



# Backstepping Fuzzy Adaptive Control Based on RBFNN for a Redundant Manipulator

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**Abstract.** Redundant manipulator is a highly nonlinear and strongly coupled system. In practical application, dynamic parameters are difficult to determine due to uncertain loads and external disturbances. These factors will adversely affect the control performance of manipulator. In view of the above problems, this paper proposes a backstepping fuzzy adaptive control algorithm based on the Radial Basis Function Neural Network (RBFNN), which effectively eliminates the influence of the internal uncertainty and external interference on the control of the manipulator. Firstly, the algorithm adopts the backstepping method to design the controller framework. Then, the fuzzy system is used to fit the unknown system dynamics represented by nonlinear function to realize model-free control of the manipulator. The fuzzy constants are optimized by RBFNN to effectively eliminate the control errors caused by unknown parameters and disturbance. Finally, in order to realize RBFNN approximating the optimal fuzzy constant, an adaptive law is designed to obtain the weight value of RBFNN. The stability of the closed-loop system is proved by using Lyapunov stability theorem. Through simulation experiments, the algorithm proposed in this paper can effectively track the target joint angle when the dynamic parameters of the 7-DOF redundant manipulator are uncertain and subject to external torque interference. Compared with fuzzy adaptive control, the tracking error of the algorithm in this paper is smaller, and the performance is better.

**Keywords:** Redundant manipulator · Fuzzy system · RBF neural network · Adaptive control

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# 1 Introduction

At present, the control task of manipulator is mainly to locate, move and transport equipment. The efficient manipulator controller can control the manipulator to complete the control task and achieve the control goal, even in the presence of uncertain parameters, external force and torque. The traditional controller design usually needs to derive the accurate mathematical model of the manipulator. However, the redundant manipulator has a complex structure, and it is difficult to determine the dynamic parameters in engineering practice, and it is difficult to obtain an accurate mathematical model. With the deepening, extensive and complex application of manipulators, these reasons promote the development of manipulator control, but also pose great challenges to the traditional controller design. For example, in manipulator-assisted rehabilitation training, the external force on the manipulator will also change due to the different muscle strength of patients [1].

Among the traditional control methods, such as PID [2, 3] control can achieve model-free control of the manipulator. Due to the simple structure of PID control algorithm and obvious intent of mathematical expression, However, PID control has been widely used in the case of disturbance and dynamic uncertainty of the manipulator. It is difficult to achieve high-precision motion control of manipulator at high speed [4]. Most cases are applied to low load and low speed control with poor adaptive ability. Therefore, in the design process of control algorithm of manipulator, intelligent control has received much attention due to various reasons. Such as in terms of intelligent control, fuzzy network [5, 6], deep learning [7] have been applied. In [8], for  $n$  DOF manipulator, this paper proposes an adaptive control algorithm based on neural network, in the process of control, eliminate the dynamic time-varying parameter uncertainty and unknown delay, and meet the state and input constraints, by using saturation function and Lyapunov-Krasovskii functional, the influence of actuator saturation and time delay is eliminated, but in the experiment part only about 2 DOF manipulator through simulation experiments, not in a high DOF manipulator for validation. Therefore, it is difficult to realize unmodeled manipulator control, real-time compensation of external interference and effective proof of controller stability at the same time.

To sum up, this paper focuses on the study of manipulator with uncertain dynamics, affected by external disturbance and uncertain load, and proposes a joint space backstepping adaptive fuzzy adaptive control algorithm based on RBF neural network. Compared with previous work, the main contributions of this paper are summarized as follows.

- (1) The controller designed in this paper does not need to obtain the fuzzy constants in the fuzzy system according to the expert knowledge, which are approximated by RBF (Radial Basis Function) neural network, which really strengthens the applicability of the controller.
- (2) Combining the traditional backstepping controller design with the fuzzy system and RBF neural network in intelligent control framework, the controller not only maintains a concise structure, which is convenient for stability verification, but also can realize the model-free control of nonlinear and strongly coupled systems.

## 2 System Description and Problem Formulation

### 2.1 System Description of Redundant Manipulator

We consider an  $n$  degree-of-freedom (DOF) redundant manipulator dynamic model in the joint space as follow:

$$\begin{aligned} M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) + d &= \tau \\ y &= q \end{aligned} \quad (1)$$

where  $q, \dot{q}, \ddot{q} \in R^n$  are the joint angular displacement, velocity and acceleration vectors,  $M(q) \in R^{n \times n}$  is the symmetric and positive definite inertia matrix,  $C(q, \dot{q})\dot{q} \in R^n$  is the vector of Coriolis and centripetal torque,  $g(q) \in R^n$  denotes the vector of the gravitational torque.  $\tau \in R^n$  denotes the vector of the control input torque,  $d \in R^n$  denotes the vector of unknown disturbance observer in manipulator dynamics and it can be friction disturbance or other forms of unknown disturbance.  $y \in R^n$  denotes the output vector of the manipulator, which are the joint angles. Because the seven- DOF redundant manipulator is used in this paper, then  $n = 7$ .

In the process of model-free control, the dynamic parameters of the manipulator are unknown, but usually they are bounded. The system has the following properties:

- (1) The inertial matrix  $M(q)$  is a positive definite symmetric matrix, and lower and upper bounded as  $m_1\|\chi\|^2 \leq \chi^T M(q)\chi \leq m_2\|\chi\|^2$ , where  $m_1, m_2$  are known positive constants and  $\|\cdot\|$  is the Euclidean 2-norm,  $\chi \in R^n$  is an arbitrary vector.
- (2) The inertia matrix  $M(q)$  and centripetal force and Coriolis moment matrix  $C(q, \dot{q})$  satisfy the following relations:  $\dot{q}^T (\dot{M} - 2C)\dot{q} = 0$ .

We define  $x_1 = q, x_2 = \dot{q}$ . Rewrite the dynamic equation of the manipulator as shown below, and then use the Backstepping controller design method.

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = M^{-1}(x_1)\tau - M^{-1}(x_1)C(x_1, x_2) - M^{-1}(x_1)g(x_1) - M^{-1}(x_1)d \\ y = x_1 \end{cases} \quad (2)$$

where  $C(x_1, x_2)$ ,  $M^{-1}(x_1)$  and  $g(x_1)$  are unknown nonlinear smooth functions related to the redundant manipulator of the controlled object, and  $y_d$  are defined as the desired joint angles, which are second-order differentiable.

### 2.2 Problem Formulation

The Control objective of this paper is formulated as when the dynamic parameters of redundant manipulator are uncertain and affected by external interference, a backstepping fuzzy adaptive control algorithm based on RBFNN is designed to adjust the joint angles  $y$  of the manipulator and realize the accurate tracking of the target joint angles  $y_d$ .

### 3 Backstepping Fuzzy Adaptive Control Based on RBFNN

#### 3.1 Backstepping Control

The actual joint angle is  $y$ , the desired joint angle is  $y_d$ . We define the error as

$$z_1 = y - y_d \quad (3)$$

If the estimate of  $x_2$  is defined as virtual control  $\alpha_1$ , the error is defined as

$$z_2 = x_2 - \alpha_1 \quad (4)$$

In order to drive  $z_1$  goes to 0 in the control process,  $\alpha_1$  needs to be designed. According to the following formula:

$$\dot{z}_1 = \dot{x}_1 - \dot{y}_d = x_2 - \dot{y}_d = z_2 + \alpha_1 - \dot{y}_d \quad (5)$$

The virtual control is selected as

$$\alpha_1 = -\lambda_1 z_1 + \dot{y}_d \quad (6)$$

for the first subsystem of (3), the Lyapunov function is constructed as

$$V_1 = \frac{1}{2} z_1^T z_1 \quad (7)$$

Then we can obtain that

$$\dot{V}_1 = z_1^T \dot{z}_1 = z_1^T (\dot{y} - \dot{y}_d) = z_1^T (\dot{x}_1 - \dot{y}_d) = z_1^T (x_2 - \dot{y}_d) \quad (8)$$

In order for the first subsystem to be stable, we need  $z_2$  converge to 0.

#### 3.2 Application of Fuzzy System in Backstepping Control

According to (3) and (5), the following equation can be obtained:

$$\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1 = -M^{-1}Cx_2 - M^{-1}g - M^{-1}d + M^{-1}\tau - \dot{\alpha}_1 \quad (9)$$

For the second subsystem

$$\dot{x}_2 = M^{-1}(x_1)\tau - M^{-1}(x_1)C(x_1, x_2) - M^{-1}(x_1)g(x_1) - M^{-1}(x_1)d \quad (10)$$

construct the Lyapunov function as follow:

$$V_2 = V_1 + \frac{1}{2} z_2^T M z_2 \quad (11)$$

therefore

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + \frac{1}{2} z_2^T M \dot{z}_2 + \frac{1}{2} \dot{z}_2^T M z_2 + \frac{1}{2} z_2^T \dot{M} z_2 \\ &= -\lambda_1 z_1^T z_1 + z_1^T z_2 + z_2^T (-C\alpha_1 - g - M\dot{\alpha}_1 + \tau) - z_2^T d \\ &= -\lambda_1 z_1^T z_1 + z_1^T z_2 + z_2^T (f + \tau) - z_2^T d \end{aligned} \quad (12)$$

by satisfying the stability of Lyapunov function, the control law is obtained as follow:

$$\tau = -\lambda_2 z_2 - z_1 - \varphi \quad (13)$$

where  $\varphi$  denotes the fuzzy system output. Where (12),  $f = -C\alpha_1 - g - M\dot{\alpha}_1$ , substitute the obtained control law (13) into (12), we can obtain:

$$\dot{V}_2 = -\lambda_1 z_1^T z_1 - \lambda_2 z_2^T z_2 + z_2^T (f - \varphi) - z_2^T d \quad (14)$$

according to (14), a fuzzy system output  $\varphi$  should be used to fit  $f$ , because  $f = -C\alpha_1 - g - M\dot{\alpha}_1$ , which contains the inertial matrix  $M$  and Coriolis force matrix  $C$  of the manipulator. Because the dynamic parameters of the manipulator is uncertain and difficult to measure, model-free control scheme is used. In this paper, the fuzzification method will be used as single-valued fuzzification. The defuzzification method is product inference machine and barycentric average.

If there are  $N$  fuzzy rules to form a fuzzy system, the  $i$ -th fuzzy rule can be expressed as

$$R^i = \text{IF } x_1 \text{ is } \mu_1^i \text{ and ...and } x_n \text{ is } \mu_n^i, \text{ then } y \text{ is } B^i (i = 1, 2, \dots, N) \quad (15)$$

where  $\mu_j^i$  denotes the subordinate function of linguistic variables  $x_j (j = 1, 2, \dots, n)$ . We define the output of the fuzzy system as follow:

$$y = \frac{\sum_{i=1}^N \theta_i \prod_{j=1}^n \mu_j^i(x_j)}{\sum_{i=1}^N \prod_{j=1}^n \mu_j^i(x_j)} = \xi(x)\theta \quad (16)$$

where  $\xi = [\xi_1(x)\xi_2(x)\dots\xi_N(x)]^T$ ,  $\xi_i(x) = \frac{\prod_{j=1}^n \mu_j^i(x_j)}{\sum_{i=1}^N \prod_{j=1}^n \mu_j^i(x_j)}$ ,  $\theta = [\theta_1\theta_2\dots\theta_N]^T$ , where  $\theta$  are

fuzzy constants. In (14),  $f$  will be obtained through the fitting of the fuzzy system, the research object of this paper is a 7-DOF redundant manipulator, where  $f \in R^7$  represents the torque control quantity of the fitted dynamic part on the manipulator of 7-DOF, which can be described as  $f(1), f(2)\dots f(7)$ . The fuzzy system is expressed as follows:

$$\varphi_1(x) = \frac{\sum_{i=1}^N \theta_{1i} \prod_{j=1}^n \mu_j^i(x_j)}{\sum_{i=1}^N \prod_{j=1}^n \mu_j^i(x_j)} = \xi_1^T(x)\theta_1 \quad \dots \quad \varphi_7(x) = \frac{\sum_{i=1}^N \theta_{7i} \prod_{j=1}^n \mu_j^i(x_j)}{\sum_{i=1}^N \prod_{j=1}^n \mu_j^i(x_j)} = \xi_7^T(x)\theta_7 \quad (17)$$

we define the fitting result of  $f$  as  $\Phi$ , we have

$$\Phi = [\varphi_1\varphi_2\dots\varphi_7]^T = \begin{bmatrix} \xi_1^T & \dots & 0 \\ \dots & \dots & \dots \\ 0 & \dots & \xi_7^T \end{bmatrix} \begin{bmatrix} \theta_1 \\ \dots \\ \theta_7 \end{bmatrix} \quad (18)$$

### 3.3 RBFNN Combined with Fuzzy System

In (18),  $\theta$  usually unknown and requires expert knowledge to make judgment and selection, because  $\theta$  is abundant and difficult to obtain, it is difficult to obtain an effective control law. Therefore, this paper uses a simple-structured RBF neural network to obtain fuzzy constants to achieve efficient control of the manipulator. RBFNN is a kind of forward neural network, which consists of three layers of network.

The first layer is the input layer, where  $x = [x_1, x_2, \dots, x_n]^T$  is the input of the network and  $n$  represents the dimension of the input.

The second layer is the hidden layer, whose output is  $h(x) = [h_1, h_2, \dots, h_m]^T$ , and the Gaussian basis function is used as the subordinate function of the input layer introduced as follow:

$$h_j(x) = \exp\left(-\frac{\|x - c\|^2}{2b^2}\right) \quad (19)$$

where  $c$  is the coordinate vector of the center point of the gaussian basis function of the hidden layer,  $b$  is the width of the gaussian basis function of the hidden layer,  $j = 1, 2, \dots, m$ , RBF neural network weight value is given as

$$W = [W_1, W_2, \dots, W_m]^T \quad (20)$$

The third layer is the output layer of neural network, and the output as follow

$$y = W^T h(x) = W_1 h_1 + \dots + W_m h_m \quad (21)$$

We define the optimal approximation fuzzy constant  $\theta_i$  in (22), and the RBF neural network is used to approximate  $\theta_i$ . The input of neural network is  $x = [e, \dot{e}]^T$ , and the ideal output of neural network as

$$\theta_i = W^{*T} h(x) - \varepsilon_i \quad (22)$$

where  $W^*$  is the ideal weight of the RBF neural network,  $h(x)$  is the output of the Gaussian function, for a given arbitrary small constant  $\varepsilon_i (\varepsilon_i > 0)$ , the following inequality holds,  $\|\theta_i - W^{*T} h(x)\| \leq \varepsilon_i$  is the approximation error of the network, and the actual output of the neural network is set as

$$\hat{\theta}_i = \hat{W}^T h(x) \quad (23)$$

where  $\hat{W}$  is the actual weight of the neural network, we define  $\tilde{W} = W^* - \hat{W}$ ,  $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$ , where  $\tilde{W}$  is the error between the ideal weight and the actual weight, and  $\tilde{\theta}_i$  is the error between the ideal output and the actual output. Therefore, the adaptive law based on RBF neural network is given as

$$\dot{\hat{W}} = \gamma h(x) (z_2^T \xi^T(x))^T - 2k \hat{W} \quad (24)$$

Then, Fig. 1 shows the system control block diagram, from (10)–(24), we can achieve the control law as follows:

$$\tau = -\lambda_2 z_2 - z_1 - \xi \int (\gamma h(z_2^T \xi^T)^T - 2k \hat{W}) dt^T h \quad (25)$$

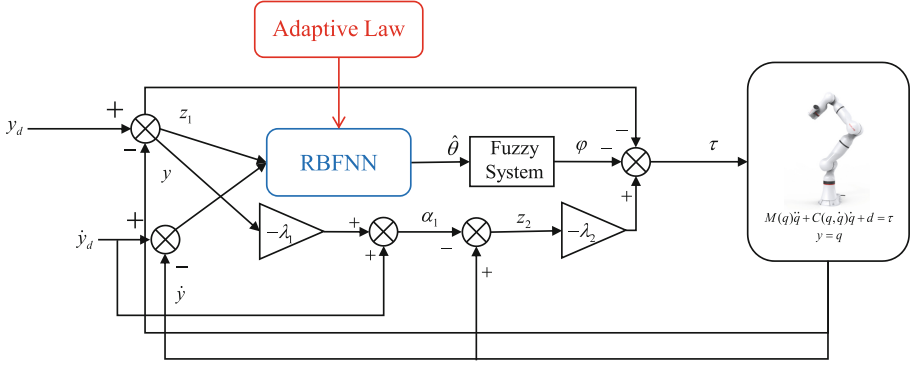


Fig. 1. Control block diagram of redundant manipulator.

### 3.4 Stability Analysis

For the whole system, we define the Lyapunov function candidate as follow

$$V = \frac{1}{2}z_1^T z_1 + \frac{1}{2}z_2^T M z_2 + \frac{1}{2\gamma} \tilde{W}^T \tilde{W} = V_2 + \frac{1}{2\gamma} \tilde{W}^T \tilde{W} \quad (26)$$

where  $\gamma > 0$ , hence

$$\begin{aligned} \dot{V} = & -\lambda_1 z_1^T z_1 - \lambda_2 z_2^T z_2 + z_2^T \left[ f - \xi(x) \left( W^{*T} h(x) \right) \right] \\ & + z_2^T \left[ \xi(x) \left( W^{*T} h(x) \right) - \xi(x) \left( \hat{W}^T h(x) \right) \right] - z_2^T d - \frac{1}{\gamma} \tilde{W}^T \dot{\tilde{W}} \end{aligned} \quad (27)$$

According to the basic inequality  $a^2 + b^2 \geq 2ab$ ,  $a, b \in R$ , the equality sign holds if and only if  $a = b$ , substitute the obtained adaptive law (24) into the above equation, we obtain

$$\begin{aligned} \dot{V} \leq & -\lambda_1 z_1^T z_1 - (\lambda_2 - 1) \lambda_2 z_2^T z_2 + \frac{k}{\gamma} (2W^{*T} \hat{W} - 2\tilde{W}^T \hat{W}) \\ & + \frac{1}{2} (\xi(x) \varepsilon)^T (\xi(x) \varepsilon) + \frac{1}{2} d^T d \end{aligned} \quad (28)$$

According to  $(\hat{W} - W^*)^T (\hat{W} - W^*) \geq 0$ , we obtain  $2W^{*T} \hat{W} - 2\hat{W}^T \hat{W} \leq -\hat{W}^T \hat{W} + W^{*T} W^*$ , plug in the formula above

$$\begin{aligned} \dot{V} \leq & -\lambda_1 z_1^T z_1 - (\lambda_2 - 1) \lambda_2 z_2^T z_2 + \frac{k}{\gamma} (-\hat{W}^T \hat{W} - W^{*T} W^*) \\ & + \frac{2k}{\gamma} W^{*T} W^* + \frac{1}{2} (\xi(x) \varepsilon)^T (\xi(x) \varepsilon) + \frac{1}{2} d^T d \end{aligned} \quad (29)$$

According to  $(W^* + \hat{W})^T (W^* + \hat{W}) \geq 0$ , we obtain  $-W^{*T} \hat{W} - \hat{W}^T W^* \leq W^{*T} W^* + \hat{W}^T \hat{W}$ .

then

$$\tilde{W}^T \tilde{W} = (W^{*T} - \hat{W}^T)(W^* - \hat{W}) \leq 2W^{*T}W^* + 2\hat{W}^T\hat{W} \quad (30)$$

Therefore  $-W^{*T}W^* - \hat{W}^T\hat{W} \leq -\frac{1}{2}\tilde{W}^T\tilde{W}$ , we obtain as follow

$$\begin{aligned} \dot{V} \leq & -\frac{2}{2}\lambda_1 z_1^T z_1 - (\lambda_2 - 1)\frac{2}{2}\lambda_2 z_2^T M^{-1}Mz_2 \\ & - \frac{k}{2\gamma}\tilde{W}^T\tilde{W} + \frac{2k}{\gamma}W^{*T}W^* + \frac{1}{2}(\xi(x)\varepsilon)^T(\xi(x)\varepsilon) + \frac{1}{2}d^T d \end{aligned} \quad (31)$$

We take  $\lambda_2 > 1$ , because  $M \leq \sigma_0 I$ , thus

$$\begin{aligned} \dot{V} \leq & -\frac{2}{2}\lambda_1 z_1^T z_1 - (\lambda_2 - 1)\frac{2}{2\sigma_0}\lambda_2 z_2^T Mz_2 - \frac{k}{2\gamma}\tilde{W}^T\tilde{W} \\ & + \frac{2k}{\gamma}W^{*T}W^* + \frac{1}{2}(\xi(x)\varepsilon)^T(\xi(x)\varepsilon) + \frac{1}{2}d^T d \end{aligned} \quad (32)$$

We define  $c_0 = \min\{2\lambda_1, 2(\lambda_2 - 1)\frac{1}{\sigma_0}, k\}$ , therefore

$$\dot{V} \leq -c_0 V + \frac{2k}{\gamma}W^{*T}W^* + \frac{1}{2}(\xi(x)\varepsilon)^T(\xi(x)\varepsilon) + \frac{1}{2}d^T d \quad (33)$$

Because  $\xi_i(x) = \frac{\prod_{j=1}^n \mu_j^i(x_j)}{\sum_{i=1}^n \prod_{j=1}^n \mu_j^i(x_j)}$ , thus  $|\xi(x)| \leq 1$ , then

$$\dot{V} \leq -c_0 V + \frac{2k}{\gamma}W^{*T}W^* + \frac{1}{2}\varepsilon^T \varepsilon + \frac{1}{2}d^T d \quad (34)$$

Since interference  $d \in R^n$  is bounded,  $D > 0$  exists and  $d^T d \leq D$  is satisfied, then

$$\dot{V} \leq -c_0 V + \frac{2k}{\gamma}W^{*T}W^* + \frac{\varepsilon^T \varepsilon}{2} + \frac{D}{2} = -c_0 V + c_{V_{\max}} \quad (35)$$

where  $c_{V_{\max}} = \frac{2k}{\gamma}W^{*T}W^* + \frac{\varepsilon^T \varepsilon}{2} + \frac{D}{2}$ . Solving (35) and we obtain as

$$\dot{V}(t) \leq V(0) \exp(-c_0 t) + \frac{c_{V_{\max}}}{c_0}(1 - \exp(-c_0 t)) \leq V(0) + \frac{c_{V_{\max}}}{c_0} \quad (36)$$

where  $V(0)$  is the initial value of  $V(t)$  and defines a compact set as

$$\Omega_0 = \left\{ X \mid V(X) \leq V(0) + \frac{c_{V_{\max}}}{c_0} \right\} \quad (37)$$

According to  $\{z_1, z_2, \tilde{W}\} \in \Omega_0$ ,  $V$  is bounded, and all signals of the closed-loop system are bounded.  $z_1$  and  $z_2$  are required to converge in order to effectively track the target value of the joint Angle and angular velocity of the manipulator. Unknown disturbance will determine the accuracy of the convergence value.



### 4 Simulation Experiment and Result Analysis

In this section, the effectiveness of the backstepping fuzzy adaptive control algorithm based on RBF neural network is verified by numerical simulation. The ROKEA redundant manipulator model xMate is selected for simulation. ROKEA has 7 revolute joints and a load capacity of 3kg. Under the action of the controller, the manipulator realizes the tracking of the target joint vector in the joint space. The controller controls the torque of the seven joints. The ROKEA xMate structure is shown in Fig. 2, Table 1 lists the masses of each link.

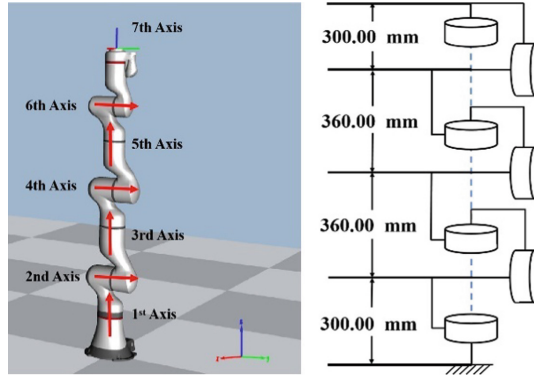


Fig. 2. The ROKEA xMate structure.

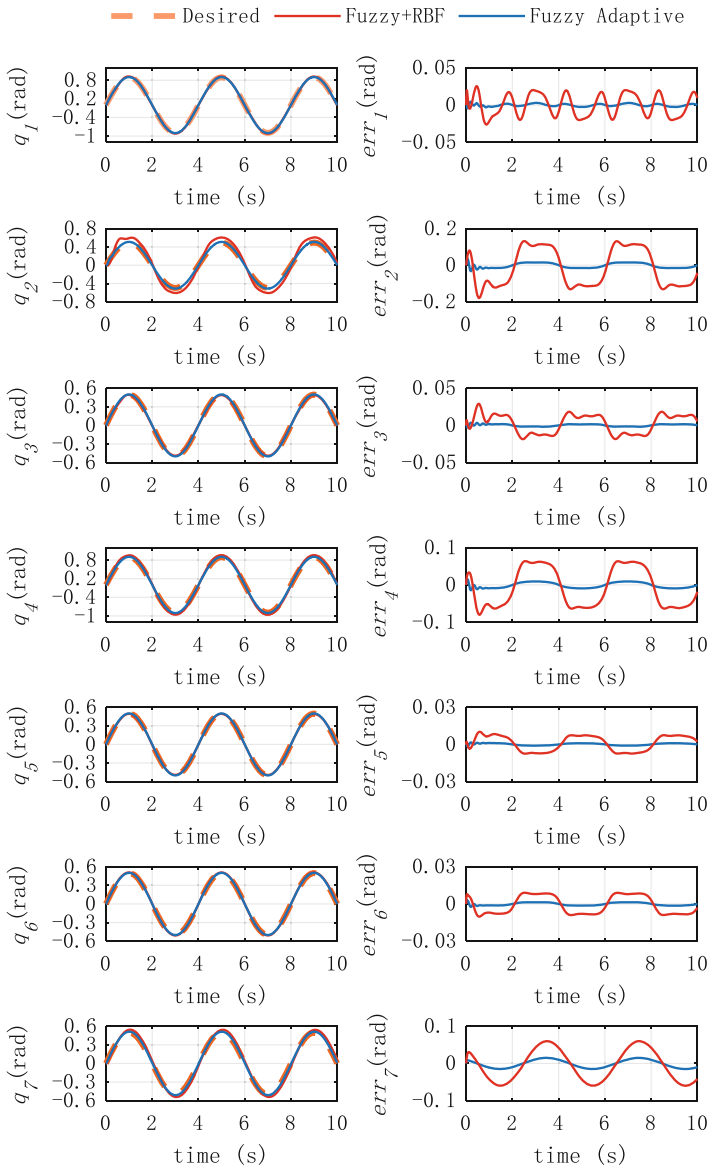
Table 1. The masses of each link.

Link (i)	1	2	3	4	5	6	7
Mass/kg	3.44	3.62	3.46	2.38	2.22	2.18	0.51

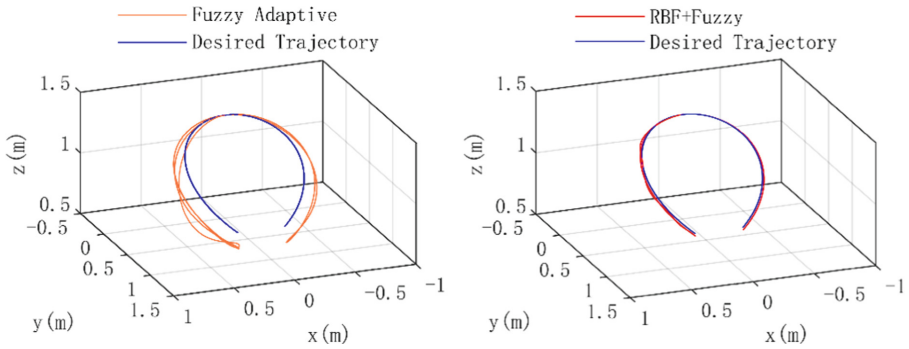
In the actual task execution, it is necessary to load a gripper at the end of the manipulator for handling tasks, and in order to expand the function of the manipulator, add cameras, sensors with different functions and other equipment on the manipulator link. In this case, it will affect dynamic parameters such as the original mass, center of mass, and moment of inertia of the manipulator affect the control performance of the manipulator. The controller uses RBF fuzzy backstepping control to realize the fitting of the nonlinear system, so as to realize the control of the manipulator without accurate manipulator model information.

Compared with the mass of the link of the original manipulator in Table 1, the mass change of each link is [+0, +1, +0, +2, +1, +0, +1] kg. The added mass of the 7th link can be regarded as the load. The control parameters  $\lambda_1 = 80$ ,  $\lambda_2 = 70$ ,  $k = 1.5$ ,  $b = 6$ , set the external interference torque as  $d = [0, 0.5, 0, 0, 0.5, 0.5, 0]^T$ , and  $q_d = [0.9, 0.5, 0.5, 0.9, 0.5, 0.5, 0.5]^T \cdot \sin(0.5\pi \cdot t)$  the desired joint angle trajectories are set to The simulation results are as follows.. The actual and desired angles of

each joint and the angle errors of each joint are shown in Fig. 3. The 3D trajectory is shown in Fig. 4. It can be observed that the RBFNN combined with fuzzy system has better robustness, smaller control error, compared with the fuzzy adaptive control in [9], smoother trajectory and better control performance under the impact of the uncertainty of dynamic parameters and unknow load of the manipulator.



**Fig. 3.** The motion of the manipulator under uncertain dynamic parameters and external disturbance torque.



**Fig. 4.** 3D motion view of the manipulator under uncertain dynamic parameters and external disturbance torque.

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