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Adaptive Control for Robotic Manipulators base on RBF Neural Network

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Abstrak

Sebuah kontroler adaptif berbasis jaringan syaraf diajukan didalam naskah untuk memecahkan masalah pelacakan lintasan manipulator robot dengan ketidakpastian. Skema pertama terdiri dari umpan balik PD dan kompensator yang dinamis yang terdiri dari kontroler jaringan syaraf dan pengendali struktur variabel. Pengendali jaringan netral dirancang untuk belajar secara adaptif dan mengkompensasi ketidakpastian, pengontrol struktur variabel dirancang untuk menghilangkan kesalahan pendekatan jaringan netral ini. Sebuah algoritma yang dapat belajar secara adatif berbasis jaringan saraf dirancang untuk memastikan penyesuaian pada online real-time, yang berakibat pada fase belajar secara offline tidak di perlukan, maka stabilitas sistem asimtotik Global (GAS) berbasis pada teori Lyapunov yang dapat menganalisis untuk memastikan konvergensi algoritma tersebut dapat dilakukan. Hasil simulasi menunjukan skema control menghasilkan efektif dan memiliki ketahanan yang baik.

Kata kunci: *Neural network, manipulator robot, kontrol adaptif, stabilitas asimtotik global*

Abstract

An adaptive neural network controller is brought forward by the paper to solve trajectory tracking problems of robotic manipulators with uncertainties. The first scheme consists of a PD feedback and a dynamic compensator which is composed by neural network controller and variable structure controller. Neutral network controller is designed to adaptive learn and compensate the unknown uncertainties, variable structure controller is designed to eliminate approach errors of neutral network. The adaptive weight learning algorithm of neural network is designed to ensure online real-time adjustment, offline learning phase is not need; Global asymptotic stability (GAS) of system base on Lyapunov theory is analysised to ensure the convergence of the algorithm. The simulation results show that the kind of the control scheme is effective and has good robustness.

Keywords*: Neural network, robotic manipulators, adaptive control, global asymptotic stability*

1. Introduction

The trajectory tracking control problems of robotic manipulators are attracted more and more attentions [1-3]. However, since robotic manipulators system is a time-varying, strong-coupling and non-linear system, and it contains many traits such as parameter errors, unmodeled dynamics external interference as well as various other unknown non-linear in the actual project. The traditional PID control schemes is difficult to obtain good control precision for the robot, Therefore, variety intelligent control schemes based on nonlinear compensation method are continuously put forward in recent years [4-13].

Recently, [14] proposed a robust adaptive sliding model tracking control using neural network for robot manipulators. In this scheme, adaptive learn laws are designed to approach the unknown upper bound of system uncertainties. However, the main drawback of this scheme is that the inverse of inertia matrix has to be calculated. [15]-[16] proposed an adaptive controller, but complex pre-calculation of the regression matrix is required. Adaptive controller depends on accurate estimate of the unknown parameters. However, it is often difficult to be achieved in practical application, because of the uncertain external interference. Karakasoglu [17] proposed a control scheme for integrating Radial Basis Function (RBF) neutral network with variable structure. in this scheme the “chattering” can be lessened by the this design that neutral network changes appropriately gain and the sliding surface. Kim [18] proposed an intelligent fuzzy control method, the method does not require an accurate model

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for the control object, but the method requires too much adjustment parameters, the reason increases the computer burden and affect the real time. [19-20] proposed a RBF neural network control method, neural network is used in identification of uncertainty model, but the control scheme can only guarantee the uniform ultimate bounded (UUB).

Motivated by the above discussion, this paper puts forward an adaptive neural-sliding model compensation control scheme. A RBF neural network is used to approximate the unknown nonlinear dynamics of the robot manipulators. But the local generalization of the RBF network is considered by the paper, because accuracy of control system is effected by approach errors of neural network, Sliding model controller is designed to eliminate approach errors to improve control accuracy and dynamic features. The adaptive laws of network weights are designed to ensure adjustment online-time, offline learning phase is not need; Globally asymptotically stable(GAS) of the closed-loop system is proved based on the Lyapunov theory. The simulations show this controller can speed up the convergence velocity of tracking error, and has good robustness.

2. Dynamic Equation of Robotic Manipulators

N-degree-of-freedom revolute-joint robot dynamic model is considered as Equation 1.

$$\left.\begin{array}{c} M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+F(q,\dot{q})=\tau \\ F(q,\dot{q})=F(\dot{q})+\tau_d(t,q,\dot{q}) \end{array}\right\} \quad (1)$$

Where, $q,\dot{q},\ddot{q}\in R^n$ are the joint position, velocity, and acceleration vectors respectively. $M(q)\in R^{n\times n}$ is the inertia matrix (symmetric and positive definite) , $C(q,\dot{q})\in R^{n\times n}$ is the centripetal-Coriolis matrix. $G(q)\in R^n$ is the gravity forces. $F(\dot{q})\in R^n$ is the friction matrix. $\tau_d(t,q,\dot{q})$ is the external disturbance. τ is the control input torque vector.

The rigid Robot dynamics (1) has the following properties :

P1) The inertia matrix $M(q)$ is uniformly bounded, and satisfies the condition of $M_m \le \| M(q) \| \le M_M$. M_m、$M_M > 0$ are all constants.

P2) 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.

Further, the following assumptions on model (1) are made.

A1) Centrifugal and Coriolis matrix $C(q,\dot{q})$ are bounded.

A2) The desired trajectory q_d、$\dot{q}_d$ and $\ddot{q}_d$ are uniformly bounded.

3. Designed of Sliding-model Controller base on Adaptive Neural Network

For robot dynamic system (1), q_r is defined as the reference trajectory, e is defined as the position tracking error, s is defined as the tracking error measure , and $\Lambda\in R^{n\times n}$ is defined as a positive definite matrix in Equation 2-4.

$$\dot{q}_r=\dot{q}_d+\Lambda e \quad (2)$$

$$e=q_d-q \quad (3)$$

$$s=\dot{e}+\Lambda e \quad (4)$$

Choose the Lyapunov function as Equation 5.

$$V = \frac{1}{2} s^T M s \tag{5}$$

Its differential is Equation 6.

$$\dot{V} = s^T M \dot{s} + \frac{1}{2} s^T \dot{M} s \ = s^T [M(q)\ddot{q}_r + C(q,\dot{q})\dot{q}_r + G(q) + F(q,\dot{q}) - \tau] \tag{6}$$

So the controller can be designed as Equation 7.

$$\tau = \hat{M}(q)\ddot{q}_r + \hat{C}(q,\dot{q})\dot{q}_r + \hat{G}(q) + \hat{F}(q,\dot{q}) + K_v s \tag{7}$$

Where, K_v is feedback gain positive matrix, $\hat{M}(q)$、 $\hat{C}(q,\dot{q})$、$\hat{G}(q)$ and $\hat{F}(q,\dot{q})$ are estimation of $M(q)$、 $C(q,\dot{q})$、$G(q)$ and $F(q,\dot{q})$ respectively.

Now, the trajectory tracking of robot dynamic system (1) is considered by the paper. If the structure of the model (1) and all the parameters inside the model are perfectly known, and there is no external disturbance, $\hat{M}(q)$、$\hat{C}(q,\dot{q})$、$\hat{G}(q)$ and $\hat{F}(q,\dot{q})$ are equal to $M(q)$、 $C(q,\dot{q})$、$G(q)$ and $F(q,\dot{q})$ respectively. Then, the above controller (3) can guarantee the global stability of closed-loop system.

Nevertheless, when the system (1) must contain some structured or unstructured uncertainties in real engineering condition. the above designed control law (3) can not ensure that the system has good dynamic and stability. In order to eliminate uncertainties effect of the system and ensure asymptotic convergence of tracking error, the control law need be redesigned renewal. For the uncertain robot system (1), $\tilde{M}(q)=M(q)-\hat{M}(q)$, $\tilde{C}(q,\dot{q})=C(q,\dot{q})-\hat{C}(q,\dot{q})$, $\tilde{G}(q)=G(q)-\hat{G}(q)$ and $\tilde{F}(q,\dot{q})=F(q,\dot{q})-\hat{F}(q,\dot{q})$ are defined by paper. Then a closed-loop system error equation can be obtained as Equation 8-10.

$$M(q)\dot{s} + C(q,\dot{q})s = -\tau + \hat{\tau} + f(\vartheta) \tag{8}$$

$$\hat{\tau} = \hat{M}(q)\ddot{q}_r + \hat{C}(q,\dot{q})\dot{q}_r + \hat{G}(q) + \hat{F}(q,\dot{q}) \tag{9}$$

$$f(\vartheta)=\tilde{M}(q)\ddot{q}_r+\tilde{C}(q,\dot{q})\dot{q}_r+\tilde{G}(q)+\tilde{F}(q,\dot{q}) \tag{10}$$

For the uncertainties of the system, because the RBF network that belongs to local generalization network can greatly accelerate the learning velocity and avoid local minimum. The neural network is used to approach the unknown uncertainties $f(\vartheta)$ as Equation 11..

$$\hat{f}(\vartheta)=\hat{\theta}^T \varphi(x) \tag{11}$$

If $\hat{\theta}$ is the estimate of weight vector θ. $\varphi(x)$ is Gaussian type of function, that is

$$\varphi_j=\exp(-\frac{\|x-c_j\|^2}{\sigma_j^2}) \tag{12}$$

Where, c_j and σ_j represent the center and the spread of j th basis function respectively. In actual application , c_j and σ_j are predetermined by using the local training technique . $\| x-c_j \|$ is a norm of the vector $x-c_j$.

For further analysis , the following assumptions are made.

A3): Given an arbitrary small positive constant ε_M, there is an optimal weight vector θ^*,so that the approach error ε of neural network satisfies $|\varepsilon| = |\theta^{*T}\varphi(x) - f(\vartheta)| < \varepsilon_M$

A4): there is a positive constant w, the optimal weight vector θ^* is bounded and meets the condition $\|\theta^*\| \leq \theta_M$.

Then

$$f(\vartheta) = \theta^{*T}\varphi(x) + \varepsilon \tag{13}$$

A new adaptive tracking control law of uncertain robot based on neural networks should be designed as Equation 14.

$$\tau = \hat{\tau} + K_p e + K_d \dot{e} + \tau_{NN} + \tau_{SL} \tag{14}$$

Where, τ_{NN} is neural network controller, τ_{SL} is the sliding model compensator which is designed to eliminate the effects of network approach error.

Then the control system can be shown in Figure 1.

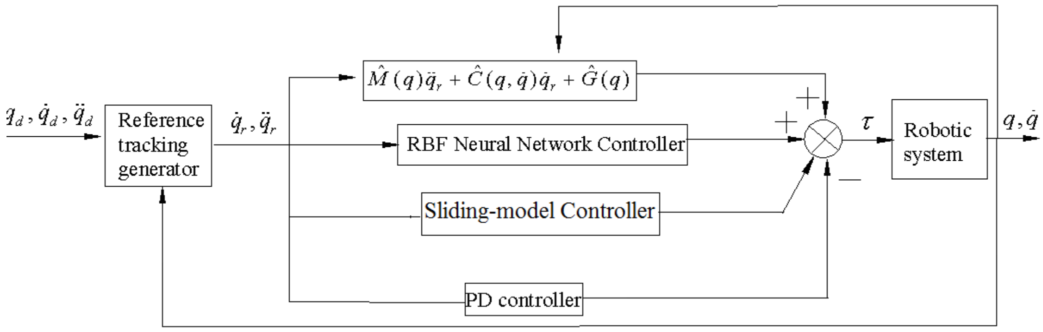

Figure1. Control system structure

Neural network controller is designed as Equation 15.

$$\tau_{NN} = \hat{\theta}^T \varphi(x) \tag{15}$$

Sliding model controller is designed as Equation 16.

$$\tau_{SL} = \varepsilon_M sgn(s) \tag{16}$$

The adaptive learning weights laws of neural network is designed as Equation 17.

$$\dot{\hat{\theta}} = -\eta\varphi s^T \tag{17}$$

Where the gain $\eta > 0$, $\tilde{\theta} = \theta^* - \hat{\theta}$ is the weight estimation error.

4. System Stability Analysis

The Lyapunov function can be choosen to prove stability of closed-loop system as equation 18.

$$V=\frac{1}{2}s^T Ms+\frac{1}{2}e^T (K_p+\Lambda K_d)e+\frac{1}{2}tr(\tilde{\theta}^T \eta^{-1}\tilde{\theta}) \quad (18)$$

Differentiating V , the following equation can be obtained as Equation 19.

$$\dot{V} = s^T M\dot{s}+\frac{1}{2}s^T \dot{M}s+e^T K_P\dot{e}+tr(\tilde{\theta}^T \eta^{-1}\dot{\tilde{\theta}}) \quad (19)$$

The trajectory of error equation (4), and using property P2), the following equation can be obtained as equation 20.

$$\dot{V} = s^T (M(q)\ddot{q}_r + C(q,\dot{q})\dot{q}_r + G(q) + F(q,\dot{q}) - \tau) + e^T K_P\dot{e} + e^T \Lambda K_d\dot{e} + tr(\tilde{\theta}^T \eta^{-1}\dot{\tilde{\theta}}) \quad (20)$$

Using (8), and(15)-(16), putting $s=\dot{e}+\Lambda e$ into it equation, can be obtained Equation 21.

$$\dot{V} = s^T (f(\vartheta) - \hat{\theta}^T \varphi(x) - \varepsilon_M sgn(s)) - \dot{e}^T K_d\dot{e} - e^T K_P\Lambda e + tr(\tilde{\theta}^T \eta^{-1}\dot{\tilde{\theta}}) \quad (21)$$

Using (13), and (17) of adaptive law $\dot{\tilde{\theta}}$, the following equation can be obtained as Equation 22.

$$\dot{V} = s^T (\varepsilon - \varepsilon_M sgn(s)) - \dot{e}^T K_d\dot{e} - e^T K_P\Lambda e = \sum_{i=1}^{n}(s_i\varepsilon_i - |s_i\varepsilon_M|) - \dot{e}^T K_d\dot{e} - e^T K_P\Lambda e \quad (22)$$

Then

$$\dot{V}<0 \quad (23)$$

Hence, it is easily concluded that $e\in L_2\bigcap L_\infty$, $\tilde{\theta}\in L_\infty$ and then $s\in L_\infty$ .Further, from A2), we obtain that $\dot{e}\in L_\infty$. According to A4), it obtain that that $\hat{\theta}$ is bounded. Moreover, According to A3), it is 0bvious that $f(\vartheta)$ is bounded. Thus According to A1), we obtain that $\hat{\tau}$ and τ are bounded. According to(4), it can be obtained that $\dot{s}$ is bounded.

5. Simulations

In order to verify the validity of this two kinds of control algorithm that are put forward by this paper, this paper utilize the following dynamic model [2].

$$M(q) = \begin{bmatrix} (m_1+m_2)r_1^2 + m_2r_2^2 + 2m_2r_1r_2\cos q_2 + J_1 & m_2r_2^2 + m_2r_1r_2\cos q_2 \\ m_2r_2^2 + m_2r_1r_2\cos q_2 & m_2r_2^2 + J_2 \end{bmatrix}$$

$$C(q,\dot{q}) = \begin{bmatrix} -m_2r_1r_2\sin(q_2)\dot{q}_2 & -m_2r_1r_2\sin(q_2)(\dot{q}_1+\dot{q}_2) \\ m_2r_1r_2\sin(q_2)\dot{q}_1 & 0 \end{bmatrix}$$

$$G(q) = \begin{bmatrix} (m_1+m_2)gr_1\cos q_1 + m_2gr_2\cos(q_1+q_2) \\ m_2gr_2\cos(q_1+q_2) \end{bmatrix}$$

In this simulation, the following parameters are chosen as:

$r_1 = 1.5m$, $r_2 = 1.2m$, $J_1 = J_2 = 10kg \cdot m^2$, $m_1 = 2.5kg$, $m_2 = 9.5kg$

Before test, the estimate values of m_1 、m_2 are respectively $m_1 = 1.7$ and $m_2 = 7.6kg$.
Friction parameters is select as:

$F_v(\dot{q}) = [0.2\,\text{sgn}(\dot{q}_1)\ ,\ 0.2\,\text{sgn}(\dot{q}_2)]^T$

External interference is selected as:

$\tau_d = [q_1\dot{q}_1 0.3\sin t\ ,\ q_2\dot{q}_2 0.3\sin t]^T$

Desired trajectories are assumed as:

$q_d = [-1.5 + 0.5(\sin 3t + \sin 2t)\quad -1.5 + 0.5(\cos 2t + \cos 4t)]^T$

The simulation parameters are select respectively as :

$U_d = diag\{35,35\}$, $\varepsilon_M = 0.6$, $\eta = 12$, $\Lambda = diag\{15,15\}$, $K_d = diag\{80,80\}$.

The initial joint position and velocity 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 Figure 2-6.

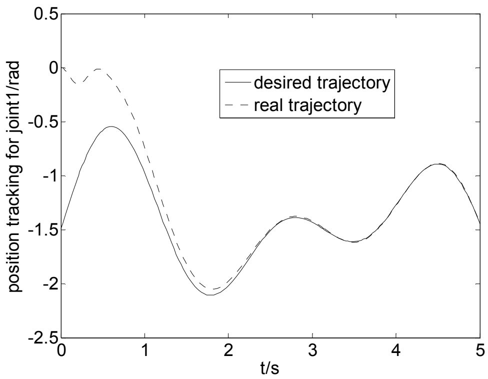

Figure 2. Trajectory tracking curves of joint 1

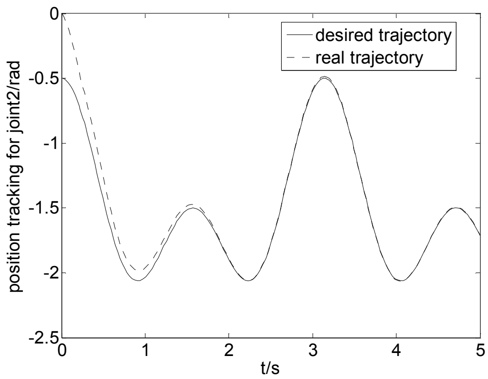

Figure 3. Trajectory tracking curves of joint 2

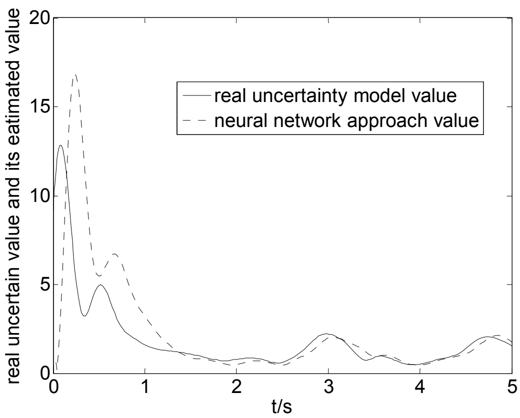

Figure 4. Unknown model and its neural network estimated

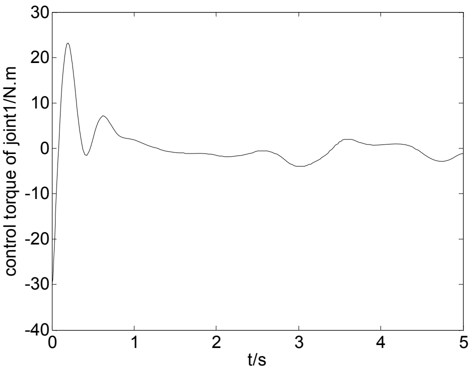

Figure 5. Control torque of space robot joint 1

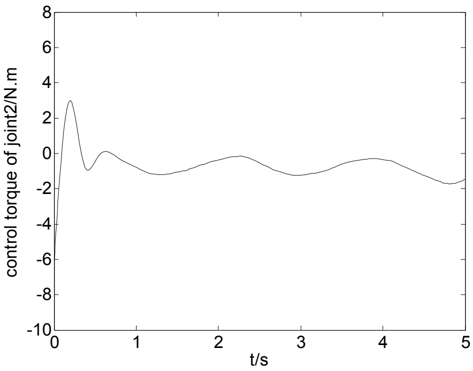

Figure.6. Control torque of space robot joint 2

As can be seen from the figure 2 - 4, the controller designed by this paper not only can track the desired trajectory effectively in a very short period of time, but also neural network controller and sliding model controller can compensate for all uncertainties. As can be seen from the figure 4,after the initial learning, neural network can get to complete learning and good approach for uncertainty model in less than 1.5 s, it shows not only the design of adaptive law is effective. The radial basis function neural network has good generalization ability and fast learning speed, and can speed up the convergence velocity of error, and improve the control precision. Control torque of space robot joints aren't big, As can be seen from the Figure 5 and 6.

6. Conclusion

An adaptive neural-sliding model compensation control scheme is put forward for robot manipulators with uncertainties by this paper. Neural network controller is designed to approach the unknown nonlinear dynamics of the robot manipulators, unknown model upper of system uncertainties is not need; Sliding model controller is designed to eliminate approach errors of neural network to improve control system accuracy; Adaptive laws of network weights are designed to ensure adjustment online-time, offline learning phase is not need; Globally asymptotically stable (GAS) of the closed-loop system is proved based on the Lyapunov theory. The simulations show that the controller can speed up the convergence velocity of tracking error, and ensure good robustness of robot manipulators with uncertainties.

Acknowledgments

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