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Control of A Lower Limb Exoskeleton Robot by Upper Limb sEMG Signal

Shuxiang Guo[1,2] and Yibin Ding[1]
[1]*Tianjin Key Laboratory for Control Theory & Applications In Complicated systems and Intelligent Robot Laboratory Tianjin University of Technology No.391,BinshuiXidao,Xiqing District,Tianjin,300384,China guo@eng.kagawa-u.ac.jp;1072867852@qq.com*

Jian Guo[1*]
[2] *Department of Intelligent Mechanical System Engineering Faculty of Engineering Kagawa University Takamatsu,Kagawa,Japan*
**corresponding author: jianguo@tjut.edu.cn*

***Abstract* –In this paper, a lower limb exoskeleton robot based on upper limb sEMG signal controlledby designed for patients with lower limb functional injury in the middle and late stage of rehabilitation. It realized the patient's active and random control when wearing the lower limb exoskeleton for rehabilitation training. It solved the problem that the lower limb sEMG signal strength of patients with mobility difficulties leads to low acquisition accuracy, and the lower limb space of patients with wearing exoskeleton robot was compacted, which was inconvenient to collect sEMG signal. In this paper, three kinds of gait, which are static, normal walking and high leg lifting to avoid obstacles, are preliminarily formulated, and controlled by three different upper arm movements. This paper first introduced the research status at home and abroad. Then the principle and characteristics of sEMG signal are studied. Then the surface EMG signal was preprocessed and features were extracted, and the Angle prediction model was established by BP neural network. Finally, it is analyzed and verified by our experimental platform.**

Index Terms - EMG signal, Active control, Angle prediction model.

I. INTRODUCTION

With the continuous improvement of the quality of life of our people, the phenomenon of aging population is becoming more and more serious, which brings great pressure and challenges to the development of medical care, pension and economy. The elderly's limb function will gradually decline with the increase of age and the decline of physical function, which leads to the increasing number of elderly patients with hemiplegia and disability. Relevant studies show that for most patients with stroke caused by moderate diseases, the more reasonable and effective rehabilitation training is carried out as soon as possible, the more likely the patients' limb motor function will be improved or even recovered. However, the traditional rehabilitation treatment requires rehabilitation physiotherapists to carry out one-to-one repetitive rehabilitation training for patients, which has many problems such as low rehabilitation efficiency and high rehabilitation cost. At the same time, China's limited medical resources, a small number of rehabilitation physiotherapists and expensive rehabilitation equipment lead to many patients can't get effective rehabilitation treatment and miss the best opportunity of rehabilitation treatment. Rehabilitation robot technology is developed to solve the problems and pain points in the process of traditional rehabilitation treatment, and has great potential in improving rehabilitation efficiency and treatment effect. In addition, many lower limb rehabilitation equipment is mainly used to assist patients in passive lower limb training in practical clinical application, which can't provide adaptive auxiliary training according to the rehabilitation status of patients' lower limbs. It is easy to cause patients fatigue or even secondary injury in the training process, and the rehabilitation training time is long and the effect is poor. Therefore, in order to better assist patients with lower limb rehabilitation training, it is of great social value and significance to study how to improve the effect of patients' active motion intention in the control system of lower limb rehabilitation robot, and realize the interactive collaborative control between lower limb rehabilitation robot and patients [1].

In the 21st century, with the rapid development of robot technology and automatic control technology, exoskeleton robot has entered a new stage of development. Foreign research on rehabilitation robot began in the 1980s. The United States, Germany, Japan, Israel and other countries are at the leading level in the world. The most representative is the exoskeleton assisted robot developed by the laboratory of Tsukuba University in Japan. Its comfort assisted control system takes the EMG signal sensor as the control input signal. When the sensor detects the EMG signal, the controller immediately analyzes the force required by the wearer to complete the target movement, and then analyzes the quantitative assistance provided by the exoskeleton. The representative of domestic wearable lower limb rehabilitation robot is the wearable exoskeleton robot designed by Shenzhen Institute of advanced technology, Chinese Academy of Sciences. Through the combination of under structure driving structure and EMG signal sensing technology to ensure the coordination between the wearer and the exoskeleton; based on the gait analysis of exoskeleton four legged crutches, the appropriate gait trajectory is obtained through continuous correction calculation, and the patient's gait planning is realized [2]-[4].

The following is the arrangement of this paper. The second part is the introduction of the experimental platform and the principle and characteristics of sEMG signal. The third part is the pretreatment and feature extraction of sEMG signal. The fourth part is the action classification by BP neural network. The last part is the experiment and conclusion.

II. Hardware Platform And Principle Introduction

A. Overall structure

Our exoskeleton structure is divided into five parts: drive module, back plate, waist link, thigh and calf. The foot structure is completed by other students in our group. Because it is only in the experimental stage at present, only the complete structure of one leg has been fabricated to verify the accuracy of the theory, as shown in Fig.1 [5]-[7].

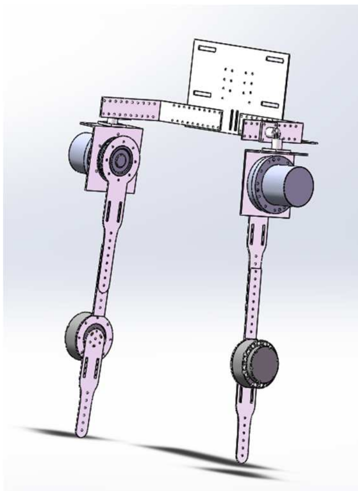


Fig. 1 Exoskeleton structure of lower limb

Safety and comfort are fully considered in the connection of all parts. According to the range of motion of human joints, the limiting device of joints is designed. The connecting part of the leg and the waist is also provided with a connecting rod structure, which has a certain range of adjustment. To meet the requirements of most wearers. The edge of the whole structure is arc structure, which further improves the safety of the structure and makes the appearance more beautiful. sEMG acquisition equipment is the instant noodle electromechanical instrument of Anhui Eli technology intelligent as shown in Fig.2. The device supports 8-channel wireless transmission, has large storage capacity, and the wireless transmission rate is 19.2kb/s. It is portable and portable. At the same time, it can analyze a variety of frequency and time domain characteristics, including median frequency, average power frequency, zero crossing rate, spectrum area, muscle activity time and muscle attack time [8][9].

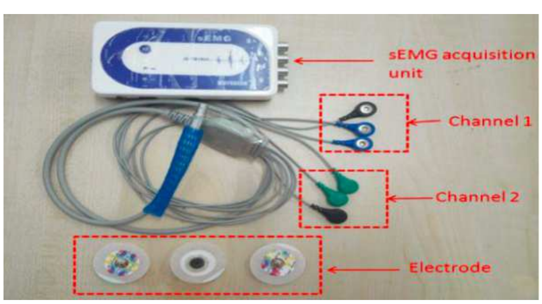


Fig. 2 EMG acquisition equipment

B. Principle of sEMG signal generation

sEMG signal is also called sEMG, which can be generated in any tissue and organ, which is usually a function of time and amplitude, frequency and waveform. Myoelectric signal is a bioelectrical signal which is produced by muscle contraction. The sEMG signal on the skin surface is called sEMG. The essence of sEMG is the sum of local electric fields formed by a cluster of motion units, which contains the information of human motion. It is an important direction to understand the characteristics of others by decoding sEMG and then to give the machine the ability to understand the human motion intention. As shown in Fig.3, the central nervous system first produces a set of pulse electrical stimulation, and then transmits to the muscle fibers to form a set of potential responses. When the response exceeds a certain threshold, myofibroblasts are activated, producing an action potential and transmitting along the muscle fibers to both ends, stimulating all muscle sections connected with the muscle fibers, which shortens them, namely, the completion of a muscle contraction. Through the study of the central nervous control system of human body, it can be found that with the increase of the frequency of electrical stimulation pulse of muscle fiber, muscle contraction will continue to increase, and the external strength will be continuously enhanced. According to the relevant research, the contraction of muscle shows that there is a certain non-linear positive correlation between muscle fiber electrical stimulation and muscle force. Muscle electrical signals can not only reflect the degree of activation of muscle stimulation, but also reflect the size of muscle force. The bandwidth of the sEMG signal is generally 0.5-2 kHz, the amplitude is mainly concentrated in 0-1.5 mV, and the time history of one action potential is generally within 5-20 ms, and the main energy is concentrated in the range of 10-200 Hz. Because the sEMG signal is the superposition of a large number of muscle fiber action potentials on the skin surface, its waveform is more complex and has more noise. After skin filtration and external environment interference, sEMG signal is often weak voltage signal, and the signal-to-noise ratio is relatively low. The sEMG signal can be collected by attaching the electrode to the skin surface, and it will not cause harm to the human body and the user will not feel pain. The method has good safety and relatively high comfort, and can be worn for a long time [10].

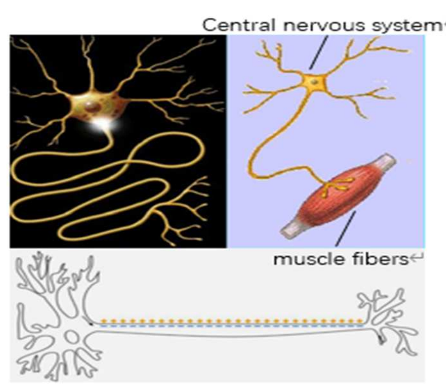


Fig. 3 Generation of sEMG signal

C. Introduction of muscle

The human upper limb is composed of bone, joint and skeletal muscle. Bone and joint constitute the skeleton supporting the whole body. These movements are the compound movements of multiple degrees of freedom coordinated by shoulder joint, elbow joint and wrist joint. When the upper limb is performing the corresponding action, each action is a single joint movement or a compound movement of multiple joints, which is dominated by different muscle groups, and the participation of each muscle group in different upper limb actions is also different. The main muscles involved in upper limb movement are pectoralis major, biceps brachii, triceps brachii, deltoid and brachioradialis. Their functions in each movement mode are shown in Table 1. The experiment shows that biceps brachii and brachioradialis brachii have higher accuracy in distinguishing arm throwing and arm lifting. sEMG signals of these two muscles are collected as input signals of BP neural network [11].

TABLE I
THE ROLE OF DIFFERENT MUSCLES

Motion joint	Motion mode	Corresponding muscle
Shoulder joint	Adduction	Pectoralis major, Deltoid
	Abduction	Deltoid,Triceps
	Front swing	Pectoralis major, Triceps
	Back swing	Triceps,Supraspinatus
Elbow joint	Flexion	Biceps, Brachioradialis muscle
	Extension	Triceps

III. PRETREATMENT AND FEATURE EXTRACTION OF SEMG SIGNAL

A. Pretreatment

Because the intensity of sEMG signal itself is very weak, it is easy to introduce other noises in the process of acquisition, such as power frequency interference, inherent noise of acquisition equipment, and other biological signal noises such as electrocardiogram signal. The introduction of a large amount of noise will seriously affect the accuracy of sEMG signal analysis and motion control. Therefore, in addition to minimizing the acquisition error in the process of sEMG acquisition, it is necessary to further process the collected sEMG signal [12][13].

This paper preprocesses the sEMG signal according to the common forms and characteristics of noise interference, including band-pass filtering, power frequency removal and harmonic interference.

Firstly, a notch filter is used to deal with the 50 Hz common frequency interference caused by the power supply. The principle of notch filter is band stop filter. The blocking frequency is set to a small distance near the notch. Taking biceps brachii as an example, the frequency domain of the signal processed by the 50 Hz notch filter is shown in the Fig.4. The green curve is the original signal, and the black curve is the filtered curve. It can be seen that the noise of the processed signal is obviously reduced [14][15].

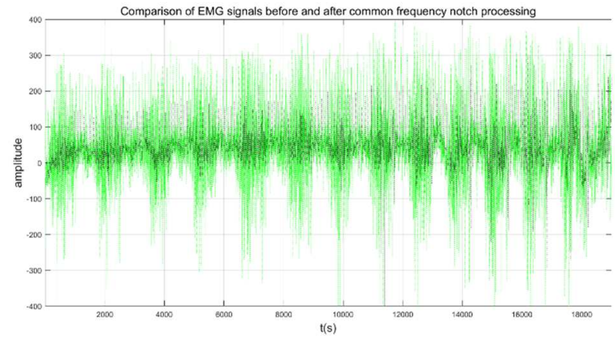


Fig. 4 Signal after frequency notch of biceps brachii

Then, since the effective signals of sEMG signal are basically concentrated in 10-200Hz, Butterworth band-pass filter is used for further processing to remove the noise of other bands. The processed muscle signal is shown in the Fig.5.The red curve is the curve after pretreatment. Compared with the original signal, the time-domain waveform of the pretreated sEMG signal is smoother, and the signal energy is mainly concentrated in 10-200Hz.

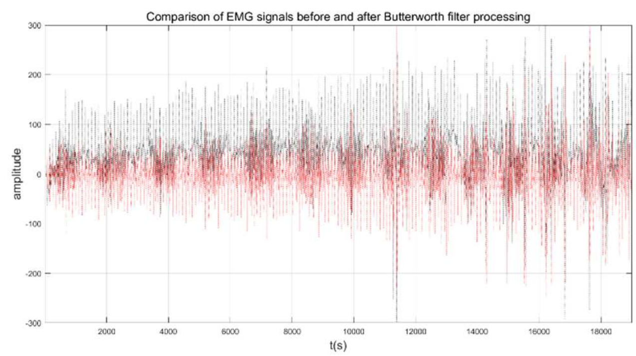


Fig. 5 Signal processing of biceps brachii Butterworth band pass filter

B. Feature extraction

sEMG has the characteristics of non-stationary signal, so it is difficult to obtain enough information from a single channel for gesture recognition in this application scenario, so it is necessary to collect data from multiple channels as recognition signals. If all the signals of the whole active segment are used as input for recognition and extraction, it is a heavy workload and difficult to achieve. Feature extraction can not only compress the dimension of feature space, but also distinguish the differences of feature signals corresponding to different gesture actions, and highlight their significance, so as to improve the recognition rate of the classification system. Therefore, we need to use the feature extraction method to extract the characteristics of a group of signals for data description, so as to more effectively classify and identify, which is the main target of feature extraction [16].

At present, the characteristics of sEMG signal can be analyzed in time domain or frequency domain. Considering that the sEMG signal can reflect the muscle force information better in time domain and has high real-time performance, this paper uses the time domain eigenvalue analysis of sEMG. In this paper, four time-domain features with large discrimination are selected: absolute mean value, root mean square value, integral sEMG value and wavelength.

Their expressions and physical meanings are as follows:

The absolute mean represents the mean value of sEMG signal in a certain period of time. The expression is as follows:

$$aEMG = \frac{1}{N}\sum_{i=1}^{N}|x(i)| \qquad (1)$$

Root mean square value reflects the energy of myoelectric signal in a certain period of time. The expression is as follows:

$$RMS = \sqrt{\frac{1}{T}\int_{t}^{t+T} EMG^2(t)dt} \qquad (2)$$

The integral sEMG value reflects the intensity change of sEMG signal with time.The expression is as follows:

$$iEMG = \frac{1}{N}\sum_{t=1}^{t+T}|EMG(t)|dt \qquad (3)$$

The wavelength reflects the cumulative length of the wave in a certain period of time. The expression is as follows:

$$WL = \frac{1}{N}\sum_{i=1}^{N}|x(i+1) - x(i)| \qquad (4)$$

Finally, the feature extraction of sEMG data is carried out by sliding window method. The length of the window is 500ms and the sliding distance is 50ms. The following waveform is obtained.

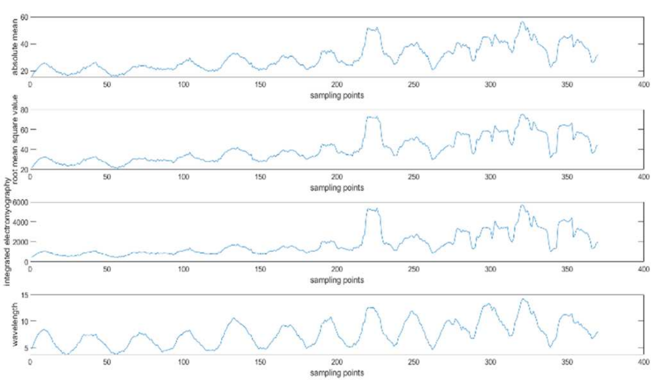


Fig. 6 Feature extraction results of biceps brachii

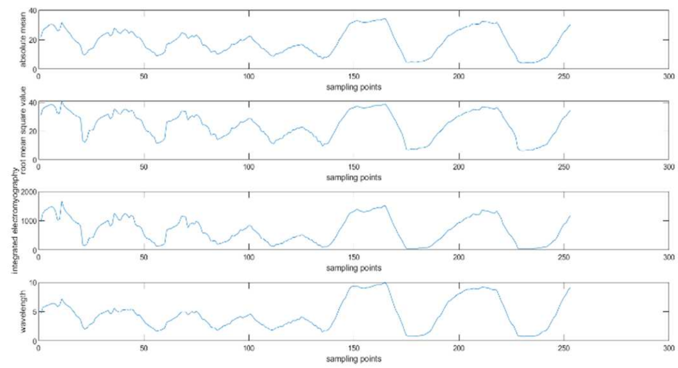


Fig. 7 Feature extraction results of brachioradialis

Ⅳ.Action Classification

In this paper, BP neural network is selected to establish the angle prediction model. Its propagation direction is one-way propagation, which belongs to multi-layer forward feedback network. Back propagation algorithm is used to train the network. The layer of BP neural network can be divided into three types, namely input layer, hidden layer and output layer. There is a complete connection between layers, but there is no connection between neurons in each layer. A three-layer BP neural network can realize any mapping from n-dimension to m-dimension, so this paper selects three-layer BP neural network to build angle estimation model [17].

The number of nodes in the input layer is determined by the number of channels of sEMG signal. The experiment shows that the absolute average value and wavelength of the two muscles collected have the highest degree of discrimination for the two arm movements set. Therefore, the absolute average value and wavelength of each muscle are selected as the input signal of BP neural network, which has four input nodes. The number of nodes in the output layer is determined by the number of actions to be classified. In this paper, it is initially set to classify the arm lifting and arm throwing actions, so the number of nodes in the output layer is 2. There are many choices for the number of hidden layer units, but the choice of the number has a great impact on the network performance. Its selection needs to be determined according to the problem to be studied, the number of nodes in the input and output layer, the designer's experience and many experiments. Finally, the number of nodes selected in this paper is 8 [18].

sEMG signal can accurately reflect the degree of contraction of related muscles, and then predict the corresponding action through sEMG signal. After preprocessing and feature extraction, the collected original signal is taken as the input data, and the corresponding two actions are replaced by 0 and 1 as the output data to the BP neural network. After training, the BP neural network model which can predict the joint angle can be obtained. The flow chart of joint angle prediction based on sEMG signal is shown in Fig.8.

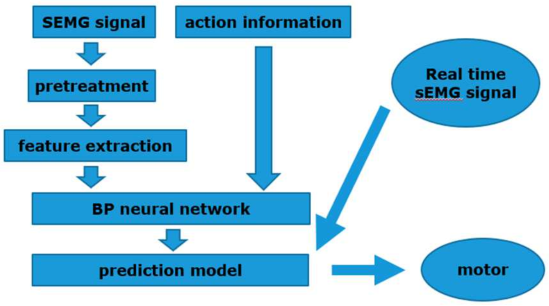


Fig. 8 Control process

In this paper, two kinds of motion states are initially set, which are normal walking gait and high leg lifting gait, corresponding to normal arm swing and arm lifting. When the left arm swings, the motors at the four joints cooperate with each other to complete a gait movement followed by the left leg after the right leg moves forward; when the right arm swings, the left leg moves forward and the right leg follows; when the same wearer lifts the arm, the wearer carries out a gait movement of high leg lifting across obstacles or up steps [19].

In the experiment, sEMG signals of 10 healthy subjects aged 20-50 were collected, including 5 males and 5 females. sEMG signals of their right upper limbs were collected to simulate the clinical rehabilitation process of hemiplegic patients. Each subject was in good health, full of rest, no muscle fatigue and relaxed. Before collection, 75% alcohol was used to wipe the surface of the muscle group to remove the dirt and enhance the conductivity. After waiting for the skin to dry naturally, the sensor was pasted on the right upper limb of the subject according to the muscle group position selected above.

During the collection, considering the influence of long-time muscle fatigue on the experimental data, each subject repeated each action 10 times, with an interval of about 3 seconds. In order to facilitate the extraction of active segments, 2-3 seconds of idle time is reserved before and after each action, and the time to complete a complete action is about 7-8 seconds. Fig.9 shows the signal acquisition site of two types of actions.

Fig 9 Collection of subjects' sEMG signal

After the sEMG signal acquisition experiment, 650 groups of data were obtained by feature extraction, 500 groups of each action were used for classifier training, and the other 150 groups were used for test experiment. The experiment shows that the absolute average value and wavelength of the two muscles collected have the highest degree of difference between the two arm movements, so these two features are selected as the input signals of BP neural network. The output signal is set to 0 and 1, corresponding to normal walking and obstacle avoidance gait respectively. The classification results are shown in Fig.10.It can be seen that basically two kinds of actions can be distinguished accurately. If the output result is set to be greater than 50%, it is regarded as the arm lifting action, otherwise it is the arm throwing action. Therefore, even if a few results are not very accurate, it will not affect the subsequent control of the motor.

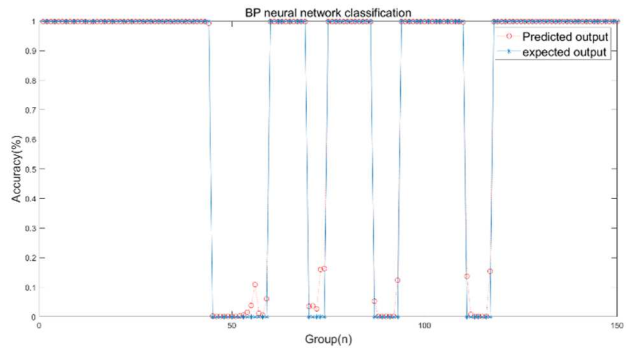
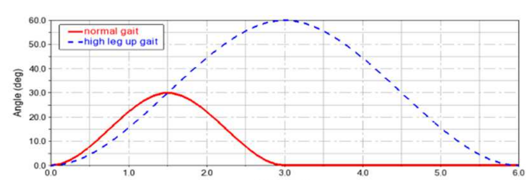


Fig. 10 The classification results of two movements

V.EXPERIMENTS AND RESULTS

Finally, the theoretical method is combined with the experimental platform to carry out preliminary experimental verification, and the knee joint elevation is used to replace the normal walking gait with knee joint elevation of 30 degrees, and the knee joint is raised 60 degrees instead of the high leg lifting gait. Because the risk of patients with lower limb dysfunction participating in the experiment, healthy young men were selected as subjects. The experimental process is shown in Fig.11.

(a)Normal gait (b)High leg up gait



(c) The motion curves of the two gaits

Fig. 11 Switching experiment of two kinds of gait

The real-time data collected by sEMG sensor is imported into the BP neural network model trained by Matlab. When the output of neural network is less than 0.5, it is considered that the normal gait should be performed at this time, and the corresponding control signal is sent to the MCU through USART serial port. When the output is greater than 0.5, the high leg lifting gait is performed. After repeated experiments, it is found that the neural network can effectively classify the arm swing and arm lift, and then control the motor to execute the corresponding gait. However, due to the instability of the real-time sEMG signal, there are a few cases of classification delay, that is, the whole arm lifting action is judged as arm lifting after it is executed, and the real-time performance will be affected to a certain extent. It is necessary to further optimize the classification algorithm to improve the real-time control.

Ⅵ.CONCLUSION

This paper mainly designed a lower limb exoskeleton robot based on the upper limb sEMG signal control, which changed the traditional control method, solved the problem that the lower limb sEMG signal strength of hemiplegic patients was weak and affected the classification effect. And also solved the problem that the lower limb space was insufficient after wearing the lower limb exoskeleton robot, which was not easy to collect the sEMG signal. The angle prediction model of BP neural network based on sEMG signal was established, and the corresponding mode of upper limb movement and gait movement was designed. The real-time performance and accuracy of motion prediction based on sEMG signal were verified by experiments. Through this control method, the human-computer interaction ability was greatly improved, and the rehabilitation enthusiasm of patients was increased. Although the project has achieved the expected goal and achieved certain research results, there is still a lot of work to be further improved: on the one hand, it is necessary to carry out further experimental design and verification for patients with lower limb dysfunction who are really in the middle and late stage of rehabilitation; on the other hand, the reaction time of gait switching and the classification accuracy of sEMG signal need to be improved.

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