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Preliminary Bilateral Upper Limb Rehabilitation System Based on sEMG and Muscle Tone

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***Abstract* - In recent years, with the increasing number of stroke patients, master-slave telerehabilitation has become one of the research hotspots in the field of rehabilitation. However, when estimating the angle of the main end, the angle estimation model is difficult to be widely applicable due to the different muscle tension of the physiotherapist itself. During remote rehabilitation training, it is difficult for physical therapists to obtain the damage of the affected limb, so it is difficult to arrange appropriate training intensity and training volume, which affects the effect of remote rehabilitation to a certain extent. To address these issues, this paper proposes a novel master-slave rehabilitation system. The therapist obtains his own muscle tension level a priori through FSR402, and jointly estimates the movement angle through the (Surface Electromyography) sEMG signal collected by MYO, so as to control the slave end. While following the rehabilitation training, the patient at the slave end reflects real-time muscle force of the affected limb and the true feeling of the movement to the master end through the muscle tension measurement arm cuff and the relevant buttons on the PC end. The overall system realizes data transmission through (User Datagram Protocol) UDP, so as to realize more secure and personalized master-slave control. The experiment proves that the new master-slave rehabilitation system is real and feasible.**

Index Terms - Upper limb rehabilitation, exoskeleton robot, master-slave system, muscle force, angle estimation.

I. INTRODUCTION

Upper limb hemiplegia is one of the common symptoms of stroke [1]. Rehabilitation training is an effective way to reduce the degree of disability of the affected limb, and it plays a vital role in restoring the normal life ability of stroke patients. However, rehabilitation training usually requires the professional guidance of physical therapists and long-term cooperative training[2], which will not only bring a heavy economic burden to the family members of patients, but also greatly affect the medical efficiency of physical therapists[3], making it difficult to Get good rehabilitation medical resources. As a result, a large number of patients are disabled due to missing the best recovery time [4].

In order to cope with the corresponding shortage of offline rehabilitation, the master-slave rehabilitation system that can provide remote rehabilitation methods has begun to attract people's attention [5]. It can not only provide patients with online telemedicine, reduce the number of patient visits, but also reduce the financial burden of patients. At the same time, it also provides a more convenient means for physical therapists to modify the rehabilitation mode of patients and reduce their workload. At the same time, the supporting driven exoskeleton auxiliary training system can also carry out a relatively standard rehabilitation training mode for patients based on the offline environment. Y. Liu et al. proposed a novel home-based powered variable-stiffness exoskeleton device (PVSED) that can adapt to the dynamic motion of the patient to improve the comfort and safety of training [6].

At present, the master-slave rehabilitation follow-up movement based on sEMG is a research hotspot in the master-slave telerehabilitation system. However, most of them ignore the influence of the therapist's own muscle tone on the model estimation. Such as G. Hajian proposed deep multi-scale fusion of convolutional neural wetworks for sEMG-based movement estimation, It only mined the sEMG signal[7]. And Y. Na proposed to estimate the angle by muscle twitch model and sEMG, however, the arm of the main physical therapist is usually in a healthy state, and we can use resting muscle tension for auxiliary angle estimation[8].

At the same time, effective judgment of the intensity of rehabilitation training is also an important premise for therapists to reasonably arrange the amount of rehabilitation exercise training. A long period of rehabilitation training under a heavy training burden will lead to further injury of the affected limb, while a light training burden will lead to inefficient training and waste a lot of time for both the therapist and the patient. Like M. Shahbazi et al. A therapist-in-the-loop on-demand assistance framework is proposed [9], but it determines the level of rehabilitation exercise more through the patient's subjective wishes. Y. Liu et al. The home telerehabilitation system was proposed, focusing on the collection of contact force information, but its purpose is to estimate the movement angle through contact force [10]. Z. Yang et al. [11] proposed a variable stiffness control strategy based on sEMG-driven bilateral upper limb rehabilitation system. It also involves the estimation of the degree of assistance required by the patient's affected limb under different forces, but it is more about the adaptive adjustment of the system stiffness, without the intuitive feedback based on the professional primary doctor. Zhang et al. designed a telerehabilitation system with a force-sensing mechanism, but it is more about collecting the force exerted by the therapist to control the slave operation [12].

In response to the above problems, this paper proposes a new master-slave upper limb rehabilitation training system (as shown in Fig.1). Its main end obtains the physical therapist's sEMG through the MYO armband, and cooperates with the prior arm muscle tension to predict the arm movement angle in real time. The slave end detects the muscle strength of the patient's affected limb in real time through the muscle strength detection arm cuff, and at the same time describes the real-time feelings of different rehabilitation stages through the PC end. Finally, the master-slave segment communicates through UDP to realize remote transmission of predicted angle, muscle tension, affected limb strength and training experience. This is not only conducive to the precise control of the master-slave follower, but also helps the physical therapist assess the damage of the patient's limb. The rest of this paper is structured as follows. The second chapter introduces the design of the exoskeleton platform and the design of the active end sensing equipment. Chapter 3 introduces the method of signal prediction and the long-range transmission model. The fourth chapter introduces the related experiments and structure. Finally, the fifth chapter gives the corresponding conclusions.

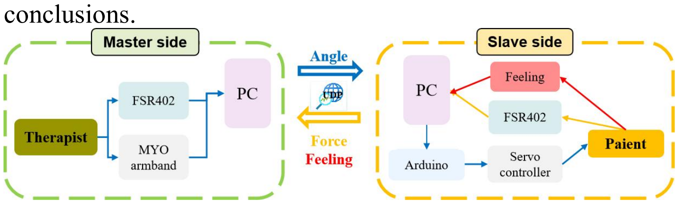


Fig. 1 The overall picture of the master-slave rehabilitation system in this study.

II. Materials

In order to make the overall system meet the needs of rehabilitation exercise and maintain its portability. When building the overall system, choose lightweight equipment to realize related functions.

A. Exoskeleton Design

In our research, we improved the previous elbow joint exoskeleton rehabilitation robot, and added two passive degrees of freedom of the shoulder joint on the basis of a single elbow joint degree of freedom, as well as shoulder joint adduction/abduction and shoulder Flexion/extension of the joint (passive degree of freedom means that it cannot be controlled by the motor and related transmission structure, and active degree of freedom means that it can be driven by the gear transmission structure to rotate). On the basis of retaining the advantage of free adjustment of the position of the bottom frame of the forearm, the upper arm support is disassembled so that the length can be freely adjusted through the screw and nut structure. The overall frame is still printed with UV resin while increasing the design thickness of the transmission part, so as to reduce the physical weight of the exoskeleton while optimizing its design stiffness (as shown in Fig.2).

The drive of the forearm exoskeleton is controlled by a brushless motor (EC 22, 40, Maxon, Switzerland). The brushless motor uses a built-in Hall sensor in conjunction with a Maxon Planetary Gearhead GP (22 HP) and an orthogonal optical encoder (MR M-512) to control the Angle of elbow rotation through bevel gears (1:2 tooth ratio). According to the calculation formula of torque, the transmission structure can drive the affected limb for elbow joint rehabilitation training.

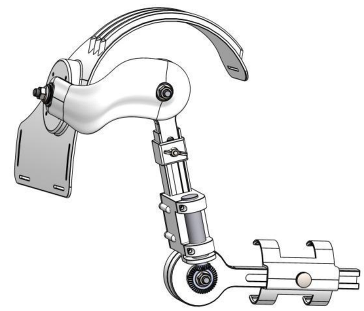


Fig. 2 The upper limb rehabilitation exoskeleton model.

The picture shows the overall structure of the upper limb rehabilitation robot. Its elbow can flex 360°, which meets the angle range of normal human elbow movement. The total weight of the exoskeleton is only 1.35kg. Through the design of the shoulder skeleton and the corresponding fabric belt opening, the overall weight of the exoskeleton can be borne by the patient's shoulders, back and waist, without adding excessive burden to the affected limb (as shown in Fig.3).

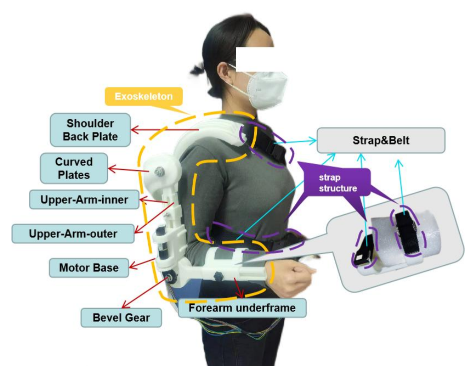


Fig. 3 The diagram of exoskeleton wearing.

B. Master Side Device

In this experiment, the master data acquisition equipment is mainly composed of MYO, FSR402, and IMU. Among them, MYO is used to collect the sEMG signals of the upper arm when the therapist guides rehabilitation exercises. FSR402 is used to assess the therapist's degree of upper arm muscle tone. The IMU is used to measure the real elbow angle signal when the therapist guides the rehabilitation exercise.

(1) MYO Armband

MYO Armband is a sEMG acquisition device with 8 sEMG sensors designed by Thalmic Laboratory in Canada(as shown in Fig.4). Its 8-channel design features can effectively detect the sEMG signals transmitted by the target arm muscles in different directions, reducing the detection threshold caused by the inaccurate location of the muscles. The sampling frequency of MYO is 200Hz, and it comes with a 50Hz notch filter, which eliminates the noise caused by power frequency interference while having good sampling accuracy. At the same time, the MYO myoelectric armband can also transmit the collected relevant data to the PC through the supporting Bluetooth module for further signal processing, which meets the needs of remote wearing. In general, compared with other sEMG data acquisition equipment, the MYO armband is light in structure and easy to use. Its elastic structure design can meet the needs of physical therapists to put on and take off freely, which is suitable for experimental needs.

Fig. 4 MYO Armband.

(2) FSR402

A Force Sensing Resistor (FSR) is a typical polymer thick film device that at its core reduces resistance when more physical force is applied. FSR402 is a single-zone force-sensing resistor, and its force-sensing accuracy is affected by many aspects such as the contact area, before and after placement, and the bending degree of the sensor. Since the actual piezoresistive curve of the resistance in the effective area can be approximated as a straight line, a voltage divider can be formed with the reduced resistance, and the corresponding resistance can be read by reading the corresponding voltage calculator.

In this experiment, due to the limited output voltage of the serial port, in order to simplify the model structure, freely adjust and reduce the resistance value, so as to accurately measure the interaction force, the resistive film pressure(RFP) sensor conversion module is connected to the FSR402 with the same principle, and the mode is also connected to the Arduino board to achieve the measurement results serial port output. The connections are shown in Fig.5.

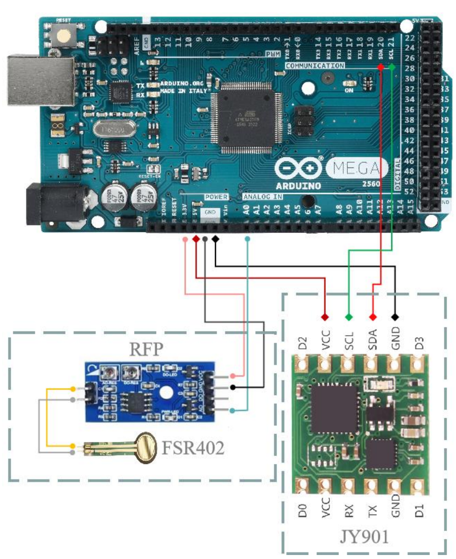


Fig. 5 FSR402 connection.

(3) JY901

JY901 is a 9-axis gyroscope produced by Witte, which integrates high-precision gyroscopes, accelerometers, and geomagnetic field sensors, and uses high-performance microprocessors, advanced dynamics calculations and Kalman filter algorithms. Quickly solve the current real-time motion state of the module. In terms of data reading, JY901 can support two digital interfaces, serial port and IIC, to connect to the PC, and display data and initialize positions through the supporting host computer (as shown in Fig.5).

III. MATHODS

A. BPNN Modeling and Feature Extraction

In order to better show the importance of physical therapist's muscle tone assessment on model prediction and reduce the influence of neural network model architecture, the BPNN model is selected for angle prediction. BPNN is a multi-layer feedforward neural network, its main characteristics are: the signal is forward propagation, and the error is backward propagation (as shown in Fig.6).

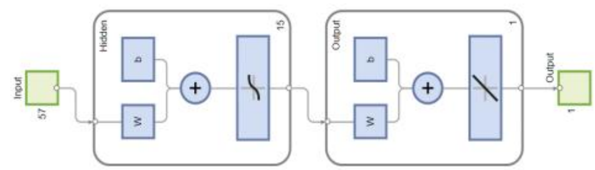


Fig. 6 BPNN architecture.

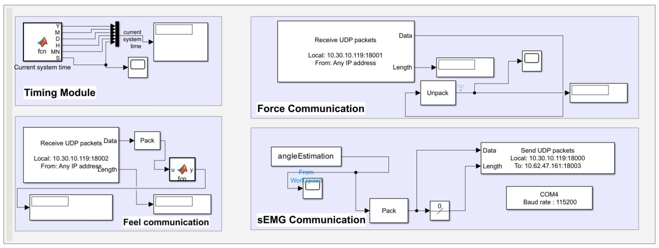
In terms of feature selection, since the time-domain features of sEMG signals can reflect its distribution features, the frequency-domain features can reflect the individual differences and fatigue levels of the acquisition subjects. In order to obtain the relationship between the assigned sEMG signal value and the elbow joint motion amplitude and further improve the accuracy of the model, six time features were selected for extraction: integral absolute value (f_{IAV}), logarithmic detection (f_{LogD}), maximum average amplitude (f_{MAV}), Maximum amplitude (f_{MAX}), root mean square (f_{RMS}), variance (f_{VAR}), wavelength (f_{WL})[13].

B. Remote Data Transmission Based on LAN and UDP

(Local Area Network) LAN is one of the most contacted network types in people's daily life and research. It is a technology that connects local abortion computers via ethernet or wifi technology. Compared with another common network type, Ethernet technology, it has the characteristics of small network coverage, high transmission rate, and high transmission quality. Due to the advantages of its transmission efficiency and relatively simple technical requirements, this experiment uses the LAN to realize the preliminary remote communication between the master and the slave.

On the basis of LAN, in order to better realize the transmission of angle data and interaction force data, UDP protocol is selected for data communication. Although the UDP protocol is only a connectionless communication protocol, it cannot guarantee the integrity of the transmitted data during a series of data transmissions, and even has a limitation on the size of the data packet. But it helps to establish the advantages of low-latency and fault-tolerant connections, which can well meet the real-time requirements of the remote rehabilitation system.

Since the PCs of the master-slave system are all under the communication connection of the LAN (campus network), the network delay is unstable. In order to measure the communication delay between the master and slave PCs during the rehabilitation exercise, the time stamp is used to record the system time. Both master and slave are obtained through the "MATLAB function" module (as shown in Fig.7).



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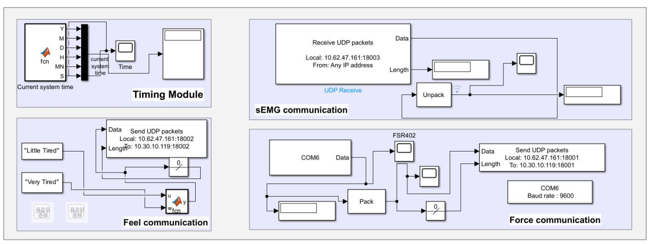


(b)

Fig. 7 UDP Communication module. (a) master side. (b) slave side.

IV. Experiments And Results

In order to verify the feasibility of the system, a master-slave control experiment was carried out. The main end of the experimental platform uses the MYO myoelectric armband and FSR402 to collect physiological signals, and predicts the corresponding angle through the PC end to control the slave end motor. The slave end uses the upper limb rehabilitation exoskeleton as a robot to drive the patient's arm to perform rehabilitation exercises, and collects muscle tension signals and feeds them back to the master end through the FSR402 fixed on the upper arm. UDP is used for data transmission between master and slave servers (as shown in Fig. 8).

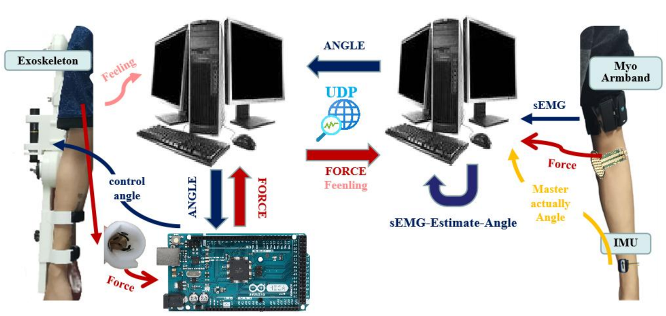


Fig. 8 The experiment platform.

A. Angle prediction based on sEMG and muscle strength level at the master end

(1) Dataset Selection

The data set samples in the study come from the sEMG and elbow joint angle data of 10 healthy and convenient individuals recruited in the laboratory during upper limb rehabilitation exercises. The relevant physiological and sampling information of the subjects is shown in TABLE I.

TABLE I
SUBJECT INFORMATION

Sampling Date	Gender	Number	Age
Day_1	Man	2	22,29
	Woman	1	25
Day_2	Man	1	24
	Woman	2	22,25
Day_3	Man	2	24,29
	Woman	2	24,25

In the data collection experiment, each subject was required to collect 6 sets of uniform flexion and extension elbow joint data (as shown in Fig.9). The single collection time was 1 minute, and the interval between two collections was at least 5 minutes. After collecting all the signals, the researchers calibrated the muscle tension signals and divided them into five levels (respectively: very weak, weak, normal, strong, and very strong), corresponding to numbers 1-5. At the same time, 20hz high-pass filtering is performed on the 8-channel sEMG signal to remove DC offset and low-frequency noise that may interfere with the body surface EMG signal, and the signal is windowed (window length 250ms, window increment 100ms) to extract features (f_{IAV}, f_{LogD}, f_{MAV}, f_{MAX}, f_{RMS} , f_{VAR}, f_{WL}). From the 10 groups of subjects, 7 groups were conveniently selected as the training set, and the remaining 3 irrelevant groups were used as the test set.

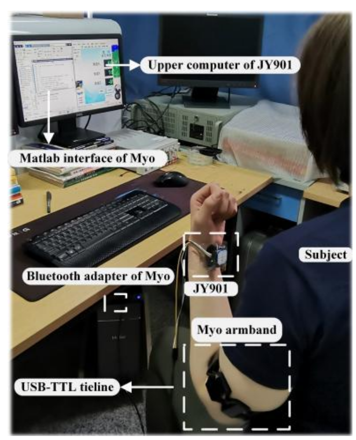


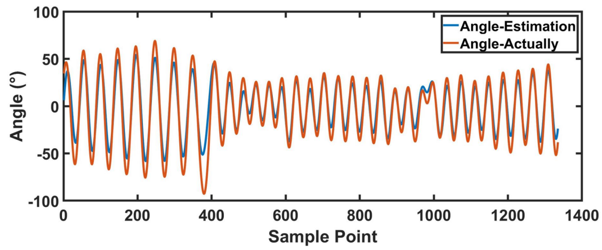
Fig. 9 Schematic diagram of data acquisition[14].

(2) Model Training and Evaluation

In order to verify the influence of the prior muscle tension signal on the constructed BPNN angle prediction model. First, use the training set that does not contain the muscle tension evaluation grade for model training, and use the test set that does not contain the muscle tension evaluation grade for model testing. Next, use the training set and test set containing muscle tone evaluation grades and sEMG features to perform model training and testing respectively. And compare the output of the two models, the results are shown in Fig. 10. The muscle tone data of the test set is shown in TABLE II.

TABLE II
MUSCLE TONE DATA OF THE TEST SET

Name	Gender	Muscle Tone Data
Test_subject#1	Man	5
Test_subject#2	Man	4
Test_subject#3	Woman	1



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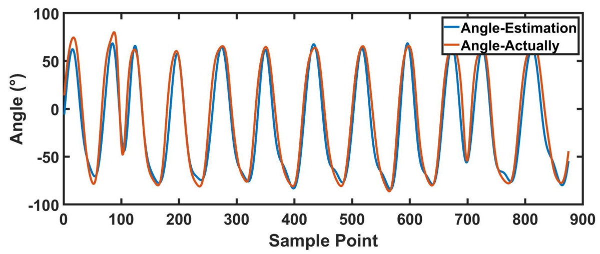


(b)

Fig. 10 Angle estimation result. (a) angle evaluation of test_subject #1 without muscle tone rating. (b) angle evaluation of test_subject #1 with muscle tone rating.

Through offline analysis and comparison, the model adding muscle tension level has better predictive effect. Therefore, the trained model is used for online angle estimation and real-time control of the exoskeleton.

Different from the offline stage, the online prediction and motor control stage should consider the delay time in addition to the prediction accuracy of the model.

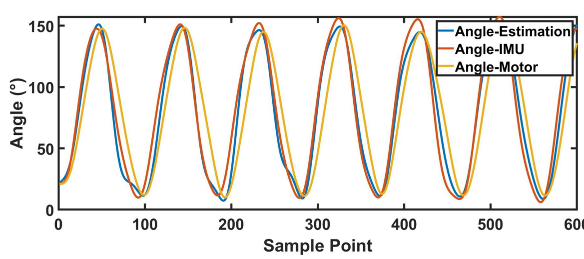


Fig. 11 The online estimation and motor angle.

Fig. 11 plots the online estimate and motor angle, and calculates the IMU angle and the time lag between the estimated angle and the target angle. From the prediction results, there is no time lag between the IMU angle and the estimated angle, but there is a delay in the motor control.

B. Slave Muscle Force Acquisition Experiment and Master-slave Communication Experiment

In this experiment, the subjects were asked to perform rehabilitation training with the assistance of the exoskeleton, and to feedback their subjective feelings through the buttons. During the rehabilitation training process, the experimenters measured the upper limb muscle strength data and elbow joint angle data in real time through the muscle tension collection arm cuff worn by the subjects on the upper arm and the IMU worn on the forearm. At the same time, the system also carried out the data transmission test in the LAN environment (as shown in Fig. 12).

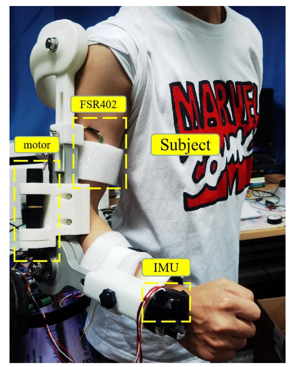
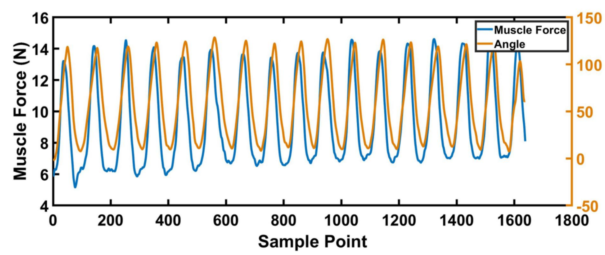


Fig. 12 Schematic diagram of data acquisition

(1) The contact force acquisition experiment was carried out in rehabilitation training from the end under different weights

In the muscle tension and subjective experience information collection experiment, the subjects performed elbow flexion training at a cycle speed of 4 seconds with the assistance of the exoskeleton. During the experiment, the subjects' upper arms were kept vertically downward. The single exercise was continued until the subject felt tired, with 10-minute rest intervals.



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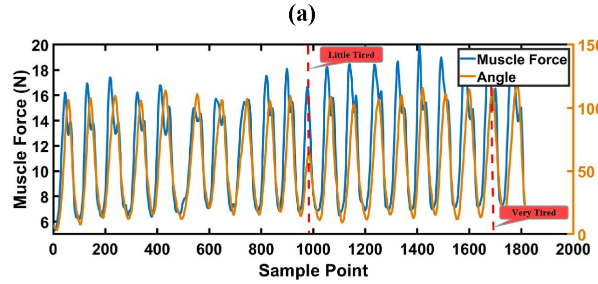

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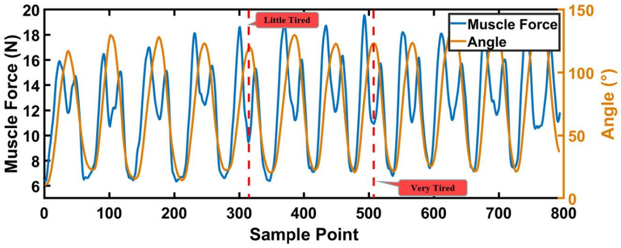

(c)

Fig.13 Muscle tension test results during rehabilitation exercises under different burden. (a) Load 0kg. (b) Load 2.5kg. (c) Load 5kg.

According to Fig. 13, the heavier the weight bearing, the greater the separation of muscle force signals during the elbow bending and extension stages, and the faster the patient will feel fatigue. Therefore, the feedback of muscle force signal and patient's feelings can make a more intuitive judgment of the intensity of rehabilitation and the length of recovery required.

(2) UDP Transmission Delay Timing

After the force feedback detection is completed, the communication delay between the master and slave ends of the system is detected. The delay is measured in the campus network environment, and the communication method is UDP transmission. In order to reduce the impact of campus network fluctuations on data transmission and delay measurement, the experiment was carried out at 5a.m. The relevant delay measurement results are shown in the TABLE III.

TABLE III
MUSCLE UDP DELAY IN CAMPUS NETWORK

Number of experiments	1	2	3	4
Slave-side Time(s)	24.44	48.68	13.13	56.93
Master-side Time(s)	24.037	48.113	12.671	56.347
Time Delay(ms)	403	567	459	583

The results show that the system can carry out remote communication, but the current high-latency and high-fluctuation environment of the campus network will affect the rehabilitation process to a certain extent.

IV. CONCLUSION

This experiment proposes a master-slave upper limb rehabilitation system based on sEMG and force. The main terminal predicts the elbow joint movement angle of the physical therapist through sEMG and muscle tension level, and the slave terminal feeds back the change of muscle strength and the burden when the patient feels uncomfortable to the main terminal, so as to assist the physician in judging the patient's limb damage situation, so as to realize a safe and individualized master-slave rehabilitation model.

In the future we will make one step improvement on the existing system. Use multi-source information fusion to improve the prediction accuracy of the elbow joint and reduce the motor control delay. And to establish a correlation model between weight bearing and the separation of flexion and extension waves of upper arm muscle force. At the same time, the remote communication capability of the system need to be further improved to meet real-time need.

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