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Research article

Memory-event-triggered consensus control for multi-UAV systems against deception attacks

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A R T I C L E I N F O

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A B S T R A C T

This paper addresses the memory-based event-triggered consensus control issue for multi-UAV systems subject to deception attacks. In order to alleviate network bandwidth burden and reduce unnecessary data transmission, a memory-based event-triggered scheme (METS) is proposed by applying historic data information (HDI). Meanwhile, the average mechanism (AM) is introduced to replace the input of conventional event triggering scheme, which eliminates adverse event-triggering caused by instantaneous random jitter and deception attacks. Through this method, data mutation, peak/trough information loss, and energy consumption issues of UAV can be effectively addressed. With the aid of attack observer, a consensus control strategy is devised for each UAV to achieve control objective and compensate for the impact of attacks on multi-UAV system. Then, sufficient conditions are constructed to co-design the parameters and guarantee the attacked multi-UAV system can achieve consensus. The simulation results are provided to demonstrate the validity and practicality of the proposed strategy.

1. Introduction

Over the past decades, unmanned aerial vehicles (UAV), as a classic delegate of agent [1], have attracted more attention due to the development of multi-agent technology and the rapidly growing market [2]. Compared with a single UAV, cooperation control of multiple UAVs can not only avoid the limitation of load capacity and endurance, but also accomplish complex tasks with higher efficiency [3–5]. As a fundamental research of multi-agent control, consensus problem has been widely investigated and extended to the field of multi-UAV research, which is of important theoretical and practical significance [6–9]. This issue is embodied in updating the state of each UAV based on local information exchange, so as to synchronize the final dynamics of autonomous UAVs. For instance, in [10], the problem of consensus-based precise flocking for multi-UAV was studied to guarantee the safe distance among UAVs. By designing distributed optimal control method and linear quadratic regulator strategy, the authors in [11] discussed the formation control with obstacle avoidance for a mixed-order multi-agent in ocean conditions. Particularly, leader-following consensus control problem appears once the agreement state is supplied by a leader UAV [12–14]. Considering the communication delay and modeling the random switching topology as Markov process, a distributed observer to estimate the leader's state and an output feedback control method to solve the mean square consensus were designed for heterogeneous systems in [15]. In order to settle the problem of joint channel and link selection, the authors in [16] proposed a two-way consensus game technology to acquire steady state and realize the master–slave formation of UAVs. Thus, based on the above discussion, the research on multi-UAV consensus is still a meaningful topic.

In the actual multi-UAV system, the continuous control strategy is usually used to obtain the state information of system when the UAVs cooperate to execute missions and react with each other in time [17,18]. However, frequent sensor sampling and controller updating will cause plenty of unnecessary waste of resources [19–21]. Therefore, an event-triggered scheme (ETS) is adopted to utilize the limited communication resources [22–24]. For a nonlinear multi-UAV system, a distributed event-based finite-time formation control strategy was given in [24] to address the matter of implementing predefined configurations with input saturation. In [25], a distributed sampling and triggering scheme was designed for the consensus problem of second-order systems, and two conditions were proposed to reduce conservatism by using LMI method. In [26], a hybrid dynamic ETS and model-based control law were put forward for multi-agent systems (MASs) with external disturbances. In order to only perform information interaction when necessary to improve communication efficiency, reinforcement learning technology was presented in [27] to design two paradigms of sending/receiving

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event-triggered communication network framework for different mission demands. In this way, whether the agent participates in communication at each step was optimally determined and the limited bandwidth constraint problem could be well solved. The efforts mentioned above adopt the error between the immediate data packet and the recently sent one to determine the next releasing time. However, as the system state is at the peak or trough, the error is much small so that the latest packet will not be sent [28,29]. In this case, we expect that more information will be sent to the controller side to ensure the control performance of the system. To address this issue, the authors in [28] proposed a memory-based ETS to improve the number of system information and event triggers at response peaks or troughs. In order to increase the observer accuracy and relieve network bandwidth pressure, an adaptive memory event-triggered control strategy was investigated in [30]. Based on the segmented weighting technique, an ETS was designed by using the information in the sliding historical window to reduce false triggering events [31]. This motivates the current work.

It is worth noting that the communication and control signals in multi-UAV systems are vulnerable to malicious attacks due to transmission through public networks [32,33]. Generally speaking, the current types of network attacks are mainly divided into denial of service attack [34] and deception attack [35,36]. As is well known, deception attacks will lead to the destruction of UAV infrastructure, the leakage of controller information, the tampering of control signals and other behaviors that seriously affect the consensus of multi-UAV system [37,38]. Among them, the injected false data may be accepted as true and the data integrity and system performance then be sabotaged in that deception attack intercepts the control signal and falsifies the data packets. For example, the secure tracking control issue of autonomous vehicles was investigated in [39] by combining learning-based ETS and deception attacks. In the presence of deception attack, an adaptive ETS based consensus control method was proposed in [40], which reduced data transmission while ensuring the system control performance. As a defender, it is difficult to know the probability and strength of attack signals, but it is possible to reduce the impact of attacks by designing security protection protocols. Recently, more effort has been made on the secure consensus research of multi-UAV systems and the topic remains challenging.

According to the aforementioned discussions, this article mainly aims at dealing with the secure consensus control problem for multi-UAV system in the leader-following framework against deception attacks. Compared with the existing research, the main contributions of this article lie three-fold.

(1) Differ to the input of general ETS, a novel METS for multi-UAV system is constructed by utilizing the average value of HDI in a specific time interval. First, the data mutation caused by deception attacks or other interference factors can be avoided and the packet transmitting rate (PTR) is reduced when the system fluctuates violently. Then, the system tendency can be indicated and an adaptive law, fusing HDI, is put forward to adjust the trigger threshold on-line.
(2) An attack observer is developed to make up for the adverse influence of attacks on the system, and the estimation precision of observer is ensured under the compensation mechanism.
(3) In view of the proposed METS, a distributed consensus control strategy is further designed for the leader-following multi-UAV system against deception attacks. With the introducing of attack observer and average sampling of HDI, the system performance can be guaranteed while reducing resource consumption and improving the navigating ability.

The remainder of this article are organized as follows. The problem formulation for multi-UAV system is introduced in Section 2. In Section 3, main theoretical results of consensus performance analysis and joint design of consensus controller and METS subject to deception attacks are provided. In Section 4, simulation examples are performed to illustrate validity of the proposed strategy. The conclusion is given in Section 5.

Notation: $\mathbb{R}^n$ denotes the n-Euclidean space. $\text{diag}_N\{S_l\}$ represents a N-dimensional (block) diagonal matrix $\text{diag}\{S_1, \ldots, S_N\}$. Likewise, $\text{col}_N\{S_l\}$ is defined as column vectors. I_{nN} and I_{2nN} denote the nN-by-nN and $2nN$-by-$2nN$ identity matrix, respectively. $\|X\|$ refers to Euclidean norm of vectors or matrices. $\otimes$ is the Kronecker product. Besides, $[X]_s$ represents $X + X^T$. $*$ represents the transpose of block matrix. 0 denotes zero matrix with all elements being zero.

2. Problem formulation

The structure of dynamic model for multi-UAV system under deception attacks is depicted in Fig. 1, where the METS in introduced to transmit the necessary information to controller i and neighbor nodes. The attacks occur in communication channel to tamper released data and can be estimated by observer i. Due to the introduction of compensation mechanism, the adverse influence of attacks on the system can be eliminated. Under the METS, the network bandwidth burden can be better alleviated while the system performance can be guaranteed. Meanwhile, each UAV is remotely controlled by a consensus controller over wireless network.

2.1. Graph theory

In this article, a directed topology consisting of one leader UAV and N homogeneous followers is depicted by graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$, where $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ denotes index set of N nodes. $\mathcal{W} = \left[w_{ij}\right]_{N\times N}$ and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ express a weighted adjacency matrix with non-negative elements and a directed edge set, respectively. For any directed edge $\mathcal{E}_{ij}$ denoted by $(\mathcal{V}_j, \mathcal{V}_i)$ in graph $\mathcal{G}$, $w_{ij} > 0$ if there exists $\mathcal{E}_{ij} \in \mathcal{E}$, and $w_{ij} = 0$ otherwise. Let $\mathcal{N}_i = \{j | (j, i) \in \mathcal{E}\}$ be the neighbor index set of the ith UAV. In the digraph, the leader UAV is globally reachable when assumed as a root node of spanning tree in $\mathcal{G}$. The Laplacian of graph $\mathcal{G}$ can be expressed by $\mathcal{L} = [l_{ij}]$ with $l_{ii} = \sum_{j\in\mathcal{N}_i} w_{ij}$, and $l_{ij} = -w_{ij}$ for $i \neq j$. Besides, the weight matrix between leader and follower UAVs is represented by $\mathcal{C} = \text{diag}\{c_1, \ldots, c_N\}$, and $c_i > 0$ if information can be transmitted from leader to the ith follower; $c_i = 0$ otherwise.

2.2. System modeling

Consider a leader-following multi-UAV system comprised of one leader (labeled by 0) and N followers, which are considered as mass point model. The dynamic of the ith UAV is constructed as:

$$\begin{cases} \dot{s}_i(t) = v_i(t), \\ \dot{v}_i(t) = u_i(t) + Da_i(t), \end{cases} \tag{1}$$

where $i = 1, \ldots, N$, $s_i(t) \in \mathbb{R}^n$, $v_i(t) \in \mathbb{R}^n$ and $u_i(t) \in \mathbb{R}^n$ denote the position state, velocity state, control input vector of the ith UAV, respectively. $a_i(t) \in \mathbb{R}^n$ represents the deception attack signal, which aims to inject or falsify the data in communication channels without changing the topology graph and interferes with the velocity variance of the UAV. D represents a constant matrix.

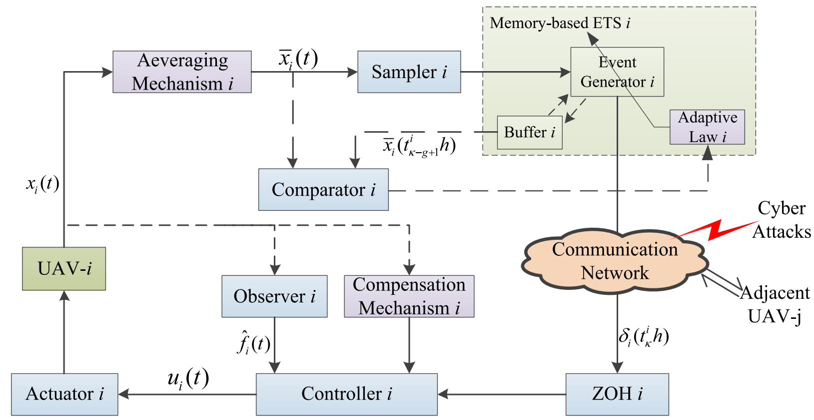

Fig. 1. Structure of the memory-based consensus control for the ith UAV against deception attacks.

Consider the dynamic of leader UAV as

$$\begin{cases}\dot{s}_0(t)=v_0(t),\\ \dot{v}_0(t)=0,\end{cases} \tag{2}$$

where $s_0(t)\in\mathbb{R}^n$, $v_0(t)\in\mathbb{R}^n$ represent position and velocity of the leader.

Define the system sate vector as $x_i(t)=\begin{bmatrix}s_i(t)\\ v_i(t)\end{bmatrix}$ and $x_0(t)=\begin{bmatrix}s_0(t)\\ v_0(t)\end{bmatrix}$, the deception attack signal as $a(t)=\text{col}\{a_1(t),a_2(t),\ldots,a_N(t)\}$. Therefore, the transformation of multi-UAV system is depicted by

$$\begin{cases}\dot{x}_i(t)=Ax_i(t)+Bu_i(t)+\bar{D}a_i(t),\\ \dot{x}_0(t)=Ax_0(t),\end{cases} \tag{3}$$

where $A=\begin{bmatrix}0_{n\times n} & I_n\\ 0_{n\times n} & 0_{n\times n}\end{bmatrix}$, $B=\begin{bmatrix}0_{n\times n}\\ I_n\end{bmatrix}$, $\bar{D}=\begin{bmatrix}0_{n\times n}\\ D\end{bmatrix}$, and $a_i(t)$ denotes the attack vector.

Remark 1. The original state of each UAV $x_i(0)$ is assumed to be free from deception attack in that the initial state cannot be acquired by adversary during system open time. Due to the openness of the unmanned aerial vehicle communication network, the information in the communication channel among UAVs is vulnerable to interception and false data creation by attackers, which can be injected into other nodes. In order to conceal deceptive attacks, the energy of the attack signal usually satisfies some constraint upper bounds. Therefore, the signal $a_i(t)$ here is energy bounded.

2.3. Design of deception attack observer and METS based controller

In practice, UAV communication is vulnerable to attack, under which the adversary will mislead the application target and make the signal receiver calculate the wrong location and time information. To estimate the attack signal, the following observer model is considered.

$$\begin{cases}\hat{a}_i(t)=F[\eta_i(t)+x_i(t)],\\ \dot{\eta}_i(t)=-[Ax_i(t)+Bu_i(t)+\bar{D}F(\eta_i(t)+x_i(t))],\end{cases} \tag{4}$$

where $\eta_i(t)$ is interval variable; F is the observer gain to be designed and $\hat{a}_i(t)$ represents the estimated deception attack signal.

As shown in Fig. 1, the AM is added before sampling, by which the average value of historic data $\bar{x}_i(t)$ over the interval T supersedes the sampling input

$$\bar{x}_i(t)=\frac{1}{T}\int_{t-T}^{t}x_i(s)ds. \tag{5}$$

According to Simpson's rule [41], one can deduce that

$$\frac{1}{T}\int_{t-T}^{t}x_i(s)ds\approx\frac{1}{6}[x_i(t)+4x_i(t-\frac{T}{2})+x_i(t-T)]. \tag{6}$$

Remark 2. In the general ETS, periodic sampling may contain anomalous information such as system instantaneous random jitter. In addition to effectively avoiding this phenomenon, eliminating the influence of noise and external disturbances, this method in (5) can also reduce unnecessary data transmission. In this way, the system trend can be better identified.

Remark 3. The adoption of Simpson's rule makes the AM approximately represented by the time delay polynomial. For the sake of rationality, T is a small positive number.

In this article, a METS based control protocol is adopted, which not only sufficiently use limited computing and communication resources, but also ensures the consensus of the multi-UAV system.

Suppose the sampling is clock synchronous for all UAVs due to the same communication network and denote the data-releasing instants $\{t_0^i,t_1^i,\ldots,t_\kappa^i,\ldots\}\subset\{0,1,2,\ldots\}$ with $t_0^i=0$ for UAV i. Then we define the tracking error $\delta_i(t)=\bar{x}_i(t)-\bar{x}_0(t)$ and event-triggering error $e_{\delta_i}(t)=\delta_i(t_\kappa^i h)-\delta_i(t_\kappa^i h+mh)$.

The METS is proposed for each UAV i as follows:

$$e_{\delta_i}^T(t)\Theta_i e_{\delta_i}(t)\le\rho_i(t)\varepsilon_i^T(t)\Theta_i\varepsilon_i(t), \tag{7}$$

where Θ_i is an event-triggered weight matrix; $\varepsilon_i(t)=\sum_{j\in\mathcal{N}_i}w_{ij}[\delta_i(t_\kappa^i h+mh)-\delta_j(t_{\kappa'}^j h+mh)]+c_i\delta_i(t_\kappa^i h+mh)$ with sampling period h, current sampling instant $t_\kappa^i h+mh$ and $t_\kappa^i h$ standing for κ-th triggering instant for UAV$_i$; $t_{\kappa'}^j h=max\{t|t\in\{t_\kappa^j h,\kappa=0,1,\ldots\},t\le t_\kappa^i h+mh\}$ represents the triggering instant of UAV$_j$. Denote $t_{\kappa+1}^i h=t_\kappa^i h+max\{(m+1)h|(7)\ \ holds\}$ and $[t_\kappa^i h,t_{\kappa+1}^i h)=\bigcup_{\nu h=t_\kappa^i h}^{(t_{\kappa+1}^i-1)h}[\nu h,(\nu+1)h)$ with $\nu h=t_\kappa^i h+mh$ as the next releasing instant.

The dynamic triggering threshold $\rho_i(t)$ satisfies the following adaptive law:

$$\rho_i(t)=\rho_m^i tanh(\iota\|e_i^s(t)\|^2)+\rho_M(1-tanh(\iota\|e_i^s(t)\|^2)), \tag{8}$$

where $\rho_i(t)\in[\rho_m^i,\rho_M]\subset(0,1]$; $e_i^s(t)=\bar{x}_i(t)-\frac{1}{s}\sum_{g=1}^{s}\bar{x}_i(t_{\kappa-g+1}^i h)$ indicates the error between historic data and current mean-valued state; ι is a positive constant used to adjust the sensitivity to the error change; s and $t_{\kappa-g+1}^i h$ stand for the amount of HDI and transmitted instant, respectively.

Remark 4. The previous transmitted packets is consolidated into the adaptive law such that the threshold can be dynamically adjusted on the basis of past s packets. In order not to occupy excessive storage space and computing resources, the amount of previous transmitted packets will not be large. When s is selected to be one, Eq. (8) degenerates to a conventional adaptive law.

Remark 5. The buffer stores the latest s historical data for releasing judgment, which can avoid data mutations caused by external disturbances and ensure the integrity of system information. Parameters ρ_m^i and ι can adjust the varying rate of state in the adaptive law, and a smaller threshold value will enable the controller to receive more information to improve transient performance.

Due to the injection of deception attacks, the signals received by the controller make the system unable to operate normally. For the purpose of compensating for the impact of attacks, consensus controller is established based on the METS and attack observer model as follows.

$$u_i(t) = -K_1 c_i \delta_i(t_\kappa^i h) - K_2\left[\sum_{j\in\mathcal{N}_i} w_{ij}(\delta_i(t_\kappa^i h) - \delta_j(t_{\kappa'}^j h))\right] - B^\dagger \bar{D}\hat{a}_i(t),\ \ t\in[\nu h,(\nu+1)h), \tag{9}$$

where K_1, K_2 are feedback gain matrices to be determined; c_i denotes the coupling weight between UAV$_i$ and the leader; w_{ij} is the weighting coefficient of directed edge $\mathcal{E}$; $B^\dagger$ is a matrix satisfying $(I - BB^\dagger)\bar{D} = 0$.

Remark 6. In some literatures of ETS on UAV system, only continuous information transmission between adjacent UAVs is avoided, but the data within the fixed sampling interval will be discarded. Therefore, an average sampling mechanism is proposed in the controller design, which uses the average value of the information during the sampling interval to better predict the system trend and make decisions on whether to send data. In addition, the attack compensation mechanism is introduced in (9) to make up for the influence of attacks on the UAV system and promote the control performance.

2.4. The overall model

The leader-following consensus error is defined by $\xi_i(t) = x_i(t) - x_0(t)$, and attack estimation error dynamic is given as

$$e_{a_i}(t) = a_i(t) - \hat{a}_i(t). \tag{10}$$

For $t\in[\nu h,(\nu+1)h)$, define the piecewise-linear function $\varsigma_i(t) = t - \nu h$ satisfying $\varsigma_i(t)\in[0,\varsigma_M)$, and it can be seen that $\dot{\varsigma}_i(t) = 1$ at $t \neq \nu h$. Then the closed-loop system (3) can be expressed as

$$\dot{\xi}_i(t) = A\xi_i(t) - BK_1 c_i(e_{\delta_i}(t) + \delta_i(\nu h)) - BK_2\sum_{j\in\mathcal{N}_i} l_{ij}(e_{\delta_i}(t) + \delta_i(\nu h)) + \bar{D}e_{a_i}(t). \tag{11}$$

Let $\delta_i(t-\varsigma_i(t)) = \frac{1}{6}[\xi_i(t-\varsigma_i(t)) + 4\xi_i(t-\varsigma_i(t)-\frac{T}{2}) + \xi_i(t-\varsigma_i(t)-T)]$, the dynamics of the system can be rewritten by

$$\begin{cases} \dot{\xi}(t) = (I_N\otimes A)\xi(t) - (\mathcal{C}\otimes BK_1 + \mathcal{L}\otimes BK_2)[e_\delta(t) + \delta(t-\varsigma(t))] + (I_N\otimes\bar{D})e_a(t), \\ \quad = (I_N\otimes A)\xi(t) - (\mathcal{C}\otimes BK_1 + \mathcal{L}\otimes BK_2) \\ \quad\quad \times\left[e_\delta(t) + \frac{1}{6}\xi(t-\varsigma(t)) + \frac{2}{3}\xi(t-\varsigma(t)-\frac{T}{2}) + \frac{1}{6}\xi(t-\varsigma(t)-T)\right] + (I_N\otimes\bar{D})e_a(t), \\ \dot{e}_a(t) = \dot{a}(t) - \dot{\hat{a}}(t), \\ \quad = \dot{a}(t) - (I_N\otimes F\bar{D})e_a(t), \end{cases} \tag{12}$$

for $t\in[\nu h,(\nu+1)h)$, where

$\xi(t) = \mathrm{col}_N\{\xi_l(t)\}$, $e_\delta(t) = \mathrm{col}_N\{e_{\delta_l}(t)\}$,

$\xi(t-\varsigma(t)-\frac{mT}{2}) = \mathrm{col}_N\{\xi_l(t-\varsigma_l(t)-\frac{mT}{2})\}(m=0,1,2)$,

$e_a(t) = \mathrm{col}_N\{e_{a_l}(t)\}$, $\dot{a}(t) = \mathrm{col}_N\{\dot{a}_l(t)\}$, $\dot{\hat{a}}(t) = \mathrm{col}_N\{\dot{\hat{a}}_l(t)\}$.

This article aims to achieve a control objective, that is, to develop a distributed consensus protocol under the METS and deception attacks. If criteria $\lim_{t\to\infty}\|x_i(t) - x_0(t)\| = 0$ and $\lim_{t\to\infty}\|a_i(t)-\hat{a}_i(t)\| = 0$ (for $i = 1,\ldots,N$) hold, it can be proved that the state of all followers can gradually track that of leader and the protocol is valid in secure sense.

3. Main results

Firstly, the stability of the closed-loop system (11) under the proposed memory-based ETS and deception attacks is analyzed in Theorem 1, which is given to guarantee that the velocity and displacement of all UAVs can converge to those of virtual leader. Then the design conditions of controller gains and METS weighting matrices will be presented in Theorem 2. In order to obtain the results, some lemmas are needed.

Lemma 1 ([42]). *Consider a function $\{\omega(v)|v\in[m,n]\}$ being integrable and a constant matrix $R > 0$, the following inequality holds:*

$$-\int_m^n \omega^T(s)R\omega(s)ds \le \frac{1}{m-n}\left(\int_m^n \omega(s)ds\right)^T R\left(\int_m^n \omega(s)ds\right). \tag{13}$$

Theorem 1. *Consider the multi-UAV system (12). For some positive scalars $\gamma, \varsigma_M, T, \rho_M$, controller gains K_1, K_2 and observer gain F, the system can achieve consensus under deception attacks and METS (7) if there exist positive matrices P_1, P_2, Q_l, R_l $(l = 0,1,2)$, S_1, S_2, Θ_i $(i = 1,2,3,4)$ and matrix U_l with appropriate dimension such that:*

$$\Gamma = \begin{bmatrix} \Gamma_1 & * & * & * & * \\ \Gamma_2 & \Gamma_3 & * & * & * \\ \Gamma_4 & 0 & -\gamma^2 I_{nN} & * & * \\ \Gamma_5 & 0 & 0 & -I_{2nN} & * \\ \Gamma_6 & \Gamma_7 & 0 & 0 & \Gamma_8 \end{bmatrix} < 0, \tag{14}$$

$$\begin{bmatrix} I_N\otimes R_l & * \\ I_N\otimes U_l & I_N\otimes R_l \end{bmatrix} > 0, \tag{15}$$

where

$$\Gamma_1 = \begin{bmatrix} \Gamma_{11} & * & * \\ I_N\otimes D^T P_1 & \Gamma_{12} & * \\ \Gamma_{13} & 0 & -\Theta \end{bmatrix},\ \Gamma_2 = \begin{bmatrix}\Gamma_{21} & 0 & 0\end{bmatrix},$$

$\Gamma_3 = \mathrm{diag}_3\{\Gamma_{3_l}\}$, $\Gamma_4 = \begin{bmatrix}0 & I_N\otimes P_2 & 0\end{bmatrix}$,

$\Gamma_5 = \begin{bmatrix}I_{2nN} & 0 & 0\end{bmatrix}$, $\Gamma_6 = \mathrm{col}\{\mathrm{col}_5\{\Gamma_{6_l}\}, 0\}$,

$\Gamma_7 = \mathrm{col}_6\{\Gamma_{7_l}\}$, $\Gamma_8 = \mathrm{diag}_3\{\Gamma_{8_l}\}$,

$$\Gamma_{11} = I_N\otimes[P_1A]_s + I_N\otimes(Q_0+Q_1+Q_2) - \frac{1}{\varsigma_M}I_N\otimes R_0 - I_N\otimes(S_1+S_2),$$

$\Gamma_{12} = -I_N\otimes[P_2F\bar{D}]_s$, $\mathcal{N} = \mathcal{C}\otimes BK_1 + \mathcal{L}\otimes BK_2$,

$\Gamma_{13} = \mathcal{N}^T(I_N\otimes P_1)$,

$$\Gamma_{21} = \mathrm{col}\{-\frac{1}{6}\Gamma_{13} + \frac{1}{\varsigma_M}I_N\otimes(R_0-U_0), \frac{1}{\varsigma_M}I_N\otimes U_0, I_N\otimes S_1, -\frac{2}{3}\Gamma_1^3, 0, I_N\otimes S_2, -\frac{1}{6}\Gamma_{13}, 0\},$$

$$\Gamma_{3_1} = \begin{bmatrix} \frac{1}{\varsigma_M}I_N\otimes[U_0-R_0]_s & * \\ \frac{1}{\varsigma_M}I_N\otimes(R_0-U_0) & -I_N\otimes(Q_0+\frac{1}{\varsigma_M}R_0) \end{bmatrix},$$

$$\varGamma_{3_2} = \begin{bmatrix} -I_N \otimes (\frac{1}{\varsigma_M}R_1 + S_1) & * & * \\ \frac{1}{\varsigma_M}I_N \otimes (R_1 - U_1) & \frac{1}{\varsigma_M}I_N \otimes [U_1 - R_1]_s & * \\ \frac{1}{\varsigma_M}I_N \otimes U_1 & \frac{1}{\varsigma_M}I_N \otimes (R_1 - U_1) & -I_N \otimes (Q_1 + \frac{1}{\varsigma_M}R_1) \end{bmatrix},$$

$$\varGamma_{3_3} = \begin{bmatrix} -I_N \otimes (\frac{1}{\varsigma_M}R_2 + S_2) & * & * \\ \frac{1}{\varsigma_M}I_N \otimes (R_2 - U_2) & \frac{1}{\varsigma_M}I_N \otimes [U_2 - R_2]_s & * \\ \frac{1}{\varsigma_M}I_N \otimes U_2 & \frac{1}{\varsigma_M}I_N \otimes (R_2 - U_2) & -I_N \otimes (Q_2 + \frac{1}{\varsigma_M}R_2) \end{bmatrix},$$

$$\mathcal{M}_1 = \begin{bmatrix} I_N \otimes A & I_N \otimes \bar{D} & -\mathcal{N} \end{bmatrix},$$

$$\mathcal{M}_2 = \begin{bmatrix} -\frac{1}{6}\mathcal{N} & 0 & 0 & -\frac{2}{3}\mathcal{N} & 0 & 0 & -\frac{1}{6}\mathcal{N} & 0 \end{bmatrix},$$

$$\varGamma_{6_1} = \varGamma_{6_2} = \varGamma_{6_3} = \sqrt{\varsigma_M}\mathcal{M}_1,\ \varGamma_{6_4} = \frac{T}{2}\mathcal{M}_1,\ \varGamma_{6_5} = T\mathcal{M}_1,$$

$$\varGamma_{7_1} = \varGamma_{7_2} = \varGamma_{7_3} = \sqrt{\varsigma_M}\mathcal{M}_2,\ \varGamma_{7_4} = \frac{T}{2}\mathcal{M}_2,\ \varGamma_{7_5} = T\mathcal{M}_2,$$

$$\varGamma_{7_6} = \begin{bmatrix} \frac{1}{6}H \otimes I_{2n} & 0 & 0 & \frac{2}{3}H \otimes I_{2n} & 0 & 0 & \frac{1}{6}H \otimes I_{2n} & 0 \end{bmatrix},$$

$$H = \mathcal{C} + \mathcal{L},\ \varTheta = \mathrm{diag}_4\{\varTheta_i\},$$

$$\varGamma_{8_1} = \mathrm{diag}_3\{-I_N \otimes R_{l-1}^{-1}\},\ \varGamma_{8_2} = \mathrm{diag}_2\{-I_N \otimes S_l^{-1}\},$$

$$\varGamma_{8_3} = -\frac{1}{\rho_M}\varTheta^{-1}.$$

Proof. Inspired by [42], construct the following LKF candidate for the multi-UAV system (12)

$$V(t) = \sum_{i=1}^{4} V_i(t), \tag{16}$$

where

$$V_1(t) = \xi^T(t)(I_N \otimes P_1)\xi(t) + e_a^T(t)(I_N \otimes P_2)e_a(t),$$

$$V_2(t) = \sum_{l=0}^{2} \int_{t-\varsigma_M-\frac{lT}{2}}^{t} \xi^T(s)(I_N \otimes Q_l)\xi(s)ds,$$

$$V_3(t) = \sum_{l=0}^{2} \int_{t-\varsigma_M-\frac{lT}{2}}^{t-\frac{lT}{2}} \int_{\theta}^{t} \dot{\xi}^T(s)(I_N \otimes R_l)\dot{\xi}(s)dsd\theta,$$

$$V_4(t) = \frac{T}{2}\int_{t-\frac{T}{2}}^{t}\int_{\theta}^{t} \dot{\xi}^T(s)(I_N \otimes S_1)\dot{\xi}(s)dsd\theta + T\int_{t-T}^{t}\int_{\theta}^{t} \dot{\xi}^T(s)(I_N \otimes S_2)\dot{\xi}(s)dsd\theta.$$

Differentiating function $V(t)$ along the trajectories of system (12) yields

$$\dot{V}_1(t) = 2\xi^T(t)(I_N \otimes P_1)\dot{\xi}(t) + 2e_a^T(t)(I_N \otimes P_2)\dot{e}_a(t),$$

$$\dot{V}_2(t) = \xi^T(t)(I_N \otimes (Q_0 + Q_1 + Q_2))\xi(t) - \sum_{l=0}^{2} \xi^T(t - \varsigma_M - \frac{lT}{2})(I_N \otimes Q_l)\xi(t - \varsigma_M - \frac{lT}{2}),$$

$$\dot{V}_3(t) = \sum_{l=0}^{2} \varsigma_M \dot{\xi}^T(t)(I_N \otimes R_l)\dot{\xi}(t) - \sum_{l=0}^{2} \int_{t-\varsigma_M-\frac{lT}{2}}^{t-\frac{lT}{2}} \dot{\xi}^T(s)(I_N \otimes R_l)\dot{\xi}(s)ds,$$

$$\dot{V}_4(t) = \sum_{l=1}^{2}(\frac{lT}{2})^2\dot{\xi}^T(t)(I_N \otimes S_l)\dot{\xi}(t) - \sum_{l=1}^{2} \frac{lT}{2}\int_{t-\frac{lT}{2}}^{t} \dot{\xi}^T(s)(I_N \otimes S_l)\dot{\xi}(s)ds.$$

By applying Kronecker product, the event-triggering condition in (7) can be formulated as

$$e_\delta^T(t)\varTheta e_\delta(t) \le \rho_M \varepsilon^T(t)\varTheta\varepsilon(t), \tag{17}$$

with $\varepsilon(t) = (H \otimes I_{2n})\delta(t - \varsigma(t))$.

For $l = 0, 1, 2$, based on Jensen's inequality, one can obtain

$$-\int_{t-\varsigma_M-\frac{lT}{2}}^{t-\frac{lT}{2}} \dot{\xi}^T(s)(I_N \otimes R_l)\dot{\xi}(s)ds \le \frac{1}{\varsigma_M}\sigma_l^{1^T}(t)\mathcal{R}_l\sigma_l^1(t), \tag{18}$$

with

$$\sigma_l^1 = \begin{bmatrix} \xi(t - \frac{l}{2}T) \\ \xi(t - \varsigma(t) - \frac{l}{2}T) \\ \xi(t - \varsigma_M - \frac{l}{2}T) \end{bmatrix},$$

$$\mathcal{R}_l = \begin{bmatrix} -I_N \otimes R_l & * & * \\ I_N \otimes (R_l - U_l) & I_N \otimes [U_l - R_l]_s & * \\ I_N \otimes U_l & I_N \otimes (R_l - U_l) & -I_N \otimes R_l \end{bmatrix}.$$

According to Lemma 1, for $l = 1, 2$, it yields that

$$-\frac{lT}{2}\int_{t-\frac{lT}{2}}^{t} \dot{\xi}^T(s)(I_N \otimes S_l)\dot{\xi}(s)ds \le \sigma_l^{2^T}(t)\mathcal{S}_l\sigma_l^2(t), \tag{19}$$

with

$$\sigma_l^2 = \begin{bmatrix} \xi(t) \\ \xi(t - \frac{l}{2}T) \end{bmatrix},\ \mathcal{S}_l = \begin{bmatrix} -I_N \otimes S_l & * \\ I_N \otimes S_l & -I_N \otimes S_l \end{bmatrix}.$$

By defining $\psi_1(t) = \mathrm{col}\{\xi(t), e_a(t), e_\delta(t), \xi(t - \varsigma(t)), \xi(t - \varsigma_M), \xi(t - \frac{T}{2}), \xi(t - \varsigma(t) - \frac{T}{2}), \xi(t - \varsigma_M - \frac{T}{2}), \xi(t - T), \xi(t - \varsigma(t) - T), \xi(t - \varsigma_M - T)\}$, $\mathcal{J} = [\varGamma_6,\ \varGamma_7]$, $\varGamma' = \begin{bmatrix} \varGamma_1 & * \\ \varGamma_2 & \varGamma_3 \end{bmatrix}$, and considering the circumstance that $\dot{a}(t) = 0$, the proposed control method can achieve leader-following consensus for multi-UAV system if the next inequality holds:

$$\begin{aligned} \dot{V}(t) \le\ & \dot{\xi}^T(t)(I_N \otimes P_1)\xi(t) + \xi^T(t)(I_N \otimes P_1)\dot{\xi}(t) + \dot{e}_a^T(t)(I_N \otimes P_2)e_a(t) \\ & + e_a^T(t)(I_N \otimes P_2)\dot{e}_a(t) + \xi^T(t)(I_N \otimes (Q_0 + Q_1 + Q_2))\xi(t) \\ & - \sum_{l=0}^{2} \xi^T(t - \varsigma_M - \frac{lT}{2})(I_N \otimes Q_l)\xi(t - \varsigma_M - \frac{lT}{2}) \\ & + \sum_{l=0}^{2} \varsigma_M\dot{\xi}^T(t)(I_N \otimes R_l)\dot{\xi}(t) + \sum_{l=1}^{2} \sigma_l^{2^T}(t)\mathcal{S}_l\sigma_l^2(t) \\ & + \sum_{l=0}^{2} \frac{1}{\varsigma_M}\sigma_l^{1^T}(t)\mathcal{R}_l\sigma_l^1(t) + \sum_{l=1}^{2}(\frac{lT}{2})^2\dot{\xi}^T(t)(I_N \otimes S_l)\dot{\xi}(t) \\ & - e_\delta^T(t)\varTheta e_\delta(t) + \rho_M\delta^T(t - \varsigma(t))(H \otimes I_{2n})^T\varTheta(H \otimes I_{2n})\delta(t - \varsigma(t)) \\ =\ & \psi_1^T(t)\varXi_1\psi_1(t), \end{aligned} \tag{20}$$

where $\varXi_1 = \varGamma' - \mathcal{J}^T\varGamma_8^{-1}\mathcal{J}$.

Taking Schur complement lemma to the above inequality, one can obtain that $\varXi_1 < 0$ can be ensured by $\varGamma < 0$ in (14), which indicates that $\dot{V}(t) < 0$ and the closed-loop system (12) is asymptotically stable.

For $t \in [\nu h, (\nu+1)h)$, define $\psi_2(t) = \mathrm{col}\{\xi(t), e_a(t), e_\delta(t), \xi(t - \varsigma(t)), \xi(t - \varsigma_M), \xi(t - \frac{T}{2}), \xi(t - \varsigma(t) - \frac{T}{2}), \xi(t - \varsigma_M - \frac{T}{2}), \xi(t - T), \xi(t - \varsigma(t) - T), \xi(t - \varsigma_M - T), \dot{a}(t)\}$.

For the circumstance that $\dot{a}(t) \ne 0$, the term $\dot{a}(t)$ is kept in (10). Then from (14) one obtains that

$$\begin{aligned} & \dot{V}(t) + \xi^T(t)\xi(t) - \gamma^2\dot{a}^T(t)\dot{a}(t) \\ & \le \Psi_2^T(t)\varGamma\Psi_2(t) < 0. \end{aligned} \tag{21}$$

When $t \to \infty$, one can deduce that

$$\int_0^\infty \xi^T(t)\xi(t) \le \gamma^2\int_0^\infty \dot{a}^T(t)\dot{a}(t). \tag{22}$$

Then the proposed attack observer protocol can asymptotically estimate the attack signal and the consensus can be achieved. That ends the proof. □

In view of the results in Theorem 1, we are in position to co-design the consensus controller gains, observer gain and event-triggering matrices next.

Theorem 2. *For some positive scalars* $\gamma, \varsigma_M, T, \rho_M, \varpi_{l_1}$ $(l_1 = 1, \ldots, 5), \pi$, *the error system* (12) *with the consensus strategy* (9) *and METS* (7) *under deception attacks is asymptotically stable, if there exist positive matrices* $\breve{\Theta}_i$ $(i = 1, 2, 3, 4), X_1, P_2, \breve{Q}_l, \breve{R}_l$ $(l = 0, 1, 2), \breve{S}_1, \breve{S}_2$, *and matrix* $\breve{U}_l$ *such that the following conditions are satisfied:*

$$\breve{\Gamma} = \begin{bmatrix} \breve{\Gamma}_1 & * & * & * & * \\ \breve{\Gamma}_2 & \breve{\Gamma}_3 & * & * & * \\ \breve{\Gamma}_4 & 0 & -\gamma^2 I_{nN} & * & * \\ \breve{\Gamma}_5 & 0 & 0 & -I_{2nN} & * \\ \breve{\Gamma}_6 & \breve{\Gamma}_7 & 0 & 0 & \breve{\Gamma}_8 \end{bmatrix} < 0, \tag{23}$$

$$\begin{bmatrix} I_N \otimes \breve{R}_l & * \\ I_N \otimes \breve{U}_l & I_N \otimes \breve{R}_l \end{bmatrix} > 0, \tag{24}$$

where

$$\breve{\Gamma}_1 = \begin{bmatrix} \breve{\Gamma}_{11} & * & * \\ I_N \otimes D^T & \breve{\Gamma}_{12} & * \\ \breve{\Gamma}_{13} & 0 & -\breve{\Theta} \end{bmatrix}, \breve{\Gamma}_2 = \begin{bmatrix} \breve{\Gamma}_{21} & 0 & 0 \end{bmatrix},$$

$$\breve{\Gamma}_3 = \mathrm{diag}_3\{\breve{\Gamma}_{3_l}\}, \breve{\Gamma}_4 = \begin{bmatrix} 0 & I_N \otimes P_2 & 0 \end{bmatrix},$$

$$\breve{\Gamma}_5 = \begin{bmatrix} I_N \otimes X_1 & 0 & 0 \end{bmatrix}, \breve{\Gamma}_6 = \mathrm{col}\{\mathrm{col}_5\{\breve{\Gamma}_{6_l}\}, 0\},$$

$$\breve{\Gamma}_7 = \mathrm{col}_6\{\breve{\Gamma}_{7_l}\}, \breve{\Gamma}_8 = \mathrm{diag}_3\{\breve{\Gamma}_{8_l}\},$$

$$\breve{\Gamma}_{11} = I_N \otimes [AX_1]_s + I_N \otimes (\breve{Q}_0 + \breve{Q}_1 + \breve{Q}_2) - \frac{1}{\varsigma_M} I_N \otimes \breve{R}_0 - I_N \otimes (\breve{S}_1 + \breve{S}_2),$$

$$\breve{\Gamma}_{12} = -I_N \otimes [Q\bar{D}]_s, \breve{\mathcal{N}} = \mathcal{C} \otimes BY_1 + \mathcal{L} \otimes BY_2, \breve{\Gamma}_{13} = \breve{\mathcal{N}}^T,$$

$$\breve{\Gamma}_{21} = \mathrm{col}\{-\frac{1}{6}\breve{\mathcal{N}}^T + \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_0 - \breve{U}_0), \frac{1}{\varsigma_M} I_N \otimes \breve{U}_0, I_N \otimes \breve{S}_1, -\frac{2}{3}\breve{\mathcal{N}}^T, 0, I_N \otimes \breve{S}_2, -\frac{1}{6}\breve{\mathcal{N}}^T, 0\},$$

$$\breve{\Gamma}_{3_1} = \begin{bmatrix} \frac{1}{\varsigma_M} I_N \otimes [\breve{U}_0 - \breve{R}_0]_s & * \\ \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_0 - \breve{U}_0) & -I_N \otimes (\breve{Q}_0 + \frac{1}{\varsigma_M}\breve{R}_0) \end{bmatrix},$$

$$\breve{\Gamma}_{3_2} = \begin{bmatrix} -I_N \otimes (\frac{1}{\varsigma_M}\breve{R}_1 + \breve{S}_1) & * & * \\ \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_1 - \breve{U}_1) & \frac{1}{\varsigma_M} I_N \otimes [\breve{U}_1 - \breve{R}_1]_s & * \\ \frac{1}{\varsigma_M} I_N \otimes \breve{U}_1 & \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_1 - \breve{U}_1) & -I_N \otimes (\breve{Q}_1 + \frac{1}{\varsigma_M}\breve{R}_1) \end{bmatrix},$$

$$\breve{\Gamma}_{3_3} = \begin{bmatrix} -I_N \otimes (\frac{1}{\varsigma_M}\breve{R}_2 + \breve{S}_2) & * & * \\ \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_2 - \breve{U}_2) & \frac{1}{\varsigma_M} I_N \otimes [\breve{U}_2 - \breve{R}_2]_s & * \\ \frac{1}{\varsigma_M} I_N \otimes \breve{U}_2 & \frac{1}{\varsigma_M} I_N \otimes (\breve{R}_2 - \breve{U}_2) & -I_N \otimes (\breve{Q}_2 + \frac{1}{\varsigma_M}\breve{R}_2) \end{bmatrix},$$

$$\breve{\mathcal{M}}_1 = \begin{bmatrix} I_N \otimes AX_1 & I_N \otimes \bar{D} & -\breve{\mathcal{N}} \end{bmatrix},$$

$$\breve{\mathcal{M}}_2 = \begin{bmatrix} -\frac{1}{6}\breve{\mathcal{N}} & 0 & 0 & -\frac{2}{3}\breve{\mathcal{N}} & 0 & 0 & -\frac{1}{6}\breve{\mathcal{N}} & 0 \end{bmatrix},$$

$$\breve{\Gamma}_{6_1} = \breve{\Gamma}_{6_2} = \breve{\Gamma}_{6_3} = \sqrt{\varsigma_M}\breve{\mathcal{M}}_1, \breve{\Gamma}_{6_4} = \frac{T}{2}\breve{\mathcal{M}}_1, \breve{\Gamma}_{6_5} = T\breve{\mathcal{M}}_1,$$

$$\breve{\Gamma}_{7_1} = \breve{\Gamma}_{7_2} = \breve{\Gamma}_{7_3} = \sqrt{\varsigma_M}\breve{\mathcal{M}}_2, \breve{\Gamma}_{7_4} = \frac{T}{2}\breve{\mathcal{M}}_2, \breve{\Gamma}_{7_5} = T\breve{\mathcal{M}}_2,$$

$$\breve{\Gamma}_{7_6} = \begin{bmatrix} \frac{1}{6} H \otimes X_1 & 0 & 0 & \frac{2}{3} H \otimes X_1 & 0 & 0 & \frac{1}{6} H \otimes X_1 & 0 \end{bmatrix},$$

$$\breve{\Gamma}_{8_1} = \mathrm{diag}_3\{\varpi_l^2 I_N \otimes \breve{R}_{l-1} - 2\varpi_l I_N \otimes X_1\},$$

$$\breve{\Gamma}_{8_2} = \mathrm{diag}_2\{\varpi_{l+3}^2 I_N \otimes \breve{S}_l - 2\varpi_{l+3} I_N \otimes X_1\},$$

$$\breve{\Gamma}_{8_3} = \frac{1}{\rho_M}\pi^2\breve{\Theta} - \frac{2}{\rho_M}\pi I_N \otimes X_1, \breve{\Theta} = \mathrm{diag}_4\{\breve{\Theta}_i\}.$$

Moreover, the controller gains K_1, K_2 *and the observer gain* F *are computed as:* $K_1 = Y_1 X_1^{-1}$, $K_2 = Y_2 X_1^{-1}$, $F = QP_2^{-1}$.

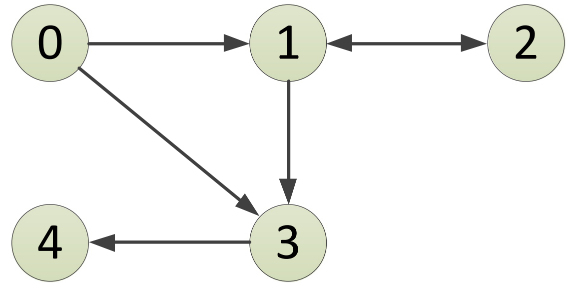

Fig. 2. Directed interaction topology among multiple UAVs.

Proof. Define the following matrix variables for $l = 0, 1, 2$

$$X_1 = P_1^{-1}, \ \breve{Q}_l = X_1^T Q_l X_1, \ \breve{R}_l = X_1^T R_l X_1, \ \breve{U}_l = X_1^T U_l X_1,$$
$$\breve{S}_1 = X_1^T S_1 X_1, \ \breve{S}_2 = X_1^T S_2 X_1, \ \breve{\Theta}_i = (I_N \otimes X_1)^T \Theta_i (I_N \otimes X_1).$$

Define the new matrix $\mathcal{Z} = \mathrm{diag}\{I_N \otimes X_1, I_{nN}, \mathcal{Z}_1, \mathcal{Z}_1, \mathcal{Z}_1, I_{nN}, I_{nN}, \mathcal{Z}_1, \mathcal{Z}_1\}$ with $\mathcal{Z}_1 = \mathrm{diag}\{I_N \otimes X_1, I_N \otimes X_1, I_N \otimes X_1\}$, then execute congruence conversion to (14) and calculating $\mathcal{Z}\Gamma\mathcal{Z}^T$, it is true that (23) can be obtained.

Similar to the method in [43], the nonlinear items in Theorem 2 can be handled by the following inequalities:

$$- I_N \otimes \breve{R}_l^{-1} \le \varpi_{l+1}^2 I_N \otimes \breve{R}_l - 2\varpi_{l+1} I_N \otimes X_1,$$
$$- I_N \otimes \breve{S}_1^{-1} \le \varpi_4^2 I_N \otimes \breve{S}_1 - 2\varpi_4 I_N \otimes X_1,$$
$$- I_N \otimes \breve{S}_2^{-1} \le \varpi_5^2 I_N \otimes \breve{S}_2 - 2\varpi_5 I_N \otimes X_1,$$
$$- \breve{\Theta}^{-1} \le \frac{1}{\rho_M}\pi^2\breve{\Theta} - \frac{2}{\rho_M}\pi I_N \otimes X_1,$$

where $\varpi_{l+1}, \varpi_4, \varpi_5$ and π are given constants. We use the above inequalities to solve the nonlinear terms in Theorem 1.

By applying Schur complement lemma, it yields that (23) is a sufficient condition to ensure (14) holds. Thus, the secure consensus of multi-UAV system under the proposed METS can be ensured. Therefore, we complete the proof. □

4. Simulation example

Consider multiple UAVs composed of one leader and four following UAVs. The information can be transmitted from leader to other UAVs and the directed interaction topology is depicted in Fig. 2, where the Laplacian $\mathcal{L}$ and the leader adjacency matrix $\mathcal{C}$ can be acquired:

$$\mathcal{L} = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 0 & 0 & -1 & 1 \end{bmatrix}, \mathcal{C} = \mathrm{diag}\{1 \ \ 0 \ \ 1 \ \ 0\}.$$

According to Theorem 2, we can obtain the event-triggered matrices

$$\Lambda_1 = \begin{bmatrix} 20.165 & -9.579 & 17.120 & -2.835 \\ -9.579 & 25.936 & -18.081 & 16.345 \\ 17.120 & -18.081 & 28.670 & -9.360 \\ -2.835 & 16.345 & -9.360 & 23.864 \end{bmatrix},$$

$$\Lambda_2 = \begin{bmatrix} 17.536 & -7.900 & 17.725 & -4.052 \\ -7.900 & 22.466 & -15.341 & 18.256 \\ 17.725 & -15.341 & 32.130 & -7.951 \\ -4.052 & 18.256 & -7.951 & 23.875 \end{bmatrix},$$

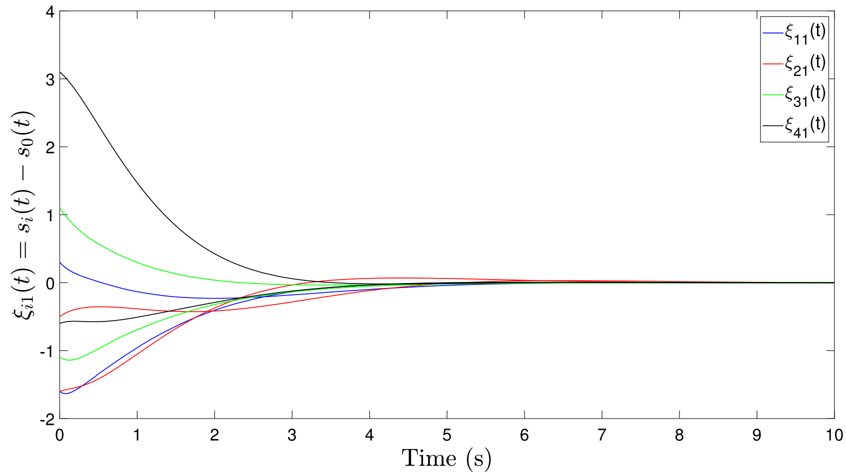

Fig. 3. Tracking errors of the displacement for UAVs.

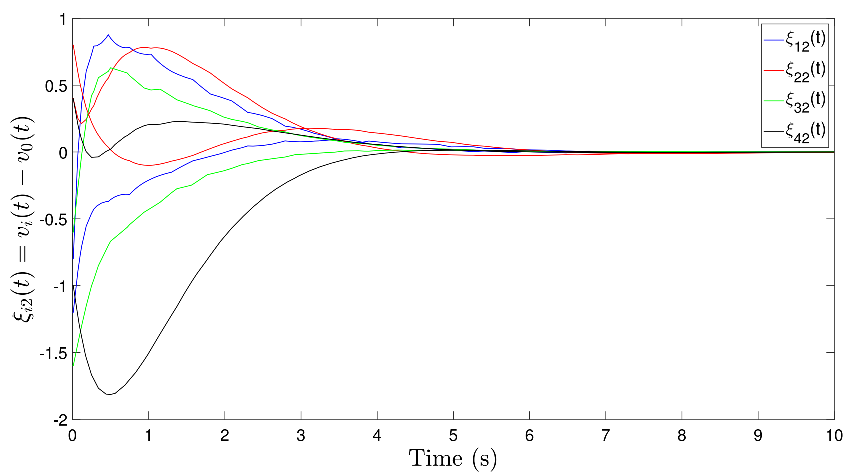

Fig. 4. Tracking errors of the velocity for UAVs.

$$\Lambda_3 = \begin{bmatrix} 20.646 & -9.135 & 18.828 & -4.348 \\ -9.135 & 25.658 & -18.646 & 18.520 \\ 18.828 & -18.646 & 32.005 & -10.449 \\ -4.348 & 18.520 & -10.449 & 25.709 \end{bmatrix},$$

$$\Lambda_4 = \begin{bmatrix} 19.208 & -5.610 & 17.376 & -3.467 \\ -5.610 & 22.907 & -13.229 & 18.095 \\ 17.376 & -13.229 & 30.411 & -7.199 \\ -3.467 & 18.095 & -7.199 & 23.644 \end{bmatrix},$$

consensus controller gains and the observer gain

$$K_1 = \begin{bmatrix} 3.978 & -2.478 & 6.414 & -1.090 \\ -0.248 & 4.230 & -0.935 & 5.916 \end{bmatrix},$$

$$K_2 = \begin{bmatrix} 1.523 & -0.851 & 2.495 & -0.336 \\ -0.068 & 1.874 & -0.366 & 2.639 \end{bmatrix},$$

$$F = \begin{bmatrix} 0 & 0 & 29.323 & -0.022 \\ 0 & 0 & -0.022 & 29.302 \end{bmatrix}.$$

Set the sampling period h=0.01s, the averaging time $T = 0.03s$, and other parameters $\varpi_{l_1} = 0.45(l_1 = 1, 2, 3, 4, 5)$, $\pi = 0.48$, $\varsigma_M = 0.01$, $\rho_M = 0.05$, $\gamma = 8.5$.

Select the initialized states of virtual leader and following UAVs as: $x_0(t) = \text{col}\{1.2, 2.6, 3.2, 2.6\}$, $x_1(t) = \text{col}\{1.5, 1, 2, 1.8\}$, $x_2(t) = \text{col}\{0.7, 1, 4, 3\}$, $x_3(t) = \text{col}\{2.3, 1.5, 1.6, 2\}$, $x_4(t) = \text{col}\{4.3, 2, 2.2, 3\}$. The time responses of error system are drawn in Figs. 3–4, in which the displacement of follower UAVs are identical to the leader's at 8.1s. The control inputs for follower UAVs with memory-based ETS (7) under deception attacks are presented in Fig. 5 to show the superiority and validity of compensation mechanism and consensus control method.

Assume the deception attacks $a_i(t) = \text{col}\{p_i e^{-t} sin(t), q_i e^{-t} sin(t)\}$ with $(p_1, q_1) = (1, -1)$, $(p_2, q_2) = (0.5, 0.8)$, $(p_3, q_3) = (-0.5, 0.5)$, $(p_4, q_4) = (0.8, 0.5)$. Note that the actual attack signal and its estimation are shown in Fig. 6 and one can see that the attack signal can be well estimated.

The adaptive thresholds integrating the HDI are presented in Fig. 7, under which the thresholds will automatically increase to save bandwidth resources when the state of UAVs tends to be identical. Fig. 8 displays the releasing instants and inter-execution intervals of the proposed METS (7). It is clear that the PTR for each UAV increases when the response curves approach the peak or trough, which means more information is provided for system to stabilize. The PTRs of UAV i within 10 s are 3.9%, 7.4%, 5.5%, 5.4%, and the results indicate plenty of packets are discarded.

In order to further testify the advantage of the proposed approach, an example is provided for comparison. We set the event-triggering threshold as a fixed value $\rho_i(t) \triangleq \frac{\rho_M + \rho_m^i}{2}$ and the attack compensation module is removed, then the METS degenerates into a AM-based ETS (AM-ETS) under fixed threshold.

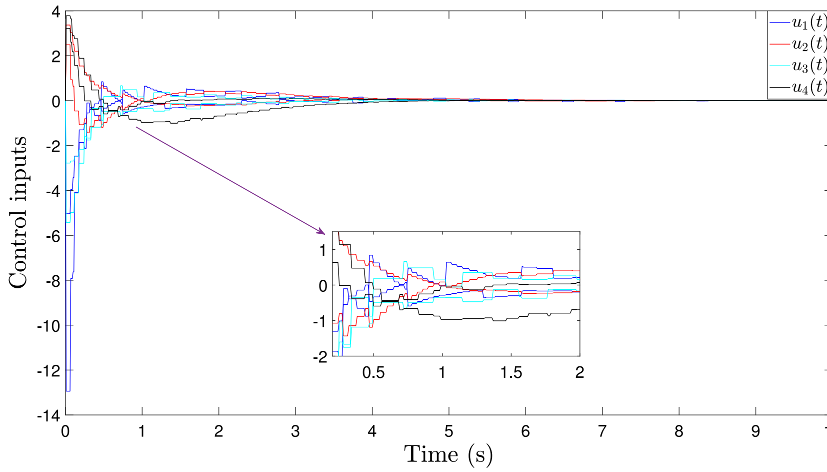

Fig. 5. Consensus control inputs for multi-UAV system under deception attacks.

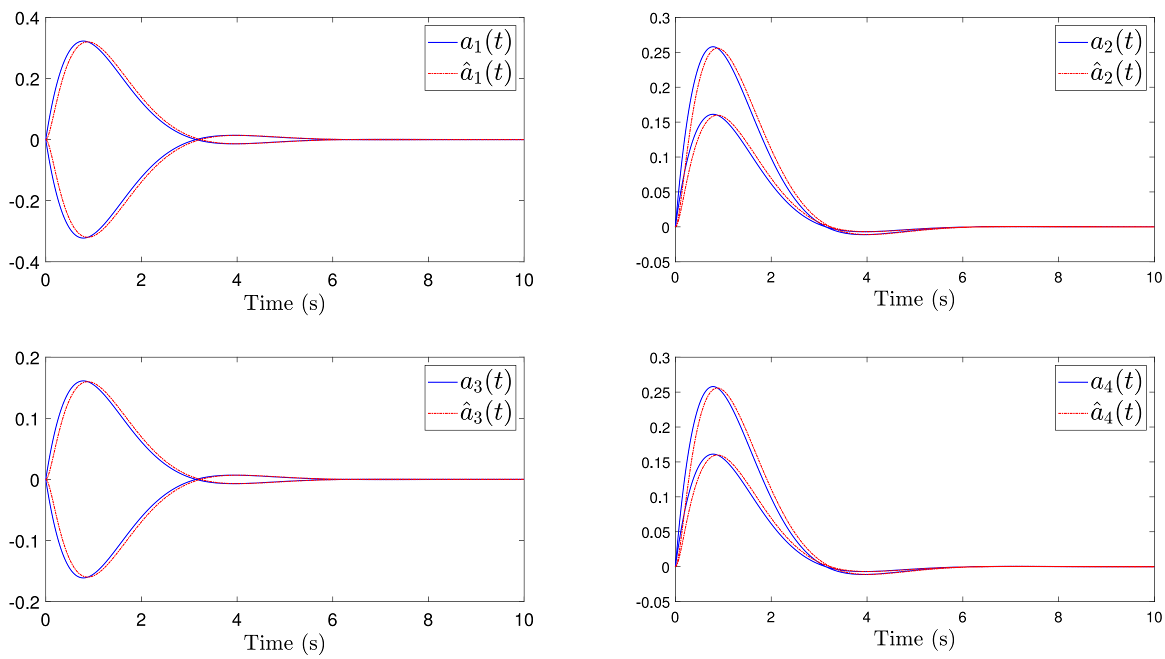

Fig. 6. The actual signal and the estimations of deception attacks.

Table 1
Comparison of ARP between METS (7) and AM-ETS under deception attacks.

UAV group	UAV1	UAV2	UAV3	UAV4
Our method	39	74	55	54
AM-ETS	51	123	89	68

The state trajectories of AM-ETS are shown in Figs. 9–10, from which one can see that the secure consensus goal is also realized in 10 s with the aid of AM. Time series of triggering instants are given in Fig. 11, and the amount of releasing packets (ARP) for different ETSs are shown in Table 1.

From Table 1, we can deduce that ARP utilizing the method in this article is less than the one with fixed threshold. Based on the above discussion, not only the networked bandwidth can be further saved, but also the control performance are guaranteed in view of deception attacks by utilizing our method.

5. Conclusion

In this article, the secure consensus control problem of multi-UAV system under limited bandwidth and deception attacks has been investigated. A memory-based ETS has been proposed by utilizing the transmitted information. What is more, an AM is introduced to better indicate the system trend and ensure the higher control performance, under which the data transmission rate is greatly diminished while it increases during the error system subject to random jitter and attacks. Thus, more information can be achieved to compensate unknown variations. Sufficient

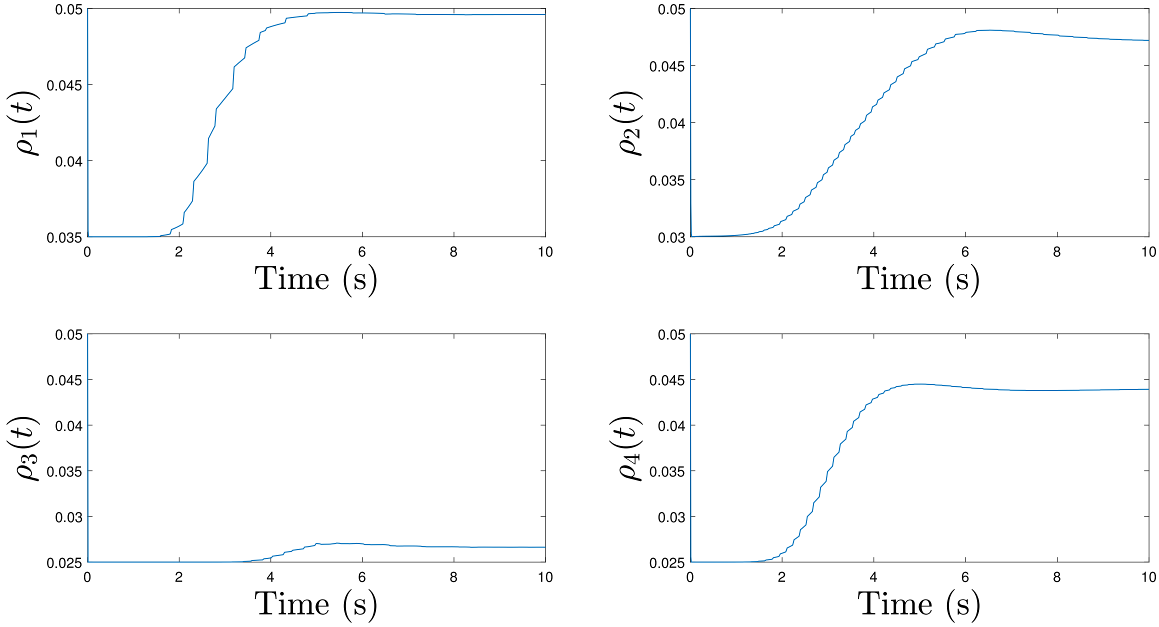

Fig. 7. Adaptive thresholds $\rho_i(t)$ of the METS.

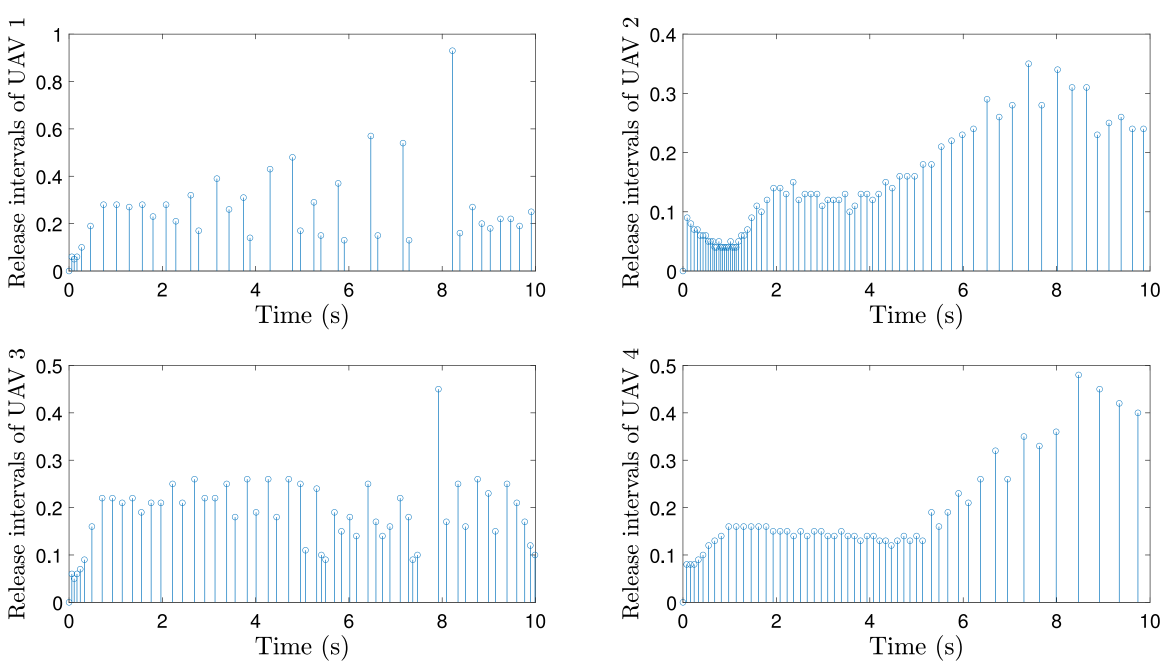

Fig. 8. Release instants and triggering intervals of followers with METS under deception attacks.

conditions have been presented to guarantee the consensus of error system in leader-following framework. Then, the co-design for consensus gains, observer gain and event-triggering parameters are all derived. Finally, simulation cases are provided to verify the effectiveness and practicability of the developed method.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

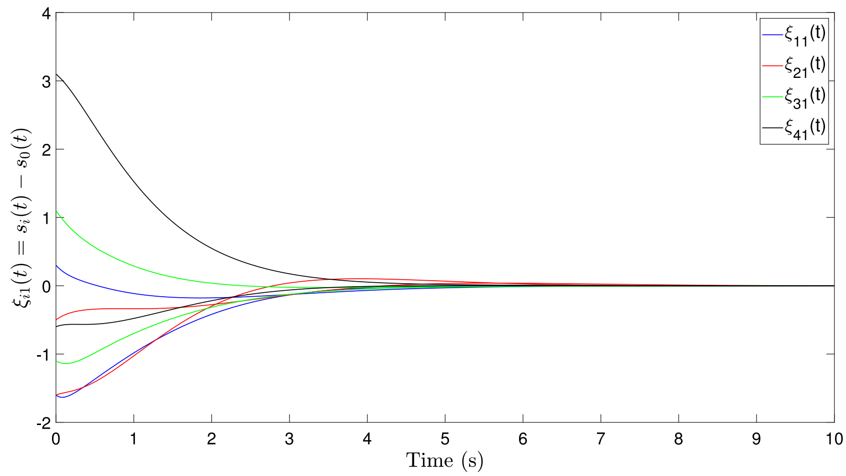

Fig. 9. Tracking errors of the displacement for UAVs with fixed threshold.

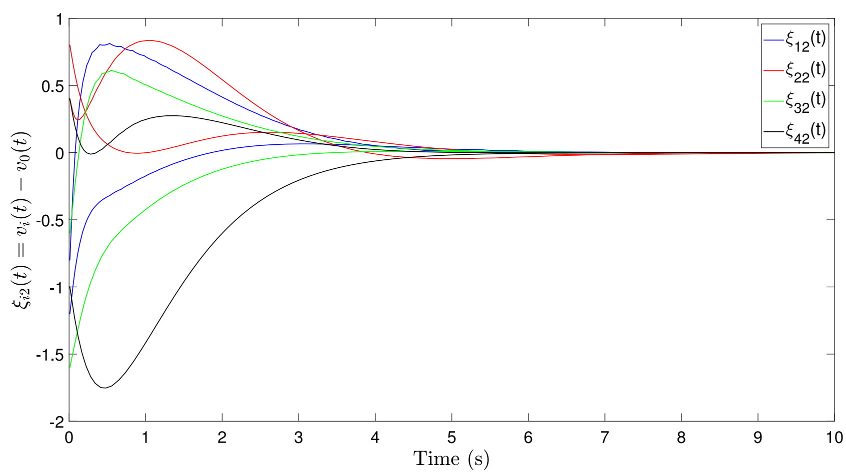

Fig. 10. Tracking errors of the velocity for UAVs with fixed threshold.

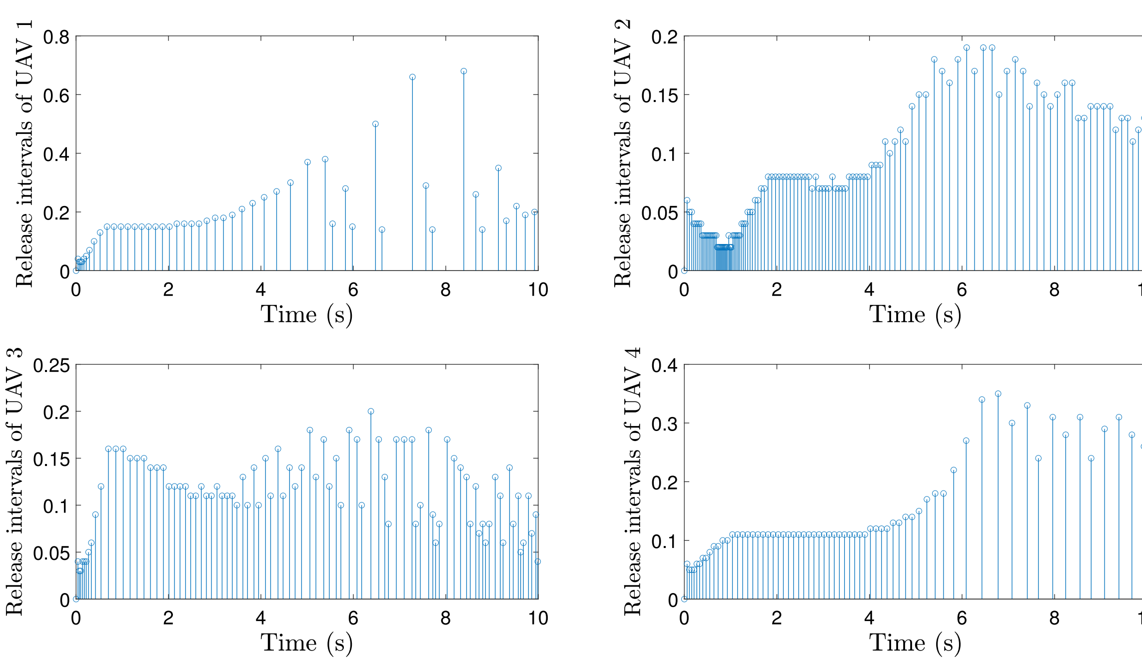

Fig. 11. Release instants and triggering intervals of followers with fixed threshold under deception attacks.

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