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Fault-Tolerant Cooperative Control of Multiple Uncertain Euler-Lagrange Systems with an Uncertain Leader

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Abstract: This paper explores the fault-tolerant cooperative control of multiagent systems, which are modeled via an uncertain leader system and multiple uncertain Euler–Lagrange systems with actuator faults. A self-adjusting observer is initially proposed to estimate the signal of the uncertain leader for different followers and compute the observer gain in real time. An adaptive fault-tolerant controller is designed based on the above observer and nonsingular fast terminal sliding mode surface. This controller estimates lumped uncertainty and ensures that tracking errors are ultimately bounded. The controller designed in this paper has the following three advantages. Firstly, the observer can estimate and transmit the leader's state to each follower even without precise knowledge of the leader's system matrix. Secondly, the controller is robust to actuator faults, uncertain parameters and external disturbances, the upper bounds of which can be arbitrarily large and unidentified. Thirdly, the controller has a simple structure and is also suitable for situations where the actuator is healthy. Lastly, simulations are provided to demonstrate the effectiveness of both the observer and the controller with or without actuator fault.

Keywords: fault-tolerant cooperative control; self-adjusting observer for uncertain leader system; uncertain Euler–Lagrange multiagent systems; actuator fault

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1. Introduction

The Euler–Lagrange system serves as a paradigmatic model for unraveling complex dynamics and finds extensive application in various engineering domains, including robotic manipulators [1,2], spacecrafts [3,4] and unmanned aerial vehicle systems [5,6]. Over the past few years, there has been a notable focus on cooperative control in multiagent systems, which involve multiple Euler–Lagrange systems and a leader system. The main difficulty in multiagent cooperative control lies in devising a distributed control law for each agent to accomplish particular global goals, such as consensus [7], synchronization [8] and formation [9].

Various efforts have been devoted to addressing this issue [10]. Networked cooperative systems offer numerous advantages over single subsystems, including enhanced efficiency and capabilities. Over recent years, there has been significant attention toward the cooperative control of multiple Euler–Lagrange systems. The fundamental challenge is to devise a distributed control scheme for each entity so that particular overarching goals (e.g., consensus [1,7], tracking [11,12], synchronization [8,13] and formation [9,14]) can be accomplished via local maneuvers. The challenge arises from the incomplete knowledge of the parameters associated with multiple Euler–Lagrange systems, and the existence of uncertainty will diminish the controllability performance of the system. Currently, the adaptive method [11,13], neural networks method [12,14] and backstepping design procedure [8] have become effective methods for addressing the uncertainties associated with multiple Euler–Lagrange systems. More specifically, Ref. [11] investigated the distributed

adaptive control of a group of underactuated flexible spacecraft operating under a leader–follower framework, relying solely on the measurements of the rigid bodies. Ref. [13] developed strategies to facilitate synchronization among networked uncertain Lagrange systems through adaptive coordination control protocols. In [12], a distributed finite-time tracking control algorithm was formulated, leveraging neural networks for estimating model uncertainties. In [14], a design of an adaptive neural network multilayer formation controller was proposed to handle model uncertainties. In [8], a fixed-time robust controller was developed by converting uncertain Euler–Lagrange systems into second-order systems and introduced the backstepping design methodology. However, these systems also exhibit increased complexity and a higher frequency of faults, attributed to their extensive array of sensors, controllers and communication equipment. At times, a fault within a system can lead to a decline in performance or even result in catastrophic accidents. Therefore, ensuring reliability is a crucial objective in engineering system design. It is imperative to maintain stable and appropriate performance in systems regardless of whether components are functioning properly or have failed. Fault-tolerant control is seen as one of the most promising control technologies because it maintains specified performance of dynamic systems even if component faults occur. Fault tolerance control is divided into passive fault tolerance and active fault tolerance according to design methods. As the complexity of the system deepens, the fixed control gain designed by passive fault tolerance and the limited conservatism of fault tolerance are amplified. Active fault tolerance can adjust the control gain or reconstruct the controller online, thereby compensating for the limitations of passive fault tolerance and having stronger fault tolerance. However, it can also lead to time delays caused by fault detection, isolation and controller reconstruction, as well as computational resource waste caused by time estimation of fault information [15].

When dealing with Euler–Lagrange systems, controlling and executing tasks becomes essential, particularly in the face of environmental disruptions, model uncertainties and actuator malfunctions. This issue has garnered significant attention in recent years due to mission failures caused by these uncertainties. To achieve the desired control performance, various studies have been carried out and put into practice, e.g., sliding mode control [16], back-stepping control [17], adaptive control [18,19], etc. In current research, the extensive use of sliding mode control for fault-tolerant control demonstrates strong robustness to parameter uncertainties and external disturbances. Nonetheless, it is vital to deal with the inherent chattering issues in sliding mode control when utilizing this control approach. In [20], a resilient fault-tolerant controller based on sliding mode was introduced to lessen chattering. Moreover, a quasi-continuous second-order sliding mode control law was developed to address system malfunctions and alleviate chattering. Terminal sliding mode has delivered satisfactory outcomes in fault-tolerant control. In [21], a decentralized fault-tolerant controller for robot manipulators was proposed by combining terminal sliding modes and a super-twist algorithm to minimize chattering and expedite convergence. In [22], a sliding mode surface for integral terminal was carefully developed, resulting in the development of a model-free finite-time resilient adaptive fault-tolerant control for robot manipulators, demonstrating advantages in global finite-time convergence. Fault-tolerant cooperative control stands out as a leading control technology ensuring consistent and optimal performance of dynamic systems despite component faults [18,19,23]. Ref. [18] devised an adaptive fault-tolerant cooperative controller to attain the coordinated tracking error to be uniformly ultimately bounded for networked uncertain Lagrange systems. Ref. [23] proposed a distributed coordinated control scheme to make the leader-following tracking error uniformly ultimately bounded. Ref. [19] introduced an adaptive neural networks-based fixed-time fault-tolerant controller to make leader-following tracking errors converge into compact sets.

In the domain of output regulation, as described in [24], it is common to reference an exosystem that produces both the reference signal and external disturbances. Furthermore, in the realm of cooperative output regulation, as discussed in [25], the exosystem is regarded as the leader system, distinct from the follower system. To design a distributed

control law, a distributed observer was proposed as a dynamic compensator following the certainty equivalence principle [26]. This observer possessed the capability to assess the leader's state and transmit it to all followers via the communication network. The observer presented in [27] initially addressed the cooperative output regulation issue in linear multiagent systems and was subsequently extended to multiple Euler–Lagrange systems [28]. Nevertheless, it was contingent on the assumption of possessing knowledge regarding the system matrix of the leader system. To loosen the above assumption, an adaptive distributed observer was introduced in [28,29], capable of estimating both the state and matrix of the leader system. A self-tuning distributed observer was designed in [30] to address the challenge of calculating the observer gain online when dealing with numerous agents. These observers assume that certain followers have knowledge of the leader system's dynamics. Nonetheless, in practice, the dynamics of the leader system might remain unknown to any follower, meaning that none of the followers possesses precise knowledge of the leader system's dynamics. In light of this, a distributed dynamic compensator was introduced in [10].

Through the above investigation, we have learned how to save resources and achieve fault-tolerant performance in multiagent collaborative control without using fault detection. The designed controller can handle actuator faults, system uncertainties and external disturbances while tracking uncertain leader signals, which is a challenging research topic. In this paper, we synthesize a controller based on an adaptive distributed observer and nonsingular fast terminal sliding mode surface to solve the fault-tolerant cooperative control problem of multiple uncertain Euler–Lagrange systems, which are subjected to actuator faults. In existing research, designing a distributed observer requires assuming that some followers know the dynamics of the leader system [27,28]. However, in many practical applications, followers may not have precise knowledge of the leader system's dynamics. The main contributions of this work can be stated as follows. Initially, an adaptive distributed observer is devised for a linear leader system with neutral stability, featuring an uncertain system matrix. This observer can estimate and transmit the leader's state to each follower via the system's communication network, even without precise knowledge of the leader's system matrix. Secondly, an adaptive approach is applied to estimate the aggregate uncertainty, removing the need to compute its upper limit. This method exhibits resilience to actuator faults, uncertain parameters and external disturbances, the upper bounds of which can be arbitrarily large and unidentified. Finally, the controller in this paper has a simple structure without fault diagnosis, and it is also suitable for situations where the actuator is healthy. The complicated and costly fault detection, diagnosis and identification are not required.

This paper is structured as follows. Section 2 presents the formulation of the fault-tolerant cooperative control problem. Section 3 describes the development of a self-adjusting observer for dynamic leader systems with unknown parameters. In Section 4, we design the adaptive fault-tolerant controller. In Section 5, an example is presented. Finally, we conclude this paper.

In what follows, the following notation will be adopted. For $x_i \in \mathbb{R}^{n_i}$, $i = 1,\ldots,m$, $\mathrm{col}(x_1,\ldots,x_m) = \left[x_1^T,\ldots,x_m^T\right]^T$. $||a||$ denotes the Euclidean norm of a vector a. For $b \in \mathbb{R}^n, c \in \mathbb{R}^n$ and $b \odot c$ is defined as $b \odot c = [b_1c_1, b_2c_2, \ldots, b_nc_n]^T$. For $d \in \mathbb{R}^n$, $|d|^r = \left[|d_1|^r, |d_2|^r, \ldots, |d_n|^r\right]^T$, $\mathrm{sgn}(d) = [\mathrm{sign}(d_1), \mathrm{sign}(d_2), \ldots, \mathrm{sign}(d_n)]^T$. For $e = \mathrm{col}(e_1,\ldots,e_{2n}) \in \mathbb{R}^{2n}$, let $\phi : \mathbb{R}^{2n} \mapsto \mathbb{R}^{n\times 2n}$ be such that $\phi(e) = \begin{bmatrix} -e_2 & e_1 & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & -e_{2n} & e_{2n-1} \end{bmatrix}$.

2. Problem Formulation

Consider the following Euler–Lagrange equations with unknown dynamic uncertainties:

$$\mathbf{M}_i(q_i)\ddot{q}_i + \mathbf{C}_i(q_i,\dot{q}_i)\dot{q}_i + \mathbf{G}_i(q_i) = \tau_i + d_i \tag{1}$$

where $i = 1, \ldots, N$, $q_i \in \mathbb{R}^n$ and $\dot{q}_i \in \mathbb{R}^n$ are the joint variable vectors of generalized position and velocity of the ith agent, $\mathbf{M}_i(q_i) \in \mathbb{R}^{n\times n}$ is the symmetric positive definite inertia matrix, $\mathbf{C}_i(q_i, \dot{q}_i) \in \mathbb{R}^{n\times n}$ is the Coriolis and Centripetal forces, $\mathbf{G}_i(q_i) \in \mathbb{R}^n$ is the gravity term, $\mathbf{M}_i = M_i(q_i) + \Delta M_i(q_i)$, $\mathbf{C}_i(q_i, \dot{q}_i) = C_i(q_i, \dot{q}_i) + \Delta C_i(q_i, \dot{q}_i)$, $\mathbf{G}_i(q_i) = G_i(q_i) + \Delta G_i(q_i)$, $M_i(q_i)$, $C_i(q_i, \dot{q}_i)$ and $G_i(q_i)$ are nominal values of inertia, Coriolis and centripetal forces and gravity, respectively, $\Delta M_i(q_i)$, $\Delta C_i(q_i, \dot{q}_i)$ and $\Delta G_i(q_i)$ are unknown dynamic uncertainties of inertia , Coriolis and centripetal forces and gravity, respectively, $\tau_i \in \mathbb{R}^n$ is the control torque and also represents the actuator's output and $d_i(t) \in \mathbb{R}^n$ signifies uncertain external disturbances.

The following exosystem produces the reference signal:

$$\begin{aligned} \dot{v} &= \Pi(\varphi)v \\ q_0 &= Cv \end{aligned} \tag{2}$$

where $v \in \mathbb{R}^m$ is the state, $\Pi(\varphi) \in \mathbb{R}^{m\times m}$ is the system matrix, $\varphi \in \mathbb{R}^l$ is an unspecified parameter vector, $C \in \mathbb{R}^{n\times m}$ is a known constant matrix and $q_0 \in \mathbb{R}^n$ is the desired trajectory to track.

Inspired by [31], this paper considers the following actuator faults:

$$\tau_i = \tau_{Ai} + [(E_i(t) - I_n)\tau_{Ai} + \bar{\tau}_i] = \tau_{Ai} + \tau_{Fi} \tag{3}$$

where τ_{Ai} is nominal actuator output, τ_{Fi} is actuator fault, $\bar{\tau}_i$ is bounded bias fault, $E_i(t) = \mathrm{diag}\{E_{i1}, E_{i2}, \ldots, E_{in}\} \in \mathbb{R}^{n\times n}$, $E_{in} \in (0, 1]$ is actuator effectiveness, I_n is the identity matrix.

The multiagent system consists of N followers as described in (1) and an uncertain leader as defined in (2). The communication graph is represented by a directed graph $\overline{\mathcal{G}} = (\overline{\mathcal{V}}, \overline{\mathcal{E}})$, where $\overline{\mathcal{V}} = \{0, 1, \ldots, N\}$ is the node set and $\overline{\mathcal{E}} \subseteq \overline{\mathcal{V}} \times \overline{\mathcal{V}}$ is the edge set. The edge set $\overline{\mathcal{E}}$ is defined such that, for $i = 1, \ldots, N$, $j = 0, 1, \ldots, N$, $i \neq j$, $(j, i) \in \overline{\mathcal{E}}$ if and only if the node i can receive information of node j. The weighted adjacency $\overline{\mathcal{A}} = [a_{ij}] \in \mathbb{R}^{(N+1)\times(N+1)}$, $i, j \in \overline{\mathcal{V}}$, where $a_{ii} = 0$; $a_{ij} > 0$, if $(j, i) \in \overline{\mathcal{E}}$; otherwise $a_{ij} = 0$. Define the Laplacian matrix associated with $\overline{\mathcal{G}}$ as $H = [h_{ij}]_{i,j=1}^{N}$, where $h_{ii} = \sum_{j=0}^{N} a_{ij}$ and $h_{ij} = -a_{ij}$ for $i \neq j$, $i, j = 1, \ldots, N$. Define the subgraph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ of $\overline{\mathcal{G}}$ where $\mathcal{V} = \{1, \ldots, N\}$ and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is obtained from $\overline{\mathcal{E}}$ by eliminating all edges between the node 0 and the nodes in $\mathcal{V}$.

Fault-tolerant Cooperative Control Problem: Consider a multiagent system composed of multiple uncertain Euler–Lagrange systems (1) subject to actuator faults (3) and a leader system (2), a fixed graph $\overline{\mathcal{G}}$; find an adaptive control law such that for any initial conditions $q_i(0)$, $\dot{q}_i(0)$ and $v(0)$, the solution of the closed-loop system exists and is bounded for all $t \geq 0$ and the leader-following cooperative tracking error $e_i(t) = q_i(t) - q_0(t)$ is ultimately bounded, $i = 1, \ldots, N$.

Remark 1. *The fault-tolerant cooperative control problem is also addressed by [32], ensuring uniform bounds on tracking errors.*

To solve the above problem, we need the following assumptions.

Assumption 1. *The actuator fault τ_{Fi} is bounded by $\|\tau_{Fi}\| \leq k_{\tau i}$, where the constant $k_{\tau i} > 0$.*

Assumption 2. *The graph $\overline{\mathcal{G}}$ contains a directed spanning tree with the leader as the root and the subgraph $\mathcal{G}$ is undirected.*

Assumption 3. *The matrix $\Pi(\varphi)$ is neutrally stable.*

Remark 2. *Assumption 1 is the standard assumption. The fault τ_{Fi} in this article considers partial loss failure fault and bounded bias fault of the actuator; thus, it can be assumed that τ_{Fi}*

is bounded [31]. Assumption 2 is standard in a communication topology graph for multiagent systems and has been widely found in existing results [26,33]. Assumption 3 is also assumed in [10,28] and it is not conservative. Under Assumption 3, without loss of generality, we can presume that $\Pi(\varphi) = \text{diag}(\varphi) \otimes a$, *where* $a = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$, *diag*$(\cdot)$ *represents a diagonal matrix,* $\varphi = \text{col}(\varphi_{01}, \ldots, \varphi_{0l}) \in \mathbb{R}^l$, $m = 2l$.

3. A Self-Adjusting Observer Design for the Uncertain Leader System

By delving deeper into prior research, we initially recollect the notion of observer as introduced in [7]:

$$\begin{aligned} \dot{\eta}_i &= S(\omega_i)\eta_i + \mu_1 \sum_{j \in \overline{\mathcal{N}}_i} (\eta_j - \eta_i) \\ \dot{\omega}_i &= \mu_2 \phi\Big(\sum_{j \in \overline{\mathcal{N}}_i} (\eta_j - \eta_i)\Big)\eta_i, \quad i = 1, \ldots, N \end{aligned} \tag{4}$$

where $\eta_0 = v$, for $i = 1, \ldots, N$, $\eta_i \in \mathbb{R}^m$, $S(\omega_i)$ is system matrix, ω_i is unknown parameter vector, $S(\omega_i) = diag(\omega_i) \otimes a$, and μ_1 and μ_2 are positive constants.

The limitation of observer (4) lies in the requirement for a sufficiently large observer gain μ_1 to ensure the problem's solvability, making it challenging to derive a suitable value of μ_1 for large values of N [34]. Therefore, in this section, we design the following self-adjusting observer:

$$\begin{aligned} \dot{\eta}_i &= \Pi(\varphi_i)\eta_i - \kappa_i \sum_{j \in \overline{\mathcal{N}}_i} \mu_{ij}(\eta_i - \eta_j) \\ \dot{\mu}_{ij} &= k_{ij} a_{ij} \kappa_i (\eta_i - \eta_j)^T (\eta_i - \eta_j) \\ \dot{\varphi}_i &= -\gamma \phi(\eta_i^*)\eta_i \end{aligned} \tag{5}$$

where $i = 1, \ldots, N, j = 0, 1, \ldots, N$; let $\eta_{vi} = \sum_{j=0}^{N} a_{ij}(\eta_i - \eta_j)$, $\kappa_i = \kappa_i(\eta_{vi}^T \eta_{vi})$ is a sufficiently smooth function, $k_{ij} = k_{ji} > 0$, $i, j = 1, \ldots, N$, $k_{i0} > 0$, $i = 1, \ldots, N$, $\mu_{ij} = \mu_{ji}$ for $i, j = 1, \ldots, N$,

$$\eta_i^* = \begin{cases} \eta_i - \eta_0, & agent \quad i \quad is \quad the \quad leader's \quad child \\ \eta_i - \eta_k + \eta_k + \cdots - \eta_p + \eta_p - \eta_0, & otherwise. \end{cases} \tag{6}$$

Let $\bar{\eta}_i = \eta_i - \eta_0$, $\bar{\varphi}_i = \varphi_i - \varphi$, for $i = 1, \ldots, N$, $j = 0, 1, \ldots, N$; let $\bar{\mu}_{ij} = \mu_{ij} - \mu$, with some unknown constant $\mu > 0$. Then, (5) can be written as:

$$\begin{aligned} \dot{\bar{\eta}}_i &= \Pi(\varphi)\bar{\eta}_i + \Pi(\bar{\varphi}_i)\eta_i - \kappa_i \sum_{j \in \overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \\ \dot{\bar{\mu}}_{ij} &= k_{ij} a_{ij} \kappa_i (\bar{\eta}_i - \bar{\eta}_j)^T (\bar{\eta}_i - \bar{\eta}_j) \\ \dot{\bar{\varphi}}_i &= -\gamma \phi(\eta_i^*)\eta_i, \quad i = 1, \ldots, N \end{aligned} \tag{7}$$

Define F_1 as follows:

$$F_1 = [f_{ij}]_{i,j=1}^{N} \tag{8}$$

where $f_{ii} = \sum_{j=0}^{N} \mu_{ij} a_{ij}$, $f_{ij} = -\mu_{ij} a_{ij}$ when $i \neq j$, $i, j = 1, \ldots, N$. Define $F_2 = diag(\mu_{i0} a_{i0}, \ldots, \mu_{N0} a_{N0})$. Define $\kappa = diag(\kappa_1, \ldots, \kappa_N)$. Let $\eta = \text{col}(\eta_1, \eta_2, \ldots, \eta_N)$, $\bar{\eta} = \text{col}(\bar{\eta}_1, \bar{\eta}_2, \ldots, \bar{\eta}_N)$, $\bar{\varphi} = \text{col}(\bar{\varphi}_1, \bar{\varphi}_2, \ldots, \bar{\varphi}_N)$, $\eta_v = \text{col}(\eta_{v1}, \ldots, \eta_{vN})$, $S_d(\bar{\varphi}) =$ block diag $(S(\bar{\varphi}_1), \ldots, S(\bar{\varphi}_N))$. Then, the compact form for (7) is:

$$\dot{\bar{\eta}} = (I_N \otimes \Pi(\varphi))\bar{\eta} + \Pi_d(\bar{\varphi})\eta - (F_3 \otimes I_m)\eta + (F_4 \otimes I_m)(\mathbf{1}_N \otimes v), \tag{9a}$$

$$\dot{\bar{\phi}} = -\gamma\phi_d(\eta^*)\eta. \tag{9b}$$

where $F_3 = \kappa F_1$, $F_4 = \kappa F_2$, $\phi_d(\bar{\eta}) =$ block diag $(\phi(\bar{\eta}_1), \ldots, \phi(\bar{\eta}_N))$, for $i = 1, \ldots, N$, $j = 0, 1, \ldots, N$, let $\eta_{vi} = \sum_{j=0}^{N} a_{ij}(\eta_i - \eta_j)$, $\kappa_i = \kappa_i(\eta_{vi}^T\eta_{vi})$ is a sufficiently smooth nondecreasing function and $\kappa_i(\cdot) \geq 1, k_{ij} = k_{ji} > 0, i, j = 1, \ldots, N, k_{i0} > 0, i = 1, \ldots, N, \mu_{ij} = \mu_{ji}$ for $i, j = 1, \ldots, N$. Define $\kappa = diag(\kappa_1, \ldots, \kappa_N)$. Let $\bar{\mu} = \text{col}(\mu_{10}, \ldots, \mu_{N0}, \mu_{12}, \ldots, \mu_{1N}, \ldots, \mu_{(N-1)1}, \cdots, \mu_{(N-1)N})$.

Lemma 1. *Given Systems (2) and (5), under Assumptions 2 and 3, there exist $\mu_{ij} > 0, k_{ij} > 0$ and a smooth nondecreasing function $\kappa_i(\cdot) \geq 1$, $i = 1, \ldots, N$, such that for any $\eta_0 \in \mathbb{R}^m$, $\eta_i(t)$ exists and is bounded and we have: (1) $\lim_{t\to\infty} \bar{\eta}_i(t) = 0$ asymptotically; (2) $\lim_{t\to\infty} \dot{\bar{\phi}}(t) = 0$ asymptotically; (3) $\lim_{t\to\infty} \Pi(\bar{\varphi}_i)\eta_i(t) = 0$ asymptotically; (4) $\bar{\mu}_{ij}(t)$, $i = 1, \ldots, N$, $j = 0, 1, \ldots, N$, are bounded for all $t \geq 0$.*

Proof. The energy function for system (7) is presented as follows:

$$W(\bar{\eta}, \bar{\varphi}, \bar{\mu}, t) = W_1(\bar{\eta}, t) + W_2(\bar{\varphi}, t) + W_3(\bar{\mu}, t) \tag{10}$$

where

$$\begin{aligned} W_1(\bar{\eta}, t) &= \frac{1}{2}\sum_{i=1}^{N} \bar{\eta}_i^T\bar{\eta}_i \\ W_2(\bar{\varphi}, t) &= \frac{1}{2}\sum_{i=1}^{N} \gamma^{-1}\bar{\varphi}_i^T\bar{\varphi}_i \\ W_3(\bar{\mu}, t) &= \frac{1}{2}\sum_{i=1}^{N}\left(\sum_{j\in\mathcal{N}_i(t)} \frac{\bar{\mu}_{ij}^2}{2k_{ij}} + \sum_{0\in\bar{N}_i(t)} \frac{\bar{\mu}_{i0}^2}{k_{i0}}\right) \end{aligned} \tag{11}$$

The derivatives of the functions W_1,W_2 and W_3 along system (7) are as follows:

$$\begin{aligned} \dot{W}_1(\bar{\eta}, t) &= \sum_{i=1}^{N} \bar{\eta}_i^T(\Pi(\varphi)\bar{\eta}_i + \Pi(\bar{\varphi}_i)\eta_i - \kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j)) \\ &= \sum_{i=1}^{N} \bar{\eta}_i^T(\Pi(\varphi)\bar{\eta}_i + \Pi(\bar{\varphi}_i)\eta_i) - \sum_{i=1}^{N} \bar{\eta}_i^T\kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \end{aligned} \tag{12}$$

Since $\Pi(\varphi)$ is the skew symmetric, we have

$$\dot{W}_1(\bar{\eta}, t) = \sum_{i=1}^{N} \bar{\eta}_i^T\Pi(\bar{\varphi}_i)\eta_i - \sum_{i=1}^{N} \bar{\eta}_i^T\kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \tag{13}$$

By proposition in [7], for $i = 1, \ldots, N$, we have, $\bar{\eta}_i^T\Pi(\bar{\varphi}_i)\eta_i = \bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i$, then

$$\begin{aligned} \dot{W}_1(\bar{\eta}, t) &= \sum_{i=1}^{N} \bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N} \bar{\eta}_i^T\kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \\ &= \sum_{i=1}^{N} \bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N} \bar{\eta}_i^T\kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \\ &= \sum_{i=1}^{N} \bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N} \sum_{j\in\overline{\mathcal{N}}_i} \kappa_i\mu_{ij}\bar{\eta}_i^T(\bar{\eta}_i - \bar{\eta}_j) \end{aligned} \tag{14}$$

The derivative of W_2 along (7) is :

$$\dot{W}_2(\bar{\varphi}, t) = \frac{1}{2}\sum_{i=1}^{N}\gamma^{-1}\bar{\varphi}_i^T\dot{\bar{\varphi}}_i = -\sum_{i=1}^{N}\bar{\varphi}_i^T\phi_(\eta_i^*)\eta_i \tag{15}$$

The derivative of W_3 along (7) is :

$$\begin{aligned}\dot{W}_3(\bar{\mu}, t) &= \sum_{i=1}^{N}\left(\sum_{j\in\mathcal{N}_i}\frac{\bar{\mu}_{ij}\dot{\bar{\mu}}_{ij}}{2k_{ij}} + a_{i0}\frac{\bar{\mu}_{i0}\dot{\bar{\mu}}_{i0}}{k_{i0}}\right)\\ &= \sum_{i=1}^{N}\left(\sum_{j=1}^{N}\frac{\bar{\mu}_{ij}}{2k_{ij}}k_{ij}a_{ij}\kappa_i(\bar{\eta}_i-\bar{\eta}_j)^T(\bar{\eta}_i-\bar{\eta}_j) + a_{i0}\frac{\bar{\mu}_{i0}}{k_{i0}}k_{i0}\kappa_i\bar{\eta}_i^T\bar{\eta}_i\right)\\ &= \sum_{i=1}^{N}\frac{1}{2}\kappa_i\left(\sum_{j=1}^{N}a_{ij}\bar{\mu}_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) + \sum_{j=1}^{N}a_{ij}\bar{\mu}_{ij}\bar{\eta}_j^T(\bar{\eta}_j-\bar{\eta}_i)\right) + \sum_{i=1}^{N}\kappa_i a_{i0}\bar{\mu}_{i0}\bar{\eta}_i^T\bar{\eta}_i\end{aligned} \tag{16}$$

Since $a_{ij}\bar{\mu}_{ij} = a_{ji}\bar{\mu}_{ji}$, $i, j = 1, \ldots, N$, we have

$$\sum_{i=1}^{N}\sum_{j=1}^{N}a_{ij}\bar{\mu}_{ij}\bar{\eta}_j^T(\bar{\eta}_j-\bar{\eta}_i) = \sum_{i=1}^{N}\sum_{j=1}^{N}a_{ij}\bar{\mu}_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) \tag{17}$$

Thus,

$$\begin{aligned}\dot{W}_3(\bar{\mu}, t) &= \sum_{i=1}^{N}\kappa_i\Big(\sum_{j\in\mathcal{N}_i}\bar{\mu}_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) + \sum_{0\in\bar{N}_i(t)}\bar{\mu}_{i0}\bar{\eta}_i^T\bar{\eta}_i\Big)\\ &= \sum_{i=1}^{N}\sum_{j\in\bar{N}_i}\kappa_i\bar{\mu}_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j)\end{aligned} \tag{18}$$

Combining (14), (15) and (18), we can obtain

$$\begin{aligned}\dot{W}(\bar{\eta}, \bar{\varphi}, \bar{\mu}, t) &= \sum_{i=1}^{N}\bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N}\sum_{j\in\overline{\mathcal{N}}_i}\kappa_i\mu_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) + \sum_{i=1}^{N}\sum_{j\in\bar{N}_i}\kappa_i\bar{\mu}_{ij}\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j)\\ &\quad - \sum_{i=1}^{N}\bar{\varphi}_i^T\phi_(\eta_i^*)\eta_i\\ &= \sum_{i=1}^{N}\bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N}\sum_{j\in\bar{N}_i}\mu\kappa_i\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) - \sum_{i=1}^{N}\bar{\varphi}_i^T\phi_(\eta_i^*)\eta_i\end{aligned} \tag{19}$$

By the definition of η_i^* in (6), we can obtain $\sum_{i=1}^{N}\bar{\varphi}_i^T\phi(\bar{\eta}_i)\eta_i - \sum_{i=1}^{N}\bar{\varphi}_i^T\phi_(\eta_i^*)\eta_i = 0$; thus,

$$\dot{W}(\bar{\eta}, \bar{\varphi}, \bar{\mu}, t) = -\sum_{i=1}^{N}\sum_{j\in\bar{N}_i}\mu\kappa_i\bar{\eta}_i^T(\bar{\eta}_i-\bar{\eta}_j) \tag{20}$$

By Lemma 4 in [35], under Assumption 2, H is positive definite and symmetric; thus, the eigenvalue of H is a positive real number. We define $\kappa = diag(\kappa_1, \kappa_2, \ldots, \kappa_N)$ above, then we have

$$\begin{aligned}\dot{W}(\bar{\eta}, \bar{\varphi}, \bar{\mu}, t) &= -\mu\bar{\eta}^T(\kappa H\otimes I_m)\bar{\eta}\\ &\le -\mu\lambda_{\min}(\kappa H)\|\bar{\eta}\|^2 \le 0\end{aligned} \tag{21}$$

Thus, $\lim_{t\to\infty}W(t)$ exists, which implies that $\bar{\eta}$, $\bar{\varphi}$ and $\bar{\mu}$ are all bounded. v is bounded by Assumption 3; thus, $\eta = \bar{\eta} + v$ is bounded. $\bar{\mu}_{ij}$ and μ_{ij} are bounded.

Next, define $W_4(t) = \int_0^t \mu\lambda_{\min}(\kappa H)\|\bar{\eta}(\tau)\|^2 d\tau$. If one can show

$$\lim_{t\to\infty} \dot{W}_4(t) = \lim_{t\to\infty} \mu\lambda_{\min}(\kappa H)\|\bar{\eta}(t)\|^2 = 0, \tag{22}$$

then, one can conclude $\lim_{t\to\infty} \bar{\eta}(t) = 0$. Integrating both sides of (21) gives

$$W_4(t) \le \int_0^t -\dot{W}(r)dr = W(0) - W(t) \le W(0). \tag{23}$$

Since $\dot{W}_4(t) = \mu\lambda_{\min}(\kappa H)\|\bar{\eta}(t)\|^2 \ge 0$, then $\lim_{t\to\infty} W_4(t)$ exists. Next, we analyze whether $\ddot{W}_4(t)$ is bounded.

$$\ddot{W}_4(t) = 2\mu\lambda_{\min}(\kappa H)\bar{\eta}(t)\dot{\bar{\eta}}(t). \tag{24}$$

Since $\bar{\eta}$ and η have already been proven to be bounded as shown above, combining Equation (9a) leads to the conclusion that $\dot{\bar{\eta}}$ is also bounded, thereby allowing us to conclude that $\ddot{W}_4(t)$ is bounded as well. Thus, applying Barbalat's lemma, we can show $\lim_{t\to\infty} \dot{W}_4(t) = 0$; thus, we can obtain

$$\lim_{t\to\infty} \bar{\eta}(t) = 0 \tag{25}$$

which together with (9b) yields $\lim_{t\to\infty} \dot{\bar{\varphi}}(t) = 0$ asymptotically. Differentiating $\dot{\bar{\eta}}_i$ gives

$$\begin{aligned}\ddot{\bar{\eta}}_i = {} & \Pi(\dot{\varphi})\bar{\eta}_i + \Pi(\varphi)\dot{\bar{\eta}}_i + \Pi(\dot{\bar{\varphi}}_i)\eta_i + \Pi(\bar{\varphi}_i)\dot{\eta}_i - \dot{\kappa}_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j) \\ & - \kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\dot{\bar{\eta}}_i - \dot{\bar{\eta}}_j)\end{aligned} \tag{26}$$

We have shown $\bar{\eta}_i$, η_i, $\bar{\varphi}$, $\bar{\mu}_{ij}$, $\kappa_i(\cdot)$, μ_{ij}, $\dot{\bar{\eta}}_i$, $\dot{\bar{\varphi}}$, $\dot{\bar{\mu}}_{ij}$, $\dot{\kappa}_i(\cdot)$ are all bounded on $t \ge 0$; thus, $\bar{\varphi}_i$ and $\dot{\bar{\varphi}}_i$ are all bounded on $t \ge 0$; by (5), we can obtain that $\dot{\eta}_i$ is bounded on $t \ge 0$; thus, $\ddot{\bar{\eta}}_i$ is bounded. Then, by Lemma 8.2 in [36], we obtain $\lim_{t\to\infty} \dot{\bar{\eta}}_i(t) = 0$, which together with $\dot{\bar{\eta}}_i = \Pi(\varphi)\bar{\eta}_i + \Pi(\bar{\varphi}_i)\eta_i - \kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\bar{\eta}_i - \bar{\eta}_j)$ in (7) yields $\lim_{t\to\infty} \Pi(\bar{\varphi}_i)\eta_i(t) = 0$ asymptotically. □

4. Adaptive Fault-Tolerant Cooperative Controller Design

For the solvability of the fault-tolerant cooperative control problem, we need three properties for system (1) [8,37].

Property 1. *There are two positive constants $k_{\underline{m}i}$ and $k_{\bar{m}i}$, such that $k_{\underline{m}i} I_m \le \mathbf{M}_i(q_i) \le k_{\bar{m}i} I_m$.*

Property 2. *There are two positive constants k_{ci} and k_{gi}, such that $\|\mathbf{C}_i(q_i, \dot{q}_i)\| \le k_{ci}\|\dot{q}_i\|$ and $\|\mathbf{G}_i(q_i)\| \le k_{gi}$, respectively..*

Property 3. *The matrix $\dot{M}_i(q_i) - 2C_i(q_i, \dot{q}_i)$ is skew-symmetric.*

Let $x_i = \left[x_{1i}^T, x_{2i}^T\right]^T = \left[q_i^T, \dot{q}_i^T\right]^T$; the dynamics model of (1) subject to actuator faults (3) is equivalently rearranged as the following form:

$$\begin{aligned}\dot{x}_{1i} &= x_{2i} \\ \dot{x}_{2i} &= M_i^{-1}(x_{1i})(\tau_{Ai} + F_i(x_i) + D_i(x_i, t))\end{aligned} \tag{27}$$

where $F_i(x_i) = -(C_i(x_i)x_{2i} + G_i(x_{1i}))$ and the lumped uncertainty $D_i(x_i, t) = d_i + \tau_{Fi} - \Delta M_i(x_{1i})\dot{x}_{2i} - \Delta C_i(x_i)x_{2i} - \Delta G_i(x_{1i})$.

Using the self-adjusting observer η_i for the leader signal v in (2) which is designed in (5), we further design an adaptive controller to solve the fault-tolerant cooperative control problem for the multiple uncertain Euler–Lagrange systems. The definition of the tracking error z_{1i} is as follows:

$$z_{1i} = x_{1i} - C\eta_i \tag{28}$$

The second error z_{2i} is defined as follows:

$$z_{2i} = x_{2i} - \alpha_i \tag{29}$$

where α_i is the virtual control, $\alpha_i = -K_i z_{1i} + C\dot{\eta}_i$, $K_i = a_i I_n$, a_i is a positive constant and I_n is an n-dimensional identity matrix. Differentiating z_{1i}, we obtain

$$\dot{z}_{1i} = \dot{x}_{1i} - C\dot{\eta}_i = -K_i z_{1i} + z_{2i} \tag{30}$$

The time derivative of z_{2i} is

$$\dot{z}_{2i} = M_i^{-1}(x_i)(\tau_{Ai} + F_i(x_i) + D_i(x_i, t)) - \dot{\alpha}_i \tag{31}$$

By Theorem 1 in [38], we can choose a nonsingular fast terminal sliding mode surface

$$s_i = z_{1i} + k_{1i} z_{1i}^{\lambda_i} + k_{2i} z_{2i}^{p_i/q_i} \tag{32}$$

where $k_{1i} = \mathrm{diag}(k_{1i1}, k_{1i2}, \ldots, k_{1in})$ and $k_{2i} = \mathrm{diag}(k_{2i1}, k_{2i2}, \ldots, k_{2in})$ are positive matrices, p_i and q_i are positive odd numbers satisfying the relations $1 < p_i/q_i < 2$ and $\lambda_i > p_i/q_i$. If $s_i = 0$, the convergence time T is defined as $T = max\{T_i\}, i = 1, \ldots, N$, where

$$\begin{aligned} T_i &= \int_0^{|z_{1i}(0)|} \frac{k_{2i}^{q_i/p_i}}{\left(z_{1i}(t) + k_{1i} z_{1i}^{\lambda_i}\right)^{q_i/p_i}} dz_{1i} \\ &= \frac{\frac{p_i}{q_i}|z_{1i}(0)|^{1-q_i/p_i}}{k_{1i}(p_i/q_i - 1)} \times F_i(q_i/p_i, \frac{p_i/q_i - 1}{(\lambda_i - 1)p_i/q_i}; 1 + \frac{p_i/q_i - 1}{(\lambda_i - 1)p_i/q_i}; -k_{1i}|z_{1i}(0)|^{\lambda_i - 1}) \end{aligned} \tag{33}$$

where $z_{1i}(0)$ is the initial value of $z_{1i}(t)$ and $F_i(\cdot)$ is Gauss' hypergeometric function.

As the quantity of follower agents expands, the task of computing the upper limit becomes more cumbersome and involved. Therefore, we design an adaptive method to estimate the lumped uncertainty D_i, denoted as $D_i = \left[D_{i1}, \ldots, D_{in}\right]^T \in \mathbb{R}^n$; we establish the lumped uncertainty estimation as $\hat{D}_i = [\hat{D}_{i1}, \ldots, \hat{D}_{in}]^T \in \mathbb{R}^n$. Subsequently, the estimation error is expressed as $\tilde{D}_i = D_i - \hat{D}_i = [\tilde{D}_{i1}, \ldots, \tilde{D}_{in}]^T \in \mathbb{R}^n$. Afterwards, we offer the subsequent assumption.

Assumption 4. *It is assumed that the lumped uncertainty $D_i(x_i, t)$ is upper bounded [31] and the rate of change is also upper bounded [39]; i.e., there exist unknown constants $\bar{D}_{im} > 0$ and Ξ_{im}, $m = 1, \ldots, n$, such that $\forall t > 0$ and $||D_{im}(t)|| \leq \bar{D}_{im}$, such that $\forall t > 0$ and $||(d/dt)D_{im}(t)|| \leq \Xi_{im}$.*

Remark 3. *In [39], the norm of partial derivatives for the unknown component is bounded, which is composed of system state variables, disturbances and actuator faults. In this paper, our lumped uncertainty $D_i(x_i, t)$ is also composed of system state variables, disturbances and actuator faults; thus, it is reasonable to make Assumption 4 in the following theoretical analysis.*

The controller τ_{Ai} is designed as

$$\tau_{Ai} = \tau_{1i} + \tau_{2i} + \tau_{3i} \tag{34}$$

where

$$\tau_{1i} = -\frac{q_i}{p_i} k_{2i}^{-1} (M_i \dot{z}_{1i} + C_i s_i + M_i k_{1i} \lambda_i \dot{z}_{1i} \odot |z_{1i}|^{\lambda_i - 1} + \sigma_i |s_i| \odot \mathrm{sgn}(s_i)) \odot |z_{2i}|^{1 - p_i/q_i} \tag{35}$$

$$\tau_{2i} = -\frac{q_i}{p_i} k_{2i}^{-1} ((s_i^T)^+ z_{1i}^T z_{2i}) \odot |z_{2i}|^{1 - \frac{p_i}{q_i}} \tag{36}$$

$$\tau_{3i} = M_i \dot{\alpha}_i - F_i - \hat{D}_i \tag{37}$$

and the adaption law is designed as

$$\dot{\hat{D}}_{im} = s_{im} k_{2im} \frac{p_i}{q_i} |z_{2im}|^{(p_i/q_i) - 1} - \delta_{im} \hat{D}_{im} \tag{38}$$

where $i = 1, \ldots, N$, $m = 1, \ldots, n$, $(s_i^T)^+$ is the Moore–Penrose pseudoinverse of s_i^T, which satisfies $s_i^T (s_i^T)^+ = \begin{cases} 0, & \text{if } \|s_i^T\| = 0 \\ 1, & \text{others} \end{cases}$, σ_i and δ_{im} are positive constants.

Theorem 1. *Consider a multiagent system consisting of (27) and (2), a fixed graph $\overline{\mathcal{G}}$ and assume that Assumptions 1–4 hold. Then, take the adaptive fault-tolerant controller (34), such that for any initial conditions $q_i(0)$, $\dot{q}_i(0)$, $\eta_i(0)$, $v(0)$, $i = 1, \ldots, N$, the solution of the closed-loop system exists and is bounded for all $t \geq 0$ and the tracking errors z_{1i}, s_i and the lumped uncertainty estimation error $\tilde{D}_i$ are ultimately bounded.*

Proof. The Lyapunov function candidate is proposed

$$V = \sum_{i=1}^{N} \frac{1}{2} z_{1i}^T z_{1i} + \frac{1}{2} \sum_{i=1}^{N} s_i^T M_i s_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{m=1}^{n} \tilde{D}_{im}^2. \tag{39}$$

Differentiating (39), we have

$$\begin{aligned} \dot{V} = & \sum_{i=1}^{N} (-z_{1i}^T K_i z_{1i} + z_{1i}^T z_{2i} + s_i^T C_i s_i + s_i^T (M_i \dot{z}_{1i} + M_i k_{1i} \lambda_i \dot{z}_{1i} \odot |z_{1i}|^{\lambda_i - 1}) \\ & + s_i^T k_{2i} \frac{p_i}{q_i} ((\tau_{Ai} + F_i + D_i - M_i \dot{\alpha}_i) \odot |z_{2i}|^{(p_i/q_i) - 1})) + \sum_{i=1}^{N} \sum_{m=1}^{n} \tilde{D}_{im} (\dot{D}_{im} - \dot{\hat{D}}_{im}) \\ \leq & \sum_{i=1}^{N} (-z_{1i}^T K_i z_{1i} + z_{1i}^T z_{2i} + s_i^T C_i s_i + s_i^T (M_i \dot{z}_{1i} + M_i k_{1i} \lambda_i \dot{z}_{1i} \odot |z_{1i}|^{\lambda_i - 1}) \\ & + s_i^T k_{2i} \frac{p_i}{q_i} ((\tau_{Ai} + F_i + D_i - M_i \dot{\alpha}_i) \odot |z_{2i}|^{(p_i/q_i) - 1})) + \sum_{i=1}^{N} \sum_{m=1}^{n} \tilde{D}_{im} \Xi_{im} \\ & - \sum_{i=1}^{N} \sum_{m=1}^{n} \tilde{D}_{im} \dot{\hat{D}}_{im} \end{aligned} \tag{40}$$

Substituting (34) into (40), we have

$$\begin{aligned}
\dot{V} &\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2 + \sum_{m=1}^{n}\tilde{D}_{im}\Xi_{im}) - \sum_{i=1}^{N}(\sum_{m=1}^{n}\tilde{D}_{im}\dot{\hat{D}}_{im} + s_i^{T}k_{2i}\frac{p_i}{q_i}((D_i - \hat{D}_i) \\
&\quad \odot |z_{2i}|^{(p_i/q_i)-1})) \\
&\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2 + \sum_{m=1}^{n}\tilde{D}_{im}\Xi_{im} + \sum_{m=1}^{n}\tilde{D}_{im}\delta_{im}\hat{D}_{im}) \\
&\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2) + \sum_{i=1}^{N}\sum_{m=1}^{n}\tilde{D}_{im}(\Xi_{im} + \delta_{im}D_{im} - \delta_{im}\tilde{D}_{im}) \\
&\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2) - \sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}\tilde{D}_{im}^2 + \sum_{i=1}^{N}\sum_{m=1}^{n}\tilde{D}_{im}\Xi_{im} + \sum_{i=1}^{N}\sum_{m=1}^{n}\tilde{D}_{im}\delta_{im}D_{im} \\
&\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2) - \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}\tilde{D}_{im}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(\tilde{D}_{im}^2 + \Xi_{im}^2 - \delta_{im}\tilde{D}_{im}^2 \\
&\quad + 2\tilde{D}_{im}\delta_{im}D_{im})
\end{aligned} \tag{41}$$

where

$$\begin{aligned}
&\frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(-\delta_{im}\tilde{D}_{im}^2 + 2\tilde{D}_{im}\delta_{im}D_{im}) \\
&\leq -\frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}(D_{im}^2 - 2D_{im}\hat{D}_{im} + \hat{D}_{im}^2) + \sum_{i=1}^{N}\sum_{m=1}^{n}(D_{im} - \hat{D}_{im})\delta_{im}D_{im} \\
&\leq \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}(D_{im}^2 - \hat{D}_{im}^2) \\
&\leq \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}D_{im}^2 \\
&\leq \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}\bar{D}_{im}^2
\end{aligned} \tag{42}$$

Hense, substituting (42) into (41), we can have

$$\begin{aligned}
\dot{V} &\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2) - \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}\delta_{im}\tilde{D}_{im}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(\tilde{D}_{im}^2 + \Xi_{im}^2 + \delta_{im}\bar{D}_{im}^2) \\
&\leq \sum_{i=1}^{N}(-z_{1i}^{T}K_i z_{1i} - \sigma_i\|s_i\|^2) - \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(\delta_{im} - 1)\tilde{D}_{im}^2 + \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(\Xi_{im}^2 + \delta_{im}\bar{D}_{im}^2) \\
&\leq -\rho_i V + c_i
\end{aligned} \tag{43}$$

where ρ_i, c_i are two positive constants provided as

$$\rho_i = \min\left\{2\lambda_{\min}(K_i), \frac{2\min\{\sigma_i\}}{\lambda_{\max}(M_i(x_{1i}))}, \min\{\delta_{im}\} - 1\right\} \tag{44}$$

$$c_i = \frac{1}{2}\sum_{i=1}^{N}\sum_{m=1}^{n}(\Xi_{im}^2 + \delta_{im}\bar{D}_{im}^2), \tag{45}$$

where $i = 1, \ldots, N$ and $m = 1, \ldots, n$. In order to guarantee that $\rho_i > 0$, the gains δ_{im} are chosen to satisfy

$$\min\{\delta_{im}\} - 1 > 0. \tag{46}$$

By multiplying both sides with $e^{\rho_i t}$ in Equation (43), we obtain

$$\begin{aligned} V(t) &\leq (V(0) - c_i/\rho_i)e^{-\rho_i t} + c_i/\rho_i \\ &\leq V(0) + c_i/\rho_i \end{aligned} \tag{47}$$

Define

$$P_i = 2(V(0) + c_i/\rho_i) \tag{48}$$

we have

$$\begin{aligned} z_{1i}^T z_{1i} &\leq P_i \\ s_i^T M_i(x_{1i}) s_i &\leq P_i \\ \sum_{m=1}^{n} \tilde{D}_{im}^2 = \|\tilde{D}_i\|^2 &\leq P_i. \end{aligned} \tag{49}$$

Thus, we obtain the compact sets

$$\begin{aligned} \Upsilon_{z_{1i}} &= \left\{ z_{1i} \in \mathbb{R}^n \mid \|z_{1i}\| \leq \sqrt{P_i} \right\} \\ \Upsilon_{s_i} &= \left\{ s_i \in \mathbb{R}^n \mid \|s_i\| \leq \sqrt{P_i/\lambda_{\min}(M_i)} \right\} \\ \Upsilon_{\tilde{D}_i} &= \left\{ \tilde{D}_i \in \mathbb{R}^n \mid \|\tilde{D}_i\| \leq \sqrt{P_i} \right\} \end{aligned} \tag{50}$$

where $P_i = 2(V(0) + c_i/\rho_i)$ with c_i, ρ_i given in (45) and (44), respectively. Consequently, we can obtain that z_{1i} and s_i and $\tilde{D}_i$ are ultimately bounded. By (25), we can obtain $\lim_{t\to\infty}(C\eta_i(t) - C\eta_0(t)) = 0$ and combine the above $z_{1i} = x_{1i} - C\eta_i$, which is ultimately bounded; thus, we can obtain that $e_i = x_{1i} - C\eta_0$ is ultimately bounded; thus, the fault-tolerant cooperative problem can be solved and the tracking error e_i can be made as small as possible. □

Remark 4. *By (48) and (49), we can see that ρ_i and c_i determine the size of $\|z_{1i}\|$, $\|s_i\|$ and $\|\tilde{D}_i\|$; that is, the smaller the tracking errors, the bigger ρ_i and the smaller c_i should be. By (44), we can see that the bigger ρ_i is, the bigger the control parameters a_i, σ_i and δ_{im} should be. By (45), we can see that the smaller c_i is, the smaller the parameter δ_{im} should be. Combining (44), (45) and (48), the influence of δ_{im} becoming smaller in (45) is greater than the influence of δ_{im} becoming larger in (44) for P_i, i.e., δ_{im} becoming smaller can make P_i smaller. Thus, the right sides of (50) can be set as small as possible, i.e., the tracking error e_i is guaranteed to be small enough by choosing the small parameter δ_{im} and the big parameters a_i, σ_i. Compared with the semi-globally bounded tracking error in [40], the tracking error in this paper is globally bounded and the bound can be sufficiently small from the above analysis.*

5. Simulation Studies

In this section, we consider a group of six robotic manipulators given by (1), where $q_i = [q_{1i}, q_{2i}]^T$, $i = 1, \ldots, 6$ and

$$M_i(q_i) = \begin{bmatrix} M_{11i} & M_{12i} \\ M_{21i} & M_{22i} \end{bmatrix}, C(q_i, \dot{q}_i) = \begin{bmatrix} C_{11i} & C_{12i} \\ C_{21i} & C_{22i} \end{bmatrix}, G(q_i) = \begin{bmatrix} G_{1i} & G_{2i} \end{bmatrix}^T \tag{51}$$

where

$$\begin{aligned}
M_{11i} &= (m_{1i} + m_{2i})r_{1i}^2 + m_{2i}r_{2i}^2 + 2m_{2i}r_{1i}r_{2i}\cos(q_{2i}) + J_{1i},\\
M_{12i} &= m_{2i}r_{2i}^2 + m_{2i}r_{1i}r_{2i}\cos(q_{2i}),\\
M_{21i} &= m_{2i}r_{2i}^2 + m_{2i}r_{1i}r_{2i}\cos(q_{2i}),\\
M_{22i} &= m_{2i}r_{2i}^2 + J_{2i},\\
C_{11i} &= -m_{2i}r_{1i}r_{2i}\sin(q_{2i})\dot{q}_{2i},\\
C_{12i} &= -m_{2i}r_{1i}r_{2i}\sin(q_{2i})(\dot{q}_{1i} + \dot{q}_{2i}),\\
C_{21i} &= m_{2i}r_{1i}r_{2i}\sin(q_{2i})\dot{q}_{1i},\\
C_{22i} &= 0,\\
G_{1i} &= (m_{1i} + m_{2i})r_{1i}g\cos(q_{1i}) + m_{2i}r_{2i}g\cos(q_{1i} + q_{2i}),\\
G_{2i} &= m_{2i}r_{2i}g\cos(q_{1i} + q_{2i})
\end{aligned} \tag{52}$$

where m_{1i} and m_{2i} are the mass of two joints, r_{1i} and r_{2i} are the length of two joints, J_{1i} and J_{2i} are the moment inertia and g is the gravity acceleration constant. The parameters of the system are selected as $m_{1i} = 0.5$ kg, $m_{2i} = 1.5$ kg, $r_{1i} = 1$ m, $r_{2i} = 0.8$ m, $J_{1i} = 5\ \text{kg}\cdot\text{m}^2$, $J_{2i} = 5\ \text{kg}\cdot\text{m}^2$, and $g = 9.81\ \text{m/s}^2$. The parameter uncertainties of the system are assumed as $\Delta m_{1i} = 0.3 * \text{rand}$ and $\Delta m_{2i} = 0.3 * \text{rand}$, where "rand" denotes the random value of interval $[0, 1]$. The disturbance is set as $d_i(t) = [0.5sin(2t) + 0.3sin(q_{1i}), 0.3cos(2t) + 0.4sin(q_{2i})]^T$.

The agents' communication network is depicted in Figure 1, thus fulfilling Assumption 2.

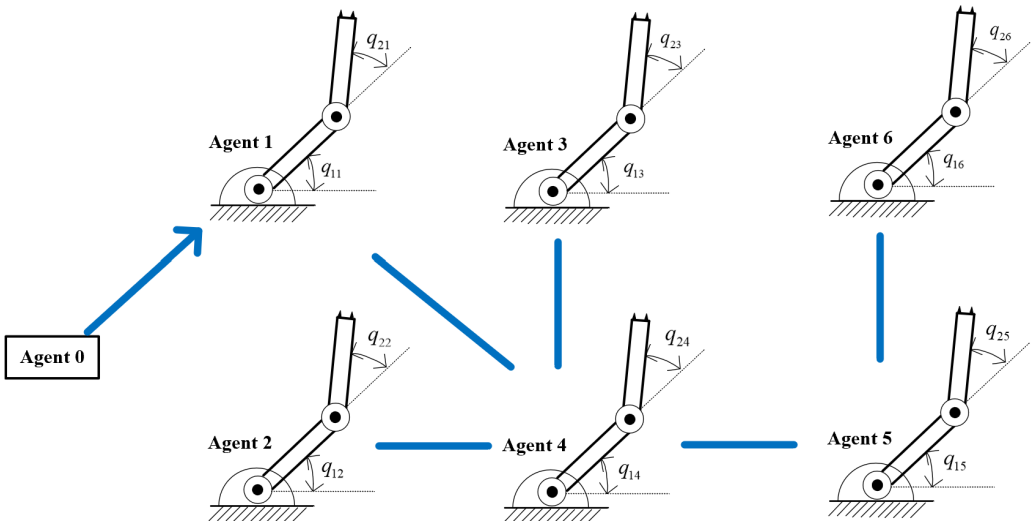

Figure 1. Communication network $\bar{\mathcal{G}}$.

The leader's signal is

$$q_0 = \text{col}(A_1\sin(\varphi_{01}t + \phi_1), A_2\sin(\varphi_{02}t + \phi_2)) \tag{53}$$

where the values of A_1, A_2, φ_{01} and φ_{02} can be any unknown positive real number, while ϕ_1 and ϕ_2 can be any arbitrary unknown real number. The leader's signal is produced by (2) with $v = col(v_{11}, v_{12}, v_{21}, v_{22})$, $\Pi(\varphi) = \text{diag}(\varphi) \otimes \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$, $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$, where $diag(\cdot)$ is a diagonal matrix and $\varphi = \text{col}(\varphi_{01}, \varphi_{02}) = \begin{bmatrix} 4 & 2 \end{bmatrix}^T$. Thus, Assumption 3 is also satisfied. The software used for simulation is Matlab2021b.

5.1. Simulation for Observer

Initially, we furnish the simulation outcomes for the self-adjusting observer. According to Lemma 1, we have the ability to formulate the observer for the leader (2) in the following manner:

$$\begin{aligned} \dot{\eta}_i &= \Pi(\varphi_i)\eta_i - \kappa_i \sum_{j\in\overline{\mathcal{N}}_i} \mu_{ij}(\eta_i - \eta_j) \\ \dot{\mu}_{ij} &= k_{ij}a_{ij}\kappa_i(\eta_i - \eta_j)^T(\eta_i - \eta_j) \\ \dot{\varphi}_i &= -\gamma\phi(\eta_i^*)\eta_i, \quad i = 1,\ldots,N \end{aligned} \tag{54}$$

where $i = 1,\ldots,6$, $j = 0,1,\ldots,6$, let $\eta_{vi} = \sum_{j=0}^{6} a_{ij}(\eta_i - \eta_j)$, $\kappa_i = 5 + (\eta_{vi}^T\eta_{vi})^2$, $k_{ij} = k_{ji} = 1$, $i,j = 1,\ldots,6$, $k_{i0} = 1$, $i = 1,\ldots,6$, $\gamma = 40$ and $\varphi_i \in \mathbb{R}^2$ and randomly generated initial conditions. The observer's performance is depicted in Figure 2, which shows that the estimation errors asymptotically converge to zero. Figure 3 shows that the dynamic gain of the observer has the ability to adaptively converge towards the desired constant. Figure 4 shows that the estimation error of the unknown leader system's parameter $\bar{\varphi}_i$ can converge to some constant, which means that the $\lim_{t\to\infty}\dot{\bar{\varphi}}_i(t) = 0$ can be achieved.

The controller designed in this article is suitable for both actuator health and the situation of actuator failure. Two sets of simulation experiments will be conducted to verify these two situations.

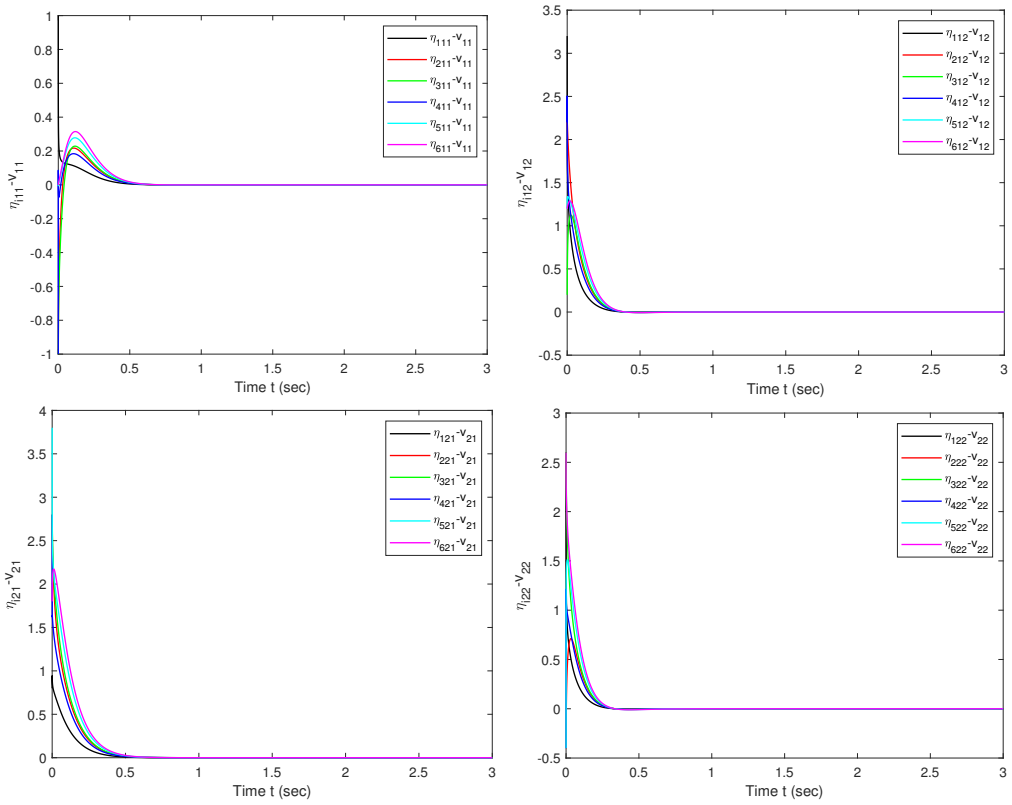

Figure 2. The error output of adaptive observer $\eta_{i11}-v_{11}$ and $\eta_{i12}-v_{12}$, $\eta_{i21}-v_{21}$ and $\eta_{i22}-v_{22}$, $i = 1,\ldots,6$.

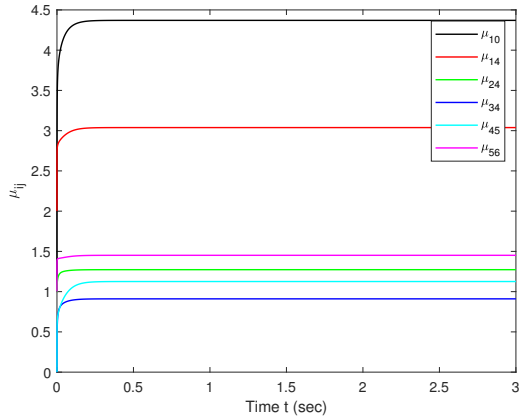

Figure 3. Dynamic gain μ_{ij} , $i = 1, \ldots, 6$, $j \in \mathcal{N}_i$.

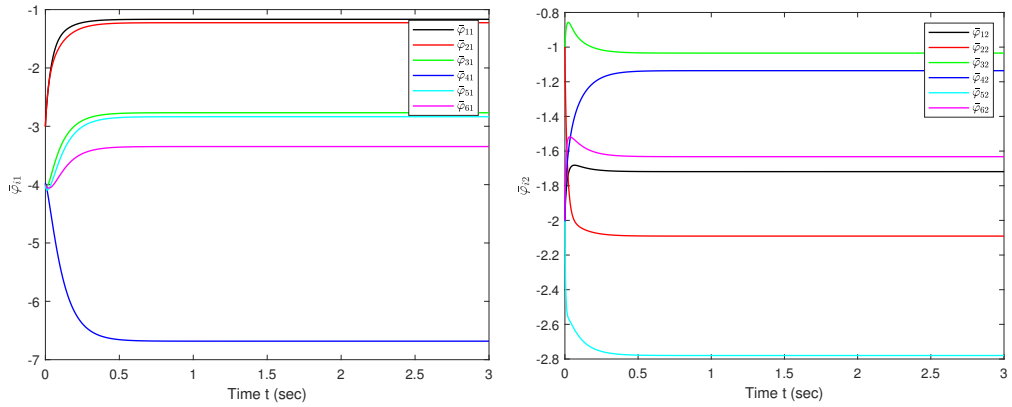

Figure 4. Trajectory of $\bar{\varphi}_{i1}$ and $\bar{\varphi}_{i1}$, $i = 1, \ldots, 6$.

5.2. *Simulation for Adaptive Fault-Tolerant Controller with Healthy Actuator*

The actuators are healthy with

$$\begin{aligned} E_{i1} &= 1, \quad E_{i2} = 1 \\ \bar{\tau}_{i1} &= 0, \quad \bar{\tau}_{i2} = 0 \end{aligned} \tag{55}$$

Based on the observer, we can design the adaptive fault-tolerant controller, which is given in (34), where $i = 1, \ldots, 6$, $j = 1, 2$, the designed parameters $\delta_{ij} = 2$, $\sigma_i = 100$, $K_i = 100 I_{2\times 2}$, $k_{1i} = 300 I_{2\times 2}$, $k_{2i} = 30 I_{2\times 2}$, $p_i = 13$, $q_i = 11$, $\lambda_i = 3$. The initial values of joint angle position and angle velocity are chosen as $q_i(0) = [1, 2]^T$ and $\dot{q}_i(0) = [0.3, 0.1]^T$, respectively, and there are randomly generated initial conditions. The performance of Controller 1 can be found in Figure 5. It can be observed that the tracking errors can converge as close to zero as possible. Figure 6 shows that the adaptive parameters $\hat{D}_{i1}$ and $\hat{D}_{i2}$ can adaptively converge to the required constant.

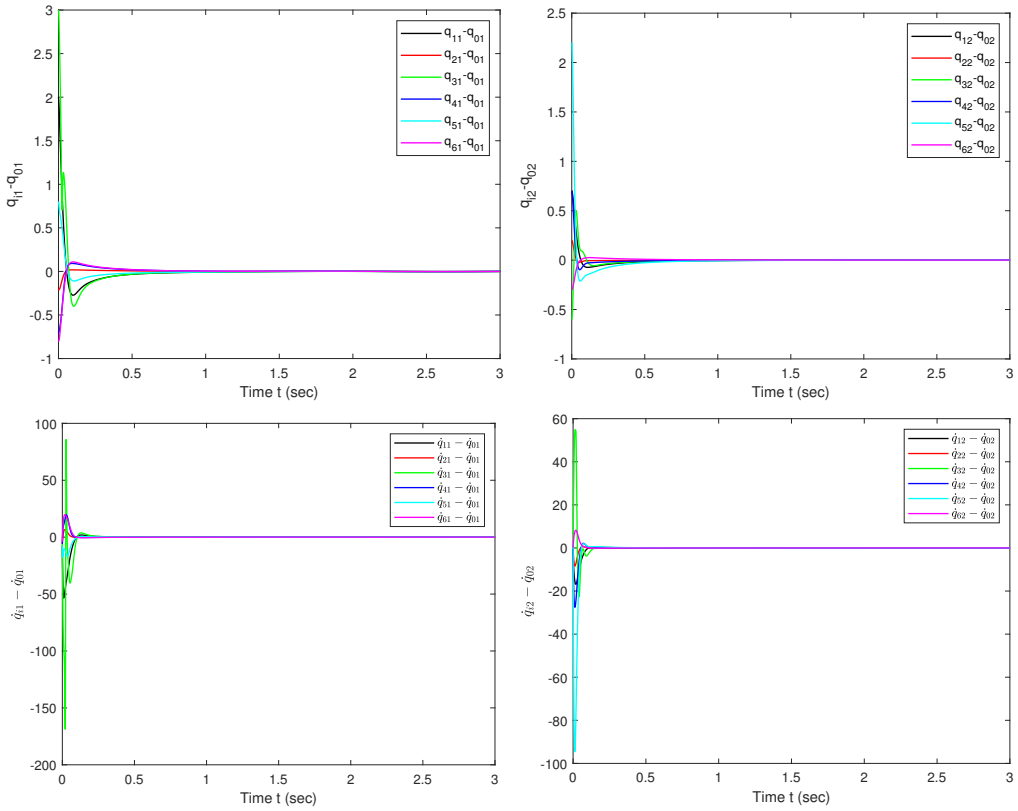

Figure 5. The tracking error $q_{i1}-q_{01}$ and $q_{i2}-q_{02}$, $\dot{q}_{i1}-\dot{q}_{01}$ and $\dot{q}_{i2}-\dot{q}_{02}$ with healthy actuator, $i = 1, \ldots, 6$.

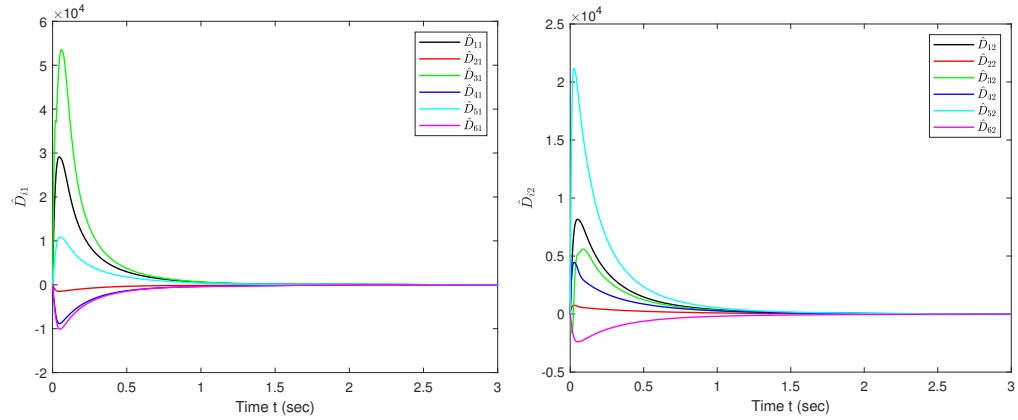

Figure 6. The adaptive parameters $\hat{D}_{i1}$ and $\hat{D}_{i2}$ with healthy actuator, $i = 1, \ldots, 6$.

5.3. *Simulation for Adaptive Fault-Tolerant Controller with Actuator Fault*

The actuators suffer from partial loss failure fault and bias fault, which are established in the following manner

$$E_{i1} = \begin{cases} 1.0 \text{ if } t < 1 \text{ s} \\ 0.5 \text{ otherwise} \end{cases}, \quad E_{i2} = \begin{cases} 1.0 \text{ if } t < 2 \text{ s} \\ 0.4 \text{ otherwise} \end{cases} \tag{56}$$
$$\bar{\tau}_{i1} = 0.2, \quad \bar{\tau}_{i2} = -0.2$$

Obviously, the fault values above satisfy Assumption 1. Based on the observer, we can design the adaptive fault-tolerant controller, which is given in (34), where $i = 1, \ldots, 6$, $j = 1, 2$, the designed parameters $\delta_{ij} = 2$, $\sigma_i = 100$, $K_i = 100 I_{2\times 2}$, $k_{1i} = 300 I_{2\times 2}$, $k_{2i} = 30 I_{2\times 2}$, $p_i = 13$, $q_i = 11$, $\lambda_i = 3$. The initial values of joint angle position and angle velocity are chosen as $q_i(0) = [2, 0.8]^T$ and $\dot{q}_i(0) = [0.2, 0.4]^T$, respectively, and there are randomly

generated initial conditions. Based on the bounded disturbances, faults and uncertain parameters above, it can be determined that Assumption 4 is satisfied. The performance of Controller 1 can be found in Figure 7. It can be observed that the tracking errors can converge as close to zero as possible. Figure 8 shows that the adaptive parameters $\hat{D}_{i1}$ and $\hat{D}_{i2}$ can adaptively converge to the required constant.

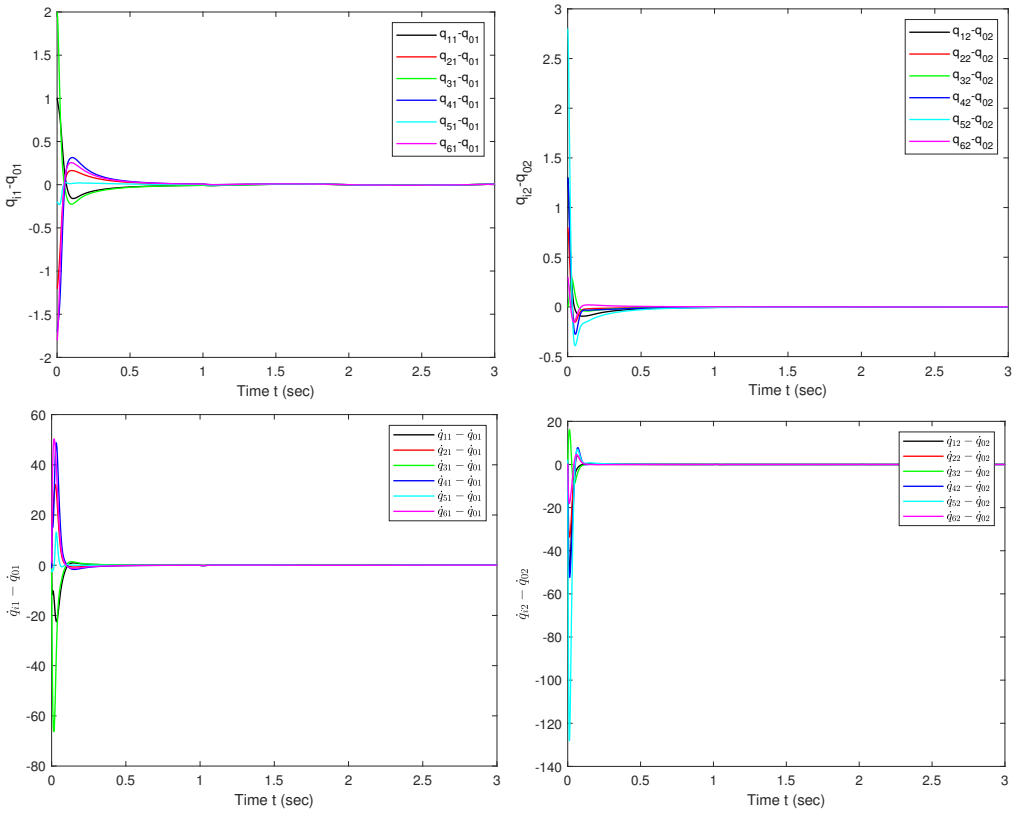

Figure 7. The tracking error $q_{i1}-q_{01}$ and $q_{i2}-q_{02}$, $\dot{q}_{i1}-\dot{q}_{01}$ and $\dot{q}_{i2}-\dot{q}_{02}$ with actuator faults, $i = 1, \ldots, 6$.

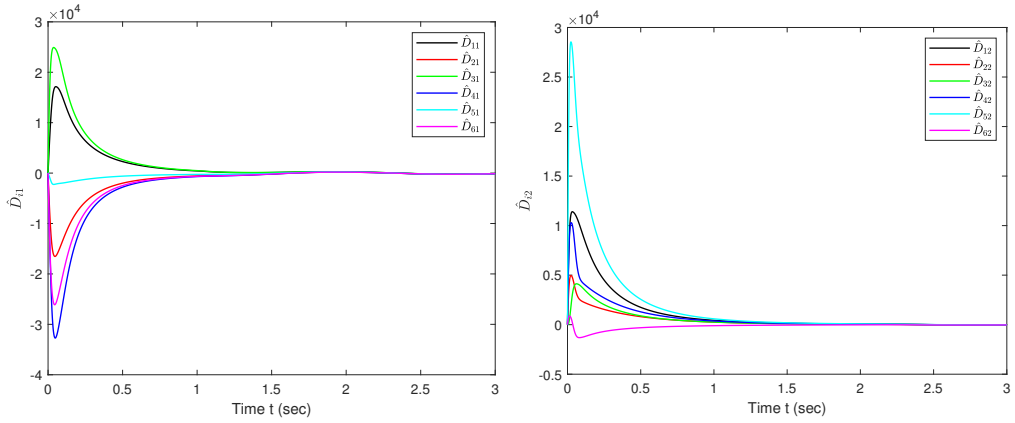

Figure 8. The adaptive parameters $\hat{D}_{i1}$ and $\hat{D}_{i2}$ with actuator faults, $i = 1, \ldots, 6$.

6. Conclusions

This paper investigates the fault-tolerant cooperative control problem in multiagent systems, which are characterized by an uncertain leader system and multiple uncertain Euler–Lagrange systems with actuator faults. A self-adjusting observer is initially designed to estimate the uncertain leader's signal for different followers and calculate the observer gain in real time. We further synthesize the controller based on the above observer and

a nonsingular fast terminal sliding mode surface to address the control problem. The adaptive approach is applied to estimate the aggregate uncertainty, removing the necessity to compute its upper limit. This method is robust to actuator faults, uncertain parameters and external disturbances. Future research will consider fault-tolerant cooperative control of strongly nonlinear multiagent systems in complex communication topologies.

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