Proceedings of the
Estonian Academy of Sciences
2026, **75**, 1, 34–46

https://doi.org/10.3176/proc.2026.1.04

www.eap.ee/proceedings
Estonian Academy Publishers

CONTROL THEORY,
MULTI-AGENT SYSTEMS

RESEARCH ARTICLE

Received 21 April 2025
Accepted 26 August 2025
Available online 26 January 2026

Keywords:
multi-agent system, reset event-triggered control, nonlinear dynamics, state error, consensus

Corresponding author:
Xingjian Fu
fxj@bistu.edu.cn

Citation:
Cheng, Y. and Fu, X. 2026. Distributed consensus for second-order multi-agent systems based on reset event-triggered mechanism. *Proceedings of the Estonian Academy of Sciences*, **75**(1), 34–46.
https://doi.org/10.3176/proc.2026.1.04

Distributed consensus for second-order multi-agent systems based on reset event-triggered mechanism

Yi Cheng and Xingjian Fu

School of Automation, Beijing Information Science and Technology University, Beijing 100192, China

ABSTRACT

This paper investigates the consensus problem of disturbed second-order nonlinear multi-agent systems (MASs) under directed topology. A reset event-triggered control (RETC) is proposed that combines the reset mechanism with dynamic event-triggered control (ETC) strategies. The introduction of RETC overcomes the limitation of the traditional ETC that frequently triggers when approaching the consensus position. The external dynamic variables in the trigger conditions can be adjusted according to the predefined reset conditions. When the local state deviation reaches the preset threshold, the dynamic variable is reset to the initial value, greatly reducing the frequency of event triggering, and the strategies are fully distributed. The parameters and reset threshold depend only on the local state of the agents, without global information. The paper applies the Lyapunov stability theory to conduct a rigorous theoretical analysis of control strategies and verifies its effectiveness in improving transient consensus and reducing communication burden through simulations.

1. Introduction

As a prominent research focus in the field of control, the cooperative control of multi-agent systems (MASs) has shown significant potential in diverse applications, including consensus control [19,27], distributed optimization [1,11], and cluster collaboration [7]. This method refers to the approach where multiple agents with perception, communication, and mobility capabilities achieve the desired objectives collectively through local information exchange in a distributed environment. As the basis of collaborative control, the consensus problem has received extensive attention [18,20,22]. The core of cooperative control lies in establishing the relationship between individual agent behaviors and the overall group objective, with consensus providing the theoretical foundation for realizing this relationship [22].

The main task of the consensus problem of the MAS is to design the controller so that all the agents in the system tend to the same state [8,14]. Based on the graph theory, the convergence properties of linear systems with connected topology were proved by [14]. By analyzing delay effects in discrete-time multi-intelligent systems, a new mathematical tool was proposed by [8] to define consistency boundaries. In order to solve the influence of external disturbance, more complex system models were considered in [17] and [13], and the control method was further extended. The problem of non-matching disturbance was discussed in [24]. Yet, most existing approaches assume that the agents can continuously communicate with each other. However, in practical application scenarios, MASs often cannot fulfill this condition.

To reduce the consumption of communication resources under the premise of system stability, an event-triggered mechanism has been introduced into the consensus control of multi-agents [4,12]. Different from the traditional periodic triggering, this approach adopts a state-driven communication strategy in which communication links are activated and control protocols are updated only when specific triggering conditions are satisfied. This mechanism enables a dynamic trade-off between control accuracy and communication load.

According to the type of trigger function, event-triggered mechanisms are generally classified into static and dynamic categories. To address errors arising from system uncertainties, Deng et al. [4] investigated the tracking problem of nonlinear MASs and developed an adaptive controller for all subsystems based on a specially designed observer. However, with the growing complexity of practical applications, the limitations of static thresholds have become increasingly evident. For example, an excessively high threshold may delay system convergence, whereas an overly low threshold can lead to redundant communications [12].

Subsequently, a dynamic event-triggered algorithm was proposed by introducing dynamic variables [9,10]. The dynamic event-triggered mechanism makes the threshold of the event-triggered function change adaptively with the measurement error, which effectively avoids the situation that the trigger threshold is invariable under the static event-triggered mechanism. In recent years, the dynamic event-triggered mechanism has become a key technique for meeting the requirements of saving communication resources and flexible design. In [9], dynamic threshold parameters were introduced into the queuing control problem of a MAS, and an optimal balance was achieved between the communication efficiency of the system and the desired queuing performance. However, the research focused on the idealized formation task and did not address the impact of system dynamic complexity on the robustness of the triggering mechanism.

To address these challenges, Ge et al. [10] applied a dynamic event-triggered mechanism to the complex energy system of islanded microgrids. For multi-unmanned boat systems with limited communication, Ding et al. [6] designed a distributed control protocol based on adaptive algorithms and slip film control. The problem of time delay in a second-order MAS was improved in [15]. However, most of the studies assumed that external disturbances were negligible and did not account for adaptability under persistent perturbations. This limitation was solved in [21]. For MASs with external disturbances, Ruan et al. adopted a dynamic threshold event-triggered method in the channels from sensor to observer and from control protocol to actuator, thereby effectively avoiding excessive updates of the control protocol. Eventually, the system stated index could converge to a bounded range.

Dynamic event-triggered mechanisms have proven effective, but a key limitation remains: while they perform well when the system is far from equilibrium, frequent triggering still occurs near consensus due to the time-decaying nature of dynamic variables. To ensure stability, conservative parameter settings were adopted in [3], yet this approach failed to eliminate the Zeno phenomenon within a prescribed time. Subsequently, a new time-varying function was used to solve this problem [2]. Further, Liu et al. [16] extended the study to second-order MASs to realize the pre-determined time utility consensus and verified the validity of the results by using the example of self-driving cars on the internet. However, most existing work has concentrated on asymptotic consensus, with limited attention to transient performance. Therefore, the problem of improving the transient performance of the system while ensuring consensus has received widespread attention.

In order to address these challenges, this paper proposes a reset-based event-triggered mechanism, providing a novel perspective for improving the transient performance of the system [5,23,25,26]. The advantage of this method is that when the system state satisfies the preset conditions, the dynamic process is reconstructed by the strategy of finite amplitude state reset. The dependence of traditional continuous control on the monotonicity of the Lyapunov function is overcome, and the convergence process is accelerated. For this reason, the reset control is innovatively introduced into the dynamic variable update process: when the system state enters the ε neighborhood, the state reset of the auxiliary variable $\eta_i(t)$ with limited amplitude is performed, rather than the continuous variable decay strategy in the traditional event trigger.

The main contributions of this article are as follows:

1. A novel hybrid reset event-triggered mechanism is proposed that overcomes the dependence of the traditional dynamic event-triggered mechanism on the monotonicity of the Lyapunov function through the ε neighborhood partitioning and the finite amplitude reset operation, and has the potential to improve the transient consensus performance of MASs.

2. Event-triggered mechanisms that rely on global parameters are required by [21]. A completely distributed control law is proposed in this paper. Triggering parameters are based only on local neighboring state errors, which significantly enhances the adaptability of the algorithm to dynamic topologies.

3. Existing studies [9,10] mostly use a single control mechanism, making it difficult to balance communication efficiency and anti-jamming capability. This paper achieves consensus while eliminating the Zeno phenomenon through the coupled design of perturbation compensation and reset-triggering conditions.

In summary, this paper innovatively combines reset control and event-triggered mechanisms in the consensus control of MASs, and proposes a solution that effectively improves the performance of transient consensus and provides a new perspective for system analysis and design.

2. Problem formulation and preliminaries

The information interaction between agents can be described by the topology graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$. For a topology graph composed of N agents, $\mathcal{V} = \{v_1, v_2, \ldots, v_n\}$ represents the set of nodes, and $\mathcal{E} = \{(v_i, v_j) \mid v_i \in \mathcal{V}, v_j \in \mathcal{V}, i \neq j\}$ denotes the set of edges. A directed edge $(v_i, v_j) \in \mathcal{E}$ indicates that agent i can receive information from agent j. At this point, v_j is called the neighboring agent of v_i. The weight adjacency matrix $\mathcal{A} = [a_{ij}] \in \mathbf{R}^{N\times N}$; if $(v_i, v_j) \in \mathcal{E}$, then $a_{ij} > 0$, otherwise $a_{ij} = 0$. The degree matrix $D = \mathrm{diag}\{d_1, \cdots, d_i, \cdots, d_M\}$ is defined, where $d_i = \sum_{j=1, j\neq i}^{M} a_{ij}$. The corresponding Laplacian matrix $\mathcal{L} = [l_{ij}] \in \mathbf{R}^{N\times N}$ of the graph $\mathcal{G}$ is defined as $\mathcal{L} = D - A$. The leader–follower adjacency matrix in a second-order MAS is $B = \mathrm{diag}\{b_1, b_2, \ldots, b_n\}$. When the follower is connected to the leader, $b_i = 1$, otherwise $b_i = 0$. When there exists a directed path between any two nodes that reaches connectivity, it is called a strongly connected graph $\mathcal{G}$.

This paper investigates second-order nonlinear MASs, where the dynamics of the leader and the follower i are described as follows:

$$\begin{cases} \dot{x}_0(t) = v_0(t) \\ \dot{v}_0(t) = f\left(t, x_0(t), v_0(t)\right) \end{cases}, \tag{1}$$

$$\begin{cases} \dot{x}_i(t) = v_i(t) \\ \dot{v}_i(t) = u_i(t) + d_i(t) + f\left(t, x_i(t), v_i(t)\right) \end{cases}, i = 1, 2, \cdots, n, \tag{2}$$

where $x_0(t) \in R^m$, $v_0(t) \in R^m$ are respectively expressed as the state and speed of the leader at the moment t; $x_i(t) \in R^m$, $v_i(t) \in R^m$, and $u_i(t) \in R^m$ are the state, speed, and control inputs of the follower i, respectively; $f(t, x_0(t), v_0(t))$ and $f(t, x_i(t), v_i(t))$ denote the unknown nonlinear continuous functions of the leader and the follower i, respectively; $d_i(t)$ denotes the unknown perturbations of the follower and satisfies $\|d(t)\| \leq D$, $d(t) = \left[d_1^{\mathrm{T}}(t), d_2^{\mathrm{T}}(t), \cdots, d_N^{\mathrm{T}}(t)\right]^{\mathrm{T}}$, where D is a positive constant.

The main lemmas and assumptions employed in the proof are summarized as follows:

Assumption 1. At least one follower can obtain the navigator's information; that is, the navigator–follower adjacency matrix $B \neq 0$.

Assumption 2. For a nonlinear continuous function $f(\cdot)$ in a second-order nonlinear MAS, which satisfies the Lipschitz condition, $\forall x, y, v, z \in \mathbb{R}$, there exist two positive constants p and q such that the following inequality holds:

$$|f(t, x, v) - f(t, y, z)| \leq p|x - y| + q|v - z|. \tag{3}$$

Lemma 1. [15] (Young's inequality) *Let* $p > 1$, $\frac{1}{p} + \frac{1}{q} = 1$. *Then, for any* $\sigma_1\sigma_2 > 0$, $\sigma_1\sigma_2 \leq \frac{\sigma_1^p}{p} + \frac{\sigma_2^q}{q}$.

Lemma 2. [2] (Sliding-mode interference compensation inequality) *Set constant* $D > 0$ *such that the jamming signal* $d(t)$ *satisfies the boundedness condition* $d(t) \leq D$*, where D is the upper bounds of known interference. For any time-varying signal* $\sigma(t) = \bar{x}^T(t) + \bar{v}^T(t)$*, the following inequality holds:*

$$\sigma(t)\left(d(t) - D\mathrm{sgn}(\sigma(t))\right) \leq 0. \tag{4}$$

Lemma 3. [25] *Let* $\mathcal{H} \in R^{n\times n}$ *be a symmetric positive definite matrix, and eigenvalues satisfy* $0 < \lambda_{\min}(\mathcal{H}) \leq \lambda_{\max}(\mathcal{H})$*. For any vector* $x \in R^n$*, the following inequality holds:*

$$\lambda_{\min}(\mathcal{H})\|x\|^2 \le x^{\mathrm{T}}\mathcal{H}x \le \lambda_{\max}(\mathcal{H})\|x\|^2, \tag{5}$$

where $\|x\|^2 = x^T x$, $\lambda_{\min}(\mathcal{H})$, *and* $\lambda_{\max}(\mathcal{H})$ *are the minimum and maximum eigenvalues of* $\mathcal{H}$, *respectively.*

Lemma 4. [26] *For* $\forall x, y \in R$ *and* $\alpha > 0$, *the following properties hold true:*

$$|xy| \le \frac{\alpha}{2}x^2 + \frac{1}{2\alpha}y^2. \tag{6}$$

Lemma 5. [23] *Consider the system described by Eqs* (1) *and* (2). *The MAS can achieve leading–following consensus if and only if the initial state of any agent satisfies the following conditions:*

$$\begin{aligned} &\lim_{t\to\infty} \|x_i(t) - x_0(t)\| = 0, i = 1, 2, \cdots, n, \\ &\lim_{t\to\infty} \|v_i(t) - v_0(t)\| = 0, i = 1, 2, \cdots, n. \end{aligned} \tag{7}$$

3. Main result

This paper investigates the consensus problem of second-order MASs under a reset event-triggered strategy. To facilitate the design of the event-triggering condition, the state measurement error is defined as follows (which also follows the idea in [12]):

$$\Delta_i(t) = \sum_{j\in\mathcal{N}_i} a_{ij}(x_i(t) - x_j(t) + v_i(t) - v_j(t)) + b_i\frac{1}{\alpha}(x_i(t) - x_0(t) + v_i(t) - v_0(t))^{\alpha}. \tag{8}$$

Define the triggering error of agent i as:

$$e_i(t) = \Delta_i(t_k) - \Delta_i(t). \tag{9}$$

The consensus error of agent i is:

$$\begin{aligned} \bar{x}_i(t) &= x_i(t) - x_0(t), \\ \bar{v}_i(t) &= v_i(t) - v_0(t). \end{aligned} \tag{10}$$

The control law for agent i is designed as follows:

$$\begin{aligned} u_i(t) = &- k\sum_{j\in\mathcal{N}_i} a_{ij}(x_i(t_k^i) - x_j(t_k^i) + v_i(t_k^i) - v_j(t_k^i)) \\ &+ b_i\frac{1}{\alpha}\left(x_i(t_k^i) - x_0(t_k^i) + v_i(t_k^i) - v_0(t_k^i)\right)^{\alpha} - D\mathrm{sgn}\left(\bar{x}^{\mathrm{T}}(t) + \bar{v}^{\mathrm{T}}(t)\right), \end{aligned} \tag{11}$$

where $k > 0$ is the control gain to be designed, $D\mathrm{sgn}\left(\bar{x}^{\mathrm{T}}(t) + \bar{v}^{\mathrm{T}}(t)\right)$ is the disturbance compensation term, t_k^i is the triggering time of the k-th event of agent i, and the trigger time sequence is $\{t_0^i, t_1^i, \ldots, t_k^i, \ldots\}$.

Define the trigger conditions for the reset event of agent i:

$$\|e_i(t)\|^2 > \left[\frac{2\alpha}{k}\lambda_{\min}k(L + B\otimes I_m) - \frac{2\alpha\omega}{k} - \alpha\,(2\alpha+1)\right]\Omega(t) - 2\alpha(C_1C_2)^2 + \eta_i(t), \tag{12}$$

where $\Omega(t) = \sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2 + \|\bar{v}_i(t)\|^2\right)$, $0 < \alpha < 1$, and $\eta_i(t)$ is a dynamic adjustment function, designed as:

$$\eta_i(\mathrm{t}) = \begin{cases} \eta_i(0), \Omega(t) < \varepsilon \\ \eta_i(0)e^{-\alpha(t-t_k)}, \Omega(t) \ge \varepsilon \end{cases}, \tag{13}$$

where $\beta > 0, \eta_i = 0$, ε is an adjustable parameter that determines when the variable $\eta_i(t)$ will be reset to its initial value, and t_k is the most recent trigger moment. Combined with the error definition, the system equation can be rewritten as:

$$\begin{cases} \dot{\bar{x}}_i(t) = \bar{v}_i(t), \\ \dot{\bar{v}}_i(t) = -ke_i(t) - k\left[\sum\limits_{j\in\mathcal{N}_i} a_{ij}(\bar{x}_i(t) - \bar{x}_j(t) + \bar{v}_i(t) - \bar{v}_j(t)) + b_i\frac{1}{\alpha}(\bar{x}_i(t) + \bar{v}_i(t))^{\alpha}\right] \\ +f\,(t, x_i(t), v_i(t)) - f\,(t, x_0(t), v_0(t)) + d_i(t) - D\mathrm{sgn}(\bar{x}^{\mathrm{T}}(t) + \bar{v}^{\mathrm{T}}(t)). \end{cases} \tag{14}$$

Using the Kronecker inner product, Eq. (14) can be further rewritten as:

$$\begin{aligned}
\dot{\bar{x}}_i(t) =& \bar{v}(t),\\
\dot{\bar{v}}_i(t) =& -ke(t) - k\left[(L\otimes I_m)\left(\bar{x}(t)+\bar{v}(t)\right) + \frac{1}{\alpha}\left(B\otimes I_m\right)\left(\bar{x}_i(t)+\bar{v}_i(t)\right)^{\alpha}\right]\\
&+ F\left(t, x_i(t), v_i(t)\right) - F\left(t, x_0(t), v_0(t)\right) + d_i(t) - D\mathrm{sgn}(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)),
\end{aligned} \tag{15}$$

where

$$\begin{aligned}
\bar{x}(t) &= \left(\bar{x}_1^{\mathrm{T}}(t), \bar{x}_2^{\mathrm{T}}(t), \cdots, \bar{x}_n^{\mathrm{T}}(t)\right)^{\mathrm{T}},\\
\bar{v}(t) &= \left(\bar{v}_1^{\mathrm{T}}(t), \bar{v}_2^{\mathrm{T}}(t), \cdots, \bar{v}_n^{\mathrm{T}}(t)\right)^{\mathrm{T}},\\
e(t) &= \left(e_1^{\mathrm{T}}(t), e_2^{\mathrm{T}}(t), \cdots, e_n^{\mathrm{T}}(t)\right)^{\mathrm{T}},\\
F(t, x_i(t), v_i(t)) &= \left(f(t, x_1(t), v_1(t)), f(t, x_2(t), v_2(t)), \cdots, f(t, x_n(t), v_n(t))\right)^{\mathrm{T}}.
\end{aligned}$$

Theorem 1. *Under Assumptions 1 and 2, consider the MAS described by Eqs* (1) *and* (2). *If the parameter α satisfies the conditions, then:*

$$0 < \alpha < \frac{\lambda_{\min}\left(k(L+B)\otimes I_m\right) - \omega}{k} - \frac{1}{2}. \tag{16}$$

Under the consensus protocol (7) and the reset event-triggered mechanism (10) and (11), the MAS can achieve leader–following consensus.

Proof. Choose the Lyapunov function

$$V(t) = \frac{1}{2}\varepsilon^{\mathrm{T}}(t)P\varepsilon(t), \tag{17}$$

where $\varepsilon(t) = \begin{bmatrix}\bar{x}^{\mathrm{T}}(t) & \bar{v}^{\mathrm{T}}(t)\end{bmatrix}^{\mathrm{T}}$, $P = \begin{bmatrix}2k(L\otimes I_m) & I_n\otimes I_m\\ I_n\otimes I_m & I_n\otimes I_m\end{bmatrix}$.

The derivation of Eq. (17) yields:

$$\begin{aligned}
\dot{V}(t) =& \dot{V}(t) = \varepsilon^{\mathrm{T}}(t)P\dot{\varepsilon}(t)\\
=& \begin{bmatrix}\bar{x}^{\mathrm{T}}(t) & \bar{v}^{\mathrm{T}}(t)\end{bmatrix}\begin{bmatrix}2k(L\otimes I_m + B\otimes I_m) & I_n\otimes I_m\\ I_n\otimes I_m & I_n\otimes I_m\end{bmatrix}\\
&\begin{bmatrix}\bar{v}(t)\\ -ke(t) - k\left[(L\otimes I_m)\left(\bar{x}(t)+\bar{v}(t)\right) + \frac{1}{\alpha}\left(B\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)^{\alpha}\right]\\ + F\left(t, x_i(t), v_i(t)\right) - F\left(t, x_0(t), v_0(t)\right) + d_i(t) - D\mathrm{sgn}(\bar{x}(t)+\bar{v}(t))\end{bmatrix}\\
=& \bar{v}^{\mathrm{T}}(t)\bar{v}(t) + 2k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m + B\otimes I_m\right)\bar{v}(t)\\
&- k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)e(t) - k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(L\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)\\
&- \frac{k}{\alpha}\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(B\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)^{\alpha}\\
&+ \left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(F\left(t, x_i(t), v_i(t)\right) - F\left(t, x_0(t), v_0(t)\right)\right)\\
&+ \left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(d(t) - D\mathrm{sgn}(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right).
\end{aligned} \tag{18}$$

According to Lemma 1, expand the nonlinear terms:

$$\begin{aligned}
&- k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(L\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)\\
&- \frac{k}{\alpha}\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(B\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)^{\alpha}\\
\le& -k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(L\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)\\
&- \frac{k}{\alpha}\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(B\otimes I_m\right)\alpha\left(\bar{x}(t)+\bar{v}(t)\right) + \left[1-\alpha\right]_{m\times 1}\\
=& -k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(L\otimes I_m + B\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)\\
&- k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(B\otimes I_m\right)\left[\frac{1-\alpha}{\alpha}\right]_{m\times 1}.
\end{aligned} \tag{19}$$

Combine the results with similar terms in Eq. (18) and process $-k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)(B\otimes I_m)\left[\frac{1-\alpha}{\alpha}\right]_{m\times 1}$:

$$
\begin{aligned}
&2k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)+\bar{v}^{\mathrm{T}}(t)\bar{v}(t)\\
&-k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left(L\otimes I_m+B\otimes I_m\right)\left(\bar{x}(t)+\bar{v}(t)\right)\\
&=2k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)\\
&-k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)-k\bar{v}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{x}(t)\\
&-k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{x}(t)-k\bar{v}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)+\bar{v}^{\mathrm{T}}(t)\bar{v}(t)\\
&=\bar{v}^{\mathrm{T}}(t)\bar{v}(t)-k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{x}(t)-k\bar{v}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)
\end{aligned}
\tag{20}
$$

$$
-k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)(B\otimes I_m)\left[\frac{1-\alpha}{\alpha}\right]_{m\times 1}\le k\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)\|B\otimes I_m\|\left\|\frac{1-\alpha}{\alpha}\right\|, \tag{21}
$$

where $0<\alpha<1$, $C_1=\left\|\frac{1-\alpha}{\alpha}\right\|$, $C_2=\|B\otimes I_m\|$. Using the variation $ab\le\frac{a^2}{2\epsilon}+\frac{\epsilon b^2}{2}(\epsilon>0)$ of Lemma 1 and taking $\epsilon=\frac{1}{k}$, we get:

$$
\begin{aligned}
k\left(\|\bar{x}_i(t)\|+\|\bar{v}_i(t)\|\right)C_1C_2&\le\frac{1}{2\epsilon}\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+\epsilon(kC_1C_2)^2\\
&\le\frac{k}{2}\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+k(C_1C_2)^2.
\end{aligned}
\tag{22}
$$

Handling $\bar{v}^{\mathrm{T}}(t)\bar{v}(t)-k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{x}(t)-k\bar{v}^{\mathrm{T}}(t)\left(L\otimes I_m+B\otimes I_m\right)\bar{v}(t)$ and according to Lemma 3, we get:

$$
\begin{aligned}
&-\bar{x}^{\mathrm{T}}(L+B)\otimes I_m\bar{x}\le 0,\quad -\bar{v}^{\mathrm{T}}(L+B)\otimes I_m\bar{v}\le 0.\\
&-k\bar{x}^{\mathrm{T}}(L+B)\otimes I_m\bar{x}\le 0,\quad -k\bar{v}^{\mathrm{T}}(L+B)\otimes I_m\bar{v}\le 0.
\end{aligned}
\tag{23}
$$

According to the properties of the eigenvalues of a diagonal matrix, we have

$$
\begin{aligned}
&\bar{v}^{\mathrm{T}}(t)\bar{v}(t)-k\bar{x}^{\mathrm{T}}(t)\left(L\otimes I_m\right)\left(\bar{x}(t)\right)-k\bar{v}^{\mathrm{T}}(t)\left(L\otimes I_m\right)\left(\bar{v}(t)\right)\\
&\le\sum_{i=1}^{n}\|\bar{v}_i(t)\|^2-\lambda_{\min}\left(k\left(L+B\right)\otimes I_m\right)\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)\le 0,
\end{aligned}
\tag{24}
$$

where $\lambda_{\min}(L)$ denotes the smallest non-zero eigenvalue of L.

Based on Assumption 2 and the basic inequality $2xy\le x^2+y^2$, we obtain:

$$
\begin{aligned}
&\left(\bar{x}(t)+\bar{v}(t)\right)\left(F\left(t,x_i(t),v_i(t)\right)-F\left(t,x_0(t),v_0(t)\right)\right)\\
&\le\sum_{i=1}^{n}\left|\bar{x}_i(t)+\bar{v}_i(t)\right|\left[p\left|x_i(t)-x_0(t)\right|+q\left|v_i(t)-v_0(t)\right|\right]\\
&\le\sum_{i=1}^{n}\left|\bar{x}_i(t)+\bar{v}_i(t)\right|\left[p\left|\bar{x}_i(t)\right|+q\left|\bar{v}_i(t)\right|\right]\\
&=\sum_{i=1}^{n}\left[p\|\bar{x}_i(t)\|^2+(p+q)\bar{x}_i(t)\bar{v}_i(t)+q\|\bar{v}_i(t)\|^2\right]\\
&\le\frac{3p+q}{2}\sum_{i=1}^{n}\|\bar{x}_i(t)\|^2+\frac{p+3q}{2}\sum_{i=1}^{n}\|\bar{v}_i(t)\|^2\\
&=\omega_1\sum_{i=1}^{n}\|\bar{x}_i(t)\|^2+\omega_2\sum_{i=1}^{n}\|\bar{v}_i(t)\|^2,
\end{aligned}
\tag{25}
$$

where $\omega_1=\frac{3p+q}{2}$, $\omega_2=\frac{p+3q}{2}$.

Remark 1. Many engineering systems operate within bounded-rate domains, such as robot swarms and unmanned aerial vehicle (UAV) formations constrained by actuator and sensor limits, as well as sensor networks whose state variables (e.g., temperature, voltage) evolve at restricted rates, leading naturally to locally Lipschitz dynamics. As noted in [15], the framework extends to local or piecewise Lipschitz continuity and broader input-to-state stability (ISS)-type conditions.

According to Lemma 2, we have $(\bar{x}(t)+\bar{v}(t))\,(d(t)-D\operatorname{sgn}(\bar{x}(t)+\bar{v}(t)))\le 0$.

To handle the error term $-k\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)e(t)$, Lemma 4 $|xy|\le\frac{\alpha}{2}x^2+\frac{1}{2\alpha}y^2$ is applied, yielding:

$$\begin{aligned}
&-k\sum_{i=1}^{n}\left[\left(\bar{x}_i^{\mathrm{T}}(t)+\bar{v}_i^{\mathrm{T}}(t)\right)e_i(t)\right]\\
&\le\frac{\alpha k}{2}\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+2\|\bar{x}_i(t)\|\,\|\bar{v}_i(t)\|+\|\bar{v}_i(t)\|^2\right)+\frac{k}{2\alpha}\sum_{i=1}^{n}\|e_i(t)\|^2\\
&\le ak\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+\frac{k}{2\alpha}\sum_{i=1}^{n}\|e_i(t)\|^2.
\end{aligned}\tag{26}$$

Therefore,

$$\begin{aligned}
\dot{V}(t)\le&\sum_{i=1}^{n}\|\bar{v}_i(t)\|^2-\lambda_{\min}\left(k(L+B)\otimes I_m\right)\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)\\
&+\frac{k}{2}\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+k(C_1C_2)^2\\
&+\omega_1\sum_{i=1}^{n}\|\bar{x}_i(t)\|^2+\omega_2\sum_{i=1}^{n}\|\bar{v}_i(t)\|^2\\
&+ak\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+\frac{k}{2\alpha}\sum_{i=1}^{n}\|e_i(t)\|^2\\
&+\left(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t)\right)\left[d(t)-D\operatorname{sgn}(\bar{x}^{\mathrm{T}}(t)+\bar{v}^{\mathrm{T}}(t))\right]\\
\le&\left[\alpha k+\omega-\lambda_{\min}\left(k(L+B)\otimes I_m\right)+\frac{k}{2}\right]\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)\\
&+k(C_1C_2)^2+\frac{k}{2\alpha}\sum_{i=1}^{n}\|e_i(t)\|^2,
\end{aligned}\tag{27}$$

where $\omega=\max\{\omega_1,\omega_2+1\}$.

When the parameters satisfy

$$\begin{aligned}
&\alpha k+\omega-\lambda_{\min}\left(k(L+B)\otimes I_m\right)+\frac{k}{2}<0\\
&\sum_{i=1}^{n}\|e_i(t)\|^2\le\left[\frac{2\alpha}{k}\lambda_{\min}(k(L+B\otimes I_m)-\frac{2\alpha\omega}{k}-\alpha\,(2\alpha+1)\right]\\
&\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)-2\alpha(C_1C_2)^2,
\end{aligned}\tag{28}$$

then

$$\begin{aligned}
&\dot{V}(t)\le\frac{k}{2\alpha}\|e_i(t)\|^2-\left[\lambda_{\min}(k(L+B\otimes I_m)-\omega-\alpha k-\frac{k}{2}\right]\\
&\sum_{i=1}^{n}\left(\|\bar{x}_i(t)\|^2+\|\bar{v}_i(t)\|^2\right)+k(C_1C_2)^2\le 0.
\end{aligned}\tag{29}$$

□

The proof of the Zeno phenomenon is provided in the following.

Theorem 2. *Consider the MAS described by Eqs* (1) *and* (2). *If the reset event-triggered condition* (13) *and the condition of Theorem 1 are satisfied, the Zeno phenomenon can be avoided. In this case, there exists a positive minimum trigger interval* $\Delta t_{\min}$ *so that the interval between the two consecutive trigger moments for any agent r satisfies* $t_{k+1}^r - t_k^r \geq \Delta t_{min} > 0$. *The minimum trigger interval* $\Delta t_{\min}$ *is:*

$$\Delta t_{\min} = \tau_r = \sqrt{\frac{\Upsilon_1 - \Upsilon_2 + \eta_{\max}}{\gamma^2}}, \tag{30}$$

where $\Upsilon_1 = \left[\frac{2a}{k}\lambda_{\min}\left(k\left(L+B\right)\otimes I_m\right) - \frac{2a\omega}{k} - \alpha\left(2\alpha+1\right)\right]\Omega_{\max}$, $\Upsilon_2 = 2\alpha(C_1C_2)^2$.

Proof. Assume that the rate of change of the state error is bounded: $\|\dot{\Delta}_i(t)\| \leq \gamma\ (\gamma > 0)$. Integrate the state error and obtain

$$\|e_i(t)\| = \|\Delta_i(t_k) - \Delta_i(t)\| \leq \gamma(t - t_k^i). \tag{31}$$

When the reset event-triggered condition is satisfied, the above equation can be rewritten as follows:

$$\begin{aligned} \gamma^2(t-t_k^i)^2 > &\left[\frac{2a}{k}\lambda_{\min}\left(k\left(L+B\right)\otimes I_m\right) - \frac{2a\omega}{k} - \alpha\left(2\alpha+1\right)\right]\Omega(t) \\ &- 2\alpha(C_1C_2)^2 + \eta_i(t). \end{aligned} \tag{32}$$

According to Theorem 1, the above equation satisfies the system consensus condition, $\Omega(t)$ is bounded, there is $\Omega_{\max} > 0$ such that $\Omega(t) \leq \Omega_{\max}$, and when $\Omega(t) \geq \epsilon$, $\eta_i(t) = e^{-\alpha t} \leq \eta_{\max} = \eta_i(0)$.

Accordingly, there exists at least a minimum event-trigger τ_r for agent r to satisfy

$$\gamma^2{\tau_r}^2 > \left[\frac{2a}{k}\lambda_{\min}\left(k\left(L+B\right)\otimes I_m\right) - \frac{2a\omega}{k} - \alpha\left(2\alpha+1\right)\right]\Omega_{\max} - 2\alpha(C_1C_2)^2 + \eta_{\max}. \tag{33}$$

The minimum trigger interval satisfies

$$\Delta t_r^k > \sqrt{\frac{\Upsilon_1 - \Upsilon_2 + \eta_{\max}}{\gamma^2}} \triangleq \tau_r > 0. \tag{34}$$

The time interval between any two triggering instants satisfies $\Delta t_r^k > \Delta t_{min} > 0$. Therefore, the minimum event-trigger interval is strictly greater than zero, and no Zeno phenomenon occurs.

Remark 2. Unlike traditional dynamic event-triggered mechanisms, which typically require a trade-off between reducing triggering frequency and preserving system-dynamic performance, the proposed reset-based triggering strategy can dynamically adjust the triggering conditions while effectively reducing the number of communications. More importantly, the proposed method achieves a lower triggering frequency without compromising convergence performance, and the Zeno behavior is also effectively avoided.

4. Simulation

This section validates the effectiveness of the proposed reset event-triggered consensus algorithm through simulation experiments. A MAS with one leader and four followers is considered. The system dynamics of the leader and the follower are described by Eqs (1) and (2), respectively, and the communication topology is shown in Fig. 1.

The nonlinearity function and the external disturbance of agent i are $(2v_i(t)) + 0.01x_i(t)$ and $d_i(t) = 0.1\cos x_i(t)$, respectively. From the communications topology of Fig. 1, the Laplacian matrix L, the leader–follower matrix B, and the adjacency matrix A are:

$$L = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & -1 & 1 \end{bmatrix},\quad B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix},\quad A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}.$$

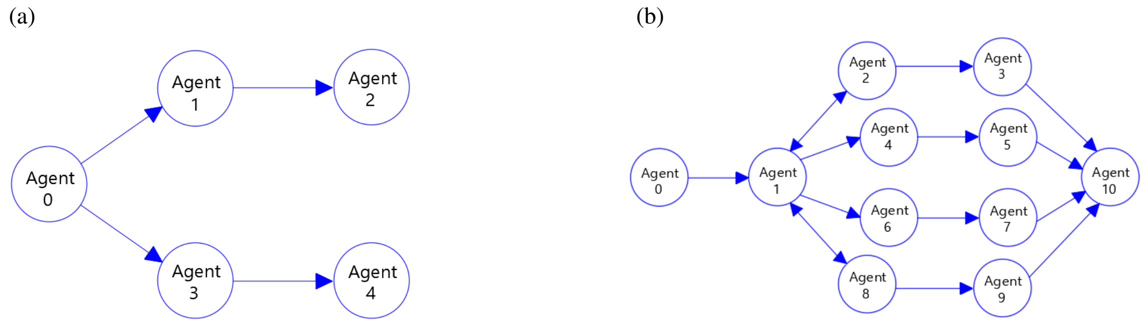

Fig. 1. System communication topology: 5-agent communication topology (a) and 11-agent communication topology (b).

The initial position and speed of the leader agent are set to $x_0(0) = 6$, $v_0(0) = 3$, and $v_0(0) = 3$, respectively. The initial position and speed of the leader agent are set to $x(0) = [-6 \quad 1 \quad 0.5 \quad -3.5]$ and $v(0) = [-5.1 \quad -1 \quad 3.2 \quad 4.5]$. According to the condition (26), choose $\varepsilon = 0.1$, $k = 1$. It can be derived from the Laplacian matrix that $\lambda_{\min}(k(L + B) \otimes I_m) \approx 0.382$. According to Eq. (14), $0 < \alpha < 1.6$. Therefore, we set $\alpha = 1$. The experimental results are shown in Figs 2–6. Figure 2a shows the system state convergence curves, and Fig. 2b presents the control inputs and triggering moments for $\eta_i(0) = 0$. Under the action of the controller (7), the speed and position of the agent gradually converge to a uniform state. Figure 2b shows the corresponding triggering moments, where agents 1–4 triggered 1053, 918, 753, and 1588 times, respectively.

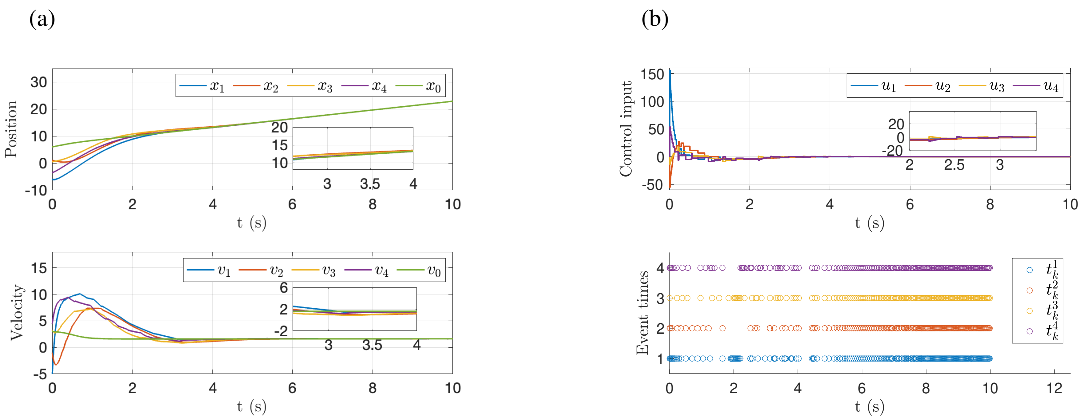

Fig. 2. Performance of 5 agents under static event-triggered control (SETC): system state convergence curves (a), control inputs $u_i(t)$ and triggering moments t_k (b).

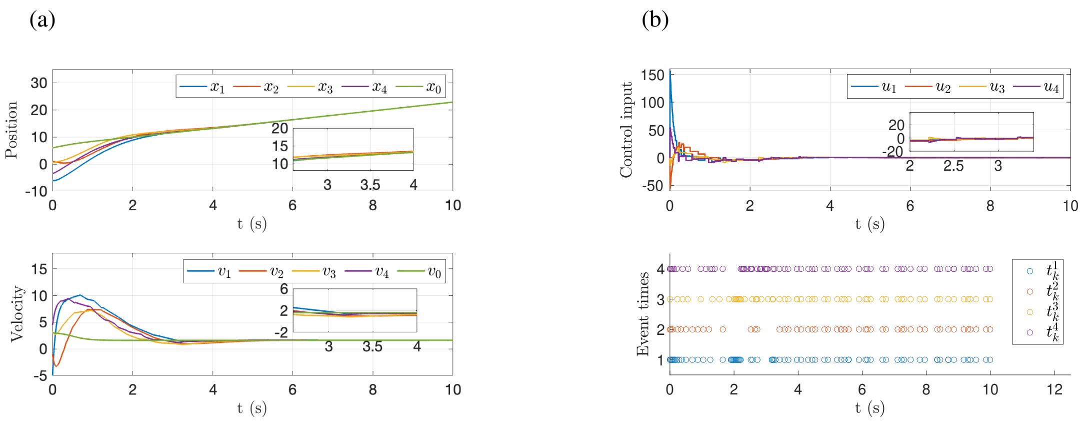

Fig. 3. Performance of 5 agents under reset event-triggered control (RETC): system state convergence curves (a), control inputs $u_i(t)$ and triggering moments t_k (b).

Let $\eta_i(0) = 0.01$, while keeping all other control parameters unchanged. The experimental results are presented in Fig. 3a,b. It can be observed that the number of triggering events is significantly reduced without compromising the original control performance. Specifically, agents 1–4 triggered 438, 180, 279, and 508 times, respectively.

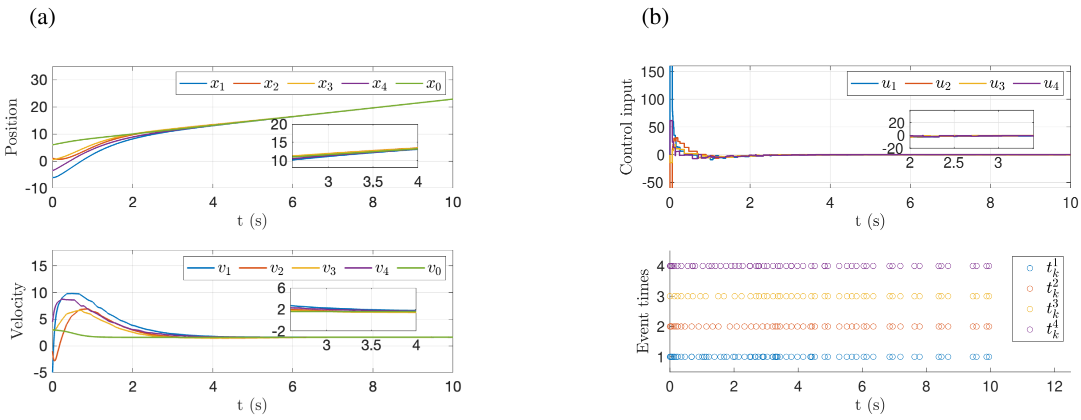

Fig. 4. Performance of 5 agents under RETC: system state convergence curves (a), control inputs $u_i(t)$ and triggering moments t_k (b).

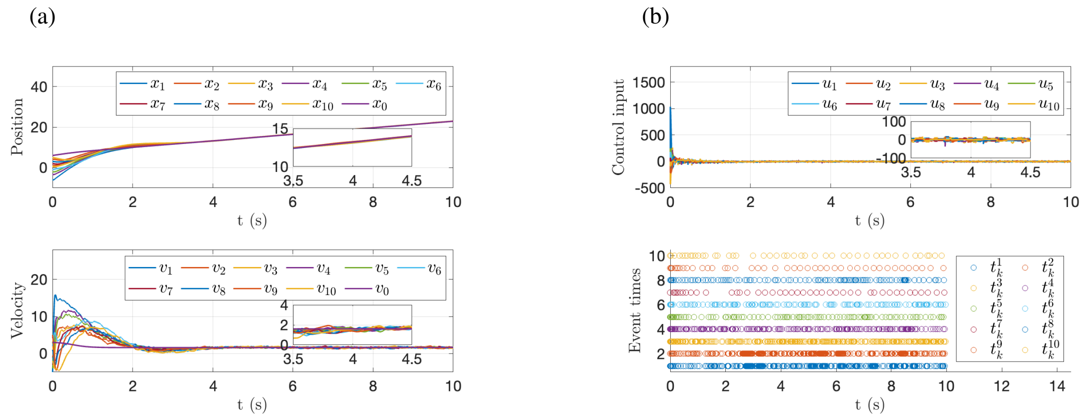

Fig. 5. Performance of 11 agents under SETC: system state convergence curves (a), control inputs $u_i(t)$ and triggering moments t_k (b).

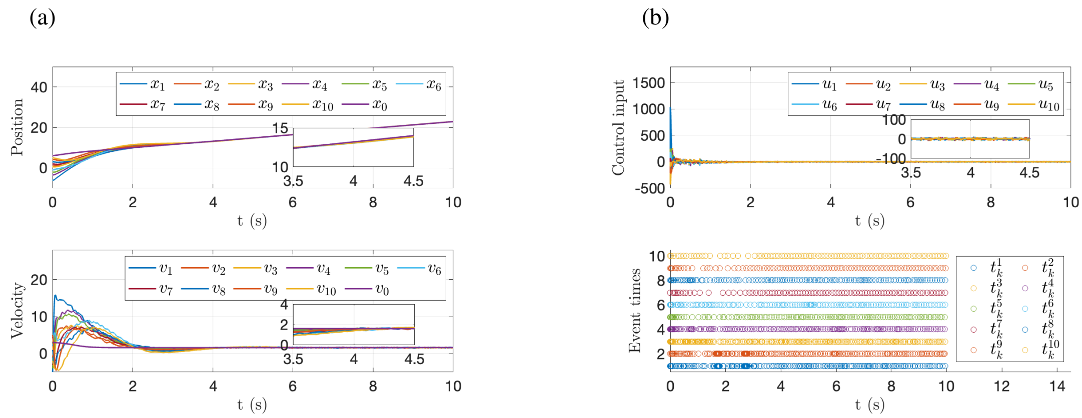

Fig. 6. Performance of 11 agents under RETC: system state convergence curves (a), control inputs $u_i(t)$ and triggering moments t_k (b).

Table 1 compares the distinction in the number of triggers between the proposed method and the general method in detail. Specifically, RETC represents the method proposed in this paper, while SETC denotes the conventional triggering approach without dynamic reset strategies. Figure 4b shows that the proposed method has a significant effect on reducing the number of triggers after the system state converges. When $\eta_i(0) = 0$, agents 1–4 trigger 670, 788, 546, and 1272 times, respectively, during 5–10 s. When $\eta_i(0) = 0.01$, the numbers are 207, 68, 80, and 244, respectively.

Table 1. Comparison of the number of triggers between RETC and SETC for 5 agents. Only follower agents are counted; the leader does not trigger events

Agent	1	2	3	4	Total
RETC	438	180	279	508	1405
SETC	1053	918	753	1588	4312

Table 2. Comparison of the number of triggers between RETC and SETC for 11 agents. Only follower agents are counted; the leader does not trigger events

Agent	1	2	3	4	5	6	7	8	9	10	Total
RETC	358	341	398	227	125	162	85	157	94	85	2032
SETC	1266	1219	959	525	146	318	43	186	48	45	4755

By using the reset event-triggering strategy proposed in this paper, the number of triggering decreases by 19.6% in the period of 0–5 s, 82.2% in the period of 5–10 s, and 67.4% in the whole period.

The issue of frequent triggering of event-triggering laws in the later stage of system convergence has been resolved. The occupation of communication resources has been greatly reduced. This is very important in large-scale clusters and complex environments.

After that, take $\alpha = 11/7$. The experimental results are shown in Fig. 4. With the increase of α, the convergence speed of the system is accelerated. At the same time, it can be seen from the triggering moments that the agents' triggering moments are asynchronous. The effectiveness of the distributed event-triggered mechanism has been verified.

Similarly, the simulation for the 11-agent topology is conducted under both SETC and RETC. The results presented in Figs 5 and 6 show that the proposed reset event-triggered mechanism significantly reduces the number of triggers, effectively minimizing communication overhead. The detailed comparison for 11 agents is provided in Table 2.

5. Conclusion

The consensus problem of second-order nonlinear multi-agent systems (MASs) under directed topology is investigated based on a reset event-triggered mechanism. A hybrid control strategy combining dynamic event triggering and reset control is introduced, where the event-triggering conditions and the initial values of external dynamic variables are constructed from the state information of each agent and its neighbors at the triggering instants. By tuning the interaction strength parameters of the system, it is determined when the dynamic variables should be reset to their initial values, thereby effectively reducing the triggering frequency as the system approaches consensus. The asymptotic stability of the closed-loop system and the exclusion of the Zeno behavior are rigorously established using the Lyapunov stability theory. Numerical simulations under external disturbances are conducted, with comparisons to the event-triggered methods in [5] and [6]. The results confirm the effectiveness of the proposed reset event-triggered mechanism and demonstrate its superiority in reducing communication burden.

Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Acknowledgments

This work was supported by the National Natural Science Foundation of China under grant No. 62103057. The publication costs of this article were partially covered by the Estonian Academy of Sciences.

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Jaotatud konsensus teist järku multiagent-süsteemide jaoks lähtestusega sündmuspõhise mehhanismi baasil

Yi Cheng ja Xingjian Fu

Uuritud on teist järku mittelineaarsete multiagent-süsteemide konsensusprobleemi suunatud topoloogia korral, tuginedes lähtestusega sündmuspõhisele mehhanismile. Kasutusele on võetud hübriidne juhtimisstrateegia, mis ühendab dünaamilise sündmuspõhise käivitamise ja lähtestusjuhtimise. Sündmuste käivitamise tingimused ja väliste dünaamiliste muutujate algväärtused konstrueeritakse iga agendi ja tema naabrite seisunditeabe põhjal käivitamishetkedel. Süsteemi interaktsioonitugevuse parameetrite konfigureerimisega määratakse kindlaks, millal dünaamilised muutujad tuleks lähtestada algväärtustega, vähendades seeläbi käivitamissagedust süsteemi konsensuse poole liikumisel. Ljapunovi stabiilsusteooria abil on rangelt tõestatud suletud ahelaga süsteemi asümptootiline stabiilsus ning Zeno-käitumise välistamine. Läbi on viidud numbrilised simulatsioonid väliste häiringute korral ning tulemusi on võrreldud töödes [5] ja [6] esitatud sündmuspõhiste meetoditega. Tulemused kinnitavad pakutud lähtestusega sündmuspõhise mehhanismi tõhusust ja näitavad selle eeliseid kommunikatsioonikoormuse vähendamisel.