

Research on Force Sensing and Zero Gravity Motion Simulation Technology of Industrial Robot

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Title page

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ORIGINAL ARTICLE

Research on Force Sensing and Zero Gravity Motion Simulation Technology of Industrial Robot

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Abstract: Towards the zero-gravity simulation test requirements of spacecraft for on-orbit service missions, the zero-gravity motion simulation technology based on industrial robot was studied. In order to realize the accurate force sensing of load on robot, the BP neural network was used to establish the force prediction model. The model uses the robot pose, acceleration, angular velocity, and angular acceleration as input layer parameters, and uses the data from force/torque sensor on robot wrist as the output layer parameter. In order to realize the accurate force perception in whole working space of the robot, the orthogonal experiment design method was adopted to determine the path points of the robot for sample data collection. Based on the established force prediction model, the accurate force sensing of the end load of the robot under moving conditions is realized. In experiment, for the load with 100kg mass on robot, the maximum error of force sensing is 39.8N, and the root mean square error of force sensing is 9.3N. The maximum error of torque sensing is 18.7Nm, and the root mean square error of torque sensing is 4.4Nm. Furthermore, according to the real-time force sensing results of the robot load, the motion speed of the load in zero-gravity state is calculated by dynamics theory. Then the robot is driven to execute the corresponding motion of the load, and the zero gravity motion simulation of the load is realized.

Keywords: Force-feedback • Zero-gravity simulation • BP

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neural network • Robot control

1 Introduction

On-orbit servicing (OOS) usually refers to the space assembly, maintenance and service that can extend the life or enhance the capability of spacecraft through human, robot or both in space [1]. In order to make the system adapt to the space environment with microgravity, vacuum, radiation etc., it is an effective measure to improve the success rate of space flight to carry out sufficient test verification on the ground. For the ground simulation of OOS technology, zero gravity simulation is the key and difficult point. At present, there are several kinds of zero gravity simulation methods, including freefall, parabolic flight, air bearing, neutral buoyancy, force compensation and hardware in loop (HIL) [2].

The HIL method combines the prototype with the mathematical model, which is a semi-physical simulation method, and can be used for the ground experiment of space mechanism [3-6]. It accurately measures the force of the simulated object in real time, further calculates the motion of the object in zero gravity environment with the help of dynamic model, and then realizes the motion by the robot [7]. Accurate force sensing is the premise of accurate motion simulation [8].

For the realization of zero gravity motion of robot, the existing technology mainly includes two ways.

One method is to carry out force-free control for the robot [9], which is necessary to identify the mass characteristics of each part of the robot, and establish the dynamic model of the robot, so as to realize the prediction of the joint torque in the process of robot movement [10-12]. The joint torque is collected in real time during

the operation of the robot, and the contact force on the robot is obtained by comparing the actual joint torque with the predicted torque, And drive the robot to achieve zero-gravity movement. This method does not need additional sensors for the robot, but an important problem of this method is that the joint friction torque can not be accurately measured or predicted [13]. For heavy load on robot, it is difficult to achieve an accurate force sensing result. This method is usually used in the direct teaching of robot with light load.

Another method is installing a 6-axis force/torque(F/T) sensor on the wrist of the robot. The F/T Sensor can accurately measure the three-dimensional orthogonal force (F_x, F_y, F_z) and three-dimensional orthogonal torque (M_x, M_y, M_z) in any force system in the space. For the robot with heavy load, it can still obtain high measurement resolution and can achieve more accurate simulation for zero gravity motion.

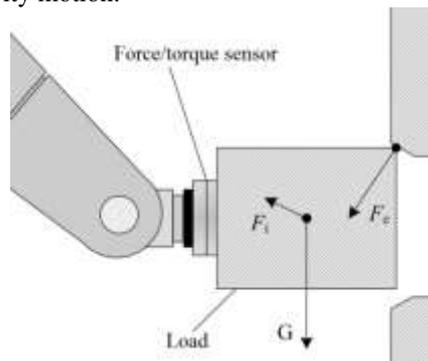


Figure 1 Schematic diagram of the force acting on the load

As shown in Figure 1, in the process of the robot motion, the force and torque data measured by force/torque sensor are mainly caused by four parts, namely, 1) system error of sensor itself, 2) load gravity effect, 3) inertia force and inertia moment of load, 4) the external contact force [14][15].

In order to get the contact force, it is necessary to eliminate the influence of sensor system error, load gravity, load inertia force and torque in force/torque sensor data. When the load weight is small, the influence of load gravity and inertia force can be ignored. When the weight of the load is large, but the dynamic degree of the robot is low and the acceleration is small, the influence of the gravity should be considered, and the influence of the inertial force can be ignored. When the load weight is large and the dynamic degree is high, the influence of load gravity and inertial force must be considered.

This paper focuses on the simulation of zero gravity motion of objects using robot. Due to the large weight of the load, high dynamic degree and large range of motion, it

is necessary to accurately sense the force on the load in the whole workspace of the robot, and the influence of the inertial force of the load must be considered.

In the existing research, the force sensing model of the robot end is usually established by analytical method, that is, considering the physical relationship between the factors affecting the force sensing, the mathematical model between the contact force and known quantities is derived [14-16]. However, there are many factors that affect the force sensing, including the installation angle of the robot base, the installation angle of the sensor on the robot, the position and pose feedback error of the robot, etc. It is difficult to take all these factors into account by using analytical method, and some factors are often ignored to simplify, which inevitably brings some sensing error.

In recent years, with the improvement of computer computing ability, machine learning, artificial intelligence and other technologies. For the situation that the influencing factors are complex and it is impossible to carry out explicit modeling, the optimal model can be obtained by collecting data samples and iteratively optimizing. It does not need to care about the specific parameters of the model, and can obtain higher prediction accuracy.

At present, there have been researches using machine learning to sense the force at the end of the robot. Lei Yao et al. established the error model of the 6-axis F/T sensor through a neural network to eliminate the error of the sensor itself [17]. Hang Su et al. established a neural network model to predict the load gravity component in the 6-axis F/T sensor data based on the end attitude data fed back by the robot, thereby eliminating the influence of the load gravity [18]. Yong Bum Kim et al. used an inertial measurement unit (IMU) to measure the posture of the end of the robot, and established a neural network model of the load gravity component with the load attitude angle, and also realized the prediction of the gravity component from the attitude angle [19]. In this method, the attitude angle feedback and gravity compensation are independent of the robot. ZeCai Lin et al. studied the force perception problem of robots under dynamic conditions, used BP neural network to predict the influence of load gravity through the robot joint angle, and further used analytical methods to calculate the influence of inertial force/moment to realize the force sensing on the end of the robot [20]. Kamal Mohy el Dine et al. used recurrent neural network (RNN), using the robot end pose and IMU feedback data as input to predict the force of the robot end [21].

In this paper, machine learning method is used to realize the force sensing of the load in the whole workspace of

robot, aiming to solve the problem that traditional analytical method is difficult to achieve. The BP neural network is used in research, the end position and attitude data of the robot, the acceleration and angular velocity data fed back by IMU, and the angular acceleration data from the difference of angular velocity were used as input, The output of the F/T sensor when the load is not subjected to external force was used as output. Compared with the existing studies, this study introduces the angular acceleration information obtained from the difference of IMU angular velocity data in the input layer, because the theoretical analysis shows that the inertia moment caused by load rotation is directly related to its angular acceleration. On the other hand, this study takes the position and attitude information of the robot end as a part of the input layer parameters, and covers the whole workspace of the robot as much as possible in the sampling, so that the trained model can obtain high accuracy in the whole workspace of the robot and meet the large-scale motion requirements of zero gravity motion simulation. the prediction model of the end force can be obtained through training. When the robot end is subjected to contact force, using the actual measurement value of the F/T sensor minus the predicted value, the contact force can be obtained. On the basis of realizing the dynamic force sensing of the robot end load, further combined with the dynamic theory, according to the force sensing data of the robot end in real time, the motion speed of the robot end load under zero gravity can be calculated, and the robot is driven to perform the corresponding motion, so as to realize the zero gravity motion simulation of the load.

2 Theoretical Analysis

For the robot load shown in Figure 1, the external force and torque are:

$$\begin{cases} \mathbf{F}_e = \mathbf{F} - \mathbf{F}_0 - \mathbf{G} - \mathbf{F}_c \\ \mathbf{M}_e = \mathbf{M} - \mathbf{M}_0 - \mathbf{M}_g - \mathbf{r}_c \times \mathbf{F}_c - \mathbf{M}_c \end{cases}, \quad (1)$$

Where \mathbf{F} and \mathbf{M} are the force and torque data directly reading from the F/T sensor, \mathbf{F}_0 and \mathbf{M}_0 are the system error of sensor itself, \mathbf{G} and \mathbf{M}_g are the load gravity and the moment brought by gravity, \mathbf{F}_c is the inertia force of load, which can be calculated by the load mass and the measured acceleration. \mathbf{r}_c is the location of the center of gravity of the load, $\mathbf{r}_c \times \mathbf{F}_c$ is the moment caused by the inertia force, and \mathbf{M}_c is the inertia moment caused by the rotation of the load.

The system error \mathbf{F}_0 and \mathbf{M}_0 is constant and can be easily obtained by static calibration. For the influence of gravity \mathbf{G} and \mathbf{M}_g , the magnitude, direction and center position of load gravity in the F/T sensor coordinate system should be considered. Assuming that the load gravity is G , the angle between the gravity direction and the X, Y, Z axes of the F/T sensor coordinate system are α 、 β 、 γ . Then the projection of the load gravity on the three coordinate axes of F/T sensor coordinate system can be calculated as follows:

$$\begin{cases} G_x = G \times \cos \alpha \\ G_y = G \times \cos \beta, \\ G_z = G \times \cos \gamma \end{cases}, \quad (2)$$

Assuming that the center of gravity of the load in the F/T sensor coordinate system are (x, y, z) , the torques caused by the load gravity on the X, Y, Z axes are:

$$\begin{cases} M_{gx} = G_z \times y - G_y \times z \\ M_{gy} = G_x \times z - G_z \times x, \\ M_{gz} = G_y \times x - G_x \times y \end{cases}, \quad (3)$$

In the process of robot movement, because the gravity direction is always vertical downward, the angle between the X, Y, Z axes and the gravity direction is also changes with the movement of the robot, so it is necessary to collect the pose data of the robot in real time to calculate the gravity influence component.

For the load inertia force \mathbf{F}_c , according to Newton's second law, the load inertia force is:

$$\mathbf{F}_c = -m \cdot \mathbf{a}_{rc}, \quad (4)$$

Where m is the mass of the load, and \mathbf{a}_{rc} is the acceleration of gravity center of the load.

For the moment of inertia caused by load rotation \mathbf{M}_c , according to Newton-Euler formula:

$$\mathbf{M}_c = -(\mathbf{I} \dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times \mathbf{I} \boldsymbol{\omega}), \quad (5)$$

Where \mathbf{I} is the inertia tensor of the load, $\boldsymbol{\omega}$ is the angular velocity of the load movement and $\dot{\boldsymbol{\omega}}$ is the angular acceleration of the load movement.

Based on the above analysis, the force sensing by traditional analytical method needs to be based on the

following data:

- 1) Constant data:
 - a) The system error of sensor.
 - b) The installation angle of robot base and the installation angle of sensor on the robot.
 - c) The mass and the center of gravity of the load.
 - d) The inertia tensor of the load.
- 2) Variable data:
 - a) Data of F/T sensor.
 - b) Pose of robot.
 - c) Acceleration, angular velocity and angular acceleration of load.

For the above variables, the pose of the robot can be obtained by the robot control system in real time. For the industrial robot in series structure form, due to its structural characteristics, the pose feedback from the robot controller often has a large error. The acceleration, angular velocity and angular acceleration of load movement can be obtained by conversion of attitude and speed feedback from the robot, and can also be measured by IMU and other sensors.

For the above constant data, the installation angle of robot base and the installation angle of sensor on the robot need to be measured and calibrated in advance, or the installation accuracy can be ensured by mechanical positioning. The other constants need to be identified in advance, especially for the load inertia tensor, which is difficult to identify accurately, its identification error will affect the final force sensing error.

If using analytical method, the above constant needs to be calibrated in advance, and the above variables are accurately collected during the robot motion. However, because some constants (such as inertia tensors) are difficult to be accurately measured, and some variables (such as robot pose) have large errors and are difficult to be accurately measured and compensated, so it is difficult to meet the precise force sensing requirements of robot under the condition of large load, high dynamic and large range of motion.

If machine learning is adopted, the above variables are collected directly under the condition that the load is not subjected to external force. The data of the F/T sensor is taken as the output, and the other variables are taken as the input. Because the robot end is not subject to external force, the output prediction value of each group of sample input pairs shall be equal to the measured value of the F/T sensor. By collecting the data samples of robot in different motion states in the whole workspace, the machine learning model can be trained iteratively, and the prediction model of the end force can be obtained. When the robot end is subjected

to external force, using the actual measurement value of the F/T sensor minus the predicted value of the machine learning model can obtain the information of external force, which realize the force sensing of the load. This method does not need to pre-calibrate the above constants, and can also accurately fit the nonlinear errors (such as robot pose errors) which are difficult to be modeled analytically.

3 Design of the Machine Learning Model

In this study, BP neural network was used to establish the force prediction model. BP neural network has strong nonlinear mapping ability, which is suitable for the force prediction in this study. The structure of neural network is shown in Figure 2. In the input layer, the position and attitude data from the robot controller, the acceleration, angular velocity data measured by the IMU, and the angular acceleration data from the difference of angular velocity are used. The output layer is the predicted F/T sensor data. A single hidden layer is used between the input layer and the output layer. The number of nodes in the hidden layer needs to be determined according to the experiment. It is necessary to obtain low prediction error for the sample data and avoid over fitting. The activation function of neurons uses sigmoid function.

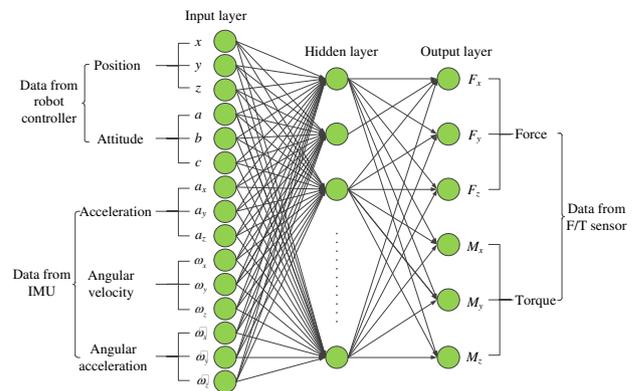


Figure 2 The structure of force prediction neural network

In order to train the neural network, make the robot move without external action, the corresponding data of input layer is collected in the process, and the data collected by F/T sensor at the same time is taken as the corresponding ideal output value of input data at this time, so as to obtain the sample data of input layer and output layer. Using these data to train the neural network, the force prediction model is obtained.

The model can be used to predict the output value of the six axis force sensor under the condition that the robot end is not affected by the external force. When the robot end is

affected by the external force, the external force information can be obtained by subtracting the predicted value from the actual measured value, so as to realize the force perception of the end load of the robot.

4 Realization of Force Sensing

4.1 System Composition

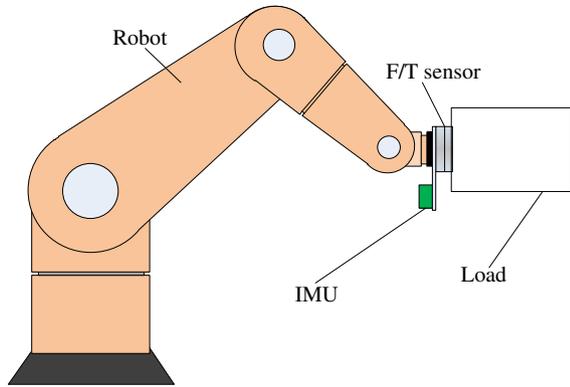


Figure 3 Schematic diagram of robot force sensing test system

The composition of the test system is shown in Figure 3. The F/T sensor is installed at the wrist of the robot, and the IMU is installed at the end of the robot. The robot adopts KR210 robot of KUKA company, and its main parameters are shown in Table 1. The F/T sensor adopts Omega191 sensor of ATI company, and its measurement range and resolution parameters are shown in Table 2.

Table 1 Performance parameters of KR210 robot

Attribute	Rated payload	Number of axes	Maximum reach	Pose repeatability
Value	210kg	6	2696mm	0.06mm

Table 2 Technical parameters of Omega191 F/T sensor

Attribute	F_x /(N)	F_y /(N)	F_z /(N)	T_x /(Nm)	T_y /(Nm)	T_z /(Nm)
Measuring range	-7200	-7200	-18000	-1400	-1400	-1400
Resolution	3/8	3/8	5/8	5/96	5/96	5/144

Table 3 Technical parameters of STIM300 IMU

Parameter	Value
Measurement range of angular velocity	$\pm 400^\circ/s$
Angular velocity resolution	$0.22^\circ/h$
Acceleration measurement range	$\pm 10g$
Acceleration measurement resolution	$1.9\mu g$
Sampling frequency	2000Hz

The IMU adopts the STIM300 of Sensoror company. The sensor adopts three high-precision MEMS gyroscopes

and MEMS accelerometers to measure the angular velocity and acceleration data of X, Y and Z axes respectively. The main technical parameters are shown in Table 3.

The IMU can directly measure the acceleration and angular velocity of the motion. From the above theoretical analysis, it can be seen that the angular acceleration of the load is also needed to calculate the inertial moment of the load. Therefore, the angular velocity data sequence of the IMU is differentiated to obtain the angular acceleration data.

The real object of the test system is shown in Figure 4. The IMU is installed in the adapter between the end of the robot and the F/T sensor, which makes the system more compact in practical application and avoids additional interference in the robot motion. The weight of the robot load is about 100kg.

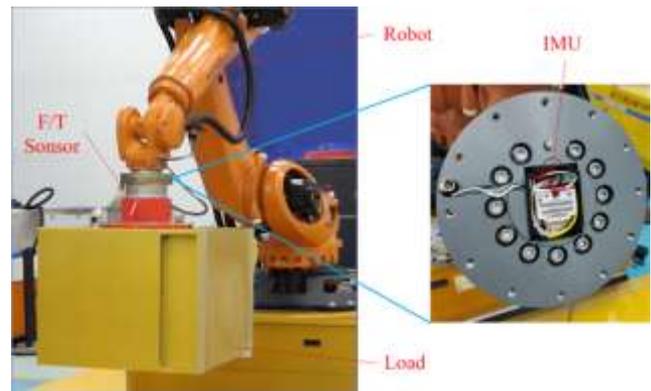


Figure 4 The real object of the force sensing test system

4.2 Collection of Sample Data

In order to make the sample data cover the entire workspace of the robot as much as possible, while reducing the total number of samples and improving the efficiency of model training, the orthogonal experimental design method was adopted in the research. For the six rotation axes A1~A6 of the robot, 10 angle values are uniformly selected within their respective rotation ranges. The value of the rotation range of each axis should be as large as possible, but also to ensure that the robot does not collide during the sample collection movement. The rotation ranges of each axis are shown in Table 4.

Table 4 Rotation ranges of each axis in experiment

Axis	A1	A2	A3	A4	A5	A6
Rotation range	-150	-138	-10	-180	-120	-180
	~150	~-70	~130	~180	~120	~180

According to the orthogonal experiment design method, the angle value of A1~A6 axis is used as 6 factors of the

experiment, and the angle value of each axis is divided into 10 levels. During the sample collection process, the angle of each axis of the robot path point is determined according to the L_{141} (10^6) orthogonal table.

The robot moves in the order of the path points arranged as the orthogonal table. From the current point to the next path point, the point-to-point (PTP) motion mode is adopted, and the robot stays at each path point for 2s, so that the motion of the robot includes acceleration, deceleration and static process. Taking into account the actual speed of the robot in the application, the operating speed of the robot is limited to 30% of the maximum rated speed in automatic mode. During the movement of the robot, the robot end position and attitude parameters, F/T sensor data, and IMU data are synchronously collected with a 12ms cycle. All sample data obtained during a sample collection process in experiment are shown in Figure 5~11.

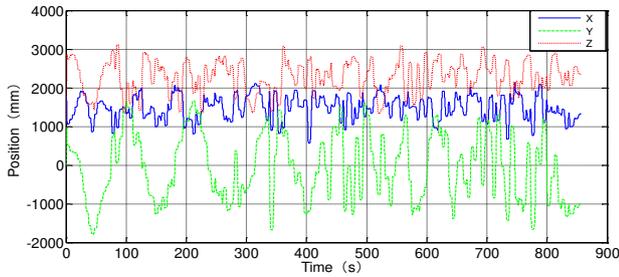


Figure 5 The position data from robot controller

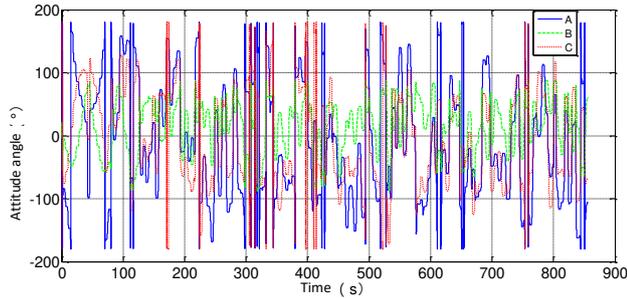


Figure 6 The attitude data from robot controller

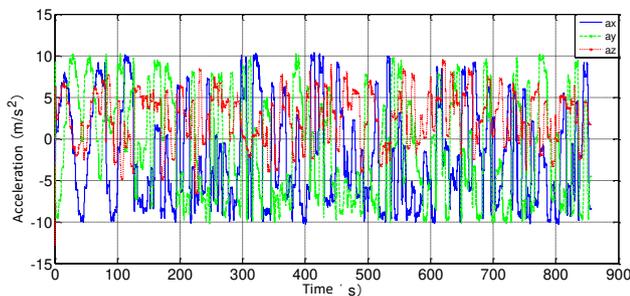


Figure 7 The acceleration data from IMU

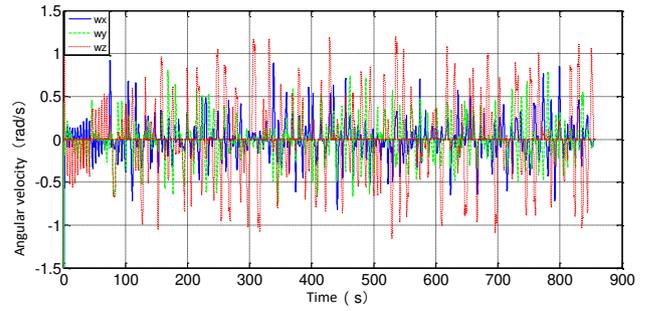


Figure 8 The angular velocity data from IMU

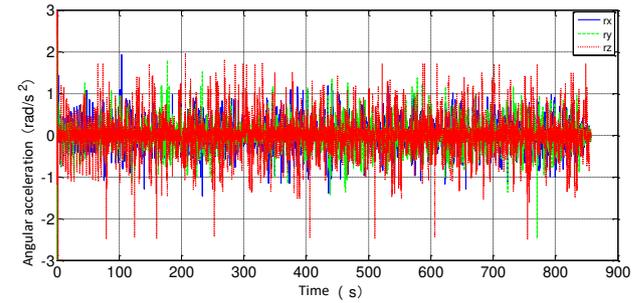


Figure 9 The angular acceleration data from difference of angular velocity

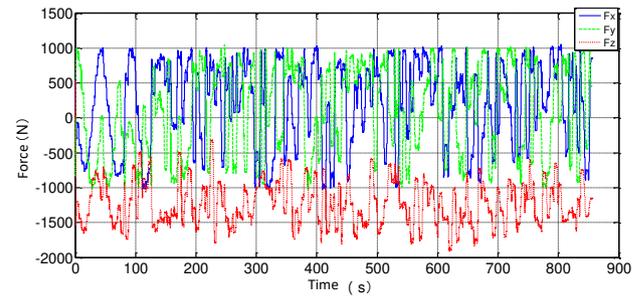


Figure 10 The force data from F/T sensor

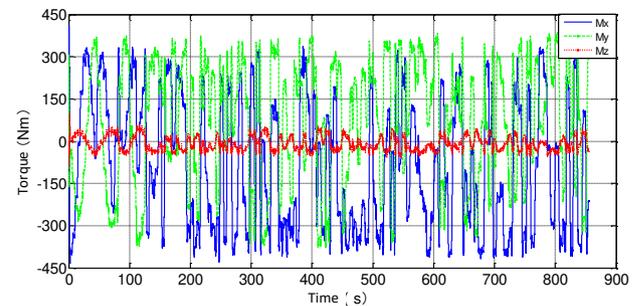


Figure 11 The torque data from F/T sensor

4.3 Model Training

Gradient descent method is used to train the neural network shown in Figure 2. The neural network uses a single hidden layer, and the number of nodes in the hidden layer needs to be determined. In the BP neural network, the number of hidden layer nodes has a great influence on the performance of the neural network model, and it is the

direct cause of overfitting. In order to avoid the phenomenon of overfitting during training as much as possible, and to ensure sufficiently high performance and generalization ability, the structure should be as compact as possible, and the number of hidden layer nodes should be as few as possible on the premise of meeting the accuracy requirements.

During training, the data samples are divided into training set, validation set and test set. The training set accounts for 60% of the total number of samples, the validation set and the test set account for 20% respectively, and 3 subsets of data are randomly selected. The training set is used to train the model, the validation set is used to evaluate the prediction of the model and adjust the corresponding parameters, and the test set is used to test the generalization ability of the trained model for new data.

To determine the number of hidden layer nodes in the neural network, different numbers of hidden layer nodes are used for training, the training is repeated three times for each number of hidden layer nodes, the mean square error obtained from 3 trainings of each hidden layer node is used to evaluate the prediction accuracy under the corresponding hidden layer node number. The comparison of the prediction accuracy under different hidden layer node numbers is shown in Figure 12. According to the result, considering the training time and accuracy requirements, the number of hidden layer nodes is determined to be 8 in the research.

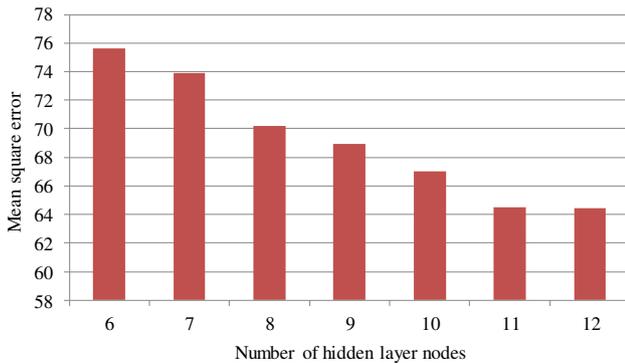


Figure 12 Prediction accuracy under different number of hidden layer nodes

4.4 Experimental Results of Model Prediction

For the system shown in Figure 4, the robot position and attitude, acceleration, angular velocity, and angular acceleration are collected in real time during the movement of the robot, and input into the trained force perception model, which can be calculated in real time to obtain the prediction value for the F/T sensor, the prediction error can be obtained by subtracting the predicted value from the

actual measured value of the F/T sensor.

Take the robot movement process of continuous 10s time, compare the measured data of the F/T sensor with the predicted data of the model, and give the corresponding error, as shown in Figure 13~18. In the figure, in the time range of 1~3s, the robot is in a static state, and in the rest of the time, the robot is in a motion state. Therefore, the selected data includes the static and dynamic processes of the robot. It can be seen from the figure that the prediction error of the robot in dynamic conditions is larger than that in static conditions.

For the error data in Figure 13-18, the maximum error and the root mean square(RMS) error of each component were calculated to evaluate the prediction error, as shown in Table 5. The results show that the maximum error of force perception is 39.8N, and the maximum root mean square error is 9.3N; the maximum error of torque perception is 18.7Nm, and the maximum root mean square error is 4.4Nm. Table 5 also lists the maximum value of the measured data of each component as a reference to illustrate the value range of each component corresponding to the obtained perceptual error, so as to evaluate the effect of the model prediction.

Table 5 Error statistics for dynamic force perception

Attribute	F_x /(N)	F_y /(N)	F_z /(N)	T_x /(Nm)	T_y /(Nm)	T_z /(Nm)
Max error	24.2	39.8	21.6	18.7	15.5	12.3
Max MSE	6.9	9.3	5.7	4.4	3.6	2.8
Max value	979.6	973.2	1009.0	396.2	354.4	47.8

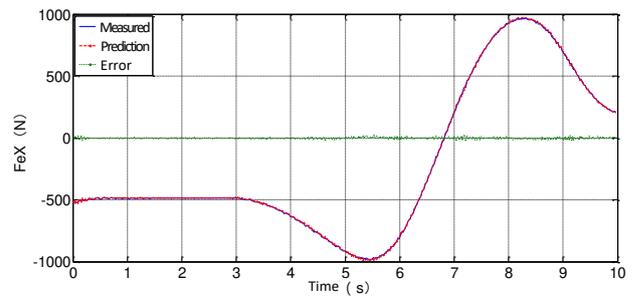


Figure 13 Force prediction error in X-direction

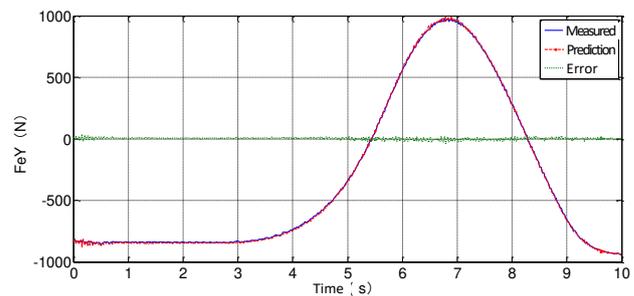


Figure 14 Force prediction error in Y-direction

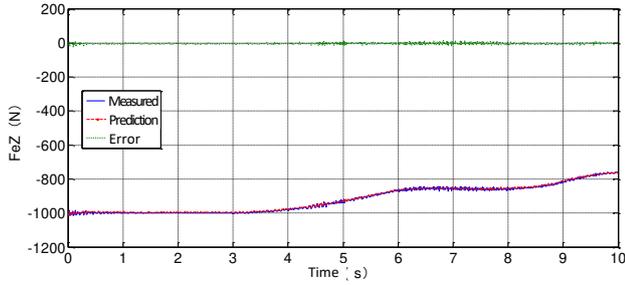


Figure 15 Force prediction error in Z-direction

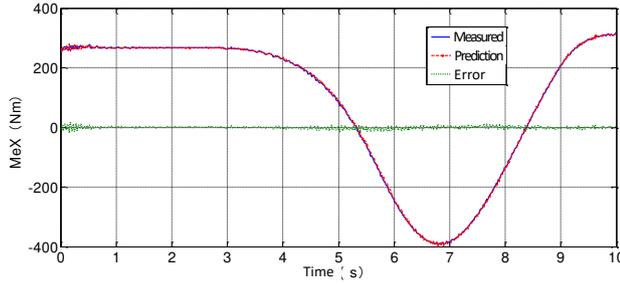


Figure 16 Torque prediction error in X-direction

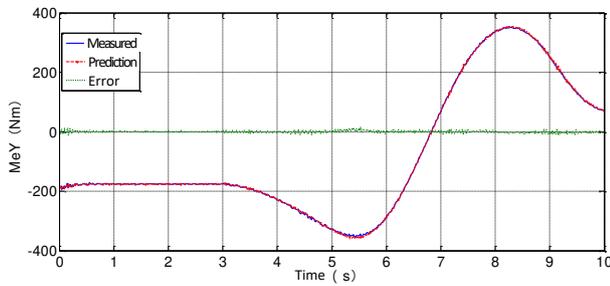


Figure 17 Torque prediction error in Y-direction

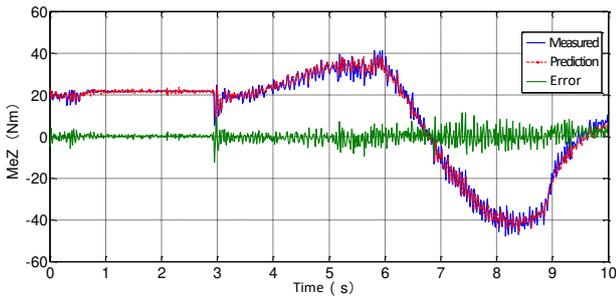


Figure 18 Torque prediction error in Z-direction

It can be seen from figures 13-18 that large errors appear in the robot movement process. This is because under dynamic conditions, the F/T sensor and IMU fluctuate more drastically, filtering the sensor data or the final force perception data can further reduce errors.

5 Zero Gravity Motion Simulation

According to Newton's second law and Euler's equation, the following relationship is obtained:

$$\begin{cases} \mathbf{F} = m \cdot \frac{d\mathbf{v}}{dt} \\ \mathbf{M} = I \cdot \frac{d\boldsymbol{\omega}}{dt} + \boldsymbol{\omega} \times I \boldsymbol{\omega} \end{cases}, \quad (6)$$

Among them, m is the mass of the simulated object, and I is the inertia tensor of the object, which is derived:

$$\begin{cases} \mathbf{v}_t = \int_0^t \frac{\mathbf{F}}{m} \cdot dt \\ \boldsymbol{\omega}_t = \int_0^t \frac{\mathbf{M} - \boldsymbol{\omega} \times I \boldsymbol{\omega}}{I} \cdot dt \end{cases}, \quad (7)$$

This formula indicates the movement speed of the robot at time t can be calculated by integrating the force and angular velocity information collected before time t . Among them, the load force/torque information at the end of the robot can be obtained in real time from the aforementioned force sensing method, and then the speed of the load movement is calculated by formula (7), and the zero-gravity motion of the load can be realized by driving the robot to move as the speed.

From equation (7), since the current speed of the robot is calculated by integrating the previous data, in the zero-gravity simulation, the real-time fluctuation of the force perception data of the above-mentioned robot under motion condition is absorbed by the integration and will not cause violent fluctuations of the robot's movement.



Figure 19 Human-robot interaction in zero-gravity state

In formula (7), the values of m and I can be selected according to the actual mass and inertia tensor of the load of the robot, or can be specified as other values that you want to be simulated to achieve semi-physical simulation. Although the mass characteristics of the load of robot are different from the object to be simulated, the equivalent motion simulation of the object can be realized by digitally specifying the parameters.

The zero-gravity motion simulation of the robot load in Figure 4 is carried out. The tester acts on the end load of the robot by hand, so that the tester can experience the zero-gravity floating state of the object in the ground environment. The process photo of human-robot interaction is shown in Figure 19.

6 Application

An antenna of the China Space Station weighs about 60kg and needs to be installed by astronauts in orbit. When the antenna fails in orbit, it also needs to be replaced by astronauts in orbit. In order to evaluate the feasibility and human-machine efficiency of this type of antenna on-orbit operation tasks. It is necessary to simulate the on-orbit installation situation on the ground to make the antenna in a zero-gravity state, and the tester will operate in accordance with the on-orbit operation procedure. The experiment will check whether the relevant operation procedure can be carried out smoothly, and record the operation force exerted by the tester for evaluation. The degree of effort required for the operation is to determine whether the force required for the operation is within the range of the normal force that the astronaut can apply in orbit.



Figure 20 Application of zero-gravity simulation for on-orbit operations

In response to the on-orbit simulation test requirements of the antenna, a simulation part that is consistent with the

real antenna shape and interface was made, and a connection interface to the end of the robot was designed in the simulation part. After the simulation part was connected with the robot, first collect sample data according to the aforementioned sample collection process, and then trained the neural network to obtain the force prediction model, and then realized the zero-gravity motion simulation method according to the aforementioned zero-gravity motion simulation method. The related technology has been successfully applied in the ground installation simulation test of the antenna.

For the zero-gravity simulation of components, commonly used traditional methods include freefall, parabolic flight, air bearing, neutral buoyancy, force and other methods. Compared with these methods, the advantages of using robots for zero-gravity simulation are:

- 1) The device is simple and the layout is flexible. Only one robot is needed to complete the simulation task. If the robot is equipped with a mobile platform, it can also be moved to different positions flexibly.
- 2) It can realize the motion simulation of all 6 degrees of freedom in three-dimensional space.
- 3) Semi-physical simulation can be realized, only the simulated part needs to have the same shape as the real part, and it does not need to have the same mass characteristics as the real part, which can save costs and simplify the simulation process.

7 Conclusions

- (1) Aiming at the requirement of ground zero-gravity simulation for spacecraft on-orbit service missions, this paper studies the use of industrial robot to achieve zero-gravity simulation of components. The BP neural network is used to establish a force perception prediction model to realize the dynamic force sensing of the robot in the whole work space.
- (2) According to the theoretical analysis of object kinematics, the robot pose, acceleration, angular velocity, and angular acceleration are used as the input layer parameters, and the F/T data is used as the output layer parameters. In the test system, a 6-axis F/T sensor is used to measure the force on the robot's wrist, and an IMU is used to measure the acceleration and angular velocity of the robot's end, and the angular acceleration of the robot's end is obtained through a differential method.
- (3) The orthogonal experiment design method was adopted to determine the path points of the robot for sample data collection. Based on the established force

prediction model, the accurate force sensing of the end load of robot under moving conditions is realized. In experiment, for the load with 100kg mass on robot, the maximum error of force sensing is 39.8N, and the root mean square error of force sensing is 9.3N; The maximum error of torque sensing is 18.7Nm, and the root mean square error of torque sensing is 4.4Nm.

- (4) Applying the force sensing technology, combined with kinematics theory, real-time calculation of the speed of the end load movement of the robot, and driving the robot to move according to the corresponding speed, realizing the zero-gravity motion simulation of the end load of robot. The related results have been successfully applied in the ground simulation test of the installation of an antenna in the China space station, providing a robot-based solution for the ground zero-gravity simulation of the spacecraft in orbit mission.

8 Declaration

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

Authors' contributions

The author's contributions are as follows: RH was in charge of the whole trial and wrote the manuscript; SM and LZ discussed and read the manuscript; QD and CZ assisted with sampling and laboratory analyses.

Competing interests

The authors declare no competing financial interests.

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References

- [1] Easdown W, Felicetti L. A Mission Architecture and Systems Level Design of Navigation, Robotics and Grappling Hardware for an On-Orbit Servicing Spacecraft. *UKSEDS Student Space Symposium 2020*, Online, October 10, 2020: 1–12.

- [2] Ding X L, Wang Y C, Wang Y B, et al. A review of structures, verification, and calibration technologies of space robotic systems for on-orbit servicing. *Science China Technological Sciences*, 2021, 64(3): 462–480.
- [3] Klionovska K, Burri M. Hardware-in-the-Loop Simulations with Umbra Conditions for Spacecraft Rendezvous with PMD Visual Sensors. *Sensors*, 2021, 21(4): 1455.
- [4] Mou F, Xiao X, Zhang T, et al. A HIL Simulation Facility for Task Verification of the Chinese Space Station Manipulator. *2018 IEEE International Conference on Mechatronics and Automation (ICMA)*, Changchun, China, August 5– 8, 2018: 2138-2144.
- [5] Mavrakis N, Hao Z, Gao Y. On-Orbit Robotic Grasping of a Spent Rocket Stage: Grasp Stability Analysis and Experimental Results. *Front Robot AI*. 2021, 8:652681.
- [6] Destefano M, Mishra H, Giordano A M, et al. A Relative Dynamics Formulation for Hardware- in-the-Loop Simulation of On-Orbit Robotic Missions. *IEEE Robotics and Automation Letters*, 2021, 6(2):3569–3576.
- [7] Liu Q, Xiao X, Mou F, et al. Study on a Numerical Simulation of a Manipulator Task Verification Facility System. *2018 IEEE International Conference on Mechatronics and Automation (ICMA)*, Changchun, China, August 5– 8, 2018: 2132-2137.
- [8] García J, Gonzalez D, Rodríguez A, et al. Application of Impedance Control in Robotic Manipulators for Spacecraft On-orbit Servicing. *24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*. Zaragoza, Spain, September 10–13, 2019: 836–842.
- [9] Dong K, Liu H, Zhu X, et al. Force-free control for the flexible-joint robot in human-robot interaction. *Computers & Electrical Engineering*, 2019, 73: 9–22.
- [10] Yao B, Zhou Z, Wang L, et al. Sensor-less external force detection for industrial manipulators to facilitate physical human-robot interaction. *Journal of Mechanical Science and Technology*, 2018, 32(10): 4909–4923.
- [11] Ren T, Dong Y, Wu D, et al. Design of direct teaching behavior of collaborative robot based on force interaction. *Journal of Intelligent & Robotic Systems*, 2019, 96(1): 83–93.
- [12] Xiao J, Zeng F, Zhang Q, et al. Research on the forcefree control of cooperative robots based on dynamic parameters identification. *Industrial Robot: the international journal of robotics research and application*, 2019,46(4): 499–509.
- [13] Tu X, Zhou Y F, Zhao P, et al. Modeling the static friction in a robot joint by genetically optimized BP neural network. *Journal of Intelligent & Robotic Systems*, 2019, 94(1): 29–41.
- [14] Zhang L J, Hu R Q, Yi W M. Research on Force Sensing for the End-load of Industrial Robot Based on a 6-axis F/T Sensor. *Acta Automatica Sinica*, 2017, 43(3):439–447. (in Chinese)
- [15] Yu Y, Shi R, Y Lou. Bias Estimation and Gravity Compensation for Wrist-mounted F/T Sensor. *IEEE Sensors Journal (Early Access)*, 2021, doi: 10.1109/JSEN.2021.3056943.
- [16] Almusawi A R J, Dulger L C, Kapucu S. Online teaching of robotic arm by human–robot interaction: end effector F/T sensing. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 2018, 40(9): 1–14.
- [17] Yao L, Gao Q, Zhang D, et al. An Integrated Compensation Method for the Force Disturbance of a Six-Axis Force Sensor in Complex Manufacturing Scenarios. *Sensors*, 2021, 21(14): 4706.

- [18]Su H, Yang C, Mdeihly H, et al. Neural network enhanced robot tool identification and calibration for bilateral teleoperation. *IEEE Access*, 2019, 7: 122041–122051.
- [19]Kim Y B, Seok D Y, Lee S Y, et al. 6-Axis F/T Sensor With a Novel Autonomous Weight Compensating Capability for Robotic Applications. *IEEE Robotics and Automation Letters*, 2020, 5(4): 6686–6693.
- [20]Lin Z C , Xin W , Yang J , et al. Dynamic trajectory-tracking control method of robotic transcranial magnetic stimulation with end-effector gravity compensation based on force sensors. *Industrial Robot*, 2018, 45(6):722–731.
- [21]El Dine K M, Sanchez J, Corrales J A, et al. Force-torque sensor disturbance observer using deep learning. *International Symposium on Experimental Robotics*, Buenos Aires, Argentina, November 5–8, 2018: 364–373.

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Appendix

Not applicable