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Practical Prescribed Tracking Control of n-DOF Robotic Manipulator with Uncertainties via Friction Compensation Approach

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Abstract: This paper presents a practical and straightforward control strategy for robotic manipulators with unknown dynamics to achieve prescribed tracking performance, which has implementation advantages compared with previous work. In particular, an improved extended state observer (ESO) synthesized with a continuously differentiable friction model and time-varying gains is presented to estimate system states and unknown dynamics. This ESO outperforms the conventional ones in dealing with friction mutations while avoiding peaking estimation values in the initial stage. By combining the prescribed performance function and the proposed ESO, an independent joint control scheme is proposed for a robotic manipulator to keep the tracking error within a predefined performance bound based only on position measurements. The effectiveness of the proposed control scheme is verified by comparative simulation and experimental results on a six-degrees-of-freedom robotic manipulator with active disturbance rejection controller and PID methods.

Keywords: prescribed performance control; extended state observer; friction model; trajectory tracking



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1. Introduction

1.1. Background and Motivation

Robotic manipulators are crucial in various applications, e.g., industrial automation, medical robotics, and space exploration. The requirements for robotic manipulator control schemes can be categorized into three primary aspects:

- (1) Achieving the control objectives efficiently and precisely.
- (2) Robustness against uncertain dynamics and external disturbances.
- (3) Easy implementation and tuning in engineering practice.

These requirements often involve trade-offs and balancing, and numerous efforts have been devoted to designing robotic manipulator control algorithms [1–8]. Due to the inherent non-linearity and external disturbances of robotic systems, previous advanced control algorithms often employ intricate and exquisite structures to improve system robustness and control accuracy. As a result, the algorithm complexity and parameters grow rapidly with the number of robot links. Meanwhile, practical scenarios rarely provide ideal conditions for the algorithms. Instead, practical robotic systems involve certain

constraints, such as limited computational resources and lacking velocity-sensing devices. Designing an easy-to-implement and effective algorithm remains challenging.

Therefore, this paper develops a straightforward and effective control algorithm for robotic systems with multi-degree-of-freedom (DOF) applications, with ease of implementation, robustness, and precision.

1.2. Related Work

The fundamental challenge of controlling a robotic system lies in its strong non-linearity, uncertainties (e.g., payload variation, parameter perturbations, and unmodeled dynamics), and external disturbances. Meanwhile, symmetry is crucial in robotics and must be considered in robot shape and structure designs to achieve balance and stability. However, asymmetry can be introduced by machining defects and external disturbances, affecting robot performance and stability. To enhance control robustness, various control strategies have been proposed, such as adaptive approaches [1,2], robust control [3,4], and neural network-based approaches [5,6]. Though effective, these algorithms are complex, involving too many parameters and requiring velocity feedback. The linear extended state observer (LESO) [9] can overcome these limitations. When applied to a single input single output (SISO) system, LESO effectively estimates the lumped uncertainty and unmeasured velocity state using a quite simple structure with only one parameter [10,11]. Nevertheless, LESO still has the following two limitations:

- (1) It cannot promptly capture abrupt perturbations, such as friction mutations resulting from velocity reversal [12].
- (2) High constant gains may bring peak values if the initial position error is significant.

Despite several improved ESOs based on non-linear structures or parameter optimization [13,14], the construction and stability analysis of practical ESOs remain open questions.

In addition to robustness, control algorithms must also exhibit accuracy. Two types of methods are commonly used to achieve high-accuracy performance: model-based strategies [7,8] and traditional high-gain control algorithms, such as various sliding mode controllers [15–17]. However, completely modeling the robot dynamics is laborious, and model-based control strategies are computationally demanding. While sliding mode algorithms can enhance control accuracy, their inevitable chattering limits their application in robotics.

Prescribed performance control (PPC) [18] represents a quantitative approach to predefine tracking transient and steady-state performance. It can be viewed as an advanced high-gain approach guaranteeing tracking accuracy within the predefined control performance. Nonetheless, PPC may exhibit significant short-term errors under large perturbations [19]. Yang et al. [20] and Lin et al. [21] proposed ESO-based PPC approaches for one-link and multi-link robot manipulators, respectively. Still, the effectiveness was only verified through simulations. In addition, limited experimental validation of the performance of ESO-based PPC algorithms for multi-DOF robotic manipulators, particularly six-DOF robotic manipulators, has been reported.

1.3. Contribution and Outline

The main contributions of this study can be summarized as follows:

- (1) A continuously differentiable non-linear friction model is introduced to mitigate the adverse effects of the friction, thereby augmenting observer estimation and overall tracking performance. In addition, a practical way of identifying friction parameters is presented.
- (2) A variable gain finite-time ESO (VGFESO) with friction compensation and time-varying gains is proposed to approximate unknown system dynamics and unmeasured velocities. Compared with the LESO in [20,22], VGFESO significantly attenuates the friction mutation and peaking value influences.
- (3) The composite controller combines the friction model, VGFESO, and a prescribed performance function (PPF) and achieves predefined performance tracking control.

Compared with [20,21], the proposed approach has a simpler structure and works under position-measurable conditions alone.

Section 2 covers the problem formulation and preliminary design for a robotic manipulator. Section 3 provides the main results, including the friction model, the controller design procedure, and the stability analysis of the closed-loop system. Numerical simulations and experiments validate the proposed method in Sections 4 and 5. Section 6 concludes this work.

2. Problem Formulation and Preliminaries

2.1. Dynamic Model and Problem Formulation

The dynamics of an n -link robotic manipulator can be expressed as follows [23]:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + F(\dot{q}) = \tau + \tau_d \quad (1)$$

where $q, \dot{q}, \ddot{q} \in \mathbb{R}^n$ are the generalized position, velocity, and acceleration, respectively; inertia matrix $M(q) \in \mathbb{R}^{n \times n}$ is symmetric and positive definite; $C(q, \dot{q})\dot{q} \in \mathbb{R}^n$ is the centrifugal and Coriolis vector; $G(q) \in \mathbb{R}^n$ denotes the gravitational vector; $F(\dot{q}) \in \mathbb{R}^n$ represents friction torques; $\tau_d \in \mathbb{R}^n$ is external disturbance; and $\tau \in \mathbb{R}^n$ is the input.

Defining $x_1 = q \in \mathbb{R}^n$, $x_2 = \dot{q} \in \mathbb{R}^n$, then, (1) can be rewritten into a state-space form:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f - B_0 F_f(x_2) + B_0 \tau \end{cases} \quad (2)$$

where $B_0 = \text{diag}\{b_{10}, \dots, b_{n0}\}$ ($i = 1, 2, \dots, n$); b_{i0} is to be determined; $F_f(\cdot)$ is the continuously differentiable non-linear friction model; and $f \in \mathbb{R}^n$ denotes the lumped uncertainty of the robotic system:

$$f = M^{-1}(q)[\tau - C(q, \dot{q})\dot{q} - G(q) + \tau_d - F(\dot{q})] + B_0(F_f - \tau). \quad (3)$$

Remark 1. Equation (3) reveals that the uncertainty term f accounts for all system uncertainties, including modeled approximation errors, unmodeled dynamics, external disturbances, and non-linear couplings among the joints. This approach enables the robot dynamic model to be deconstructed into several subsystems, as expressed in (1).

Assumption 1. The joint position $q \in \mathbb{R}^n$ is real-time measurable; the desired trajectory $q_d \in \mathbb{R}^n$ is in C^2 and bounded.

Assumption 2. The rate of change of lumped uncertainty f is bounded, i.e., $|\dot{f}| \leq L$.

2.2. Error Transformation

We define the tracking error $e(t) = q(t) - q_d(t)$. To satisfy predefined transient and steady-state performance specifications, $e_i(t)$ should be retained within a prescribed bound [18]:

$$-\rho_{i1}\mu_i(t) < e_i(t) < \rho_{i2}\mu_i(t), \forall t > 0 \quad (4)$$

where $e_i(t)$ is the i -th element of $e(t)$, $\rho_{i1} > 0$, $\rho_{i2} > 0$. PPF $\mu_i(t)$ can be selected as

$$\mu_i(t) = (\mu_{i0} - \mu_{i\infty})e^{-l_i t} + \mu_{i\infty} \quad i = 1, \dots, n \quad (5)$$

where $\mu_{i0} > \mu_{i\infty} > 0$ and $l_i > 0$; $\mu_{i\infty} = \lim_{t \rightarrow \infty} \mu_i(t) > 0$ represents the desirable steady-state tracking error; μ_{i0} is the initial value of $\mu_i(t)$, and $\mu_i(t)$ is strictly positive, smooth, and exponential-decreasing. As expressed in (4) and (5), $\rho_{i1}\mu_i(t)$ and $\rho_{i2}\mu_i(t)$ describe the lower and upper bounds of tracking errors, respectively; and l_i represents the convergence rate. Therefore, by selecting ρ_{i1} , ρ_{i2} , l_i , μ_{i0} , and $\mu_{i\infty}$, the prescribed performance of tracking error $e_i(t)$ can be determined.

To achieve the prescribed performance for $e_i(t)$, we introduce a smooth and strictly increasing error transformation function $S(z_i)$ of the transformed error z_i . $S(z_i)$ transforms (4) into an equivalent “unconstrained” one with the following properties:

Property 1. $-\rho_{i1} < S(z_i) < \rho_{i2}, \forall z_i \in L_{i\infty}$.

Property 2. $\lim_{z_i \rightarrow +\infty} S(z_i) = \rho_{i2}, \lim_{z_i \rightarrow -\infty} S(z_i) = -\rho_{i1}$.

Based on Properties 1 and 2, (4) can be rewritten as:

$$e_i(t) = \mu_i(t)S(z_i). \quad (6)$$

A candidate error transformation function [24] is selected as follows:

$$S(z_i) = \frac{\rho_{i2}e^{z_i} - \rho_{i1}e^{-z_i}}{e^{z_i} + e^{-z_i}}. \quad (7)$$

Based on (6) and (7), z_i can be derived as:

$$z_i = S^{-1}\left(\frac{e_i(t)}{\mu_i(t)}\right) = \frac{1}{2} \ln \frac{\lambda_i(t) + \rho_{i1}}{\rho_{i2} - \lambda_i(t)} \quad (8)$$

where $\lambda_i(t) = e_i(t)/\mu_i(t)$. Then, the derivative of z_i is

$$\dot{z}_i = \frac{\partial S^{-1}}{\partial \lambda} \dot{\lambda}_i = r_i(\dot{e}_i - e_i \dot{\mu}_i / \mu_i) \quad (9)$$

where $r_i = (1/2\mu_i)[1/(\lambda_i + \rho_{i1}) - 1/(\lambda_i - \rho_{i2})]$.

Lemma 1 ([24]). *The control of system (2) is invariant under the error transform (8) with $S(z_i)$, fulfilling Properties 1 and 2. Therefore, stabilizing z_i is sufficient to guarantee the tracking error of original (2) within prescribed error bound (4).*

3. Practical Tracking Control Design

3.1. Continuously Differentiable Friction Model

Designing controllers using discontinuous or piecewise continuous friction models can lead to abrupt changes or instabilities in the control signal at points of discontinuity, making them unsuitable for designing high-performance continuous controllers. Therefore, we use a continuously differentiable friction model [25]:

$$F_f(\dot{q}) = \gamma_1(\tanh(\gamma_2\dot{q}) - \tanh(\gamma_3\dot{q})) + \gamma_4 \tanh(\gamma_5\dot{q}) + \gamma_6\dot{q} \quad (10)$$

where $\gamma_i|_{i=1,\dots,6} > 0$ are constants. Model parameter identification is discussed in Section 4.

Remark 2. *Unlike other friction models, model (10) is continuously differentiable and symmetric about the origin. The stiction coefficients are dominated by γ_1 and γ_4 ; the Stribeck effect is modeled by $\tanh(\gamma_2\dot{q}) - \tanh(\gamma_3\dot{q})$; the Coulomb friction can be approximated by $\gamma_4 \tanh(\gamma_5\dot{q})$; and the viscous dissipation is captured by $\gamma_6\dot{q}$. For example, the profile of friction model (10) is shown in Figure 1 when $\gamma_1 = 0.3$, $\gamma_2 = 20$, $\gamma_3 = 1$, $\gamma_4 = 0.3$, $\gamma_5 = 50$, and $\gamma_6 = 0.01$. For a more detailed explanation, see [25].*

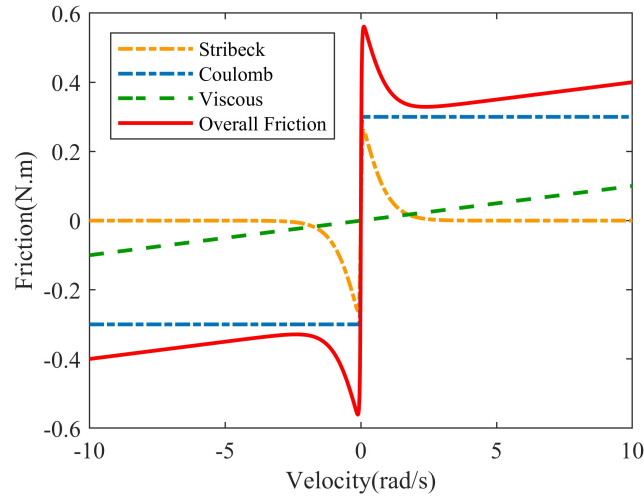


Figure 1. Profile of friction model (10).

3.2. VGFESO Design

According to Equation (2), the dynamic model of the i -th link is

$$\begin{cases} \dot{x}_{i1} = x_{i2} \\ \dot{x}_{i2} = f_i - B_{i0}F_{if}(x_{i2}) + B_{i0}\tau_i. \end{cases} \quad (11)$$

Then, we design the observer for each subsystem to estimate the lumped uncertainty and unmeasurable velocity state. Subscript i is omitted for simplicity. We define an augmented state $x_3 = f$, and let $h(t) = \dot{x}_3$, then the subsystem (11) can be re-written as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 - b_0F_f(x_2) + b_0\tau \\ \dot{x}_3 = h. \end{cases} \quad (12)$$

To capture the friction behaviors effectively, friction model (10) is introduced into ESO,

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 + \beta_1(x_1 - \hat{x}_1) \\ \dot{\hat{x}}_2 = \hat{x}_3 + \beta_2(x_1 - \hat{x}_1) - b_0F_f(\hat{x}_2) + b_0\tau \\ \dot{\hat{x}}_3 = \beta_3(x_1 - \hat{x}_1) \end{cases} \quad (13)$$

where $\hat{x}_i$ is the estimation of state x_i . According to the poly assignment method [9], $\beta_1 = 3\omega_o, \beta_2 = 3\omega_o^2, \beta_3 = \omega_o^3$, where ω_o denotes the bandwidth of the observer. ESO with constant gains may exhibit peaking values as high-gain observers due to huge initial estimate errors. To tackle this issue, a monotonic increasing function is used to replace ω_o in β_i as the observer gains, specifically,

$$\omega(t) = \begin{cases} \omega_0 + (\omega_T - \omega_0) \cdot \left(\frac{t}{t_L}\right)^3, & t \leq t_L \\ \omega_T, & t > t_L. \end{cases} \quad (14)$$

The VGFESO with the friction model and time-varying gains can be reconstructed as follows:

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 + 3\omega(t)(x_1 - \hat{x}_1) \\ \dot{\hat{x}}_2 = \hat{x}_3 + 3\omega(t)^2(x_1 - \hat{x}_1) - b_0F_f(\hat{x}_2) + b_0\tau \\ \dot{\hat{x}}_3 = \omega(t)^3(x_1 - \hat{x}_1). \end{cases} \quad (15)$$

We define the state estimation error $\tilde{x}_j = x_j - \hat{x}_j, j = 1, 2, 3$. Then, we have the estimation error dynamics as follows:

$$\begin{cases} \dot{\tilde{x}}_1 = \tilde{x}_2 - 3\omega(t)\tilde{x}_1 \\ \dot{\tilde{x}}_2 = \tilde{x}_3 - 3\omega(t)^2\tilde{x}_1 + \tilde{F}_f \\ \dot{\tilde{x}}_3 = h - \omega(t)^3\tilde{x}_1 \end{cases} \quad (16)$$

where $\tilde{F}_f = F_f(\hat{x}_2) - F_f(x_2)$ is the friction model error. To facilitate the stability analysis, we define a scaled estimation error $\eta = [\eta_1, \eta_2, \eta_3]^\top$ with $\eta_j := \tilde{x}_j / \omega(t)^{j-1}, j = 1, 2, 3$, and

$$\dot{\eta} = \omega(t)A\eta + \frac{\dot{\omega}(t)}{\omega(t)}B\eta + C\frac{h}{\omega(t)^2} + D\frac{1}{\omega(t)}\tilde{F}_f \quad (17)$$

where

$$A = \begin{bmatrix} -3 & 1 & 0 \\ -3 & 0 & 1 \\ -1 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & & \\ & 1 & \\ & & 2 \end{bmatrix}, \\ C = [0 \ 0 \ 1]^\top, D = [0 \ 1 \ 0]^\top. \quad (18)$$

Then, $\exists P > 0$, satisfying:

$$\begin{aligned} A^\top P + PA &\leq -I_3, \\ B^\top P + PB &\geq 0 \end{aligned} \quad (19)$$

where I_3 denotes a three-dimensional identity matrix. Since $F_f(x_2)$ is continuously differentiable, it is globally Lipschitz with respect to x_2 ; thus, there exists a known constant c , such that

$$|\tilde{F}_f| \leq c|\tilde{x}_2| \leq c\omega(t)\|\eta\|^2. \quad (20)$$

Assumption 3. $h(t)$ is bounded.

Theorem 1. Consider the error system (17) and the VGFESO (15). If $\omega(t) \geq 4c\|P\|$, then the scale estimation error η is uniformly ultimately bounded.

Proof. The detailed proof is shown in Appendix A. $\square$

3.3. Controller Design and Stability Analysis

This section proposes the control strategy based on PPF, friction model, and VGFESO via the backstepping method. We use a two-step approach:

Step 1: We choose a virtual control law as

$$\alpha_1 = -k_1 z r + \dot{q}_d + e\dot{\mu}/\mu \quad (21)$$

where $k_1 > 0$. Choose a Lyapunov function $V_1 = \frac{1}{2}z^2$, then

$$\dot{V}_1 = z r (x_2 - \dot{q}_d - e\dot{\mu}/\mu). \quad (22)$$

We define $\varepsilon = x_2 - \alpha_1$, then

$$\begin{aligned} \dot{V}_1 &= z r (\varepsilon + \alpha_1 - \dot{q}_d - e\dot{\mu}/\mu) \\ &= z r (\varepsilon - k_1 z r + \dot{q}_d + e\dot{\mu}/\mu - \dot{q}_d - e\dot{\mu}/\mu) \\ &= -k_1 z^2 r^2 + z \varepsilon r. \end{aligned} \quad (23)$$

Therefore, $\dot{V}_1 = -k_1 z^2 r^2 \leq 0$ can be derived when $\varepsilon = 0$.

Step 2: The actual control law τ is determined. Based on (12),

$$\dot{\varepsilon} = \dot{x}_2 - \dot{\alpha}_1 = x_3 - b_0 F_f(\hat{x}_2) + b_0 \tau - \dot{\alpha}_1. \quad (24)$$

Due to the differentiation of the non-linear function μ , repeated differentiations will trigger an increase in complexity. Therefore, a tracking differentiator (TD) [26] is introduced to approximate $\dot{\alpha}_1$, which can be expressed as

$$\begin{cases} \dot{r}_1 = r_2 \\ \dot{r}_2 = -R \operatorname{sgn}(r_1 - r(t) + \frac{|r_2|r_2}{2R}) \end{cases} \quad (25)$$

where $r(t)$ is input signal; r_1, r_2 are the states of TD; and R is the parameter to be determined. Properly selecting R can ensure precise tracking of $r(t)$ and $\dot{r}(t)$ by r_1 and r_2 , respectively. The performance of TD has been verified in [27]. Since the VGFESO approximates the unknown states x_2 and x_3 , and the TD estimates $\dot{\alpha}_1$, we design the actual control law τ as follows:

$$\tau = \frac{-\hat{x}_3 + \hat{\alpha}_1 - zr - k_2 \hat{z}_2}{b_0} + F_f(\hat{x}_2) \quad (26)$$

where $k_2 > 0$; and $\hat{\varepsilon} = \hat{x}_2 - \alpha_1$.

The following performance theorem is proposed.

Theorem 2. For the robotic systems (1), the proposed controller (26), TD (25), and VGFESO (15) can guarantee that the error z and ε are ultimately bounded, and the tracking error e can converge to the region defined by the prescribed performance bound (4).

Proof. Define the following Lyapunov function candidate

$$V_2 = V_1 + \frac{1}{2}\varepsilon^2. \quad (27)$$

Then, the time derivative of (27) is

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + \varepsilon \dot{\varepsilon} \\ &= -k_1 r^2 z^2 + rz\varepsilon + \varepsilon(x_3 - b_0 F_f(\hat{x}_2) + b_0 \tau - \dot{\alpha}_1). \end{aligned} \quad (28)$$

Noting that $\varepsilon = x_2 - \alpha_1$, then

$$\hat{\varepsilon} = \hat{x}_2 - \alpha_1 = x_2 - \tilde{x}_2 - \alpha_1 = \varepsilon - \tilde{x}_2. \quad (29)$$

Defining $\tilde{\alpha}_1 = \hat{\alpha}_1 - \dot{\alpha}_1$, we have

$$\begin{aligned} \dot{V}_2 &= -k_1 r^2 z^2 + rz\varepsilon \\ &\quad + \varepsilon(\tilde{x}_3 - rz - k_2 \varepsilon + k_2 \tilde{x}_2 + b_0 \tilde{F}_f + \tilde{\alpha}_1) \\ &= -k_1 r^2 z^2 - k_2 \varepsilon^2 + \varepsilon \tilde{x}_3 + k_2 \varepsilon \tilde{x}_2 + b_0 \varepsilon \tilde{F}_f + \varepsilon \tilde{\alpha}_1. \end{aligned} \quad (30)$$

Based on Young's inequality,

$$\begin{aligned} b_0 \varepsilon \tilde{F}_f &\leq \frac{1}{2}\varepsilon^2 + \frac{1}{2}b_0^2 \tilde{F}_f^2, & \varepsilon \tilde{x}_3 &\leq \frac{1}{2}\varepsilon^2 + \frac{1}{2}\tilde{x}_3^2, \\ k_2 \varepsilon \tilde{x}_2 &\leq \frac{1}{2}\varepsilon^2 + \frac{1}{2}k_2^2 \tilde{x}_2^2, & \varepsilon \tilde{\alpha}_1 &\leq \frac{1}{2}\varepsilon^2 + \frac{1}{2}\tilde{\alpha}_1^2. \end{aligned} \quad (31)$$

We define the upper bound of approximation errors as $\sigma = \sup(|\tilde{F}_f|, |\tilde{x}_2|, |\tilde{x}_3|, |\tilde{\alpha}_1|)$. According to (31), the upper bound of the right-hand side of (30) can be defined as

$$\begin{aligned}
\dot{V}_2 &\leq -k_1 r^2 z^2 - k_2 \varepsilon^2 + 2\varepsilon^2 + \frac{1}{2}(b_0^2 \tilde{F}_f^2 + k_2^2 \tilde{x}_2^2 + \tilde{x}_3^2 + \tilde{\alpha}_1^2) \\
&\leq -k_1 r^2 z^2 - (k_2 - 2)\varepsilon^2 + \frac{1}{2}(b_0^2 + k_2^2 + 2)\sigma^2 \\
&\leq -2\min\{k_1 r^2, (k_2 - 2)\}V_2 + \frac{1}{2}(b_0^2 + k_2^2 + 2)\sigma^2 \\
&\leq -\varphi V_2 + \xi
\end{aligned} \tag{32}$$

where $k_1 > 0, k_2 > 2$; $\varphi = 2\min\{k_1 r^2, (k_2 - 2)\}$; and $\xi = \sup(\frac{1}{2}(b_0^2 + k_2^2 + 2)\sigma^2)$. The solution of (32) is

$$V_2 \leq (V_2(0) - \frac{\xi}{\varphi}) \exp(-\varphi t) + \frac{\xi}{\varphi}. \tag{33}$$

This completes the proof. $\square$

Based on (33) and the definition of V_2 , the signals z and ε are uniformly bounded. Therefore, the tracking error e remains within the prescribed performance bounds (4) according to Lemma 1 and can be made arbitrarily small by selecting appropriate predefined parameters.

4. Numerical Simulation

This section presents the simulation results. The controller is simulated on a two-link rigid robotic manipulator, and the dynamic model has been detailed in [12]. Table 1 provides the parameters. The actual friction torque for each joint is modeled as $F(\dot{q}) = 0.5(\tanh(1000\dot{q}) - \tanh(60\dot{q})) + 2.5 \tanh(1000\dot{q}) + 3\dot{q}$.

Table 1. Parameters of the robotic manipulator.

Symbol	Definition	Value
m_1, m_2	Mass of links 1 and 2	4 kg, 2 kg
l_1, l_2	Length of links 1 and 2	0.5 m, 0.25 m
l_{c1}, l_{c2}	Distance to the centers of mass of links 1 and 2	0.25 m, 0.15 m
I_1, I_2	Inertia tensors of links 1 and 2	1 kg·m ² , 0.8 kg·m ²
g	Gravity acceleration	9.8 m/s ²

The predefined trajectory is $q_d = [q_{d1}, q_{d2}]^T$, where $q_{d1} = q_{d2} = (1 - e^{-0.05t}) \sin(\pi t)$. The control input limits for joints 1 and 2 are $|\tau_1|_{\max} = 300 \text{ N}\cdot\text{m}$ and $|\tau_2|_{\max} = 200 \text{ N}\cdot\text{m}$, respectively. The initial states are $x_1(0) = x_2(0) = 0.5 \text{ rad}$, with other initial values set to zero. $\tau_d = [0.2 \sin(t) + 0.05 \sin(200\pi t), 0.05 \sin(200\pi t)]^T$ serves as an external disturbance. To further test the robustness of the proposed method, m_2 is increased from 2 kg to 6 kg at $t = 3 \text{ s}$, simulating the process of picking up a load.

The following three controllers are compared:

- (1) PPC-VGFESO: This is the controller (26) designed in this paper. The PPF parameters are set as $\mu_{i0} = 0.51, \mu_{i\infty} = 0.005, l_i = 4, \rho_{i1} = \rho_{i2} = 1.1, i = 1, 2$. The controller parameters are set as $k_{i1} = 0.01, k_{i2} = 40, \omega_{i0} = 0, \omega_{iT} = 120, t_{iL} = 0.5 \text{ s}, R_i = 2000, i = 1, 2, b_{10} = 0.5, b_{20} = 1$. The nominal friction model is selected as $F_f(x_2) = 0.8F(x_2)$.
- (2) ADRC [22]: The control law can be expressed as

$$u(t) = \frac{k_p(q_d(t) - \hat{x}_1) + k_v(\dot{q}_d(t) - \hat{x}_2) + \ddot{q}_d - \hat{x}_3}{b_0} \tag{34}$$

where $\hat{x}_i(t)$ is the estimation of state $x_i(t)$ by LESO. The controller parameters are set as $k_{1p} = 400, k_{1v} = 30, b_{10} = 0.5, k_{2p} = 324, k_{2v} = 25, b_{20} = 1$. To compare with VGFESO, the parameter of LESO is also chosen as $\omega_{i0} = 120$.

- (3) Proportional-integral-derivative (PID): A PID controller is defined as $u = k_p e + k_i \int e dt + k_d \dot{e}$. Its gains are $k_{1p} = 5000$, $k_{1i} = 2000$, $k_{1d} = 400$, $k_{2p} = 2000$, $k_{2i} = 1000$, and $k_{2d} = 150$, which are adjusted through trial and error to balance steady-state and transient performance.

The simulation results in Figure 2 demonstrate that the proposed controller ensures that the tracking errors of the manipulator remain within prescribed bounds and converge to a small predefined vicinity around the origin. In contrast, the tracking errors for the other two controllers without prescribed performance obviously exceed these bounds. Notably, the system guided by the proposed controller exhibits better robustness against perturbations. With disturbances at $t = 3$ s, the system quickly returns to a stable condition with minimal oscillation. This is attributed to the following two factors:

- (1) The rapid disturbance estimation by VGFESO and effective compensation, as shown in Figure 3;
- (2) The steady-state performance is strictly constrained by the PPF.

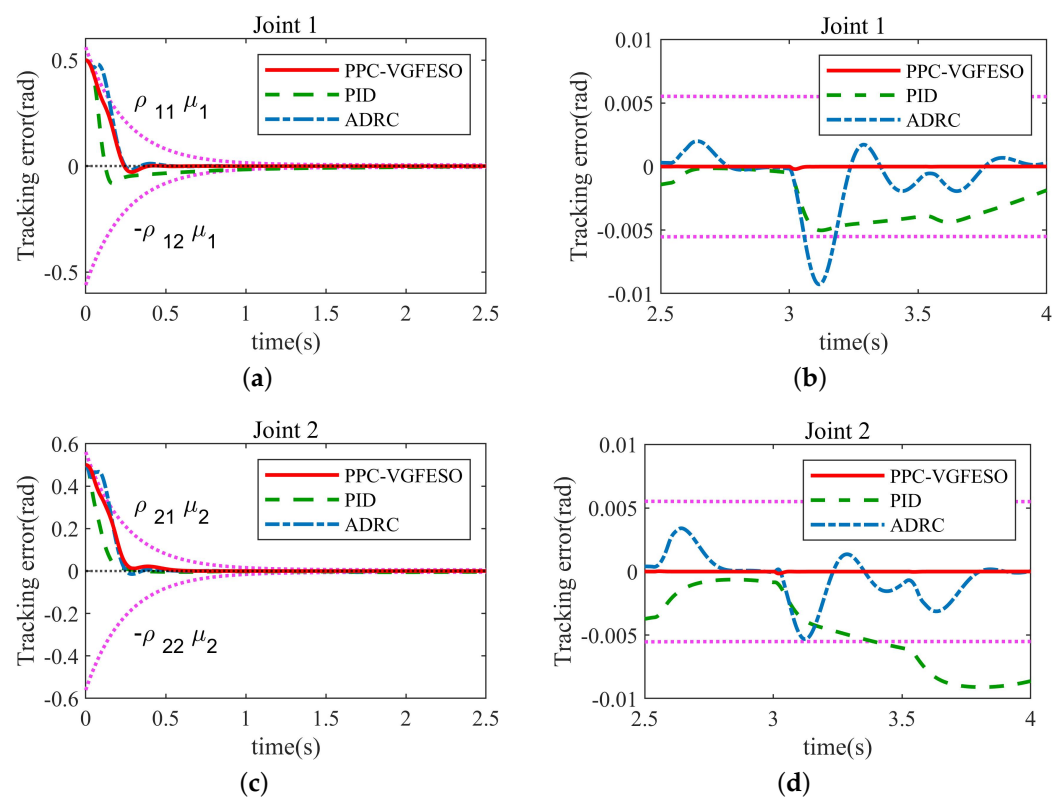


Figure 2. Position tracking errors of joints 1 and 2 for $q_d = (1 - e^{-0.05t}) \sin(\pi t)$: (a) Transient tracking error of joint 1; (b) Steady-state tracking error of joint 1; (c) Transient tracking error of joint 2; (d) Steady-state tracking error of joint 2.

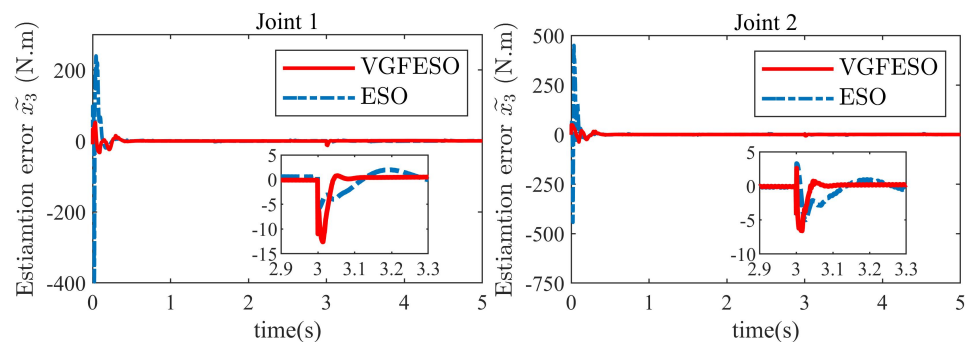


Figure 3. The disturbance estimation errors of VGFESO and ESO.

Figure 4 presents the control input signals. It is worth noting that the actuators in PID and ADRC may operate at the upper/lower saturation limits for extended periods or experience more abrupt changes, potentially causing motor damage. The proposed method avoids actuator saturation issues, as VGFESO effectively compensates for uncertainties while the time-varying gains address the peaking value problem.

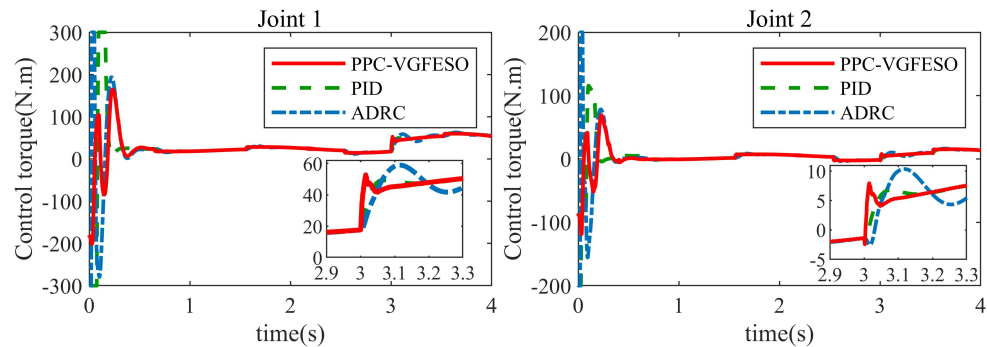


Figure 4. Control input signals of joints 1 and 2 for $q_d = (1 - e^{0.05t}) \sin(\pi t)$.

5. Experiment Verification

The effectiveness of the proposed method is demonstrated on a six-DOF robotic system.

5.1. Experiment Setup

Figure 5 displays the test rig structure, which consists of a collaborative robotic manipulator (Elfin-E03 of Shenzhen Han's Robot, <https://www.hansrobot.net/elfin> (accessed on 1 February 2024)), a PC-based motion controller, and monitoring software. This robot has six joints, a 3 kg payload capacity, an operational range of up to 590 mm, and a repeatability accuracy of ± 0.02 mm. The gear reduction ratio of the joint reducer is 100, and the encoder has a resolution of 19 bits. The PC-based motion controller developed by our team with Intel(R) Core (TM) i7-6700HQ 2.6 GHz CPU, 8.00 GB RAM and Windows 10 operating system (OS). The proposed PPC-VGFESO and the contrast control strategies are developed in Microsoft Visual Studio 2015 and the Kithara real-time suite (KRTS). As a modular real-time extension software for Windows, KRTS provides a real-time working environment for control software. The robot and controller are connected via an EtherCAT bus.

The experimental system is designed for tracking control of specified joint position references. In this system, the servomotor is operated in torque control mode and the joint tracking error is determined using the rotary encoder. The sampling rate is set to 1 ms, which is significantly faster than the control requirements considered later.

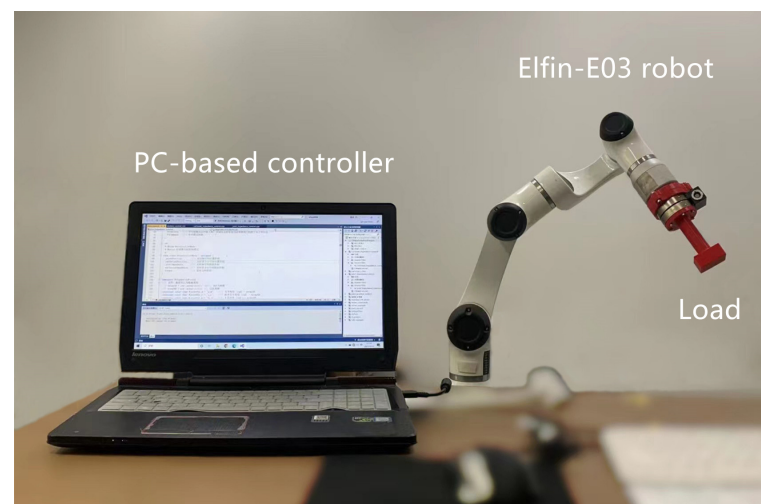


Figure 5. The experimental platform of a robotic system.

5.2. Friction Parameter Identification

The parameter identification process involves two steps. First, we plot friction forces against corresponding velocities to create a friction–velocity map. The velocities are calculated using backward difference and filtered with a second-order Butterworth low-pass filter [28] to reduce measurement noise. After applying different constant velocities to each joint, a mapping between friction forces and joint velocities is constructed. Second, the friction parameters in (10) are identified using the Differential Evolution (DE) algorithm [29]. Taking joints 2 and 3 as examples, Figure 6 displays the friction–velocity map and friction models identified by DE. Table 2 lists the corresponding parameters.

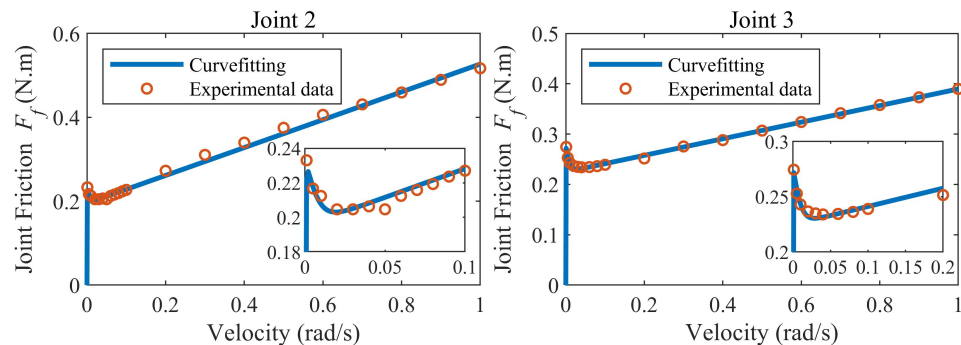


Figure 6. Experimental results and curve fitting of non-linear friction.

Table 2. Friction parameters of joints 2 and 3 obtained by DE.

Parameters	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6
Joint 2	0.0386	1500	99.0837	0.1970	1500	0.3320
Joint 3	0.0510	1800	79.7978	0.2248	1800	0.1648

5.3. Comparative Experimental Results

This section compares the trajectory tracking performance of three controllers (PPC-VGFESO, ADRC, and PID) in a joint space and Cartesian space.

5.3.1. Trajectory Tracking in Joint Space

We focus on joints 2 and 3, which are most affected by gravity and kinematic coupling.

To test the generality and robustness of the three control methods, control parameters are determined under a given reference trajectory $q_d = 0.0873(1 - \cos(\pi t))$, and remain fixed in all experiments. Table 3 lists the parameters. For safety considerations, the time-varying gains in (14) are also used in the ADRC to avoid torque saturation that could damage the actuator.

Table 3. Control parameters of joints 2 and 3.

Controller	Parameters
PPC-VGFESO	$\mu_{i0} = 0.025, \mu_{i\infty} = 0.005, l_i = 10, \rho_{i1} = 1, \rho_{i2} = 1, k_{i1} = 1, \omega_{i0} = 0, \omega_{iT} = 80, t_{iL} = 0.3, R_i = 20, d_i = 0.001, i = 2, 3, k_{22} = 30, k_{32} = 40$
ADRC	$k_{2p} = 361, k_{2v} = 38, \omega_{2T} = 40, b_{20} = 0.17, \omega_{i0} = 0, t_{iL} = 0.3, i = 2, 3, k_{3p} = 576, k_{3v} = 48, \omega_{3T} = 80, b_{30} = 0.3$
PID	$k_{2p} = 3000, k_{2i} = 30, k_{2d} = 250, k_{3p} = 2800, k_{3i} = 20, k_{3d} = 200$

- **Case 1—Low-frequency sinusoidal signal tracking and no load:** In this experiment, the reference trajectory is $q_d = 0.0873(1 - \cos(\pi t))$, and the robot operates without a load. The initial angular position of each joint is set to 0.0175 rad (1°), and the initial velocity is zero. Figures 7 and 8 present the experimental results. The proposed method exhibits faster convergence and smaller steady-state error than the PID and

ADRC controllers. It effectively keeps tracking errors within predefined performance boundaries while successfully addressing abrupt friction changes.

- Case 2—Doubled frequency sinusoidal signal tracking and 1 kg load: A higher frequency sinusoidal trajectory signal $q_d = 0.0873(1 - \cos(2\pi t))$ is employed, with a 1 kg load added to the end. Importantly, the controller parameters remain unchanged from Case 1. The analysis of the experimental results, as shown in Figures 9 and 10, reveals that the proposed PPC-VGFESO maintains satisfactory tracking performance, demonstrating its robustness. In contrast, the overall tracking performance of the PID algorithm deteriorated significantly, while the convergence speed of the ADRC algorithm decreased, accompanied by more pronounced fluctuations in tracking errors. These results highlight the effectiveness of the proposed method.

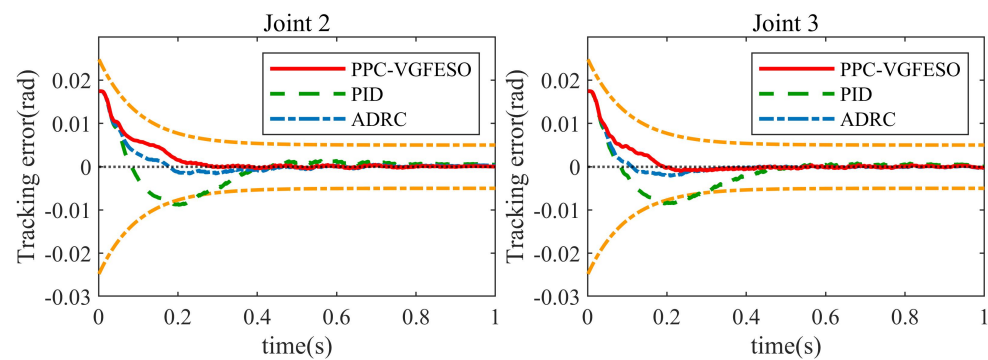


Figure 7. Transient position tracking error comparison for Case 1: $q_d = 0.0873(1 - \cos(\pi t))$ and no load.

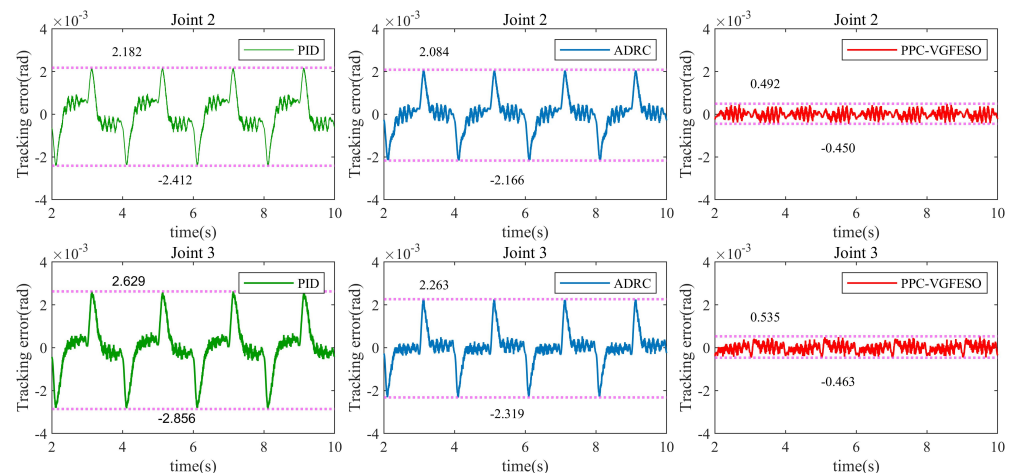


Figure 8. Steady-state position tracking error comparison for Case 1: $q_d = 0.0873(1 - \cos(\pi t))$ and no load.

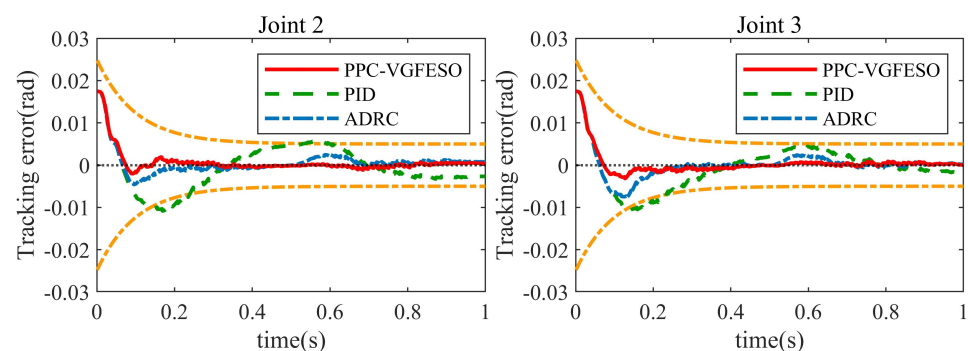


Figure 9. Transient position tracking error comparison for Case 2: $q_d = 0.0873(1 - \cos(2\pi t))$ and 1 kg load.

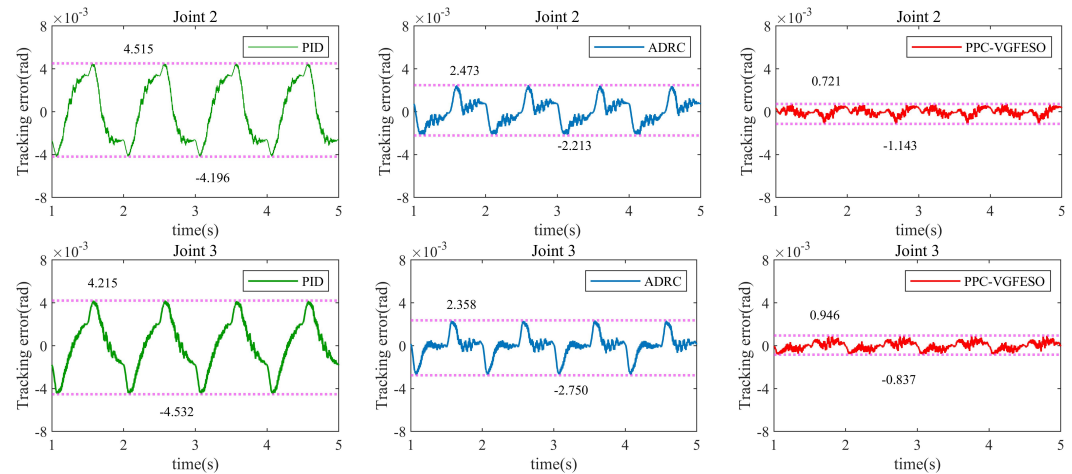


Figure 10. Steady-state position tracking error comparison for Case 2: $q_d = 0.0873(1 - \cos(2\pi t))$ and 1 kg load.

5.3.2. Trajectory Tracking in Cartesian Space

To validate the trajectory tracking performance of the algorithm in Cartesian space, a square with a side length of 100 mm is selected as the target trajectory in the horizontal XOY plane, maintaining a constant height in the Z direction. The line segment is interpolated using an S-curve, and the target positions in each joint are calculated using inverse kinematics. The end-effector position is obtained by calculating the forward kinematics of the joint positions. We define the end position error of the i -th communication cycle as:

$$e_i = \sqrt{(x_i - x_{id})^2 + (y_i - y_{id})^2 + (z_i - z_{id})^2} \quad (35)$$

where x_{id} , y_{id} , and z_{id} denote the target positions at the i -th cycle; and x_i , y_i , and z_i denote the actual positions.

To provide convincing results, the performance of the three controllers is compared under different end-effector velocities and loads. The control parameters for the six joints are carefully tuned for the trajectory $q_d = 0.0873(1 - \cos(\pi t))$ and held constant throughout the experiment. Due to space limitations, the parameters are not listed in this paper. Two performance indices are employed, the maximum absolute tracking error $M_e = \max |e_i|$ and the average tracking error $A_e = (1/N) \sum_{i=1}^N |e_i|$, to evaluate the quality of different control algorithms. The following three cases are tested:

- Case 3—Low speed and no load: The velocity of the end effector is set at 300 mm/s, with an acceleration of 600 mm/s² and a jerk of 4000 mm/s³.
- Case 4—Doubled speed and no load: The velocity of the end effector is doubled to 600 mm/s, with an acceleration of 1200 mm/s² and a jerk of 8000 mm/s³.
- Case 5—Doubled speed and 1 kg load: The velocity, acceleration, and jerk remain the same as in Case 4, with a 1 kg load added.

The experimental results are displayed in Figure 11, and the performance indices are summarized in Table 4. It is evident that the proposed PPC-VGFESO outperforms the other two control algorithms in all cases, as indicated by the significantly lower values of M_e and A_e . These results demonstrate that the proposed algorithm exhibits excellent tracking control performance and robustness. Furthermore, the fact that the control parameters are adjusted under sinusoidal trajectories highlights the broad applicability of the proposed algorithm.

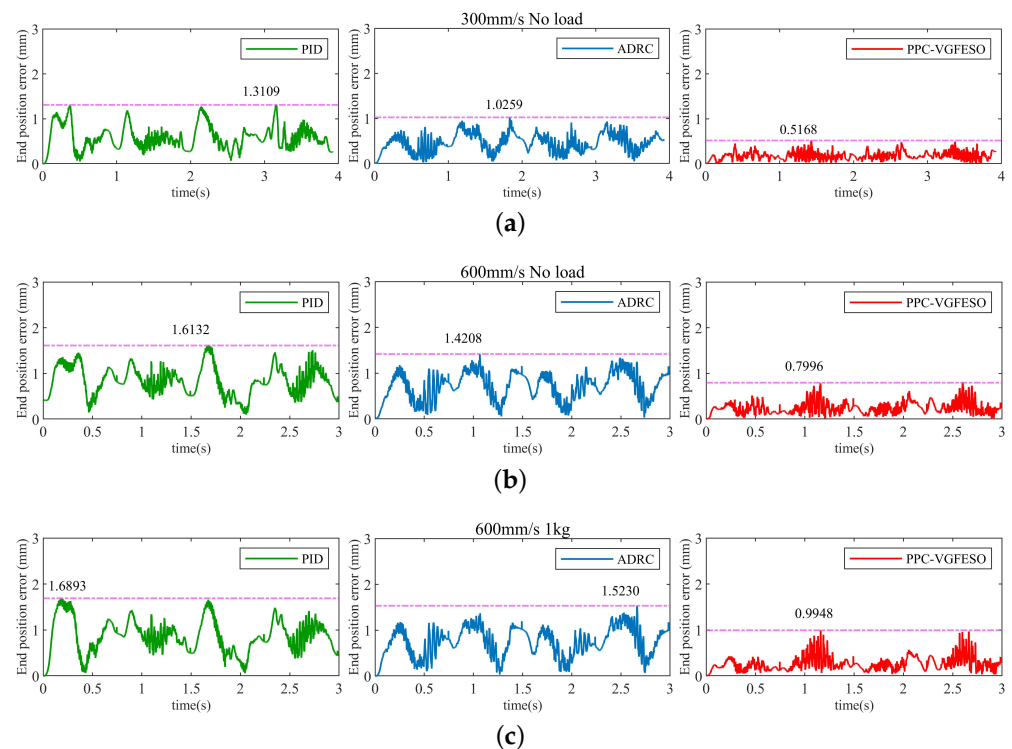


Figure 11. Position tracking errors at different end-effector speeds and loads in Cartesian space: (a) Case 3: 300 mm/s and no load; (b) Case 4: 600 mm/s and no load; (c) Case 5: 600 mm/s and 1 kg load.

Table 4. Comparison of performance indices for experimental results.

Controller	300 mm/s, No Load			600 mm/s, No Load			600 mm/s, 1 kg Load		
	PID	ADRC	PPC-VGFESO	PID	ADRC	PPC-VGFESO	PID	ADRC	PPC-VGFESO
M_e	1.3109	1.0259	0.5168	1.6132	1.4208	0.7996	1.6893	1.5230	0.9948
A_e	0.5777	0.4698	0.1797	0.8421	0.7202	0.2472	0.8678	0.7481	0.2725

6. Conclusions

This paper considers a composite control strategy for the trajectory tracking of a rigid n-link robotic manipulator. The strategy combines PPC, VGFESO, and a continuously differentiable friction model to ensure that the transient and steady-state tracking errors of the manipulator remain within the predefined bounds. Specifically, the friction model is employed to compensate for joint non-linear friction, and VGFESO is designed to accurately estimate the unmodeled dynamics and external disturbances of the system. The closed-loop stability of the new controller and observer and the convergence of the tracking error within the predefined bounds are proven using Lyapunov methods. Simulation and extensive comparative experimental results demonstrate the effectiveness of the proposed strategy. With a simple structure, the proposed method can be easily adapted to other types of electromechanical systems, such as biomimetic bat robots. We plan to focus our subsequent research efforts on developing a novel algorithm that incorporates anti-saturation compensation techniques [30] to ensure that the algorithm maintains robust performance even under conditions of actuator saturation.

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Appendix A

Proof of Theorem 1. Choose the Lyapunov function $V_o = \eta^\top P \eta$, then

$$\begin{aligned}\dot{V}_o &= \dot{\eta}^\top P \eta + \eta^\top P \dot{\eta} \\ &= \omega(t) \eta^\top (A^\top P + PA) \eta - \frac{\dot{\omega}(t)}{\omega(t)} \eta^\top (B^\top P + PB) \eta \\ &\quad + 2 \frac{h_i}{\omega(t)^2} \eta^\top PC + 2 \frac{1}{\omega(t)} \tilde{F}_f \eta^\top PD.\end{aligned}\quad (\text{A1})$$

Consider $\frac{\dot{\omega}(t)}{\omega(t)} \geq 0$ and inequality (19),

$$\dot{V}_o \leq -\omega(t) \|\eta\|^2 + 2 \frac{h}{\omega(t)^2} \eta^\top PC + 2 \frac{1}{\omega(t)} \tilde{F}_f \eta^\top PD. \quad (\text{A2})$$

Considering the Cauchy–Schwarz inequality and Equation (20),

$$\frac{2h}{\omega(t)^2} \eta^\top PC \leq \frac{2h}{\omega(t)^2} \|\eta\| \|P\| \leq \frac{\|\eta\|^2 \omega(t)}{2} + \frac{2h^2 \|P\|^2}{\omega(t)^5} \quad (\text{A3})$$

$$2 \frac{1}{\omega(t)} \tilde{F}_f \eta^\top PD \leq 2 \frac{1}{\omega(t)} \tilde{F}_f \|\eta\| \|P\| \leq 2c \|\eta\|^2 \|P\|. \quad (\text{A4})$$

Choosing $\omega(t) \geq 4c \|P\|$, the upper bound of the right-hand side of (A2) can be defined as follows:

$$2 \frac{1}{\omega(t)} \tilde{F}_f \eta^\top PD \leq 2 \frac{1}{\omega(t)} \tilde{F}_f \|\eta\| \|P\| \leq 2c \|\eta\|^2 \|P\|. \quad (\text{A5})$$

Then,

$$\begin{aligned}\dot{V}_o &\leq -\omega(t) \|\eta\|^2 + \frac{\|\eta\|^2 \omega(t)}{2} + \frac{2h^2 \|P\|^2}{\omega(t)^5} + 2c \|\eta\|^2 \|P\| \\ &\leq -\left(\frac{\omega(t)}{2} - 2c \|P\|\right) \|\eta\|^2 + \frac{2h^2 \|P\|^2}{\omega(t)^5} \\ &\leq -\chi V_o(\eta) + \rho\end{aligned}\quad (\text{A6})$$

where $\chi = 2 \min\left(\frac{\omega(t) - 4c \|P\|}{2a_2}\right)$, and $\rho = \sup\left(\frac{2h^2 \|P\|^2}{\omega(t)^5}\right)$. According to (A5),

$$V_o \leq \left(V_o(0) - \frac{\rho}{\chi}\right) \exp(-\chi t) + \frac{\rho}{\chi}. \quad (\text{A7})$$

According to ([31] Lemma 2), V is uniformly ultimately bounded. Consequently, the scale estimate error η is bounded, which further ensures the boundedness of the state estimate errors. This completes the proof. $\square$

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