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Trans Humeral Prosthesis Based on sEMG and SSVEP-EEG Signals*

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***Abstract* - The loss of forearm muscle in amputees above elbow joint make it impossible to control the prosthesis of elbow joint and upper limb only by using surface electromyography (sEMG) signals. Electroencephalogram (EEG) signals can be used as input signal to control the motion of the upper limb prosthetic hand for it can reflect the user's motion intention. This paper introduces a method of controlling the trans humeral prosthesis by combining sEMG and EEG signals. In this method, the control of elbow flexion and extension motions are based on sEMG signals of biceps and triceps. Combined with the collected elbow angles, the elbow angle of prosthetic arm is predicted by back propagation neural network after training and then the angle can be used to control the elbow joint. In order to control the motion of the prosthetic hand, a control method based on EEG is proposed. The EEG control method is named as steady state visual evoked potential (SSVEP). User can use his EEG signals to control the motion of hand prosthesis. Canonical correlation analysis (CCA) algorithm is used to classify SSVEP signals, then different SSVEP signals can be used to control different motions of prosthetic hands. Some experiments were carried out on healthy subjects to verify the performance of the proposed system.**

Index Terms - Trans humeral prosthesis; sEMG; back propagation neural network; SSVEP; CCA

I. Introduction

About 3 million people in the world suffer from upper limb amputation [1]. By 2017, the number of disabled limbs in China had reached 4.846 million. The causes of amputation included cardiovascular diseases, traumatic accidents, infections and so on. The most common causes of upper limb amputation are trauma and cancer, followed by vascular complications in the right arm of the disease, more common in industrial injuries. For upper limb amputees, it is difficult to carry out daily life, because daily life depends on upper limb movements very much. Although replicating the complex movements of the upper body of humans is always a challenging task, many attempts have been carried out on passive and active artificial limbs [2]. Most passive prostheses lack the required degrees of freedom, which results in unnatural arm movements. More and more researchers pay attention to active upper limb prosthesis. There have been some successful commercial prostheses, such as Michelangelo prostheses [3]and Bebioni [4]. However, many of these prostheses still need to be improved, otherwise it is difficult for users to use them. The control of active upper limb prosthesis must be based on the user's motional intention [5], that is, the upper limb prosthesis must be able to be controlled by the user. And sEMG is widely used in medical rehabilitation, active control and other fields because of its non-invasive, convenient measurement and good reflection of human motion intention [6]. However, for amputees above the elbow, only the muscles controlling the elbow joint may be retained but the muscles used to control wrist and hand movements do not exist, and the sEMG signals of the forearm cannot be used to control the prosthesis. For this reason, many existing trans humeral prostheses only provide elbow motion, but do not have hand control.

A five degrees of freedom (DOFs) [7] trans-humeral robotic prosthesis can realize elbow flexion/extension, forearm supination/pronation, wrist radial/ulnar deviation, wrist flexion/extension, and the compound movement of thumb and index finger. The control method based on EMG signals uses the EMG signals of biceps and triceps to control the prosthesis together with the motion switching mechanism. However, the operation is too complex, users may get confused in the use process. Nathanael Jarrasssle et al. [8] successfully identified phantom hand, wrist and elbow movements by measuring different parts of the residual biceps, triceps and pectoralis major muscles with up to 24 pairs of sEMG signal electrodes attached to the residual upper arm. Guillaume Gaudet et al. [9] used 6 sEMG signal electrodes distributed equidistantly in the residual upper arm to identify eight kinds of fantastic movements of the upper limb. However, these methods need more electrodes and the location of electrodes needs to be adjusted. And it can only prove that the residual muscle tissue still has sEMG signals, which is not conducive to the control of prosthetic limbs. There is a successful method [10] which uses the target muscle regeneration (TMR) to control trans humeral prostheses. TMR is a surgical method for improving the control of upper limb prosthesis. Although this method is very effective, it is an invasive method, accompanied by high operating costs. EEG signal can be used as input signals. Many attempts have been made to use EEG signals in the application of assistant robots, and the results of its research show its effectiveness. Recently, an EMG combined with EEG -SSVEP signal method is proposed [11]. The EMG signals are used to control the trans humeral prosthesis, and the EEG-SSVEP signals are used to control the hand part. But only 2 channels

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are used and the hand part can only use for opening and closing. That is not enough for daily life, and it needs to improve. Therefore, it is necessary to find a safe, low-cost and effective way to control trans humeral prothesis.

In this proposed scheme, back propagation (BP) neural network is used to control the motion of elbow joint of prosthesis by using sEMG signals of biceps and triceps. An EEG signal method based on SSVEP is proposed to control the movement of prosthetic hand. Canonical correlation analysis (CCA) algorithm is used to extract SSVEP signals, and the classification accuracy of CCA algorithm is improved by setting threshold. After SSVEP signals are classified by the CCA algorithm, the instructions will be sent to the controller at the hand joint. Experiments verify the control of trans humeral prosthesis based on sEMG and SSVEP-EEG signals. Fig.1 shows the scheme of the control of the trans humeral prothesis.

The structure of this paper is as follows, section 2 introduces the elbow control scheme based on sEMG signal. Section 3 introduces the hand motion control scheme based on SSVEP. The fourth section introduces the experimental results. Finally, it summarizes the paper and its future works.

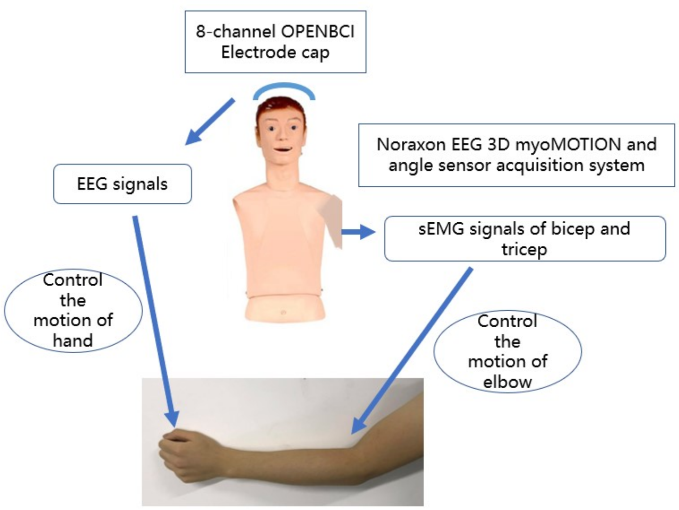

Fig. 1 The scheme of the trans humeral prothesis control.

II. Elbow Joint Control Scheme Based On EMG Signal

A. *Muscles for sEMG Signal*

In the flexion movement of human upper limbs, biceps are the main driving force, while stretching are the triceps. Generally speaking, any amputee has some muscles left at the stump, including biceps and triceps. Therefore, in this experiment, the EEG signals of biceps and triceps are used to control the motion of elbow joint of upper arm prosthesis.

B. *sEMG Signal and Elbow Joint Angle Acquisition Equipmentuscles for sEMG Signal*

The equipment for collecting sEMG signal is Noraxon acquisition system. It has eight EMG sensors, which can be attached to the muscle surface to measure EMG signals. The sampling frequency of EMG acquisition equipment is set to the maximum sampling frequency of NORAXON system (Noraxon Co., USA), 1500Hz. The EMG sensor has a low-pass filter. Noraxon system also has eight 3D myoMOTION motion sensors which can be used to measure joint angle and acceleration. The acquisition frequency of the 3D motion angle sensor is 100 Hz. When measuring elbow joint angle, two myoMOTION angle sensors are used, and the sensors are tied to the upper arm and forearm respectively with bands. After calibration, the angle between the upper arm and the forearm can be measured.

C. *Data Processing*

The original sEMG signal is difficult to identify, so it is necessary to extract features. In this scheme, Root Mean Square (RMS) of sEMG signal is used as the feature. EMG signals collected by sEMG sensors are first processed, filtering. In order to process sEMG signals, a sliding observe window approach is used to segment the signals. The sampling frequency of the experimental equipment is 1500Hz, the number of points used for processing is 375 (0.25s) and the step length is 50 points. The RMS of 375 points is extracted as feature. Meanwhile, the mean angle of 375 points is used as the angle corresponding to the RMS value, because 0.25s is very short, the corresponding angle will not change greatly.

D. *BP neural network*

In the experiment, BP neural network is used to identify the motion intention of the user's sEMG signal to control the elbow joint of the prosthetic limb [12]. The sEMG RMS signals of biceps and triceps of the subject are used as input and generate the desired angle of elbow joint. Before the training of neural network, sEMG signals collected by sEMG sensors need to be processed. Then, the angle of elbow joints collected synchronously by motion sensors is sent to BP neural network for training. The purpose of training is to reduce the error between the predicted angle and the actual angle of elbow joints. The whole data processing process is carried out in MATLAB (MathWorks Co., USA). After the training, the sEMG signals of biceps and triceps can be used as inputs to predict the elbow joint angle. The elbow angle predicted can be used to control the motor of prosthetic elbow joint. Fig.2 shows the structure of elbow control.

III. Hand Joint Control Scheme Based On EEG Signal

Human's hands are very flexible. The human hand has 27 DOFs, while the fingers have 21 DOFs [13], so it can achieve complex and accurate daily activities. The motion of fingers is controlled by the muscles in the forearm, but for amputees above the elbow joint, they have lost the whole forearm. In this case, it is impossible to extract sEMG signals from the muscles in the forearm. In this experiment, EEG signals which can obtain the intention of hand movement are used as the substitute input signal to control the prosthetic hand movement.

Compared with the invasive acquisition method, the non-invasive acquisition of EEG signals has greater interference, but due to its non-invasive and easy operation, it is the focus of current research. Dry electrode cap is used in this paper, surface dry electrodes depend on the electrode cap, which is immersed in brine to enhance conductivity. In different EEG potentials, SSVEP is widely recognized as a response signal in this field, because SSVEP provides high information transmission rate and is effective for almost every user, with almost no training cycle [14].

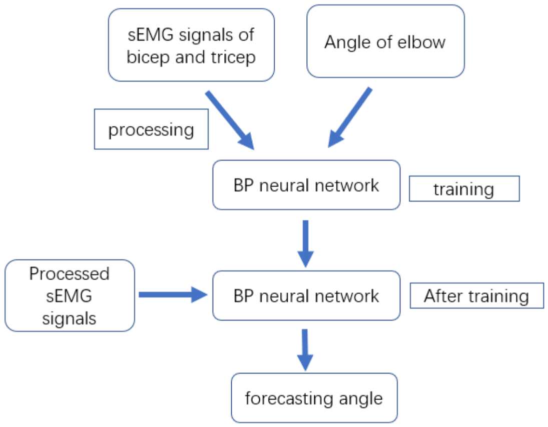

Fig. 2 Structure of Elbow Joint Control Scheme Based on sEMG.

A. SSVEP

SSVEP is a kind of biological feedback of visual cortex to visual blink stimulation when human body receives visual stimulation (with a fixed frequency). In most cases, the frequency of periodic patterns of stimulation should be usually more than 6 Hz, at which time the brain will produce corresponding stable EEG waveforms. Studies have found that the human brain's scalp, occipital lobe is most sensitive to visual stimuli [15].

1) Ways to Generate Visual Stimuli

There are three ways to generate visual stimuli for SSVEP [16]: Light Emitting Diode (LED), Liquid Crystal Display (LCD) and Cathode Ray Tube (CRT). Because the number of stimuli is small and easy to program, the black and white blocks of LCD display are chosen as visual stimuli in the experiment.

LCD may be not a convenient choice for users now, but portable stimulation device may be studied in the future.

2) Structure Based on SSVEP

The EEG signal method based on SSVEP proposed in this paper can control the movement of prosthetic hand by observing LCD stimuli of different frequencies. When a user watches LCD flickering at different frequencies at a specific frequency, SSVEP signals with the same frequency are generated in the user's brain. These brain potentials are captured as EEG signals and then converted into motion instructions for prosthetic hands. In this experiment, the stimulus source is LCD display. The stimulus frequency is 6 Hz, 8 Hz, 10 Hz and 15 Hz. That is to say, these four different stimuli will be transformed into four different hand action instructions. The structure of the prosthetic hand system based on SSVEP is shown in Fig.3. The number of the types of SSVEP signals can be incresed, it depends on the requirement and the performance of the acquisition equipment.

B. EEG Signals Acquisition System

In this experiment, EEG signals are collected by a low-cost OPENBCI 8 channel electrode cap. According to the International Electrode Installation System, eight channels chosen are O1, O2, Oz, PO3, PO4, POz, Fp1 and Fp2, there are also two reference electrodes clipped to the earlobes. Six electrodes were located in the occipital lobe and its adjacent area, and two in the prefrontal lobe. The reason for choosing the two channels in the prefrontal lobe is that some studies have shown that the combined acquisition of signals in the frontal and occipital lobes can increase the amplitude of SSVEP [17]. The image of the actual EEG electrode installation and mapping system is shown in Fig.4.

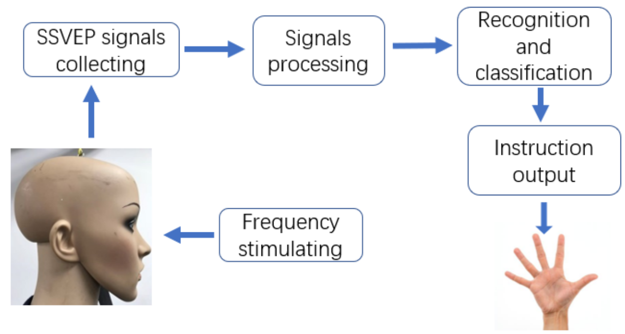

Fig. 3 The structure of the prosthetic hand system based on SSVEP.

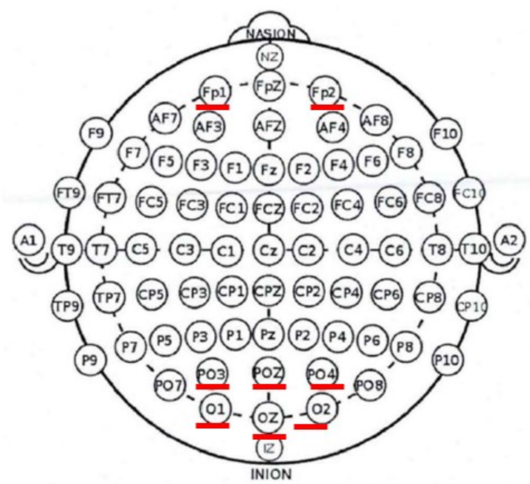

Fig. 4 The structure of the prosthetic hand system based on SSVEP.

C. EEG Signals Process

The original EEG signal data is transmitted to PC through Wi-Fi. The sampling frequency is 250 Hz. The main algorithm based on EEG signal runs on PC. The initial data processing, including EEG signal filtering and notch processing, are carried out in MATLAB. The time of EEG signal processed in the experiment is 4 seconds, that is to say, the total number of data sample points is 1000.The collected EEG signals need to be processed. Firstly, they need to be filtered. Then, a notch filter is used to eliminate the interference of 50 Hz power frequency.

D. EEG Analysis Method

1) Power Spectral Density Analysis (PSDA)

One method for EEG signal analysis is PSDA [18]. However, the PSDA method can only carry out single channel analysis, and is unstable. Because the EEG signal is unstable, the peak value cannot be detected every time by single channel analysis, and the effect is not very ideal. As shown in Fig.5 below. The PSDA method is not used in this experiment.

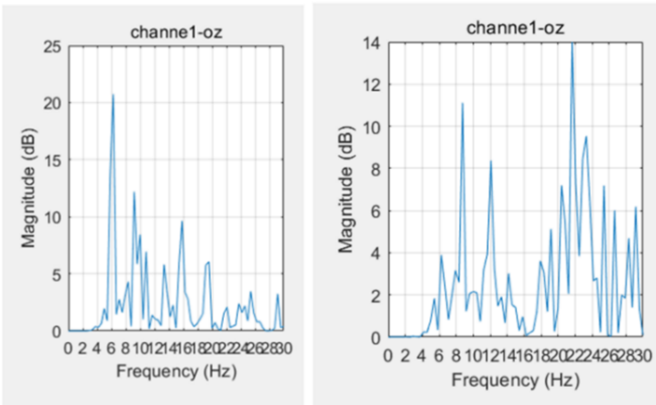

Fig.5 Result of EEG analysis by PSDA

2) CCA

Another method is CCA [19]. As shown in Fig.6 below, CCA is an analytical method for calculating the linear relationship between two sets of multivariable data. In the SSVEP system, two groups of multi variables are SSVEP signal X and reference signal Y related to the artificial stimulus frequency f on the display screen. The maximum correlation coefficient between X and Y was obtained by CCA analysis. The frequency corresponding to the maximum correlation coefficient was considered as stimulus frequency. SSVEP signals can be classified by using 8 channels acquisition signal and CCA method.

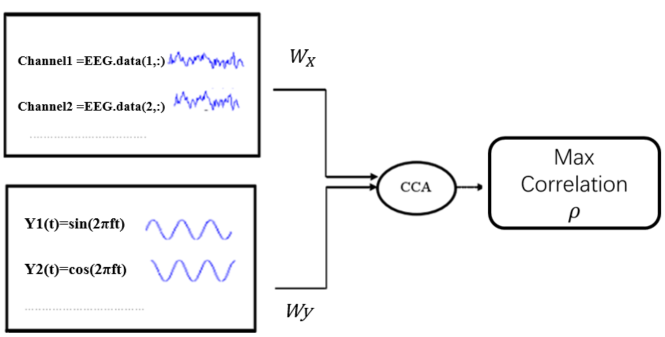

Fig.6 Structure of CCA algorithm.

3) Choice for EEG Signals Analysis

Compared with the PSDA method based on fast Fourier transformation (FFT) algorithm, CCA algorithm can analyze the relationship between multiple channels and stimulus reference signals, overcome the shortcomings of single channel spectrum anti-jamming ability, and achieve higher accuracy. Finally, CCA is chosen to classify SSVEP signals. If the frequency of the corresponding stimulus is detected, instructions are sent to the motor of the hand to control the different movements of the hand.

IV. Experiments And Result

A. sEMG Experiment

In the elbow joint control scheme experiment based on sEMG, a healthy subject join in, and sEMG sensors were attached to biceps and triceps respectively. The motion sensor was then attached to the upper arm and forearm. After calibration, the subjects were allowed to flex and extend elbow joint randomly. Fig.7 shows the sEMG experiment. The experimental time was 3 minutes.

Fig.7 sEMG experiment.

Fig.8 shows part of sEMG signals, we can get nothing without processing them. After the experiment, the sEMG signals are processed, and then the BP neural network is used to train with the angle. Then a processed sEMG signal is used to detect the elbow joint.

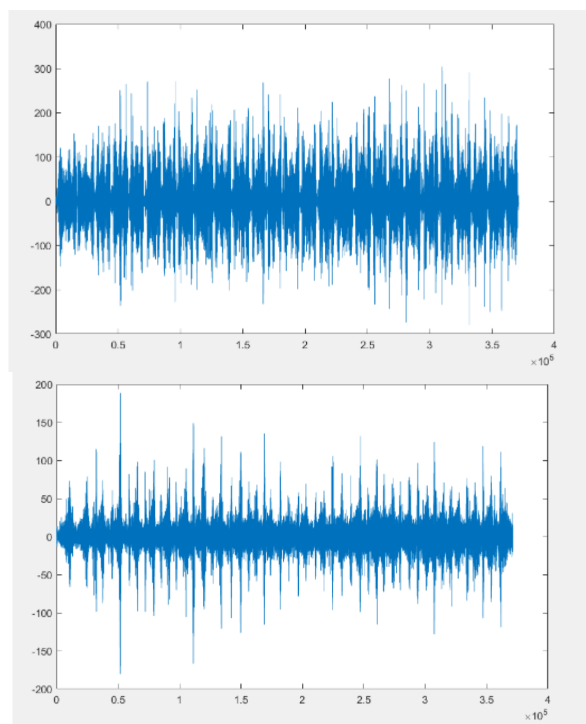

Fig.8 sEMG signals of biceps and triceps.

B. sEMG Result

According to the prediction result of BP neural network, as shown in Fig.9. It shows the result of the subject. The elbow joint control scheme based on sEMG signal can predict the elbow joint angle of prosthetic limb which is close to the actual elbow joint angle of the subjects. The validity of the experimental method can be proved.

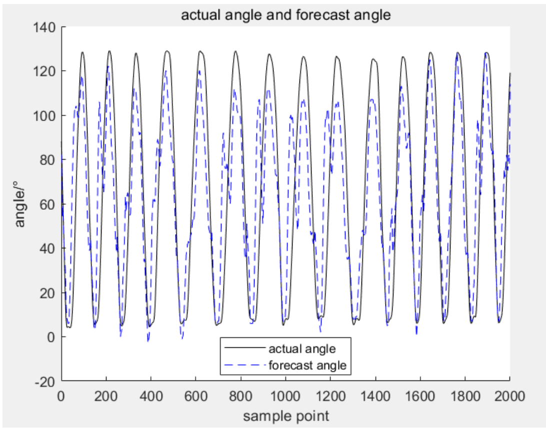

Fig.9 Actual elbow angle and forecast eblow joint.

C. EEG Experiment

In the EEG signal prosthetic hand control scheme experiment based on SSVEP, three healthy eyesight subjects, average 24 years old, took part in the experiment voluntarily. The subjects need to clean the scalp first, keep the scalp clean, and wear an electrode cap with eight electrodes. The positions of eight electrodes are as mentioned above. The experimental environment requires darkness and quietness, and the subjects should remain focused and undisturbed. The interference of 50Hz power frequency should be avoided during the experiment. The subjects sat 0.5 meters away from the stimulus source and focused on the different stimulus frequencies of LCD. There are four frequencies in the experiment: 6 Hz, 8 Hz, 10 Hz and 15 Hz. As showing in Fig10, a subject was doing the EEG experiment.

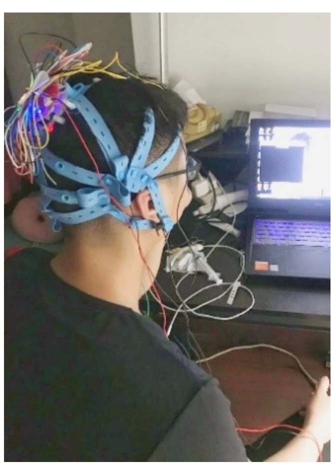

Fig.10 EEG experiment.

The EEG experiment is divided into four groups, corresponding to four frequencies. Each group was conducted 10 times, each experiment lasted 5 seconds, that is, the subjects needed to watch the stimulus for 5 seconds, avoiding blinking as much as possible and keeping focus during the experiment. According to the collected EEG signals directly, nothing can be observed, as showing in Fig.11.

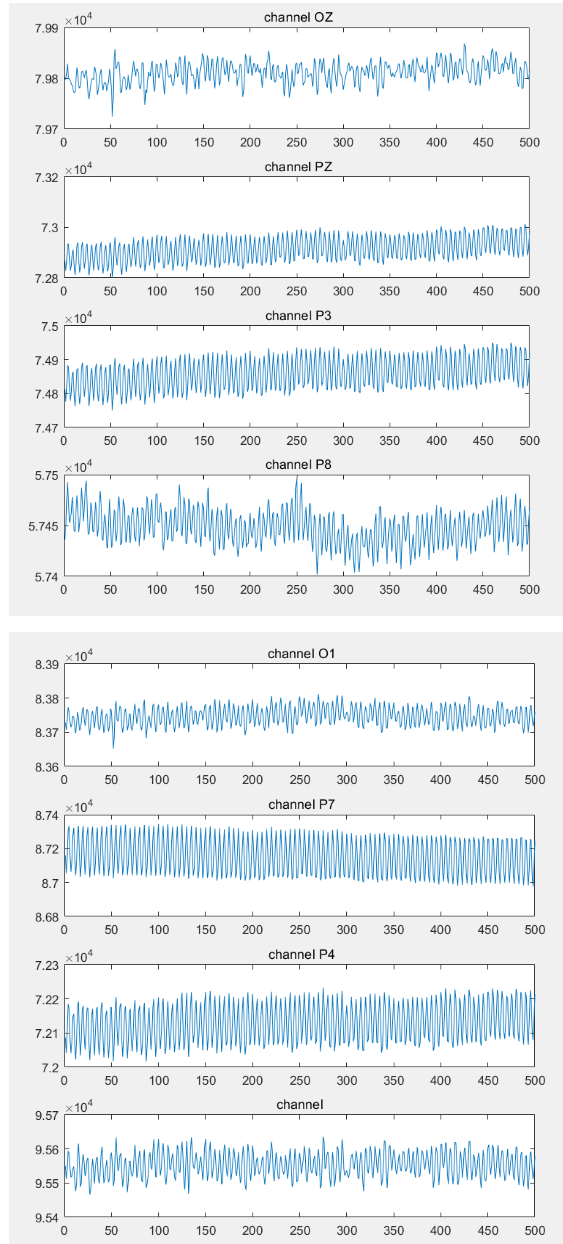

Fig.11 8-channel EEG signals.

D. Results of CCA

The results of CCA algorithm are shown in Fig.12. The frequency corresponding to the maximum correlation coefficient, 6Hz, is the stimulus frequency. CCA algorithm is applied to 8-channel SSVEP signals and reference signal with 4 frequencies. The frequency corresponding to the maximum correlation coefficient is the stimulus frequency. For the accuracy of classification, a threshold is set for the maximum correlation coefficient, and the maximum correlation coefficient below the threshold is identified as no stimulus. That is, no operation will be performed.

The experimental results are shown in Table I below. In the three subjects, the experimental results vary from person to person, so the threshold setting is also different. There are many reasons for inaccurate results. First, each subject's physical condition is different, too long time gazing at the stimulus source will lead to visual fatigue. Second, the interference of the surrounding environment, the surrounding environment is not unchanged. Thirdly, the electrode cap, the dry electrode used in this experiment, which is not as stable as the wet one. Although the accuracy needs to be improved, the results show that CCA algorithm is effective for SSVEP signal classification.

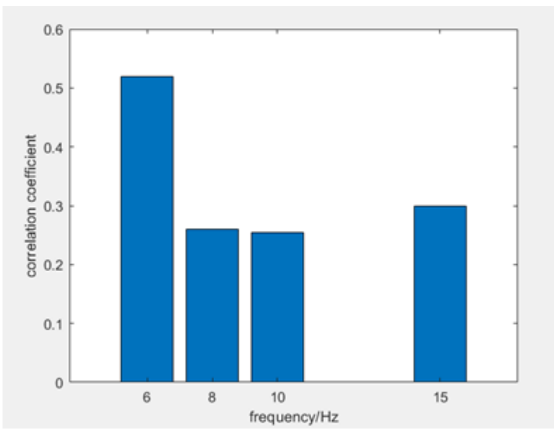

Fig.12 One result of CCA algorithm.

TABLE I
CCA ALGORITHM ACCURACY OF THREE SUBJECTS

Accuracy	6Hz	8Hz	10Hz	15Hz
Subject1	90%	75%	85%	60%
Subject2	80%	70%	85%	100%
Subject3	90%	80%	100%	60%

V. CONCLUSION

In this paper, a trans humeral prosthesis control method combining sEMG and EEG signals is proposed. This method is totally non-invasive, and absolutely safe for the user. Elbow movement is controlled by sEMG signals of biceps and triceps. BP neural network is used to predict elbow motion angle from sEMG signals. The EEG signal based on SSVEP is used to control the movement of prosthetic hand, and CCA algorithm is used to classify the SSVEP signals, and a simple and effective threshold method is set up to improve the accuracy of classification. After classifying different SSVEP signals by CCA algorithm, different instructions can be sent to hand controller (4 SSVEP signals in this paper, then 4 instructions can be sent to the hand controller, make it do 4 different actions). The experimental results show that the scheme can predict the angle of elbow joint in motion, and the CCA algorithm can classify SSVEP signals at a certain stimulus frequency, which proves the effectiveness of the control method.

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