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Research Article

Leader-Following Consensus for Second-Order Nonlinear Multiagent Systems with Input Saturation via Distributed Adaptive Neural Network Iterative Learning Control

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In this paper, the consensus tracking control problem of leader-following nonlinear multiagent systems with iterative learning control is investigated. The model of each following agent consists of second-order unknown nonlinear dynamics and the external disturbance. Moreover, the input of each following agent is subject to saturation constraint. It is assumed that the information of leader is not available to any following agents, and the radial basis function neural network is introduced to approximate the nonlinear dynamics. Then, a distributed adaptive neural network iterative learning control protocol and the adaptive updating laws for the time-varying parameters are proposed, respectively. A new Lyapunov function is constructed to analyze the validity of the presented control protocol. Finally, a numerical example is provided to verify the effectiveness of theoretical results.

1. Introduction

In the past few decades, cooperative control problems of multiagent systems have been paid outstanding attention owing to their applications in aerospace engineering, sensor networks, and power systems [1–3]. The basic issue for the cooperative control of multiagent systems is consensus, which means that the states of a group of agents arrive at agreement under a designed control protocol. The consensus problems of multiagent systems are usually divided into two types depending on whether there is a leader in a multiagent system, namely, leaderless consensus problem [4, 5] and leader-following consensus problem [6–8]. For the latter, the leader plays the role of a trajectory generator and other agents try to track the leader.

Recently, the consensus problems, such as the first-order multiagent systems [9, 10], the second-order multiagent systems [6, 7, 11–15], the high-order multiagent systems [16, 17], and the fractional-order systems [18, 19], have been extensively considered. Compared with other multiagent systems, the second-order multiagent systems is more popular for researchers. Many efforts on the consensus of second-order multiagent systems have been seen in the existing literature. For examples, in [6, 7], the leader-following consensus problem with directed communication topology was addressed. In [11], the consensus tracking problem with disturbances and unmodeled dynamics was studied, and the consensus problem with communication delay was developed in [12]. Moreover, the formation control problem with time-varying delays and the finite-time consensus problem with switching topology were discussed as well [13–15].

However, it should be noted that the consensus problems mentioned in the above papers do not take into account the case of input saturation. In the practical multiagent systems, input saturation may exist due to the limitation of sensors or actuators. The occurrence of input saturation may reduce the performance of a system, cause oscillations, and even result in instability. Some papers have explored the consensus problems of multiagent systems with input saturation. The consensus control problems of first-order and second-order multiagent systems with input saturation were considered in [20–23]. The finite-time consensus control problem for the second-order linear multiagent systems with bounded input and without velocity measurements was developed in [24], while the coordinated tracking problem of a class of linear multiagent systems with actuator magnitude constraint was studied in [25]. However, the related results achieved in [22–24] are mainly based on the linear multiagent systems with input saturation. Hence, the first motivation of this paper is to discuss the consensus problem of nonlinear multiagent systems with input saturation.

It is worth pointing out that the consensus problems mentioned in the above literatures are only obtained in the time domain. Based on the prior knowledge of the system, the iterative learning control can repeatedly perform tasks within a finite time interval and increase the tracking accuracy as the number of repetitions increases [26]. The main difference from the traditional control methods is that the iterative learning control can achieve the tracking problem from the perspective of time domain and iterative domain. Currently, the method has been used to achieve the consensus problems of multiagent systems. In [27], the consensus problem of multiagent systems with sliding mode iterative learning control was investigated. In [28, 29], the tracking problems of multiagent systems were addressed by using the designed iterative learning control method. In [30], the formation tracking control problem with distributed formation iterative learning approach was discussed, while the nonrepetitive formation tracking problem of multiagent systems with line-of-sight and angle constraints under a novel iterative learning control method was discussed in [31]. Moreover, the iterative learning control for the high-order and heterogeneous multiagent systems were studied in [32, 33], respectively. Different from [27–33], the iterative learning control method was applied to deal with the input saturation problem of robotic arm systems in [34], and the iterative learning control protocol for the nonrepetitive trajectory tracking of mobile robots with fault-tolerant and output constraints was presented in [35]. However, to the best of our knowledge, there are few papers that discussed the issue of the iterative learning control for the consensus problem of nonlinear multiagent systems with external disturbances and input saturation, which is the second motivation of this paper.

Inspired by the above analysis, the iterative learning control for the nonlinear multiagent systems with external disturbance and input saturation is discussed in this work. The main contributions are summarized as follows:

(i) A class of leader-following second-order nonlinear multiagent systems with external disturbance and input saturation is considered. The nonlinear dynamics of each following agent is unknown. Compared with [22–24], the control protocol design will be more complicated.

(ii) Motivated by [28, 36], the radial basis function (RBF) neural network is adopted to approximate the unknown nonlinear terms of all following agents in this paper. Also, it is supposed that the information of leader is not available to any following agents.

(iii) Based on the RBF neural network and iterative learning control approach, a distributed adaptive neural network iterative learning control protocol is proposed and the adaptive updating laws for time-varying parameters are presented, respectively. Then, the effectiveness of the designed control protocol is checked by simulation example.

The rest of this paper is planned as follows. In Section 2, graph theory, RBF neural network, and some useful definitions and lemmas are introduced. In Section 3, the consensus problem formulation, the control protocol design, and convergence analysis are described. Finally, the simulation analysis and conclusions are provided in Sections 4 and 5, respectively.

2. Preliminaries

In this section, the preliminaries on the graph theory, neural network approximation, and some useful definitions and lemmas are introduced for the discussion and analysis below.

2.1. Graph Theory. Let an undirected graph $\mathscr{G} = (\mathscr{V}, \mathscr{E}, \mathscr{A})$ consist of n nodes, where the set of nodes is $\mathscr{V} = \{v_1, \cdots, v_n\}$ and the set of edges is $\mathscr{E} \subseteq \mathscr{V} \times \mathscr{V}$. The weighted adjacency matrix is defined as $\mathscr{A} = [a_{ij}] \in R^{n\times n}$, in which $a_{ij} = a_{ji} > 0$ if $(i, j) \in \mathscr{E}$ and $a_{ij} = a_{ji} = 0$ otherwise. It is assumed that $a_{ii} = 0$. The set of neighbors of node i is defined by $\mathscr{N}_i = \{v_j : (v_j, v_i) \in \mathscr{E}\}$. The Laplacian matrix of $\mathscr{G}$ is defined as $\mathscr{L} = \mathscr{D} - \mathscr{A}$, where $\mathscr{D} = \mathrm{diag}\{d_1, \cdots, d_n\}$ with $d_i = \sum_{j=1}^{n} a_{ij}$.

In this paper, an augmented graph $\overline{\mathscr{G}}$ with n following agents whose information topology graph is $\mathscr{G}$ and one leader agent is considered. Let b_i be the connection matrix between agent i and the leader. If agent i gets the information of leader, then $b_i > 0$; otherwise $b_i = 0$. Hence, the connection matrix between the leader and following agents is defined as $\mathscr{B} = \mathrm{diag}\{b_1, \cdots, b_n\}$. Also, it is obtained that $\mathscr{H} = \mathscr{L} + \mathscr{B}$ is a matrix associated with $\overline{\mathscr{G}}$.

Lemma 1 (see [37]). *If the graph $\overline{\mathscr{G}}$ is connected, then the symmetric matrix $\mathscr{H}$ associated with $\overline{\mathscr{G}}$ is positive definite.*

2.2. Neural Network Approximation. As a method of processing nonlinear dynamics, the neural network is mostly used because of its universal approximation capabilities. In this paper, the RBF neural network is considered to approximate the unknown nonlinear dynamics of agents. Consider a continuous function $y(\boldsymbol{x}) : R^n \longrightarrow R$, which can be approximated by the RBF neural network as

$$y(\boldsymbol{x}) = W^{\mathrm{T}} \varphi(\boldsymbol{x}) \tag{1}$$

where $\boldsymbol{x} \in \Omega_{\boldsymbol{x}} \subset R^n$ is the input vector of neural network, $W = [w_1, \cdots, w_L]^{\mathrm{T}} \in R^L$ is the weight matrix of output layer, $\varphi(\boldsymbol{x}) = [\varphi_1(\boldsymbol{x}), \cdots, \varphi_L(\boldsymbol{x})]^{\mathrm{T}} \in R^L$ is the basis function vector, and the basis function is considered to be Gaussian function as $\varphi_i(\boldsymbol{x}) = \exp(-(\boldsymbol{x} - \xi_i)^{\mathrm{T}}(\boldsymbol{x} - \xi_i)/2\theta_i^2)$ for $i = 1, \cdots, L$, where $\xi_i = [\xi_{i1}, \cdots, \xi_{in}]^{\mathrm{T}} \in R^n$ is the center vector and θ_i is the width of the Gaussian function; L is the node number of hidden layer.

The optimal approximation can be defined as

$$y_{op}(\boldsymbol{x}) = W^{*\mathrm{T}} \varphi(\boldsymbol{x}) + o(\boldsymbol{x}) \tag{2}$$

where W^* is the optimal constant weight vector and $o(\boldsymbol{x}) \in R$ is the approximation error which satisfies $\|o(\boldsymbol{x})\| \le o^*$ with o^* being an unknown positive constant.

It should be highlighted that the optimal weight vector W^* is only used for analytical purpose. The optimal weight vector W^* is defined so that $o(\boldsymbol{x})$ is minimized for all $\boldsymbol{x} \in \Omega_{\boldsymbol{x}} \subset R^n$; that is,

$$W^* = \arg\min_{W\in R^L} \left\{ \sup_{\boldsymbol{x}\in\Omega_{\boldsymbol{x}}} \left| y_{op}(\boldsymbol{x}) - W^{\mathrm{T}}\varphi(\boldsymbol{x}) \right| \right\} \quad (3)$$

Remark 2. The approximation ability of a neural network relies on the number of hidden layer nodes L. The larger the number of L, the better the approximation effect. However, there is no good way to select L in the existing literature. It can be roughly estimated according to the control requirements. In addition, the Gaussian function for $\varphi_i(\boldsymbol{x})$ is considered in this paper and it can be replaced by other basis functions, such as the spline function, the sigmoid function, and the hyperbolic tangent function, as long as they satisfy the nature of the basis function.

Some useful definitions and lemmas are given as follows.

Definition 3 (see [38]). A convergent series sequence $\{\Delta_k\}$ is denoted by $\Delta_k = c/k^m$, where $k \in Z^+$, $c > 0$, and $m(\in Z^+) \geq 2$ are the parameters to be designed.

Lemma 4 (see [38]). *For a given sequence $\{c/k^m\}$, where $k \in Z^+$, $c > 0$, and $m(\in Z^+) \geq 2$, it is held that $\lim_{k\to\infty} \sum_{j=1}^{k}(c/j^m) \leq 2c$.*

Lemma 5 (see [39]). *For any $b(\in R) > 0$ and $\zeta > 0$, the hyperbolic tangent function satisfies $0 \leq |b| - b\tanh(b/\zeta) \leq q\zeta$, where $q = 0.2785$.*

Lemma 6. *Let $\boldsymbol{a} \in R^{n\times 1}$, $\boldsymbol{b} \in R^{n\times 1}$, and $\boldsymbol{C} \in R^{n\times n}$, then it can be obtained that $\boldsymbol{a}^{\mathrm{T}}\boldsymbol{C}\boldsymbol{b} = \mathrm{tr}\{\boldsymbol{C}\boldsymbol{b}\boldsymbol{a}^{\mathrm{T}}\}$, where $\mathrm{tr}(\cdot)$ represents the trace operation.*

3. Main Results

In this section, the tracking problem of nonlinear multiagent systems with input saturation is discussed. Based on the neural network approximation technique and the iterative learning control approach, the distributed adaptive control protocol and the adaptive updating laws are presented, respectively. Then, the convergence of proposed control protocol is illustrated by a designed Lyapunov function.

3.1. Problem Formulation. Consider a class of leader-following second-order nonlinear multiagent systems with the external disturbance and input saturation, the dynamics of the ith following agent at kth iteration are described as follows:

$$\begin{aligned} \dot{x}_i^k(t) &= v_i^k(t) \\ \dot{v}_i^k(t) &= f\left(x_i^k(t), v_i^k(t)\right) + \mathrm{sat}\left(u_i^k(t)\right) + d_i^k(t) \end{aligned} \quad (4)$$

where $x_i^k(t) \in R$, $v_i^k(t) \in R$, and $u_i^k(t) \in R$ are the position, velocity, and control input of the ith following agent, respectively; $f(x_i^k(t), v_i^k(t))$ represents the unknown nonlinear function; $d_i^k(t)$ is unknown but bounded external disturbance; that is, there exists $\|d_i^k(t)\| \leq d_i^*$ with d_i^* being an unknown positive constant; and k denotes the iteration number and $t \in [0, T]$. $\mathrm{sat}(u_i^k(t))$ is the saturation function, which is defined as

$$\mathrm{sat}\left(u_i^k(t)\right) = \begin{cases} \overline{u}, & u_i^k(t) > \overline{u} \\ u_i^k(t), & -\overline{u} \leq u_i^k(t) \leq \overline{u} \\ -\overline{u}, & u_i^k(t) < -\overline{u} \end{cases} \quad (5)$$

where $\overline{u} > 0$ is the upper bound of saturation function and prespecified.

The vector form of (4) can be written as

$$\begin{aligned} \dot{x}^k(t) &= v^k(t) \\ \dot{v}^k(t) &= f\left(x^k(t), v^k(t)\right) + \mathrm{sat}\left(u^k(t)\right) + d^k(t) \end{aligned} \quad (6)$$

where $x^k(t) = [x_1^k(t), \cdots, x_n^k(t)]^{\mathrm{T}}$, $v^k(t) = [v_1^k(t), \cdots, v_n^k(t)]^{\mathrm{T}}$, $\mathrm{sat}(u^k(t)) = [\mathrm{sat}(u_1^k(t)), \cdots, \mathrm{sat}(u_n^k(t))]^{\mathrm{T}}$, $d^k(t) = [d_1^k(t), \cdots, d_n^k(t)]^{\mathrm{T}}$, and $f(x^k(t), v^k(t)) = [f(x_1^k(t), v_1^k(t)), \cdots, f(x_n^k(t), v_n^k(t))]^{\mathrm{T}}$.

The dynamics of leader are given as

$$\begin{aligned} \dot{x}_0(t) &= v_0(t) \\ \dot{v}_0(t) &= f\left(x_0(t), v_0(t)\right) + u_0(t) \end{aligned} \quad (7)$$

where $x_0(t) \in R$, $v_0(t) \in R$, and $u_0(t) \in R$ are the position, velocity, and input of leader, respectively and $f(x_0(t), v_0(t))$ represents the unknown nonlinear function. Referring to the literature [40], it is also assumed that the control input of leader is nonzero but bounded; that is, there exists $\|u_0(t)\| \leq u_0^*$ with u_0^* being a positive constant.

According to the multiagent systems (4) and (7), the tracking errors of position and velocity are defined as

$$e_{xi}^k(t) = x_0(t) - x_i^k(t) \quad (8)$$

$$e_{vi}^k(t) = v_0(t) - v_i^k(t) \quad (9)$$

Let $e_x^k(t) = [e_{x1}^k(t), \cdots, e_{xn}^k(t)]^{\mathrm{T}}$ and $e_v^k(t) = [e_{v1}^k(t), \cdots, e_{vn}^k(t)]^{\mathrm{T}}$; then

$$e_x^k(t) = \mathbf{1}_n x_0(t) - x^k(t) \quad (10)$$

$$e_v^k(t) = \mathbf{1}_n v_0(t) - v^k(t) \quad (11)$$

where $\mathbf{1}_n = [1, \cdots, 1]^{\mathrm{T}}$.

Assumption 7. The unknown nonlinear item $f(x_0(t), v_0(t))$ is bounded; namely, there exists $\|f(x_0(t), v_0(t))\| \leq f_0^*$, where f_0^* is an unknown constant.

Assumption 8. The alignment initial conditions, that is, $x_i^k(0) = x_i^{k-1}(T)$ and $v_i^k(0) = v_i^{k-1}(T)$, for each following agent are satisfied. Also, it is assumed that the trajectory of leader is spatially closed; that is, $x_0(0) = x_0(T)$ and $v_0(0) = v_0(T)$.

According to Assumption 8, hence, it can be gotten that $e_{xi}^k(0) = e_{xi}^{k-1}(T)$ and $e_{vi}^k(0) = e_{vi}^{k-1}(T)$ for each following agent.

Definition 9. For any initial condition, the consensus tracking problem of leader-following second-order nonlinear multiagent systems with input saturation is achieved if $\lim_{k\longrightarrow\infty} x_i^k(t) = x_0(t)$ and $\lim_{k\longrightarrow\infty} v_i^k(t) = v_0(t)$ for $i = 1,\cdots,n$ over the interval $[0,T]$ are satisfied.

The control objective of this paper is to design the appropriate control scheme $u_i^k(t)$ for $i = 1,\cdots,n$ and the adaptive updating laws such that the states of all the following agents can track the trajectory of leader over the interval $[0,T]$ as the iteration number k tends to infinity.

3.2. Control Protocol Design. According to the multiagent systems (4) and (7), the consensus tracking errors are defined as

$$\varepsilon_{xi}^k(t) = \sum_{j\in\mathcal{N}_i} a_{ij}\left(x_j^k(t) - x_i^k(t)\right) + b_i\left(x_0(t) - x_i^k(t)\right) \tag{12}$$

$$\varepsilon_{vi}^k(t) = \sum_{j\in\mathcal{N}_i} a_{ij}\left(v_j^k(t) - v_i^k(t)\right) + b_i\left(v_0(t) - v_i^k(t)\right) \tag{13}$$

And directly from (12) and (13), we get

$$\varepsilon_x^k(t) = \mathscr{H}\left(\mathbf{1}_n x_0(t) - x^k(t)\right) = \mathscr{H} e_x^k(t) \tag{14}$$

$$\varepsilon_v^k(t) = \mathscr{H}\left(\mathbf{1}_n v_0(t) - v^k(t)\right) = \mathscr{H} e_v^k(t) \tag{15}$$

where $\varepsilon_x^k(t) = [\varepsilon_{x1}^k(t),\cdots,\varepsilon_{xn}^k(t)]^{\mathrm{T}}$ and $\varepsilon_v^k(t) = [\varepsilon_{v1}^k(t),\cdots,\varepsilon_{vn}^k(t)]^{\mathrm{T}}$.

Remark 10. In this paper, we only discuss the states of each agent as $x_i^k(t)\in R$, $v_i^k(t)\in R$, $x_0(t)\in R$, and $v_0(t)\in R$. For the case of $x_i^k(t)\in R^p$, $v_i^k(t)\in R^p$, $x_0(t)\in R^p$, and $v_0(t)\in R^p$, we have

$$\varepsilon_x^k(t) = \left(\mathscr{H}\otimes I_p\right) e_x^k(t) \tag{16}$$

$$\varepsilon_v^k(t) = \left(\mathscr{H}\otimes I_p\right) e_v^k(t) \tag{17}$$

where $\otimes$ is the Kronecker product, I_p is the unit matrix with p dimension, and all of the related results can be changed by applying the Kronecker product operation.

Considering $\varepsilon_x^k(t)$ and $\varepsilon_v^k(t)$, a sliding mode function is designed as

$$s^k(t) = \varepsilon_v^k(t) + \alpha\varepsilon_x^k(t) \tag{18}$$

where $\alpha > 0$ is a positive constant and $s^k(t) = [s_1^k(t),\cdots,s_n^k(t)]^{\mathrm{T}}$.

So, the derivative of $s^k(t)$ is

$$\begin{aligned}\dot{s}^k(t) &= \dot{\varepsilon}_v^k(t) + \alpha\dot{\varepsilon}_x^k(t) = \mathscr{H}\left(\mathbf{1}_n\dot{v}_0(t) - \dot{v}^k(t)\right) \\ &+ \alpha\mathscr{H} e_v^k(t) = \mathscr{H}\left(\mathbf{1}_n f\left(x_0(t), v_0(t)\right)\right. \\ &- f\left(x^k(t), v^k(t)\right) + \mathbf{1}_n u_0(t) - \mathrm{sat}\left(u^k(t)\right) \\ &\left.- d^k(t)\right) + \alpha\mathscr{H} e_v^k(t)\end{aligned} \tag{19}$$

For the unknown nonlinear parts $f(x^k(t), v^k(t))$, we introduce the RBF neural network to approximate them. In view of the approximation properties of RBF neural network, $f(x_i^k(t), v_i^k(t))$ can be described as

$$\begin{aligned}f\left(x_i^k(t), v_i^k(t)\right) &= \left(W_i^*\right)^{\mathrm{T}}\varphi_i\left(x_i^k(t), v_i^k(t)\right) \\ &+ o\left(x_i^k(t), v_i^k(t)\right)\end{aligned} \tag{20}$$

where $W_i^* = [W_{i1}^*,\cdots,W_{iL}^*]^{\mathrm{T}}$, $\varphi_i(x_i^k(t), v_i^k(t)) = [\varphi_{i1}(x_i^k(t), v_i^k(t)),\cdots,\varphi_{iL}(x_i^k(t), v_i^k(t))]^{\mathrm{T}}$, and $o(x_i^k(t), v_i^k(t))$ is the approximation error.

In addition, the estimate $\widehat{f}(x_i^k(t), v_i^k(t))$ can be written as

$$\widehat{f}\left(x_i^k(t), v_i^k(t)\right) = \left(\widehat{W}_i^k(t)\right)^{\mathrm{T}}\varphi_i\left(x_i^k(t), v_i^k(t)\right) \tag{21}$$

where $\widehat{W}_i^k(t) = [\widehat{W}_{i1}^k(t),\cdots,\widehat{W}_{iL}^k(t)]^{\mathrm{T}}$.

From (20) and (21), we can get

$$\begin{aligned}f\left(x^k(t), v^k(t)\right) &= \left(W^*\right)^{\mathrm{T}}\varphi\left(x^k(t), v^k(t)\right) \\ &+ o\left(x^k(t), v^k(t)\right)\end{aligned} \tag{22}$$

$$\widehat{f}\left(x^k(t), v^k(t)\right) = \left(\widehat{W}^k(t)\right)^{\mathrm{T}}\varphi\left(x^k(t), v^k(t)\right) \tag{23}$$

where $\varphi(x^k(t), v^k(t)) = [(\varphi(x_1^k(t), v_1^k(t)))^{\mathrm{T}},\cdots,(\varphi(x_n^k(t), v_n^k(t)))^{\mathrm{T}}]^{\mathrm{T}}$, $\widehat{W}^k(t) = \mathrm{diag}\{\widehat{W}_1^k(t),\cdots,\widehat{W}_n^k(t)\}$, $W^* = \mathrm{diag}\{W_1^*,\cdots,W_n^*\}$, and $o(x^k(t), v^k(t)) = [o(x_1^k(t), v_1^k(t)),\cdots,o(x_n^k(t), v_n^k(t))]^{\mathrm{T}}$.

Consequently, the distributed adaptive neural network iterative learning control protocol is designed as

$$\begin{aligned}u_i^k(t) &= \beta\left(s_i^k(t) + \sigma_i^k(t)\right) \\ &+ \eta_i^k(t)\tanh\left(\frac{\eta_i^k(t)\, s_i^k(t)}{\Delta_k}\right) \\ &+ \left(\widehat{W}_i^k(t)\right)^{\mathrm{T}}\varphi_i\left(x_i^k(t), v_i^k(t)\right)\end{aligned} \tag{24}$$

And the adaptive updating laws for $\sigma_i^k(t)$, $\eta_i^k(t)$, and $\widehat{W}_i^k(t)$ are given as

$$\begin{aligned}\dot{\sigma}_i^k(t) &= \beta s_i^k(t) \\ &\quad - \frac{\left(\delta u^k(t)\right)^{\mathrm{T}} \delta u^k(t) + \left(e_v^k(t)\right)^{\mathrm{T}} e_v^k(t)}{2\left\|\sigma^k(t)\right\|^2} \sigma_i^k(t) \\ \sigma_i^k(0) &= \sigma_i^{k-1}(T)\end{aligned} \quad (25)$$

$$\begin{aligned}\dot{\eta}_i^k(t) &= \vartheta_i \left|s_i^k(t)\right| \\ \eta_i^k(0) &= \eta_i^{k-1}(T), \quad \eta_i^0(0) > 0\end{aligned} \quad (26)$$

$$\begin{aligned}\dot{\widehat{W}}_i^k(t) &= -\gamma_i \varphi_i\left(x_i^k(t), v_i^k(t)\right) s_i^k(t) \\ \widehat{W}_i^k(0) &= \widehat{W}_i^{k-1}(T)\end{aligned} \quad (27)$$

where $\beta > 0$, $\vartheta_i > 0$, and $\gamma_i > 0$ are constants to be designed and $\delta u^k(t) = u^k(t) - \mathrm{sat}(u^k(t))$ with $u^k(t) = [u_1^k(t), \cdots, u_n^k(t)]^{\mathrm{T}}$ and $\sigma^k(t) = [\sigma_1^k(t), \cdots, \sigma_n^k(t)]^{\mathrm{T}}$.

The vector form of control protocol (24) can be written as

$$\begin{aligned}u^k(t) &= \beta\left(s^k(t) + \sigma^k(t)\right) + \upsilon^k(t) \\ &\quad - \left(\widehat{W}^k(t)\right)^{\mathrm{T}} \varphi\left(x^k(t), v^k(t)\right)\end{aligned} \quad (28)$$

where $\sigma^k(t) = [\sigma_1^k(t), \cdots, \sigma_n^k(t)]^{\mathrm{T}}$and $\upsilon^k(t) = [\upsilon_1^k(t), \cdots, \upsilon_n^k(t)]^{\mathrm{T}}$ with $\upsilon_i^k(t) = \eta_i^k(t)\tanh(\eta_i^k(t)s_i^k(t)/\Delta_k)$.

Remark 11. In the control protocol (24), the time-varying parameters $\sigma_i^k(t)$ and $\eta_i^k(t)$ are introduced. The purpose of designing $\sigma_i^k(t)$ is to compensate the saturation error $\delta u_i^k(t)$, and the purpose of designing $\eta_i^k(t)$ is to eliminate the influence of approximation error $o(x_i^k(t), v_i^k(t))$ and external disturbance $d_i^k(t)$. In other words, the objective of designing adaptive updating laws is to seek the distributed adaptive iterative learning control protocol for time-varying parameters such that the tracking problem can be solved over the interval $[0, T]$.

3.3. Convergence Analysis. In what follows, the main result of this paper is given in Theorem 12.

Theorem 12. *Consider the leader-following second-order nonlinear multiagent systems with input saturation (4) and (7), and suppose that Assumptions 7 and 8 are held, and the communication topology $\overline{\mathscr{G}}$ is connected. Let the distributed adaptive neural network iterative learning control protocol (24) and the adaptive updating laws (25), (26), and (27) be applied, then all the following agents can track the trajectory of leader; namely,* $\lim_{k\longrightarrow\infty} x_i^k(t) = x_0(t)$ *and* $\lim_{k\longrightarrow\infty} v_i^k(t) = v_0(t)$ *for* $i = 1, \cdots, n$ *over the interval* $[0, T]$.

Proof. Design the following Lyapunov function candidate:

$$\begin{aligned}V^k(t) &= \frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) + \frac{1}{2}\left(\sigma^k(t)\right)^{\mathrm{T}} \sigma^k(t) \\ &\quad + \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(t)\right)^{\mathrm{T}} \mathbf{\Gamma}^{-1} \widetilde{W}^k(t)\right\} \\ &\quad + \frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^k(t) - \eta_0\right)^2\end{aligned} \quad (29)$$

where $\widetilde{W}^k(t) = W^* - \widehat{W}^k(t)$, $\mathbf{\Gamma} = \mathrm{diag}\{\gamma_1 I_L, \cdots, \gamma_n I_L\}$, and $\eta_0 > 0$ is a constant to be determined later.

Consider the difference between $V^k(t)$ and $V^{k-1}(t)$; that is,

$$\begin{aligned}\Delta V^k(t) &= V^k(t) - V^{k-1}(t) \\ &= \frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) \\ &\quad - \frac{1}{2}\left(s^{k-1}(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^{k-1}(t) \\ &\quad + \frac{1}{2}\left(\sigma^k(t)\right)^{\mathrm{T}} \sigma^k(t) \\ &\quad - \frac{1}{2}\left(\sigma^{k-1}(t)\right)^{\mathrm{T}} \sigma^{k-1}(t) \\ &\quad + \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(t)\right)^{\mathrm{T}} \mathbf{\Gamma}^{-1} \widetilde{W}^k(t)\right\} \\ &\quad - \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^{k-1}(t)\right)^{\mathrm{T}} \mathbf{\Gamma}^{-1} \widetilde{W}^{k-1}(t)\right\} \\ &\quad + \frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^k(t) - \eta_0\right)^2 \\ &\quad - \frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^{k-1}(t) - \eta_0\right)^2\end{aligned} \quad (30)$$

due to

$$\begin{aligned}\frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) &= \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(0) \\ &\quad + \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \mathscr{H}^{-1} \dot{s}^k(\tau)\, d\tau\end{aligned} \quad (31)$$

Substituting (19) and (22) into (31) yields

$$\begin{aligned}&\frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) = \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(0) \\ &\quad + \alpha \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} e_v^k(\tau)\, d\tau - \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \left(W^*\right)^{\mathrm{T}} \\ &\quad \cdot \varphi\left(z^k(\tau)\right) d\tau + \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \\ &\quad \cdot \left(\mathbf{1}_n f\left(x_0(\tau), v_0(\tau)\right) + \mathbf{1}_n u_0(\tau) - o\left(z^k(\tau)\right)\right. \\ &\quad \left. - d^k(\tau)\right) d\tau - \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \left(\mathrm{sat}\left(u^k(\tau)\right)\right) d\tau\end{aligned} \quad (32)$$

where $z^k(t) = [x^k(t), v^k(t)]^{\mathrm{T}}$.

Noting $\mathrm{sat}(u^k(t)) = u^k(t) - \delta u^k(t)$ and substituting (28) into (32), we have

$$\begin{aligned}
\frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) &= \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(0) \\
&+ \alpha \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} e_v^k(\tau)\,d\tau - \beta \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \\
&\cdot s^k(\tau)\,d\tau - \beta \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \sigma^k(\tau)\,d\tau \\
&- \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}} \varphi\left(z^k(\tau)\right)d\tau \\
&+ \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \delta u^k(\tau)\,d\tau + \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \\
&\cdot \left(\mathbf{1}_n f\left(x_0(\tau), v_0(\tau)\right) + \mathbf{1}_n u_0(\tau) - o\left(z^k(\tau)\right)\right. \\
&\left. - d^k(\tau)\right)d\tau - \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \upsilon^k(\tau)\,d\tau
\end{aligned} \tag{33}$$

Owing to

$$\begin{aligned}
&\int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \left(\mathbf{1}_n f\left(x_0(\tau), v_0(\tau)\right) + \mathbf{1}_n u_0(\tau)\right. \\
&\quad \left. - o\left(z^k(\tau)\right) - d^k(\tau)\right)d\tau \\
&\quad \le \sum_{i=1}^n \int_0^t \left(f_0^* + u_0^* + o_i^* + d_i^*\right)\left|s_i^k(\tau)\right| d\tau
\end{aligned} \tag{34}$$

$$\begin{aligned}
&\int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \delta u^k(\tau)\,d\tau \le \frac{1}{2}\int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} s^k(\tau)\,d\tau + \frac{1}{2} \\
&\quad \cdot \int_0^t \left(\delta u^k(\tau)\right)^{\mathrm{T}} \delta u^k(\tau)\,d\tau
\end{aligned} \tag{35}$$

$$\begin{aligned}
&\int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \upsilon^k(\tau)\,d\tau = \sum_{i=1}^n \int_0^t s_i^k(\tau)\,\upsilon_i^k(\tau)\,d\tau \\
&\quad = \sum_{i=1}^n \int_0^t \eta_i^k(\tau)\,s_i^k(\tau) \tanh\left(\frac{\eta_i^k(\tau)\,s_i^k(\tau)}{\Delta_k}\right)d\tau
\end{aligned} \tag{36}$$

and according to Lemma 6, one has

$$\begin{aligned}
&\int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}} \varphi\left(z^k(\tau)\right)d\tau \\
&\quad = \int_0^t \mathrm{tr}\left\{\left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}} \varphi\left(z^k(\tau)\right)\left(s^k(\tau)\right)^{\mathrm{T}}\right\} d\tau
\end{aligned} \tag{37}$$

Then,

$$\begin{aligned}
&\frac{1}{2}\left(s^k(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(t) \\
&\quad \le \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^k(0) + \alpha \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} e_v^k(\tau)\,d\tau \\
&\quad + \left(\frac{1}{2} - \beta\right) \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} s^k(\tau)\,d\tau \\
&\quad - \int_0^t \mathrm{tr}\left\{\left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}} \varphi\left(z^k(\tau)\right)\left(s^k(\tau)\right)^{\mathrm{T}}\right\} d\tau \\
&\quad + \sum_{i=1}^n \int_0^t \left(f_0^* + u_0^* + o_i^* + d_i^*\right)\left|s_i^k(\tau)\right| d\tau \\
&\quad + \frac{1}{2}\int_0^t \left(\delta u^k(\tau)\right)^{\mathrm{T}} \delta u^k(\tau)\,d\tau \\
&\quad - \beta \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \sigma^k(\tau)\,d\tau \\
&\quad - \sum_{i=1}^n \int_0^t \eta_i^k(\tau)\,s_i^k(\tau) \tanh\left(\frac{\eta_i^k(\tau)\,s_i^k(\tau)}{\Delta_k}\right)d\tau
\end{aligned} \tag{38}$$

Similarly, we have

$$\begin{aligned}
&\frac{1}{2}\left(\sigma^k(t)\right)^{\mathrm{T}} \sigma^k(t) = \frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}} \sigma^k(0) + \int_0^t \left(\sigma^k(\tau)\right)^{\mathrm{T}} \\
&\quad \cdot \dot{\sigma}^k(\tau)\,d\tau = \frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}} \sigma^k(0) \\
&\quad + \int_0^t \left(\sigma^k(\tau)\right)^{\mathrm{T}} \left(\beta s^k(\tau)\right. \\
&\quad - \frac{\left(\delta u^k(\tau)\right)^{\mathrm{T}} \delta u^k(\tau) + \left(e_v^k(\tau)\right)^{\mathrm{T}} e_v^k(\tau)}{2\left\|\sigma^k(\tau)\right\|^2} \\
&\quad \left. \cdot \sigma^k(\tau)\right) d\tau = \frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}} \sigma^k(0) \\
&\quad + \beta \int_0^t \left(s^k(\tau)\right)^{\mathrm{T}} \sigma^k(\tau)\,d\tau - \frac{1}{2}\int_0^t \left(\delta u^k(\tau)\right)^{\mathrm{T}} \\
&\quad \cdot \delta u^k(\tau)\,d\tau - \frac{1}{2}\int_0^t \left(e_v^k(\tau)\right)^{\mathrm{T}} e_v^k(\tau)\,d\tau
\end{aligned} \tag{39}$$

$$\begin{aligned}
&\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(t)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1} \widetilde{W}^k(t)\right\} = \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(0)\right)^{\mathrm{T}}\right. \\
&\quad \left. \cdot \boldsymbol{\Gamma}^{-1} \widetilde{W}^k(0)\right\} + \int_0^t \mathrm{tr}\left\{\left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1} \dot{\widetilde{W}}^k(\tau)\right\} d\tau \\
&\quad = \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(0)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1} \widetilde{W}^k(0)\right\} + \int_0^t \mathrm{tr}\left\{\left(\widetilde{W}^k(\tau)\right)^{\mathrm{T}}\right. \\
&\quad \left. \cdot \varphi\left(z^k(\tau)\right)\left(s^k(\tau)\right)^{\mathrm{T}}\right\} d\tau
\end{aligned} \tag{40}$$

$$\begin{aligned}
&\frac{1}{2\vartheta_i}\sum_{i=1}^n \left(\eta_i^k(t) - \eta_0\right)^2 = \frac{1}{2\vartheta_i}\sum_{i=1}^n \left(\eta_i^k(0) - \eta_0\right)^2 \\
&\quad + \sum_{i=1}^n \int_0^t \frac{1}{\vartheta_i}\left(\eta_i^k(\tau) - \eta_0\right)\dot{\eta}_i^k(\tau)\,d\tau = \frac{1}{2\vartheta_i}\sum_{i=1}^n \left(\eta_i^k(0)\right.
\end{aligned}$$

$$-\eta_0)^2+\sum_{i=1}^{n}\int_0^t\eta_i^k(\tau)\left|s_i^k(\tau)\right|d\tau$$
$$-\sum_{i=1}^{n}\int_0^t\eta_0\left|s_i^k(\tau)\right|d\tau \tag{41}$$

where $\dot{\widetilde{W}}^k(t)=\dot{W}^*-\dot{\widehat{W}}^k(t)=-\dot{\widehat{W}}^k(t)$ is considered in (40) and the adaptive updating laws $\dot{\sigma}^k(t)$, $\dot{\eta}_i^k(t)$, and $\dot{\widehat{W}}^k(t)$ are applied.

Substituting (38)-(41) into (30), it can be obtained that

$$\begin{aligned}
\Delta V^k(t) &\le \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}}\mathscr{H}^{-1}s^k(0) \\
&-\frac{1}{2}\left(s^{k-1}(t)\right)^{\mathrm{T}}\mathscr{H}^{-1}s^{k-1}(t) \\
&+\frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}}\sigma^k(0)-\frac{1}{2}\left(\sigma^{k-1}(t)\right)^{\mathrm{T}}\sigma^{k-1}(t) \\
&+\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(0)\right)^{\mathrm{T}}\mathbf{\Gamma}^{-1}\widetilde{W}^k(0)\right\} \\
&-\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^{k-1}(t)\right)^{\mathrm{T}}\mathbf{\Gamma}^{-1}\widetilde{W}^{k-1}(t)\right\} \\
&+\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^k(0)-\eta_0\right)^2-\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^{k-1}(t)-\eta_0\right)^2 \\
&-\sum_{i=1}^{n}\int_0^t\left(\eta_0-\left(f_0^*+u_0^*+o_i^*+d_i^*\right)\right)\left|s_i^k(\tau)\right|d\tau \\
&+\left(\frac{1}{2}-\beta\right)\int_0^t\left(s^k(\tau)\right)^{\mathrm{T}}s^k(\tau)\,d\tau \\
&+\alpha\int_0^t\left(s^k(\tau)\right)^{\mathrm{T}}e_v^k(\tau)\,d\tau \\
&-\frac{1}{2}\int_0^t\left(e_v^k(\tau)\right)^{\mathrm{T}}e_v^k(\tau)\,d\tau \\
&+\sum_{i=1}^{n}\int_0^t\eta_i^k(\tau)\left|s_i^k(\tau)\right|d\tau \\
&-\sum_{i=1}^{n}\int_0^t\eta_i^k(\tau)s_i^k(\tau)\tanh\left(\frac{\eta_i^k(\tau)s_i^k(\tau)}{\Delta_k}\right)d\tau
\end{aligned} \tag{42}$$

because of

$$\begin{aligned}
&\left(\frac{1}{2}-\beta\right)\int_0^t\left(s^k(\tau)\right)^{\mathrm{T}}s^k(\tau)\,d\tau \\
&\quad+\alpha\int_0^t\left(s^k(\tau)\right)^{\mathrm{T}}e_v^k(\tau)\,d\tau \\
&\quad-\frac{1}{2}\int_0^t\left(e_v^k(\tau)\right)^{\mathrm{T}}e_v^k(\tau)\,d\tau \\
&=-\int_0^t\left(Y^k(\tau)\right)^{\mathrm{T}}\mathbf{\Phi}Y^k(\tau)\,d\tau
\end{aligned} \tag{43}$$

where $Y^k(t)=[(s^k(t))^{\mathrm{T}},(e_v^k(t))^{\mathrm{T}}]^{\mathrm{T}}$ and $\mathbf{\Phi}=(1/2)[(2\beta-1)I_n,-\alpha I_n;-\alpha I_n,I_n]$.

It is clear that $\mathbf{\Phi}$ is the positive-definite matrix if it satisfies $\beta>(\alpha^2+1)/2$. In addition, we have $\eta_i^k(t)>0$ from the adaptive updating law (26); then it can be obtained from Lemma 5 that

$$\begin{aligned}
&\sum_{i=1}^{n}\int_0^t\eta_i^k(\tau)\left|s_i^k(\tau)\right|d\tau \\
&\quad-\sum_{i=1}^{n}\int_0^t\eta_i^k(\tau)s_i^k(\tau)\tanh\left(\frac{\eta_i^k(\tau)s_i^k(\tau)}{\Delta_k}\right)d\tau \\
&\le nTq\Delta_k
\end{aligned} \tag{44}$$

And there exists a sufficiently large η_0 such that

$$\eta_0>\max_{1\le i\le n}\left(f_0^*+u_0^*+o_i^*+d_i^*\right) \tag{45}$$

Then, based on (43)-(45), equation (42) becomes

$$\begin{aligned}
\Delta V^k(t) \le{}& \frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}}\mathscr{H}^{-1}s^k(0) \\
&-\frac{1}{2}\left(s^{k-1}(t)\right)^{\mathrm{T}}\mathscr{H}^{-1}s^{k-1}(t) \\
&+\frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}}\sigma^k(0) \\
&-\frac{1}{2}\left(\sigma^{k-1}(t)\right)^{\mathrm{T}}\sigma^{k-1}(t) \\
&+\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(0)\right)^{\mathrm{T}}\mathbf{\Gamma}^{-1}\widetilde{W}^k(0)\right\} \\
&-\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^{k-1}(t)\right)^{\mathrm{T}}\mathbf{\Gamma}^{-1}\widetilde{W}^{k-1}(t)\right\} \\
&+\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^k(0)-\eta_0\right)^2 \\
&-\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^{k-1}(t)-\eta_0\right)^2 \\
&-\int_0^t\left(Y^k(\tau)\right)^{\mathrm{T}}\mathbf{\Phi}Y^k(\tau)\,d\tau+nTq\Delta_k
\end{aligned} \tag{46}$$

Accordingly, it can be gotten from (46) that

$$\begin{aligned}
V^k(t)&=V^{k-1}(t)+\Delta V^k(t) \\
&\le\frac{1}{2}\left(s^k(0)\right)^{\mathrm{T}}\mathscr{H}^{-1}s^k(0)+\frac{1}{2}\left(\sigma^k(0)\right)^{\mathrm{T}}\sigma^k(0) \\
&\quad+\frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^k(0)\right)^{\mathrm{T}}\mathbf{\Gamma}^{-1}\widetilde{W}^k(0)\right\} \\
&\quad+\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^k(0)-\eta_0\right)^2 \\
&\quad-\int_0^t\left(Y^k(\tau)\right)^{\mathrm{T}}\mathbf{\Phi}Y^k(\tau)\,d\tau+nTq\Delta_k
\end{aligned} \tag{47}$$

Considering Assumption 8, we have $\varepsilon_x^k(0) = \varepsilon_x^{k-1}(T)$ and $\varepsilon_v^k(0) = \varepsilon_v^{k-1}(T)$; then $s^k(0) = s^{k-1}(T)$ is easily obtained. Moreover, we have $\sigma_i^k(0) = \sigma_i^{k-1}(T)$ from (25), $\eta_i^k(0) = \eta_i^{k-1}(T)$ from (26) and $\widehat{W}_i^k(0) = \widehat{W}_i^{k-1}(T)$ from (27). Consequently, we get from (47)

$$\begin{aligned} V^k(t) \le{}& \frac{1}{2}\left(s^{k-1}(T)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^{k-1}(T) \\ &+ \frac{1}{2}\left(\sigma^{k-1}(T)\right)^{\mathrm{T}} \sigma^{k-1}(T) \\ &+ \frac{1}{2}\mathrm{tr}\left\{\left(\widetilde{W}^{k-1}(T)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1}\widetilde{W}^{k-1}(T)\right\} \\ &+ \frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^{k-1}(T) - \eta_0\right)^2 \\ &- \int_0^t \left(Y^k(\tau)\right)^{\mathrm{T}} \boldsymbol{\Phi} Y^k(\tau)\,d\tau + nTq\Delta_k \\ ={}& V^{k-1}(T) - \int_0^t \left(Y^k(\tau)\right)^{\mathrm{T}} \boldsymbol{\Phi} Y^k(\tau)\,d\tau \\ &+ nTq\Delta_k \le V^{k-1}(T) + nTq\Delta_k \end{aligned} \tag{48}$$

Let $t = T$, one can get the following result from (48):

$$\begin{aligned} V^k(T) \le{}& V^{k-1}(T) - \lambda_{\min}(\boldsymbol{\Phi}) \int_0^T \left(Y^k(\tau)\right)^{\mathrm{T}} Y^k(\tau)\,d\tau \\ &+ nTq\Delta_k \end{aligned} \tag{49}$$

where $\lambda_{\min}(\boldsymbol{\Phi})$ represents the minimum eigenvalue of $\boldsymbol{\Phi}$. Hence, we have from (49) and Lemma 4

$$\begin{aligned} V^k(T) \le{}& V^1(T) \\ &- \lambda_{\min}(\boldsymbol{\Phi}) \sum_{j=2}^{k} \int_0^T \left(Y^j(\tau)\right)^{\mathrm{T}} Y^j(\tau)\,d\tau \\ &+ nTq\sum_{j=2}^{k}\Delta_2 \le V^1(T) + 2nTqc \end{aligned} \tag{50}$$

Obviously, it can be derived that the boundedness of $V^k(T)$ is guaranteed for any iteration provided $V^1(T)$ is bounded. In the Appendix, the boundedness of $V^1(t)$ is proved.

The boundedness of $V^1(t)$ indicates the boundedness of $V^1(T)$. Hence, $V^k(T)$ is bounded from (50) for all $k \in Z^+$. From (48), it is gotten that $V^k(t)$ is uniformly bounded over the interval $[0, T]$.

According to (50), we have

$$\begin{aligned} V^k(T) \le{}& V^1(T) - \lambda_{\min}(\boldsymbol{\Phi}) \sum_{j=2}^{k} \int_0^T \left(Y^j(\tau)\right)^{\mathrm{T}} Y^j(\tau)\,d\tau \\ &+ 2nTqc \end{aligned} \tag{51}$$

Owing to the boundedness of $V^1(T)$ and the positiveness of $V^k(T)$, we obtain that the series $\sum_{j=2}^{k}\int_0^T (Y^j(\tau))^{\mathrm{T}} Y^j(\tau)d\tau$ is convergent. Furthermore, it is easy to get that $\lim_{k\longrightarrow\infty}\int_0^T (s^k(\tau))^{\mathrm{T}} s^k(\tau)d\tau = 0$ and $\lim_{k\longrightarrow\infty}\int_0^T (e_v^k(\tau))^{\mathrm{T}} e_v^k(\tau)d\tau = 0$. According to (14) and (18), we have $\lim_{k\longrightarrow\infty}\int_0^T (e_x^k(\tau))^{\mathrm{T}} e_x^k(\tau)d\tau = 0$. Consider the Barbalat-like Lemma [41], we obtain $\lim_{k\longrightarrow\infty} e_x^k(t) = \mathbf{0}$ and $\lim_{k\longrightarrow\infty} e_v^k(t) = \mathbf{0}$ uniformly over the interval $[0, T]$. Then, it follows from (10) and (11) that $\lim_{k\longrightarrow\infty} x_i^k(t) = x_0(t)$ and $\lim_{k\longrightarrow\infty} v_i^k(t) = v_0(t)$ for $i = 1, \cdots, n$, which implies that all the following agents can track the leader uniformly over the interval $[0, T]$. The proof is completed. □

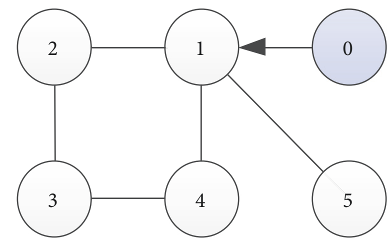

Figure 1: Communication topology.

4. Simulation Analysis

In this section, a numerical example is provided to check the validity of the proposed distributed adaptive neural network iterative learning control protocol (24). The undirected communication topology consists of five following agents and one leader agent (labelled as 0) is given in Figure 1.

The weighted adjacency matrices from Figure 1 are

$$\begin{aligned} \mathscr{A} &= \begin{bmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \\ \mathscr{B} &= \mathrm{diag}\{1, 0, 0, 0, 0\} \end{aligned} \tag{52}$$

The dynamics of five following agents are described as

$$\begin{aligned} \dot{x}_i^k(t) &= v_i^k(t) \\ \dot{v}_i^k(t) &= x_i^k(t)\cos\left(v_i^k(t)\right) + \mathrm{sat}\left(u_i^k(t)\right) + d_i^k(t) \\ & \qquad i = 1, 2, 3, 4, 5 \end{aligned} \tag{53}$$

The disturbance of the ith following agent is $d_i^k(t) = z_1\sin(w_1 t) + z_2\sin(w_2 t)$, where z_i and w_i $(i = 1, 2)$ are arbitrary real numbers, $z_i \in [0, 1]$ and $w_i \in [1, 2]$.

The dynamics of leader are given as

$$\begin{aligned} \dot{x}_0(t) &= v_0(t) \\ \dot{v}_0(t) &= \left(x_0(t)\right)^2 \sin\left(v_0(t)\right) - \cos(2\pi t) \end{aligned} \tag{54}$$

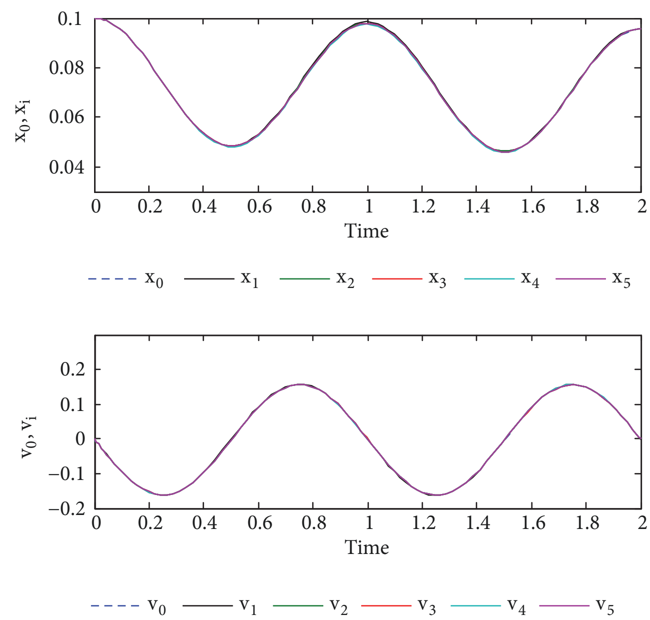

FIGURE 2: Tracking results of position and velocity.

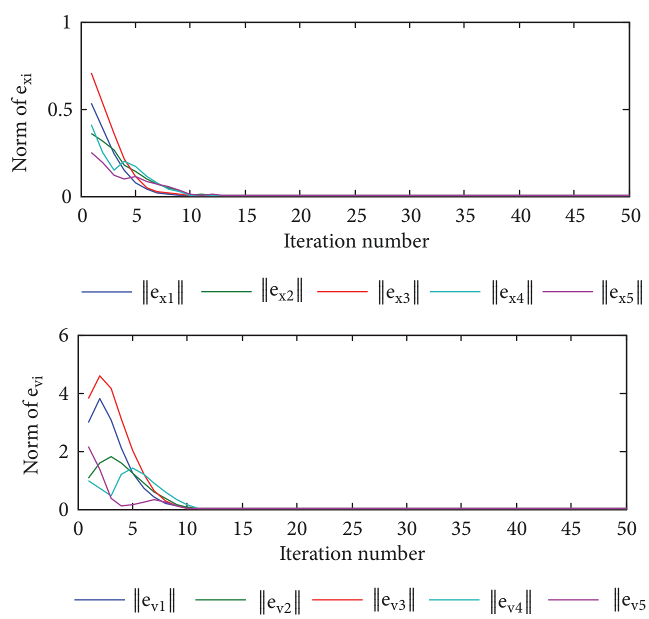

FIGURE 3: Error norms of position and velocity.

The initial states of five following agents and the leader are set as $x(0) = [-0.5, 0.5, 0.9, 0.3, -0.2]^{\mathrm{T}}$, $v(0) = [0.2, 0.6, -0.4, -0.8, 1.0]^{\mathrm{T}}$, $x_0(0) = 0.1$, and $v_0(0) = 0$. The simulation time $t \in [0, 2]$ and the iteration number $k_{\max} = 50$.

The RBF neural network for $f(x_i^k(t), v_i^k(t)))$ contains 7 nodes with the centers ξ_i evenly spaced in the range $[-3, 3]$, and the widths $\theta_i = 2.0$ for $i = 1, \cdots, 5$. The initial values of $\sigma_i(0)$, $\eta_i(0)$, and $W_i(0)$ are $\sigma_1(0) = 0.1$, $\sigma_2(0) = 0.05$, $\sigma_3(0) = 0.15$, $\sigma_4(0) = 0.1$, and $\sigma_5(0) = 0.05$; $\eta_1(0) = 0.5$, $\eta_2(0) = 1.5$, $\eta_3(0) = 2.0$, $\eta_4(0) = 1.5$, $\eta_5(0) = 0.5$, and $W_i(0) = [1, 1, 1, 1, 1, 1, 1]^{\mathrm{T}}$ $(i = 1, \cdots, 5)$. Other parameters are selected as $c = 1.5$, $m = 2$, $\overline{u} = 5$, $\alpha = 1.5$, $\beta = 3$, and $\eta_0 = 4$; $\vartheta_1 = 0.2$, $\vartheta_2 = 0.25$, $\vartheta_3 = 0.15$, $\vartheta_4 = 0.2$, and $\vartheta_5 = 0.25$; and $\gamma_1 = 0.1$, $\gamma_2 = 0.15$, $\gamma_3 = 0.1$, $\gamma_4 = 0.2$, and $\gamma_5 = 0.15$.

By applying the control protocol (24) and the adaptive updating laws (25)-(27), the simulation results for 50 iterations are shown in Figures 2, 3, 4, 5, 6, and 7.

The tracking results of five following agents at the 50th iteration are shown in Figure 2, which implies that the consensus tracking problem of leader-following second-order nonlinear multiagent systems with input saturation can be solved by adopting the proposed control protocol (24). Due

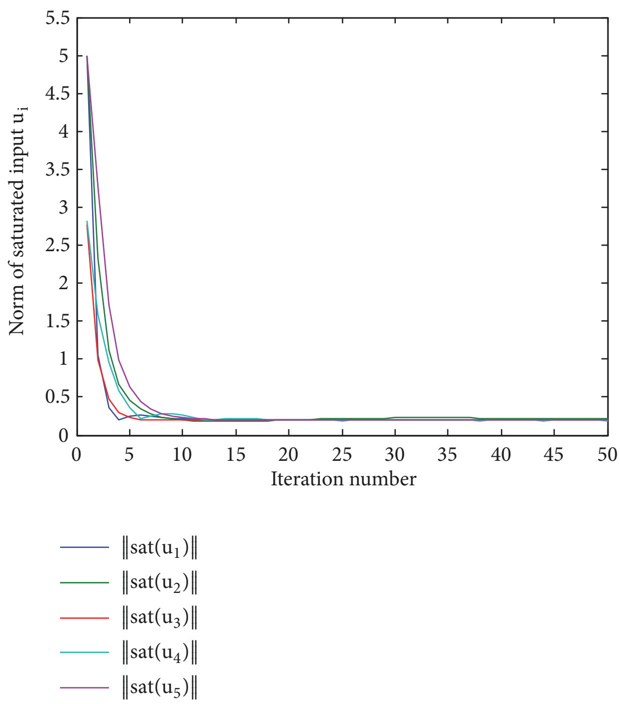

Figure 4: Norm of saturated inputs.

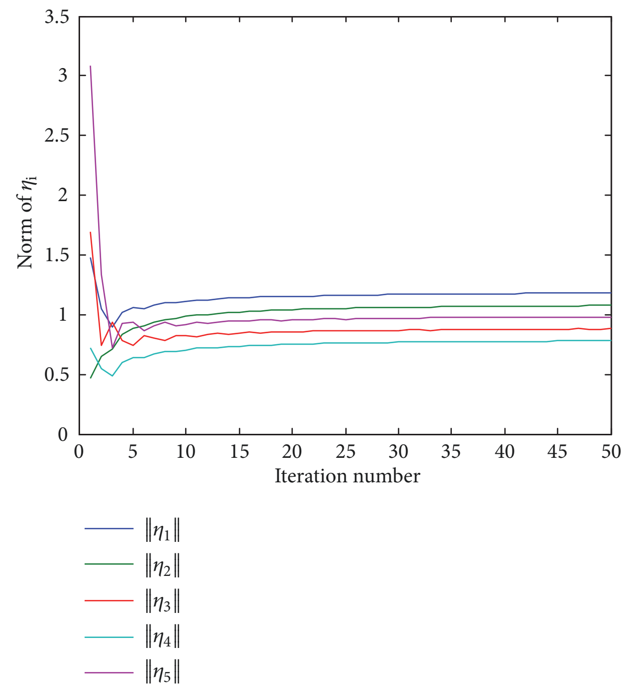

Figure 6: Response of $\eta_i^k(t)$.

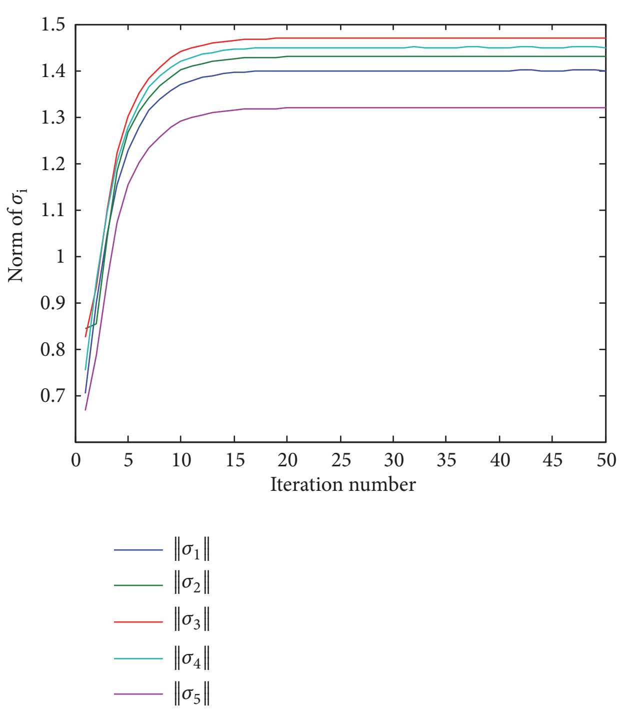

Figure 5: Response of $\sigma_i^k(t)$.

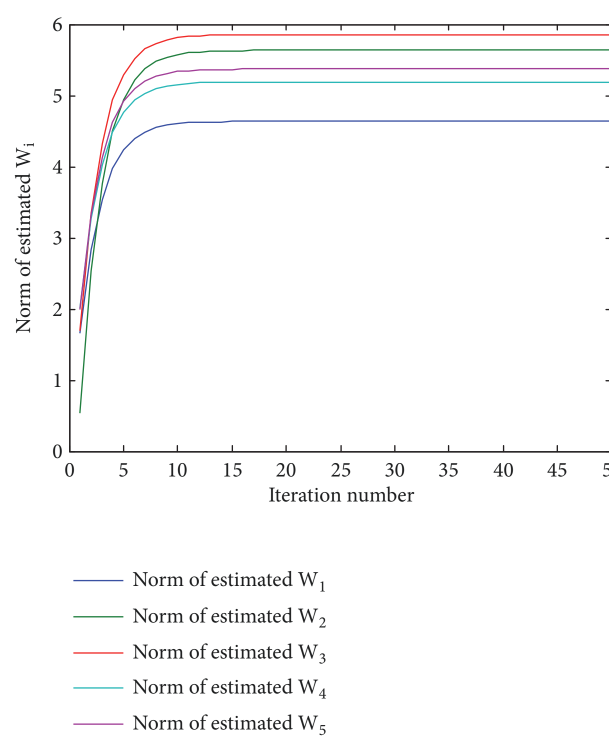

Figure 7: Response of estimated $\widehat{W}_i^k(t)$.

to the application of alignment initial condition, the final trajectories of five following agents can be synchronized with the leader. The error curves of position and velocity at 50 iterations are shown in Figure 3.

Figure 4 gives the saturated input results at 50 iterations. Although the control inputs are constrained, the tracking problem with the designed distributed adaptive neural network iterative learning control protocol can be achieved very well. It means that the proposed control protocol is effective from another perspective. In addition, the responses of adaptive updating laws $\sigma_i^k(t)$, $\eta_i^k(t)$, and $\widehat{W}_i^k(t)$ at 50 iterations are given in Figures 5, 6, and 7, respectively.

5. Conclusions

In this paper, the consensus tracking problem of the leader-following nonlinear multiagent systems was addressed. The RBF neural network was adopted to approximate the unknown nonlinear terms of all following agents. The distributed adaptive neural network iterative learning control protocol was designed, and the adaptive updating laws for time-varying parameters were proposed, respectively. Then, the convergence of proposed control protocol was analyzed by a designed Lyapunov function. It was proved that when there exists the input saturation, the tracking control problem was solved under the designed control protocol. Finally, for the validity of the theoretical analysis, a simulation example was verified by the simulation example.

Appendix

The Proof of the Boundedness of $V^1(t)$

From the definition of $V^k(t)$, we have

$$\begin{aligned} V^1(t) = {} & \frac{1}{2}\left(s^1(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^1(t) + \frac{1}{2}\left(\sigma^1(t)\right)^{\mathrm{T}} \sigma^1(t) \\ & + \frac{1}{2}\operatorname{tr}\left\{\left(\widetilde{W}^1(t)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1} \widetilde{W}^1(t)\right\} \\ & + \frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^1(t) - \eta_0\right)^2 \end{aligned} \tag{A.1}$$

Hence, the derivative of $V^1(t)$ is

$$\begin{aligned} \dot{V}^1(t) = {} & \left(s^1(t)\right)^{\mathrm{T}} \mathscr{H}^{-1} \dot{s}^1(t) + \left(\sigma^1(t)\right)^{\mathrm{T}} \dot{\sigma}^1(t) \\ & + \operatorname{tr}\left\{\left(\widetilde{W}^1(t)\right)^{\mathrm{T}} \boldsymbol{\Gamma}^{-1} \dot{\widetilde{W}}^1(t)\right\} \\ & + \frac{1}{\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^1(t) - \eta_0\right)\dot{\eta}_i^1(t) \end{aligned} \tag{A.2}$$

Substituting $\dot{s}^1(t)$, $\dot{\sigma}^1(t)$, $\dot{\widehat{W}}^1(t)$, and $\dot{\eta}_i^1(t)$ into $\dot{V}^1(t)$, we have

$$\begin{aligned} \dot{V}^1(t) = {} & \alpha\left(s^1(t)\right)^{\mathrm{T}} e_v^1(t) - \left(s^1(t)\right)^{\mathrm{T}} \left(W^*\right)^{\mathrm{T}} \varphi\left(z^1(t)\right) \\ & - \left(s^1(t)\right)^{\mathrm{T}} \operatorname{sat}\left(u^1(t)\right) + \left(s^1(t)\right)^{\mathrm{T}} \\ & \cdot \left(\mathbf{1}_n f_0\left(x_0(t), v_0(t)\right) + \mathbf{1}_n u_0(t) - o\left(z^1(t)\right)\right. \\ & \left. - d^1(t)\right) + \beta\left(s^1(t)\right)^{\mathrm{T}} \sigma^1(t) - \frac{1}{2}\left(\delta u^1(t)\right)^{\mathrm{T}} \\ & \cdot \delta u^1(t) - \frac{1}{2}\left(e_v^1(t)\right)^{\mathrm{T}} e_v^1(t) \\ & - \operatorname{tr}\left\{\left(\widetilde{W}^1(t)\right)^{\mathrm{T}} \varphi\left(z^1(t)\right)\left(s^1(t)\right)^{\mathrm{T}}\right\} \\ & + \sum_{i=1}^{n}\eta_i^1(t)\left|s_i^1(t)\right| - \sum_{i=1}^{n}\eta_0\left|s_i^1(t)\right| \end{aligned} \tag{A.3}$$

Consider

$$\begin{aligned} & -\left(s^1(t)\right)^{\mathrm{T}} \left(W^*\right)^{\mathrm{T}} \varphi\left(z^1(t)\right) - \left(s^1(t)\right)^{\mathrm{T}} \operatorname{sat}\left(u^1(t)\right) \\ & \quad = -\left(s^1(t)\right)^{\mathrm{T}} \left(W^*\right)^{\mathrm{T}} \varphi\left(z^1(t)\right) + \left(s^1(t)\right)^{\mathrm{T}} \\ & \quad \cdot \left(\widehat{W}^1(t)\right)^{\mathrm{T}} \varphi\left(z^1(t)\right) - \beta\left(s^1(t)\right)^{\mathrm{T}} s^1(t) \\ & \quad - \beta\left(s^1(t)\right)^{\mathrm{T}} \sigma^1(t) - \left(s^1(t)\right)^{\mathrm{T}} v^1(t) + \left(s^1(t)\right)^{\mathrm{T}} \\ & \quad \cdot \delta u^1(t) \le -\operatorname{tr}\left\{\left(\widetilde{W}^1(t)\right)^{\mathrm{T}} \varphi\left(z^1(t)\right)\left(s^1(t)\right)^{\mathrm{T}}\right\} \\ & \quad - \beta\left(s^1(t)\right)^{\mathrm{T}} s^1(t) - \beta\left(s^1(t)\right)^{\mathrm{T}} \sigma^1(t) \\ & \quad - \sum_{i=1}^{n}\eta_i^1(t) s_i^1(t) \tanh\left(\frac{\eta_i^1(t) s_i^1(t)}{\Delta_1}\right) + \frac{1}{2}\left(s^1(t)\right)^{\mathrm{T}} \\ & \quad \cdot s^1(t) + \frac{1}{2}\left(\delta u^1(t)\right)^{\mathrm{T}} \delta u^1(t) \\ & \left(s^1(t)\right)^{\mathrm{T}} \left(\mathbf{1}_n f_0\left(x_0(t), v_0(t)\right) + \mathbf{1}_n u_0(t) - o\left(z^1(t)\right)\right. \\ & \quad \left. - d^1(t)\right) \le \sum_{i=1}^{n}\left(f_0^* + u_0^* + o_i^* + d_i^*\right)\left|s_i^1(t)\right| \end{aligned} \tag{A.4}$$

Then, it can be obtained that

$$\begin{aligned} \dot{V}^1(t) \le {} & \left(\frac{1}{2} - \beta\right)\left(s^1(t)\right)^{\mathrm{T}} s^1(t) + \alpha\left(s^1(t)\right)^{\mathrm{T}} e_v^1(t) \\ & - \frac{1}{2}\left(e_v^1(t)\right)^{\mathrm{T}} e_v^1(t) \\ & - \sum_{i=1}^{n}\left(\eta_0 - \left(f_0^* + u_0^* + o_i^* + d_i^*\right)\right)\left|s_i^1(t)\right| \\ & + \sum_{i=1}^{n}\eta_i^1(t)\left|s_i^1(t)\right| \\ & - \sum_{i=1}^{n}\eta_i^1(t) s_i^1(t) \tanh\left(\frac{\eta_i^1(t) s_i^1(t)}{\Delta_1}\right) \\ \le {} & -\left(Y^1(t)\right)^{\mathrm{T}} \boldsymbol{\Phi} Y^1(t) + nq\Delta_1 \end{aligned} \tag{A.5}$$

Obviously, the following result can be derived:

$$\begin{aligned} V^1(t) = {} & V^1(0) + \int_0^t \dot{V}^1(\tau)\, d\tau \\ \le {} & \frac{1}{2}\left(s^1(0)\right)^{\mathrm{T}} \mathscr{H}^{-1} s^1(0) + \frac{1}{2}\left(\sigma^1(0)\right)^{\mathrm{T}} \sigma^1(0) \end{aligned}$$

$$
\begin{aligned}
&+\frac{1}{2}\operatorname{tr}\left\{\left(\widetilde{W}^{1}(0)\right)^{\mathrm{T}}\boldsymbol{\Gamma}^{-1}\widetilde{W}^{1}((t))\right\}\\
&+\frac{1}{2\vartheta_i}\sum_{i=1}^{n}\left(\eta_i^{1}(0)-\eta_0\right)^2\\
&-\int_0^t\left(Y^{1}(\tau)\right)^{\mathrm{T}}\boldsymbol{\Phi}Y^{1}(\tau)\,d\tau+nTq\Delta_1\\
=&\,V^{0}(T)-\int_0^t\left(Y^{1}(\tau)\right)^{\mathrm{T}}\boldsymbol{\Phi}Y^{1}(\tau)\,d\tau+nTq\Delta_1\\
<&\,\infty
\end{aligned}
\tag{A.6}
$$

Thus, the boundedness of $V^1(t)$ is obtained. The proof is completed.

Data Availability

No data were used to support this study.

Conflicts of Interest

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

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