Continuous Robust State-Feedback Control for Robot Manipulators with Lumped Uncertainty

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Abstract: **This paper proposes a continuous adaptive state-feedback controller for tracking control of robot manipulators subject to lumped uncertainty, which encompasses unknown dynamics and external disturbances. First, the dynamic model of the robot manipulator is derived. Then, an adaptive controller based on state feedback is formulated. To avoid requiring knowledge of the upper bound of the lumped uncertainty during controller design, an adaptive law is proposed to estimate the lumped uncertainty online. In addition, a continuous robust control term is designed to compensate for the estimation error of the lumped uncertainty. The proposed controller consists of three distinct terms: the first provides state feedback, the second performs uncertainty estimation, and the third acts as a continuous robust controller. Using Lyapunov stability theory, it is proven that the tracking errors converge asymptotically to zero. Finally, simulation results validate the effectiveness of the proposed adaptive state-feedback method.**

Keywords: **State-feedback control, Robot manipulators, Robust control, Lumped uncertainty, Lyapunov stability**

I Introduction

Robots have been extensively utilized in both industrial and academic applications [1]–[3]. In these applications, achieving stable and high-precision trajectory tracking control is critical for both system performance and safety. In [4], a novel tube-based geometric model predictive control framework on Lie groups is proposed for robust and real-time trajectory tracking control of robot manipulators under uncertainties. In [5], a composite tracking control strategy for fully actuated systems, combined with a high-order disturbance observer, is developed for robot manipulators to effectively handle unknown dynamics and external disturbances. In [6], an optimized Q-learning-based trajectory tracking method with real-time obstacle avoidance capability is proposed for wheeled mobile robots in dynamic environments; this method designs an observation-space data processing scheme and optimizes the Q-table structure. In [7], a novel proactive robotic manipulation control method for human-robot collaborative assembly is presented, in which large-scale models are leveraged for cognitive computing and reasoning to enable dynamic robotic control path planning, while small-scale models are deployed to efficiently perceive dynamic robotic control demands and verify control constraints.

Tracking control for nonlinear systems subject to various structural and parametric nonlinearities is of considerable importance and remains a challenging issue in both theory and practice [8]–[13].

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In recent years, trajectory tracking control for robot manipulators has attracted considerable research attention [14]–[16]. The primary objective of tracking control is to design a feedback control law such that the controlled system tracks the reference signal with asymptotic or exponential convergence [17] or within a finite time [18, 19]. A major challenge in state-feedback control is to address the uncertainties present in the controlled system without prior knowledge of them. Efforts to achieve this objective have led to the development of various adaptive control methods [20]–[24]. Indeed, when the system dynamics are completely known, an appropriate controller can be designed based on the system states [25]. However, most nonlinear systems, such as robotic systems, are subject to various unknown uncertainties. Therefore, these uncertainties must be appropriately estimated.

In many existing adaptive control approaches, the robust control term is discontinuous because these methods use the upper bound of the approximation error as the basis for robust control design. In some studies [26], this upper bound is determined by trial and error. In other methods, this gain is adjusted through adaptive laws typically formulated based on the norm or absolute value of the error [27]. Nevertheless, such a design can lead to a continuous and uncontrolled increase in the robust gain, potentially compromising system stability. To mitigate this issue, this paper presents a new adaptive law for directly estimating the lumped uncertainty. A key feature of the proposed method is that it designs a continuous robust control term without requiring the value or even an estimate of the upper bound of the approximation error. Accordingly, the uncertainties are estimated online, and this estimate is used in the proposed state-feedback control law.

This paper proposes a state-feedback robust controller for electrically driven robots that directly computes the applied motor voltages. In the proposed control structure, the lumped uncertainty of the system is estimated online using a novel adaptive law, and the resulting estimation error is subsequently compensated for. The main contribution of this research is the design of a state-feedback robust controller in which the adaptive law is formulated to eliminate the need for the upper bound of the approximation error or an estimate thereof. In addition, to compensate for the estimation error, a continuous robust control term is proposed, which replaces the conventional discontinuous term used in many previous studies. The system considered in this study is a SCARA robot manipulator equipped with permanent-magnet DC (PMDC) motors. Simulation results validate the effectiveness and robustness of the proposed controller.

The remainder of this paper is organized as follows. Section II presents the system description and problem formulation. Section III develops the robust state-feedback control design and provides the stability analysis. Section IV presents the simulation results, and Section V concludes the paper.

II System Description and Problem Formulation

The dynamics of an electric robot system, encompassing the manipulators and DC motors, are modeled as follows [27]–[29]:

$$\begin{cases} D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau_l \\ J_m r^{-1}\ddot{q} + B_m r^{-1}\dot{q} + r\tau_l = K_m I_a \\ RI_a + K_m r^{-1}\dot{q} + \phi = U \\ \phi = L\dot{I}_a + d \end{cases} \tag{1}$$

where U and d denote the motor voltage vector and the external disturbance vector, respectively.

For a given reference signal q_d, the control objectives of this paper are as follows:

1. The designed adaptive state-feedback controller ensures that the tracking error of the uncertain robotic system converges asymptotically to zero in the presence of lumped uncertainty.
2. All closed-loop signals remain bounded.

Under the proposed controller, it is proven that all closed-loop signals remain bounded and the output tracking error converges asymptotically to zero despite the presence of disturbances.

III Robust State-Feedback Control Design and Stability Analysis

This section presents a robust tracking control method based on the state-feedback technique. In addition, stability analysis is performed using Lyapunov stability theory during the controller design process.

A Robust State-Feedback Control Design

Substituting (1) into the mechanical equation yields:

$$I_a = K_m^{-1}\left[(J_m r^{-1} + rD)\ddot{q} + (B_m r^{-1} + rC)\dot{q} + rG + \phi\right] \tag{2}$$

Substituting the above expression into the electrical equation yields:

$$\begin{aligned} U = {} & RK_m^{-1}\left[(J_m r^{-1} + rD)\ddot{q} + (B_m r^{-1} + rC)\dot{q} + rG + \phi\right] \\ & + K_m r^{-1}\dot{q} + \phi \end{aligned} \tag{3}$$

This can be rearranged as:

$$U = \overline{D}\ddot{q} + \overline{C}\dot{q} + \overline{G} + \phi \tag{4}$$

where

$$\begin{aligned} \overline{D} &= RK_m^{-1}(J_m r^{-1} + rD) \\ \overline{C} &= RK_m^{-1}(B_m r^{-1} + rC) + K_m^{-1} r \\ \overline{G} &= RK_m^{-1} rG \end{aligned} \tag{5}$$

From (4), it follows that:

$$U = \ddot{q} + \mathcal{L} \tag{6}$$

$$\mathcal{L} = (\overline{D} - I)\ddot{q} + \overline{C}\dot{q} + \overline{G} + \phi \tag{7}$$

where $\mathcal{L}$ represents the lumped uncertainty.

Now, a robust state-feedback control law is proposed as follows:

$$U = \ddot{q}_d + k_1\dot{e} + k_2 e + \hat{\mathcal{L}} + u_r \tag{8}$$

where q_d denotes the desired trajectory, $e = q_d - q$ is the tracking error, k_1 and k_2 are positive design gains, $\hat{\mathcal{L}}$ represents the estimate of the lumped uncertainty, and u_r is the robust control term. The terms $\hat{\mathcal{L}}$ and u_r are determined via stability analysis.

B Stability Analysis

By substituting (8) into (6) and defining $\tilde{\mathcal{L}} = \mathcal{L} - \hat{\mathcal{L}}$ as the estimation error, it can be shown that:

$$\begin{aligned} \ddot{q}_d + k_1\dot{e} + k_2 e + \hat{\mathcal{L}} + u_r &= \ddot{q} + \mathcal{L} \\ \Rightarrow \quad \ddot{e} + k_1\dot{e} + k_2 e &= \tilde{\mathcal{L}} - u_r \end{aligned} \tag{9}$$

where $\hat{\mathcal{L}}$ denotes the estimate of $\mathcal{L}$.

Using (6), the state-space representation can be formulated as follows:

$$\dot{E} = AE + B\Gamma \tag{10}$$

where

$$E = \begin{bmatrix} e \\ \dot{e} \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 1 \\ -k_2 & -k_1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \Gamma = \tilde{\mathcal{L}} - u_r \tag{11}$$

The Lyapunov function is defined as follows:

$$V = \frac{1}{2}E^T PE + \frac{1}{2\eta}\tilde{\mathcal{L}}^2 \tag{12}$$

where $\eta > 0$ is a design parameter. There exist symmetric positive definite matrices P and Q satisfying the following condition:

$$A^T P + PA = -Q \tag{13}$$

The time derivative of V is written as:

$$\dot{V} = \frac{1}{2}\dot{E}^T PE + \frac{1}{2}E^T P\dot{E} + \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}} \tag{14}$$

Substituting (10) and (13) into (14) yields:

$$\begin{aligned}\dot{V} &= \frac{1}{2}(AE + B\Gamma)^T PE \\ &\quad + \frac{1}{2}E^T P(AE + B\Gamma) - \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}} \\ &= \frac{1}{2}(E^T A^T + \Gamma^T B^T)PE \\ &\quad + \frac{1}{2}E^T P(AE + B\Gamma) - \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}} \\ &= \frac{1}{2}E^T(A^T P + PA)E \\ &\quad + \frac{1}{2}\Gamma^T B^T PE + \frac{1}{2}E^T PB\Gamma - \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}} \\ &= -\frac{1}{2}E^T QE + \Gamma^T B^T PE - \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}}\end{aligned} \tag{15}$$

Using Γ defined in (11) and noting that $\Gamma^T = \Gamma$, we have:

$$\dot{V} = -\frac{1}{2}E^T QE + (\tilde{L} - u_r)B^T PE - \frac{1}{\eta}\tilde{\mathcal{L}}\dot{\hat{\mathcal{L}}} \tag{16}$$

Here, the following adaptive law is proposed:

$$\dot{\hat{\mathcal{L}}} = \eta B^T PE \tag{17}$$

Consequently, (16) can be written as follows:

$$\dot{V} = -\frac{1}{2}E^T QE - u_r B^T PE \tag{18}$$

Now, the following continuous robust control term is proposed:

$$u_r = \mu B^T PE \tag{19}$$

Using (19), (18) is written as follows:

$$\dot{V} = -\frac{1}{2}E^T QE - \mu(B^T PE)^2 \leq 0 \tag{20}$$

Consequently, based on $\dot{V} \leq 0$ and by applying Barbalat's lemma [26], the tracking errors converge asymptotically to zero, and all closed-loop signals remain bounded.

IV Simulation Results

The robotic system considered in this study is a SCARA manipulator with the configuration shown in Fig. 1. The maximum allowable input voltage for each actuator is $U_{\max} = 40\,\mathrm{V}$. The parameters of the robotic system are chosen as $m_1 = 11.94\,\mathrm{kg}$, $m_2 = 37.973\,\mathrm{kg}$, $m_3 = 0.263\,\mathrm{kg}$, $a_1 = 0.33\,\mathrm{m}$, $a_2 = 0.27\,\mathrm{m}$, $R = 1.26\,\Omega$, $L = 0.001\,\mathrm{H}$, $K_m = 0.26\,\mathrm{V \cdot s/rad}$, $r = 0.01\,\mathrm{m}$, $J_m = 0.0002\,\mathrm{kg \cdot m^2}$, and $B_m = 0.001\,\mathrm{N \cdot m \cdot s/rad}$. The parameters of the proposed controller are selected as $k_1 = 100$, $k_2 = 100$, and $\mu = 600$. The initial joint positions are given by $q(0) = (-0.03, -0.04, 0.05)^T$. The controller parameters were selected through an iterative tuning process. The primary design objective during this selection was to achieve a suitable trade-off between tracking performance and control effort, while ensuring that the actuator voltages remain strictly within the admissible physical bounds. Although this heuristic approach effectively demonstrates the efficacy of the proposed control scheme, future research could focus on integrating automated parameter selection methods, such as metaheuristic optimization algorithms with well-defined fitness functions, to systematically derive optimal gain configurations for complex robotic applications [30]–[37]. The desired trajectories of the robot joints are defined as follows:

$$q_d = 0.7\big(1 - \cos(\frac{\pi t}{16})\big) \tag{21}$$

In the simulation, the external disturbance is modeled as a pulse signal, as shown in Fig. 2. The position-tracking performance of the three robot joints is illustrated in Figs. 3–5. As shown in these figures, the output of the controlled system tracks the desired trajectory effectively. Moreover, the tracking errors in Fig. 6 demonstrate the satisfactory tracking performance of the proposed controller. The control signals of the proposed method are shown in Fig. 7. These signals are smooth, free of chattering, and remain within the admissible bounds, confirming their practical applicability. Overall, based on Figs. 3–7, the proposed robust method provides satisfactory trajectory-tracking performance for the SCARA robot subject to a pulse disturbance.

To evaluate the effectiveness of the proposed controller and its ability to suppress chattering, its performance is compared with that of a conventional sliding mode controller (SMC) [27]. The tracking errors and control signals of the SMC are shown in Figs. 8 and 9, respectively. Figures 7 and 9 show that the control signals of both the proposed scheme and the conventional SMC remain within the admissible limits. Furthermore, Fig. 8 demonstrates that the tracking errors obtained with the SMC are satisfactory. However, the control signals of the SMC in Fig. 9 exhibit severe chattering. Consequently, this approach is practically unsuitable for trajectory tracking of the considered robotic manipulator.

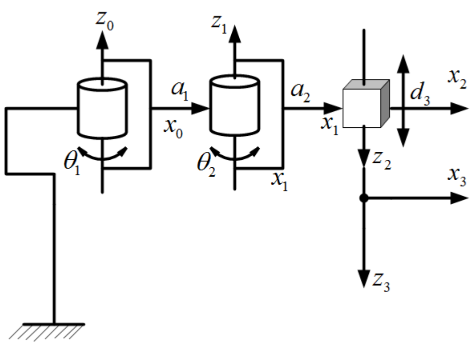

Figure 1. Configuration of the SCARA robot.

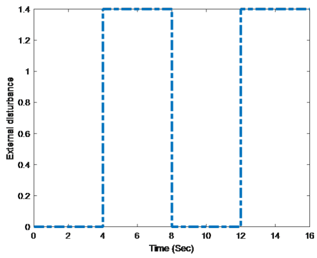

Figure 2. Profile of the external disturbance applied to the system.

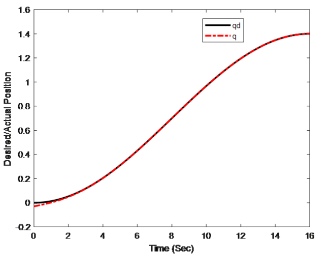

Figure 3. Position tracking performance of Joint 1.

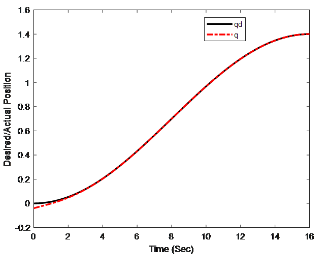

Figure 4. Position tracking performance of Joint 2.

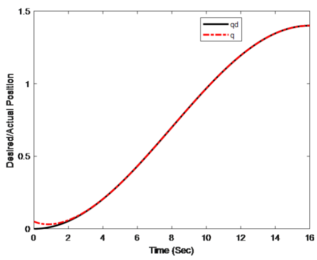

Figure 5. Position tracking performance of Joint 3.

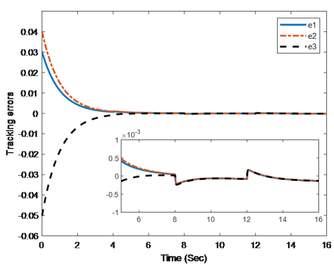

Figure 6. Tracking errors obtained by the proposed robust controller.

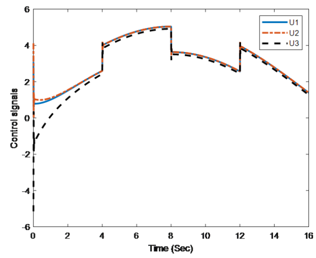

Figure 7. Control signals generated by the proposed robust controller.

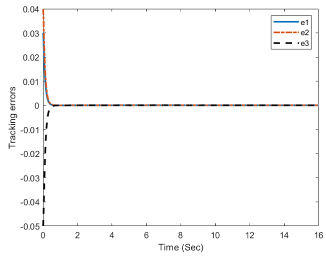

Figure 8. Tracking errors obtained by the sliding mode controller.

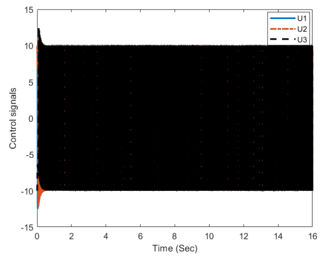

Figure 9. Control signals generated by the sliding mode controller.

V Conclusion

In this paper, a continuous robust state-feedback control method was proposed for robot manipulators subject to lumped uncertainty. The model uncertainties and external disturbances were aggregated into a single lumped term, and the proposed control law was designed to guarantee accurate trajectory tracking. Using Lyapunov stability analysis and Barbalat's lemma, the boundedness of all closed-loop signals and the asymptotic convergence of the tracking error were established. The effectiveness of the proposed method was evaluated through simulations of a SCARA robot under a pulse disturbance. The results demonstrated that the positions of all three joints tracked the desired trajectories with adequate accuracy and that the tracking errors converged to zero. Moreover, the generated control signals were continuous, free of chattering, and remained within the admissible bounds. The simulation results confirm that the proposed robust controller provides an effective solution for accurate trajectory tracking in robots subject to uncertainties and external disturbances.

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