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Secure consensus control for multi-agent systems under communication constraints via adaptive sliding mode technique

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Abstract

The consensus tracking problem is investigated for a class of multi-agent systems (MASs) under communication constraints. In particular, as a result of the impact of amplitude attenuation and random interference, communication among followers may inevitably suffer from the fading phenomenon. Meanwhile, the controllers may also be subject to malicious deception attacks, which will disrupt the correct operation of the MASs. Thus, the agents can only update their states based on fading information exchanged with their neighbors and the false control input under attacks. The consensus tracking error variables are first designed via the fading signal received from neighbors. Then, an online estimation strategy is introduced to estimate the unknown attacks, based on which the adaptive sliding mode controller is designed to attenuate the effect of the time-varying attacks on MASs. Convergence analysis of the MASs under the designed control strategy is provided by using the Lyapunov stability theory and adaptive sliding mode control method. Finally, the effectiveness of the theoretical results is verified via numerical simulations.

Keywords: Multi-agent systems, consensus tracking, adaptive mechanism, sliding mode control, deception attacks, channel fading

1. INTRODUCTION

As typical autonomous cyber-physical systems, multi-agent systems (MASs) provide an effective means to coordinate spatially distributed and networked agents, where agents interact together to optimize decisions and achieve system objectives. In recent decades, the development of cluster control has motivated more and more research on the consensus problem for MASs, such as multi-UAVs (Unmanned Aerial Vehicles) control[1–3], underwater cooperative operations[4], robot formation control[5–8], wireless sensors collaboration[9], microgrids control[10] and so on. As a key issue in the research of MASs, the consensus problem has received extensive attention in the past few decades. For example, Hu et al. proposed a new consensus protocol for complex networks composed of multiple subnetworks to ensure convergence[11]. Yao *et al.* considered the finite-time consensus problem of MASs based on the finite-time Lyapunov stability theory[12]. Rehman *et al.* investigated the consensus problem of leader-following MASs in both fixed undirected topology and fixed directed topology and proposed two distributed control protocols[13]. Liu *et al.* studied the positive consensus problem of MASs with directed communication topologies where all agents have identical continuous-time positive linear dynamics[14].

To handle the consensus problem, various control methods have been proposed including fuzzy control[15], robust H_∞ control[16], predictive control[17,18], adaptive control[19–21], sliding mode control (SMC)[22], and so on. Due to the strong robustness to external disturbance and parameter uncertainties, the sliding mode control method has been used widely in the MASs consensus research. For the leaderless MASs, Wang *et al.* designed a special SMC protocol for the consensus problem[23]. Cong *et al.* proposed a distributed nonsingular controller to deal with the consensus problem for a class of nonlinear single-integrator MASs with input uncertain dynamics[24]. Rahmani *et al.* proposed a projection recurrent neural network, which was suitable for robotic MASs, and designed a new optimal SMC technique to achieve consensus tracking[25].

However, a key feature of the aforementioned works is that the information can be transmitted accurately among agents. In practical MASs, a satisfying communication environment cannot be guaranteed under wireless transmission networks. As a result of the impact of amplitude attenuation and random interference, the wireless link communication among agents will suffer from the fading phenomenon, resulting in the distortion of the data. This unfavorable factor motivated some interesting research on consensus tracking of wireless MASs subject to channel fading. Oral *et al.*[26] considered link outages between agents and obtained the probability expression for MASs reaching consensus. Gu *et al.* designed a distributed SMC law to deal with the impact of the information fading phenomenon in communication channels[27]. Ding et al. investigated the finite-time consensus control for MASs with channel fading via SMC technique.[28]

Another adverse phenomenon in the wireless transmission network is the inevitable malicious attacks, thereby rendering the secure control of MASs fundamental significance[29]. Considering the different mechanisms and effects on the MASs consensus problem, cyber-attacks can be divided into various types, for example, deception attacks[30], replay attacks[31] and denial-of-service (DoS) attacks[32]. Among them, deception attacks may lead to erroneous information feedback by tampering with the real packets via injecting false data. Cui *et al.* investigated the consensus tracking problem of MASs, which may be subject to deception attacks randomly. Recently, SMC strategy combined with adaptive mechanism has shown promising performance for constrained systems, for example, Chen *et al.* constructed an adaptive sliding mode control law to deal with the effects of adversarial cyber injection attacks[33]. It is of great practical significance to investigate the consensus problem for MASs against deception attacks[34]. Meanwhile, it is challenging to design a feasible SMC law under unknown and time-varying deception attacks.

Inspired by the above discussion and based on the expanded research of ref.[28], this paper will be concerned with the secure consensus control problem for multi-agent systems with malicious attacks and channel fading via the adaptive sliding mode technique, and the main contributions are highlighted as follows: (1) Both the position error and the velocity error are used to reflect the consistency of MASs, then the consensus tracking problem of MASs can be transformed into the stability problem of the tracking error system (2) Coping with the effect of the fading channel between followers, the incomplete fading information received by the agent is introduced into the controller design (3) An online estimation strategy is employed to estimate the unknown and time-varying attacks, based on which, an adaptive sliding mode controller is designed to attenuate the effect of the attacks on MASs and (4) The distributed adaptive SMC strategy is designed to ensure the mean square consistency of MASs, despite the communication constraints.

Notation: $\mathbb{R}^n$ and $\mathbb{R}^{m\times n}$ mean the n dimension Euclidean space and the $m \times n$ real matrix set. The symbol $|\cdot|$ denotes the Euclidean norm and $\otimes$ denotes the Kronecker product. Denote $\mathrm{sgn}(x)$ the sign symbolic function, $\mathbf{1}_N = [1, 1, \cdots, 1]^T$, $\mathbf{0}_N = [0, 0, \cdots, 0]^T$.

2. PROBLEM FORMULATION

2.1. Graph theory

Graph theory is an important tool to study MASs, which is a graph composed of several nodes and edges connecting the node. Each agent can be represented as a node, and the information interaction between agents can be denoted as an edge in graph theory. A directed weighted graph is represented by $G = \{\mathbb{V}, \mathbb{E}\}$. For MASs with one leader and N agents, the node-set $\mathbb{V} = \{v_1, v_2, \cdots, v_N\}$ indicates the set of all points on the graph and $\mathbb{E} = \{(i, j), i, j \in \mathbb{V}, i \neq j\}$ represents the set of all edges. $A = [a_{ij}] \in \mathbb{R}^{N\times N}$ is a non-negatively weighted adjacency matrix. If $a_{ij} > 0$, it means that agent i can receive information from agent j; conversely, if $a_{ij} = 0$, agent i cannot receive information from agent j. Define the matrix $B = \mathrm{diag}(b_1, b_2, \cdots, b_N)$ to denote the communication between the leader and all followers, and the degree matrix $D = [d_{ii}]$ with $d_{ii} = \sum_{j=1}^{N} a_{ij}$. So, we can obtain the Laplace matrix $L = [l_{ij}]$ as:

$$L = D - A. \tag{1}$$

with

$$l_{ij} = \begin{cases} \sum_{k=1}^{N} a_{ik}, & i = j, \\ -a_{ij}, & i \neq j. \end{cases} \tag{2}$$

Lemma 1 [35] The matrix $L + B$ is invertible if the directed graph G has a directed spanning tree.

Definition 1 Consider a multi-agent system with N agents and let $x_i(t)$ represent the state of agent i. If $lim_{t\to\infty}\|x_i(t) - x_j(t)\| = 0$, for all $i, j = 1, 2, \cdots, N$, it is said that the multi-agent system can reach a consensus. Furthermore, if there exists a leader whose state is $x_0(t)$, then $lim_{t\to\infty}\|x_i(t) - x_0(t)\| = 0$, for all $i, j = 1, 2, \cdots, N$, means the tracking consensus is achieved.

2.2.System model

Consider a second-order MASs consisting of a leader labeled as node 0 and N followers indexed by $i \in \{1, 2, \cdots, N\}$, and the ith follower's dynamic is given as:

$$\begin{cases} \dot{x}_i(t) = v_i(t), \\ \dot{v}_i(t) = u_i(t), \end{cases} \tag{3}$$

where $x_i(t) \in \mathbb{R}^m$, $v_i(t) \in \mathbb{R}^m$, $u_i(t) \in \mathbb{R}^m$ represent the ith follower's position, velocity and the control input, respectively. According to equation (3), it is obvious that we are focused on double integrators.
The leader's dynamic is of the following form:

$$\begin{cases} \dot{x}_0(t) = v_0(t), \\ \dot{v}_0(t) = u_0(t), \end{cases} \tag{4}$$

with $x_0(t) \in \mathbb{R}^m$, $v_0(t) \in \mathbb{R}^m$ the leader's position and velocity, respectively, and $u_0(t) \in \mathbb{R}^m$ representing the control input.

Define the ith follower's consensus tracking errors as follows:

$$\begin{cases} e_{1i}(t) &= \sum_{j=1}^{N} a_{ij}\left(x_i(t) - x_j(t)\right) + b_i\left(x_i(t) - x_0(t)\right), \\ e_{2i}(t) &= \sum_{j=1}^{N} a_{ij}\left(v_i(t) - v_j(t)\right) + b_i\left(v_i(t) - v_0(t)\right), \end{cases} \tag{5}$$

with $e_{1i}(t)$ and $e_{2i}(t)$ the tracking error variables of position and velocity, a_{ij} represents the element of A, b_i determines whether there is information interaction between the leader and the followers, when $b_i > 0$, agent i can receive information from the leader, otherwise, $b_i = 0$.

The tracking errors can be rewritten in the compact form:

$$\begin{cases} e_1(t) &= (L+B) \otimes I_m \cdot (x(t) - \mathbf{1}_N \otimes x_0(t)), \\ e_2(t) &= (L+B) \otimes I_m \cdot (v(t) - \mathbf{1}_N \otimes v_0(t)), \end{cases} \tag{6}$$

with $e_1(t) \triangleq [e_{11}^T(t), \cdots, e_{1N}^T]^T$, $e_2(t) \triangleq \left[e_{21}^T(t), \cdots, e_{2N}^T(t)\right]^T$, $x(t) \triangleq \left[x_1^T(t), \cdots, x_N^T(t)\right]^T$, $v(t) \triangleq \left[v_1^T(t), \cdots, v_N^T(t)\right]^T$, $u(t) \triangleq \left[u_1^T(t), \cdots, u_N^T(t)\right]^T$, $B \triangleq \mathrm{diag}\{b_1, b_2, \cdots, b_N\}$.

From the above definition, one can obtain the tracking error system as:

$$\begin{cases} \dot{e}_1(t) &= e_2(t), \\ \dot{e}_2(t) &= (L+B) \otimes I_m \cdot (u(t) - \mathbf{1}_N \otimes u_0(t)). \end{cases} \tag{7}$$

Now, the consensus tracking problem of MASs (3)-(4) converts to the stabilization problem of the tracking error system (7). The objective of this work is to achieve leader-follower consistency.

2.3. Fading channel

As stated in the Introduction, the transmission between followers may be inevitably suffered from the channel fading phenomenon. In this work, the network channel is considered as a continuous one with time-varying channel gain, the transmitted data will be modeled as the actually received information with random attenuation. Hence, introduce the following memoryless multiplicative fading model:

$$\begin{cases} x_{ij}(t) = \rho_{ij}(t) x_j(t), \\ v_{ij}(t) = \rho_{ij}(t) v_j(t), \end{cases} \tag{8}$$

where $x_{ij}(t)$ and $v_{ij}(t)$ are the fading position and speed signal of the jth agent received by the ith agent, and $x_j(t)$ and $v_j(t)$ are the signal and speed signal sent by the jth agent, respectively. The random coefficient $\rho_{ij}(t) \in (0, 1]$ are mutually independent random variables with mathematical expectation $\mathbb{E}\left(\rho_{ij}(t)\right) = \bar{\rho}$.

Assuming that fading occurs only in the channel between followers, the special case of channel fading from the leader to the followers is not considered in this work. Hence, based on the fading information (8), the tracking errors (5) are rewritten as:

$$\begin{cases} \bar{e}_{1i}(t) &= \sum_{j=1}^{N} a_{ij}\left(x_i(t) - \frac{1}{\bar{\rho}}\Lambda_{ij}(t) x_j(t)\right) + b_i\left(x_i(t) - x_0(t)\right), \\ \bar{e}_{2i}(t) &= \sum_{j=1}^{N} a_{ij}\left(v_i(t) - \frac{1}{\bar{\rho}}\Lambda_{ij}(t) v_j(t)\right) + b_i\left(v_i(t) - v_0(t)\right). \end{cases} \tag{9}$$

It can be seen that the tracking errors (9) involve the expectation of the random variable $\rho_{ij}(t)$, which is introduced to compute the consistent tracking error variable among the agents more accurately.

Define $\bar{e}_1(t) \triangleq [\bar{e}_{11}^T(t), \cdots, \bar{e}_{1N}^T(t)]^T$, $\bar{e}_2(t) \triangleq [\bar{e}_{21}^T(t), \cdots, \bar{e}_{2N}^T(t)]^T$. Then, the compact form of tracking errors (9) is of the following form:

$$\begin{cases} \bar{e}_1(t) &= \sum_{i=1}^{N} \alpha_i (A \otimes I_m) \cdot \frac{1}{\bar{\rho}}\Lambda_i(t) x(t) - (L+B) \otimes I_m \left(\mathbf{1}_n \otimes x_0(t)\right) \\ & \quad -(B+D) \otimes I_m \cdot x(t), \\ \bar{e}_2(t) &= \sum_{i=1}^{N} \alpha_i (A \otimes I_m) \cdot \frac{1}{\bar{\rho}}\Lambda_i(t) v(t) - (L+B) \otimes I_m \left(\mathbf{1}_n \otimes v_0(t)\right) \\ & \quad -(B+D) \otimes I_m \cdot v(t), \end{cases} \tag{10}$$

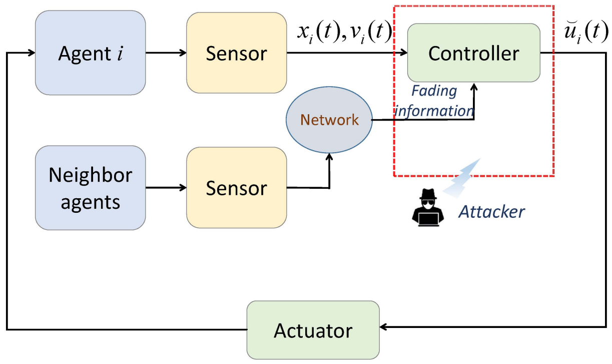

Figure 1. System over fading network subject to attacks on agent i.

where $\alpha_i \triangleq \text{diag}\{\delta_i^1, \delta_i^2, \ldots, \delta_i^N\}$, $\delta_i^k(\cdot)$ being the Kronecker delta function, which compares values of i and k and returns 0 when they are not equal; otherwise, it returns 1. $\Lambda_1(t) \triangleq \text{diag}\{0, \rho_{12}(t), \cdots, \rho_{1N}(t)\}, \cdots$, $\Lambda_N(t) \triangleq \text{diag}\{\rho_{N1}(t), \rho_{N2}(t), \cdots, 0\}$. Considering the effect of channel fading, since only faded data is available, accurate neighbors' information cannot be used for the controller design. In the following section 3.1, the SMC law will be designed based on the consensus tracking errors $\bar{e}_1(t)$ and $\bar{e}_2(t)$.

Remark 1. There are two special cases considered in the channel fading model (8): when $\rho_{ij}(t) = 0$, it means that there is no information interaction between agents and the communication channel is blocked, that is, the channel fading model is simplified to a packet loss model. In contrast, if $\rho_{ij}(t) = 1$, it indicates that the data transmission between agents is complete and without any attenuation.

2.4. Deception attacks

Among various cyber-attacks, the deception attack on controllers is a common form and usually satisfies the following assumptions: the hackers can steal the state information or measurement output of the agents to generate false data, which can then be injected into the controller. As shown in Figure 1, the hackers can attack the controller of agent i by injecting false data. Thus, the actual data received by the actuator of agent i is as follows:

$$\breve{u}_i(t) = u_i(t) + W(t)\Psi_a(x_i(t), t). \tag{11}$$

The compact form of expression (11) can be written as:

$$\breve{u}(t) = u(t) + W(t)\Psi_a(x(t), t). \tag{12}$$

where $u(t)$ is the designed control input and $W(t)\Psi_a(x(t), t)$ is the false data. The matrix $W(t)$ is an unknown and time-varying matrix that satisfies $\|W(t)\| \le \mu(t)$ with $\mu(t)$ unknown and bounded, represents the injection patterns of the false data, for example, $W(t)$ may be a matrix composed of elements 0 and 1, that is, sometimes false data is injected, sometimes not, to confuse users. Thus, the attack is difficult to be detected by users. $\Psi_a(x(t), t)$ is a function of $x(t)$, which means the false data generated via the state $x(t)$, and satisfy $\|\Psi_a(x(t), t)\| \le \psi(x(t), t)$ with $\psi(x(t), t)$ a known nonnegative function.

Remark 2. The deception attacks considered in this work focus on the controller, that is, $u(t)$ may be suffered from the false data injection, such as the problem considered in some literature[30,36] and so on. The deception attacks can also occur in the communication channel between agents, that is, $x(t)$ may be affected by false data injection during transmission[34].

3. MAIN RESULTS

3.1. Adaptive SMC law

To cope with the impact of the deception attacks, the information about the attack is usually utilized to design the controller. For example, when the upper bounds $\mu(t)$ and $\psi(x(t), t)$ of the attack are known, the design of the controller is relatively easy to implement, but the fixed upper bounds will inevitably lead to larger conservativeness. To overcome this problem, an online estimation strategy will be employed to estimate the time-varying and unknown attacks, based on which, an adaptive sliding mode controller will be designed to attenuate the effect of the unknown attacks on MASs.

Design the sliding function as follows:

$$s_i(t) = ce_{1i}(t) + e_{2i}(t), \tag{13}$$

with $c > 0$ the sliding gain, denoted $s(t) \triangleq \left[s_1^T(t), s_2^T(t), \cdots, s_N^T(t)\right]^T$, the compact form of sliding function (13) can be written as:

$$s(t) = ce_1(t) + e_2(t), \tag{14}$$

From (7), we can obtain the derivative of the sliding function:

$$\begin{aligned} \dot{s}(t) &= ce_2(t) + \dot{e}_2(t) \\ &= ce_2(t) + (L+B) \otimes I_m \cdot (\check{u}(t) - I_N \otimes u_0(t)) . \end{aligned} \tag{15}$$

Under these constraints considered in this work, the ith agent cannot receive accurate and complete information from neighbor agents, the switching function (13) under fading channel is rewritten as:

$$\overline{s}_i(t) = c\overline{e}_{1i}(t) + \overline{e}_{2i}(t). \tag{16}$$

The compact form of expression (16) as:

$$\overline{s}(t) = c\overline{e}_1(t) + \overline{e}_2(t). \tag{17}$$

Then, construct the sliding mode controller as follow:

$$u(t) = u_a(t) + u_b(t), \tag{18}$$

where the robust term $u_a(t)$ is designed as :

$$u_a(t) = -(L+B)^{-1} \otimes I_m \cdot (k_1 \cdot \operatorname{sgn}(\bar{s}(t)) + c\bar{e}_2(t)) + I_N \otimes u_0(t), \tag{19}$$

with $k_1 > 0$, and the adaptive term $u_b(t)$ is designed as:

$$u_b(t) = -(L+B)^{-1} \otimes I_m \cdot (\|L+B\| \hat{\mu}(t) \psi(x(t), t) \cdot \operatorname{sgn}(\bar{s}(t))). \tag{20}$$

where $\hat{\mu}(t)$ is the estimation of $\mu(t)$ under the following adaptive law:

$$\dot{\hat{\mu}}(t) = \theta \|L+B\| \cdot \operatorname{Proj}(\hat{\mu}(t), \left\|\bar{s}^T(t)\right\| \psi(x(t), t)), \tag{21}$$

with θ an adaptive parameter, and Proj the smooth projection [37] as:

$$\begin{aligned} &\operatorname{Proj}(\hat{\mu}(t), \left\|s^T(t)\right\| \psi(x(t), t)) \\ &= \begin{cases} \left\|s^T(t)\right\| \psi(x(t), t), \text{ if } \varphi(\hat{\mu}(t)) \leq 0, \\ \left\|s^T(t)\right\| \psi(x(t), t), \text{ if } \varphi(\hat{\mu}(t)) \geq 0 \text{ and } \varphi'(\hat{\mu}(t)) \left\|s^T(t)\right\| \psi(x(t), t) \leq 0, \\ \left\|s^T(t)\right\| \psi(x(t), t) - \frac{\varphi(\hat{\mu}(t))\varphi'(\hat{\mu}(t)) \left\|s^T(t)\right\| \psi(x(t),t)}{\|\varphi'(\hat{\mu}(t))\|'} \varphi'^T(\hat{\mu}(t)), \text{ otherwise}, \end{cases} \end{aligned} \tag{22}$$

where the continuous function $\varphi(\hat{\mu}(t))$ defined as:

$$\varphi(\hat{\mu}(t)) \triangleq \frac{2}{\delta}(\frac{\hat{\mu}^2(t)}{\hat{\mu}_{max}^2} - 1 + \delta) \tag{23}$$

with $\hat{\mu}_{max}$ the given bound of projection, and scalar $0 < \delta < 1$.

According to Imbedded Convex Sets Assumption[37], we obtain:

$$\left\|\text{Proj}\left(\hat{\mu}(t), \left\|s^T(t)\right\|\psi(x(t),t)\right)\right\| \leq \|s^T(t)\|\psi(x(t),t), \tag{24}$$

and

$$(\hat{\mu}(t)-\mu(t))(\text{Proj}(\hat{\mu}(t), \left\|s^T(t)\right\|\psi(x(t),t)) - \left\|s^T(t)\right\|\psi(x(t),t)) \leq 0 \tag{25}$$

and these two conditions will be used in the following derivation.

Remark 3. In some existing reliable control methods, the known bounds of attacks are usually utilized, which may inevitably yield larger conservativeness. To overcome this shortcoming, the online estimation mechanism for unknown attacks/faults was proposed in some related works[33,38]. Inspired by these works, the online estimation mechanism of the attack is integrated with the SMC technique in this work.

3.2. Consistence and Reachability

Theorem 1. Consider the MASs (3)-(4) with channel fading (8) and deception attacks (12), under the proposed SMC law (19)-(20), the reachability of the sliding surface $s(t) = 0$ can be guaranteed in the sense of mean square.

Proof. Choose the Lyapunov function as follows:

$$V(s,t) = \frac{1}{2}s^T(t)s(t) + \frac{1}{2}\theta^{-1}\tilde{\mu}^2(t), \tag{26}$$

where $\tilde{\mu}(t) = \hat{\mu}(t) - \mu(t)$ is the estimated error with $\dot{\tilde{\mu}}(t) = \dot{\hat{\mu}}(t)$.

Then, by the expressions (15) and (21), the derivative of $V_1(s,t)$ can be given as:

$$\begin{aligned} \dot{V}(s,t) =& s^T(t)\dot{s}(t) + \theta^{-1}\tilde{\mu}(t)\dot{\tilde{\mu}}(t) \\ =& s^T(t)(ce_2(t) - c\bar{e}_2(t) + (L+B)\otimes I_m \cdot W(t)\Psi_a(x(t),t)) \\ &- \|L+B\| \cdot \hat{\mu}\psi(x(t),t) \cdot \text{sgn}(\bar{s}(t)) - k_1\,\text{sgn}(\bar{s}(t))) + \theta^{-1}\tilde{\mu}(t)\dot{\tilde{\mu}}(t). \end{aligned} \tag{27}$$

Taking mathematical expectation to the above expression (27), one has:

$$\begin{aligned} \mathbb{E}[\dot{V}(s,t)] =& s^T(t)[ce_2(t) - c\mathbb{E}(\bar{e}_2(t)) - k_1\mathbb{E}(\text{sgn}(\bar{s}(t))) + (L+B)\otimes I_m \\ &\cdot W(t)\Psi_a(x(t),t) - \|L+B\|\hat{\mu}\psi(x(t),t)\mathbb{E}(\text{sgn}(\bar{s}(t)))] \\ &+ \|L+B\|(\hat{\mu}(t)-\mu(t))\text{Proj}(\hat{\mu}(t), \left\|\bar{s}^T(t)\right\|\psi(x(t),t)). \end{aligned} \tag{28}$$

It can be easily verified from expressions (5) and (9) that $\mathbb{E}(e_1(t)) = \mathbb{E}(\bar{e}_1(t))$, $\mathbb{E}(e_2(t)) = \mathbb{E}(\bar{e}_2(t))$. Meanwhile, it follows from (14) and (17) that $\mathbb{E}(s(t)) = \mathbb{E}(\bar{s}(t))$. Then, one can obtain:

$$\begin{aligned} \mathbb{E}\left[\dot{V}(s,t)\right] =& -k_1 s^T(t)\,\text{sgn}(s(t)) + s^T(t)(L+B)\otimes I_m \cdot W(t)\Psi_a(x(t),t) \\ &+ \|L+B\|(\hat{\mu}(t)-\mu(t))\text{Proj}(\hat{\mu}(t), \left\|s^T(t)\right\|\psi(x(t),t)) \\ &- s^T(t)\|L+B\|\hat{\mu}(t)\cdot\psi(x(t),t)\,\text{sgn}(s(t)) \\ \leq& -k_1\|s^T(t)\| + \|L+B\|\|W(t)\|\,\|\Psi_a(x(t),t)\|\,\|s^T(t)\| \\ &+ \|L+B\|(\hat{\mu}(t)-\mu(t))\text{Proj}(\hat{\mu}(t), \|s^T(t)\|\cdot\psi(x(t),t)) \\ &- \|L+B\|\hat{\mu}(t)\psi(x(t),t)\|s^T(t)\|. \end{aligned} \tag{29}$$

By the conditions $\|W(t)\| \leq \mu(t)$, $\|\Psi_a(x(t),t)\| \leq \psi(x(t),t)$, one has:

$$\begin{aligned} \mathbb{E}\left[\dot{V}(s,t)\right] \leq& -k_1\|s^T(t)\| + \|L+B\|(\mu(t)-\hat{\mu}(t))(\|s^T(t)\| \\ &\cdot\psi(x(t),t) - \text{Proj}(\hat{\mu}(t), \left\|s^T(t)\right\|\cdot\psi(x(t),t))). \end{aligned} \tag{30}$$

Then, it follows from (25) that:

$$\begin{aligned}\mathbb{E}\left[\dot{V}(s,t)\right] \leq & -k_1\|s^T(t)\| \\ \leq & 0.\end{aligned} \tag{31}$$

Hence, the reachability of the sliding surface $s(t) = 0$ can be ensured in the sense of mean square. □

Theorem 2. Considering the MASs (3)-(4) subject to deception attacks (12) and channel fading model (8), the consensus tracking for MASs (3)-(4) will be achieved under the proposed sliding surface (14) and the SMC law (19)-(20).

Proof. Select the Lyapunov function:

$$U(t) = \frac{1}{2}e_1(t)^T e_1(t) + \frac{1}{2}e_2(t)^T e_2(t), \tag{32}$$

Its derivative is given as:

$$\begin{aligned}\dot{U}(t) &= e_1^T(t)\dot{e}_1(t) + e_2^T(t)\dot{e}_2(t) \\ &= e_1^T(t)e_2(t) + e_2^T(t)\dot{e}_2(t).\end{aligned} \tag{33}$$

When the sliding surface $s(t) = 0$, it follows from (14) and (7) that $e_2(t) = -ce_1(t)$ and $\dot{e_2}(t) = -ce_2(t)$, then we can obtain:

$$\begin{aligned}\dot{U}(t) &= e_1^T(t)e_2(t) + e_2^T(t)\dot{e}_2(t) \\ &= -ce_1(t)^T e_1(t) - ce_2^T(t)e_2(t) \\ &= -c\left\|e_1(t)\right\|^2 - c\left\|e_2(t)\right\|^2 \\ &\leq 0.\end{aligned} \tag{34}$$

Combining the results of Theorem 1, the consensus tracking of MASs (3)-(4) can be ensured under the proposed sliding surface (14) and the SMC law (19)-(20). □

4. SIMULATION

Consider the second-order MASs with one leader and 4 followers, where the communication topology between agents is shown in Figure 2. The blue arrows indicate that the followers receive the complete information from the leader, while the red arrows indicate that the information interaction between followers is over fading channel. Thereby, follower 1 and follower 2 can receive accurate information from the leader, follower 3 can only receive the fading data from follower 1, and follower 4 can only receive the incomplete data from both follower 1 and follower 2. For simplicity, in this simulation example, the adjacency weights between neighbor agents are set as 1.

Then, according to the leader and followers' topology, we can get the adjacency matrix A, the diagonal matrix B, and the Laplace matrix L of these MASs as follows:

$$A = \begin{bmatrix}0 & 0 & 0 & 0\\0 & 0 & 0 & 0\\1 & 0 & 0 & 0\\1 & 1 & 0 & 0\end{bmatrix}, L = \begin{bmatrix}0 & 0 & 0 & 0\\0 & 0 & 0 & 0\\-1 & 0 & 1 & 0\\-1 & -1 & 0 & 2\end{bmatrix}, B = diag\begin{Bmatrix}1 & 1 & 0 & 0\end{Bmatrix}.$$

In this simulation, the initial state of the leader's position, speed, and control input are set as $x_0 = [10, -10]^T$, $v_0 = [10, -10]^T$, $u_0 = [cos(t), sin(t)]^T$, the initial state of the followers' position and speed are set as $x_1 = [10, -2]^T$, $v_1 = [20, -2]^T$, $x_2 = [15, 15]^T$, $v_2 = [20, 3]^T$, $x_3 = [25, 5]^T$, $v_3 = [15, 0]^T$, $x_4 = [45, 15]^T$, $v_4 = [35, 0]^T$, and the injection packets $W(t)\Psi_a(x(t), t)$ set as $W(t) = [1, 1, 1, 1]$ and $\Psi_a(x(t), t) = 10x(t)sin(t)$.

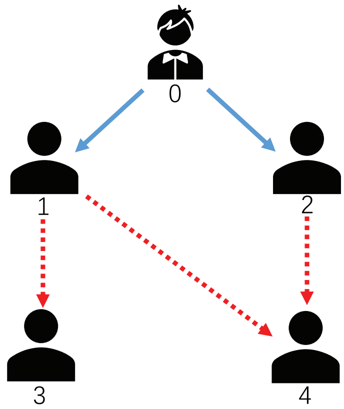

Figure 2. Communication topology diagram of MASs. MASs: multi-agent systems.

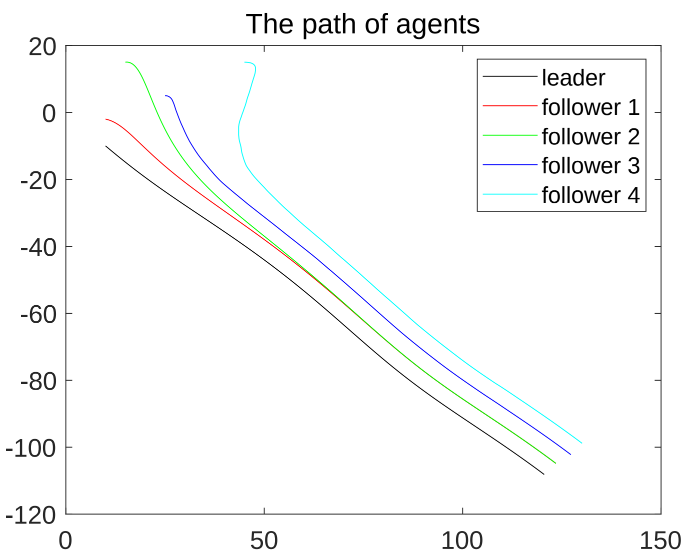

Figure 3. The trajectories of the MASs under the robust control term $u_a(t)$(19). MASs: multi-agent systems.

The sliding mode controller parameters are chosen as $c = 1$, $k_1 = 0.1$.

Simulation results are shown in Figures 3-7. Among them, Figure 3 shows the tracking trajectories of MASs under the robust control term $u_a(t)$ (19), and the horizontal and vertical axis represent the position state of different dimensions, respectively. As we can see from the Figure 3, the trajectories of the agents don't converge to a point, which indicates that the MASs under the robust control term $u_a(t)$ (19) can't achieve consensus under the deception attacks. For comparison, Figure 4 shows the tracking trajectories of the agents under the proposed adaptive SMC law (18), and it is shown that the closed-loop MASs under channel fading and deception attacks can achieve consensus tracking. Figures 5 and 6 show the position error $e_1(t)$ and velocity error $e_2(t)$ between followers respectively. Figure 7 shows the sliding variable $s(t)$ of the followers, respectively.

Remark 4. As shown in Figures 5-7, agents 1 and 2 have better consensus tracking performance with smaller amplitude oscillating and smoother curves, that is, because they can receive accurate information from the leader. In contrast, agents 3 and 4 perform worse because they cannot obtain information from the leader, but only from neighbor agents over fading channel (as shown in Figure 2). Even so, the proposed adaptive SMC scheme can still guarantee consensus tracking of all followers, as shown in Figure 4.

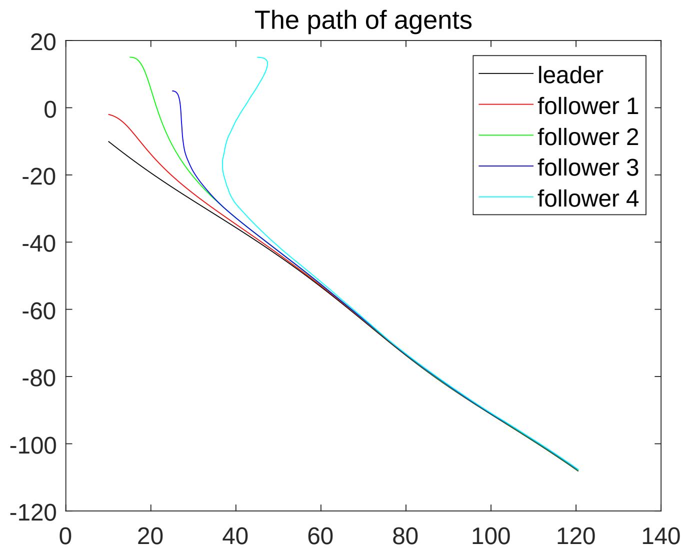

Figure 4. The trajectories of the MASs under the adaptive SMC law (18). SMC: sliding mode control.

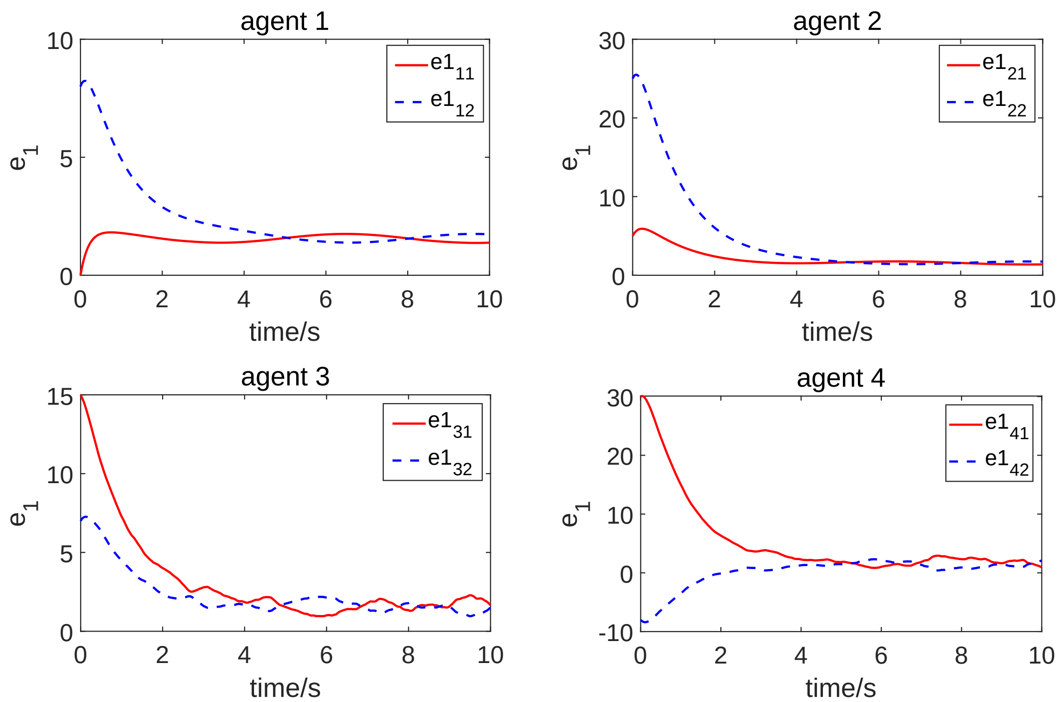

Figure 5. The position error $e_1(t)$ of the followers in Figure 5A-D. A: Position error of the 1st agent; B: Position error of the 2nd agent; C: Position error of the 3rd agent; D: Position error of the 4th agent.

5. CONCLUSION

This work considered the consensus control problem of MASs under deception attacks and fading channels. Due to the fading channels, the position and velocity errors cannot be calculated accurately. To solve this problem, the consensus tracking error variables have been designed based on the fading data received from neighbor agents. Meanwhile, the distributed adaptive SMC strategy via fading information has been proposed to deal with the time-varying and unknown deception attacks injected by the hacker. Utilizing the proposed

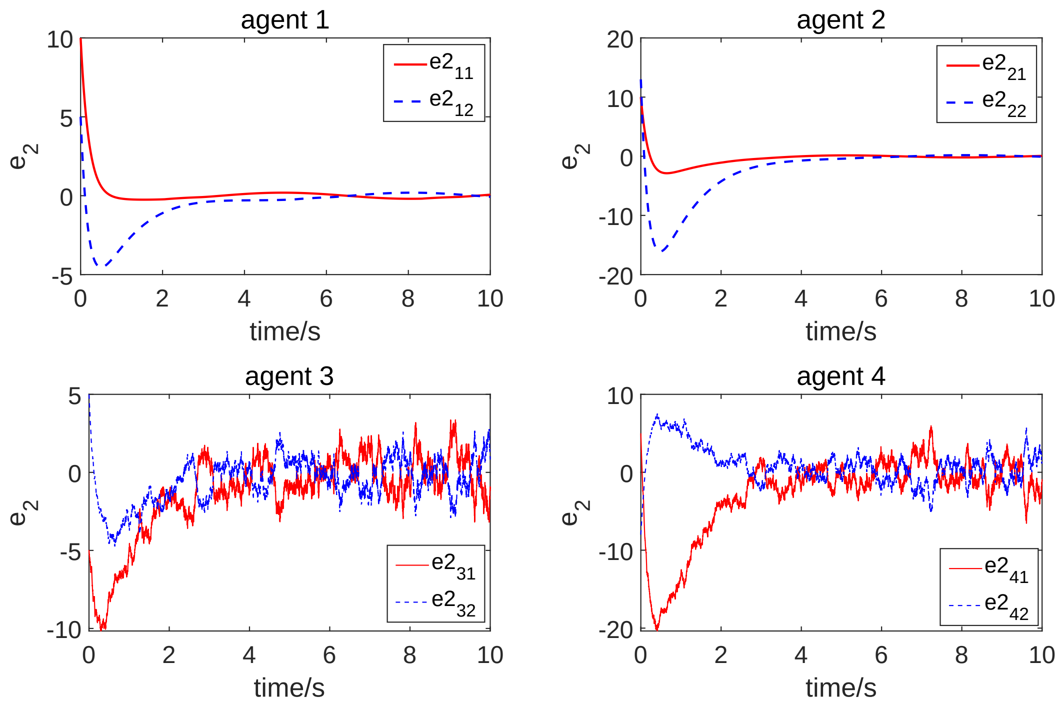

Figure 6. The velocity error $e_2(t)$ of the followers in Figure 6A-D. A: Velocity error of the 1st agent; B: Velocity error of the 2nd agent; C: Velocity error of the 3rd agent; D: Velocity error of the 4th agent.

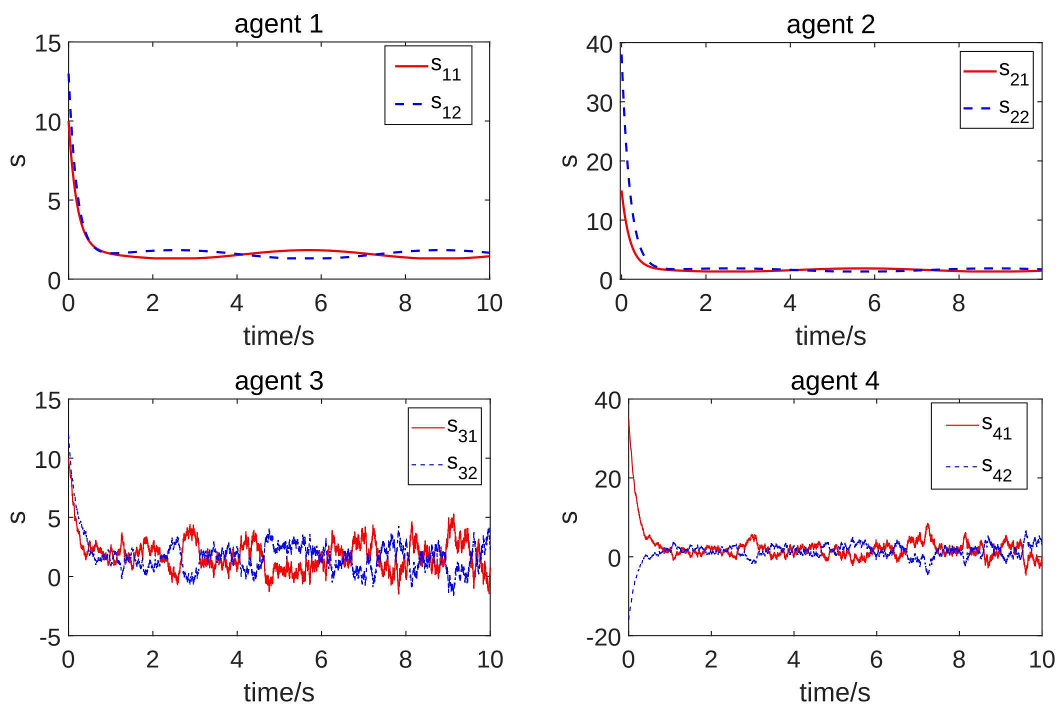

Figure 7. Sliding variables $s(t)$ of the followers in Figure 7A-D. A: Sliding variable $s(t)$ of the 1st agent; B: Sliding variable $s(t)$ of the 2nd agent; C: Sliding variable $s(t)$ of the 3rd agent; D: Sliding variable $s(t)$ of the 4th agent.

scheme, consensus tracking can be achieved. Only malicious attacks and channel fading have been considered in this work. In practical applications, there may coexist multiple constraints, such as actuator/sensor faults, packet dropout, random noise[39,40], etc. Under these constraints, how to design a feasible consensus control method is worthy to research in future work.

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Authors' contributions
Methodology, software, validation, data curation, visualization, writing- original draft: Ding M
Conceptualization, riting-reviewing and editing, investigation: Chen B

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Not applicable.

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Conflicts of interest
Both authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

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