Adaptive Robust Control Free-Floating Space Robotic Manipulators based on RBF Neural Network

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Abstract

Problems of trajectory tracking of the free-floating space robotic manipulators model with uncertainties are studied. An adaptive robust control algorithm of space manipulators based on radial basis function neural network (RBFNN) is proposed by the paper. Neural network controller is used to adaptive learn and compensate the unknown system, approach errors as disturbance are eliminated by robust controller. The weight adaptive laws on-line based on Lyapunov theory can ensure stability of system. The robust controller was proposed based on H_∞ theory. Above these assured the stability of the whole system, and L_2 gain also was less than the index. This control scheme possesses great control accuracy and dynamic function. The simulation results show that the presented neural network control algorithm is effective.

Keywords: *Neural network, Space robotic manipulators, Adaptive robust control, Trajectory tracking*

1. Introduction

Space robot will play an important role in space exploration. Owing to the economization of fuel, increase life-span of space robot, and decrease in launch expenditure, positions and attitude of the base are entirely free. Thus there is intense dynamic coupling existing between the manipulator and base. Meanwhile, there are many uncertainties existing in the space robot dynamic model [1] ~[5]. such as machine arm quality, inertial matrix, load quality etc. the dynamics model can not be acquired accurately, and the external perturbation signals all influence on controller. Because adaptive control, neural network control and fuzzy control can compare an advantage to manage various nonlinear system [6]~[10].

The intelligent controller currently already extensively applied at the space robot trajectory control. Guo [11] puts forward an adaptive Fuzzy Sliding Mode controller for robotic manipulators .Chen[12] puts forward adaptive control for space robot, but the method can be used for base controlled, can not used for base of free-floating. Kim [13] and Hu [14] put forward RBF neural network control scheme, making use of a neural network to adaptive recognize indetermination model, but the scheme only can acquire uniformly ultimately bounded. Guo [15] puts forward Adaptive Neural Network control for coordinated motion of a dual-arm space robot system with uncertain parameters.

For the above discussion, aimed at tracking problems of free-floating space robot manipulators with uncertainties, the paper proposed a neural network robust control algorithm based on H_∞ robust theory for free-floating space robot manipulators. By taking advantage of the RBF network. Adaptive neural network control laws which are designed based on Lyapunov can ensure the convergence of the algorithm . The proposed schemes all need not precise model of robot manipulators, and can guarantee the fast tracking. the adaptive robust controller based on H_∞ theory is able to compensate for the system uncertainties more effectively. The simulation results show that the controller can speed up the convergence velocity of error.

2. Dynamics Model of Free-Floating Space Robotic Manipulators

The Figure 1 shows the model of one-arm space robot. The coordinate system can be defined as follows: 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}, $k_i \in R^3$: the unit vector of rotative direction J_i, $r_i \in R^3$: the position vector of the mass' center B_i, $r_g \in R^3$: the unknown vector of the system's centroid, $p_e \in R^3$: position vector of the manipulator's end, $I_i \in R^3$: the inertia of the link-rod relative to its centroid, O_I : the inertial origin, O_g : : the centroid of the whole system, m_i : the mass of B_i, M : $M=\sum_{i=1}^{n} m_i$ $\sum_I$、$\sum_E$、$\sum_B$ respectively : the inherits coefficient, manipulator's end coordinates system, the basic body coordinates system.

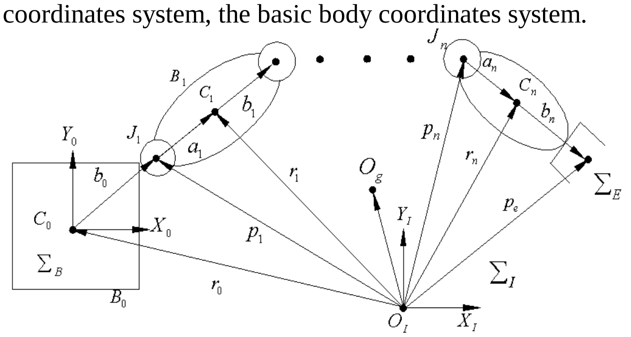


Fig.1 Parameters of space manipulators

In the environment of micro-gravity, body posture and position are not controlled space robot is [15]~[17]:

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

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. $f(q,\dot{q})\in R^n$ is the friction matrix. τ is the control input torque vector.

3. Design of Adaptive Robust Controller base on Neural Network

Considering the uncertain robot system (1), the controller should be designed as follows:

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

Where u acts as compensate items. When putting (2) into (1), the paper may reach the error equation of closed-loop system:

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

Where $f(q,\dot{q})=\tilde{M}(q)\ddot{q}_d+\tilde{C}(q,\dot{q})\dot{q}_d+d$, $e=q-q_d$, $\tilde{M}=M-\hat{M}$, $\tilde{C}=C-\hat{C}$ 。

Firstly, the paper define the state variables $x=(x_1,x_2)^T$

$$\begin{cases} x_1=e \\ x_2=\dot{e}+\alpha e \end{cases} \qquad (4)$$

Then the equation (5) should be rewritten as

$$\begin{cases} M(q)\dot{x}_2=-C(q,\dot{q})x_2+w-f(q,\dot{q})+u \\ w=M\alpha\dot{e}+C\alpha e \end{cases} \qquad (5)$$

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

For further analysis, the following assumptions are made [8]:

A1): Given an arbitrary small positive constant ξ_{dm} , There exists an optimal weight vector θ^*, so that the approximation error ξ of neural network satisfies $|\xi|=|\theta^{*T}\varphi(x)-f(\vartheta)|<\xi_{dm}$.

A2): there is a positive constant m_3 , the optimal weight vector θ^* is bounded and meets the condition $\|\theta^*\|\le m_3$.

Then

$$f(\vartheta)=\theta^{*T}\varphi(x)+\xi \qquad (6)$$

$$\tau_{NN}=\theta^{*T}\varphi(x) \qquad (7)$$

Where τ_{NN} is neural network controller.

So

$$\hat{f}(q,\dot{q})=\hat{\theta}^T\varphi(\vartheta) \qquad (8)$$

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

$$\varphi_j=\exp\left(-\frac{\|\vartheta-c_j\|^2}{\sigma_j^2}\right) \qquad (9)$$

Where c_j and σ_j represent the center and the spread of jth basis function , respectively. 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 external disturbances. Then the equation (5) should be amended as affine nonlinear system form with model error and disturbances.

$$\begin{cases} \dot{x} = f(x) + g(x)\varepsilon \\ z = h(x) \end{cases} \quad (10)$$

In which, $f(x) = \begin{bmatrix} x_2 - \alpha x_1 \\ -M^{-1}(Cx_2 - w - u + \tau_{NN}) \end{bmatrix}$, $g(x) = \begin{bmatrix} 0 \\ -M^{-1} \end{bmatrix}$, $z = pe = px_1$ Stand for evaluation signal, α , p are positive constant.

The following equation is defined as performance indicators that reflects the system's interference suppression ability.

$$J = \sup_{\|\xi_f\| \neq 0} \frac{\| z \|_2}{\| \xi_f \|_2} \quad (11)$$

In above equation, J represents the gain L_2 of system (10). The system's disturbance suppression, that is designing controller, makes the gain L_2 is less than the given value γ.

The control law of the compensation term u should be designed as:

$$u = -w - x_1 - \frac{1}{2\gamma^2} x_2 + \hat{\theta}^T \varphi(x) \quad (12)$$

The adaptive learning algorithm of neural network weight matrices should be redesigned as

$$\dot{\hat{\theta}} = -\eta x_2 \varphi^T(x) \quad (13)$$

Where the gain $\eta > 0$, The parameters p of the evaluation signal $z = h(x) = px_1$ meets the following equation:

$$\alpha - \frac{1}{2} p^2 = \varepsilon_1 \quad (14)$$

Where ε_1 represents given constant. Then the gain J of L_2 of the closed-loop system is less than the given value γ .

Theorem [17]**:** (HJI inequality) Given a positive number $\gamma > 0$, if there are positive-definite quasi-differentiable function $V(x) \geq 0$ satisfy the following HJI inequality:

$$\dot{V} \leq \frac{1}{2} \left\{ \gamma^2 \| \xi_f \|^2 - \| z \|^2 \right\} \quad (\forall \xi_f) \quad (15)$$

Then the gain L_2 of the above system equation (10) is less than a given value γ , that is, performance indicators $J \leq \gamma$.

Proof: Defining the following function Lyapunov :

$$V = \frac{1}{2} x_2^T M x_2 + \frac{1}{2} x_1^T x_1 + \frac{1}{2\eta} tr(\tilde{\theta}^T \tilde{\theta}) \quad (16)$$

Where, $\tilde{\theta} = \theta^* - \hat{\theta}$ represents estimation errors of the network weight. Then

$$\dot{V} = \frac{1}{2} x_2^T \dot{M} x_2 + x_2^T M \dot{x}_2 + x_1^T \dot{x}_1 + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) \quad (17)$$

Where, putting (6) in the above equation, the paper can reach the following new expression:

$$\dot{V} = -\alpha \| x_1 \|^2 + x_2^T \tilde{\theta} \varphi(x) - x_2^T \varepsilon - \frac{1}{2\gamma^2} x_2^T x_2 + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) \quad (18)$$

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

Then

$$\begin{aligned} H &= -\alpha \| x_1 \|^2 + x_2 \tilde{\theta} \varphi(x) - x_2^T \varepsilon - \frac{1}{2\gamma^2} x_2^T x_2 \\ &\quad + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) - \frac{1}{2} \left\{ \gamma^2 \| \varepsilon \|^2 - \| z \|^2 \right\} \\ &\leq -(\alpha - \frac{1}{2} p^2) \| x_1 \|^2 + x_2^T \tilde{\theta} \varphi(x) + \frac{1}{\eta} tr(\dot{\tilde{\theta}}^T \tilde{\theta}) \\ &= -\mu \| x_1 \|^2 + x_2^T \tilde{\theta} \varphi(x) - tr(\varphi(x) x_2^T \tilde{\theta}) \\ &= -\mu \| x_1 \|^2 \\ &\leq 0 \end{aligned} \quad (19)$$

According to Theorem 1, the gain L_2 of the closed-loop system (10) is less than the given value γ .

4. Simulation

About the free-floating space robot, the table 1 shows two-DOF space robot simulation parameters. The simulation environment Matlab is 7.0, simulation time is 20S.

Table 1 Parameters of 2-DOF space manipulator

m_0	40kg	a_1	0.65m
m_1	15kg	a_2	0.7m
m_2	7 kg	b_0	0.25m
I_0	80kg㎡	b_1	0.55m
I_1	1.5kg㎡	b_2	0.6m
I_2	1.5 kg㎡		

External interference select

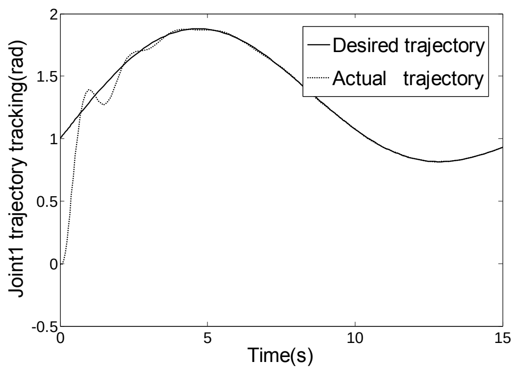
$$f = [q_1\dot{q}_1 0.8\sin t, q_2\dot{q}_2 0.8\sin t]^T$$

Desired trajectory are assumed to be

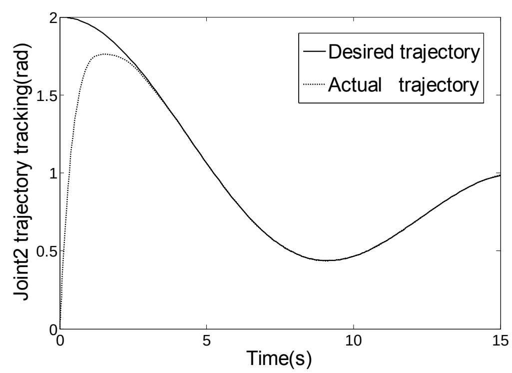
$$q_{1d} = 1.0 + 0.5(\sin 0.2t + \sin 0.4t)$$

$$q_{2d} = 1.0 + 0.5(\cos 0.2t + \cos 0.4t)$$

The simulation parameters are respectively $\hat{M} = 0.8M$, $\hat{C} = 0.8C$; $\alpha = 50$, $\eta = 150$, $\gamma = 0.1$. The initial joint position and velocity are chosen as 0 The network initial weights are 0. 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～Figure 3.



(a) Joint1 trajectory tracking



(b) Joint2 trajectory tracking

Fig.2 Trajectory tracking curves of Space robot

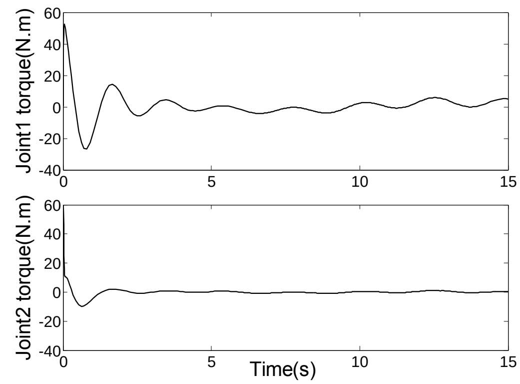


Fig.3 Control torque of joints

As can be seen from the figure, controller designed by this paper not only can track effectively the desired trajectory in a very short period of time (about 5s), but also can compensate for all uncertainties. Especially at the early period of control, because the robust controller compensate for the comparatively large approximation errors which are caused by the neural network as a result of no completing study, the neural network robust controller base H_∞ theory can improve control precision and speed up the error convergence velocity more effectively.

5. Conclusion

Tracking problems of free-floating space robot manipulators with uncertainties are studied, the paper proposed a neural network robust control algorithm based on H_∞ robust theory for free-floating space robot manipulators. Adaptive neural network control laws which are designed based on Lyapunov can ensure the convergence of the algorithm . The proposed schemes all need not precise model of robot manipulators, and can guarantee the fast tracking. the adaptive robust controller based on H_∞ theory is able to compensate for the system uncertainties more effectively. The simulation results show that the controller can speed up the convergence velocity of error.

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