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# An EMG-based Force Prediction and Control Approach for Robot-assisted Lower Limb Rehabilitation

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**Abstract**—This paper proposes an electromyography (EMG)-based method for online force prediction and control of a lower limb rehabilitation robot. Root mean square (RMS) features of EMG signals from four muscles of the lower limb are used as the inputs to a support vector regression (SVR) model to estimate the human-robot interaction force. The autoregressive algorithm is utilized to construct the relationship between EMG signals and the impact force. Combining the force prediction model with the position-based impedance controller, the robot can be controlled to track the desired force of the lower limb, and so as to achieve an adaptive and active rehabilitation mode, which is adaptable to the individual muscle strength and movement ability. Finally, the method was validated through experiments on a healthy subject. The results show that the EMG-based SVR model can predict the lower limb force accurately and the robot can be controlled to track the estimated force by using simplified impedance model.

**Keywords**—EMG; force prediction; rehabilitation robot; SVR; impedance control

## I. INTRODUCTION

According to the official statistical data from the United Nations, the proportion of the world's population over 60 will be doubled from 11% to 22% between 2000 and 2050. With the tendency of aging society, there is a considerable increase in the needs of health care and rehabilitation, especially among elderly and disabled people[1]. The healing training with a proper robot assistance and scientific method will play a significant role in recovering and improving of limb motor function[2]. Rehabilitation and assistive robots, which can provide the patients with proper training and exercise modes and strategies, have been recognized as a promising solution to this problem. Moreover, the real-time evaluation for patient's recovery condition and active interaction control strategy that can provide appropriate and comfortable training or assistance is essentially necessary during rehabilitation [3].

It is widely accepted that one basic idea of assistive and rehabilitation robot is to consider the patient's muscle activity or recovery conditions and modify the robot motion in a way that is desired by the patient, which is believed to be most appropriate for patients' rehabilitation. The electromyography (EMG) is able to characterize the state of human nerves and muscles, and has been widely used in action recognition, force prediction, and medical rehabilitation. Krebs et al. described a concept of performance-based progressive robot therapy that

used EMG thresholds to initiate the robot assistance[4] when the muscles' EMG activity increased above a certain threshold. However, this approach may not receive satisfied outcomes for interactive rehabilitation, because it will break the movement into two separate phases, an active phase driven by patient, and a passive phase driven by the robot, rather than providing a seamless robot assistance to the subject-driven motion[5]. A model-based control approach was proposed by Wolbrecht et al. to learn the patient's ability and achieved the assistance-as-needed by adding a force reducing term to the control term[5]. Song et al. proposed a continuous robot assistance method to provide the robot assistive torques that were proportional to the amplitude of multi-channel EMG signals[6]. However, the relationship between EMG and joint torque was simplified as a linear model, which may vary in different situations.

One of the most important issues for assist-as-needed method is to understand the muscle strength conditions and make the human-robot interaction suit the recovery, to increase the training effects. It has been observed in a lot of research that the force of human limbs is derived from the contraction of skeletal muscles. The application of EMG for estimating the joint torque or muscle strength forces can be found in many works. For example, Lenzi et al. studied a torque estimation-based EMG control method for powered exoskeletons, and the assistance was provided by a proportional EMG controller[7]. These methods could provide effective support to the user. However, their usability is strongly limited by the application environment and the estimation of muscular torque is quite rough. On the other hand, Kiguchi and Hayashi proposed an EMG-based method to control an upper-limb robot according to user's movement intention[8], in which, however, sixteen channels of EMG signals had to be captured to estimate the upper-limb joint torque vector.

Nevertheless, a majority of current research on force/torque estimation is conducted on upper extremities (e.g. [8] [9] [10]). The problem is that the strict requirement of the real-time contraction and active interaction for the lower extremity is different from that of the upper limb. Another problem is that many works of force/torque estimation have been done on exoskeleton robots (e.g. [2] [8] [11]), while few can be found on end-effector robots. But, the end-effector robot is a very important type of rehabilitation and assistive devices. This may be due to the fact that it is difficult to process EMG signals from many muscles involved in the end-effector force generation.

And accurately modeling the relationship between EMG and human posture and interactive force is even more difficult. For example, Fan and Yin predicted the human motion intention and achieved the active joint torque by a linear form integrating the moment arm and muscle contraction[2]. Hussain estimated the degree of subject activity walking by calculating the Euclidian distance between the measured torque and each of the generated torque profile[12]. Song estimated the assistive torque based on the normalized EMG signals[10], which was also a proportional formula with EMG-torque gain coefficients. Other similar works can also be found in [13] and [7].

The model-based or “black box” prediction algorithms are generally employed to obtain the relationship between items. Loconsole et al. proposed a method to estimate the joint torque of the exoskeleton using an artificial neural network trained by EMG signals, and used the model for an active exoskeleton to provide slow movement of the upper limb[9]. However, it is hard to find an accurate prediction model that can be widely used to predict the muscle force of human lower limbs. The motivation of this work is to predict the interaction force of the lower limb when contacting with the end-effector robot, so that we can understand the muscle strength and contraction force, and then an impedance controller can be designed to drive the robot according to the individual movement ability.

In this work, we propose and test a method for on-line control a lower limb rehabilitation robot through sEMG signals acquired from four muscles. More in detail, we estimate the lower limb muscle force by using a SVR prediction model. An impedance control model is designed to drive the rehabilitation to track the desired force of the lower extremities. Finally, the method is validated on a healthy subject for active interaction training of the lower limb on a 6-DOF parallel robot.

## II. METHODS

### A. EMG and Force Signals Pre-processing

The force of human lower limbs is mainly deprived from the contraction of muscles including peroneus longus (PL), tibialis anterior (TA), extensor digitorum longus (EDL) and peroneus brevis (PB), etc. In this paper, a Bluetooth wireless EMG acquisition device with four-channel is utilized to extract surface EMG signals. Then the EMG signals are amplified, filtered and digitally sampled by the data processing card and then are transmitted to a PC for further processing. Many researches have verified that lower limbs contraction is directly affect by the action potentials. In this study, a time-domain feature, root mean square (RMS) of EMG signals, was applied as feature samples and the calculation formula is as follows:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N z^2(i)} \quad (1)$$

where  $z(i)$  presents the discrete series of single-channel EMG signal  $\{z(i) | i=1, 2, \dots, N\}$ ,  $N$  is the length of  $z(i)$ . In this study, EMG signals are sampled at the frequency of 2 KHz and the RMS of each four channels are computed by using 512 samples as a data segment. The interactive force between robot and limb is measured by a tri-axial load cell sensor, which is

sampled at the same frequency with EMG signals, so that the force and EMG can be acquired at the same sampling rate. The mean absolute value (MAV) of force data during this period is utilized as the training data. It is calculated according to (2).

$$F = \frac{1}{N} \sum_{k=0}^N |f_k| \quad (2)$$

In this study, 1000 samples data containing EMG and force signals are used to train the model. The subject will be asked to slowly increase the limb force until it reaches the maximum contraction and maintain the exerted force for a while. In order to synchronize the EMG and force sensor data, we mark the beginning and end of the EMG and force measurements. Fig. 1 shows the synchronization of EMG signals and force feedback.

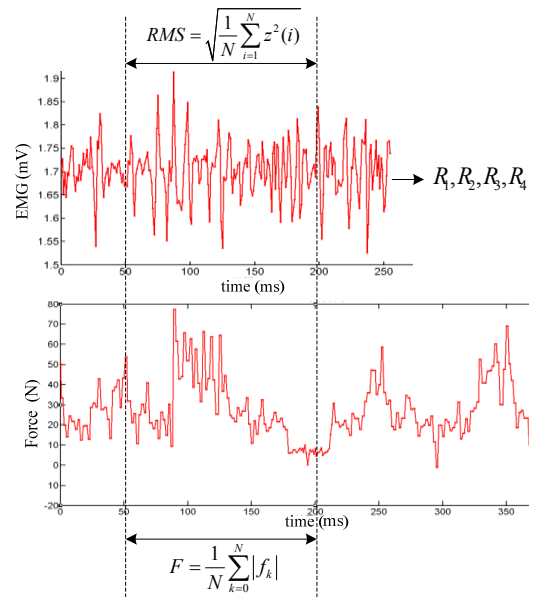


Fig. 1. The synchronization of EMG signals and force feedback.

### B. Force Prediction Based on SVR Model

In this paper, the SVR algorithm is applied to map EMG signals to lower limb force. A key issue of SVR algorithm is the function approximation, namely, finding a deterministic function  $g(x)$  that has the minimum distance to the non-deterministic function  $f(x)$  [15]. It can be described by (3).

$$R(f, g) = \int L(f, g) dx \quad (3)$$

where  $L(f, g)$  is the penalty function. Function  $f(x)$  is described by the samples and  $g(x)$  can be obtained by regression analysis. Finally, the solution to such a SVR model can be converted to a Lagrangian dual problem, as described in (4).

$$\begin{aligned} \min & \left\{ \frac{1}{2} \sum_{i=1}^m (a_i - a_i^*)(a_j - a_j^*) \langle x_i, x_j \rangle + \sum_{i=1}^m a_i (\varepsilon - y_i) + \sum_{i=1}^m a_i^* (\varepsilon + y_i) \right\} \\ \text{s.t.} & \begin{cases} \sum_{i=1}^m (a_i - a_i^*) = 0 \\ a_i, a_i^* \in [0, C] \end{cases} \end{aligned} \quad (4)$$

Then we can get the regression function:

$$f(x) = \sum_{sv} (a_i - a_i^*) \langle x_i \cdot x \rangle + b \quad (5)$$

where  $sv$  is the support vector,  $a_i, a_i^*$  are Lagrange multiplier coefficient vectors,  $b$  is the offset. We utilize kernel function to map the linear SVR vectors to the nonlinear SVR vectors, then the mapping relationship between them can be obtained.

$$f(z_0) = \sum_{i=1}^l (a_i - a_i^*) K(z_i, z_0) + b \quad (6)$$

where  $z_i, z_0$  are training samples,  $K$  is the kernel function, and radial basis function (RBF) is employed as the kernel function here. In addition, the generalization ability of auto-regression (AR) model is greatly affected by its parameters. Thus, if the penalty factor is set too high the prediction error may be large. On the contrary, if the penalty is set too low the generalization ability will be weakened. Considering the relationship between EMG signals and the limb force, in this paper, the training parameters in (4) are set to  $C=32, \mathcal{E}=0.01$ . Finally, the SVR model is implemented by LibSVM using C++ language[16].

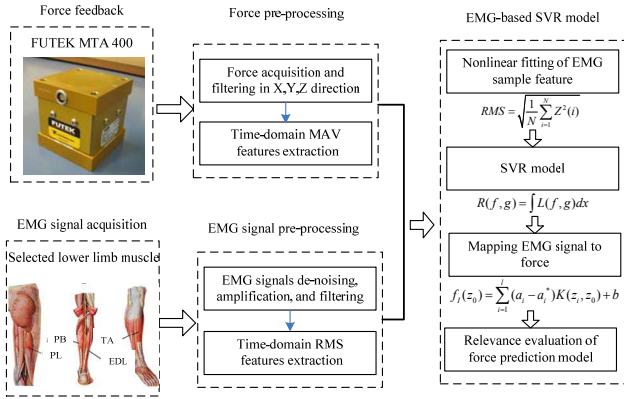


Fig. 2. The EMG-based force prediction process by using SVR model

The EMG-based force prediction process based on SVR model in this study is illustrated in Fig. 2. After setting up the robot system, the RMS features of EMG signals and the MAV of force feedback data are adopted as the training samples of the SVR prediction model. In the first part, EMG signals and actual force exerted by subjects are acquired and processed to obtain the corresponding features simultaneously. Then, the SVR model accumulates the RMS features of EMG signals and combines that with MAV of the actual interaction force to train the support vectors and get the Lagrange coefficients of SVR. In this way, the SVR-based force prediction model can be built. In next part, according to the previous established relationship between EMG signals and lower limb force, the subject can perform continuous movements and the predicted force can be obtained online based on the trained SVR model. Finally, the correlation coefficient between actual force and output force of model will be analyzed to evaluate the prediction accuracy.

### C. Position-based Impedance Model

In order to provide a compliant environment when the patient interacts with the robot, the flexible assistance must be provided by monitoring the interaction force between the user and the robot. Therefore, a position-based impedance model is established in this context. The robot can be controlled in admittance to track the desired force estimated from EMG signals, and in this way the human robot interaction can be adjusted with the people's muscle strength or contraction force. The control objective of this impedance controller is to modify the robot assistance movement in each direction of the task space with the user's interaction, so the dynamic relationship between the robot end-effector position and the interaction force need to be established[17]. In order to fulfill such task space requirements, a second-order, end-effector impedance model is chosen and it can be expressed by (7).

$$M_d(\ddot{x} - \ddot{x}_d) + B_d(\dot{x} - \dot{x}_d) + K_d(x - x_d) = F_e - F_d \quad (7)$$

where  $M_d, B_d$  and  $K_d$  are the diagonal matrices representing the desired inertia, damping, and stiffness parameters,  $x$  and  $x_d$  are the actual and desired end-effector position in task space [17].  $F_e$  is the interaction force the user exerts upon the robot,  $F_d$  is the desired end-effector force estimated from EMG signals.

In this parallel robot-assisted lower limb rehabilitation, the end-effector's acceleration and velocity change very slowly, so the impact of the acceleration and velocity changes  $\ddot{x} - \ddot{x}_d, \dot{x} - \dot{x}_d$  may be ignored[18], and the desired inertia, damping matrix can be set to zero. Considering the actions of desired stiffness and damping, equation (7) can be simplified as:

$$K_d(x - x_d) = F_e - F_d \quad (8)$$

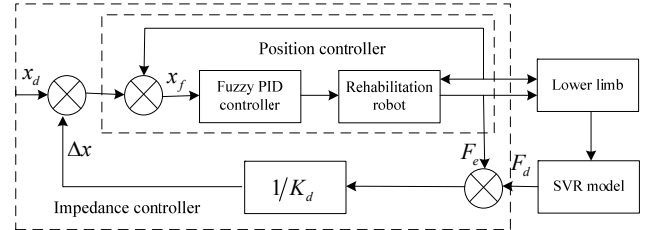


Fig. 3. The simplified impedance model with only stiffness parameter

The obtained impedance model is similar with the spring extension equation, which can be illustrated by Fig. 3. The objective of this model is to control the robot and make the actual interaction force to track the predicted force. When the subject wants to deviate the robot from the reference position, the desired end-effector force predicted from EMG signals and the actual force from sensor will be feedback, then the robot position will be modified and controlled to track the desired force. In this process, the stiffness parameter is very important. The smaller stiffness is, the more compliance robot is, and the larger position changes will be done to reach the force tracking control, and vice versa. In this way, the robot impedance can be adjusted to patients with different recovery conditions by tuning impedance model and stiffness coefficient.



### III. EXPERIMENTS AND RESULTS

#### A. Experimental Setup

In order to evaluate the ability of the force prediction model and the simplified impedance controller to provide interactive rehabilitation for lower limbs, the previously described SVR model and controller were implemented in an experiment.

The surface EMG signals in this paper are acquired by a portable Bluetooth EMG acquisition equipment (DataLOG MWX8, Biometrics Ltd. UK), as shown in Fig. 4(a), with a 20db pre-amplifier, a 20~500Hz band pass filter, a 50Hz notch filter, a 40db final-amplifier, and an A/D converter. In this test, four channels of EMG signals from lower limb were captured. Prior to the experiment, four pairs of electrodes are attached on the subject's peroneus longus (PL), tibialis anterior (TA), extensor digitorum longus (EDL) and peroneus brevis (PB) muscles of the lower limb, to capture useful information during the experiment. The location of electrodes is shown in Fig. 4(b).



Fig. 4. The EMG acquisition system. (a) DataLOG MWX8 EMG acquisition device (b) the location of electrodes.

The designed lower limb rehabilitation robot is basically a parallel mechanism with six transitional and rotational DOFs. The parallel robot consists of two platforms (upper platform and base platform) and six joints. The Stewart platform shown in Fig. 5 was designed by the authors' research group for the purpose of investigating lower limb rehabilitation[14]. The radius of the upper platform is 180 mm, and the angle is 28°, likewise, the parameters of the fixed platform are 270 mm and 22°, respectively. The controller is implemented on a PC. The device is interfaced through a CAN BUS interface. With the proposed control scheme, it is possible to simultaneously control six parallel actuators of the rehabilitation robot and achieve full rotational degrees of freedom for lower limbs.

A footplate is employed to fix patients' limb on the upper platform. The Futek force sensor is mounted between the upper platform and the footplate to sense the equivalent interaction force acting between human and robot. The Futek MTA400 force sensor is a tri-axial load cell (Futek, Advanced Sensor Technology, INC. USA) which was chosen to measure forces in the  $x$ ,  $y$  and  $z$  directions, and these signals are amplified before being sent to the PC by the Futek amplifier modules. This force sensor has a big measuring range and its maximum payload capacity in  $x$ ,  $y$  directions and  $z$  direction are 112.5 kg and 225 kg respectively. After processing by amplifiers and filters, the force data were transmitted to a PC through USB interface, which also can be recorded for off-line analysis.

The preliminary experiment was carried out on a healthy male subject of age 26. The subject sat on a chair with his right foot constrained to the robotic device, as illustrated in Fig. 5.

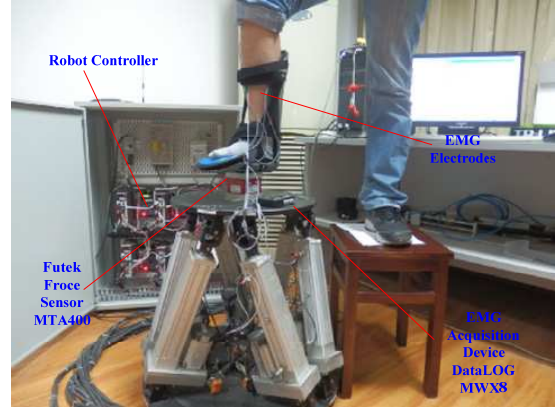


Fig. 5. The experimental setup for active lower limb rehabilitation.

The experiment consisted of two parts. In the first part, the training dataset (including EMG signals and the force feedback) was acquired to train the SVR model. In the second part, instead, the trained SVR were used to on-line predict the end-effector force and control the lower limb robot according to the proposed impedance approach presented in Section II. In the SVR training part, the subject was asked to perform limb contractions while bounded to the footplate, in which the movement session took about 15 seconds. The EMG signals during this period and the force feedback were recorded and input to the SVR model to train it. After that, the relationship between the four-channel EMG signals and the interaction force had been established. In the SVR online prediction part, the trained SVR model was used to predict the end-effector force by using EMG signals. The subject was asked to perform voluntary movements with muscle contraction and interaction force. Once obtaining the estimated force from SVR model, the impedance model can be used to control the parallel robot to track the desired force by adjusting the stiffness parameter and modifying the reference position. The experimental process of this rehabilitation training control is shown in Fig. 6.

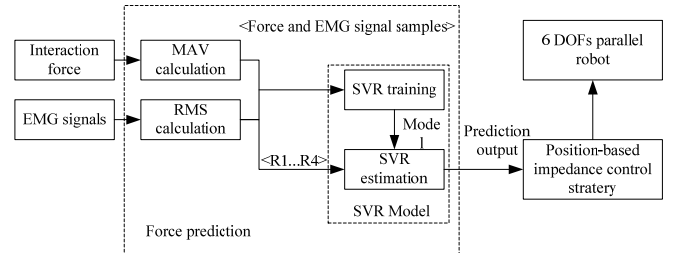


Fig. 6. Experiment process of proposed force prediction and control method.

#### B. Results and Discussion

Firstly, the experiment was performed to verify whether the SVR model can predict the limb end-effector force correctly. The lower limb forward force in horizontal plane was selected in this test. Using force sensor and EMG acquisition device to collect actual lower limb force and surface EMG signals, 1000 samples were utilized as the inputs to force prediction model. After finishing the training process of SVR model, 1000 EMG samples were utilized to predict the interaction force based on SVR model, and the lower limb force was simultaneously

measured in real time for comparison. The predicted force and the actual force are presented in Fig.7.

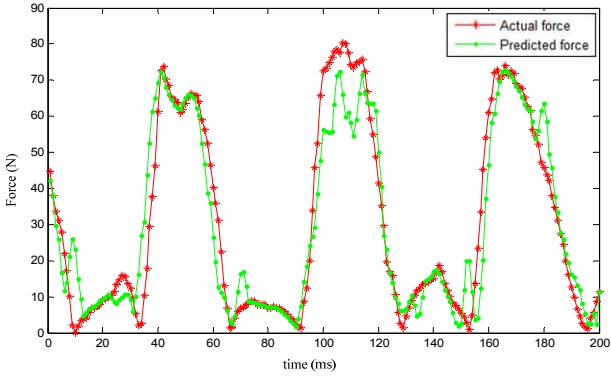


Fig. 7. The EMG-based force prediction results. The red line is the actual force feedback from load cell sensor, while the green line is the estimated force based on EMG signals and SVR model.

It is demonstrated that the predicted force can track the actual force in a satisfactory accuracy, though there is a small time delay. Specifically, the accuracy of proposed model can be evaluated by calculating the correlation coefficient between output force and actual force according to (9).

$$\delta = \frac{100 \sum_{i=1}^n y_i \cdot \hat{y}_i}{\sqrt{\sum_{i=0}^n y_i^2} \cdot \sqrt{\sum_{i=0}^n \hat{y}_i^2}} \quad (9)$$

where  $y_i$  and  $\hat{y}_i$  denote measured force and prediction force respectively,  $n$  is the sample size. In our experiments, 1000 samples including predicted force and measured force were selected to calculate the relevance and finally the correlation coefficient is  $\delta = 87.2\%$ . Therefore, there is a relatively high relevance between the measured force and predicted force.

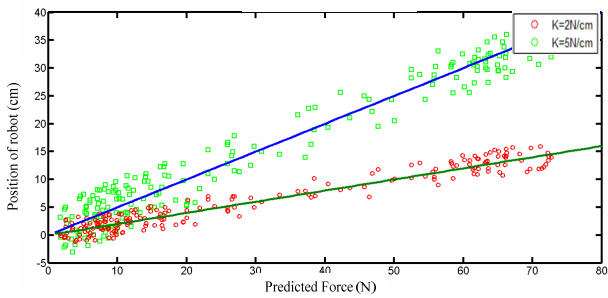


Fig. 8. The position-based impedance control results with different stiffness.

Secondly, we examined how the stiffness parameter would influence the robot compliance when a subject interacted with the robot. The active rehabilitation training experiments were conducted based on the aforementioned simplified impedance model, in which stiffness parameter  $K_d$  was set to 2N/cm and 5N/cm, respectively. The objective of this experiment was to simulate the stretching process of spring by adjusting robot's

position according to the force error. The force applied by the subject reached its maximum when robot arrived at equilibrium position. The robot position change was in proportion to the force error. The maximum speed of robot was set to 5cm/s and 200 samples including robot position, actual interactive force and desired force were recorded and illustrated in Fig. 8.

As illustrated in Fig. 8, the smaller  $K_d$  leads to the larger position modification of the robot. The force obtained from prediction model present the subject's muscle strength level and thus can be used as the reference force in active tracking control. In this experiment process, subject's motion intention can be detected by measuring the interactive force through the force sensor, and then the robot can be controlled according to the subject's intended motion. In this paper, the interactive force was utilized to modify the robot position according to the proposed simplified impedance model.

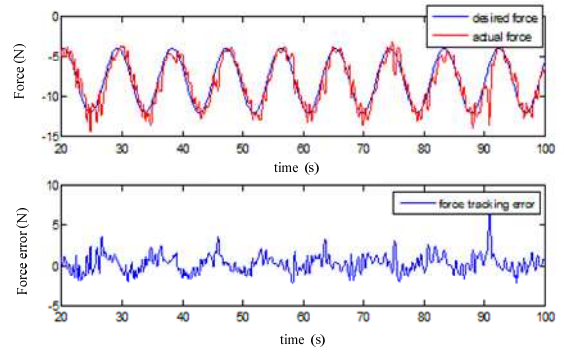


Fig. 9. Force tracking results of the simplified impedance controller.

Thirdly, the simplified impedance controller performance, the EMG-based force prediction and control approach were analyzed and evaluated. In the first part of this experiment, the impedance controller was used to track the desired force. The desired force here is not predicted from EMG signals but is an ideal curve, as  $F_z = -8 + 4 * \sin(\omega t)$ . The objective of this test is to verify that the simplified impedance model can track the desired force in a good performance. The force tacking results is presented in Fig. 9, in which the actual force, the desired force, as well as the tracking errors are illustrated. The average tacking error is 0.189N, and the standard deviation is 0.105N, which is satisfied to meet the general requirement.

In the second part of this experiment, the EMG-based force prediction and control approach was evaluated. In this part, the subject was asked to perform continuous movements. During the experiment, EMG signal and actual force were recorded in real time, and the limb end-effector contact force would be estimated online based on SVR model. Once obtaining the predicted force, the robot was controlled to track the reference force by using impedance model, just like the first part of this experiment. As shown in Fig. 10, where  $K_d$  was set to 2N/cm, the actual force and the predicted force are presented for comparison. It is illustrate that the force error is small enough. Furthermore, the designed active rehabilitation system is able

to provide different patients and different recovery conditions with different compliance by adjusting the stiffness parameter.

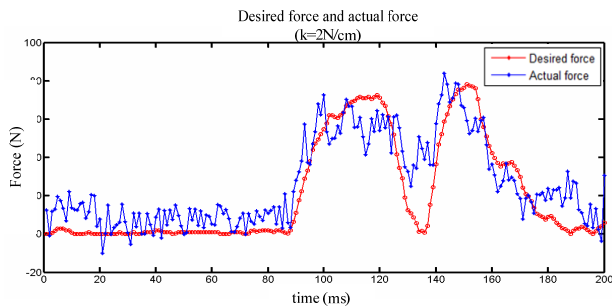


Fig. 10. The EMG-based force prediction and force tracking results based on impedance model. The red line is the desired force estimated from EMG signals by SVR model, while the blue line is the actual force feedback from force sensor and controlled by the impedance model.

Experimental results on a healthy subject demonstrate that it is comfortable and convenient to control the robot according his movement intention. The designed system is characterized by stability and reliability. Moreover, considering the force control in real environment, it is advised to combine motor rehabilitation theory and pathology to develop more reasonable force control strategies. The compliant control of robot which aims at assisted-as-needed is also an important issue to ensure the safety and effectiveness of rehabilitation.

#### IV. CONCLUSION

In this paper, SVM and AR model were adopted to predict the lower limb end-effector contact force. The samples data set consisting of actual force and EMG signal RMS was used as the inputs and to train the SVR model. Furthermore, a position based simplified impedance control method was applied to make the robot compliant and flexible to different recovery conditions. Taking rehabilitation requirement into account, the muscle strength and lower limb force can be predicted by using EMG signals and SVR model. In order to provide the patient with different interaction force to different movement abilities, the proposed impedance controller can make the robot track the desired interaction force obtained from EMG signals by using various stiffness parameters. In this way, the robot can provide adaptable human-robot interaction to fit the individual ability.

However, there are still some limitations of the current rehabilitation strategies. For instance, the trajectory may be not physiologically meaningful and the force prediction is limited to a two-dimensional plane space. In the future work, the force control model in three-dimensional space and corresponding EMG processing method should be investigated. Moreover, the physiologically meaningful trajectories should be designed by taking the therapists' suggestions.

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