Hindawi
Mathematical Problems in Engineering
Volume 2020, Article ID 6760521, 14 pages
https://doi.org/10.1155/2020/6760521

Research Article

Adaptive Decentralized Output Feedback Tracking Control for Large-Scale Interconnected Systems with Time-Varying Output Constraints

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Received 20 January 2020; Revised 23 March 2020; Accepted 2 April 2020; Published 21 April 2020

Academic Editor: Xinggang Yan

This paper investigates a novel adaptive output feedback decentralized control scheme for nonstrict feedback large-scale interconnected systems with time-varying constraints. A decentralized linear state observer is designed to estimate the unmeasurable states of subsystems. Time-varying barrier Lyapunov functions are designed to ensure outputs are not violating constraints. A variable separation approach is applied to deal with the nonstrict feedback problem. Moreover, dynamic surface control and minimal parameter learning technologies are adopted to reduce the computation burden, and there are only two parameters for every subsystem to be updated online. The proof of stability is obtained by the Lyapunov method. Finally, simulation results are given to show the effectiveness of the proposed control scheme.

1. Introduction

No matter in practical engineering application or theoretical research field, the high-precision trajectory tracking control of the nonlinear system is a very valuable research topic. For example, the welding robot needs to carry out welding according to the given trajectory, and the accuracy of the trajectory tracking control is an important indicator of the performance of the welding robot. The drilling guide system needs to control the well trajectory continuously to ensure the drilling quality. However, it is very difficult to design the control scheme of the nonlinear system due to various uncertainties [1–3]. Because the fuzzy logic system has been proved to have universal approximation property, it has become one of the effective measures to solve the uncertainty problem [4]. In [5], an adaptive fuzzy quantized tracking control scheme was proposed for the stochastic nonlinear uncertain strict feedback system. In [6], a direct model reference adaptive fuzzy control was discussed for a class of networked SISO nonlinear uncertain systems. In [7], for the nonlinear system with parametric uncertainties and unknown modelling errors, a robust adaptive control scheme was presented. In [8], an adaptive dynamic surface asymptotic tracking control was proposed for the uncertain nonlinear system. In [9], for the nontriangular stochastic uncertain nonlinear system with unmeasured states, an adaptive robust control was studied. In [10], for the pure-feedback nonlinear system with time-varying delay and unknown dead zone, an adaptive fuzzy tracking control was investigated. However, none of the above literature has solved the output constraint problem of the uncertain nonlinear system.

Output constraint is a very important engineering problem. If the system outputs exceed the given range, it will cause control performance degradation, equipment damage, and even endanger the safety of operators and environment. Therefore, in recent years, the output constraint problem has become a hot research issue, and a large number of valuable research results have emerged. When the relevant states approach the boundary, the barrier Lyapunov function tends to infinity, so as long as the function value is bounded, the correlation states can be kept in the given constraints.

Because of the above property, the barrier Lyapunov function becomes an effective measure to solve the problem of constraints. In [11], by using a barrier Lyapunov function, an indirect adaptive fuzzy control was designed for the output-constrained nonlinear system. In [12], an adaptive neural network control was proposed for the nonlinear system with full-state constraints. In [13], for a class of nonlinear pure-feedback full-state constraint systems, an adaptive control based on barrier Lyapunov functions was studied. In [14], an adaptive fuzzy backstepping output constrain tracking control was proposed for the uncertain nonlinear system in strict feedback form. In [15], by adopting barrier Lyapunov functions, an adaptive neural network control was presented for nonlinear state-constrained systems with input delay. In [16, 17], adaptive full-state constraint control methods were discussed for stochastic nonlinear systems based on barrier Lyapunov functions. All of the above literature studies considered the static constraint problem, and then the time-varying constraint is more suitable for practical engineering. In [18], an adaptive fuzzy control was proposed for the nontriangular system with time-varying error constraint. In [19], for the uncertain nonlinear system with time-varying prescribed performance, a fuzzy adaptive control based on the observer was presented. In [20], a fuzzy state observer-based adaptive control for the strict feedback system with time-varying constraint was studied. However, for the time-varying output constraints of large-scale interconnected systems, there are no relevant research results.

In practical engineering, many electromechanical systems consist of many subsystems, such as multirobot cooperative control system, offshore platform, drilling system, and aerospace. Because a large-scale interconnected system has the coupling effect between subsystems, the design of its controller is very difficult. Therefore, the research on the control scheme of large-scale systems has obvious practical value and theoretical significance. In [21, 22], decentralized H_∞ performance control methods were studied for switched and nonswitched large-scale systems, respectively. In [23, 24], based on the observer and backstepping technology, adaptive decentralized control methods were presented for uncertain large-scale systems with unmeasured states. In [25], for the switched uncertain large-scale system with dead zones, an adaptive output decentralized tracking control scheme was proposed. However, the output constraints of large-scale systems are not considered in the above literature. Although the control problem of large-scale systems with output constraints has been studied in [26], the system is in strict feedback form, and there are no corresponding research results about the control scheme of nonstrict feedback large-scale systems with time-varying output constraints.

Based on the above results, this paper studies an adaptive output feedback decentralized control for the nonstrict feedback large-scale system with unmeasurable states and time-varying output constraints. Compared with the existed works, there are two contributions in this paper: (1) for the first time, the output feedback control problem of nonstrict feedback large-scale systems with time-varying constraints is studied. The proposed control scheme is quite different from the existed results. The proposed control scheme can not only solve the output feedback tracking control problem for a class of uncertain large-scale systems in nonstrict feedback form but also ensure all the outputs are not violating the time-varying constraints. Moreover, time-varying constraint relaxes the initial conditions of the system. (2) The control method which is proposed in this paper does not need n-order differentiable and bounded conditions of input signals and the monotonically increasing condition of unknown functions, which are common in the existing literature [27, 28]. Because of using the dynamic surface control, the "complexity explosion" problem is avoided. Moreover, each subsystem has only two adaptive parameters, and the number of parameters does not increase with the increase of system's order.

2. Problem Description and Preliminaries

The nonstrict feedback large-scale system considered in this paper has M interconnected subsystems. kth $(k = 1, 2, \ldots M)$ subsystem is shown as follows:

$$\begin{cases} \dot{x}_{k,1} = x_{k,2} + f_{k,1}(\underline{x}_k) + h_{k,1}(\underline{y}), \\ \dot{x}_{k,2} = x_{k,3} + f_{k,2}(\underline{x}_k) + h_{k,2}(\underline{y}), \\ \vdots \\ \dot{x}_{k,n_k-1} = x_{k,n_k} + f_{k,n_k-1}(\underline{x}_k) + h_{k,n_k-1}(\underline{y}), \\ \dot{x}_{k,n_k} = u_k + f_{k,n_k}(\underline{x}_k) + h_{k,n_k}(\underline{y}), \\ y_k = x_{k,1}, \end{cases} \tag{1}$$

where $\underline{x}_k = [x_{k,1}, x_{k,2}, \ldots, x_{k,n_k}]^T \in R^{n_k}$ is the state vector, and only $x_{k,1}$ can be measured. $\underline{y} = [y_1, \ldots, y_M] \in R^M$ is the output vector of the large-scale system. $f_{k,l}(\underline{x}_k)$ and $h_{k,l}(\underline{y})$ $(1 \le k \le M,\ 1 \le l \le n_k)$ are unknown smooth functions, and $h_{k,l}(\underline{y})$ represents the coupling effect between M subsystems of the large-scale system. $u_k \in R$ is the actual control input of the kth subsystem. In practical engineering, the mathematical models of the two-stage chemical reactor, air traffic control, spring connected two-stage inverted pendulum, and other large-scale systems can be expressed as (1) [22, 29–31].

Assumption 1 (see [23, 24]). For $1 \le k \le M$ and $1 \le l \le n_k$, there exists unknown smooth function $\hbar_{k,l,i}(y_i)$ such that

$$\left|h_{k,l}(\underline{y})\right|^2 \le \sum_{i=1}^{M} \left(y_i \hbar_{k,l,i}(y_i)\right)^2. \tag{2}$$

Assumption 2 (see [23, 24]). There exists unknown smooth function $\overline{f}_{k,l}(\underline{x}_k)$ such that $f_{k,l}(\underline{x}_k) = x_{k,1}\overline{f}_{k,l}(\underline{x}_k)$, where $l = 1, 2, \ldots, n_k$.

Assumption 3 (see [32, 33]). The reference signal $y_{k,d}(t)$ and its first derivative are bounded.

Control objective: the control objective is to design an adaptive output feedback decentralized control scheme to keep all the outputs $y_k(t)$ of the subsystems tracking desired trajectories $y_{k,d}(t)$, respectively. Moreover, the tracking errors can be kept as small as possible, and all the signals of the closed system are bounded.

3. Fuzzy Logic System and Observer Design

A fuzzy logic system can be written as $\hat{f}(x \mid \theta) = \theta^T \xi(x)$, where $\xi(x)$ is the fuzzy basis function vector and $\theta \in R^N$ is the adjustable weight parameter vector.

Lemma 1 (see [34, 35]). *If $f(x)$ is a continuous function defined on the compact set Ω, then for any given small constant $\varepsilon > 0$, there exists a fuzzy logic system such that* $\sup_{x\in\Omega}|f(x) - \theta^{\mathrm{T}}\xi(x)| \le \varepsilon$.

In order to estimate the unmeasured states, we design a linear state observer for the kth subsystem as follows [23]:

$$\begin{cases} \dot{\hat{x}}_{k,1} = \hat{x}_{k,2} - \ell_{k,1}\left(\hat{x}_{k,1} - y_k\right), \\ \dot{\hat{x}}_{k,2} = \hat{x}_{k,3} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right), \\ \vdots \\ \dot{\hat{x}}_{k,n_k-1} = \hat{x}_{k,n_k} - \ell_{k,n_k-1}\left(\hat{x}_{k,1} - y_k\right), \\ \dot{\hat{x}}_{k,n_k} = u_k - \ell_{k,n_k}\left(\hat{x}_{k,1} - y_k\right), \end{cases} \tag{3}$$

where $\hat{x}_{k,l}\,(l = 1, 2, \ldots, n_k)$ is the estimation of $x_{k,l}$. $\ell_{k,1}, \ldots, \ell_{k,n_k}$ are the observer design parameters. Define observer error vector as $\underline{\tilde{x}}_k = \underline{x}_k - \underline{\hat{x}}_k$, where $\underline{x}_k = [x_{k,1}, x_{k,2}, \ldots, x_{k,n_k}]^T$ and $\underline{\hat{x}}_k = [\hat{x}_{k,1}, \hat{x}_{k,2}, \ldots, \hat{x}_{k,n_k}]^T$.

Then, from (1) and (3), we can have

$$\dot{\underline{\tilde{x}}}_k = A_k \underline{\tilde{x}}_k + F_k + H_k, \tag{4}$$

where $A_k = \begin{bmatrix} -\ell_{k,1} & & \\ \vdots & I_{(n_k-1)\times(n_k-1)} & \\ -\ell_{k,n_k} & 0 & 0 \end{bmatrix}$, $F_k = [f_{k,1}(\underline{x}_k), \ldots, f_{k,n_k}(\underline{x}_k)]^T$, and $H_k = [h_{k,1}(\underline{y}), \ldots, h_{k,n_k}(\underline{y})]^T$. We can choose appropriate parameters $\ell_{k,1}, \ldots, \ell_{k,n_k}$ to ensure A_k is a Hurwitz matrix, that is, for any given positive definite matrix $Q_k = Q_k^T > 0$, there exists a positive definite matrix $P_k = P_k^T > 0$ such that

$$A_k^T P_k + P_k A_k = -Q_k. \tag{5}$$

Choose the Lyapunov function candidate as [23]

$$V_0 = \sum_{k=1}^{M} \underline{\tilde{x}}_k^T P_k \underline{\tilde{x}}_k. \tag{6}$$

Then, we can obtain the time derivative of V_0:

$$\dot{V}_0 = -\sum_{k=1}^{M} \underline{\tilde{x}}_k^T Q_k \underline{\tilde{x}}_k + \sum_{k=1}^{M} 2\underline{\tilde{x}}_k^T P_k \left(F_k + H_k\right). \tag{7}$$

According to Yang's inequalities, we have

$$2\underline{\tilde{x}}_k^T P_k F_k \le \left\|\underline{\tilde{x}}_k\right\|^2 + \left\|P_k\right\|^2 \sum_{j=1}^{n_k} \left(f_{k,j}(\underline{x}_k)\right)^2. \tag{8}$$

Based on Assumption 2, $f_{k,j}(\underline{x}_k)$ satisfies

$$f_{k,j}(\underline{x}_k) = y_k \overline{f}_{k,j}(\underline{x}_k), \tag{9}$$

where $\overline{f}_{k,j}(\underline{x}_k)$ is an unknown nonlinear function which can be approximated by a fuzzy logic system.

From (8) and (9), we have

$$\begin{aligned} \left\|P_k\right\|^2 \sum_{j=1}^{n_k} \left(f_{k,j}(\underline{x}_k)\right)^2 &= \left\|P_k\right\|^2 \sum_{j=1}^{n_k} y_k^2 \left(\overline{f}_{k,j}(\underline{x}_k)\right)^2 \\ &= y_k \left\|P_k\right\|^2 \sum_{j=1}^{n_k} y_k \left(\overline{f}_{k,j}(\underline{x}_k)\right)^2. \end{aligned} \tag{10}$$

Based on Assumption 1, we obtain

$$\begin{aligned} \sum_{k=1}^{M} 2\underline{\tilde{x}}_k^T P_k H_k &\le \sum_{k=1}^{M} \frac{1}{\lambda} \left\|\underline{\tilde{x}}_k\right\|^2 + \sum_{k=1}^{M} \lambda \left\|P_k\right\|^2 \left\|H_k\right\|^2 \\ &\le \frac{1}{\lambda} \sum_{k=1}^{M} \left\|\underline{\tilde{x}}_k\right\|^2 + \overline{\lambda} \sum_{k=1}^{M} \sum_{l=1}^{n_k} \sum_{i=1}^{M} \left(y_i \hbar_{k,l,i}(y_i)\right)^2 \\ &\le \frac{1}{\lambda} \sum_{k=1}^{M} \left\|\underline{\tilde{x}}_k\right\|^2 + \overline{\lambda} \sum_{i=1}^{M} \sum_{l=1}^{n_k} \sum_{k=1}^{M} \left(y_i \hbar_{k,l,i}(y_i)\right)^2 \\ &\le \frac{1}{\lambda} \sum_{k=1}^{M} \left\|\underline{\tilde{x}}_k\right\|^2 + \overline{\lambda} \sum_{k=1}^{M} \sum_{i=1}^{M} \sum_{l=1}^{n_k} y_k^2 \left(y_i \hbar_{k,l,i}(y_i)\right)^2 \\ &\le \frac{1}{\lambda} \sum_{k=1}^{M} \left\|\underline{\tilde{x}}_k\right\|^2 + \sum_{k=1}^{M} y_k^2 \sum_{i=1}^{M} \sum_{l=1}^{n_k} \overline{\lambda} \left(\hbar_{k,l,i}(y_i)\right)^2, \end{aligned} \tag{11}$$

where $\lambda > 0$ is the design parameter and $\overline{\lambda} = \lambda \max_{1\le k\le M}(\|P_k\|)^2$.

Substituting equations (8)–(11) into (7) results in

$$\begin{aligned} \dot{V}_0 &\le \sum_{k=1}^{M} \left\{ -\underline{\tilde{x}}_k^T Q_k \underline{\tilde{x}}_k + \left(1 + \frac{1}{\lambda}\right) \left\|\underline{\tilde{x}}_k\right\|^2 + y_k^2 \sum_{i=1}^{M} \sum_{l=1}^{n_k} \overline{\lambda} \left(\hbar_{i,l,k}(y_k)\right)^2 + y_k \left\|P_k\right\|^2 \sum_{j=1}^{n_k} y_k \left(\overline{f}_{k,j}(\underline{x}_k)\right)^2 \right\} \\ &\le \sum_{k=1}^{M} \left\{ -\underline{\tilde{x}}_k^T Q_k \underline{\tilde{x}}_k + \left(1 + \frac{1}{\lambda}\right) \left\|\underline{\tilde{x}}_k\right\|^2 + y_k \left[y_k \sum_{i=1}^{M} \sum_{l=1}^{n_k} \overline{\lambda} \left(\hbar_{i,l,k}^{s}(y_k)\right)^2 + \left\|P_k\right\|^2 \sum_{j=1}^{n_k} y_k \left(\overline{f}_{k,j}(\underline{x}_k)\right)^2 + \sum_{i=1}^{M} y_k \left(\hbar_{i,1,k}(y_k)\right)^2 \right] - \sum_{i=1}^{M} y_k^2 \left(\hbar_{i,1,k}(y_k)\right)^2 \right\}. \end{aligned} \tag{12}$$

Let $\Phi_k(\underline{x}_k) = y_k\sum_{i=1}^{M}\sum_{l=1}^{n_k}\overline{\lambda}(\hbar_{i,l,k}(y_k))^2 + \|P_k\|^2\sum_{j=1}^{n_k}y_k(\overline{f}_{k,j}(\underline{x}_k))^2 + \sum_{i=1}^{M}y_k(\hbar_{i,1,k}(y_k))^2$. By using fuzzy system $\widehat{f}_k(\underline{x}_k \mid \theta_k) = \theta_k^T\xi_k(\underline{x}_k)$ to approximate $\Phi_k(\underline{x}_k)$, there exists optimal parameter vector

$$\theta_k^* = \arg\min_{\theta_k\in\Omega_k}\left[\sup_{\underline{x}_k\in U_k}\left|\widehat{f}_k\left(\underline{x}_k \mid \theta_k\right) - \Phi_k(\underline{x}_k)\right|\right], \tag{13}$$

where Ω_k and U_k are the compact set of θ_k and $\underline{x}_k$, respectively. Then, the minimal error can be written as

$$\varepsilon_k(\underline{x}_k) = \Phi_k(\underline{x}_k) - \widehat{f}_k\left(\underline{x}_k \mid \theta_k^*\right), \tag{14}$$

where $|\varepsilon_k(\underline{x}_k)| \le \varepsilon_k^*$ and ε_k^* is an unknown positive constant.

From (13) and (14), we can obtain

$$\begin{aligned}\dot{V}_0 \le \sum_{k=1}^{M}\Bigg\{&-\left(\lambda_{\min}(Q_k) - 1 - \frac{1}{\lambda}\right)\|\underline{\tilde{x}}_k\|^2 \\ &+ y_k\left[\theta_k^{*T}\xi_k(\underline{x}_k) + \varepsilon_k(\underline{x}_k)\right] - \sum_{i=1}^{M}y_k^2\left(\hbar_{i,1,k}(y_k)\right)^2\Bigg\},\end{aligned} \tag{15}$$

where $\lambda_{\min}(Q_k)$ is the minimal eigenvalue of matrix Q_k.

4. Adaptive Control Law Design

Define the tracking error $z_{k,1}$, virtual error $z_{k,l}$, virtual control law $\alpha_{k,l-1}$, and first-order filters as

$$\begin{cases} z_{k,1} = y_k - y_{k,d}, \\ z_{k,l} = \widehat{x}_{k,l} - \omega_{k,l-1}, \\ \upsilon_{k,l-1}\dot{\omega}_{k,l-1} + \omega_{k,l-1} = \alpha_{k,l-1}, \\ \omega_{k,l-1}(0) = \alpha_{k,l-1}(0), \end{cases} \tag{16}$$

where $l = 2, \ldots, n_k$. $\upsilon_{k,l-1}$ is the time constant of the filter, that is, by letting $\alpha_{k,l-1}$ pass through a filter that has the time constant $\upsilon_{k,l-1}$, we can obtain $\omega_{k,l-1}$.

Step 1. Define $\omega_{k,0} = y_{k,d}$. From (16), we have

$$\begin{aligned}\upsilon_{k,1}\dot{\omega}_{k,1} + \omega_{k,1} &= \alpha_{k,1}, \\ \omega_{k,1}(0) &= \alpha_{k,1}(0).\end{aligned} \tag{17}$$

Define $e_{k,1}$ as the first filter output error; then, we can obtain $e_{k,1} = \omega_{k,1} - \alpha_{k,1}$ and $\dot{\omega}_{k,1} = -(e_{k,1}/\upsilon_{k,1})$.

The time derivative of $z_{k,1}$ is as follows:

$$\begin{aligned}\dot{z}_{k,1} &= x_{k,2} + f_{k,1} + h_{k,1} - \dot{\omega}_{k,0} \\ &= z_{k,2} + e_{k,1} + \alpha_{k,1} + \tilde{x}_{k,2} + f_{k,1}(\underline{x}_k) + h_{k,1}(\underline{y}) - \dot{y}_{k,d}.\end{aligned} \tag{18}$$

By using fuzzy system $\widehat{F}_k(\underline{x}_k \mid \varphi_k) = \varphi_k^T\zeta_k(\underline{x}_k)$ to approximate $f_{k,1}(\underline{x}_k)$ and defining φ_k^* as the optimal parameter vector, we have

$$\varphi_k^* = \operatorname{argmin}_{\varphi_k\in\overline{\Omega}_k}\left[\sup_{\underline{x}_k\in U_k}\left|\widehat{F}_k\left(\underline{x}_k \mid \varphi_k\right) - f_{k,1}(\underline{x}_k)\right|\right], \tag{19}$$

where $\overline{\Omega}_k$ is the compact set of φ_k. Then, the minimal approximation error is as follows:

$$\delta_k(\underline{x}_k) = f_{k,1}(\underline{x}_k) - \widehat{F}_k\left(\underline{x}_k \mid \varphi_k^*\right), \tag{20}$$

where $|\delta_k(\underline{x}_k)| \le \delta_k^*$, and δ_k^* is an unknown positive constant.

Define

$$\begin{aligned} k_{k,a}(t) &= y_{k,d}(t) - \overline{k}_{k,c1}(t), \\ k_{k,b}(t) &= \overline{k}_{k,c1}(t) - y_{k,d}(t), \\ q_k\left(z_{k,1}\right) &= \begin{cases} 1, & z_{k,1} > 0, \\ 0, & z_{k,1} \le 0. \end{cases}\end{aligned} \tag{21}$$

Choose the Lyapunov function candidate as

$$\begin{aligned} V_1 = V_0 + \sum_{k=1}^{M}\Bigg[&\frac{q_k\left(z_{k,1}\right)}{2}\log\frac{k_{k,b}^2(t)}{k_{k,b}^2(t) - z_{k,1}^2} \\ &+ \frac{1 - q_k\left(z_{k,1}\right)}{2}\log\frac{k_{k,a}^2(t)}{k_{k,a}^2(t) - z_{k,1}^2} + \frac{1}{2}e_{k,1}^2 \\ &+ \frac{1}{2\gamma_{k,1}}\tilde{\varpi}_{k,1}^2 + \frac{1}{2\gamma_{k,2}}\tilde{\varpi}_{k,2}^2\Bigg],\end{aligned} \tag{22}$$

where $\gamma_{k,1} > 0$ and $\gamma_{k,2} > 0$ are design parameters, $\varpi_{k,1}^* = \theta_k^{*T}\theta_k^*$, $\varpi_{k,2}^* = \varphi_k^{*T}\varphi_k^*$, and $\varpi_{k,1}$ and $\varpi_{k,2}$ are estimations of $\varpi_{k,1}^*$ and $\varpi_{k,2}^*$, respectively. Define $\tilde{\varpi}_{k,1} = \varpi_{k,1}^* - \varpi_{k,1}$ and $\tilde{\varpi}_{k,2} = \varpi_{k,2}^* - \varpi_{k,2}$.

Let $\varsigma_{k,a} = (z_{k,1}(t)/k_{k,a}(t))$, $\varsigma_{k,b} = (z_{k,1}(t)/k_{k,b}(t))$, and $\varsigma_k = q_k\varsigma_{k,b} + (1 - q_k)\varsigma_{k,a}$; then, we can have

$$V_1 = V_0 + \sum_{k=1}^{M}\left[\frac{1}{2}\log\frac{1}{1 - \varsigma_k^2} + \frac{1}{2}e_{k,1}^2 + \frac{1}{2\gamma_{k,1}}\tilde{\varpi}_{k,1}^2 + \frac{1}{2\gamma_{k,2}}\tilde{\varpi}_{k,2}^2\right]. \tag{23}$$

Now, we can infer that $\dot{V}_1$ satisfies

$$\dot{V}_1 = \dot{V}_0 + \sum_{k=1}^{M}\left[\frac{\varsigma_k\dot{\varsigma}_k}{1 - \varsigma_k^2} + e_{k,1}\dot{e}_{k,1} - \frac{1}{\gamma_{k,1}}\tilde{\varpi}_{k,1}\dot{\varpi}_{k,1} - \frac{1}{\gamma_{k,2}}\tilde{\varpi}_{k,2}\dot{\varpi}_{k,2}\right]. \tag{24}$$

Because we have

$$
\begin{aligned}
\frac{\varsigma_k\dot{\varsigma}_k}{1-\varsigma_k^2} &= \frac{q_k\varsigma_{k,b}+(1-q_k)\varsigma_{k,a}}{1-\varsigma_k^2}\left(q_k\dot{\varsigma}_{k,b}+(1-q_k)\dot{\varsigma}_{k,a}\right),\\
\dot{\varsigma}_{k,b} &= \frac{\dot{z}_{k,1}k_{k,b}(t)-z_{k,1}\dot{k}_{k,b}(t)(t)}{k_{k,b}^2(t)},\\
\dot{\varsigma}_{k,a} &= \frac{\dot{z}_{k,1}k_{k.a}(t)-z_{k,1}\dot{k}_{k,a}(t)}{k_{k,a}^2(t)},\\
\dot{V}_1 &= \dot{V}_0+\sum_{k=1}^{M}\left[\frac{q_k\varsigma_{k,b}+(1-q_k)\varsigma_{k,a}}{1-\varsigma_k^2}\left(q_k\dot{\varsigma}_{k,b}+(1-q_k)\dot{\varsigma}_{k,a}\right)+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right]\\
&= \dot{V}_0+\sum_{k=1}^{M}\left[\frac{q_k\varsigma_{k,b}}{1-\varsigma_k^2}\dot{\varsigma}_{k,b}+\frac{(1-q_k)\varsigma_{k,a}}{1-\varsigma_k^2}\dot{\varsigma}_{k,a}+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right]\\
&= \dot{V}_0+\sum_{k=1}^{M}\left[\frac{q_k\varsigma_{k,b}}{k_{k,b}\left(1-\varsigma_{k,b}^2\right)}\left(\dot{z}_{k,1}-\frac{z_{k,1}\dot{k}_{k,b}}{k_{k,b}}\right)+\frac{(1-q_k)\varsigma_{k,a}}{k_{k,a}\left(1-\varsigma_{k,a}^2\right)}\left(\dot{z}_{k,1}-\frac{z_{k,1}\dot{k}_{k,a}}{k_{k,a}}\right)+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right].
\end{aligned}
\tag{25}
$$

Let $\mu_k = (q_k/k_{k,b}^2 - z_{k,1}^2) + ((1-q_k)/k_{k,a}^2 - z_{k,1}^2)$, and we can have

$$
\begin{aligned}
\dot{V}_1 &= \dot{V}_0+\sum_{k=1}^{M}\left[\mu_k z_{k,1}\left(\dot{z}_{k,1}-q_k\frac{z_{k,1}\dot{k}_{k,b}}{k_{k,b}}-(1-q_k)\frac{z_{k,1}\dot{k}_{k,a}}{k_{k,a}}\right)+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right]\\
&= \dot{V}_0+\sum_{k=1}^{M}\left[\mu_k z_{k,1}\left(z_{k,2}+e_{k,1}+\alpha_{k,1}+\widetilde{x}_{k,2}+f_{k,1}(\underline{x}_k)+h_{k,1}(\underline{y})-\dot{y}_{k,d}-q_k\frac{z_{k,1}\dot{k}_{k,b}}{k_{k,b}}-(1-q_k)\frac{z_{k,1}\dot{k}_{k,a}}{k_{k,a}}\right)\right.\\
&\quad\left.+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right].
\end{aligned}
\tag{26}
$$

According to Yang's inequalities and Assumption 1, we have

$$
\sum_{k=1}^{M}\mu_k z_{k,1}h_{k,1}(\underline{y}) \le \sum_{k=1}^{M}\frac{\mu_k^2 z_{k,1}^2}{4}+\sum_{k=1}^{M}\left(h_{k,1}(\underline{y})\right)^2 \le \sum_{k=1}^{M}\frac{\mu_k^2 z_{k,1}^2}{4}+\sum_{k=1}^{M}\sum_{i=1}^{M}y_k^2\left(\hbar_{k,1,i}(y_k)\right)^2.
\tag{27}
$$

Substituting (15) and (27) into (26), we obtain

$$
\begin{aligned}
\dot{V}_1 &\le \sum_{k=1}^{M}\left\{-\left(\lambda_{\min}(Q_k)-1-\frac{1}{\lambda}\right)\left\|\underline{\widetilde{x}}_k\right\|^2+y_k\left[\theta_k^{*T}\xi_k(\underline{x}_k)+\varepsilon_k(\underline{x}_k)\right]+\frac{\mu_k^2 z_{k,1}^2}{4}\right\}\\
&\quad+\sum_{k=1}^{M}\left[\mu_k z_{k,1}\left(z_{k,2}+e_{k,1}+\alpha_{k,1}+\widetilde{x}_{k,2}+\varphi_k^{*T}\zeta_k(\underline{x}_k)+\delta_k(\underline{x}_k)-\dot{y}_{k,d}-q_k\frac{z_{k,1}\dot{k}_{k,b}}{k_{k,b}}-(1-q_k)\frac{z_{k,1}\dot{k}_{k,a}}{k_{k,a}}\right)\right.\\
&\quad\left.+e_{k,1}\dot{e}_{k,1}-\frac{1}{\gamma_{k,1}}\widetilde{\omega}_{k,1}\dot{\omega}_{k,1}-\frac{1}{\gamma_{k,2}}\widetilde{\omega}_{k,2}\dot{\omega}_{k,2}\right].
\end{aligned}
\tag{28}
$$

Based on $\xi_k^T(\cdot)\xi_k(\cdot)\leq 1$ and Yang's inequalities, we can infer inequalities (29)–(31):

$$\begin{aligned} y_k\left[\theta_k^{*T}\xi_k(\underline{x}_k)+\varepsilon_k(\underline{x}_k)\right] &\leq z_{k,1}\left[\theta_k^{*T}\xi_k(\underline{x}_k)+\varepsilon_k(\underline{x}_k)\right]+y_{k,d}\left[\theta_k^{*T}\xi_k(\underline{x}_k)+\varepsilon_k(\underline{x}_k)\right] \\ &\leq \frac{z_{k,1}^2\varpi_{k,1}^*}{4\tau_k}+\frac{z_{k,1}^2}{4}+\frac{y_{k,d}^2}{2}+\varpi_{k,1}^*+2\varepsilon_k^{*2}+\tau_k, \end{aligned} \tag{29}$$

$$\mu_k z_{k,1}\left[\varphi_k^{*T}\zeta_k(\underline{x}_k)+\delta_k(\underline{x}_k)\right]\leq\frac{\mu_k^2 z_{k,1}^2\varpi_{k,2}^*}{4\tau_k}+\frac{\mu_k^2 z_{k,1}^2}{4}+\delta_k^{*2}+\tau_k, \tag{30}$$

$$\mu_k z_{k,1}\tilde{x}_{k,2}\leq\frac{1}{\lambda_k}\left\|\underline{\tilde{x}}_k\right\|^2+\lambda_k\frac{\mu_k^2 z_{k,1}^2}{4}, \tag{31}$$

where $\tau_k>0$ and $\lambda_k>0$ are design parameters.

Substituting (29)–(31) into (28) results in

$$\begin{aligned} \dot V_1 \leq{}& \sum_{k=1}^{M}\left\{-\left(\lambda_{\min}(Q_k)-1-\frac{1}{\lambda}-\frac{1}{\lambda_k}\right)\left\|\underline{\tilde{x}}_k\right\|^2\right\} \\ &+\sum_{k=1}^{M}\left[\mu_k z_{k,1}\left(z_{k,2}+e_{k,1}+\alpha_{k,1}+\frac{z_{k,1}\varpi_{k,1}^*}{4\tau_k\mu_k}+\frac{\mu_k z_{k,1}\varpi_{k,2}^*}{4\tau_k}+\frac{(1+2\mu_k+\mu_k\lambda_k)z_{k,1}}{4}-\dot y_{k,d}-q_k\frac{z_{k,1}\dot k_{k,b}}{k_{k,b}}-(1-q_k)\frac{z_{k,1}\dot k_{k,a}}{k_{k,a}}\right)\right. \\ &\left.+e_{k,1}\dot e_{k,1}-\frac{1}{\gamma_{k,1}}\tilde\varpi_{k,1}\dot\varpi_{k,1}-\frac{1}{\gamma_{k,2}}\tilde\varpi_{k,2}\dot\varpi_{k,2}+\frac{\overline{y}_{k,d}^2}{2}+\varpi_{k,1}^*+2\varepsilon_k^{*2}+\delta_k^{*2}+2\tau_k\right], \end{aligned} \tag{32}$$

where $\overline{y}_{k,d}=\max_{t\in[0,+\infty]}\left\{y_{k,d}(t)\right\}$ is a constant. Then, (32) can be rearranged as

$$\begin{aligned} \dot V_1 \leq{}& \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\} \\ &+\sum_{k=1}^{M}\left[\mu_k z_{k,1}\left(z_{k,2}+e_{k,1}+\alpha_{k,1}+\frac{z_{k,1}\varpi_{k,1}}{4\tau_k\mu_k}+\frac{\mu_k z_{k,1}\varpi_{k,2}}{4\tau_k}+\frac{(1+2\mu_k+\mu_k\lambda_k)z_{k,1}}{4}-\dot y_{k,d}-q_k\frac{z_{k,1}\dot k_{k,b}}{k_{k,b}}-(1-q_k)\frac{z_{k,1}\dot k_{k,a}}{k_{k,a}}\right)\right. \\ &\left.+\frac{1}{\gamma_{k,1}}\tilde\varpi_{k,1}\left(\frac{\gamma_{k,1}z_{k,1}^2}{4\tau_k}-\dot\varpi_{k,1}\right)+\frac{1}{\gamma_{k,2}}\tilde\varpi_{k,2}\left(\frac{\gamma_{k,2}\mu_k^2 z_{k,1}^2}{4\tau_k}-\dot\varpi_{k,2}\right)+e_{k,1}\dot e_{k,1}+d_{k,1}\right], \end{aligned} \tag{33}$$

where $\pi_{k,1}=\lambda_{\min}(Q_k)-1-(1/\lambda)-(1/\lambda_k)$ and $d_{k,1}=(\overline{y}_{k,d}^2/2)+\varpi_{k,1}^*+2\varepsilon_k^{*2}+\delta_k^{*2}+2\tau_k$.

Now, we can choose $\alpha_{k,1}$, $\varpi_{k,1}$, and $\varpi_{k,2}$ as follows:

$$\begin{aligned} \alpha_{k,1}={}&-c_{k,1}z_{k,1}+\hat c_{k,1}z_{k,1}-\frac{z_{k,1}\varpi_{k,1}}{4\tau_k\mu_k}-\frac{\mu_k z_{k,1}\varpi_{k,2}}{4\tau_k} \\ &-\frac{(1+2\mu_k+\mu_k\lambda_k)z_{k,1}}{4}+\dot y_{k,d}, \end{aligned} \tag{34}$$

$$\dot\varpi_{k,1}=\frac{\gamma_{k,1}z_{k,1}^2}{4\tau_k}-2\sigma_{k,1}\varpi_{k,1}, \tag{35}$$

$$\dot\varpi_{k,2}=\frac{\gamma_{k,2}\mu_k^2 z_{k,1}^2}{4\tau_k}-2\sigma_{k,2}\varpi_{k,2}, \tag{36}$$

where $c_{k,1}>0$, $\hat c_{k,1}=\sqrt{(\dot k_{k,b}/k_{k,b})^2+(\dot k_{k,a}/k_{k,a})^2+\beta_k}$, and $\sigma_{k,1}>0$ and $\sigma_{k,2}>0$ are design parameters. β_k is a positive design constant.

Substituting (34)–(36) into (33) results in

$$\begin{aligned} \dot V_1 &\leq \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\}+\sum_{k=1}^{M}\left[-c_{k,1}\mu_k z_{k,1}^2+\mu_k z_{k,1}z_{k,2}+\mu_k z_{k,1}e_{k,1}+\frac{2\sigma_{k,1}}{\gamma_{k,1}}\tilde\varpi_{k,1}\varpi_{k,1}+\frac{2\sigma_{k,2}}{\gamma_{k,2}}\tilde\varpi_{k,2}\varpi_{k,2}+e_{k,1}\left(-\frac{e_{k,1}}{\upsilon_{k,1}}-\dot\alpha_{k,1}\right)+d_{k,1}\right] \\ &\leq \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\}+\sum_{k=1}^{M}\left[-c_{k,1}\mu_k z_{k,1}^2+\mu_k z_{k,1}z_{k,2}+\mu_k z_{k,1}e_{k,1}+\frac{2\sigma_{k,1}}{\gamma_{k,1}}\tilde\varpi_{k,1}\varpi_{k,1}+\frac{2\sigma_{k,2}}{\gamma_{k,2}}\tilde\varpi_{k,2}\varpi_{k,2}-\frac{e_{k,1}^2}{\upsilon_{k,1}}+e_{k,1}^2+\frac{1}{4}\psi_{k,1}^2+d_{k,1}\right], \end{aligned} \tag{37}$$

where $\psi_{k,1}$ is the maximum absolute value of $\dot{\alpha}_{k,1}$.

According to Yang's inequalities, there exist (38)–(40):

$$\frac{2\sigma_{k,1}}{\gamma_{k,1}}\tilde{\varpi}_{k,1}\varpi_{k,1} \leq -\frac{\sigma_{k,1}}{\gamma_{k,1}}\varpi_{k,1}^2 + \frac{\sigma_{k,1}}{\gamma_{k,1}}\varpi_{k,1}^{*2}, \tag{38}$$

$$\frac{2\sigma_{k,2}}{\gamma_{k,2}}\tilde{\varpi}_{k,2}\varpi_{k,2} \leq -\frac{\sigma_{k,2}}{\gamma_{k,2}}\varpi_{k,2}^2 + \frac{\sigma_{k,2}}{\gamma_{k,2}}\varpi_{k,2}^{*2}, \tag{39}$$

$$\mu_k z_{k,1} e_{k,1} \leq \mu_k z_{k,1}^2 + \frac{\mu_k}{4} e_{k,1}^2. \tag{40}$$

Substituting (38)–(40) into (37) results in

$$\begin{aligned}\dot{V}_1 \leq& \sum_{k=1}^{M}\left\{-\pi_{k,1}\|\tilde{\underline{x}}_k\|^2\right\} \\ &+ \sum_{k=1}^{M}\left[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 + \mu_k z_{k,1} z_{k,2} + \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 \right. \\ &\left. - \sum_{i=1}^{2}\frac{\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^2 + \sum_{i=1}^{2}\frac{\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \frac{1}{4}\psi_{k,1}^2 + d_{k,1}\right].\end{aligned} \tag{41}$$

Substituting the following inequality

$$-\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 \geq -\frac{\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^2 - \frac{\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2}, \tag{42}$$

into equation (41) results in

$$\begin{aligned}\dot{V}_1 \leq& \sum_{k=1}^{M}\left\{-\pi_{k,1}\|\tilde{\underline{x}}_k\|^2\right\} \\ &+ \sum_{k=1}^{M}\left[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 + \mu_k z_{k,1} z_{k,2} + \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 \right. \\ &\left. - \sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 + \sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \frac{1}{4}\psi_{k,1}^2 + d_{k,1}\right].\end{aligned} \tag{43}$$

Step 2. Define $z_{k,2} = \hat{x}_{k,2} - \omega_{k,1}$ and $z_{k,3} = \hat{x}_{k,3} - \omega_{k,2}$. From (16), we have

$$\begin{aligned}\upsilon_{k,2}\dot{\omega}_{k,2} + \omega_{k,2} &= \alpha_{k,2}; \\ \omega_{k,2}(0) &= \alpha_{k,2}(0).\end{aligned} \tag{44}$$

Define $e_{k,2}$ as the filter output error; then, we have $e_{k,2} = \omega_{k,2} - \alpha_{k,2}$ and $\dot{\omega}_{k,2} = -(e_{k,2}/\upsilon_{k,2})$.

The time derivative of $z_{k,2}$ is as follows:

$$\begin{aligned}\dot{z}_{k,2} &= \hat{x}_{k,3} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1} \\ &= z_{k,3} + \alpha_{k,2} + e_{k,2} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1}.\end{aligned} \tag{45}$$

Choose the Lyapunov function candidate as

$$V_2 = V_1 + \sum_{k=1}^{M}\left[\frac{1}{2}z_{k,2}^2 + \frac{1}{2}e_{k,2}^2\right]. \tag{46}$$

The time derivative of V_2 is as follows:

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + \sum_{k=1}^{M}\left(z_{k,2}\dot{z}_{k,2} + e_{k,2}\dot{e}_{k,2}\right) \\ &= \dot{V}_1 + \sum_{k=1}^{M}\left[z_{k,2}\left(z_{k,3} + \alpha_{k,2} + e_{k,2} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1}\right) \right. \\ &\quad \left. + e_{k,2}\dot{e}_{k,2}\right] \\ &\leq \dot{V}_1 + \sum_{k=1}^{M}\left[z_{k,2}\left(z_{k,3} + \alpha_{k,2} + e_{k,2} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1}\right) \right. \\ &\quad \left. - \frac{e_{k,2}^2}{\upsilon_{k,2}} + e_{k,2}^2 + \frac{1}{4}\psi_{k,2}^2\right],\end{aligned} \tag{47}$$

where $\psi_{k,2}$ is the maximum absolute value of $\dot{\alpha}_{k,2}$.

According to Yang's inequalities, we have

$$\begin{aligned}\dot{V}_2 \leq& \dot{V}_1 + \sum_{k=1}^{M}\left[z_{k,2}\left(z_{k,3} + \alpha_{k,2} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1}\right) \right. \\ &\left. + z_{k,2}^2 + \frac{1}{4}e_{k,2}^2 - \frac{e_{k,2}^2}{\upsilon_{k,2}} + e_{k,2}^2 + \frac{1}{4}\psi_{k,2}^2\right] \\ \leq& \sum_{k=1}^{M}\left\{-\pi_{k,1}\|\tilde{\underline{x}}_k\|^2\right\} + \sum_{k=1}^{M}\left[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 + \mu_k z_{k,1} z_{k,2} \right. \\ &+ \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 - \sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 \\ &\left. + \sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \frac{1}{4}\psi_{k,1}^2 + d_{k,1}\right] \\ &+ \sum_{k=1}^{M}\left[z_{k,2}\left(z_{k,3} + \alpha_{k,2} - \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,1}\right) \right. \\ &\left. + z_{k,2}^2 + \left(\frac{5}{4} - \frac{1}{\upsilon_{k,2}}\right)e_{k,2}^2 + \frac{1}{4}\psi_{k,2}^2\right].\end{aligned} \tag{48}$$

Design $\alpha_{k,2}$ as follows:

$$\alpha_{k,2} = -c_{k,2}z_{k,2} - \mu_k z_{k,1} + \ell_{k,2}\left(\hat{x}_{k,1} - y_k\right) - \frac{\omega_{k,1} - \alpha_{k,1}}{\upsilon_{k,1}}, \tag{49}$$

where $c_{k,2} > 0$ is the design parameter.

Substituting (49) into (48) leads to

$$\begin{aligned}
\dot{V}_2 \leq{}& \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\} + \sum_{k=1}^{M}\Bigg[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 + \mu_k z_{k,1}z_{k,2} + \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 - \sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 + \sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \frac{1}{4}\psi_{k,1}^2 + d_{k,1}\Bigg] \\
&+ \sum_{k=1}^{M}\left[z_{k,2}z_{k,3} - \mu_k z_{k,2}z_{k,1} - \left(c_{k,2}-1\right)z_{k,2}^2 + \left(\frac{5}{4}-\frac{1}{\upsilon_{k,2}}\right)e_{k,2}^2 + \frac{1}{4}\psi_{k,2}^2\right] \\
\leq{}& \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\} + \sum_{k=1}^{M}\Bigg[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 - \left(c_{k,2}-1\right)z_{k,2}^2 + z_{k,2}z_{k,3} + \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 + \left(\frac{5}{4}-\frac{1}{\upsilon_{k,2}}\right)e_{k,2}^2 \\
&- \sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 + \sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \sum_{i=1}^{2}\frac{1}{4}\psi_{k,i}^2 + d_{k,1}\Bigg].
\end{aligned} \tag{50}$$

Step lth $(l = 3, \ldots, n_k - 1)$: define $z_{k,l} = \hat{x}_{k,l} - \omega_{k,l-1}$ and $z_{k,l+1} = \hat{x}_{k,l+1} - \omega_{k,l}$. We have

$$\begin{aligned} \upsilon_{k,l}\dot{\omega}_{k,l} + \omega_{k,l} &= \alpha_{k,l}; \\ \omega_{k,l}(0) &= \alpha_{k,l}(0). \end{aligned} \tag{51}$$

Define the filter output error as $e_{k,l}$; then, we obtain $e_{k,l} = \omega_{k,l} - \alpha_{k,l}$ and $\dot{\omega}_{k,l} = -(e_{k,l}/\upsilon_{k,l})$.

The time derivative of $z_{k,l}$ is as follows:

$$\begin{aligned} \dot{z}_{k,l} &= \hat{x}_{k,l+1} - \ell_{k,l}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,l-1} \\ &= z_{k,l+1} + \alpha_{k,l} + e_{k,l} - \ell_{k,l}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,l-1}. \end{aligned} \tag{52}$$

Choose the Lyapunov function candidate as

$$V_l = V_{l-1} + \sum_{k=1}^{M}\left[\frac{1}{2}z_{k,l}^2 + \frac{1}{2}e_{k,l}^2\right]. \tag{53}$$

The time derivative of V_l is as follows:

$$\begin{aligned} \dot{V}_l &= \dot{V}_{l-1} + \sum_{k=1}^{M}\left(z_{k,l}\dot{z}_{k,l} + e_{k,l}\dot{e}_{k,l}\right) \\ &= \dot{V}_{l-1} + \sum_{k=1}^{M}\Big[z_{k,l}\Big(z_{k,l+1} + \alpha_{k,l} + e_{k,l} - \ell_{k,l}\left(\hat{x}_{k,1} - y_k\right) \\ &\quad - \dot{\omega}_{k,l-1}\Big) + e_{k,l}\dot{e}_{k,l}\Big]. \end{aligned} \tag{54}$$

Design $\alpha_{k,l}$ as follows:

$$\alpha_{k,l} = -c_{k,l}z_{k,l} - z_{k,l-1} + \ell_{k,l}\left(\hat{x}_{k,1} - y_k\right) - \frac{\omega_{k,l-1} - \alpha_{k,l-1}}{\upsilon_{k,l-1}}, \tag{55}$$

where $c_{k,l} > 0$ is the design parameter.

Using the same recursive method in Step 2, we can get

$$\begin{aligned} \dot{V}_l \leq{}& \sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\} \\ &+ \sum_{k=1}^{M}\Bigg[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2 - \sum_{i=2}^{l}\left(c_{k,i}-1\right)z_{k,i}^2 + z_{k,l}z_{k,l+1} \\ &+ \left(1+\frac{\mu_k}{4}-\frac{1}{\upsilon_{k,1}}\right)e_{k,1}^2 + \sum_{i=2}^{l}\left(\frac{5}{4}-\frac{1}{\upsilon_{k,i}}\right)e_{k,i}^2 - \sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2 \\ &+ \sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2} + \sum_{i=1}^{2}\frac{1}{4}\psi_{k,i}^2 + d_{k,1}\Bigg]. \end{aligned} \tag{56}$$

Step n_kth: define $z_{k,n_k} = \hat{x}_{k,n_k} - \omega_{k,n_k-1}$, and we can get the time derivative of z_{k,n_k} as follows:

$$\dot{z}_{k,n_k} = u_k - \ell_{k,n_k}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,n_k-1}. \tag{57}$$

Choose the Lyapunov function candidate as

$$V_{n_k} = V_{n_k-1} + \sum_{k=1}^{M}\left[\frac{1}{2}z_{k,n_k}^2\right]. \tag{58}$$

Now, we can have the time derivative of V_{n_k} as follows:

$$\begin{aligned} \dot{V}_{n_k} &= \dot{V}_{n_k-1} + \sum_{k=1}^{M}\left(z_{k,n_k}\dot{z}_{k,n_k}\right) \\ &= \dot{V}_{n_k-1} + \sum_{k=1}^{M}\left[z_{k,n_k}\left(u_k - \ell_{k,n_k}\left(\hat{x}_{k,1} - y_k\right) - \dot{\omega}_{k,n_k-1}\right)\right]. \end{aligned} \tag{59}$$

Choose the final control law as

$$u_k = -c_{k,n_k}z_{k,n_k} - z_{k,n_k-1} + \ell_{k,n_k}\left(\hat{x}_{k,1} - y_k\right) - \frac{\omega_{k,n_k-1} - \alpha_{k,n_k-1}}{\upsilon_{k,n_k-1}}, \tag{60}$$

where $c_{k,n_k} > 0$ is the design parameter.

Substituting (60) into (59) results in

$$\begin{aligned}\dot{V}_{n_k} \leq &\sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\}\\&+\sum_{k=1}^{M}\Bigg[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2-\sum_{i=2}^{n_k}\left(c_{k,i}-1\right)z_{k,i}^2\\&+\left(1+\frac{\mu_k}{4}-\frac{1}{v_{k,1}}\right)e_{k,1}^2+\sum_{i=2}^{n_k}\left(\frac{5}{4}-\frac{1}{v_{k,i}}\right)e_{k,i}^2-\sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2\\&+\sum_{i=1}^{2}\frac{2\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2}+\sum_{i=1}^{n_k-1}\frac{1}{4}\psi_{k,i}^2+d_{k,1}\Bigg].\end{aligned} \tag{61}$$

Define

$$H=\sum_{i=1}^{2}\frac{\sigma_{k,i}}{\gamma_{k,i}}\varpi_{k,i}^{*2}+\sum_{i=1}^{n_k-1}\frac{1}{4}\psi_{k,i}^2+d_{k,1}. \tag{62}$$

Substituting (62) into (61) leads to

$$\begin{aligned}\dot{V}_{n_k} \leq &\sum_{k=1}^{M}\left\{-\pi_{k,1}\left\|\underline{\tilde{x}}_k\right\|^2\right\}\\&+\sum_{k=1}^{M}\Bigg[-\left(c_{k,1}-1\right)\mu_k z_{k,1}^2-\sum_{i=2}^{n_k}\left(c_{k,i}-1\right)z_{k,i}^2\\&+\left(1+\frac{\mu_k}{4}-\frac{1}{v_{k,1}}\right)e_{k,1}^2+\sum_{i=2}^{n_k}\left(\frac{5}{4}-\frac{1}{v_{k,i}}\right)e_{k,i}^2\\&-\sum_{i=1}^{2}\frac{\sigma_{k,i}}{2\gamma_{k,i}}\tilde{\varpi}_{k,i}^2+H\Bigg].\end{aligned} \tag{63}$$

5. Stability Analysis

Define Lyapunov function of the closed-loop system as $\widehat{V}=V_{n_k}$, and we can have $\dot{\widehat{V}}=\dot{V}_{n_k}$. Let the design parameters satisfy

$$\begin{aligned}&c_{k,i}-1>0, \quad i=1,2,\ldots,n_k,\\&1+\frac{\mu_k}{4}-\frac{1}{v_{k,1}}<0,\\&\frac{5}{4}-\frac{1}{v_{k,i}}<0, \quad i=2,\ldots,n_k-1.\end{aligned} \tag{64}$$

Define

$$\begin{aligned}C_k=\min\Bigg\{&\frac{2\pi_{k,1}}{\lambda_{\max}\left(P_k\right)},2\left(c_{k,i}-1\right),2\sigma_{k,1},2\sigma_{k,2},\\&2\left(\frac{1}{v_{k,1}}-1-\frac{\mu_k}{4}\right),2\left(\frac{1}{v_{k,i}}-\frac{5}{4}\right)\Bigg\},\end{aligned} \tag{65}$$

where $i=2,\ldots,n_k$.

Define $C=\min_{k=1,\ldots,M}\{C_k\}$, and (75) can be rearranged as

$$\dot{\widehat{V}}\leq -C\widehat{V}+H. \tag{66}$$

Then, we have

$$e^{Ct}\dot{\widehat{V}}\leq(-C\widehat{V}+H)e^{Ct}, \tag{67}$$

$$\frac{\mathrm{d}}{\mathrm{d}t}\left(\widehat{V}e^{Ct}\right)\leq He^{Ct}, \tag{68}$$

$$\widehat{V}e^{Ct}-\widehat{V}(0)\leq\frac{H}{C}\left(e^{Ct}-1\right), \tag{69}$$

$$0\leq\widehat{V}(t)\leq\widehat{V}(0)e^{-Ct}+\frac{H}{C}\left(1-e^{-Ct}\right)\leq\widehat{V}(0)+\frac{H}{C}. \tag{70}$$

From (70), we can get that all the signals of the closed system, such as $x_{k,i}(t)$, $\widehat{x}_{k,i}(t)$, $z_{k,i}(t)$, $a_{k,i}(t)$, and $u_k(t)$, are semiglobally uniformly ultimately bounded (SGUUB). Moreover, the observer error satisfies $\|\underline{\tilde{x}}_k\|\leq\sqrt{(2\widehat{V}(0)e^{-Ct}+(H/C))/\lambda_{\min}(P_k)}$, and the tracking error satisfies $\|z_{k,1}\|\leq\sqrt{2\widehat{V}(0)e^{-Ct}+(H/C)}$.

6. Comparisons with Some Previous Results

Comparisons with previous results will be given in this section.

(1) The control methods in [11–20, 34] can deal with only nonlinear system (71) without interconnected subsystems:

$$\begin{cases}\dot{x}_i=x_{i+1}+f_i(x),\\\dot{x}_n=u(t)+f_n(x),\\y=x_1,\end{cases} \tag{71}$$

where $x=[x_1,x_2,\ldots,x_n]^T$ and $i=1,2,\ldots,n-1$. y is the only output of the system and is only affected by x, $f_i(x)$, and $u(t)$. Therefore, there is no coupling effect $h_{k,l}(\underline{y})$ between subsystems.

The control methods in [22, 25, 26] deal with large-scale systems in strict feedback form while not in nonstrict feedback structure (72):

$$\begin{cases}\dot{x}_{k,1}=x_{k,2}+f_{k,1}\left(x_{k,1}\right)+h_{k,1}\left(\underline{y}\right),\\\dot{x}_{k,2}=x_{k,3}+f_{k,2}\left(x_{k,1},x_{k,2}\right)+h_{k,2}\left(\underline{y}\right),\\\vdots\\\dot{x}_{k,n_k-1}=x_{k,n_k}+f_{k,n_k-1}\left(x_{k,1},\ldots,x_{k,n_k-1}\right)+h_{k,n_k-1}\left(\underline{y}\right),\\\dot{x}_{k,n_k}=u_k+f_{k,n_k}\left(x_{k,1},\ldots,x_{k,n_k}\right)+h_{k,n_k}\left(\underline{y}\right),\\y_k=x_{k,1},\end{cases} \tag{72}$$

where $f_{k,i}(x_{k,1},\ldots,x_{k,i})(i=1,2,\ldots,n)$ are the functions of partial state variables, and large-scale system (72) has a strict lower triangle structure.

However, the control method in this paper is designed for nonstrict feedback large-scale systems (73) that are more complex compared with (71) and (72):

$$\begin{cases} \dot{x}_{k,1} = x_{k,2} + f_{k,1}(\underline{x}_k) + h_{f_{k,1}}(\underline{y}), \\ \dot{x}_{k,2} = x_{k,3} + f_{k,2}(\underline{x}_k) + h_{f_{k,2}}(\underline{y}), \\ \vdots \\ \dot{x}_{k,n_k-1} = x_{k,n_k} + f_{k,n_k-1}(\underline{x}_k) + h_{k,n_k-1}(\underline{y}), \\ \dot{x}_{k,n_k} = u_k + f_{k,n_k}(\underline{x}_k) + h_{k,n_k}(\underline{y}), \\ y_k = x_{k,1}, \end{cases} \tag{73}$$

where $\underline{x}_k = [x_{k,1}, x_{k,2}, \ldots, x_{k,n_k}]^T \in R^{n_k}$. Then, $f_{k,i}(x_{k,1}, \ldots, x_{k,i})$ is a function of full-state variables. It is well known that an interconnected large-scale system comprises some subsystems with obvious interconnections, which lead to the increasing difficulty of controller design and stability proof for the large-scale system. We unable to use the control methods in [11–20, 34] to control the large-scale system due to the coupling effect between subsystems. Moreover, when the controller of the nonstrict feedback large-scale system is designed by the control methods in [22, 25, 26], the virtual control signal and adaptive law of each subsystem are the functions of full-state variables. Consequently, the algebraic loop problem arises, which makes the controller design of a nonstrict feedback large-scale system very difficult. Therefore, the controller design method of nonstrict feedback large-scale system (73) considered in this paper is quite different from that of the controller design methods in [11–20, 22, 25, 26, 34].

(2) [21–25, 29–31] proposed adaptive control methods for the large-scale system, but output constraints were not considered. Though [32, 33] presented the control schemes for constrained systems, the system considered in [32, 33] is not a large-scale system, and all states should be measurable. The strict limitation makes these control methods difficult to realize in practical applications. Therefore, control methods in [21–25, 32, 33] cannot be used to control a large-scale system with unmeasurable state and output constraints that is discussed in this paper. To the best of our knowledge, by far, no results have been reported on the adaptive control for the nonstrict feedback large-scale nonlinear system with output constraints and unmeasured states.

(3) This proposed adaptive control scheme does not need n-order differentiable and bounded conditions of the input signals and a monotonically increasing condition of unknown functions. However, these strict assumptions are common in the existing references [27, 28]. Moreover, this control scheme has only $2M$ adaptive parameters, and the number of parameters does not increase with the increase of system's order n_k. Therefore, this control scheme not only conforms to engineering practice but also has a simple algorithm and requires a small number of calculations.

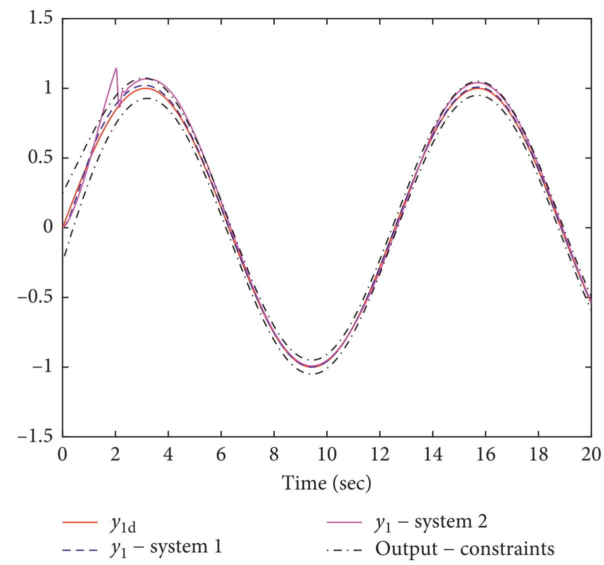

Figure 1: Trajectories of $y_{1,d}$, y_1, and the output constraints.

7. Simulations

Consider the following nonstrict feedback large-scale system [23]:

$$\begin{cases} \dot{x}_{1,1} = x_{1,2} + x_{1,1}^2\left(1 - \cos\left(x_{1,1}x_{1,2}\right) + x_{1,2}\right) \\ \quad -0.2x_{1,1}\sin\left(x_{1,1}x_{1,2}\right) + y_1 y_2, \\ \dot{x}_{1,2} = u_1 + x_{1,1}x_{1,2} + x_{1,1} + y_1^2 + y_2^2, \\ y_1 = x_{1,1}, \end{cases}$$
$$\begin{cases} \dot{x}_{2,1} = x_{2,2} + x_{2,1}\sin\left(x_{2,1}x_{2,2}\right) - 0.5x_{2,1}\sin\left(x_{2,1}x_{2,2}\right) + y_1^3 y_2^3, \\ \dot{x}_{2,2} = u_2 + x_{2,1}x_{2,2} + y_1 - 2y_2, \\ y_2 = x_{2,1}. \end{cases} \tag{74}$$

The given tracking signals are $y_{1,d} = \sin(0.5t)$ and $y_{2,d} = 0.5\sin(t)$. The constraints are given as $\underline{k}_{1,c1} = -0.2 \times 2^{-t} - 0.05 + y_{1,d}$, $\overline{k}_{1,c1} = 0.2 \times 2^{-t} + 0.05 + y_{1,d}$, $\underline{k}_{2,c1} = -0.2 \times 2^{-t} - 0.05 + y_{2,d}$, and $\overline{k}_{2,c1} = 0.2 \times 2^{-t} + 0.05 + y_{2,d}$.

Choose the parameters as $\ell_{1,1} = \ell_{1,2} = \ell_{2,1} = \ell_{2,2} = 10$, $c_{1,1} = 40$, $c_{1,2} = 20$, $c_{2,1} = 20$, $c_{2,2} = 20$, $\lambda_1 = \lambda_2 = 1$, $\tau_1 = \tau_2 = 1$, $\gamma_{1,1} = \gamma_{1,2} = 1$, $\gamma_{2,1} = \gamma_{2,2} = 2$, $\sigma_{1,1} = \sigma_{1,2} = 0.05$, $\sigma_{2,1} = \sigma_{2,2} = 0.1$, and $\upsilon_{1,1} = \upsilon_{1,2} = \upsilon_{2,1} = \upsilon_{2,2} = 0.5$.

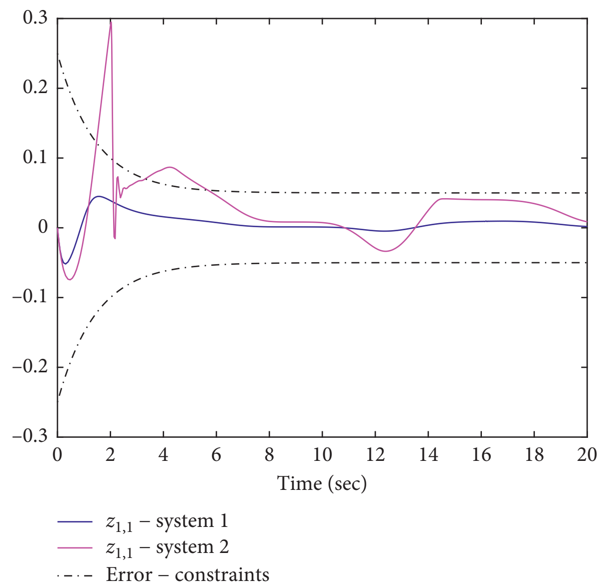

FIGURE 2: The tracking error $z_{1,1}$ and the error constraints.

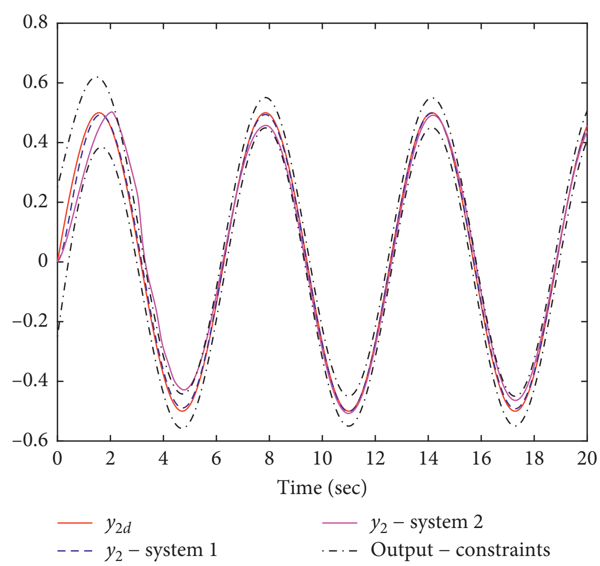

FIGURE 3: Trajectories of $y_{2,d}$, y_2, and the output constraints.

To show the superiority and validity of the method proposed in this paper, we compare it with a scheme proposed for large-scale systems without considering the output constraints [23]. The design parameters and initial conditions of the two methods are the same. In the simulation, system 1 is controlled by the method in this paper, whereas system 2 is controlled by the method without output constraints [23].

Figures 1–5 show the simulation results. From Figures 1–4, we can see that the output $(y_{1,d}, y_{2,d})$ and the tracking error $(z_{1,1}, z_{2,1})$ of system 1 can both be kept within the constraints, whereas the output and the tracking error of system 2 violate the constraints. Figure 5 shows control input signals u_k of the two systems, respectively. From the simulation results, it can be seen that the proposed adaptive control approach in this paper not only guarantees the boundedness of all the signals and not violating of output constraints but also achieves better control performance than that of the control method without considering output constraints [23].

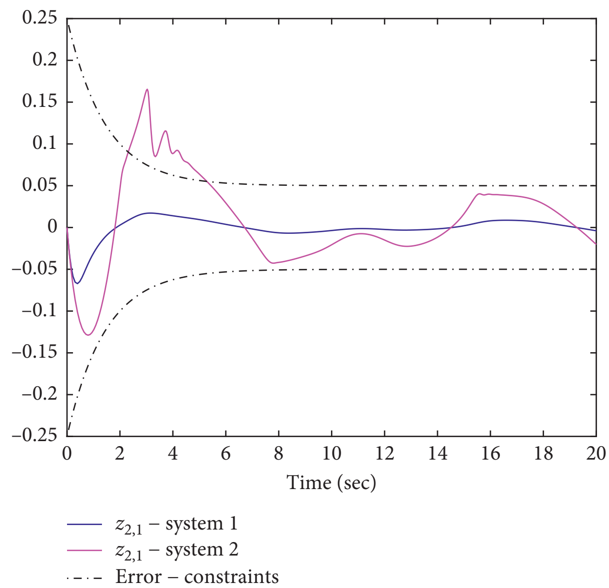

Figure 4: The tracking error $z_{2,1}$ and the error constraints.

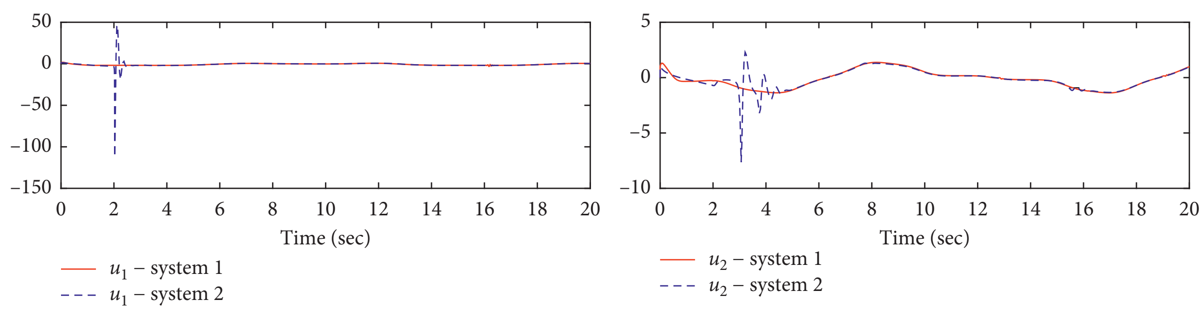

Figure 5: Control input signals u_k.

8. Conclusion

This paper proposes an adaptive fuzzy dynamic surface decentralized output feedback control scheme for a class of large-scale interconnected uncertain nonstrict feedback systems with time-varying output constraints. By using a decentralized linear state observer, the unmeasurable states can be estimated. Based on fuzzy logic systems, the uncertain nonlinear functions and interconnected influence between the subsystems can be compensated. The problems of nonstrict feedback and time-varying constraints are solved by variable separation technology and time-varying barrier Lyapunov function, respectively. The proposed scheme can not only achieve good tracking performance but also keep the output trajectories within the given ranges. Finally, the stability of the large-scale interconnected system is proved by using the Lyapunov direct method.

Data Availability

All the data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (grant no. 51775463).

References

[1] Y. Pan, H. Yu, and T. Sun, "Global asymptotic stabilization using adaptive fuzzy PD control," *IEEE Transactions on Cybernetics*, vol. 45, no. 3, pp. 588–596, 2015.

[2] Y.-J. Liu and S. Tong, "Adaptive fuzzy control for a class of unknown nonlinear dynamical systems," *Fuzzy Sets and Systems*, vol. 263, pp. 49–70, 2015.

[3] L.-Y. Hao, J. H. Park, and D. Ye, "Fuzzy logic systems-based integral sliding mode fault-tolerant control for a class of uncertain non-linear systems," *IET Control Theory & Applications*, vol. 10, no. 3, pp. 300–311, 2016.

[4] W. Min and Q. Liu, "An improved adaptive fuzzy backstepping control for nonlinear mechanical systems with mismatched uncertainties," *Automatika*, vol. 60, no. 1, pp. 1–10, 2019.

[5] Z. Liu, F. Wang, Y. Zhang, and C. L. Philip Chen, "Fuzzy adaptive quantized control for a class of stochastic nonlinear uncertain systems," *IEEE Transactions on Cybernetics*, vol. 46, no. 2, pp. 524–534, 2016.

[6] M. A. Khanesar, Y. Oniz, O. Kaynak, and H. Gao, "Direct model reference adaptive fuzzy control of networked SISO nonlinear systems," *IEEE/ASME Transactions on Mechatronics*, vol. 21, no. 1, pp. 205–213, 2016.

[7] J. Cai, C. Wen, H. Su, Z. Liu, and L. Xing, "Adaptive backstepping control for a class of nonlinear systems with non-triangular structural uncertainties," *IEEE Transactions on Automatic Control*, vol. 62, no. 10, pp. 5220–5226, 2017.

[8] Y.-H. Liu, "Adaptive dynamic surface asymptotic tracking for a class of uncertain nonlinear systems," *International Journal of Robust and Nonlinear Control*, vol. 28, no. 4, pp. 1233–1245, 2018.

[9] Y. Li, L. Liu, and G. Feng, "Robust adaptive output feedback control to a class of non-triangular stochastic nonlinear systems," *Automatica*, vol. 89, pp. 325–332, 2018.

[10] Q. Zhou, L. Wang, C. Wu, and H. Li, "Adaptive fuzzy tracking control for a class of pure-feedback nonlinear systems with time-varying delay and unknown dead zone," *Fuzzy Sets and Systems*, vol. 329, pp. 36–60, 2017.

[11] Y. Li, T. Li, and X. Jing, "Indirect adaptive fuzzy control for input and output constrained nonlinear systems using a barrier Lyapunov function," *International Journal of Adaptive Control and Signal Processing*, vol. 28, no. 2, pp. 184–199, 2014.

[12] Y.-J. Liu, J. Li, S. Tong, and C. L. P. Chen, "Neural network control-based adaptive learning design for nonlinear systems with full-state constraints," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 7, pp. 1562–1571, 2016.

[13] Y.-J. Liu and S. Tong, "Barrier Lyapunov Functions-based adaptive control for a class of nonlinear pure-feedback systems with full state constraints," *Automatica*, vol. 64, pp. 70–75, 2016.

[14] H. Li, L. Wang, H. Du, and A. Boulkroune, "Adaptive fuzzy backstepping tracking control for strict-feedback systems with input delay," *IEEE Transactions on Fuzzy Systems*, vol. 25, no. 3, pp. 642–652, 2017.

[15] D.-P. Li, Y.-J. Liu, S. Tong, C. L. P. Chen, and D.-J. Li, "Neural networks-based adaptive control for nonlinear state constrained systems with input delay," *IEEE Transactions on Cybernetics*, vol. 49, no. 4, pp. 1249–1258, 2019.

[16] K. Sun, S. Mou, J. Qiu, T. Wang, and H. Gao, "Adaptive fuzzy control for nontriangular structural stochastic switched nonlinear systems with full state constraints," *IEEE Transactions on Fuzzy Systems*, vol. 27, no. 8, pp. 1587–1601, 2019.

[17] Y.-J. Liu, S. Lu, S. Tong, X. Chen, C. L. P. Chen, and D.-J. Li, "Adaptive control-based Barrier Lyapunov Functions for a class of stochastic nonlinear systems with full state constraints," *Automatica*, vol. 87, pp. 83–93, 2018.

[18] Y. Li, Z. Ma, and S. Tong, "Adaptive fuzzy fault-tolerant control of non-triangular structure nonlinear systems with error-constraint," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 4, pp. 2062–2074, 2018.

[19] J.-X. Zhang and G.-H. Yang, "Fuzzy adaptive output feedback control of uncertain nonlinear systems with prescribed performance," *IEEE Transactions on Cybernetics*, vol. 48, no. 5, pp. 1342–1354, 2018.

[20] M. Wan, Q. Liu, J. Zheng, and J. Song, "Fuzzy state observer-based adaptive dynamic surface control of nonlinear systems with time-varying output constraints," *Mathematical Problems in Engineering*, vol. 2019, Article ID 3683581, 11 pages, 2019.

[21] L. E. Younsi, A. Benzaouia, and A. E. Hajjaji, "Decentralized control design for switching fuzzy large-scale T-S systems by switched Lyapunov function with H_∞ performance," *International Journal of Fuzzy Systems*, vol. 21, no. 4, pp. 1104–1116, 2019.

[22] X. Li and X. Liu, "Backstepping-based decentralized adaptive neural H∞ tracking control for a class of large-scale nonlinear interconnected systems," *Journal of the Franklin Institute*, vol. 355, no. 11, pp. 4533–4552, 2018.

[23] Y. Li and S. Tong, "Fuzzy adaptive control design strategy of nonlinear switched large-scale systems," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 12, pp. 2209–2218, 2018.

[24] T. Wang and S. Tong, "Decentralised output-feedback control design for switched fuzzy large-scale systems," *International Journal of Systems Science*, vol. 48, no. 1, pp. 171–181, 2017.

[25] S. Tong, L. Zhang, and Y. Li, "Observed-based adaptive fuzzy decentralized tracking control for switched uncertain nonlinear large-scale systems with dead zones," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 46, no. 1, pp. 37–47, 2016.

[26] L. Zhang and G.-H. Yang, "Adaptive fuzzy output constrained decentralized control for switched nonlinear large-scale systems with unknown dead zones," *Nonlinear Analysis: Hybrid Systems*, vol. 23, pp. 61–75, 2017.

[27] B. Chen, C. Lin, X. Liu, and K. Liu, "Adaptive fuzzy tracking control for a class of MIMO nonlinear systems in nonstrict-feedback form," *IEEE Transactions on Cybernetics*, vol. 45, no. 12, pp. 2744–2755, 2015.

[28] H. Wang, X. Liu, K. Liu, and H. R. Karimi, "Approximation-based adaptive fuzzy tracking control for a class of nonstrict-feedback stochastic nonlinear time-delay systems," *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 5, pp. 1746–1760, 2015.

[29] Y.-S. Huang and Z.-Y. Wang, "Decentralized adaptive fuzzy control for a class of large-scale MIMO nonlinear systems with strong interconnection and its application to automated highway systems," *Information Sciences*, vol. 274, pp. 210–224, 2014.

[30] X. Zhang and Y. Lin, "Nonlinear decentralized control of large-scale systems with strong interconnections," *Automatica*, vol. 50, no. 9, pp. 2419–2423, 2014.

[31] S. J. Yoo and J. B. Park, "Decentralized adaptive output-feedback control for a class of nonlinear large-scale systems with unknown time-varying delayed interactions," *Information Sciences*, vol. 186, no. 1, pp. 222–238, 2012.

[32] L. Edalati, A. Khaki Sedigh, M. Aliyari Shooredeli, and A. Moarefianpour, "Adaptive fuzzy dynamic surface control of nonlinear systems with input saturation and time-varying output constraints," *Mechanical Systems and Signal Processing*, vol. 100, pp. 311–329, 2018.

[33] Q. Zhou, L. Wang, C. Wu, H. Li, and H. Du, "Adaptive fuzzy control for nonstrict-feedback systems with input saturation and output constraint," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 1, pp. 1–12, 2017.

[34] S. Tong, Y. Li, and S. Sui, "Adaptive fuzzy tracking control design for SISO uncertain nonstrict feedback nonlinear systems," *IEEE Transactions on Fuzzy Systems*, vol. 24, no. 6, pp. 1441–1454, 2016.

[35] M. Wan, Q. Tian, and M. Wang, "Adaptive sliding mode control of robot manipulator based on second order approximation accuracy and decomposed fuzzy compensator," *Wireless Personal Communications*, vol. 103, no. 2, pp. 1207–1218, 2018.