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Constrained Manipulator Force Position Hybrid Control Based on Fuzzy Neural Network

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Abstract: Aiming at the problem that the end motion of a robot arm is constrained and cannot be accurately modeled when it is in contact with the working environment, a reduced order fuzzy neural network sliding mode control method is designed to realize the high-precision tracking of the Angle, angular velocity and contact force of each joint. Firstly, the model of constrained double-joint manipulator is reduced to simplify the dynamic model and reduce the computational difficulty. Then, fuzzy neural network is used to approximate the friction and nonlinear control quantity generated during the movement of constrained manipulator. Finally, sliding mode control method is used to improve the robustness of the controller and the stability of the system is proved by Lyapunov function. The simulation results show that the tracking error of each joint of the constrained manipulator is controlled within 0.003.

Keywords: Constrained Robotic Arm; Fuzzy Neural Network; Sliding Mode Control Algorithm; Model Reduction.

1. Introduction

In today's industrial automation production practice, the robotic arm is undoubtedly one of the core roles, widely involved in all kinds of production operations. When the robot arm only undertakes simple handling, welding and spraying tasks, it only needs to accurately control its position and carry out position tracking control. However, once complex product assembly, fine grinding, or tube grasping operations in the chemical field are involved, it is necessary not only to precisely plan the joint position of the robotic arm and the end effector, but also to fine-regulate the force exerted on the constraint surface during the operation of the robotic arm, in order to complete these relatively difficult production tasks [1,2]. Conventional control methods mainly include neural network control[3], robust control[4], fuzzy control[5], sliding mode control[6] and PID control[7]. The hybrid force/bit control technology of constrained manipulator has become a key research topic in the field of industrial automation.

Naveen Kumar et al.[8]designed an intelligent optimal control method for constrained reconfigurable manipulator position/force control under uncertainty, which overcomes the uncertainty of complex systems and can achieve the required performance. Aiming at the manipulator based on 3-DOF series elastic actuator (SEA) under partial state constraints, Yangchun Wei et al.[9]designed a model-free hybrid force/position controller (PPMHC) with specified performance, which improved the control accuracy and realized the fitting of Angle and angular velocity. Mohammad-Hossein Ghajar et al.[10]designed an intelligent hybrid position/force controller for a constrained robotic manipulator, which greatly reduced the tracking error of each joint of the manipulator despite the presence of large parameters and dynamic uncertainties. Tuo Yaoyao et al.[11]designed an event-triggered adaptive specified performance controller, which reduces the update frequency of the control signal and improves the resource utilization rate. Ruchika et al.[12], aiming at the problem that deformable links cause frequent changes in shape, which makes it difficult to model and control the longitudinal, proposed a segmented control method in which a neural network system is used to estimate nonlinear components, and the friction term and binding force of each joint are compensated by adaptive control, thus improving the control performance.

This chapter focuses on the problem of position and force control of the manipulator, takes the dynamic equation of the constrained manipulator as the research object, integrates the position control and force control in the same controller, and combines the advantages of fuzzy neural network algorithm, sliding mode control algorithm and order reduction method. A design scheme of constrained mechanical arm force/bit hybrid controller based on fuzzy neural network reduced order sliding mode algorithm is proposed

2. Dynamic Model of Constrained Manipulator

The dynamic equation of the double-joint robotic arm is as follows:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+f(q,\dot{q})+d+\tau_f=\tau \quad (1)$$

Where, $M(q)\in R^{(n^*n)}$ is the inertia matrix; $C(q,\dot{q})\in R^{(n^*n)}$ is the centrifugal force and Coriolis force matrix, $G(q)\in R^n$ is the gravity term vector, $f(q,\dot{q})$ is friction link, d is unknown external disturbance torque, τ_f is the binding vector; τ is input torque vector error for control! No reference source found.

Let x be the position of the end effector of the robotic arm, then the constraint equation is

$$\Phi(q)=\varnothing(h(q))=0 \quad (2)$$

The Jacobian matrix of the constraint equation is

$$J_\phi(q)=\frac{\partial\Phi(q)}{\partial q}=\frac{\partial\varnothing(x)}{\partial x}\frac{\partial x}{\partial q}=\frac{\partial\varnothing(x)}{\partial x}\frac{\partial h(q)}{\partial q} \quad (3)$$

Since the dynamic model of the robot arm is constrained, the double-joint robot arm is constrained by a force, so two degrees of freedom of the double-joint robot arm become one, and q_2 is expressed by q_1 as:

$$q_2 = \psi(q_1) \quad (4)$$

then

$$\dot{q} = \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} = \begin{bmatrix} \dot{q}_1 \\ \dfrac{\partial \Psi(q_1)}{\partial q_1}\dot{q}_1 \end{bmatrix} = L(q_1)\dot{q}_1 \quad (5)$$

$$\ddot{q} = \dot{L}(q_1)\dot{q}_1 + L(q_1)\ddot{q}_1 \quad (6)$$

In the formula, $L(q_1) = \begin{bmatrix} 1 \\ \dfrac{\partial \Psi(q_1)}{\partial q_1} \end{bmatrix}$

Therefore, the dynamic equation of a constrained two-degree-of-freedom manipulator is:

$$M_1(q_1)\ddot{q}_1 + C_1(q_1,\dot{q}_1)\dot{q}_1 + G_1(q_1) + f(\dot{q}_1) + d + J_\phi^{\mathrm{T}}(q_1)\lambda = \tau \quad (7)$$

In the formula,

$$M_1(q_1) = M(q)L(q_1)$$
$$C_1(q_1,\dot{q}_1) = M(q)\dot{L}(q_1) + C(q,\dot{q})L(q_1)$$
$$G_1(q_1) = G(q)$$
$$J_\phi^{\mathrm{T}}(q_1) = J_\phi^{\mathrm{T}}(q)$$

Multiply equation (1.7) by $L^T(q_1)$ left to obtain a reduced order constrained manipulator model:

$$M_L(q_1)\ddot{q}_1 + C_L(q_1,\dot{q}_1)\dot{q}_1 + G_L(q_1) + L^{\mathrm{T}} f(\dot{q}_1) + L^{\mathrm{T}} d = L^{\mathrm{T}}(q_1)\tau \quad (8)$$

Among them:

$$M_L(q_1) = L^{\mathrm{T}}(q_1)M(q)L(q_1)$$
$$C_L(q_1,\dot{q}_1) = L^{\mathrm{T}}(q_1)C_1(q_1,\dot{q}_1) = L^{\mathrm{T}}(q_1)(D(q)\dot{L}(q_1) + C(q,\dot{q})L(q_1))$$
$$G_L(q_1) = L^{\mathrm{T}}(q_1)G_1(q_1) + L^{\mathrm{T}}(q_1)J_\phi^{\mathrm{T}}(q_1)\lambda$$

The dynamic model in the formula has the following properties:

Property 1: $J_\phi(q_1)L(q_1) = L^{\mathrm{T}}(q_1)J_\phi^{\mathrm{T}}(q_1) = 0$

Property 2: $\dot{M}_L(q_1) - 2C_L(q_1,\dot{q}_1)$ is a skew symmetric matrix.

3. Fuzzy Neural Network Sliding Mode Control Algorithm

3.1. Controller Design

Let $q_d(t)$ 1 be the expected Angle of motion of the robot arm, and τ_f^d be the expected binding force on the end of the robot arm. In a double-joint robot arm, since $q_2(t)$ is a function of $q_1(t)$, the actual output of the system $q(t)$ is $q_1(t)$, and the system satisfies $\varnothing(q_d) = 0$, $\tau_f^d = J_\phi^{\mathrm{T}}(q_d)\lambda_d$. Definition:

$$e_1 = q_{\mathrm{d}1} - q_1, \quad e_\lambda = \lambda_{\mathrm{d}} - \lambda \quad (9)$$

The design sliding surface is:

$$s = \dot{e} + k_1 e$$
$$s_L = \begin{bmatrix} \dot{e}_1 + k_1 e_1 \\ \dot{e}_\lambda + k_1 e_\lambda \end{bmatrix} \quad (10)$$

Construct the auxiliary function as:

$$\dot{q}_{r1} = \dot{q}_{d1} - k_1 e_1$$
$$\ddot{q}_{r1} = \ddot{q}_{d1} - k_1 \dot{e}_1 \quad (11)$$
$$\lambda_r = \lambda_d - A_\lambda e_\lambda$$

Substituting formula (11) into formula (7) yields:

$$\begin{cases} M_1\dot{s} = \tau - F - C_1 s - J_\phi^{\mathrm{T}}(q_1)\lambda \\ F = M_1\ddot{q}_{r1} + C_1\dot{q}_{r1} + G + f + d \end{cases} \quad (12)$$

Where F is a nonlinear function containing the friction term.

In this paper, a four-layer Mamdani-type fuzzy neural network is adopted for design to approximate the nonlinear links of the robotic arm system.

The first layer is the input layer, x_i(i= 1,... ,n_1) is the input term representing the fuzzy neural network, and n_1 is the number of inputs.

The second layer is the fuzzy membership degree calculation layer, which adopts the Gaussian function and is expressed by the formula as follows:

$$\mu_i^j(x_i) = e^{\left(-\left(\frac{x_i - c_i^j}{b_i^j}\right)^2\right)} \quad (13)$$

In the formula, c_i^j, b_i^j (i=1,... n_1; j=1,... n_2) represent the center and width of the fuzzy basis functions (FNNBF), respectively. The center value and width of the basis functions are as follows:

$$c = [c_1^1,\ldots,c_1^{n2},c_2^1,\ldots c_2^{n2},\ldots,c_{n1}^1,\ldots c_{n1}^{n2}]^T,$$
$$\kappa = \left[\kappa_1^1,\ldots,\kappa_1^{n_2},\kappa_2^1,\ldots,\kappa_2^{n_2},\ldots,\kappa_{n1}^1,\ldots,\kappa_{n1}^{n_2}\right]^T$$

The third layer is the fuzzy reasoning normalization layer, where corresponding fuzzy reasoning tuning regulations are set to perform fuzzy reasoning operations on the signal:

$$h_j = \frac{\prod_{i=1}^{n1}\mu_i^j}{\sum_{j=1}^{n2}[\prod_{i=1}^{n1}\mu_i^j]} \quad (14)$$

The fourth layer is the output layer: The output of each node in the fourth layer is the weighted sum of all input signals of that node as follows:

$$y_i = \sum_{j=1}^{n2}\omega_i^j h_j \quad (15)$$

Among them, $y_i(i = 1,2,\ldots,n1)$ is the output of the fuzzy neural network.

Fuzzy neural network algorithm is used to approximate it:

$$F=WH+\varepsilon \quad (16)$$

Where, W, ε is bounded, that is, $\|W\|<W_{max}$, $\|H\| < H_{max}$, W_{max}, H_{max} are constants, W and H are respectively the ideal weight matrix of the fuzzy neural network and the output basis vector of the fuzzy basis function, ε is the error vector, and s_L is the network input value when the fuzzy neural network approximates. Since the actual value of 8 is unknown, the estimated values of the vector parameters are set to be W、c、k respectively, the estimated errors are $\tilde{W} = W - \hat{W}$, $\tilde{c} = \hat{c} - c$, $\tilde{\kappa} = \hat{\kappa} - \kappa$ and the approximation error of the nonlinear function $\tilde{F}$ is:

$$\tilde{F} = F - \hat{W}\hat{H}$$
$$= WH + \varepsilon - \hat{W}\hat{H} \quad (17)$$
$$= \tilde{W}\hat{H} + \hat{W}h_c\tilde{c} + \hat{W}h_x\tilde{\kappa} + \Delta F$$

therein, $h_c = \frac{\partial H}{\partial c}, h_k = \frac{\partial H}{\partial k}$,and

$$\Delta F = \hat{W}_c\tilde{c} + \hat{W}_k\tilde{\kappa} + Wo_n + \varepsilon \quad (18)$$

The design control rate is

$$\tau = \hat{W}\hat{H} - k_d s_L - k_r \operatorname{sgn}(s_L) + J_\phi^T \lambda_r \quad (19)$$

Where, $\hat{W}\hat{H}$ is the output of the fuzzy neural network and k_d, k_r is the positive definite matrix.

The adaptive law of fuzzy neural network design is as follows:

$$\begin{cases} \dot{\hat{W}}_f = -\Gamma_w LsH \\ \dot{\hat{c}} = -\Gamma_c h_c \hat{W}^T Ls \\ \dot{\hat{k}} = -\Gamma_k h_k \hat{W}^T Ls \end{cases} \quad (20)$$

Among them, Γ_w、Γ_c、Γ_k are positive definite diagonal matrices.

Substituting formula (15) (16) into formula (12) yields:

$$\begin{aligned} M_1\dot{s} &= \tau - F - C_1 s - J_\phi^T(q_1)\lambda \\ &= \hat{W}\hat{H} - k_d s - k_r \operatorname{sgn}(s) + J_\phi^T(q_1)\lambda_r \text{-} WH \text{-} \varepsilon \text{-} C_1 s - J_\phi^T(q_1)\lambda \\ &= -\tilde{W}\hat{H} - \hat{W}h_c\tilde{c} - \hat{W}h_x\tilde{\kappa} - \Delta F - d - k_d s - k_r \operatorname{sgn}(s) \text{-} C_1 s - J_\phi^T(q_1)(\lambda - \lambda_r) \\ &= -\tilde{W}\hat{H} - \hat{W}h_c\tilde{c} - \hat{W}h_x\tilde{\kappa} - \Delta F - d - k_d s - k_r \operatorname{sgn}(s) \text{-} C_1 s \end{aligned} \quad (21)$$

By multiplying both sides of the formula (18) by $L^T(q_1)$ left at the same time, we get:

$$M_L\dot{s} = -L^T\tilde{W}\hat{H} - L^T\hat{W}h_c\tilde{c} - L^T\hat{W}h_k\tilde{\kappa} - L^T\Delta F - L^T k_d s - L^T k_r \operatorname{sgn}(s) \text{-} L^T\varepsilon \text{-} C_L s \quad (22)$$

Theorem: Considering the constrained manipulator dynamics model (4.6) and fuzzy neural network adaptive sliding mode controller (4.11) and adaptive rate (4.12) in a closed loop system, if the ideal trajectory q, $\dot{q}$, $\ddot{q}$, λ_d converges and is bounded, the sliding mode function s converges, and the fuzzy neural network estimation error is continuous, if $k_r > \Delta F^*$ is satisfied, the system can be proved stable.

3.2. Stability Analysis of Control System

Define the Lyapunov function as:

$$\begin{aligned} V &= \frac{1}{2}s_L^T M_1 s_L + \frac{1}{2}tr(\tilde{W}^T\Gamma_w^{-1}\tilde{W}) + \frac{1}{2}\tilde{c}^T\Gamma_c^{-1}\tilde{c} + \frac{1}{2}\tilde{k}^T\Gamma_k^{-1}\tilde{k} \\ &= \frac{1}{2}s^T M_L s + \frac{1}{2}tr(\tilde{W}^T\Gamma_w^{-1}\tilde{W}) + \frac{1}{2}\tilde{c}^T\Gamma_c^{-1}\tilde{c} + \frac{1}{2}\tilde{k}^T\Gamma_k^{-1}\tilde{k} \end{aligned} \quad (23)$$

Derivation of formula (20) is obtained

This shows that the closed-loop system is stable.

4. Simulation Analysis

4.1. Simulation Parameter Setting

In order to verify the effectiveness of the design method, a double-joint robotic arm is selected for simulation, and the dynamic equation is as follows:

$$\begin{aligned} \dot{V} &= s^T M_L\dot{s} + \frac{1}{2}s^T\dot{M}_L s + tr\left(\tilde{W}^T\Gamma_w^{-1}\dot{\tilde{W}}\right) + \tilde{c}^T\Gamma_c^{-1}\dot{\tilde{c}} + \tilde{\kappa}^T\Gamma_\kappa^{-1}\dot{\tilde{\kappa}} \\ &= s^T L^T M_1\dot{s} + \frac{1}{2}s^T L^T\dot{M}_1 s + tr\left(\tilde{W}^T\Gamma_w^{-1}\dot{\tilde{W}}\right) + \tilde{c}^T\Gamma_c^{-1}\dot{\tilde{c}} + \tilde{\kappa}^T\Gamma_\kappa^{-1}\dot{\tilde{\kappa}} \\ &= s^T L^T(-\tilde{W}\hat{H} - \hat{W}h_c\tilde{c} - \hat{W}h_x\tilde{\kappa} - \Delta F - d - k_d s - k_r \operatorname{sgn}(s) \text{-} \varepsilon \text{-} C_L s) \\ &\quad + \tilde{c}^T\Gamma_c^{-1}\dot{\tilde{c}} + \tilde{\kappa}^T\Gamma_\kappa^{-1}\dot{\tilde{\kappa}} \\ &= s^T L^T(-K_d s - K_r \operatorname{sgn}(s) - \tilde{W}\hat{H} - \hat{W}h_c\tilde{c} - \hat{W}h_\kappa\tilde{k} - d - \Delta F) + tr\left(\tilde{W}^T\Gamma_w^{-1}\dot{\tilde{W}}\right) \\ &\quad + \tilde{c}^T h_c^T\hat{W}^T Ls + \tilde{k}^T h_k^T\hat{W}^T Ls \\ &= s^T L^T(-k_d s - k_r \operatorname{sgn}(s) - \Delta F - d) + tr\left(\tilde{W}^T\Gamma_w^{-1}\dot{\tilde{W}}\right) - s^T L^T\tilde{W}\hat{H} \\ &= s^T L^T(-k_d s - k_r \operatorname{sgn}(s) - \Delta F - d) \\ &\le -s^T L^T k_d s - s^T L^T k_r \operatorname{sgn}(s) + L^T\sum_{i=1}^{n}|s_i|\Delta F^*) \\ &= -s^T L^T k_d s - s^T L^T k_r \operatorname{sgn}(s) + s^T L^T\Delta F^* \operatorname{sgn}(s)) \\ &= -s^T L^T k_d s - s^T L^T(k_r - \Delta F^*)\operatorname{sgn}(s) \\ &\le 0 \end{aligned} \quad (24)$$

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+f(q,\dot{q})+d+\tau_f=\tau \quad (25)$$

Therein,

$$M_0(q)=\begin{bmatrix} l_2^2m_2+2l_1l_2m_2c_2+l_1^2(m_1+m_2) & l_2^2m_2+l_1l_2m_2c_2 \\ l_2^2m_2+l_1l_2m_2c_2 & l_2^2m_2 \end{bmatrix}$$

$$C_0(q,\dot{q})=\begin{bmatrix} -m_2l_2s_2\dot{q}_2 & -\frac{1}{2}l_1l_2m_2s_1\dot{q}_2 \\ -\frac{1}{2}l_1l_2m_2s_1\dot{q}_2 & 0 \end{bmatrix}$$

$$G_0(q)=\begin{bmatrix} m_2l_2gc_{12}+(m_1+m_2)l_1gc_1 \\ m_2l_2gc_{12} \end{bmatrix}$$

$$J_\phi^T(q)=\begin{bmatrix} -l_1\sin(q_1)-l_2\sin(q_1+q_2) \\ -l_2\sin(q_1+q_2) \end{bmatrix}$$

$$d=[\begin{matrix}3\sin(4\pi t)\\2\sin(5\pi t)\end{matrix}]$$

Among them, the simulation expected value is set to $qd_1=\sin(t),\lambda_d=10\sin(t)$, the initial state is $[0,0]$, the length of the mechanical arm connecting rod is $l_1=1m,\ l_2=1m$, the mass is $m_1=1kg,\ m_2=1kg$, the acceleration of gravity is $g=9.8$, and the controller parameter is $c_i^j=[\begin{matrix}-6 & -4 & -2 & 0 & 2 & 4 & 6\\-6 & -4 & -2 & 0 & 2 & 4 & 6\end{matrix}]$, $k=[\begin{matrix}2 & 2 & 2 & 2 & 2 & 2 & 2\\2 & 2 & 2 & 2 & 2 & 2 & 2\end{matrix}]$,The adaptive law parameter is $\Gamma_w=5000I,\ \Gamma_c=50I,\ \Gamma_k=50I$, $k_r=diag(20,10),\ k_d=diag(200,80)$, $k_1=10$, $A_\lambda=10$.

Take $l_1=l_2=1$ to get it

$$\varnothing(q_1)=l_1\cos q_1+l_2\cos(q_1+q_2)=\cos q_1+\cos(q_1+q_2)=0$$

As can be seen from the figure:

$$q_1+q_2<\pi,0<q_1\le\frac{\pi}{2},0\le q_2<\pi \quad (26)$$

and,

$$\begin{aligned}&\cos(\pi\text{-}q_1)=\cos(q_1+q_2)\\&\pi\text{-}q_1=q_1+q_2\\&q_2=\pi\text{-}2q_1\end{aligned} \quad (27)$$

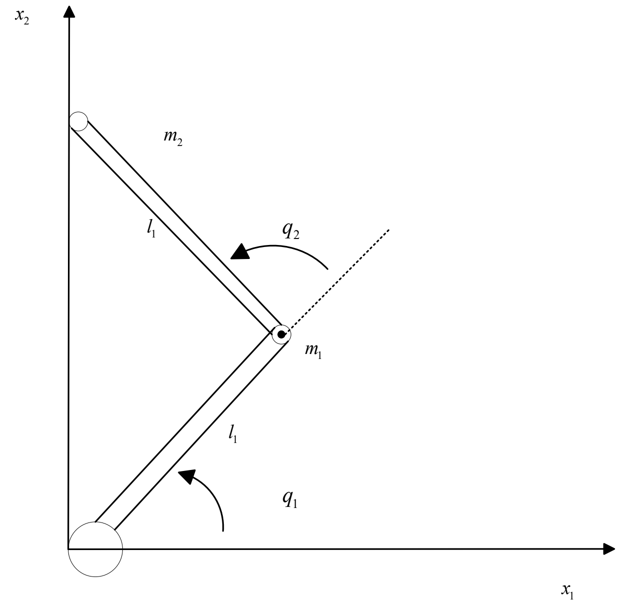

Fig 1. Structure diagram of constrained manipulator

Since $q_2=\Psi(q_1)$, then $\Psi(q_1)=\pi-2q_1$, yields:

$$L(q_1)=\begin{bmatrix}1\\ \frac{\Psi(q_1)}{q_1}\end{bmatrix}=\begin{bmatrix}1\\-2\end{bmatrix} \quad (28)$$

Thus, the properties of constrained robotic arm 1 can be proved.

$$\begin{aligned}J_\phi(q_1)L(q_1)&=[-l_1\sin q_1-l_2\sin(q_1+q_2)\quad -l_2\sin(q_1+q_2)]\begin{bmatrix}1\\-2\end{bmatrix}\\&=-l_1\sin q_1-l_2\sin(q_1+q_2)+2l_2\sin(q_1+q_2)\\&=-l_1\sin q_1+l_2\sin(q_1+q_2)\\&=-l_1\sin q_1+l_2\sin(\pi-q_1)\\&=0\end{aligned} \quad (29)$$

4.2. Analysis of Simulation Results

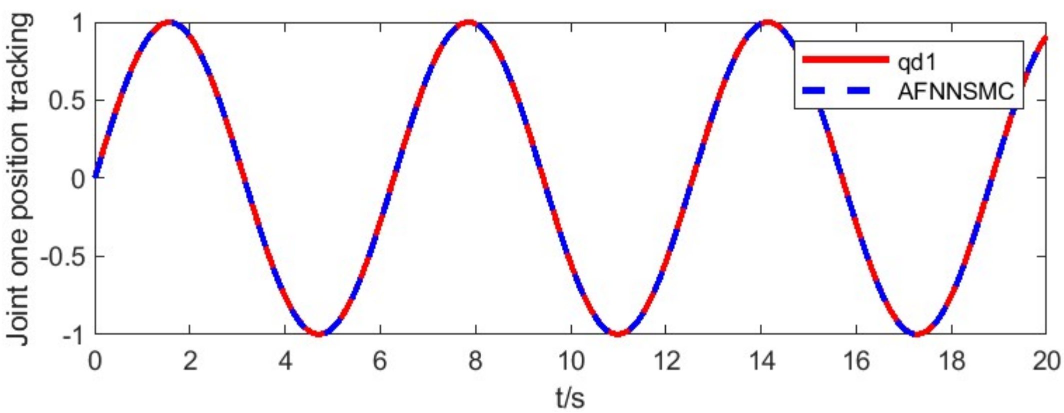

Fig 2 (a)

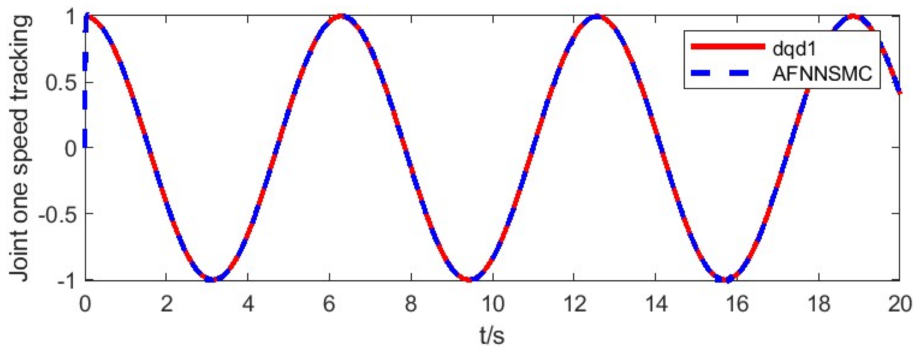

Fig 2 (b)

Fig 2. joints 1 Angle angular velocity tracking curve

Fig. 2 shows the simulation curves of the Angle variable and the angular velocity variable of the constrained robotic arm joint 1. The simulation results show that the fuzzy neural network sliding mode control can make the actual trajectory track the expected trajectory well.

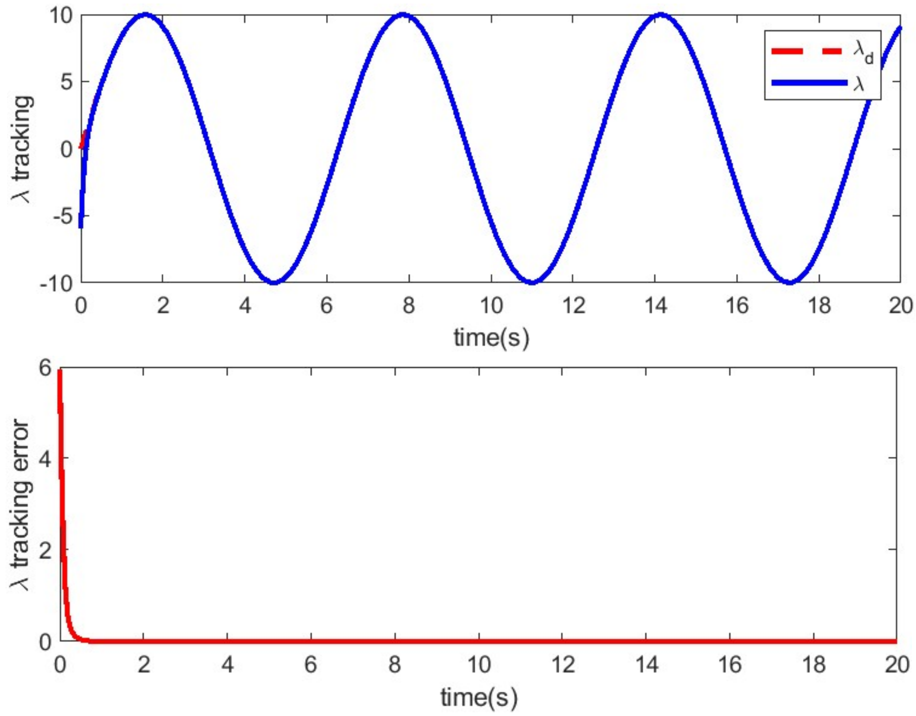

Fig 3. Contact force tracking and tracking error curve

Fig. 3 shows the contact force tracking errorless simulation curve of the constrained manipulator joint. The simulation results show that the fuzzy neural network sliding mode controller can make the tracking error converge to 0.001 within 0.2s. It can be seen that the design method improves the tracking accuracy of the mechanical arm in force control.

5. Summary

A hybrid force position control system based on fuzzy neural network is designed in this paper. Firstly, the constrained double-joint robot arm is reduced in price, and then the fuzzy neural network is designed to approximate the uncertainties in the robot arm system. The sliding mode controller is used to increase the stability and robustness of the control system, and finally the high-precision control of the constrained robot arm is realized. The simulation results show that the controller involved in this paper can ensure the accurate control of angular velocity and contact force in the presence of friction and other uncertainties, so that the system can maintain good performance.

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