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Safety analysis via forward kinematics of delta parallel robot using machine learning

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ABSTRACT

Aiming at solving the problems of complex forward kinematics of Delta parallel robot and multiple solutions, and further improving celerity and accuracy of positioning for the spatial pose of the manipulator end effecter, in this paper, we present a method to kinematics solution of Delta parallel robot based on BP neural network. Taking the three-degree-of-freedom Delta parallel robot as the research object, according to analysis of its the kinematics principle, the basic BP neural network model and the optimized BP neural network model for kinematics solution of Delta parallel robot are simulated by using MATLAB, respectively. The results indicate that using BP neural network model improved by Genetic Algorithms to address the forward kinematics problems of Delta parallel robot is feasible, which can achieve the requirement of higher celerity and accuracy of Delta parallel robot control and avoid the shortcomings of traditional methods to a certain extent, furthermore, ensures the reliability of production safety.

1. Introduction

In comparison with serial robots, parallel industrial robots have a series of excellent features, such as compact structure, high stiffness, fast pickup and placing operation, high repetitive positioning accuracy, strong load-bearing capacity, etc. (Brinker, 2017; Xue sheng et al., 2002). Therefore, under the application of high-speed and high-precision, it must be widely concerned. A significant amount of research on kinematics analysis of Delta parallel mechanisms have been conducted by scholars at home and abroad have done, which indicates that the forward solution of parallel mechanism has practical significance, such as the forward design of scale synthesis, avoidance of singular position, etc. (Zhao et al., 2003; Misyurin, 2016; Morell et al., 2013; Meng et al., 2014; Milutinovic et al., 2012; You et al., 2017).

At present, most of the forward solutions of parallel mechanisms have been solved mathematically, but the solution time is too long or not accuracy, moreover, there are many error sources in the actual work, therefore, it is not enough to meet the requirements of real-time control by studying the forward kinematics solution of the mechanism from the mathematical point of view (Misyurin, 2016; Morell et al., 2013; Milutinovic et al., 2012). For solving the problems above, a kinematics solution method of Delta parallel robot based on BP neural network is presented. One three-layer BP neural network model is designed to solve the forward kinematics of parallel manipulators, which has the advantages of good non-linear fitting ability of BP neural network and fast convergence of Levenberg-Marquardt (LM) optimization training method. However, the prediction accuracy of the basic BP cannot achieve the requirements, one optimized neural network further should be took into account. For this purpose, the basic BP neural network model and the optimized BP neural network model through Genetic Algorithms (GA) are respectively built, trained and simulated in Matlab to verify the feasibility, rapidity and accuracy of alternative to the traditional mathematical kinematics solution. Compared with the solution approach based on geometric normal equations, the derivation process of BP neural network is simple and intuitive, and the unique solution satisfying the condition of continuous motion can be given directly in real-time control.

2. Kinematics analysis of parallel robot

The Delta parallel robot studied in this paper is composed of fixed platform, three active arms, three parallel quadrilateral driven arms, mobile platform and other basic parts. Three closed chains (O-Ai-Ci-Bi-P-O) are composed through rotary pair connections between the parts. The active arm receives the rotating input of three input motors at the same time and controls end-mobile platform of robot move simultaneously in x-axis, y-axis and z-axis direction. The base and the active arm are connected by rotating pairs, the active arm and the driven arm

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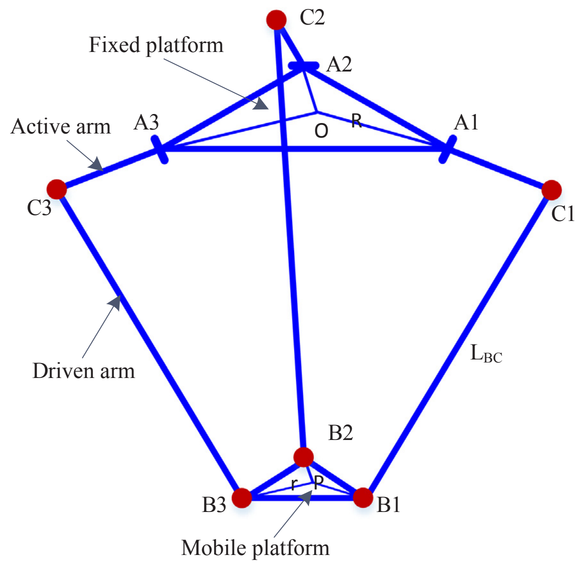

Fig. 1. Mechanism sketch of three-degree-of-freedom Delta robot.

are connected by spherical hinges, and the driven arm and the mobile platform are also connected by spherical hinges (Zhao et al., 2003; Misyurin, 2016).

The structure sketch of Delta parallel robot is depicted in Fig. 1. A1A2A3 is a fixed platform, B1B2B3 is a mobile platform, Ai is a rotating joint, Bi and Ci are spherical joints, AiCi is an active arm and CiBi is a driven arm,i = 1, 2, 3. O is the fixed platform center and P is the mobile platform center. R is the outer circle radius of the fixed platform, and r is the outer circle radius of the mobile platform. Both A1A2A3 and B1B2B3 are regular triangles.

2.1. Establishing coordinate system

Delta robot coordinate system is established as depicted in Fig. 2. the sketch of three-dimensional coordinate system is laid out the left side of Fig. 2, and the analysis and modeling of a single connecting rod on the XOZ plane is laid out the right side of Fig. 2. The mechanism parameters of the Delta robot system are as follows: the distance between the active arm center point and the coordinate system center point is R (205 mm), the active arm length is L_1 (400 mm), the driven arm length is L_2 (1000 mm), the distance between the mobile platform center point and the driven arm center point is r (50 mm), the angle between the active arm and the X axis is θ, and L_2' is the projection of the driven arm on the cross section of the arm, and it is perpendicular to y of the mobile platform at the end.

2.2. Forward kinematics analysis

In fact, the forward kinematics of Delta robot is procedure to obtain the three dimensional position coordinate $P = [x \quad y \quad z]$ of the terminal mobile platform by knowing the angle θ_i of three active arms. For a group of connecting rods on the XOZ plane, the three dimensional coordinates of the end point B of the connecting rod of the active arm can be obtained through Formula (1).

$$B_i = [R + L_1 \cos\theta_i \quad 0 \quad L_1 \sin\theta_i]^T \tag{1}$$

For the other two groups of connecting rods, the same method can be used to solve Bi, which only needs to be multiplied by the rotation transformation matrix R in the form of:

$$R = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

Hypothetical the installation angles of the three active arms on the fixed base are α_1, α_2 and α_3 respectively. For the three connecting rods, they can be written as follows:

$$\begin{cases} (x - [(R-r) + L_1\cos\theta_1]\cos\alpha_1)^2 + (y - [(R-r) + L_1\cos\theta_1]\sin\alpha_1)^2 \\ \quad + (z - L_1\sin\theta_1)^2 = L_2^2 \\ (x - [(R-r) + L_1\cos\theta_2]\cos\alpha_2)^2 + (y - [(R-r) + L_1\cos\theta_2]\sin\alpha_2)^2 \\ \quad + (z - L_1\sin\theta_2)^2 = L_2^2 \\ (x - [(R-r) + L_1\cos\theta_3]\cos\alpha_3)^2 + (y - [(R-r) + L_1\cos\theta_3]\sin\alpha_3)^2 \\ \quad + (z - L_1\sin\theta_3)^2 = L_2^2 \end{cases} \tag{3}$$

For the three groups of connecting rods, the installation angles of the active arm on the fixed base are $\alpha_1 = 0$, $\alpha_2 = \frac{2}{3}\pi$, $\alpha_3 = \frac{4}{3}\pi$, respectively. Formula (3) is simplified to Formula (4).

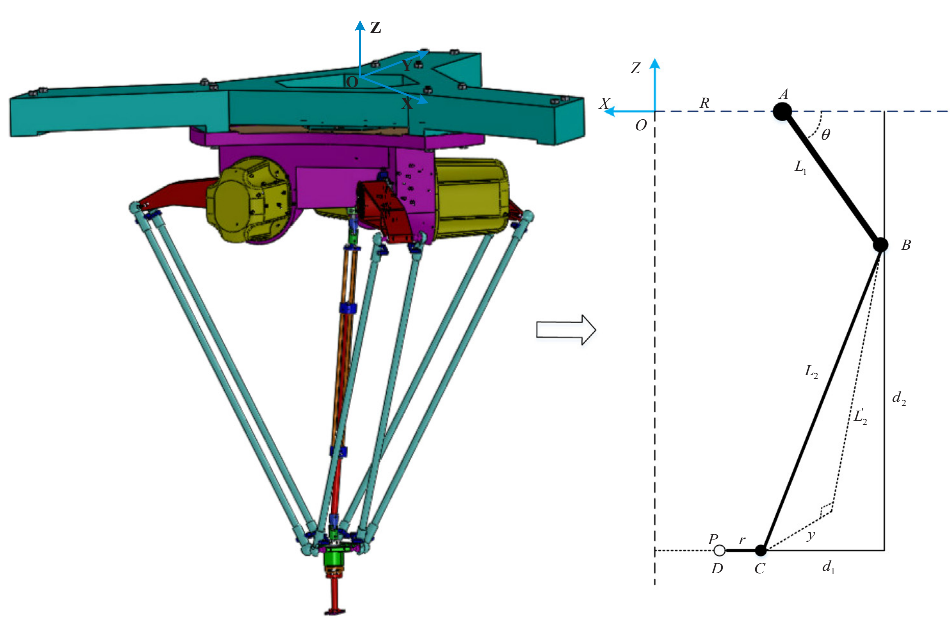

Fig. 2. Establishment of Delta Robot Coordinate System.

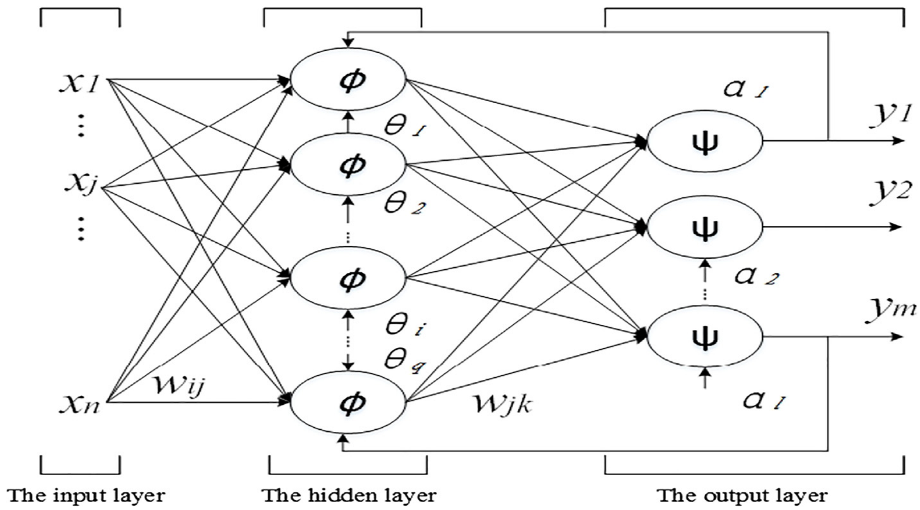

Fig. 3. Typical three-layer BP neural network structure.

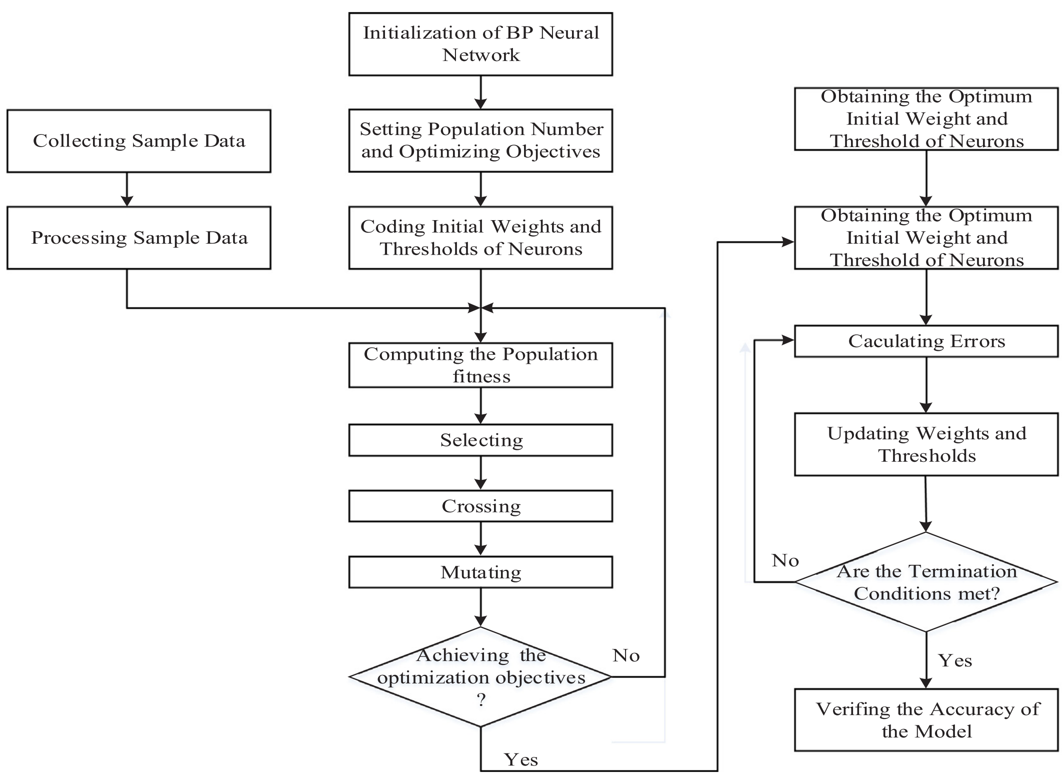

Fig. 4. BP Neural Network Flow Chart Based on Genetic Algorithms.

$$\begin{cases} (x + k_{11})^2 + (y + k_{12})^2 + (z + k_{13})^2 = L_2^2 \\ (x + k_{21})^2 + (y + k_{22})^2 + (z + k_{23})^2 = L_2^2 \\ (x + k_{31})^2 + (y + k_{32})^2 + (z + k_{33})^2 = L_2^2 \end{cases} \quad (4)$$

Here, $k_{11} = -(R - r) + L_1 \cos\theta_1$, $k_{12} = 0$, $k_{13} = -L_1 \sin\theta_1$, $k_{21} = \frac{1}{2}[(R - r) + L_1 \cos\theta_2]$, $k_{22} = -\frac{\sqrt{3}}{2}[(R - r) + L_1 \cos\theta_2]$, $k_{23} = -L_1 \sin\theta_2$, $k_{31} = \frac{1}{2}[(R - r) + L_1 \cos\theta_3]$, $k_{32} = \frac{\sqrt{3}}{2}[(R - r) + L_1 \cos\theta_3]$, $k_{33} = -L_1 \sin\theta_3$.

In Formula (4), the first equation is subtracted from the second equation and the third equation, respectively, to obtain the two formulas are combined and decomposed as follows:

$$\begin{cases} a_1 x + b_1 y + c_1 z = d_1 \\ a_2 x + b_2 y + c_2 z = d_2 \end{cases} \quad (5)$$

Here, $a_1 = 2(k_{11} - k_{21})$, $b_1 = 2(k_{12} - k_{22})$, $c_1 = 2(k_{13} - k_{23})$, $a_2 = 2(k_{11} - k_{31})$, $b_2 = 2(k_{12} - k_{32})$, $c_2 = 2(k_{13} - k_{33})$, $d_1 = (k_{21}^2 + k_{22}^2 + k_{23}^2) - (k_{11}^2 + k_{12}^2 + k_{13}^2)$, $d_2 = (k_{31}^2 + k_{32}^2 + k_{33}^2) - (k_{11}^2 + k_{12}^2 + k_{13}^2)$, Let $\Delta = a_1 b_2 - a_2 b_1$, And guarantee $\Delta \neq 0$. Formula (6) is written in matrix form as follow:

$$\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} d_1 - c_1 z \\ d_2 - c_2 z \end{bmatrix} \quad (6)$$

Solving Formula (6) to obtain the expressions of x and y as Formula (7).

$$\begin{cases} x = x_1 + f_x z \\ y = f_2 + f_y z \end{cases} \quad (7)$$

The parameters are as follows: $f_1 = \frac{b_2 d_1 - b_1 d_2}{\Delta}$, $f_2 = \frac{b_1 c_2 - b_2 c_1}{\Delta}$,

Table 1
Range of rotation angle of joint.

Rotation angle of joint θ_i	Range(rad)
θ_1	$-\frac{2}{9}\pi \sim \frac{4}{9}\pi$
θ_2	$-\frac{2}{9}\pi \sim \frac{4}{9}\pi$
θ_3	$-\frac{2}{9}\pi \sim \frac{4}{9}\pi$

$f_x = \frac{a_1d_2 - a_2d_1}{\Delta}$, $f_y = \frac{a_2c_1 - a_1c_2}{\Delta}$.

And then, Formula (6) is substituted into the third equation in Formula (3), and the equation for variable Z is obtained as follows:

$$(1+f_x^2 + f_y^2)z^2 + 2([f_xf_1 + f_xk_{31}] + [f_xf_2 + f_yk_{32}] + k_{33})z + f_{11}^2 + f_{22}^2 + k_{33}^2 - L_2^2 = 0 \quad (8)$$

Here, $f_{11} = f_1 + k_{31}$, $f_{22} = f_2 + k_{32}$. set

$$\begin{cases} A = (1 + f_x^2 + f_y^2) \\ B = ([f_xf_1 + f_xf_{31}] + [f_xf_2 + f_xf_{32}] + k_{33}) \\ c = f_{11}^2 + f_{22}^2 + k_{33}^2 - L_2^2 \end{cases} \quad (9)$$

Formula (9) is solved by using the root formula of one-dimensional quadratic equation, and the coordinates z of the mobile platform is obtained as follows:

$$z = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A} \quad (10)$$

According to the geometric method, the forward kinematics of the three-degree- of-freedom parallel manipulator is solved by two sets of analytical solutions. However, there are two shortcomings in this method when solving forward kinematics: (1) there is a complex coupling relationship between manipulator joint angles, which makes the decoupling process very complicated; (2) the relationship between manipulator joint angles and the space position of the end of the manipulator is many-to-one, thereby it is difficult to obtain a single optimal solution by traditional analytical solution. Therefore, the optimal solution needs to be selected according to the structural characteristics of the manipulator. The feasibility of using neural network to address the kinematics of Delta parallel robot is put forward in this paper to avoid the shortcomings of geometric method for the forward kinematics, improve speed of operation, and meet the real-time requirements of the system.

3. Design of BP neural network

The solutions for forward kinematics of a parallel robot is essentially to solve three joint variables of the manipulator by three variables which determine the pose of the manipulator end-effector, this process can be accomplished by neural network model. Neural networks with nonlinear characteristics can well approximate any complex nonlinear system and deal with multi-input and multi-output (MIMO) system, it is very suitable for multivariable systems.

3.1. Structural design of neural network

Typical BP neural network includes input layer, hidden layer and output layer. There is no same layer connection between neurons. The hidden layer can have one or more layers. Typical three-layer network topology is shown in Fig. 3.

This paper designs one three-layer BP neural network model to solve the forward kinematics problems of the three-degree-of-freedom parallel robot. The hidden layer uses a single-layer structure. The input of the neural network is the rotational angle of three joints which is respectively corresponding to three neuron nodes in the input layer, three input signals constitute the input vector x, as expressed in Formula (11).

$$x = [\theta_1, \theta_2, \theta_3] \quad (11)$$

Here, θ_1, θ_2 and θ_3 correspond the rotation angle of three servomotors, respectively.

The outputs of the BP neural network is the spatial pose of the manipulator end effector, three output signals constitute the output vector y, as expressed in Formula (12).

$$y = [P_x, P_y, P_z] \quad (12)$$

Here, P_x, P_y and P_z is the spatial position coordinates of the

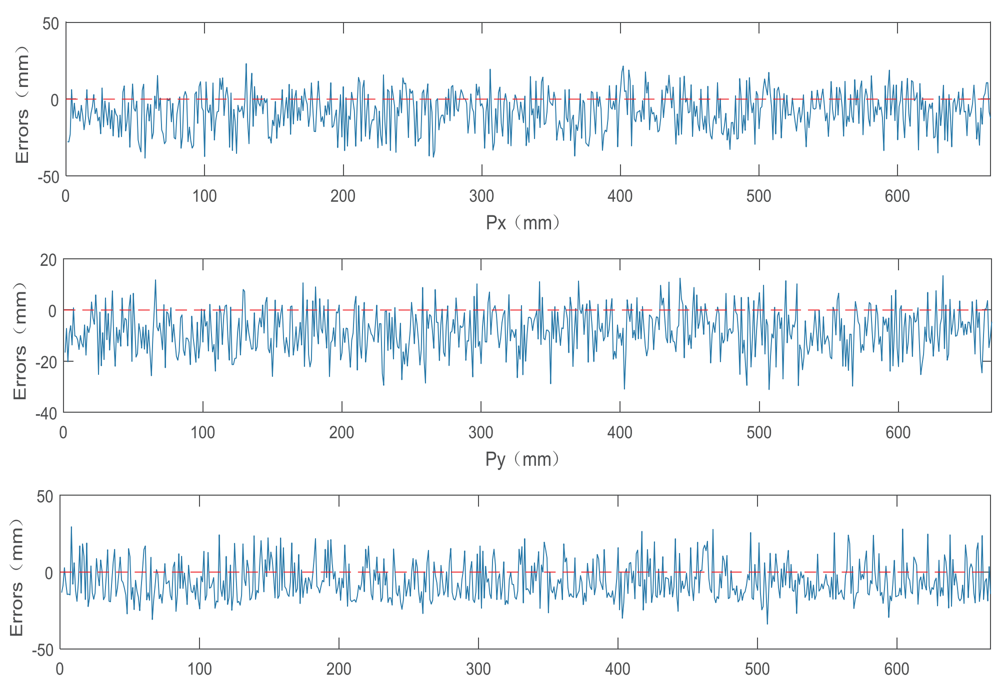

Fig. 5. Prediction Errors of the Basic BP Neural Network.

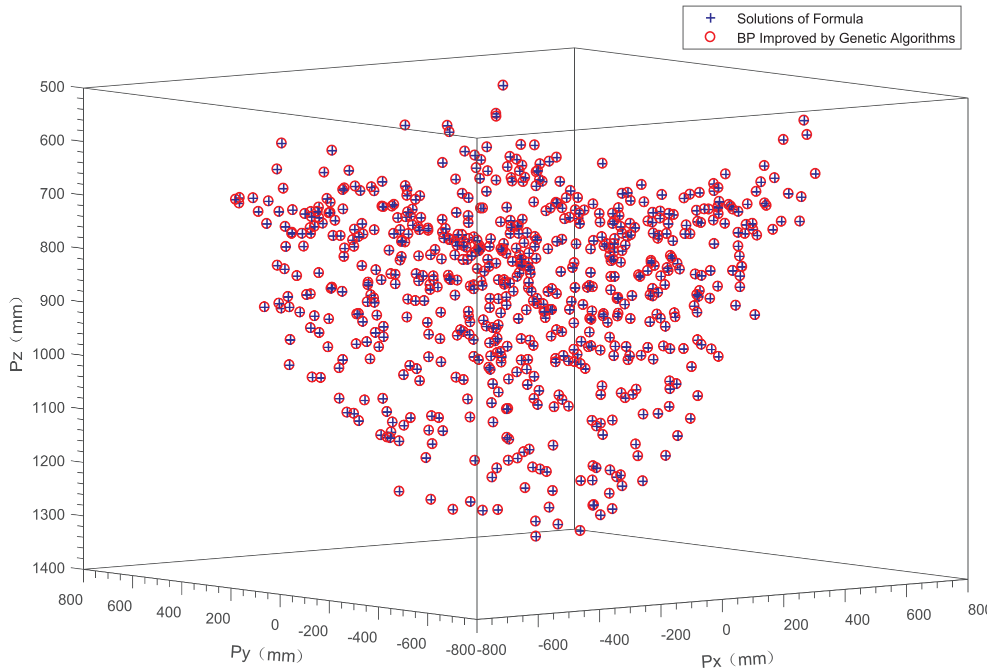

Fig. 6. 3D scatter of the Predicted Coordinate Pairs and The Target Coordinate Pairs.

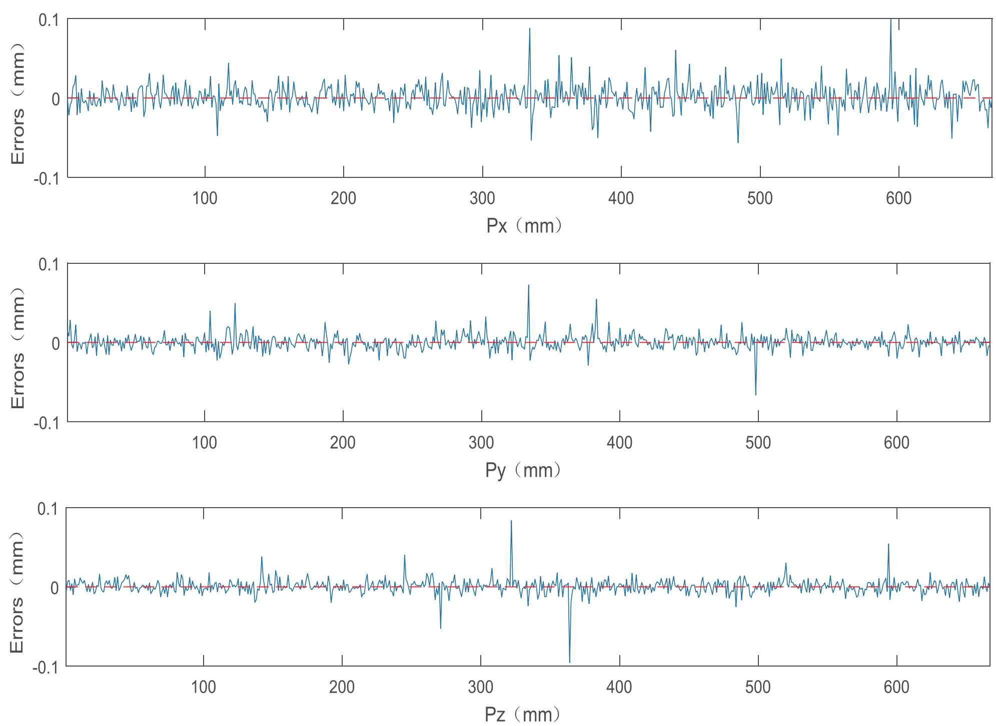

Fig. 7. Prediction Errors of the BP Neural Network Improved by GA.

manipulator end effector, respectively.

The learning rate of the network determines the amount of weights generated in each cycle training, in general, choosing a smaller learning rate is preferable to ensure the stability of the system choose. The learning rate is selected in the range of [0.01 0.8]. The transfer function Tansig is chosen in hidden layer. Because the output of the whole network is arbitrary, the transfer function Purelin is chosen in the output layer.

3.2. Improved BP neural network Algorithms

BP neural network is vulnerable to initial weights, learning rate, momentum factors and other parameters, and the high-intensity training mode will produce “over-fitting” phenomenon which affects the generalization ability of the network, consequently, the results of repeated training are very different, sometimes even not convergent. In addition, low-speed of constringency and easily falling into local minimum are also common defects of BP neural network, resulting in large training errors, which can not meet the accuracy of prediction requirements. In view of the reasons above, this paper selects GA as optimization method to further improve prediction accuracy of basic BP network.

A parallel stochastic optimization method GA simulates the genetic mechanism of nature and the biological evolution theory. Based on the biological evolution principle of "survival of the fittest", Search algorithm with "survival + detection" iteration process is introduced into the coding tandem population formed by optimization parameters. According to gene heredity, Individuals are screened through selection process, crossover process and mutation process to approach and meet fitness target value, consequently, some individuals who have good fitness value are preserved, at the same time, some poor individuals with lower fitness value are eliminated, and These good genomes form new populations that not only inherit the information of the previous generation, but also outperform the previous generation, gene evolution is repeated until conditions are met.

BP neural network improved by GA includes determining the structure of neural network, optimizing BP neural network by means of genetic algorithm and the prediction of BP neural network. Among them, GA is applied to optimize the initial weights and thresholds of BP neural network, which makes the improved BP neural network can achieve better prediction. Individual representing initial weights and thresholds is used to initialize BP neural network whose prediction error is used to be as the fitness value of the individual to find the optimal individual by selection process operate, cross process and mutation process. These optimal individuals are the optimal initial weights of BP neural network. Fig. 4 depicts flow chart of BP neural network improved by GA.

The main processes of GA are described as follows:

(1) Population initialization

This paper selects real number coding as individual coding. Each individual represents a real number string including connection weights between input layer and hidden layer, thresholds of hidden layer, connection weight between hidden layer and output layer, and thresholds of output layer. Individuals include all the weights and thresholds of the BP neural network. Under the condition that the network structure is constant, a BP neural network with definite structure, weights and thresholds can be constructed.

(2) Function fitness

According to the initial weights and thresholds of BP neural network obtained by individuals, the output of the prediction system is trained by training data. The absolute value of error between the expected output and the prediction output is taken as the individual fitness Fit which is expressed in Formula (13).

$$Fit_i = k\left(\sum_{i=1}^{n} abs(E_i - O_i)\right) \tag{13}$$

Here, n is the number of network output node; E_i is the expected output of the ith node of BP neural network; O_i of the actual output of the ith node of BP neural network; k is the coefficient.

(3) Selection operation

There are roulette and championship methods in selection operation of GA. The roulette base on selection strategy is chosen analysis in this paper, the selected probability P_i of each individual i can be calculated by following:

$$\begin{aligned} f_i &= \frac{k}{Fit_i} \\ P_i &= \frac{f_i}{\sum_{j=1}^{N} f_j} \end{aligned} \tag{14}$$

Fiti is the fitness value of ith individual. Since the smaller the fitness value is the better, the reciprocal fit ability is calculated before individual selection; k is the coefficient, in the analysis let k = 1; N is the number of individual population.

(4) Crossover operation

Because real number coding is used to individual, the real number crossover method is applied in the crossover operation. The cross-operation method of kth chromosome x_k and lth chromosome x_l in ith place is as follows:

$$\begin{cases} x_{kj} = x_{kj}(1-y) + x_{lj}y \\ x_{lj} = x_{lj}(1-y) + x_{kj}y \end{cases} \tag{15}$$

Here, y is a random number between (Brinker, 2017).

(5) Mutation operation

The method of mutation of jth gene x_{ij} of the ith individual is as follows:

$$x_{ij} = \begin{cases} x_{ij} + f(g) \times (x_{\max} - x_{ij}) & r > 0.5 \\ x_{ij} - f(g) \times (x_{ij} - x_{\min}) & r \leqslant 0.5 \end{cases}$$
$$f(g) = r'\left(1 - \frac{g}{G_{\max}}\right)^2 \tag{16}$$

$x_{\max}$ is the upper bound of x_{ij} and $x_{\min}$ is the lower bound of x_{ij}; g is the current number of iterations; G_{ij} is the maximum number of evolution; r and r' are random numbers between [0,1].

4. Simulation and results analysis

Matlab integrates many powerful functions, such as numerical analysis, matrix calculation, visualization of scientific data and modeling and simulation of nonlinear dynamic systems into an easy-to-use window environment, which provides a comprehensive solution for scientific research, engineering design and many scientific fields that must carry out effective numerical calculation. In this paper, combining of programming M files and the nntool neural network toolbox of MATLAB is used to model and simulate robotic arm.

4.1. Simulation design

The model of three-degree-of-freedom manipulator is established by programming, the range of each arm joint variable is determined according to the manipulator structure, as summarized in Table 1.

For increasing training and prediction accuracy, range of rotation angle of each joint is divided into 6667 parts, and randomly selecting an angle without repetition from rotation angles of each joint, and then compose an array of three elements, a total of 6667 groups angles by which the corresponding 6667 groups forward kinematics solutions are solved as coordinates of mobile platform endpoint of the Delta robot system. Randomly selecting 6000 groups without repetition from 6667 groups angles as input training data, remained 667 groups as input test data. Randomly selecting 6000 groups without repetition from 6667 groups forward kinematics solutions as output training data, remained 667 groups as target test data.

Firstly, BP neural network with Levenberg-Marquardt (LM) is used to as neural network, training and test are conducted through setting a large number of combinations of hidden layers and corresponding number of neurons, training results indicate that the three hidden layers structure [7 5 4] can achieve best results in the case of using BP neural network with LM, the test predication errors of the basic BP neural network is illustrated in Fig. 5.

Mean Squared Error (MSE) of prediction errors in Fig. 5 is 213.73 which is unacceptable to high-precision control requirements of the Delta robot system only by means of using BP neural network with LM.

Therefore, this paper proposes to use GA to optimize training and learning ability of the basic BP neural network to reduce prediction errors BP neural network to meet high-precision control requirements. Major parameters of the BP neural network based on GA are summarized as follows: the number of input layer is 3, the number of output layer is 3; one hidden layer of 95 neuron; the number of iterations is 50; the size of population is 30; the probability of cross is 0.3; the probability of mutation is 0.1. Simulation output data of 667 groups corresponding to input test data of 667 groups are predicted through well trained BP neural network improved by Genetic Algorithms, 3D scatter of target test data of 667 groups and 3D scatter of simulation output data of 667 groups are plotted in Fig. 6 which indicates the predicted coordinate points of mobile platform endpoint of the Delta robot system coincide completely with the target coordinate points of mobile platform endpoint of the Delta robot system. Detailed prediction errors are shown in Fig. 7.

MSE of prediction errors in Fig. 7 is 3.73 × 10–4 Which indicates that if the tolerance prediction error of ± 0.1 mm is acceptable, mobile platform endpoint of the Delta robot system can achieve 100% accurate positioning according to the Predicted Coordinate Pairs. If the tolerance prediction error of ± 0.05 mm is acceptable, mobile platform endpoint of the Delta robot system can achieve 97.75% accurate positing according to the Predicted Coordinate Pairs. Therefore, the prediction model of BP neural network improved by Genetic Algorithms can meet high-precision control requirements of the Delta robot system.

5. Conclusion

For reducing analysis difficulty on complex forward kinematics of Delta parallel robot and multiple solutions, under the condition of ensuring safe production, this paper put forwards a rapidly and accurately solving kinematics solution approach for the three-degree-of-freedom Delta parallel robot by means of the BP neural network based on GA. For comparative analysis, the kinematics solution approach based on the basic BP neural network and the kinematics solution approach based on the BP neural network improved by GA for the three-degree-of-freedom Delta parallel robot are modeled and simulated, respectively. The simulation results indicate that if the tolerance prediction error of ± 0.05 mm is acceptable to the high precision control of Delta parallel robot system, mobile platform endpoint of the Delta robot system can achieve 97.75% accurate positing according to the Predicted Coordinate Pairs, which verifies that using BP neural network model improved by GA to address the forward kinematics problems of the three-degree-of-freedom Delta parallel robot is feasible, celerity and accuracy in overcoming many shortcomings of traditional methods resolving forward kinematics problems of the three-degree-of-freedom Delta parallel robot and multiple solutions.

Acknowledgments

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