Unknown System Dynamics Estimator for Motion Control of Nonlinear Robotic Systems

Jing Na, *Member, IEEE*, Baorui Jing, Yingbo Huang, *Student Member, IEEE*, Guanbin Gao, and Chao Zhang

***Abstract*—In this paper, we propose an alternative, simple, yet efficient estimation method to handle unknown dynamics and external disturbances for motion control of robotic systems. An unknown system dynamics estimator (USDE) is first proposed by introducing filter operations and simple algebraic calculations, where the external disturbances and unknown Coriolis/gravity dynamics can be estimated simultaneously. In the specific case where only the external disturbance is unknown, a further modified unknown disturbance estimator (MUDE) is introduced. These proposed USDE and MUDE can be easily implemented and their parameter tuning is straightforward compared with the nonlinear disturbance observer that requires calculation of the inverse of the inertia matrix. The acceleration signal of robotic joints is not used in the design of estimators. Moreover, we also show that the proposed estimators can be incorporated into the design of composite controllers to achieve satisfactory motion tracking response. The closed-loop control system stability and convergence of both the tracking error and estimation error are all guaranteed. Finally, the effectiveness of the two proposed methods is validated by using simulations and experiments based on a SCARA robot test-rig.**

***Index Terms*—Motion control, nonlinear disturbance observer (NDO), robotic systems, unknown system dynamics estimator (USDE).**

I. Introduction

ROBOTIC systems, as one of the emerging techniques, have attracted considerable attentions in both the industrial and academic communities [1]–[6]. Although various types of robotic manipulators have been allocated in manufacturing and modern factories to replace human being to carry out some repeated, overload, and dangerous work, most of robotic systems are controlled by the traditional proportional-integral-derivative (PID) controller and thus may fail to satisfy the ever-increasing high-accuracy control requirements [7]. In fact, retaining precision motion tracking performance of robotic systems has always been a major focus in the control community. Therefore, many advanced control approaches have been also explored for robotic systems, such as robust control [8], adaptive control [2], [9], boundary control [10], sliding mode control [11], [12], etc.

In general, the difficulties in the control design for robotic systems mainly stem from unknown dynamics and external disturbances. It is well known that the undesired dynamics that cannot be precisely modeled may degrade the performance of model-based control schemes or even trigger instability. To compensate for the unknown dynamics, computed torque control was then proposed [13], which has been regarded as an effective control method due to its superior control accuracy over PID controllers. In this framework, the dynamic model of robotics is assumed to be perfectly known, which may be unrealistic in practice. Although the sliding mode control [14]–[16] was suggested to address bounded uncertainties or disturbances, the induced chattering issue of the control signal limits its practical applications.

To address uncertainties that can be presented in the linearly parametric form, adaptive control has been studied in [17], where the unknown model parameters can be online updated based on the tracking error. To relax the linearly parametric condition, function approximation techniques such as neural networks (NNs) [18]–[22] and fuzzy logic systems (FLSs) [23], [24] were also incorporated into adaptive control designs for robotic systems. The basic idea is that the NNs and FLSs are used to estimate and compensate the unknown dynamics in the robot systems, where the weights of NNs and FLSs can be online updated, without offline learning phases. However, the use of NNs and FLSs imposes heavy computational burden and requires fairly long time to achieve convergence, which in turn induces a sluggish transient control response [25]. More specifically, there are no general, unified parameter-tuning guidelines for adaptive control designs. This creates difficulties for practitioners to apply adaptive controllers.

Apart from the unknown dynamics, external disturbances are also unavoidably encountered in practical control for robotic systems. A well-recognized idea to deal with this issue is to estimate and then compensate the disturbances in the control synthesis [26], which stimulates the development of disturbance observer (DOB). In [27], Ohishi *et al*. first proposed a DOB design for a dc motor system to estimate the applied load torque. This idea was then extended to a microprocessor control system [28]. However, the early proposed DOBs are mainly

Manuscript received January 15, 2019; revised April 15, 2019 and May 11, 2019; accepted May 16, 2019. Date of publication June 7, 2019; date of current version January 3, 2020. This work was supported by National Natural Science Foundation of China under Grant 61873115 and Grant 61573174. *(Corresponding author: Jing Na.)*

The authors are with the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, Kunming 650500, China (e-mail: najing25@163.com; jingbarry@163.com; Yingbo_Huang@126.com; gbgao@163.com; zhangchao_1398@163.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIE.2019.2920604

suitable for linear systems only, as they have been developed via the frequency-domain analysis. Subsequently, Chen *et al.* [29] proposed a new nonlinear disturbance observer (NDO) for robotic manipulators, where the global convergence of the observer error was proved. This method has been further tailored for nonlinear systems with mismatched disturbances in [30]. In parallel, the extended state observer (ESO) was also proposed by Han [31], which has a similar function as DOB to deal with the lumped uncertainties in the system. The ESO was also tailored for a nonintegral-chain system with mismatched disturbances and uncertainties in [32]. In fact, the development and application of DOBs have drawn significant attentions in the control field [26], [31], [33]–[37]. In particular, the paper [26] provides an extensive review of DOB-based control methods. However, although the aforementioned DOB- or ESO-based methods have been applied to specific robotic systems, they need to construct an observer-like structure to provide the observer error to construct the estimator, which requires a relatively complex implementation and a nontrivial parameter tuning phase, i.e., the convergence rate of DOB or ESO depends heavily on the observer gains. Moreover, most of the existing DOB designs for robotic systems require calculation of the inverse of the inertia matrix [29], which may not be always feasible in practice. These two facts motivate the current paper, aiming to develop new estimators to address the unknown dynamics for precise motion control of robotic systems.

In this paper, we will introduce a new methodology to design estimators for motion control of robotic systems with unknown dynamics and external disturbances. First, a new efficient unknown system dynamics estimator (USDE) is developed, which applies low-pass filters on the measured joint position and velocity, while the acceleration signal is not required. Moreover, only the inertia matrix is assumed to be known, where both the unknown external disturbances and internal Coriolis/gravity dynamics can be estimated simultaneously. The specific case with only the external disturbances being unknown is further studied by introducing a modified unknown disturbance estimator (MUDE). Compared with the NDO [29] designed for robotic systems, the proposed USDE and MUDE have a simpler structure and an easier parameter tuning phase, and they do not need to calculate the inverse of inertia matrix, which is preferable in practical applications. Finally, we also show how to use the estimators to design composite controllers to achieve satisfactory motion tracking control of robotic systems. The closed-loop system stability and the convergence of both the estimation error and control error are rigorously proved. Comparative simulations and experiments based on a SCARA robot test-rig are provided. The results illustrate that the proposed methods can achieve comparable estimation and control response as the NDO-based control, but require less-stringent requirements.

The paper is structured as follows. Section II provides the problem description, and the reformulation of robotic model to avoid using the acceleration. The USDE and the corresponding control design are given in Section III. The MUDE and the control design are discussed in Section IV. Comparative simulations and experiments are shown in Section V and Section VI. Section VII concludes this paper.

II. Problem Description and Preliminaries

A. Modeling of Robotic Systems

In this paper, we consider an n-degree of freedom (DOF) nonlinear robotic system, whose dynamics are described as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau + d \tag{1}$$

where $q, \dot{q}, \ddot{q} \in \Re^n$ are the robot joint position, velocity, and acceleration, respectively; $\tau \in \Re^n$ is the control torque/force; $M(q) \in \Re^{n\times n}$ is the inertia matrix and $C(q,\dot{q}) \in \Re^{n\times n}$ is the Coriolis/centripetal torque, including the viscous friction and nonlinear damping. $G(q) \in \Re^n$ represents the gravity torque and d denotes the unknown external disturbance.

The essential properties of robotic system (1) to be used in this paper are as follows:

Property 1 [38]: The matrix $\dot{M}(q) - 2C(q,\dot{q})$ is skew symmetric such that $x^T[\dot{M}(q) - 2C(q,\dot{q})]x = 0$ holds for any $x, q, \dot{q} \in \Re^n$.

Property 2 [38]: The inertia matrix $M(q)$ is bounded, i.e., $\lambda_{\min}\{M\}\mathrm{I} \le M(q) \le \lambda_{\max}\{M\}\mathrm{I}$ is true, where $\lambda_{\min}\{M\}$ and $\lambda_{\max}\{M\}$ denote the minimum and maximum eigenvalues of the matrix $M(q)$, respectively.

Moreover, the following assumption is used in this paper:

Assumption 1: The external disturbance d and its derivative are bounded, i.e., $\sup_{t\ge 0}\|\dot{d}\| \le \hbar$ holds for a constant $\hbar > 0$.

The above properties have been well known for robotic systems. Moreover, Assumption 1 has been also widely used in the DOB designs, e.g., [29]. This condition can be fulfilled in practical robotic systems, in particular when they are operated to track any bounded motion reference. Nevertheless, the upper bound of the disturbance, $\hbar$, is used for analysis only, but not in the control implementation. The aim of control design is to find proper control τ for robotic system (1), such that q can track a given trajectory q_d, while the unknown dynamics $C(q,\dot{q})$ and disturbance d can be tackled.

Although many control methods have been reported for robotic system (1), e.g., PID control [3], [4], computed torque control [13], adaptive control [2], [9], there are two certain issues deserving further investigations. The first is the use of acceleration signal $\ddot{q}$ in the control implementation [17]. In fact, the direct measurement of acceleration is difficult, while the calculation based on the measured joint position or velocity is sensitive to sensor noise. The second issue is the requirement of an accurate robotic model, i.e., the exact knowledge of $C(q,\dot{q}), G(q)$ and even disturbance d. Although adaptive controls with NNs or FLSs have been explored (e.g., [6], [19], [23], and references therein), the complex parameter tuning and sluggish response limit their applications. Nevertheless, as pointed out in the introduction, the existing DOB designs for robotic systems usually need to calculate the inverse of inertia matrix [29].

Hence, the main idea to be presented in this paper is to provide alternative, efficient, and robust unknown dynamics estimators for robotic system (1) without using the acceleration signal and the inverse of inertia matrix, which can achieve same function of

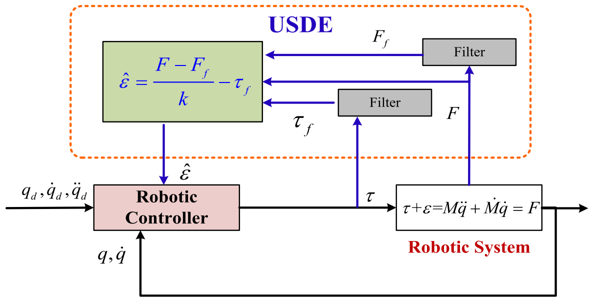


Fig. 1. Schematic of robotic control system with USDE.

NDOs. Moreover, we will also show how to easily incorporate the estimators into the control design as an extra compensation to achieve enhanced motion tracking response.

B. Reformulate Robotics System Model

It is found that the acceleration signal $\ddot{q}$ in the robotic system (1) stems from the term $M(q)\ddot{q}$. To avoid the direct measurement of acceleration signal, we first reformulate the system model (1) by defining the intermediate vector as

$$\begin{cases} F(q,\dot{q}) = M(q)\dot{q} \\ H(q,\dot{q}) = -\dot{M}(q)\dot{q} + C(q,\dot{q})\dot{q} + G(q) \end{cases} \tag{2}$$

where $F(q,\dot{q}), H(q,\dot{q}) \in \Re^n$ are the newly defined vectors without the joint acceleration $\ddot{q}$.

Then, system (1) can be rewritten by using (2) as

$$\dot{F}(q,\dot{q}) + H(q,\dot{q}) = \tau + d \tag{3}$$

where $\dot{F}(q,\dot{q}) = d[M(q)\dot{q}]/dt$ is the derivative of the term $F(q,\dot{q})$ with respect to time t.

As shown in the reformulated model (3), the acceleration signal $\ddot{q}$ has been replaced by the derivative of $F(q,\dot{q})$. Then, in the following developments, we can introduce filter operations to avoid the calculation of $\dot{F}(q,\dot{q})$ in the estimator designs for the unknown dynamics $C(q,\dot{q}), G(q)$ and disturbance d involved in the term $H(q,\dot{q})$.

III. USDE Design and Control for Robotic System

In this section, we will first introduce an USDE to reconstruct the unknown dynamics $C(q,\dot{q}), G(q)$ and disturbance d, where only the inertia matrix $M(q)$ and the measured joint position and velocity are used. This USDE has simpler structure and parameter tuning phase but better convergence than function approximators (e.g., [6], [19], [23]). Specifically, it requires low-pass filters with one scalar only and simple algebraic calculations. Moreover, different to the NDO in [29], we do not need to calculate the inverse of inertia matrix, i.e., $M^{-1}(q)$. This estimator can also be easily incorporated into the feedback control (e.g., computed torque control) to achieve accurate motion tracking. The schematic of the derived closed-loop control system with the USDE is given in Fig. 1.

A. USDE Design

In the recent work [39], [40], an unknown input observer has been proposed for the vehicle engine torque. In this paper, we will further tailor this method by using the idea of invariant manifold [41] to design a robust USDE to reconstruct the unknown dynamics $C(q,\dot{q}), G(q)$ in the robotic system (1).

In this case, we assume that $q, \dot{q}$ and τ are measurable, and thus $F(q,\dot{q})$ can be obtained and used for designing the USDE. The two unknown terms $C(q,\dot{q}), G(q)$ embedded in $H(q,\dot{q})$ are taken as the internal uncertainties, which can be estimated together with the external disturbance d. Then we can define the lumped dynamics to be estimated as

$$\varepsilon = d - H(q,\dot{q}) = d + \dot{M}(q)\dot{q} - C(q,\dot{q})\dot{q} - G(q). \tag{4}$$

Then system (1) can be reformulated by using (2) and (4) as

$$\dot{F}(q,\dot{q}) = M(q)\ddot{q} + \dot{M}(q)\dot{q} = \tau + \varepsilon. \tag{5}$$

We can design an USDE based on (5) to reconstruct the lumped dynamics ε by using $F(q,\dot{q})$ and τ only. Define the filtered variables $F_f(q,\dot{q}), \tau_f$ of the variables $F(q,\dot{q}), \tau$ in system (5) as follows:

$$\begin{cases} k\dot{F}_f(q,\dot{q}) + F_f(q,\dot{q}) = F(q,\dot{q}), & F_f|_{t=0} = 0 \\ k\dot{\tau}_f + \tau_f = \tau, & \tau_f|_{t=0} = 0 \end{cases} \tag{6}$$

where $k > 0$ is a scalar filter parameter. The low-pass filter in (6) aims to derive an invariant manifold for constructing the estimator without using the acceleration of joints.

Then we have the following Lemma:

Lemma 1: Consider system (5) with filtered variables defined in (6), then the manifold $Z = (F - F_f)/k - \tau_f - \varepsilon = 0$ is an invariant manifold [41] for any positive constant k, and $\lim_{k\to 0}\{\lim_{t\to\infty}[(F - F_f)/k - \tau_f - \varepsilon]\} = 0$ is true.

Proof: To prove that $Z = 0$ is an invariant manifold, we first calculate the derivative of Z based on (5) and (6) as

$$\begin{aligned} \dot{Z} &= \frac{\dot{F} - \dot{F}_f}{k} - \dot{\tau}_f - \dot{\varepsilon} = \frac{1}{k}\left[\dot{F} - \frac{F - F_f}{k} - (\tau - \tau_f) - k\dot{\varepsilon}\right] \\ &= \frac{1}{k}(\dot{F} - (Z + \varepsilon) - \tau - k\dot{\varepsilon}) \\ &= -\frac{1}{k}(Z + k\dot{\varepsilon}). \end{aligned} \tag{7}$$

From Assumption 1 and the fact that the robotic system is controlled to track given bounded, smooth motion position, and velocity, we know that ε and its derivative are bounded, i.e., $\sup_{t\geq 0}\|\dot{\varepsilon}\| \leq \lambda$ for a constant $\lambda > 0$. Then we use a Lyapunov function $V_Z = Z^T Z/2$, and can apply Young's inequality $a^T b \leq a^T a/2k + kb^T b/2$ on the term $Z^T\dot{\varepsilon}$ to obtain

$$\begin{aligned} \dot{V}_Z &= -\frac{1}{k}Z^T Z - Z^T\dot{\varepsilon} \leq -\frac{1}{k}Z^T Z + \frac{1}{2k}Z^T Z + k/2\dot{\varepsilon}^2 \\ &\leq -\frac{1}{k}V_Z + \frac{k}{2}\lambda^2. \end{aligned} \tag{8}$$

Solving the solution of (8) yields $V_Z(t) \leq e^{-t/k}V_Z(0) + k^2\lambda^2/2$ which indicated that $V_Z(t)$ and $Z(t)$ are all bounded, and $Z(t)$ will exponentially converge to a residual set defined by $\|Z(t)\| = \sqrt{2V_Z(t)} \le \sqrt{Z^2(0)e^{-t/k} + k^2 \bar{\lambda}^2}$, where the ultimate bound is affected by the constant k and the upper bound of ε, i.e., $\sup_{t\ge 0}\|\dot{\varepsilon}\| \le \bar{\lambda}$. Moreover, we can verify that $\lim_{k\to 0}[\lim_{t\to\infty} Z(t)] = 0$, which indicates that $Z = 0$ is an invariant manifold. ■

The manifold $Z = 0$ indicates a relationship between the variables (F, F_f, τ_f) and the lumped dynamics ε. Thus, a constructive estimator of ε can be designed as

$$\hat{\varepsilon} = \frac{F(q,\dot{q}) - F_f(q,\dot{q})}{k} - \tau_f. \tag{9}$$

Note that the variables used to construct the USDE in (6) and (9) do not use the acceleration signal $\ddot{q}$ since we reformulate the robotic model (1) into (5) and introduce the filter operations in (6). Hence, only the measured joint position q and velocity $\dot{q}$ are used in the estimator. Consequently, the two critical issues mentioned in Section II-A are all solved successfully. Hence, in the following developments, to seek for simple notations, the coordinate $(q,\dot{q})$ in the functions will not be used unless it is necessary.

Before we prove the convergence property of USED (9), an insight of this USDE is first presented.

Lemma 2: Considering the USDE (9) for system (5) by using the filtered variables given in (6), then $\hat{\varepsilon} = \varepsilon_f$ is true, where ε_f given by $k\dot{\varepsilon}_f + \varepsilon_f = \varepsilon, \varepsilon_f|_{t=0} = 0$ is the filtered version of ε. Moreover, the estimation error $\tilde{\varepsilon} = \varepsilon - \hat{\varepsilon}$ is given by

$$\dot{\tilde{\varepsilon}} = -\frac{1}{k}\tilde{\varepsilon} + \dot{\varepsilon}. \tag{10}$$

Proof: By applying the filter operation in (6) (i.e., $1/(ks+1)$) on both side of (5) and according to the first equation of (6), one can deduce that

$$\dot{F}_f = \frac{F - F_f}{k} = \tau_f + \varepsilon_f \tag{11}$$

where ε_f is the filtered version of the lumped uncertainties ε. Hence, the fact $\hat{\varepsilon} = \varepsilon_f$ can be verified from (9) and (11).

Moreover, from the definition of estimation error $\tilde{\varepsilon} = \varepsilon - \hat{\varepsilon}$ and (5), (6), and (9), we can calculate the derivative $\dot{\tilde{\varepsilon}}$ as

$$\begin{aligned}\dot{\tilde{\varepsilon}} &= \dot{\varepsilon} - \dot{\hat{\varepsilon}} = \dot{\varepsilon} - \frac{\dot{F} - \dot{F}_f}{k} + \dot{\tau}_f \\ &= \dot{\varepsilon} - \frac{1}{k}\left(\dot{F} - \frac{F - F_f}{k} - \tau + \tau_f\right) \\ &= \dot{\varepsilon} - \frac{1}{k}\left(\varepsilon - \frac{F - F_f}{k} + \tau_f\right) \\ &= -\frac{1}{k}\tilde{\varepsilon} + \dot{\varepsilon}.\end{aligned} \tag{12}$$

This completes the proof. ■

Now, we prove the convergence of the estimator (9).

Theorem 1: Consider system (1) with USDE (9) for lumped uncertainties ε, then the estimation error $\tilde{\varepsilon}$ is bounded by $\|\tilde{\varepsilon}(t)\| \le \sqrt{\varepsilon^2(0)e^{-t/k} + k^2 \bar{\lambda}^2}$, and thus the fact $\hat{\varepsilon} \to \varepsilon$ holds for $k \to 0$ and/or $\bar{\lambda} \to 0$.

Proof: We select a Lyapunov function as $V_1 = \tilde{\varepsilon}^T\tilde{\varepsilon}/2$ and can calculate its time derivative along (12) and Young's inequality on the term $\tilde{\varepsilon}^T\dot{\varepsilon}$ as

$$\begin{aligned}\dot{V}_1 &= -\frac{1}{k}\tilde{\varepsilon}^T\tilde{\varepsilon} + \tilde{\varepsilon}^T\dot{\varepsilon} \le -\frac{1}{k}\tilde{\varepsilon}^T\tilde{\varepsilon} + \frac{\tilde{\varepsilon}^T\tilde{\varepsilon}}{2k} + \frac{k}{2}\dot{\varepsilon}^T\dot{\varepsilon} \\ &\le -\frac{1}{k}V_1 + \frac{k}{2}\bar{\lambda}^2.\end{aligned} \tag{13}$$

Then, following the proof of Lemma 1, we can obtain that the estimation error is bound as $\|\tilde{\varepsilon}(t)\| = \sqrt{2V(t)} \le \sqrt{\tilde{\varepsilon}^2(0)e^{-t/k} + k^2\bar{\lambda}^2}$, which indicates that $\hat{\varepsilon} \to \varepsilon$ holds for constant dynamics $\varepsilon \equiv Const.$ (such that $\bar{\lambda} = 0$) and/or for $k \to 0$. ■

As shown in the above proof, the constant k in the filter (6) may lead to a phase lag when k is set too large, while a too small gain k may make the proposed estimator sensitive to noise. Hence, it should be set as a tradeoff between the robustness and convergence speed.

Remark 1: The idea to avoid using the acceleration signal $\ddot{q}$ in the proposed USDE is that by applying the filter operation on the function $\dot{F}(q,\dot{q})$, the term $[F(q,\dot{q}) - F_f(q,\dot{q})]/k$ used in (9) does not contain $\ddot{q}$. Moreover, only the inertial matrix $M(q)$ is used in the USDE, while $C(q,\dot{q})$ and $G(q)$ are all unknown and can be estimated together with the disturbance d. Hence, the proposed USDE has the ability of eliminating the required modeling effort for the control design, because it can be easily incorporated into the control design.

B. USDE-Based Control Design

After obtaining an accurate estimate of lumped uncertainties ε, we can use the USDE (9) to design a composite control for robotic system (1), where the convergence of both the tracking error and estimation error can be proved simultaneously.

To achieve motion tracking control, we define the control variable S as

$$S = \dot{e} + \eta e \tag{14}$$

where $e = q - q_d$ is the tracking error and η is a diagonal positive definite matrix. Hence, the tracking error e is bounded/convergent as long as S is bounded/convergent [17].

Then a composite control with USDE (9) is designed as

$$\tau = -K_1 S - \hat{\varepsilon} + M(q)\dot{q}_r + \dot{M}(q)q_r + \frac{1}{2}\dot{M}(q)S \tag{15}$$

where $q_r = \dot{q}_d - \eta e$ is the intermediate error, the gain K_1 is a diagonal positive definite matrix. The term $K_1 S$ is the proportional-derivative (PD) control action, $\hat{\varepsilon}$ is the estimate of the lumped uncertainties given in the USDE (9), and $M(q)\dot{q}_r + \dot{M}(q)q_r + \dot{M}(q)S/2$ is the computed torque control action. Again, it is noted that the dynamics $C(q,\dot{q})$ and $G(q)$ are not used in the control (15).

The closed-loop system stability with the USDE (9) and control (15) can be given in the following theorem.

Theorem 2: Consider robotic system (1) with control (15) and USDE (9), then the tracking errors S, e and estimator error $\tilde{\varepsilon}$ will converge to a small compact set around zero, of which the ultimate bound depends on the variation rate of the lumped uncertainties, i.e., $\dot{\varepsilon}$.

Proof: Substituting (15) into (5), we can obtain the tracking error equation as

$$M(q)\dot{S} = -\frac{1}{2}\dot{M}(q)S + \tilde{\varepsilon} - K_1 S. \tag{16}$$

Select a Lyapunov function as $V_2 = S^T M(q)S/2 + \tilde{\varepsilon}^T\tilde{\varepsilon}/2$ and then its time derivative $\dot{V}_2$ can be derived from (10) and (16) and Young's inequality on the terms $S^T\tilde{\varepsilon}$ and $\tilde{\varepsilon}^T\dot{\varepsilon}$ as

$$\begin{aligned}\dot{V}_2 &= S^T M\dot{S} + \frac{1}{2}S^T\dot{M}S + \tilde{\varepsilon}^T\dot{\tilde{\varepsilon}}\\ &= -S^T K_1 S + S^T\tilde{\varepsilon} - \frac{1}{k}\tilde{\varepsilon}^T\tilde{\varepsilon} + \tilde{\varepsilon}^T\dot{\varepsilon}\\ &\le -\gamma_1 S^T S + \frac{\gamma_1}{2}S^T S + \frac{1}{2\gamma_1}\tilde{\varepsilon}^T\tilde{\varepsilon} - \frac{1}{2k}\tilde{\varepsilon}^T\tilde{\varepsilon} + \frac{k}{2}\hbar^2\\ &\le -\frac{\gamma_1}{2m}S^T MS - \left(\frac{1}{2k} - \frac{1}{2\gamma_1}\right)\tilde{\varepsilon}^T\tilde{\varepsilon} + \frac{k}{2}\hbar^2\\ &\le -\alpha_1 V_2 + \beta_1\end{aligned} \tag{17}$$

where $\gamma_1 = \lambda_{\min}(K_1), m = \lambda_{\max}(M)$ denote the minimum and maximum eigenvalues of the associated matrix, respectively. $\alpha_1 = \min\{\gamma_1/m, 1/k - 1/\gamma_1\}$ and $\beta_1 = k\hbar^2/2$ are positive constants for any $0 < k < \gamma_1$. Then, by solving the inequality (17), we have $V_2(t) \le e^{-\alpha t}V_2(0) + \beta_1/\alpha_1$. This implies that the errors S and $\tilde{\varepsilon}$ will exponentially converge to a residual set defined by $\Omega_1 := \{S, \tilde{\varepsilon} | \|S\| \le \sqrt{2e^{-\alpha t}V_2(0) + k\hbar^2/\alpha_1 m}, \|\tilde{\varepsilon}\| \le \sqrt{2e^{-\alpha t}V_2(0) + k\hbar^2/\alpha_1}\}$. Thus, based on the definition of filtered error in (14), we can conclude that the tracking error e is bounded and convergent to a small set around zero, and its ultimate bound is determined by the variation rate of lumped uncertainties $\sup_{t\ge0}\|\dot{\varepsilon}\| \le \hbar$.

Remark 2: To implement the proposed estimator and control, we need to set the filter constant k, the feedback gain K_1, and constant η, which is straightforward. As shown in the proof of Theorem 2, a large K_1 will lead to a large α_1, which contributes to a fast convergence rate. A small filter constant k can reduce the size of ultimate bound of residual error $k\hbar^2$ and help to increase α_1, while a too small k may lead to high sensitivity to the measurement noise of the proposed estimator. Moreover, the constant η denotes the differential gain in the control term $K_1 S$, which is also influenced by the sensor noise.

IV. MUDE Design and Control for Robotic System

In the previous section, we proposed a composite control with the USDE for robotic system (1), where both the internal dynamics $C(q,\dot{q}), G(q)$ and the external disturbance d are unknown. This section will further tailor the proposed estimator and control to address a specific case, where only the external disturbance d needs to be estimated. In this case, the knowledge of $M(q), C(q,\dot{q})$, and $G(q)$ is assumed to be known. Then, a MUDE and the associated control design will be introduced. The schematic diagram of the proposed control system is shown in Fig. 2.

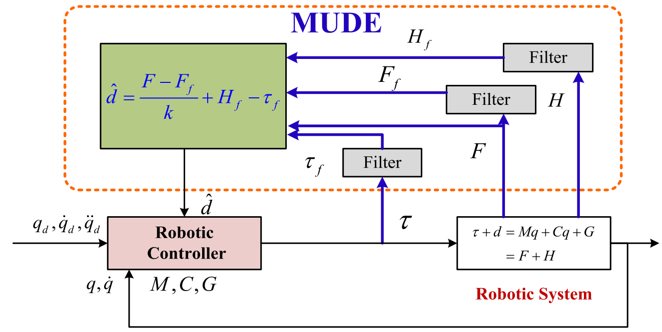


Fig. 2. Schematic of robotic control system with MUDE.

A. MUDE Design

In this case, since the robot dynamics $C(q,\dot{q}), G(q)$ are known, the function $H(q,\dot{q})$ defined in (2) can be used. Then, to avoid using the joint acceleration $\ddot{q}$ induced by $\dot{F}(q,\dot{q})$, we define the filtered variables $F_f(q,\dot{q}), H_f(q,\dot{q}), \tau_f$ of available dynamics $F(q,\dot{q}), H(q,\dot{q}), \tau$ in (3) as

$$\begin{cases} k\dot{F}_f(q,\dot{q}) + F_f(q,\dot{q}) = F(q,\dot{q}), & F_f(q,\dot{q})|_{t=0} = 0\\ k\dot{H}_f(q,\dot{q}) + H_f(q,\dot{q}) = H(q,\dot{q}), & H_f(q,\dot{q})|_{t=0} = 0\\ k\dot{\tau}_f + \tau_f = \tau, & \tau_f|_{t=0} = 0\end{cases} \tag{18}$$

where $k > 0$ is a scalar constant as introduced before.

Then similar to (11), we can obtain from (18) and (3) that

$$\frac{F(q,\dot{q}) - F_f(q,\dot{q})}{k} + H_f(q,\dot{q}) = \tau_f + d_f \tag{19}$$

where d_f is the filtered version of disturbance d defined by $k\dot{d}_f + d_f = d, d_f|_{t=0} = 0$.

In this case, a MUDE to estimate the unknown disturbance d can be designed as

$$\hat{d} = d_f = \frac{F(q,\dot{q}) - F_f(q,\dot{q})}{k} + H_f(q,\dot{q}) - \tau_f. \tag{20}$$

Similar to Lemma 1, we have the following results.

Lemma 3: Consider system (3) with filtered variables defined in (18), then the manifold $Z = (F - F_f)/k - \tau_f + H_f - d = 0$ is an invariant manifold for any positive constant k, and $\lim_{k\to0}\{\lim_{t\to\infty}[(F - F_f)/k - \tau_f + H_f - d]\} = 0$ is true.

The proof of Lemma 3 is similar to the proof of Lemma 1 by recalling the definitions given in (18) and (19) and system (3), and thus will not be detailed here.

Lemma 4: Consider the MUDE (20) with variables given in (18) for system (3), then the estimation error $\tilde{d} = d - \hat{d}$ is

$$\dot{\tilde{d}} = -\frac{1}{k}\tilde{d} + \dot{d}. \tag{21}$$

The proof of Lemma 4 can be deduced from the error dynamics $\tilde{d} = d - \hat{d} = -\dot{F}_f - H_f + \tau_f + d$, and the filtered operation given in (18), which is similar to the proof of Lemma 2.

Theorem 3: Consider system (1) with MUDE (20) for bounded external disturbance d with $\sup_{t\ge0}||\dot{d}|| \le \hbar$, then the estimation error $\tilde{d}$ is bounded by $\|\tilde{d}(t)\| \le \sqrt{\tilde{d}^2(0)e^{-t/k} + k^2\hbar^2}$. Thus, $\hat{d} \to d$ holds for $k \to 0$ and/or $\hbar \to 0$.

Proof: Select a Lyapunov function as $V_3 = \tilde{d}^T\tilde{d}/2$, then we can apply Young's inequality on the term $\tilde{d}^T\dot{d}$ and obtain its derivative along (21) and as

$$\dot{V}_3 = -\frac{1}{k}\tilde{d}^T\tilde{d} + \tilde{d}^T\dot{d} \leq -\frac{1}{k}\tilde{d}^T\tilde{d} + \frac{1}{2k}\tilde{d}^T\tilde{d} + \frac{k}{2}\dot{d}^T\dot{d}$$
$$\leq -\frac{1}{2k}V_3 + \frac{k}{2}\hbar^2. \tag{22}$$

Then we can conclude that V_3 and the estimation error $\tilde{d}$ are bounded, and calculate the residual error bound as given in Theorem 3. ■

Remark 3: The design of MUDE is again inspired by the invariant manifold as given in Lemma 3, which implies a relationship between the variables $F(q,\dot{q}), F_f(q,\dot{q}), H_f(q,\dot{q}), \tau_f$ and unknown disturbance d. Again, the acceleration signal $\ddot{q}$ induced by $\dot{F}(q,\dot{q})$ is avoided by using filter (18). Specifically, it is interesting to find that for constant disturbances ($\dot{d}=0$ and $\hbar = 0$), the fact $\tilde{d} \to 0$ is true, i.e., any constant disturbance can be precisely estimated. The essential difference between USDE and MUDE is that only the unknown disturbance *d* is estimated in the MUDE as the NDO design in [29], where the robotic dynamics $C(q,\dot{q}), G(q)$ are known. Thus, the MUDE can be taken as a specific case of UMDE.

Remark 4: Compared with the NDO developed for robotic systems [29], the proposed USDE and MUDE have a simpler structure and are easier to be implemented, since only low-pass filters (6) and (18) are used to conduct algebraic calculations given in (9) and (20). On the other hand, for the NDO design in [29], an auxiliary vector z has to be online calculated to obtain the disturbance estimate $\hat{d} = z + p(q,\dot{q})$, where the function $p(q,\dot{q})$ to be determined varies for different type of robotics. Moreover, the inverse of the inertial matrix, $M^{-1}(q)$, has to be online calculate to design the time-varying gain as shown in [29], requiring significant calculation cost. However, the convergence and robustness of the proposed USDE and MUDE are the same as the NDO. In this sense, the proposed USDE and MUDE provide alternative, simple, yet efficient estimator design methods.

B. MUDE-Based Control Design

To achieve tracking control with the estimated disturbance given in (20), we define the error variable S as (14), Then the MUDE-based composite controller can be designed as

$$\tau = -K_2 S - \hat{d} + M(q)\dot{q}_r + C(q,\dot{q})q_r + G(q) \tag{23}$$

where $q_r = \dot{q}_d - \eta e$ is the intermediate error, K_2 is a diagonal positive matrix for the PD control $K_2 S$, $\hat{d}$ is the estimate of the unknown disturbance derived by MUDE (20), and the term $M(q)\dot{q}_r + C(q,\dot{q})q_r + G(q)$ is a computed torque action.

Substituting (23) into robotic system (1), one can obtain the tracking error dynamics as

$$M(q)\dot{S} = -C(q,\dot{q})S - K_2 S + \tilde{d}. \tag{24}$$

Now, the stability and convergence of the proposed control system in this section can be summarized as follows.

Theorem 4: Consider robotic system (1) with control (23) and MUDE (20), then the tracking errors S, e and the estimation error $\tilde{d}$ will converge to a small compact set around zero, of which the ultimate bound depends on the variation rate of disturbance, i.e., $\dot{d}$.

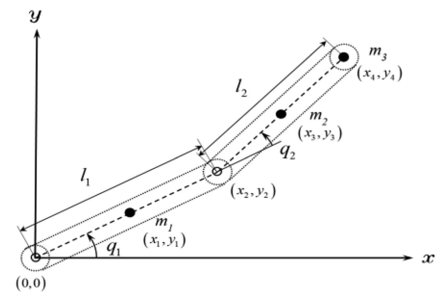


Fig. 3. Schematic diagram of the 2-DOF SCARA robot.

Proof: Select a Lyapunov function as $V_4 = S^T M S/2 + \tilde{d}^T\tilde{d}/2$ and apply Young's inequality on the terms $S^T\tilde{d}, \tilde{d}^T\dot{d}$, then the time derivative $\dot{V}_4$ is computed along with (24) and (21) as

$$\dot{V}_4 = S^T M(q)\dot{S} + \frac{1}{2}S^T\dot{M}(q)S + \tilde{d}^T\dot{\tilde{d}}$$
$$= S^T\left[\frac{1}{2}\dot{M}(q) - C(q,\dot{q})\right]S - S^T K_2 S + S^T\tilde{d} + \tilde{d}^T$$
$$\left(-\frac{1}{k}\tilde{d} + \dot{d}\right)$$
$$\leq -\gamma_2 S^T S + \frac{\gamma_2}{2}S^T S + \frac{1}{2\gamma_2}\tilde{d}^T\tilde{d} - \frac{1}{2k}\tilde{d}^T\tilde{d} + \frac{k}{2}\hbar^2$$
$$\leq -\frac{\gamma_2}{2m}S^T M(q)S - \left(\frac{1}{2k} - \frac{1}{2\gamma_2}\right)\tilde{d}^T\tilde{d} + \frac{k}{2}\hbar^2$$
$$\leq -\alpha_2 V_4 + \beta_2 \tag{25}$$

where $\gamma_2 = \lambda_{\min}(K_2)$, $\alpha_2 = \min\{\gamma_2/m, 1/k - 1/\gamma_2\}$, and $\beta_2 = k\hbar^2/2$ are positive constants for any $0 < k < \gamma_2$. Then similar to the discussions given in the proof of Theorem 2, we can claim the boundedness and convergence of the tracking errors S, e and estimation error $\tilde{d}$. ■

Remark 5: The structure of the USDE-based control (15) and the MUDE-based control (23) is similar, i.e., they all consists of a PD control, a computed torque control, and an estimator-based compensation, while the MUDE-based control (23) requires the robotic dynamics $C(q,\dot{q}), G(q)$. It is noted that the inertial matrix $M(q)$ is required in the controls (15) and (23), thus relaxing the requirements on the inertial matrix will be investigated in our future work.

V. Comparative Simulations

In this section, we first use a SCARA robot model as the numerical example to validate the estimation and tracking performance of the proposed USDE- and MUDE-based control schemes. The schematic structure of this 2-DOF robot and its motion dynamics are all given in Fig. 3. This SCARA robot is a prototype built in our lab, which will be also used as the experimental test-rig in the following section. Hence, to derive the

TABLE I
PARAMETERS FOR SCARA ROBOT

Parameter	Description	Value	Unit
l_1	Length of link 1	0.25	m
l_2	Length of link 2	0.25	m
m_1	Mass of link 1	3.9	kg
m_2	Mass of joint 2	5	kg
m_3	Mass of link 2	2.7	kg
m_4	Mass of actuator	1.5	kg

SCARA model, we have measured some physical parameters of this SCARA robot, which are listed in Table I.

By carrying out modeling work for this SCARA robot with model (1), the matrices $M(q), C(q,\dot{q})$ and $G(q)$ are given as

$$M = \begin{bmatrix} \alpha l_1^2 + \beta l_2^2 + 2\gamma l_1 l_2 c_2 & \beta l_2^2 + \gamma l_1 l_2 c_2 \\ \beta l_2^2 + \gamma l_1 l_2 c_2 & \beta l_2^2 \end{bmatrix}, G = 0$$

$$C = \begin{bmatrix} -2\gamma l_1 l_2 \dot{q}_2 s_2 & -\gamma l_1 l_2 \dot{q}_2 s_2 \\ \gamma l_1 l_2 \dot{q}_1 s_2 & 0 \end{bmatrix} \tag{26}$$

where the parameters are $\alpha = m_{1/4} + m_2 + m_3 + m_4, \beta = m_{3/4} + m_4$ and $\gamma = m_{3/2} + m_4$, and the variables are defined as $c_2 = \cos(q_2)$ and $s_2 = \sin(q_2)$, respectively.

Moreover, based on the definition given in (2), the vectors $F(q,\dot{q})$ and $H(q,\dot{q})$ can be obtained as

$$F = \begin{bmatrix} (\alpha l_1^2 + \beta l_2^2 + 2\gamma l_1 l_2)\dot{q}_1 + (\beta l_2^2 + \gamma l_1 l_2 c_2)\dot{q}_2 \\ (\beta l_2^2 + \gamma l_1 l_2 c_2)\dot{q}_1 + \beta l_2^2 \dot{q}_2 \end{bmatrix}$$

$$H = \begin{bmatrix} 0 \\ \gamma l_1 l_2 s_2 (\dot{q}_1^2 + \dot{q}_1 \dot{q}_2) \end{bmatrix}. \tag{27}$$

To show the efficacy of the proposed USDE and MUDE, we inject an artificial external disturbance d into the model as [29], which denotes the effect of frictions

$$d = f + (T - f)e^{-(\dot{q}/\ell)^2} \tag{28}$$

where $\ell = 0.1$ defines the steepness of the disturbance, and T is defined as

$$T = \begin{cases} \zeta, & \tau > \zeta \\ \tau, & -\zeta \le \tau \le \zeta \\ -\zeta, & \tau < -\zeta \end{cases} \tag{29}$$

where τ is the control torque; f in (28) is a combination of Coulomb and viscous frictions, which is defined as

$$f = \zeta \text{sign}(\dot{q}) + \psi \dot{q} \tag{30}$$

where $\zeta = [0.541, 0.876]^T$ and $\psi = [0.0676, 0.088]^T$. The profiles of disturbance injected into the two joints are shown in Fig. 4.

To validate the benefits of the proposed MUDE, the NDO reported in [29] is also considered, where the unknown disturbance d is estimated as

$$\begin{cases} \dot{z} = -L(q,\dot{q})z + L(q,\dot{q})(C(q,\dot{q}) + G(q) - \tau - p(q,\dot{q})) \\ \hat{d} = z + p(q,\dot{q}) \end{cases}$$

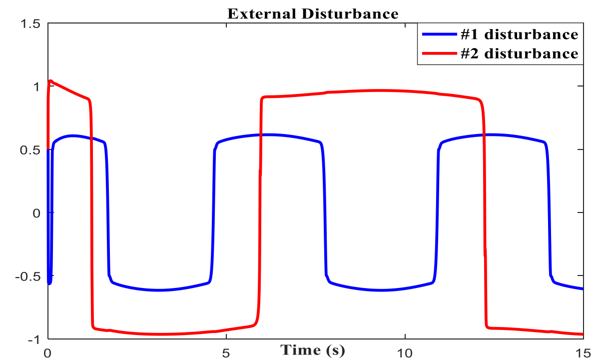


Fig. 4. Profile of disturbances.

where $p(q,\dot{q})$ can be selected as

$$p(q,\dot{q}) = \sigma \begin{bmatrix} \dot{q}_1 \\ \dot{q}_1 + \dot{q}_2 \end{bmatrix}$$

for a large constant $\sigma > 0$, and $L(q,\dot{q})$ is defined as

$$L(q,\dot{q})M(q)\ddot{q} = \begin{bmatrix} \frac{\partial p(q,\dot{q})}{\partial q} & \frac{\partial p(q,\dot{q})}{\partial \dot{q}} \end{bmatrix} \begin{bmatrix} \dot{q} \\ \ddot{q} \end{bmatrix}$$

which leads to

$$L(q,\dot{q}) = \sigma \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} M^{-1}(q).$$

Clearly, the inverse of the inertial matrix, $M^{-1}(q)$, should be calculated in this NDO, and the selection of parameter σ requires priori information of the inertial matrix as well [29].

For fair comparison, we set the simulation conditions of the NDO as same as the USDE and MUDE methods, including the initial conditions $q(0) = \dot{q}(0) = \ddot{q}(0) = 0$. The filter parameter used in the USDE and MUDE is set as $k = 0.01$ and the constant in (14) is $\eta = I$; the feedback gains in (15) and (23) are $K_1 = K_2 = \text{diag}([5, 5])$. Moreover, as explained in Remark 4 and the above discussions, extra filters and auxiliary matrix should be constructed in the NDO [29], where the parameter $\sigma = 50$ is used. Finally, to show the necessity for using the estimators to extract and compensate the unknown dynamics and/or disturbance to improve the control response, a PD control without estimators is also tested [i.e., $\hat{d} = 0$ in (23)].

The estimation and control performances are illustrated in Figs. 5–8. Figs. 5 and 6 show the estimation profiles of the lumped uncertainties ε and disturbance d by using the proposed USDE, MUDE, and the NDO, respectively. As we claimed that the proposed USDE, MUDE, and the NDO have the same convergence property. However, from the estimation error profiles shown in Fig. 6, it is found that the NDO has a relatively large transient error when there are rapid changes in the dynamics to be estimated. This is reasonable because the NDO has more differential equations than the MUDE, which requires longer period to achieve convergence. However, the proposed USDE and MUDE both give satisfactory responses.

Moreover, for the motion tracking control performance of PD control, the proposed controllers (15) and (23) are

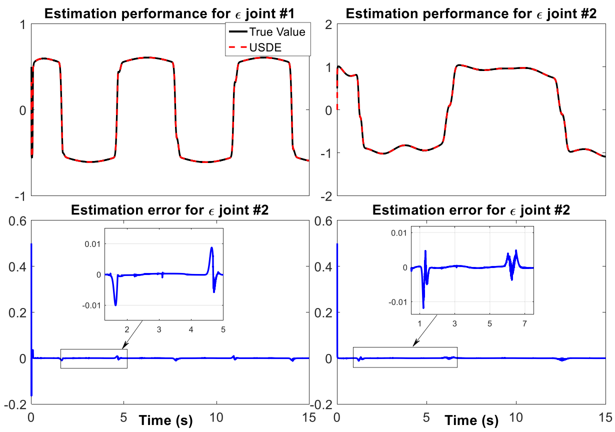


Fig. 5. Estimation of lumped uncertainties ε via USDE.

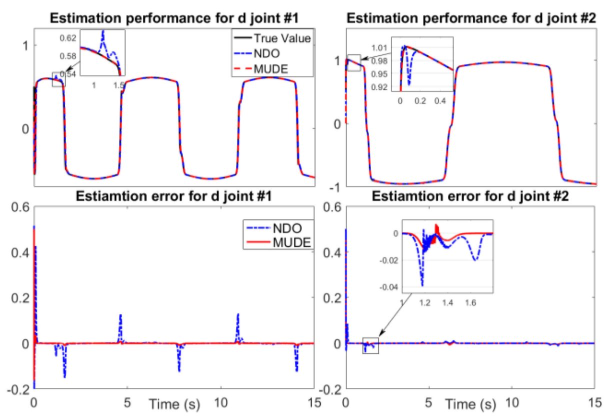


Fig. 6. Estimation of disturbance d via MUDE and NDO.

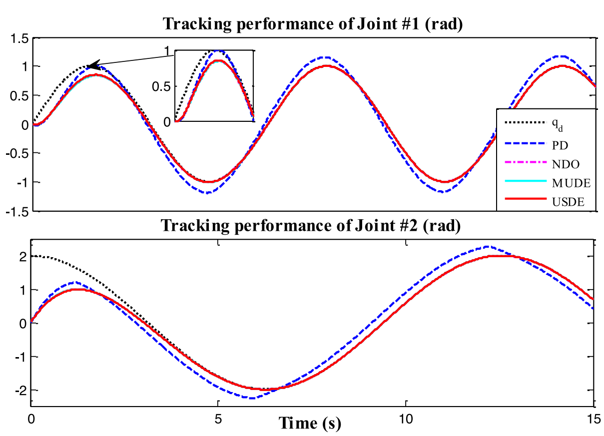


Fig. 7. Comparative tracking responses.

compared and given in Fig. 7. It is shown that the traditional PD control fails to make the output q track the given trajectory perfectly, i.e., the tracking errors shown in Fig. 8 are significant. Nevertheless, fairly good tracking performance can be achieved via the proposed controllers with USDE and MUDE. This can be further confirmed from the tracking errors given in Fig. 8.

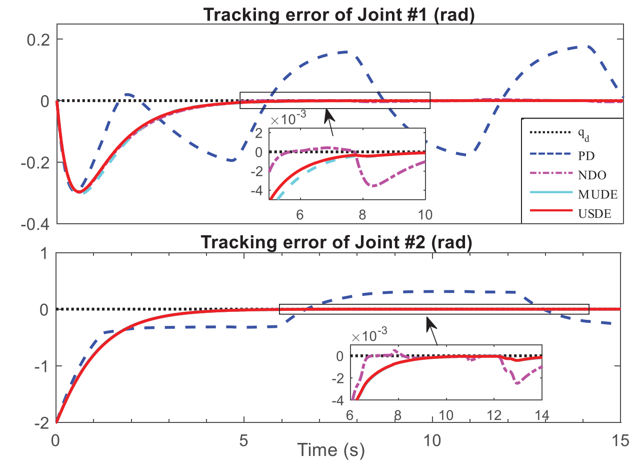


Fig. 8. Comparative tracking errors.

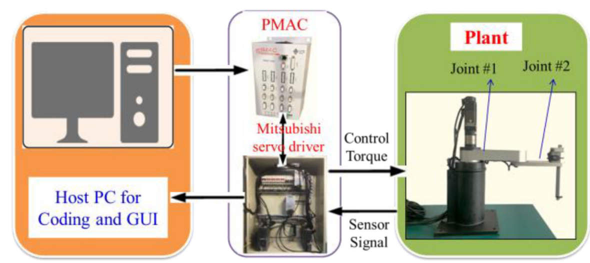


Fig. 9. Diagram of control system for SCARA robot test-rig.

In particular, one can find from Fig. 8 that both the USDE- and MUDE-based controllers can achieve smaller tracking errors than the NDO-based control [29].

VI. Experiments

To verify the applicability of the two suggested estimators and the corresponding controls, experiments are conducted using a practical SCARA robot test-rig. The schematic of the robotic control system is shown in Fig. 9, which includes a graphical user interface (GUI), a motion control board [programmable multiaxis controller (PMAC) produced by Delta Tau, Inc.], two Mitsubishi servo motors with driver boards and the mechanical body. In the experiments, we set the servo driver in the torque control mode, which can make the servo motors track the given position and velocity by coding the estimators and controls in the PMAC environment. The physical parameters of the test-rig used in the experiments are the same as those listed in Table I.

To demonstrate the effectiveness and improved performance of the proposed estimator-based control methods, a PD control is also tested. In the experiments, the sampling frequency determined by PMAC is 0.8 kHz. The parameters used in the estimators and controllers are the same as those used in the simulations, except the filter constant is set as $k = 0.3$, which is set to eliminate the effect of measurement noise as justified in Remark 2. Two different cases are tested with a step reference and a sinusoidal reference, in order to cover generic robot operation scenarios. To further test the ability of these

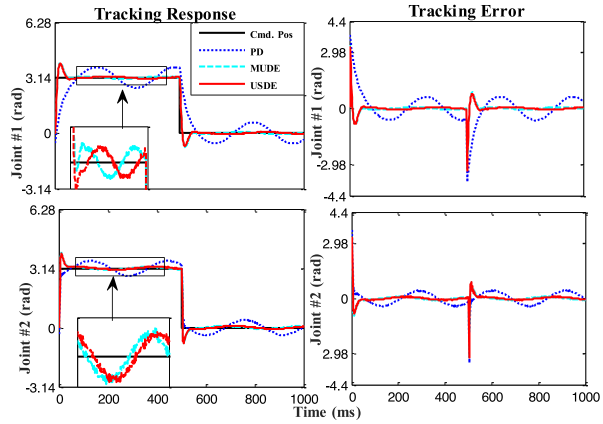


Fig. 10. Tracking performance of step reference.

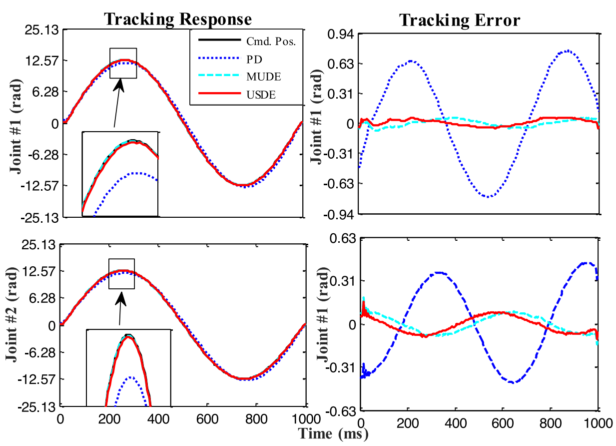


Fig. 11. Tracking performance of sinusoidal reference.

estimators to handle disturbances, a sinusoidal signal with a 3.33 Hz frequency is manually added in the measured system output to simulate the external disturbance d. Note that in the case with a step reference, a low-pass filter is applied on the reference signal to obtain its approximated derivative $\dot{q}_d$.

Experiment results are given in Figs. 10 and 11, where the tracking performance and tracking errors are all illustrated. As shown in Figs. 10 and 11, both the proposed USDE- and MUDE-based controllers can retain clearly superior tracking performance than PD control in both cases, since the unknown dynamics and the added disturbance can be estimated and then compensated in the control. Moreover, it is also found that the responses of the developed composite controllers with the USDE and MUDE schemes are very similar in terms of the transient convergence rate and steady-state error bound. This reconfirms the claims given in Theorem 1 and Theorem 3.

VII. Conclusion

In this paper, we introduced alternative estimator design methods to deal with the unknown dynamics and disturbances in the robotic systems. Two new estimators, USDE and MUDE, were developed, where the difference lied in the required model information. In the USDE, only the inertial matrix was used, and the unknown Coriolis/gravity dynamics and disturbances can be estimated simultaneously; while in the MUDE, the case with only disturbance being unknown was studied. The implementations of these two estimators were simpler than the NDO as they apply the first-order filter operations only and trivial algebraic calculations on the measured dynamics, and they do not need to calculate the inverse of the inertial matrix. The convergence of these two estimators is the same as the NDO, while their parameter tuning is more straightforward, i.e., only a scalar defining the filter bandwidth needed to be adjusted. We also showed how to use these estimators to design composite controls for robotic motion tracking, where simultaneous convergence of both the tracking error and estimation error can be proved. Comparative simulations and experiments were given to show the efficacy and improved performance of the proposed estimators and controllers. The proposed estimators can be incorporated into other advanced control synthesis for nonlinear systems, which deserves further investigations.

References

[1] Z.H. Ma, A. P. Paplinski, and H. R. Wu, "A robust MIMO terminal sliding mode control scheme for rigid robotic manipulators," *IEEE Trans. Autom. Control*, vol. 39, no. 12, pp. 2464–2469, Dec.1994.

[2] J. Na, M. N. Mahyuddin, G. Herrmann, X. Ren, and P. Barber, "Robust adaptive finite-time parameter estimation and control for robotic systems," *Int. J. Robust Nonlin. Control*, vol. 25, pp. 3045–3071, 2015.

[3] K. J. Åström, C. C. Hang, P. Persson, and W. K. Ho, "Towards intelligent PID control," *Automatica*, vol. 28, pp. 1–9, 1992.

[4] T. L. Blevins, "PID advances in industrial control," *IFAC Proc. Volumes*, vol. 45, pp. 23–28, 2012.

[5] C. Yang, K. Huang, H. Cheng, Y. Li, and C.-Y. Su, "Haptic identification by ELM-controlled uncertain manipulator," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 8, pp. 2398–2409, Aug. 2017.

[6] Z. Liu, C. Chen, and Y. Zhang, "Decentralized robust fuzzy adaptive control of humanoid robot manipulation with unknown actuator backlash," *IEEE Trans. Fuzzy Syst.*, vol. 23, no. 3, pp. 605–616, Jun. 2014.

[7] Y. Jia, "Robust control with decoupling performance for steering and traction of 4WS vehicles under velocity-varying motion," *IEEE Trans. Control Syst. Technol.*, vol. 8, no. 3, pp. 554–569, May 2000.

[8] R.-J. Wai and P.-C. Chen, "Robust neural-fuzzy-network control for robot manipulator including actuator dynamics," *IEEE Trans. Ind. Electron.*, vol. 53, no. 4, pp. 1328–1349, Jun. 2006.

[9] C. Yang, Y. Jiang, W. He, J. Na, Z. Li, and B. Xu, "Adaptive parameter estimation and control design for robot manipulators with finite-time convergence," *IEEE Trans. Ind. Electron.*, vol. 65, no. 10, pp. 8112–8123, Oct. 2018.

[10] W. He and S. Zhang, "Control design for nonlinear flexible wings of a robotic aircraft," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 1, pp. 351–357, Jan. 2017.

[11] S. Islam and X. P. Liu, "Robust sliding mode control for robot manipulators," *IEEE Trans. Ind. Electron.*, vol. 58, no. 6, pp. 2444–2453, Jun. 2010.

[12] C.-Y. Su and T.-P. Leung, "A sliding mode controller with bound estimation for robot manipulators," *IEEE Trans. Robot*, vol. 9, no. 2, pp. 208–214, Apr. 1993.

[13] H. Davis and W. Book, "Torque control of a redundantly actuated passive manipulator," in *Proc. 1997 Amer. Control Conf.*, 1997, pp. 959–963.

[14] J.-X. Xu, Z.-Q. Guo, and T. H. Lee, "Design and implementation of integral sliding-mode control on an underactuated two-wheeled mobile robot," *IEEE Trans. Ind. Electron.*, vol. 61, no. 7, pp. 3671–3681, Jul. 2014.

[15] L. M. Capisani and A. Ferrara, "Trajectory planning and second-order sliding mode motion/interaction control for robot manipulators in unknown environments," *IEEE Trans. Ind. Electron.*, vol. 59, no. 8, pp. 3189–3198, Aug. 2011.

[16] Q. Chen, S. Xie, M. Sun, and X. He, "Adaptive nonsingular fixed-time attitude stabilization of uncertain spacecraft," *IEEE Trans. Aerosp. Electro. Syst.*, vol. 54, no. 6 pp. 2937–2950, Dec. 2018.

[17] J.-J. E. Slotine and W. Li, "Composite adaptive control of robot manipulators," *Automatica*, vol. 25, pp. 509–519, 1989.

[18] J. Na, Y. Huang, X. Wu, G. Gao, G. Herrmann, and J. Z. Jiang, "Active adaptive estimation and control for vehicle suspensions with prescribed performance," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 6, pp. 2063–2077, Nov. 2018.

[19] C. Yang, Y. Jiang, Z. Li, W. He, and C.-Y. Su, "Neural control of bimanual robots with guaranteed global stability and motion precision," *IEEE Trans. Ind. Electron.*, vol. 13, no. 3, pp. 1162–1171, Jun. 2016.

[20] Y.-J. Liu, S. Tong, C. P. Chen, and D.-J. Li, "Neural controller design-based adaptive control for nonlinear MIMO systems with unknown hysteresis inputs," *IEEE Trans. Cybern.*, vol. 46, no. 1, pp. 9–19, Jan. 2016.

[21] C. Yang, X. Wang, L. Cheng, and H. Ma, "Neural-learning-based telerobot control with guaranteed performance," *IEEE Trans. Cybern.*, vol. 47, no. 10, pp. 3148–3159, Oct. 2016.

[22] J. Na, S. Wang, Y.-J. Liu, Y. Huang, and X. Ren, "Finite-time convergence adaptive neural network control for nonlinear servo systems," *IEEE Trans. Cybern.*, to be published, doi: 10.1109/TCYB.2019.2893317.

[23] C. Yang, Y. Jiang, J. Na, Z. Li, L. Cheng, and C.-Y. Su, "Finite-time convergence adaptive fuzzy control for dual-arm robot with unknown kinematics and dynamics," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 3, pp. 574–588, Mar. 2019.

[24] Y. J. Liu, G. Ying, S. Tong, and Y. Li, "Fuzzy approximation-based adaptive backstepping optimal control for a class of nonlinear discrete-time systems with dead-zone," *IEEE Trans. Fuzzy Syst.*, vol. 24, no. 1, pp. 16–28, Feb. 2016.

[25] Y. Huang, J. Na, W. Xing, and G. Gao, "Approximation-free control for vehicle active suspensions with hydraulic actuator," *IEEE Trans. Ind. Electron.*, vol. 65, no. 9, pp. 7258–7267, Sep. 2018.

[26] W. H. Chen, J. Yang, G. Lei, and S. Li, "Disturbance observer-based control and related methods: An overview," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1083–1095, Feb. 2016.

[27] K. Ohishi, "Torque-speed regulation of DC motor based on load torque estimation," in *Proc. IEEJ Int. Power Electron. Conf.*, 1983, pp. 1209–1216.

[28] K. Ohishi, M. Nakao, K. Ohnishi, and K. Miyachi, "Microprocessor-controlled DC motor for load-insensitive position servo system," *IEEE Trans. Ind. Electron.*, vol. 34, no. 1, pp. 44–49, Feb. 1987.

[29] W. H. Chen, D. J. Ballance, P. J. Gawthrop, and J. O'Reilly, "A nonlinear disturbance observer for robotic manipulators," *IEEE Trans. Ind. Electron.*, vol. 47, no. 4, pp. 932–938, Aug. 2000.

[30] J. Yang, W. H. Chen, and S. H. Li, "Non-linear disturbance observer-based robust control for systems with mismatched disturbances/uncertainties," *IET Control Theory Appl.*, vol. 5, pp. 2053–2062, 2011.

[31] J. Han, "From PID to active disturbance rejection control," *IEEE Trans. Ind. Electron.*, vol. 56, no. 3, pp. 900–906, Mar. 2009.

[32] S. Li, J. Yang, W. H. Chen, and X. Chen, "Generalized extended state observer based control for systems with mismatched uncertainties," *IEEE Trans. Ind. Electron.*, vol. 59, no. 12, pp. 4792–4802, Dec. 2012.

[33] C. Johnson, "Accomodation of external disturbances in linear regulator and servomechanism problems," *IEEE Trans. Autom. Control.*, vol. 16, no. 6, pp. 635–644, Dec. 1971.

[34] J. Yang, S. Li, and X. Yu, "Sliding-mode control for systems with mismatched uncertainties via a disturbance observer," *IEEE Trans. Ind. Electron.*, vol. 60, no. 1, pp. 160–169, Jan. 2013.

[35] S. Wang, X. Ren, N. Jing, and T. Zeng, "Extended-state-observer-based funnel control for nonlinear servomechanisms with prescribed tracking performance," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 1, pp. 98–108, Jan. 2017.

[36] J. Na, Y. Li, Y. Huang, G. Gao, and Q. Chen, "Output feedback control of uncertain hydraulic servo systems," *IEEE Trans. Ind. Electron.*, to be published, doi: 10.1109/TIE.2019.2897545.

[37] S. Wang, N. Jing, and X. Ren, "RISE-based asymptotic prescribed performance tracking control of nonlinear servo mechanisms," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 12, pp. 2359–2370, Dec. 2018.

[38] D. M. Dawson, C. T. Abdallah, and F. L. Lewis, *Robot Manipulator Control: Theory and Practice*. Boca Raton, FL, USA: CRC Press, 2003.

[39] J. Na, G. Herrmann, R. Burke, and C. Brace, "Adaptive input and parameter estimation with application to engine torque estimation," in *Proc. 54th IEEE Conf. Decis. Control*, 2015, pp. 3687–3692.

[40] J. Na, A. S. Chen, G. Herrmann, R. Burke, and C. Brace, "Vehicle engine torque estimation via unknown input observer and adaptive parameter estimation," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 409–422, Jan. 2018.

[41] A. Astolfi and R. Ortega, "Immersion and invariance: A new tool for stabilization and adaptive control of nonlinear systems," *IEEE Trans. Autom. Control.*, vol. 48, no. 4, pp. 590–606, Apr. 2003.

Jing Na (M'15) received the B.Eng. and Ph.D. degrees in control engineering from the School of Automation, Beijing Institute of Technology, Beijing, China, in 2004 and 2010, respectively.

From 2011 to 2013, he was a Monaco/ITER Postdoctoral Fellow with the ITER Organization, Saint-Paul-les, Durance, France. From 2015 to 2017, he was a Marie Curie Intra-European Fellow with the Department of Mechanical Engineering, University of Bristol, Bristol, U.K. Since 2010, he has been with the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, Kunming, China, where he became a Full Professor in 2013. He has coauthored one monograph published in Elsevier and authored or coauthored more than 100 international journal and conference papers. His research interests include intelligent control, adaptive parameter estimation, nonlinear control and applications for robotics, vehicle systems and wave energy convertor, etc.

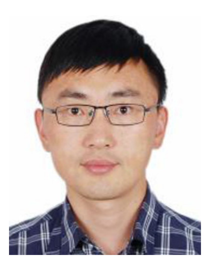
Dr. Na is currently an Associate Editor for *Neurocomputing* and was the IPC Chair of International Conference on Modeling, Identification and Control 2017. He was the recipient of a Marie Curie Fellowship from EU, the Best Application Paper Award of the third International Federation of Automatic Control International Conference on Intelligent Control and Automation Science (IFAC ICONS in 2013), and the 2017 Hsue-shen Tsien Paper Award.

Baorui Jing received the B.Eng. and M.Sc. degrees in mechanical electronic engineering from the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, Kunming, China, in 2013 and 2017, respectively.

His current research interests include adaptive control with applications to robotic system.

Yingbo Huang (S'18) received the B.Sc. degree in mechanical engineering from Lanzhou City University, China, in 2013. He is currently working toward the Ph.D. degree in mechanical engineering with the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and Technology, Kunming, China.

His current research interests include adaptive control and transient performance improvement of nonlinear systems with application to vehicle suspension systems.



Guanbin Gao received the B.Sc. and M.Sc. degrees in mechanical engineering and automation from Northeastern University, Shenyang, China, in 2001 and 2004, respectively, and the Ph.D. degree in mechanical manufacturing and automation from Zhejiang University, Hangzhou, China, in 2010.

His current research interests include precision measuring and control, kinematics of industrial robots, and neural networks (NNs).

Chao Zhang received the B.Sc. degree in mechanical engineering from the Hefei University of Technology, Hefei, China, in 2017. He is currently working toward the M.Sc. degree in mechanical engineering with the Faculty of Mechanical and Electrical Engineering, Kunming University of Science and technology, Kunming, China.

His main research interests include adaptive control with applications to robotic systems.