39	82.09	84.78	77.62	71.02	71.20
	No.2	82.82	75.30	87.48	86.27	68.30	83.78
S3	No.1	69.54	77.91	78.94	83.45	87.08	76.99
	No.2	85.66	83.06	82.92	83.43	83.51	83.90
S4	No.1	88.91	90.88	80.73	76.94	75.51	82.95
	No.2	88.97	91.85	86.95	89.87	82.69	87.86

In action stage, the length of the energy bar will change dynamically, each time the pattern classification result from the BCI system is given every 100ms. The rule of the length changing of the energy bar which reflexes user's intention is as follows: 1) Each action threshold is set to 300, and when the energy bar length exceeds 300, action output command is sent through serial port to trigger the stimulator. 2) If a correct pattern is detected, the corresponding energy bar increases by 20, and otherwise it decreases by 10 each time. 3) When the length value of energy bar is below zero or above the action threshold, the length value is set to zero automatically. 4) The increase /decrease parameters and threshold value of the energy bar should be set according to the performance of the subject for the purpose of better interaction with the system. Table 2 shows the action result of the subjects, and it indicates that all four subjects could accurately accomplish the desired action sequence in controlling FES by SSVEP based BCI within two sessions.

Table 2.Action results of the four subjects

subject	session	TP	FN	BP
S1	No.1	6	0	0
	No.2	6	0	0
S2	No.1	6	0	0
	No.2	6	0	0
S3	No.1	6	0	0
	No.2	6	0	0
S4	No.1	6	0	0
	No.2	6	0	0

IV. Conclusion and Prospect

Basically SSVEP based BCI system has a very good online recognition accuracy and relatively high transfer rate. In the experiment, the time window for frequency amplitude spectrum calculation is about 1000ms, with sliding length of 100ms. When subject changes his focus from one flickering block to another, because of continuously EEG acquiring, the 1000ms time window for calculation contains the previous flickering frequency component in online experiment, and it will increase the false recognition rate to some extent. Besides, the five frequency blocks flicker simultaneously, so some subjects may feel uncomfortable such as dazzling, which will also increase the false recognition rate.

The length changing rule of energy bar could increase the accuracy of action output command, but it delays the action triggering time to some extent. In BCI controlled FES training experiment, the system should accurately and quickly recognize the subject's intention and then trigger FES in time. So it is important to find a good compromise between accuracy and reliability for such a training system.

In this work, BCI only provides a command for the lower FES control system, and the desired trajectories of upper limb cannot be guaranteed, so this is an open-loop system in nature. In order to improve the control performance, some feedback mechanism will be introduced in future.

Now the experiments are mainly carried out on healthy subjects, the next-stage work will transform to patients, and more practical intelligent rehabilitation training system will be designed.

Acknowledgment

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