Control design of upper limb rehabilitation exoskeleton robot based on long and short-term memory network

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Abstract. The increasing human resources in rehabilitation training for patients with upper extremity impairment, more convenient and objective in rehabilitation training. Therefore, an upper limb rehabilitation exoskeleton robot controller based on a long-short-term memory network (LSTM), combined with impedance control is proposed. The design adopts the LSTM deep learning network to realize the preprocessing and classification of the collected patient's subtle intention signals to obtain the patient's real movement intention. The impedance controller based on the compliant control method is designed, and completed the auxiliary exercise for the patient. In the whole process, the LSTM algorithm effectively handles the timing problem, that is, effectively and continuously processes the patient's data. The impedance control provides a good buffer for assisting the patient's movement, ensuring the good physical compatibility of the patient-robot system with the outside world. Finally, through the model data test, the recognition and differentiation of 18 human body movements were tested, and the accuracy reached 59.3%.

1. Introduction
Stroke is one of the primary diseases that cause motion dysfunction. In recent years, upper-limb rehabilitation robots have been widely used in the rehabilitation of stroke patients. [1]. Studies have shown that patients' biased limbs are treated with robot-assisted upper limbs after stroke, their athletic ability and functional results have been significantly improved [2]. There are two main training modes for rehabilitation robots: passive training and active training [3]. Functional training is aimed at patients with specific movement abilities, assisted by the robot according to its active movement intention. There are mainly three types of methods for the acquisition of active movement intention: 1) Strategy control based on surface electromyography (aEMG) [4-5]; 2) Detection of human active movement intention based on EEG signal [6]; 3) The method based on force/position sensor. Among them, the surface EMG signal is the electrical activity signal generated by the skeletal muscle, which can be obtained in a simple way such as collection of electrodes attached to the skin's surface. Compared with the other two methods, it has the characteristics of non-intrusive, easy to obtain, strong operability and high safety [7].

The present control methods still lack strict stability guarantees, and there is a potential risk of secondary harm to patients. Based on this problem, this paper proposes a method of impedance control to perform rehabilitation training for patients based on LSTM processing time-changing biological signals. LSTM, also known as long and short-term memory network, has a good effect on processing time series data to ensure better extraction of biological signal characteristics. We are just considering the weak recognition reliability of biological signals, and only let the network complete the classification function. For labeled movements and strengths, we then combined the impedance.
control method to adjust the robot's compliance, minimize the possibility of secondary injury to the patient, and realize automatic adjustment of compliance according to the patient's recovery phase. The goal is to meet the needs of patients in the recovery phase most efficiently.

2. Lstm Model And Applied Database

Long-short-term memory network (LSTM) is a specific cyclic neural network structure, which is used for better model analysis of time series data and the relationship between them.

In order to realize the action classification function, we first need to have a sEMG-based action category database, so that when receiving real-time patient data, there will be corresponding judgments. For this reason, we chose the Ninapro (Non Invasive Adaptive Prosthetics) database as our data source. The research objects of this data set are 67 individuals with no injuries and 11 individuals with hand injuries. The electromyographic signal data (sEMG) of these individuals were recorded during the behavior of repeating some gesture movements.

The first is to choose a suitable data set: our whole experiment is to hope that the neural network can analyze the various characteristics of the input time series sEMG signal, so as to complete the classification of its movement actions to grasp its movement intention. Through comprehensive consideration, we selected the data of individual 1 in database 2 and exercise 1 in individual 2 to complete the training and testing of the network, respectively.

![LSTM Architecture Diagram](image)

3. Design Of Rehabilitation Impedance Controller

The principle of active rehabilitation training control is shown in the figure below. The dashed box is the inner loop of position control, and the impedance controller is added to the outer loop of the position control system.
When force feedback is not considered, $\ddot{x}_c$, $\dot{x}_c$, $x_c$ are the acceleration, velocity and displacement of the controlled joint angle trajectory of the upper limb manipulator, respectively, and the conversion relationship of the dynamic model is reflected by the related kinematics. Control the amount of motors to achieve passive rehabilitation training for the expected trajectory.

When we take into account the force feedback, that is, when the human-computer interaction force is added, $\ddot{x}_r$, $\dot{x}_r$, $x_r$ becomes the controlled quantity of the expected trajectory, and the driving force $F_s$ of the external part is measured by the force sensor, and the measured force $F_s$ is fed back to the impedance controller to generate the position, velocity and acceleration corrections of the corresponding auxiliary motion, that is, satisfy the following impedance relationship:

$$F_s = M_d(\ddot{x}_d - \ddot{x}) + B_d(\dot{x}_d - \dot{x}) + K_d(x_d - x).$$

4. Experimental Results And Analysis

4.1. sEMG signal processing and recognition

In the first part of the experiment using LSTM classification process, we randomly selected 6000 time continuous data from Database2 as our training set, and 2000 data as the test set. Since the data categories in the training set do not even contain all categories, some errors are caused in the results. The initial data distribution diagram is shown below. The overall data fluctuates greatly, and necessary data preprocessing operations are required to make the final convergence as easy as possible. For this experiment, we considered three-axis accelerometers on 12 electrodes, sEMG signals of 12 electrical levels, and uncalibrated signals from 22 sensors of electronic gloves, a total of 70 features. Due to the large differences in the above feature numbers, we mainly use normalization processing. The normalized data distribution is shown in Fig. 3.

Throughout the experiment, this experiment debugged epoch, batch_size and other parameters, and observed the accuracy rate to get the optimal parameters. After repeated experiments, the classification effect is best when epoch=3 and batch_size=1.
Based on the accuracy results, the overall accuracy rate reached 59.3%. Of course, this accuracy rate is affected by a small number of categories, imperfect preprocessing and other reasons, so the overall effect is quite impressive.

4.2. Impedance controller simulation experiment
We mainly adjust the size of the robot's output compliance force in real time through the impedance control method according to the difference of the patient's force to achieve our control purpose. In this way, we continuously adjust the four parameters F, B, K, and M to observe the transformation of position, velocity and acceleration to determine the main influencing factors of the impedance controller.

After conducting a large number of parameter experimental tests, we observed the transformation relationship between position, velocity and acceleration as follows:

![Figure 4. The relationship between sports index and stiffness](image)

(From left to right, k=2000, 12000, 48000 and m=2,b=100)

The above experimental data show that, relative to the position, the speed and acceleration are less affected by the changes of several parameters. The above experimental data shows that the stiffness coefficient has a more significant impact on the displacement change than the damping coefficient and the mass coefficient. The displacement adapts to the patient's movement to have a more obvious effect.

5. Conclusions
This paper is proposed an impedance controller for upper limb rehabilitation robot based on the fusion of sEMG and force feedback information. Based on the establishment of the human-machine system dynamics model, the various action categories are calibrated according to the existing huge sEMG database, and then the sEMG signals are extracted online in real time to identify the patient’s motion intention, and the corresponding action matching force is input into In the corresponding impedance controller, the robot is adapted to the patient's movement through the principle of impedance control.

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