

Neural Network Disturbance Observer-Based Adaptive Tracking Control for Robot Manipulator

Hui Hu¹, Peng Guo² and Xilong Qu³

¹*Hunan Provincial Key Laboratory of Wind Generator and Its Control, School of Electrical and Information, Hunan Institute of Engineering, Hunan Xiangtan 411104, P. R. China*

^{2,3}*School of Computer Science and Communication, Hunan Institute of Engineering, Hunan Xiangtan 411104, P. R. China
21230122@qq.com, da_peng219@126.com, quxilong@126.com*

Abstract

A novel neural network disturbance observer-based adaptive tracking control approach for robot manipulator is presented in the paper. Using the concept of ‘dominant input’, the robot manipulator is transferred into several SISO systems with the unknown compound disturbance which consists of external disturbance, internal parameter uncertainty and cross-coupling of subsystems. In order to reduce the restrained conditions on the disturbance, the compound disturbance is monitored by the designed neural network observer. Then parameters update laws and control laws based on Lyapunov theory and neural network observer are proposed to guarantee that all the signals in the system are uniformly ultimately bounded and achieve given tracking performance index. Finally, the simulation results are presented to demonstrate the efficiency of the control scheme.

Keywords: *robot manipulator, neural network disturbance observer, tracking control, dominant input*

1. Introduction

In the three decades, the progress of robotics goes from the standard applications of industrial robots to new fields, such as space, service robotics, medical service, and force feedback systems *etc.* In general, robot manipulators are multivariable nonlinear systems. Its dynamics is governed by highly nonlinear coupled, time-varying system with many uncertainties such as load variation, friction, and external disturbance *etc.* Due to these uncertainties system error becomes large, when a robot manipulator operates at high speed. It is a challenging problem in control field to find an effective control scheme to achieve accurate tracking of the desired motion (Khoiyani *et al.*, 2015; Singh *et al.*, 2013; Han *et al.*, 2015; Cuong *et al.*, 2016).

The control technology for robotic motion and force has developed closely along with the development of control theories. Recently, the application of intelligent control such as fuzzy control and neural control to the position control of robotic manipulator have received considerable attention. A robust neural network output feedback control scheme that includes a novel neural network observer is presented for the motion control of robot manipulator (Kim *et al.*, 1999). A kind of fuzzy disturbance observer approach is presented (Kim *et al.* 2002; Kim *et al.* 2004) for a class of SISO nonlinear system. This approach aims to observe the compound disturbance made of external disturbance and internal uncertainties through application of the universal approximation of fuzzy logic

Received (June 3, 2016), Review Result (January 13, 2017), Accepted (January 23, 2017)

system, and to design control law of system based on this observer. A neural network disturbance observer approach for a class of MIMO system is introduced (Chen al., 2006).

To further simplify the system design, this paper proposes a novel robust tracking control method for robot manipulators with unknown external disturbances and internal uncertainties based on neural network observer. A prominent feature of this method is its application of the concept of ‘dominant input’ (Liu *et al.* 2002). That is to say, a $m \times m$ -dimensional MIMO system will be decomposed into m SISO systems for their respective design. As for each subsystem, the neural network disturbance observer will be designed to observe the compound disturbance which consists of external disturbance, internal uncertainty and cross-coupling of subsystems, and novel control law and parameter update law will be deduced from observer to guarantee that all the signals in the system are uniformly ultimately. At the same time, robust control is introduced in controller for overcoming the effects of observational error. This paper proves the availability of the method in both theory and simulation experiment.

The rest of the paper is organized as follows. Firstly, the problem is formulated in Section II. Design of neural network disturbance observer and H_∞ controller is given in III. Stability analysis of control system is given in Section IV. In Section V, simulation results are presented to confirm the effectiveness and applicability of the proposed method. Section VI contains the conclusions.

2. Problem Formulation

The traditional dynamic model of a n -Degree of Freedom (DOF) robot manipulator is presumed to be in the subsequent form by Lewis *et al.* (1999)

$$H(q)\ddot{q} + C(q, \dot{q}) + \phi(q) + \tau = u(t) \quad (1)$$

Where $H(q) \in R^{n \times n}$ represents the inertia matrix, $C(q, \dot{q}) \in R^{n \times n}$ represents the centripetal-coriolis matrix, $\phi(q) \in R^n$ represents the gravity effects, $\tau \in R^n$ denotes the friction effects, $u(t) \in R^n$ signifies the torque input control vector and $q, \dot{q}, \ddot{q} \in R^n$ signify link position, velocity and acceleration correspondingly. Figure 1 describes the configuration of 2-DOF robot manipulator

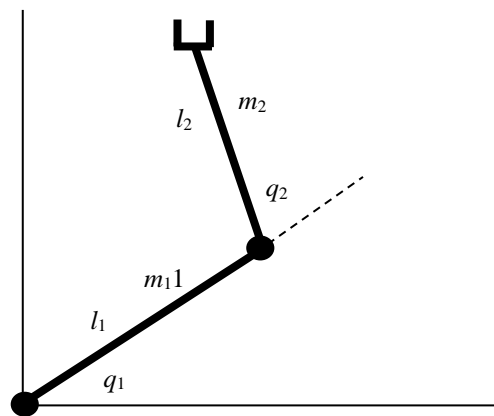


Figure 1. Configuration of 2-DOF Robot Manipulator

$$\text{Where } H(q) = \begin{bmatrix} a_1 + 2a_3 \cos q_2 + 2a_4 \sin q_2 & a_2 + a_3 \cos q_2 + a_4 \sin q_2 \\ a_2 + a_3 \cos q_2 + a_4 \sin q_2 & a_2 \end{bmatrix},$$

$$M(q, \dot{q}) = C(q, \dot{q}) + \phi(q) = \begin{bmatrix} -(a_3 \sin q_2 - a_4 \cos q_2) \dot{q}_1 \dot{q}_2 - (a_3 \sin q_2 - a_4 \cos q_2) (\dot{q}_1 + \dot{q}_2) \dot{q}_2 \\ (a_3 \sin q_2 - a_4 \cos q_2) \dot{q}_1^2 \\ \begin{pmatrix} -h\dot{q}_2 & -h\dot{q}_1 - h\dot{q}_2 \\ h\dot{q}_1 & 0 \end{pmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} \end{bmatrix}$$

The other parameters are as following

$$a_1 = I_1 + m_1 l_{c1}^2 + I_e + m_e l_{ce}^2 + m_e l_1^2, a_2 = I_e + m_e l_{ce}^2, a_3 = m_e l_1 l_{ce} \cos 30^\circ, a_4 = m_e l_1 l_{ce} \sin 30^\circ, m_1 = 1 \text{ kg}, m_e = 2 \text{ kg}, l_1 = 1 \text{ m}, l_{c1} = 0.5 \text{ m}, l_{ce} = 0.6 \text{ m}, I_1 = 0.12 \text{ kgm}^2, I_e = 0.25 \text{ kgm}^2.$$

According to the above parameters, $H(q) = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}$ is a positive definite matrix.

Rewriting equation (1) as

$$\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}^{-1} \left(- \begin{pmatrix} -h\dot{q}_2 & -h\dot{q}_1 - h\dot{q}_2 \\ h\dot{q}_1 & 0 \end{pmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} - \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \right) \\ = \frac{1}{H_{11}H_{22} - H_{12}H_{21}} \left\{ \begin{pmatrix} -H_{22}h\dot{q}_2 + H_{12}h\dot{q}_1 & H_{22}(h\dot{q}_1 + h\dot{q}_2) \\ -H_{21}h\dot{q}_2 - H_{11}h\dot{q}_1 & -H_{21}(h\dot{q}_1 + h\dot{q}_2) \end{pmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} + \begin{pmatrix} H_{22} & -H_{12} \\ -H_{21} & H_{11} \end{pmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \right\} \quad (2)$$

The relative order of the system is $[r_1, r_2] = [2, 2]$. Defining $x^T = [x_1^T, x_2^T]$, $x_i^T = [q_i, \dot{q}_i]$, $i = 1, 2$.

Rewriting equation (2) as

$$\begin{cases} \dot{x} = A'x + B'[F(x) + G(x)u + \tau(x)] \\ y = C'^T x \end{cases} \quad (3)$$

According to the relative order of the system, the input-output equation is

$$\begin{bmatrix} y_1^{(r_1)} \\ y_2^{(r_2)} \end{bmatrix} = F(x) + \Delta F(x) + G(x)u + \Delta G(x)u + \tau(x), y_1 = x_{11}, y_2 = x_{21} \quad (4)$$

Where

$$F(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \end{bmatrix} = -H^{-1}(q)M(q, \dot{q}), G(x) = \begin{bmatrix} g_{11}(x) & g_{12}(x) \\ g_{21}(x) & g_{22}(x) \end{bmatrix} = H^{-1}(q) \cdot \Delta F(x) = \begin{bmatrix} \Delta f_1(x) \\ \Delta f_2(x) \end{bmatrix} \text{ and}$$

$\Delta G(x) = \begin{bmatrix} \Delta g_{11}(x) & \Delta g_{12}(x) \\ \Delta g_{21}(x) & \Delta g_{22}(x) \end{bmatrix}$ are the parameter uncertainty.

$$\tau(q, \dot{q}) = \begin{bmatrix} \tau_1(q, \dot{q}) \\ \tau_2(q, \dot{q}) \end{bmatrix} = -H^{-1}(q)\tau, A' = \text{diag}[A'_1, A'_2], B' = \text{diag}[B'_1, B'_2], C'^T = \text{diag}[C'_1, C'_2]$$

$$A'_i = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, B'_i = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, C'_i = [1 \quad 0], i = 1, 2.$$

The 2×2 -dimensional MIMO system given in (4) can be seen as 2 SISO systems. And its subsystem is as the following

$$y_i^{(r_i)} = f_i(x) + \Delta f_i(x) + g_{i1}(x)u_1 + g_{i2}(x)u_2 + \sum_{j=1}^2 \Delta g_{ij}(x)u_j + \tau_i \quad (5)$$

and $i = 1, 2$. The output of this subsystem will be influenced by the input from u_1 to u_2 .

Choosing an input as 'dominant input' among these 2 inputs marked as u_i and the rest will be taken as the disturbance. We obtain

$$y_i^{(r_i)} = f_i(x) + g_{ii}(x)u_i + \omega_i(x, u) \\ \omega_i(x, u) = \Delta f_i(x) + \sum_{j=1}^2 \Delta g_{ij}(x)u_j + \sum_{\substack{j=1 \\ j \neq i}}^2 g_{ij}(x)u_j + \tau_i \quad (6)$$

In this way, a 2×2 -dimensional MIMO system can be decomposed into 2 SISO systems.

In this paper, the universal approximation of neural networks is used as disturbance observer to observe the overall compound disturbance of system. And a robust adaptive controller is designed consequently to make input y_i in system (3) and $y_i, \dots, y_i^{(r_i-1)}$ to track the bounded reference signal y_{id} and its corresponding derivatives. As for a given disturbance attenuation level constant $\rho > 0$, the following H_∞ tracking performance index will be obtained

$$\frac{1}{2} \int_0^T e^T Q e dt \leq \frac{1}{2} e^T(0) P e(0) + \sum_{i=1}^2 \frac{1}{2\gamma_i} \tilde{\theta}_i^T(0) \tilde{\theta}_i(0) + \sum_{i=1}^2 \left(\frac{1}{2} \zeta_i^2(0) + \int_0^T \left(\frac{1}{2} \rho^2 + \frac{1}{2\sigma_i} \right) \bar{\varepsilon}_i^2 dt \right) \quad (7)$$

Where $\gamma_i > 0$ is learning rate. $\sigma_i > 0$ is design parameter, $T \in [0, \infty)$, $e = [e_1^T, e_2^T]^T$ are output vectors of tracking error. $\tilde{\theta}_i$ is vector of parameter approximating error. ζ_i is error of disturbance observation. $\bar{\varepsilon}_i$ is the upper bound for neural networks approximating error. $P = \text{diag}(P_1, P_2)$, $Q = \text{diag}(Q_1, Q_2)$.

3. Designs of Neural Network Disturbance Observer and H_∞ Controller

Considering system (6), and we also define

$$\bar{e}_i = y_{id} - y_i, e_i = [\bar{e}_i, \dot{\bar{e}}_i, \dots, \bar{e}_i^{(r_i-1)}]^T, k_i = [k_{i r_i} \dots k_{i 1}]^T \in R^{r_i}$$

The output of neural network disturbance observer is $\hat{\omega}_i$. If $\hat{\omega}_i$ can approximate the disturbance ω_i of system well, then we can choose the controller in the following form for system (6) with considering $g_{ii}(x) \neq 0$

$$u_i = \frac{1}{g_{ii}(x)} (-f_i(x) + v_i - \hat{\omega}_i - u_{ia}) \quad (8)$$

where $v_i = y_{id}^{(r_i)} + k_i^T e_i$, u_{ia} is the robust control input proposed subsequently.

Substituting (8) to (6), we can get

$$e_i^{(r_i)} = -k_i^T e_i + \hat{\omega}_i - \omega_i + u_{ia} \quad (9)$$

Rewriting equation (9) as following

$$\dot{e}_i = A_i e_i + B_i (\hat{\omega}_i - \omega_i) + B_i u_{ia} \quad (10)$$

$$\text{where } A_i = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -k_{i r_i} & -k_{i r_i-1} & -k_{i r_i-2} & \dots & -k_{i 1} \end{bmatrix}, B_i = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}.$$

Assumption 1: if $x \in M_x$, M_x is a compact set, then the optimal parameter of neural networks is defined as

$$\theta_i^* = \arg \min_{\theta_i \in \Omega_i} \left[\sup_{x \in M_x} |\omega_i - \hat{\omega}_i| \right] \quad (11)$$

where $\Omega_i = \{\theta_i \mid \|\theta_i\| \leq M_i\}$ means the subset with hope border, M_i is the design parameter. And the output of neural network disturbance observer is $\hat{\omega}_i = \theta_i^T \xi$. $\theta_i = (\theta_{i1}, \dots, \theta_{im})^T$ is adjustable parameter vector. $\xi(x) = (\xi_1(x) \dots \xi_M(x))^T$ is the basis function vector.

According to universal approximation theorem, the existence of optimal parameter θ_i^* can make $\hat{\omega}_i(x | \theta_i^*)$ approximate to compound disturbance ω_i as much as possible. Therefore

$$\omega_i(x) = \hat{\omega}_i(x | \theta_i^*) + \varepsilon_i = \theta_i^{*T} \xi + \varepsilon_i, \|\varepsilon_i\| \leq \bar{\varepsilon}_i \quad (12)$$

where ε_i is the approximation error. $\bar{\varepsilon}_i$ is the upper bound of approximation error. Then equation (10) can be written as

$$\begin{aligned}\dot{e}_i &= A_i e_i + B_i (\theta_i^T \xi(x) - \tilde{\theta}_i^{*T} \xi(x) - \varepsilon_i) + B_i u_{ia} \\ &= A_i e_i + B_i \tilde{\theta}_i^T \xi(x) + B_i u_{ia} - B_i \varepsilon_i\end{aligned}\quad (13)$$

$\tilde{\theta}_i = \theta_i - \theta_i^*$ is the parameter approximating error. The H_∞ controller of error is chosen as

$$u_{ia} = -\frac{1}{r} B_i^T P_i e_i \quad (14)$$

$P_i = P_i^T \geq 0$ is the solution to the following equation

$$P_i A_i + A_i^T P_i + Q_i - \frac{2}{r} P_i B_i B_i^T P_i + \frac{1}{\rho^2} P_i B_i B_i^T P_i = 0 \quad (15)$$

Where $Q_i > 0$. The proper weight is chosen to make $2\rho^2 \geq r$ to obtain a symmetric positive semi-definite solution. Choosing i -th disturbance observer system as the following

$$\dot{\mu}_i = -\sigma_i \mu_i + p_i(x, \hat{\omega}_i), \quad \mu_i \in R^p \quad (16)$$

where $p_i(x, \hat{\omega}_i) = \sigma_i y_i^{(\sigma_i-1)} + f_i(x) + g_{ii}(x)u + \hat{\omega}_i$.

Define disturbance observation error $\zeta_i = y_i^{(\sigma_i-1)} - \mu_i$, then from (6) and (16), the dynamic of disturbance observation error can be derived as

$$\dot{\zeta}_i = -\sigma_i \zeta_i + \omega_i - \hat{\omega}_i \quad (17)$$

If $\zeta_i \rightarrow 0$, which means $\mu_i \rightarrow y_i^{(\sigma_i-1)}$, then output $\hat{\omega}_i$ of neural network is proved to approximate to unknown disturbance ω_i .

Theorem 1: Assuming using neural network disturbance observer (16) to estimate disturbance, taking the controller (8) as the controller of system (6), and choosing adaptive law of neural network parameters as:

$$\dot{\theta}_i = \gamma_i e_i^T P_i B_i \xi(x) + \gamma_i \zeta_i \xi(x) \quad (18)$$

Then the observation errors are uniformly ultimately bounded, and the tracking error of system (6) is smaller than the given performance index:

$$\frac{1}{2} \int_0^T e_i^T Q_i e_i dt \leq \frac{1}{2} e_i^T(0) P_i e_i(0) + \frac{1}{2\gamma_i} \tilde{\theta}_i^T(0) \tilde{\theta}_i(0) + \frac{1}{2} \zeta_i^2(0) + \int_0^T \left(\frac{1}{2} \rho^2 + \frac{1}{2\sigma_i} \right) \bar{\varepsilon}_i^2 dt \quad (19)$$

$\gamma_i > 0$ is learning rate. $\sigma_i > 0$ is design parameter. $\tilde{\theta}_i = \theta_i^* - \theta_i$.

Proof: Choosing an adequate Lyapunov function as

$$V_i = \frac{1}{2} e_i^T P_i e_i + \frac{1}{2\gamma_i} \tilde{\theta}_i^T \tilde{\theta}_i + \frac{1}{2} \zeta_i^2 \quad (20)$$

Taking the time derivative of V_i , and considering (14), then we get

$$\dot{V}_i = \frac{1}{2} e_i^T (A_i^T P_i + P_i A_i) e_i + e_i^T P_i B_i \tilde{\theta}_i^T \xi(x) + e_i^T P_i B_i u_{ia} - e_i^T P_i B_i \varepsilon_i + \frac{1}{\gamma_i} \tilde{\theta}_i^T \dot{\tilde{\theta}}_i + \zeta_i \dot{\zeta}_i \quad (21)$$

Taking (14), (15), (17), (18) into account in above equation.

$$\dot{V}_i = -\frac{1}{2} e_i^T Q_i e_i - \frac{1}{2\rho^2} e_i^T P_i B_i B_i^T P_i e_i - e_i^T P_i B_i \varepsilon_i - \sigma_i \zeta_i^2 + \zeta_i \bar{\varepsilon}_i \quad (22)$$

We know $-\sigma_i \zeta_i^2 + \zeta_i \bar{\varepsilon}_i \leq -\frac{\sigma_i}{2} \zeta_i^2 + \frac{1}{2\sigma_i} \bar{\varepsilon}_i^2$, then

$$\begin{aligned}\dot{V}_i &\leq -\frac{1}{2} e_i^T Q_i e_i - \frac{1}{2\rho^2} e_i^T P_i B_i B_i^T P_i e_i - e_i^T P_i B_i \varepsilon_i + \frac{1}{2\sigma_i} \bar{\varepsilon}_i^2 \\ &= -\frac{1}{2} e_i^T Q_i e_i - \frac{1}{2} \left[\left(\frac{1}{\rho} B_i^T P_i e_i + \rho \varepsilon_i \right)^T \left(\frac{1}{\rho} B_i^T P_i e_i + \rho \varepsilon_i \right) \right]\end{aligned}$$

$$\begin{aligned}
 & + \frac{1}{2} \rho^2 \bar{\varepsilon}_i^2 + \frac{1}{2\sigma_i} \bar{\varepsilon}_i^2 \\
 & \leq -\frac{1}{2} \lambda_{\min}(Q_i) \|e_i\|^2 + \frac{1}{2} \rho^2 \bar{\varepsilon}_i^2 + \frac{1}{2\sigma_i} \bar{\varepsilon}_i^2
 \end{aligned} \tag{23}$$

If $\|e_i\| \geq \sqrt{\frac{1}{\lambda_{\min}(Q_i)}} |\rho| \bar{\varepsilon}_i + \sqrt{\frac{1}{\sigma_i \lambda_{\min}(Q_i)}} \bar{\varepsilon}_i$ then $\dot{V}_i < 0$.

The Lyapunov function for the overall system structure is $V = V_1 + V_2$, taking the time derivative of V , we get $\dot{V} = \dot{V}_1 + \dot{V}_2$. Then

$$\dot{V} = \dot{V}_1 + \dot{V}_2 < 0 \tag{24}$$

So, the closed-loop system's stability is guaranteed with the effect of designed controller. And the error of observer will be uniformly ultimately bounded.

Integrating equation (24), we can get

$$V_i(T) - V_i(0) \leq -\frac{1}{2} \int_0^T e_i^T Q_i e_i dt + \int_0^T \left(\frac{1}{2} \rho^2 \bar{\varepsilon}_i^2 + \frac{1}{2\sigma_i} \bar{\varepsilon}_i^2 \right) dt \tag{25}$$

Because $V_i(T) \geq 0$, according to (25), we can get equation (19). This completes the proof. The overall system will get H_∞ tracking performance (7).

4. Simulation Study

The design parameters are selected as

$$Q_1 = Q_2 = \begin{pmatrix} 10 & \\ & 10 \end{pmatrix}, \quad \rho = 0.05, \quad r = 0.005, \quad k_1 = k_2 = [1, 2]^T, \quad \sigma_1 = \sigma_2 = 10,$$

$\gamma_1 = 18, \gamma_2 = 5$. $P_1 = P_2 = \begin{pmatrix} 15 & 5 \\ 5 & 5 \end{pmatrix}$ is the solution to Riccati equation (15). The control objective is to force the system output y to follow the desired trajectory that is employed as $q_d = [q_{1d}, q_{2d}] = [\cos \frac{\pi}{4}(t-0.5), \cos \left(\frac{\pi}{6} t \right)]$.

RBF neural network disturbance observer is $\hat{\omega}_i = \theta_i^T \xi, i = 1, 2$. $\xi(x) = (\xi_1(x) \cdots \xi_M(x))^T$ is the basic function vector, where $\xi_i(x) = \exp \left[\frac{-(x - \mu_i)^T (x - \mu_i)}{\sigma_i^2} \right], i = 1, \dots, M$,

$\mu_i = [\mu_{i1}, \mu_{i2}, \mu_{i3}, \mu_{i4}]^T$ is the center of Gaussian function. σ_i is the width. M is the node number.

According to the design process, we can get the control law as following

$$\begin{aligned}
 u_1 &= \frac{1}{g_{11}(q)} \left(-f_1(q, \dot{q}) + \ddot{q}_{1d} + e_1 + 2\dot{e}_1 - \theta_1^T \xi(x) - u_{1a} \right) \\
 u_{1a} &= -200(5e_1 + 5\dot{e}_1) \\
 \dot{\theta}_1 &= 18(5e_1 + 5\dot{e}_1) \xi(x) + 18\zeta_1 \xi(x) \\
 \dot{\zeta}_1 &= -10\zeta_1 - \tilde{\theta}_1^T \xi(x) \\
 u_2 &= \frac{1}{g_{22}(q)} \left(-f_2(q, \dot{q}) + \ddot{q}_{2d} + e_2 + 2\dot{e}_2 - \theta_2^T \xi(x) - u_{2a} \right) \\
 u_{2a} &= -200(5e_2 + 5\dot{e}_2) \\
 \dot{\theta}_2 &= 5(5e_2 + 5\dot{e}_2) \xi(x) + 5\zeta_2 \xi(x) \\
 \dot{\zeta}_2 &= -10\zeta_2 - \tilde{\theta}_2^T \xi(x)
 \end{aligned}$$

The system initial conditions are $x(0)=[1,0,0,0]^T$. Considering the disturbance $\tau = [0.1\sin(0.3t), 0.2\sin(0.2t)]$, The simulation results using MATLAB are shown in Figure 2 and Figure 3.

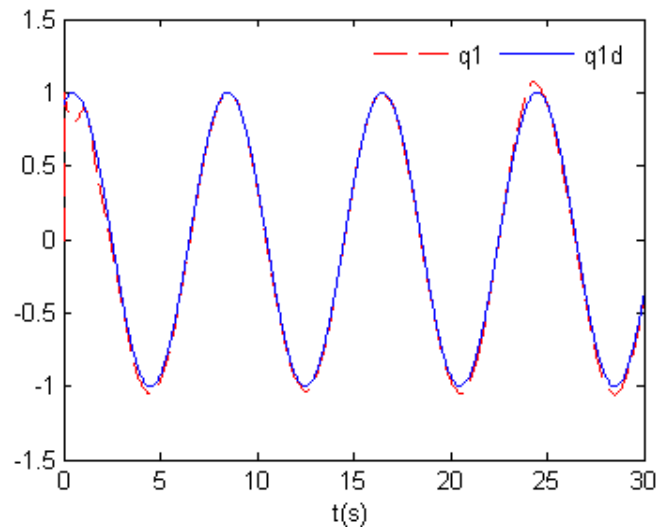


Figure 2. Plots of Output 1 Tracking of System

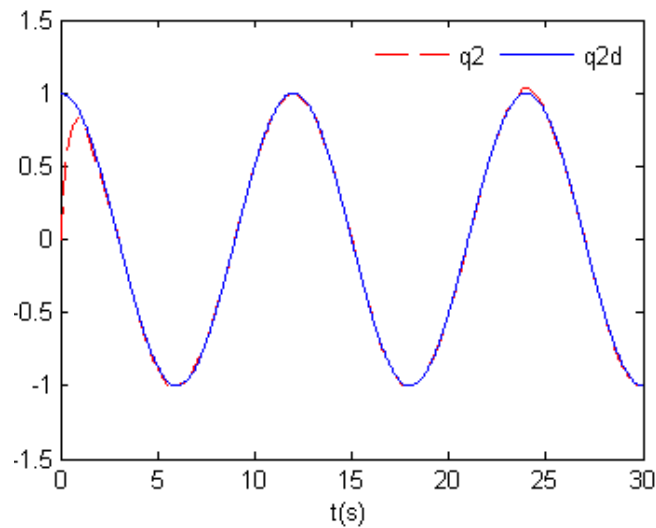


Figure 3. Plots of Output 2 Tracking of System

Considering the influence of system parameters uncertainty, $\Delta F(q, \dot{q}) = \begin{bmatrix} -0.25 \sin(q_1) \\ 0.25 \sin(q_2) \end{bmatrix}$,

$$\Delta G(q, \dot{q}) = \begin{bmatrix} 0.25 & 0.125(\sin(q_1)\sin(q_2) + \cos(q_1)\cos(q_2)) \\ -0.125(\sin(q_1)\sin(q_2) + \cos(q_1)\cos(q_2)) & 0.25 \end{bmatrix}$$

The simulation results are shown in Figure 4 and Figure 5.

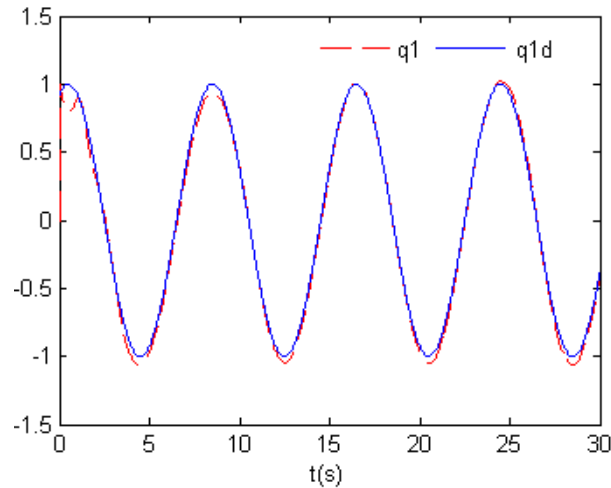


Figure 4. Plots of Output 1 Tracking of System

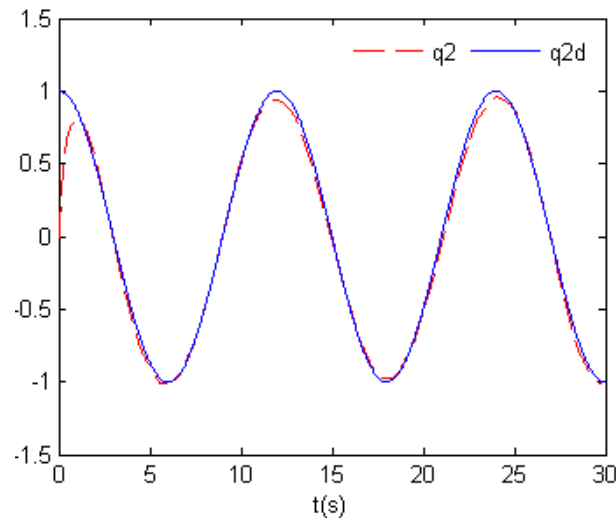


Figure 5. Plots of Output 2 Tracking of System

It can be seen that the actual trajectory converges rapidly to the desired one and the system has strong anti-disturbance ability. It can also realize the tracking control when the system has the parameters uncertainty and disturbance. These simulation results demonstrate the tracking capability of the proposed controller and its effectiveness for control tracking of robot manipulator with disturbance and parameter uncertainty.

5. Conclusions

The paper presents a neural network tracking control approach based on disturbance observer for robot manipulator with unknown external disturbance and parameter uncertainty. By using the concept of ‘dominant input’, the robot manipulator is transferred into several SISO systems with the unknown compound disturbance which consists of external disturbance, internal parameter uncertainty and cross-coupling of subsystems. The compound disturbance is monitored by the designed neural network observer and then control law and parameters update law of system are designed based on the neural network disturbance observer. The simulation results show that the tracking capability of the proposed controller which can guarantee all the signals in the system are uniformly ultimately bounded. Our further research will be focused on such applications of the proposed neural network disturbance observer.

Acknowledgment

It is a project supported by National Natural Science Fund, China (Grant No.5177040). Supported by Scientific Research Fund of Hunan Provincial Education Department, China (Study of Intelligent Vehicle's Lateral Robust Stable Controller on Neural Network). Supported by Provincial Natural Science Foundation of Hunan, China (Grant No. 13JJ9022). Supported by Provincial Natural Science Foundation of Hunan, China (Grant No. 14JJ6041). Supported by the Construct Program of the Key Discipline in Hunan Province: Control Science and Engineering, Science and Technology Innovation Team of Hunan Province: Complex Network Control. Supported by CIC-WEP.

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Authors



Hui Hu, she is an associate professor of Department of electrical and information engineering, Hunan institute of engineering. Dr. Hu received the B.S. degree in electronics and information engineering from Hunan University of Science and Technology in 2001. And received the M.S. degree in power electronics and drives from Xiangtan University in 2004. And received the Ph. D degree in control theory and control engineering from Hunan University in 2010. Her research interests include nonlinear systems tracking control, MIMO systems control, uncertain nonlinear system control and intelligent control.



Peng Guo, he is an associate professor of Department of Computer and Science, Hunan institute of engineering. He received the B.S. degree in electronics and information engineering from Hunan University of Science and Technology in 2000 and received the M.S. degree in computer science from Hunan University in 2006. His research interests include intelligent control and computing theory, multimedia computing and networking and agent technology.



Xilong Qu, he was born in 1978. He received his Ph. D from Southwest Jiaotong University in 2006. He is an associate professor of Hunan Institute of Engineering, master supervisor of Xiangtan University, the key young teacher of Hunan province, academic leader of computer application technology in Hunan Institute of Engineering. His research interesting is web service technology, information safety and networked manufacturing. He presided the projects supported by Scientific Research Fund of Hunan Provincial Education Department (08A009), the projects supported by Provincial Natural Science Foundation of Hunan (13JJ9022) and the project supported by Provincial Science & Technology plan project of Hunan (2010GK3048). He has published more than 30 papers in some important magazines.