RBF Neural Network Adaptive Control for Space Robots without Speed Feedback Signal

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Tracking control problems for space robots are studied under conditions without speed feedback signals. An adaptive RBF neural network control method with a speed observer is proposed. Specially, we conduct the following.
1) A dynamic model of space robots is established. 2) A speed observer based on a neural network is designed to reconstruct speed information. 3) A controller based on a neural network is designed to compensate the nonlinear model of system. 4) A weight adaptive learning laws of the neural network is designed to ensure on-line tuning without an off-line learning phase. 5) The uniformly ultimately bounded state of the closed-loop system is proved based on Lyapunov theory. Simulation results show that the adaptive neural network control method with the speed observer can achieve good precision. This has important engineering value.

Key Words: RBF Neural Network, Speed Observer, Adaptive Learning Laws, Adaptive Control, Space Robots

1. Introduction

Space robots will have an increasingly important role in the future. In the free-floating condition, space robots are different from ground robots in terms of dynamic characteristics and constraints;1–4) specially in terms of dynamic coupling of machine arms and the base, dynamic singularity, a limited supply of fuel and restrictions of the attitude control system. Therefore, unlike robots with a fixed base on the ground, a general control method cannot be adopted for space robots.5–7) 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 cannot be accurately acquired, and external disturbance signals have a certain impact on the controller. To eliminate the impact of these nonlinear factors, various advanced control strategies.8–15)

The above control strategies were proposed under the condition that the speed information of joints can be accurately obtained. However, in practical engineering control, although joint speed measurements can be obtained by means of tachometers, the speed information is often contaminated by noise disturbance. In particular, joint motors of space robots are usually run under low speed conditions. Moreover, moment fluctuations and other high frequency effects are engendered because of discontinuity of the stator magnetic field in tachometers. These reasons further reduce the quality of the speed signal.16) Moreover, tachometers increase the weight of moving parts and reduce the efficiency of space robotic manipulators. Therefore, it is difficult to achieve the high control precision in practical engineering. The method becomes especially important in without speed feedback signals.

There has been some success in robot research based on speed observers. A position feedback control strategy was put forward,17,18) but the design of the observer requires exact knowledge of robot dynamics, which is difficult to acquired. An output feedback controller was designed,19,20) where the design of the observer does not need an exact dynamics model owing to use of a neural network. All signals in the closed-loop dynamic can be uniformly ultimately bounded (UUB); however, the exact inverse of the inertia matrix is still required by the observer, and too much calculating is required.

Control problems for space robots are studied under conditions without speed feedback signals and an adaptive neural network control method with a speed observer is proposed in this paper. A radial basis function (RBF) neural network control strategy without speed signals is presented for space robots. A dynamic model of space robots is established. Then, the neural network is used to compensate the nonlinear model and a speed observer based on the neural network is designed to reconstruct the speed information. A controller based on the neural network is designed to approach the unknown model. A weights adaptive learning law of the neural network is designed to ensure on-line tuning. Stability of the closed-loop system based on Lyapunov theory is analyzed.

2. Dynamic Model of Space Robots

A dynamic equation of space robots can be written as21–23)

\[
M(q)\ddot{q} + C(q, \dot{q})\dot{q} + F = \tau. \tag{1}
\]

where joint position, velocity and acceleration vectors are defined respectively as \(q, \dot{q}\) and \(\ddot{q}\in \mathbb{R}^n\), the inertia matrix is defined as \(M(q) \in \mathbb{R}^{n \times n}\), Coriolis forces are defined as...
C(q, ˙q) ˙q ∈ R^n×1, the external disturbances are defined as F ∈ R^n×1 and control torques are defined as τ ∈ R^n×1.

The following properties are defined for space robots system.22-24

P1: choosing C(q, ˙q), the matrix M(q) − 2C(q, ˙q) is a skew symmetric matrix.

3. Design of Adaptive RBF Neural Network Control System

x_1 and x_2 are defined as

\[
\begin{align*}
x_1 &= q \\
x_2 &= ˙q.
\end{align*}
\]

(2)

Equation (1) can be described as:

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= h_o(x_1, x_2, \dot{x}_2) + τ.
\end{align*}
\]

(3)

A neural network is used to reconstruct speed signals, and approach the unknown system. The control structure is shown in Fig. 1.  

\[q \quad \dot{q} \quad \ddot{q} \quad \dddot{q} \] are defined respectively as joint position and speed estimation value, and \( \dddot{q} \) and \( \dddot{q} \) are defined respectively as the position estimation error and speed estimation error.

\[
\begin{align*}
\dddot{q} &= q - \dot{q} \\
\dddot{q} &= \dddot{q} - \dddot{q}.
\end{align*}
\]

(4)

Further, Eq. (2) can be described as

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= h_o(x_1, x_2, \dot{x}_2) + τ.
\end{align*}
\]

(5)

The RBF neural network belongs to a local generalization network, so it can greatly accelerate the learning speed and avoid local minimum.

\[h_o(x_1, x_2, \dot{x}_2) = f(x_1, x_2, W_o) = W_o^T \phi(x).
\]

(6)

where \( x = (x_1, x_2) \), \( W_o \) is defined as the weight matrix of observer and \( \phi(x) \) is a Gaussian function.

According to the approximation ability of the RBF network, assume

A1: The optimal weight \( W_o^* \) is bounded and meets \( \| W_o^* \| \leq W_{o,M} \); \( W_{o,M} \) is the positive constant.

A2: For any given small positive constant \( \epsilon_{o,M} \), there exists a approximation error \( \epsilon_{o}(x) \) where \( \| \epsilon_{o}(x) \| \leq \epsilon_{o,M} \).

The RBF neural network is used to approach \( h_o(x_1, x_2, \dot{x}_2) \). The optimal approximation can be written as

\[h_o(x_1, x_2, \dot{x}_2) = f_o(x_1, x_2, W_o^*) = W_o^{*T} \phi(x) + \epsilon_{o}(x).
\]

(8)

where \( x = (x_1, x_2) \).

The functional estimation of Eq. (8) with \( \dot{x}_1, \dot{x}_2 \) is described as

\[\hat{f}_o(\dot{x}, \dot{W}_o) = \dot{W}_o^{T} \phi(\dot{x})\]

(9)

where \( \dot{W}_o \) is the estimation weight.

\[\dot{x}_1, \dot{x}_2 \] are defined as

\[
\begin{align*}
\dot{x}_1 &= \dot{z}_1 \\
\dot{x}_2 &= \dot{z}_2 + k_1 \dot{x}_1.
\end{align*}
\]

(10)

Defining, \( \dot{x}_1 = x_1 - \dot{x}_1 \) and \( \dot{x}_2 = x_2 - \dot{x}_2 \), Eq. (10) has the following form.

\[
\begin{align*}
\dot{z}_1 &= \dot{x}_2 + k_2 \dot{x}_1 \\
\dot{z}_2 &= W_o^{T} \phi(\dot{x}) + τ + (K + k_1 k_2 I_{m,n}) \dot{x}_1.
\end{align*}
\]

(11)

where \( K = K^T \) are positive definite matrices, \( k_1 > 0 \) and \( k_2 > 0 \).

Further, the following expression can be obtained.

\[
\begin{align*}
\dot{z}_1 &= \dot{x}_2 + k_2 \dot{x}_1 \\
\dot{z}_2 &= W_o^{T} \phi(\dot{x}) + τ + (K + k_1 k_2 I_{m,n}) \dot{x}_1 + k_1 \dot{x}_1.
\end{align*}
\]

(12)

The observer error dynamics can be obtained by subtracting Eq. (4) from Eq. (12).

\[
\begin{align*}
\dot{\hat{x}}_1 &= \dot{x}_2 - k_2 \dot{x}_1 \\
\dot{\hat{x}}_2 &= W_o^{T} \phi(x) - W_o^{T} \phi(\dot{x}) + \epsilon_{o}(x) - K \dot{x}_1 - k_1 \dot{x}_2.
\end{align*}
\]

(13)

Since \( W_o^{*T} \phi(x) - W_o^{T} \phi(\dot{x}) = W_o^{*T} \dot{\phi} + W_o^{T} \ddot{\phi} \), the following equation can be obtained.

\[
\begin{align*}
\dot{\hat{x}}_1 &= \dot{x}_2 - k_2 \dot{x}_1 \\
\dot{\hat{x}}_2 &= W_o^{*T} \dot{\phi} + W_o^{T} \ddot{\phi} + \epsilon_{o}(x) - K \dot{x}_1 - k_1 \dot{x}_2.
\end{align*}
\]

(14)

where \( \ddot{\phi} = \phi - \dot{\phi}, \phi = \phi(x, \dot{x}, \ddot{x}^c), \dot{\phi} = \phi(\dot{x}) \). The weight estimation error is defined as \( \dot{W}_o = W_o^* - \dot{W}_o \).

The adaptive learning law is designed as

\[\dot{W}_o = -K_{W_o} \dddot{x}_1 \phi + \eta_o K_{W_o} \| \dot{x}_1 \| \| W_o \|
\]

(15)

where \( K_{W_o} \) is defined as the diagonal matrix and \( \eta_o \) is defined as a positive real constant.

4. Speed Observer Based on RBF Neural Network

\( e \) and \( \dot{e} \) are defined respectively as the position tracking error and the speed tracking error.

\[
\begin{align*}
e &= q_d - q - q_d - x_1 \\
\dot{e} &= \dot{q}_d - \dot{q} - \dot{q}_d - x_2.
\end{align*}
\]

(16)

Modified filtered tracking error \( \dot{x} \) is defined as

\[\dot{x} = \dot{e} + A e
\]

(17)

where \( A \) is defined as the positive definite matrix.

According to Eqs. (16) and (17) and \( \dddot{x}_2 = x_2 - \dddot{x}_2 \). The
speed tracking error can be written as
\[ \dot{e} = s - \xi_2 - A e \] (18)

According to Eqs. (17) and (18) and Eq. (1), the space robots dynamic system error equation can be written as
\[
\begin{aligned}
\dot{M}\hat{s} &= -CS + \eta_c - \tau \\
\eta_c &= M(\dot{\mathbf{q}}_i + \ddot{\mathbf{x}}_2) + C(\dot{\mathbf{q}}_i + \ddot{\mathbf{x}}_2) - F.
\end{aligned}
\] (19)

The neural network optimal approach of \( h_c(x_1, x_2) \) can be written as

\[ h_c(x_1, x_2) = f_c(x_1, x_2, W_c^*) = W_c^T \phi(x) + \varepsilon_c(x). \] (20)

A3: Network approximation error \( \varepsilon_c(x) \) and the optimal weight \( W_c^* \) are bounded by \( \| \varepsilon_c(x) \| \leq \varepsilon_{c,M}, \| W_c^* \| \leq W_{c,M} \).

The control law is designed as
\[
\tau = \hat{W}_c^T \phi(\hat{x}) + K_p e + K_d \dot{e} + \ddot{\nu},
\] (22)

\[
\dot{\nu} = \frac{1}{K_v} \hat{s}.
\] (23)

where \( K_p \) and \( K_d \) are defined as positive definite matrices and \( K_v > 0 \).

Further, Eq. (19) can be written as
\[
\begin{aligned}
M(x_1)\dot{\hat{s}} + C(x_1, x_2)\hat{s} + W_c^* \tau \phi(\hat{x}, \dot{\hat{x}}, \hat{\epsilon}) + \varepsilon_c(x) = \\
- \hat{W}_c^T \phi(\hat{x}, \dot{\hat{x}}, \hat{\epsilon}) - K_p e - K_d \dot{e} - \ddot{\nu}.
\end{aligned}
\] (24)

Since \( W_c^* \tau \phi = \hat{W}_c^T \phi + \hat{W}_c^T \phi \), Eq. (24) can be written as
\[
\begin{aligned}
M\dot{\hat{s}} &= -C\hat{s} + \hat{W}_c^T \phi + \hat{W}_c^T \phi + \varepsilon_c - K_p e - K_d \dot{e} - \ddot{\nu} \\leq \\| W_c^* \| \| \phi \| \| \hat{s} \| \| \hat{W}_c \|,
\end{aligned}
\] (25)

The weight adaptive learning law is designed as
\[
\dot{\hat{W}}_c = -K_{W_e} \ddot{\nu} \phi^T + \eta_e K_{W_e} \| \hat{s} \| \| \hat{W}_c \|,
\] (26)

where \( K_{W_e} \) is defined as diagonal matrices and \( \eta_e \) is defined as the positive constant.

5. UUB Analysis Based on Lyapunov Theory

UUB can be proved using the following system based on Lyapunov theory.

Proof: The Lyapunov function is defined as
\[ V = V_c + V_o, \]

where
\[
\begin{aligned}
V_o &= \frac{1}{2} \ddot{x}_1^T K \ddot{x}_1 + \frac{1}{2} \ddot{x}_2^T K \ddot{x}_2 + \frac{1}{2} \text{tr} (\hat{W}_o^T K_{W_o}^{-1} \hat{W}_o), \\
V_c &= \frac{1}{2} e^T K_p e + \frac{1}{2} s^T M \ddot{s} + \frac{1}{2} \text{tr} (\hat{W}_c^T K_{W_c}^{-1} \hat{W}_c).
\end{aligned}
\] (27)

The derivative of \( V_o \) can be written as
\[
\dot{V}_o = \ddot{x}_1^T K \ddot{x}_1 + \ddot{x}_2^T K \ddot{x}_2 + \frac{1}{2} \text{tr} (\hat{W}_o^T \eta_e^{-1} \hat{W}_o),
\] (29)

where \( k_2 \hat{W}_o^T \phi = d_1 \) and \( W_o^* \phi + \hat{W}_o^T \phi + \varepsilon_o(x) = d_2 \).

Then
\[
\dot{V}_o = -k_2 \ddot{x}_1^T K \ddot{x}_1 + \ddot{x}_2^T K \ddot{x}_2 + \frac{1}{2} \text{tr} (\hat{W}_o^T \eta_e^{-1} \hat{W}_o).
\] (30)

The derivative of \( V_c \) can be written as
\[
\dot{V}_c = e^T K_p \dot{e} + \frac{1}{2} \ddot{M} M(x_1) \ddot{e} + \frac{1}{2} \text{tr} (\hat{W}_c^T K_{W_c}^{-1} \hat{W}_c)
\] (31)

According to Eqs. (25) and (26) and P1, Eq. (31) can be written as
\[
\dot{V}_c = e^T K_p \dot{e} + \frac{1}{2} \ddot{s} M(x_1) \ddot{e} + \frac{1}{2} \text{tr} (\hat{W}_c^T K_{W_c}^{-1} \hat{W}_c)
\] (32)

Thus
\[
\begin{aligned}
\dot{V} &\leq -k_2 \ddot{x}_1^T K \ddot{x}_1 + \ddot{x}_2^T K \ddot{x}_2 + \frac{1}{2} \ddot{s}^T M(x_1) \ddot{s} + \frac{1}{2} \text{tr} (\hat{W}_c^T K_{W_c}^{-1} \hat{W}_c)
\end{aligned}
\] (33)

Based on
\[ 2ab \leq a^2 + b^2 \]

Thus
\[
\begin{aligned}
\dot{V} &\leq -k_2 \ddot{x}_1^T K \ddot{x}_1 + \ddot{x}_2^T K \ddot{x}_2 + \frac{1}{2} \ddot{s}^T M(x_1) \ddot{s} + \frac{1}{2} \text{tr} (\hat{W}_c^T K_{W_c}^{-1} \hat{W}_c)
\end{aligned}
\] (34)

Based on
\[
\begin{aligned}
\text{tr} (A^T B) &\leq \| A \| \| B \|
\end{aligned}
\] (35)

where \( K_{W} \) is defined as diagonal matrices and \( K_{W} \) is defined as the positive constant.
\[ V \leq -\| s \| \left\{ K_s \| s \| + \eta_s (\| \tilde{W}_c \| - \lambda_s s^2 - \rho_s) \right\} \\
- \| \ddot{x}_1 \| \left\{ K_{s1} \| \ddot{x}_1 \| + \eta_{s1} (\| \tilde{W}_{d1} \| - \lambda_{s1})^2 - \rho_{s1} \right\} \\
- \| \ddot{x}_2 \| \left\{ K_{s2} \| \ddot{x}_2 \| - \rho_{s2} \right\} \]

where \( \rho_s = \eta_s J_1s^2 + d_{s1}K_{s1} \), \( \rho_{s1} = \eta_{s1}J_1s^2 + d_{s1}K_{s1} \), \( \rho_{s2} = d_{s2}K_{s2} \), \( \lambda_s = \frac{W_{sM}}{2} \), \( \lambda_{s1} = \frac{W_{s1M}}{2} \), \( K_s = K_d - \frac{1}{2}K_dA + \frac{1}{k_0}I_{M \times M} \), \( K_s1 = k_3K \) and \( K_s2 = 2k_1I_{M \times M} + K_p \). \( K_s > 0 \), \( K_s1 > 0 \), \( K_s2 > 0 \) is defined.

If
\[ \| s \| > \frac{\rho_s}{\lambda_s} \quad \text{or} \quad \| \tilde{W}_c \| > \frac{\rho_s}{\eta_s} + \lambda_s \]
\[ \| \ddot{x}_1 \| > \frac{\rho_{s1}}{\lambda_{s1}} \quad \text{or} \quad \| \tilde{W}_{d1} \| > \frac{\rho_{s1}}{\eta_{s1}} + \lambda_{s1} \]
\[ \| \ddot{x}_2 \| > \frac{\rho_{s2}}{\lambda_{s2}} \],

then
\[ V \leq 0. \]

This shows that \( V \) is negative. Therefore, according to Lyapunov theory all the signals \( \dot{s} \), \( \ddot{x}_1 \), \( \ddot{x}_2 \), \( \tilde{W}_c \) and \( \tilde{W}_{d1} \) are UUB.

6. Numerical Analysis

A simulation study of a planar two-link space robot is presented. The simulation parameters of the two-link space robot are given in Table 1.

Unmodelled dynamics and external disturbances can be expressed as
\[ F = [q_1\dot{q}_10.1 \sin t, \ q_2\dot{q}_20.1 \sin t]^T. \]

The desired trajectory can be expressed as
\[ q_{1d} = 1.0 + 0.5(\sin 0.2t + \sin 0.4t) \]
\[ q_{2d} = 1.0 + 0.5(\cos 0.2t + \cos 0.4t). \]

The number of hidden neurons: \( n = 25 \).

The corrected filter tracking error parameters are as follows.
\[ \Lambda = \text{diag} (5, 5) \quad K = \text{diag} (100, 100) \quad k_1 = 100 \]
\[ k_2 = 20 \quad K_p = \text{diag} (40, 40) \quad k_s = 0.005 \]
\[ K_d = \text{diag} (60, 60) \quad K_{d1} = \text{diag} (20, 20) \]
\[ \eta_o = 0.005 \quad K_{d2} = \text{diag} (100, 100) \quad \eta_s = 0.01 \]

The initial conditions of all the states were zero, i.e.:

\[ q_0(0) = 0, \ q_1(0) = \dot{q}_1(0) = 0, \ q_2(0) = \dot{q}_2(0) = 0 \quad \text{and} \quad q_2(0) = \dot{q}_2(0) = 0. \]

The network initial weight value, basis function width and the basis function center are randomly selected in the group (0-0.01). Fig. 2 shows the comparison between the desired trajectory \( q_{1d}, q_{2d} \) of two joints and the actual trajectory \( q_1, q_2 \). Fig. 3 shows the situation of two-joint position tracking errors \( e = q_d - q \). Fig. 4 shows the situation of the two-joint speed estimation errors \( \dot{q} = \dot{q} - \dot{q} \). Fig. 5 shows the output control torque of the two-joint.

From the simulation results, if can be found that the designed observer is able to preferably reconstruct the actual

| Parameter | Value |
|-----------|-------|
| \( m_0 \) | 400 kg |
| \( m_1 \) | 10 kg |
| \( m_2 \) | 7 kg |
| \( l_0 \) | 66 kg m² |
| \( l_1 \) | 1.5 kg m² |
| \( l_2 \) | 0.5 kg m² |
| \( a_1 \) | 0.75 m |
| \( b_0 \) | 0.5 m |
| \( b_1 \) | 0.75 m |

Fig. 3. Position tracking errors curves of the joints.
speed information of joints at 4 s, and that the output feedback controller can effectively track the desired trajectory at 5 s. In addition the control torques of joints are not large. This indicates that the neural network controller can overcome and compensate for the uncertain effects, and has good robustness.

From further simulations, if can be also found that within the proximity of zero, the choice of weight values and initial values for structure parameters of the neural network has little effect on system stability. The learning rate will affect system stability. For control parameters, the observer gain and controller gain become greater, and the approximation system stability. For control parameters, the observer gain becomes smaller. The convergence radius of $\varepsilon_M$ of the neural network and $k_b$ become smaller. The convergence radius of $\varepsilon$ and $\varepsilon_2$ become smaller and the tracking effect improves.

7. Conclusion

Tracking control problems for space robots were studied under conditions without speed feedback signals. An adaptive neural network control method with a speed observer was proposed in this paper.

1) A dynamic model of space robot was established
2) A speed observer based on a neural network was designed to reconstruct speed information
3) A controller based on the neural network was designed to approach the unknown model

4) A weights adaptive learning law of the neural network was designed to ensure on-line tuning
5) UUB of the closed-loop system based on Lyapunov theory was proved.

The simulation results showed that the proposed neural network control strategy without speed signal was able to achieve higher control precision. This has important value engineering for applications.

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