Hindawi
Journal of Control Science and Engineering
Volume 2018, Article ID 2572846, 10 pages
https://doi.org/10.1155/2018/2572846

Research Article

Event-Triggered H_∞ Filtering for Multiagent Systems with Markovian Switching Topologies

Jiahao Li, Tingting Zhang, Jinfeng Gao, and Ping Wu

Faculty of Mechanical Engineering and Automation, Zhejiang Sci-Tech University, Hangzhou 310018, China

Correspondence should be addressed to Jinfeng Gao; gaojf163@163.com

Received 11 May 2018; Revised 1 July 2018; Accepted 12 July 2018; Published 14 August 2018

Academic Editor: Cui-Qin Ma

This paper is concerned with the problem of event-triggered H_∞ filtering for multiagent systems with Markovian switching topologies and network-induced delay. An event-triggered mechanism is given to ease the information transmission. Consider that the network topology is directed in this paper, which represents the communication links among agents. Due to the existence of network-induced delay, the time-delay approach is adopted, which can effectively deal with filtering error system. By constructing a Lyapunov-Krasovskii functional and employing linear matrix inequality technique, sufficient conditions are established to ensure the filtering error system to achieve asymptotically stable with H_∞ performance index. A simulation example is given to illustrate the effectiveness of the proposed method.

1. Introduction

Recently, multiagent systems (MASs) have received much interest due to their widespread applications in various fields such as formation control [1, 2], sensor network [3], synchronization [4], and flocking [5, 6]. Due to the fact that communication networks consist of lots of agents, their states are usually not fully available in network outputs. Hence, filtering or state estimation problem is to estimate the states of the agent by the available output measurement, which is very important both in theory and in practice. In the past decades, the consensus-based filtering or estimation problem for a special multiagent system, i.e., the multi-sensor networked system, has received much attention. For example, Kalman filters are the filters primarily proposed in [7, 8] for multi-sensor networked systems, while H_∞ filters are given in [9] for sensor networks with multiple missing measurements. In most existing literatures, the study of multiagent systems has been investigated in the ideal situation without considering external interference. However, in practical engineering, the existence of external disturbances cannot be ignored, which may have a great impact on agent dynamics. Furthermore, the research history of multiagent systems on H_∞ filtering or state estimation is very short; there are many problems which need to be studied extensively. Thus, it is necessary to study the H_∞ filtering problem of multiagent systems with many practical factors.

The exchange of information between agents on a communication network is usually completed on the basis of sampled packets. Many articles have presented more and more methods based on rapid development of the theory of sampling data systems. In the early results, time-triggered communication is a common way to transfer every sampled signal to the controller and update control signal periodically, which wastes a lot of network bandwidth resources and increases network load. Compared with the widely used time-triggered sampling scheme [10–13], event-triggered communication schemes [14–16] can avoid the unnecessary transmission and reduce the release times of the sensor and the burden of communication network. Event-triggered filtering/estimation for different systems has received considerable attention in the past few years [17–22]. Paper [17] addresses event-triggered state estimation problem for a class of complex networks with mixed time delays and [20] presents H_∞ filter design for a class of neural network systems with quantization. The filtering problem for discrete-time networked control system (NCS) under event-triggered scheme is proposed in [18, 19, 21]. Paper [22] designs the H_∞

fuzzy filter for a class of nonlinear networked control system based on event-triggered communication scheme.

In the real world, because of the uncertainty of the network, the communication topology may change. Hence, it is significant to design a filtering network with time-varying and switching topology to estimate or monitor a target; see [23–28]. Event-based H_∞ filtering for discrete-time and continue-time Markov jump system with network-induced delay is investigated in [23, 24], respectively. Paper [25, 26] addresses asynchronous $l_2 - l_\infty$ filtering with sensor nonlinearity and delay-dependent robust H_∞ control and filtering with parameter uncertainties, respectively. Paper [27] investigates the problem of H_∞ estimation for a class of discrete-time Markov jump systems with time-varying transition probabilities. The problem of distributed state estimation about vehicle formation with time-varying measurement topology is discussed in [28]. To the best of our knowledge, there is no article that considers H_∞ filtering problem for multiagent systems with Markovian switching topologies and network-induced delay based on event-triggered strategy. The theoretical results of such systems will be attractive and have extensive practical applications, which inspired the research presented in this paper.

In the view of the above discussion, this paper addresses the event-triggered H_∞ filtering for multiagent systems with Markovian switching topologies and network-induced delay. The main contributions are summarized as follows: (1) different from the general event-triggered sampled-data strategy, this paper takes into account the effect of network-induced delay and Markovian switching topologies. A distributed event-triggered scheme is presented to release the load of the network. (2) By employing the time-delay system method, H_∞ filtering performance is derived, the co-design method of the event-triggered condition and the filter design are also given. (3) The Laplacian matrices of switching topologies are not required to be symmetric.

The rest of this paper is organized as follows. In Section 2, we give some preliminaries and present the problem formulation. The main results for stability analysis and event-triggered H_∞ filter design are elaborated in Section 3. In Section 4, a numerical example is provided to illustrate the feasibility and effectiveness of the proposed method. Finally, conclusions are drawn in Section 5.

Notations. R^n represents the n-dimension Euclidean space and $R^{n\times m}$ denotes the set of $n \times m$ real matrices. Let I_N represent the $N \times N$ identity matrix and $\mathbf{0}$ denote zero matrix with an appropriate dimension. The superscripts -1 and T stand for the inverse and the transpose of a matrix, respectively. We use the notation $\otimes$ and $*$ to represent Kronecker product and the elements below the main diagonal of some symmetric matrix, respectively. The real matrix $P > 0$ shows that P is positive definite.

2. Problem Formulation

2.1. Graph Theory. Let $G = (V, \xi, A)$ denote a directed weighted graph of N order, where the set of nodes is denotes by $V = \{v_1, v_2, \ldots, v_n\}$ and the set of edges is denoted by $\xi \subseteq V \times V$. An edge in graph G is described by (v_j, v_i), $i, j \in 1, 2, \ldots, n$ which represents that the jth agent transmit information to the ith agent. Matrix $A = [a_{ij}]_{n\times n}$ is called weighted adjacency matrix. The set of neighbors of agent i is denoted as $N_i = \{j \mid (v_j, v_i) \in \xi\}$. If $j \in N_i$, $a_{ij} > 0$; otherwise, $a_{ij} = 0$. The diagonal matrix $D = \operatorname{diag}\{d_1, d_2, \ldots, d_N\} \in R^{N\times N}$ is called the degree matrix of graph G with diagonal elements $d_i = \Sigma_{j\in N_i} a_{ij}$. The Laplacian matrix of G is defined as $L = D - A = [l_{ij}] \in R^{N\times N}$, where $l_{ii} = \sum_{j\in N_i} a_{ij}$ and $l_{ij} = -a_{ij}$ for $i \neq j$.

2.2. System Description. We consider MASs composed of N interconnected agents in this paper, where each agent is assumed to have the following state-space description:

$$\begin{aligned} \dot{x}_i(t) &= Ax_i(t) + Bw_i(t) \\ y_i(t) &= C_2 \Sigma_{j\in N_i} a_{ij}^{r(t)} \left(x_i(t) - x_j(t)\right) + Dw_i(t) \\ z_i(t) &= C_1 \Sigma_{j\in N_i} a_{ij}^{r(t)} \left(x_i(t) - x_j(t)\right) \end{aligned} \tag{1}$$

for $i = 1, 2, \ldots, N$, where $x_i(t)$, $y_i(t)$, and $z_i(t)$ are the state, the measured output, and the signal to be estimated of agent i. $w_i(t)$ denotes the external disturbance which belongs to $L_2[0, \infty)$.

The switching communication topologies are described by $G_{r(t)} \in \{G_1, G_2, \ldots, G_q\}$, where $r(t)$ represents the continuous process of Markov chain. Furthermore, it takes values in a given finite set $S = \{1, 2, \ldots, q\}$. We define the transition probability as follows:

$$\begin{aligned} &prob\{r(t+\Delta t) = s \mid r(t) = r\} \\ &\quad = \begin{cases} \pi_{rs}\Delta t + o(\Delta t), & r \neq s \\ 1 + \pi_{rr}\Delta t + o(\Delta t), & r = s \end{cases} \end{aligned} \tag{2}$$

where $\lim_{\Delta t\longrightarrow 0}(o(\Delta t)/\Delta t) = 0, \Delta t > 0$, and the transition probability satisfies $\pi_{rs} > 0$ when $r, s \in S$ and $\pi_{rr} = -\sum_{s=1,s\neq r}^{q} \pi_{rs}$.

For MASs (1), we design the following full-order filter to estimate signal $z_i(t)$:

$$\begin{aligned} \dot{x}_{fi}(t) &= A_{fr} x_{fi}(t) + B_{fr} y_{fi}(t) \\ z_{fi}(t) &= C_{fr} x_{fi}(t) \end{aligned} \tag{3}$$

where $x_{fi}(t)$ represents the state of the ith filtering subsystem, $z_{fi}(t)$ is the estimation signal of $z_i(t)$, and A_{fr}, B_{fr}, C_{fr} are filter parameters to be determined.

2.3. Event-Triggered Scheme. In order to reduce the communication network burden, event-triggered scheme is adopted in this paper. The sampler is assumed to be time-driven; the zero-order-hold (ZOH) is event-driven. Then, we construct the following event-triggered strategy.

$$\begin{aligned} t_{k+1}^i h = t_k^i h + \min_{l_i > 1} \Big\{ & l_i h \mid \chi_i^T \left(t_k^i h + l_i h\right) \phi_r \chi_i \left(t_k^i h + l_i h\right) \\ & \geq \sigma_r y_i^T \left(t_k^i h + l_i h\right) \phi_r y_i \left(t_k^i h + l_i h\right) \Big\} \end{aligned} \tag{4}$$

where $l_i \in N$, $\chi_i(t_k^i h + l_i h) \triangleq y_i(t_k^i h + l_i h) - y_i(t_k^i h)$ is the threshold error, $t_k^i h$ represents the latest kth triggering instant of the ith agent, $t_k^i h + l_i h$ denotes the currently sampled instant, and $t_{k+1}^i h$ denotes the next broadcast instant. Then $\sigma_r > 0$ represents the threshold and $\phi_r > 0$ stands for a symmetric positive definite matrix.

Remark 1. From the event-triggered strategy (4), we can automatically exclude Zeno behavior.

Proof. Zeno behavior in the event-triggered communication framework is defined as the infinite number of communication in a finite time. Due to the fact that each agent's state is periodically sampled and the sampling time sequence is $\{0, h, 2h, \ldots\}$, we can obtain that the event-triggered time sequence is a subsequence of the sampling time sequence, namely, $\{t_0^i h, t_1^i h, t_2^i h, \ldots\} \subseteq \{0, h, 2h, \ldots\}$, which means that the minimum interevent time $\min_k\{t_{k+1}^i h - t_k^i h\}$, $\forall i$, is lower bounded by the sampling period h. Since the number of agents is finite, the communication events in any finite time cannot be infinite. Therefore, the event-triggered strategy (4) can rule out Zeno behavior automatically. □

Remark 2. Different from traditional filtering problem, due to the existence of network-induced delays, taking the property of ZOH into account, we get

$$y_{fi}(t) = y_i\left(t_k^i h\right) \tag{5}$$

Substituting (5) into (3), we have

$$\begin{aligned} \dot{x}_{fi}(t) &= A_{fr} x_{fi}(t) + B_{fr} y_i\left(t_k^i h\right) \\ z_{fi}(t) &= C_{fr} x_{fi}(t), \\ & t \in \left[t_k^i h + \tau\left(t_k^i\right), t_{k+1}^i h + \tau\left(t_{k+1}^i\right)\right) \end{aligned} \tag{6}$$

Remark 3. Suppose that the network delay is bounded, i.e., $0 < \tau_m \le \tau_k^i \le \overline{\tau}$, where τ_m and $\overline{\tau}$ denote the lower and upper bound of $\tau(t)$, respectively. It is worth noting that when $\sigma_r = 0$, all the sampled signals are transmitted, the event-triggered strategy (4) reduces to a periodic time-triggered scheme.

2.4. Time-Delay Modeling. Using the same technique as in [29], we assume that there is a integer $q > 0$, which satisfies $t_{k+1}^i = t_k^i + q + 1$. Hence, we can obtain the following equality:

$$\left[t_k^i h + \tau\left(t_k^i\right), t_{k+1}^i h + \tau\left(t_{k+1}^i\right)\right) = \bigcup_{n=0}^{q} \Omega_n \tag{7}$$

with $\Omega_n = [t_k^i h + nh + \tau(t_k^i + n), t_k^i h + (n+1)h + \tau(t_k^i + n + 1))$, $t_{k+1}^i = t_k^i + n + 1$.

For convenience, we define

$$\tau(t) = t - t_k^i h - nh, \quad t \in \Omega_n \tag{8}$$

Then, we can know that

$$0 < \tau_m \le \tau(t) \le h + \overline{\tau} = \tau_M \tag{9}$$

To show the effect of the event-triggered scheme (4) in deriving system stability and stabilization criterion, we define a new variable $e_{ki}(t)$, which satisfies the following equality:

$$e_{ki}(t) = y_i\left(t_k^i h\right) - y_i\left(t_k^i h + nh\right), \quad t \in \Omega_n \tag{10}$$

Substituting (8), (10) into (6), we have

$$\begin{aligned} \dot{x}_{fi}(t) &= A_{fr} x_{fi}(t) + B_{fr}\left[y_i(t - \tau(t)) + e_{ki}(t)\right] \\ z_{fi}(t) &= C_{fr} x_{fi}(t) \end{aligned} \tag{11}$$

From (10) and (4), we can obtain

$$e_{ki}^T(t)\,\phi_r e_{ki}(t) \le \sigma_r y_i^T(t - \tau(t))\,\phi_r y_i(t - \tau(t)) \tag{12}$$

where $t \in [t_k^i h + \tau(t_k^i), t_{k+1}^i h + \tau(t_{k+1}^i))$.

2.5. Event-Triggered H_∞ Filter Problem. By defining $\xi_i^T(t) = \left[x_i^T(t) \;\; x_{fi}^T(t)\right]$, $\widehat{w}_i(t) = \left[w_i^T(t) \;\; w_i^T(t - \tau(t))\right]^T$, and $e_i(t) = z_i(t) - z_{fi}(t)$, we can obtain the following filtering error system:

$$\begin{aligned} \dot{\xi}_i(t) &= \overline{A}\xi_i(t) + \Sigma_{j\in N_i} a_{ij}\overline{B}H\xi_i(t - \tau(t)) + \overline{E}e_{ki}(t) \\ &\quad + \overline{D}\widehat{w}_i(t) \\ e_i(t) &= \overline{C}_1\xi_i(t) + \Sigma_{j\in N_i} a_{ij}\overline{C}_2\left(\xi_i(t) - \xi_j(t)\right) \end{aligned} \tag{13}$$

where

$$\begin{aligned} \overline{A} &= \begin{bmatrix} A & 0 \\ 0 & A_{fr} \end{bmatrix}, \\ \overline{B} &= \begin{bmatrix} 0 \\ B_{fr}C_2 \end{bmatrix}, \\ H &= \begin{bmatrix} I_n & 0 \end{bmatrix}, \\ \overline{D} &= \begin{bmatrix} B & 0 \\ 0 & B_{fr}D \end{bmatrix}, \\ \overline{C}_1 &= \begin{bmatrix} 0 & -C_{fr} \end{bmatrix}, \\ \overline{C}_2 &= \begin{bmatrix} C_1 & 0 \end{bmatrix} \\ \overline{E} &= \begin{bmatrix} 0 \\ B_{fr} \end{bmatrix} \end{aligned} \tag{14}$$

Then, we define some new augment variables to compact system:

$$\begin{aligned} \xi(t) &= \left[\xi_1^T(t) \;\; \xi_2^T(t) \;\; \ldots \;\; \xi_N^T(t)\right]^T, \\ e(t) &= \left[e_1^T(t) \;\; e_2^T(t) \;\; \ldots \;\; e_N^T(t)\right]^T, \\ \widehat{w}(t) &= \left[\widehat{w}_1^T(t) \;\; \widehat{w}_2^T(t) \;\; \ldots \;\; \widehat{w}_N^T(t)\right]^T, \\ e_k(t) &= \left[e_{k1}^T(t) \;\; e_{k2}^T(t) \;\; \ldots \;\; e_{kN}^T(t)\right]^T \end{aligned} \tag{15}$$

Therefore, the filtering error system can be rewritten as follows:

$$\begin{aligned}\dot{\xi}(t) &= \left(I_N \otimes \overline{A}\right)\xi(t) + \left(L \otimes \overline{B}H\right)\xi(t-\tau(t)) \\ &\quad + \left(I_N \otimes \overline{E}\right)e_k(t) + \left(I_N \otimes \overline{D}\right)\widehat{w}(t) \\ e(t) &= \left(I_N \otimes \overline{C}_1 + L \otimes \overline{C}_2\right)\xi(t)\end{aligned} \tag{16}$$

Definition 4. The filtering error system (16) with $w(t) = 0$ is asymptotically stable in mean square, if for any initial conditions, such that

$$\lim_{t\longrightarrow+\infty}\|\xi(t)\|^2 = 0 \tag{17}$$

Definition 5. Given a positive scalar γ, and for all nonzero $w(t) \in L_2[0,\infty)$, the filtering error system (16) is asymptotically stable in mean square with a guaranteed H_∞ performance γ if the filtering error $e(t)$ satisfies

$$E\left\{\int_0^\infty e^T(t)e(t)\,dt\right\} \le \gamma^2 E\left\{\int_0^\infty w^T(t)w(t)\,dt\right\} \tag{18}$$

Before proceeding further, we introduce the following lemmas that will be helpful for deriving the following results.

Lemma 6 (see [30]). *Given scalar $\tau > 0$, matrix $M > 0$, and vector function w, $[0,\tau] \longrightarrow R^n$ satisfy the following inequality:*

$$\begin{aligned}&\left(\int_0^\tau w(s)\,ds\right)^T M\left(\int_0^\tau w(s)\,ds\right) \\ &\quad\le \tau\left(\int_0^\tau w^T(s)Mw(s)\,ds\right).\end{aligned} \tag{19}$$

Lemma 7 (see [31]). *Suppose that $f_1(t), f_2(t), \ldots, f_N(t) : \mathbf{R}^m \longmapsto \mathbf{R}^n$ is positive values, which satisfies*

$$\min\sum_{i=1}^{N}\frac{1}{\alpha_i}f_i(t) = \sum_{i=1}^{N}f_i(t) + \max\sum_{i=1}^{N}\sum_{j=1,j\ne i}^{N}g_{i,j}(t) \tag{20}$$

subject to

$$\left\{g_{i,j} : \mathbf{R}^m \longmapsto \mathbf{R}^n,\ g_{j,i}(t) \equiv g_{i,j}(t),\ \begin{bmatrix} f_i(t) & g_{i,j} \\ g_{i,j} & f_i(t)\end{bmatrix} \ge 0\right\} \tag{21}$$

3. Main Results

3.1. Asymptotical Stability Analysis

Theorem 8. *For given scalars $\sigma_r > 0$, $\tau_M > \tau_m > 0$, the filtering error system (16) without external disturbance can achieve mean square stable under Definition 4 if there exist appropriate dimensional matrices $P_r > 0$, $Q_1 > 0$, $Q_2 > 0$, $R_1 > 0$, $R_2 > 0$, $\phi_r > 0$ and S_1 such that the following LMIs hold:*

$$\begin{bmatrix} R_2 & S_1 \\ * & R_2\end{bmatrix} > 0 \tag{22}$$

$$\begin{bmatrix} \Pi & \tau_m\Gamma^T\widehat{H}^T R_1 & (\tau_M-\tau_m)\Gamma^T\widehat{H}^T R_2 \\ * & -R_1 & 0 \\ * & * & -R_2\end{bmatrix} < 0 \tag{23}$$

$$\sum_{s=1}^{q}\pi_{rs}P_s \le P_r \tag{24}$$

where

$$\begin{aligned}\Pi &= \begin{bmatrix}\Xi_{11} & \Xi_{12} & \Xi_{13} & 0 & \Xi_{15} \\ * & \Xi_{22} & \Xi_{23} & \Xi_{24} & 0 \\ * & * & \Xi_{33} & \Xi_{34} & 0 \\ * & * & * & \Xi_{44} & 0 \\ * & * & * & * & -\widehat{\phi}_r\end{bmatrix} \\ \Gamma &= \left[I_N \otimes \overline{A} \quad L \otimes \overline{B} \quad 0 \quad 0 \quad I_N \otimes \overline{E}\right] \\ \Xi_{11} &= \left(I_N \otimes \overline{A}\right)^T P_r + P_r\left(I_N \otimes \overline{A}\right) + P_r + \widehat{H}^T Q_1\widehat{H} \\ &\quad + \widehat{H}^T Q_2\widehat{H} - \widehat{H}^T R_1\widehat{H} \\ \Xi_{12} &= P_r\left(L \otimes \overline{B}\right) \\ \Xi_{13} &= \widehat{H}^T R_1 \\ \Xi_{15} &= P_r\left(I_N \otimes \overline{E}\right) \\ \Xi_{22} &= \sigma_r\left(L \otimes C_2\right)^T\widehat{\phi}_r\left(L \otimes C_2\right) - 2R_2 + S_1 + S_1^T \\ \Xi_{23} &= -S_1^T + R_2 \\ \Xi_{24} &= -S_1 + R_2 \\ \Xi_{33} &= -Q_1 - R_1 - R_2 \\ \Xi_{34} &= S_1 \\ \Xi_{44} &= -Q_2 - R_2 \\ \widehat{H} &= I_N \otimes H, \\ \widehat{H}_2 &= I_N \otimes H_2, \\ \widehat{\phi}_r &= I_N \otimes \phi_r, \\ H_2 &= \left[0 \quad I_n\right]\end{aligned} \tag{25}$$

Proof. Consider that there is no external disturbance, i.e., $w(t) = 0$. We construct the following Lyapunov functional:

$$V\left(t,\xi(t),\dot{\xi}(t),r(t)\right) = \sum_{i=1}^{5}V_i\left(t,\xi(t),\dot{\xi}(t),r(t)\right) \tag{26}$$

where

$$\begin{aligned}V_1\left(t,\xi(t),\dot{\xi}(t),r(t)\right) &= \xi^T(t)P_r\xi(t) \\ V_2\left(t,\xi(t),\dot{\xi}(t)\right) &= \int_{t-\tau_m}^{t}\xi^T(s)\widehat{H}^T Q_1\widehat{H}\xi(s)\,ds \\ V_3\left(t,\xi(t),\dot{\xi}(t)\right) &= \int_{t-\tau_M}^{t}\xi^T(s)\widehat{H}^T Q_2\widehat{H}\xi(s)\,ds\end{aligned}$$

$$
\begin{aligned}
&V_4\left(t, \xi(t), \dot{\xi}(t)\right) \\
&\quad = \tau_m \int_{-\tau_m}^{0} \int_{t+\theta}^{t} \dot{\xi}^T(s) \widehat{H}^T R_1 \widehat{H} \dot{\xi}(s)\, ds\, d\theta \\
&V_5\left(t, \xi(t), \dot{\xi}(t)\right) \\
&\quad = \left(\tau_M - \tau_m\right) \int_{-\tau_M}^{-\tau_m} \int_{t+\theta}^{t} \dot{\xi}^T(s) \widehat{H}^T R_2 \widehat{H} \dot{\xi}(s)\, ds\, d\theta
\end{aligned} \tag{27}
$$

then its derivative along system (16) with $w(t) = 0$ is

$$
\begin{aligned}
\dot{V}_1 &= \dot{\xi}^T(t) P_r \xi(t) + \xi^T(t) P_r \dot{\xi}(t) \\
&\quad + \xi^T(t) \left\{ \sum_{s=1}^{q} \pi_{rs} P_s \right\} \xi(t) \\
\dot{V}_2 &= \xi^T(t) \widehat{H}^T Q_1 \widehat{H} \xi(t) \\
&\quad - \xi^T\left(t - \tau_m\right) \widehat{H}^T Q_1 \widehat{H} \xi\left(t - \tau_m\right) \\
\dot{V}_3 &= \xi^T(t) \widehat{H}^T Q_2 \widehat{H} \xi(t) \\
&\quad - \xi^T\left(t - \tau_M\right) \widehat{H}^T Q_2 \widehat{H} \xi\left(t - \tau_M\right) \\
\dot{V}_4 &= \tau_m^2 \dot{\xi}^T(t) \widehat{H}^T R_1 \widehat{H} \dot{\xi}(t) \\
&\quad - \tau_m \int_{t-\tau_m}^{t} \dot{\xi}^T(s) \widehat{H} R_1 \widehat{H} \dot{\xi}(s)\, ds \\
\dot{V}_5 &= \left(\tau_M - \tau_m\right)^2 \dot{\xi}^T(t) \widehat{H}^T R_2 \widehat{H} \dot{\xi}(t) \\
&\quad - \left(\tau_M - \tau_m\right) \int_{t-\tau(t)}^{t-\tau_m} \dot{\xi}^T(s) \widehat{H} R_2 \widehat{H} \dot{\xi}(s)\, ds \\
&\quad - \left(\tau_M - \tau_m\right) \int_{t-\tau_M}^{t-\tau(t)} \dot{\xi}^T(s) \widehat{H} R_2 \widehat{H} \dot{\xi}(s)\, ds
\end{aligned} \tag{28}
$$

Applying Lemmas 6 and 7 to deal with the integral items and combining the event-triggered scheme (12), we have

$$
\begin{aligned}
&\dot{V}\left(t, \xi(t), \dot{\xi}(t), r(t)\right) \\
&\quad \le \sum_{i=1}^{5} V_i\left(t, \xi(t), \dot{\xi}(t), r(t)\right) - e_k^T(t) \widehat{\phi}_r e_k(t) \\
&\qquad + \sigma_r y^T(t - \tau(t)) \widehat{\phi}_r y(t - \tau(t)) = \zeta^T(t) \psi \zeta(t)
\end{aligned} \tag{29}
$$

where

$$
\begin{aligned}
\zeta^T(t) &= \left[\xi^T(t) \quad \xi^T(t - \tau(t)) \widehat{H}^T \quad \xi^T\left(t - \tau_m\right) \widehat{H}^T \quad \xi^T\left(t - \tau_M\right) \widehat{H}^T \quad e_k^T(t)\right] \\
\psi &= \Pi + \tau_m^2 \Gamma^T \widehat{H}^T R_1 \widehat{H} \Gamma + \left(\tau_M - \tau_m\right)^2 \Gamma^T \widehat{H}^T R_2 \widehat{H} \Gamma
\end{aligned} \tag{30}
$$

By employing the Schur complement, we can find easily that (23) ensures $\psi < 0$. According to Definition 4, the filtering error system (16) is asymptotically stable in mean square under the event-triggered scheme (12) if (22), (23), and (24) hold. The proof is completed. □

3.2. H_∞ Performance Analysis

Theorem 9. *For given scalars $\sigma_r > 0$, $\tau_M > \tau_m > 0$, considering the existence of external disturbance, the filtering error system (16) can achieve being asymptotically stable with an H_∞ performance index γ under Definition 5 if there exist appropriate dimensional matrices $P_r > 0$, $Q_1 > 0$, $Q_2 > 0$, $R_1 > 0$, $R_2 > 0$, $\phi_r > 0$ and S_1 such that the following LMIs hold:*

$$
\begin{bmatrix} R_2 & S_1 \\ * & R_2 \end{bmatrix} > 0 \tag{31}
$$

$$
\begin{bmatrix}
\Theta & \tau_m \Gamma_1^T \widehat{H}^T R_1 & \left(\tau_M - \tau_m\right) \Gamma_1^T \widehat{H}^T R_2 & \Gamma_2^T \\
* & -R_1 & 0 & 0 \\
* & * & -R_2 & 0 \\
* & * & * & -I
\end{bmatrix} < 0 \tag{32}
$$

$$
\sum_{s=1}^{q} \pi_{rs} P_s \le P_r \tag{33}
$$

where

$$
\begin{aligned}
\Theta &= \begin{bmatrix}
\Xi_{11} & \Xi_{12} & \Xi_{13} & 0 & \Xi_{15} & \Xi_{16} \\
* & \Xi_{22} & \Xi_{23} & \Xi_{24} & 0 & \Xi_{26} \\
* & * & \Xi_{33} & \Xi_{34} & 0 & 0 \\
* & * & * & \Xi_{44} & 0 & 0 \\
* & * & * & * & -\widehat{\phi}_r & \\
* & * & * & * & * & \Xi_{66}
\end{bmatrix} \\
\Gamma_1 &= \left[I_N \otimes \overline{A} \quad L \otimes \overline{B} \quad 0 \quad 0 \quad I_N \otimes \overline{E} \quad I_N \otimes \overline{D}\right] \\
\Gamma_2 &= \left[I_N \otimes \overline{C}_1 + L \otimes \overline{C}_2 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0\right] \\
\Xi_{16} &= P_r \left(I_N \otimes \overline{D}\right) \\
\Xi_{26} &= \sigma_r \left(L \otimes C_2\right)^T \widehat{\phi}_r \left(I_N \otimes D\right) \widehat{H}_2 \\
\Xi_{66} &= -\gamma^2 I + \sigma_r \widehat{H}_2^T \left(I_N \otimes D\right)^T \widehat{\phi}_r \left(I_N \otimes D\right) \widehat{H}_2
\end{aligned} \tag{34}
$$

and the other parameters are defined as in Theorem 8.

Proof. Consider the existence of external disturbance, i.e., $w(t) \neq 0$, and choose the same Lyapunov functional like Theorem 8; we have

$$\begin{aligned}
&\dot{V}\left(t, \xi(t), \dot{\xi}(t), r(t)\right) \\
&\quad = \dot{V}\left(t, \xi(t), \dot{\xi}(t), r(t)\right) + e^T(t) e(t) \\
&\qquad - \gamma^2 \widehat{w}^T(t) \widehat{w}(t) - e^T(t) e(t) + \gamma^2 \widehat{w}^T(t) \widehat{w}(t) \\
&\quad = \eta^T(t) \Omega \eta(t) - e^T(t) e(t) + \gamma^2 \widehat{w}^T(t) \widehat{w}(t)
\end{aligned} \tag{35}$$

where

$$\begin{aligned}
&\eta^T(t) = \left[\zeta^T(t) \;\; \widehat{w}^T(t)\right] \\
&\Omega = \Theta + \tau_m^2 \Gamma_1^T \widehat{H}^T R_1 \widehat{H} \Gamma_1 \\
&\qquad + \left(\tau_M - \tau_m\right)^2 \Gamma_1^T \widehat{H}^T R_2 \widehat{H} \Gamma_1 + \Gamma_2^T \Gamma_2
\end{aligned} \tag{36}$$

By using the Schur complement, we can find easily that (32) guarantees $\Omega < 0$. According to Definition 5, the filtering error system (16) is asymptotically stable with H_∞ norm bound γ if (31), (32), and (33) are satisfied. The proof is completed. □

3.3. Filter Design

Theorem 10. *For given scalars $\sigma_r > 0$, $\tau_M > \tau_m > 0$ and H_∞ performance index γ, the filtering error system (16) under the event-triggered scheme (12) is asymptotically stable in mean square for $w(t) = 0$ and satisfies the H_∞ performance constraint (18) for all nonzero $w(t) \in L_2[0, +\infty)$ under the zero initial condition if there exist real matrices $P_r > 0$, $W_r > 0$, $\phi_r > 0$ $(r \in S)$, $Q_1 > 0$, $Q_2 > 0$, $R_1 > 0$, $R_2 > 0$ and matrices $S_1, \overline{A}_{fr}, \overline{B}_{fr}, \overline{C}_{fr} (r \in S)$ with appropriate dimension such that the following LMIs hold:*

$$\begin{bmatrix} R_2 & S_1 \\ * & R_2 \end{bmatrix} > 0, \tag{37}$$

$$\begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} \\ * & -R_1 & 0 & 0 \\ * & * & -R_2 & 0 \\ * & * & * & -I \end{bmatrix} < 0, \tag{38}$$

$$\sum_{s=1}^{q} \pi_{rs} \left(U_{1s} - W_s\right) \leq U_{1r} - W_r \tag{39}$$

where

$$\begin{aligned}
&\phi_{11} = \begin{bmatrix} \widehat{\Xi}_{11} & \widehat{\Xi}_{12} & \widehat{\Xi}_{13} & 0 & \widehat{\Xi}_{15} & \widehat{\Xi}_{16} \\ * & \Xi_{22} & \Xi_{23} & \Xi_{24} & 0 & \Xi_{26} \\ * & * & \Xi_{33} & \Xi_{34} & 0 & 0 \\ * & * & * & \Xi_{44} & 0 & 0 \\ * & * & * & * & -\widehat{\phi}_r & 0 \\ * & * & * & * & * & \Xi_{66} \end{bmatrix} \\
&\phi_{12} = \left[\tau_m R_1 \left(I_N \otimes A\right) \widehat{H} \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \tau_m R_1 \left(I_N \otimes B\right) \widehat{H}\right]^T, \\
&\phi_{13} = \left[\left(\tau_M - \tau_m\right) R_2 \left(I_N \otimes A\right) \widehat{H} \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; \left(\tau_M - \tau_m\right) R_2 \left(I_N \otimes B\right) \widehat{H}\right]^T, \\
&\phi_{14} = \left[\left(I_N \otimes -\overline{C}_{fr}\right) \widehat{H}_2 + \left(L \otimes C_1\right) \widehat{H} \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0\right]^T, \\
&\widehat{\Xi}_{11} = I_N \otimes \begin{bmatrix} U_{1r} + A^T U_{1r} + U_{1r} A & W_r + \overline{A}_{fr} + A^T W_r \\ * & W_r + \overline{A}_{fr} + \overline{A}_{fr}^T \end{bmatrix} + \widehat{H}^T \left(Q_1 + Q_2 - R_1\right) \widehat{H}, \\
&\widehat{\Xi}_{12} = L \otimes \begin{bmatrix} \overline{B}_{fr} C_2 \\ \overline{B}_{fr} C_2 \end{bmatrix}, \\
&\widehat{\Xi}_{13} = \widehat{H}^T R_1, \\
&\widehat{\Xi}_{15} = I_N \otimes \begin{bmatrix} \overline{B}_{fr} \\ \overline{B}_{fr} \end{bmatrix}, \\
&\widehat{\Xi}_{16} = I_N \otimes \begin{bmatrix} U_{1r} B & \overline{B}_{fr} D \\ W_r B & \overline{B}_{fr} D \end{bmatrix}
\end{aligned} \tag{40}$$

Moreover, if the above conditions are feasible, the parameter matrices of the filter are given by

$$\begin{aligned} A_{fr} &= W_r^{-1}\overline{A}_{fr} \\ B_{fr} &= W_r^{-1}\overline{B}_{fr} \\ C_{fr} &= \overline{C}_{fr} \end{aligned} \tag{41}$$

Proof. Let $P_r = I_N \otimes U_r$ for conditions (32) in Theorem 8. Let matrix U_r be partitioned as

$$U_r = \begin{bmatrix} U_{1r} & U_{2r} \\ * & U_{3r} \end{bmatrix} \tag{42}$$

where $U_{1r} > 0$, U_{2r}, and U_{3r} are nonsingular matrices, satisfying $W_r = U_{2r}U_{3r}^{-1}U_{2r}^T$. By Schur complement, we can obtain that $U_r > 0$ is equivalent to $U_{1r} - W_r > 0$. Define the following invertible matrix:

$$J_1 = \begin{bmatrix} I & 0 \\ 0 & U_{2r}U_{3r}^{-1} \end{bmatrix} \tag{43}$$

Then, pre- and postmultiply (32) by J_2 and J_2^T, respectively, where $J_2 = \mathrm{diag}\{J_1, \underbrace{I, \ldots, I}_{8}\}$ and define new variables:

$$\begin{aligned} \overline{A}_{fr} &= U_{2r}A_{fr}U_{3r}^{-1}U_{2r}^T \\ \overline{B}_{fr} &= U_{2r}B_{fr} \\ \overline{C}_{fr} &= C_{fr}U_{3r}^{-1}U_{2r}^T \end{aligned} \tag{44}$$

By the linear transformation above, we can find easily that (32) is equivalent to (38). Therefore, we can obtain (41). The proof is completed. □

Remark 11. Comparing with the previous results [32], lower bounds theorem [31] is adopted in this paper, which not only achieves performance behavior identical to approaches based on the integral inequality lemma, but also decreases the number of decision variables dramatically.

4. Simulation

The parameters of MASs (1) are given as follows:

$$\begin{aligned} A &= \begin{bmatrix} -1 & 1 \\ 0.8 & -4 \end{bmatrix}, \\ B &= \begin{bmatrix} 0.5 \\ 0.1 \end{bmatrix} \\ C1 &= \begin{bmatrix} 0.1 & 0 \end{bmatrix}, \\ C2 &= \begin{bmatrix} 0.2 & 0 \end{bmatrix}, \\ D &= 0.1 \end{aligned} \tag{45}$$

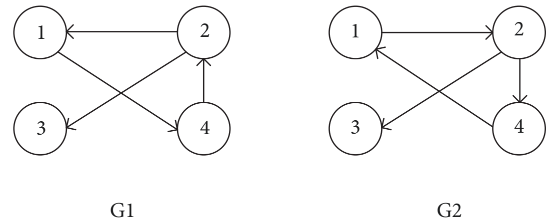

FIGURE 1: Directed communication topology graphs.

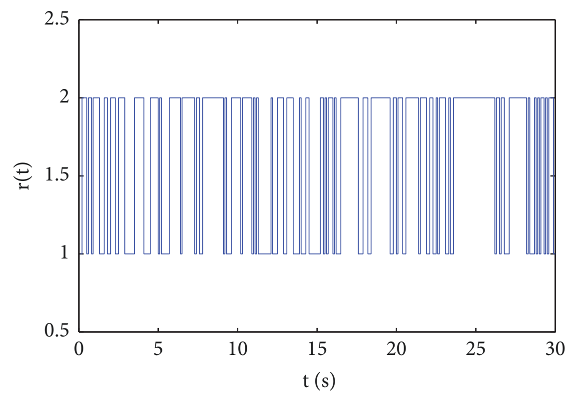

FIGURE 2: Evolution of Markov chain.

In addition, the external disturbances of MASs (1) are defined as follows:

$$w_i(t) = 0.4e^{-0.2t}\cos(0.6t). \tag{46}$$

All the possible information transmission relationships among agents are shown in Figure 1. Then, the corresponding Laplacian matrices are given as follows, respectively.

$$\begin{aligned} L_1 &= \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & 0 & -1 \\ 0 & -1 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix}, \\ L_2 &= \begin{bmatrix} 1 & 0 & 0 & -1 \\ -1 & 1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix} \end{aligned} \tag{47}$$

Figure 2 shows the switching of two modes in a Markov chain. Suppose that the probability transition matrix is defined as

$$\Pi = \begin{bmatrix} -5 & 5 \\ 2 & -2 \end{bmatrix} \tag{48}$$

Given that $h = 0.1$, $\sigma_1 = 0.1$, $\sigma_2 = 0.2$, minimum allowable delay $\tau_m = 0.1$ and the maximum allowable delay $\tau_M = 0.5$. Let the initial states $x_1(0) = [3; -1], x_2(0) = [1; -1], x_3(0) = [1; -3], x_4(0) = [-3; 3]$. By solving LMIs in

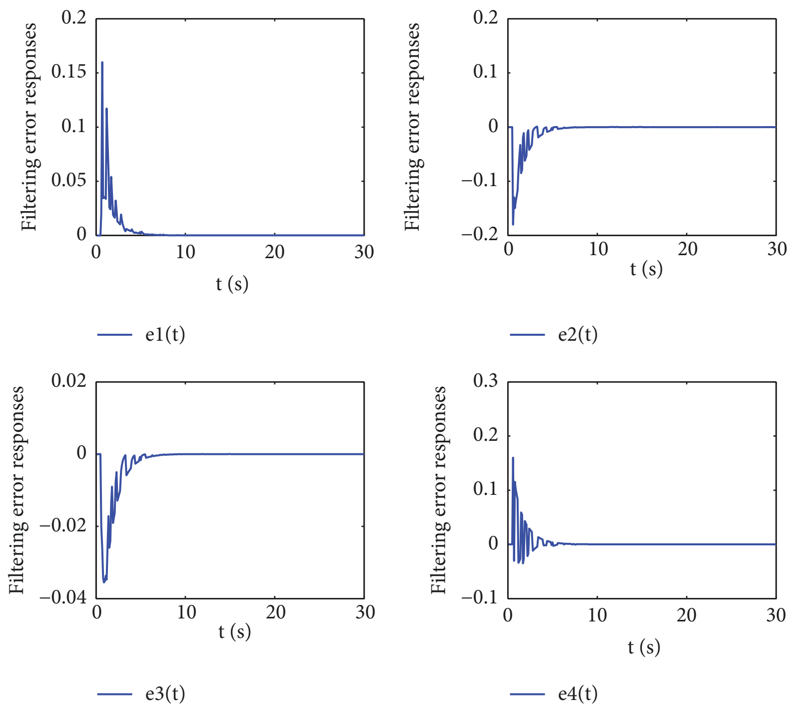

Figure 3: Filtering error response.

Theorem 9, we can obtain parameters of the designed filter (3),

$$
\begin{aligned}
A_{f1} &= \begin{bmatrix} -24.8840 & 52.462 \\ -9.6761 & 20.1822 \end{bmatrix}, \\
B_{f1} &= \begin{bmatrix} -0.6878 \\ -0.2918 \end{bmatrix} \\
C_{f1} &= \begin{bmatrix} -1.3535 & 0.0581 \end{bmatrix} \\
A_{f2} &= \begin{bmatrix} -58.5910 & 137.6004 \\ -22.9133 & 53.7343 \end{bmatrix}, \\
B_{f2} &= \begin{bmatrix} 0.8893 \\ 0.3558 \end{bmatrix} \\
C_{f2} &= \begin{bmatrix} -0.1373 & -0.0623 \end{bmatrix} \times 10^{-5},
\end{aligned}
\tag{49}
$$

and the event-triggered parameters,

$$
\begin{aligned}
\phi_1 &= 15.5816, \\
\phi_2 &= 7.9041
\end{aligned}
\tag{50}
$$

In Figure 3, it shows the filtering error of agent i ($i = 1, 2, 3, 4$). In Figure 4, it depicts the state curves of $z_i(t)$ and estimation signal $z_{fi}(t)$ ($i = 1, 2, 3, 4$). The event-triggered release instants and intervals of agent i ($i = 1, 2, 3, 4$) are shown in Figure 5. Letting the simulation time t=30, we can get that agent 1 triggers 84 times, agent 2 triggers 36 times, agent 3 triggers 40 times, and agent 4 triggers 92 times. If $\sigma_r = 0$ (time-triggered), there are 300 times transmitted. We can find clearly that the event-triggered control strategy (12) efficiently saves the network resources.

5. Conclusion

In this paper, we study the problem of H_∞ filtering for MASs with Markovian switching topologies. Considering the effect of switching topologies and network-induced delay, we adopt a reasonable event-triggered mechanism to reduce the amount of network transmission. By employing Lyapunov stability theory and LMI technique, some sufficient conditions are obtained which can ensure filtering error system to achieve mean square stable with an H_∞ norm bound. Finally, a numerical example is provided to show that the method we proposed is feasible and effective.

Data Availability

(i) The system parameters A, B, C1, C2, D used to support the findings of this study are included within the article. (ii) The external disturbance wi(t) used to support the findings of this study titled "Event-triggered H_∞ Filtering for Discrete-Time Neural Networks with Missing Measurements" is available from the corresponding author upon request. (iii) The initial states $x1(0)$, $x2(0)$, $x3(0)$, $x4(0)$ used to support the findings of this study are included within the article. (iv) The Laplacian matrices $L1$, $L2$ and probability transition matrix Π used to support the findings of this study are included within the article. (v) The filter parameters $Af1, Af2, Bf1, Bf2, Cf1, Cf2$ and event-triggered parameters $\Phi1$, $\Phi2$ used to support the findings of this study are derived by solving LMIs, which are included in the article.

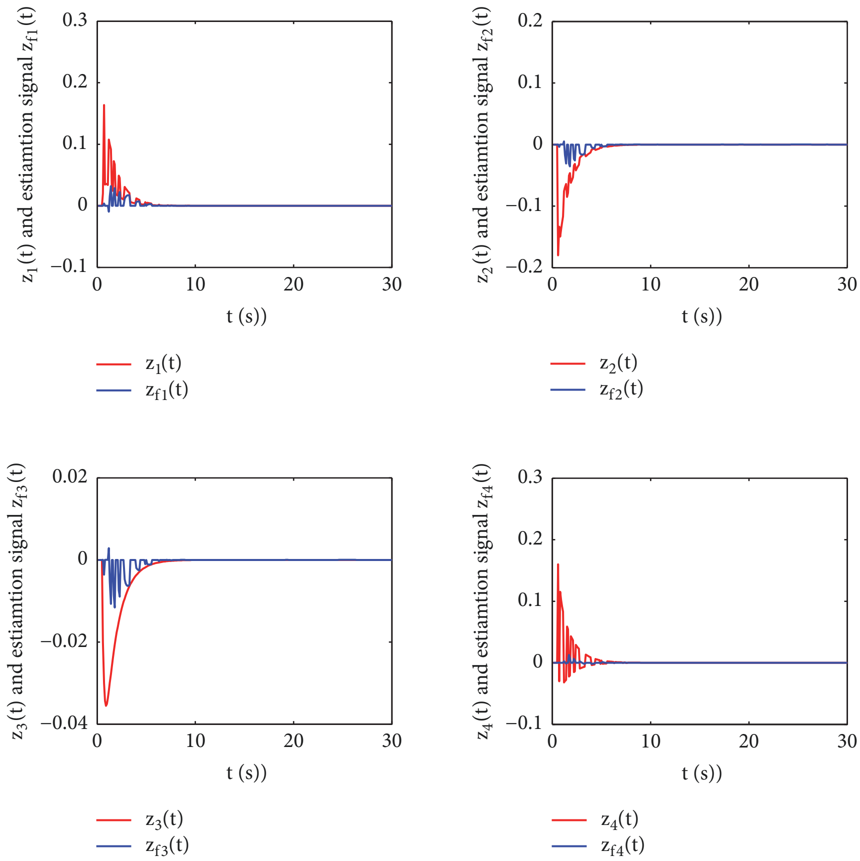

FIGURE 4: $z_i(t)$ and their estimation $z_{fi}(t)$.

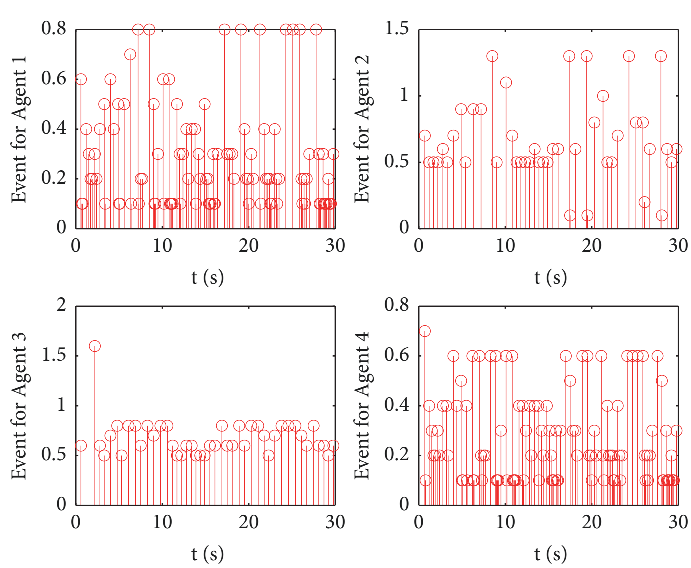

FIGURE 5: The release instants and release interval of each agent.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (61374083 and 61703371).

References

[1] X. Ge and Q.-L. Han, "Distributed Formation Control of Networked Multi-Agent Systems Using a Dynamic Event-Triggered Communication Mechanism," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 10, pp. 8118–8127, 2017.

[2] T. Han, Z. H. Guan, M. Chi, B. Hu, T. Li, and X. H. Zhang, "Multi-formation control of nonlinear leader-following multi-agent systems," *ISA Transactions®*, vol. 69, pp. 140–147, 2017.

[3] X. Ge and Q.-L. Han, "Distributed event-triggered H_∞ filtering over sensor networks with communication delays," *Information Sciences*, vol. 291, pp. 128–142, 2015.

[4] C. P. Bechlioulis and G. A. Rovithakis, "Decentralized robust synchronization of unknown high order nonlinear multi-agent systems with prescribed transient and steady state performance," *IEEE Transactions on Automatic Control*, vol. 62, no. 1, pp. 123–134, 2017.

[5] J. Gao, X. Xu, N. Ding, and E. Li, "Flocking motion of multi-agent system by dynamic pinning control," *IET Control Theory & Applications*, vol. 11, no. 5, pp. 714–722, 2017.

[6] L. Zhou and S. Li, "Distributed model predictive control for multi-agent flocking via neighbor screening optimization," *International Journal of Robust and Nonlinear Control*, vol. 27, no. 9, pp. 1690–1705, 2017.

[7] R. Olfati-Saber, "Distributed Kalman filtering for sensor networks," in *Proceedings of the 46th IEEE Conference on Decision and Control*, pp. 5492–5498, December 2007.

[8] R. Olfati-Saber, "Kalman-consensus filter: optimality, stability, and performance," in *Proceedings of the 48th IEEE Conference on Decision and Control Held Jointly with the 28th Chinese Control Conference (CDC/CCC '09)*, pp. 7036–7042, IEEE, Shanghai, China, December 2009.

[9] B. Shen, Z. Wang, and Y. S. Hung, "Distributed H_∞-consensus filtering in sensor networks with multiple missing measurements: the finite-horizon case," *Automatica*, vol. 46, no. 10, pp. 1682–1688, 2010.

[10] Y. Xu, H. Y. Su, Y. J. Pan, and Z. Wu, "Robust H_∞ filtering for networked stochastic systems with randomly occurring sensor nonlinearities and packet dropouts," *Signal Processing*, vol. 93, no. 7, pp. 1794–1803, 2013.

[11] X. Ge, Q. Han, D. Ding, X. Zhang, and B. Ning, "A survey on recent advances in distributed sampled-data cooperative control of multi-agent systems," *Neurocomputing*, vol. 275, pp. 1684–1701, 2018.

[12] R. Yang, P. Shi, G. P. Liu, and H. Gao, "Network-based feedback control for systems with mixed delays based on quantization and dropout compensation," *Automatica*, vol. 47, no. 12, pp. 2805–2809, 2011.

[13] Z. G. Wu, P. Shi, H. Y. Su, and J. Chu, "Network-based robust passive control for fuzzy systems with randomly occurring uncertainties," *IEEE Transactions on Fuzzy Systems*, vol. 21, no. 5, pp. 966–971, 2013.

[14] Y. Wu, R. Lu, P. Shi, H. Su, and Z. Wu, "Sampled-Data Synchronization of Complex Networks With Partial Couplings and T–S Fuzzy Nodes," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 2, pp. 782–793, 2018.

[15] Y. Wu, R. Lu, P. Shi, H. Su, and Z. Wu, "Analysis and Design of Synchronization for Heterogeneous Network," *IEEE Transactions on Cybernetics*, vol. 48, no. 4, pp. 1253–1262, 2018.

[16] Y. Wu and R. Lu, "Event-based control for network systems via integral quadratic constraints," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 65, no. 4, pp. 1386–1394, 2018.

[17] L. Zou, Z. Wang, H. Gao, and X. Liu, "Event-triggered state estimation for complex networks with mixed time delays via sampled data information: The continuous-time case," *IEEE Transactions on Cybernetics*, vol. 45, no. 12, pp. 2804–2815, 2015.

[18] J. Hu, Z. Wang, J. Liang, and H. Dong, "Event-triggered distributed state estimation with randomly occurring uncertainties and nonlinearities over sensor networks: a delay-fractioning approach," *Journal of The Franklin Institute*, vol. 352, no. 9, pp. 3750–3763, 2015.

[19] S. Hu and D. Yue, "Event-based H_∞ filtering for networked system with communication delay," *Signal Processing*, vol. 92, no. 9, pp. 2029–2039, 2012.

[20] J. Liu, J. Tang, and S. Fei, "Event-triggered H∞ filter design for delayed neural network with quantization," *Neural Networks*, vol. 82, pp. 39–48, 2016.

[21] S. Li, D. Sauter, and B. Xu, "Fault isolation filter for networked control system with event-triggered sampling scheme," *Sensors*, vol. 11, no. 1, pp. 557–572, 2011.

[22] H. Wang, P. Shi, and J. Zhang, "Event-triggered fuzzy filtering for a class of nonlinear networked control systems," *Signal Processing*, vol. 113, pp. 159–168, 2015.

[23] H. Wang, A. Xue, J. Wang, and R. Lu, "Event-based H∞ filtering for discrete-time markov jump systems with network-induced delay," *Journal of The Franklin Institute*, vol. 354, no. 14, pp. 6170–6189, 2017.

[24] H. Wang, D. Zhang, and R. Lu, "Event-triggered H∞ filter design for markovian jump systems with quantization," *Nonlinear Analysis: Hybrid Systems*, vol. 28, pp. 23–41, 2018.

[25] Z. G. Wu, P. Shi, H. Su, and J. Chu, "Asynchronous l_2-l_∞ filtering for discrete-time stochastic Markov jump systems with randomly occurred sensor nonlinearities," *Automatica*, vol. 50, no. 1, pp. 180–186, 2014.

[26] S. Xu, J. Lam, and X. Mao, "Delay-dependent H_∞ control and filtering for uncertain Markovian jump systems with time-varying delays," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 54, no. 9, pp. 2070–2077, 2007.

[27] L. X. Zhang, "H_∞ estimation for discrete-time piecewise homogeneous Markov jump linear systems," *Automatica*, vol. 45, no. 11, pp. 2570–2576, 2009.

[28] D. Viegas, P. Batista, P. Oliveira, C. Silvestre, and C. L. Chen, "Distributed state estimation for linear multi-agent systems with time-varying measurement topology," *Automatica*, vol. 54, pp. 72–79, 2015.

[29] D. Yue, E. Tian, and Q. Han, "A delay system method for designing event-triggered controllers of networked control systems," *IEEE Transactions on Automatic Control*, vol. 58, no. 2, pp. 475–481, 2013.

[30] K. Gu, "An integral inequality in the stability problem of time-delay systems," in *Proceedings of the 39th IEEE Confernce on Decision and Control*, pp. 2805–2810, Sydney, Australia, December 2000.

[31] P. G. Park, J. W. Ko, and C. Jeong, "Reciprocally convex approach to stability of systems with time-varying delays," *Automatica*, vol. 47, no. 1, pp. 235–238, 2011.

[32] H. Y. Shao, "New delay-dependent stability criteria for systems with interval delay," *Automatica*, vol. 45, no. 3, pp. 744–749, 2009.


Journal of Engineering
The Scientific World Journal
International Journal of Rotating Machinery
Journal of Sensors
Advances in Multimedia
Advances in Civil Engineering
Hindawi
Submit your manuscripts at
www.hindawi.com
Journal of Control Science and Engineering
Journal of Robotics
Journal of Electrical and Computer Engineering
Advances in OptoElectronics
VLSI Design
International Journal of Navigation and Observation
Modelling & Simulation in Engineering
International Journal of Aerospace Engineering
International Journal of Chemical Engineering
International Journal of Antennas and Propagation
Active and Passive Electronic Components
Shock and Vibration
Advances in Acoustics and Vibration