Lecture Notes in Networks and Systems 1205

Phung Trung Nghia · Vu Duc Thai ·
Nguyen Thanh Thuy · Van-Nam Huynh ·
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This book provides a comprehensive overview of cutting-edge research and innovations in Information and Communication Technology (ICT), offering new insights into both theoretical foundations and practical applications.

The proceedings contain 1 keynote paper and 113 peer-reviewed papers selected from the 211 submissions at the 3rd International Conference on Advances in ICT (ICTA 2024), which share research results and practical applications in ICT research and education. The topics cover all ICT-related areas and their contributions to socio-economic development, focusing on the most advanced technologies, such as AI and automation. Researchers and practitioners in academia and industry can use the book as a valuable reference for their research activities, teaching, learning, and advancing current technologies.

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November 2024

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Electronics

Adaptive Terminal Sliding Mode Control Using RBF Neural Network for Industrial Robot Manipulators

Le Van Chuong(✉), Ho Sy Phuong, Duong Dinh Tu, Phan Van Du, Dang Thai Son, Mai The Anh, Dinh Van Nam, Ta Hung Cuong, and Phan Van Vy

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Abstract. This paper presents an adaptive terminal sliding mode control method for industrial robot manipulators. The proposed approach ensures finite-time error convergence without requiring prior knowledge of the bounds of uncertainties and external disturbances. This is accomplished by employing an RBF neural network and an adaptive control algorithm to estimate the upper limits of these uncertainties. Additionally, the controller eliminates chattering effects while maintaining robustness and accuracy. The stability of the control algorithm is rigorously validated using Lyapunov theory. The proposed controller has been tested through simulations on a three-degree-of-freedom robot to demonstrate its effectiveness. The simulation results confirm the controller's ability to handle uncertainties and disturbances effectively, highlighting its potential for real-world industrial applications.

Keywords: Adaptive Control · Terminal Sliding Mode Control · Neural Network · Industrial Robot Manipulators

1 Introduction

Sliding mode control (SMC) has proven effective in industrial robot control due to its robustness, simplicity, and efficiency in handling parameter variations and disturbances [1–3]. The Lyapunov theory ensures its stability and stabilization, which guarantees asymptotic stability. However, asymptotic stability implies that state convergence slows down as the system approaches equilibrium, precluding reaching equilibrium in finite-time. While practical applications may tolerate this, achieving higher steady-state precision would necessitate greater control force, often impractical with constrained control equipment or actuators [4]. Terminal sliding mode control (TSMC) was developed to address this limitation for faster, finite-time convergence. TSMC accelerates convergence near the equilibrium point and has been successfully applied in high-precision industrial robot manipulators [3–8]. Despite these benefits, TSMC commonly encounters chattering, a typical issue in sliding mode controllers. Reducing chattering in the control law usually requires knowledge of uncertainty bounds, posing challenges in

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measuring uncertainties in robot dynamics. Adaptive TSMC techniques have emerged to estimate these uncertainty bounds [9–11] or integrate them with other control methods like fuzzy control [12, 13] or neural networks [14, 15]. Despite that, while studies typically bound the impact of external disturbances within known values, practical systems are susceptible to unmeasured external disturbances.

This paper proposes an adaptive TSMC method for industrial robot manipulators. This method guarantees finite-time error convergence without requiring prior knowledge of the upper bounds of parameter uncertainties and unmeasured external disturbances. These uncertainties are identified and compensated for using an adaptive control algorithm and an RBF neural network, minimizing the chattering effect while maintaining robustness and accuracy. The proposed controller's effectiveness is validated through simulations on a three-degree-of-freedom robot, demonstrating its capability to manage uncertain dynamics efficiently and unmeasured external disturbances.

2 Synthesis of an Adaptive Terminal Sliding Mode Controller

2.1 Dynamic Model of Industrial Robot Manipulator

Generally, the dynamics model of an n-degree-of-freedom (n-DOF) industrial robot manipulator can be formulated as follows [1–3]:

$$\mathbf{H}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) + \mathbf{f}(\dot{\mathbf{q}}) + \mathbf{d}(t) = \mathbf{u}, \tag{1}$$

where $\mathbf{q} \in \mathbb{R}^n$ is the vector of joint angles; $\mathbf{H}(\mathbf{q}) \in \mathbb{R}^{n\times n}$ is the inertia matrix; $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) \in \mathbb{R}^{\mathrm{n\times n}}$ is the matrix containing Coriolis and centrifugal forces; $\mathbf{g}(\mathbf{q}) \in \mathbb{R}^n$ is the vector of gravitational torques; $\mathbf{f}(\dot{\mathbf{q}}) \in \mathbb{R}^n$ is the vector of the friction force; $\mathbf{d}(t) \in \mathbb{R}^n$ is a vector of external disturbances that vary slowly, cannot be measured, and are bounded; $\mathbf{u} \in \mathbb{R}^n$ is the vector of input torque.

In reality, the dynamics model of the industrial robot manipulator (1) contains uncertainties resulting from parameter variations, operating conditions, or unknown loads. Consequently, $\mathbf{H}(\mathbf{q})$, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})$, and $\mathbf{g}(\mathbf{q})$ can be expressed as follows:

$$\mathbf{H}(\mathbf{q}) = \mathbf{H}_0 + \delta\mathbf{H};\ \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}) = \mathbf{C}_0 + \delta\mathbf{C};\ \mathbf{g}(\mathbf{q}) = \mathbf{g}_0 + \delta\mathbf{g}; \tag{2}$$

where $\mathbf{H}_0$, $\mathbf{C}_0$, and $\mathbf{g}_0$ denote the estimated terms; $\delta\mathbf{H}$, $\delta\mathbf{C}$, and $\delta\mathbf{g}$ denote the uncertain terms. Accordingly, the dynamic Eq. (1) can be written as follows:

$$\mathbf{H}_0\ddot{\mathbf{q}} + \mathbf{C}_0\dot{\mathbf{q}} + \mathbf{g}_0 + \boldsymbol{\delta}(\mathbf{x}) + \mathbf{d}(t) = \mathbf{u}, \tag{3}$$

with $\mathbf{x} = \left[\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}\right]^{\mathrm{T}}$ and:

$$\boldsymbol{\delta}(\mathbf{x}) = \delta\mathbf{H}\ddot{\mathbf{q}} + \delta\mathbf{C}\dot{\mathbf{q}} + \delta\mathbf{g} + \mathbf{f}(\dot{\mathbf{q}}). \tag{4}$$

In the following section, the article synthesizes the control law to ensure that the industrial robot manipulator tracks the desired trajectory.

2.2 Propose Control Algorithm

Considering a desired trajectory $\mathbf{q}_d \in \mathbb{R}^n$ for the robot (3), the tracking error is:

$$\mathbf{e} = \mathbf{q}_d - \mathbf{q}. \tag{5}$$

The control goal is to devise a feedback law **u** so that the robot manipulator's output **q** follows the desired trajectory $\mathbf{q}_d$ and ensures that the tracking error **e** converges to zero within a finite-time. To achieve this, we introduce the sliding surface:

$$\mathbf{s} = \dot{\mathbf{e}} + \beta|\mathbf{e}|^{\alpha}\text{sgn}(\mathbf{e}), \tag{6}$$

where β is a positive constant; α is a positive exponent, $0 < \alpha < 1$.

From (6), we have:

$$\ddot{\mathbf{q}} = \ddot{\mathbf{q}}_d - \dot{\mathbf{s}} + \beta\alpha|\mathbf{e}|^{\alpha-1}\dot{\mathbf{e}}. \tag{7}$$

Substituting (7) into the robot's dynamic Eq. (3) and transforming:

$$\mathbf{H}_0\dot{\mathbf{s}} = \mathbf{H}_0\left[\ddot{\mathbf{q}}_d + \beta\alpha|\mathbf{e}|^{\alpha-1}\dot{\mathbf{e}}\right] + \mathbf{C}_0\dot{\mathbf{q}} + \mathbf{g}_0 + \delta(\mathbf{x}) + \mathbf{d}(t) - \mathbf{u} \tag{8}$$

The proposed control law for the robot manipulator (8) is as follows:

$$\begin{aligned}\mathbf{u} = \mathbf{H}_0\left[\ddot{\mathbf{q}}_d + \beta\alpha|\mathbf{e}|^{\alpha-1}\dot{\mathbf{e}}\right] + \mathbf{C}_0\left[\dot{\mathbf{q}}_d + \beta|\mathbf{e}|^{\alpha}\text{sgn}(\mathbf{e})\right] + \mathbf{g}_0 \\ + \mathbf{K}_1\mathbf{s} + \mathbf{K}_2\text{sgn}(\mathbf{s}) + \hat{\delta}(\mathbf{x}) + \hat{\mathbf{d}}(t)\end{aligned} \tag{9}$$

where $\mathbf{K}_1 = \text{diag}(k_{11}, k_{12}, \ldots, k_{1n})$; $\mathbf{K}_2 = \text{diag}(k_{21}, k_{22}, \ldots, k_{2n})$; $k_{1i} > 0$, $k_{2i} > 0$, $i = \overline{1, n}$; $\hat{\boldsymbol{\delta}}(\mathbf{x})$ is an estimate of $\boldsymbol{\delta}(\mathbf{x})$; $\hat{\mathbf{d}}(t)$ is an estimate of $\mathbf{d}(t)$. The control system block diagram for the robot manipulator (8) using control law (9) is shown in Fig. 1.

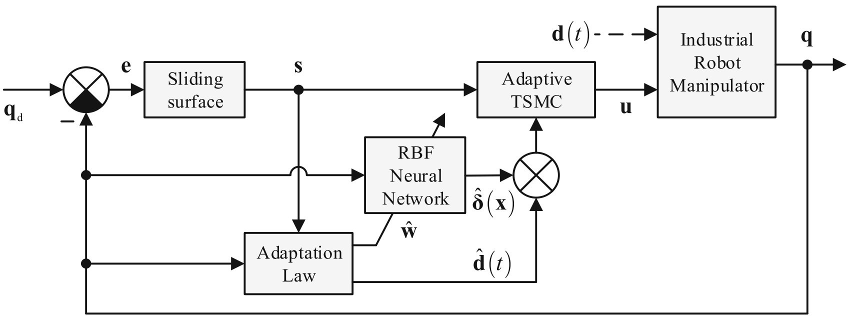

Fig. 1. The block diagram for the robot manipulator's control system (8) with control law (9).

We use the RBF neural network, capable of estimating any nonlinear function, to estimate $\boldsymbol{\delta}(\mathbf{x})$, and the network's output is defined as follows:

$$\boldsymbol{\delta}(\mathbf{x}) = \left[\sum_{j=1}^{M} w_{1j}^{*}\varphi_{1j}(\mathbf{x}) + \varepsilon_1, \sum_{j=1}^{M} w_{2j}^{*}\varphi_{1j}(\mathbf{x}) + \varepsilon_2, \ldots, \sum_{j=1}^{M} w_{nj}^{*}\varphi_{nj}(\mathbf{x}) + \varepsilon_n\right]^{\mathrm{T}}, \tag{10}$$

where w_{ij}^{*} represents the ideal weight; $\varphi_{ij}(\mathbf{x})$ is defined as Gaussian function as:

$$\varphi_{ij}(\mathbf{x}) = \exp\left(-\frac{\|\mathbf{x} - \mathbf{c}_{ij}\|^2}{2b_{ij}^2}\right); \tag{11}$$

where b_{ij} signifies the spread of the ij-th basis function; $\mathbf{c}_{ij}$ denotes a vector with dimensions equal to $\mathbf{x}$, defining the center of the basis function; $i = \overline{1, n}$; $j = \overline{1, M}$ with M represents the number of basis functions, selected to be large enough to ensure the estimation error ε_i.

The nonlinear function vector $\boldsymbol{\delta}(\mathbf{x})$ is estimated as:

$$\hat{\boldsymbol{\delta}}(\mathbf{x}) = \left[\sum_{j=1}^{M} \hat{w}_{1j}\varphi_{1j}(\mathbf{x}), \sum_{j=1}^{M} \hat{w}_{2j}\varphi_{2j}(\mathbf{x}), \ldots, \sum_{j=1}^{M} \hat{w}_{nj}\varphi_{nj}(\mathbf{x})\right]^{\mathrm{T}}; \tag{12}$$

where $\hat{w}_{ij}$ is the estimated weight. The process of estimating the nonlinear function is to adjust the weight $\hat{w}_{ij}$ such that $\hat{w}_{ij} \to w_{ij}^{*}$.

In this study, using the Lyapunov stability theorem, we design an adaptive update law for the weights of the RBF neural network and an adaptive control algorithm to estimate the unmeasured external disturbances component as follows:

$$\dot{\hat{w}}_{ij} = p_i s_i \varphi_{ij}(\mathbf{x}); \tag{13}$$

$$\dot{\hat{d}}_i(t) = q_i s_i; \tag{14}$$

where p_i, q_i are positive coefficients; $i = \overline{1, n}; j = \overline{1, M}$.

2.3 Stability Analysis

To demonstrate control system stability, we select the Lyapunov function as:

$$V = \frac{1}{2}\mathbf{s}^{\mathrm{T}}\mathbf{H}_0\mathbf{s} + \frac{1}{2p_i}\sum_{i=1}^{n}\sum_{j=1}^{M}\tilde{w}_{ij}^2 + \frac{1}{2q_i}\sum_{i=1}^{n}\tilde{d}_i^2(t), \tag{15}$$

where $\tilde{w}_{ij} = w_{ij}^{*} - \hat{w}_{ij}$; $\tilde{d}_i(t) = d_i(t) - \hat{d}_i(t)$; $i = \overline{1, n}; j = \overline{1, M}$.

Compute the derivative of the Lyapunov function:

$$\dot{V} = \mathbf{s}^{\mathrm{T}}\mathbf{H}_0\dot{\mathbf{s}} + \frac{1}{2}\mathbf{s}^{\mathrm{T}}\dot{\mathbf{H}}_0\mathbf{s} + \frac{1}{p_i}\sum_{i=1}^{n}\sum_{j=1}^{M}\tilde{w}_{ij}\dot{\hat{w}}_{ij} + \frac{1}{q_i}\sum_{i=1}^{n}\tilde{d}_i(t)\dot{\hat{d}}_i(t). \tag{16}$$

From (8) and (9) we have:

$$\mathbf{H}_0\dot{\mathbf{s}} = \tilde{\boldsymbol{\delta}}(\mathbf{x}) + \tilde{\mathbf{d}}(t) - \mathbf{C}_0\mathbf{s} - \mathbf{K}_1\mathbf{s} - \mathbf{K}_2\mathrm{sgn}(\mathbf{s}), \tag{17}$$

where $\tilde{\boldsymbol{\delta}}(\mathbf{x}) = \boldsymbol{\delta}(\mathbf{x}) - \hat{\boldsymbol{\delta}}(\mathbf{x})$; $\tilde{\mathbf{d}}(t) = \mathbf{d}(t) - \hat{\mathbf{d}}(t)$.

Substituting (17) into (16) and continuing to transform:

$$\begin{aligned}\dot{V} =& \frac{1}{2}\mathbf{s}^{\mathrm{T}}[\mathbf{H}_0 - 2\mathbf{C}_0]\mathbf{s} + \mathbf{s}^{\mathrm{T}}\tilde{\boldsymbol{\delta}}(\mathbf{x}) + \mathbf{s}^{\mathrm{T}}\tilde{\mathbf{d}}(t) + \mathbf{s}^{\mathrm{T}}\big[-\mathbf{K}_1\mathbf{s} - \mathbf{K}_2\mathrm{sgn}(\mathbf{s})\big] \\ &+ \frac{1}{p_i}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{M}\tilde{w}_{ij}\dot{\tilde{w}}_{ij} + \frac{1}{q_i}\sum\nolimits_{i=1}^{n}\tilde{d}_i(t)\dot{\tilde{d}}_i(t).\end{aligned} \tag{18}$$

For manipulator robots, we have $[\mathbf{H}_0 - 2\mathbf{C}_0]$ as a skew-symmetric matrix [1–3], so $\mathbf{s}^{\mathrm{T}}[\mathbf{H}_0 - 2\mathbf{C}_0]\mathbf{s} = 0$.

Besides, from (10) and (12), we get:

$$\tilde{\boldsymbol{\delta}}(\mathbf{x}) = \left[\sum\nolimits_{j=1}^{M}\tilde{w}_{1j}\varphi_{1j}(\mathbf{x}), \sum\nolimits_{j=1}^{M}\tilde{w}_{2j}\varphi_{2j}(\mathbf{x}), \ldots, \sum\nolimits_{j=1}^{M}\tilde{w}_{nj}\varphi_{nj}(\mathbf{x})\right]^{\mathrm{T}} + \boldsymbol{\varepsilon}, \tag{19}$$

where $\tilde{w}_{ij} = w_{ij}^* - \hat{w}_{ij}$; $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n]^{\mathrm{T}}$, $|\varepsilon_i| \le \varepsilon_i^*$, $i = \overline{1, n}$. From there, we have:

$$\begin{aligned}\dot{V} =& \sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{M}s_i\tilde{w}_{ij}\varphi_{ij}(\mathbf{x}) + \sum\nolimits_{i=1}^{n}s_i\tilde{d}_i(t) + \frac{1}{p_i}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{M}\tilde{w}_{ij}\dot{\tilde{w}}_{ij} + \\ & \frac{1}{q_i}\sum\nolimits_{i=1}^{n}\tilde{d}_i(t)\dot{\tilde{d}}_i(t) + \mathbf{s}^{\mathrm{T}}\big[-\mathbf{K}_1\mathbf{s} - \mathbf{K}_2\mathrm{sgn}(\mathbf{s}) + \boldsymbol{\varepsilon}\big].\end{aligned} \tag{20}$$

Notice that: $w_{ij}^* = \text{const}$ so $\dot{w}_{ij}^* = 0$ and $\dot{\tilde{w}}_{ij} = -\dot{\hat{w}}_{ij}$; the external disturbances change slowly, thus $\dot{d}_i(t) \approx 0$ and $\dot{\tilde{d}}_i(t) \approx -\dot{\hat{d}}_i(t)$. Continue substituting adaptive update laws (13) and (14) into (20):

$$\dot{V} = -\mathbf{s}^{\mathrm{T}}\mathbf{K}_1\mathbf{s} - \Big[\mathbf{s}^{\mathrm{T}}\mathbf{K}_2\mathrm{sgn}(\mathbf{s}) - \mathbf{s}^{\mathrm{T}}\boldsymbol{\varepsilon}\Big]. \tag{21}$$

If we choose $k_{2i} > \varepsilon_i^*$, then $\mathbf{s}^{\mathrm{T}}\mathbf{K}_2\mathrm{sgn}(\mathbf{s}) \ge \mathbf{s}^{\mathrm{T}}\boldsymbol{\varepsilon}$, and therefore we can ensure:

$$\dot{V} \le -\mathbf{s}^{\mathrm{T}}\mathbf{K}_1\mathbf{s} \le 0, \tag{22}$$

and system (8) is stable. Adopting the terminal sliding surface (6) will ensure finite-time convergence of the tracking errors [3, 4].

3 Simulation Results

Next, the proposed controller is simulated in Matlab/Simulink with a model of the 3-DOF robot manipulator to demonstrate its accuracy and efficiency. The article uses a dynamic model of robot manipulators [16] with specific parameters as follows:

$$\mathbf{H}_0 = 10^{-3}\begin{bmatrix} h_{11} & 0 & 0 \\ 0 & h_{22} & h_{23} \\ 0 & h_{32} & h_{33} \end{bmatrix};\ \mathbf{C}_0 = 10^{-3}\begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix};\ \mathbf{g}_0 = 10^{-3}\begin{bmatrix} 0 \\ g_2 \\ g_2 \end{bmatrix};$$

$$h_{11} = 15.1\sin(q_2)\sin(q_3) + 22.9\cos^2(q_1) - 5.4\cos^2(q_3) + 62.6;$$

$$h_{22} = 7.55\cos(q_2 - q_3) + 199.1; \qquad h_{23} = 7.55\cos(q_2 - q_3) + 60.3;$$

$$h_{32} = 7.55\cos(q_2 - q_3) + 90.6; \qquad h_{33} = 103.3;$$

$$c_{11} = 470.1; \qquad c_{12} = 109.4\dot{q}_1\sin(q_2)\cos(q_2) + 15.1\dot{q}_1\cos(q_2)\sin(q_3);$$

$$c_{13} = 15.1\dot{q}_1\sin(q_2)\cos(q_3) + 59.1\dot{q}_1\sin(q_3)\cos(q_3);$$

$$c_{21} = 469\dot{q}_1\sin(q_2)\cos(q_2) + 146.2\dot{q}_1\sin(q_3)\cos(q_3) - 7.55\dot{q}_1\sin(q_2 + q_3);$$

$$c_{22} = 7.55\dot{q}_2\sin(q_3 - q_2) + 774.1; \quad c_{23} = 7.55\dot{q}_3\left[\sin(q_2)\cos(q_3) - \cos(q_2)\sin(q_3)\right];$$

$$c_{31} = 146.2\dot{q}_1\sin(q_3)\cos(q_3) - 7.55\dot{q}_1\sin(q_2)\cos(q_3); \quad c_{23} = 721.8;$$

$$c_{22} = 7.55\dot{q}_2\sin(q_3 - q_2) - 721.8; \quad g_2 = -\ 5.1\sin(q_2) + 9.7\sin(q_3); \quad g_3 = 9.7\sin(q_3).$$

Suppose the forms of the uncertain parameter components $\delta\mathbf{H}$, $\delta\mathbf{C}$, $\delta\mathbf{g}$; the friction force vector $\mathbf{f}(\dot{\mathbf{q}})$; the external disturbance vector $\mathbf{d}(t)$; and the desired trajectory $\mathbf{q}_\mathrm{d}$ are given as:

$$\delta\mathbf{H} = 30\%\mathbf{H}_0;\ \delta\mathbf{C} = 30\%\mathbf{C}_0;\ \delta\mathbf{g} = 30\%\mathbf{g}_0;\ \mathbf{f}(\dot{\mathbf{q}}) = 0.2\mathrm{sgn}(\mathbf{q})$$

$$\boldsymbol{d}(t) = \begin{bmatrix} 2.0\cos(1.5t + 0.3) \\ -3.6\sin(3t - 0.1) \\ -2.8\sin(2t + 0.2) \end{bmatrix};\ \boldsymbol{q}_\mathrm{d} = \begin{bmatrix} 2.0\sin(0.60t + 0.5) \\ 3.0\cos(0.75t + 0.8) \\ -5.0\sin(0.8t + 0.6) \end{bmatrix}$$

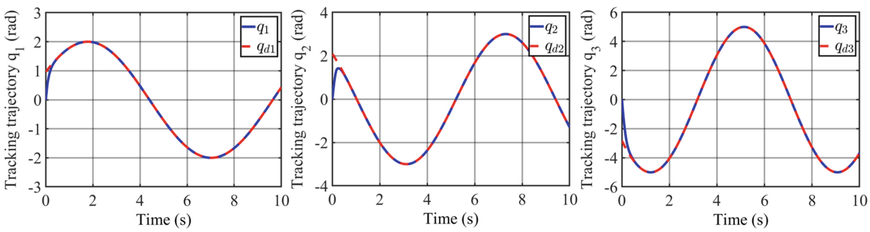

Fig. 2. Trajectory tracking of the robot manipulator.

The proposed controller (9) and adaptive updating algorithms (13) and (14) were applied to the robot manipulator. The resulting simulations are shown in Figs. 2, 3, 4 and 5.

The results in Fig. 2 show that with the proposed controller (9), the robot manipulator's trajectory quickly tracks the desired trajectory. Figure 3 reveals that the uncertain dynamic parameters and external disturbances are effectively estimated using adaptive updating laws (13) and (14), with the estimation error tending to zero in Fig. 4. This estimate is incorporated into control law (9), as shown in the control signal simulation results in Fig. 5. Notably, once the uncertain components are estimated and compensated,

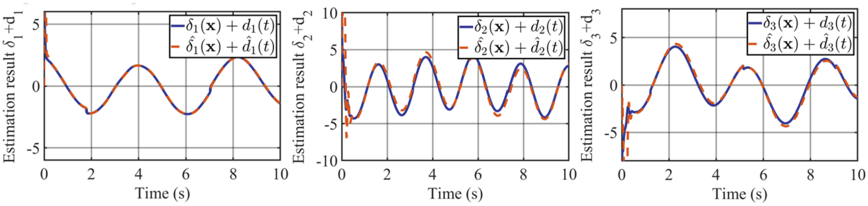

Fig. 3. The estimation results of the uncertain components.

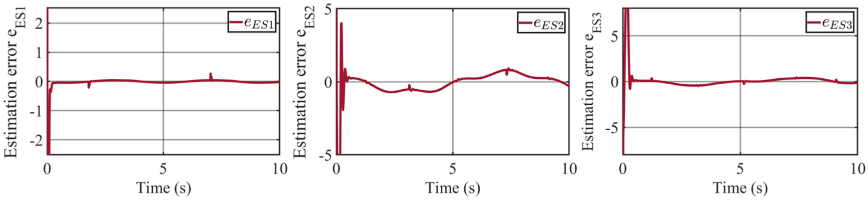

Fig. 4. The estimation error of the uncertain components.

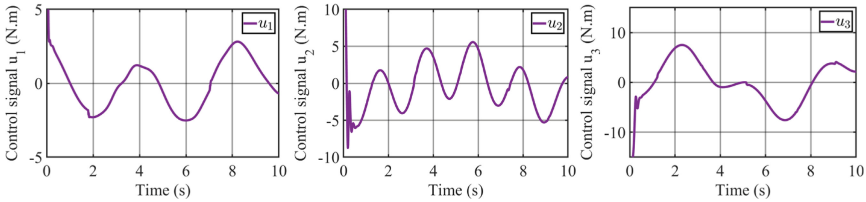

Fig. 5. The signal from the adaptive TSMC controller.

the chattering phenomenon in the control signal is reduced to a minimum because the sliding mode control component depends only on the RBF neural network estimation error. These simulation results confirm the precision and effectiveness of the proposed adaptive TSMC.

4 Conclusions

This paper presents an adaptive TSMC method for industrial robot manipulators. The proposed TSMC ensures finite-time convergence of tracking errors without requiring knowledge of the bounds of uncertain parameters and unmeasured external disturbances by employing RBF neural networks and adaptive control algorithms. This approach also minimizes the chattering phenomenon in the control signal. Stability is rigorously demonstrated using Lyapunov theory and mathematical analysis. Simulation results on the 3-DOF robot manipulator confirm the controller's efficacy, adaptability, and robustness. The proposed controller demonstrates high precision and reliability, even with dynamic uncertainties and external disturbances. This adaptive TSMC method significantly improves industrial robot control, delivering robust performance in complex operating environments.

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