Neural Network Control with Disturbance Observer for Uncertain Robot Manipulator

San-Xiu Wang *, Guang Chen, Ling-Wei Wu
College of electronic and Information Engineering, Taizhou University, Taizhou, Zhejiang, 318000, China.

* Corresponding author. Email: wsx8188@163.com
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Abstract: Robot manipulators are subject to different types of uncertainties which may degrade the tracking control performance or even make the system unstable. In this paper, a neural network tracking controller with disturbance observer is developed to deal with both the external disturbance and the dynamic parametric uncertainties. First, RBF neural network is introduced to learn and approximate the uncertain robot dynamic by using adaptive algorithm. Next, a nonlinear disturbance observer is designed to estimate and compensate for external disturbances and remove the effect of the disturbance. Simulation results show that the proposed control scheme has good tracking performance, which can effectively suppress the uncertain dynamics and external disturbances of the manipulator systems.

Key words: Robot manipulators, disturbance observer, RBF neural network, uncertain dynamic.

1. Introduction

Robot manipulator is a very complex multi-input and multi-output nonlinear dynamics system. It is inevitable to have kinds of uncertainties, and cannot obtain the accurate dynamic model of the system. From the inside system, because of the measure and modeling inaccuracy, the parameters of the dynamic model are very difficult to know, such as the quality and length of each link. From the outside, the robot system is easily affected by the load change and the unpredictable disturbances. So, for the robot manipulator with parameters uncertainties and external disturbance, how to design appropriate control scheme to ensure the robustness of the system is a complex problem.

In order to improve the tracking accuracy of the robot manipulator control system with parameter uncertainties and external disturbance, Many control algorithm such as the adaptive control [1], [2], intelligent control [3], [4], disturbance observer [5] and robust control [6], [7] have been proposed to deal with this robotic control problem. However, as well known, the adaptive control and robust control depended on the complete dynamics of robots, or the unknown parameters must be of linear structure, moreover, the unknown parameters are assumed to be constant or slowly varying. But, as the robotic dynamic systems are nonlinear, highly coupled and time varying, the linear parameterization properly may not be applicable. While neural network has the universal approximation characteristics of approximating any nonlinear function with arbitrary precision. It is not relied on the robot dynamic model and suitable for approximating the unknown parameters of the dynamics model and remove the influence of the un-modeled dynamics. The basic idea of the disturbance observer is to observe or estimate the uncertainties by constructing a new dynamic system. Then, the observer's estimation output is used to
offset the impact of uncertainties and improve the control performance [8]. Therefore, disturbance observer can well suppress the unpredictable or random external disturbances, which greatly enhances the system's robustness.

Combined with the advantages of neural network and disturbance observer, in this paper, a stable neural network tracking controller with disturbance observer is proposed for robot manipulator system with un-modeled dynamics and external disturbances. In which, the neural network is introduced to approximate the un-modeled dynamic caused by parameters uncertainties, and the nonlinear disturbance observer is used to estimate and compensate for the external disturbances. Finally, the validity of the control algorithm for suppression un-modeled dynamics and external disturbance is verified by the simulation experiment on a single joint robot manipulator.

This paper is organized as follows. The problem is formulated in Section 2. The RBF neural controller and disturbance observer are presented in Section 3 and Section 4, respectively. Simulation results are provided in Section 5. Finally, some concluding remarks given in Section 6.

2. Problem Formulations

The dynamic equation of an $N$-joint robot can be expressed as

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

(1)

where $q$, $\dot{q}$ and $\ddot{q}$ denote joint position, velocity and acceleration vectors respectively. $M(q) \in \mathbb{R}^{n \times n}$ is the positive definite inertia matrix, $C(q, \dot{q}) \in \mathbb{R}^n$ is the Coriolis and centrifugal force vector, $G(q) \in \mathbb{R}^n$ is the gravity vector. $d$ is external disturbances. $\tau$ represents the control torque vector.

If the complete dynamics of robots are known and there is no external disturbance, then according to the computed torque method, the robot control torque can be designed as

$$\tau = M(q)(\ddot{q}_d - \dot{k}_p e - k_v e) + C(q, \dot{q})\dot{q} + G(q)$$

(2)

where, $q_d$, $\dot{q}_d$ and $\ddot{q}_d$ are the desired joint position, velocity and acceleration respectively, $e = q - q_d$, $\dot{e} = \dot{q} - \dot{q}_d$ are the position tracking error and velocity tracking error respectively. $K_p$, $K_v$ are proportional and derivative constant matrices.

According to the Eq.(1). and Eq.(2), the stable closed loop system can be expressed as

$$\ddot{e} + k_p \dot{e} + k_v e = 0$$

(3)

However, due to parameter measurement error, external environment and load change, the perfect robot model could be difficult to obtain and external disturbances are always present in practice. The parameter matrix $M(q)$, $C(q, \dot{q})$ and $G(q)$ can be divided into two parts: Nominal model parameter matrix $M_0(q)$, $C_0(q, \dot{q})$ and $G_0(q)$; and model error $\Delta M(q)$, $\Delta C(q, \dot{q})$ and $\Delta G(q)$, which represent the parameter uncertainties. And denoting

$$\Delta M = M - M_0$$

(4)

$$\Delta C = C - C_0$$

(5)

$$\Delta G = G - G_0$$

(6)
Based on the nominal model of robot, the control law is

$$
\tau_0 = M_o(q)(\ddot{q} - k_v \dot{q} + k_p e) + C_o(q, \dot{q}) \dot{q} + G_o(q)
$$

(7)

Substituting Eq. (7) into Eq. (1), yields

$$
M(q) \ddot{q} + C(q, \dot{q}) \dot{q} + G(q) = M_o(q)(\ddot{q} - k_v \dot{q} + k_p e) + C_o(q, \dot{q}) \dot{q} + G_o(q) - d
$$

(8)

$$
M_o(q)\ddot{q} + C_o(q, \dot{q}) \dot{q} + G_o(q) \quad \text{is used to subtract the upper left and right sides respectively, and get}
$$

$$
\ddot{e} + k_v \dot{e} + k_p e = M_o^{-1}(\Delta M(q) \ddot{q} + \Delta C(q, \dot{q}) \dot{q} + \Delta G(q) - d) = M_o^{-1}(\Delta M(q) \ddot{q} + \Delta C(q, \dot{q}) \dot{q} + \Delta G(q)) - M_o^{-1} d
$$

(9)

where, $M_o^{-1}(\Delta M(q) \ddot{q} + \Delta C(q, \dot{q}) \dot{q} + \Delta G(q))$ is un-modeled dynamics caused by the model uncertainties, let $f(x) = M_o^{-1}(\Delta M(q) \ddot{q} + \Delta C(q, \dot{q}) \dot{q} + \Delta G(q)); -M_o^{-1} d$ represents the disturbance uncertainties caused by the external disturbance.

It is well known that imperfect robot model will lead to degradation of tracking performance. So it is necessary to approximate the un-modeled dynamics and external disturbance. Next, the neural network and disturbance observer are employed to approximate the un-modeled dynamic and external disturbance respectively

3. Controller Design

3.1. RBF Neural Network Controller Design

RBF neural networks are capable of universal approximations, i.e. approximation of any continuous function over a compact set to any degree of accuracy. Therefore, in this section, without considering the external disturbance, we use RBF neural network to approximate nonlinear un-modeled dynamics function $f(x)$.

RBF neural network algorithm can be characterized by

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

(10)

$$
\varphi_i(x) = \exp\left(-\frac{|x-c_i|^2}{\sigma_i^2}\right) \quad i = 1, 2, \ldots, n
$$

(11)

where, $x \in \mathbb{R}^n$ is the input vector, $\theta$ is the Neural network weight vector. $\hat{\theta}$ is the network weight estimation of $\theta$, $\varphi(x) = [\varphi_1(x), \varphi_2(x), \ldots, \varphi_n(x)]^T$ is a Gauss function. $c_i$ and $\sigma_i$ are the center and width of the $i$th basis function.

RBF neural network structure with $m$ input, $n$ output and $h$ hidden layer is shown in Fig. 1.

![Fig. 1. Structure of RBF neural network.](image-url)
It has been proved that RBF neural network can approximate any continuous function with arbitrary precision [9], that is

\[ f(x) = \theta^T \varphi(x) + \varepsilon_0 \]  

(12)

In which, \( \theta^* \) is the optimal weight vector, \( \varepsilon_0 \) is neural network approximation error.

Without considering external perturbation, the Eq. (9) is expressed as

\[ \ddot{e} + k_e \dot{e} + k_p e = M_0^{-1}(\Delta M(q)\ddot{q} + \Delta C(q, \dot{q})\dot{q} + \Delta G(q)) = f(x) \]  

(13)

Define state vector \( \mathbf{x} = (e, \dot{e})^T \), the error equation (13) can be rewritten as the following state space equation

\[ \dot{\mathbf{x}} = A\mathbf{x} + Bf \]  

(14)

where, \( A = \begin{bmatrix} 0 & I \\ -K_p & -K_v \end{bmatrix} \), \( B = \begin{bmatrix} 0 \\ I \end{bmatrix} \)

Neural network adaptive law is designed as

\[ \dot{\theta} = \gamma \varphi(x)x^T PB \]  

(15)

where, the matrix \( P \) is a symmetric positive definite matrix, and satisfies the following Lyapunov equation

\[ A^T P + PA = -Q \quad Q \geq 0 \]  

(16)

3.2. Disturbance Observer Design

In order to reduce the influence of external disturbance and improve the system control accuracy, the disturbance observer is introduced to approximate the external disturbance.

Without considering the un-modeling dynamic, the Eq. (1) is written as

\[ \ddot{q} = -M_0^{-1}C_0\dot{q} + M_0^{-1}\tau - M_0^{-1}d - M_0^{-1}G_0 \]  

(17)

Define \( a = M_0^{-1} \), \( b = -M_0^{-1}C_0 \), \( d' = M_0^{-1}d \), then Eq.(17) can be expressed as

\[ \ddot{q} = -b\dot{q} + a\tau - d' - M_0^{-1}G_0 \]  

(18)

Disturbance observer is designed as

\[ \hat{d}' = k_1(\dot{\hat{\omega}} - \dot{q}) \]  

(19)

\[ \dot{\hat{\omega}} = -\hat{d}' + a\tau - k_1(\dot{\hat{\omega}} - \dot{q}) - b\dot{q} - M_0^{-1}G_0 \]  

(20)

where, \( \hat{d}' \) is the estimation of the disturbance \( d' \), \( \hat{\omega} \) is the estimation of \( \dot{q} \), \( k_1 > 0 \), \( k_2 > 0 \)

Stability analysis

Define
\[ V = \frac{1}{2k_i} \ddot{\omega}^2 + \frac{1}{2} \dot{\omega}^2 \]  

(21)

where, \( \ddot{\omega} = \dot{\omega}' - \dot{\omega}, \quad \dot{\omega} = \dot{q} - \dot{\omega} \)

Taking the time derivative of \( V \), we have

\[ \dot{V} = \frac{1}{k_i} \ddot{\omega}' \dot{\omega} + \ddot{\omega} \dot{\omega}' = \frac{1}{k_i} \ddot{\omega}' (\dot{\omega}' - \dot{\omega}) + \dot{\omega}(\ddot{q} - \dot{\omega}) \dot{\omega} \]

(22)

Supposed external disturbance \( d' \) changes slowly, \( \dot{d}' \) is a small value, and have

\[ \frac{1}{k_i} \ddot{d}' = 0 \]

(23)

Substituting observer Eq.(19) and (20) into Eq.(22). And have

\[ \dot{V} = \frac{1}{k_i} \ddot{\omega}' \dot{\omega} + \ddot{\omega} \dot{\omega}' = \frac{1}{k_i} \ddot{\omega}' \dot{\omega} = \frac{1}{k_i} \ddot{\omega}' \dot{\omega} \]  

(24)

So, the disturbance \( d' \) can be observer and compensated effectively by the disturbance observer proposed in this section.

Combined with computed torque control, neural network controller and disturbance observer, the whole control input of the system is

\[ \tau = \tau_0 + \hat{f} + \hat{\dot{d}}' \]

(25)

Controller structure diagram is shown as Fig. 2:

![Controller structure diagram](image)

Fig. 2. Structure of neural network controller based on disturbance observer.

4. Simulation

In this section, the effectiveness of the control algorithm is verified by simulation study on a single arm manipulator. The dynamic model of robot utilized in this experiment is given as
follows. \( M \ddot{q} + C \dot{q} + G + d = r \),

where, \( M = \frac{3}{4} ml^2 \), \( G = mg l \cos \theta \), unknown external disturbance \( d = 1.3 \sin(0.5 \pi t) \). The simulation parameters are chosen as \( m = 1, \ l = 0.25, \ g = 9.8 \). Desired trajectory is chosen to be \( q_d = \sin(t) \), and the initial joint position and velocity are assumed to be 0.15 and 0, respectively.

Simulation parameters of controller are chosen as: computed torque controller with \( K_p = 10, K_v = 15 \); neural network controller with \( Q = \begin{bmatrix} 200 & 0 \\ 0 & 200 \end{bmatrix} \), \( \gamma = 50 \); The center and width of neural network function is 0.6 and 3 respectively; disturbance observer with \( k_1 = 500, \ k_2 = 300 \). Simulation results are shown in Fig. 3-6.

From the simulation results, it can be seen that the proposed control algorithm has a good tracking performance; the system just has a small tracking error in the initial stage and can keep pace with the desired trajectory quickly. It can be observer from Fig. 5 and Fig. 6, the un-modeled dynamic and external disturbance are effectively approximated and compensated by the neural network controller and disturbance observer respectively, so that the system control performance and robustness are further enhanced.

5. Conclusions

A new neural network tracking control scheme with disturbance observer for the robot with external
disturbance and dynamic parametric uncertainties is developed in this paper. The proposed scheme consists of a well-known computed torque controller, which is based on the known nominal robot dynamics model, and a RBF neural network is used to approximate the un-modeled dynamics, a nonlinear disturbance observer is employed to approximate the external disturbance. Simulation results have demonstrated the efficiency of the proposed control scheme.

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Sanxiu Wang was born in Dongyang, Zhejiang province, China, in 1981. She received her B.S. and M.S. degrees from Nanchang University, Nanchang, China, in 2003 and 2006, respectively, and her Ph.D degrees from Zhejiang University of Technology in 2015. She is currently an associate professor in the School of Electronics and Information Engineering, Taizhou University. She has authored or co-authored over 20 journal or conference papers. Her research interests include robot control, motion control and neural network.

Guang Chen was born in Zhejiang, China, in 1987. He received his B.S degree in automation engineering and Ph.D degree in control theory and engineering both from Zhejiang University of Technology, Hangzhou, China, respectively in 2009 and 2012. He currently serves as a lecturer in Taizhou University, Taizhou, China. He has authored or co-authored over 10 journal or conference papers. His research interests include traffic modeling and optimization of complex networks, data mining and deep learning algorithm.
Lingwei Wu was born in Zhejiang, China, in 1985. He received the B.E. degree in electronic information engineering and the Ph.D. degree in control science and engineering from the Zhejiang University of Technology, Hangzhou, China, in 2008, and 2016, respectively. He is currently a lecturer in Taizhou University. He has authored or co-authored over 10 journal or conference papers. His current research interests include repetitive control and sliding mode control with applications.