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Study on Contact Force Prediction for the Vascular Interventional Surgical Robot based on Parameter Identification

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***Abstract* –With the development of science and technology, surgical robots have made it possible for doctors to perform remote operations, which has also brought good news to patients in remote areas. However, there are some factors that cause the problem of force feedback lag, such as network delay and network instability, so we can use the model-based force feedback prediction method. In this paper, the contact force is modeled in the master manipulator side, which is used to predict the contact force when the slave manipulator side contacts the real tissue. It can obtain better system transparency. In order to ensure the accuracy of the contact force model, autoregressive least squares method is used for parameter identification, so that the environmental model parameters can be identified in real time and the master side prediction model can be corrected. Experimental results indicated that this method can perform force prediction well.**

Index Terms – Force feedback,Contact force model prediction, Parameter identification.

I. Introduction

With the development of master-slave teleoperation robots, it can help people to perform remote operations, among which master-slave teleoperation robots are an important application of teleoperation robots [1]. Traditional minimally invasive surgery requires doctors to insert surgical instruments into real tissues around the patient, and vascular interventional operations also need to use X-ray images, but the use of master-slave surgical robots can help doctors stay away from radiation, and remote master-slave surgical robots make it easy for doctors to operate on patients in remote areas[2]. In 2001, doctors operated a master robot in the United States and placed a slave robot in France to perform cholecystectomy on patients. This was the first remote surgical operation based on a Zeus robot [3]. In March 2020, Zhong Nanshan's team worked with Shenyang Institute of Automation Chinese Academy of Sciences to design a remote teleoperation robot with force feedback for throat swab sampling, and put it into emergency use. The robot can not only perform throat swab sampling well, but also use remote operation to effectively prevent the spread of the virus.

A very important point when using minimally invasive surgical robots for surgical operations is force feedback. In particular, vascular interventional surgical robots need to contact soft tissues such as blood vessels, which requires higher real-time force feedback[4]. The remote surgical robot will inevitably have the network delay and network instability, especially when operating remotely with remote areas, the force feedback information will lag[5]. When the end of the actuator interacts with the soft tissue, the insufficient force felt by the doctor can easily lead to the puncture of soft tissues such as blood vessels and happen surgical accidents[6]. Therefore, the research on solving the problem of force feedback lag is very meaningful.

In order to solve the problem of force feedback lag, this paper proposes a method to establish a contact force model at the master side to predict the interaction force with soft tissue. Remote teleoperation systems based on model prediction usually include environmental geometric models and contact force models. This paper mainly studies the solution to the problem of force feedback lag, so the main research is on contact force models[7]. Environmental modeling and model updating are key technologies for remote operation of model-based force feedback. In this paper, a contact force model for prediction is established on the master side. When the slave side cannot feed back the force to the master side in time due to network delay or instability, the contact force model established by the master side can give timely predictions force. Secondly, in order to ensure the accuracy of the model, the autoregressive least square method is used for parameter identification, real-time update of parameters, and correction of the prediction model.

This paper is divided into five chapters: The first part is the introduction. The second part is an overview of the platform of the surgical robot system. The third part is the prediction method of contact force model. The fourth part is experiment and result analysis. The last part is the conclusion and the future work.

II. Overview Of The Platform

The master-slave minimally invasive surgical robot system includes an operator, a master manipulator, a slave manipulator, a communication channel and a real tissue[8]. The master-slave vascular interventional surgical robot system can assist the doctor in the operation. The doctor can operate the master manipulator far away from the operating room, and send the operation command through the master manipulator, and then transmit it to the slave manipulator through the communication channel, using the catheter guide wire complete of relevant surgical operation orders[9]. In this paper, a contact force model is established on the master side, and in order to be able to identify parameters in real time, the autoregressive least square method is also placed on the master side to identify and correct the contact force model, so when the doctor sends an operation command, you can feel the the prediction force of the contact force model in real time . The Contact force model prediction system composition diagram is shown as in Fig. 1.

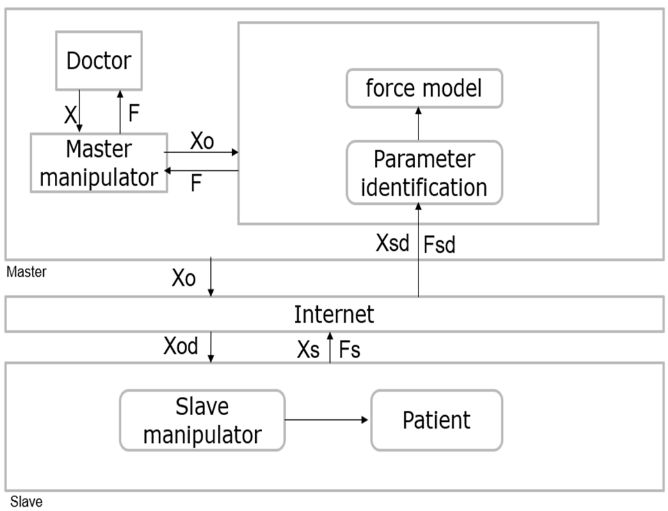

Fig. 1 Contact force model prediction system

The working method of the system is that the doctor directly sends the surgical operation command on the master manipulator, and then writes the relevant operation information into the master controller, and when the doctor sends out the command, the contact force model immediately feeds back the force to the doctor's hand in real time, and simulates the force that will be generated from the slave side[10]. At the same time, the command issued by the master controller will be sent to the slave controller through the network to control the slave manipulator to perform relevant surgical operations, and the force sensor at the slave side can measure the force generated by the interaction between the surgical instrument and the real tissue[11], the measured force is transmitted back to the master side, and the parameters are identified by the autoregressive least square method to modify the contact force model and ensure the accuracy of the contact force model.

The master manipulator designed by our team is simple to operate, conforms to the doctor's operating habits, and the force feedback function based on the principle of electromagnetic induction[12]. The master side structure design is shown as in Fig. 2. The slave manipulator is mainly composed of linear displacement platform, fixture and sensor detection modules[13]. The slave side structure design is shown as in Fig. 3.

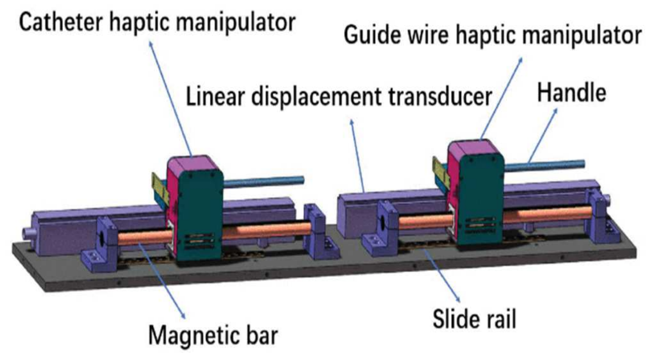

Fig. 2 The master manipulator

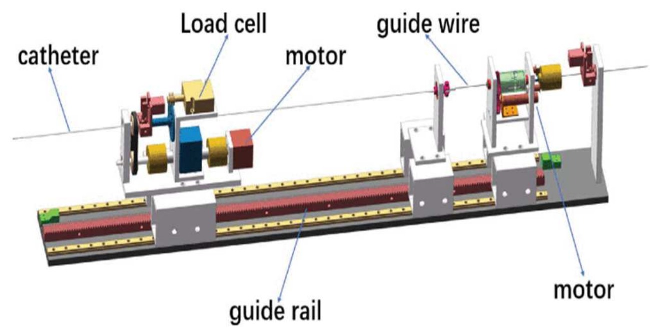

Fig. 3 The slave manipulator

III. Contact Force Model Prediction Method

A. *Overview of the Contact Force Model Prediction Principle*

The surgical robot system designed in this paper based on the prediction of the contact force model is to establish a local contact force model at the master side:

$$f(t) = mx''(t) + bx'(t) + kx(t) + \varepsilon(t) \quad (1)$$

Among them, $f(t)$ is the contact force, $x(t)$ is the displacement change, $x'(t)$ is the speed, $x''(t)$ is the acceleration, $\varepsilon(t)$ is the modeling error and noise, m is the mass coefficient, b is the damping coefficient, and k is the elastic coefficient.

After the master side sends a motion command, the contact force model will calculate the magnitude of the contact force and feed it back in real time, then it can predicting the force generated when the slave contacts the real tissue. At this time, the master operator obtains a real-time predictive force, it ensures the transparency and real-time of the system. Due to the non-linearity and time-varying nature of the real environment, in order to ensure the accuracy of the contact force model, it is necessary to use the signal measured by the slave side sensors to transmit back to the master side for parameter identification and correction of the contact force model parameters.This paper uses autoregressive least squares parameter identification, it can use past state information to iteratively predict current or future state information, and the algorithm does not need to store a large amount of data to ensure real-time performance. The above is an overview of the principle of the contact force model prediction method used to solve the problem of force feedback lag.

B. Model Parameter Identification Method

Considering that the contact force model of the master side will be different from the real model of the slave side under actual conditions, it needs a fast and accurate model parameter identification method to ensure the accuracy of the model. First, the parameter identification algorithm needs to be able to identify on-line in real time, quickly reflect changes in environmental parameters, and make the model more accurate. Secondly, the amount of data storage and calculation in the identification process is small, and the parameters can be updated in real time. Therefore, this paper chooses autoregressive least squares method for parameter identification.

Least squares method is a mathematical optimization technique and one of the classic algorithms commonly used in the field of machine learning[14]. It finds the best function match of the data by minimizing the sum of squares of errors. The least squares method can be used to simply predict unknown data, and the sum of squares of errors between the output data and the real data is guaranteed to be the smallest[15]. The square sum of error E can be expressed by the following formula:

$$E = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left(y_i - y_o \right)^2 \tag{2}$$

Among them, y_i is the real data, and y_o is the estimated value.

For general single-input single-output (SISO) discrete systems:

$$\begin{aligned} & y(k) + a_1 y(k-1) + \ldots + a_{na} y(k-na) = \\ & b_1 u(k-1) + \ldots + b_{nb} u(k-nb) + e(k) \end{aligned} \tag{3}$$

Among them, *y(n)* is the output value of the nth observation, *u(n)* is the nth input value, and *e(k)* is the error and noise.

Rewrite this formula as:

$$\begin{aligned} & y(k) = -a_1 y(k-1) - \ldots - a_{na} y(k-na) + \\ & b_1 u(k-1) + \ldots + b_{nb} u(k-nb) + e(k) \end{aligned} \tag{4}$$

Let:

$$\begin{aligned} & \varphi^T(k) = [-y(k-1), \ldots, -y(k-na), \\ & u(k-1), \ldots, u(k-nb)] \end{aligned} \tag{5}$$

$$\theta = [a_1, a_2, \ldots, a_{na}, b_1, b_2, \ldots, b_{nb}] \tag{6}$$

So as to convert the system into the least square format:

$$y(k) = \varphi^T(k) \cdot \theta + \varepsilon(k) \tag{7}$$

Where $\varphi^T(k)$ is the sample set, θ is the parameter set to be identified, and $\varepsilon(t)$ is the error between the estimated response and the actual feedback.

Because this paper requires the selection of an algorithm that can identify online parameters, and it needs to ensure the algorithm's ability to modify parameters, to ensure that each iteration can achieve strong tracking capabilities and fast parameter convergence. Therefore, the autoregressive least squares method is selected[16]. The algorithm ignores the time lag in the transmission process between the master side and the slave side. It uses the past status information to predict the status information that will occur in real time, and continuously uses the actual measurement value to make the difference between the predicted value to obtain the prediction error, then according to the last prediction parameters and error conditions, make corrections to the next prediction to reduce the error, so that accurate prediction can be made.

For the autoregressive least squares method, it is first necessary to determine the parameters to be identified, as well as the input and output signals[17]. Then assign initial values to the identification parameters and covariance matrix:

$$\theta(0) = 0; \quad P(0) = \delta^{-1} \cdot I \tag{8}$$

Where δ is a very small number.

Use the input and output signals to construct the information vector $\varphi^T(k)$, so that the Kalman gain vector $K(k)$ and the covariance matrix $P(k)$ can be calculated, as shown below:

$$K(k) = P(k-1)\varphi(k) \big/ \lambda \cdot I + \varphi^T(k) \cdot P(k-1)\varphi(k) \tag{9}$$

$$P(k) = [I - K(k) \cdot \varphi^T(k)] \cdot P(k-1) / \lambda \tag{10}$$

Among them λ is the forgetting factor, when it is 1, it is the ordinary recursive least square method, and it is better to take 0.95-0.99 to achieve the effect.

Then pass the error between the measured value and the predicted value:

$$\varepsilon(k) = y(k) - \varphi^T(k) \cdot \theta(k-1) \tag{11}$$

Then multiply the error by the covariance matrix and add the parameters of the previous prediction to predict the parameters that need to be identified:

$$\theta(k) = \theta(k-1) + K(k)\varepsilon(k) \tag{12}$$

Until the parameters converge to meet the requirements, the calculated values can be obtained by substituting the parameters into the model.

C. Simulation of Parameter Identification

In this paper, autoregressive least squares method is used to identify the parameters of the prediction model. In order to verify the effect of parameter identification, Matlab/Simulink software is used for simulation. In the simulation, it is assumed that the movement trajectory when the slave side touches the real tissue is x=sin(t). Because the master-slave tracking performance of this system is good, the movement trajectory input by the master side is also set to xm=x. And in the simulation, let the forgetting factor λ=0.96 and the parameters of contact force model *m*= 0.01, *b*= 0.1 and *k* = 1.This paper has carried out two simulation experiments, one is a simulation with a 300ms delay, and the other is a time-delayed simulation to verify the effect of the prediction.

As shown in the two pictures below, Fig. 4 represents the result of parameter identification without delay, Fig. 5 represents the result of parameter identification with delay, the red dotted line represents the predictive power calculated by the master side, and the blue solid line represents the actual measured force from the slave side.

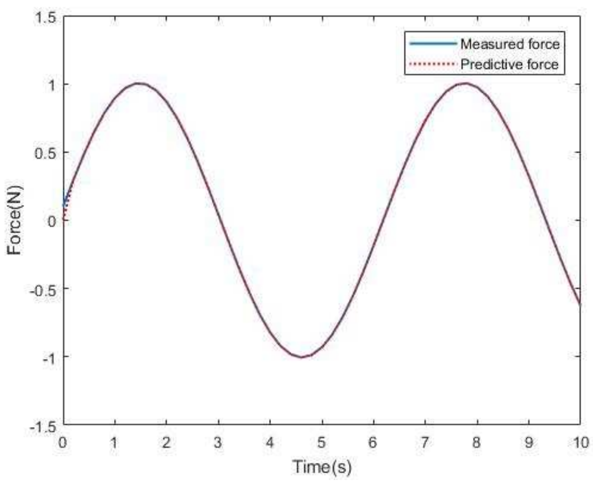

Fig. 4 Parameter identification without delay

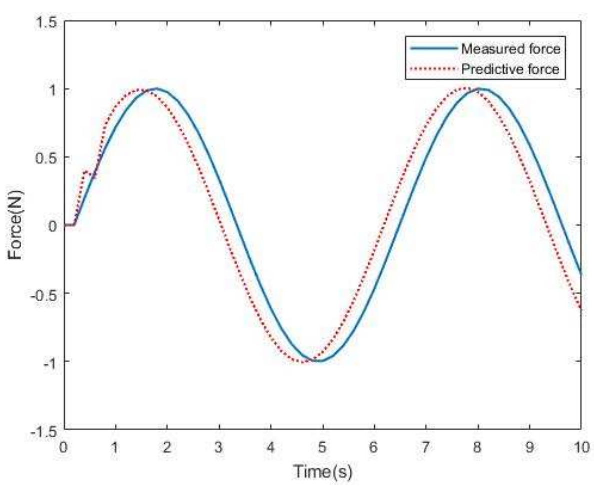

Fig. 5 Parameter identification with delay

It can be seen from Fig. 4 that the effect of parameter identification is very small, and the calculated predictive force is basically consistent with the actual measured force, which proves the accuracy and real-time performance of parameter identification using the autoregressive least squares method. From Fig. 5, it can be seen that the force predicted by the model on the master side can get the force perception earlier than that on the slave side.

IV. Experimental Results And Analysis

A. The Experimental Set Up

In order to verify the accuracy and real-time performance of the contact force model prediction, we conducted experimental verification through the vascular interventional surgery robot platform. This experiment measures the predicted force calculated by the contact force model of the master controller and the actual force measured by the slave force sensor. As shown in Fig. 6.

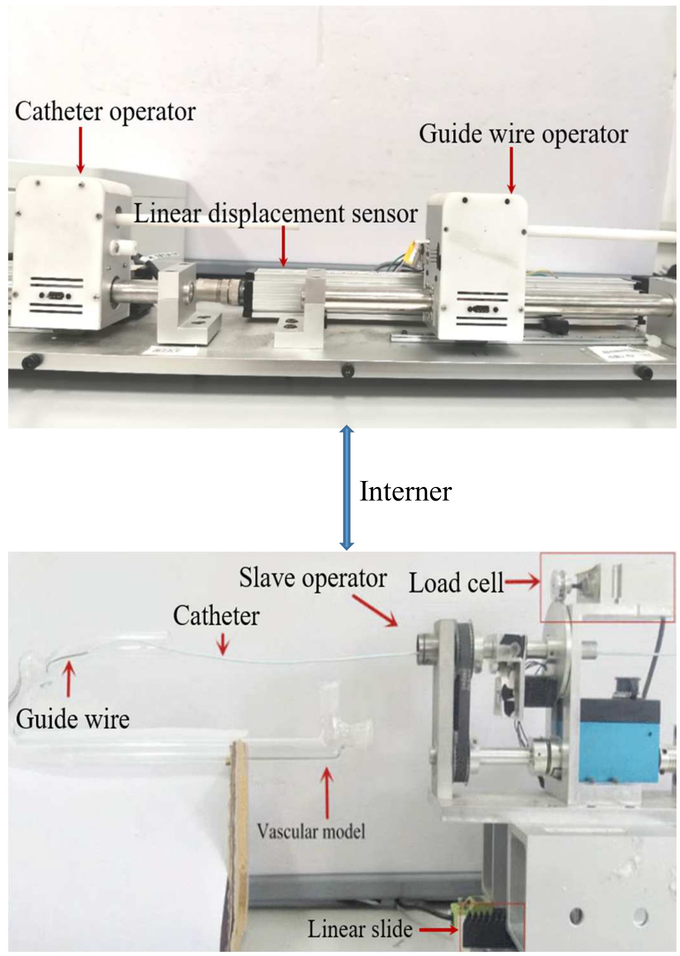

Fig. 6 Contact force prediction experiment

Firstly, operate the master manipulator to send a displacement command, and input the displacement command as a control signal to the master controller. At this time, the contact force model will calculate a predictive force in real time, and the master controller will collect the predictive force signal at this time. Then, the control signal is sent to the slave surgical robot, which controls the catheter and guide wire to interact with the blood vessel model to generate contact force, and then the actual contact force signal is measured by the load cell force sensor from the slave and returned to the master controller, using the master parameter identification link online correction model. And the delay of this experimental environment is mainly caused by the system delay and network delay.

In order to reflect the real-time predictability of the contact force, the real-time measured force sensor signal from the slave side with a time delay is compared with the real-time predictive force of the master side without delay; in order to reflect the accuracy of the predictive force, the error between the actual measured force and the predictive force is used to verify.

B. The Experimental Results

In order to evaluate the effect of the experiment, We collected the contact force of the guide wire and the catheter measured by the force sensor and compared it with the predicted force calculated by the contact force model. The experimental results of the catheter contact force are shown in Fig. 7. The red dotted line represents the predicted force calculated by the catheter contact force model, and the blue solid line represents the force measured from the end force sensor at this time. It can be seen that due to the accuracy and real-time nature of parameter identification, the predictive force of the catheter can track the measured force of the slave sensor very well, and because of the contact force model established directly at the master side, a real-time contact force can be obtained. Therefore, the predictive force in advance to generate the force signal from the slave side measured force. Perform error analysis through the collected data, as shown in Fig. 8 is the generated error, and it can be seen that it is basically stable at 0-15mN.

We also carried out the experiment of operating the guide wire. The experimental results are shown in Fig. 9. The red dotted line represents the predicted force calculated by the guide wire contact force model, and the blue solid line represents the measured force from the slave side force sensor. It can be seen that the guide wire contact predictive force can track the measuring force of the sensor very well, and the force signal is generated in advance of the measuring force. Perform error analysis through the collected data, as shown in Fig. 10 is the generated error, and it can be seen that it is basically stable at 0-13mN.

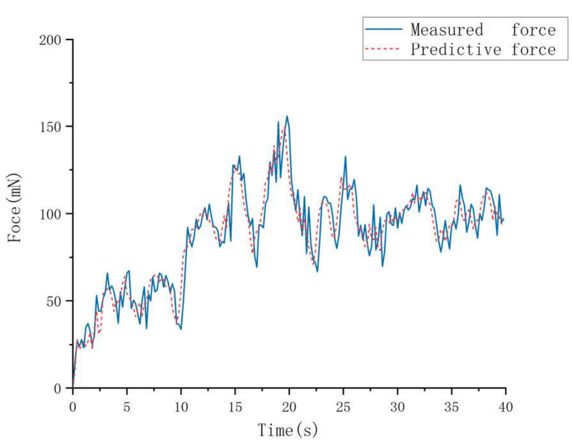

Fig. 7 Prediction experiment of catheter contact force

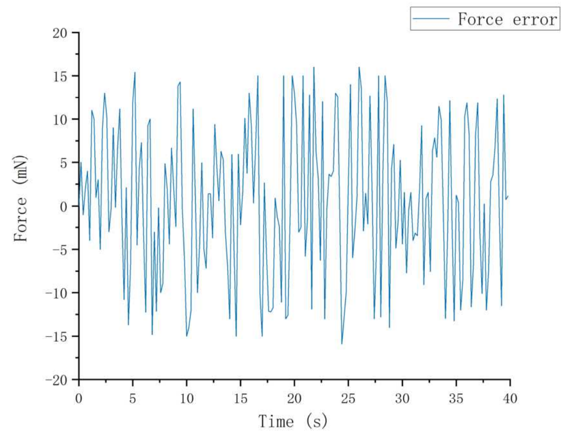

Fig. 8 Prediction error of catheter contact force

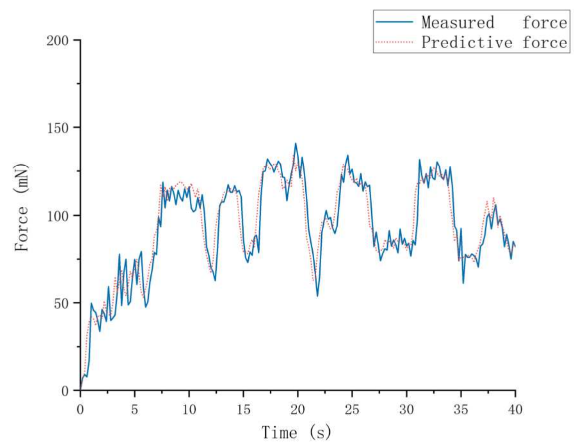

Fig. 9 Prediction experiment of guide wire contact force

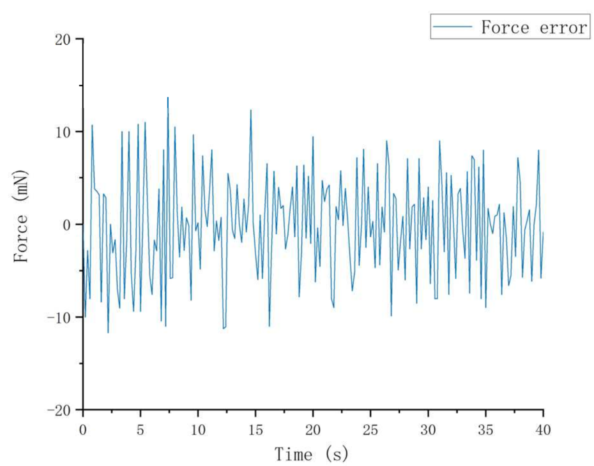

Fig. 10 Prediction error guide wire contact force

Through the above analysis, it can be seen that the contact force obtained by the method in this paper can be predicted ahead of the contact force of the slave side, and a real-time contact force is generated on the master side, thereby solving the problem of force feedback lag; and benefiting from parameter identification method, the error of the predictive force is small, the accuracy of the predictive force is guaranteed, and the minimum perceptible force error of the manpower and the surgeon's requirements are met. It is worth noting that the prediction effect of different operators may be different, and with the development of scientific research, in order to improve the prediction effect, the contact force model and parameter identification methods can be further studied.

VI.CONCLUSIONS AND FUTURE WORK

In order to solve the problem of force feedback lag, this paper proposed a method of contact force model prediction. The contact force model was established at the master side and the model was corrected by parameter identification method. And conducted experiments to verify the feasibility of the method proposed in this paper. The experimental results showed that the master side could predict the contact force in real time and ensure the accuracy of the predictive force, which can well solve the problem of force feedback lag. The future work will be to further study the contact force model and prediction method.

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