TELKOMNIKA, Vol. 11, No. 5, May 2013, pp. 2315 ~ 2322
ISSN: 2302-4046

Real-time Pose Measurement of Parallel Robot Based on GRNN

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Abstract

The real-time pose measurement of parallel robot helps to achieve the closed loop pose control and improve the control and operating performance of parallel robot. But it is difficult to implement the real-time pose measurement directly. In order to solve the pose measurement problem of a 6-DOF parallel robot, the kinematics analysis of the parallel robot is made, and a Generalized Regression Neural Network which has fast convergence and strong nonlinear mapping ability is established by setting the desired pose and its inverse kinematics results as the neural network training samples to implement the map of parallel robot from the joint variable space to the work variable space. Finally, the real-time pose measurement of parallel robot is achieved by using the trained neural network and the actual motion states of the active joints easily detected. The simulation experiment results show that the method of measuring the parallel robot pose based on the GRNN has the faster convergence rate and higher measurement accuracy than those of the BPNN and RBFNN methods. The research establishes the basis for the direct closed control of parallel robot pose.

Keywords: *Parallel Robot, Pose Measurement, Kinematics Analysis, GRNN*

1. Introduction

Compared with the serial robots [1, 2], parallel robots have the advantages of higher rigidity, higher accuracy, faster response speed and higher load capacity, and have drawn great interest in both academia and industry in the last few decades [3, 4].

The end-effector pose of parallel robot is the important performance index that reflects parallel robot motion state and system performance. Implementing the real-time pose measurement of parallel robot is the basis of the closed-loop control of parallel robot. At present, in the actual parallel robot system the motion states of servo motors are obtained mainly from the encoders, but it is difficult to get the real time pose directly. In recent years, there are some researches about the pose measurement of parallel robot. In [5] a feedback system of pose measurement for parallel robot based on vision is designed. In [6] a immune evolutionary algorithm to develop a pose measurement method for a parallel manipulator is proposed. In [7] a multi-sensor measurement method which is used in the whole working space of parallel manipulator is studied. In [8] a method based on detecting synchronously multi-beam of position sensitive detector (PSD) is proposed. The measurement method for parallel robot based on the vision has a good flexibility, but is susceptible to noise and light impact, and large errors will be brought in for this reason [9]. The parallel robot pose measurement method based on immune evolutionary algorithm has certain robustness, but is easy to fall into local minimum, and has the low precision [10]. The parallel robot pose measurement method based on additional sensors although can be used in the whole working space, but it introduces the sensor installation error, the sensor error, the data acquisition system error and so on [11]. The PSD pose measurement method for parallel robot has fast response speed and high resolution, but has the nonlinear error [12].

According to the problems of parallel robot pose measurement mentioned above, the methods based on neural networks are proposed to implement real-time pose measurements of parallel robots without increasing the hardware costs of parallel robots. At present, the methods based on the BP neural network [13] and RBF neural network [14] have been proposed to solve the problem of the pose measurement of parallel robots. The BP neural network method is

Received January 21, 2013; Revised February 27, 2013; Accepted March 12, 2013

globally convergent, but is easy to fall into a local minimum, and the speed of convergence is slow. So it is difficult to meet the requirement of the real-time measurement and control [15]. The RBF neural network method overcomes the shortcomings of the BP neural network method, but for a complex parallel robot system with multi-degree of freedom, multi-variables, high non-linearity and multi-parameter coupling, the structure parameters are acquired by means of the global search to reach the high recognition accuracy [16]. And it is unfavorable for the pose measurement of parallel robot. GRNN has the strong nonlinear mapping ability and the flexible network structure, as well as the high fault-tolerance and robustness, can overcome the shortcomings of RBF neural network, has good approximation capability and fast learning speed, and can process the unstable data. So GRNN is more suitable for the pose measurement of parallel robot.

In view of the above analysis, for a 6-DOF parallel robot, a generalized regression neural network (GRNN) which has the fast convergence and strong nonlinear mapping ability is established based on the kinematics analysis in order to solve the pose measurement problem of the 6-DOF parallel robot. By setting the desired pose and its inverse kinematics results as the neural network training samples to train the neural network, it can realize the map of parallel robot from the joint variable space to the work variable space, the real-time pose measurement of parallel robot is achieved by using the trained neural network and the actual motion states of the active joints easily detected.

2. Kinematics Analysis of Parallel Robot

The parallel mechanism of parallel robot studied in this paper is of 6-PTRT type. Figure.1 shows a sketch of the parallel robot with a 6-PTRT parallel mechanism studied in this paper. Each kinematic limb consists of a prismatic joint, a hook Hinge, a revolute joint and a hook hinge. The prismatic joint controlled by a motor can make a one-dimensional translational movement in a vertical direction. It is composed of a AC serve motor, a ball screw and a guide bar. The moving platform is inverted. The six limbs of the mechanism are driven by AC servo motors. The movements of the sliders drive the ball screws and then make the links into a certain angle to achieve the desired movement of the moving platform. The AC servo drive system consists of an AC servo motor 500DC2-T2A-B in the series FALDIC-W GYS and a servo amplifier RYC500D3-VVT2. The servo motors are added with 17 bits incremental encoders to achieve the closed loop control of the braches.

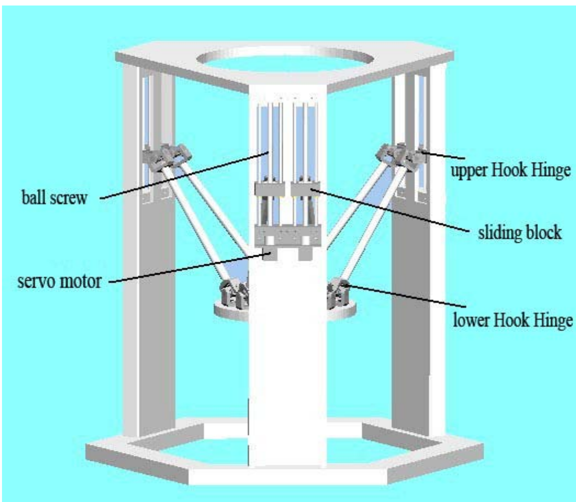


Figure 1. The parallel mechanism of a 6-DOF parallel robot

In order to make the kinematics analysis of the parallel robot mechanism, the dynamic and static two-coordinates are established, as shown in Figure 2.

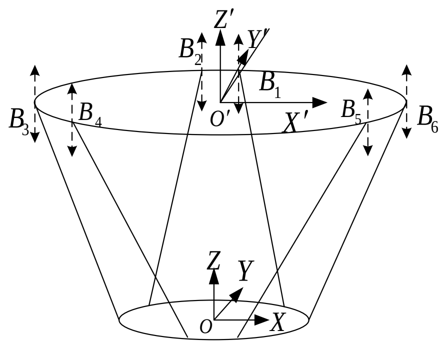


Figure 2. The coordinates of the 6-DOF parallel robot

For a point *P* in the dynamic coordinate, when the dynamic coordinate *O-XYZ* translates x_P、y_P、z_P respectively along the static coordinate, and then rotates the angle α, the angle β, the angle γ respectively around the *X* axis, the *Y* axis, the *Z* axis, its homogeneous coordinates P' in the static coordinate can be calculated by the following Eq. (1)

$$P' = TP \tag{1}$$

where ***T*** denotes the directional cosine matrix of the moving platform pose. ***T*** can be introduced as

$$\boldsymbol{T} = \begin{pmatrix} c\beta c\gamma & -c\beta s\gamma & s\beta & x_P \\ s\alpha s\beta c\gamma + c\alpha s\gamma & c\alpha c\gamma - s\alpha s\beta s\gamma & -s\alpha c\beta & y_P \\ s\alpha s\beta - c\alpha s\beta c\gamma & c\alpha s\beta s\gamma + s\alpha c\gamma & c\alpha c\beta & z_P \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{2}$$

where $c\alpha = \cos\alpha$, $s\alpha = \sin\alpha$, $c\beta = \cos\beta$, $s\beta = \sin\beta$, $c\gamma = \cos\gamma$, $s\gamma = \sin\gamma$.

Since the link lengths of the 6-PTRT parallel mechanism are fixed, in the movement, only the *Z* coordinate of the hinge point B_i changes, while the *X, Y* coordinates do not change, it is obtained as

$$(x_{B_i} - x_{P_i})^2 + (y_{B_i} - y_{P_i})^2 + (z_{B_i} - z_{P_i})^2 = (x_{B_i} - x_{P_i'})^2 + (y_{B_i} - y_{P_i'})^2 + (z_{B_i} - z_{P_i'})^2 \tag{3}$$

According to Eqs. (1) and (2), the coordinate of z'_{Bi} is arrived. The displacement of the screw is

$$h_i = z'_{Bi} - z_{Bi} \tag{4}$$

The Eq. (4) is the pose inverse kinematics of the 6-DOF parallel robot mechanism. The motor rotation angle can be further obtained by the screw pitch.

3. Building of GRNN

The topology structure of GRNN is shown in Figure 3, which includes the input layer, the pattern layer, the summation layer and output layer. The input of GRNN is $X = [x_1, x_2, \cdots x_n]^T$ (n=6), ***X*** denotes the moving displacement vector of the six drive rods, and the output $Y = [y_1, y_2, \cdots y_m]^T$ (m=6) denotes the pose of the parallel robot.

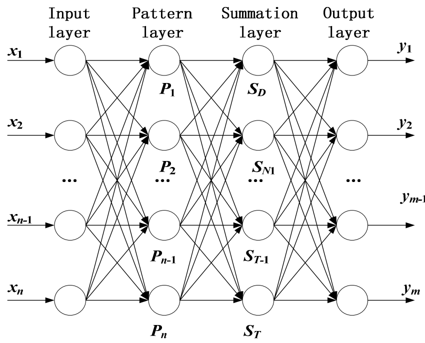


Figure 3. The topology of GRNN

(1) Input layer. The unit number of input layer is equal to the dimension n of the input vector. Every unit directly passes the elements of the input vector to the pattern layer respectively.

(2) Pattern layer. The neurons number of the pattern layer is equal that of learning samples m. The transfer function of neuron is as follows

$$P_i = \exp\left[\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \tag{5}$$

where ***X*** denotes the input variable of the network, $\boldsymbol{X_i}$ denotes the learning sample of neuron *i*.

(3) Summation layer. The way to sum is selected as

$$\sum Y_i \exp\left[\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \tag{6}$$

The weighted summation of all the outputs of the pattern layer neurons is calculated. The connection weight between the *i*th neuron of the pattern layer and the *j*th neuron of the summation layer is the *j*th element of $\boldsymbol{Y_i}$. The transfer function is as follows

$$S_{Nj} = \sum y_{ij} P_i \quad j = 1, 2 \cdots, m \tag{7}$$

(4) Output layer. The neuron number in the output layer is equal to the dominion n of the output vector of the learning sample.

$$y_j = S_{Nj} / S_D \quad j = 1, 2, ..., m \tag{8}$$

For the GRNN, once the training samples is determined, then the network structure and the connection weight between neurons are determined, the factor that affects the network outputs is the smooth parameter σ, so the GRNN learning depends entirely on the sample data. The real-time pose measurement of parallel robot is realized based on the GRNN which is off-line trained, which can improve the working accuracy of parallel robot without increasing the costs of parallel robot system.

4. Pose Measurement of the Parallel Robot and Analysis of Experiment

4.1. Pose Measurement of the Parallel Robot

The procedure of real-time pose measurement of parallel robot is as follows.

(1) According to the measurement requirement, the initial and terminal poses are determined, and then the parallel robot movement trajectory planning of the end-effector is made.

(2) Take m groups of data points $\{x_p, y_p, z_p, \alpha_p, \beta_p, \gamma_p\}$ (p=1, 2, 3…m) from the planned trajectory, and obtain the corresponding six screw displacements $\{h_{1p,} h_{2p,} h_{3p,} h_{4p,} h_{5p,} h_{6p}\}$ (p=1, 2, 3…m) of the parallel robot by the inverse kinematics.

(3) Take the other n groups from the planned trajectory and obtain the corresponding n groups displacements in the same method, which are used as the testing samples.

(4) The m groups of input and output data normalized are used as the training samples to build the GRNN.

(5) After obtaining the corresponding actual poses of the n groups samples by the GRNN, compare the actual poses with the desired poses and calculate the errors between them in order to examine the effectiveness and accuracy of the parallel robot pose measurement.

In the end-effector of parallel robot, the angular displacement signals of the motors are measured by the encoders. When the rotation angles of the motors are obtained, supposing the screw pitch to be 5mm, the displacements of the screws are as follows

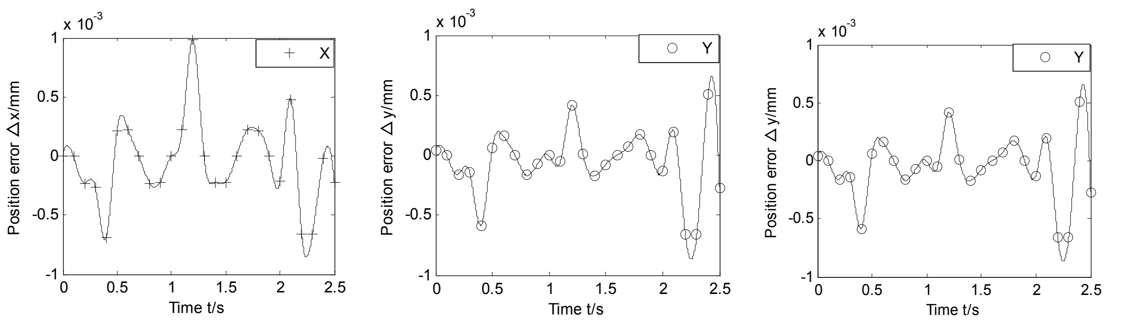
$$l_i = \frac{5}{2\pi}\theta_i \tag{9}$$

Using the above screw displacements as the input vector of the trained GRNN, the output vector is the pose of the parallel robot in the current state.

4.2. Experimental Analysis

Experiment 1: the movement of end-effector is a straight line, and α=β=γ=0.

For the straight moving, set the start location as (0, 0, 0, 0, 0, 0), the terminal location as (45.55, 45.55, -45.55, 0, 0, 0). From the straight trajectory, select 250 points as the input and output samples. After the neural network is established, 80 points are selected from the desired straight-line trajectory and used as the testing samples. The moving displacements of the screws are solved by the inverse kinematics, and then the data is normalized as the input and output of the trained GRNN. The error curves when the end-effector moves in a line are shown in Figure 4. The error range of the curves reflects the measurement accuracy of the neural network.

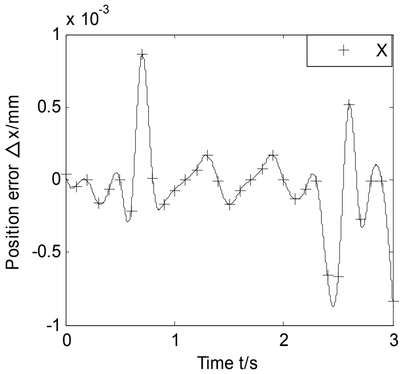


(a) The error curve in x-axis (b) The error curve in y-axis (c) The error curve in z-axis

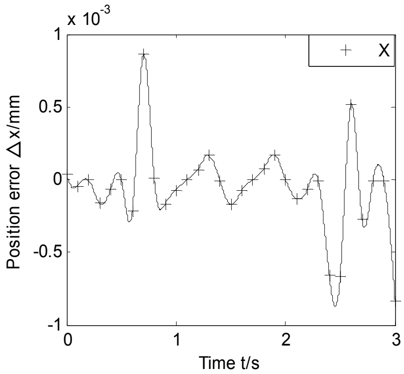
Figure 4. The error curves when the end-effector moves in a line

Experiment 2: the end-effector of the parallel robot makes a movement in an arc.

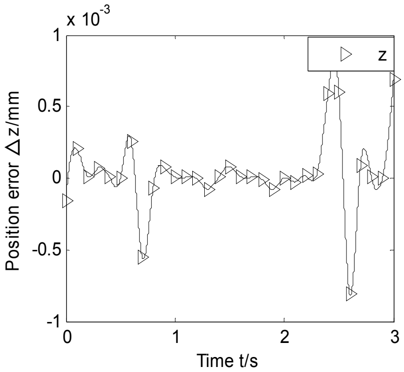
For the arc movement, set the start location is (0, 0, 0, 0, 0, 0), the terminal location is (45.55, 45.55, -45.55, 0, 0, 0.18°). The error curves are shown in Figure 5.



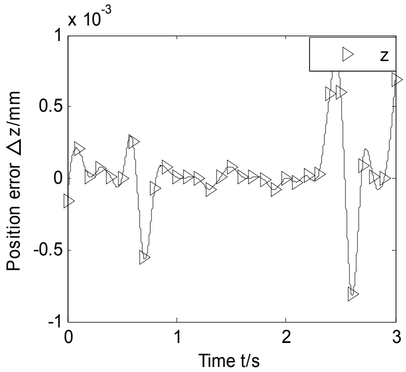
(a) The error curve in x-axis



(b) The error curve in y-axis



(c) The error curve in z-axis



(d) The error curve of γ

Figure 5. The error curves when the end-effector moves in an arc

In Figure 4, when the end-effector moves in a line, the absolute value of the errors in x, y and z axis is less than 1×10^{-3}mm. It can be seen from Figure 5 that, when the end-effector moves in an arc, the absolute value of the errors in x, y and z axis is less than 1×10^{-3}mm, and the absolute value of the error of γ is less than 4×10^{-17} rad.

4.3. Experimental Comparison with BP and RBF Neural Network Detection

BP neural network is a multi-layer feed-forward network, and its structure is shown in Figure 6, where, $\boldsymbol{X}=[x_1,x_2,\ldots,x_n]^T$ and $\boldsymbol{Y}=[y_1,y_2,\ldots,y_m]^T$ are the input and output vectors of the network respectively, $\boldsymbol{X}$ denotes the moving displacement vector of the six drive rods, $\boldsymbol{Y}$ denotes the pose of the parallel robot end-effector.

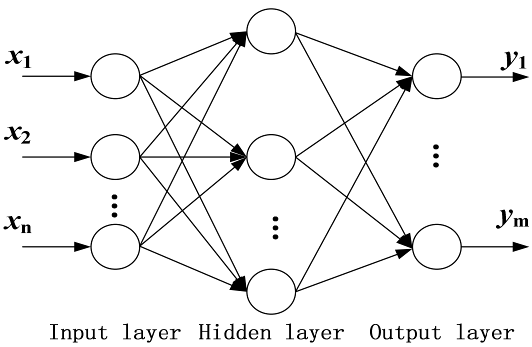


Figure 6. BP neural network

The RBF neural network is a three-layer feed-forward network which consists of the input layer, the hidden layer, and the output layer. Its structure is shown in Figure 7, where $\boldsymbol{X}=[x_1,x_2,\ldots,x_n]^T$ and $\boldsymbol{Y}=[y_1,y_2,\ldots,y_m]^T$ are the input and output vectors of the network respectively, $\boldsymbol{X}$ denotes the moving displacement vector of the six drive rods, $\boldsymbol{Y}$ denotes the pose of the parallel robot.

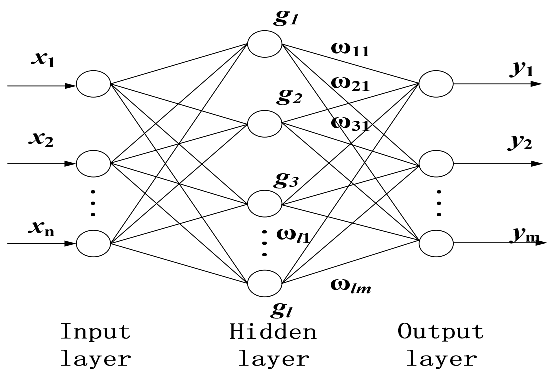


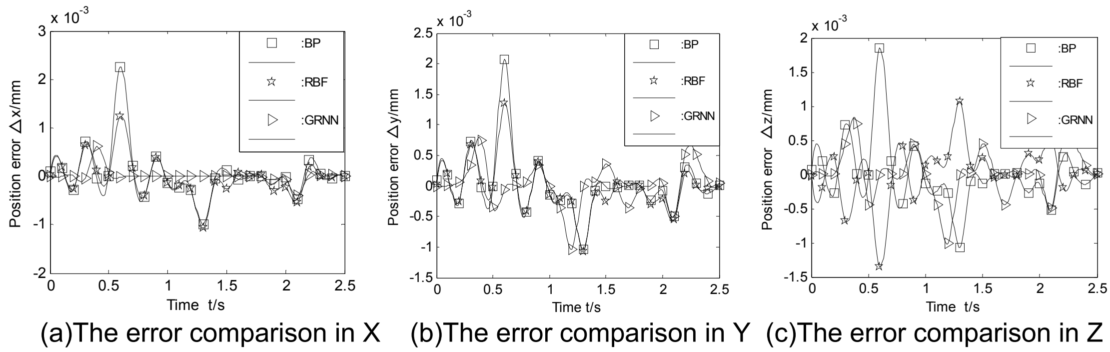
Figure 7. RBF neural network

Using the same test samples to train the BP, RBF and GRNN, the convergence time of the BP, RBF and GRNN is shown in Table 1.

Table 1. The convergence time of the BP, RBF and GRNN

	BP	RBF	GRNN
convergence time (s)	1.582	0.012	0.010

With the same test samples, the errors of the BP, RBF and GRNN methods are shown in Figure 8.



(a)The error comparison in X (b)The error comparison in Y (c)The error comparison in Z

Figure 8. The error comparison of GRNN, BP and RBF when the end-effector moves in a line

In Figure 8, when the end-effector moves in a line, the absolute values of the errors in x, y and z axis of the BPNN method are less than 2.5×10^{-3}mm, the absolute values of the errors in x, y and z axis of the RBFNN method are less than 1.5×10^{-3}mm, and those of GRNN method are less than 1×10^{-3}mm. Table 1 shows that the convergence time of the GRNN method is less than that of the BPNN and RBFNN methods with the same training samples. So the real-time pose measurement of Parallel robot based on the GRNN has the faster convergence rate and higher measurement accuracy.

5. Conclusion

The real-time, precise pose measurement of parallel robot may be used for realizing the full closed-loop control of parallel robot in order to enhance its control and operation performance. For a 6-DOF parallel robot, based on the kinematics analysis, a generalized regression neural network which has the strong nonlinear mapping ability and the flexible network structure, as well as the high fault-tolerance and robustness is established to solve the pose measurement problem of the 6-DOF parallel robot. The experiment results show that the pose measurement of the parallel robot based on the GRNN has the faster convergence rate and higher measurement accuracy than those of the BPNN and RBFNN methods. The research establishes the basis for the direct full closed-loop control of parallel robot.

Acknowledgements

This work was financially supported by the Priority Academic Program Development of Jiangsu Higher Education Institutions (NO. 6, 2011), Zhenjiang Municipal Key Technology R&D Program (Grant No. NY2011013) and the Postgraduate Research and Innovation Program of Jiangsu Higher Education Institutions (1221140046).

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