

ADAPTIVE CONTROL FOR ROBOTIC MANIPULATOR USING DISTURBANCE COMPENSATOR

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ABSTRACT

This paper proposes an adaptive control strategy for robotic manipulators subject to parametric and external uncertainties. A neural network is employed to approximate unknown nonlinear dynamics over a compact input space. An adaptive control law is developed to compensate for approximation errors and enhance robustness. The controller effectively handles both structured uncertainties, such as payload variation, and unstructured disturbances, including friction and external forces. Simulation results on a two-degree-of-freedom robotic manipulator, implemented in MATLAB, demonstrate the tracking performance and robustness of the proposed method.

Keyword: Adaptive control, robotic manipulator, neural network, disturbance compensation.

1. INTRODUCTION

In the past decade, the application of intelligent control techniques, particularly those utilizing neural networks, has gained significant attention for controlling the motion of robotic manipulators [7], [8]. In general, robotic manipulators face uncertain variations in their dynamics, such as friction, parameter changes, and external disturbances. It is very difficult to establish an accurate mathematical model for model-based control system design.

Therefore, a common requirement for intelligent control methods is to reduce the impact of structural parameter uncertainties and unstructured disturbances by leveraging the strong learning capabilities of neural networks without requiring detailed knowledge of the controlled system during the design process.

The primary focus of this paper is the design of an intelligent control system for position control of an n -link robotic manipulator. A neural network-based controller is employed to compensate for uncertain dynamic models and external disturbances through the self-learning capability of the neural network.

2. DYNAMICAL MODEL

For motion control, consider dynamics of an n -link robot manipulator given by a set of uncertainties and unknown input disturbances model as (1)

$$[M(q) + \Delta M]\ddot{q} + [C(q, \dot{q}) + \Delta C]\dot{q} + [g(q) + \Delta g] + F_r\dot{q} + \tau_d = \tau \quad (1)$$

where $M(q)$ is the $n \times n$ inertia matrix and C , g , are, respectively, the $n \times 1$ vectors of the Coriolis and centrifugal forces, the gravity loading. And τ is the $n \times 1$ torque vector of joint control inputs to be designed. q , $\dot{q}$ and $\ddot{q}$ are the $n \times 1$ vectors representing angular position, velocity and acceleration, respectively

And friction in the dynamic equation (1) is represented through two components. Friction depends only on the angular velocity $\dot{q}$. $F_r(\dot{q}) = F_v\dot{q} + F_d(\dot{q})$ (2)

Here, F_v is the friction coefficient matrix, and $F_d(\dot{q})$ represents the dynamic friction expression. Friction depends only on the joint angular velocity $\dot{q}$ and this characteristic is used to reduce the number of parameters in the neural network compensators.

The dynamic model of the robot possesses the following characteristic property:

$$[M(q) + \Delta M]\ddot{q} + [C(q, \dot{q}) + \Delta C]\dot{q} + g(q) + F_r\dot{q} + \tau_d = \psi(q, \dot{q}, \ddot{q})\alpha, \quad (3)$$

that is, there exists a vector $\alpha \in R^m$, whose elements depend on the parameters of the manipulator such as masses, internal moments, etc.,.

3. ADAPTIVE CONTROL OF ROBOTIC MANIPULATOR

The tracking control problem is formulated as follows: Given a reference trajectory $q^{ref} \in R^n$ and reference velocity $\dot{q}^{ref} \in R^n$, with some or all parameters of the manipulator being unknown, determine a control law τ and a sliding surface $s = 0$ such that the system's trajectory tracks the sliding surface with a predefined tracking error $\tilde{q} = q - q^{ref}$ and converges to zero as time progresses $t \rightarrow \infty$.

To solve this problem, a sliding surface is selected as follows:

$$s = \dot{\tilde{q}} + \Lambda \tilde{q} \quad (4)$$

Let Λ be a positive definite matrix whose eigenvalues lie on the left half of the complex plane, and let $\tilde{q}$ be the tracking error vector. If the sliding mode exists on the sliding surface $s = 0$, then according to the theory of Variable Structure Systems stability, the sliding mode is ensured based on the design of the matrix Λ

$$\dot{\tilde{q}} = -\Lambda \tilde{q} \quad (5)$$

Observation of equation (4) shows that the tracking error depends on the eigenvalues of the matrix Λ . If the control law is designed to ensure the sliding mode on the sliding surface $s = 0$, then the tracking error response is the solution of the linear dynamic equation (5). Based on the sliding mode control law, the control input influences the tracking error along the sliding surface $s = 0$, and a vector of desired variables is selected to achieve:

$$\dot{q}^{des}(t) = \dot{q}^{ref}(t) - \Lambda \tilde{q}(t) \quad (6)$$

The dynamic equation (1) of the manipulator can be rewritten in the following form:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) + F(q, \dot{q}, t) = \tau \quad (7)$$

With $F(q, \dot{q}, t) = F_r(\dot{q}) + \tau_d$. However, in this study, the vector of uncertain functions is replaced by $F(q, \dot{q}, \ddot{q}, t) = F_r(\dot{q}) + \tau_d$, because it includes not only disturbances and friction but also load disturbances. Therefore, equation (4.9) must be rewritten as the following equation,

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) + F(q, \dot{q}, \ddot{q}, t) = \tau \quad (8)$$

Under the assumption that $M(q), C(q, \dot{q}), g(q)$ is known in advance and all the system's state variables are measurable

To design a control law using a neural network with an adaptive mechanism, a Lyapunov function is defined as follows:

$$V(t) = \frac{1}{2}(s^T D s + \sum_{i=1}^n \tilde{\theta}_i^T \Gamma_i \tilde{\theta}_i) \quad (9)$$

where $\tilde{\theta}_i = \theta_i^* - \theta_i$, θ_i^* is the i column vector of the optimal parameter matrix θ^* , and Γ_i is a positive real constant. The time derivative of $V(t)$ has the following form:

$$\dot{V}(t) = s^T \dot{M} s + \frac{1}{2} s^T \dot{M} s + \sum_{i=1}^n \tilde{\theta}_i^T \Gamma_i \dot{\tilde{\theta}}_i = -s^T (M\dot{q}^{des} + C\dot{q}^{des} + g + F - \tau) + \sum_{i=1}^n \tilde{\theta}_i^T \Gamma_i \dot{\tilde{\theta}}_i \quad (10)$$

Where $F(q, \dot{q}, \ddot{q}, t)$ is an unknown nonlinear function vector. We replace $F(q, \dot{q}, \ddot{q}, t)$ with a MIMO neural network $\hat{N}(q, \dot{q}, \ddot{q} | \theta)$, as represented in equation (13). Now, we define a control law as follows:

$$\tau = M(q)\ddot{q}^{des} + C(q, \dot{q})\dot{q}^{des} + g(q) + \hat{N}(q, \dot{q}, \ddot{q} | \theta) - K_D s; \quad K_D = \text{diag} K_i, \quad i = 1, 2, \dots, n \quad (11)$$

Assuming the optimal parameter matrix θ^* of the neural network is known, we can determine the minimum approximation error vector by: $w = F(q, \dot{q}, \ddot{q}, t) - \hat{N}(q, \dot{q}, \ddot{q} | \theta)$. From that, we have:

$$\dot{V} = -s^T K_D s - s^T w + \sum_{i=1}^m (\tilde{\theta}_i^T \Gamma_i \dot{\tilde{\theta}}_i - s_i \tilde{\theta}_i^T \zeta(q, \dot{q}, \ddot{q}))$$

$\tilde{\theta}_i = \theta_i^* - \theta_i$; $\zeta(q, \dot{q}, \ddot{q})$ is the activation function vector of the neural network

To obtain: $\dot{V}(t) = -s^T K_D s - s^T w$

we choose the adaptive update (adaptation) law as follows: $\dot{\theta}_i = -\Gamma_i^{-1} s_i \zeta(q, \dot{q}, \ddot{q})$, $i = 1, 2, \dots, n$ (12)

The structural diagram of a simple two-layer MIMO neural network is shown in Fig 1.

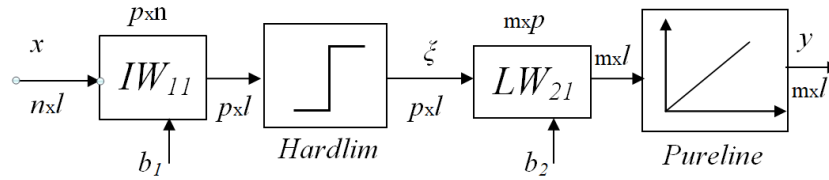


Fig 1: Structure of a two-layer MIMO neural network

Therefore, the neural network can be expressed in the following form:

$$y_j = \sum_{l=1}^p w_{jl} \zeta_l(x) = \theta_j^T \zeta(x), \quad j = 1, 2, \dots, m$$

$$\zeta(x) = (\zeta_1(x), \zeta_2(x), \dots, \zeta_p(x))^T \in R^p$$

$$\theta_j = (w_{j1}, w_{j2}, \dots, w_{jp})^T$$

Thus, the MIMO neural network can be rewritten in the following form:

$$y = \theta^T \zeta(x) \quad (13)$$

θ is an $m \times p$ matrix representing the parameter vector, and θ_j is the j row with dimensions $l \times p$ of the matrix. $\zeta(x)$ is the activation function vector of the neural network.

4. APPLICATION OF THE ALGORITHM TO A TWO-DOF ROBOTIC MANIPULATOR

In this example, a two-dof robotic manipulator is used to illustrate the proposed controller. The two-dof robotic manipulator is described as follows

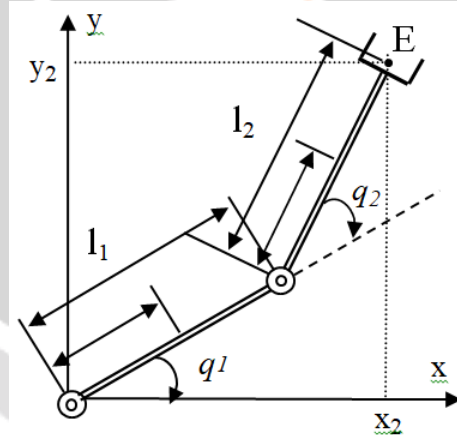


Fig.2 The two-dof robotic manipulator

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

Where

$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \end{bmatrix} + \begin{bmatrix} -C_{12}\dot{q}_2 & -C_{12}(\dot{q}_1 + \dot{q}_2) \\ C_{12}\dot{q}_1 & 0 \end{bmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} + \begin{bmatrix} g_1(q) \\ g_2(q) \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}$$

$$M_{11} = m_2(l_1^2 + l_2^2) / 4 + m_1 l_1^2 / 4 + m_2 l_1 l_2 \cos(q_2) + J_1 + J_2$$

$$M_{12} = M_{21} = m_2 l_2 (l_1 + l_2) / 4 + m_2 l_1 l_2 \cos(q_2) / 2 + J_2$$

$$M_{22} = m_2 l_2^2 / 2 + J_2$$

$$g_1(q) = g m_1 l_1 \cos(q_1) / 2 + g m_2 l_1 \cos(q_1) + l_2 \cos(q_1 + q_2) / 2$$

$$g_2(q) = g m_2 l_2 \cos(q_1 + q_2) / 2$$

$$c_{11} = -g\dot{q}_2 m_2 l_1 l_2 \sin(q_2); c_{12} = c_{11} / 2$$

$$c_{21} = \dot{q}_1 m_2 l_1 l_2 \sin(q_2) / 2; c_{22} = 0$$

m_1 and m_2 are mass of link1 and link2, l_1 and l_2 are length of link1 and link2, J_1 and J_2 are inertia moment of link1 and link2, g is gravity acceleration.

For simulation, parameters for the planar robot are given as $g = 9.81 \text{ m/s}^2$, $m_1 = 1 \text{ kg}$, $m_2 = 0.8-1.2 \text{ kg}$, $l_1 = 1 \text{ m}$, $l_2 = 0.8 \text{ m}$, $J_1 = J_2 = 0.6$, To verify the robustness of the system under load variations, the payload is changed to 1.2 kg.

The initial values of the state variables are chosen as follows:

$$\begin{bmatrix} q_1(0) \\ \dot{q}_1(0) \end{bmatrix} = \begin{bmatrix} q_2(0) \\ \dot{q}_2(0) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Additionally, the friction force is also taken into account in this simulation and is given as follows:

$$F(\dot{q}) = \begin{bmatrix} 3\dot{q}_1 + 0.05 \text{sgn}(\dot{q}_1) \\ 2\dot{q}_2 + 0.1 \text{sgn}(\dot{q}_2) \end{bmatrix}$$

In this case, the disturbances are external forces applied to the robot system, and the form of the disturbance is given as follows:

$$\tau_d = \begin{bmatrix} 0.08 \sin(20t) \\ 0.12 \sin(20t) \end{bmatrix}$$

is chosen as the unknown compound disturbance consisting of model error and unknown input disturbance.

The reference trajectory is given as

$$q_1^{ref} = q_2^{ref} = 0.75 \sin(0.4189t - \pi/2) - 0.45 \cos(1.6755t)$$

The sliding surface: $s_1 = \ddot{q}_1 + \lambda_1 \tilde{q}_1$, $s_2 = \ddot{q}_2 + \lambda_2 \tilde{q}_2$;

The control constants are chosen as follows:

$\lambda_1 = 2$, $\lambda_2 = 3$, The matrix K_D in the control law has the form: $K_D = \text{diag}[7, 8]$

The activation function vector of the neural network for each joint is a neural network with the structure shown in Fig 1: It consists of two layers, the input layer has one neuron using the hardlims activation function, and the output layer has one neuron using the purelin activation function. The input is the joint velocity $\dot{q}$ and the output is ξ .

The simulation results of the adaptive control law based on the neural network are presented in Fig 3, 4, and 5.

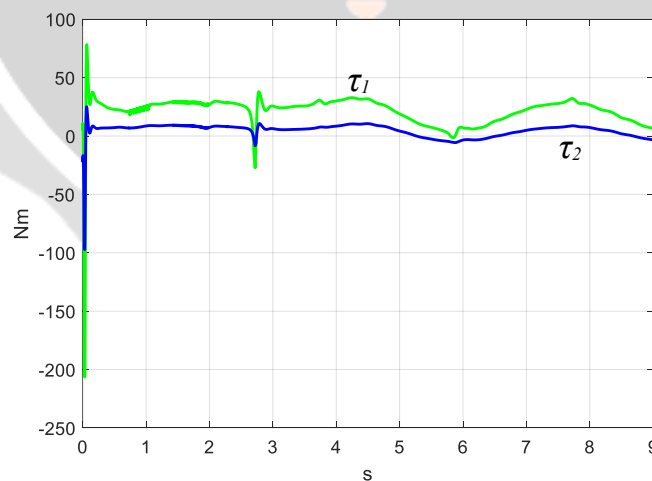


Fig.3 Control torques corresponding to Joint 1 and Joint 2

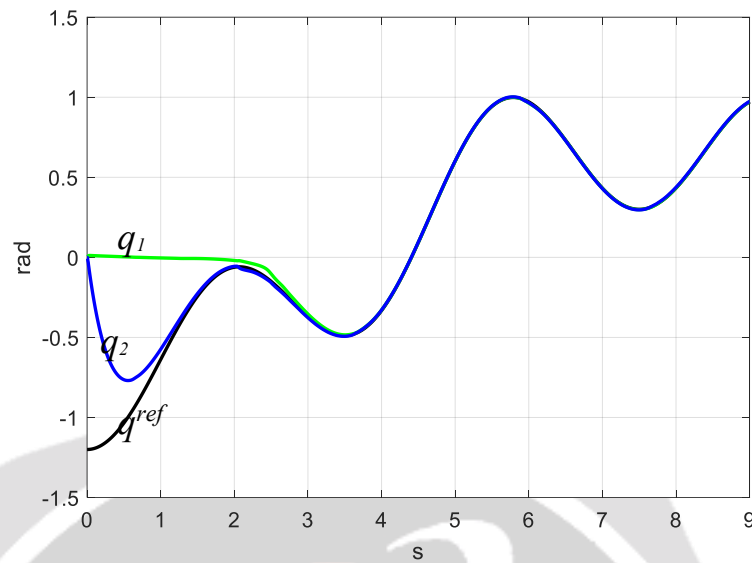


Fig.4 Joint 1, Joint 2, and the reference trajectory

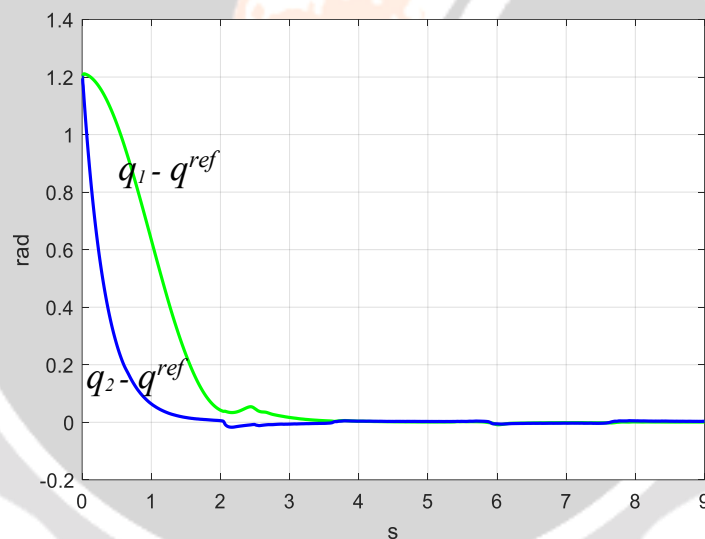


Fig.5 Tracking errors of the joints

5. CONCLUSIONS

This study has successfully applied an adaptive controller to control the joint positions of a two-dof robotic manipulator in order to achieve desired trajectory tracking in the presence of system parameter uncertainties.

A neural network was used to compensate for the uncertainties in the system. The adaptive learning law was designed based on the Lyapunov stability theory to ensure convergence and stability of the closed-loop tracking system, regardless of the presence of uncertainties.

Simulation results for the two-dof robotic manipulator, using the proposed control system, are presented in this study. According to the results shown in Fig 4, the reference tracking performance of the system can be accurately controlled to follow the given reference trajectory, even under significant disturbances.

The simulation results demonstrate that the quality of the control system using the adaptive control law is excellent and can potentially be applied to robotic manipulators with more than two degrees of freedom.

6. ACKNOWLEDGEMENT

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7. REFERENCES

- [1].Nguyen Nam Trung, On the feedback-feedforward control for robot manipulator used disturbance estimator. IJARIE-ISSN(O)-2395-4396, Vol-9 Issue-3 2023.
- [2].F.L.Lewis, D.M.Dawson and C.T.Abdallah: Robot Manipulator Control. Theory and Practice. Marcel Dekker, Inc. 2004.
- [3].A. Sabanovic, K. Ohnishi, "Motion Control Systems", Willey Publisher (2011).
- [4].Chen, W., Yang, J., Guo, L., & Li, S. (2016). Disturbance-observer-based control and related methods-An overview. IEEE Transactions on Industrial Electronics, 63(2), 1083-1095.
- [5].Manjeet And Pooja Khatri trajectory control of two link robotic manipulator using PID Volume-3, Issue-5, Nov-2013.
- [6].Åstrom, K. J., Wittenmark, B., Adaptive Control, 2^a ed., New York: Ed. Addison Wesley Publishing Company, Inc., 1995.
- [7].Miller III, W. T. & Sutton, R. S. & Werbos, P. J., Neural Networks for Control, The MIT Press, London, 1995.
- [8].Jinzhu Peng, Yaonan Wang, Wei Sun, Yan Liu, "A neural network sliding mode controller with application to robotic manipulator," IEEE Conf. Int. Control, vol. 1, pp. 2101-2105, Apr. 2000.
- [9].R. Murray, G. Goodwin, "Adaptive computed torque control for rigid link manipulators," Syst. Cont. 10 (4) (1988).
- [10]. H. K. Khalil, Nonlinear Systems. Englewood Cliffs, NJ: Prentice-Hall, 1996.