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Robust Control of Robotic Manipulators Based on Adaptive Neural Network

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Abstract: As robotic manipulators are increasingly applied in industrial production, higher precision control methods are being studied by researchers. But robotic manipulators are a coupled system with a lot of uncertainties; higher precision is difficult to obtain by traditional control methods. A novel adaptive robust control method based on neural network is proposed by the paper. Neural network controller has been designed for adaptive learning and compensate for the unknown system and approach errors as disturbance is eliminated by robust controller. The weight adaptive laws on-line based on Lyapunov theory are designed. Robust controller is proposed based on H_∞ theory. These can assure the stability of the whole system, and L_2 gain also is less than the index value. Simulation studies show that the proposed control strategy is able to achieve higher control precision and has important engineering applications value.

Keywords: Adaptive control, Neural network, Robotic manipulators, Robust control.

1. INTRODUCTION

Robotic manipulators are increasingly applied in industrial production. The coupled system has a lot of uncertainty, such as quality, inertia matrix and load, its dynamic model is difficult to be accurate and external disturbance signal will also have certain influence on the controller. The variable structure control, adaptive control, neural network control and fuzzy control have great advantages in the application of the unknown nonlinear, so these methods are becoming a hot spot in the study of direction in recent years [1-5].

Because neural network has structural characteristics of parallel distribution, it possesses certain fault tolerances and strong learning ability. It can approach any unknown nonlinear system, due to which neural network control methods have been studied in recent years the world over. It is becoming a hot topic in control fields [6-11].

Optimization characteristic of neural network is used to weaken "chattering" of variable structure controller as mentioned in ref [12] and ref [13]. But the control form belongs to a kind of optimal control of the bandwidth and control precision, the result will reduce the robustness and control precision, based on which the neural network adaptive control method based on Lyapunov theory has been designed [14, 15]. Ref [16] puts forward neural network adaptive control strategy by GL matrix and its product operator. Ref [17] proposes a neural network adaptive control scheme to solve parameter uncertainties of system dynamics equation and Jacobian matrix. Ref [18] proposes an adaptive fuzzy control theory and H_∞ combination. Ref [19] and Ref [20] put forward neural network adaptive compensation control scheme based on the existing modeling error of robotic system and the control method achieved good control effects.

Aimed at the robotic manipulators with model error and interference, the tracking control scheme based on neural network has been designed based on H_∞ theory. The control method can transform a nonlinear dynamic model into an affine nonlinear system. Thus, the advantage of the RBF network can be used, the uncertainty of the system can be adaptively learned and compensated by neural network controller. So the approximation errors which are treated as external disturbances are eliminated by the robust controller. The controller can ensure the good robustness of the system and good stability of closed-loop system. Simulation results show that the proposed control strategy is able to achieve higher control precision and has important engineering applications' value.

2. DYNAMICS MODEL OF ROBOTIC MANIPULATORS

N-degree-of-freedom revolute-joint robotic manipulators dynamic model is considered as follows [21-27]:

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

where

$q \in R^n$ are the joint positions of robotic manipulators; $\dot{q} \in R^n$ are the joint velocities of robotic manipulators;

$\ddot{q} \in R^n$ are the joint acceleration vectors of robotic manipulators;

$M(q) \in R^{n\times n}$ is the inertia matrix (symmetric and positive definite) of robotic manipulators;

$C(q,\dot{q}) \in R^{n\times n}$ is the centripetal-Coriolis matrix of robotic manipulators;

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$G(q) \in R^n$ is the gravity forces of robotic manipulators.; d is the external disturbance;

τ is the control input torque vector of robotic manipulators.

The rigid robotic manipulators dynamics (1) has the following properties [28-33]:

1) The inertia matrix $M(q)$ is uniformly bounded, and satisfies $M_m \le \| M(q) \| \le M_M$. M_m and $M_M > 0$ are all constants.

2) The inertia and centripetal-coriolis matrices satisfy $X^T \left[\dot{M}(q) - 2C(q,\dot{q})\right] X = 0$, $\forall X \in R^n$. Where $M(q)$ is the time derivative of the inertia matrix.

3. DESIGN OF NEURAL NETWORK ROBUST CONTROLLER BASED ON H∞ THEORY FOR ROBOTIC MANIPULATORS

The robotic manipulators system (1) is considered, based on which the controller can be designed as follows:

$$\tau = \hat{M}(q)\ddot{q}_d + \hat{C}(q,\dot{q})\dot{q}_d + \hat{G}(q) + u \tag{2}$$

where

u is compensation item;

$\hat{M}(q) \in R^{n\times n}$ is estimated value of the inertia matrix for robotic manipulators;

$\hat{C}(q,\dot{q}) \in R^{n\times n}$ is estimated value of the centripetal-Coriolis matrix for robotic manipulators;

$\hat{G}(q) \in R^n$ is estimated value of the gravity forces for robotic manipulators;

The equation (2) is put into (1), the paper can reach the error equation of closed-loop system as follows:

$$u = M(q)\ddot{e} + C(q,\dot{q})\dot{e} + f(q,\dot{q}) \tag{3}$$

$$f(q,\dot{q}) = \tilde{M}(q)\ddot{q}_d + \tilde{C}(q,\dot{q})\dot{q}_d + \tilde{G}(q) + d \tag{4}$$

$$e = q - q_d \tag{5}$$

Where,

$\tilde{M}(q) = M(q) - \hat{M}(q)$;

$\tilde{C}(q,\dot{q}) = C(q,\dot{q}) - \hat{C}(q,\dot{q})$;

$\tilde{G}(q) = G(q) - \hat{G}(q)$.

Firstly, the state variables x is defined as follows:

$x = (x_1, x_2)^T$

x_1, x_2 are designed further as follows:

$$\begin{cases} x_1 = e \\ x_2 = \dot{e} + \alpha e \end{cases} \tag{6}$$

Then, the equation (7) can be rewritten as

$$\begin{cases} M(q)\dot{x}_2 = -C(q,\dot{q})x_2 + w - f(q,\dot{q}) + u \\ w = M\alpha\dot{e} + C\alpha e \end{cases} \tag{7}$$

For the uncertainties of the system $f(q,\dot{q})$: because the RBF neutral network that belongs to local generalization network can greatly accelerate the learning velocity and avoid local minimum value, so neural network is used to approach the unknown uncertainty $f(\vartheta)$.

The following assumptions are made to further analyze control system [8]:

3): An arbitrary small positive constant ξ_{dm} is given. There is an optimal weight vector θ^* , so that the approximation error ξ of neural network satisfies $|\xi| = |\theta^{*T} \varphi(x) - f(\vartheta)| < \xi_{dm}$.

Then, neural network controller is designed as follows

$$f(\vartheta) = \theta^{*T} \varphi(x) + \xi \tag{8}$$

$$\tau_{NN} = \theta^{*T} \varphi(x) \tag{9}$$

Where,

τ_{NN} is neural network controller.

So

$$\hat{f}(q,\dot{q}) = \hat{\theta}^T \varphi(\vartheta) \tag{10}$$

Where,

$\hat{f}(q,\dot{q})$ is the estimate value;

$\hat{\theta}$ is the estimate of weight vector θ ;

$\varphi(\vartheta)$ is Gaussian type of function, that is

$$\varphi_j = \exp\left(-\frac{\| \vartheta - c_j \|^2}{\sigma_j^2}\right) \tag{11}$$

Where,

c_j is the center of j^{th} is basic function;

σ_j is the center and the spread of j^{th} is basic function.

In actual application, c_j and σ_j are predetermined by using the local training technique. $\| \vartheta - c_j \|$ is a norm of the vector $\vartheta - c_j$.

Where,

Approximation error ε can be taken as the system's external disturbances.

Then, the equation (7) can be amended as affine nonlinear system form with model error and disturbances.

$$\begin{cases} \dot{x} = f(x) + g(x)\varepsilon \\ z = h(\boldsymbol{x}) \end{cases} \tag{12}$$

Where,

$$f(x) = \begin{bmatrix} x_2 - \alpha x_1 \\ -M^{-1}(Cx_2 - w - u + \tau_{NN}) \end{bmatrix} \tag{13}$$

$$g(x) = \begin{bmatrix} 0 \\ -M^{-1} \end{bmatrix} \tag{14}$$

where

$z = pe = px_1$ is evaluation signal, α and p are positive constants.

The following equation (15) is defined as performance, an indicator that reflects the system's interference suppression ability.

$$J = \sup_{\|\xi_f\| \neq 0} \frac{\| z \|_2}{\| \xi_f \|_2} \tag{15}$$

In above equation, J is the gain L_2 of system (10). It can make the gain L_2 less than the given value γ .

The compensation term u as the control law can be designed as:

$$u = -w - x_1 - \frac{1}{2\gamma^2} x_2 + \hat{\theta}^T \varphi(x) \tag{16}$$

Neural network weight matrices as the adaptive learning algorithm can be designed as:

$$\dot{\hat{\theta}} = -\eta x_2 \varphi^T(x) \tag{17}$$

where,

$\eta > 0$;

$z = h(x) = px_1$.

The parameters meet the following equation:

$$\alpha - \frac{1}{2} p^2 = \varepsilon_1 \text{ (ε_1 represents given constant)} \tag{18}$$

Then the gain J can be less than the given value γ .

Theorem: (HJI inequality) A positive number $\gamma > 0$ is given, if there are positive-definite quasi-differentiable function $V(x) \geq 0$, that satisfies the following HJI inequality:

$$\dot{V} \leq \frac{1}{2} \left\{ \gamma^2 \| \xi_f \|^2 - \| z \|^2 \right\} \quad (\forall \xi_f) \tag{19}$$

Then, the gain L_2 of the above system equation (12) must be less than a given value γ , that is, $J \leq \gamma$.

Proof: The Lyapunov function is defined in the following equation:

$$V = \frac{1}{2} x_2{}^T M x_2 + \frac{1}{2} x_1{}^T x_1 + \frac{1}{2\eta} tr(\tilde{\theta}^T \tilde{\theta}) \tag{20}$$

Where,

$\tilde{\theta} = \theta^* - \hat{\theta}$ is estimation errors of the network weight.

Then

$$\dot{V} = \frac{1}{2} x_2{}^T \dot{M} x_2 + x_2{}^T M \dot{x}_2 + x_1{}^T \dot{x}_1 + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) \tag{21}$$

where

The equation (6) is put in the above equation (21), the following new expression can be obtained:

$$\dot{V} = -\alpha \| x_1 \|^2 + x_2^T \tilde{\theta} \varphi(x) - x_2^T \varepsilon - \frac{1}{2\gamma^2} x_2^T x_2$$

$$+ \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) \tag{22}$$

where

$$H = \dot{V} - \frac{1}{2} \left\{ \gamma^2 \| \xi_f \|^2 - \| z \|^2 \right\}$$

Then

$$H = -\alpha \| x_1 \|^2 + x_2 \tilde{\theta} \varphi(x) - x_2^T \varepsilon - \frac{1}{2\gamma^2} x_2^T x_2$$

$$+ \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) - \frac{1}{2} \left\{ \gamma^2 \| \varepsilon \|^2 - \| z \|^2 \right\} \tag{23}$$

Further

$$H \leq -(\alpha - \frac{1}{2} p^2) \| x_1 \|^2 + x_2{}^T \tilde{\theta} \varphi(x) + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta})$$

$$= -\mu \| x_1 \|^2 + x_2{}^T \tilde{\theta} \varphi(x) - tr(\varphi(x) x_2{}^T \tilde{\theta})$$

$$= -\mu \| x_1 \|^2 \leq 0 \tag{24}$$

According to HJI, inequality can be obtained:

The gain L_2 of the closed-loop system (10) must less than the given value γ .

4. SIMULATIONS

In order to verify the validity of the control algorithm, a simulation example is put forward by the paper.

In this simulation, the following reality robotic manipulators parameters have been chosen as follows:

$m_1 = 4.5kg$, $m_2 = 8.5kg$, $r_1 = 2.1m$, $r_2 = 2.0m$, $J_1 = J_2 = 7.5kg \cdot m^2$.

$$M(q) = \begin{bmatrix} (m_1 + m_2) r_1^2 + m_2 r_2^2 + 2 m_2 r_1 r_2 \cos q_2 + J_1 & m_2 r_2^2 + m_2 r_1 r_2 \cos q_2 \\ m_2 r_2^2 + m_2 r_1 r_2 \cos q_2 & m_2 r_2^2 + J_2 \end{bmatrix}$$

$$C(q, \dot{q}) = \begin{bmatrix} -m_2 r_1 r_2 \sin(q_2) \dot{q}_2 & -m_2 r_1 r_2 \sin(q_2)(\dot{q}_1 + \dot{q}_2) \\ m_2 r_1 r_2 \sin(q_2) \dot{q}_1 & 0 \end{bmatrix}$$

$$G(q) = \begin{bmatrix} (m_1 + m_2) g r_1 \cos q_1 + m_2 g r_2 \cos(q_1 + q_2) \\ m_2 g r_2 \cos(q_1 + q_2) \end{bmatrix}$$

In this simulation, the following parameters are chosen as follows.

External interferences are assumed as follows:

$$d = [q_1 0.3\sin t, q_2 0.3\sin t]^T$$

Desired trajectory are assumed as follows:

$$q_{1d} = 1.5 + 0.5\ (\sin 0.3t + \sin 0.2t)$$

$$q_{2d} = 1.5 + 0.5\ (\cos 0.2t + \cos 0.4t)$$

Estimated values are assumed as follows:

$\hat{m}_1 = 5.1kg,\ \hat{m}_2 = 9.5kg$;

The simulation parameters are chosen respectively,

$\alpha = 20,\ \eta = 120,\ \gamma = 0.05.$

The initial joints position and velocity of robotic manipulators are chosen as zero, the network initial weights are zero. The width of Gaussian function is 10. The center of Gaussian function is randomly selected within the input and output range.

The simulation results are shown in Figs. (**1-5**). Fig. (**1**) shows position tracking curves of robotic manipulators joint 1, Fig. (**2**) shows position tracking curves of robotic manipulators of joint 2; Fig. (**3**) shows parameters uncertainty model and its neural network estimated value; Fig. (**4**) shows control torque curves for joint 1 of robotic manipulators; Fig. (**5**) shows control torque curves for joint 2 of robot manipulators.

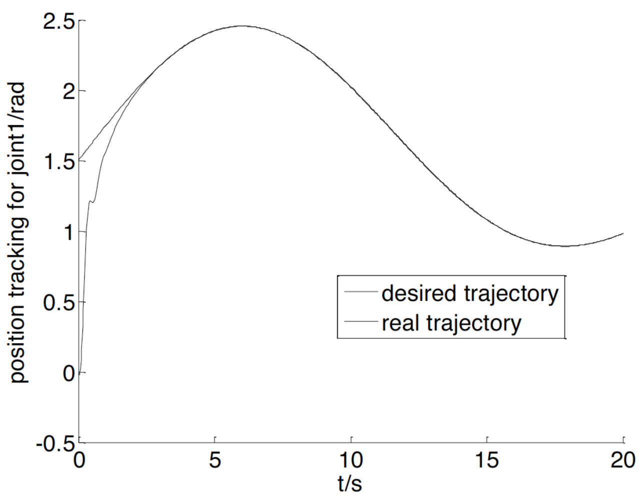

Fig. (1). Position trajectory tracking curves of joint 1.

The Fig. (**1**) shows that the joints have an initial error and deviates from the actual path for less than 3s but regulates itself quickly to achieve the desired trajectory and is with high precision. The Fig. (**2**) shows that joint 2 is also has initial error and in about 2s it rapidly tracks the desired trajectory. The torque required for the whole control process is not large. It shows not only that the design of adaptive law is effective but also the radial basis function neural network has good generalization ability and fast learning speed.

Figs. (**3**, **4**) show that control torque of robotic manipulators joints is not large. As can be seen from the Figs. (**4**, **5**), that the neural network controller designed based on H_∞ robust theory can effectively track the desired trajectory in a very short period of time, especially,

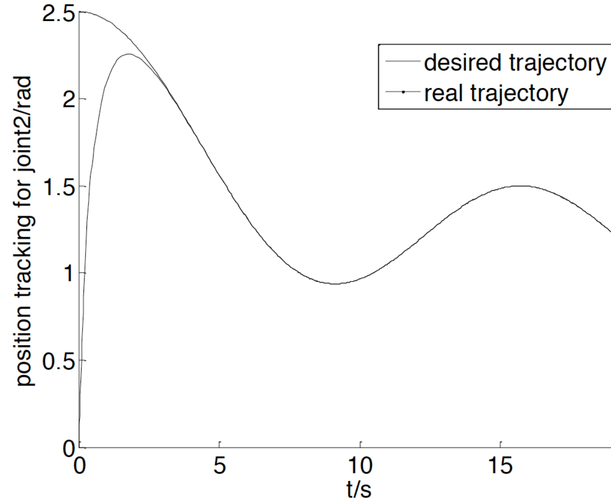

Fig. (2). Position trajectory tracking curves of joint 2.

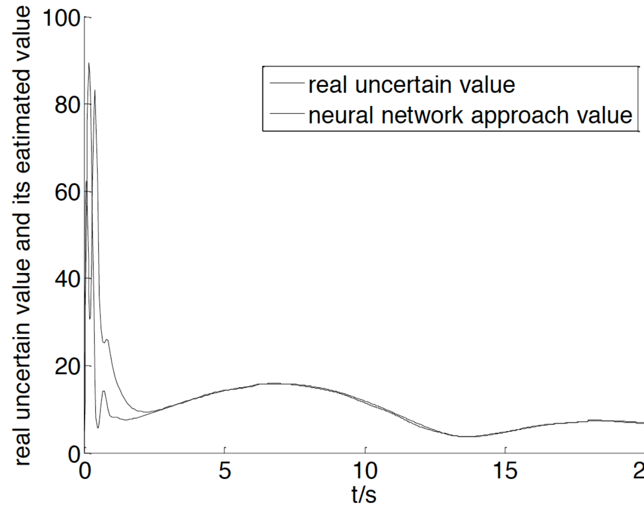

Fig. (3). Uncertainty value and its NN estimated value.

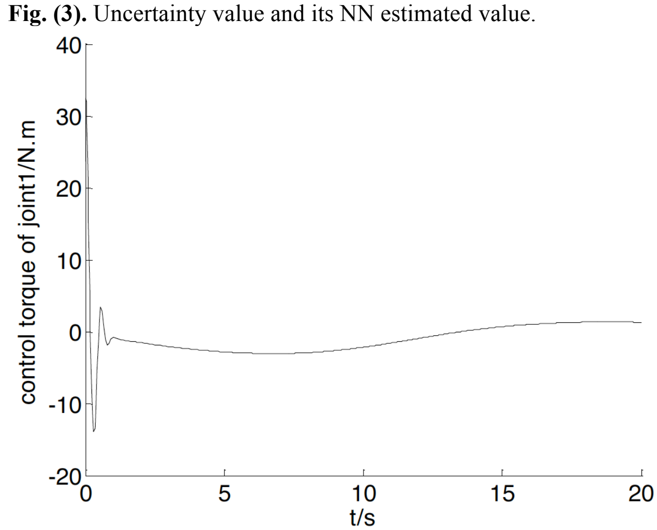

Fig. (4). Control input curves of joint 1.

in the early period of the control process, because the robust controller compensates for the comparatively large approximation errors of neural network. The controller can improve control precision and speed up the error convergence velocity more effectively.

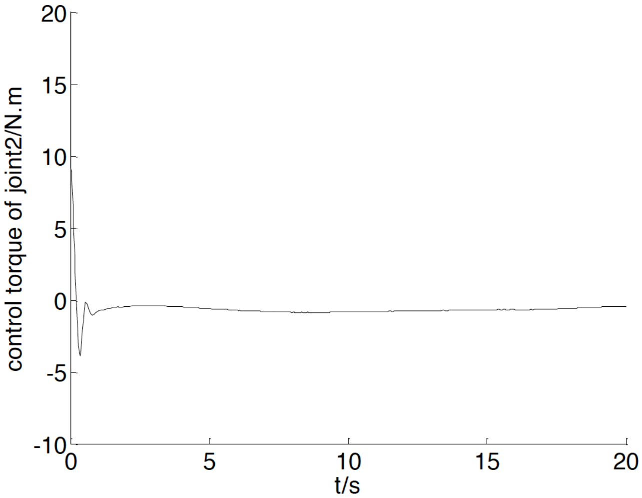

Fig. (5). Control input curves of joint 2.

CONCLUSION

A neural network robust control algorithm based on Lyapunov theory for robotic manipulators was proposed by the paper.

1) An adaptive neural network controller was designed to approach and estimate the upper bound of uncertainty of robotic manipulators;
2) The robust controller based on H_∞ theory was designed to eliminate the approximation errors and external interference.
3) The adaptive laws on-line based on Lyapunov theory was designed to ensure online real-time weighted adjustment.
4) The simulation could assure the stability of the whole system. L_2 gain also must be less than the index γ .

Simulation results showed that the proposed control strategy could achieve higher control precision and has important engineering applications value.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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