An Optimal Tracking Method for Moving Trajectory of Rigid-Flexible Coupled Manipulator Based on Large Data Analysis

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Abstract. The manipulator has dynamic characteristics, and the trajectory tracking system of the manipulator has non-holonomic constraints and various uncertainties, which makes tracking control of the mobile manipulator more difficult. There is a big error in tracking a rigid flexible coupling manipulator with a single neural network. A new method for trajectory optimization tracking of a rigid-flexible coupled manipulator based on big data analysis is proposed. This method takes neural network as the research object, introduces fuzzy control into neural network, optimizes a single neural network, forms a composite method of fuzzy neural network, and uses a hybrid method to track the trajectory of the manipulator. Experimental results show that the tracking error of this method is less than 0.035 rad, which improves the tracking efficiency and improves the tracking accuracy. The method can complete the operation faster and more accurately according to the predetermined trajectory, and has higher practical applicability.

Keywords: Rigid-flexible coupling · Manipulator · Moving trajectory · Tracking method · Fuzzy nerve

1 Introduction

With the progress of science and technology, mechanized production gradually replaces manual production, completes all kinds of dangerous work that human beings can not directly contact, saves production costs greatly for enterprises, improves production efficiency, and its application in industry and other fields is of great practical significance. In the manipulator control, the most difficult part is how to accurately control the arm in accordance with the predetermined trajectory, which is also one of the basic tasks of robot control [1]. At present, there are many control methods, such as feedforward compensation control, sliding mode variable structure control, adaptive control, robust control, neural network control, iterative learning control, inversion control and so on. However, with the development of the manipulator industry, these methods have been unable to meet the requirements of accurate control in various environments. This paper takes the neural network as the research object. This method has great advantages in solving the non-linearity and uncertainties in the process of

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modeling. However, this method needs a lot of time training, and it is difficult to meet the requirements of high control accuracy.

Therefore, in order to solve the above problems, this study introduces the fuzzy control into the neural network, and uses the fuzzy neural network to optimize the tracking of the rigid-flexible coupling manipulator trajectory [2]. Firstly, the kinematics and dynamics model of the manipulator is established, and then the desired trajectory of the manipulator is tracked by designing corresponding control methods.Experiments show that the tracking error of the proposed method is much smaller than that of the single neural network method, and it can complete the operation more quickly and accurately according to the predetermined trajectory.

2 An Optimal Tracking Method for the Moving Trajectory of a Rigid-Flexible Coupled Manipulator

The goal of trajectory tracking is to reach the desired position according to the given trajectory. The whole process is to change the angle and velocity of the manipulator joint according to the output torque of the controller. Mobile manipulator is a highly nonlinear and strongly coupled system. Mobile platform and manipulator have different dynamic characteristics. In addition, the system also has non-holonomic constraints and various uncertainties, which make the tracking control of mobile manipulator more difficult. Multi-mobile manipulators cooperate to accomplish a target task, which is a hot research direction in recent years [3].

2.1 Mathematical Model of Manipulator

The trajectory tracking of the most common six-joint manipulator is studied in this paper. The model part of the manipulator is mainly divided into two aspects, kinematics and dynamics. Kinematics is the research object of path planning and trajectory control of manipulator, and dynamics is to calculate the control moment input of space robot according to the planned path and trajectory [4]. The kinematics model establishes the mathematical relationship between the position, velocity and other states of the end of the robot and the position, velocity (or angular velocity) of each link (degree of freedom), which is an intuitive description of the motion. The dynamic model reflects the relationship between the driving moment of each joint and the position and velocity of the system. A complete robot control system needs to study not only kinematics model but also dynamics model. The establishment of model in this chapter is the basis of research [5].

(1) Kinematics Modeling

The manipulator consists of a series of joints and connecting rods, and each joint is assigned a reference coordinate system. The transformation from one coordinate system to the next coordinate system is the state transformation from one joint to the next. By combining all the transformations from the base to the last joint, the total transformation matrix of the manipulator can be obtained.

Figure 1 shows two connecting rods and three joints (either moving or rotating).

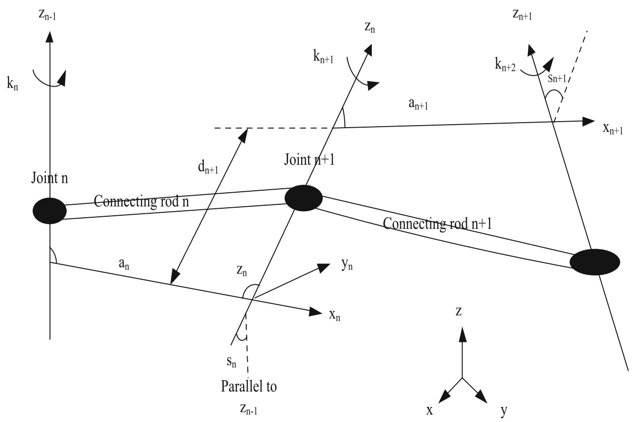

Fig. 1. Robot arm.

As can be seen from Fig. 1, the connecting rod n is between joint n and joint n + 1, and the connecting rod n + 1 is between joint n + 1 and joint n + 2. A reference coordinate system is specified for each joint, i.e. an X-axis and a z-axis.Since the y-axis is perpendicular to the x-axis and the z-axis, the y-axis can be determined by specifying the x-axis and the z-axis, so it is not necessary to specify the y-axis, nor does the D-H method need the y-axis.The coordinates of joint n + 1 are expressed in xn-z n coordinate system. An represents the common vertical length between Z n-1 an d z (if the z-axis of two joints is parallel, there are countless common vertical lines. If the z-axis of two adjacent joints is related, the common vertical line is zero). Angle K represents the rotation angle around the z-axis, D represents the distance between the adjacent two common vertical lines on z-axis, an d angle s represents the angle between adjacent z-axis, also known as joint torsion angle.Generally, only K and D are joint variables [6]. Usually, a local coordinate system can be transformed to the next local coordinate system by the following four steps.

1) Firstly, the rotation angle kn + 1 around the Zn axis makes the xn axis and the xn + 1 axis parallel to each other.
2) Translating the distance of dn + 1 along the Zn axis to make the xn axis and the xn + 1 axis collinear;
3) Translating an + 1 distance along the xn axis to make the origin of the xn axis coincide with that of the xn + 1 axis.
4) Finally, the Z-N axis is rotated around the x-n + 1 axis to align the Z-N with the z-n + 1 axis. At this time, the N coordinate system and the N + 1 coordinate system are identical, one coordinate system is transformed to the next coordinate system.

If there are multiple coordinate systems to be transformed, the above steps can be repeated between the two coordinate systems. For the manipulator, starting from the reference coordinate system, it can be converted to the base, then to the first joint, then to the second joint, then to the n joint, until the end of the actuator. Thus the coordinate transformation of the whole manipulator joint is completed, and the total coordinate transformation matrix, namely kinematics equation, is obtained. Since each transformation is relative to the current coordinate system, the transformation matrix A can be obtained by multiplying four matrices representing four motions by right, and the following results can be obtained:

$$Q_n = Rot(z, k_n) \cdot Trans(z, d_n) \cdot Trans(a_n, x) \cdot Rot(x, s_n) \tag{1}$$

Among them, Q_n represents transformation matrix of coordinate system; Rot represents rotation matrix; Trans represents translation transformation.

From the base of the manipulator to the end-effector, the transformation matrix of each joint can be obtained by defining each joint. The total transformation between the base and the end effector is as follows:

$$^{R}Q_m = ^{R} Q_1^1 Q_2^2 Q_3^3 Q_4 \ldots Q_n \tag{2}$$

Among them, R represents the reference coordinate system, m represents the coordinate system where the end effector is located, and n represents the number of joints of the manipulator.

(2) Dynamics Modeling

Dynamics of manipulator mainly analyses and studies the interaction between joint moment and motion, and then expresses the relationship between them through mathematical model, and deeply understands the meaning of its mathematical and physical model, which will improve the tracking effect of the system to a certain extent. Lagrange function method and Newton-Euler method are commonly used to establish the mathematical model of manipulator [7]. Among them, Newton-Euler method is a method to analyze the force between the joints of the manipulator using dynamic equilibrium analysis method. This method is easy to understand, but it needs to analyze the relationship between various forces. When the complexity of the system is high and the number of forces between the systems is large, the analysis method is cumbersome and unsuitable for engineering application. Lagrange function considers the overall energy distribution of the current system, and then calculates the system dynamics equation by mathematical calculation. Although the understanding process is abstract, the calculation process is relatively simple and convenient, which is suitable for engineering application. In this chapter, Lagrange function is used to analyze the whole process of dynamic model of manipulator in detail, considering the constraints in the actual process.

Lagrange function:

$$L(q, \dot{q}) = H - P \tag{3}$$

Among them, q represents the rotation angle of each joint of the manipulator in the joint space; $\dot{q}$ is the angular velocity of each joint of the manipulator in the joint space; H is the total kinetic energy of the system, P is the total potential energy of the system, and they can be expressed in any convenient coordinate system.

Lagrange equation:

$$L_i^{'} = \frac{1}{t}\frac{L}{\dot{q}_i} - \frac{L}{q_i}(i = 1, 2, \ldots, j) \tag{4}$$

Among them: $L^{'}$ is the force or moment acting on the first joint; J is the degree of freedom, that is, the number of connecting rods.

The kinetic energy H of the system is defined as the sum of the translational and rotational kinetic energies of the connecting rods. Its expression is as follows (5). Potential energy P is defined as the sum of the gravitational potential energies of the connecting rods. Its expression is shown in formula (6):

$$H = \sum_{i=1}^{j}\left(\frac{1}{2}b_i c_i^2 + \frac{1}{2}j_i\dot{r}_i \times \dot{r}_i\right) \tag{5}$$

$$P = \sum_{i=1}^{j}\left(j_i g_i \times r_{iy}\right) \tag{6}$$

Among them, b_i is the central inertial tensor of the connecting rod; c_i is the angular velocity of the connecting rod in the inertial coordinate system; $\dot{r}$ is the linear velocity of the connecting rod in the inertial coordinate system; r_{iy} is the component along the y-axis in the inertial coordinate system.

The total kinetic energy and total potential energy equation of the connecting rod of the manipulator are introduced into the Lagrange function as shown in Eq. (3), and then the partial derivative is introduced into Eq. (4). Finally, the dynamic equation of the manipulator is obtained as follows:

$$F(q)\dot{q} + W(q,\dot{q})\dot{q} + U(q) = L' \tag{7}$$

Among them, $F(q)$ is the inertia matrix of the system, $W(q,\dot{q})$ is the centrifugal force and the Gothic force matrix of the system, $U(q)$ is the gravity term matrix, q is the current joint angle vector, and L' is the driving moment output by the controller on the joints of the controlled manipulator.

2.2 Manipulator Trajectory Tracking Control Strategy

In recent decades, artificial intelligence methods and theories represented by fuzzy logic, neural network and evolutionary computation have been applied to the control of robotic arms, especially neural networks. In the application of manipulator control, almost all neural network models and learning algorithm application examples can be found. Because the neural network has the ability to learn in the control process, in order to make up for the lack of prior knowledge, so there are great advantages in solving the nonlinear and uncertain problems in the process of modeling. However, due to the lack of systematic and standardized methods to construct neural networks, and the fact that neural networks need a lot of time to train, have no clear physical significance, and are difficult to prove the stability of the system, many problems exist, which restrict the popularization and application of neural network control in the field of joint manipulator trajectory tracking control. So many experts and scholars have improved it a lot [8].

Fuzzy control draws lessons from the fuzziness of human thinking and uses control experience to realize control. It is the earliest form of intelligent control. Because the control system design does not require precise mathematical model, many effective membership functions are relatively simple, the required rule base is not very complex, robust and many other advantages, fuzzy control has been widely used. In the field of manipulator control, people seldom apply fuzzy control directly to manipulator control, but combine fuzzy algorithm with other control methods to construct composite control system. With the development of neural network technology, people begin to combine fuzzy control with neural network, and use fuzzy method, membership function and fuzzy rules to adjust the node function and connection weight of neural network.Fuzzy method is used to adjust and optimize the structure of the neural network. This not only makes the fuzzy control adaptive, but also makes the neural network have the ability of fuzzy reasoning. The weights of the network have a clear meaning of fuzzy logic [9].

2.3 Structure of Fuzzy Neural Network

In this paper, a four-layer Mamdani-type fuzzy neural network (FNN) is used to approximate the nonlinear link of the manipulator system. The center and width of the fuzzy basis function are variable. The structure of the FNN is shown in Fig. 2.

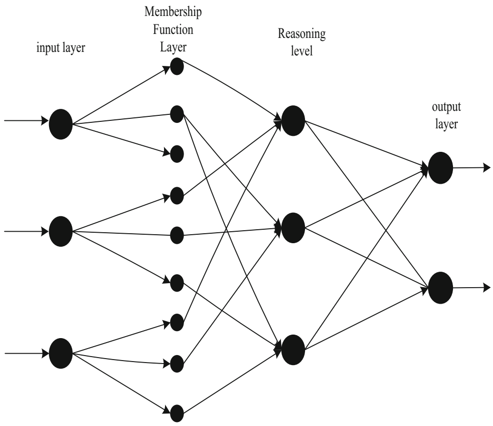

Fig. 2. Structure of fuzzy neural network.

It consists of input layer, membership function layer, reasoning layer and output layer. In the input layer, the data samples are input into a feedforward neural network, and the shape of the activation function of the network represents the shape of the fuzzy membership function. Activation functions can be linear or exponential, which represent triangular and Gaussian membership functions, respectively. The adjustment of the width and center position of the activation function can be obtained by adjusting the weights and deviations of the input layer of the network. The number of neurons in the input layer represents the number of fuzzy markers, which can be selected as needed. The membership function layer and inference layer belong to the middle layer of the neural network, which realizes the fuzzification and fuzzy reasoning of the input. The fourth layer is the output layer, which realizes the de-fuzzification of the control quantity [10].

The combination of fuzzy and neural network has both learning ability and reasoning ability. It provides an effective method to solve the high non-linearity, coupling and unmodeled uncertainty in robot control. The proposed controller consists of two parts: a fuzzy neural network (F'NN) controller and a CMAC controller.

FNN controllers need to be trained with samples, that is, supervised learning. This process is carried out offline, and then applied to the corresponding system. The training samples are taken from the system based on computational moment control. The system achieves better control performance with lower accuracy requirements. But in fact, the system can not be accurately modeled, and the existence of uncertainty is inevitable. The training data can not reflect the structural or non-structural uncertainties in the robot model, so the real-time performance of these data can not be guaranteed. In order to overcome this shortcoming, the self-learning ability of CMAC controller and the advantages of fast convergence are used to compensate the control error online [11, 12].

The first layer of FNN controller is the fuzzification layer. Each node of FNN controller corresponds to a linguistic variable, completes the calculation of an input membership function, and realizes the fuzzification of input variables [13, 14]. The second layer performs the large operation. In the third layer, the minimization of all outputs of the first ten neurons in the two layers and the minimization of all outputs of the last ten neurons are taken as the output of the three layers [15, 16].

CMAC controller is adopted because its self-learning ability can compensate for the control error of the system. Therefore, the output of the controller must reflect the change of joint position and speed, and drive the robot to the desired position and speed.

3 Tracking Error Simulation Experiment

The simulation experiment takes a rigid-flexible coupling manipulator of a six-joint machine as the research object, and chooses one of the joints to carry out the trajectory tracking test by using the optimization method of fuzzy neural trajectory tracking and the single neural network trajectory tracking method. The length of the joint arm is 6.73 m, the mass is 1.8 kg, and the simulation is carried out by MATLAB software. Figure 3 shows the experimental environment. The expectation given in Fig. 4 below is shown as follows. Track the trajectory curve.

Fig. 3. Experimental environment.

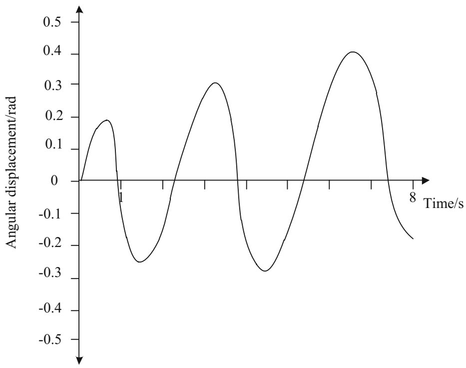

Fig. 4. Expected tracking trajectory curve.

Figure 5 below shows the tracking trajectory curve of the joint given by the fuzzy neural network and the neural network.

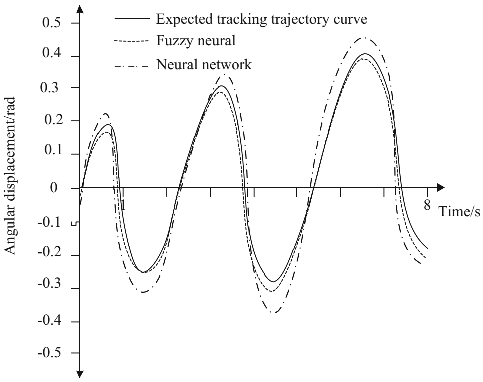

Fig. 5. Tracking trajectory curve given by fuzzy neural network and neural network.

Figure 6 below shows the error curve between the track curve given by the two methods and the desired track curve.

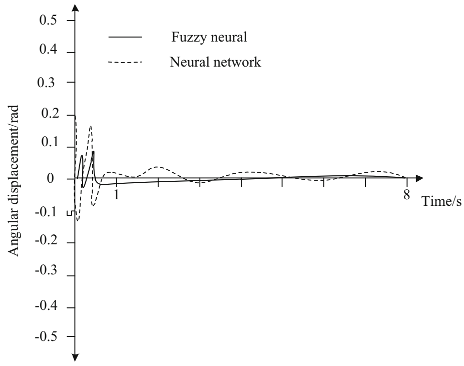

Fig. 6. Error curve.

From the simulation results, it can be seen that the fuzzy neural network can quickly and accurately plan the motion trajectory and complete the operation requirements in a short time. The average tracking error is 0.021 rad, while the average tracking error of the neural network is 0.056 rad. This shows that the tracking performance of this method is better, and it can more accurately and effectively complete the tracking control task of the manipulator. This is because the fuzzy control is introduced into the neural network to optimize the single neural network to form a compound method of fuzzy neural network, and the hybrid method is used to track the trajectory of the manipulator, so as to improve the accuracy of the tracking results.

In order to further verify the effectiveness of the proposed method, the feedforward compensation control method, sliding mode variable structure control method and the method in this paper are compared by taking the trajectory tracking time as the index. The results are shown in Fig. 7.

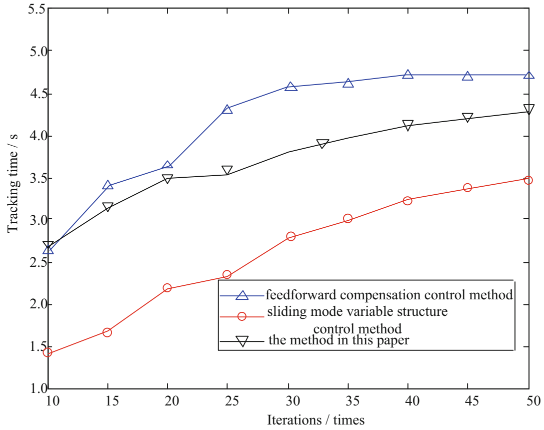

Fig. 7. Comparison of tracking time of different methods.

It can be seen from Fig. 7 that when the rigid flexible coupling manipulator trajectory is tracked by our method, the time spent is always less than 3.5 s, while the feedforward compensation control method, The tracking time of sliding mode variable structure control method is significantly higher than that of the method in this paper, which shows that the tracking efficiency of this method is higher, and it can effectively track the moving trajectory of the manipulator in a short time.

4 Conclusion

In summary, the development of computer information technology promotes the mechanized production. In the mechanized production, the application of the manipulator is more and more widely. Manipulator replaces human manual labor, and the production efficiency has been greatly improved. However, the manipulator also has a shortcoming. The elastic deformation of the rigid flexible manipulator will cause the manipulator operation deviation and vibration problems. In this context, an optimal tracking method for rigid-flexible coupling manipulator is studied. This method solves the problems in using single neural network to track the moving trajectory of manipulator by using fuzzy control algorithm, optimizes single neural network, provides a reference for the control of manipulator and improves the production efficiency of mechanization.

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