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EVENT–TRIGGERED COOPERATIVE CONTROL FOR HIGH–ORDER NONLINEAR MULTI–AGENT SYSTEMS WITH FINITE–TIME CONSENSUS

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An event-triggered adaptive control algorithm is proposed for cooperative tracking control of high-order nonlinear multi-agent systems (MASs) with prescribed performance and full-state constraints. The algorithm combines dynamic surface technology and the backstepping recursive design method, with radial basis function neural networks (RBFNNs) used to approximate the unknown nonlinearity. The barrier Lyapunov function and finite-time stability theory are employed to prove that all agent states are semi-globally uniform and ultimately bounded, with the tracking error converging to a bounded neighborhood of zero in a finite time. Numerical simulations are provided to demonstrate the effectiveness of the proposed control scheme.

Keywords: multi-agent systems, cooperative control, event-triggered control, neuro-adaptive control, prescribed performance.

1. Introduction

In recent years, the cooperative control problem of nonlinear leader-following multi-agent systems (MASs) has received a great deal of attention and has been put to use in a variety of applications, such as unmanned aerial vehicles (Wu *et al*., 2020), formation control (Zhou *et al*., 2013), smart grid, sensor networks, etc. In the leader-following MAS scenario, all the followers track the leader's state trajectory through limited local neighborhood information with a distributed control protocol (Ni and Cheng, 2010; Chen *et al*., 2020; Zegers *et al*., 2022; Farrera *et al*., 2020; Yang *et al*., 2021). The design of co-operative controllers for nonlinear systems, especially higher order nonlinear systems, is more difficult than for linear MASs in general (Zhang *et al*., 2018; Liu *et al*., 2020; Yang and Li, 2020; Peng *et al*., 2021; Li *et al*., 2023). Related research work is also continuously attracting the attention of researchers worldwide.

Finite-time consensus is a hot topic in the field of MASs. El-Ferik *et al*. (2018) propose a neuro-adaptive cooperative tracking control with a prescribed performance function for highly nonlinear MASs. Hui *et al*. (2008) combine the concepts of semi-stability and finite-time performance to nonlinear MASs, giving sufficient conditions for semi-stable finite-time consensus. A distributed finite-time cooperative control protocol based on continuous state feedback is proposed by Wang and Feng (2010). For second-order MASs with perturbations, two cases with and without leaders are

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discussed by Li *et al*. (2011), and two finite-time cooperative protocols are given.

Several works have proposed neuro-adaptive cooperative tracking control, a distributed finite-time cooperative control protocol, and finite-time cooperative protocols for nonlinear MASs with perturbations and leaders. However, the finite-time convergence in these works is related to the initial state of the agents. To solve this problem, a fixed-time control method is proposed by Polyakov (2012) to ensure that the prescribed performance to reach a consensus is independent of the initial state. Hong *et al*. (2017) propose a nonlinear control protocol based on the undirected topology to solve the fixed-time consensus problem for MASs with nonlinear dynamics and uncertain perturbations. In the work of Defoort *et al*. (2015), the finite-time leader-following consensus problem is studied for a system with unknown nonlinear dynamics in an undirected topology. Moreover, a new finite-time control strategy is proposed by Wang *et al*. (2016) to solve the fixed-time intermittent communication problem in the directed communication topology, which can save communication resources.

Most of the controllers proposed in the above literature require the continuous updating of control inputs; it would be an unnecessary waste of resources if the control tasks were still performed periodically when the system is operating under ideal conditions. To this end, event-triggered control strategies have been developed. Huang *et al*. (2016) investigate the problem of distributed cooperative tracking based on event-triggered information interactions under a fixed directed topology. In most of the research results, the triggering of each agent event is not only related to its own triggering time, but also to the triggering time of its neighbours. Girard (2015) introduces internal dynamic variables on the basis of static event triggering control and proposes a dynamic event triggering mechanism that can further reduce the triggering frequency. In order to save system communication resources while improving the convergence time of the system, event-triggered finite-time consistency has been developed. In the work of Zhu *et al*. (2015), two nonlinear event-triggered control strategies are proposed to solve the finite-time consensus problem in the undirected communication topology. Zhang *et al*. (2016) investigate the event-triggered finite-time consensus problem in fixed and switched topologies, and the event-triggered finite-time consensus problem in a directed communication topology.

This paper proposes a neuro-adaptive cooperative control protocol based on an event-triggered mechanism for nonlinear high-order MASs with a non-strict output feedback and a prescribed finite-time performance. Unlike traditional event-triggered mechanisms that use time-varying trigger thresholds, the proposed algorithm only uses fixed thresholds that do not need to be repeatedly computed, significantly reducing computational overhead. Additionally, the backstepping method is used to design the corresponding controller for each order of state in the higher order dynamics model of the system. The main contributions of this paper are the following: (i) considering full-state constrained and prescribed performance conditions, making it more realistic and able to converge to a given tracking accuracy at the desired time performance; (ii) proposing a controller with a fixed trigger threshold, which drastically reduces the computational burden when controlling input signal updates; (iii) applying dynamic surface technology (Li *et al*., 2010) in the backstepping method to significantly alleviate the problem of "calculation explosion."

The rest of this paper is organized as follows. Section 2 introduces some basic preliminaries and the problem formulation to be addressed. In Section 3, the main results, including the proposed event-triggered neuro-adaptive controller, the prescribed finite-time performance function, and steady-state analysis, are presented. Section 4 reports a numeric simulation to verify the feasibility and effectiveness of the proposed control method. Finally, conclusions are drawn in Section 5.

2. Preliminaries and the problem statement

2.1. Graph theory. Define a directed graph as $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, where $\mathcal{V} = \{v_1, \dots, v_N\}$ is the set of N nodes, $\mathcal{E} \in \mathcal{V} \times \mathcal{V}$ is the edge set, and $\boldsymbol{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ is the adjacency matrix. Here $a_{ij} = 1$ if $(v_j, v_i) \in \mathcal{E}$, otherwise, $a_{ij} = 0$. The in-degree matrix is $\mathcal{D} = \operatorname{diag}\{a_1, \dots, a_N\}$, where $a_i = \sum_{j=1}^{N} a_{ij}$. The Laplacian matrix is defined as $\mathcal{L} = \mathcal{D} - \mathcal{A}$.

Lemma 1. (Zhang *et al*., 2012) *Let* $\mathcal{B} = \operatorname{diag}\{b_1, \dots, b_N\}$*, where* b_i $(i = 1, \dots, N)$ *denotes the edge between the leader and following agent* i*. If an information connection is established from the leader to agent* i*,* $b_i = 1$*, otherwise,* $b_i = 0$*. There exists a spanning tree in graph* $\mathcal{G}$ *with the leader being the root of the spanning tree; then the matrix* $\mathcal{L} + \mathcal{B}$ *is non-singular.*

2.2. Radial basis function neural networks. Due to the universal approximation theorem (Girosi and Poggio, 1990), radial basis function neural networks (RBFNNs) have been widely used to approximate continuous nonlinear functions. The output layer is

$$f(\mathcal{Z}) = W^T \phi(\mathcal{Z}), \tag{1}$$

where $\phi(\mathcal{Z}) = \left[\phi_1(\mathcal{Z}), \phi_2(\mathcal{Z}), \cdots, \phi_H(\mathcal{Z})\right]^T$ is the radial basis vector, H is the number of hidden neurons.

$$\phi_i(\mathcal{Z}) = \exp\left(-\frac{(\mathcal{Z}-c_i)^T(\mathcal{Z}-c_i)}{\omega_i^2}\right), \qquad (2)$$

where $W \in \mathbb{R}^H$ denotes the output weights, c_i and ω_i are the center and width of a Gaussian function, respectively.

According to the universal approximation theorem, there always exists an ideal weight vector W^* with sufficiently large H, such that for arbitrary small constant δ, we have

$$\|f(\mathcal{Z}) - {W^*}^T\phi(\mathcal{Z})\| \le \delta(\mathcal{Z}). \qquad (3)$$

An estimate of the ideally optimal weights W^* is

$$\tilde{W} = \arg\min_{W\in\mathbb{R}^H}[\sup\|W^T\phi - f(\mathcal{Z})\|]. \qquad (4)$$

To implement this approximation, an adaptive neural network is designed in this paper, and the neural weights will be updated through an adaptive law proposed later in this paper.

2.3. Problem formulation. Consider a high-order nonlinear MASs consisting of N homogeneous followers, where the follower $i \in \mathcal{V} = 1,\dots,N$ can be described by M-th order non-strict feedback dynamics,

$$\begin{aligned}\dot{x}_{i,m} &= x_{i,m+1} + f_{i,m}(x_i),\\ &\quad m = 1,2,\dots,M-1,\\ \dot{x}_{i,M} &= u_i + f_{i,M}(x_i),\\ y_i &= x_{i,1},\end{aligned} \qquad (5)$$

where $x_i = [x_{i,1}, x_{i,2},\dots,x_{i,M}]^\mathrm{T} \in \mathbb{R}^M$ is the state vector; $u_i \in \mathbb{R}$ and $y_i \in \mathbb{R}$ are the controller input and agent output, respectively; $f_{i,m}(x_i), i = 1,2,\dots,N$ and $m = 1,2,\dots,M$ are unknown smooth nonlinear functions with $f_{i.m}(0) = 0$.

Denoting by y_0 the desired state output of the leader agent, it is directly known to some follower agents, and its M-order derivatives are all continuous and bounded.

2.4. Prescribed performance. Define the system tracking error as

$$\rho_{i,1} = \sum_{j\in\mathcal{N}_i} a_{i,j}(y_i - y_j) + a_{i,0}(y_i - y_0). \qquad (6)$$

As in the work of Zhou *et al*. (2022), the prescribed performance functions are defined by using the inequality

$$-\delta_{\min}\mu(t) < \rho_{i,1}(t) < \delta_{\max}\mu(t), \quad \forall t \ge 0, \qquad (7)$$

where $\delta_{\min}$ and $\delta_{\max}$ are adjustable parameters, $\mu(t) = (\mu_0 - \mu_\infty)\exp(-vt) + \mu_\infty$ with v, μ_∞ being positive real numbers, and $\mu_0 = \mu(0)$. By selecting the appropriate value of μ_0, we can proceed with $\mu_0 > \mu_\infty$, and $-\delta_{\min}\mu(0) < \rho_{i,1}(0) < \delta_{\max}\mu(0)$. To achieve the prescribed performance, define

$$\rho_{i,1}(t) = \mu(t)\Phi_i(\zeta_i(t)), \quad \forall t \le 0, \qquad (8)$$

where $\zeta_i(t)$ is the transformed error, and $\Phi_i(\zeta_i(t)) = \big(\delta_{\max}\exp(\zeta_i(t)) - \delta_{\min}\exp(\zeta_i(t))\big)/\big(\exp(\zeta_i(t)) + \exp(-\bar{\omega}_i(t))\big)$. $\Phi_i(\zeta_i(t))$ is a strictly monotonically increasing function, and further,

$$\frac{\partial\Phi_i}{\partial\zeta_i} = \frac{2(\delta_{\max}+\delta_{\min})}{\big(\exp(\zeta_i(t)) + \exp(-\bar{\omega}_i(t))\big)^2} > 0 \qquad (9)$$

Thus, by Eqn. (7), we have

$$\zeta_i(t) = \Phi_i^{-1}\left(\frac{\rho_{i,1}(t)}{\mu_i(t)}\right) = \frac{1}{2}\ln\frac{\phi_i + \delta_{\min}}{\delta_{\max} - \Phi_i} \qquad (10)$$

and

$$\dot{\zeta}_i(t) = r_i\left(\dot{\rho}_{i,1} - \frac{\dot{\mu}\rho_{i,1}}{\mu}\right), \qquad (11)$$

where

$$r_i = \frac{1}{2\mu}\left(\frac{1}{\Phi_i + \delta_{\min} - \frac{1}{\Phi_i - \delta_{\max}}}\right).$$

Define the state transformation as

$$\xi_{i,1}(t) = \zeta_i(t) - \frac{1}{2}\ln\frac{\delta_{\min}}{\delta_{\max}}. \qquad (12)$$

Then, we obtain its derivative

$$\dot{\xi}_{i,1}(t) = r_i\left(\dot{\rho}_{i,1} - \frac{\dot{\mu}\rho_{i,1}}{\mu}\right). \qquad (13)$$

If $\xi_{i,1}(t)$ is bounded, $\rho_{i,1}(t)$ is said to satisfy the prescribed performance in Eqn. (7).

Definition 1. (*Yang et al., 2008*) If for any prior compact set $\Omega \in \mathbb{R}^M, x(0) \in \Omega$, there is a bounded $\varepsilon > 0$ and a constant $C(\varepsilon, x(0))$ such that

$$\|x(t)\| < \varepsilon, \quad \forall t \ge t_0 + C,$$

then the solution of the system (5) is semi-globally uniform and ultimately bounded.

3. Cooperative controller design

In this section, we propose an event-triggered neuro-adaptive control algorithm using the backstepping design method and dynamic surface technology. The event-triggered mechanism employs fixed thresholds to trigger the computation of control signals, resulting in a significant reduction in the computational burden.

Define

$$\vartheta_{i,m} = x_{i,m} - z_{i,m},$$
$$\lambda_{i,m} = z_{i,m} - \alpha_{i,m-1}, \quad m = 2, \dots, M. \tag{14}$$

where $\vartheta_{i,m}$ represents the virtual error surface, $z_{i,m}$ denotes the output signal of the first-order filter, and $\lambda_{i,m}$ and $\alpha_{i,m-1}$ are the filter error and virtual control signal, respectively.

Define

$$\theta^*_{i,m} = \|W^*_{i,m}\|^2, \quad m = 1, \dots, M, \tag{15}$$

where $W^*_{i,m}$ is the ideal setting of weights of the RBFNNs which approximates the m-th order nonlinear function of agent i. Denote by $\hat{\theta}_{i,m}$ the estimate of $\theta^*_{i,m}$, and set the residual error as $\tilde{\theta}_{i,m} = \theta^*_{i,m} - \hat{\theta}_{i,m}$.

Lemma 2. (Ren *et al.*, 2010) *For any positive constant k_{bl}, if it satisfies $|\vartheta_{i,l}| < k_{bl}, \vartheta_{i,l} \in \mathbb{R}$, then*

$$\log \frac{k_{bl}^2}{k_{bl}^2 - \vartheta_{i,l}^2} < \frac{\vartheta_{i,l}^2}{k_{bl}^2 - \vartheta_{i,l}^2}. \tag{16}$$

Lemma 3. (Zhang and Lewis, 2012) *Let $\vartheta_1 = [\vartheta_{1,1}, \vartheta_{2,1}, \dots, \vartheta_{N,1}]^T$, $y = [y_1, y_2, \dots, y_N]^T$, $\bar{y}_0 = [y_0, y_0, \dots, y_0]^T \in \mathbb{R}^N$. Then*

$$\|y - \bar{y}_0\| \le \frac{\|\vartheta_1\|}{\underline{\sigma}(\mathcal{L} + \mathcal{B})}, \tag{17}$$

where $\underline{\sigma}(\mathcal{L} + \mathcal{B})$ is the minimal singular value of matrix $\mathcal{L} + \mathcal{B}$.

Lemma 4. (Young's inequality (Henry, 1912)) *For any $\forall(x, y) \in \mathbb{R}^n$, we have*

$$xy \le \frac{p^a}{a}|x|^a + \frac{1}{bp^b}|y|^b, \tag{18}$$

where $p > 0, a > 1, b > 1, (a-1)(b-1) = 1$.

We design the distributed cooperative control protocol based on the backstepping method, which proceeds as follows.

Step 1. The barrier Lyapunov candidate function is chosen as

$$V_{i,1} = \frac{1}{2} \log \frac{k_{bl}^2}{k_{bl}^2 - \vartheta_{i,1}^2} + \frac{1}{2}\tilde{\theta}_{i,1}^2. \tag{19}$$

Therefore, its derivative is

$$\begin{aligned}\dot{V}_{i,1} = {} & \frac{\vartheta_{i,1} r_i}{k_{bl}^2 - \vartheta_{i,1}^2}\Big[(d_i + a_{i,0})(\vartheta_{i,2} + \lambda_{i,2} + \alpha_{i,1}) \\ & + \bar{f}_{i,1} - \sum_{j \in \mathcal{N}_i} a_{i,j} x_{j,2} - a_{i,0}\dot{y}_0 - \frac{\dot{\mu} e_{i,1}}{\mu}\Big] \\ & - \tilde{\theta}_{i,1}\dot{\hat{\theta}}_{i,1},\end{aligned} \tag{20}$$

where $\bar{f}_{i,1} = (d_i + a_{i,0}) f_{i,1}(x_i) - \sum_{j \in \mathcal{N}_\rangle} a_{i,j} f_{j,1}(x_j)$.

For the nonlinear term $\bar{f}_{i,1}$, we approximate it by using the RBFNN,

$$\bar{f}_{i,1} = \tilde{\mathbb{W}}_{i,1}^T \phi_{i,1}(\mathcal{Z}_{i,1}) + \delta(\mathcal{Z}_{i,1}). \tag{21}$$

Subsequently, according to Lemmas 2 and 4, we get

$$\begin{aligned}& \bar{f}_{i,1} \frac{\vartheta_{i,1} r_i}{k_{bl}^2 - \vartheta_{i,1}^2} \\ & \le \frac{r_i^2 s_{i,1}^2 \parallel \tilde{W}_{i,1} \parallel^2 \phi_{i,1}^T(\mathcal{Z}_{\rangle,\infty})\phi_{i,1}(\mathcal{Z}_{i,1})}{2p_{i,1}^2 (k_{bl}^2 - \vartheta_{i,1}^2)^2} \\ & \quad + \frac{1}{2}p_{i,1}^2 + \frac{r_i^2 s_{i,1}^2}{2(k_{bl}^2 - \vartheta_{i,1}^2)^2} + \frac{1}{2}\bar{\varepsilon}_{i,1}^2 \\ & \le \frac{r_i^2 s_{i,1}^2 \theta^*_{i,1} \phi_{i,1}^T(X_{i,1})\phi_{i,1}(X_{i,1})}{2p_{i,1}^2 (k_{bl}^2 - \vartheta_{i,1}^2)^2} \\ & \quad + \frac{r_i^2 s_{i,1}^2}{2(k_{bl}^2 - \vartheta_{i,1}^2)^2} + \frac{p_{i,1}^2 + \bar{\varepsilon}_{i,1}^2}{2},\end{aligned} \tag{22}$$

where $X_{i,1} = [x_{i,1}, x_{j,1}]^T$. Moreover,

$$\begin{aligned}& \frac{(d_i + a_{i,0}) r_i s_{i,1}}{k_{bl}^2 - \vartheta_{i,1}^2}\big(\vartheta_{i,2} + \lambda_{i,2}\big) \\ & \quad \le \frac{(d_i + a_{i,0})^2 r_i^2 s_{i,1}^2}{2(k_{bl}^2 - \vartheta_{i,1}^2)^2} + \frac{\vartheta_{i,2}^2 + \lambda_{i,2}^2}{2}.\end{aligned} \tag{23}$$

Let the virtual control signal $\alpha_{i,1}$ be

$$\begin{aligned}\alpha_{i,1} = {} & \frac{1}{d_i + a_{i,0}}\Big[-\frac{c_{i,1}\vartheta_{i,1}}{r_i} - \frac{r_i s_{i,1}}{2(k_{bl}^2 - \vartheta_{i,1}^2)} \\ & - \frac{r_i s_{i,1}}{2p_{i,1}^2 (k_{bl}^2 - \vartheta_{i,1}^2)}\hat{\theta}_{i,1}\phi_{i,1}^T(X_{i,1})\phi_{i,1}(X_{i,1}) \\ & - \frac{(d_i + a_{i,0})^2 r_i s_{i,1}}{k_{bl}^2 - \vartheta_{i,1}^2} + a_{i,0}\dot{y}_0 \\ & + \sum_{j \in \mathcal{N}_i} a_{i,j} x_{j,2} + \frac{\dot{\mu} e_{i,1}}{\mu}\Big].\end{aligned} \tag{24}$$

In addition, design the distributed adaptive control procotol $\dot{\hat{\theta}}_{i,1}$ for Step 1 as

$$\begin{aligned}\dot{\hat{\theta}}_{i,1} = {} & \frac{r_i^2 s_{i,1}^2}{2p_{i,1}^2 (k_{bl}^2 - \vartheta_{i,1}^2)^2}\phi_{i,1}^T(X_{i,1})\phi_{i,1}(X_{i,1}) \\ & - \sigma_{i,1}\hat{\theta}_{i,1},\end{aligned} \tag{25}$$

where $p_{i,1}, c_{i,1}$ and $\sigma_{i,1}$ are positive parameters to be designed.

Substituting (22)–(25) into (20), we have

$$\begin{aligned}\dot{V}_{i,1} \le {} & \frac{c_{i,1}\vartheta_{i,1}^2}{k_{bl}^2 - \vartheta_{i,1}^2} + \frac{1}{2}\vartheta_{i,2}^2 + \frac{1}{2}\lambda_{i,2}^2 \\ & + \frac{1}{2}p_{i,1}^2 \frac{1}{2}\bar{\varepsilon}_{i,1}^2 + \sigma_{i,1}\tilde{\theta}_{i,1}\hat{\theta}_{i,1}.\end{aligned} \tag{26}$$

Step 2. In this paper, we utilize a first-order filter design based on the dynamic surface technique to address the "computational explosion" problem often encountered in traditional backstepping design methods. We have

$$\begin{aligned}\tau_{i,2}\dot{z}_{i,2}+z_{i,2}&=\alpha_{i,1},\\ z_{i,2}(0)&=\alpha_{i,1}(0),\end{aligned}\tag{27}$$

where $\tau_{i,2}$ is a positive designed parameter. Since $\lambda_{i,2}=z_{i,2}-\alpha_{i,1}$, we have $\dot{z}+i,2=\lambda_{i,2}/\tau_{i,2}$, and

$$\dot{\varepsilon}_{i,2}=-\frac{\lambda_{i,2}}{\tau_{i,2}}+\gamma_{i,2}(\cdot),\tag{28}$$

where $\gamma_{i,2}(\cdot)=-\dot{s}_{i,1}$ is a continuous function.

Remark 1. In the traditional backstepping design method, after deriving $\alpha_{i,1}$ from Step 1, the derivative must be calculated in the next virtual control signal design process, and the virtual control signal must be repeatedly derived in each subsequent step, leading to a "calculation explosion" problem. To address this issue, we introduce dynamic surface technology, which passes the virtual control signal through a first-order low-pass filter to obtain its estimated value $z_{i,2}$. In the subsequent design process, the estimated value can replace the virtual control signal, avoiding the need for derivation and simplifying the controller structure.

Choose the Lyapunov candidate function for Step m $(m=2,\dots,M-1)$,

$$\begin{aligned}V_{i,m}=V_{i,m-1}&+\frac{1}{2}\log\frac{k_{bm}^2}{k_{bm}^2-\vartheta_{i,m}^2}\\ &+\frac{1}{2}\tilde{\theta}_{i,m}^2+\frac{1}{2}\lambda_{i,m}^2.\end{aligned}\tag{29}$$

By (5), (14) and (29), we obtain

$$\begin{aligned}\dot{V}_{i,m}=&\dot{V}_{i,m-1}+\frac{\vartheta_{i,m}}{k_{bm}^2-\vartheta_{i,m}^2}\big[\vartheta_{i,m+1}+\lambda_{i,m+1}\\ &+\alpha_{i,m}f_{i,m}(x_i)-\dot{z}_{i,m}\big]-\tilde{\theta}_{i,m}\dot{\hat{\theta}}_{i,m}\\ &+\lambda_{i,m}\Big[-\frac{\lambda_{i,m}}{\tau_{i,m}}+\gamma_{i,m}(\cdot)\Big].\end{aligned}\tag{30}$$

According to Lemmas 2 and 4, we have

$$\begin{aligned}\frac{\vartheta_{i,m}f_{i,m}(x_i)}{k_{bm}^2-\vartheta_{i,m}^2}\le&\frac{\vartheta_{i,m}^2\theta_{i,m}^*\phi_{i,m}^T(\bar{x}_{i,m})\phi_{i,m}(\bar{x}_{i,m})}{2p_{i,m}^2(k_{bm}^2-\vartheta_{i,m}^2)^2}\\ &+\frac{\vartheta_{i,m}^2}{2(k_{bm}^2-\vartheta_{i,m}^2)^2}+\frac{1}{2}p_{i,m}^2+\frac{1}{2}\bar{\varepsilon}_{i,m}^2,\end{aligned}\tag{31}$$

$$\begin{aligned}\frac{\vartheta_{i,m}(\vartheta_{i,m+1}+\lambda_{i,m+1})}{k_{bm}^2-\vartheta_{i,m}^2}\le&\frac{1}{2}\vartheta_{i,m+1}^2+\frac{1}{2}\lambda_{i,m+1}^2\\ &+\frac{\vartheta_{i,m}^2}{(k_{bm}^2-\vartheta_{i,m}^2)^2}.\end{aligned}\tag{32}$$

Therefore, we design the virtual control signal $\alpha_{i,m}$ as

$$\begin{aligned}\alpha_{i,m}=&-c_{i,m}\vartheta_{i,m}-\frac{3s_{i,m}}{2(k_{bm}^2-\vartheta_{i,m}^2)}\\ &-\frac{\vartheta_{i,m}\hat{\theta}_{i,m}\phi_{i,m}^T(\bar{x}_{i,m})\phi_{i,m}(\bar{x}_{i,m})}{2p_{i,m}^2(k_{bm}^2-\vartheta_{i,m}^2)}\\ &-\frac{k_{bm}^2-\vartheta_{i,m}^2}{2}\vartheta_{i,m}+\dot{z}_{i,m}\end{aligned}\tag{33}$$

and also design the adaptive control protocol $\dot{\hat{\theta}}_{i,m}$ as

$$\begin{aligned}\dot{\hat{\theta}}_{i,m}=&\frac{\vartheta_{i,m}^2}{2p_{i,m}^2(k_{bm}^2-\vartheta_{i,m}^2)^2}\phi_{i,m}^T(\bar{x}_{i,m})\phi_{i,m}(\bar{x}_{i,m})\\ &-\sigma_{i,m}\hat{\theta}_{i,m},\end{aligned}\tag{34}$$

where $p_{i,m}, c_{i,m}$ and $\sigma_{i,m}$ are positive parameters. Recursively substituting (26), (31)–(34) into (30), we get

$$\begin{aligned}\dot{V}_{i,m}\le&-\sum_{l=1}^{m}\frac{c_{i,l}\vartheta_{i,l}^2}{k_{bl}^2-\vartheta_{i,l}^2}+\sum_{l=1}^{m}\sigma_{i,l}\tilde{\theta}_{i,l}\hat{\theta}_{i,l}\\ &+\sum_{l=2}^{m}\Big[-\frac{\lambda_{i,l}^2}{\tau_{i,l}}+\lambda_{i,l}\gamma_{i,l}(\cdot)\Big]+\frac{1}{2}\sum_{l=2}^{m+1}\lambda_{i,l}^2\\ &+\frac{1}{2}\sum_{l=1}^{m}(p_{i,l}^2+\bar{\varepsilon}_{i,l}^2)+\frac{1}{2}\vartheta_{i,m+1}^2.\end{aligned}\tag{35}$$

Step 3. In much the same way as in Step 2, we first define the filter as

$$\tau_{i,m+1}\dot{z}_{i,m+1}+z_{i,m+1}=\alpha_{i,m},\tag{36}$$

$$z_{i,m+1}(0)=\alpha_{i,m}(0),\tag{37}$$

where $\tau_{i,m+1}$ is a positive parameter. Due to $\lambda_{i,m+1}=z_{i,m+1}-\alpha_{i,m}$, we have $\dot{z}_{i,m+1}=\frac{\lambda_{i,m+1}}{\tau_{i,m+1}}$; therefore,

$$\dot{\lambda}_{i,m+1}=-\frac{\lambda_{i,m+1}}{\tau_{i,m+1}}+\gamma_{i,m+1}(\cdot),\tag{38}$$

where $\gamma_{i,m+1}(\cdot)=-\dot{s}_{i,m}$ is a continuous function.

Choose the Lyapunov candidate function for step M as

$$\begin{aligned}V_{i,M}=V_{i,M-1}&+\frac{1}{2}\log\frac{k_{bM}^2}{k_{bM}^2-\vartheta_{i,M}^2}\\ &+\frac{1}{2}\tilde{\theta}_{i,M}^2+\frac{1}{2}\lambda_{i,M}^2\end{aligned}\tag{39}$$

Thus we have the derivative of $V_{i,M}$,

$$\begin{aligned}\dot{V}_{i,M}=&\dot{V}_{i,M-1}+\frac{\vartheta_{i,M}}{k_{bM}^2-\vartheta_{i,M}^2}\big(u_i+f_{i,M}(x_i)-\dot{z}_{i,M}\big)\\ &+\Big[-\frac{\lambda_{i,M}^2}{\tau_{i,M}}+\lambda_{i,M}\gamma_{i,M}(\cdot)\Big]-\tilde{\theta}_{i,M}\dot{\hat{\theta}}_{i,M}.\end{aligned}\tag{40}$$

Referring to Lemma 4, we get

$$\begin{aligned}\frac{\vartheta_{i,M} f_{i,M}(x_i)}{k_{bM}^2-\vartheta_{i,M}^2} &\leq \frac{\vartheta_{i,M}^2 \theta_{i,M}^{*} \phi_{i,M}^T(x_i)\phi_{i,M}(x_i)}{2p_{i,M}(k_{bM}^2-\vartheta_{i,M}^2)^2} \\ &+ \frac{\vartheta_{i,M}^2}{2(k_{bM}^2-\vartheta_{i,M}^2)^2}+\frac{1}{2}p_{i,M}^2+\frac{1}{2}\bar{\varepsilon}_{i,M}^2. \qquad (41)\end{aligned}$$

We design the adaptive control protocol as

$$\omega_i(t) = \alpha_{i,M} - \bar{m}_i \tanh\left[\frac{\vartheta_{i,M}\bar{m}_i}{\epsilon_i(k_{bM}^2-\vartheta_{i,M}^2)}\right], \qquad (42)$$

$$\begin{aligned}\alpha_{i,M} =& -c_{i,M}\vartheta_{i,M} - \frac{\vartheta_{i,M}}{2(k_{bM}^2-\vartheta_{i,M}^2)} \\ &- \frac{\vartheta_{i,M}\hat{\theta}_{i,M}\phi_{i,M}^T(x_i)\phi_{i,M}(x_i)}{2p_{i,M}^2(k_{bM}^2-\vartheta_{i,M}^2)} \\ &- \frac{k_{bM}^2-\vartheta_{i,M}^2}{2}\vartheta_{i,M}+\dot{z}_{i,M}, \qquad (43)\end{aligned}$$

$$\begin{aligned}\dot{\hat{\theta}}_{i,M} =& \frac{\vartheta_{i,M}^2}{2p_{i,M}^2(k_{bM}^2-\vartheta_{i,M}^2)}\phi_{i,M}^T(x_i)\phi_{i,M}(x_i) \\ &- \sigma_{i,M}\hat{\theta}_{i,M}, \qquad (44)\end{aligned}$$

where the formulation for the event triggering mechanism is

$$u_i(t) = \omega_i(t_k), \quad \forall t \in [t_k, t_{k+1}), \qquad (45)$$

$$t_{k+1} = \inf\{t \in \mathbb{R}, \|\varrho(t)\| \geq m_i\}, \quad t_1 = 0. \qquad (46)$$

Here, $e_i(t) = \omega_i(t) - u_i(t)$ represents the measurement error, and $p_{i,M}$, $c_{i,M}$, $\sigma_{i,M}$, ϵ_i, and $\bar{m}_i$ are positive parameters such that $m_i < \bar{m}_i$. The time of the occurrence of the event trigger is denoted as t_k, where $k \in \mathbb{Z}^+$. In other words, when the condition of (46) is satisfied, the control signal is triggered to update to $u_i(t_{k+1})$. Within the time interval $t \in [t_k, t_{k+1})$, the control signal remains constant at $\omega_i(t_k)$. Therefore, there exists a continuous time-varying function $\tau(t_k)$ such that $\tau(t_k) = 0$, $\tau(t_{k+1}) = \pm$, $|\tau(t)| \leq 1$, and $\omega_i(t) = u_i(t) + \tau(t)m_i$ holds.

According to Huang and Wang (2019), we obtain

$$\begin{aligned}\dot{V}_{i,M} =& \dot{V}_{i,M} - \frac{c_{i,M}\vartheta_{i,M}^2}{k_{bM}^2-\vartheta_{i,M}^2} - \frac{\vartheta_{i,M}^2}{2} + \sigma_{i,M}\tilde{\theta}_{i,M}\hat{\theta}_{i,M} \\ &+ 0.2785\epsilon_i + \left[-\frac{\lambda_{i,M}^2}{\tau_{i,M}}+\lambda_{i,M}\gamma_{i,M}(\cdot)\right] \\ &+ \frac{1}{2}p_{i,M}^2 + \frac{1}{2}\bar{\varepsilon}_{i,M}^2 \\ \leq& \sum_{l=1}^{M}\frac{-c_{i,l}\vartheta_{i,l}^2}{k_{bM}^2-\vartheta_{i,M}^2} + \sum_{l=2}^{M}\left[-\frac{\lambda_{i,l}^2}{\tau_{i,l}}+\lambda_{i,l}\gamma_{i,l}(\cdot)\right] \\ &+ \sum_{l=1}^{M}\sigma_{i,l}^{M}\sigma_{i,l}\tilde{\theta}_{i,l}\hat{\theta}_{i,l} + \frac{1}{2}\sum_{l=2}^{2}\lambda_{i,l}^2 \\ &+ \frac{1}{2}\sum_{l=1}^{M}\left(p_{i,l}^2+\bar{\varepsilon}_{i,l}^2\right) + 0.2785\epsilon_i. \qquad (47)\end{aligned}$$

The following inequalities are obtained from Lemma 4:

$$\sigma_{i,l}\tilde{\theta}_{i,l}\hat{\theta}_{i,l} \leq -\frac{\sigma_{i,l}\tilde{\theta}_{i,l}^2}{2}+\frac{\sigma_{i,l}\theta_{i,l}^{*2}}{2}, \qquad (48)$$

$$\lambda_{i,l}\gamma_{i,l}(\cdot) \leq \frac{\lambda_{i,l}^2\gamma_{i,l}^2(\cdot)}{2}+\frac{1}{2}. \qquad (49)$$

By Lemma 2, we get

$$-\frac{c_{i,l}\vartheta_{i,l}^2}{k_{bM}^2-\vartheta_{i,M}^2} \leq -c_{i,l}\log\frac{k_{bl}^2}{k_{bM}^2-\vartheta_{i,M}^2}. \qquad (50)$$

There exists a scalar $\bar{\gamma}_{i,l} > 0$ that satisfies $|\gamma_{i,l}(\cdot)| < \bar{\gamma}_{i,l}$. Substituting (48)–(50) into (47), we have

$$\begin{aligned}\dot{V}_{i,M} \leq& -\sum_{l=1}^{M}c_{i,l}\log\frac{k_{bl}^2}{k_{bM}^2-\vartheta_{i,M}^2} - \sum_{l=1}^{M}\frac{\sigma_{i,l}\tilde{\theta}_{i,l}^2}{2} \\ &- \sum_{l=2}^{M}\left(\frac{1}{\tau_{i,l}}-\frac{\bar{\gamma}_{i,l}^2}{2}-\frac{1}{2}\right)\lambda_{i,l}^2+\Lambda_i, \qquad (51)\end{aligned}$$

where

$$\begin{aligned}\Lambda_i =& \frac{1}{2}\sum_{l=1}^{M}\left(p_{i,l}^2+\bar{\varepsilon}_{i,l}^2\right)+\sum_{l=1}^{M}\frac{\sigma_{i,l}\theta_{i,l}^{*2}}{2} \\ &+ \frac{M-1}{2}+0.2785\epsilon_i. \qquad (52)\end{aligned}$$

Theorem 1. *Under Assumption 1 we consider the virtual control signals* (24), (33) *and* (43), *the adaptive protocols* (25), (34) *and* (44), *and the event-triggered adaptive controllers* (42), (45), *and* (46). *By utilizing these controllers, we can ensure that the MAS described by* (5) *satisfies the following conditions:*

(i) all signals in the system are semi-globally homogeneous and ultimately bounded;

(ii) the tracking error converges to a bounded neighborhood of the origin and satisfies the specified performance.

Moreover, for the time interval $[t_k, t_{k+1})$, *there exists a lower bound of* t^*, *where* $t^* > 0$, *for triggered events. This ensures that when the adaptive controller is triggered by an event, the Zeno phenomenon does not occur.*

Proof. Choose the Lyapunov function as

$$V = \sum_{i=1}^{N} V_{i,M}. \tag{53}$$

According to (51), we have

$$\begin{aligned}\dot{V} \le \sum_{i=1}^{N} \Big[& - \sum_{l=1}^{M} c_{i,l} \log \frac{k_{bl}^2}{k_{bl}^2 - \vartheta_{i,l}^2} - \sum_{l=1}^{M} \frac{\sigma_{i,l}\tilde{\theta}_{i,l}^2}{2} \\ & - \sum_{l=2}^{M} \left(\frac{1}{\tau_{i,l}} - \frac{\bar{\gamma}_{i,l}^2}{2} - \frac{1}{2} \right) \lambda_{i,l}^2 + \Lambda_i \Big].\end{aligned} \tag{54}$$

Choose design parameters such that

$$\frac{1}{\tau_{i,1}} - \frac{\bar{\gamma}_{i,l}}{2} - \frac{1}{2} > 0.$$

Let

$$\begin{aligned}\Gamma &= \min \left\{ 2c_{i,l}, 2\left[\frac{1}{\tau_{i,l}} - \frac{\bar{\gamma}_{i,l}}{2} - \frac{1}{2} \right], \sigma_{i,l} \right\}, \\ \Lambda &= \sum_{i=1}^{N} \Lambda_i.\end{aligned} \tag{55}$$

Thus (54) can be rewritten as

$$\dot{V}(t) \le -\Gamma V(t) + \Lambda \tag{56}$$

such that all the signals are semi-globally uniform and ultimately bounded. According to (56), we have

$$\begin{aligned}\frac{1}{2}\vartheta_{i,l}^2 &\le V(t) \\ &\le \exp(-\Gamma t)V(0) + \frac{\Lambda}{\Gamma}(1 + \exp(-\Gamma t)).\end{aligned} \tag{57}$$

From Lemma 4 it follows that

$$\lim_{t\to\infty} \|y - \bar{y}_0\| \le \frac{\sqrt{\frac{2\Lambda}{\Gamma}}}{\underline{\sigma}(\mathcal{L} + \mathcal{B})}. \tag{58}$$

By selecting appropriate design parameters, the tracking error can converge in a bounded neighborhood centered at the origin. Further, since $e_i(t) = \omega_i(t) - u_i(t), \forall t \in [t_k, t_{k+1})$, we have

$$\frac{\mathrm{d}|\varrho(t)|}{\mathrm{d}t} = \frac{\mathrm{d}}{\mathrm{d}t}(\varrho \times \varrho)^{\frac{1}{2}} = \mathrm{sign}(\varrho)\dot{e}_i \le |\dot{\omega}_i|. \tag{59}$$

All signals in the system are bounded, implying $|\dot{\omega}_i| \le \kappa$ for a constant κ. Given $e_i(t_k) = 0$ and $\lim_{t\to t_{k+1}} \varrho(t) = m_i$, the lower bound t^* of the event-triggered time interval satisfies $t^* \ge m_i/\kappa$. The event trigger mechanism proposed in this paper is shown to be immune to the Zeno phenomenon. ■

4. Numerical simulations

This section presents the leader-following simulation experiment, as shown in Fig. 1. The network communication topology of the system includes one leader and five following agents, where the direction of the arrows represents the transmission direction of agent state information. We assume that the connection weight between each pair of two agents is 1.

Let the desired state output of leader be

$$y_0 = \sin(t) + 1.5\sin(2t + 1)$$

and the system dynamics of the followers be

$$\begin{aligned}\dot{x}_{i,1}(t) &= x_{i,2}(t), \\ \dot{x}_{i,2}(t) &= x_{i,3}(t) - \cos x_{i,1}(t) - 0.5\sin x_{i,2}(t), \\ \dot{x}_{i,3}(t) &= 0.2x_{i,2}(t) - 0.1x_{i,3}(t) + u_i(t), \\ y_i(t) &= x_{i,1}(t).\end{aligned}$$

Set the initial states of the leader $\boldsymbol{x}_0$ and following agents ($\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \boldsymbol{x}_4, \boldsymbol{x}_5$) as

$$\begin{aligned}\boldsymbol{x}_0 &= [x_{d,1}, x_{d,2}, x_{d,3}]^{\mathrm{T}} = [-6, 0, 0]^{\mathrm{T}}, \\ \boldsymbol{x}_1 &= [x_{1,1}, x_{1,2}, x_{1,3}]^{\mathrm{T}} = [-1.8, 0, 84]^{\mathrm{T}}, \\ \boldsymbol{x}_2 &= [x_{2,1}, x_{2,2}, x_{2,3}]^{\mathrm{T}} = [-0.3, 0, 3]^{\mathrm{T}}, \\ \boldsymbol{x}_3 &= [x_{3,1}, x_{3,2}, x_{3,3}]^{\mathrm{T}} = [-11.6, 0, 60]^{\mathrm{T}}, \\ \boldsymbol{x}_4 &= [x_{4,1}, x_{4,2}, x_{4,3}]^{\mathrm{T}} = [-3.8, 0, -48]^{\mathrm{T}}, \\ \boldsymbol{x}_5 &= [x_{5,1}, x_{5,2}, x_{5,3}]^{\mathrm{T}} = [-4, 0, 76]^{\mathrm{T}}.\end{aligned}$$

As can be seen in Fig. 2, the system output states of all followers can track the leader and eventually form a consensus. The second and third order states of the following agents in Figs. 3 and 4 gradually converge over time, and the simulation results comprehensively demonstrate the effectiveness of our designed control protocol.

In Fig. 5, we show the variation in the consensus error over time, and we can see that the error decreases rapidly in the initial phase and subsequently approaches zero, implying that the states of the following agents reach a consensus. The event triggering of the five followers is shown in Fig. 6, where the update of the control protocol of the different agents is triggered asynchronously, with its own trigger condition that relies on its own fixed threshold, which is seen to effectively implement the sparse computation.

5. Conclusion

This paper investigates the leader–follower tracking problem for a class of high-order nonlinear MAS with full state constraints under prescribed performance condition.

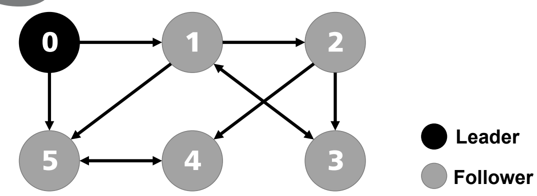

Fig. 1. Directed communication topology with five followers and a leader.

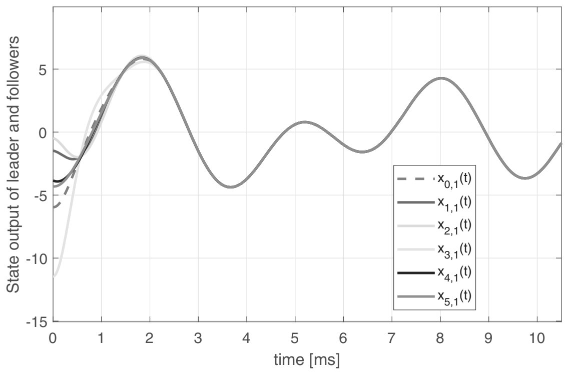

Fig. 2. Tracking trajectory x_1 of system output of the leader and followers.

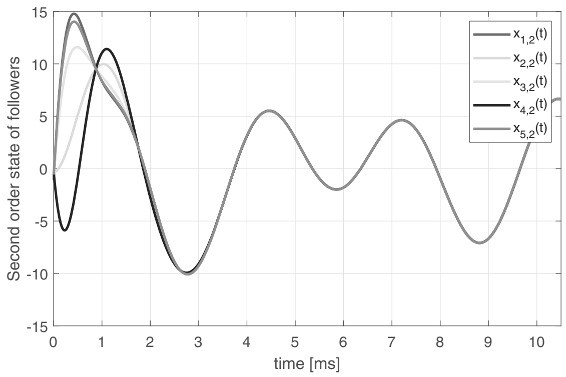

Fig. 3. Consensus of the second order state x_2 of the five followers.

In this context, the prescribed performance is introduced to enable the system to achieve the desired steady-state error convergence within a given time constraint. In the design of the controller we also introduce an event triggering mechanism with a fixed threshold. Event triggering allows the agent to significantly reduce the computational and communication load overhead during control, which is further enhanced by the fixed threshold feature. In the derivation and stability analysis of the control algorithm based on the backstepping design method, we demonstrate the effectiveness of the proposed cooperative control rate using the Lyapunov method and subsequently validate it through numerical simulations.

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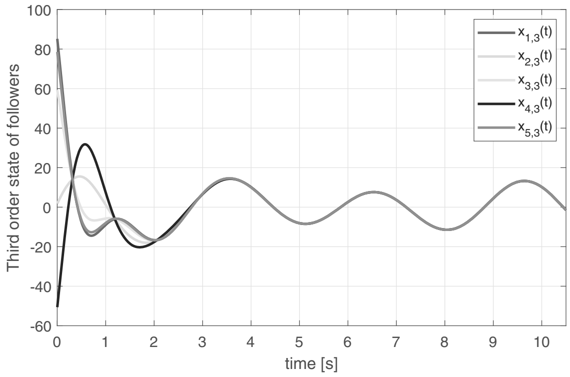

Fig. 4. Consensus of the second order state x_3 of the five followers.

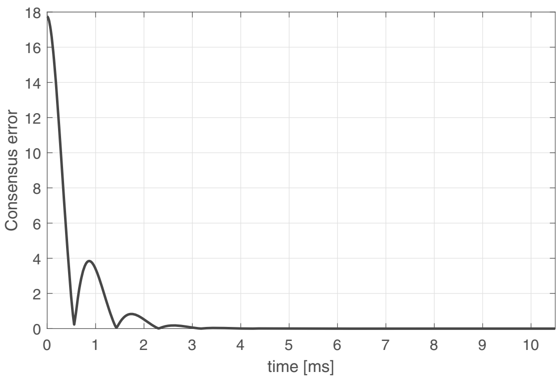

Fig. 5. Consensus error of the state output of the five followers.

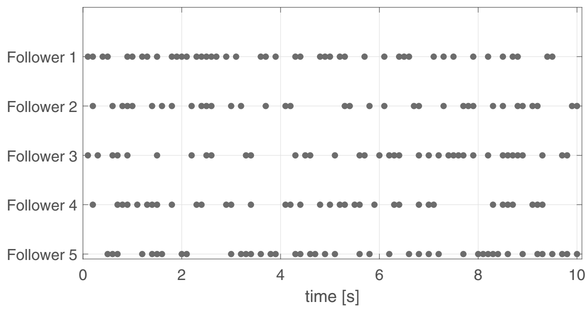

Fig. 6. Triggered event of control update.

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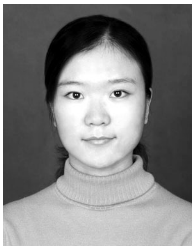

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