A Novel Disturbance Observer Design for a Larger Class of Nonlinear Strict-Feedback Systems via Improved DSC Technique

Zhang, Wenqian; Dong, Wenhan; Dong, Shuangyu; Lv, Maolong; Liu, Zongcheng

DOI
10.1109/ACCESS.2019.2931059

Publication date
2019

Document Version
Final published version

Published in
IEEE Access

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received July 11, 2019, accepted July 22, 2019, date of publication July 25, 2019, date of current version August 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2931059

A Novel Disturbance Observer Design for a Larger Class of Nonlinear Strict-Feedback Systems via Improved DSC Technique

WENQIAN ZHANG[1], WENHAN DONG[1], SHUANGYU DONG[2], MAOLONG LV[3,4], AND ZONGCHENG LIU[1]

[1]Aeronautics Engineering College, Air Force Engineering University, Xi'an 710038, China
[2]SMZ Telecom Pty Ltd., Melbourne, VIC 3130, Australia
[3]Delft Center for Systems and Control, Delft University of Technology, 2628 CD Delft, The Netherlands
[4]Equipment Management and UAV Engineering College, Air Force Engineering University, Xi'an 710051, China

Corresponding author: Zongcheng Liu (liu434853780@163.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61304120, Grant 61473307, and Grant 61603411.

ABSTRACT A novel scheme for disturbance observer is designed for an extended class of strict-feedback nonlinear systems with possibly unbounded, non-smooth, and state-independent compounded disturbance. To overcome these problems in disturbance observer design, the typical slide mode differentiators are improved by introducing hyperbolic tangent function to make the signals smooth, and then the improved slide mode differentiators are constructively used to estimate the errors of variables in the presence of disturbances. The unbounded, non-smooth or state-independent disturbances are therefore able to be eliminated by using the estimated variable errors. Thus, the bounded or differentiable conditions for disturbance observer design are removed. Furthermore, the convergence of the new disturbance observer is rigorously proved based on Lyapunov stability theorem, and the tracking error can be arbitrarily small. Finally, the simulation results are given to validate the feasibility and superiority of the proposed approach.

INDEX TERMS Disturbance observer, dynamic surface control, sliding mode differentiator.

I. INTRODUCTION

As is well known, external disturbances, unmodeled dynamics and system uncertainties exist in a wide range of real control processes, which may cause the performance degradation and even the instability of the closed-loop control system. Thus, it is challenging to investigate disturbance estimation and rejection techniques in control systems societies [1]–[4]. Among numerous advanced disturbance estimations and attenuation techniques, disturbance observer-based control schemes have been extensively studied over the past years [5]–[8]. Since the promising properties of improving the control performance, disturbance observers have been widely used to estimate various disturbances and parametric uncertainties for many practical control systems, such as mechanical systems [9], optical disk drive systems [10], air vehicle systems [11], and so on [12], [13]. More precisely, under the assumption that the bounds of the disturbance were unknown positive constants, a robust adaptive control scheme was presented by introducing a Nussbaum function in [14]. A disturbance observer–based dynamic surface control (DSC) approach was studied for the mobile wheeled inverted pendulum system with bounded lumped disturbance vector in [15]. To achieve output tracking for the saturated nonlinear systems with bounded external disturbance, a terminal sliding-mode-based disturbance observer is investigated in [16]. In [17], a disturbance observer combined with terminal sliding mode technique was proposed for the uncertain structural systems, the convergence of disturbance estimate error was guaranteed in finite time with differentiable disturbance. In [18], a disturbance observer-based robust backstepping control approach was developed for spacecraft attitude control systems in the presence of measurement uncertainties, while the time derivatives of the measurement uncertainties were assumed to be bounded. Furthermore, an output-feedback controller was designed based on the composite state observer and disturbance observer for nonlinear time-delay systems with input

The associate editor coordinating the review of this manuscript and approving it for publication was Shuping He.

saturation, since the derivatives of the disturbances were required to be bounded for the disturbance estimators in the error dynamics [19]. The aforementioned control schemes have shown prominent disturbance rejection capability by introducing the designed disturbance observers. However, it has to be mentioned that for all the aforementioned strategies to work, the unknown disturbance is always assumed to be bounded and differentiable [20]–[23], which is very restrictive due to the fact that the compounded disturbances are usually unbounded or differentiable. This is because unmodeled dynamics, as same as some non-smooth nonlinearities such as dead zone and backlash, often occur in many physical systems. To the best of the authors' knowledge, no such disturbance observer designs that can handle both unbounded and non-differentiable compounded disturbances have been reported, which require new techniques go beyond the existing methods. This open issue is of great significance both in applicability and theory research.

On the other hand, adaptive control with disturbance observer has become an active area and attracted considerable attention. Different adaptive design approaches of disturbance observers have been developed by introducing fuzzy systems or neural networks (NNs) approximators [24]–[26]. In [27], a fuzzy nonlinear disturbance observer was designed based on the fuzzy approximation system in which the disturbance is observable. Similarly, combined with fuzzy approximator, a disturbance observer-based adaptive fuzzy control approach was investigated for a class of uncertain MIMO mechanical systems subject to unknown input nonlinearities in [28]. For nonlinear system with the states information being unavailable for the controller design, a novel fuzzy controller was presented by employing fuzzy logic systems (FLS) to construct the composite updating law in [29], [30], thus the adaptive compensation was given to minimize the effects of dynamic uncertainties to the control system. Moreover, neural networks as the universal approximator have been widely employed in control design. For instance, by using the powerful approximation ability of NNs, Chen *et al.* [31] studied an adaptive neural control method based on a disturbance observer for a class of MIMO nonlinear systems with control input saturation. In [32], a constrained adaptive neural controller was designed for the nonstrict-feedback system with the disturbance observer. In view of the unknown function term, the radial basis function neural networks (RBFNNs) were utilized to approximate the compounded disturbances in [33] and a nonlinear disturbance observer was proposed for control law design in the backstepping process. However, the performance of disturbance suppression is related to the approximation accuracy of neural networks, and the prior knowledge of the disturbance is required. For example, a common disturbance observer design approach using FLSs or NNs techniques is investigated under the condition that the input variable information of the disturbance term is known *a priori*. When the input variable information is insufficient, the methods based on NNs and FLSs would not work. It should be noted that this condition can be commonly seen since the unmodeled dynamics included in the compounded disturbance may contain unknown variables. Moreover, the effect of disturbance rejection will heavily depend on the capability of the FLSs or NNs, which are not always robust when faced with strong disturbance. Therefore, it is urgent to propose a new method for disturbance estimation and attenuation.

Motivated by the above discussion, this paper first proposes a novel disturbance observer which, to the best of the authors' knowledge, successfully deals with the typical unbounded and non-smooth compounded disturbances. Combined with the designed disturbance observers, an adaptive tracking control scheme is presented for a class of nonlinear strict-feedback systems for the first time. The innovations are summarized as follows.

1) Unlike most of the existing control schemes, the restrictive assumptions that the compounded disturbance must be bounded, differentiable or slow time-varying have been removed and replaced by a possibly unbounded, non-differentiable and fast time-varying disturbances. To the best of our knowledge, this is the first work to design a disturbance observer relaxing all above restrictions simultaneously.
2) By combining first order sliding mode differentiator with improved DSC technique, the derivatives of the non-disturbance term are constructed. In what follows, a novel disturbance observer is designed, and the corresponding robust compensator is considered in adaptive control law in the meantime.
3) Considering that the prior knowledge of the compounded disturbance cannot be obtained precisely during the control design process, the stability and robustness of the closed loop system can be enhanced without involving FLSs or NNs approximators. Furthermore, it is analytically proved that the tracking error can be regulated to arbitrarily small in the absence of a compact set definition.

The organization of this paper is as follows. The problem description of the uncertain SISO strict-feedback nonlinear system is addressed in Section II. The disturbance observers and the corresponding adaptive controllers are designed by employing sliding mode differentiators and improved DSC techniques in Section III. In Section IV, the convergence of the new disturbance observer is rigorously proved based on Lyapunov stability theorem. Simulation examples are performed to demonstrate the effectiveness of the designed scheme in Section V. The concluding work is stated in Section VI.

II. PROBLEM DESCRIPTION AND PRELIMINARIES

Consider a class of nonlinear strict-feedback systems given by

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + \delta_i(t) \\ \dot{x}_n = f_n(x) + g_n(x)u + \delta_n(t) \\ y = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \ldots, x_i]^T \in R^i$ and $x = [x_1, x_2, \ldots, x_n]^T \in R^n$ denote the state variables of the system, $u \in R$ is system control input, $y \in R$ is system output. $f_i(\bar{x}_i)$ are known differentiable system functions, $g_i(\bar{x}_i)$ represent the known differentiable control-gain functions. Particularly, the term $\delta_i(t) = \Delta f_i(\bar{x}_i) + \Delta g_i(\bar{x}_i)x_{i+1} + d_i(t)$are the compounded disturbance and continuous function, $d_i(t)$, $i = 1, 2 \ldots, n$ are the external disturbance and system uncertainties, $\Delta f_i(\bar{x}_i(t))$ are the uncertain parts of system functions $f_i(\bar{x}_i)$, and $\Delta g_i(\bar{x}_i)$ are the uncertain parts of control-gain functions $g_i(\bar{x}_i)$.

The control objective is to design an adaptive tracking controller such that the system output y follows the desired trajectory y_d and the resulting tracking error can converge to a small neighborhood of the origin by appropriately choosing design parameters.

Assumption 1 [34]: The desired trajectory y_d is a sufficiently smooth function of t, and y_d, $\dot{y}_d$ and $\ddot{y}_d$ are bounded, that is, there exists a positive constant B_0 such that $\Pi_0 := \left\{(y_d, \dot{y}_d, \ddot{y}_d) : (y_d)^2 + (\dot{y}_d)^2 + (\ddot{y}_d)^2 \le B_0\right\}$.

Assumption 2: For the known virtual control-gain functions $g_i(\bar{x}_i)$, $i = 1, 2, \cdots, n-1$, there exist unknown positive constants g_m and g_M such that $0 < g_m \le g_i(\bar{x}_i) \le g_M$.

Remark 1: It is worth noting that, in most of the existing control schemes, the disturbance term $\delta_i(t)$, $i = 1, 2, \cdots, n$ are assumed to satisfy $|\delta_i(t)| \le \delta_0^*$ or $\left|\dot{\delta}_i(t)\right| \le \delta_1^*$ with δ_0^* and δ_1^* being unknown positive constants. However, the disturbance may be possibly unbounded due to unmodeled dynamic and system uncertainties, and it may also be difficult to acquire prior knowledge of $\delta_i(t)$ in practice. If taking no account of these factors, the system performance will be seriously degraded and even be unstable. Thus, the proposed scheme aims to remove these restrictive assumptions and to enlarge the application range of disturbance observer.

Lemma 1 [35]: Hyperbolic tangent function $\tanh(\cdot)$ will be used in this paper, and it is well known that $\tanh(\cdot)$ is continuous and differentiable, and it fulfills that for any $q \in R$ and $\forall \upsilon > 0$

$$\begin{cases} 0 \le |q| - q\tanh\left(\dfrac{q}{\upsilon}\right) \le 0.2785\upsilon \\ 0 \le q\tanh\left(\dfrac{q}{\upsilon}\right) \end{cases} \tag{2}$$

Lemma 2: The first order sliding mode differentiator [36] is designed as

$$\begin{aligned} \dot{\rho}_0 &= \zeta_0 = -\tau_0 \left|\rho_0 - f(t)\right|^{\frac{1}{2}} sign(\rho_0 - f(t)) + \rho_1 \\ \dot{\rho}_1 &= -\tau_1 sign(\rho_1 - \zeta_0) \end{aligned} \tag{3}$$

where ρ_0, ρ_1 and ζ_0 are the states of the system, τ_0 and τ_1 are the designed parameters of the first order sliding mode differentiator, and $f(t)$ is a known function. Then, ζ_0 can approximate the differential term $\dot{f}(t)$ to any arbitrary accuracy if the initial deviations $\rho_0 - f(t_0)$ and $\zeta_0 - \dot{f}(t_0)$ are bounded.

Lemma 3: For any $x \in R$, the following inequality holds

$$\left| |x|^{\frac{1}{2}} sign(x) - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} \tanh\left(\frac{x}{\mu}\right) \right| \le \gamma \tag{4}$$

where μ is the designed parameter and γ is a unknown positive constant.

Proof: See the Appendix.

Remark 2: It has to be noticed that if a discontinuous tracking differentiator is constructed through the first order sliding mode differentiator in Lemma 2, as a consequence, the resulted dynamic system is discontinuous owing to the sign functions that are employed and certain issues on the uniqueness and existence of the solution of the closed loop system will raise. Such issues are very significant since they affect the closed loop performance severely, thus Lemma 3 is introduced by employing hyperbolic tangent function to ensure the feasibility in backstepping process.

Lemma 4: Let $\tau\dot{\beta} + \beta = \alpha$, $y = \beta - \alpha$, where α and β are the input and output of low pass filter respectively, y denotes the filtering error. Then, the filtering error y can be bounded and β can approximate α to any arbitrary accuracy if $\frac{1}{2\tau} = \hat{\dot{\alpha}}^2 + \varepsilon_0$, where ε_0 is a positive constant and $\hat{\dot{\alpha}}$ is the estimate of the differential term $\dot{\alpha}$.

Proof: See the Appendix.

III. ADAPTIVE TRACKING CONTROLLER DESIGN

In this section, backstepping technique is used to construct an adaptive controller for nonlinear system (1). To facilitate the readers' comprehension, the general block diagram of the proposed control scheme is given in Fig. 1.

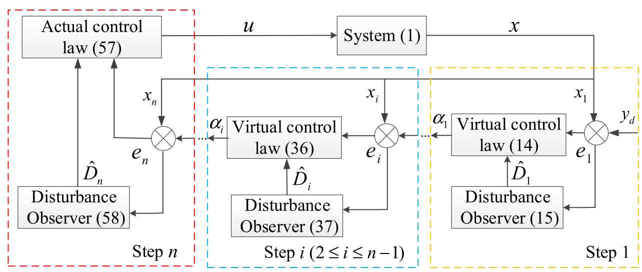


FIGURE 1. Block diagram of the proposed control scheme.

The design of adaptive control laws is based on the following change of coordinates:

$$\begin{cases} e_1 = x_1 - y_d \\ e_i = x_i - \alpha_{i-1} \end{cases}, \quad i = 2, 3, \ldots, n \tag{5}$$

where e_1 is the tracking error and α_{i-1} is the virtual control input that will be designed later.

The recursive design procedure contains n steps. First, at each step of the backstepping design, the intermediate control α_{i-1} is designed to make the corresponding subsystem toward equilibrium position. And at the final step, the stabilization of system (1) can be achieved with the actual control input u being designed.

Step 1: To start, considering the following subsystem of (1) and noting $e_1 = x_1 - y_d$,

$$\dot{e}_1 = f_1(x_1) + g_1(x_1)x_2 + \delta_1 - \dot{y}_d \tag{6}$$

where x_2 is regarded as a virtual control input.

Consider the following quadratic Lyapunov function candidate:

$$V_{e1} = \frac{1}{2}e_1^2 \tag{7}$$

The time derivative of V_{e1} along (6) is

$$\dot{V}_{e1} = e_1[f_1(x_1) + g_1(x_1)x_2 + \delta_1 - \dot{y}_d] \tag{8}$$

Invoking (6), we obtain

$$\delta_1 = \dot{e}_1 - (f_1(x_1) + g_1(x_1)x_2 - \dot{y}_d) \tag{9}$$

Since $\dot{e}_1$ is unavailable, the following first order sliding mode differentiator is adopted so as to produce an auxiliary variable to estimate $\dot{e}_1$.

$$\begin{aligned} \dot{\rho}_{1,0} &= \zeta_{1,0} = -\varepsilon_{1,0} \left|\rho_{1,0} - e_1(t)\right|^{\frac{1}{2}} sign(\rho_{1,0} - e_1(t)) + \rho_{1,1} \\ \dot{\rho}_{1,1} &= -\varepsilon_{1,1} sign(\rho_{1,1} - \zeta_{1,0}) \end{aligned} \tag{10}$$

where $\rho_{1,0}$, $\rho_{1,1}$ and $\zeta_{1,0}$ are the states of the system, $\varepsilon_{1,0}$ and $\varepsilon_{1,1}$ are positive design constants.

Remark 3: In view of Eq. (6), it can be seen that there need assumptions for the signal e_1 [37], [38] and meanwhile, derivative term $\dot{e}_1$ involves the disturbance term δ_1. We would emphasize that if the disturbance term δ_1 is unbounded, the computation of the derivative term $\dot{e}_1$ is therefore complicated. To efficiently handle this problem, the first order sliding mode differentiator according to Lemma 2 can be used to approach the value of $\dot{e}_1$ in disturbance observer design to reduce the computational burden, and this method will show capable of preserving the closed-loop system tracking performance later.

According to Lemma 2, we have

$$\left|\zeta_{1,0} - \dot{e}_1(t)\right| \le \upsilon_{1,0} \tag{11}$$

where $\upsilon_{1,0}$ is a positive constant due to the approximation property of the first order sliding mode differentiator.

Define

$$\hat{\zeta}_{1,0} = -\varepsilon_{1,0} \left(\left(\rho_{1,0} - e_1(t)\right) \tanh\left(\frac{\rho_{1,0} - e_1(t)}{\mu_{1,0}}\right)\right)^{\frac{1}{2}} \times \tanh\left(\frac{\rho_{1,0} - e_1(t)}{\mu_{1,0}}\right) + \rho_{1,1} \tag{12}$$

where $\hat{\zeta}_{1,0}$ is the estimate of the auxiliary variable $\zeta_{1,0}$.

According to Lemma 3 and replace x with $\rho_{1,0} - e_1(t)$, then using (10) and (12), one has

$$\left|\zeta_{1,0} - \hat{\zeta}_{1,0}\right| \le \gamma_1 \tag{13}$$

where γ_1 is a positive constant that can converge to arbitrarily small by appropriately selecting design parameters.

Remark 4: It can be seen that an auxiliary variable $\zeta_{1,0}$ is designed to estimate $\dot{e}_1$ by a first order sliding mode differentiator and then, $\hat{\zeta}_{1,0}$ can be regarded as the approximator of $\dot{e}_1$ similarly, which can be utilized to design the disturbance observer with the help of (6) and the estimation error can converge to arbitrarily small by appropriately adjusting design parameters. Both variables have well estimation performance for $\dot{e}_1$, but to avoid the discontinuity of the sign functions, $\hat{\zeta}_{1,0}$ is presented necessarily according to Lemma 3 by employing hyperbolic tangent function to ensure the feasibility in backstepping process.

Invoking (5), we obtain $x_2 = e_2 + \alpha_1$.

Now, we construct a virtual control law α_1 and the adaptation function $\hat{\delta}_1$ as follows

$$\alpha_1 = g_1^{-1}(x_1)\left(-k_1 e_1 - f_1(x_1) + \dot{y}_d - \lambda_1 \hat{D}_1^2 e_1\right) \tag{14}$$

$$\hat{\delta}_1 = \hat{\zeta}_{1,0} - (f_1(x_1) + g_1(x_1)x_2 - \dot{y}_d) \tag{15}$$

where $\tau_1 \dot{\hat{D}}_1 + \hat{D}_1 = \hat{\delta}_1$, $y_1 = \hat{D}_1 - \hat{\delta}_1$ and λ_1 is a design constant. According to Lemma 4, we know that the filtering error y_1 can be a positive constant by appropriately tuning the design parameters τ_1.

Then, substituting (14) into (8) gives

$$\dot{V}_{e_1} = g_1(x_1)e_1e_2 - k_1e_1^2 - \lambda_1\hat{D}_1^2e_1^2 + \delta_1 e_1 \tag{16}$$

In view of (6) and (15), one has

$$\begin{aligned} -\hat{D}_1 + \delta_1 &= \dot{e}_1 - (f_1(x_1) + g_1(x_1)x_2 - \dot{y}_d) \\ &\quad - \left(\hat{\zeta}_{1,0} - (f_1(x_1) + g_1(x_1)x_2 - \dot{y}_d) + y_1\right) \\ &= \dot{e}_1 - \hat{\zeta}_{1,0} - y_1 \end{aligned} \tag{17}$$

With the aid of (11) and (13), it yields

$$\begin{aligned} \left|-\hat{D}_1 + \delta_1\right| &= \left|\dot{e}_1 - \hat{\zeta}_{1,0} - y_1\right| \\ &\le \left|\dot{e}_1 - \zeta_{1,0}\right| + \left|\zeta_{1,0} - \hat{\zeta}_{1,0}\right| + y_1 \\ &\le \upsilon_{1,0} + \gamma_1 + y_1 = \gamma_1^* \end{aligned} \tag{18}$$

It further gives rise to

$$\begin{aligned} \delta_1^2 - \hat{D}_1^2 &\le \left|\delta_1^2 - \hat{D}_1^2\right| = \left|\delta_1 - \hat{D}_1\right| \left|\delta_1 + \hat{D}_1\right| \\ &\le \gamma_1^* \left(2\left|\delta_1\right| + \gamma_1^*\right) \le 3\gamma_1^{*2} + \frac{\delta_1^2}{2} \end{aligned} \tag{19}$$

which implies

$$\frac{\delta_1^2}{2} \le 3\gamma_1^{*2} + \hat{D}_1^2 \tag{20}$$

Thus, we can rewrite (16) as

$$\begin{aligned} \dot{V}_{e1} &\le g_1(x_1)e_1e_2 - k_1e_1^2 - \lambda_1\hat{D}_1^2e_1^2 + \frac{\lambda_1\delta_1^2e_1^2}{2} + \frac{1}{2\lambda_1} \\ &\le g_1(x_1)e_1e_2 - \left(k_1 - 3\lambda_1\gamma_1^{*2}\right)e_1^2 + \frac{1}{2\lambda_1} \end{aligned} \tag{21}$$

Let $k_1 = 3\lambda_1\gamma_1^{*2} + k_{10}$, where $k_{10} > 0$

$$\dot{V}_{e1} \le g_1(x_1)e_1e_2 - k_{10}e_1^2 + \frac{1}{2\lambda_1} \tag{22}$$

As e_2 is presented in (21), therefore, the regulation of e_2 will be investigated in the next step as follows.

Step $i\,(2 \le i \le n-1)$: A similar procedure is employed recursively for each step $i\,(2 \le i \le n-1)$.

Noting $e_i = x_i - \alpha_{i-1}$, the dynamics of e_i-subsystem can be described as follows

$$\dot{e}_i = f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + \delta_i - \dot{\alpha}_{i-1} \tag{23}$$

Consider the following quadratic Lyapunov function candidate:

$$V_{ei} = \frac{1}{2}e_i^2 \tag{24}$$

The time derivative of V_{ei} along (23) is

$$\dot{V}_{ei} = e_i[f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + \delta_i - \dot{\alpha}_{i-1}] \tag{25}$$

To estimate the differential term $\dot{\alpha}_{i-1}$, an auxiliary variable $\Theta_{i,0}$ is designed as

$$\begin{aligned}\dot{\vartheta}_{i-1,0} &= \Theta_{i,0}\\ &= -\sigma_{i,0}\left|\vartheta_{i-1,0}-\alpha_{i-1}\right|^{\frac{1}{2}} sign(\vartheta_{i-1,0}-\alpha_{i-1})+\vartheta_{i-1,1}\\ \dot{\vartheta}_{i-1,1} &= -\sigma_{i,1}sign(\vartheta_{i-1,1} - \Theta_{i,0})\end{aligned} \tag{26}$$

where $\vartheta_{i-1,0}$, $\vartheta_{i-1,1}$ and $\Theta_{i,0}$ are the states of the system, $\sigma_{i,0}$ and $\sigma_{i,1}$ are positive design constants.

By virtue of the approximation property of the first order sliding mode differentiator, we arrive

$$\left|\Theta_{i,0} - \dot{\alpha}_{i-1}\right| \le \upsilon_{i,1} \tag{27}$$

where $\upsilon_{i,1}$ is a positive constant.

According to (26), the estimate of the differential term $\dot{\alpha}_{i-1}$ is defined as follows:

$$\begin{aligned}\hat{\dot{\alpha}}_{i-1} = -\sigma_{i,0}&\left(\left(\vartheta_{i-1,0} - \alpha_{i-1}\right)\tanh\left(\frac{\vartheta_{i-1,0} - \alpha_{i-1}}{\mu_{i,1}}\right)\right)^{\frac{1}{2}}\\ &\times \tanh\left(\frac{\vartheta_{i-1,0} - \alpha_{i-1}}{\mu_{i,1}}\right) + \vartheta_{i-1,1}\end{aligned} \tag{28}$$

Noting (26), (28) and Lemma 3, one reaches

$$\left|\hat{\dot{\alpha}}_{i-1} - \Theta_{i,0}\right| \le \varsigma_i \tag{29}$$

where ς_i is a positive constant.

Therefore, the following inequality satisfies

$$\begin{aligned}\left|\hat{\dot{\alpha}}_{i-1} - \dot{\alpha}_{i-1}\right| &\le \left|\Theta_{i,0} - \dot{\alpha}_{i-1}\right| + \left|\hat{\dot{\alpha}}_{i-1} - \Theta_{i,0}\right|\\ &\le \upsilon_{i,1} + \varsigma_i\end{aligned} \tag{30}$$

Invoking(23), we obtain

$$\delta_i = \dot{e}_i - (f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} - \dot{\alpha}_{i-1}) \tag{31}$$

Similar to Step 1, since $\dot{e}_i$ is unavailable, the following first order sliding mode differentiator is adopted as follows:

$$\begin{aligned}\dot{\rho}_{i,0} &= \zeta_{i,0} = -\varepsilon_{i,0}\left|\rho_{i,0} - e_i(t)\right|^{\frac{1}{2}} sign(\rho_{i,0} - e_i(t)) + \rho_{i,1}\\ \dot{\rho}_{i,1} &= -\varepsilon_{i,1}sign(\rho_{i,1} - \zeta_{i,0})\end{aligned} \tag{32}$$

where $\rho_{i,0}$, $\rho_{i,1}$ and $\zeta_{i,0}$ are the states of the system, $\varepsilon_{i,0}$ and $\varepsilon_{i,1}$ are positive design constants.

According to Lemma 2, it holds that

$$\left|\zeta_{i,0} - \dot{e}_i(t)\right| \le \upsilon_{i,0} \tag{33}$$

where $\upsilon_{i,0}$ is any positive constant due to the approximation property of the first order sliding mode differentiator.

Similarly, define functions $\hat{\zeta}_{i,0}$ as follows

$$\begin{aligned}\hat{\zeta}_{i,0} = -\varepsilon_{i,0}&\left(\left(\rho_{i,0} - e_i(t)\right)\tanh\left(\frac{\rho_{i,0} - e_i(t)}{\mu_{i,0}}\right)\right)^{\frac{1}{2}}\\ &\times \tanh\left(\frac{\rho_{i,0} - e_i(t)}{\mu_{i,0}}\right) + \rho_{i,1}\end{aligned} \tag{34}$$

where $\hat{\zeta}_{i,0}$ is the estimate of the auxiliary variable $\zeta_{i,0}$.

According to (32), (34) and Lemma 3, it follows that

$$\left|\zeta_{i,0} - \hat{\zeta}_{i,0}\right| \le \gamma_i \tag{35}$$

where γ_i is a positive constant.

Then, we construct the virtual control law α_i and the adaptation function $\hat{\delta}_i$ as follows

$$\alpha_i = g_i^{-1}(\bar{x}_i)\left(-k_ie_i - f_i(\bar{x}_i) + \hat{\dot{\alpha}}_{i-1} - \lambda_i\hat{D}_i^2e_i\right) \tag{36}$$

$$\hat{\delta}_i = \hat{\zeta}_{i,0} - \left(f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} - \hat{\dot{\alpha}}_{i-1}\right) \tag{37}$$

where $\tau_i\dot{\hat{D}}_i + \hat{D}_i = \hat{\delta}_i$, $y_i = \hat{D}_i - \hat{\delta}_i$ and λ_i is a design constant.

Noting that $e_i = x_i - \alpha_{i-1}$, one has $x_{i+1} = e_{i+1} + \alpha_i$.

Substituting (36) into (25) and following a similar way as Step 1 lead to

$$\begin{aligned}\dot{V}_{ei} = g_i(\bar{x}_i)e_ie_{i+1} - k_ie_i^2 + e_i\left(\hat{\dot{\alpha}}_{i-1} - \dot{\alpha}_{i-1}\right)\\ + e_i(-\lambda_i\hat{D}_i^2e_i + \delta_i)\end{aligned} \tag{38}$$

In view of (23) and (37), it immediately gets

$$\begin{aligned}-\hat{D}_i + \delta_i &= \dot{e}_i - (f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} - \dot{\alpha}_{i-1})\\ &\quad - \left(\hat{\zeta}_{i,0} - \left(f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} - \hat{\dot{\alpha}}_{i-1}\right) + y_i\right)\\ &= \dot{e}_i - \hat{\zeta}_{i,0} + \dot{\alpha}_{i-1} - \hat{\dot{\alpha}}_{i-1} - y_i\end{aligned} \tag{39}$$

Utilizing (30), (33) and (35) gives

$$\begin{aligned}\left|-\hat{D}_i + \delta_i\right| &= \left|\dot{e}_i - \zeta_{i,0}\right| + \left|\zeta_{i,0} - \hat{\zeta}_{i,0}\right| + \left|\dot{\alpha}_{i-1} - \hat{\dot{\alpha}}_{i-1}\right| + y_i\\ &\le \upsilon_{i,0} + \gamma_i + \upsilon_{i,1} + \varsigma_i + y_i = \gamma_i^*\end{aligned} \tag{40}$$

It further gives rise to

$$\begin{aligned}\delta_i^2 - \hat{D}_i^2 &\le \left|\delta_i^2 - \hat{D}_i^2\right| = \left|\delta_i - \hat{D}_i\right|\left|\delta_i + \hat{D}_i\right|\\ &\le \gamma_i^*\left(2\left|\delta_i\right| + \gamma_i^*\right) \le 3\gamma_i^{*2} + \frac{\delta_i^2}{2}\end{aligned} \tag{41}$$

which suggests

$$\frac{\delta_i^2}{2} \le 3\gamma_i^{*2} + \hat{D}_i^2 \tag{42}$$

Thus, we can rewrite (38) as

$$\begin{aligned}\dot{V}_{ei} &\leq g_i(\bar{x}_i)e_ie_{i+1} - k_ie_i^2 + \left(\upsilon_{i,1} + \varsigma_i\right)e_i - \lambda_i\hat{D}_i^2e_i^2 \\ &\quad + \frac{\lambda_i\delta_i^2e_i^2}{2} + \frac{1}{2\lambda_i} \\ &\leq g_i(\bar{x}_i)e_ie_{i+1} + \left(\upsilon_{i,1} + \varsigma_i\right)|e_i| - \left(k_i - 3\lambda_i\gamma_i^{*2}\right)e_i^2 \\ &\quad + \frac{1}{2\lambda_i} \end{aligned} \tag{43}$$

Let $k_i = 3\lambda_i\gamma_i^{*2} + k_{i0}$, where $k_{i0} > 0$

$$\dot{V}_{ei} \leq g_i(\bar{x}_i)e_ie_{i+1} + \left(\upsilon_{i,1} + \varsigma_i\right)|e_i| - k_{i0}e_i^2 + \frac{1}{2\lambda_i} \tag{44}$$

Step n: Noting $e_n = x_n - \alpha_{n-1}$, the dynamics of e_n-subsystem can be written as

$$\dot{e}_n = f_n(x) + g_n(x)u + \delta_n - \dot{\alpha}_{n-1} \tag{45}$$

Similarly, consider the following quadratic Lyapunov function candidate:

$$V_{en} = \frac{1}{2}e_n^2 \tag{46}$$

The time derivative of V_{en} along (45) is

$$\dot{V}_{en} = e_n[f_n(x) + g_n(x)u + \delta_n - \dot{\alpha}_{n-1}] \tag{47}$$

Similarly, utilizing the first order sliding mode differentiator to estimate $\dot{\alpha}_{n-1}$.

$$\begin{aligned}\dot{\vartheta}_{n-1,0} &= \Theta_{n,0} = -\sigma_{n,0}\left|\vartheta_{n-1,0} - \alpha_{n-1}\right|^{\frac{1}{2}} \\ &\quad \times sign(\vartheta_{n-1,0} - \alpha_{n-1}) + \vartheta_{n-1,1} \\ \dot{\vartheta}_{n-1,1} &= -\sigma_{n,1}sign(\vartheta_{n-1,1} - \Theta_{n,0}) \end{aligned} \tag{48}$$

where $\vartheta_{n-1,0}$, $\vartheta_{n-1,1}$ and $\Theta_{n,0}$ are the states of the system, $\sigma_{n,0}$ and $\sigma_{n,1}$ are positive design constants.

In view of (48) and Lemma 2, one has

$$\left|\Theta_{n,0} - \dot{\alpha}_{n-1}\right| \leq \upsilon_{n,1} \tag{49}$$

where $\upsilon_{n,1}$ is any positive constant.

Similar to Step i, the estimate of the differential term $\dot{\alpha}_{n-1}$ is defined as:

$$\begin{aligned}\hat{\dot{\alpha}}_{n-1} &= -\sigma_{n,0}\left(\left(\vartheta_{n-1,0} - \alpha_{n-1}\right)\tanh\left(\frac{\vartheta_{n-1,0} - \alpha_{n-1}}{\mu_{n,1}}\right)\right)^{\frac{1}{2}} \\ &\quad \times \tanh\left(\frac{\vartheta_{n-1,0} - \alpha_{n-1}}{\mu_{n,1}}\right) + \vartheta_{n-1,1} \end{aligned} \tag{50}$$

Noting (48), (50) and Lemma 3, one gets

$$\left|\hat{\dot{\alpha}}_{n-1} - \Theta_{n,0}\right| \leq \varsigma_n \tag{51}$$

where ς_n is a positive constant.

Therefore, the following inequality satisfies

$$\begin{aligned}\left|\hat{\dot{\alpha}}_{n-1} - \dot{\alpha}_{n-1}\right| &= \left|\Theta_{n,0} - \dot{\alpha}_{n-1}(t)\right| + \left|\hat{\dot{\alpha}}_{n-1} - \Theta_{n,0}\right| \\ &\leq \upsilon_{n,1} + \varsigma_n \end{aligned} \tag{52}$$

Invoking (45), we can get

$$\delta_n = \dot{e}_n - (f_n(x) + g_n(x)u - \dot{\alpha}_{n-1})$$

Similar to Step 1, the first order sliding mode differentiator is adopted as follows:

$$\begin{aligned}\dot{\rho}_{n,0} &= \zeta_{n,0} = -\varepsilon_{n,0}\left|\rho_{n,0} - e_n(t)\right|^{\frac{1}{2}} sign(\rho_{n,0} - e_n(t)) + \rho_{n,1} \\ \dot{\rho}_{n,1} &= -\varepsilon_{n,1}sign(\rho_{n,1} - \zeta_{n,0}) \end{aligned} \tag{53}$$

where $\rho_{n,0}$, $\rho_{n,1}$ and $\zeta_{n,0}$ are the states of the system, $\varepsilon_{n,0}$ and $\varepsilon_{n,1}$ are positive design constants.

According to Lemma 2, one reaches

$$\left|\zeta_{n,0} - \dot{e}_n(t)\right| \leq \upsilon_{n,0} \tag{54}$$

where $\upsilon_{n,0}$ is any positive constant.

Similarly, define functions $\hat{\zeta}_{n,0}$ as follows

$$\begin{aligned}\hat{\zeta}_{n,0} &= -\varepsilon_{n,0}\left(\left(\rho_{n,0} - e_n(t)\right)\tanh\left(\frac{\rho_{n,0} - e_n(t)}{\mu_{n,0}}\right)\right)^{\frac{1}{2}} \\ &\quad \times \tanh\left(\frac{\rho_{n,0} - e_n(t)}{\mu_{n,0}}\right) + \rho_{n,1} \end{aligned} \tag{55}$$

where $\hat{\zeta}_{n,0}$ is the estimate of the auxiliary variable $\zeta_{n,0}$.

According to (53), (55) and Lemma 3, we can know that

$$\left|\zeta_{n,0} - \hat{\zeta}_{n,0}\right| \leq \gamma_n \tag{56}$$

where γ_n is a positive constant.

Then, we construct the actual control law u and the adaptation function $\hat{\delta}_n$ as follows

$$u = g_n^{-1}(x)\left(-k_ne_n - f_n(x) + \hat{\dot{\alpha}}_{n-1} - \lambda_n\hat{D}_n^2e_n\right) \tag{57}$$

$$\hat{\delta}_n = \hat{\zeta}_{n,0} - \left(f_n(x) + g_n(x)u - \hat{\dot{\alpha}}_{n-1}\right) \tag{58}$$

where $\tau_n\dot{\hat{D}}_n + \hat{D}_n = \hat{\delta}_n$, $y_n = \hat{D}_n - \hat{\delta}_n$ and λ_n is a design constant.

Similarly, substituting (57) into (47) yields, it holds that

$$\dot{V}_{en} = -k_ne_n^2 + e_n(-\lambda_n\hat{D}_n^2e_n + \delta_n) + e_n\left(\hat{\dot{\alpha}}_{n-1} - \dot{\alpha}_{n-1}\right) \tag{59}$$

In view of (45) and (58), we arrive

$$\begin{aligned}-\hat{D}_n + \delta_n &= \dot{e}_n - (f_n(x) + g_n(x)u - \dot{\alpha}_{n-1}) \\ &\quad - \left(\hat{\zeta}_{n,0} - \left(f_n(x) + g_n(x)u - \hat{\dot{\alpha}}_{n-1}\right) + y_n\right) \\ &= \dot{e}_n - \hat{\zeta}_{n,0} + \dot{\alpha}_{n-1} - \hat{\dot{\alpha}}_{n-1} - y_n \end{aligned} \tag{60}$$

Utilizing (52), (54) and (56) leads to

$$\begin{aligned}\left|-\hat{D}_n + \delta_n\right| &= \left|\dot{e}_n - \zeta_{n,0}\right| + \left|\zeta_{n,0} - \hat{\zeta}_{n,0}\right| \\ &\quad + \left|\hat{\dot{\alpha}}_{n-1} - \dot{\alpha}_{n-1}\right| + y_n \\ &\leq \upsilon_{n,0} + \gamma_n + \upsilon_{n,1} + \varsigma_n + y_n = \gamma_n^* \end{aligned} \tag{61}$$

It further gives rise to

$$\begin{aligned}\delta_n^2 - \hat{D}_n^2 &\leq \left|\delta_n^2 - \hat{D}_n^2\right| = \left|\delta_n - \hat{D}_n\right|\left|\delta_n + \hat{D}_n\right| \\ &\leq \gamma_n^*\left(2|\delta_n| + \gamma_n^*\right) \leq 3\gamma_n^{*2} + \frac{\delta_n^2}{2} \end{aligned} \tag{62}$$

which indicates

$$\frac{\delta_n^2}{2} \leq 3\gamma_n^{*2} + \hat{D}_n^2 \tag{63}$$

Thus, we can rewrite (59) as

$$\dot{V}_{en} \leq \left(\upsilon_{n,1} + \varsigma_n\right)|e_n| - \left(k_n - 3\lambda_n\gamma_n^{*2}\right)e_n^2 + \frac{1}{2\lambda_n} \tag{64}$$

Let $k_n = 3\lambda_n\gamma_n^{*2} + k_{n0}$, where $k_{n0} > 0$

$$\dot{V}_{en} \leq \left(\upsilon_{n,1} + \varsigma_n\right)|e_n| - k_{n0}e_n^2 + \frac{1}{2\lambda_n} \tag{65}$$

The design process of adaptive tracking controller has been completed.

IV. STABILITY ANALYSIS

In this section, the main results will be stated and the convergence of the disturbance observer will be proven.

Theorem 1: Consider the nonlinear system (1) under Assumptions 1-2. The virtual control laws are constructed as (14) and (36). The sliding mode disturbance observers without any bounded conditions are designed according to (15), (37) and (58). Based on the designed disturbance observers, the actual control law is proposed as (57). The tracking error $e_1 = x_1 - y_d$ converges to a small neighborhood of the origin by appropriately choosing designed parameters.

Proof: To analyze the stability of the closed-loop system, we consider the following Lyapunov function candidate:

$$V = \sum_{i=1}^{n} V_{ei} \tag{66}$$

It follows from (22), (44) and (65) that the time derivative of V is:

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{n} k_{i0}e_i^2 + \sum_{i=2}^{n}\left(\upsilon_{i,1} + \varsigma_i\right)|e_i| \\ & + \sum_{i=1}^{n-1} g_i(x_i)e_ie_{i+1} + \sum_{i=1}^{n}\frac{1}{2\lambda_i} \\ \leq & -\sum_{i=1}^{n} k_{i0}e_i^2 + \sum_{i=2}^{n}\upsilon_{i,2}|e_i| \\ & + \sum_{i=1}^{n-1} g_i(x_i)e_ie_{i+1} + \sum_{i=1}^{n}\frac{1}{2\lambda_i}\end{aligned} \tag{67}$$

where $\upsilon_{i,2} = \upsilon_{i,1} + \varsigma_i$.

In combination with Assumption 2 and the following inequalities:

$$\upsilon_{i,2}|e_i| \leq \frac{1}{2}\left(\frac{\upsilon_{i,2}^2e_i^2}{c_1} + c_1\right) \tag{68}$$

$$g_i(x_i)e_ie_{i+1} \leq \frac{1}{2}g_M(e_i^2 + e_{i+1}^2) \tag{69}$$

Then, we can rewrite (67) as

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{n} k_{i0}e_i^2 + \sum_{i=2}^{n}\frac{1}{2}\left(\frac{\upsilon_{i,2}^2e_i^2}{c_1} + c_1\right) + \sum_{i=1}^{n}\frac{1}{2\lambda_i} \\ & + \sum_{i=1}^{n-1}\frac{1}{2}g_M(e_i^2 + e_{i+1}^2)\end{aligned} \tag{70}$$

Noting that $\sum_{i=1}^{n-1}\frac{1}{2}g_M(e_i^2 + e_{i+1}^2) \leq \sum_{i=1}^{n} g_Me_i^2$, one further has

$$\begin{aligned}\dot{V} \leq & -\sum_{i=1}^{n} k_{i0}e_i^2 + \sum_{i=1}^{n}\frac{1}{2}\frac{\upsilon_{i,2}^2}{c_1}e_i^2 + \sum_{i=1}^{n} g_Me_i^2 \\ & + \frac{1}{2}nc_1 + \sum_{i=1}^{n}\frac{1}{2\lambda_i}\end{aligned} \tag{71}$$

where c_1, $\upsilon_{i,2}$ and g_M are positive constants.

Setting $k_{i0} = \frac{1}{2}\frac{\upsilon_{i,2}^2}{c_1} + g_M + k_{i1}$, with k_{i1} being a positive constant, then (71) can be expressed by

$$\begin{aligned}\dot{V} & \leq -\sum_{i=1}^{n} k_{i1}e_i^2 + \frac{1}{2}nc_1 + \sum_{i=1}^{n}\frac{1}{2\lambda_i} \\ & \leq -C_1V + C_2\end{aligned} \tag{72}$$

where $C_1 = 2k_{i1}$ and $C_2 = \frac{1}{2}nc_1 + \sum_{i=1}^{n}\frac{1}{2\lambda_i}$.

Using (72), we can obtain

$$\begin{aligned}V(t) & \leq (V(0) - C_3)\,e^{-C_1t} + C_3 \\ & \leq V(0) + C_3\end{aligned} \tag{73}$$

According to (66) and (73), the following inequality holds:

$$\lim_{t\to\infty}|e_1| \leq \sqrt{2C_3} \tag{74}$$

It can be observed from the definition that $C_3 = C_2/C_1$ can be adjusted to arbitrarily small by increasing λ_i. Therefore, by appropriately online-tuning the design parameters, the tracking error e_1 converges to an arbitrarily small neighborhood of the origin.

Remark 5: Specifically, two cases on the compounded disturbance $\delta_i(x,t)$ (i.e. $\delta_i(x,t)$ is bounded and unbounded) are considered: 1) As for the case of $\delta_i(x,t)$ being bounded, one sees that V and the tracking error e_i, $i = 1, 2, \ldots, n$ are bounded from (73). So for $e_1 = x_1 - y_d$ and y_d being bounded, x_1 is certainly bounded. Taking (18) into account, the estimate of the compounded disturbance $\hat{D}_1$ is bounded under this case. Since α_1 is a function of bounded signals x_1, e_1, $\dot{y}_d$ and $\hat{D}_1$, the virtual control law α_1 is also bounded. Noting $x_i = e_i + \alpha_{i-1}$, it can be seen that α_{i-1} and state variables x_i,$i = 2, 3, \ldots, n$ are bounded, and similarly, the actual control law u is bounded. Therefore, all the signals of the closed-loop system are bounded; 2) As for the case of $\delta_i(x,t)$ being unbounded, the estimates of $\delta_i(x,t)$, namely $\hat{D}_i$, are unbounded according to (40), which results in that the virtual control laws α_i and the control input u are unbounded since $\hat{D}_i$ are included in them as seen in (36) and (57). This means that an unbounded control effort is required so as to circumvent the influence brought by unbounded disturbances. However, it should be pointed out that the boundedness of the tracking error e_1 and the tracking performance can be still guaranteed in this case.

This completes the proof. ■

V. SIMULATION RESULTS

In this section, two simulation examples are given to demonstrate the effectiveness of designed method.

Example 1: To illustrate the validity of the proposed control scheme, consider the following second-order nonlinear system with disturbance and its derivative being unbounded as follows:

$$\begin{cases} \dot{x}_1 = x_1 e^{-0.5x_1} + (1 + e^{-0.1x_1^2})x_2 \\ \dot{x}_2 = -p_1 x_1 - p_2 x_2 - x_1^3 + q\cos(\omega t) + u + \delta(x,t) \\ y = x_1 \end{cases} \tag{75}$$

where the compounded disturbance is given by $\delta(x,t) = x_1^2 + x_1 + t\sin(t)$. For the purpose of simulation, we suppose that $p_1 = 0.3 + 0.2\sin(10t)$, $p_2 = 0.2 + 0.2\cos(5t)$, $q_0 = 5 + 0.1\cos(t)$ and $\omega = 0.5 + 0.1\sin(t)$. Let the desired trajectory be $y_d = \sin(0.5t)$.

Remark 6: Differently from the state-of-the-art, it can be seen that the compounded disturbance $\delta(x,t)$ grows with time t, so it can be easily verified that the compounded disturbance $\delta(x,t)$ is not bounded by upper and lower bounds, and moreover, its derivative is also unbounded. This specific example breaks the conventional bound assumptions and makes the control design extremely challenging, so in authors' opinion, the existing works cannot be applied. To overcome this difficulty, we firstly propose a disturbance observer design method without bounded assumptions, which basically distinguishes our work from all available methods.

In accordance with Theorem 1, the adaptive tracking controller is proposed as (57) and the disturbance observers are given as (15) and (58). For the compounded disturbance $\delta(x,t)$, the design parameters are set as: $\varepsilon_{1,0} = 10$, $\varepsilon_{1,1} = 1$, $\mu_{1,0} = 0.1$; $\sigma_{2,0} = 30$, $\sigma_{2,1} = 1$, $\mu_{2,1} = 0.5$; $\varepsilon_{2,0} = 20$, $\varepsilon_{2,1} = 1$, $\mu_{2,0} = 0.1$. The other design parameters are taken as $k_1 = 6$, $\lambda_1 = 1$ and $k_2 = 4$, $\lambda_2 = 1$. Let the initial conditions for $[x_1(0), x_2(0)]^T = [0,\ 0]^T$, $\rho_{1,1}(0) = \rho_{2,1}(0) = \vartheta_{1,1}(0) = 0$, $\hat{\zeta}_{1,0}(0) = \hat{\zeta}_{2,0}(0) = \hat{\alpha}_1(0) = 0$. The simulation results are shown as Figs. 2-6.

It can be obviously observed from Fig. 2 that the system output y can follow the desired trajectory y_d and fairly good tracking performance is obtained. Fig. 3 shows the tracking error e converges to an allowable range. The response curve of the system state x_2 is depicted in Fig. 4. And the control input u is shown in Fig. 5 Specially, it can be seen from Fig. 6 that the disturbance observer $\hat{D}$ can approach the growing compounded disturbance δ effectively. It should be noted that excellent tracking performance has been achieved even though the compounded disturbance is unbounded by utilizing the first order sliding mode differentiator in our paper, which enhances the robustness and reliability of the system drastically.

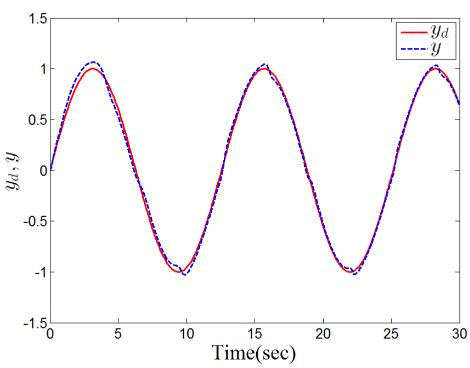


FIGURE 2. System output y and desired trajectory y_d.

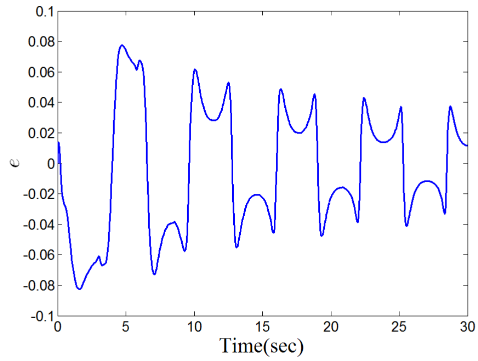


FIGURE 3. Tracking error e.

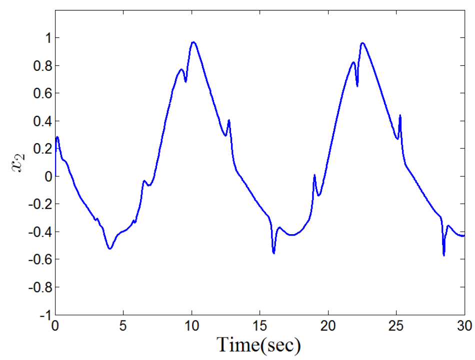


FIGURE 4. System state x_2.

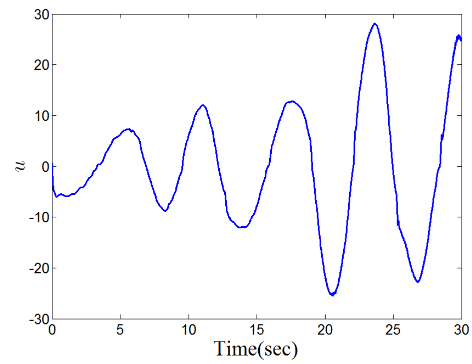


FIGURE 5. Control input u.

Remark 7: In most existing traditional disturbance observer design approaches, to the best of authors' knowledge, the disturbance observer is always designed using a constant.

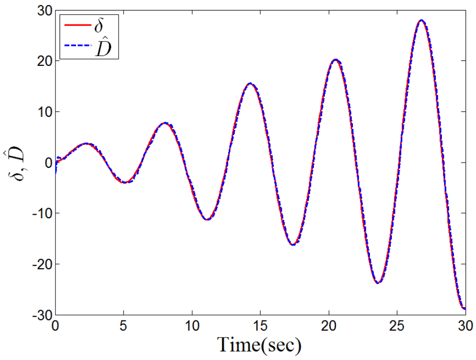


FIGURE 6. Compounded disturbance δ and its estimate $\hat{D}$.

It is very restrictive arising from the fact that the bound for disturbance may not exist with the system state and time in practice, implies that the effect of disturbance cannot be assumed to be bounded before obtaining stability. Thanks to the slide mode differentiators and hyperbolic tangent function, the error dynamics in our paper have a clear advantage over it in standard disturbance observer-based design, even under the case that the disturbance is unbounded and non-smooth. It is noticed that the proposed disturbance observer can come across these difficulties for the reason that the restrictive assumptions on the disturbance terms are removed. Therefore, compared with conventional disturbance observer designs, our scheme has more relaxed condition and a wider range of application.

Example 2: To further verify the effectiveness of the proposed scheme, consider the following tracking control problem for a pole-balancing of an inverted pendulum [39]. The system is represented by

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \dfrac{mlx_2^2 \sin x_1 \cos x_1 - (M+m)g \sin x_1}{ml \cos^2 x_1 - 4/3l(M+m)} \\ \qquad + \dfrac{-\cos x_1}{ml \cos^2 x_1 - 4/3l(M+m)} u + \delta(x,t) \\ y = x_1 \end{cases} \tag{76}$$

where x_1 represents the angle θ (in radians) of the pendulum from the vertical, M is the mass of the cart and m is the mass of the pole, g is gravitational constant, l is the half length of the pole, u means force applied to the cart and $\delta(x,t)$ is the compounded disturbance.

The parameters employed in this simulation are given as follows: $M = 1$ Kg, $m = 0.1$ Kg, $l = 0.5$ m, $g = 9.8$ m/s^2. The disturbance term $\delta(x_2, t)$ is a dead-zone model in the presence of non-smooth nonlinearity, which can be given as follows

$$\delta(x,t) = \begin{cases} 10(x_2 - 0.3) + \dfrac{(x_2-0.3)^2}{7}, & x_2 \geq 0.3 \\ 0, & -0.3 < x_2 < 0.3 \\ 10(x_2 + 0.3) + \dfrac{(x_2+0.3)^2}{7}, & x_2 \leq -0.3 \end{cases} \tag{77}$$

It can be seen that the compounded disturbance $\delta(x_2, t)$ is not partial differentiable with respect to x_2 as non-smooth nonlinearity is present in it. Furthermore, we assume the desired trajectory $y_d = 0.5(\sin(t) + \sin(0.5t))$.

In this simulation, the designed parameters are taken as $\varepsilon_{1,0} = 10$, $\varepsilon_{1,1} = 1$, $\mu_{1,0} = 1$; $\sigma_{2,0} = 10$, $\sigma_{2,1} = 1$, $\mu_{2,1} = 0.1$; $\varepsilon_{2,0} = 10$, $\varepsilon_{2,1} = 1$, $\mu_{2,0} = 0.1$ and $k_1 = 4$, $\lambda_1 = 1$; $k_2 = 4$, $\lambda_1 = 1$. Set the initial conditions as $[x_1(0), x_2(0)]^T = [0.2, \ 0]^T$, $\rho_{1,1}(0) = \rho_{2,1}(0) = \vartheta_{1,1}(0) = 0$ and $\hat{\zeta}_{1,0}(0) = \hat{\zeta}_{2,0}(0) = \hat{\alpha}_1(0) = 0$. The simulation results are shown in Figs. 7-10.

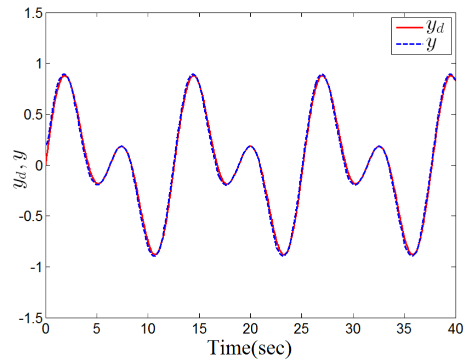


FIGURE 7. System output y and desired trajectory y_d.

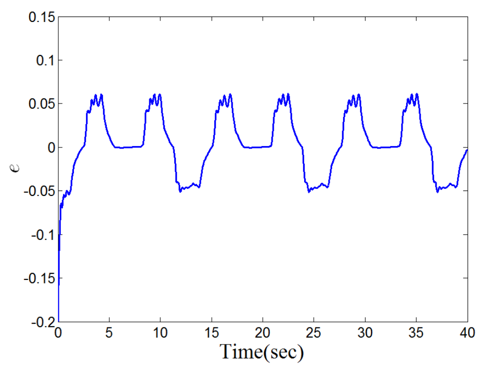


FIGURE 8. Tracking error e.

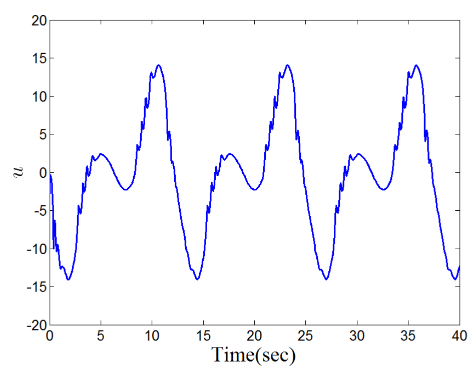


FIGURE 9. Control input u.

To show the good compensation effect of the disturbance observers on the dynamic response, the output response curves are depicted in Fig. 7 and it can be observed clearly

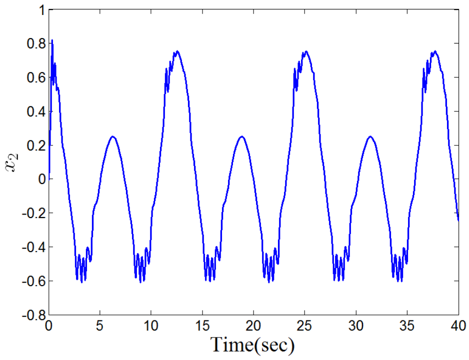


FIGURE 10. System state x_2.

that system output y can converge rapidly to the desired trajectory y_d. The tracking error is acceptable from Fig. 8. And it can be seen from Fig. 9 and Fig. 10 that the control input u and system state x_2 are bounded. The simulation results of physical system model indicate that the proposed controller based on disturbance observer can achieve excellent tracking performance even though the compounded disturbance is non-differentiable. Particularly, the input variable information of the compounded disturbance is not mentioned in the controller design, thus the prior knowledge of the compounded disturbance can be unknown, which has wide application prospects in practical control systems.

VI. CONCLUSION

A novel adaptive tracking control scheme based on disturbance observer has been proposed for a class of strict-feedback nonlinear systems under loose disturbance constraint conditions. Compared with the existing approaches, the restrictive assumptions that the compounded disturbance must be bounded, differentiable or slow time-varying are relaxed by only assuming that the disturbance functions are continuous. Without NNs or FLSs techniques, the sliding mode differentiator and the backstepping method have been utilized to estimate the compounded disturbance and design adaptive control laws in proposed control scheme. Moreover, the influences of unknown disturbance and system uncertainties are eliminated without knowing any prior knowledge of the compounded disturbance.

APPENDIX

Proof of Lemma 3: To obtain the conclusion, two cases are discussed as follows:

Case 1: For any $x \in R$, $|x|^{\frac{1}{2}} + \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} \geq 1$

$$\begin{aligned}&\left||x|^{\frac{1}{2}} - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\right|\\ &\leq \left||x|^{\frac{1}{2}} - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\right| \cdot \left||x|^{\frac{1}{2}} + \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\right|\\ &= \left||x| - x\tanh\left(\frac{x}{\mu}\right)\right| \end{aligned} \tag{78}$$

According to Lemma 1, one has

$$\left||x|^{\frac{1}{2}} - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\right| \leq |x| - x\tanh\left(\frac{x}{\mu}\right) \leq 0.2785\mu \tag{79}$$

Consider the property of the sign function, we know that

$$\begin{aligned}&\left||x|^{\frac{1}{2}}\,sign(x) - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign(x)\right|\\ &\qquad = \left||x|^{\frac{1}{2}} - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\right|\\ &\qquad \leq 0.2785\mu \end{aligned} \tag{80}$$

$$\begin{aligned}&\left|\left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign(x)\right.\\ &\left.- \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign\left(\frac{x}{\mu}\right)\right| = 0 \end{aligned} \tag{81}$$

Noting that μ is an unknown positive constant, it holds that

$$\begin{aligned}&\left|\left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign\left(\frac{x}{\mu}\right) - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\tanh\left(\frac{x}{\mu}\right)\right|\\ &\leq \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\left|sign\left(\frac{x}{\mu}\right) - \tanh\left(\frac{x}{\mu}\right)\right| \end{aligned} \tag{82}$$

When $x > 0$,

$$\begin{aligned}&\left|sign\left(\frac{x}{\mu}\right) - \tanh\left(\frac{x}{\mu}\right)\right|\\ &= \left|1 - \frac{e^{(x/\mu)} - e^{-(x/\mu)}}{e^{(x/\mu)} + e^{-(x/\mu)}}\right|\\ &= \frac{2e^{-(x/\mu)}}{e^{(x/\mu)} + e^{-(x/\mu)}} \leq e^{-(x/\mu)} \end{aligned} \tag{83}$$

When $x < 0$,

$$\begin{aligned}&\left|sign\left(\frac{x}{\mu}\right) - \tanh\left(\frac{x}{\mu}\right)\right|\\ &= \left|-1 - \frac{e^{(x/\mu)} - e^{-(x/\mu)}}{e^{(x/\mu)} + e^{-(x/\mu)}}\right|\\ &= \frac{2e^{(x/\mu)}}{e^{(x/\mu)} + e^{-(x/\mu)}} \leq e^{(x/\mu)} \end{aligned} \tag{84}$$

In view that the difference between the sign function and the hyperbolic tangent function shows exponential growth, one reaches

$$\begin{aligned}&\left|\left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign\left(\frac{x}{\mu}\right) - \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\tanh\left(\frac{x}{\mu}\right)\right|\\ &\leq \left(x\tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}\left(e^{-|x/\mu|}\right) \leq \gamma^* \end{aligned} \tag{85}$$

where γ^* is a positive constant.

Therefore, we can obtain that

$$\begin{aligned}&\left||x|^{\frac{1}{2}} sign(x)-\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} \tanh\left(\frac{x}{\mu}\right)\right|\\ &\leq\left||x|^{\frac{1}{2}} sign(x)-\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign(x)\right|\\ &\quad+\left|\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign(x)\right.\\ &\quad\left.-\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign\left(\frac{x}{\mu}\right)\right|\\ &\quad+\left|\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} sign\left(\frac{x}{\mu}\right)\right.\\ &\quad\left.-\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} \tanh\left(\frac{x}{\mu}\right)\right|\\ &\leq 0.2785\mu+\gamma^{*}=\gamma\end{aligned} \tag{86}$$

Case 2: For any $x \in R$, $|x|^{\frac{1}{2}}+\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}}<1$

It is easy to know that$|x|<1$,and then we further have

$$\left||x|^{\frac{1}{2}} sign(x)-\left(x \tanh\left(\frac{x}{\mu}\right)\right)^{\frac{1}{2}} \tanh\left(\frac{x}{\mu}\right)\right| \leq \gamma \tag{87}$$

This completes the proof. ■

Proof of Lemma 4: By noting that $\tau\dot{\beta}+\beta=\alpha$ and $y=\beta-\alpha$, one has $\dot{\beta}=-\frac{y}{\tau}$

Choose the following quadratic function as

$$V_F=\frac{1}{2}y^2 \tag{88}$$

The time derivative of V_F is

$$\dot{V}_F=y\dot{y}=y(-\frac{y}{\tau}-\dot{\alpha})=-\frac{y^2}{\tau}-y\dot{\alpha} \tag{89}$$

Applying a first order sliding mode differentiator in Lemma 2 yields to get $\hat{\dot{\alpha}}$, it follows that

$$\left|\dot{\alpha}-\hat{\dot{\alpha}}\right| \leq \varepsilon \tag{90}$$

where ε is a positive constant.

Choose $\frac{1}{2\tau}=\hat{\dot{\alpha}}^2+\varepsilon_0$ where $\varepsilon_0>0$ being the designed parameter, and then we can obtain

$$\begin{aligned}-\frac{y^2}{2\tau}-y\dot{\alpha}&=-(\hat{\dot{\alpha}}^2+\varepsilon_0)y^2-y\dot{\alpha}\\ &\leq\frac{1}{4}-\varepsilon_0 y^2-\left|\hat{\dot{\alpha}}\right||y|-y\dot{\alpha}\\ &\leq\frac{1}{4}-\varepsilon_0 y^2+|\varepsilon y|\end{aligned} \tag{91}$$

Substituting (91) into (89) yields, it holds that

$$\begin{aligned}\dot{V}_F&\leq-\frac{y^2}{2\tau}+\frac{1}{4}-\varepsilon_0 y^2+|\varepsilon y|\\ &\leq-(\varepsilon_0-\frac{1}{2}+\frac{1}{2\tau})y^2+\frac{1}{4}+\frac{1}{2}\varepsilon^2\\ &\leq-c_1 V_F+c_2\end{aligned} \tag{92}$$

where $c_1=2\varepsilon_0-1+\frac{1}{\tau}$ and $c_2=\frac{1}{4}+\frac{1}{2}\varepsilon^2$.

Therefore, we can know that the filtering error y can be regulated to arbitrarily small by appropriately online-tuning the design parameters.

This completes the proof. ■

ACKNOWLEDGMENT

This work was supported by National Science Foundation of China (Grant no. 61304120, 61473307 and 61603411).

REFERENCES

[1] X. Zhao, X. Wang, G. Zong, and H. Li, "Fuzzy-approximation-based adaptive output-feedback control for uncertain nonsmooth nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3847–3859, Dec. 2018.

[2] B. Niu, P. Duan, J. Li, and X. Li, "Adaptive neural tracking control scheme of switched stochastic nonlinear pure-feedback nonlower triangular systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published. doi: 10.1109/TSMC.2019.2894745.

[3] H. Li, S. Zhao, W. He, and R. Lu, "Adaptive finite-time tracking control of full state constrained nonlinear systems with dead-zone," *Automatica*, vol. 100, pp. 99–107, Feb. 2019.

[4] B. Niu, H. Li, Z. Zhang, J. Li, T. Hayat, and F. E. Alsaadi, "Adaptive neural-network-based dynamic surface control for stochastic interconnected nonlinear nonstrict-feedback systems with dead zone," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 7, pp. 1386–1398, Jul. 2019. doi: 10.1109/TSMC.2018.2866519.

[5] W.-H. Chen, J. Yang, L. Guo, 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.

[6] H. Ma, H. Liang, Q. Zhou, and C. K. Ahn, "Adaptive dynamic surface control design for uncertain nonlinear strict-feedback systems with unknown control direction and disturbances," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 3, pp. 506–515, Mar. 2018.

[7] M. Lv, S. Baldi, and Z. Liu, "The non-smoothness problem in disturbance observer design: A set-invariance-based adaptive fuzzy control method," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 3, pp. 598–604, Mar. 2019.

[8] H. Li, Y. Wang, D. Yao, and R. Lu, "A sliding mode approach to stabilization of nonlinear Markovian jump singularly perturbed systems," *Automatica*, vol. 97, pp. 404–413, Nov. 2018.

[9] C.-E Ren, T. Du, G. Li, and Z. Shi, "Disturbance observer-based consensus control for multiple robotic manipulators," *IEEE Access*, vol. 6, pp. 51348–51354, 2018.

[10] Y.-S. Lu, "Sliding-mode disturbance observer with switching-gain adaptation and its application to optical disk drives," *IEEE Trans. Ind. Electron.*, vol. 56, no. 9, pp. 3743–3750, Sep. 2009.

[11] W. He, Z. Yan, C. Sun, and Y. Chen, "Adaptive neural network control of a flapping wing micro aerial vehicle with disturbance observer," *IEEE Trans. Cybern.*, vol. 47, no. 10, pp. 3452–3465, Oct. 2017.

[12] W. Zheng and M. Chen, "Tracking control of manipulator based on high-order disturbance observer," *IEEE Access*, vol. 6, pp. 26753–26764, 2015.

[13] A. Hasan, O. M. Aamo, and M. Krstic, "Boundary observer design for hyperbolic PDE–ODE cascade systems," *Automatica*, vol. 68, pp. 75–86, Jun. 2016.

[14] C. Wen, J. Zhou, Z. Liu, and H. Su, "Robust adaptive control of uncertain nonlinear systems in the presence of input saturation and external disturbance," *IEEE Trans. Autom. Control*, vol. 56, no. 7, pp. 1672–1678, Jul. 2011.

[15] J. Huang, S. Ri, L. Liu, Y. Wang, J. Kim, and G. Pak, "Nonlinear disturbance observer-based dynamic surface control of mobile wheeled inverted pendulum," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 6, pp. 2400–2407, Nov. 2015.

[16] H. Pan, W. Sun, H. Gao, and X. Jing, "Disturbance observer-based adaptive tracking control with actuator saturation and its application," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 868–875, Apr. 2016.

[17] X. Wei, H.-F. Zhang, and L. Guo, "Composite disturbance-observer-based control and terminal sliding mode control for uncertain structural systems," *Int. J. Syst. Sci.*, vol. 40, no. 10, pp. 1009–1017, Jul. 2008.

[18] L. Sun and Z. Zheng, "Disturbance-observer-based robust backstepping attitude stabilization of spacecraft under input saturation and measurement uncertainty," *IEEE Trans. Ind. Electron.*, vol. 64, no. 10, pp. 7994–8002, Oct. 2017.

[19] H. Min, S. Xu, Q. Ma, B. Zhang, and Z. Zhang, "Composite-observer-based output-feedback control for nonlinear time-delay systems with input saturation and its application," *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5856–5863, Jul. 2018.

[20] Z. Liu, X. Dong, J. Xue, and Y. Chen, "Adaptive neural control for a class of time-delay systems in the presence of backlash or dead-zone nonlinearity," *IET Control Theory Appl.*, vol. 8, no. 11, pp. 1009–1022, 2014.

[21] Z.-J. Yang, S. Hara, S. Kanae, K. Wada, and C.-Y. Su, "A general adaptive robust nonlinear motion controller combined with disturbance observer," *IEEE Trans. Control Syst. Technol.*, vol. 18, no. 2, pp. 454–462, Jul. 2010.

[22] M. L. Lv, Y. Wang, S. Baldi, and Z. Wang, "A DSC method for strict-feedback nonlinear systems with possibly unbounded control gain functions," *Neurocomputing*, vol. 275, pp. 1383–1392, Jan. 2018.

[23] 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.

[24] M. Chen and S. S. Ge, "Direct adaptive neural control for a class of uncertain nonaffine nonlinear systems based on disturbance observer," *IEEE Trans. Cybern.*, vol. 43, no. 4, pp. 1213–1225, Aug. 2013.

[25] C. Shi, Z. C. Liu, Y. Chen, and X. M. Dong, "A novel error-compensation control for a class of high-order nonlinear systems with input delay," *IEEE Trans. Neural Netw.*, vol. 29, no. 9, pp. 4077–4087, Sep. 2018.

[26] M. Lv, W. Yu, and S. Baldi, "The set-invariance paradigm in fuzzy adaptive DSC design of large-scale nonlinear input-constrained systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, to be published. doi: 10.1109/TSMC.2019.2895101.

[27] Z. Liu, X. Dong, W. Xie, Y. Chen, and H. Li, "Adaptive fuzzy control for pure-feedback nonlinear systems with nonaffine functions being semi-bounded and indifferentiable," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 395–408, Apr. 2018.

[28] Z. Chen, Z. Li, and C. L. P. Chen, "Disturbance observer-based fuzzy control of uncertain MIMO mechanical systems with input nonlinearities and its application to robotic exoskeleton," *IEEE Trans. Cybern.*, vol. 47, no. 4, pp. 984–994, Apr. 2016.

[29] Y. Li, S. Tong, Y. Liu, and T. Li, "Adaptive fuzzy robust output feedback control of nonlinear systems with unknown dead zones based on a small-gain approach," *IEEE Trans. Fuzzy Syst.*, vol. 22, no. 1, pp. 164–176, Feb. 2014.

[30] B. Xu, Z. Shi, and C. Yang, "Composite fuzzy control of a class of uncertain nonlinear systems with disturbance observer," *Nonlinear Dyn.*, vol. 80, no. 1, pp. 341–351, Jan. 2015.

[31] M. Chen, S.-Y. Shao, and B. Jiang, "Adaptive neural control of uncertain nonlinear systems using disturbance observer," *IEEE Trans. Cybern.*, vol. 47, no. 10, pp. 3110–3123, Oct. 2017.

[32] K. Yong, M. Chen, and Q. Wu, "Constrained adaptive neural control for a class of nonstrict-feedback nonlinear systems with disturbances," *Neurocomputing*, vol. 27, no. 2, pp. 405–415, Jan. 2018.

[33] M. Chen and S. S. Ge, "Adaptive neural output feedback control of uncertain nonlinear systems with unknown hysteresis using disturbance observer," *IEEE Trans. Ind. Electron.*, vol. 62, no. 12, pp. 7706–7716, Dec. 2015.

[34] C. Shi, X. Dong, J. Xue, Y. Chen, and J. Zhi, "Robust adaptive neural control for a class of non-affine nonlinear systems," *Neurocomputing*, vol. 22, no. 3, pp. 118–128, Feb. 2017.

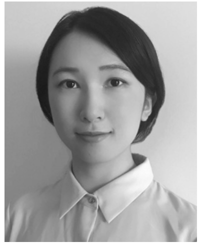
[35] Z. Liu, X. Dong, J. Xue, H. Li, and Y. Chen, "Adaptive neural control for a class of pure-feedback nonlinear systems via dynamic surface technique," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 27, no. 9, pp. 1969–1975, Sep. 2016.

[36] A. Levant, "Robust exact differentiation via sliding mode technique," *Automatica*, vol. 34, no. 3, pp. 379–384, Mar. 1998.

[37] H. Pan and W. Sun, "Nonlinear output feedback finite-time control for vehicle active suspension systems," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2073–2082, Apr. 2019.

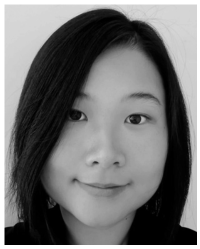
[38] Q. Li, R. Yang, and Z. Liu, "Adaptive tracking control for a class of nonlinear non-strict-feedback systems," *Nonlinear Dyn.*, vol. 88, no. 3, pp. 1537–1550, Mar. 2017.

[39] E. Kim, "A fuzzy disturbance observer and its application to control," *IEEE Trans. Fuzzy Syst.*, vol. 10, no. 1, pp. 77–84, Feb. 2002.



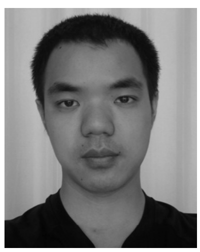
WENQIAN ZHANG received the B.Sc. degree in mathematics and applied mathematics from Xi'an Jiaotong University, Xi'an, China, in 2015, and the M.Sc. degree in control science and engineering from Air Force Engineering University, Xi'an, China, in 2017, where she is currently pursuing the Ph.D. degree. Her research interests include adaptive control and flight control.

WENHAN DONG received the B.Sc. degree in electrical engineering and automation from Air Force Engineering University, Xi'an, China, in 2000, and the M.Sc. and Ph.D. degrees in control theory and engineering from Air Force Engineering University, in 2003 and 2006, respectively, where he is currently a Professor with the College of Aeronautics Engineering. His research interests include adaptive control and flight simulation.



SHUANGYU DONG received the B.Sc. degree in electrical engineering and automation from Xi'an Jiao Tong University, Xi'an, China, in 2015, and the M.Sc. degree in electrical engineering from the University of Melbourne, Melbourne, Australia, in 2017. She is currently an Engineer with SMZ Telecom Pty Ltd., Melbourne. Her research interests include deep learning and adaptive control.

MAOLONG LV received the B.Sc. and M.Sc. degrees from Air Force Engineering University, Xi'an, China, in 2014 and 2016, respectively. He is currently pursuing the Ph.D. degree with the Delft Center for Systems and Control, Delft University of Technology, The Netherlands. His research interests include adaptive control and switched systems. In 2018, he was awarded a Descartes Excellence Fellowship from the Institut Français des Pays-Bas (first Asian student receiving this award), which allowed him a research visit and a cooperation with the University of Grenoble on the topic of adaptive networked systems.



ZONGCHENG LIU received the B.Sc. degree in electrical engineering and automation from Air Force Engineering University, Xi'an, China, in 2009, and the M.Sc. and Ph.D. degrees in control theory and engineering from Air Force Engineering University, in 2011 and 2015, respectively, where he is currently a Lecturer with the Aeronautics Engineering College. His research interests include flight control, intelligent and autonomous control, and neural networks.