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Design of Control System for Lower Limb Rehabilitation Robot on the Healthy Side sEMG Signal

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***Abstract* - With the number of stroke patients increasing year by year, rehabilitation exoskeleton robot has been paid more and more attention. For the rehabilitation exoskeleton robot, human-computer interaction ability is an important index, which affects the effect of rehabilitation therapy to a great extent. Surface Electromyography (sEMG) signals are the combined effect of sEMG signals and electrical activities on nerve stem on the skin surface, which can reflect neuromuscular activities in advance and can be used to predict movement intention by sEMG signals. Therefore, this article proposes to use sEMG signals to monitor the motion information of the healthy leg in real-time, extract the characteristics of the electromyography signals, use the sEMG of the healthy leg as the control signal, reflect the motion patterns reflected by the sEMG collected from the healthy side, and then use the motion intention recognition method of Long Short Term Memory(LSTM) neural network to identify the motion intention of the prosthetic limb by identifying the motion patterns of the swing phase of the healthy side. The results indicate that the predicted maximum Root Mean Squared Error(RMSE) is 5.3729, which proves the feasibility of using LSTM model for motion intention recognition and contributes to the real-time and accuracy of lower limb exoskeleton rehabilitation.**

Index Terms - Machine learning, surface EMG signal, active rehabilitation training

I. INTRODUCTION

Social progress and the rapid development of science and technology make people's living standards continue to improve, the average life expectancy is becoming longer and longer, followed by the human society slowly into the aging stage. Along with the increase in the elderly population, the number of patients with chronic diseases is also on the rise. Stroke is highly disabling, and the most common dysfunction is the decline of motor function. Within 1 week after the onset of the disease, 13% ~ 86% of patients have one limb paralysis, 73% ~ 77% of patients have difficulty walking, which significantly reduces people's quality of life[1]. Motor dysfunction after stroke due to the damage of the central nervous system, the motor system lost the control of the upper center, resulting in the release of the originally inhibited lower motor neurons, the performance of the side limb muscle tone abnormalities, muscle strength decline, coordination disorders between muscle groups, movement disorders.

Lower limb exoskeleton robot can provide auxiliary power for human walking, especially for the elderly or people with gait disorders. One of the key problems in rehabilitation exoskeleton control is to predict the appropriate rehabilitation trajectory for the wearer[2]. Predefined trajectories are usually pre-recorded from healthy people, or inferred from gait analysis data profiles, and played back on the exoskeleton. However, most pre-recorded gait trajectories are usually irrelevant to the wearer, and in fact it is not appropriate to impose an exoskeleton gait that is irrelevant to the wearer's gait profile. Even if the exoskeleton gait helps the wearer walk, it is not the best and appropriate gait for the wearer. Lower limb amputation can not only affect the body's mobility, but also affect the body's health status after amputation. Lower limb amputation often causes the amputee walking gait is not normal, and the abnormal gait is easy to cause sports injury[3]-[4]. For example, patients with unilateral thigh amputation use crutches to walk with the healthy leg after healing. Due to the asymmetry of body weight, the whole body weight of patients is often borne by the healthy limb, which will lead to the injury of the healthy bone and joint, thus further worsening the mobility of amputees. In addition, the stump is subjected to the force of the prosthesis receiving cavity for a long time, which is easy to cause the skin and muscle injury of the wearing site, resulting in infection and deterioration of the condition of the amputation site.

In order to solve the shortcomings of traditional rehabilitation training, a rehabilitation training system with various rehabilitation training modes, accurate and effective control strategies, and rich biological information and feedback signals is needed. The lower limb rehabilitation robot can well meet these conditions. The lower limb rehabilitation robot can set up appropriate rehabilitation training methods one on one according to the actual situation of patients, provide different schemes for the whole cycle, and do a good job in data recording and patient status monitoring[5]. At the same time, the combination of virtual technology greatly improves the awareness of patients' active participation in the process of rehabilitation training and the interest of practice.

The research of rehabilitation robot began in the 1960s at the earliest. Through continuous development and research, its structure design, control strategy and multi-information fusion technology have been greatly improved and enhanced. The United States, Germany, Japan, Israel and other countries are leading the world. The most prominent example is an exoskeleton-assisted robot developed in a laboratory at the University of Tsukuba in Japan[6]. HAL is a wearable exoskeleton robot developed by the University of Tsukuba in Japan for therapeutic and nursing purposes. In addition, the robot system is equipped with an active drive device composed of a harmonic reducer and a DC motor in the hip joint, knee joint and ankle joint, as well as a surface EMG sensor and a surface reaction force sensor[7]. HAL has a bio-conscious control mode, which uses surface EMG sensors to determine the body's motion intentions and thus controls the lower extremity exoskeleton to move according to the user's intentions, and an autonomous control mode, which uses ground reaction forces sensors placed under the foot. Combined with the motion intention judgment algorithm based on the change of the user's center of gravity, the exoskeleton movement is controlled.

The following is a collation of this article. The second part introduces the principle and characteristics of experimental platform and surface EMG signals. The third part is the preprocessing and feature extraction of surface EMG signals. The fourth part is action classification based on LSTM neural network. The last part is experiment and conclusion.

II. Surface EMG Signal Acquisition

A. Principle of surface EMG signal generation

Surface EMG signal is an extremely weak bioelectrical signal, but it contains a lot of motor information closely related to human activities. It is generated because muscles are stimulated by external information and respond to contraction under stress, and electrical signals are generated[8]. The signals are transmitted to the nerve center of the brain through nerve fibers, and the nerve center captures the signals and feeds back to the muscle to control the behavior of the muscle.

Electromyographic signal is the electrical signal generated by external stimulation of muscles, which brings impulse through nerve endings. After amplification and transmission by acetylcholine, the electromyographic signal is transmitted to muscle joints, forming muscle impulse, stimulating muscle contraction and completing corresponding actions, as shown in Fig. 1. It has been proved by relevant studies that sEMG signals are generated 30ms-50ms before the limbs perform relevant movements. Therefore, sEMG is widely used in the fields of medical rehabilitation and robot control to predict people's motion intentions.

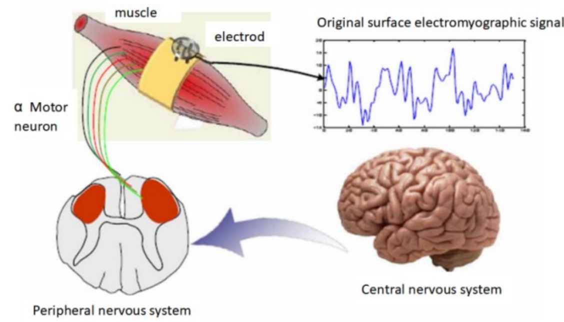


Fig. 1 Schematic diagram of action potential generation

B. Choice of target muscle

Human lower limb movement not only needs the support of bone joints, but also needs various muscles to cooperate with each other to provide power for movement. The joint activity of lower limb transmits nerve signals to the corresponding muscle movement through the cerebral cortex and the central nervous system, and then the movement is realized by the contraction of the skeletal muscle of lower limb. The movement of lower limb joints is mainly coordinated and controlled by four muscle groups, which are: the front thigh muscle group, the back thigh muscle group, the front calf muscle group and the back calf muscle group. The purpose of this study is to study the sEMG signals of each muscle during single joint movement and gait movement and to apply them to intention recognition and joint Angle prediction. The above four muscle groups were fully considered in the collection of lower limb sEMG signals, so four important muscles were selected for signal collection and research, namely, rectus femoris, biceps femoris, tibialis anterior and gastrocnemius[9], as shown in Fig. 2.

Fig. 2 Distribution diagram of muscles in lower limbs

C. Acquisition of EMG signals

The EMG acquisition equipment selected in this paper is the surface EMG instrument of Anhui Aili Intelligent Technology , which mainly includes EMG acquisition instrument, wireless connector, synchronizer, dual-channel EMG cable, electrode, etc, as shown in the Fig. 3. The electromyograph supports the simultaneous acquisition of four channels. Each channel adopts a dual-channel electromyographic cable, which can simultaneously collect the electromyographic signals of eight muscles at a sampling frequency of 1000Hz[10]. Combined with the supporting upper computer software, the measurement template can be developed for each patient, and the preliminary preprocessing function of the surface EMG signal can be completed to suppress the common frequency interference, and a variety of data analysis of the surface EMG signal can be done at the same time.

Fig. 3 Surface EMG acquisition system

The subjects in this experiment did not do strenuous exercise before collection. They cleaned the skin surface at the location of relevant muscles with alcohol to remove surface impurities[11]. Each muscle is collected by three motors, namely, the positive electrode, the negative electrode and the reference electrode, which are pasted around the two target muscles according to the position indicated on the upper computer software. In order to collect single joint motion data, 6 kinds of experimental movements were designed, which were sitting and standing hook, sitting and standing leg lift, front kick, front lift, back kick and back lift. During the experiment, the motion should be kept at a constant speed, and each motion cycle should be kept at about 3s. In the training process, take the ankle rotating outward as an example to collect the surface EMG signals.

III. SURFACE EMG SIGNAL PROCESSING

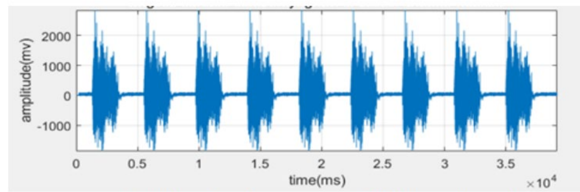
A. Filtering processing of surface EMG signal

In the surface EMG signal acquisition experiment, the surface EMG signal will be interfered due to the changes of the tester and the experimental environment. Since the amplitude of surface EMG signal is weak, the addition of noise will greatly affect the subsequent surface EMG signal analysis results. The filtering method in this paper is Butterworth filtering method, which mainly realizes Butterworth filtering of surface EMG signal through MATLAB software. The formula of Butterworth low-pass filtering is as follows:

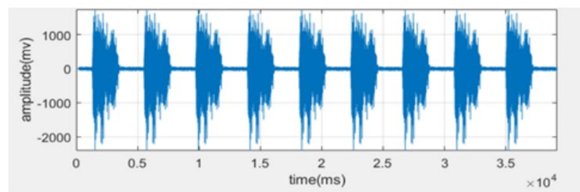
$$|H(j\Omega)^2| = \frac{1}{1+\varepsilon^2\left(\frac{\Omega}{\Omega_c}\right)^{2N}} \quad (1)$$

In the formula, Ω is the filtering order, Ω_c is the cut-off frequency, so that the main frequency of the surface EMG signal is concentrated between 50-350HZ. When $\varepsilon = 1$, the Butterworth bandpass filter attenuates to 3dB at the frequency Ω_c, and N is the system order.

Use Butterworth band-pass filter to de-noise the collected original signal. During the training, take the ankle outward as an example, the collected surface EMG signal can be seen that the waveform of the signal after processing in the time domain is smoother, the noise and burr are significantly reduced, and most of the original surface EMG signal is retained, as shown in Fig.4.In the frequency domain, the noise below 50Hz and high-frequency noise are effectively eliminated, as shown in Fig.5.Which is conducive to the subsequent feature extraction and action classification.

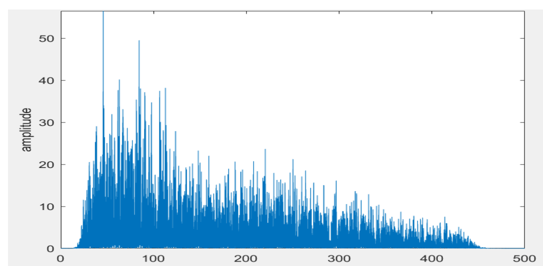


(a)Original surface electromyogram of tibialis anterior muscle

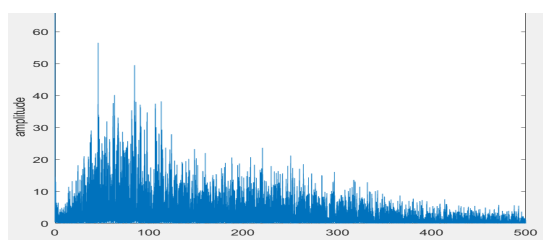


(b)Signal processing of tibialis anterior Butterworth bandpass filter

Fig. 4 Time domain comparison before and after EMG filtering



(a) frequency before filtering of electromyographic signals



(b) frequency of electromyographic signal

Fig. 5 Comparison of frequency domain of surface EMG signal before and after filtering

B. Selection of features

Feature extraction is to further select the features that play a key role in the classification effect, so as to reduce the training time, enhance the generalization ability of the model and prevent the training over-fitting. In this paper, the sliding window method is used to extract the features of surface EMG signals. The selection of window length is particularly important, which directly affects the accuracy of classification. In this paper, 90ms data window length is selected, and each move is 40ms, that is, 50ms overlap time, for feature extraction[12]. In this paper, four eigenvalues, wavelength, variance, root mean square and absolute mean, are selected for analysis.

The absolute mean value represents the average value of the surface EMG signal within a certain time, N represents the length of the sliding window, and represents the surface EMG amplitude of the ith sampling point.

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x(i)| \tag{2}$$

Variance represents the degree of change of surface EMG signal intensity with time, and reflects the intensity of muscle movement.

$$VAR = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \frac{1}{N}\sum_{i=1}^{N}x_i\right)^2 \tag{3}$$

Wavelength reflects the cumulative length of surface EMG signal in a certain time.

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

According to the above expression, four eigenvalues of surface EMG signal can be obtained. In the process of training, take the outward rotation of the ankle as an example to extract the features of the collected surface EMG signal, as shown in Fig. 6.

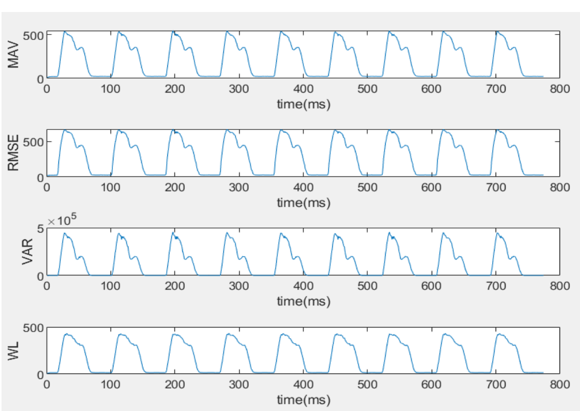


Fig. 6 Surface EMG signal feature extraction results

IV. Intent Recognition Algorithm Based on LSTM

A. Control strategy

Surface EMG can directly reflect the state of muscle contraction with high degree of information, so the strategy adopted in the experiment is to imitate the gait of the healthy leg, use the surface EMG signal to monitor the joint motion information of the healthy leg in real time, extract the characteristics of the surface EMG signal, train the appropriate classification model, decode the movement intention of the healthy side, make the affected side follow the walking gait of the healthy side, and automatically adjust the stride and step frequency of the affected side, The affected side can sense the movement intention of the healthy side and adjust its movement by sensing the ground conditions.

During the data collection, the subjects were required to complete each action with the maximum force possible, and the experimental actions were performed in the order of kicking, squatting and lifting[13]. At the beginning of the experiment, the subjects were required to keep each action for 5s, and perform each action five times. In order to avoid the muscle fatigue caused by the subjects' three actions for a long time, when each action is repeated, the action interval shall be kept at a rest state of 5s.

B. Principle and implementation of LSTM neural network

The intention recognition based on surface EMG can help the exoskeleton control system to identify different motion modes, and to realize the flexible motion following of the lower limb exoskeleton control system, accurate prediction of each joint angle is also required.

As shown in Fig.7,LSTM is a kind of time-cycle neural network, which has the ability of memory and can process and recognize long-distance dependencies. Its main advantage is that it can process extremely complex data sequences, and can learn long-distance correlation without the problem of gradient disappearing or exploding. LSTM network is composed of four parts: input gate, forgetting gate, output gate and unit state. LSTM network can be trained by back propagation to enable it to learn long-distance dependence[14].

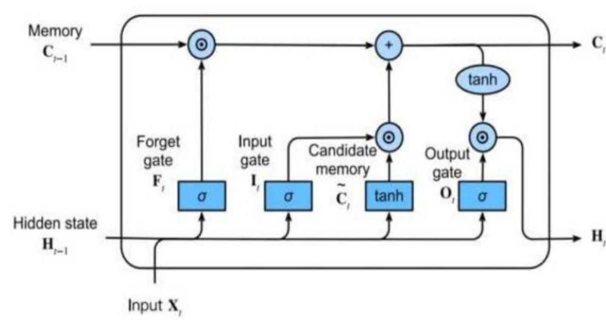


Fig. 7 Schematic diagram of LSTM neural network

Each module of LSTM has a memory unit to store the time c_t of t, and the output h_t of the module is as follows:

$$h_t = o_t \tan h(c_t) \tag{5}$$

Where o_t is the input gate that adjusts the current input x_t and the pre-neuron information h_{t-1}, and its output gate can be calculated by the following formula:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o c_t) \tag{6}$$

Where σ is the $sigmoid$ function, which outputs a value between 0 and 1 to describe how much data can pass through each part. V_o is a diagonal matrix representing the amount of intermediate computation required to compute the output control.

The state information of memory unit c_t is updated by forgetting part of memory unit and adding a new memory unit $\tilde{c}_t$.

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t \tag{7}$$

The new memory unit is calculated as:

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1}) \tag{8}$$

The content of the memory unit is adjusted by the forgetting gate f_t, and the degree to which the content of the new memory unit is added to the memory unit is adjusted by the input gate i_i, whose calculation formula is

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + V_f c_{t-1}\right) \tag{9}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1}) \tag{10}$$

Where, V_f and V_i are diagonal matrices, representing the intermediate computation amount of computational oblivion control and input control, without special meaning.

C. Experiments and results

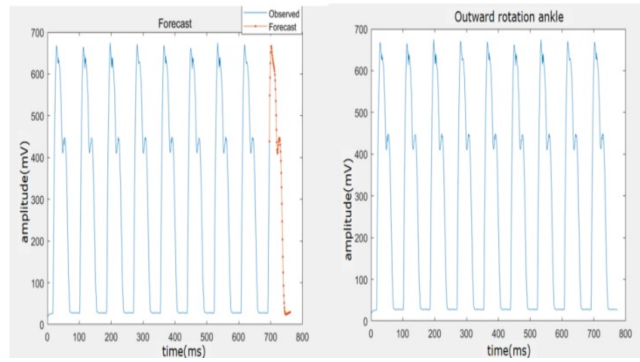
In order to verify the rationality of the designed control method and combine it with the established experimental platform to verify the accuracy of the above control method, this experiment selected 5 healthy young men as the subjects. The experimental steps are as follows:

1. Subjects wear lower extremity exoskeleton, and establish communication between electromyography acquisition device, STM32 control board and upper computer.
2. Wash the skin of the subject's humerus with alcohol, and apply the electrode patch according to the standard collection position indicated by the electromyography collection software.
3. The trained network parameters were loaded into Matlab, the classification program was run, and the exoskeleton was controlled to drive the subjects to walk.

In the experimental scheme, 5 subjects with healthy limbs were invited to wear the exoskeleton structure on their left leg, and the surface EMG signal on their right leg was used as the control signal, and 9 groups of pre-set actions were carried out in cycles. The experiment is shown in Fig.8.

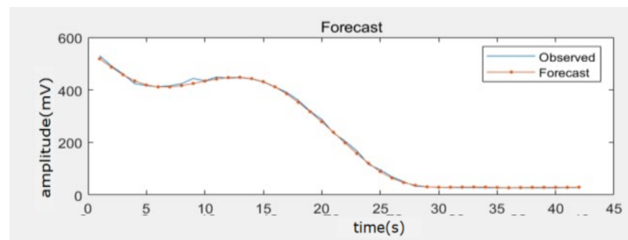
Fig. 8 Rehabilitation training wearing effect picture

According to the time-domain feature extraction results of outward rotation of the ankle, root mean square was selected as the input of the LSTM model to record the accuracy of the results. The expected trajectories of the measured leg joints and the actual leg motion trajectories are shown in the Fig. 9 and Fig.10.

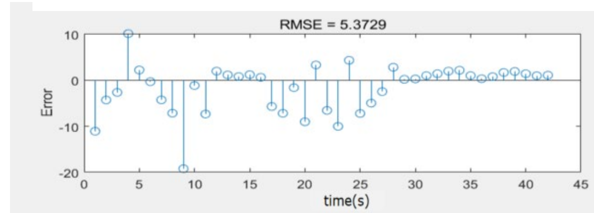


(a) expected trajectory diagram (b) actual motion trajectory diagram

Fig. 9 Expected trajectory and actual motion trajectory diagram



(a) expected trajectory and actual trajectory comparison diagram



(b) error graph

Fig. 10 Expected trajectory and actual trajectory error comparison diagram

Further analysis of the experimental results shows that the exoskeleton can drive the subjects' legs to carry out rehabilitation training, and the movement curve is gentle, basically consistent with the expected Angle, and the rehabilitation effect is good, which proves the effectiveness of the lower limb exoskeleton system proposed in this paper based on the healthy side the surface EMG signals control, and the RMSE is 5.3729. Compared with most current rehabilitation robots, the proposed method in this paper has better advantages in predicting lower limb motion. Analyzing models under different motion modes using root mean square as an indicator is more stable and accurate. Experiments have shown that using LSTM has higher stability and accuracy in predicting different motion modes.

V. Conclusions

This paper proposed an LSTM neural network prediction model based on surface electromyography signals. By collecting sEMG signals data and analyzing sEMG features, corresponding motion intention recognition and joint angle prediction algorithms were designed. The LSTM neural network were used for motion intention recognition training and recognition reliability analysis of joint motion. The results showed that the maximum RMSE of the prediction result was 5.3729, which was idealized. Proved the feasibility of using the LSTM model to predict joint angles. The accuracy of bone joint motion prediction has been verified through experiments, shortening and avoiding motion lag, providing basic data for exoskeleton motion control.

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