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The event-based consensus of multi-agent networks with control gain in normal distribution

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Abstract: This paper addresses the event-triggered consensus in mean square of multi-agent systems (MASs) with the control gains in normal distributions. For each involved agent, the controller is updated only at event instants, i.e, the time of the triggering condition is satisfied. Based on stability theory and event-triggered control method, a sufficient condition of the mean square consensus for MASs is established, where the control gains of agents are no need to be set as some constants any more. This leads the criterion to being less conservativeness. Finally, a numerical simulation is given to illustrate the consensus criterion.

Key Words: event-triggered control, mean square consensus, multi-agent systems, normal distributions.

1 Introduction

The past decades have witnessed the rapid development of multi-agent systems (MASs) as its widely applications in many fields, such as flocking of agent networks, sensor network, cooperative control of UAV, and so forth [1–3]. In the field of complex systems, consensus of MASs is forming an research hotspots [4, 5, 12].

On the one hand, as we known, agents are usually equipped with digital microprocessor for some practical reasons, which indicates that these agents only have limited handling capacity for information, computation, and communication. On the other hand, the consumption of resources in communication is enormous when agents work. However, the resources equipped for each agent is limited, especially in battery-powered systems. The traditional control schemes based on time-triggered sampling are difficult to meet the requirement, i.e., agents should save resources as much as possible while they complete the tasks. Thus, regarding the consensus of MASs, it is very important that designing a communication and control strategy such that the involved agents will reach an agreement with less consumption as time goes on. Event-triggered control approach provides a new idea for us to solve the consensus problems of MASs, and rich research results have been achieved based on stability theory [6–11]. The mean square consensus for delay MASs by the event-triggered scheme was discussed in [7], and an intermittent control algorithm based on the double event-triggered scheme was presented in [8]. Xu et. al. discussed the clustered event-based consensus of MASs under a impulsive framework in [9]. Wei et. al. designed the control strategy for MASs based on the edge event-triggered method [11]. These methods have reduced the communication consumption of agent networks successfully, which improved the efficiency of resource utilization. However, the most aforementioned discussed models are too ideal. This leads a long way to go before the corresponding event-triggered schemes can be applied in practice.

Actually, when an agent moves in practical environment, it disturbed by noise is avoidless [7, 12]. Therefore, consensus problems of MASs with random disturbance are more usefully in application, and they have aroused interests of many scholars. In our previous work [7], some consensus criteria in mean square for delay agent networks were obtained. Xu et. al. studied the case of stochastic MASs over fading networks with directed graphs [12]. It should be pointed out that the sampling frequency may be increased due to the random factor, which leads to more consumption on resource and energy. Thus, it is necessary to design more effective trigger strategies for MASs with different random disturbance, which also is so challenging such that only a few results has been reported up to now.

Motivated by all above-mentioned discussion, this paper aims to present a distributed event-based control algorithm for handling the mean square consensus of MASs with control gain obeying the normal distributions. The main contributions of this paper are shown as follows:

i) The case of MASs with control gain in normal distributions has been investigated for the first time, and the model is more accordant with practical circumstances.

ii) Based on the event-driven control approach and the stability theory, a consensus criterion in mean square for MASs with control gain in normal distributions is established, which has greater potential than previous schemes in terms of application.

This paper is organized as follows. Some preliminaries on algebraic graph theory are recalled, a class of linear multi-agent model with control gains obeying some normal distributions is described, and a mean square consensus definition, an assumption and two lemmas are introduced in Section 2. Section 3 presents the main results of the paper. A numerical example is given in Section 4, which is utilized to illustrate the effectiveness of the presented control algorithm. This

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paper is concluded in Section 5.

Some notations are given before closing the section. The mathematical expectation and variance operators are represented by $\mathbb{E}(\cdot)$ and $\mathbb{D}(\cdot)$, respectively. Suppose that $\lambda_{\max}(Q)$ ($\lambda_{\min}(Q)$) stands for the maximal (minimal) eigenvalue of matrix Q, and $\|x\|$ means the vector norm of vector x. Let $\mathbb{R}^n$ and $\mathbb{R}^{n\times m}$ denote the sets of n-dimensional real vectors and $n \times m$ real matrices, respectively.

2 Problem formulation and preliminaries

Consider the multi-agent systems (MASs) with N agents as follows:

$$\dot{x}_i(t) = Ax_i(t) + Bu_i(t), \tag{1}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times m}$. Let $x_i(t) \in \mathbb{R}^n$ and $u_i(t) \in \mathbb{R}^m$ denote the state and input of agent i ($i = 1, 2, \cdots, N$), respectively.

Suppose that the communication topology of agent systems $\mathscr{G} = (\mathscr{V}, \mathscr{E}, \Pi)$ is a directed digraph, where $\mathscr{V} = \{0, 1, \cdots, N\}$ and $\mathscr{E} \subseteq \mathscr{V} \times \mathscr{V}$ stand for the node set and the edge set of the agent networks, respectively. If agent j is a neighbor of agent i, there exists an directed edge $\bar{e}_{ij} \in \mathscr{E}$ of $\mathscr{G}$ from j to i, which is denoted by the ordered pair of node (j, i). The set of neighbors of agent i is $\mathscr{N}_i = \{j \in \mathscr{V} |\ \bar{e}_{ij} \in \mathscr{E}\}$. Let $\Pi = (\pi_{ij})_{N\times N}$ stand for the adjacency matrix of the networks, where π_{ij} means the weight of edge $\bar{e}_{ij}$. $\pi_{ij} > 0$ if and only if $\bar{e}_{ij} \in \mathscr{E}$, otherwise, $\pi_{ij} = 0$. In addition, $D = \mathrm{diag}\{d_1, d_2, \cdots, d_n\}$ is the degree matrix, where $d_i = \sum_{j\in\mathscr{N}_i} \pi_{ij}$. Let $L = \Pi - D$ be the Laplacian, and it can be rewritten as $L = \begin{pmatrix} -d_1 & \hat{L}_1 \\ \tilde{L}_1 & L_2 \end{pmatrix}$ where $\hat{L}_1 = [\pi_{12}, \pi_{13}, \cdots, \pi_{1N}]$, $\tilde{L}_1 = [\pi_{21}, \pi_{31}, \cdots, \pi_{N1}]^T$, and $L_2 = [L_{22}^T, L_{23}^T, \cdots, L_{2N}^T]^T$, and $L_{2i} = \big(\pi_{i2}, \cdots, -\sum_{j=1, j\neq i}^{N} \pi_{ij}, \cdots, \pi_{iN}\big), i = 2, 3, \cdots, N.$

Assume that

$$u_i(t) = K\rho_i(t_k^i), t \in [t_k^i, t_{k+1}^i) \tag{2}$$

where $K = (k_{ij})_{m\times n} \in \mathbb{R}^{m\times n}$ is the control gain matrix, in which the elements of K obey some normal distributions, i.e., $k_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma_{ij})$. For any pair (k_{ij}, k_{lk}) $(i \neq l)$, both elements k_{ij} and k_{lk} are independent of each other. In this paper, we consider the case of control gain in normal distributions due to the noise is unavoidable in physics environment, and the noise obeying normal distribution is the most common case.

$$\rho_i(t) = \sum_{j\in\mathscr{N}_i} \pi_{ij} \left(x_j(t) - x_i(t)\right). \tag{3}$$

Let $\{t_k^i\}$ stand for the triggering instants sequence of agent i, where instant $t_{k=1}^i$ is generated by

$$t_{k+1}^i = \inf\big\{t : t > t_k^i, f_i(t) \geq 0\big\}. \tag{4}$$

The trigger function of agent i is defined as

$$f_i(t) = \| e_i(t) \|^2 - \frac{\beta}{2} \| \rho_i(t_k^i) \|^2 - \eta\theta^{-\lambda t}, \tag{5}$$

where $1 > \beta > 0$, $\eta > 0$, $\theta > 0$, $\lambda > 0$ and $e_i(t) = \rho_i(t) - \rho_i(t_k^i)$. Agent i can receive the state information from its neighbors at t_k^i, and then $e_i(t)$ is reset to 0.

Let $\zeta_i(t) = x_i(t) - x_1(t)$, $\zeta(t) = [\zeta_2^T(t), \zeta_3^T(t), \cdots, \zeta_N^T(t)]^T$, $e(t) = [e_2^T(t), e_3^T(t), \cdots, e_N^T(t)]^T$, and $\hat{e}_1(t) = [e_1^T(t), e_1^T(t), \cdots, e_1^T(t)]^T$, and $\mathbf{1}_{N-1} = \underbrace{[1, 1, \cdots, 1]}_{N-1}$.

According to formula (1) and (2), one has

$$\begin{aligned} \dot{\zeta}(t) =& [I_{N-1} \otimes A + (L_2 - \mathbf{1}_{N-1}^T\hat{L}_1) \otimes BK]\zeta(t) \\ & - I_{N-1} \otimes BKe(t) \\ & + I_{N-1} \otimes BK\hat{e}_1(t), t \in [t_0, +\infty) \end{aligned} \tag{6}$$

For follow-up analysis, the following definition, assumptions and lemmas are introduced as below.

Definition 1 *The event-based consensus in mean square of MASs (1) is achieved if* $\lim_{t\to\infty} \mathbb{E}(\|x_i(t) - x_1(t)\|^2) = 0$, *for any agent i with any initial conditions holds.*

Assumption 1
1) A directed spanning tree with the any agent as the root in the communication topology of the agent networks can be found.
2) State feedback stochastic system (1) is stabilizable.

Assumption 2
1) For the K of (2), suppose that there exists a constant matrix $\breve{K}$ such that $\mathbb{E}\big[\zeta^T(t)K\zeta(t)\big] \leq \mathbb{E}\big[\zeta^T(t)\breve{K}\zeta(t)\big]$.

Lemma 1 *(**Gronwell Inequality**) For any $t \in [t_0, +\infty)$, suppose that the nonnegative and continuous function $G(t)$ satisfies the inequality*

$$G(t) < \mathcal{N} + \int_{t_0}^{t} \alpha G(s)\mathrm{d}s,$$

where α and $\mathcal{N}$ are a constant and a nonnegative constant, respectively. Then

$$G(t) \leq \mathcal{N}e^{\alpha(t-t_0)}, t \in [t_0, +\infty).$$

3 Main results

In this section, the event-based consensus of multi-agent networks (1) with control gain obeying the normal distributions are considered, and a mean square consensus condition is presented as follows.

Theorem 1 *Under the Assumptions 1) and 2), consider the agent networks (1) with the control scheme (2) and (4). For any $\beta \in (0, 1)$, $\eta > 0$, $\theta > 1$, if there are a constant α ($\alpha > 0$) and positive definite matrixes P, $\bar{K}$, $\hat{K}$, such that*

$$\begin{aligned} \Theta + & 2\lambda_{\max}(B^TB)P(I_{N-1} \otimes \hat{K})P \\ & + \frac{\beta}{1-\beta}L_2^TL_2 \otimes I_n + \frac{\beta}{1-\beta}\hat{L}_1^T\hat{L}_1 \otimes I_n \leq 0, \end{aligned} \tag{7}$$

where

$$\begin{aligned} \Theta =& (I_{N-1} \otimes A + (L_2 - \mathbf{1}_{N-1}^T\hat{L}_1) \otimes B\bar{K})^TP \\ & + P(I_{N-1} \otimes A + (L_2 - \mathbf{1}_{N-1}^T\hat{L}_1) \otimes B\bar{K}) \\ & + \alpha I_{N-1} \otimes I_n. \end{aligned}$$

Then, the event-based consensus in mean square can be realized, and there is no Zeno-behavior in the closed-loop system.

Proof: Construct the Lyapunov function as below

$$V(t)=\zeta^T(t)P\zeta(t),t\geq t_0 \tag{8}$$

where P is a positive definite matrix.

We have

$$\begin{aligned}\dot{V}(t)|_{(6)}=&\dot{\zeta}^T(t)P\zeta(t)+\zeta^T(t)P\dot{\zeta}(t)\\=&\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\zeta(t)\\&+I_{N-1}\otimes BK\hat{e}_1(t)-I_{N-1}\otimes BKe(t)\}^TP\zeta(t)\\&+\zeta^T(t)P\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\zeta(t)\\&-I_{N-1}\otimes BKe(t)+I_{N-1}\otimes BK\hat{e}_1(t)\}\\\leq&\zeta^T(t)\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]^TP\\&+P[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\\&+2P(I_{N-1}\otimes BK)^T(I_{N-1}\otimes BK)P\}\zeta(t)\\&+e^T(t)e(t)+\hat{e}_1^T(t)\hat{e}_1(t)\end{aligned} \tag{9}$$

The triggering condition enforces that

$$\begin{aligned}\|e_i(t)\|^2\leq&\frac{\beta}{2}\parallel\rho_i(t_k^i)\parallel^2+\eta\theta^{-\lambda t}\\\leq&\frac{\beta}{2}\|\rho_i(t)-e_i(t)\|^2+\eta\theta^{-\lambda t}\\\leq&\beta\left(\|\rho_i(t)\|^2+\|e_i(t)\|^2\right)+\eta\theta^{-\lambda t}.\end{aligned} \tag{10}$$

Depending on formula (3), we obtain

$$\begin{aligned}\rho_1(t)=&\big(\pi_{12},\pi_{13},\cdots,\pi_{1N}\big)\zeta(t)\\=&\hat{L}_1\otimes I_n\zeta(t),\\\rho_i(t)=&\big(\pi_{i2},\cdots,-\sum_{\substack{j=1,\\j\neq i}}^{N}\pi_{ij},\cdots,\pi_{iN}\big)\zeta(t)\\=&L_{2i}\otimes I_n\zeta(t),i=2,3,\cdots,N.\end{aligned}$$

Therefore

$$\|\rho(t)\|^2=\zeta^T(t)L_2^TL_2\otimes I_n\zeta(t).$$

Then

$$\|\hat{e}_1(t)\|^2<\frac{\beta}{1-\beta}\zeta^T(t)\hat{L}_1^T\hat{L}_1\otimes I_n\zeta(t)+\frac{(N-1)\eta}{1-\beta}\theta^{-\lambda t}.$$

$$\|e(t)\|^2<\frac{\beta}{1-\beta}\zeta^T(t)L_2^TL_2\otimes I_n\zeta(t)+\frac{(N-1)\eta}{1-\beta}\theta^{-\lambda t}.$$

Hence

$$\begin{aligned}&\dot{V}(t)|_{(6)}\\\leq&\zeta^T(t)\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]^TP\\&+P[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\\&+2\lambda_{\max}(B^TB)P(I_{N-1}\otimes K^TK)P\\&+\frac{\beta}{1-\beta}L_2^TL_2\otimes I_n+\frac{\beta}{1-\beta}\zeta^T(t)\hat{L}_1^T\hat{L}_1\otimes I_n\}\zeta(t)\\&+\frac{2(N-1)\eta}{1-\beta}\theta^{-\lambda t}.\end{aligned} \tag{11}$$

Taking the integration and mathematical expectation for the formula, one has

$$\begin{aligned}&\mathbb{E}(V(t))-\mathbb{E}(V(t_0))\\\leq&\mathbb{E}\int_{t_0}^{t}\zeta^T(s)\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]^TP\\&+P[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\\&+2\lambda_{\max}(B^TB)P(I_{N-1}\otimes K^TK)P\\&+\frac{\beta}{1-\beta}L_2^TL_2\otimes I_n+\frac{\beta}{1-\beta}\hat{L}_1^T\hat{L}_1\otimes I_n\}\zeta(s)\mathrm{d}s.\end{aligned}$$

Based on the Assumption 2, we can find the constant matrixes $\bar{K}$ and $\hat{K}$, such that $\mathbb{E}\big\{\zeta^T(s)[((L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK)^TP+P(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes BK]\zeta(s))\big\}\leq\mathbb{E}\big\{\zeta^T(s)[((L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes B\bar{K})^TP+P(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes B\bar{K}]\zeta(s))\big\}$ and $\mathbb{E}\big\{\zeta^T(s)[2\lambda_{\max}(B^TB)P(I_{N-1}\otimes K^TK)P]\zeta(s))\big\}\leq\mathbb{E}\big\{\zeta^T(s)[2\lambda_{\max}(B^TB)P(I_{N-1}\otimes\hat{K})P]\zeta(s))\big\}$. Thus, one has

$$\begin{aligned}&\mathbb{E}(V(t))-\mathbb{E}(V(t_0))\\\leq&\mathbb{E}\int_{t_0}^{t}\zeta^T(s)\{[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes B\bar{K}]^TP\\&+P[I_{N-1}\otimes A+(L_2-\mathbf{1}_{N-1}^T\hat{L}_1)\otimes B\bar{K}]\\&+2\lambda_{\max}(B^TB)P(I_{N-1}\otimes\hat{K})P\\&+\frac{\beta}{1-\beta}L_2^TL_2\otimes I_n+\frac{\beta}{1-\beta}\hat{L}_1^T\hat{L}_1\otimes I_n\}\zeta(s)\mathrm{d}s\\&+\frac{2(N-1)\eta}{1-\beta}\int_{t_0}^{t}\theta^{-\lambda s}\mathrm{d}s.\end{aligned} \tag{12}$$

According to (7), we have

$$\begin{aligned}\mathbb{E}(\|\zeta(t)\|^2)\leq&\frac{1}{\lambda_{\min}(P)}\mathbb{E}[\zeta^T(t_0)P\zeta(t_0)]\\&+\frac{1}{\lambda_{\min}(P)}\int_{t_0}^{t}(-\alpha\mathbb{E}\|\zeta(t)\|^2)\mathrm{d}s\\&+\frac{2(N-1)\eta}{\lambda_{\min}(P)(1-\beta)}\int_{t_0}^{t}\theta^{-\lambda s}\mathrm{d}s\\\leq&\frac{1}{\lambda_{\min}(P)}\mathbb{E}[\zeta^T(t_0)P\zeta(t_0)]\\&+\frac{1}{\lambda_{\min}(P)}\int_{t_0}^{t}(-\alpha\mathbb{E}(\|\zeta(s)\|^2))\mathrm{d}s\\&+\frac{2(N-1)\eta}{\lambda_{\min}(P)(1-\beta)\ln(\theta)}\theta^{-\lambda(t-t_0)}\\\leq&\frac{1}{\lambda_{\min}(P)}\{\mathbb{E}[V(t_0)]+\frac{2(N-1)\eta}{(1-\beta)\ln(\theta)}\}\\&+\frac{1}{\lambda_{\min}(P)}\int_{t_0}^{t}(-\alpha\mathbb{E}(\|\zeta(s)\|^2))\mathrm{d}s.\end{aligned}$$

Applying the Gronwell inequality to the above formula yields, we obtain that

$$\mathbb{E}(\|\zeta(t)\|^2)\leq\mathcal{M}\exp\left(-\frac{\alpha}{\lambda_{\min}(P)}(t-t_0)\right),t\in[t_0,+\infty)$$

where $\mathcal{M} = \frac{1}{\lambda_{\min}(P)}\{\mathbb{E}[V(t_0)] + \frac{2(N-1)\eta}{(1-\beta)\ln(\theta)}\}$. Then the event-based consensus in mean square of MASs is realized with exponential convergence rate. Furthermore, the proof of the excluding the Zeno-behavior is similar with our previous works [7]. Thus, it is omitted here. The proof of Theorem 1 is completed. ■

4 Numerical simulation

In this section, a numerical example is introduced to illustrate the effectiveness of the theoretical results. Suppose that there are five agents in the agent networks, and the corresponding adjacency matrix of the networks is listed as follows

$$\Pi = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix}.$$

Assume that

$$A = \begin{bmatrix} 0.03 & 1.5 & 0 \\ -1.5 & 0.01 & 0 \\ -1.4 & 0 & -3 \end{bmatrix}, \quad B = \begin{bmatrix} 1.5 \\ 2 \\ 1 \end{bmatrix}.$$

Let $x_i(t_0) = i \times [1\ 2\ 3]', i = 1, 2, \cdots, 5$. The parameters of the event-triggered function are $\beta = 0.006$, $\eta = 0.03$, $\theta = 2.1$, $\lambda = 0.5$, respectively. By the formula (7), the consensus in mean square for the agent systems is achieved when $k_{11} \sim \mathcal{N}(0.4844, 0.1)$, $k_{12} \sim \mathcal{N}(0.5438, 0.2)$, $k_{13} \sim \mathcal{N}(0.5813, 0.15)$. The simulation results of the presented algorithm are depicted in Fig. 2 - Fig. 5.

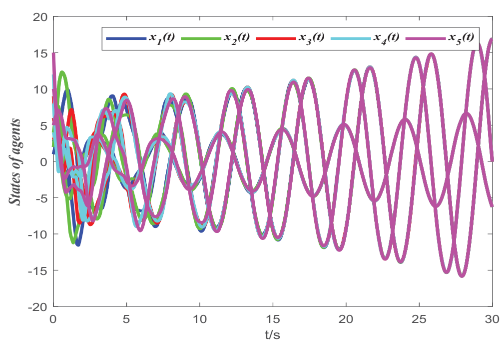

Fig. 1: The states of agents.

Fig. 1 is the states evolution of agents, and Fig. 2 represents the state errors between agent 1 and agent i ($i = 2, 3, \cdots, 5$). The control input is shown in Fig. 3. Fig. 4 denotes the control gains which obey some normal distributions. The trigging error and threshold evolution of agent 1 is given in Fig. 5. The simulation depicts that the event-based consensus in mean square of agent networks has realized while the agents with the control gains obeying some normal distributions. It is should be pointed that the control gains need not to be set as some fixed constants any more. The values of the gains degenerate into random values in some normal distributions. Hence, the presented method has great advantages in reducing the conservativeness of the multi-agent systems.

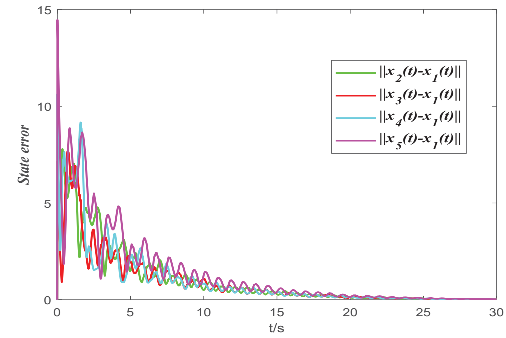

Fig. 2: The state errors between agent i and agent 1.

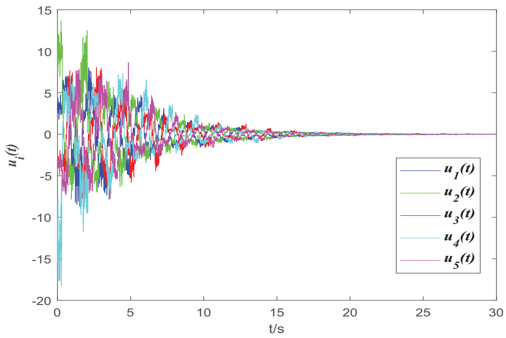

Fig. 3: The control input of agents.

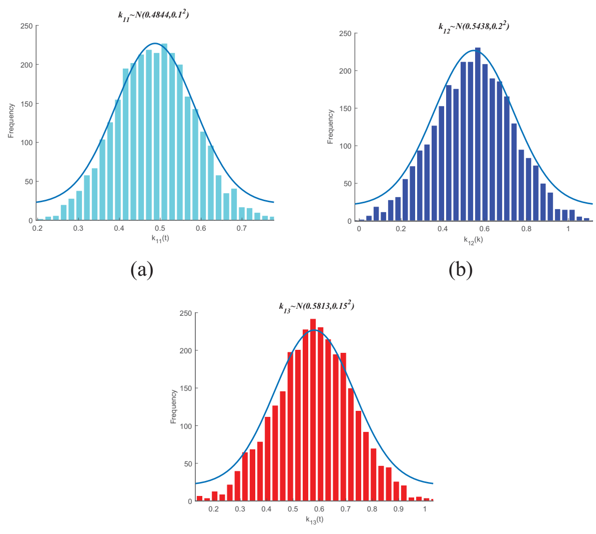

Fig. 4: The control gains of agents.

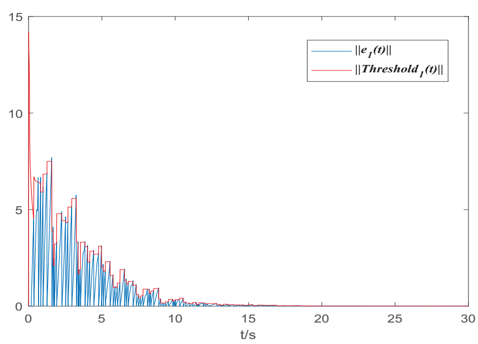

Fig. 5: The triggering error and the threshold of agent 1.

5 Conclusions

This paper investigated a class of general linear multi-agent systems with the control gains obeying some normal distributions. A distributed event-triggered control algorithm is proposed to realize the mean square consensus of MASs. A consensus criterion for the agents with the control gain in normal distributions is derived. Different with previous reports, this paper discussed the case of MASs with control gain in normal distributions for the first time. The corresponding consensus condition allows that the values of the control gains degenerate into the random values in some specific normal distributions, and the effectiveness of the presented algorithm is illustrated by a simulation example. Obviously, the consensus criterion is helpful for the practical applications of agent networks in which the controllers are disturbed by some stochastic factors.

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