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Finite-Time Adaptive Dynamic Surface Asymptotic Tracking Control of Uncertain Multi-Agent Systems with Unknown Control Gains

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Abstract: In this work, the finite-time asymptotic tracking control problem of uncertain multi-agent systems with unknown control gains is studied. For the unknown control gain of each subsystem in multi-agent systems, we consider using the Nussbaum gain function techniques to handle them. To deal with the unknown uncertain nonlinear dynamics, the radial basis function neural network is introduced in each step of the dynamic surface control design. In addition, a nonlinear compensating term with the estimation of an unknown bounded parameter is designed to avoid repeated differentiation of each virtual control law. Then, based on the neural network control method, dynamic surface control technique, and finite-time control theory, an adaptive neural network finite-time dynamic surface control law is finally designed. Using stability analysis, it is proven that the presented adaptive control law can guarantee all signals of the closed-loop system semi-global practical finite-time stable, and the tracking error of each follower agent can converge to a small neighborhood of zero in finite time. Finally, a class of single-link robot systems is provided to illustrate the effectiveness of the designed control law.

Keywords: multi-agent systems; finite-time control; dynamic surface control; unknown control direction

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1. Introduction

The control problems of multi-agent systems have been widely studied in the past two decades, such as distributed control problems [1,2], robust control problems [3,4], formation control problems [5,6], and so on. Additionally, many researchers have paid attention to the control problems of practical multi-agent systems because they have obvious advantages in solving complex control problems. In [7], the authors implemented the task allocation problem for wireless sensor networks using the multi-agent method. To achieve the finite-time tracking control problem of robotic systems, the authors of [8] proposed an improved integral sliding mode control method. In addition, the event-triggered adaptive tracking control problems of six-degrees-of-freedom unmanned aerial vehicles were solved in [9,10]. However, it should be pointed out that multi-agent systems may not be accurately modeled due to the existence of uncertain nonlinear dynamics, unknown disturbances, or parameter uncertainties. Therefore, how to solve the control problems of nonlinear multi-agent systems caused by these factors is worth studying.

Many excellent recent achievements for control problems of nonlinear multi-agent systems can be found in the existing literature. In [11], a class of uncertain lower triangular, nonlinear, multi-agent systems was addressed, where an adaptive asynchronous event-triggered strategy was designed to achieve the distributed consensus tracking problem. In [12], an exosystem observer-based output regulation controller was presented to solve the distributed optimization problem of uncertain heterogeneous linear multi-agent systems.

Moreover, a distributed tracking controller for a class of uncertain heterogeneous nonlinear multi-agent systems was investigated in [13]. In addition, for the tracking control problems of uncertain fractional-order multi-agent systems [14,15], uncertain multi-agent systems with stochastic measurement noises [16], and stochastic multi-agent systems with uncertain actuator faults [17], some scholars have carried out research and put forward their own control methods. Although these papers studied the control problems of multi-agent systems, there is no in-depth study on the finite-time control problem of multi-agent systems.

In addition, some control methods are often used, such as the model predictive control method [18], metaheuristic optimization algorithm [19,20], and sliding mode control method [21], to solve the control problems of complex nonlinear systems. Nevertheless, as an effective tool, the backstepping control technique is widely applied for uncertain nonlinear systems [22–24]. It should be noted that repeated differentiation of the virtual control law is required when applying the backstepping control method. This may cause the "explosion of complexity" issue. For this reason, the dynamic surface control technique is proposed to improve the traditional backstepping control method, and many meaningful results can be found in [25–27]. For multi-agent systems, some control schemes are addressed, such as the adaptive cooperative neural dynamic surface control scheme [28], the robust adaptive distributed dynamic surface control scheme [29], and the event-trigger-based recursive sliding mode dynamic surface scheme [30], to solve the desired control problems. Therefore, the dynamic surface control method provides a good solution for the control problems of complex uncertain nonlinear multi-agent systems.

For practical systems, sometimes we need to consider the issue of control direction, which is the sign of the control coefficient. In many existing results, the sign is considered to be known and usually to be assumed positive. However, the control direction may not be predicted in advance due to the existence of unpredictable states or uncertainties. As a common processing method, the Nussbaum gain function control technique is widely used to solve the problems of unknown control directions [26,31–34]. Although the consensus problems of multi-agent systems were studied in [35,36], the authors further considered high-power nonlinear dynamics and communication delays. In addition, it is well known that the control objective of practical industrial systems needs to be achieved in a finite time to be meaningful. However, in most existing works, such as [37–40] and references therein, the control methods designed are usually used to solve the infinite time control problem. Therefore, designing effective control laws to realize the finite-time control of complex systems is worth considering.

Inspired by the above observations, we consider the finite-time asymptotic tracking control problem of uncertain multi-agent systems with unknown control gains. Given the existence of uncertain dynamics and unknown control gains, the dynamic surface control technique and the Nussbaum gain function technique are used, respectively. To deal with unknown uncertain nonlinear dynamics, the radial basis function neural network (RBFNN) is applied to the final control law design. The main contributions of this paper are highlighted as follows:

1. Different from the multi-agent systems considered in [13,36], the control gain of each subsystem in multi-agent systems considered in this work is unknown. Moreover, the Nussbaum gain function technique is applied to deal with the unknown control gain in recursive design.
2. The unknown nonlinear dynamics of multi-agent systems are approximated by using the RBFNN. Unlike the direct estimation of ideal weights in [24,37], this paper redesigns the weights of RBFNN to implement estimation and design adaptive control laws.
3. A nonlinear compensating term with the estimation of an unknown bounded parameter is designed to avoid repeated differentiation of each virtual control law. Furthermore, a class of first-order nonlinear filters is designed to overcome the issue of "explosion of complexity". This consideration simplifies the analysis process compared with [26,31].

4. An adaptive neural network finite-time dynamic surface control law is constructed to solve the finite-time asymptotic tracking control of given multi-agent systems. It is proven that all signals of the closed-loop system are semi-global practical finite-time stable, and by selecting appropriate design parameters, the tracking error of each follower agent can converge to a small neighborhood of zero in a finite time.

The rest of this paper is structured as follows. In Section 2, some useful preliminaries and the problem description of uncertain multi-agent systems are introduced. In Section 3, the detailed control law design and stability analysis are shown. In what follows, the simulation example and brief conclusions are given in Sections 3 and 4, respectively.

2. Preliminaries and Problem Description

2.1. Graph Theory

In this work, a weighted directed graph is introduced to describe the connection relationship between agents: the agents are labeled by nodes, and the interactions by edges. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \boldsymbol{\mathcal{A}})$ stand for a weighted directed graph with N nodes, where $\mathcal{V} = \{v_1, \cdots, v_n\}$ denotes the set of vertices and $\mathcal{E} = \{(i,j),\ i,j \in \mathcal{V},\ \text{and}\ i \neq j\}$ denotes the set of edges, respectively. The adjacency weight matrix $\boldsymbol{\mathcal{A}} = [a_{ij}] \in R^{N\times N}$ is used to represent the communication topology among the agents. If the agent i can obtain information from the agent j, then $a_{ij} > 0$; otherwise, $a_{ij} = 0$. The set of neighbors for agent i is denoted by $\mathcal{J}_i = \{v_j :\ (v_j,\ v_i) \in \mathcal{E}\}$. In addition, the Laplace matrix of $\mathcal{G}$ is denoted by $\boldsymbol{\mathcal{L}} = \boldsymbol{\mathcal{D}} - \boldsymbol{\mathcal{A}}$, where $\boldsymbol{\mathcal{D}} = \text{diag}\{d_1, \cdots, d_N\}$ and $d_i = \sum_{j=1}^{\mathcal{J}_i} a_{ij}$. The graph $\mathcal{G}$ is connected if there is a path between any two vertices.

The communication topology for one leader agent and N follower agents is defined as an extended directed graph $\overline{\mathcal{G}} = (\overline{\mathcal{V}},\ \overline{\mathcal{E}})$ with $\overline{\mathcal{V}} = \{v_0, v_1, \cdots, v_n\}$ and $\overline{\mathcal{E}} \subseteq \overline{\mathcal{V}} \times \overline{\mathcal{V}}$, where the index 0 represents the leader agent. Let the leader adjacency matrix be $\boldsymbol{\mathcal{B}} = \text{diag}\{b_1, \cdots, b_N\}$, where $b_i > 0$ means that the follower agent i can obtain the information of the leader agent, and otherwise, $b_i = 0$. It is supposed that at least one follower agent can obtain the information from the leader agent.

Assumption 1 [39]. *The directed graph $\overline{\mathcal{G}}$ contains a spanning tree, and the leader node is the root node.*

2.2. Radial Basis Function Neural Network

As one of the most useful tools for dealing with unknown nonlinear functions, the radial basis function neural network (RBFNN) has been widely applied in many studies. Using an RBFNN to approximate the unknown nonlinear function $F_{nn}(x) : R^n \to R$ can be described as

$$F_{nn}(x) = \Phi^T \zeta(x) \tag{1}$$

where $x \in R^n$ is the input of RBFNN, $\Phi = [\psi_1, \cdots, \psi_l]^T \in R^l$ is the weight vector, $l > 1$ is the neural network node number, $\zeta(x) = [\zeta_1(x), \cdots, \zeta_l(x)]^T \in R^l$ is the basis function vector, and $\zeta_i(x)$ is the Gaussian basis function with the following form

$$\zeta_i(x) = \exp\left(-\frac{(x-\ell_i)^T(x-\ell_i)}{b_i^2}\right),\ i = 1, \cdots, l \tag{2}$$

where $\ell_i = [\ell_{i1}, \cdots, \ell_{in}]^T$ is the center of the basis function and b_i is the width of the Gaussian function.

Lemma 1 [24]. *For any continuous nonlinear function $F(x)$, which is defined over a compact set $\Omega_x \subset R^n$, there exists an RBFNN $(\Phi^*)^T\zeta(x)$ such that*

$$F(x) = (\Phi^*)^T \zeta(x) + \varepsilon(x) \tag{3}$$

where $\varepsilon(x)$ is the approximation error and bounded Φ^* is the ideal weight vector with the following form

$$\Phi^* := \arg\min_{\Phi \in R^n} \left\{ \sup_{x \in \Omega_x} \left| F(x) - \Phi^T \zeta(x) \right| \right\} \tag{4}$$

2.3. Problem Description

Consider a class of nonlinear multi-agent systems consisting of N follower agents and one leader agent, the dynamics of the ith follower agent are given as

$$\begin{aligned} \dot{x}_{i,m} &= g_{i,m} x_{i,m+1} + f_{i,m}(\bar{x}_{i,m}),\ m = 1, \cdots, n-1 \\ \dot{x}_{i,n} &= g_{i,n} u_i(t) + f_{i,n}(\bar{x}_{i,n}) \\ y_i &= x_{i,1} \end{aligned} \tag{5}$$

where $\bar{x}_{i,m} = [x_{i,1}, x_{i,2}, \cdots, x_{i,m}]^T \in R^m$, $i = 1, \cdots, N$ and $m = 1, \cdots, n$; $\bar{x}_{i,n} \in R^n$, $u_i(t) \in R$ and $y_i \in R$ are the state, control input, and output of the ith follower agent, respectively. In addition, $f_{i,m}(\cdot)$ represents unknown uncertain dynamics and $g_{i,m}$ represents unknown control gains, where $i = 1, \cdots, N$ and $m = 1, \cdots, n$.

The objective of this paper is to design an adaptive neural network finite-time control law $\mu_i(t)$ for the system (1), such that: (1) in the presence of unknown control gains, all signals of the closed-loop system are semi-global practical finite-time stable (SGPFS) and (2) the output of all follower agents can achieve asymptotic tracking of the leader agent's trajectory y_d in finite time, and tracking errors can converge to a small neighborhood of zero.

Assumption 2. *The reference signal y_d and its first and second derivatives $\dot{y}_d$ and $\ddot{y}_d$ are smooth, available, and bounded.*

Assumption 3. *The unknown control gains $g_{i,m}$, $i = 1, \cdots, N$ and $m = 1, \cdots, n$, are bounded. That is, there exist unknown positive constants $g^*_{i,m}$ such that $|g_{i,m}| \leq g^*_{i,m}$.*

Remark 1. *Regarding Assumption 2, this is one of the common conditions for adaptive control problems based on dynamic surface control design and can be seen in [25,31]. Assumption 3 requires that the unknown control gain is bounded, and then we can apply the Nussbaum gain function technique to deal with the control problem of unknown control direction.*

2.4. Useful Lemmas

Lemma 2 [41]. *Consider the nonlinear system $\dot{\sigma} = f(\sigma)$; if there exist constants $a_0 > 0$, $a_1 > 0$, and $\mu \in (0, 1)$, and a smooth positive definite function $V(\sigma)$ such that $\dot{V}(\sigma) \leq -a_0 V^\mu(\sigma) + a_1$, $t \geq 0$, then the nonlinear system $\dot{\sigma} = f(\sigma)$ is SGPFS, and $V(\sigma)$ satisfies*

$$V^\mu(\sigma) \leq \frac{a_1}{(1-\lambda)a_0},\ \forall t \geq T_r \tag{6}$$

$$T_r = \frac{1}{(1-\mu)\lambda a_0} \left[V^{1-\mu}(\sigma(0)) - \left(\frac{a_1}{(1-\lambda)a_0} \right)^{\frac{1-\mu}{\mu}} \right] \tag{7}$$

where $\lambda \in (0, 1)$ and $\sigma(0)$ is the initial value of the system.

Lemma 3 [33]. *Let $V(t)$ be a smooth function defined as $[0, \bar{t})$ with bounded initial value $V(0)$ and $\varsigma(t)$ be smooth functions with bounded initial value $\varsigma(0)$. $\mathcal{N}(\varsigma) = \varsigma^2 \cos(\varsigma)$ is the given Nussbaum gain function. If the following inequality holds*

$$V(t) \leq \int_0^t (\hbar \mathcal{N}(\varsigma(\tau)) + 1)\dot{\varsigma}(\tau) d\tau + A_0 \tag{8}$$

then $V(t)$, $\varsigma(t)$, *and* $\int_0^t(\hbar\mathcal{N}(\varsigma(\tau))+1)\dot{\varsigma}(\tau)d\tau$ *are bounded on the interval* $[0,\bar{t})$ *when* $\bar{t}<+\infty$, *where* $\hbar\in R-\{0\}$ *and* $A_0\in R$ *are constants.*

Lemma 4 [2]. *For* $\alpha_k\in R$, $k=1,\cdots,n$ *and* $0<p<1$, *the following relation holds*

$$\left(\sum_{k=1}^{n}|\alpha_k|\right)^p\leq\sum_{k=1}^{n}|\alpha_k|^p\leq n^{1-p}\left(\sum_{k=1}^{n}|\alpha_k|\right)^p \tag{9}$$

Lemma 5 [41]. *For any real variables* x *and* y *and any positive constants* z_1, z_2, *and* z_3, *the following inequality holds*

$$|x|^{z_1}|y|^{z_2}\leq\frac{z_1}{z_1+z_2}z_3|x|^{z_1+z_2}+\frac{z_2}{z_1+z_2}z_3^{-\frac{z_1}{z_2}}|y|^{z_1+z_2} \tag{10}$$

Lemma 6 [42]. *For any* $\eta>0$ *and* $z\in R$, *the following inequality holds*

$$0\leq|z|-\frac{z^2}{\sqrt{z^2+\eta^2}}\leq\eta \tag{11}$$

Lemma 7 (Young's inequality) [42]. *For any* $x\in R$ *and* $y\in R$, *the following inequality holds*

$$xy\leq\frac{\kappa^p}{p}|x|^p+\frac{1}{q\kappa^q}|y|^q \tag{12}$$

where $\kappa>0$, $p>1$, $q>1$, *and* $(p-1)(q-1)=1$.

3. Control Law Design and Stability Analysis

In this section, combining the dynamic surface control technique, neural network approximation technique with the Nussbaum gain function method, an adaptive neural network finite-time dynamic surface control law for uncertain multi-agent systems will be derived. The complete design process is given below.

3.1. Adaptive Neural Network Finite-Time Dynamic Surface Control Law Design

Similar to the backstepping control technique, the analysis process includes n steps. Firstly, the consensus error and coordinate transformation are defined as

$$e_{i,1}=\sum_{j\in\mathcal{J}_i}a_{ij}(y_i-y_j)+b_i(y_i-y_d) \tag{13}$$

$$e_{i,m}=x_{i,m}-s_{i,m-1} \tag{14}$$

$$z_{i,m-1}=s_{i,m-1}-\alpha_{i,m-1} \tag{15}$$

where $i=1,\cdots,N$ and $m=2,\cdots,n$, $s_{i,m-1}$ is the output of the given first-order filter with the virtual control law $\alpha_{i,m-1}$ as the input, and $z_{i,m-1}$ is called the output error of the first-order filter.

Step 1: Applying (5) and (13)–(15), the derivative of consensus error $e_{i,1}$ is given as

$$\dot{e}_{i,1}=(\sum_{j\in\mathcal{J}_i}a_{ij}+b_i)\dot{y}_i-\sum_{j\in\mathcal{J}_i}a_{ij}\dot{y}_j-b_i\dot{y}_d=\hbar_{i,1}\alpha_{i,1}+F_{i,1}-b_i\dot{y}_d \tag{16}$$

where $\hbar_{i,1}=(\sum_{j\in\mathcal{J}_i}a_{ij}+b_i)g_{i,1}$ and

$$F_{i,1}=\hbar_{i,1}(e_{i,2}+z_{i,1})+(\sum_{j\in\mathcal{J}_i}a_{ij}+b_i)f_{i,1}-\sum_{j\in\mathcal{J}_i}a_{ij}(g_{j,1}x_{j,2}+f_{j,1}) \tag{17}$$

Considering the fact that the information of the nonlinear function $F_{i,1}$ may be unavailable directly, an RBFNN is utilized to approximate the unknown nonlinear function $F_{i,1}$. According to Lemma 1, one has

$$F_{i,1} = (\Phi_{i,1}^*)^T \zeta_{i,1} + \varepsilon_{i,1}(X_{i,1}) \tag{18}$$

where $X_{i,1} = \left[x_{i,1}, x_{i,2}, x_{j,1}, x_{j,2}, y_d\right]^T$, and there exists a positive constant $\Xi_{i,1}$, such that $|\varepsilon_{i,1}(X_{i,1})| \leq \Xi_{i,1}$.

Construct the following Lyapunov function candidate as

$$V_{i,1} = \frac{1}{2}e_{i,1}^2 + \frac{1}{2\Gamma_{i,1}}\widetilde{\Xi}_{i,1}^2 + \frac{1}{2\Upsilon_{i,1}}\widetilde{\Phi}_{i,1}^T\widetilde{\Phi}_{i,1} \tag{19}$$

where $\widetilde{\Xi}_{i,1} = \hat{\Xi}_{i,1} - \Xi_{i,1}$ and $\widetilde{\Phi}_{i,1} = \hat{\Phi}_{i,1} - \Phi_{i,1}$, $\hat{\Xi}_{i,1}$ and $\hat{\Phi}_{i,1}$ are the estimations of $\Xi_{i,1}$ and $\Phi_{i,1}$, respectively. $\Gamma_{i,1}$ and $\Upsilon_{i,1}$ are designed positive constants, respectively.

Taking the derivative of (19) along with (16), and considering (18), we have

$$\begin{aligned} \dot{V}_{i,1} &= e_{i,1}\dot{e}_{i,1} + \tfrac{1}{\Gamma_{i,1}}\widetilde{\Xi}_{i,1}\dot{\hat{\Xi}}_{i,1} + \tfrac{1}{\Upsilon_{i,1}}\widetilde{\Phi}_{i,1}^T\dot{\hat{\Phi}}_{i,1} \\ &\leq \hbar_{i,1}e_{i,1}\alpha_{i,1} + e_{i,1}\left((\Phi_{i,1}^*)^T\zeta_{i,1} - b_i\dot{y}_d\right) + \Xi_{i,1}|e_{i,1}| + \tfrac{1}{\Gamma_{i,1}}\widetilde{\Xi}_{i,1}\dot{\hat{\Xi}}_{i,1} + \tfrac{1}{\Upsilon_{i,1}}\widetilde{\Phi}_{i,1}^T\dot{\hat{\Phi}}_{i,1} \end{aligned} \tag{20}$$

Let

$$\Phi_{i,1}^T\Psi_{i,1} = (\Phi_{i,1}^*)^T\zeta_{i,1} + \frac{\hat{\Xi}_{i,1}e_{i,1}}{\sqrt{e_{i,1}^2 + \eta^2}} - b_i\dot{y}_d \tag{21}$$

where

$$\Phi_{i,1} = \left[\Phi_{i,1}^*, 1\right]^T \tag{22}$$

$$\Psi_{i,1} = \left[\zeta_{i,1}, \hat{\Xi}_{i,1}e_{i,1}\Big/\sqrt{e_{i,1}^2 + \eta^2} - b_i\dot{y}_d\right]^T \tag{23}$$

Using Lemma 6, one obtains

$$\Xi_{i,1}|e_{i,1}| \leq \frac{\Xi_{i,1}e_{i,1}^2}{\sqrt{e_{i,1}^2 + \eta^2}} + \eta\Xi_{i,1} \tag{24}$$

Design the virtual control $\alpha_{i,1}$ as

$$\alpha_{i,1} = \mathcal{N}(\varsigma_{i,1})\beta_{i,1} \tag{25}$$

$$\dot{\varsigma}_{i,m} = e_{i,1}\beta_{i,1} \tag{26}$$

$$\beta_{i,1} = c_{i,1}e_{i,1}^{2\mu_i - 1} + \hat{\Phi}_{i,1}^T\Psi_{i,1} \tag{27}$$

where $c_{i,1}$ is a designed positive constant.

Design adaptive laws $\dot{\hat{\Xi}}_{i,1}$ and $\dot{\hat{\Phi}}_{i,1}$ as

$$\dot{\hat{\Xi}}_{i,1} = \frac{\Gamma_{i,1}e_{i,1}^2}{\sqrt{e_{i,1}^2 + \eta^2}} - \gamma_{i,1}\hat{\Xi}_{i,1} \tag{28}$$

$$\dot{\hat{\Phi}}_{i,1} = \Upsilon_{i,1}\Psi_{i,1}e_{i,1} - \rho_{i,1}\hat{\Phi}_{i,1} \tag{29}$$

where $\gamma_{i,1}$ and $\rho_{i,1}$ are designed positive constants.

Substituting (21) and (24)–(27) into (20), and applying the adaptive laws (28) and (29), one has

$$\dot{V}_{i,1} \leq (\hbar_{i,1}\mathcal{N}(\varsigma_{i,1})+1)\dot{\varsigma}_{i,1} - c_{i,1}e_{i,1}^{2\mu_i} - \frac{\gamma_{i,1}}{\Gamma_{i,1}}\widetilde{\Xi}_{i,1}\dot{\hat{\Xi}}_{i,1} - \frac{\rho_{i,1}}{\Upsilon_{i,1}}\widetilde{\Phi}_{i,1}^{T}\dot{\hat{\Phi}}_{i,1} + \eta\Xi_{i,1} \tag{30}$$

On the other hand, to overcome the issue of "explosion of complexity" in recursive design, let $\alpha_{i,1}$ pass through the following first-order nonlinear filter with time constant $\tau_{i,1}$ to obtain the new state variable $s_{i,1}$, that is

$$\tau_{i,1}\dot{s}_{i,1} = -z_{i,1} - \frac{\tau_{i,1}\hat{\Pi}_{i,1}^{2}z_{i,1}}{\sqrt{(\hat{\Pi}_{i,1}z_{i,1})^{2}+\eta^{2}}},\ s_{i,1}(0) = \alpha_{i,1}(0) \tag{31}$$

where $\hat{\Pi}_{i,1}$ is the estimation of $\Pi_{i,1}$, which will be given later.

Noting (15) and (31), one has

$$\dot{z}_{i,1} = \dot{s}_{i,1} - \dot{\alpha}_{i,1} = -\frac{z_{i,1}}{\tau_{i,1}} - \frac{\hat{\Pi}_{i,1}^{2}z_{i,1}}{\sqrt{(\hat{\Pi}_{i,1}z_{i,1})^{2}+\eta^{2}}} + M_{i,1}(\cdot) \tag{32}$$

where $M_{i,1}(\cdot)$ is a continuous function of variables $e_{i,1}$, $\Psi_{i,1}$, $\hat{\Xi}_{i,1}$, $\hat{\Phi}_{i,1}$, y_d, $\dot{y}_d$, and $\ddot{y}_d$. Referring to the existing dynamic surface control results [26,31], there is an unknown constant $\Pi_{i,1} > 0$ such that $|M_{i,1}(\cdot)| \leq \Pi_{i,1}$ in a given compact set $\Omega_{i,1}$, which will be given in the following stability analysis section.

Step m ($m = 2, \cdots, n-1$): Similar to the analysis in step 1, the derivative of $e_{i,m}$ along with (14) and (15) is

$$\dot{e}_{i,m} = \dot{x}_{i,m} - \dot{s}_{i,m-1} = \hbar_{i,m}\alpha_{i,m} + F_{i,m} + \frac{z_{i,m-1}}{\tau_{i,m-1}} + \frac{\hat{\Pi}_{i,m-1}^{2}z_{i,m-1}}{\sqrt{(\hat{\Pi}_{i,m-1}z_{i,m-1})^{2}+\eta^{2}}} \tag{33}$$

where $\hbar_{i,m} = g_{i,m}$ and

$$F_{i,m} = \hbar_{i,m}(e_{i,m+1} + z_{i,m}) + f_{i,m} \tag{34}$$

Thus, an RBFNN is utilized to approximate the unknown nonlinear function $F_{i,m}$; then, one has

$$F_{i,m} = (\Phi_{i,m}^{*})^{T}\zeta_{i,m} + \varepsilon_{i,m}(X_{i,m}) \tag{35}$$

where $X_{i,m} = \left[x_{i,1}, \cdots, x_{i,m+1}, x_{j,1}, x_{j,2}, y_d\right]^{T}$, and there exists a positive constant $\Xi_{i,m}$, such that $|\varepsilon_{i,m}(X_{i,m})| \leq \Xi_{i,m}$.

Construct the following Lyapunov function candidate as

$$V_{i,m} = \frac{1}{2}e_{i,m}^{2} + \frac{1}{2}z_{i,m-1}^{2} + \frac{1}{2\Gamma_{i,m}}\widetilde{\Xi}_{i,m}^{2} + \frac{1}{2\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^{T}\widetilde{\Phi}_{i,m} + \frac{1}{2N_{i,m-1}}\widetilde{\Pi}_{i,m-1}^{2} \tag{36}$$

where $\widetilde{\Xi}_{i,m} = \hat{\Xi}_{i,m} - \Xi_{i,m}$, $\widetilde{\Phi}_{i,m} = \hat{\Phi}_{i,m} - \Phi_{i,m}$ and $\widetilde{\Pi}_{i,m-1} = \hat{\Pi}_{i,m-1} - \Pi_{i,m-1}$, $\hat{\Xi}_{i,m}$, $\hat{\Phi}_{i,m}$, and $\hat{\Pi}_{i,m-1}$ are the estimations of $\Xi_{i,m}$, $\Phi_{i,m}$, and $\Pi_{i,m-1}$, respectively. $\Gamma_{i,m}$, $\Upsilon_{i,m}$, and $N_{i,m-1}$ are designed positive constants, respectively.

Taking the derivative of (36) along with (33), and considering (35), we have

$$\begin{aligned}\dot{V}_{i,m} \leq{}& \hbar_{i,m}e_{i,m}\alpha_{i,m} + e_{i,m}(\Phi_{i,m}^{*})^{T}\zeta_{i,m} + \Xi_{i,m}|e_{i,m}| + \frac{e_{i,m}z_{i,m-1}}{\tau_{i,m-1}} + \frac{\hat{\Pi}_{i,m-1}^{2}z_{i,m-1}e_{i,m}}{\sqrt{(\hat{\Pi}_{i,m-1}z_{i,m-1})^{2}+\eta^{2}}}\\ &- \frac{\hat{\Pi}_{i,m-1}^{2}z_{i,m-1}^{2}}{\sqrt{(\hat{\Pi}_{i,m-1}z_{i,m-1})^{2}+\eta^{2}}} - \frac{z_{i,m-1}^{2}}{\tau_{i,m-1}} + \Pi_{i,m-1}|z_{i,m-1}| + \frac{1}{\Gamma_{i,m}}\widetilde{\Xi}_{i,m}\dot{\hat{\Xi}}_{i,m}\\ &+ \frac{1}{\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^{T}\dot{\hat{\Phi}}_{i,m} + \frac{1}{N_{i,m-1}}\widetilde{\Pi}_{i,m-1}\dot{\hat{\Pi}}_{i,m-1}\end{aligned} \tag{37}$$

Let

$$\Phi_{i,m}^T \Psi_{i,m} = (\Phi_{i,m}^*)^T \zeta_{i,m} + \frac{\hat{\Xi}_{i,m} e_{i,m}}{\sqrt{e_{i,m}^2 + \eta^2}} \tag{38}$$

where

$$\Phi_{i,m} = \left[\Phi_{i,m}^*, 1\right]^T \tag{39}$$

$$\Psi_{i,m} = \left[\zeta_{i,m}, \hat{\Xi}_{i,m} e_{i,m} \Big/ \sqrt{e_{i,m}^2 + \eta^2}\right]^T \tag{40}$$

Using Lemma 6, one obtains

$$\Xi_{i,m} |e_{i,m}| \leq \frac{\Xi_{i,m} e_{i,m}^2}{\sqrt{e_{i,m}^2 + \eta^2}} + \eta \Xi_{i,m} \tag{41}$$

$$\Pi_{i,m-1} |z_{i,m-1}| \leq \frac{\hat{\Pi}_{i,m-1}^2 z_{i,m-1}^2}{\sqrt{\left(\hat{\Pi}_{i,m-1} z_{i,m-1}\right)^2 + \eta^2}} - \widetilde{\Pi}_{i,m-1} |z_{i,m-1}| + \eta \tag{42}$$

Design the virtual control $\alpha_{i,m}$ as

$$\alpha_{i,m} = \mathcal{N}(\varsigma_{i,m}) \beta_{i,m} \tag{43}$$

$$\dot{\varsigma}_{i,m} = e_{i,m} \beta_{i,m} \tag{44}$$

$$\beta_{i,m} = c_{i,m} e_{i,m}^{2\mu_i - 1} + \hat{\Phi}_{i,m}^T \Psi_{i,m} + \frac{z_{i,m-1}}{\tau_{i,m-1}} + \frac{\hat{\Pi}_{i,m-1}^2 z_{i,m-1}}{\sqrt{\left(\hat{\Pi}_{i,m-1} z_{i,m-1}\right)^2 + \eta^2}} \tag{45}$$

where $c_{i,m}$ is designed positive constant.

Design adaptive laws $\dot{\hat{\Xi}}_{i,m}$, $\dot{\hat{\Phi}}_{i,m}$ and $\dot{\hat{\Pi}}_{i,m-1}$ as

$$\dot{\hat{\Xi}}_{i,m} = \frac{\Gamma_{i,m} e_{i,m}^2}{\sqrt{e_{i,m}^2 + \eta^2}} - \gamma_{i,m} \hat{\Xi}_{i,m} \tag{46}$$

$$\dot{\hat{\Phi}}_{i,m} = e_{i,m} \Upsilon_{i,m} \Psi_{i,m} - \rho_{i,m} \hat{\Phi}_{i,m} \tag{47}$$

$$\dot{\hat{\Pi}}_{i,m-1} = N_{i,m-1} |z_{i,m-1}| - \omega_{i,m-1} \hat{\Pi}_{i,m-1} \tag{48}$$

where $\gamma_{i,m}$, $\rho_{i,m}$, and $\omega_{i,m-1}$ are designed positive constants.

Substituting (38) and (41)–(45) into (37) and applying the adaptive laws (46)–(48) yields

$$\begin{aligned} \dot{V}_{i,m} \leq\ & (\hbar_{i,m} \mathcal{N}(\varsigma_{i,m}) + 1) \dot{\varsigma}_{i,m} - c_{i,m} e_{i,m}^{2\mu_i} - \tfrac{z_{i,m-1}^2}{\tau_{i,m-1}} - \tfrac{\gamma_{i,m}}{\Gamma_{i,m}} \widetilde{\Xi}_{i,m} \hat{\Xi}_{i,m} - \tfrac{\rho_{i,m}}{\Upsilon_{i,m}} \widetilde{\Phi}_{i,m}^T \hat{\Phi}_{i,m} \\ & - \tfrac{\omega_{i,m-1}}{N_{i,m-1}} \widetilde{\Pi}_{i,m-1} \hat{\Pi}_{i,m-1} + \eta \Xi_{i,m} + \eta \end{aligned} \tag{49}$$

Let $\alpha_{i,m}$ pass through the following nonlinear filter with time constant $\tau_{i,m}$ to obtain the new state variable $s_{i,m}$, that is

$$\tau_{i,m} \dot{s}_{i,m} = -z_{i,m} - \frac{\tau_{i,m} \hat{\Pi}_{i,m}^2 z_{i,m}}{\sqrt{\left(\hat{\Pi}_{i,m} z_{i,m}\right)^2 + \eta^2}},\ s_{i,m}(0) = \alpha_{i,m}(0) \tag{50}$$

where $\hat{\Pi}_{i,m}$ is the estimation of $\Pi_{i,m}$, which will be given later.

Considering (15) and (50), we have

$$\dot{z}_{i,m} = \dot{s}_{i,m} - \dot{\alpha}_{i,m} = -\frac{z_{i,m}}{\tau_{i,m}} - \frac{\hat{\Pi}_{i,m}^2 z_{i,m}}{\sqrt{\left(\hat{\Pi}_{i,m} z_{i,m}\right)^2 + \eta^2}} + M_{i,m}(\cdot) \tag{51}$$

where $M_{i,m}(\cdot)$ is a continuous function of variables $e_{i,1}, \cdots, e_{i,m+1}$, $\Psi_{i,1}, \cdots, \Psi_{i,m}$, $\hat{\Xi}_{i,1}, \cdots, \hat{\Xi}_{i,m}$, $\hat{\Phi}_{i,1}, \cdots, \hat{\Phi}_{i,m}$, $\hat{\Pi}_{i,1}, \cdots, \hat{\Pi}_{i,m-1}$, y_d, $\dot{y}_d$, and $\ddot{y}_d$. There is an unknown constant $\Pi_{i,m} > 0$, such that $|M_{i,m}(\cdot)| \leq \Pi_{i,m}$ in a given compact set $\Omega_{i,m}$.

Step n: In this step, the adaptive neural network finite-time dynamic surface control law $u_i(t)$ will be given. Similar to the above steps, we have

$$\dot{e}_{i,n} = \hbar_{i,n} u_i(t) + f_{i,n} + \frac{z_{i,n-1}}{\tau_{i,n-1}} + \frac{\hat{\Pi}_{i,n-1}^2 z_{i,n-1}}{\sqrt{\left(\hat{\Pi}_{i,n-1} z_{i,n-1}\right)^2 + \eta^2}} \tag{52}$$

where $\hbar_{i,n} = g_{i,n}$.

An RBFNN is utilized to approximate the unknown nonlinear function $f_{i,n}$, yielding

$$f_{i,n} = \left(\Phi_{i,n}^*\right)^T \zeta_{i,n} + \varepsilon_{i,n}(X_{i,n}) \tag{53}$$

where $X_{i,n} = [x_{i,1}, \cdots, x_{i,n}]^T$, and there exists a positive constant $\Xi_{i,n}$, such that $|\varepsilon_{i,n}(X_{i,n})| \leq \Xi_{i,n}$.

Construct the following Lyapunov function candidate as

$$V_{i,n} = \frac{1}{2} e_{i,n}^2 + \frac{1}{2} z_{i,n-1}^2 + \frac{1}{2\Gamma_{i,n}} \widetilde{\Xi}_{i,n}^2 + \frac{1}{2\Upsilon_{i,n}} \widetilde{\Phi}_{i,n}^T \widetilde{\Phi}_{i,n} + \frac{1}{2\mathrm{N}_{i,n-1}} \widetilde{\Pi}_{i,n-1}^2 \tag{54}$$

where $\widetilde{\Xi}_{i,n} = \hat{\Xi}_{i,n} - \Xi_{i,n}$, $\widetilde{\Phi}_{i,n} = \hat{\Phi}_{i,n} - \Phi_{i,n}$ and $\widetilde{\Pi}_{i,n-1} = \hat{\Pi}_{i,n-1} - \Pi_{i,n-1}$, $\hat{\Xi}_{i,n}$, $\hat{\Phi}_{i,n}$, and $\hat{\Pi}_{i,n-1}$ are the estimations of $\Xi_{i,n}$, $\Phi_{i,n}$, and $\Pi_{i,n-1}$, respectively. $\Gamma_{i,n}$, $\Upsilon_{i,n}$, and $N_{i,n-1}$ are designed positive constants.

Taking the derivative of (54) along with (52), and considering (53), we have

$$\begin{aligned} \dot{V}_{i,n} \leq\ & \hbar_{i,n} e_{i,n} u_i(t) + e_{i,n} \left(\Phi_{i,n}^*\right)^T \zeta_{i,n} + \Xi_{i,n} |e_{i,n}| + \frac{e_{i,n} z_{i,n-1}}{\tau_{i,n-1}} + \Pi_{i,n-1} |z_{i,n-1}| \\ & + \frac{\hat{\Pi}_{i,n-1}^2 z_{i,n-1} e_{i,n}}{\sqrt{\left(\hat{\Pi}_{i,n-1} z_{i,n-1}\right)^2 + \eta^2}} - \frac{z_{i,n-1}^2}{\tau_{i,n-1}} - \frac{\hat{\Pi}_{i,n-1}^2 z_{i,n-1}^2}{\sqrt{\left(\hat{\Pi}_{i,n-1} z_{i,n-1}\right)^2 + \eta^2}} \\ & + \frac{1}{\Gamma_{i,n}} \widetilde{\Xi}_{i,n} \dot{\hat{\Xi}}_{i,n} + \frac{1}{\Upsilon_{i,n}} \widetilde{\Phi}_{i,n}^T \dot{\hat{\Phi}}_{i,n} + \frac{1}{\mathrm{N}_{i,n-1}} \widetilde{\Pi}_{i,n-1} \dot{\hat{\Pi}}_{i,n-1} \end{aligned} \tag{55}$$

Let

$$\Phi_{i,n}^T \Psi_{i,n} = \left(\Phi_{i,n}^*\right)^T \zeta_{i,n} + \frac{\hat{\Xi}_{i,n} e_{i,n}}{\sqrt{e_{i,n}^2 + \eta^2}} \tag{56}$$

where

$$\Phi_{i,n} = \left[\Phi_{i,n}^*, 1\right]^T \tag{57}$$

$$\Psi_{i,n} = \left[\zeta_{i,n}, \hat{\Xi}_{i,n} e_{i,n} \Big/ \sqrt{e_{i,n}^2 + \eta^2}\right]^T \tag{58}$$

Using Lemma 6, one obtains

$$\Xi_{i,n} |e_{i,n}| \leq \frac{\Xi_{i,n} e_{i,n}^2}{\sqrt{e_{i,n}^2 + \eta^2}} + \eta \Xi_{i,n} \tag{59}$$

$$\Pi_{i,n-1} |z_{i,n-1}| \leq \frac{\hat{\Pi}_{i,n-1}^2 z_{i,n-1}^2}{\sqrt{\left(\hat{\Pi}_{i,n-1} z_{i,n-1}\right)^2 + \eta^2}} - \widetilde{\Pi}_{i,n-1} |z_{i,n-1}| + \eta \tag{60}$$

Design the actual control law $u_i(t)$ as

$$u_i(t) = \mathcal{N}(\varsigma_{i,n})\beta_{i,n} \tag{61}$$

$$\dot{\varsigma}_{i,n} = e_{i,n}\beta_{i,n} \tag{62}$$

$$\beta_{i,n} = c_{i,n}e_{i,n}^{2\mu_i-1} + \hat{\Phi}_{i,n}^T\Psi_{i,n} + \frac{z_{i,n-1}}{\tau_{i,n-1}} + \frac{\hat{\Pi}_{i,n-1}^2 z_{i,n-1}}{\sqrt{\left(\hat{\Pi}_{i,n-1}z_{i,n-1}\right)^2 + \eta^2}} \tag{63}$$

where $c_{i,n}$ is a designed positive constant.

Design adaptive laws $\dot{\hat{\Xi}}_{i,n}$, $\dot{\hat{\Phi}}_{i,n}$, and $\dot{\hat{\Pi}}_{i,n-1}$ as

$$\dot{\hat{\Xi}}_{i,n} = \frac{\Gamma_{i,n}e_{i,n}^2}{\sqrt{e_{i,n}^2 + \eta^2}} - \gamma_{i,n}\hat{\Xi}_{i,n} \tag{64}$$

$$\dot{\hat{\Phi}}_{i,n} = e_{i,n}\Upsilon_{i,n}\Psi_{i,n} - \rho_{i,n}\hat{\Phi}_{i,n} \tag{65}$$

$$\dot{\hat{\Pi}}_{i,n-1} = N_{i,n-1}|z_{i,n-1}| - \omega_{i,n-1}\hat{\Pi}_{i,n-1} \tag{66}$$

where $\gamma_{i,n}$, $\rho_{i,n}$, and $\omega_{i,n-1}$ are designed positive constants.

Substituting (56) and (59)–(63) into (54) and applying the adaptive laws (64)–(66) yields

$$\begin{aligned}\dot{V}_{i,n} \le {} & (\hbar_{i,n}\mathcal{N}(\varsigma_{i,n})+1)\dot{\varsigma}_{i,n} - c_{i,n}e_{i,n}^{2\mu_i} - \tfrac{z_{i,n-1}^2}{\tau_{i,n-1}} - \tfrac{\gamma_{i,n}}{\Gamma_{i,n}}\widetilde{\Xi}_{i,n}\hat{\Xi}_{i,n} - \tfrac{\rho_{i,n}}{\Upsilon_{i,n}}\widetilde{\Phi}_{i,n}^T\hat{\Phi}_{i,n} \\ & - \tfrac{\omega_{i,n-1}}{\mathrm{N}_{i,n-1}}\widetilde{\Pi}_{i,n-1}\hat{\Pi}_{i,n-1} + \eta\Xi_{i,n} + \eta\end{aligned} \tag{67}$$

3.2. Stability Analysis

Based on the above analysis, the main results can be summarized as Theorem 1.

Theorem 1. *Under Assumptions 1–3, consider the uncertain multi-agent systems with unknown control gains (5), the virtual control laws (25) and (43), the actual control law (61), and the adaptive laws (26)–(29), (44)–(48), and (62)–(66). Then, it can be guaranteed that: (1) all signals of the closed-loop system SGPFS and (2) the tracking error converges to a small neighborhood of zero in a finite time.*

Proof. *Construct the following Lyapunov function candidate*

$$\begin{aligned}V = \sum_{i=1}^{N}\sum_{m=1}^{n}V_{i,m} = {} & \sum_{i=1}^{N}\sum_{m=1}^{n}\tfrac{1}{2}e_{i,m}^2 + \sum_{i=1}^{N}\sum_{m=2}^{n}\tfrac{1}{2}z_{i,m-1}^2 + \sum_{i=1}^{N}\sum_{m=1}^{n}\tfrac{1}{2\Gamma_{i,m}}\widetilde{\Xi}_{i,m}^2 \\ & + \sum_{i=1}^{N}\sum_{m=1}^{n}\tfrac{1}{2\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m} + \sum_{i=1}^{N}\sum_{m=2}^{n}\tfrac{1}{2\mathrm{N}_{i,m-1}}\widetilde{\Pi}_{i,m-1}^2\end{aligned} \tag{68}$$

Define the compact sets as $\Omega_i = \Omega_{i,1} \vee \Omega_{i,2} \cdots \vee \Omega_{i,n-1}$, and $\Omega = \Omega_1 \vee \Omega_1 \cdots \vee \Omega_N = \{V(t) \le p\}$, where $p > 0$, thus, there are positive constants $\Pi_{i,m}$, such that $|M_{i,m}(\cdot)| \le \Pi_{i,m}$ on Ω for all $i = 1, \cdots, N$ and $m = 1, \cdots, n-1$.

Taking the derivative of (68) and applying (30), (49) and (67), we obtain

$$\begin{aligned}\dot{V} \le {} & \sum_{i=1}^{N}\sum_{m=1}^{n}(\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m} - \sum_{i=1}^{N}\sum_{m=1}^{n}c_{i,m}e_{i,m}^{2\mu_i} - \sum_{i=1}^{N}\sum_{m=2}^{n}\tfrac{z_{i,m-1}^2}{\tau_{i,m-1}} - \sum_{i=1}^{N}\sum_{m=1}^{n}\tfrac{\gamma_{i,m}}{\Gamma_{i,m}}\widetilde{\Xi}_{i,m}\hat{\Xi}_{i,m} \\ & - \sum_{i=1}^{N}\sum_{m=1}^{n}\tfrac{\rho_{i,m}}{\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^T\hat{\Phi}_{i,m} - \sum_{i=1}^{N}\sum_{m=2}^{n}\tfrac{\omega_{i,m-1}}{\mathrm{N}_{i,m-1}}\widetilde{\Pi}_{i,m-1}\hat{\Pi}_{i,m-1} + \eta\sum_{i=1}^{N}\sum_{m=1}^{n}\Xi_{i,m} + \eta(n-1)\end{aligned} \tag{69}$$

Applying Lemma 7, the following inequalities hold

$$-\frac{\gamma_{i,m}}{\Gamma_{i,m}}\widetilde{\Xi}_{i,m}\hat{\Xi}_{i,m} \leq -\frac{\gamma_{i,m}}{2\Gamma_{i,m}}\widetilde{\Xi}_{i,m}^2 + \frac{\gamma_{i,m}}{2\Gamma_{i,m}}\Xi_{i,m}^2 \tag{70}$$

$$-\frac{\rho_{i,m}}{\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^T\hat{\Phi}_{i,m} \leq -\frac{\rho_{i,m}}{2\Upsilon_{i,m}}\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m} + \frac{\rho_{i,m}}{2\Upsilon_{i,m}}\Phi_{i,m}^T\Phi_{i,m} \tag{71}$$

$$-\frac{\omega_{i,m-1}}{\mathrm{N}_{i,m-1}}\widetilde{\Pi}_{i,m-1}\hat{\Pi}_{i,m-1} \leq -\frac{\omega_{i,m-1}}{2\mathrm{N}_{i,m-1}}\widetilde{\Pi}_{i,m-1}^2 + \frac{\omega_{i,m-1}}{2\mathrm{N}_{i,m-1}}\Pi_{i,m-1}^2 \tag{72}$$

Considering Lemma 5, let $x = z_{i,m-1}^2/2$, $\widetilde{\Xi}_{i,m}^2/2\Gamma_{i,m}$, $\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m}/2\Upsilon_{i,m}$ or $\widetilde{\Pi}_{i,m-1}^2/2\mathrm{N}_{i,m-1}$, and accordingly $y = 1$, $z_1 = \mu_i$, $z_2 = 1-\mu_i$ and $z_3 = 1/\mu_i$, we have the following results:

$$-\frac{2}{\tau_{i,m-1}}\frac{z_{i,m-1}^2}{2} \leq -\frac{2}{\tau_{i,m-1}}\left(\frac{z_{i,m-1}^2}{2}\right)^{\mu_i} + \frac{2}{\tau_{i,m-1}}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} \tag{73}$$

$$-\gamma_{i,m}\frac{\widetilde{\Xi}_{i,m}^2}{2\Gamma_{i,m}} \leq -\gamma_{i,m}\left(\frac{\widetilde{\Xi}_{i,m}^2}{2\Gamma_{i,m}}\right)^{\mu_i} + \gamma_{i,m}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} \tag{74}$$

$$-\rho_{i,m}\frac{\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m}}{2\Upsilon_{i,m}} \leq -\rho_{i,m}\left(\frac{\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m}}{2\Upsilon_{i,m}}\right)^{\mu_i} + \rho_{i,m}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} \tag{75}$$

$$-\omega_{i,m-1}\frac{\widetilde{\Pi}_{i,m-1}^2}{2\mathrm{N}_{i,m-1}} \leq -\omega_{i,m-1}\left(\frac{\widetilde{\Pi}_{i,m-1}^2}{2\mathrm{N}_{i,m-1}}\right)^{\mu_i} + \omega_{i,m-1}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} \tag{76}$$

Substituting (69)–(74) into (68) yields

$$\begin{aligned}\dot{V} \leq & \sum_{i=1}^{N}\sum_{m=1}^{n}(\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m} - \sum_{i=1}^{N}\sum_{m=1}^{n}(c_{i,m}2^{\mu_i})\left(\frac{e_{i,m}^2}{2}\right)^{\mu_i} - \sum_{i=1}^{N}\sum_{m=2}^{n}\frac{2}{\tau_{i,m-1}}\left(\frac{z_{i,m-1}^2}{2}\right)^{\mu_i} \\ & - \sum_{i=1}^{N}\sum_{m=1}^{n}\gamma_{i,m}\left(\frac{\widetilde{\Xi}_{i,m}^2}{2\Gamma_{i,m}}\right)^{\mu_i} - \sum_{i=1}^{N}\sum_{m=1}^{n}\rho_{i,m}\left(\frac{\widetilde{\Phi}_{i,m}^T\widetilde{\Phi}_{i,m}}{2\Upsilon_{i,m}}\right)^{\mu_i} - \sum_{i=1}^{N}\sum_{m=2}^{n}\omega_{i,m-1}\left(\frac{\widetilde{\Pi}_{i,m-1}^2}{2\mathrm{N}_{i,m-1}}\right)^{\mu_i} + B_0\end{aligned} \tag{77}$$

where

$$\begin{aligned}B_0 = & \eta(n-1) + \eta\sum_{i=1}^{N}\sum_{m=1}^{n}\Xi_{i,m} + \sum_{i=1}^{N}\sum_{m=1}^{n}\frac{\gamma_{i,m}}{2\Gamma_{i,m}}\Xi_{i,m}^2 + \sum_{i=1}^{N}\sum_{m=1}^{n}\frac{\rho_{i,m}}{2\Upsilon_{i,m}}\Phi_{i,m}^T\Phi_{i,m} \\ & + \sum_{i=1}^{N}\sum_{m=2}^{n}\frac{\omega_{i,m-1}}{2\mathrm{N}_{i,m-1}}\Pi_{i,m-1}^2 + \sum_{i=1}^{N}\sum_{m=2}^{n}\frac{2}{\tau_{i,m-1}}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} + \sum_{i=1}^{N}\sum_{m=1}^{n}\gamma_{i,m}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} \\ & + \sum_{i=1}^{N}\sum_{m=1}^{n}\rho_{i,m}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}} + \sum_{i=1}^{N}\sum_{m=2}^{n}\omega_{i,m-1}(1-\mu_i)\mu_i^{\frac{\mu_i}{1-\mu_i}}\end{aligned} \tag{78}$$

Further, using Lemma 4, we obtain

$$\dot{V} \leq -C_1V^{\mu} + \sum_{i=1}^{N}\sum_{m=1}^{n}(\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m} + B_0 \tag{79}$$

where

$$\mu = \max\{\mu_1, \cdots, \mu_N\} \tag{80}$$

$$C_1 = \min\left\{c_{i,m}2^{\mu_i}, \gamma_{i,m}, \rho_{i,m}, 2/\tau_{i,k}, \omega_{i,k}; i = 1, \cdots, N, m = 1, \cdots, n, k = 1, \cdots, n-1\right\} \tag{81}$$

Integrating (79) over the interval $[0, t]$ when $t < +\infty$, we have

$$V(t) \leq \sum_{i=1}^{N}\sum_{m=1}^{n}\int_0^t(\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m}(\tau)d\tau + \int_0^t B_0d\tau + V(0) - C_1\int_0^t V(\tau)^{\mu}d\tau \tag{82}$$

From (82), because $\int_0^t B_0 d\tau$ and $V(0)$ are bounded and $-C_1\int_0^t V(\tau)^\mu d\tau < 0$, there exists a positive constant A_0, such that $\int_0^t B_0 d\tau + V(0) - C_1\int_0^t V(\tau)^\mu d\tau \leq A_0$. Further, according to (82) and applying Lemma 3, it is obtained that $V(t)$, $\varsigma_{i,m}(t)$ and $\int_0^t (\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m}(\tau)d\tau$, $i = 1,\cdots,N$, $m = 1,\cdots,n$, are bounded over the interval $[0,t]$ when $t < +\infty$, which implies that $\sum_{i=1}^{N}\sum_{m=1}^{n}\int_0^t (\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m}(\tau)d\tau$ is bounded over $[0,t]$. Thus, we have

$$\dot{V} \leq -C_1 V^\mu + C_0 \tag{83}$$

where $C_0 = \max_{1\leq i\leq N,\, 1\leq m\leq n}(\hbar_{i,m}\mathcal{N}(\varsigma_{i,m})+1)\dot{\varsigma}_{i,m} + B_0$.

Considering (83) and Lemma 2, we can easily obtain that the inequality $V^\mu \leq C_0/(1-\mathfrak{\lambda})C_1$ for $\mathfrak{\lambda} \in (0,1)$ and $\forall t \geq T_r$ holds, where the form of T_r is described as

$$T_r = \frac{1}{(1-\mu)\mathfrak{\lambda}C_1}\left[V^{1-\mu}(\sigma(0)) - \left(\frac{C_0}{(1-\mathfrak{\lambda})C_1}\right)^{\frac{1-\mu}{\mu}}\right]$$

where $V(\sigma(0))$ is the initial value of V. Therefore, all signals of the closed-loop system are SGPFS.

Moreover, observing (68) and $V^\mu \leq C_0/(1-\mathfrak{\lambda})C_1$, one has

$$\frac{1}{2}e_1^T e_1 = \sum_{i=1}^{N}\frac{1}{2}e_{i,1}^2 \leq \left(\frac{C_0}{(1-\mathfrak{\lambda})C_1}\right)^{\frac{1}{\mu}} \tag{84}$$

where $e_1 = [e_{1,1},\cdots,e_{N,1}]^T$.

According to (14), we have

$$e_1 = \boldsymbol{\mathcal{H}} s_1 \tag{85}$$

where $\boldsymbol{\mathcal{H}} = \boldsymbol{\mathcal{L}} + \boldsymbol{\mathcal{B}}$, $s_1 = [y_1 - y_d,\cdots,y_N - y_d]^T$ represents the tracking error vector.

Together with (84) and (85), we have

$$|y_i - y_d| \leq \frac{\sqrt{2}}{\lambda_{\min}(\boldsymbol{\mathcal{H}}^T\boldsymbol{\mathcal{H}})}\left(\frac{C_0}{(1-\mathfrak{\lambda})C_1}\right)^{\frac{1}{2\mu}},\ \forall t \geq T_r \tag{86}$$

where $i = 1,\cdots,N$ and $\lambda_{\min}(\boldsymbol{\mathcal{H}}^T\boldsymbol{\mathcal{H}})$ is the minimum eigenvalue of $\boldsymbol{\mathcal{H}}^T\boldsymbol{\mathcal{H}}$.

By selecting appropriate C_0 and C_1, it can be ensured from (86) that the tracking errors $|y_i - y_d|$ $(i = 1,\cdots,N)$ converge to a small neighborhood of zero in a finite time, namely, the asymptotic tracking control can be achieved. This completes the proof. □

Remark 2. *Considering (86), we can adjust the values of C_0 and C_1 to change the size of tracking errors $|y_i - y_d|$. In other words, by selecting the appropriate C_0 and C_1, the tracking errors can converge to a small neighborhood of zero.*

Remark 3. *Observing (86) further, to achieve the desired tracking goal, we can decrease the value of C_0 or increase the value of C_1. For this purpose, we can decrease the values of $\gamma_{i,m}$, $\rho_{i,m}$, and $\omega_{i,m-1}$ or increase the values of $\Gamma_{i,m}$, $\Upsilon_{i,m}$, $\mathrm{N}_{i,k}$, and $\tau_{i,k}$ to decrease C_0; and we can also increase the values of $c_{i,m}$, $\gamma_{i,m}$, $\rho_{i,m}$, and $\omega_{i,k}$ or decrease the value of $\tau_{i,k}$ to increase C_1, where $i = 1,\cdots,N$, $m = 1,\cdots,n$, and $k = 1,\cdots,n-1$. However, the changes in $\gamma_{i,m}$, $\rho_{i,m}$, $\omega_{i,k}$, and $\tau_{i,k}$ will affect both C_0 and C_1. Therefore, when selecting appropriate design parameters, we should make a trade-off between the tracking performance and the amplitude of the control signal.*

4. Simulation Example

In this section, a practical simulation example is given to illustrate the validity of the adaptive neural network finite-time control law.

Consider a practical uncertain multi-agent system with unknown control gains as discussed in [43,44], where each follower agent stands for a single-link robot. The communication topology graph of four single-link robots is given in Figure 1, where the leader agent is marked as "0". The leader agent is used to generate a tracking signal. The dynamics of the ith single-link robot are described as

$$J_i\ddot{a}_i + B_i\dot{a}_i + M_i \sin(a_i) = q_i u_i(t) + d_i(t),\ i = 1,2,3,4 \tag{87}$$

where a_i and $\dot{a}_i$ are the angle and angular velocity of the single-link robot, respectively, $u_i(t)$ is the actuator voltage input, J_i represents the rotational inertia, B_i represents the damping coefficient, M_i denotes the single-link robot's mass, and $d_i(t)$ and q_i represent the unknown torque disturbance and unknown correlation coefficient, respectively. Let $x_{i,1} = a_i$ and $x_{i,2} = \dot{a}_i$; then, the system (87) can be changed as

$$\begin{aligned} \dot{x}_{i,1} &= x_{i,2} \\ \dot{x}_{i,2} &= \tfrac{q_i}{J_i} u_i(t) - \tfrac{B_i}{J_i} x_{i,2} - \tfrac{M_i}{J_i} \sin(x_{i,1}) + \tfrac{d_i(t)}{J_i} \end{aligned} \tag{88}$$

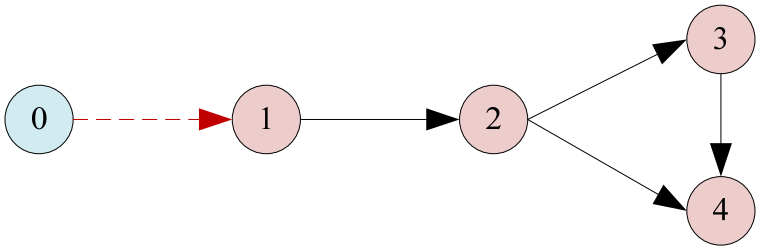


Figure 1. Communication topology graph.

With reference to [44], the parameters of system (88) are set as $J_i = 1 + 0.04i$ (kg·m^2), $B_i = 0.5 + 0.04i$ (N·m·s/rad), $M_i = 1.5 + 0.04i$ (N·m), $q_1 = q_3 = 2$ (N·m/V), $q_2 = q_4 = -4$ (N·m/V), and $d_i(t) = 0.5i\cos(t)$ (N·m), where $i = 1,2,3,4$. The initial states of the single-link robots are set as $x_{11} = 0.5$, $x_{21} = 0.35$, $x_{31} = 0.2$, $x_{41} = 0.15$, and $x_{22} = x_{22} = x_{32} = x_{42} = 0.0$. The trajectory of the leader agent is given as $y_d = 0.5\sin(2t) + 0.5\sin(1.5t)$. The simulation time is $t = 10$ s.

To approximate unknown functions $F_{i,1}$ and $f_{i,2}$, the RBFNN $\Phi_{i,1}^T \Psi_{i,1}(X_{i,1})$ for $F_{i,1}$ contains nine nodes with centers evenly spaced in $[-4,4] \times [-4,4] \times [-4,4] \times [-4,4] \times [-4,4]$; and the RBFNN $\Phi_{i,2}^T \Psi_{i,2}(X_{i,2})$ for $f_{i,2}$ contains five nodes with centers evenly spaced in $[-2,2] \times [-2,2]$, and all the widths are selected as 2.

The designed parameters are given as $\mu_1 = \mu_2 = \mu_3 = \mu_4 = 0.8$, $\eta = 0.25$, $\tau_{11} = \tau_{21} = \tau_{31} = \tau_{41} = 0.02$, $c_{11} = 2.1$, $c_{21} = 1.8$, $c_{31} = 2.5$, $c_{41} = 0.3$, $c_{12} = 1.5$, $c_{22} = 1.9$, $c_{32} = 3.5$, $c_{42} = 0.5$, $\Gamma_{11} = 6.0$, $\Gamma_{21} = 7.0$, $\Gamma_{31} = 4.0$, $\Gamma_{41} = 2.0$, $\Gamma_{12} = 3.6$, $\Gamma_{22} = 4.5$, $\Gamma_{32} = 6.3$, $\Gamma_{42} = 5.1$, $\gamma_{11} = \gamma_{21} = \gamma_{31} = \gamma_{41} = 2.4$, $\gamma_{12} = \gamma_{22} = \gamma_{32} = \gamma_{42} = 1.6$, $\Upsilon_{11} = 1.1$, $\Upsilon_{21} = 1.5$, $\Upsilon_{31} = 3.9$, $\Upsilon_{41} = 2.3$, $\Upsilon_{12} = 2.5$, $\Upsilon_{22} = 2.7$, $\Upsilon_{32} = 0.9$, $\Upsilon_{42} = 1.4$, $\rho_{11} = \rho_{21} = \rho_{31} = \rho_{41} = 1.2$, $\rho_{12} = \rho_{22} = \rho_{32} = \rho_{42} = 3.1$, $N_{11} = 1.5$, $N_{21} = 2.5$, $N_{31} = 4.2$, $N_{41} = 3.2$, $\omega_{11} = 1.2$, $\omega_{21} = 2.1$, $\omega_{31} = 1.4$, and $\omega_{41} = 2.0$. The initial conditions $\varsigma_{i1}(0) = \varsigma_{i2}(0) = 0.0$, $\hat{\Xi}_{i,1} = \hat{\Xi}_{i,2} = 0.01$, $\hat{\Pi}_{i,1} = 0.0$, $\hat{\Phi}_{i,1} = [0.01]_{9\times1}$, and $\hat{\Phi}_{i,2} = [0.01]_{5\times1}$, where $i = 1,2,3,4$.

The simulation results are shown in Figures 2–10.

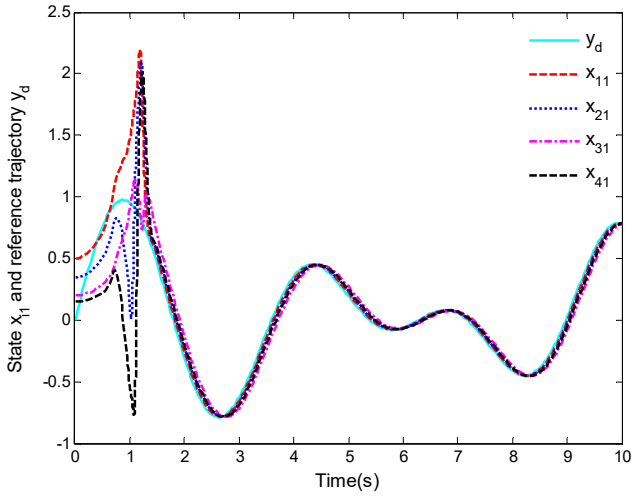


Figure 2. Curves of system states x_{i1} and reference trajectory y_d.

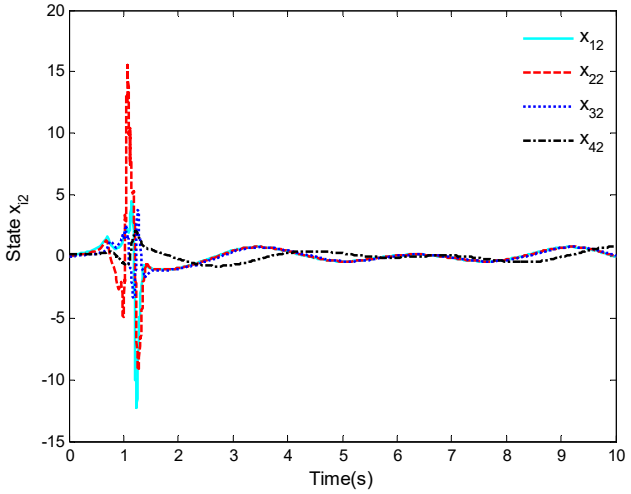


Figure 3. Curves of system states x_{i2}.

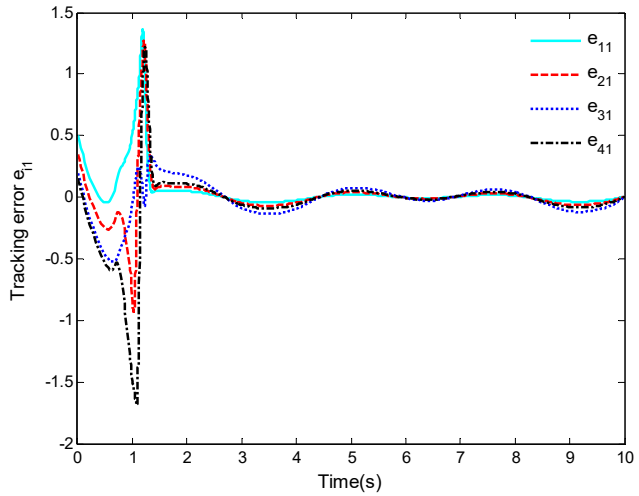


Figure 4. Curves of tracking errors e_{i1}.

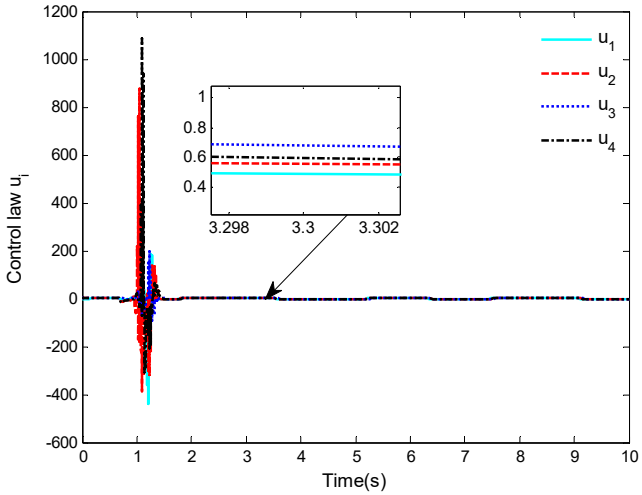


Figure 5. Curves of control law u_i.

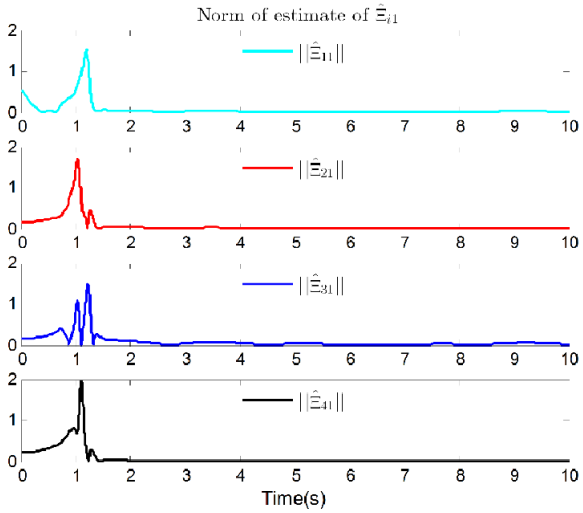


Figure 6. Curves of adaptive laws $\hat{\Xi}_{i1}$.

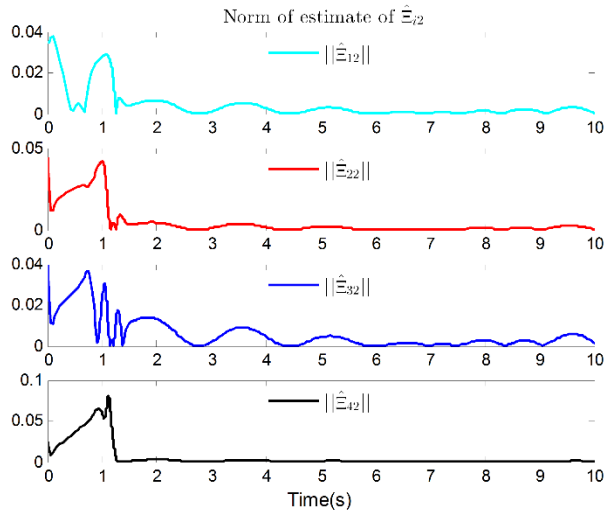


Figure 7. Curves of adaptive laws $\hat{\Xi}_{i2}$.

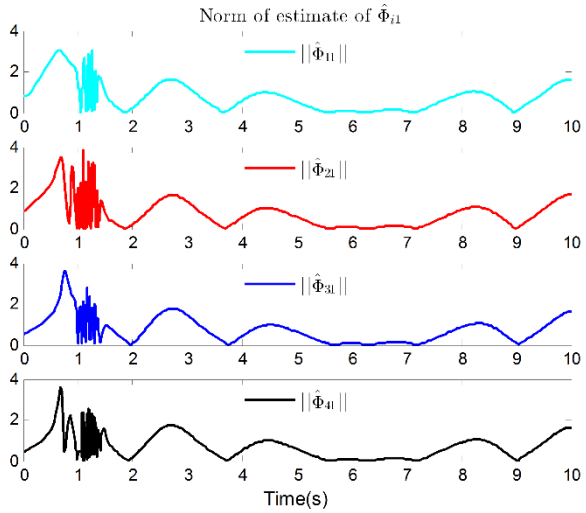


Figure 8. Curves of adaptive laws $\hat{\Phi}_{i1}$.

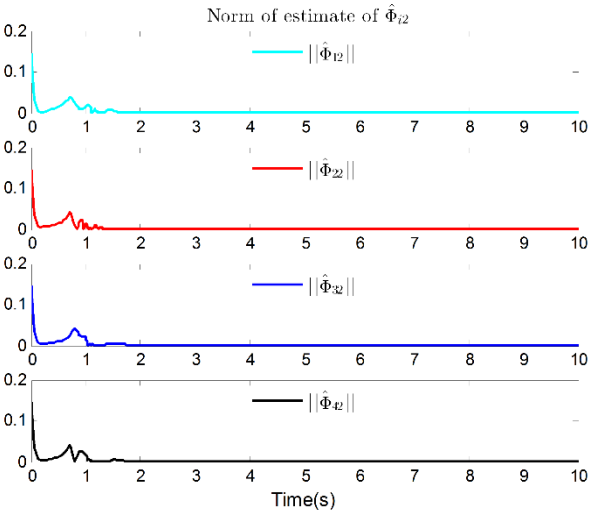


Figure 9. Curves of adaptive laws $\hat{\Phi}_{i2}$.

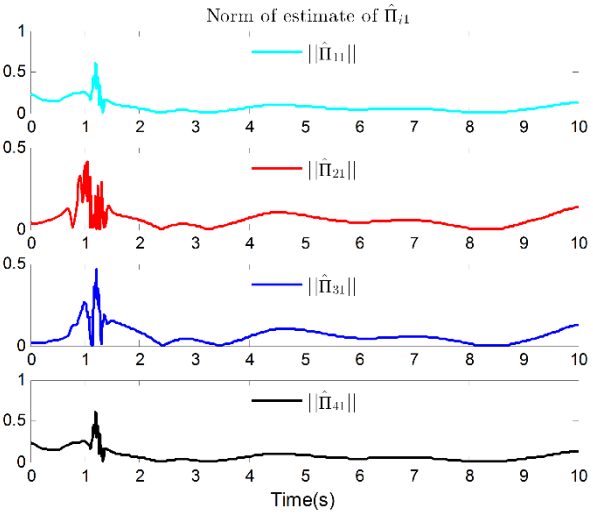


Figure 10. Curves of adaptive laws $\hat{\Pi}_{i1}$.

The asymptotic tracking performance curves for the four follower agents are shown in Figure 2. As can be seen from the figure, using the designed control law, the outputs x_{i1} of follower agents can track the trajectory of the leader agent in a finite time. The states x_{i2} of the four follower agents are given in Figure 3, and the curves for tracking errors e_{i1} are shown in Figure 4. From Figure 4, it is not difficult to see that the tracking errors of the four follower agents can converge to a small neighborhood of zero in a finite time. That is to say, the asymptotic tracking control of uncertain multi-agent systems can be achieved. Based on the results of Figures 2–4 it is shown that the finite time control law designed in this paper is effective. In other words, although the nonlinear multi-agent systems given in this work are affected by an unknown control direction and uncertain dynamics, the system can still achieve the desired control goal under the designed finite-time control law.

Further, the curves for control laws u_i are given in Figure 5. As shown in Figure 5, during the initial period, the amplitude of the control law is relatively large. As described in Remark 3, we can only choose between tracking performance and control law amplitude. Obviously, our focus here is on tracking performance.

In addition, the curves for adaptive laws $\hat{\Xi}_{i1}$, $\hat{\Xi}_{i2}$, $\hat{\Phi}_{i1}$, $\hat{\Phi}_{i2}$, and $\hat{\Pi}_{i1}$ are shown in Figures 6–10 respectively. From these figures, we can find that all signals of the closed-loop system are bounded after a finite time. Further, in view of the results in Figures 2–10, we can deduce that the finite-time control law and adaptive laws designed in this paper can make the nonlinear multi-agent systems SGPFS. This also illustrates the correctness of the theoretical analysis results from another perspective.

5. Conclusions

In this work, the finite-time asymptotic tracking control problem of uncertain multi-agent systems with unknown control gains was studied. By applying the dynamic surface control method, the Nussbaum gain function technique, and neural network control method, a new adaptive neural network finite-time dynamic surface control law was finally presented. To avoid repeated differentiation of virtual control laws in recursive design, a nonlinear compensating term with the estimation of an unknown bounded parameter was considered in this work. Furthermore, the "explosion of complexity" issue in the presence of the traditional backstepping control method was well overcome. Based on the application of the designed adaptive neural network finite-time tracking control law, it was shown that all the signals of the closed-loop system SGPFS and the tracking errors can converge to a small neighborhood of zero in a finite time. Considering that multi-agent systems may be affected by unknown actuator faults or unknown time-varying control gains, our future work will develop an effective finite-time control strategy for uncertain nonlinear multi-agent systems subject to unknown actuator faults or unknown time-varying control gains.

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