Neural Network Observer-Based Prescribed-Time Fault-Tolerant Tracking Control for Heterogeneous Multiagent Systems With a Leader of Unknown Disturbances

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***Abstract*—This study investigates the prescribed-time leader-follower formation strategy for heterogeneous multiagent systems including unmanned aerial vehicles and unmanned ground vehicles under time-varying actuator faults and unknown disturbances based on adaptive neural network observers and backstepping method. Compared with the relevant works, the matching and mismatched disturbances of the leader agent are further taken into account in this study. A distributed fixed-time observer is developed for follower agents in order to timely obtain the position and velocity states of the leader, in which neural networks are employed to approximate the unknown disturbances. Furthermore, the actual sensor limitations make each follower only affected by local information and measurable local states. As a result, another fixed-time neural network observer is proposed to obtain the unknown states and the complex uncertainties. Then, a backstepping prescribed-time fault-tolerant formation controller is constructed by utilizing the estimations, which not only guarantees that the multiagent systems realize the desired formation configuration in a user-assignable finite time, but also ensures that the control action can be smooth everywhere. Finally, simulation examples are designed to testify the validity of the developed theoretical method.**

***Index Terms*—heterogeneous multiagent systems, air-ground cooperation, formation tracking, prescribed-time control, neural network observers, actuator faults.**

I. INTRODUCTION

IN RECENT years, formation control, as one of the important research area in cooperative tracking of multiagent systems (MASs), has drawn great attention because of its feasible and extensive applications, such as autonomous underwater vehicles, unmanned aerial vehicles, and mobile robots [1], [2]. Usually, the central algorithms rely on perfect communication and prone to fail due to connection failure or occurring fault in the central controller, it is significant to develop a distributed formation strategy. The target of a distributed formation protocol is that the followers not only achieve the specified geometric configuration based on the local information but also accomplish the path tracking according to the leader signal [3]. In practice, the agents often have nonidentical dynamics and even dimensions in real applications, heterogeneous MASs have been increasingly explored in the last decades [4], [5]. As a typical scenario of heterogeneous MASs, the distributed air-ground formation of unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) has many potential advantages over single-robot systems by improving efficiency, reliability and flexibility to achieve complex tasks, such as exploration and rescue in large-scale environments [6]–[8]. Enhancing the visibility zone by cooperating the UAVs with the UGVs is an important application of it. Specifically, the aerial platform provides a wide field of vision, which makes up for the disadvantage of limited observation distance of the ground platform. Meanwhile, the high target localization accuracy of UAV perfectly solves the problem of unsatisfactory accuracy produced by the uncertainty of sensor measurement in UAV positioning performance [9]. Hence, the research of cooperative formation problem for air-ground systems has important theoretical and practical significance. However, due to the heterogeneity, high nonlinearity and coupling dynamics of UAVs and UGVs, the existing results of realizing formation configuration through air-ground coordination are still lacked [10]–[12].

In the study of formation tracking of MASs, improving tracking speed is a significant issue and the above-mentioned results only guarantee asymptotic stability. Different from the above, finite-time tracking can ensure satisfactory convergence rate and provide strong robustness against uncertainties [13]. Thus, extensive research has been conducted on finite-time tracking of MASs [14]–[17]. Unfortunately, the obtained settling time in the above-mentioned works always depend on initial conditions, which means that the convergence time can be sufficiently large while increasing in initial conditions. To solve this problem, fixed-time conception was introduced in [18], in which the settling time is uniformly bounded and not rely on the initial conditions of the system. This property is extremely appealing and many fixed-time tracking protocols

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for MASs were reported [19]–[22]. It is worth emphasizing that the upper bound of the settling time in fixed-time control is subjected to certain restrictions and cannot be arbitrarily preassigned, which constrains the widespread application of this method in the aerospace field. Furthermore, the finite/fixed-time control can not always provide continuous and smooth control input due to the utilizing of the signum function. However, it is critical for air-ground formation systems that the constructed tracking strategy can not only guarantee that the control system approach to the desired performance within a preassigned time, but also generate smooth control action everywhere, which is challenging. Recently, prescribed-time tracking has gained significant research because it provides the solution of the aforementioned problems [23]–[26]. The convergence time can be set in advance irrespective of any controller gains, the initial states of the MASs and the network algebraic connectivity. Moreover, by utilizing the regular feedback control approach, the prescribed-time method can offer both chattering elimination and satisfactory tracking performance, which is more preferable in practice. However, the above results are devoted to homogeneous MASs and studying more general heterogeneous MAS is interesting and meaningful. Specifically, because of the existing heterogeneity between UAVs and UGVs, prescribed-time observer and controller should be redeveloped, which represents a key point of this article.

Due to the increasing number of the equipped actuators and other system components, the reliability and stability requirements of MASs are rapidly enhanced. Specifically, actuators may undergo faults during operation. In a safety-critical system, such as UAVs-UGVs cooperative systems, reliability is particularly important because a minor actuator fault in any subsystem can result in significant system degradation or even a complete collapse [27], [28]. Therefore, it is important to design fault-tolerant control scheme for MASs to ensure the safe operation. As a result, many fault-tolerant control strategies are developed for MASs, for example, adaptive fault-tolerant control [29]–[32], sliding-mode fault-tolerant control [33], [34], observer-based fault estimation and fault-tolerant control [35], [36], event-triggered fault-tolerant control [37], [38]. Generally, in passive fault-tolerant strategies, the system fault can be considered as an additional uncertain nonlinear function [39]. In addition, since the most practical systems, such as UAVs, have strong coupled nonlinearity and uncertainty, thus, by using the universal approximation capability of Fuzzy Logic Systems (FLSs) or Neural Networks (NNs), adaptive FLS or NN strategies are constructed to MASs to estimate complex nonlinear terms or uncertainties [40]–[44]. However, the existing results focus on homogeneous MASs, not on heterogeneous MASs, especially in air-ground heterogeneous formation systems with actuator faults. Therefore, the crucial challenge in this paper is how to guarantee the performance of intelligent estimation, while achieving prescribed-time formation tracking.

In view of the above status, this study proposes an adaptive prescribed-time fault-tolerant tracking protocol combined with adaptive fixed-time NN observers and prescribed-time tracking controller through backstepping technique to deal with uncertain air-ground heterogeneous MASs under actuator faults and disturbances. The chief features of this study are as below.

1) This study first presents a fixed-time NN observer-based prescribed-time control method of air-ground heterogeneous MASs under time-varying actuator faults, disturbances and unknown parameter uncertainties. The developed control framework not only ensures that all the followers realize the desired formation configuration in prescribed finite time under undirected connected topology containing a spanning tree, but also guarantees that the control input signals of all follower agents are smooth, which has more practical application value. Compared with the traditional finite-time [14]–[17] and fixed-time [19]–[22] methods, the obtained formation realizing time of this strategy is not determined by initial states or other designed parameters, thus it can be uniformly prespecified.

2) The new distributed fixed-time NN observers are constructed in this paper to estimate the unknown position or velocity states based on the local information of each agent system, which effectively reduces the burden of information exchange in the topology network. Moreover, the obtained settling time is explicitly linked with several observer gains, which facilitates the adjustment of the convergence time under different operation environments.

3) In this paper, the adaptive NN mechanism is designed to effectively estimate the effects of the unknown disturbances and the time-varying actuator faults. Then, by using these estimations, a new prescribed-time backstepping formation tracking algorithm is developed for each follower, which guarantees bounded formation tracking under unmeasured states and actuator faults within a preassignable finite time. Furthermore, the designed approach can avoid excessively large driving force due to the use of regular feedback control, which is beneficial for the promotion of this method on air-ground formation applications under multiobjective constraints.

Notations: In this article, define the set of real numbers and n-dimensional real vectors as R and R^n, respectively. Denote $\mathrm{sig}^k(x) = \mathrm{sign}(x)|x|^k$, where $k > 0, x \in R$, and $\mathrm{sign}(.)$ is the standard signum function and $|.|$ is the absolute value operation. For a vector $x = [x_1, x_2, ..., x_n]^T \in R^n$, define $\mathrm{sig}^k(x) = \left[\mathrm{sign}(x_1)|x_1|^k, \mathrm{sign}(x_2)|x_2|^k, ..., \mathrm{sign}(x_n)|x_n|^k\right]^T$.

II. Probelm Formulations and Preliminaries

A. Graph Theory

Let's define the studied heterogeneous MASs including of N follower agents and a leader agent. The leader is mark as 0 and the followers are indicated as $i = 1, 2, ..., N$. By utilizing an undirected graph $G = (V, E, A)$ to denote the network topology between the follower agent, where V is the follower set, $E \in \{(i, j) \in V \times V\}$ is the edge set, and $A = [a_{ij}] \in R^{N\times N}$ is the weighted adjacency matrix of the graph. The element $a_{ij} > 0$ if there is an edge from the jth follower to the ith follower, and $a_{ij} = 0$ otherwise. Define the in-degree matrix of graph G is $D = \mathrm{diag}\{d_1, d_2 ..., d_N\}$ with $d_i = \sum_{j=1}^{N} a_{ij}$ for $i = 1, 2, ..., N$. Then, the Laplacian matrix is defined as $L = D - A$. The communication weights between the followers and the leader are described by the diagonal matrix $B=\mathrm{diag}(b_1, b_2..., b_N)$, where $b_i > 0$ if the information of the leader is obtainable to the ith follower, and $b_i = 0$ otherwise. In this study, $H = L + B$ is designed.

Assumption 1: There is at least one feasible way from the leader to each follower, and the connected network without leader is undirected connected.

Remark 1: For the communication topology of $N+1$ agents, Assumption 1 is a prerequisite to guarantee that the follower get access to the information of the leader. It is also the prerequisite to solve the cooperative formation tracking issue. If the leader is isolated from other followers, the considered distributed formation cannot be completed due to a lack of reference signals.

B. System Description

In this study, since the UGV can provide a larger payload capability and get a better target localization performance than UAV in complex unknown environments, it is selected as the leader to study cooperative formation tracking protocol. Its dynamics can be described by the following expression:

$$\begin{cases} \dot{x}_0 = v_0 \cos\theta_0 \\ \dot{y}_0 = v_0 \sin\theta_0 \\ \dot{\theta}_0 = \omega_0 \end{cases} \tag{1}$$

where $(x_0, y_0) \in R^2$ represents the position, $v_0 \in R$ denotes the velocity, $\theta_0 \in R$ denotes the angular orientation, $\omega_0 \in R$ is the angular velocity of the leader. Based on the modeling results in [45], we further take the disturbances and model uncertainties into consideration, and the dynamic system of Eq. (1) can be reformulated as the following system.

$$\begin{cases} \dot{x}_0^p = v_0^p + \Delta_{01} \\ \dot{v}_0^p = u_0^p + \Delta_{02} \\ y_0^p = x_0^p \end{cases} \tag{2}$$

where $x_0^p \in R^2$, $v_0^p \in R^2$, and $u_0^p \in R^2$ are the position, velocity and control signal of the leader agent, respectively, y_0^p denotes the output of the controlled system, Δ_{01} is the so-called mismatched disturbance and Δ_{02} represents the lumped uncertainty composed of the nonlinear function and the matching disturbance.

Consider the team of N followers consisting of N_1 UGVs and N_2 UAVs. For convenience, $\mathrm{X}_1=\{1, 2, ..., N_1\}$, $\mathrm{X}_2=\{N_1 + 1, N_1 + 2, ..., N_1 + N_2\}$, and $\mathrm{X}=\{1, 2, ..., N\}$ are defined. Then, similar to Eq. (2), the follower $i(i \in \mathrm{X}_1)$ is described as the following dynamic model:

$$\begin{cases} \dot{x}_i^p = v_i^p + \Delta_{i1}^p \\ \dot{v}_i^p = u_i^p + \Delta_{i2}^p. \end{cases} \tag{3}$$

The dynamics of the ith ($i \in \mathrm{X}_2$) follower is represented by the following nonlinear system [45]:

$$\begin{cases} \ddot{x}_i^q = (\cos\phi_i \sin\theta_i \cos\psi_i + \sin\phi_i \sin\psi_i)u_{i1}/m_i - \dot{x}_i^q \frac{\xi_{xi}}{m_i} \\ \ddot{y}_i^q = (\cos\phi_i \sin\theta_i \sin\psi_i - \sin\phi_i \sin\psi_i)u_{i1}/m_i - \dot{y}_i^q \frac{\xi_{yi}}{m_i} \\ \ddot{z}_i^q = (\cos\theta_i \cos\phi_i)u_{i1}/m_i - g - \dot{z}_i^q \frac{\xi_{zi}}{m_i} \\ \ddot{\phi}_i = \dot{\theta}_i \dot{\psi}_i \frac{I_{yi}-I_{zi}}{I_{xi}} - \frac{I_{ri}}{I_{xi}} \dot{\theta}_i \bar{w}_i + \frac{1}{I_{xi}} u_{i2} - \frac{\xi_{\phi i}}{I_{xi}} \dot{\phi}_i \\ \ddot{\theta}_i = \dot{\phi}_i \dot{\psi}_i \frac{I_{zi}-I_{xi}}{I_{yi}} - \frac{I_{ri}}{I_{yi}} \dot{\phi}_i \bar{w}_i + \frac{1}{I_{yi}} u_{i3} - \frac{\xi_{\theta i}}{I_{yi}} \dot{\theta}_i \\ \ddot{\psi}_i = \dot{\phi}_i \dot{\theta}_i \frac{I_{xi}-I_{yi}}{I_{zi}} + \frac{1}{I_{zi}} u_{i4} - \frac{\xi_{\psi i}}{I_{zi}} \dot{\psi}_i \end{cases} \tag{4}$$

where $(x_i^q, y_i^q, z_i^q) \in R^3$ and $(\phi_i, \theta_i, \psi_i) \in R^3$ are the inertial position and Eular angles, respectively; I_{xi}, I_{yi}, and I_{zi} represent the moments of inertia; ξ_{xi}, ξ_{yi}, ξ_{zi} and $\xi_{\varphi i}$, $\xi_{\theta i}$ and $\xi_{\psi i}$ denote the aerodynamic damping coefficients; I_{ri} is the inertia of the rotor; $\bar{w}_i = w_{i4}+w_{i3}-w_{i2}-w_{i1}$. The control inputs include control thrust u_{i1} and three control torques u_{i2}, u_{i3} and u_{i4}, which are related by the relations of Eq. (5)

$$\begin{cases} u_{i1} = r_i(w_{i1}^2 + w_{i2}^2 + w_{i3}^2 + w_{i4}^2) \\ u_{i2} = r_i l_i(w_{i4}^2 - w_{i2}^2) \\ u_{i3} = r_i l_i(w_{i3}^2 - w_{i1}^2) \\ u_{i4} = t_i(w_{i2}^2 + w_{i4}^2 - w_{i1}^2 - w_{i3}^2) \end{cases} \tag{5}$$

where l_i denotes the distance between the rotor axis and the center of mass, r_i and t_i denote the different moment parameters.

In this study, the core mission of the UAV followers is to make the trajectory of the position subsystem to track and maintain the desired formation configuration. As a result, the system model of the ith UAV can be expressed as:

$$\begin{cases} \ddot{x}_i^q = u_{xi}/m_i + f_{xi} \\ \ddot{y}_i^q = u_{yi}/m_i + f_{yi} \\ \ddot{z}_i^q = u_{zi}/m_i + f_{zi} \end{cases} \tag{6}$$

where u_{xi}, u_{yi}, and u_{zi}, represented in Eq. (7), denote the virtual control inputs for the X, Y, and Z axis, respectively:

$$\begin{cases} u_{xi} = (\cos\phi_i \sin\theta_i \cos\psi_i + \sin\phi_i \sin\psi_i)u_{i1} \\ u_{yi} = (\cos\phi_i \sin\theta_i \sin\psi_i - \sin\phi_i \sin\psi_i)u_{i1} \\ u_{zi} = (\cos\theta_i \cos\phi_i)u_{i1} \end{cases} \tag{7}$$

and f_{xi}, f_{yi}, and f_{zi} are given in Eq. (8):

$$\begin{cases} f_{xi} = -\xi_{xi}\dot{x}_i/m_i \\ f_{yi} = -\xi_{yi}\dot{y}_i/m_i \\ f_{zi} = -\xi_{zi}\dot{z}_i/m_i + g. \end{cases} \tag{8}$$

C. Transformed System and Problem Formulation

According to the definition of actuator faults in [31] and [34], the fault model for the agent i ($i \in \mathrm{X}$) is described as:

$$u_i^o = u_i + (\Lambda_i(t) - I_{n_i})u_i + \delta_i(t) = u_i + u_i^F \tag{9}$$

where u_i, u_i^F, and u_i^o denote the actuator desired input, faulty input, and actual output, respectively. Let n_i represent the state dimension of the ith agent. $\Lambda_i(t) = \mathrm{diag}\{\rho_{i1}, ..., \rho_{in_i}\}$ denote the actuator effectiveness parameter and $0 \leq \rho_{ij} < 1$ denotes the fault indicator for the jth ($j = 1, ..., n_i$) actuator of the ith agent. $\delta_i(t)$ denotes the bias fault, which is time-varying and bounded, i.e., there is a positive constant $\bar{\delta}$ such that $\|\delta_i(t)\| \leq \bar{\delta}$.

Next, in order to construct the distributed formation tracking protocol, we transform the follower agents of Eqs. (3) and (4) into an uniform form under disturbances and actuator faults. Specifically, the follower i ($i \in \mathrm{X}$) is modeled as:

$$\begin{cases} \dot{x}_i = v_i + \Delta_{i1} \\ \dot{v}_i = u_i + \Omega_i \\ y_i = x_i \end{cases} \tag{10}$$

where $\Omega_i = \Delta_{i2} + u_i^F$, $x_i, v_i, y_i \in R^{n_i}$ denote the position state, velocity state, and output state, respectively, Δ_{i1} is the mismatched disturbance, Δ_{i2} is the lumped uncertainty and u_i denote the control signal.

Assumption 2: The disturbance Δ_{i1} is bounded by an unknown positive constant $\bar{\Delta}_1$, i.e., $\|\Delta_{i1}\| \leq \bar{\Delta}_1$.

Assumption 3: The time-varying unknown uncertainty Δ_{i2} is bounded, i.e., there is a positive scalar $\bar{\Delta}_2$, such that $\|\Delta_{i2}\| \leq \bar{\Delta}_2$.

Assumption 4: It is assumed that the uncertain fault u_i^F satisfies $\left\|u_i^F\right\| \leq \bar{u}^F$, in which $\bar{u}^F$ is a positive constant.

Remark 2: Note that Assumptions 2-4 are required to guarantee the fault-tolerant tracking for MASs under the effect of disturbances. These assumptions are general controllability conditions, which can be found, e.g. in [34], [39].

By using the approximation characteristics of the NNs, the unknown nonlinear terms Δ_{i1} and Ω_i can be estimated with arbitrary accuracy as follows:

$$\left\{ \begin{array}{l} \Delta_{i1} = \omega_{i1}^{*T} s_{i1}(x_i) + \delta_{i1}(x_i, v_i) \\ \Omega_i = \omega_{i2}^{*T} s_{i2}(x_i, v_i) + \delta_{i2}(x_i, v_i) \end{array} \right. \tag{11}$$

where ω_{i1}^* and ω_{i2}^* denote the ideal weight vectors, δ_{i1} and δ_{i2} are the approximation errors, and s_{ij} $(j = 1, 2)$ is the following Gaussian function:

$$s_{ij}(.) = \exp\left(-\frac{(Z_i - \mu_i)^T (Z_i - \mu_i)}{\nu_i^2}\right) \tag{12}$$

where Z_i denotes the NN input vector, μ_i and ν_i denote the center and width of the NN, respectively. It is reasonable that ω_{ij}^* and δ_{ij} satisfy $\left\|\omega_{ij}^*\right\| \leq \omega_m$, $\|\delta_{ij}\| \leq \delta_m$ with ω_m and δ_m being the unknown positive constants.

To better describe the formation configuration, a time-varying vector $h_i(t) \in R^{n_i}$ is designed to represent the predefined formation between the follower i $(i \in \mathrm{X})$ and the leader. Next, the definition of the prescribed-time formation control for the studied UAVs-UGVs heterogeneous MASs is given.

Definition 1: For the heterogeneous MASs described by Eqs. (2) and (10), the prescribed-time fault-tolerant formation is said to be realized, if for arbitrarily given initial states $x_i(0)$, the following equation can be achieved:

$$\lim_{t \to T_c} (x_i(t) - x_0(t) - h_i(t)) = 0, i \in \mathrm{X}. \tag{13}$$

in which $T_c > 0$ denotes the prescribed convergence time, which can be preassigned arbitrarily by the user without dependence on the initial conditions.

D. Further Definitions and Lemmas

Consider the following dynamic system

$$\dot{x}(t) = g(t, x(t)), \qquad x(0) = x_0 \tag{14}$$

in which $x \in R^n$ and $g(\cdot) \in R^n$ denotes a time-varying unknown function. Suppose that the equilibrium point for the system of Eq. (14) is the origin.

Definition 2: [18] The origin of the dynamic system of Eq. (14) realizes the global fixed-time stability when it achieves finite-time stability and the settling time $T(x)$ satisfies that, for $\exists T_m > 0, T(x) \leq T_m, \forall x_0 \in R^n$.

Definition 3 [26]: The equilibrium point of the system of Eq. (14) achieves the globally prescribed-time stability when it accomplishes globally finite-time stability and the convergence time $T(x)$ is an user-assignable positive constant, i.e., $\forall 0 < T_c \leq T_m$, $T(x)$ can be prescribed such that $T_c \leq T(x) \leq T_m$.

Lemma 1: [18] For the system of Eq. (14), if the following inequality can be satisfied

$$\dot{V}(x) \leq -aV^e(x) - bV^f(x) \tag{15}$$

in which $V(x)$ is a continuous radially unbounded function, $a > 0, b > 0$, $0 < e < 1$, and $f > 1$. Then, the system achieves the globally fixed-time stability of Eq. (14) and the convergence time $T(x)$ is upper bounded by:

$$T(x) \leq T_m := \frac{1}{b(f-1)} + \frac{1}{a(1-e)}. \tag{16}$$

Lemma 2([18]): For the system of Eq. (14), if the following inequality can be satisfied

$$\dot{V}(x) \leq -cV^g(x) - dV^h(x) + \vartheta \tag{17}$$

for some $g, h, c, d > 0$, $0 < g < 1, h > 1$, and $0 < \vartheta < \infty$. Then, the system of Eq. (14) achieves the practical fixed-time stability. Moreover, the convergence threshold is expressed as:

$$\Omega = \left\{ x | V(x) \leq \min\left\{ \left[\frac{\vartheta}{c(1-o)}\right]^{\frac{1}{g}}, \left[\frac{\vartheta}{d(1-o)}\right]^{\frac{1}{h}} \right\} \right\} \tag{18}$$

where $0 < o < 1$. The fixed time required to reach the residual set is $T \leq T_{\max} := \frac{1}{c\chi(1-p)} + \frac{1}{d\chi(q-1)}$.

Lemma 3 [26]: For the system of Eq. (14), if the following inequality holds

$$\dot{V}(x) \leq -\lambda V(x) - 2\frac{\dot{\mu}(t_0, T)}{\mu(t_0, T)} V(x), t \in [t_0, t_0 + T) \tag{19}$$

with:

$$\mu(t_0, T) = \left\{ \begin{array}{l} \left(\frac{T}{t_0 + T - t}\right)^l, t \in [t_0, t_0 + T) \\ 1, t \in [t_0 + T, \infty) \end{array} \right. \tag{20}$$

where λ is a designed constant, $l > 2$ and T is the duration of the time-varying period of the function of Eq. (20). Then, the equilibrium point of the system of Eq. (14) is globally prescribed-time stability within the needed prescribed time T.

Lemma 4([22]): Let $\varsigma_1, \varsigma_2, ..., \varsigma_N \geq 0$ and $0 < r \leq 1$. Then,

$$\sum_{i=1}^{N} \varsigma_i^r \geq \left(\sum_{i=1}^{N} \varsigma_i\right)^r;$$

Lemma 5([22]): Let $\varsigma_1, \varsigma_2, ..., \varsigma_N \geq 0$ and $r > 1$. Then,

$$\sum_{i=1}^{N} \varsigma_i^r \geq N^{1-r}\left(\sum_{i=1}^{N} \varsigma_i\right)^r.$$

Remark 3: Many existing results of formation control for air-ground systems only achieve asymptotical tracking without considering external disturbances and unknown actuator faults [10]–[12], which is unsatisfactory to engineering realizing of UAVs-UGVs real-time formation systems. Different from the above results, the disturbances of the leader and the lumped uncertainties for each follower are further considered in this paper, which is closer to the real engineering application

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environment. Moreover, this study proposes an observer-based prescribed-time formation tracking algorithm, the control error can approach to a small enough region of origin within a prespecified time. The settling time completely not relies on the initial states and any controller parameters, which facilitates the implementation in an unknown environment by the new users.

III. Theoretical Results

A distributed adaptive NN observer is firstly constructed to evaluate the leader state within a fixed convergence time. Next, to address the unknown faults and external disturbances, another decentralized fixed-time NN observer is constructed in the presence of partial unmeasured states of followers. Finally, a backstepping-based prescribed-time formation tracking controller is designed for each follower.

A. Adaptive Distributed Fixed-Time NN Observer for Leader

For leader, the unknown functions Δ_{01} and Δ_{02} can be approximated by NNs as:

$$\left\{\begin{array}{l}\Delta_{01}=\hat{\omega}_{i01}^T s_{i01}(\hat{x}_0)+\delta_{i01}(x_0,\hat{v}_0)\\ \Delta_{02}=\hat{\omega}_{i02}^T s_{i02}(\hat{x}_0,\hat{v}_0)+\delta_{i02}(x_0,v_0,\hat{x}_0,\hat{v}_0)\end{array}\right. \tag{21}$$

where $\hat{\omega}_{i01}^T$ and $\hat{\omega}_{i02}^T$ denote the estimations of the optimal weight matrix, δ_{i01} and δ_{i02} denote the approximate errors, and satisfy $\|\delta_{i01}\|\le\delta_{m1}$, $\|\delta_{i02}\|\le\delta_{m2}$ with δ_{m1} and δ_{m2} being the unknown positive constants.

Let $\hat{x}_{i0}$ and $\hat{v}_{i0}$ denote the estimated states held at agent i $(i\in \mathrm{X})$ for states x_0^p and v_0^p, respectively. A distributed fixed-time NN observer has the form:

$$\left\{\begin{aligned}\dot{\hat{x}}_{i0}(t)&=\hat{v}_{i0}(t)+\hat{\Delta}_{i01}(t)\\ &\quad+k_{i01}\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\\ &\quad+\vartheta_1\mathrm{sig}^{\alpha}\left(\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\right)\\ &\quad+\vartheta_2\mathrm{sig}^{\beta}\left(\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\right)\\ \dot{\hat{v}}_{i0}(t)&=u_{i0}(t)+\hat{\Delta}_{i02}(t)\\ &\quad+k_{i02}\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\\ &\quad+\vartheta_1\mathrm{sig}^{\alpha}\left(\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\right)\\ &\quad+\vartheta_2\mathrm{sig}^{\beta}\left(\sum_{j=1}^{N}a_{ij}\left(\hat{x}_{i0}-\hat{x}_{j0}\right)+b_i\left(x_0-\hat{x}_{i0}\right)\right)\end{aligned}\right. \tag{22}$$

where k_{i01}, k_{i02}, ϑ_1, ϑ_2 are positive observer design parameters, and $0<\alpha<1$, $\beta>1$.

Let $e_{i0}=\left[e_{i01}^T,e_{i02}^T\right]^T$, $e_{i01}=y_0^p-\hat{y}_i$, and $e_{i02}=v_0^p-\hat{v}_i$. Next, the following dynamics can be derived:

$$\begin{aligned}\dot{e}_{i0}&=\left(A_{i0}\otimes I_2\right)e_{i0}+\sum_{j=1}^{2}\left(F_{ij}\otimes\left(\Delta_{ij}-\hat{\Delta}_{ij}\right)\right)\\ &\quad-\vartheta_1\mathrm{sig}^{\alpha}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]-\vartheta_2\mathrm{sig}^{\beta}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\\ &=\left(A_{i0}\otimes I_2\right)e_{i0}+\delta_{i0}\\ &\quad-\vartheta_1\mathrm{sig}^{\alpha}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]-\vartheta_2\mathrm{sig}^{\beta}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\end{aligned} \tag{23}$$

where $A_{i0}=\begin{bmatrix}-k_{i01}H & 1\\ -k_{i02}H & 0\end{bmatrix}$, satisfying $A_{i0}^T\Theta_i+\Theta_iA_{i0}=-2Q_{i0}$, with $\Theta_i=C_{i0}HP_{i0}$, $C_{i0}=\begin{bmatrix}1&0\\1&0\end{bmatrix}$, P_{i0} and Q_{i0} being positive definite matrixes, $\delta_{i0}=\left[\delta_{i01}^T,\delta_{i02}^T\right]^T$, $F_{i1}=[1,0]^T$ and $F_{i2}=[0,1]^T$.

Theorem 1: Under Assumption 1, consider the heterogeneous MASs of Eqs. (2) and (10), while disturbances, uncertainties and actuator faults satisfy Assumptions 2-4. By the fixed-time NN observer of Eq. (22), if the adaptive law can be constructed according to the relation:

$$\dot{\hat{\omega}}_{i0m}=\Gamma_{im}\left[e_{i0m}C_{i0}^TA_{i0}^{-1}s_{i0m}-\sigma_{im}\hat{\omega}_{i0m}\right] \tag{24}$$

where $m=1,2$, $\Gamma_{im}=\Gamma_{im}^T>0$, and $\sigma_{im}>\frac{1}{2}\left\|C_{i0}^TA_{i0}^{-1}\right\|^2\|s_{i0m}\|^2$, the error e_i is ensured to practical fixed-time stability, and the adaptive parameter $\hat{\omega}_{i0m}$ will be uniformly ultimately bounded.

Proof: The following Lyapunov function is constructed:

$$V_0=\frac{1}{2}\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)e_{i0}+\frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\mathrm{tr}\left[\tilde{\omega}_{i0m}^T\Gamma_{im}^{-1}\tilde{\omega}_{i0m}\right] \tag{25}$$

where $\tilde{\omega}_{i0m}=\omega_{i0m}^*-\hat{\omega}_{i0m}$. For convenience, let's define $V_e=\frac{1}{2}\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)e_{i0}$ and $V_\omega=\frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\mathrm{tr}\left[\tilde{\omega}_{i0m}^T\Gamma_{im}^{-1}\tilde{\omega}_{i0m}\right]$.

The time derivative of V_e along Eq. (23) has the following form:

$$\begin{aligned}\dot{V}_e&=\frac{1}{2}\sum_{i=1}^{N}\left[e_{i0}^T\left(A_{i0}^T\Theta_i\otimes I_2\right)e_{i0}+e_{i0}^T\left(\Theta_iA_{i0}\otimes I_2\right)e_{i0}\right]\\ &\quad+\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)\delta_{i0}\\ &\quad-\vartheta_1\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)\mathrm{sig}^{\alpha}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\\ &\quad-\vartheta_2\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)\mathrm{sig}^{\beta}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\\ &\le\frac{1}{2}\sum_{i=1}^{N}\left[e_{i0}^T\left(A_{i0}^T\Theta_i\otimes I_2\right)e_{i0}+e_{i0}^T\left(\Theta_iA_{i0}\otimes I_2\right)e_{i0}\right]\\ &\quad+\sum_{i=1}^{N}\left(\frac{1}{2}\|e_{i0}\|^2+\frac{1}{2}\|\Theta_i\otimes I_2\|^2\bar{\delta}_i^2\right)\\ &\quad-\vartheta_1\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)\mathrm{sig}^{\alpha}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\\ &\quad-\vartheta_2\sum_{i=1}^{N}e_{i0}^T\left(\Theta_i\otimes I_2\right)\mathrm{sig}^{\beta}\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right]\end{aligned} \tag{26}$$

Taking the derivative of V_ω, we have:

$$\dot{V}_\omega=-\sum_{i=1}^{N}\sum_{m=1}^{2}\mathrm{tr}\left[\tilde{\omega}_{i0m}^T\Gamma_{im}^{-1}\dot{\hat{\omega}}_{i0m}\right] \tag{27}$$

Substituting the adaptive law of Eq. (24) into Eq. (27), it follows that:

$$\begin{aligned}\dot{V}_\omega = &-\sum_{i=1}^{N}\sum_{m=1}^{2}\operatorname{tr}\left[\tilde{\omega}_{i0m}^T e_{i0m} C_{i0}^T A_{i0}^{-1} s_{i0m} - \tilde{\omega}_{i0m}^T \sigma_{im}\hat{\omega}_{i0m}\right] \\ \leq &\sum_{i=1}^{N} 2\|e_{i0}\|^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\Big[\frac{1}{2}\left\|C_{i0}^T A_{i0}^{-1}\right\|^2\left\|\tilde{\omega}_{i0m}^T\right\|^2\|s_{i0m}\|^2 \\ &+\sigma_{im}\|\omega_{i0m}^*\|^2 - \sigma_{im}\|\tilde{\omega}_{i0m}\|^2\Big]\end{aligned} \tag{28}$$

Combining Eq. (26) with the inequality of Eq. (28), it yields to:

$$\begin{aligned}\dot{V}_0 \leq &-\sum_{i=1}^{N}\left[e_{i0}^T\left(\left(Q_{i0} - \tfrac{5}{2}I_2\right)\otimes I_2\right)e_{i0}\right] + \varphi_0 \\ &- \vartheta_1\sum_{i=1}^{N} e_{i0}^T\left(\Theta_i\otimes I_2\right)\operatorname{sig}^\alpha\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right] \\ &- \vartheta_2\sum_{i=1}^{N} e_{i0}^T\left(\Theta_i\otimes I_2\right)\operatorname{sig}^\beta\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right] \\ &- \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\Big[\left(\sigma_{im} - \tfrac{1}{2}\left\|C_{i0}^T A_{i0}^{-1}\right\|^2\|s_{i0m}\|^2\right) * \\ &\qquad \Gamma_{im}\left(\tilde{\omega}_{i0m}^T\Gamma_{im}^{-1}\tilde{\omega}_{i0m}\right)\Big]\end{aligned} \tag{29}$$

where $\varphi_0 = \sum_{i=1}^{N}\left(\frac{1}{2}\|\Theta_i\otimes I_2\|^2\bar{\delta}_i^2\right) + \sum_{i=1}^{N}\sum_{m=1}^{2}\sigma_{im}\|\omega_{i0m}^*\|^2$.

Then, Eq. (29) can be converted into the following expression:

$$\begin{aligned}\dot{V}_0 \leq &-\frac{1}{2}\sum_{i=1}^{N}\left[\frac{2\lambda_{\min}\left(Q_{i0}-\frac{5}{2}I_2\right)}{\lambda_{\max}(\Theta_i)}e_{i0}^T\left(\Theta_i\otimes I_2\right)e_{i0}\right] + \varphi_0 \\ &- \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\Big[\left(\frac{2\sigma_{im} - \left\|C_{i0}^T A_{i0}^{-1}\right\|^2\|s_{i0m}\|^2}{2\lambda_{\max}(\Gamma_{im})}\right) * \\ &\qquad \operatorname{tr}\left[\tilde{\omega}_{i0m}^T\Gamma_{im}^{-1}\tilde{\omega}_{i0m}\right] \\ \leq &-\eta_0 V_0 + \varphi_0\end{aligned} \tag{30}$$

where $\lambda_{\min}\left(Q_{i0} - \frac{5}{2}I_2\right)$ is the minimum eigenvalue of $Q_{i0} - \frac{5}{2}I_2 > 0$, $\lambda_{\max}(\Theta_i)$ and $\lambda_{\max}(\Gamma_{im})$ are the maximal eigenvalues of Θ_i and Γ_{im}, respectively.

Based on Eq. (30), we have that the error system can achieve asymptotical stability, and e_{i0} and $\tilde{\omega}_{i0m}$ are all bounded at any finite time interval. Next, the practical fixed-time stability of the estimation error e_{i0} will be proved.

The time derivative of V_e in Eq. (26) can be represented as:

$$\begin{aligned}\dot{V}_e \leq &-\sum_{i=1}^{N}\left[e_{i0}^T\left(\left(Q_{i0} - \tfrac{1}{2}I_2\right)\otimes I_2\right)e_{i0}\right] \\ &- \vartheta_1\sum_{i=1}^{N} e_{i0}^T\left(\Theta_i\otimes I_2\right)\operatorname{sig}^\alpha\left[\left(C_{i0}H\otimes I_2\right)e_i\right] \\ &- \vartheta_2\sum_{i=1}^{N} e_{i0}^T\left(\Theta_i\otimes I_2\right)\operatorname{sig}^\beta\left[\left(C_{i0}H\otimes I_2\right)e_{i0}\right] \\ &+ \frac{1}{2}\sum_{i=1}^{N}\|\Theta_i\otimes I_2\|^2\bar{\delta}_i^2 \\ \leq &-\vartheta_1\lambda_{\min}\left(P_{i0}\right)\|C_{i0}H\otimes I_2\|^{\alpha+1}e_{i0}^T\operatorname{sig}^\alpha\left(e_{i0}\right) \\ &- \vartheta_2\lambda_{\min}\left(P_{i0}\right)\|C_{i0}H\otimes I_2\|^{\beta+1}e_{i0}^T\operatorname{sig}^\beta\left(e_{i0}\right) \\ &+ \tfrac{1}{2}\|\Theta_i\otimes I_2\|^2\bar{\delta}_i^2 \\ \leq &-\chi_1 V_1^{\frac{\alpha+1}{2}} - \chi_2 V_1^{\frac{\beta+1}{2}} + \gamma_0\end{aligned} \tag{31}$$

where

$\chi_1 = \vartheta_1\lambda_{\min}\left(P_{i0}\right)\|C_{i0}H\otimes I_2\|^{\alpha+1}\frac{\lambda_{\min}\left(\Theta_i^2\right)}{\lambda_{\max}(\Theta_i)}$,

$\chi_2 = \vartheta_2\lambda_{\min}\left(P_{i0}\right)\|C_{i0}H\otimes I_2\|^{\beta+1}\frac{\lambda_{\min}\left(\Theta_i^2\right)}{\lambda_{\max}(\Theta_i)}(2N)^{\frac{\beta+1}{2}}$,

and

$\gamma_0 = \frac{1}{2}\sum_{i=1}^{N}\|\Theta_i\otimes I_2\|^2\bar{\delta}_i^2$.

According to Lemma 2 and the above analysis, we have that the trajectories of observer errors e_{i0} $(i\in \mathrm{X})$ can be practical fixed-time stability within T_e, and this concludes the proof.

Remark 4: As seen in the proof, the practical fixed-time convergence property is used to avoid the excessive convergence time in NN observer design. By introducing the adaptive law of Eq. (24), the parameters ω_{i0m} and ω_{im} can be estimated effectively. Moreover, the convergence time is fixed and independent of initial conditions. The convergence rate can be adjusted by turning the observer parameters α, β, ϑ_1 and ϑ_2 for different followers to cater to the requirement of different tasks, which can further improve conservative and is more reasonable.

B. Adaptive Decentralized Fixed-Time NN Observer for Followers

This section is focused on the derivation of a decentralized NN-based observer to estimate the unmeasured state v_i within a fixed time, the unknown mismatched disturbance Δ_{i1}, and the lumped uncertainty Ω_i.

Theorem 2: Consider the faulty system represented by (10), and consider that the terms Δ_{i1}, Δ_{i2} and u_i^F satisfy Assumptions 2-4. If the intelligent NN observer adopt the following form:

$$\begin{cases}\dot{\hat{x}}_i(t) = \hat{v}_i(t) + \hat{\Delta}_{i1}(t) + k_{i1}\left(y_i - \hat{y}_i\right) \\ \qquad + \mu_1\operatorname{sig}^\chi\left(y_i - \hat{y}_i\right) + \mu_2\operatorname{sig}^\varepsilon\left(y_i - \hat{y}_i\right) \\ \dot{\hat{v}}_i(t) = u_i(t) + \hat{\Omega}_i(t) + k_{i2}\left(y_i - \hat{y}_i\right) \\ \qquad + \mu_1\operatorname{sig}^\chi\left(y_i - \hat{y}_i\right) + \mu_2\operatorname{sig}^\varepsilon\left(y_i - \hat{y}_i\right) \\ \hat{y}_i(t) = \hat{x}_i(t)\end{cases} \tag{32}$$

and updated by the law:

$$\dot{\hat{\omega}}_{im} = \Upsilon_{im}\left[e_{im}C_i^T A_i^{-1}s_{im} - \theta_{im}\hat{\omega}_{im}\right] \tag{33}$$

under the condition

$$A_i^T R_i + R_i A_i = -2Q_i \tag{34}$$

where $A_i = \begin{bmatrix} -k_{i1} & 1 \\ -k_{i2} & 0\end{bmatrix}$, $R_i = C_i P_i$, P_i and Q_i are positive definite matrixes, $C_i = \begin{bmatrix} 1 & 0 \\ 1 & 0\end{bmatrix}$, $\theta_{im} > \frac{1}{2}\left\|C_i^T A_i^{-1}\right\|^2\|s_{im}\|^2$, k_{i1}, k_{i2}, μ_1, and μ_2 are design positive constants, $\Upsilon_{im} = \Upsilon_{im}^T > 0$, $0 < \chi < 1$ and $\varepsilon > 1$. Then, the trajectories of the observer errors $\tilde{\Delta}_{i1} = \Delta_{i1} - \hat{\Delta}_{i1}$ and $\tilde{\Omega}_i = \Omega_i - \hat{\Omega}_i$ are guaranteed to be uniformly ultimately bounded, and the state observer errors $e_{i1} = y_i - \hat{y}_i$ and $e_{i2} = v_i - \hat{v}_i$ are guaranteed to be practical stable in fixed time $\bar{T}_e$.

Similar to the proof procedure of Theorem 1, the error vector $e_i = \left[e_{i1}^T, e_{i2}^T\right]^T$ can be constructed and define the Lyapunov function $\bar{V}_0 = \frac{1}{2}\sum_{i=1}^{N} e_i^T\left(R_i\otimes I_2\right)e_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{2}\operatorname{tr}\left[\tilde{\omega}_{im}^T\Upsilon_{im}^{-1}\tilde{\omega}_{im}\right]$ for the observer of Eq. (32). By following the procedure of Eqs. (26)-(31), the proof can be obtained in the same way. To save space, more details have been omitted here.

Remark 5: The effect produced by actuator fault is estimated and compensated by utilizing Radial Basis Function NN (RBFNN) similar to the results represented in [15], [42], [43]. Different information of the unknown terms Δ_{i1} and Ω_i in different subsystem is completely embodied in the ideal weight vectors ω_i^* and Gaussian function s_{ij}. Then, compared with the existing asymptotical fault-tolerant methods [33]–[35] where the estimation errors can be eliminated with time goes to infinity, we further improve the convergence performance of RBFNN-based observer by utilizing the practical fixed-time stability [18], which is more useful and effective.

Remark 6: In practical fault-tolerant formation applications, the dynamics of unmanned vehicles are usually subject to external inputs, such as the actuator faults and unknown disturbances. Usually, if the tracking error is ultimately uniformly bounded by a sufficiently small boundary, then the MASs is said to achieve the formation missions. Therefore, after the practical fixed-time stability of the proposed observers, the estimated states $\hat{x}_{i0}$, $\hat{v}_{i0}$, $\hat{x}_i$, and $\hat{v}_i$ can be used for the controller design.

Remark 7: So far, the common fixed-time observer, for example, the proposed in [20], [21], is usually used to reconstruct the unknown leader state without the effect of disturbances. Compared with the relevant observer, a fixed-time observer of Eq. (22) is developed to estimate the leader state based on a distributed strategy under matching and mismatched disturbances by using the intelligent compensation technique. Moreover, in [42], an asymptotical adaptive NN observer is constructed for second-order MASs to obtain the unknown follower states. Inspired by the above theoretical achievement, we further derive a decentralized fixed-time follower state observer under the effects of actuator faults and unknown disturbances. Furthermore, the obtained settling time is explicitly linked with several parameters of the adaptive laws. Since the observers are designed by using fixed-time theorem, the obtained settling time of the observers can be arbitrarily set according to the designer requirement, which provides the possibility of perfect integration with subsequent prescribed-time tracking controller.

Remark 8: Although the convergence time of fixed-time control can be intervened by humans, one-sided pursuit of fast convergence can inevitably lead to excessive control input signals, which may cause that the amplitude of the control input to exceed the maximum acceptable value of the actuator device. Therefore, a key issue for fixed-time control is that the users need to find a compromise between time complexity and control speed in practical engineering. In contrast, because the use of regular feedback control in the proposed prescribed-time control method, the chattering problem will not be caused, and the amplitude of the control input can be effectively regulated.

C. Prescribed-Time Fault-Tolerant Formation Controller Design

By using the estimations of the proposed fixed-time observers in Section III-A, novel prescribed-time fault-tolerant formation strategies are designed to achieve leader-follower tracking. Firstly, let the tracking error be:

$$z_i(t) = x_i(t) - x_0(t) - h_i(t). \tag{35}$$

To possess the prescribed-time formation performance, a virtual velocity $v_i^*(t)$ is designed in the velocity channel, and the following error expression can be obtained:

$$\xi_i(t) = v_i(t) - v_i^*(t) \tag{36}$$

Then, based on the results of Theorems 1-2, the following relations hold:

$$\begin{cases} x_0(t) = \hat{x}_0(t) - k_{i01} H e_{i01} + e_{i02} + \tilde{\Delta}_{i01} \\ \qquad - \vartheta_1 \mathrm{sig}^{\alpha}\left[(H \otimes I_2) e_{i01}\right] - \vartheta_2 \mathrm{sig}^{\beta}\left[(H \otimes I_2) e_{i01}\right] \\ v_0(t) = \hat{v}_0(t) - k_{i02} H e_{i02} + \tilde{\Delta}_{i02} \\ \qquad - \vartheta_1 \mathrm{sig}^{\alpha}\left[(H \otimes I_2) e_{i02}\right] - \vartheta_2 \mathrm{sig}^{\beta}\left[(H \otimes I_2) e_{i02}\right] \end{cases} \tag{37}$$

and

$$\begin{cases} x_i(t) = \hat{x}_i(t) - k_{i1} e_{i1} + e_{i2} + \tilde{\Delta}_{i1} \\ \qquad - \mu_1 \mathrm{sig}^{\chi}(e_{i1}) - \mu_2 \mathrm{sig}^{\varepsilon}(e_{i1}) \\ v_i(t) = \hat{v}_i(t) - k_{i2} e_{i2} + \tilde{\Omega}_{i2} - \mu_1 \mathrm{sig}^{\chi}(e_{i1}) - \mu_2 \mathrm{sig}^{\varepsilon}(e_{i1}) \end{cases} \tag{38}$$

Then, since the terms e_{i01}, e_{i02}, e_{i1}, e_{i2}, $\tilde{\Delta}_{i01}$, $\tilde{\Delta}_{i02}$, $\tilde{\Delta}_{i1}$ and $\tilde{\Omega}_{i2}$ are uniformly ultimately bounded, the following system can be designed involving coordination of $(\hat{x}_i, \zeta_i)$ based on Remark 6.

$$\begin{cases} \zeta_i(t) = \hat{v}_i(t) - v_i^*(t) \\ \dot{\hat{x}}_i(t) = \zeta_i(t) + v_i^*(t) + \hat{\Delta}_{i1}(t) + k_{i1}(y_i - \hat{y}_i) \\ \qquad + \mu_1 \mathrm{sig}^{\chi}(y_i - \hat{y}_i) + \mu_2 \mathrm{sig}^{\varepsilon}(y_i - \hat{y}_i) \\ \dot{\zeta}_i(t) = u_i^*(t) + \hat{\Omega}_i(t) + k_{i2}(y_i - \hat{y}_i) \\ \qquad + \mu_1 \mathrm{sig}^{\chi}(y_i - \hat{y}_i) + \mu_2 \mathrm{sig}^{\varepsilon}(y_i - \hat{y}_i) \end{cases} \tag{39}$$

where $u_i^*(t)$ is considered as the virtual control input.

To stabilize the system of Eq. (37) within a prescribed time, we construct the following virtual input signals:

$$\begin{aligned} u_i^*(t) = &- \left(\varpi_i + \tfrac{\dot{\varsigma}_{i1}}{\varsigma_{i1}}\right) \zeta_i - \hat{\Omega}_i(t) - k_{i2}(y_i - \hat{y}_i) \\ &- \mu_1 \mathrm{sig}^{\chi}(y_i - \hat{y}_i) - \mu_2 \mathrm{sig}^{\varepsilon}(y_i - \hat{y}_i) \end{aligned} \tag{40}$$

and

$$\begin{aligned} v_i^*(t) = &- \left(\phi_i + \tfrac{\dot{\varsigma}_{i2}}{\varsigma_{i2}}\right) z_i - \hat{\Delta}_{i1}(t) - k_{i1}(y_i - \hat{y}_i) + \dot{\hat{x}}_0 + \dot{h}_i \\ &- \mu_1 \mathrm{sig}^{\chi}(y_i - \hat{y}_i) - \mu_2 \mathrm{sig}^{\varepsilon}(y_i - \hat{y}_i) \end{aligned} \tag{41}$$

where ς_{i1}, and ς_{i2} are defined as μ in Lemma 3, $\varpi_i, \phi_i > 0$. Besides, the closed-loop control protocol for the system of Eq. (10) is:

$$u_i(t) = u_i^*(t) + \dot{v}_i^*(t). \tag{42}$$

Theorem 3: Under Assumptions 1-4, with the fixed-time observers of Eqs. (22) and (32), and the virtual control protocol designed in Eqs. (38)-(40), the heterogeneous MASs of Eqs. (2) and (10) can achieve the desired formation tracking in a preassignable finite time.

Proof: To analyze the prescribed-time stability of the closed-loop system of Eq. (37), the velocity tracking error $\zeta_i(t)$ should finish the prescribed-time convergence first. The corresponding Lyapunov function is expressed as:

$$V_\zeta = \frac{1}{2} \sum_{i=1}^{N} \zeta_i^T \zeta_i \tag{43}$$

Computing the derivate of V_ζ along the trajectory of Eq. (36) with the input of Eq. (42), it yields to:

$$\begin{aligned}\dot{V}_\zeta &= \sum_{i=1}^{N} \zeta_i^T \dot{\zeta} \\ &\leq \sum_{i=1}^{N} \zeta_i^T \left[\dot{\hat{v}}_i(t) - \dot{v}_i^*(t)\right] \\ &\leq \sum_{i=1}^{N} \zeta_i^T \left[u_i^*(t) + \hat{\Omega}_i(t) + k_{i2}\left(y_i - \hat{y}_i\right)\right. \\ &\quad \left. + \mu_1 \mathrm{sig}^\chi \left(y_i - \hat{y}_i\right) + \mu_2 \mathrm{sig}^\varepsilon \left(y_i - \hat{y}_i\right)\right] \\ &\leq -\sum_{i=1}^{N} \zeta_i^T \left(\varpi_i + \frac{\dot{\varsigma}_{i1}}{\varsigma_{i1}}\right)\zeta_i \\ &\leq -2\varpi_i V_\zeta - 2\frac{\dot{\varsigma}_{i1}}{\varsigma_{i1}} V_\zeta\end{aligned} \tag{44}$$

According to Lemma 3, there is a finite time constant T_ζ, such that $\hat{v}_i(t) = v_i^*(t)$ when $t \geq T_\zeta$.

The second Lyapunov function is selected with the form:

$$V_z = \frac{1}{2}\sum_{i=1}^{N} z_i^T z_i \tag{45}$$

Then, taking into account Eqs. (35, (36) and (37), we obtain:

$$\begin{aligned}z_i &= x_i(t) - x_0(t) \\ &= \hat{x}_i(t) - \hat{x}_0(t) - k_{i1}e_{i1} + e_{i2} + \tilde{\Delta}_{i1} - \mu_1 \mathrm{sig}^\chi\left(e_{i1}\right) \\ &\quad -\mu_2 \mathrm{sig}^\varepsilon\left(e_{i1}\right) + k_{i01}He_{i01} - e_{i02} - \tilde{\Delta}_{i01} - h_i(t) \\ &\quad + \vartheta_1 \mathrm{sig}^\alpha\left[\left(H \otimes I_2\right)e_{i01}\right] + \vartheta_2 \mathrm{sig}^\beta\left[\left(H \otimes I_2\right)e_{i01}\right] \\ &\leq \hat{x}_i(t) - \hat{x}_0(t) + \bar{\Delta}_i\end{aligned} \tag{46}$$

where $\bar{\Delta}_i$ is the upper bound of the lumped estimation error.

Then, based on Remark 6, we can observe that the following inequality is feasible.

$$\begin{aligned}\dot{V}_z &= \sum_{i=1}^{N} z_i^T \dot{z}_i \\ &\leq \sum_{i=1}^{N} z_i^T \left[\zeta_i(t) + v_i^*(t) + \hat{\Delta}_{i1}(t) + k_{i1}\left(y_i - \hat{y}_i\right)\right. \\ &\quad \left. + \mu_1 \mathrm{sig}^\chi\left(y_i - \hat{y}_i\right) + \mu_2 \mathrm{sig}^\varepsilon\left(y_i - \hat{y}_i\right) - \dot{\hat{x}}_0(t) - \dot{h}_i(t)\ \right] \\ &\leq\ -\sum_{i=1}^{N} z_i^T\left(\phi_i + \frac{\dot{\varsigma}_{i2}}{\varsigma_{i2}}\right)z_i \\ &\leq\ -2\phi_i V_z - 2\frac{\dot{\varsigma}_{i2}}{\varsigma_{i2}} V_z\end{aligned} \tag{47}$$

Based on Lemma 3, one has that the formation error z_i can comply with the prescribed convergence time. Then, by using Theorems 1-3, we can conclude that the developed NN observer-based fault-tolerant formation controller can achieve the desired tracking tasks in a finite time $T_e + \bar{T}_e + T_\zeta + T_z$. This completes the proof.

Remark 9: In some fixed-time formation results, it is complicated to establish the relationship between the controller parameters and the theoretical value of the convergence time, since the obtained theoretic convergence time usually depends on many parameters. Different from the existing finite-time tracking [14]–[17], and fixed-time tracking [19]–[22], the upper bound of convergence time in this article is not related to any controller parameters, which is convenient for the new users to adjust the convergence time under different operating scenarios. This represents an inherent characteristic stating that the settling time is finite and can be preassignable based on the user requirement.

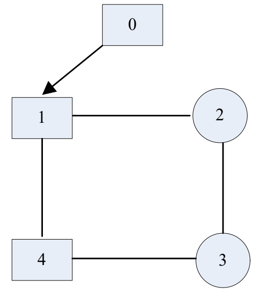

Fig.1 Topology network.

Remark 10: Different from the existing formation results for homogeneous MASs, more practical heterogeneous UAVs-UGVs systems are considered in this study. Furthermore, the actuator faults occurring in the model of each follower agent and the matching and mismatched disturbances are dealt with the proposed NN-based prescribed-time compensator and controller, which represents a new fault-tolerant control framework for leader-follower formation tracking of heterogeneous MASs. Technically, adaptive fixed-time NN observer is first constructed to estimate the unknown states and time-varying actuator faults in air-ground formation scenario. Then, based on the estimations, a backstepping controller is designed to achieve trajectory tracking. Compared with other finite-time controller schemes, the proposed prescribed-time algorithm is able to effectively address the distributed fault-tolerant formation tracking issue with simplified computation.

IV. Simulation Example

To confirm the availability of the constructed techniques, simulations are conducted for a heterogeneous MAS involving one leader ($i = 0$), two UGV followers ($i = 1, 4$), and two UAV followers ($i = 2, 3$). The communication network is described in Fig. 1. The model parameters of agents are derived from [45]. The control input for the leader agent is $u_0^p = [0.5, 0.7\sin t]^T$. The initial conditions of the formation system have been set to $x_0 = [0, 0]^T$, $x_1 = [-0.26, -0.37]^T$, $x_2 = [3, 2, 2]^T$, $x_3 = [-3.2, -4.8, -1]^T$, and $x_4 = [-6, -5]^T$, respectively. The four followers need to realize a predesigned formation configuration, and the desired formation configurations for followers are $h_1 = [3, 3]^T$, $h_2 = [5, 5, t]^T$, $h_3 = [-3, -3, 2t]^T$, and $h_4 = [-5, -5]^T$. Moreover, the vehicles are subject to the following heterogeneous mismatched disturbances: $\Delta_{01} = [0.1\sin t, 0.1\cos t]^T$, $\Delta_{11} = [0.13\cos t, 0.2\cos(0.6t)]^T$, $\Delta_{21} = [0.23\sin t, -0.12\cos t, 0.1\sin(0.5t)]^T$, $\Delta_{31} = [0.13\sin(3t), 0.13\cos(1.2t), 0.08\sin(0.75t)]^T$, and $\Delta_{41} = [0.08\cos t, 0.03\sin t]^T$. The followers 2 and 3 are assumed to suffer from time-varying uncertainty (20% variation) in rotary inertia and aerodynamic damping parameters.

To further illustrate the fault-tolerant performance, the actuator fault variables of each follower are designed as follows:

$$\rho_{1x} = \begin{cases} 0, t \leq 3s \\ 0.2, t > 3s \end{cases}, \rho_{1y} = \begin{cases} 0, t \leq 3s \\ 0.18, t > 3s \end{cases},$$

$$\rho_{2x} = \begin{cases} 0, t \leq 5s \\ 0.15, t > 5s \end{cases}, \rho_{2y} = \begin{cases} 0, t \leq 5s \\ 0.1, t > 5s \end{cases},$$

$$\rho_{2z} = \begin{cases} 0, t \le 5s \\ 0.15, t > 5s \end{cases}, \rho_{3x} = \begin{cases} 0, t \le 7s \\ 0.2, t > 7s \end{cases},$$
$$\rho_{3y} = \begin{cases} 0, t \le 7s \\ 0.25, t > 7s \end{cases}, \rho_{3z} = \begin{cases} 0, t \le 7s \\ 0.3, t > 7s \end{cases},$$
$$\rho_{4x} = \begin{cases} 0, t \le 10s \\ 0.14, t > 10s \end{cases}, \rho_{4y} = \begin{cases} 0, t \le 10s \\ 0.3, t > 10s \end{cases}.$$

and

$\delta_1 = [-0.1\sin(t), -0.3\cos(0.5t)]^T$,
$\delta_2 = [0.15\cos(0.3t), 0.35\cos(2t), 0.2\cos(3t)]^T$,
$\delta_3 = [0.1\sin(0.6t), -0.2\cos(1.5t), 0.12\sin(2t)]^T$,
$\delta_4 = [0.15\cos(t), 0.2\cos(t)]^T$.

Some relevant parameters of the designed observers are $\alpha = 0.1$, $\beta = 1.1$, $\vartheta_1 = 0.5$, $\vartheta_2 = 0.7$, $k_{i01} = 50$, $k_{i02} = 47$, $\sigma_{i1} = 4$, $\sigma_{i2} = 10$, $\Gamma_{im} = \mathrm{diag}\{3, 3\}$. By using Theorem 3, relevant controller parameters are designed as $\varpi_i = 10$, $\phi_i = 15$, and $T = 5$.

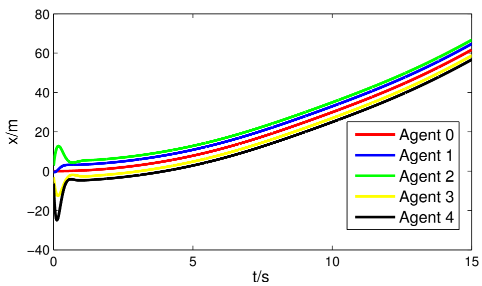

Fig.2 Formation configuration of agents in the X axis.

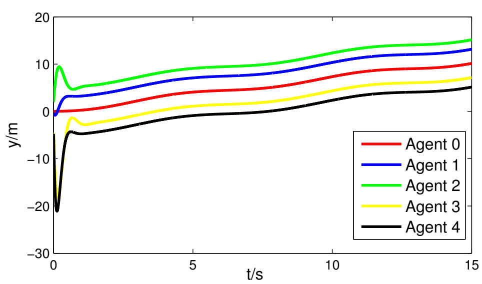

Fig.3 Formation configuration of agents in the Y axis.

The time responses of the formation control process in XY axis are described in Figs. 2-3. We can note how the designed NN observer-based formation approach realizes the desired tracking mission with faster transient and steady responses. At the same time, this also proves that the designed fixed-time NN observers can effectively finish the estimations of the leader's state, the unknown state of followers and the lumped uncertainties, respectively. Figs. 4-6 highlight that the tracking errors in XYZ three-dimensional space converge to a small neighborhood of zero within finite time. Figs. 7-8 show the trajectories of ω_{im}, which proves that the parameters can achieve fast adaptive adjustment and ultimately achieve uniformly bounded convergence.

Because of the effective estimation capability of proposed fixed-time observer for various unknown uncertainties, the constructed observer-based controller has good robustness and fault tolerance in practical implementation. On the other hand, the actual settling time of tracking error is still less than the predesigned settling value 5s. Therefore, the actual settling time must be smaller than the sum of the observer settling time and controller settling time, which proves the availability of the constructed prescribed-time fault-tolerant strategy. Due to the use of observers, the convergence process of tracking error relatively lagged. Moreover, the fixed/prescribed-time theorem can not obtain the exact realized time, but only a theoretical maximum. As a result, the theoretical value of the finite convergence time is conservative compared with the actual value. In order to improve the reference value of theoretical values, designers should adjust the controller parameters appropriately based on the initial state of the system and the difficulty of the task.

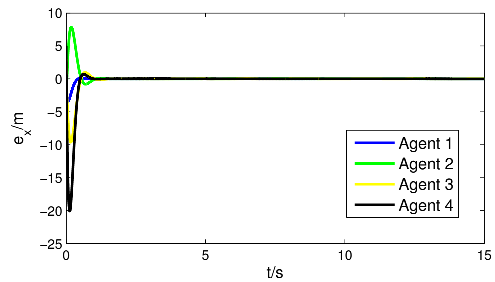

Fig.4 Tracking errors of agents in the X axis.

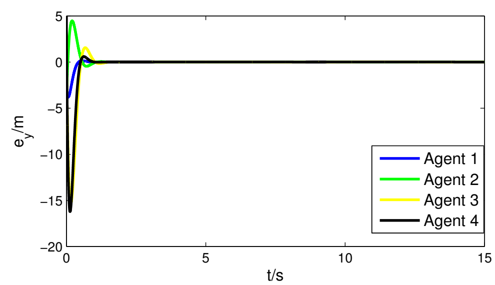

Fig.5 Tracking errors of agents in the Y axis.

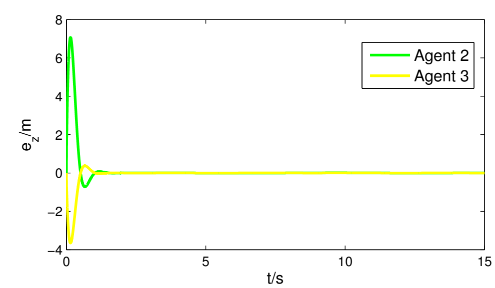

Fig.6 Tracking errors of agents in the Z axis.

V. Conclusion

This paper studied the adaptive neural network observer-based prescribed-time fault-tolerant tracking problem for air-ground heterogeneous MASs. Firstly, the estimation of state information of the leader was obtained by designing a fixed-time neural network observer under the effects of mismatched

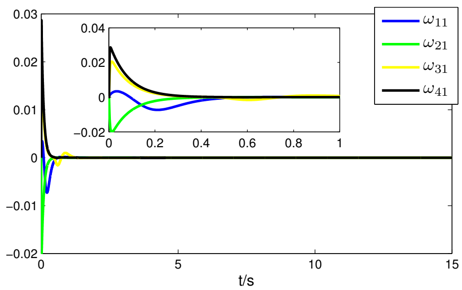

Fig.7 Trajectories of the adaptive gains ω_{i1}.

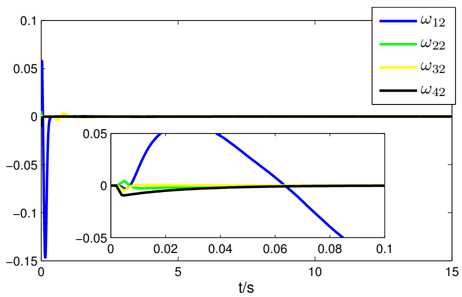

Fig.8 Trajectories of the adaptive gains ω_{i2}.

and matching disturbances. Then, another decentralized fixed-time neural network observer was constructed to estimate the unknown velocity state and the lumped uncertainty. By using the estimations, a backstepping prescribed-time fault-tolerant formation tracking protocol was developed to achieve the expected formation. Finally, the availability of the constructed results was authenticated by a simulation experiment.

Future research direction will consider the analysis of the achievable performance in terms of numerical metrics and indices. Moreover, before applying the proposed solutions to real scenarios, the presence of measurement errors, unstructured uncertainty and disturbance effects has to be investigated in more detail.

REFERENCES

[1] X. Wang, J. H. Park, H. Liu, and X. Zhang, "Cooperative output-feedback secure control of distributed linear cyber-physical systems resist intermittent dos attacks," *IEEE Trans. Cybern.*, vol. 51, no. 10, pp. 4924–4933, Oct. 2021.

[2] R. Babazadeh and R. Selmic, "Distance-based multiagent formation control with energy constraints using sdre," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 56, no. 1, pp. 41–56, Feb. 2020.

[3] Y. Tang, D. Zhang, P. Shi, W. Zhang, and F. Qian, "Event-based formation control for nonlinear multiagent systems under dos attacks," *IEEE Trans. Autom. Control*, vol. 66, no. 1, pp. 452–459, Jan. 2021.

[4] J. Han, H. Zhang, Y. Wang, and H. Ren, "Output consensus problem for linear heterogeneous multiagent systems with dynamic event-based impulsive control," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 53, no. 1, pp. 334–345, Jan. 2023.

[5] C. Deng, W.-W. Che, and Z.-G. Wu, "A dynamic periodic event-triggered approach to consensus of heterogeneous linear multiagent systems with time-varying communication delays," *IEEE Trans. Cybern.*, vol. 51, no. 4, pp. 1812–1821, Apr. 2021.

[6] W. Zhao, H. Liu, Y. Wan, and Z. Lin, "Data-driven formation control for multiple heterogeneous vehicles in air–ground coordination," *IEEE Trans. Control Netw. Syst.*, vol. 9, no. 4, pp. 1851–1862, Dec. 2022.

[7] Z. Su, X. Wang, and H. Wang, "Neural-adaptive constrained flight control for air–ground recovery under terrain obstacles," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 58, no. 1, pp. 374–390, Feb. 2022.

[8] A. Rucco, P. B. Sujit, A. P. Aguiar, J. B. de Sousa, and F. L. Pereira, "Optimal rendezvous trajectory for unmanned aerial-ground vehicles," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 54, no. 2, pp. 834–847, Apr. 2018.

[9] L. Zhang, F. Gao, F. Deng, L. Xi, and J. Chen, "Distributed estimation of a layered architecture for collaborative air-ground target geolocation in outdoor environments," *IEEE Trans. Ind. Electron.*, pp. 1–10, 2022.

[10] D. Liu, Y. Xu, Y. Xu, Y. Sun, A. Anpalagan, Q. Wu, and Y. Luo, "Opportunistic data collection in cognitive wireless sensor networks: Air–ground collaborative online planning," *IEEE Internet Things J.*, vol. 7, no. 9, pp. 8837–8851, Sep. 2020.

[11] M. Vallejo-Alarcón, R. Castro-Linares, and M. Velasco-Villa, "Unicycle-type robot & quadrotor leader-follower formation backstepping control," *IFAC-PapersOnLine*, vol. 48, no. 19, pp. 51–56, 2015.

[12] R. Rahimi, F. Abdollahi, and K. Naqshi, "Time-varying formation control of a collaborative heterogeneous mult-agent system," *Robot. Autom. Syst.*, vol. 62, no. 12, pp. 1799–1805, 2014.

[13] S. P. Bhat and D. S. Bernstein, "Finite-time stability of continuous autonomous systems," *SIAM J.contr.opti*, vol. 38, no. 3, pp. 751–766, 2000.

[14] Y. Lin, Z. Lin, Z. Sun, and B. D. O. Anderson, "A unified approach for finite-time global stabilization of affine, rigid, and translational formation," *IEEE Trans. Autom. Control*, vol. 67, no. 4, pp. 1869–1881, Apr. 2022.

[15] C.-L. Hwang and H. B. Abebe, "Generalized and heterogeneous nonlinear dynamic multiagent systems using online RNN-based finite-time formation tracking control and application to transportation systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 13 708–13 720, Aug. 2022.

[16] Y. Hua, X. Dong, L. Han, Q. Li, and Z. Ren, "Finite-time time-varying formation tracking for high-order multiagent systems with mismatched disturbances," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 50, no. 10, pp. 3795–3803, Oct. 2020.

[17] M. Doostmohammadian, "Single-bit consensus with finite-time convergence: Theory and applications," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 56, no. 4, pp. 3332–3338, Aug. 2020.

[18] A. Polyakov, "Nonlinear feedback design for fixed-time stabilization of linear control systems," *IEEE Trans. Autom. Control*, vol. 57, no. 8, pp. 2106–2110, Aug. 2012.

[19] C. Xu, B. Wu, D. Wang, and Y. Zhang, "Distributed fixed-time output-feedback attitude consensus control for multiple spacecraft," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 56, no. 6, pp. 4779–4795, Dec. 2020.

[20] S. Chang, Y. Wang, Z. Zuo, and H. Yang, "Fixed-time formation control for wheeled mobile robots with prescribed performance," *IEEE Trans. Control Syst. Technol.*, vol. 30, no. 2, pp. 844–851, Mar. 2022.

[21] Y. Cai, H. Zhang, Y. Wang, Z. Gao, and Q. He, "Adaptive bipartite fixed-time time-varying output formation-containment tracking of heterogeneous linear multiagent systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 9, pp. 4688–4698, Sep. 2022.

[22] S.-L. Dai, K. Lu, and X. Jin, "Fixed-time formation control of unicycle-type mobile robots with visibility and performance constraints," *IEEE Trans. Ind. Electron.*, vol. 68, no. 12, pp. 12 615–12 625, Dec. 2021.

[23] B. Ning, Q.-L. Han, Z. Zuo, L. Ding, Q. Lu, and X. Ge, "Fixed-time and prescribed-time consensus control of multiagent systems and its applications: A survey of recent trends and methodologies," *IEEE Trans. Ind. Informat.*, vol. 19, no. 2, pp. 1121–1135, Feb. 2023.

[24] X. Li, Y. Zhu, X. Zhao, and J. Lu, "Bearing-based prescribed time formation tracking for second-order multi-agent systems," *IEEE Trans. Circuits Syst. II*, vol. 69, no. 7, pp. 3259–3263, Jul. 2022.

[25] X. Gong, Y. Cui, J. Shen, Z. Shu, and T. Huang, "Distributed prescribed-time interval bipartite consensus of multi-agent systems on directed graphs: Theory and experiment," *IEEE Trans. Netw. Sci. Eng.*, vol. 8, no. 1, pp. 613–624, Mar. 2021.

[26] Y. D. Song, Y. J. Wang, J. Holloway, and M. Krstic, "Time-varying feedback for regulation of normal-form nonlinear systems in prescribed finite time," *Automatica*, vol. 83, pp. 243–251, Jul. 2017.

[27] K. Zhang, B. Jiang, and P. Shi, "Adjustable parameter-based distributed fault estimation observer design for multiagent systems with directed graphs," *IEEE Trans. Cybern.*, vol. 47, no. 2, pp. 306–314, Feb. 2017.

[28] X. Yu, X. Zhou, K. Guo, J. Jia, L. Guo, and Y. Zhang, "Safety flight control for a quadrotor uav using differential flatness and dual-loop observers," *IEEE Trans. Ind. Electron.*, vol. 69, no. 12, pp. 13 326–13 336, Dec. 2022.

[29] Q. Hou and J. Dong, "Robust adaptive event-triggered fault-tolerant consensus control of multiagent systems with a positive minimum interevent time," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 53, no. 7, pp. 4003–4014, Jul. 2023.

[30] Q.-Y. Fan, C. Deng, X. Ge, and C.-C. Wang, "Distributed adaptive fault-tolerant control for heterogeneous multiagent systems with time-varying communication delays," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 7, pp. 4362–4372, Jul. 2022.

[31] G. Song, P. Shi, and C. P. Lim, "Distributed fault-tolerant cooperative output regulation for multiagent networks via fixed-time observer and adaptive control," *IEEE Trans. Control Netw. Syst.*, vol. 9, no. 2, pp. 845–855, Jun. 2022.

[32] S. Xiao and J. Dong, "Distributed fault-tolerant containment control for nonlinear multi-agent systems under directed network topology via hierarchical approach," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 4, pp. 806–816, Apr. 2021.

[33] C. Liu, B. Jiang, R. J. Patton, and K. Zhang, "Decentralized output sliding-mode fault-tolerant control for heterogeneous multiagent systems," *IEEE Trans. Cybern.*, vol. 50, no. 12, pp. 4934–4945, Dec. 2020.

[34] J. Qin, G. Zhang, W. X. Zheng, and Y. Kang, "Adaptive sliding mode consensus tracking for second-order nonlinear multiagent systems with actuator faults," *IEEE Trans. Cybern.*, vol. 49, no. 5, pp. 1605–1615, May 2019.

[35] C. Deng and C. Wen, "Distributed resilient observer-based fault-tolerant control for heterogeneous multiagent systems under actuator faults and dos attacks," *IEEE Trans. Control Netw. Syst.*, vol. 7, no. 3, pp. 1308–1318, Sep. 2020.

[36] J. Han, X. Liu, X. Gao, and X. Wei, "Intermediate observer-based robust distributed fault estimation for nonlinear multiagent systems with directed graphs," *IEEE Trans. Ind. Informat.*, vol. 16, no. 12, pp. 7426–7436, Dec. 2020.

[37] Y. Cai, H. Zhang, W. Li, Y. Mu, and Q. He, "Distributed bipartite adaptive event-triggered fault-tolerant consensus tracking for linear multiagent systems under actuator faults," *IEEE Trans. Cybern.*, vol. 52, no. 11, pp. 11 313–11 324, Nov. 2022.

[38] X.-G. Guo, P.-M. Liu, J.-L. Wang, and C. K. Ahn, "Event-triggered adaptive fault-tolerant pinning control for cluster consensus of heterogeneous nonlinear multi-agent systems under aperiodic dos attacks," *IEEE Trans. Netw. Sci. Eng.*, vol. 8, no. 2, pp. 1941–1956, Jun. 2021.

[39] M. Van, S. S. Ge, and H. Ren, "Robust fault-tolerant control for a class of second-order nonlinear systems using an adaptive third-order sliding mode control," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 2, pp. 221–228, Feb. 2017.

[40] Z. Dong, X. Wang, X. Zhang, M. Hu, and T. N. Dinh, "Global exponential synchronization of discrete-time high-order switched neural networks and its application to multi-channel audio encryption," *Nonlinear Anal. Hybrid Syst*, vol. 47, pp. 334–345, Feb. 2023.

[41] Y. Li, K. Li, and S. Tong, "An observer-based fuzzy adaptive consensus control method for nonlinear multiagent systems," *IEEE Trans. Fuzzy Syst.*, vol. 30, no. 11, pp. 4667–4678, Nov. 2022.

[42] J. Lan, Y.-J. Liu, D. Yu, G. Wen, S. Tong, and L. Liu, "Time-varying optimal formation control for second-order multiagent systems based on neural network observer and reinforcement learning," *IEEE Trans. Neural Netw. Learn. Syst.*, pp. 1–12, 2022.

[43] S. Zheng, P. Shi, S. Wang, and Y. Shi, "Adaptive neural control for a class of nonlinear multiagent systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 2, pp. 763–776, Feb. 2021.

[44] Y. Liu and G.-H. Yang, "Neural learning-based fixed-time consensus tracking control for nonlinear multiagent systems with directed communication networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 2, pp. 639–652, Feb. 2021.

[45] W. Cheng, K. Zhang, B. Jiang, and S. X. Ding, "Fixed-time fault-tolerant formation control for heterogeneous multi-agent systems with parameter uncertainties and disturbances," *IEEE Trans. Circuits Syst. I*, vol. 68, no. 5, pp. 2121–2133, May 2021.

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