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Adaptive Neural Network Robust Control for Space Robot with Uncertainty

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Abstrak

Pelacakan masalah dari sebuah robot manipulator dengan parameter dan ketidakpastian non-parameter sangat perlu dipertimbangkan, dimana sebuah algoritma kontrol yang adaptive dan tangguh berbasis jaringan syaraf diusulkan dalam naskah ini. Jaringan netral digunakan untuk pembelajaran yang adaptif dan mengkompensasi sistem tidak diketahui untuk menjadi parameter ketidakpastian, begitu pula aturan sebuah perancangan sistem yang adaptif dikemukakan dalam kerta ini juga. Sistem yang stabil berbasis pada teori Lyapunov di analisi untuk mememastikan konvergensi algoritma yang ditawarkan. Ketidakpastian non-parameter dapat diperkirakan dan dikompensasi oleh sebuah kontroller yang tangguh. Hal ini terbukti bahwa kontroler yang dirancang dapat menjamin konvergensi asymptotic untuk pelacakan kesalahan. Controller tersebut dapat menjamin ketangguhan dan stabilitas dari model sistem loop tertutup dengan menunjukkan hasil yang efektif dari simulasi yang dilakukan dalam penelitian ini.

Kata kunci: *Neural network, robust control, space robotic manipulators, adaptive control*

Abstract

The trajectory tracking problems of a class of space robot manipulators with parameters and non-parameters uncertainty are considered. An adaptive robust control algorithm based on neural network is proposed by the paper. Neutral network is used to adaptive learn and compensate the unknown system for parameters uncertainties, the weight adaptive laws are designed by the paper, System stability base on Lyapunov theory is analysised to ensure the convergence of the algorithm. Non-parameters uncertainties are estimated and compensated by robust controller. It is proven that the designed controller can guarantee the asymptotic convergence of tracking error. The controller could guarantee good robust and the stability of closed-loop system. The simulation results show that the presented method is effective.

Keywords: *Neural network, robust control, space robotic manipulators, adaptive control*

1. Introduction

The main task of the free-floating space robots is used to instead of the astronauts to complete satellite capture, to repair space station facilities. Because positions and attitude of the base of space robot that are entirely free, as will result in economization of fuel, increase life-span of space robot, and decrease in launch expenditure, free-floating space robot would have played an more and more important role in the future. In the free floating condition, space robots are different from ground robots in dynamic characteristics and constraints: dynamics coupling of machine arms and the base, dynamic singularity,a limited supply of fuel and restrictions of the attitude control system.

Therefore not like robot with fixed-base on ground, space robots can't adopt a general control method. Meanwhile, there are many uncertainties existing in the space robot dynamic model, for example, the dynamic model of manipulator mass, inertia matrix and load quality can not be accurately acquired, and external disturbance signals have a certain impact on the controller. To eliminate impact of these non-linear factors, all sorts of advanced control strategies [1-5].such as adaptive control [6-7], fuzzy control [8-13] and neural network control [14-17] have been used in robot tracking control.

Ref [6] and [7] proposed adaptive control methods, but required complex pre-calculation of the regression matrix, and adaptive control depends on accurate estimate of the unknown parameters. However, it is often difficult to be achieved in practical application, because of the

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uncertain external interference. Intelligent fuzzy control method is proposed by [18], the method does not require an accurate model for the control object, but the method requires too much adjustment parameters, the reason increases the computer burden and affects the real time. A Radial Basis Function (RBF) neural network control method proposed by [19-20], neural network is used to identificate to uncertainty model, but the control scheme can only guarantee the uniform ultimate bounded (UUB). A sliding mode variable structure base on neural network control scheme is proposed by [21], neural network is used to learn unknown parameters system model. However, the scheme needs to know the upper bound of the unknown uncertainty.

An adaptive robust control scheme base on neural network is proposed to overcome these shortcomings. Robust controller is used to estimate real-time the non-parameters uncertainty upper bound, neural network controller is used to approximate the parameters uncertainty, sliding mode controller is designed to eliminate the approximation error. This kind of control scheme does not need the accurate mathematical model, and overcome the defects that only robust controller usually needs to predict the non-parameters uncertainties, such as errors and disturbances upper bound. The global asymptotic stability (GAS) of the closed-loop system based on Lyapunov theory is proved by the paper. PID feedback strategy is introduced to makes the control scheme more easy to be implemented in Engineering. The simulation results show that the scheme is effective.

2. Dynamic Equation of Space Manipulators

Free-floating space robot dynamic equation can be written as Equation 1 [20-21]:

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

Where, $q,\dot{q},\ddot{q} \in R^n$ are joint position, velocity and acceleration vectors; $M(q) \in R^{n\times n}$ is symmetric positive definite inertia matrix; $C(q,\dot{q}) \in R^{n\times 1}$ is Coriolis/ centrifugal forces ; $d \in R^n$ is the sum of the external disturbance and the friction, $\tau \in R^{n\times 1}$ is control input torque.

Space robot dynamics equation (1) has the following properties [21-23].

P1: Inertia matrix $M(q)$ is a symmetric positive definite matrix.

P2: By suitably choosing $C(q,\dot{q})$, the matrix $\dot{M}(q) - 2C(q,\dot{q})$ can be the skew symmetric matrix.

The following research will use the following assumptions:

A1: Space robot trajectory q_d 、 $\dot{q}_d$ and $\ddot{q}_d$ are bounded.

A2: Existing normal numbers λ_1, λ_2 and λ_3 make the friction and disturbance d norm satisfy $\| d \| \le \lambda_1 + \lambda_2 \| e \| + \lambda_3 \| \dot{e} \|$.

If space robot system (1) does not exist the unmodeled dynamics and parameters uncertainty, where,the reference trajectory is definited as q_r, the position tracking error is definited as e ,the following error tolerance is definited as s, positive definite matrix is $\Lambda \in R^{n\times n}$.

Lyapunov function is definited as Equation 2.

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

Then

$$\dot{V} = s^T M \dot{s} + \frac{1}{2} s^T \dot{M} s = s^T [M(q)\ddot{q}_r + C(q,\dot{q})\dot{q}_r - \tau] \tag{3}$$

Where, $\dot{q}_r = \dot{q}_d + \Lambda e$, $e = q_d - q$ and $s = \dot{e} + \Lambda e$ are defined separately. The controller designed as Equation 4.

$$\tau = \hat{M}(q)\ddot{q}_r + \hat{C}(q,\dot{q})\dot{q}_r + K_v s \tag{4}$$

Where, K_v is positive definite matrix, $\hat{M}(q)$ and $\hat{C}(q,\dot{q})$ are its separate estimation.

If the system all parameters are known accurately and there isn't non-parameters uncertainty conditions. Namely, the estimated value $\hat{M}(q)$ and $\hat{C}(q,\dot{q})$ are $M(q)$ and $C(q,\dot{q})$, and non-parameters uncertainty(the external disturbance and the friction) are 0. The controller (2) and Lyapunov theory are used ,then

$$\dot{V} < 0 \tag{5}$$

However, the system all parameters can not be measured accurately, only estimated parameters can be obtained. and non-parameters uncertainties(the external disturbance and the friction) are not equal to 0. A new control law needs to be designed.

3. Adaptive Robust Controller Designed base on Neural Network

If the system all parameters are known accurately and there isn't non-parameters uncertainty conditions. Namely, the estimated value $\hat{M}(q)$ and $\hat{C}(q,\dot{q})$ are $M(q)$ and $C(q,\dot{q})$, and non-parameters uncertainty(the external disturbance and the 10 friction) are 0. The controller (2) and Lyapunov theory are used, then, considering the uncertainty space robot system (1), then the error equation of closed loop system is written as Equation.

$$M\dot{s} + Cs = M\ddot{q}_r + C\dot{q}_r + \boldsymbol{d} - \tau \tag{6}$$

Where, the system unknown parameters and non-parameters uncertainty are considered. f is designed to compensate unknown parameters uncertainty.

$$f = M(q)\ddot{q}_r + C(q,\dot{q})\dot{q}_r \tag{7}$$

PD controller is introducted So the controller (4) is corrected as Equation 8.

$$\tau = f + K_p e + K_d \dot{e} + \tau_{rc} \tag{8}$$

Where, K_p and K_d are positive definite matrix, τ_{rc} is adaptive robust controller, it designed to compensated unknown non-parameters uncertainty as Equation 9.

$$\tau_{rc} = \frac{(\rho\hat{\lambda})^2}{\rho\hat{\lambda}\|s\| + \omega^2} s \tag{9}$$

$$\dot{\hat{\lambda}} = \gamma_1 \rho \|s\| \tag{10}$$

$$\dot{\omega} = -\gamma_2 \omega \tag{11}$$

Where, $\rho = \max(1, \|e\|, \|\dot{e}\|)$, $\hat{\lambda}$ is the estimated value of λ; γ_1 and γ_2 are normal constant.RBF (Radial Basis Function) neural network has good local generalization ability. It can accelerate greatly the learning speed and avoid local minimum problem. So it is used to approach the unknown parameters uncertainty in the system.

The optimal output of neural network is definited as f, the optimal network weights matrix is definited as θ^*, the neural network approximation errors is defined as ε.

Then

$$f = \theta^{*T}\varphi(x) + \varepsilon \tag{12}$$

$$\varphi_j = \exp(-\frac{\| x - c_j \|^2}{\sigma_j^2}) \tag{13}$$

Where, Gauss type function is definited as $\varphi(x)$. The j basis function center is definited as c_j, Basis function width is definited as σ_j, Norm of $x - c_j$ is definited as $\| x - c_j \|$.

According to the approximation ability of fuzzy basis function network,the paper makes following assumptions:

A3: For any given small positive constant ε_M, there exist the optimal weight vector θ^*,so that $\varepsilon(x)$ meets $|\varepsilon| = |\theta^{*T}\varphi(x) - f| < \varepsilon_M$.

A4: Optimal weight θ^* is bounded . $\|\theta^*\| \le \theta_M$, θ_M is the positive constant .

But actual output of neural network should be $\hat{f}$, actual weights matrix of network should be $\hat{\theta}$.

Then

$$\hat{f} = \hat{\theta}^T\varphi(x) \tag{14}$$

For approximation errors of neural network, Sliding mode controller is designed to compensate approximation errors of neural network.

$$\tau_{SL} = \varepsilon_M sgn(s) \tag{15}$$

In order to eliminate the chattering of sliding mode controller and convenient application in engineering, the saturated function is used to instead of sign function.

Then

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

Thus,the adaptive robust controller base on neural network is designed as

$$\tau = \hat{f} + \tau_{SL} + K_p e + K_d \dot{e} + \tau_{rc} \tag{17}$$

Where, $\hat{f}$ is Neural network controller to compensate parameters uncertainty, τ_{rc} is adaptive controller to compensate non-parameters uncertainty .

Adaptive learning algorithm of neural network weights matrix is designed as

$$\dot{\tilde{\theta}} = -\eta\varphi s^T \tag{18}$$

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

4. System Stability Analysis

Theorem: If the system (1) meets the assumption 1 and assumption 2, controller (17) and weights adaptive learning law (18) are adopted. Then global asymptotic stability (GAS) of the closed-loop system can be guaranteed.

Lyapunov function is defined to prove the stability of the closed loop system.

$$V = \frac{1}{2}s^T M s + e^T(K_P + \Lambda K_d)e + tr(\tilde{\theta}\eta^{-1}\tilde{\theta}^T) + \gamma_1^{-1}\tilde{\lambda}^2 + \gamma_2^{-1}\omega^2 \quad (19)$$

The two sides of equation (19) is derivatived.

$$\dot{V} = s^T M\dot{s} + \frac{1}{2}s^T\dot{M}s + e^T K_P\dot{e} + e^T\Lambda K_d\dot{e} + tr(\tilde{\theta}^T\eta^{-1}\dot{\tilde{\theta}}) + \gamma_1^{-1}\tilde{\lambda}\dot{\tilde{\lambda}} + \gamma_2^{-1}\omega\dot{\omega} \quad (20)$$

According to the error of closed-loop system equation (6), then

$$s^T M\dot{s} = s^T(f + d - \tau - C(q,\dot{q})s) \quad (21)$$

Since $\varepsilon_M > |\varepsilon_i|$, according to (21), when $\tanh(s_i) \geq \frac{\varepsilon_i}{\varepsilon_M}$, the adaptive law(18),control law (9) and (10) are substituted,assumption 2 is considered, following equation can be got

$$\begin{aligned}\dot{V} &\leq s^T(-\tau_{rc} - d) + \gamma_1^{-1}\tilde{\lambda}\dot{\hat{\lambda}} + \gamma_2^{-1}\omega\dot{\omega}\\ &\leq -\frac{(\rho\hat{\lambda})^2}{\rho\hat{\lambda}\|s\| + \omega^2}\|s\|^2 + \|s\|\|d\| - \gamma_1^{-1}\tilde{\lambda}\dot{\hat{\lambda}} - \omega^2\\ &\leq -\frac{\omega^4}{\hat{\rho}\lambda\|s\| + \omega^2}\end{aligned} \quad (22)$$

So, $\dot{V} \leq 0$ is satisfied in a very small neighborhood near the origin.As can be known form the Lyapunov stability theory system, signal s 、 e and $\tilde{\theta}$ are uniformly bounded. Because of $s = \dot{e} + \Lambda e$, $\dot{e}$ are uniformly bounded..According to assumption 1 and assumption 2, $\ddot{q}_r$ 、 $\dot{q}_r$ 、 q and $\dot{q}$ are bounded.

$$V_1(t) = V(t) - \int_0^t(\dot{V}(t) + s^T K_v s)dt \; ; \qquad \dot{V}_1(t) = -s^T K_v s$$

Since $\dot{s}$ is bounded,that means $\dot{V}_1(t)$ is the uniformly continuous function of time. Because the $V_1(t)$ is bounded and the greater than zero, $\dot{V}_1(t) \leq 0$. Base on Barbalat theory , as can be obtained, if $t \to \infty$, $\lim_{t\to\infty}\dot{V}_1(t) = 0$, that is $s \to 0$. Because Λ is positive definite matrix, so $e \to 0$ and $\dot{e} \to 0$.

5. Simulation and Analysis

In this section, simulation for a planar two-link space robot is studied. B_0 : the spacecraft platform; $B_i(i-1,\cdots,n)$: the i st link-rod of manipulator; J_i : the joint which connects B_{i-1} with B_i;

C_i: the mass' center of B_i; a_i, $b_i \in R^3$ respectively: position vector that is from J_i to C_i and from C_i to J_{i+1}; $I_i \in R^3$: the inertia of the link-rod relative to its centroid; m_i: the mass of B_i .Simulation parameters of the two-link space robot shows: $m_0 = 300kg$, $m_1 = 10\text{kg}$, $m_2 = 12\text{kg}$, $a_1 = 0.6\text{m}$, $a_2 = 0.4\text{m}$, $b_0 = 0.5\text{m}$, $b_1 = 0.5\text{m}$, $b_2 = 0.6\text{m}$, $I_0 = 70kg.m^2$, $I_1 = 1.2kg.m^2$, $I_2 = 1.0kg.m^2$.

The estimate values of parameters are assumed:

$\hat{m}_0 = 280kg$, $\hat{m}_1 = 8\text{kg}$, $\hat{m}_2 = 15\text{kg}$, $\hat{a}_1 = 0.5\text{m}$, $\hat{a}_2 = 0.3\text{m}$, $\hat{b}_1 = 0.45\text{m}$, $\hat{b}_2 = 0.55\text{m}$.

External disturbances and friction:

$d = [q_1\dot{q}_1 0.1\sin t\ , q_2\dot{q}_2 0.1\sin t]^T$

The desired trajectory:

$q_{1d} = 0.5(\sin t + \sin 2t)$, $q_{2d} = 0.5(\cos 3t + \cos 4t)$.

Controller parameters:

$K_d = diag\{15,15\}$, $K_p = diag\{20,20\}$, $\varepsilon_M = 0.9$, $\eta = 20$, $\Lambda = diag\{6,6\}$, $\gamma_1 = 8$, $\gamma_2 = 0.1$.

The initial value of joint position and velocity:

$q_1(0) = 0$, $q_2(0) = 0$, $\dot{q}_1(0) = \dot{q}_2(0) = 0$

Network initial weight value, basis function width and the basis function center were randomly selected in the group (0 ~ 0.01). The simulation results are shown in Figure 1 ~ Figure 5. Figure 1 shows parameters uncertainty model and its neural network estimated value; Figure 2 shows position tracking curves of space robot joint 1, Figure 3 shows position tracking curves of space robot joint 2; Figure 4 shows control torque curves of space robot joint 1; Figure 5 shows control torque curves of space robot joint 2.

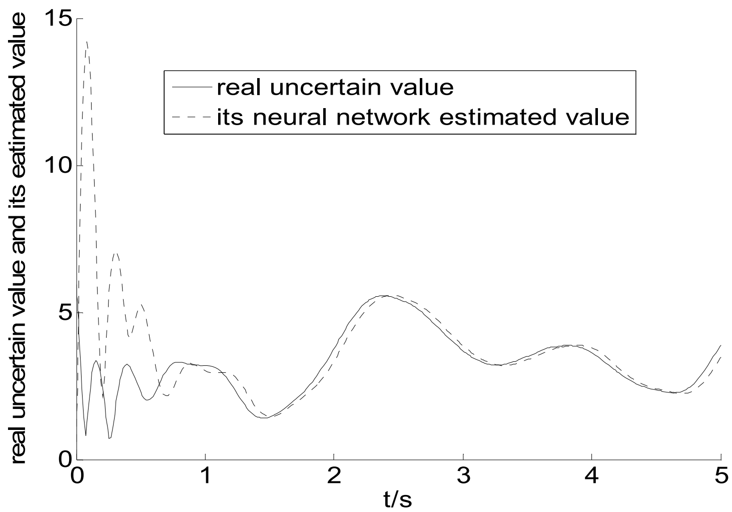

Fig.1 Unknow model and its neural network estimated

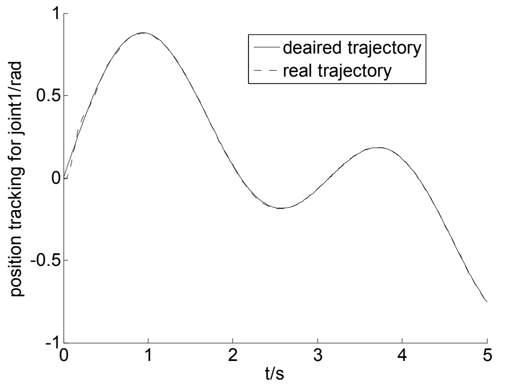

Figure 2. Trajectory tracking curves of joint 1

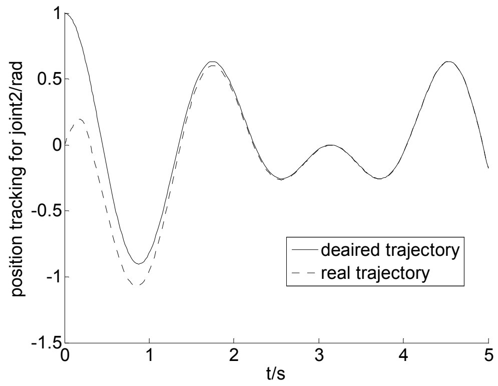

Figure 3.Trajectory tracking curves of joint 2

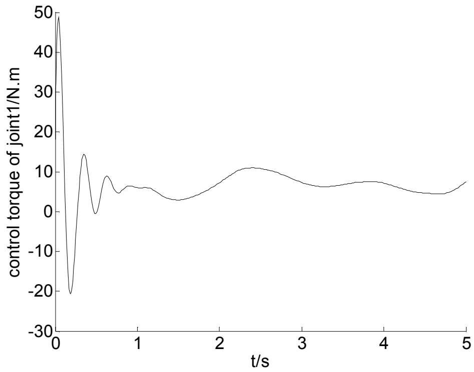

Figure 4. Control torque of space robot joint 1

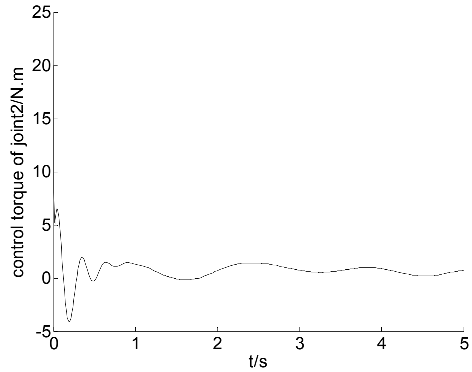

Figure 5. Control torque of space robot joint 2

As can be seen from the figure 1,after the initial learning, neural network can get to complete learning and good approximation for parameters uncertainty model in less than 2s, it shows not only the design of adaptive law is effective, also the radial basis function neural network has good generalization ability and fast learning speed Figure 2 and Figure 3 show position tracking chart that this control method can reach better control effect only in about 3s, Figure 3 and Figure 4 show position tracking chart that this control method can reach better control effect only in about 3s. Control torque of space robot joints aren't big, As can be seen from the figure 4 and Figure 5.

6. Conclusion

The trajectory tracking problems of a class of space robot manipulators with parameters and non- parameters uncertainty are studied by the paper. An adaptive robust control scheme based on neural network is put forward by the paper.

1) An adaptive robust controller is designed to compensate to non-parameters uncertainty, neural network controller is designed to approach and estimate the upper bound of parameters uncertainty real-time;
2) The sliding mode variable structure controller is designed to compensate the approximation error, saturated function instead of sign function is used to eliminate chattering;
3) The adaptive weight learning algorithm of neural network is designed to ensure online real-time adjustment, offline learning phase is not need;
4) Globally asymptotically stable(GAS) of the closed-loop system is proved based on the Lyapunov theory.

Simulation results show that the designed adaptive robust controller based on neural network is effective and has good engineering value.

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