

Article

Adaptive Event-Triggered-Based Consensus Control for QUAV Formation System with External Disturbances and State Constraints

Lijun Liu ¹, Tongwei Lu ² , Guoxiang Hao ³, Kun Yan ^{3,*}  and Chaobo Chen ³ 

¹ Department of Mathematics and Artificial Intelligence, Lyuliang University, Lvliang 033001, China; liulijun199108@163.com

² Hubei Key Laboratory of Intelligent Robot, Wuhan Institute of Technology, Wuhan 430205, China; lutongwei@wit.edu.cn

³ College of Electronic Information Engineering, Xi'an Technological University, Xi'an 710021, China; 18003460960@163.com (G.H.); chenchao@xatu.edu.cn (C.C.)

* Correspondence: yankun@xatu.edu.cn

Abstract

In this work, an adaptive event-triggered-based consensus control strategy is proposed for the quadrotor unmanned aerial vehicle (QUAV) formation system in the presence of external disturbances and state constraints. Firstly, the disturbed QUAV formation system dynamic model is established. Then, to address the initial peaking explosion problem in the traditional active disturbance rejection control method, a time-varying gain extended state observer (TGESO) is designed to suppress external disturbances. Meanwhile, a novel barrier Lyapunov function (BLF) is constructed to cope with the adverse effects caused by state constraints. Furthermore, aiming to alleviate network congestion and reduce communication burden, the adaptive event-triggered mechanism (AETM) is adopted to design the formation flight controller. Finally, the stability of the developed consensus controller and the boundedness of all error signals are proved via Lyapunov theory. Comparative simulation results demonstrate the practicality of the presented control algorithm.

Keywords: formation control; consensus theory; time-varying gain extended state observer; state constraints; adaptive event-triggered mechanism

1. Introduction

Along with the rapid advancement of automatic control and artificial intelligence technologies [1], quadrotor unmanned aerial vehicle (QUAV) has been widely applied in numerous scenarios, including agricultural production [2], environmental protection [3], and disaster monitoring [4]. However, single QUAV exhibits significant limitations when handling complex tasks. Consequently, research on QUAV formation cooperative control has garnered extensive attention from researchers and scholars. In particular, substantial research outcomes have emerged from control methods based on consensus theory. In [5], a distributed adaptive formation control scheme based on consensus theory was proposed for QUAV formation in the face of uncertainties and unknown external disturbances. In [6], a consensus formation control method with prescribed performance constraints was developed for quadrotor UAVs formation to address trajectory tracking and internal collision avoidance problems. Despite the promising application prospects of the QUAV formation system, the problem of safe cooperative control remains a critical challenge to be addressed.



Academic Editor: Gokhan Inalhan

Received: 10 February 2026

Revised: 11 March 2026

Accepted: 23 March 2026

Published: 25 March 2026

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During practical flight operations, external disturbances seriously affect the flight performance of the QUAV formation system. To deal with this problem, a variety of anti-disturbance control approaches have been proposed, such as the disturbance observer method [7], sliding mode control [8], and active disturbance rejection control (ADRC) [9–11]. Among these methods, the ADRC technique, whose core is an extended state observer (ESO), has found extensive application in recent years. In [9], an ESO-based finite-time fault-tolerant formation control method was proposed for the QUAV formation system in the presence of actuator faults and unmeasurable states. In [10], a distributed cooperative control algorithm based on a finite-time ESO was designed for the disturbed multi-agent system to solve the output consensus problem. In [11], an ESO-based distributed double-loop sliding mode controller design method was proposed for a multi-UAV swarm in the presence of unit failure or loss. However, to enhance anti-disturbance capability, the ESO typically requires a relatively large gain to achieve rapid convergence of the observation error, which also gives rise to the so-called initial peaking phenomenon. To address this issue, several time-varying gain ESO (TGESO) methods have attracted increasing attention. In [12], an adaptive ESO was proposed for a class of nonlinear disturbed systems. In [13], a TGESO-based finite-time fault-tolerant control strategy was proposed for QUAV. In [14], a robust control scheme based on the TGESO and adaptive dynamic programming was developed for the disturbed unmanned helicopter to achieve optimal tracking control. On account of the special rotor structure, the state constraint problem is another factor that severely affects the flight safety of the system besides disturbances, which merits in-depth research.

As a typical rotorcraft, the special mechanical structure of the QUAV determines that its flight state must be strictly constrained within a reasonable range. In particular, if the roll and pitch angles exceed their predefined limits, the QUAV can easily become unstable. To deal with the problem of state constraints, numerous effective approaches have been proposed, such as model predictive control [15], sliding mode control [16], and the barrier Lyapunov function (BLF) methods [17–24]. Among these, the BLF method has been widely adopted to handle issues related to constrained QUAV. In [17,18], the adaptive controllers were designed for nonlinear systems with full-state constraints by applying the integral BLF. In [19], by utilizing BLF, a robust adaptive fault-tolerant flight controller was designed for the unmanned autonomous helicopter with full-state constraints and actuator faults. In [20,21], the BLF-based formation control issues were investigated for multi-QUAVs under the state constraints. However, the aforementioned BLF-based methods face a potential singularity problem, and thus their improvement has become a prominent new challenge in relevant research. In [22,23], a novel controller design method based on the time-varying barrier Lyapunov function (TBLF) was proposed to address the singularity problem. In [24], a robust anti-saturation fault-tolerant control scheme was presented for an unmanned autonomous helicopter with multi-constrained conditions. However, most of the aforementioned studies adopt time-driven control strategy while neglecting the problem of limited communication resources, which is a crucial constraint for the cooperative flight of the QUAV formation system.

It should be pointed out that most research findings on the QUAV formation system fail to consider the limitation of network resources. Prolonged repetitive and ineffective network transmission will give rise to resource waste and network congestion. In contrast to time-triggered mechanism-based methods, the event-triggered mechanism-based strategies [25] can effectively alleviate this problem. In [26], an event-triggered control strategy was proposed for the fixed-time consensus tracking control problem of a multi-agent system. In [27], a robust control scheme based on an adaptive event-triggered mechanism (AETM) was developed for a saturated nonlinear system with state constraints. In [28],

an event-triggered-based supertwisting algorithm was proposed to achieve the attitude control of UAVs. In [29], a distributed adaptive event-triggered neural network control strategy was proposed for the six-rotor UAVs' cooperative control problem. In [30], a cooperative event-triggered filtering algorithm was proposed for the multi-agent systems consensus control problem. However, when state constraints, external disturbances and event-triggered mechanisms are considered simultaneously, the problem of safe control for the QUAV formation system remains to be further investigated in depth.

Based on the preceding analysis, an adaptive event-triggered anti-disturbance control strategy is presented for the QUAV formation system based on the TBLF and consensus theory. The main contributions are summarized as follows:

- (1) The proposed TGESO can overcome the initial peaking explosion problem existing in the traditional fixed-gain ESO approach, thus improving the transient performance of the QUAV formation system.
- (2) Compared with the traditional BLF-based method when dealing with state constraints, the developed TBLF technique can overcome the singularity problem that the denominator of the controller may be zero under certain circumstances.
- (3) Compared with the traditional time-triggered control strategy, the designed AETM can conserve network resources and reduce the computational burden.

This article is structured as follows. Section 2 introduces the problems to be solved. Section 3 describes the proposed adaptive event-triggered consensus control strategy in detail. Section 4 conducts simulation experiments. Finally, Section 5 concludes the paper.

Notations: In this article, $X \in R^{n \times m}$ is the $n \times m$ dimension of a matrix X , $I_{n \times n}$ is the unit matrix of $R^{n \times n}$, $\|\cdot\|$ is the Euclidean norm of a matrix, $\lambda_{\max}(\cdot)$ is the maximum eigenvalue of the a matrix, and $\lambda_{\min}(\cdot)$ is the minimum eigenvalue of a matrix.

2. Problem Formulation and Preparation

2.1. Graph Theory

Define an undirected graph $\Lambda = (V, E, A)$ to establish the information interaction between virtual leader and i -th QUAV, where $V = (1, \dots, N)$ denotes the set of the nodes, $E \in V \times V(\Lambda)$ represents the set of edges, and $(i, j) \in E$ indicates that i -th QUAVs and j -th QUAV can exchange information. The neighborhood set of the i -th QUAV is denoted as $N(j) = \{j \in V | (i, j) \in E\}$. The matrix $A = [a_{ij}] \in \mathbb{R}^{N \times N}$ is the adjacency matrix, where $a_{ij} > 0$ if the i -th QUAV can obtain information from the j -th QUAV. $\Delta = \text{diag}\{\Delta_1, \dots, \Delta_N\}$ as the diagonal matrix, Laplacian matrix is $L = \Delta - A$.

When a virtual leader exists in the undirected graph, an incidence matrix exists $B = \text{diag}\{b_1, \dots, b_N\}$, and $b_i > 0$ indicates that the i -th QUAV can interact with the leader for information exchange, otherwise $b_i = 0$.

2.2. The Model of QUAV

The structure of the QUAV is shown in Figure 1, where $C_E = \{x_E, y_E, z_E\}$ and $C_B = \{x_B, y_B, z_B\}$ represent the inertial frame and the body frame, respectively. On the basis of the Newton–Euler theorem, the nonlinear model of the i -th QUAV can be formulated as follows [31]:

$$\begin{cases} \dot{P}_i = V_i \\ \dot{V}_i = R_i U_i + G_i + D_{i,1} \\ \dot{\Sigma}_i = H_i \Omega_i \\ \dot{\Omega}_i = -J_i^{-1} \Omega_i \times J_i \Omega_i + J_i^{-1} M_i + D_{i,2} \end{cases} \quad (1)$$

where $i = 1, \dots, N$ represents the i -th QUAV, $P_i = [x_i, y_i, z_i]^T$ is the position vector of the i -th QUAV in the inertial frame C_E , $V_i = [u_i, v_i, w_i]^T$ is velocity vector, $\Sigma_i = [\phi_i, \theta_i, \psi_i]^T$ stands

for the three Euler angles in the body frame C_B , $\Omega_i = [p_i, q_i, r_i]^T$ is the angular velocity, $R_i = R_B^E/m$, m is the mass of the QUAV, $G_i = [0, 0, g]^T$, g denotes the gravitational acceleration, $U_i = [0, 0, -F_i]^T$, F_i denotes the total lift, H_i stands for the attitude kinematics matrix, $J_i = \text{diag}\{J_{i,xx}, J_{i,yy}, J_{i,zz}\}$ represents the moment of inertia matrix, $M_i = [M_{ix}, M_{iy}, M_{iz}]^T$ denotes the three-dimensional torque, $D_{i,1} = [D_{ix}, D_{iy}, D_{iz}]^T$ and $D_{i,2} = [D_{i\phi}, D_{i\theta}, D_{i\psi}]^T$ indicate the external disturbances acting on the QUAV.

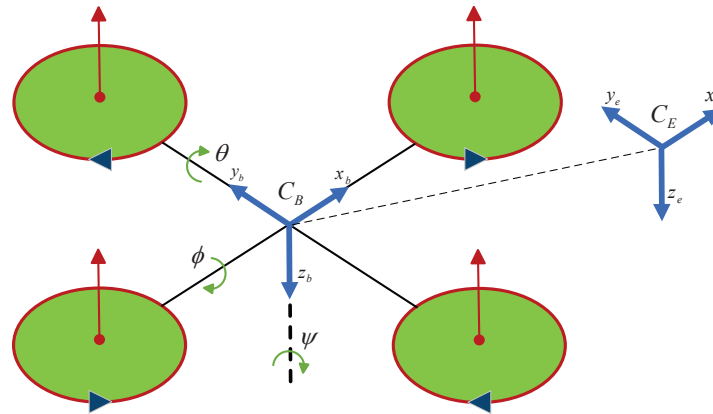


Figure 1. The QUAV structure diagram.

2.3. State Constraint-Related Descriptions

The full-state constraint of the i -th QUAV is described as

$$\underline{\pi}_i^{mn} < \pi_i^{mn} < \overline{\pi}_i^{mn} \quad (2)$$

where $m = p, \Theta$ and $n = 1, 2$.

To tackle the potential singularity issue, $-k_{d_i,mn}$ and $k_{c_i,mn}$ are constructed such that [24]

$$-k_{d_i,mn} < -k_{b_i,mn} < e_{i,mn} < k_{a_i,mn} < k_{c_i,mn} \quad (3)$$

where $k_{c_i,mn} = \delta_1 k_{a_i,mn}$, $k_{d_i,mn} = \delta_2 k_{b_i,mn}$, and $\delta_1 \in (1, 2]$, $\delta_2 \in (1, 2]$ are the positive constants.

Select the following TBLF

$$V_i^{mn} = \frac{H_i^{mn}}{2} \ln \frac{k_{a_i,mn}^2}{k_{a_i,mn}^2 - e_{i,mn}^2} + \frac{1-H_i^{mn}}{2} \ln \frac{k_{b_i,mn}^2}{k_{b_i,mn}^2 - e_{i,mn}^2} \quad (4)$$

The specific definition is

$$\begin{cases} k_{b_i,mn}(t) = y_{i,m}^d - \underline{\pi}_i^{mn} \\ k_{a_i,mn}(t) = \overline{\pi}_i^{mn} - y_{i,m}^d \end{cases}, H_i^{mn}(e) = \begin{cases} 1, e > 0 \\ 0, e \leq 0 \end{cases} \quad (5)$$

where e is shorthand for $e_{i,mn}$.

Differentiating V_i^{mn} yields

$$\dot{V}_i^{mn} = \zeta_{i,mn} e_{i,mn} \left(\dot{e}_{i,mn} - (1 - H_i^{mn}) \frac{\dot{k}_{b_i,mn}}{k_{b_i,mn}} e_{i,mn} - H_i^{mn} \frac{\dot{k}_{a_i,mn}}{k_{a_i,mn}} e_{i,mn} \right) \quad (6)$$

where $\zeta_{i,mn} = \frac{1-H_i^{mn}}{k_{b_i,mn}^2 - e_{i,mn}^2} + \frac{H_i^{mn}}{k_{a_i,mn}^2 - e_{i,mn}^2}$.

The control objective is to design an event-triggered anti-disturbance controller for the QUAV formation system with full-state constraints and external disturbances, ensuring that each QUAV can track the virtual leader and maintain a certain tracking distance.

$\chi_{i,p}^d = [x_i^d, y_i^d, z_i^d]^T$ and $[\phi_d, \theta_d, \psi_d]^T = [0, 0, 0]^T$ are the desired positioning offsets of the i -th QUAV. The target trajectory of each QUAV is dynamically adjusted based on the information of its neighboring QUAV. Moreover, ensure that the formation tracking signal $y_{i,m}^d = y_{0,p} + \chi_{i,m}^d$ tracks the virtual leader's trajectory $y_{0,p}$, and further ensure that the i -th QUAV tracks its desired roll angle ϕ_{id} and desired pitch angle θ_{id} .

In order to fulfill the control objective, it is essential to introduce the assumptions and lemmas below.

Assumption 1 ([13]). Suppose that the disturbances $d_{i,p}(t)$ and $d_{i,\Theta}(t)$ are bounded, and there exist constants $\alpha_1, \alpha_2, \bar{\alpha}_1, \bar{\alpha}_2 > 0$ such that

$$\begin{aligned} \|d_{i,p}(t)\| &\leq \alpha_1, \|d_{i,\Theta}(t)\| \leq \alpha_2 \\ \|\dot{d}_{i,p}(t)\| &\leq \bar{\alpha}_1, \|\dot{d}_{i,\Theta}(t)\| \leq \bar{\alpha}_2 \end{aligned} \quad (7)$$

Assumption 2 ([22,24]). The time-varying constraints $\underline{\pi}_i^{mn}$ and $\bar{\pi}_i^{mn}$ and their first-order derivatives are smooth and bounded.

Assumption 3 ([29,32]). The directed graph contains a spanning tree with the root node leader.

Lemma 1 ([29,33]). For any positive constant $\xi_p > 0$ and variable $s \in \mathbb{R}$, the following inequality holds

$$0 \leq |s| - s \tanh\left(\frac{s}{\xi_p}\right) \leq \xi_p \omega_p \quad (8)$$

where $\omega_p = 0.2785$.

Lemma 2 ([22,24]). For any constant $|k_1| > |b_1|$, the following inequality holds

$$\frac{b_1^2}{k_1^2 - b_1^2} \geq \ln \frac{k_1^2}{k_1^2 - b_1^2} \quad (9)$$

Lemma 3 ([22,24]). For variable c_1, k_2 and k_3 such that $|k_2| > |k_3| > |c_1|$ and $k_3^2 / \tanh(k_3^{-2}) \geq k_2^2$, the following inequality holds

$$\frac{c_1^2}{k_3^2 - c_1^2} \geq \frac{c_1^2}{k_2^2 - c_1^2} \ln \frac{k_1^2}{k_2^2 - c_1^2} \quad (10)$$

Lemma 4 ([19]). For the bounded initial conditions, and a positive definite function $A(x)$ satisfying $\partial_1(\|x\|) \leq A(x) \leq \partial_2(\|x\|)$, if $\dot{A}(x) \leq -\wp_\alpha A(x) + \wp_\beta$ holds, where $\wp_\alpha > 0$, $\wp_\beta > 0$, ∂_1 and $\partial_2: \mathbb{R}^n \rightarrow \mathbb{R}$ are class K functions, then the solution $x(t)$ is uniformly bounded.

3. Main Results

In this section, the design of the adaptive event-triggered consensus controller is detailed. To clarify the controller design process, the model of the i -th QUAV is rewritten as:

$$\begin{cases} \dot{\pi}_{i,p1} = \pi_{i,p2} \\ \dot{\pi}_{i,p2} = l_{i,p} u_{i,p} + G_i + D_{i,p} \\ \dot{\pi}_{i,\Theta1} = H_i \pi_{i,\Theta2} \\ \dot{\pi}_{i,\Theta2} = l_{i,\Theta}^{-1} \tau_i + f_{i,\Theta} + D_{i,\Theta} \end{cases} \quad (11)$$

where $\pi_{i,p1} = P_i$, $\pi_{i,\Theta1} = \Sigma_i$, $\pi_{i,\Theta2} = \Omega_i$, $u_{i,p}$ denotes the control input of the position subsystem, $D_{i,p} = D_{i,1}$, $u_{i,p} = [-F_i, -F_i, -F_i]^T$, $l_{i,p} = \text{diag}\{\Lambda_1, \Lambda_2, \Lambda_3\}$,

$$\Lambda_1 = \frac{(\cos \phi_i \sin \theta_i \cos \psi_i + \sin \phi_i \sin \psi_i)}{m}, \Lambda_2 = \frac{(\cos \phi_i \sin \theta_i \sin \psi_i - \sin \phi_i \cos \psi_i)}{m}, \Lambda_3 = \frac{(\cos \phi_i \cos \theta_i)}{m}, l_{i,\Theta} = J_i, f_{i,\Theta} = -J_i^{-1} \Omega_i \times J_i \Omega_i, \tau_i = M_i, D_{i,\Theta} = D_{i,2}.$$

3.1. Design of TGESO for Position Loop

By regarding $d_{i,p}$ as a new state $\pi_{i,p3}$, the nonlinear dynamics of i -th QUAUV can be further described as:

$$\begin{cases} \dot{\pi}_{i,p1} = \pi_{i,p2} \\ \dot{\pi}_{i,p2} = l_{i,p} u_{i,p} + G_{i,p} + \pi_{i,p3} \\ \dot{\pi}_{i,p3} = \eta_1 \end{cases} \quad (12)$$

where $d_{i,p} = \pi_{i,p3}$. According to Assumption 1, it can be obtained η_1 is bounded with $\|\eta_1\| \leq \alpha_1$.

Based on (12), the TGESO is constructed as follows:

$$\begin{cases} \tilde{\pi}_{i,p1} = \pi_{i,p1} - \hat{\pi}_{i,p1} \\ \dot{\hat{\pi}}_{i,p1} = \hat{\pi}_{i,p2} + \gamma_{i,p1} \varepsilon(t) \tilde{\pi}_{i,p1} \\ \dot{\hat{\pi}}_{i,p2} = l_{i,p} u_{i,p} + G_{i,p} + \hat{\pi}_{i,p3} + \gamma_{i,p2} \varepsilon^2(t) \tilde{\pi}_{i,p1} \\ \dot{\hat{\pi}}_{i,p3} = \gamma_{i,p3} \varepsilon^3(t) \tilde{\pi}_{i,p1} \end{cases} \quad (13)$$

where $\hat{\pi}_{i,pj} (j = 1, 2, 3)$ are the estimations of $\pi_{i,pj} (j = 1, 2, 3)$, $\gamma_{i,p1} = \text{diag}\{\gamma_{11}, \gamma_{12}, \gamma_{13}\}$, $\gamma_{i,p2} = \text{diag}\{\gamma_{21}, \gamma_{22}, \gamma_{23}\}$, and $\gamma_{i,p3} = \text{diag}\{\gamma_{31}, \gamma_{32}, \gamma_{33}\}$ are the designed positive constants. $\varepsilon(t)$ is a time-varying function, which is given by:

$$\varepsilon(t) = \begin{cases} \varepsilon_0, & t \geq \frac{\ln \varepsilon_0}{\kappa \ln(1+\kappa)} \\ (1+\kappa)^{\kappa t}, & 0 \leq t < \frac{\ln \varepsilon_0}{\kappa \ln(1+\kappa)} \end{cases} \quad (14)$$

where ε_0 and κ are the positive constants.

By defining the observation error of the TGESO is $\tilde{\pi}_{i,pj} = \pi_{i,pj} - \hat{\pi}_{i,pj} (j = 1, 2, 3)$, according to (12) and (13), we have

$$\begin{cases} \dot{\tilde{\pi}}_{i,p1} = \tilde{\pi}_{i,p1} - \dot{\hat{\pi}}_{i,p1} = \tilde{\pi}_{i,p2} - \gamma_{i,p1} \varepsilon(t) \tilde{\pi}_{i,p1} \\ \dot{\tilde{\pi}}_{i,p2} = \tilde{\pi}_{i,p2} - \dot{\hat{\pi}}_{i,p2} = \tilde{\pi}_{i,p3} - \gamma_{i,p2} \varepsilon^2(t) \tilde{\pi}_{i,p1} \\ \dot{\tilde{\pi}}_{i,p3} = \eta_1 - \gamma_{i,p3} \varepsilon^3(t) \tilde{\pi}_{i,p1} \end{cases} \quad (15)$$

By defining the new auxiliary variable $\vartheta_i (i = 1, 2, 3)$ as follows:

$$\begin{cases} \vartheta_1 = \varepsilon^2(t) \tilde{\pi}_{i,p1} \\ \vartheta_2 = \varepsilon(t) \tilde{\pi}_{i,p2} \\ \vartheta_3 = \tilde{\pi}_{i,p3} \end{cases} \quad (16)$$

Since $\varepsilon(t)$ is a piecewise function, the analysis is split into two cases.

Case 1: when $t \geq \frac{\ln \varepsilon_0}{\kappa \ln(1+\kappa)}$, it is recognized that $\varepsilon(t) = \varepsilon_0$, we have

$$\begin{cases} \vartheta_1 = \varepsilon_0^2 \tilde{\pi}_{i,p1} \\ \vartheta_2 = \varepsilon_0 \tilde{\pi}_{i,p2} \\ \vartheta_3 = \tilde{\pi}_{i,p3} \end{cases} \quad (17)$$

Based on (15)–(17) and taking the time derivative of $\vartheta_i (i = 1, 2, 3)$, we can obtain

$$\begin{cases} \dot{\vartheta}_1 = -\gamma_{i,p1}\varepsilon_0\vartheta_1 + \varepsilon_0\vartheta_2 = \varepsilon_0^2\tilde{\pi}_{i,p1} \\ \dot{\vartheta}_2 = -\gamma_{i,p2}\varepsilon_0\vartheta_1 + \varepsilon_0\vartheta_3 = \varepsilon_0\tilde{\pi}_{i,p2} \\ \dot{\vartheta}_3 = -\gamma_{i,p3}\varepsilon_0\vartheta_1 + \eta_1 = \tilde{\pi}_{i,p3} \end{cases} \quad (18)$$

By defining $\vartheta_p = [\vartheta_1^T, \vartheta_2^T, \vartheta_3^T]^T$, it gives

$$\begin{aligned} \dot{\vartheta} &= \varepsilon_0 \begin{bmatrix} -\gamma_{i,p1} & I_{3 \times 3} & 0_{3 \times 3} \\ -\gamma_{i,p2} & 0_{3 \times 3} & I_{3 \times 3} \\ -\gamma_{i,p3} & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix} \vartheta_p + \begin{bmatrix} 0_{3 \times 1} \\ 0_{3 \times 1} \\ \eta_1 \end{bmatrix} \\ &= \varepsilon_0 A_p \vartheta_p + B_p \end{aligned} \quad (19)$$

where 0 and I represent the zero matrix and the identity matrix, respectively. 3×3 and 3×1 specify the dimensional information of matrix, respectively.

Here, by selecting parameters properly A_p can be guaranteed to be a Hurwitz matrix. This indicates the existence of a positive definite matrix M_p verifying

$$A_p^T M_p + M_p A_p = -Q_p \quad (20)$$

where Q_p is the positive definite matrix.

The Lyapunov candidate function is chosen as:

$$V_{i,1} = \vartheta_p^T M_p \vartheta_p \quad (21)$$

Invoking (19) and differentiating (21), we can deduce

$$\begin{aligned} \dot{V}_{i,1} &= \vartheta_p^T M_p \dot{\vartheta}_p + \dot{\vartheta}_p^T M_p \vartheta_p \\ &= -\varepsilon_0 \vartheta_p^T Q_p \vartheta_p + 2\vartheta_p^T M_p B_p \\ &\leq -\varepsilon_0 \vartheta_p^T Q_p \vartheta_p + \|\vartheta_p\|^2 + \nu_2^2 \\ &\leq -\vartheta_p^T (\varepsilon_0 Q_p - I_{3 \times 3}) \vartheta_p + \nu_2^2 \\ &\leq -o_1 \vartheta_p^T \vartheta_p + \nu_2^2 \end{aligned} \quad (22)$$

where $\|M_p B_p\| \leq \nu_2$, ν_2 is the positive constants, $o_1 = \lambda_{\min}(\varepsilon_0 Q_p - I_{3 \times 3})$.

Case 2: when $0 \leq t \leq \frac{\ln \varepsilon_0}{\kappa \ln(1+\kappa)}$, we have $\varepsilon(t) = (1 + \kappa)^{\kappa t}$, based on (15) and (16)

$$\begin{cases} \dot{\vartheta}_1 = 2\varepsilon(t)\dot{\varepsilon}(t)\tilde{\pi}_{i,p1} + \varepsilon^2(t)\left(\tilde{\pi}_{i,p2} - \gamma_{i,p1}\varepsilon(t)\tilde{\pi}_{i,p1}\right) \\ \quad = 2\kappa\varepsilon^2(t)\tilde{\pi}_{i,p1} + \varepsilon^2(t)\left(\tilde{\pi}_{i,p2} - \gamma_{i,p1}\varepsilon(t)\tilde{\pi}_{i,p1}\right) \\ \quad = -\gamma_{i,p1}\varepsilon(t)\vartheta_1 + 2\kappa\vartheta_1 + \varepsilon(t)\vartheta_2, \\ \dot{\vartheta}_2 = \dot{\varepsilon}(t)\tilde{\pi}_{i,p2} + \varepsilon(t)\left(\tilde{\pi}_{i,p3} - \gamma_{i,p2}\varepsilon^2(t)\tilde{\pi}_{i,p1}\right) \\ \quad = \kappa\varepsilon(t)\tilde{\pi}_{i,p2} + \varepsilon(t)\left(\tilde{\pi}_{i,p3} - \gamma_{i,p2}\varepsilon^2(t)\tilde{\pi}_{i,p1}\right) \\ \quad = -\gamma_{i,p2}\varepsilon(t)\vartheta_1 + \kappa\vartheta_2 + \varepsilon(t)\vartheta_3, \\ \dot{\vartheta}_3 = -\gamma_{i,p3}\varepsilon(t)\vartheta_1 + \eta_1. \end{cases} \quad (23)$$

Similar to case 1, it can be concluded that

$$\begin{aligned}\dot{\vartheta} &= \varepsilon(t) \begin{bmatrix} -\gamma_{i,p1} & I_{3 \times 3} & 0_{3 \times 3} \\ -\gamma_{i,p2} & 0_{3 \times 3} & I_{3 \times 3} \\ -\gamma_{i,p3} & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix} \vartheta \\ &+ \begin{bmatrix} 2\kappa I_{3 \times 3} & \varepsilon(t) & 0_{3 \times 3} \\ 0_{3 \times 3} & \kappa I_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \end{bmatrix} \vartheta + \begin{bmatrix} 0_{3 \times 1} \\ 0_{3 \times 1} \\ \eta_1 \end{bmatrix} \\ &= \varepsilon(t) A_p \vartheta + B_{p1} \vartheta + B_{p2}\end{aligned}\quad (24)$$

Now, the same Lyapunov function (21) is adopted, and its time derivative becomes

$$\begin{aligned}\dot{V}_{i,1} &= \vartheta_p^T M_p \dot{\vartheta}_p + \dot{\vartheta}_p^T M_p \vartheta_p \\ &= -\varepsilon(t) \vartheta_p^T Q_p \vartheta_p + 2\vartheta_p^T M_p B_{p1} \vartheta_p + 2\vartheta_p^T M_p B_p \\ &\leq -\varepsilon(t) \vartheta_p^T Q_p \vartheta_p + 2\nu_1 \|\vartheta_p\|^2 + \|\vartheta_p\|^2 + \nu_2^2\end{aligned}\quad (25)$$

where $\|M_p B_{p1}\| \leq \nu_1$, and ν_1 is the positive constant.

By analyzing the properties of the function $\varepsilon(t) = (1 + \kappa)^{\kappa t}$, the variation range of $\varepsilon(t) \in (1, \varepsilon_m)$, where $\varepsilon_m = (1 + \kappa)^{\frac{\ln \varepsilon_0}{\ln(1+\kappa)}}$. Thus, it is determined that

$$-\varepsilon(t) \vartheta_p^T Q_p \vartheta_p \leq -\vartheta_p^T Q_p \vartheta_p \quad (26)$$

Substituting (25) into (26), we can obtain

$$\begin{aligned}\dot{V}_{i,1} &\leq -\vartheta_p^T (Q_p - 2\nu_1 I_{3 \times 3} - I_{3 \times 3}) \vartheta_p + \nu_2^2 \\ &\leq -o_2 \vartheta_p^T \vartheta_p + \nu_2^2\end{aligned}\quad (27)$$

where $o_2 = \lambda_{\min}(Q_p - 2\nu_1 I_{3 \times 3} - I_{3 \times 3})$.

By combining the conclusions from (22) and (27), we obtain

$$\dot{V}_{i,1} \leq -o_{M1} \vartheta_p^T \vartheta_p + \nu_2^2 \quad (28)$$

where $o_{M1} = \max\{o_1, o_2\}$.

3.2. Design of TGESO for Attitude Loop

By regarding $d_{i,\Theta}$ as a new state $\pi_{i,\Theta3}$, the nonlinear model of i -th QUAV can be further described as:

$$\begin{cases} \dot{\pi}_{i,\Theta1} = H_i \pi_{i,\Theta2} \\ \dot{\pi}_{i,\Theta2} = l_{i,\Theta}^{-1} \tau_i + f_{i,\Theta} + \pi_{i,\Theta3} \\ \dot{\pi}_{i,\Theta3} = \eta_2 \end{cases} \quad (29)$$

where $d_{i,\Theta} = \pi_{i,\Theta3}$. According to Assumption 2, we arrive at η_2 is bounded with $\|\eta_2\| \leq \alpha_2$.

Based on (29), the TGESO is constructed as follows:

$$\begin{cases} \tilde{\pi}_{i,\Theta1} = \pi_{i,\Theta1} - \hat{\pi}_{i,\Theta1} \\ \dot{\hat{\pi}}_{i,\Theta1} = H_i \hat{\pi}_{i,\Theta2} + \gamma_{i,\Theta1} \varepsilon(t) \tilde{\pi}_{i,\Theta1} \\ \dot{\hat{\pi}}_{i,\Theta2} = l_{i,\Theta}^{-1} \tau_i + f_{i,\Theta} + \pi_{i,\Theta3} + \gamma_{i,\Theta2} \varepsilon^2(t) \tilde{\pi}_{i,\Theta1} \\ \dot{\hat{\pi}}_{i,\Theta3} = \gamma_{i,\Theta3} \varepsilon^3(t) \tilde{\pi}_{i,\Theta1} \end{cases} \quad (30)$$

where $\hat{\pi}_{i,\Theta j}(j = 1, 2, 3)$ are the estimations of $\pi_{i,\Theta j}(j = 1, 2, 3)$, $\gamma_{i,\Theta 1} = \text{diag}\{\gamma_{41}, \gamma_{42}, \gamma_{43}\}$, $\gamma_{i,\Theta 2} = \text{diag}\{\gamma_{51}, \gamma_{52}, \gamma_{53}\}$, and $\gamma_{i,\Theta 3} = \text{diag}\{\gamma_{61}, \gamma_{62}, \gamma_{63}\}$ are the designed positive constants. The time-varying function $\varepsilon(t)$ is consistent with that of the position loop.

By defining the observation error of the TGESO is $\tilde{\pi}_{i,\Theta j} = \pi_{i,\Theta j} - \hat{\pi}_{i,\Theta j}(j = 1, 2, 3)$, according to (29) and (30), we have

$$\begin{cases} \dot{\tilde{\pi}}_{i,\Theta 1} = \dot{\pi}_{i,\Theta 1} - \dot{\hat{\pi}}_{i,\Theta 1} = \tilde{\pi}_{i,\Theta 2} - \gamma_{i,\Theta 1}\varepsilon(t)\tilde{\pi}_{i,\Theta 1} \\ \dot{\tilde{\pi}}_{i,\Theta 2} = \dot{\pi}_{i,\Theta 2} - \dot{\hat{\pi}}_{i,\Theta 2} = \tilde{\pi}_{i,\Theta 3} - \gamma_{i,\Theta 2}\varepsilon^2(t)\tilde{\pi}_{i,\Theta 1} \\ \dot{\tilde{\pi}}_{i,\Theta 3} = \eta_2 - \gamma_{i,\Theta 3}\varepsilon^3(t)\tilde{\pi}_{i,\Theta 1} \end{cases} \quad (31)$$

The proof process of the observer in the attitude loop is analogous to that in the position loop, and is abbreviated herein due to space constraints.

The Lyapunov function candidate is selected by:

$$V_{i,2} = \vartheta_{\Theta}^T M_{\Theta} \vartheta_{\Theta} \quad (32)$$

Then, we can obtain

$$\dot{V}_{i,2} \leq -o_{M2}\vartheta_{\Theta}^T \vartheta_{\Theta} + v_4^2 \quad (33)$$

where $o_{M2} = \max\{o_3, o_4\}$.

3.3. Design of Controller for Position Loop

The consensus error is defined as:

$$e_{i,p1} = \sum_{j=1}^N a_{i,j} \left((\pi_{i,p1} - \chi_{i,p}^d) - (\pi_{j,p1} - \chi_{j,p}^d) \right) + b_i (\pi_{i,p1} - y_{0,p} - \chi_{i,p}^d) \quad (34)$$

where $\chi_{i,p}^d$ denotes the desired position offset.

Taking (34) the time derivative gives

$$\begin{aligned} \dot{e}_{i,p1} &= \sum_{j=1}^N a_{i,j} (\dot{\pi}_{i,p1} - \dot{\pi}_{j,p1}) + b_i (\dot{\pi}_{i,p1} - \dot{\pi}_{i,p1}^d) \\ &= \Gamma_i \pi_{i,p2} - \sum_{j=1}^N a_{i,j} \dot{\pi}_{j,p1} - b_i \dot{\pi}_{i,p1}^d \\ &= \Gamma_i (e_{i,p2} + \alpha_{i,p1}) - \sum_{j=1}^N a_{i,j} \dot{\pi}_{j,p1} - b_i \dot{\pi}_{i,p1}^d \end{aligned} \quad (35)$$

where $\Gamma_i = v_i + b_i$, $v_i = \sum_{j=1}^N a_{i,j}$, and $e_{i,p2} = \pi_{i,p2} - \alpha_{i,p1}$.

Then, the virtual control law is designed as:

$$\alpha_{i,p1} = \frac{1}{\Gamma_i} \left(-k_{i,1}^* e_{i,p1} + \sum_{j=1}^N a_{i,j} \dot{\pi}_{j,p1} + b_i \dot{\pi}_{i,p1}^d - \mu_{i,1} \right) \quad (36)$$

where $k_{i,1}^* = (k_{i,1} + \bar{k}_{i,1})$, $k_{i,1} = \text{diag}\{k_{i,11}, k_{i,12}, k_{i,13}\}$ is a designed positive matrix, $\bar{k}_{i,1} = \text{diag}\{\bar{k}_{i,11}, \bar{k}_{i,12}, \bar{k}_{i,13}\}$, $\bar{k}_{i,1n} = \sqrt{(1 - H_i^{p1}) \left(\frac{k_{b_i,p1}}{k_{b_i,p1}} \right)^2 + H_i^{p1} \left(\frac{k_{a_i,p1}}{k_{a_i,p1}} \right)^2} + \delta_{i,1n}$, $\delta_{i,1n}$ is the designed positive constant, $\mu_{i,1} = [\mu_{i,11}, \mu_{i,12}, \mu_{i,13}]^T$, $\mu_{i,1n} = \frac{1}{2\beta_1} e_{i,p1n} \chi_{i,p1n} \tanh\left(\frac{1}{2\beta_1} e_{i,p1n}^2 \chi_{i,p1n}^2\right)$, $\chi_{i,p1n} = \frac{H_i^{p1}(e_{i,p1n})}{k_{c_i,pn}^2 - e_{i,p1n}^2} + \frac{1 - H_i^{p1}(e_{i,p1n})}{k_{a_i,pn}^2 - e_{i,p1n}^2}$, and β_1 is the designed positive constant.

Substituting (36) into (35) produces

$$\dot{e}_{i,p1} = -k_{i,1}^* e_{i,p1} + \Gamma_i e_{i,p2} - \mu_{i,1} \quad (37)$$

Select the following TBLF:

$$V_i^{p1} = \frac{H_i^{p1}(e_{i,p1})}{2} \ln \frac{k_{b_i,p1}^2}{k_{b_i,p1}^2 - e_{i,p1}^2} + \frac{1 - H_i^{p1}(e_{i,p1})}{2} \ln \frac{k_{a_i,p1}^2}{k_{a_i,p1}^2 - e_{i,p1}^2} \quad (38)$$

Differentiating (38) yields

$$\dot{V}_i^{p1} = \sum_{n=1}^3 \zeta_{i,1n} e_{i,p1} \left(\dot{e}_{i,p1} - (1 - H_i^{p1}) \frac{\dot{k}_{b_i,p1}}{k_{b_i,p1}} e_{i,p1} - H_i^{p1} \frac{\dot{k}_{a_i,p1}}{k_{a_i,p1}} e_{i,p1} \right) \quad (39)$$

Substituting (37) into (39), we can acquire

$$\begin{aligned} \dot{V}_i^{p1} &= \sum_{n=1}^3 \zeta_{i,1n} e_{i,p1} \left[-k_{i,1}^* e_{i,p1} + \Gamma_i e_{i,p2} - \mu_{i,1} - (1 - H_i^{p1}) \frac{\dot{k}_{b_i,p1}}{k_{b_i,p1}} e_{i,p1} - H_i^{p1} \frac{\dot{k}_{a_i,p1}}{k_{a_i,p1}} e_{i,p1} \right] \\ &\leq \sum_{n=1}^3 \left[\zeta_{i,pn} e_{i,p1} \Gamma_i e_{i,p2} - \frac{1}{2\beta_1} \zeta_{i,pn} e_{i,p1}^2 \chi_{i,p1} \tanh\left(\frac{1}{2\beta_1} e_{i,p1}^2 \chi_{i,p1}^2\right) \right] - N_{i,1} k_{i,1} e_{i,p1}^2 \end{aligned} \quad (40)$$

where $N_{i,1} = \text{diag}\{\zeta_{i,11}, \zeta_{i,12}, \zeta_{i,13}\}$.

Passing $\alpha_{i,p1}$ through first-order filter yields

$$\begin{cases} \eta_{i,p} \dot{\varsigma}_{i,p2} + \varsigma_{i,p2} = \alpha_{i,p1} \\ \varsigma_{i,p2}(0) = \alpha_{i,p1}(0) \end{cases} \quad (41)$$

where $\eta_{i,p} = \text{diag}\{\eta_{i,p1}, \eta_{i,p2}, \eta_{i,p3}\}$.

Defining the filtering error as $\kappa_{i,p} = \varsigma_{i,p2} - \alpha_{i,p1}$, and we have

$$\dot{\kappa}_{i,p} = -\eta_{i,p}^{-1} \kappa_{i,p} + Q_{i,1} \quad (42)$$

where $Q_{i,1}$ is a bounded smooth function, and $Q_{i,1} \leq \bar{Q}_{i,1}$.

Taking the derivative of $e_{i,p2}$ yields

$$\begin{aligned} \dot{e}_{i,p2} &= \dot{\pi}_{i,p2} - \dot{\alpha}_{i,p1} \\ &= l_{i,p} u_{i,p} + G_{i,p} + D_{i,p} - \dot{\alpha}_{i,p1} \end{aligned} \quad (43)$$

Defining $\alpha_{i,p2} = l_{i,p} u_{i,p}$, we propose the position loop control signal $\alpha_{i,p2}$ as follows:

$$\alpha_{i,p2} = -k_{i,2}^* e_{i,p2} + \dot{\varsigma}_{i,p2} - G_{i,p} - \hat{D}_{i,p} + 3\mu_{i,2} + \frac{\beta_1}{2} N_{i,2}^{-1} e_{i,p2} - \Gamma_i e_{i,p1} \quad (44)$$

where $k_{i,2}^* = (k_{i,2} + \bar{k}_{i,2})$, $k_{i,2} = \text{diag}\{k_{i,21}, k_{i,22}, k_{i,23}\}$ is a designed positive matrix, $\bar{k}_{i,2} = \text{diag}\{\bar{k}_{i,21}, \bar{k}_{i,22}, \bar{k}_{i,23}\}$, $\bar{k}_{i,2n} = \sqrt{\left(1 - H_i^{p2}\right) \left(\frac{\dot{k}_{b_i,p2}}{k_{b_i,p2}}\right)^2 + H_i^{p2} \left(\frac{\dot{k}_{a_i,p2}}{k_{a_i,p2}}\right)^2} + \delta_{i,2n}$, $\delta_{i,2n}$ is the designed positive constant. $\mu_{i,1} = [\mu_{i,21}, \mu_{i,22}, \mu_{i,23}]^T$, $\mu_{i,2n} = \frac{1}{2\beta_2} e_{i,p2n} \chi_{i,p2n} \tanh\left(\frac{1}{2\beta_2} e_{i,p2n}^2 \chi_{i,p2n}^2\right)$, $\chi_{i,p2n} = \frac{H_i^{p2}(e_{i,p2n})}{k_{c_i,p2n}^2 - e_{i,p2n}^2} + \frac{1 - H_i^{p2}(e_{i,p2n})}{k_{d_i,p2n}^2 - e_{i,p2n}^2}$, and β_2 is the designed positive constant.

To conserve the system's limited network resources, the AETM is designed at $t_i \in [t_i^k, t_i^{k+1})$ as [34,35]:

$$\begin{cases} \omega_{i,p}(t) = \alpha_{i,p2} - \bar{\chi}_{i,p} \tanh\left(\frac{\bar{\chi}_{i,p} e_{i,p2}}{\rho_{i,p}}\right) \\ u_{i,p}(t) = \omega_{i,p}(t_i^k), k \in \mathbb{Z}^+, \forall t \in [t_i^k, t_i^{k+1}) \\ t_i^{k+1} = \inf\{t > t_i^k \mid \|\tilde{e}_{i,pu}(t)\| \geq \chi_{i,p}^*\}, t_i^1 = 0 \end{cases} \quad (45)$$

where $\omega_{i,p}(t)$ is the auxiliary control input signal, $u_{i,p}(t)$ is the actual control input signal. triggering error $\tilde{e}_{i,pu}(t) = \omega_{i,p}(t) - u_{i,p}(t)$, triggering threshold $\chi_{i,p}^* = \chi_{i,p} + \frac{\sigma_{i,p1}}{\alpha_{i,p}\|e_{i,p1}\| + \sigma_{i,p2}}$, $\alpha_{i,p}, \sigma_{i,p1}, \sigma_{i,p2}, \bar{\chi}_{i,p}, \chi_{i,p}, \rho_{i,p}$ are positive parameters to be designed. $\omega_{i,p}(t) = u_{i,p}(t) + o_{i,p}(t)\chi_{i,p}$, $o_{i,p}(t)$ is a continuous time-varying parameter, $|o_{i,p}(t)| < 1$.

Substituting (44) into (43), we can deduce

$$\dot{e}_{i,p2} = -k_{i,2}e_{i,p2} + 3\mu_{i,2} + \frac{\beta_1}{2}N_{i,1}^{-1}e_{i,p2} + \tilde{\pi}_{i,p3} - \eta_{i,p}^{-1}\kappa_{i,p} + Q_{i,1} \quad (46)$$

The Lyapunov candidate function is chosen as:

$$V_{i,p} = V_i^{p1} + V_i^{p2} + V_{i,1} + \frac{1}{2}\kappa_{i,p}^T\kappa_{i,p} \quad (47)$$

Taking the time derivative of (47), we have

$$\begin{aligned} \dot{V}_{i,p} \leq & \sum_{n=1}^3 \left[\zeta_{i,1n}e_{i,p1}\Gamma_i e_{i,p2} - \frac{1}{2\beta_1}\zeta_{i,1n}e_{i,p1}^2\chi_{i,p1} \tanh\left(\frac{1}{2\beta_1}e_{i,p1}^2\chi_{i,p1}^2\right) \right] \\ & + \sum_{n=1}^3 \left[\zeta_{i,2n}e_{i,p2}\left(-\frac{\kappa_{i,p}}{\eta_{i,1}} + Q_{i,1}\right) - \frac{3}{2\beta_2}\zeta_{i,2n}e_{i,p2}^2\chi_{i,p1} \tanh\left(\frac{1}{2\beta_2}e_{i,p2}^2\chi_{i,p1}^2\right) \right] \\ & - N_{i,1}k_{i,1}e_{i,p1}^2 - N_{i,2}k_{i,2}e_{i,p2}^2 - o_{M1}\vartheta_p^T\vartheta_p + e_{i,p2}^T N_{i,2}\tilde{\pi}_{i,p3} - \frac{\beta_1}{2}e_{i,p2}^T e_{i,p2} + v_2^2 \\ & + \kappa_{i,p}^T\left(-\eta_{i,p}^{-1}\kappa_{i,p} + Q_{i,1}\right) \end{aligned} \quad (48)$$

where $N_{i,2} = \text{diag}\{\zeta_{i,21}, \zeta_{i,22}, \zeta_{i,23}\}$.

Let

$$\begin{cases} \Xi_1 = \zeta_{i,1n}e_{i,p1}\Gamma_i e_{i,p2} - \frac{1}{2\beta_1}\zeta_{i,1n}e_{i,p1}^2\chi_{i,p1} \tanh\left(\frac{1}{2\beta_1}e_{i,p1}^2\chi_{i,p1}^2\right) \\ \Xi_2 = \zeta_{i,2n}e_{i,p2}\left(-\frac{\kappa_{i,p}}{\eta_{i,1}} + Q_{i,1}\right) - \frac{3}{2\beta_2}\zeta_{i,2n}e_{i,p2}^2\chi_{i,p1} \tanh\left(\frac{1}{2\beta_2}e_{i,p2}^2\chi_{i,p1}^2\right) \end{cases} \quad (49)$$

Then, by using the Lemma 1 and Young's inequality, we can obtain

$$\begin{cases} \Xi_1 \leq \frac{\beta_1}{2}e_{i,p2}^2 + 2\omega_p \\ \Xi_2 \leq \frac{\beta_2}{2}\left(\frac{\kappa_{i,p}^2}{\eta_{i,p}} + Q_{i,1}^2\right) + 4\omega_p \\ \kappa_{i,p}^T Q_{i,1} \leq \frac{1}{2}\kappa_{i,p}^T\kappa_{i,p} + \frac{1}{2}Q_{i,1}^2 \\ e_{i,p2}^T N_{i,2}\tilde{\pi}_{i,p3} \leq \frac{1}{2}e_{i,p2}^T N_{i,2}e_{i,p2} + \frac{1}{2}\tilde{\pi}_{i,p3}^T N_{i,2}\tilde{\pi}_{i,p3} \end{cases} \quad (50)$$

Invoking (50) into (48), we can compute

$$\begin{aligned}
 \dot{V}_{i,p} &\leq -e_{i,p1}^T N_{i,1} k_{i,1} e_{i,p1} - e_{i,p2}^T N_{i,2} k_{i,2} e_{i,p1} + \frac{1}{2} e_{i,p2}^T N_{i,2} e_{i,p2} + \frac{1+\beta_2}{2} \bar{Q}_{i,1}^2 \\
 &\quad + \kappa_{i,p}^T \left(-\eta_{i,p}^{-1} + \frac{\beta_2}{2\eta_{i,p}} + \frac{1}{2} \right) \kappa_{i,p} - o_{M1} \vartheta_p^T \vartheta_p + \frac{1}{2} \tilde{\pi}_{i,p3}^T N_{i,2} \tilde{\pi}_{i,p3} \\
 &\quad + 18\omega_p + v_2^2 \\
 &\leq -e_{i,p1}^T N_{i,1} k_{i,1} e_{i,p1} - e_{i,p2}^T N_{i,2} (k_{i,2} - 1) e_{i,p1} - \kappa_{i,p}^T \left(\frac{-I - \beta_2 \eta_{i,p}^{-1} + 2\eta_{i,p}^{-1}}{2} \right) \kappa_{i,p} \\
 &\quad - \vartheta_p^T \left(o_{M1} - \frac{N_{i,2}}{2} \right) \vartheta_p + \frac{1+\beta_2}{2} \bar{Q}_{i,1}^2 + 18\omega_p + v_2^2
 \end{aligned} \tag{51}$$

Defining $u_{i,p} = [u_{i,1}, u_{i,2}, u_{i,3}]^T$ and giving the reference attitude angle $\psi_{i,d}$, the i -th QUAUV total lift F_i and the reference attitude angles $\theta_{i,d}$ and $\phi_{i,d}$ can be given by the following equations: [13,31]

$$\begin{cases} \phi_{i,d} = \arctan \left[\frac{(u_{i,1} \sin \psi_{i,d} - u_{i,2} \cos \psi_{i,d}) \cos \theta_{i,d}}{u_{i,3}} \right] \\ \theta_{i,d} = \arctan \left[\frac{u_{i,1} \cos \psi_{i,d} + u_{i,2} \sin \psi_{i,d}}{u_{i,3}} \right] \\ F_i = -\frac{m u_{i,3}}{\cos \phi_{i,d} \cos \theta_{i,d}} \end{cases} \tag{52}$$

3.4. Design of Controller for Attitude Loop

Define the i -th QUAUV tracking errors as:

$$\begin{aligned} e_{i,\Theta 1} &= \pi_{i,\Theta 1} - \pi_{i,\Theta 1}^d \\ e_{i,\Theta 2} &= \pi_{i,\Theta 2} - \alpha_{i,\Theta 1} \end{aligned} \tag{53}$$

where $\pi_{i,\Theta 1}^d$ denote the desired attitude angle, and $\alpha_{i,\Theta 1}$ represent the designed virtual control law.

Differentiating $e_{i,\Theta 1}$ yields

$$\begin{aligned} \dot{e}_{i,\Theta 1} &= \dot{\pi}_{i,\Theta 1} - \dot{\pi}_{i,\Theta 1}^d \\ &= H_i(e_{i,\Theta 2} + \alpha_{i,\Theta 1}) - \dot{\pi}_{i,\Theta 1}^d \end{aligned} \tag{54}$$

Passing $\pi_{i,\Theta 1}^d$ through first-order filter yields

$$\begin{cases} \eta_{i,21} \dot{\varsigma}_{i,\Theta 1} + \varsigma_{i,\Theta 1} = \pi_{i,\Theta 1}^d \\ \varsigma_{i,\Theta 1}(0) = \pi_{i,\Theta 1}^d(0) \end{cases} \tag{55}$$

where $\eta_{i,21} = \text{diag}\{\eta_{i,\Theta 1}, \eta_{i,\Theta 2}, \eta_{i,\Theta 3}\}$.

Define the filter error as $\kappa_{i,\Theta 1} = \varsigma_{i,\Theta 1} - \pi_{i,\Theta 1}^d$, and we have

$$\dot{\kappa}_{i,\Theta 1} = -\eta_{i,21}^{-1} \kappa_{i,\Theta 1} + Q_{i,2} \tag{56}$$

where $Q_{i,2}$ is a bounded smooth function, and $Q_{i,2} \leq \bar{Q}_{i,2}$.

Then, we design the virtual control law as:

$$\alpha_{i,\Theta 1} = H^{-1}(-k_{i,3}^* e_{i,\Theta 1} + \dot{\varsigma}_{i,\Theta 1} - 3\mu_{i,3}) \tag{57}$$

where $k_{i,3}^* = (k_{i,3} + \bar{k}_{i,3})$, $k_{i,3} = \text{diag}\{k_{i,31}, k_{i,32}, k_{i,33}\}$ is a designed positive matrix, $\bar{k}_{i,3} = \text{diag}\{\bar{k}_{i,31}, \bar{k}_{i,32}, \bar{k}_{i,33}\}$, $\bar{k}_{i,3m} = \sqrt{(1 - H_i^{\Theta 1}) \left(\frac{\dot{k}_{b_i, \Theta 1}}{k_{b_i, \Theta 1}} \right)^2 + H_i^{\Theta 1} \left(\frac{\dot{k}_{a_i, \Theta 1}}{k_{a_i, \Theta 1}} \right)^2} + \delta_{i,3n}$, $\delta_{i,3n}$ is the designed positive constant. $\mu_{i,3} = \frac{1}{2\beta_3} e_{i, \Theta 1n} \chi_{i, \Theta 1n} \tanh\left(\frac{1}{2\beta_3} e_{i, \Theta 1n}^2 \chi_{i, \Theta 1n}^2\right)$, $\chi_{i, \Theta 1n} = \frac{H_i^{\Theta 1}(e_{i, \Theta 1n})}{k_{c_i, \Theta 1n}^2 - e_{i, \Theta 1n}^2} + \frac{1 - H_i^{\Theta 1}(e_{i, \Theta 1n})}{k_{d_i, \Theta 1n}^2 - e_{i, \Theta 1n}^2}$, and β_3 is the designed positive constant.

Substituting (57) into (54), we can compute

$$\dot{e}_{i, \Theta 1} = -k_{i,3}^* e_{i, \Theta 1} + H e_{i, \Theta 2} - 3\mu_{i,3} - \eta_{i,21}^{-1} \kappa_{i, \Theta 1} + Q_{i,2} \quad (58)$$

Select the following TBLF:

$$V_i^{\Theta 1} = \frac{H_i^{\Theta 1}(e_{i, \Theta 1})}{2} \ln \frac{k_{b_i, \Theta 1}^2}{k_{b_i, \Theta 1}^2 - e_{i, \Theta 1}^2} + \frac{1 - H_i^{\Theta 1}(e_{i, \Theta 1})}{2} \ln \frac{k_{a_i, \Theta 1}^2}{k_{a_i, \Theta 1}^2 - e_{i, \Theta 1}^2} \quad (59)$$

Taking (59) the time derivative gives

$$\dot{V}_i^{\Theta 1} = \sum_{n=1}^3 \zeta_{i,3n} e_{i, \Theta 1} \left(\dot{e}_{i, \Theta 1} - H_i^{\Theta 1} \frac{\dot{k}_{a_i, \Theta 1}}{k_{a_i, \Theta 1}} e_{i, \Theta 1} - \left(1 - H_i^{\Theta 1}\right) \frac{\dot{k}_{b_i, \Theta 1}}{k_{b_i, \Theta 1}} e_{i, \Theta 1} \right) \quad (60)$$

Substituting (58) into (60), we can calculate

$$\begin{aligned} \dot{V}_i^{\Theta 1} &= \sum_{n=1}^3 \zeta_{i,3n} e_{i, \Theta 1} \left[-k_{i,3} e_{i, \Theta 1} - H_i^{\Theta 1} \frac{\dot{k}_{a_i, \Theta 1}}{k_{a_i, \Theta 1}} e_{i, \Theta 1} - \left(1 - H_i^{\Theta 1}\right) \frac{\dot{k}_{b_i, \Theta 1}}{k_{b_i, \Theta 1}} e_{i, \Theta 1} + e_{i, \Theta 2} - \mu_{i,3} \right] \\ &\leq \sum_{n=1}^3 \left[\zeta_{i,3n} e_{i, \Theta 1} \left(-\eta_{i,21}^{-1} \kappa_{i, \Theta 1} + Q_{i,2} \right) - \frac{3}{2\beta_3} \zeta_{i,3n} e_{i, \Theta 1}^2 \chi_{i, \Theta 1} \tanh\left(\frac{1}{2\beta_3} e_{i, \Theta 1}^2 \chi_{i, \Theta 1}^2\right) \right] \\ &\quad - e_{i, \Theta 1}^T N_{i,3} k_{i,3} e_{i, \Theta 1} + e_{i, \Theta 1}^T N_{i,3} H e_{i, \Theta 2} \end{aligned} \quad (61)$$

where $N_{i,3} = \text{diag}\{\zeta_{i,31}, \zeta_{i,32}, \zeta_{i,33}\}$.

Passing $\alpha_{i, \Theta 1}$ through first-order filter yields

$$\begin{cases} \eta_{i,31} \dot{\varsigma}_{i, \Theta 2} + \varsigma_{i, \Theta 2} = \alpha_{i, \Theta 1} \\ \varsigma_{i, \Theta 2}(0) = \pi_{i, \Theta 2}^d(0) \end{cases} \quad (62)$$

where $\eta_{i,31} = \text{diag}\{\eta_{i, \Theta 4}, \eta_{i, \Theta 5}, \eta_{i, \Theta 6}\}$.

Define the filter error as $\kappa_{i, \Theta 2} = \varsigma_{i, \Theta 2} - \alpha_{i, \Theta 1}$, and we have

$$\dot{\kappa}_{i, \Theta 2} = -\eta_{i,31}^{-1} \kappa_{i, \Theta 2} + Q_{i,3} \quad (63)$$

where $Q_{i,3}$ is a bounded smooth function, and $Q_{i,3} \leq \bar{Q}_{i,3}$.

Differentiating $e_{i, \Theta 2}$ yields

$$\begin{aligned} \dot{e}_{i, \Theta 2} &= \dot{\pi}_{i, \Theta 2} - \dot{\alpha}_{i, \Theta 1} \\ &= f_{i, \Theta} + l_{i, \Theta}^{-1} \tau_i + D_{i, \Theta} - \dot{\alpha}_{i, \Theta 1} \end{aligned} \quad (64)$$

Defining $l_{i, \Theta}^{-1} \tau_i = \alpha_{i, \Theta 2}$, we propose the attitude loop control signal $\alpha_{i, \Theta 2}$ as follows:

$$\alpha_{i, \Theta 2} = -k_{i,4}^* e_{i, \Theta 2} + \dot{\varsigma}_{i, \Theta 2} - f_{i, \Theta} - \hat{D}_{i, \Theta} + 3\mu_{i,4} + \frac{\beta_3}{2} N_{i,4}^{-1} H^T H e_{i, p2} \quad (65)$$

where $k_{i,4}^* = (k_{i,4} + \bar{k}_{i,4})$, $k_{i,4} = \text{diag}\{k_{i,41}, k_{i,42}, k_{i,43}\}$ is a designed positive matrix, $\bar{k}_{i,4} = \text{diag}\{\bar{k}_{i,41}, \bar{k}_{i,42}, \bar{k}_{i,43}\}$, $\bar{k}_{i,4n} = \sqrt{(1 - H_i^{\Theta 2}) \left(\frac{k_{b_i, \Theta 2}}{k_{b_i, \Theta 2}} \right)^2 + H_i^{\Theta 2} \left(\frac{k_{a_i, \Theta 2}}{k_{a_i, \Theta 2}} \right)^2} + \delta_{i,4n}$, $\delta_{i,4n}$ is the designed positive constant. $\mu_{i,4} = \frac{1}{2\beta_4} e_{i, \Theta 2n} \chi_{i, \Theta 2n} \tanh\left(\frac{1}{2\beta_4} e_{i, \Theta 2n}^2 \chi_{i, \Theta 2n}^2\right)$, $\chi_{i, \Theta 2n} = \frac{H_i^{\Theta 2}(e_{i, \Theta 2n})}{k_{c_i, \Theta 2n}^2 - e_{i, \Theta 2n}^2} + \frac{1 - H_i^{\Theta 2}(e_{i, \Theta 2n})}{k_{d_i, \Theta 2n}^2 - e_{i, \Theta 2n}^2}$, and β_4 is the designed positive constant.

Similarly to the position system, the attitude system AETM is designed as:

$$\begin{cases} \omega_{i, \Theta}(t) = \alpha_{i, \Theta} - \bar{\chi}_{i, \Theta} \tanh\left(\frac{\bar{\chi}_{i, \Theta} e_{i, p2}}{\rho_{i, \Theta}}\right) \\ u_{i, \Theta}(t) = \omega_{i, \Theta}(t_i^k), k \in \mathbb{Z}^+ \\ t_i^{k+1} = \inf\{t > t_i^k \mid \|\bar{e}_{i, \Theta u}(t)\| \geq \chi_{i, \Theta}^*\}, t_i^1 = 0 \end{cases} \quad (66)$$

where $\omega_{i, \Theta}(t)$ is the auxiliary control input signal, $u_{i, \Theta}(t)$ is the actual control input signal. $\bar{e}_{i, \Theta u}(t) = \omega_{i, \Theta}(t) - u_{i, \Theta}(t)$ is triggering error, triggering threshold $\chi_{i, \Theta}^* = \chi_{i, \Theta} + \frac{\sigma_{i, \Theta 1}}{\|e_{i, \Theta 1}\| + \sigma_{i, \Theta 2}}$, $\alpha_{i, \Theta}, \sigma_{i, \Theta 1}, \sigma_{i, \Theta 2}, \bar{\chi}_{i, \Theta}, \rho_{i, \Theta}$ are positive parameters to be designed. $\omega_{i, \Theta}(t) = u_{i, \Theta}(t) + o_{i, \Theta}(t) \chi_{i, \Theta}$ is a continuous time-varying parameter, $|o_{i, \Theta}(t)| < 1$.

Substituting (65) into (64), we can deduce

$$\dot{e}_{i, \Theta 2} = -k_{i,4}^* e_{i, \Theta 2} + 3\mu_{i,4} + \tilde{\pi}_{i, \Theta 3} + Q_{i,3} + \frac{\beta_3}{2} N_{i,4}^{-1} H^T H e_{i, p2} - \eta_{i,31}^{-1} \kappa_{i, \Theta 2} \quad (67)$$

The Lyapunov candidate function is chosen as:

$$V_{i, \Theta} = V_i^{\Theta 1} + V_i^{\Theta 2} + V_{i,2} + \frac{1}{2} \kappa_{i, \Theta 1}^T \kappa_{i, \Theta 1} + \frac{1}{2} \kappa_{i, \Theta 2}^T \kappa_{i, \Theta 2} \quad (68)$$

Differentiating $V_{i, \Theta}$ yields

$$\begin{aligned} \dot{V}_{i, \Theta} \leq & \sum_{n=1}^3 \left[\zeta_{i,3n} e_{i, \Theta 1} \left(-\frac{\kappa_{i, \Theta 1}}{\eta_{i,21}} + Q_{i,2} \right) - \frac{3}{2\beta_3} \zeta_{i,3n} e_{i, \Theta 1}^2 \chi_{i, \Theta 1} \tanh\left(\frac{1}{2\beta_3} e_{i, \Theta 1}^2 \chi_{i, \Theta 1}^2\right) \right] \\ & + \sum_{n=1}^3 \left[\zeta_{i,4n} e_{i, \Theta 2} \left(-\frac{\kappa_{i, \Theta 2}}{\eta_{i,31}} + Q_{i,3} \right) - \frac{3}{2\beta_4} \zeta_{i,4n} e_{i, \Theta 2}^2 \chi_{i, \Theta 2} \tanh\left(\frac{1}{2\beta_4} e_{i, \Theta 2}^2 \chi_{i, \Theta 2}^2\right) \right] \\ & - e_{i, \Theta 1}^T N_{i,3} \kappa_{i,3} e_{i, \Theta 1} + e_{i, \Theta 1}^T N_{i,3} H e_{i, \Theta 2} - \frac{\beta_3}{2} e_{i, \Theta 2}^T H^T H e_{i, \Theta 2} - e_{i, \Theta 2}^T N_{i,4} \kappa_{i,4} e_{i, \Theta 2} \\ & + e_{i, \Theta 2}^T N_{i,4} \tilde{\pi}_{i, \Theta 3} + \kappa_{i, \Theta 1}^T \left(-\eta_{i,2}^{-1} \kappa_{i, \Theta 1} + Q_{i,2} \right) \\ & + \kappa_{i, \Theta 2}^T \left(-\eta_{i,3}^{-1} \kappa_{i, \Theta 2} + Q_{i,3} \right) - o_{M2} \theta_{\Theta}^T \theta_{\Theta} + v_4^2 \end{aligned} \quad (69)$$

where $N_{i,4} = \text{diag}\{\zeta_{i,41}, \zeta_{i,42}, \zeta_{i,43}\}$.

Then, by using Young's inequality and Lemmas 1–2, it yields

$$\begin{cases} e_{i, \Theta 1}^T N_{i,3} H e_{i, \Theta 2} \leq \frac{1}{2\beta_3} e_{i, \Theta 1}^T N_{i,3}^T N_{i,3} e_{i, \Theta 1} + \frac{\beta_3}{2} e_{i, \Theta 2}^T H^T H e_{i, \Theta 2} \\ e_{i, \Theta 2}^T N_{i,4} \tilde{\pi}_{i, \Theta 3} \leq \frac{1}{2} e_{i, \Theta 2}^T N_{i,4} e_{i, \Theta 2} + \frac{1}{2} \tilde{\pi}_{i, \Theta 3}^T N_{i,4} \tilde{\pi}_{i, \Theta 3} \\ \kappa_{i, \Theta 1}^T Q_{i,2} \leq \frac{1}{2} \kappa_{i, \Theta 1}^T \kappa_{i, \Theta 1} + \frac{1}{2} \bar{Q}_{i,2}^2 \\ \kappa_{i, \Theta 2}^T Q_{i,3} \leq \frac{1}{2} \kappa_{i, \Theta 2}^T \kappa_{i, \Theta 2} + \frac{1}{2} \bar{Q}_{i,3}^2 \end{cases} \quad (70)$$

Substituting (70) into (69), we can derive

$$\begin{aligned}
 \dot{V}_{i,\Theta} \leq & \sum_{n=1}^3 \left[\zeta_{i,3n} e_{i,\Theta 1} \left(-\frac{\mathcal{K}_{i,\Theta 1}}{\eta_{i,21}} + Q_{i,2} \right) - \frac{3}{2\beta_3} \zeta_{i,3n} e_{i,\Theta 1}^2 \chi_{i,\Theta 1} \tanh \left(\frac{1}{2\beta_3} e_{i,\Theta 1}^2 \chi_{i,\Theta 1}^2 \right) \right] \\
 & + \sum_{n=1}^3 \left[\zeta_{i,4n} e_{i,\Theta 2} \left(-\frac{\mathcal{K}_{i,\Theta 2}}{\eta_{i,31}} + Q_{i,3} \right) - \frac{3}{2\beta_4} \zeta_{i,4n} e_{i,\Theta 2}^2 \chi_{i,\Theta 2} \tanh \left(\frac{1}{2\beta_4} e_{i,\Theta 2}^2 \chi_{i,\Theta 2}^2 \right) \right] \\
 & + \sum_{n=1}^3 \left[\frac{1}{2\beta_4} \gamma_{i,3n}^2 e_{i,\Theta 2}^2 - \frac{1}{2\beta_4} \gamma_{i,pm} e_{i,\Theta 2}^2 \chi_{i,p1} \tanh \left(\frac{1}{2\beta_4} e_{i,p1}^2 \chi_{i,p1}^2 \right) \right] + \nu_4^2 \\
 & + -e_{i,\Theta 1}^T N_{i,3} k_{i,3} e_{i,\Theta 1} - e_{i,\Theta 2}^T N_{i,4} k_{i,4} e_{i,\Theta 2} + \frac{1}{2} e_{i,\Theta 2}^T N_{i,4} e_{i,\Theta 2} + \frac{1}{2} \bar{Q}_{i,2}^2 + \frac{1}{2} \bar{Q}_{i,3}^2 \\
 & - \kappa_{i,\Theta 1}^T \eta_{i,2}^{-1} \kappa_{i,\Theta 1} - \kappa_{i,\Theta 2}^T \eta_{i,3}^{-1} \kappa_{i,\Theta 2} + \frac{1}{2} \kappa_{i,\Theta 1}^T \kappa_{i,\Theta 1} + \frac{1}{2} \kappa_{i,\Theta 2}^T \kappa_{i,\Theta 2} + \frac{1}{2} \tilde{\pi}_{i,\Theta 3}^T N_{i,4} \tilde{\pi}_{i,\Theta 3} \\
 & - o_{M2} \vartheta_{\Theta}^T \vartheta_{\Theta}
 \end{aligned} \quad (71)$$

Let

$$\begin{cases}
 \Xi_3 = \zeta_{i,3n} e_{i,\Theta 1} \left(-\frac{\mathcal{K}_{i,\Theta 1}}{\eta_{i,2n}} + Q_{i,2} \right) - \frac{1}{\beta_3} \zeta_{i,3n} e_{i,\Theta 1}^2 \chi_{i,\Theta 1} \tanh \left(\frac{1}{2\beta_3} e_{i,\Theta 1}^2 \chi_{i,\Theta 1}^2 \right) \\
 \Xi_4 = \zeta_{i,4n} e_{i,\Theta 2} \left(-\frac{\mathcal{K}_{i,\Theta 2}}{\eta_{i,3n}} + Q_{i,3} \right) - \frac{3}{2\beta_4} \zeta_{i,4n} e_{i,\Theta 2}^2 \chi_{i,\Theta 2} \tanh \left(\frac{1}{2\beta_4} e_{i,\Theta 2}^2 \chi_{i,\Theta 2}^2 \right) \\
 \Xi_5 = \frac{1}{2\beta_3} \zeta_{i,3n}^2 e_{i,\Theta 2}^2 - \frac{1}{2\beta_3} \zeta_{i,pm} e_{i,\Theta 2}^2 \chi_{i,p1} \tanh \left(\frac{1}{2\beta_3} e_{i,p1}^2 \chi_{i,p1}^2 \right)
 \end{cases} \quad (72)$$

Applying Young's inequality, we can derive

$$\begin{cases}
 \Xi_3 + \Xi_5 \leq \frac{\beta_3}{2} \left(e_{i,\Theta 2}^2 + \frac{\kappa_{i,\Theta 1}^2}{\eta_{i,2n}} + Q_{i,2}^2 \right) + 6\omega_p \\
 \Xi_4 \leq \frac{\beta_4}{2} \left(\frac{\kappa_{i,\Theta 2}^2}{\eta_{i,3n}} + Q_{i,3}^2 \right) + 4\omega_p
 \end{cases} \quad (73)$$

Substituting (73) into (71), we can compute

$$\begin{aligned}
 \dot{V}_{i,\Theta} \leq & -e_{i,\Theta 1}^T N_{i,3} k_{i,3} e_{i,\Theta 1} - e_{i,\Theta 2}^T \left(N_{i,4} k_{i,4} - \frac{1+\beta_3}{2} \right) e_{i,\Theta 2} \\
 & - \kappa_{i,\Theta 1}^T \left(\frac{\eta_{i,2}^{-1} - \beta_3 \eta_{i,2}^{-1} - I}{2} \right) \kappa_{i,\Theta 1} + \nu_4^2 + \frac{1+\beta_3}{2} \bar{Q}_{i,2}^2 \\
 & - \kappa_{i,\Theta 2}^T \left(\frac{\eta_{i,3}^{-1} - \beta_4 \eta_{i,3}^{-1} - I}{2} \right) \kappa_{i,\Theta 2} + 30\omega_p \\
 & - \vartheta_{\Theta}^T \left(o_{M2} - \frac{N_{i,4}}{2} \right) \vartheta_{\Theta} + \frac{1+\beta_4}{2} \bar{Q}_{i,3}^2
 \end{aligned} \quad (74)$$

3.5. Stability Analysis

To sum up, the main contributions of the above study can be summarized as the following theorem.

Theorem 1. For the i -th QUAV model (1), the TGESO are constructed as (13) and (30). By applying the proposed event-triggered consensus formation controllers (44) and (65) together with the AETM (45) and (66), all state variables of the QUAV formation system satisfy the state constraints, all tracking error signals are uniformly bounded, and the Zeno behavior is avoided.

Proof of Theorem 1. Consider the Lyapunov function candidate as: $\square$

$$V_{H_i} = V_{i,p} + V_{i,\Theta} \quad (75)$$

Differentiating V_{H_i} , we can deduce

$$\begin{aligned} \dot{V}_{H_i} \leq & -e_{i,p1}^T N_{i,1} k_{i,1} e_{i,p1} - e_{i,p2}^T N_{i,2} (k_{i,2} - I) e_{i,p1} - \kappa_{i,p}^T \left(\frac{-I - \beta_2 \eta_{i,p}^{-1} + 2\eta_{i,p}^{-1}}{2} \right) \kappa_{i,p} \\ & - \vartheta_p^T \left(o_{M1} - \frac{N_{i,2}}{2} \right) \vartheta_p - e_{i,\Theta 1}^T N_{i,3} k_{i,3} e_{i,\Theta 1} - e_{i,\Theta 2}^T \left(N_{i,4} k_{i,4} - \frac{1 + \beta_3}{2} I \right) e_{i,\Theta 2} \\ & - \kappa_{i,\Theta 1}^T \left(\frac{\eta_{i,2}^{-1} - \beta_3 \eta_{i,2}^{-1} - I}{2} \right) \kappa_{i,\Theta 1} + 48\omega_p - \kappa_{i,\Theta 2}^T \left(\frac{\eta_{i,3}^{-1} - \beta_4 \eta_{i,3}^{-1} - I}{2} \right) \kappa_{i,\Theta 2} \\ & - \vartheta_\Theta^T \left(o_{M2} - \frac{N_{i,4}}{2} \right) \vartheta_\Theta + v_2^2 + v_4^2 + \frac{1 + \beta_2}{2} \bar{Q}_{i,1}^2 + \frac{1 + \beta_3}{2} \bar{Q}_{i,2}^2 + \frac{1 + \beta_4}{2} \bar{Q}_{i,3}^2 \end{aligned} \quad (76)$$

Furthermore, we can obtain

$$\begin{aligned} \dot{V}_{H_i} \leq & - \sum_{j=1}^3 k_{i,1j} V_{i,1j}^p - \sum_{j=1}^3 \left(k_{i,2} - \frac{1}{\gamma_{i,2j}} \right) V_{i,2j}^p - \sum_{j=1}^3 k_{i,3} V_{i,2j}^\Theta - \sum_{j=1}^3 \left(k_{i,4} - \frac{1 + \beta_3}{2\gamma_{i,4j}} \right) V_{i,2j}^\Theta \\ & - \kappa_{i,p}^T \left(\frac{-I - \beta_2 \eta_{i,p}^{-1} + 2\eta_{i,p}^{-1}}{2} \right) \kappa_{i,p} - \kappa_{i,\Theta 1}^T \left(\frac{\eta_{i,2}^{-1} - \beta_3 \eta_{i,2}^{-1} - I}{2} \right) \kappa_{i,\Theta 1} \\ & - \kappa_{i,\Theta 2}^T \left(\frac{\eta_{i,3}^{-1} - \beta_4 \eta_{i,3}^{-1} - I}{2} \right) \kappa_{i,\Theta 2} - \vartheta_p^T \left(o_{M1} - \frac{N_{i,2}}{2} \right) \vartheta_p + 48\omega_p \\ & - \vartheta_\Theta^T \left(o_{M2} - \frac{N_{i,4}}{2} \right) \vartheta_\Theta + v_2^2 + v_4^2 + \frac{1 + \beta_2}{2} \bar{Q}_{i,1}^2 + \frac{1 + \beta_3}{2} \bar{Q}_{i,2}^2 + \frac{1 + \beta_4}{2} \bar{Q}_{i,3}^2 \\ \leq & -\Psi_{i1} V_{H_i} + \Psi_{i2} \end{aligned} \quad (77)$$

where

$$\begin{aligned} \Psi_{i1} = \min & \left\{ \begin{array}{l} \lambda_{\min}(2k_{i,1}), \lambda_{\min}\left(2k_{i,2} - \frac{2}{\gamma_{i,2j}} I\right), \lambda_{\min}(2k_{i,3}), \lambda_{\min}\left(2k_{i,4} - \frac{1 + \beta_3}{\gamma_{i,4j}} I\right), \\ \lambda_{\min}(2o_{M1} - N_{i,2}), \lambda_{\min}(2o_{M2} - N_{i,4}), \lambda_{\min}\left(-I - \beta_2 \eta_{i,p}^{-1} + 2\eta_{i,p}^{-1}\right), \\ \lambda_{\min}\left(\eta_{i,2}^{-1} - \beta_3 \eta_{i,2}^{-1} - I\right), \lambda_{\min}\left(\eta_{i,3}^{-1} - \beta_4 \eta_{i,3}^{-1} - I\right) \end{array} \right\} > 0, \\ \Psi_{i2} = & v_2^2 + v_4^2 + \frac{1 + \beta_2}{2} \bar{Q}_{i,1}^2 + \frac{1 + \beta_3}{2} \bar{Q}_{i,2}^2 + \frac{1 + \beta_4}{2} \bar{Q}_{i,3}^2 + 48\omega_p \end{aligned}$$

Furthermore, it can be obtained that $\lim_{t \rightarrow \infty} V_{H_i}(t) \rightarrow \frac{\Psi_{i2}}{\Psi_{i1}}$. Taking the definition of V_{H_i} into account, when $H_i^{mn} = 1$, we have

$$\ln \frac{k_{a_i,m,n}^2(t)}{k_{a_i,m,n}^2(t) - e_{i,mn}^2} \leq 2\sqrt{2\Psi_{i2}\Psi_{i1}^{-1}} = \Pi_i \quad (78)$$

In addition, according to $\Sigma_i = e_{i,\Theta} = \pi_{i,\Theta} - \pi_{i,\Theta}^d$ and $|\pi_{i,\Theta}^d| \leq \iota_1$, we can obtain $|\Sigma_i| \leq |\pi_{i,\Theta}^d| + |e_{i,\Theta}| \leq h_{i,\Theta} + \iota_1 \leq \partial_1$. Therefore, the system state Σ_i satisfy the requirement. And $\alpha_{i,\Theta}$ is a function of $e_{i,\Theta}$ and $\dot{\pi}_{i,\Theta}^d$. Since $e_{i,\Theta}$ and $\dot{\pi}_{i,\Theta}^d$ are all bounded, the boundary of Σ_i exists. Considering $e_{i,\Theta} = \pi_{i,\Theta} - \alpha_{i,\Theta}$, it can be proved that system state Ω_i also satisfy the requirement in the same way. Ultimately, all states of the QUAV formation system are in the required compact set. We obtain the following inequality:

$$\underline{\pi}_i^{mn} < \pi_i^{mn} < \overline{\pi}_i^{mn} \quad (79)$$

Moreover, for the AETM, we have [36]

$$\frac{d}{dt} |\tilde{e}_{i,pu}(t)| = \frac{d}{dt} |\omega_{i,p}(t) - u_{i,p}(t)| \leq \dot{\omega}_{i,p}(t) \quad (80)$$

According to (45), $\dot{\omega}_{i,p}(t)$ is continuous and bounded, we have $\dot{\omega}_{i,p} \leq p$, with $p > 0$. Then, due to $\tilde{e}_{i,pu}(t_i^k) = 0$ and $\lim_{t \rightarrow t_i^k} \tilde{e}_{i,pu}(t) = \chi_{i,p}^*$, we have $t^\alpha \geq \chi_{i,p}^*/p$. Therefore, Zeno behavior is proven to be excluded. This concludes the proof.

4. Simulation Results

To demonstrate the performance of the proposed adaptive event-triggered consensus control strategy, we carry out simulations with one virtual leader and four followers. The corresponding communication topology is shown in Figure 2. The initial states of the four followers are given as follows: $P_{10} = [1, -1, 0]^T$, $P_{20} = [-1, 1, 0]^T$, $P_{30} = [2, -2, 0]^T$, $P_{40} = [-2, 2, 0]^T$, $\Sigma_{10} = \Sigma_{20} = \Sigma_{30} = \Sigma_{40} = [0, 0, 0]^T$. The position offsets in the formation are selected as: $\chi_{1,p}^d = [1, -1, 0]^T$, $\chi_{2,p}^d = [-1, 1, 0]^T$, $\chi_{3,p}^d = [2, -2, 0]^T$, $\chi_{4,p}^d = [-2, 2, 0]^T$. The virtual leader is specified the following desired trajectory: $y_{0,p} = [0.5 \sin(\pi t/8), 0.5 \cos(\pi t/8), 0.1t, 0.5 \text{rad}]^T$.

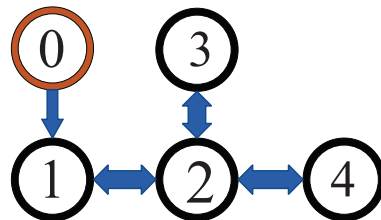


Figure 2. The communication topology of the QUAV formation system.

The mass of each QUAV is $m = 1.4$ kg, the gravitational acceleration is $g = 9.8$ m/s², the inertia matrix is $J = \text{diag}\{0.0211, 0.0219, 0.0366\}$ kg · m². The selected controller parameters are given as: $k_{i,1} = \text{diag}\{2, 2, 2\}$, $k_{i,2} = \text{diag}\{5, 5, 5\}$, $k_{i,3} = \text{diag}\{10, 10, 10\}$, $k_{i,4} = \text{diag}\{15, 15, 15\}$, $\delta_{i,1n} = \delta_{i,2n} = \delta_{i,3n} = \delta_{i,4n} = 0.01$, $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0.5$. The parameters of the AETM are given as: $\tilde{\chi}_{i,p} = 0.01$, $\tilde{\chi}_{i,\Theta} = 0.5$, $\chi_{i,p} = \chi_{i,\Theta} = 0.03$, $\sigma_{i,p1} = \sigma_{i,\Theta1} = 0.001$, $\sigma_{i,p2} = \sigma_{i,\Theta2} = 0.1$, $\alpha_{i,p} = 1$. The parameters of the TGESO are given as: $\kappa = 2$, $\varepsilon_0 = 80$, $\gamma_{i,p1} = \text{diag}\{1, 1, 1\}$, $\gamma_{i,p2} = \text{diag}\{1, 1, 1\}$, $\gamma_{i,p3} = \text{diag}\{1.5, 1.5, 1.5\}$, $\gamma_{i,\Theta1} = \text{diag}\{1, 1, 1\}$, $\gamma_{i,\Theta2} = \text{diag}\{3, 3, 3\}$, $\gamma_{i,\Theta3} = \text{diag}\{1.5, 1.5, 1.5\}$. The external disturbances applied to the four followers are as follows:

$$\begin{aligned}
D_{1,1} &= \begin{bmatrix} 0.3 \sin(0.4t) \\ 1.2 \sin(0.3t) \\ 1.3 \sin(0.5t) \end{bmatrix}, & D_{1,2} &= \begin{bmatrix} 1.1 \cos(0.5t) \\ 1.2 \cos(0.1t) \\ 1.2 \cos(0.4t) \end{bmatrix} \\
D_{2,1} &= \begin{bmatrix} 1.2 \sin(0.1t) \\ 1.3 \sin(0.2t) \\ 1.1 \sin(0.4t) \end{bmatrix}, & D_{2,2} &= \begin{bmatrix} 1.1 \cos(0.2t) \\ 1.1 \cos(0.3t) \\ 1.1 \cos(0.1t) \end{bmatrix} \\
D_{3,1} &= \begin{bmatrix} 1.2 \sin(0.3t) \\ 1.1 \sin(0.3t) \\ 1.2 \sin(0.3t) \end{bmatrix}, & D_{3,2} &= \begin{bmatrix} 1.3 \cos(0.3t) \\ 1.1 \cos(0.1t) \\ 1.2 \cos(0.4t) \end{bmatrix} \\
D_{4,1} &= \begin{bmatrix} 1.1 \sin(0.4t) \\ 1.3 \sin(0.3t) \\ 1.2 \sin(0.5t) \end{bmatrix}, & D_{4,2} &= \begin{bmatrix} 1.4 \cos(0.5t) \\ 1.2 \cos(0.2t) \\ 1.3 \cos(0.1t) \end{bmatrix}
\end{aligned}$$

Meanwhile, the following state constraints are considered ($i = 1, 2, 3, 4$):

$$\begin{cases}
\bar{\pi}_1^{p1} = [0.5 \sin(\pi t/8) + 5, 0.5 \cos(\pi t/8) + 3, 0.1t + 2]^T \\
\underline{\pi}_1^{p1} = [0.5 \sin(\pi t/8) - 3, 0.5 \cos(\pi t/8) - 5, 0.1t - 2]^T \\
\bar{\pi}_2^{p1} = [0.5 \sin(\pi t/8) + 3, 0.5 \cos(\pi t/8) + 5, 0.1t + 2]^T \\
\underline{\pi}_2^{p1} = [0.5 \sin(\pi t/8) - 5, 0.5 \cos(\pi t/8) - 3, 0.1t - 2]^T \\
\bar{\pi}_3^{p1} = [0.5 \sin(\pi t/8) + 6, 0.5 \cos(\pi t/8) + 2, 0.1t + 2]^T \\
\underline{\pi}_3^{p1} = [0.5 \sin(\pi t/8) - 2, 0.5 \cos(\pi t/8) - 6, 0.1t - 2]^T \\
\bar{\pi}_4^{p1} = [0.5 \sin(\pi t/8) + 2, 0.5 \cos(\pi t/8) + 6, 0.1t + 2]^T \\
\underline{\pi}_4^{p1} = [0.5 \sin(\pi t/8) - 6, 0.5 \cos(\pi t/8) - 2, 0.1t - 2]^T \\
\bar{\pi}_i^{p2} = [\sin(0.4t) + 4, \sin(0.4t) + 4, \sin(0.4t) + 4]^T \\
\underline{\pi}_i^{p2} = [-\sin(0.4t) - 4, -\sin(0.4t) - 4, -\sin(0.4t) - 4]^T \\
\bar{\pi}_i^{\Theta 1} = [\frac{\pi}{6}, \frac{\pi}{6}, \pi]^T \\
\underline{\pi}_i^{\Theta 1} = [-\frac{\pi}{6}, -\frac{\pi}{6}, -\pi]^T \\
\bar{\pi}_i^{\Theta 2} = [10e^{-t} + 4, 10e^{-t} + 4, 10e^{-t} + 4]^T \\
\underline{\pi}_i^{\Theta 2} = [-10e^{-t} - 4, -10e^{-t} - 4, -10e^{-t} - 4]^T
\end{cases}$$

Figure 3 illustrates the 3D trajectory tracking of the formation composed of four QUAVs. The black solid line represents the trajectory of the virtual leader, while the orange-red, light-blue, purple, and green curves correspond to the flight trajectories of the four QUAVs, respectively. Moreover, Figure 4 presents the 2D side view the flight trajectories of all QUAVs. In summary, the four QUAVs achieve tracking of the virtual leader trajectory and maintenance of a prescribed formation.

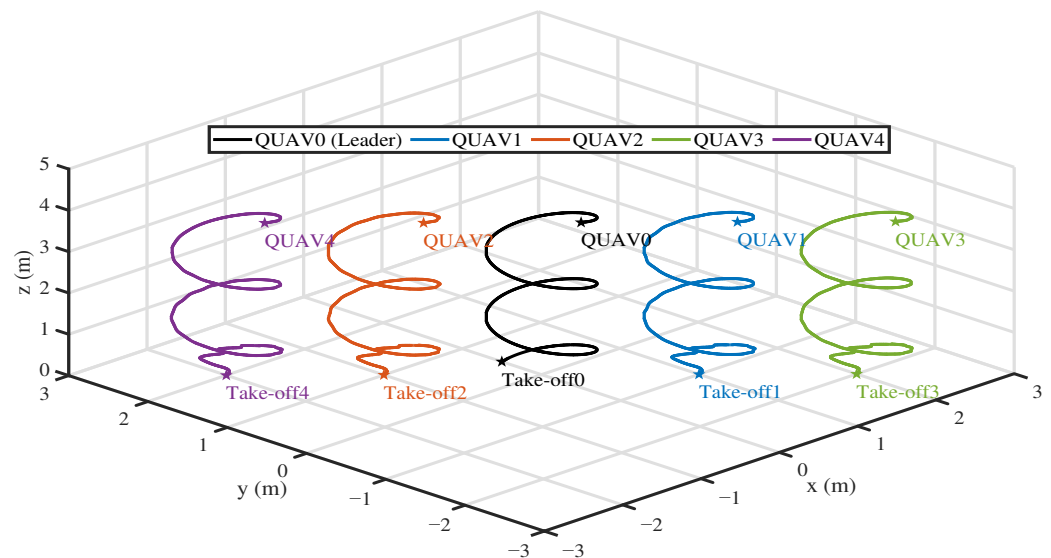


Figure 3. The 3D trajectories of the QUAV formation system.

Specifically, Figures 5–8 show the tracking results of each QUAV under position constraints, respectively. Figure 9 shows the attitude angle constraint curves of the four QUAVs, where the black dashed lines represent the constraint boundaries of the attitude angles. It can be observed that the four QUAVs under external disturbances can still quickly track the trajectory of the virtual leader in terms of position and attitude outputs while maintaining a fixed offset, thereby preserving the predefined formation. Figure 10 shows the velocity constraint curves of the four QUAVs, where the black dashed lines represent the constraint boundaries of the velocity. Figure 11 shows the angular rate constraint curves of the four QUAVs, where the black dashed lines represent the constraint boundaries of the angular rate. From Figures 10 and 11, it can be observed that the angular rate and velocity are able to track the derivatives of the virtual leader trajectory. The four QUAVs exhibit fast trajectory tracking responses, and all state variables satisfy the full-state constraints.

Figures 12–15 show the estimation errors between the actual disturbance values and the estimated disturbance values of the four QUAVs. For the sake of clarity, the blue solid line denotes the estimation results of the ESO, and the red solid line denotes the estimation results of the TGESO. The parameters of the conventional ESO are given as: $\gamma_{i,p1} = \text{diag}\{1, 1, 1\}$, $\gamma_{i,p2} = \text{diag}\{3, 3, 3\}$, $\gamma_{i,p3} = \text{diag}\{25, 25, 25\}$, $\gamma_{i,\Theta1} = \text{diag}\{1, 1, 1\}$, $\gamma_{i,\Theta2} = \text{diag}\{10, 10, 10\}$, $\gamma_{i,\Theta3} = \text{diag}\{100, 100, 100\}$. From the figures, it is evident that the conventional ESO can achieve basic disturbance estimation, but there is an obvious peaking phenomenon in the initial stage. In contrast, the TGESO adopts a smaller gain in the initial stage, thus avoiding the obvious initial peaking phenomenon in disturbance estimation. The simulation results indicate that the TGESO not only effectively suppresses the initial estimation overshoot but also improves the accuracy of disturbance estimation. Figures 16 and 17 present the observer estimation performance test under strong disturbances. The given strong disturbance is set as: $D_1 = [100 \sin(0.2t); 100 \sin(0.3t); 100 \sin(0.05t)]$, $D_2 = [100 \sin(0.5t); 100 \sin(0.1t); 100 \sin(0.4t)]$. It can be seen that the disturbance estimates still maintain good tracking performance under stronger disturbances.

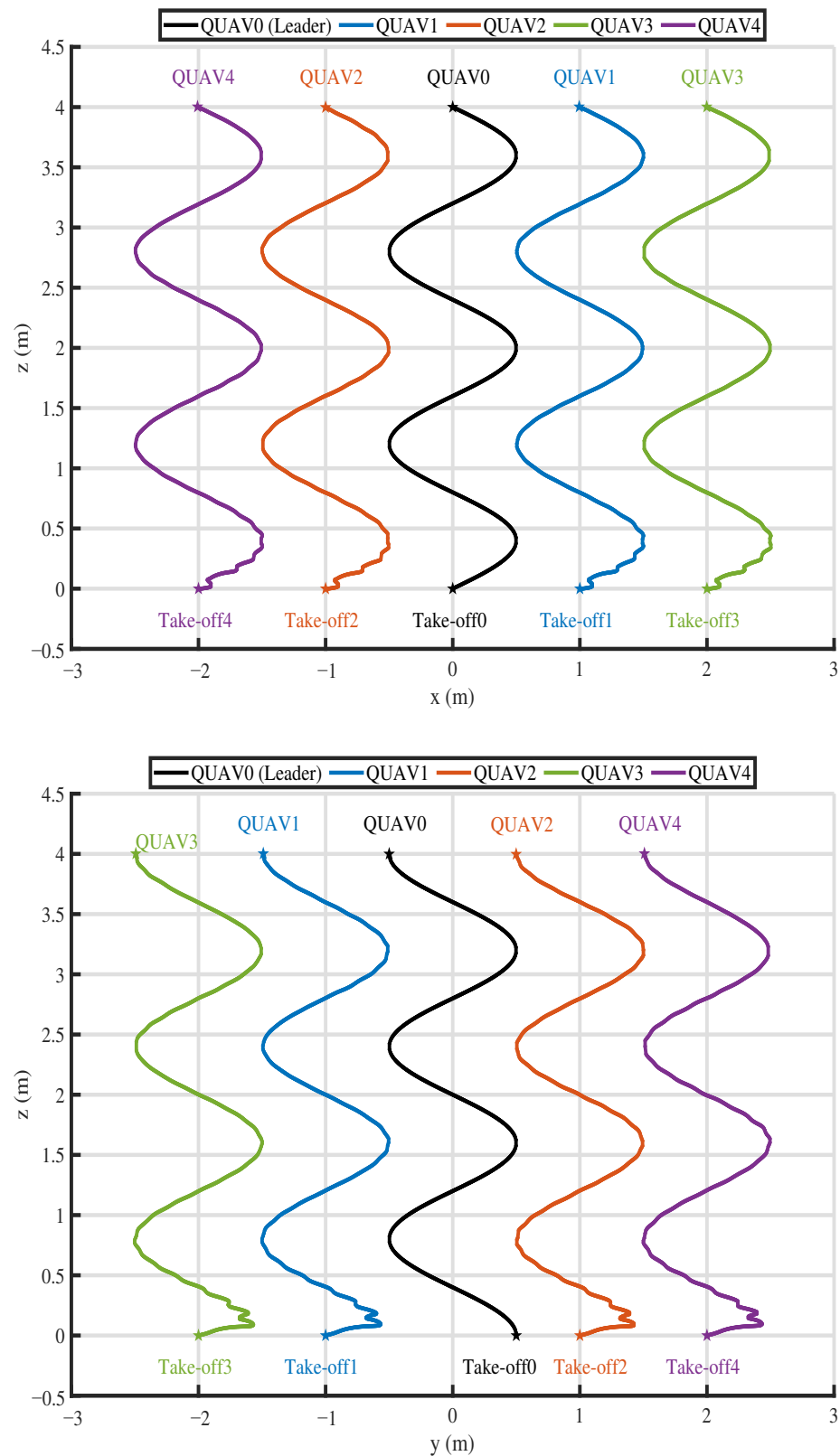


Figure 4. The 2D trajectories of the QUAV formation system.

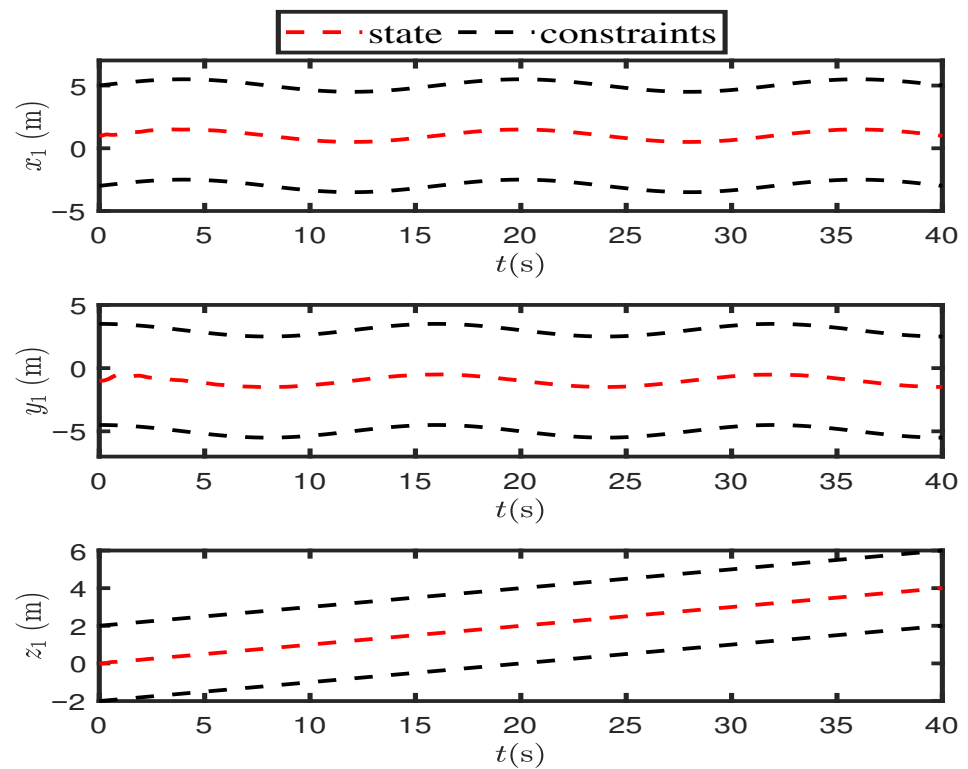


Figure 5. Position of QUAV 1 under state constraints.

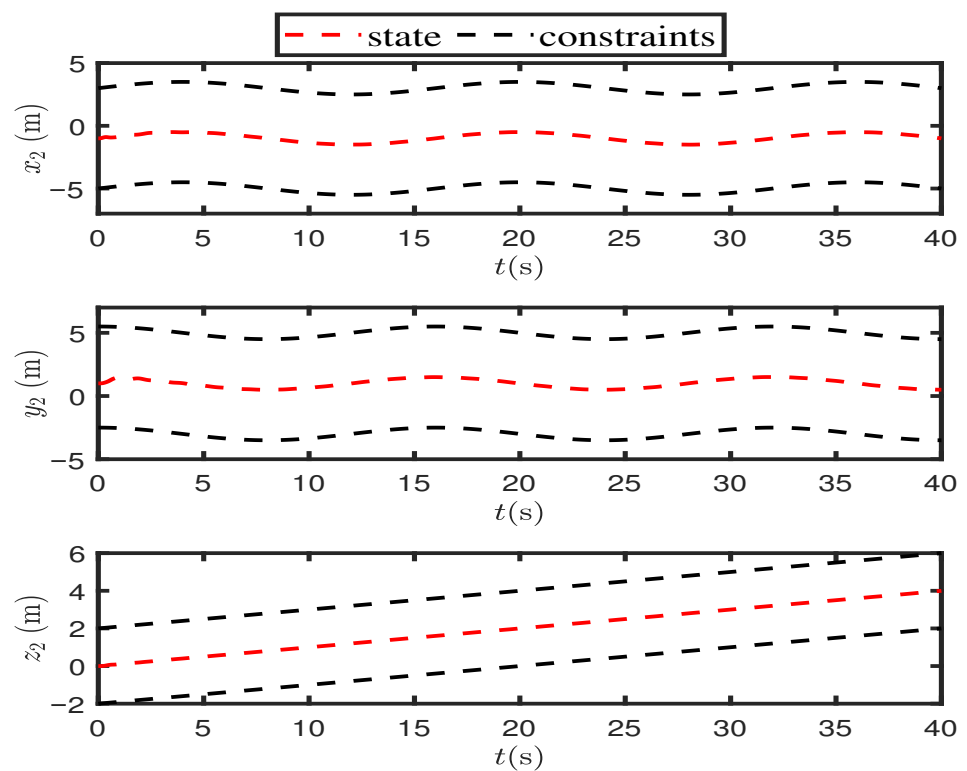


Figure 6. Position of QUAV 2 under state constraints.

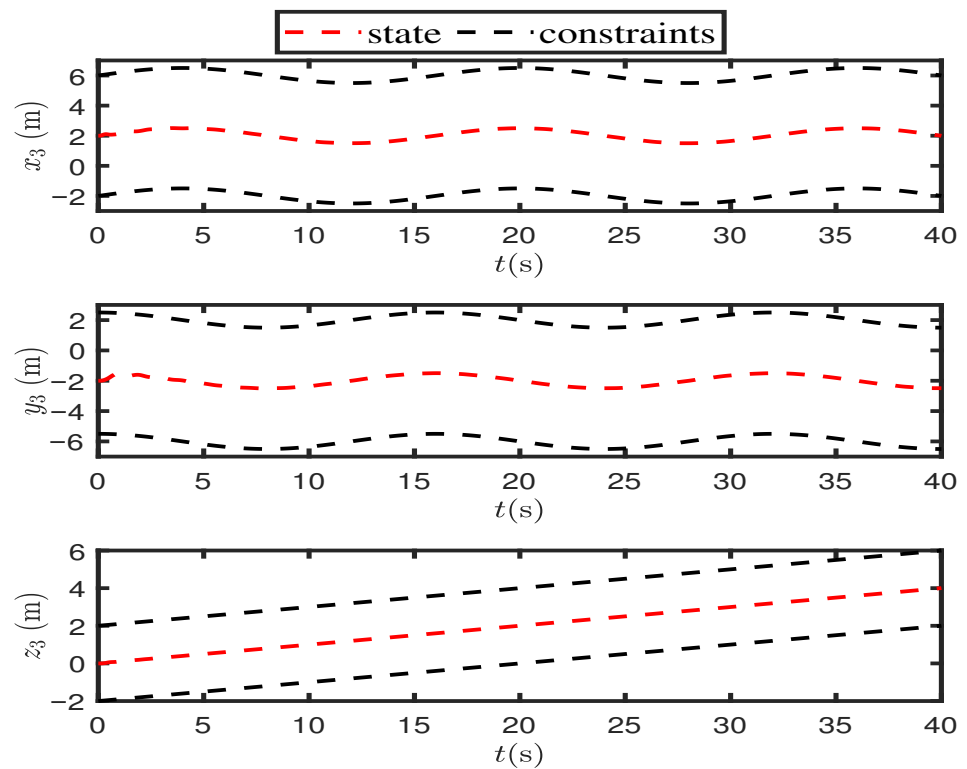


Figure 7. Position of QUAUV 3 under state constraints.

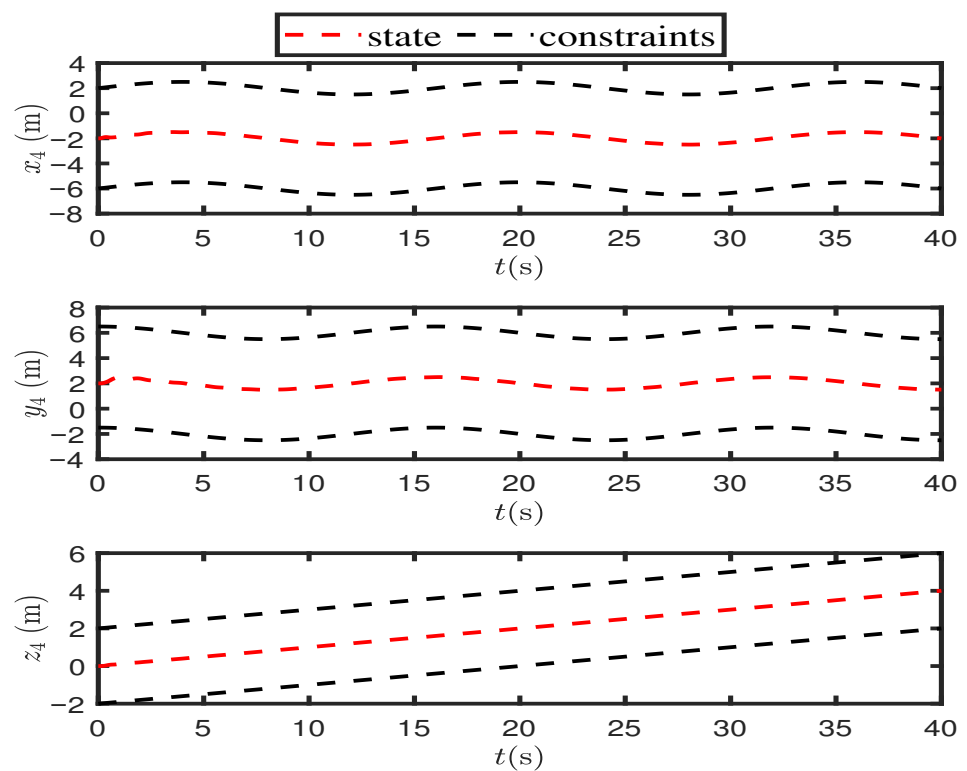


Figure 8. Position of QUAUV 4 under state constraints.

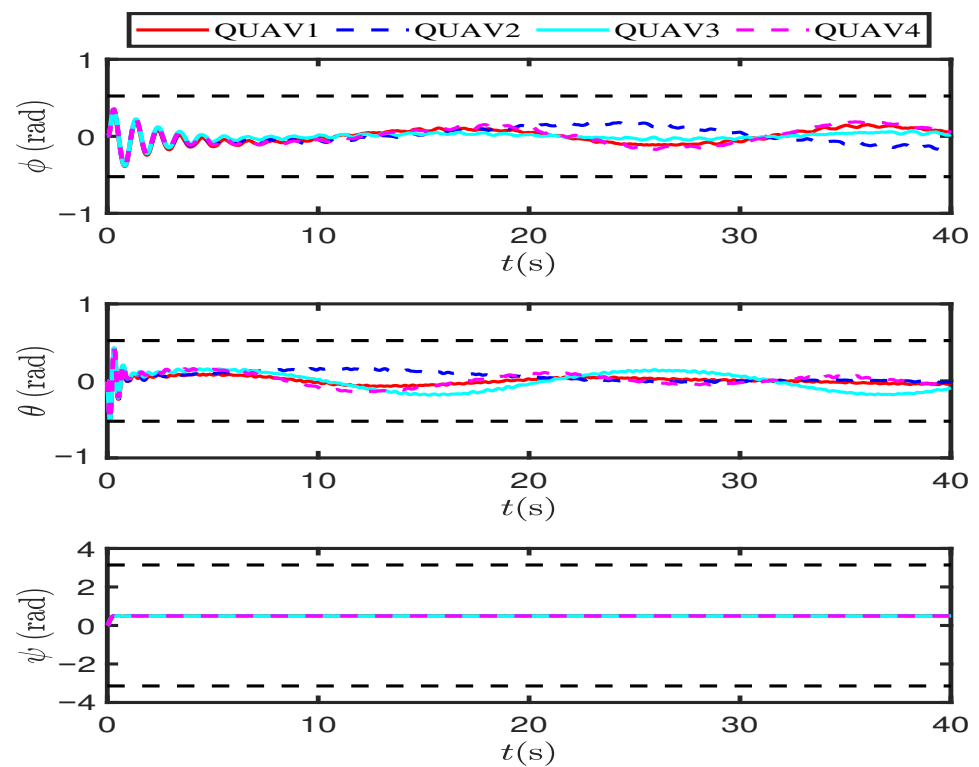


Figure 9. Attitude angle of each QUAV under state constraints.

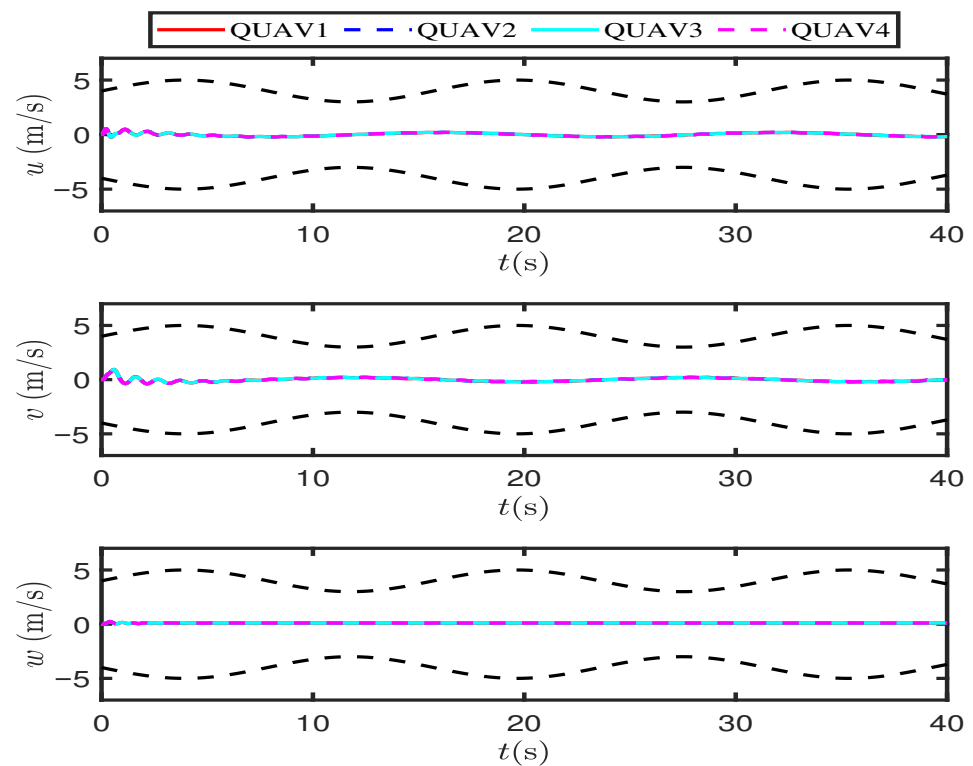


Figure 10. Velocity of each QUAV under state constraints.

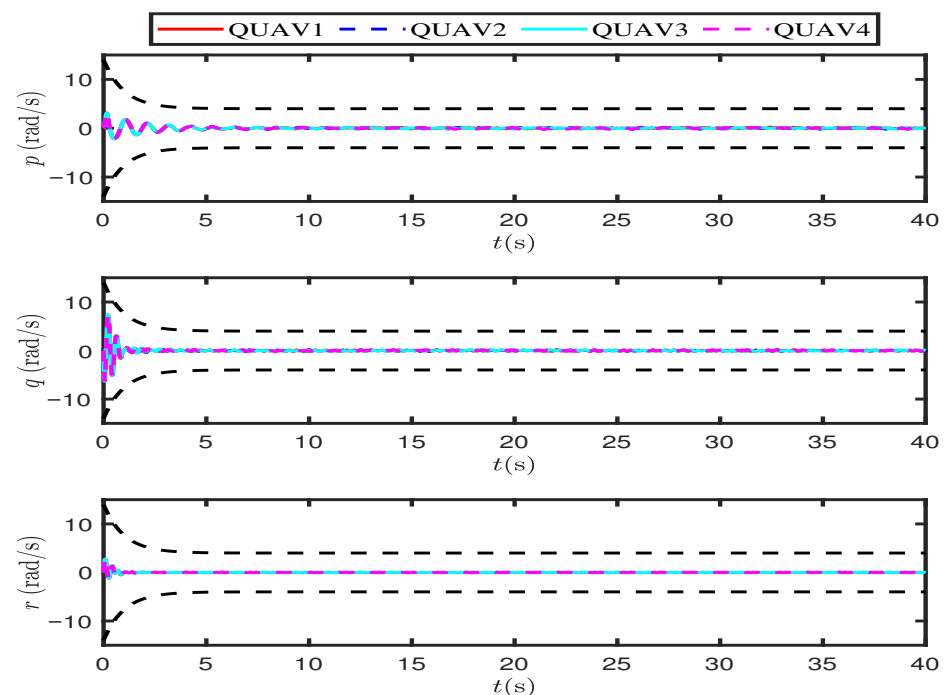


Figure 11. Angular rate of each QUAUV under state constraints.

Figures 18 and 19 take the three-dimensional torque of QUAUV 2 as the illustration object and conduct a comparative analysis of the event-triggered mechanism with the adaptive threshold proposed in this paper and one with a fixed threshold. Specifically, in Figure 18, the black solid line, red solid line, and blue solid line correspond to the control input signals under time-driven, AETM, and fixed threshold, respectively. Figure 19a shows the number of trigger under the AETM, and Figure 19b shows the number of triggers under the fixed threshold. Figure 19 illustrates that, with basic tracking performance guaranteed, the event-triggered strategy with adaptive threshold has fewer trigger counts and positive sampling intervals, which avoids Zeno behavior and eases the system communication burden.

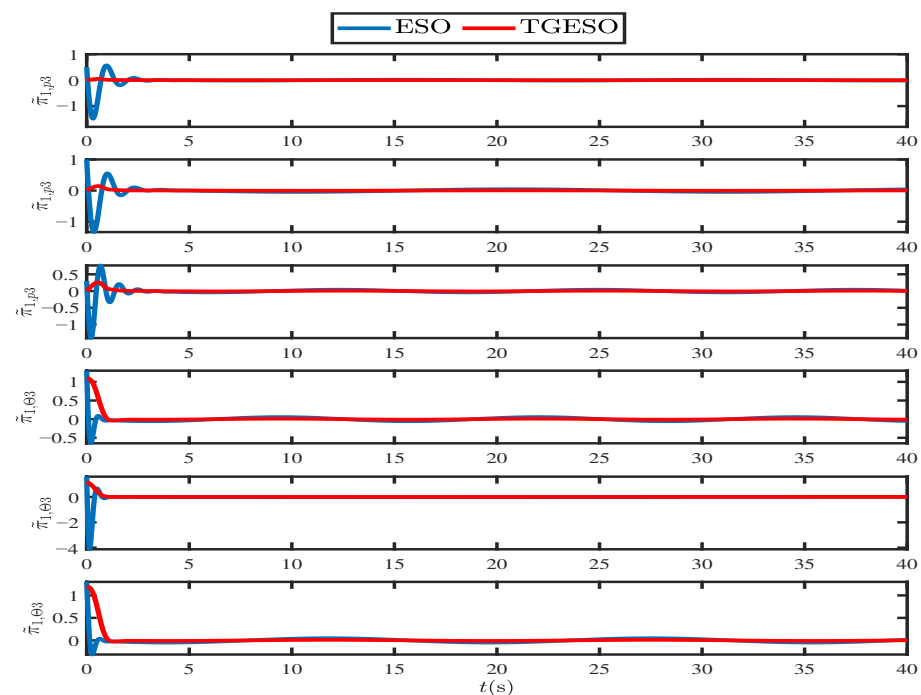


Figure 12. Comparative estimation errors under the TGESO and ESO.

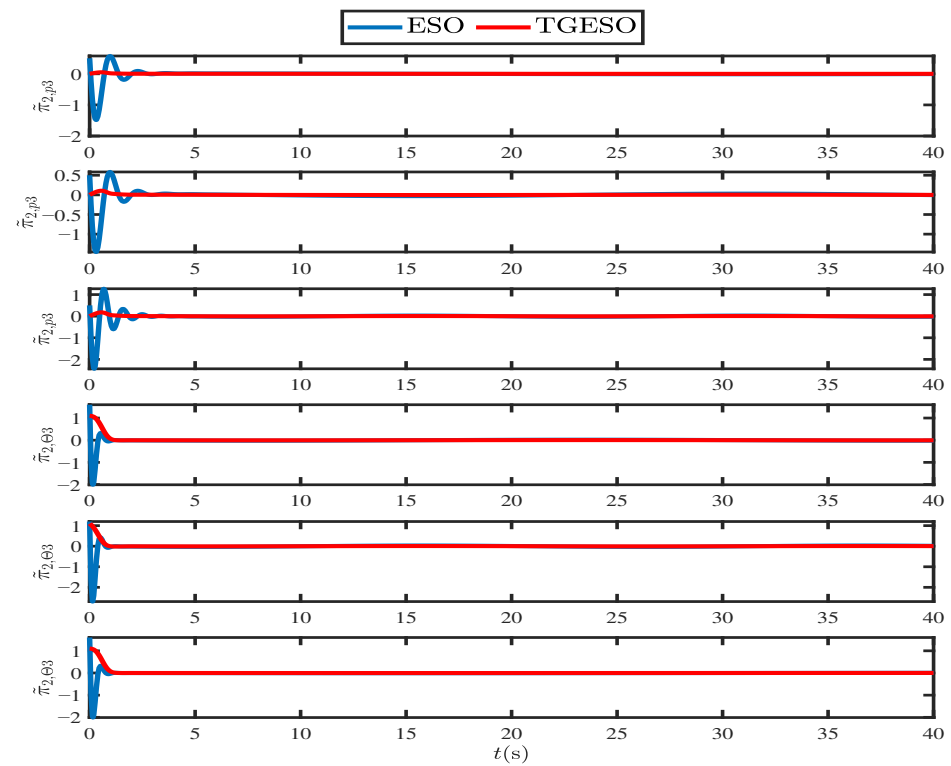


Figure 13. Comparative estimation errors under the TGESO and ESO.

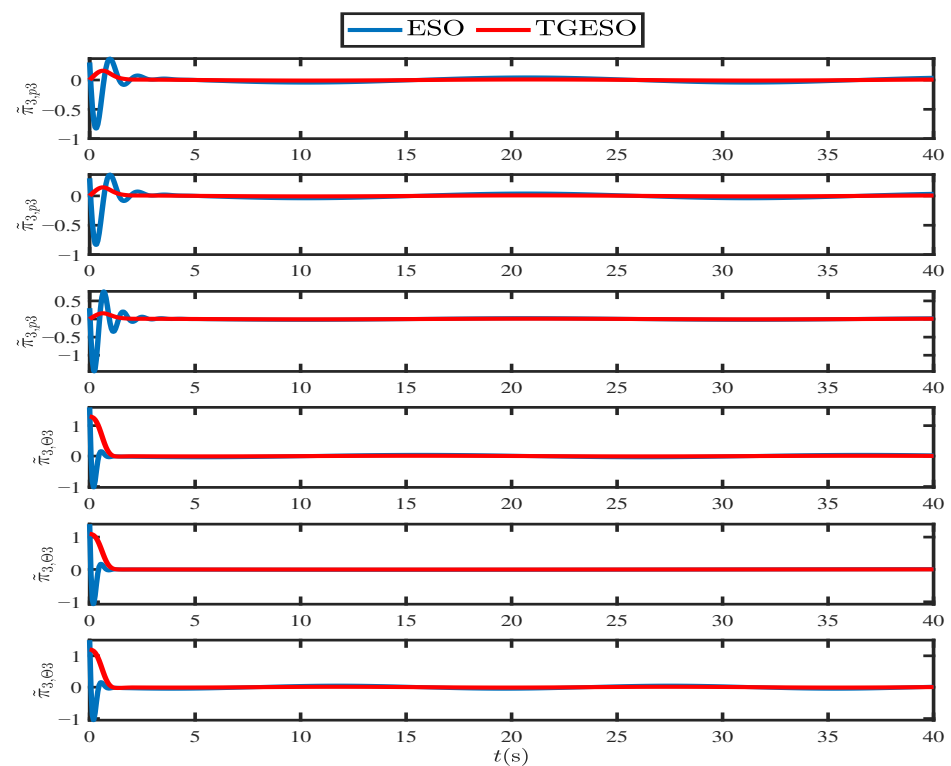


Figure 14. Comparative estimation errors under the TGESO and ESO.

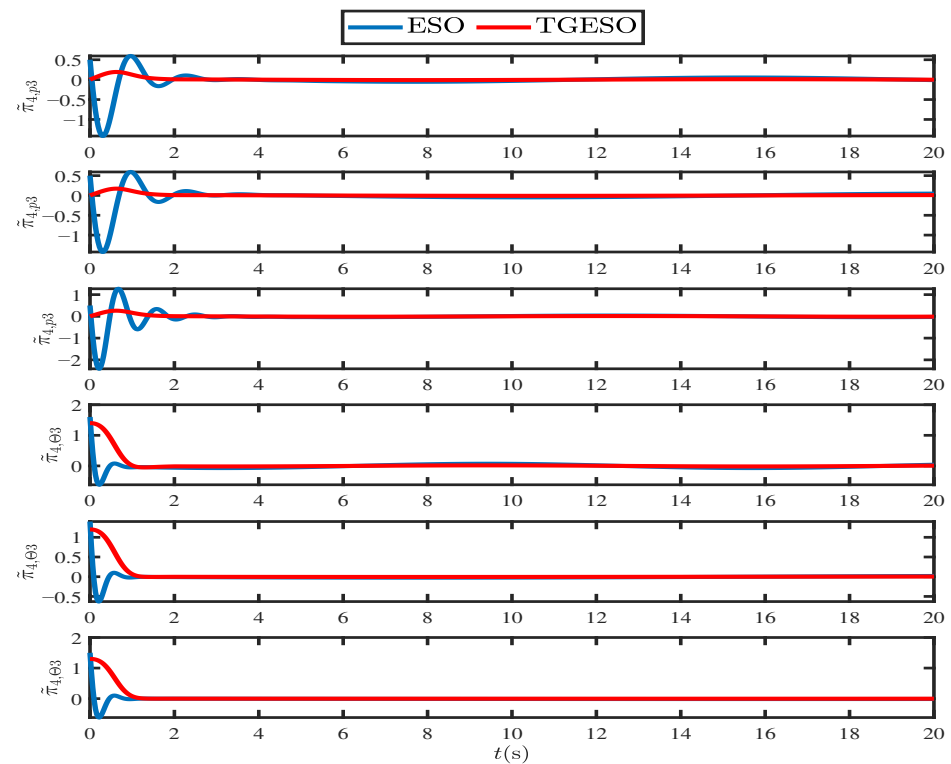


Figure 15. Comparative estimation errors under the TGESO and ESO.

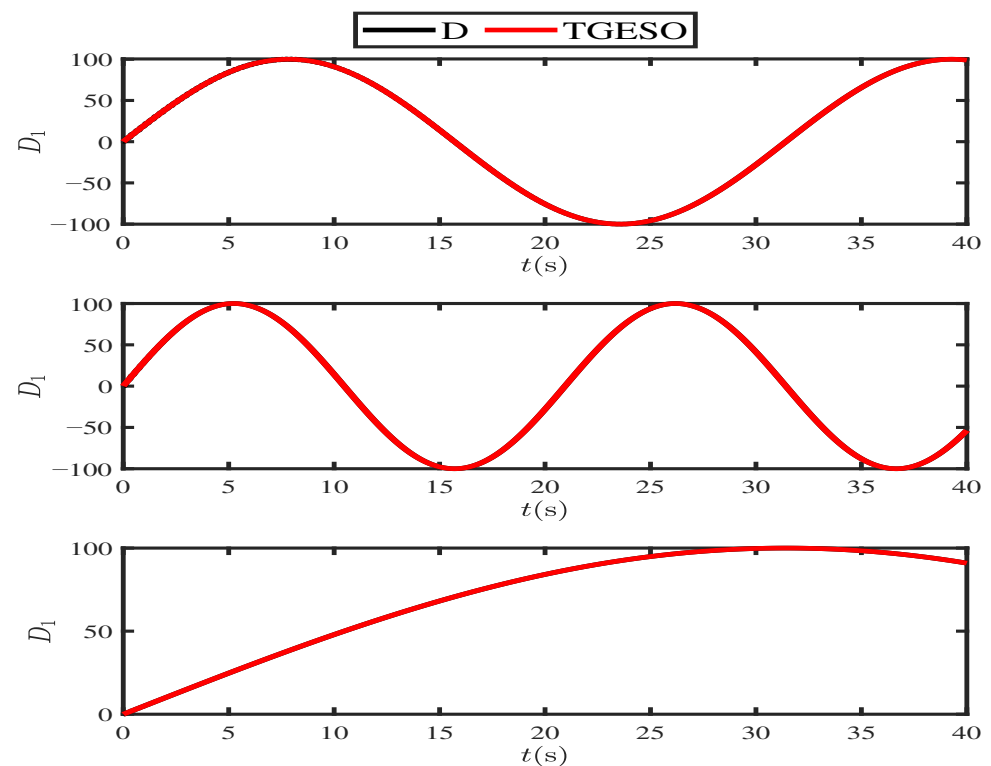


Figure 16. Estimation results of the TGESO under strong disturbances.

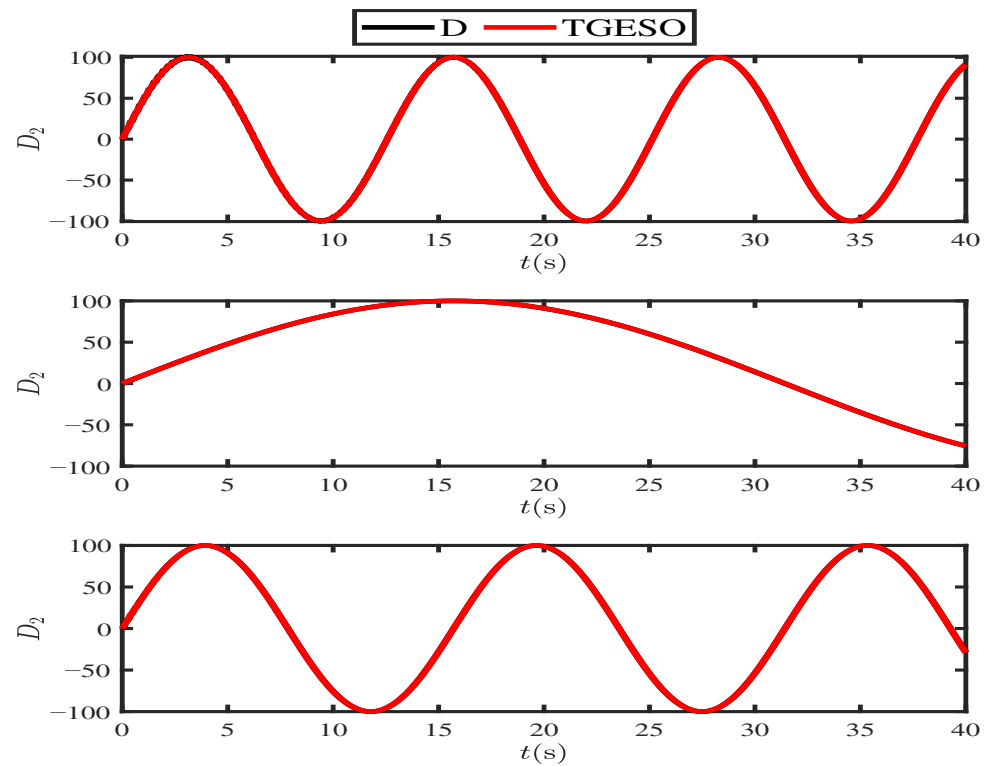


Figure 17. Estimation results of the TGESO under strong disturbances.

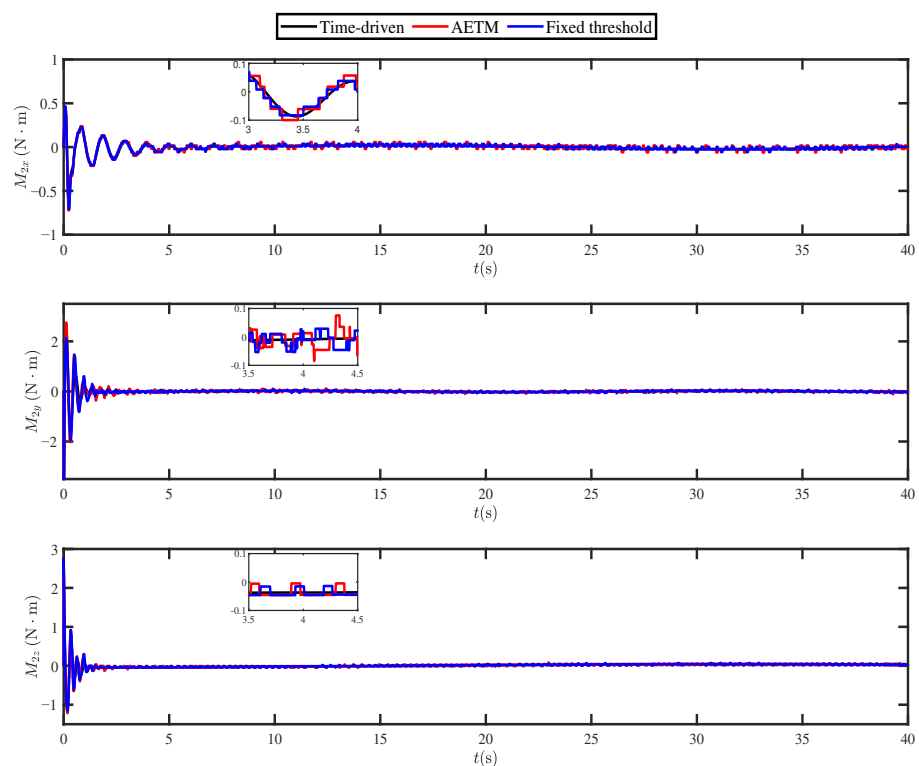


Figure 18. Comparison of control input signal under adaptive and fixed thresholds.

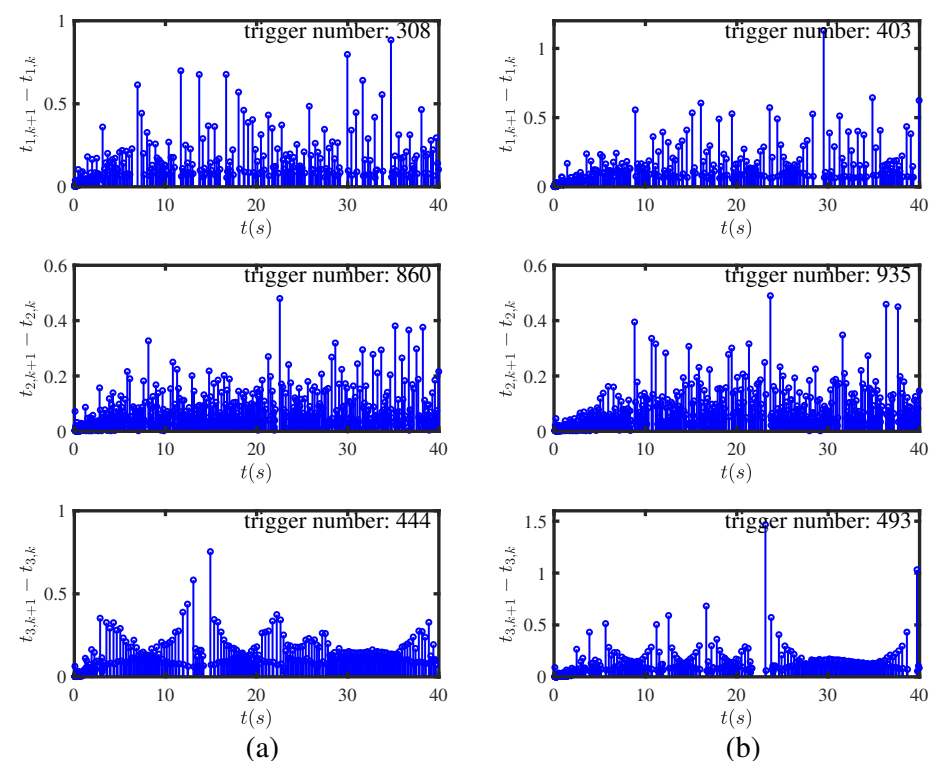


Figure 19. The trigger numbers for adaptive (a) and fixed (b) thresholds.

To more clearly observe the influence of different triggering mechanisms on system performance, a simulation period of 40s is used. The system's transmission cycle h , actual transmitted data volume n , and data transmission rate r are shown in Table 1.

Table 1. Comparison of system performance under different trigger mechanisms.

Method	n	h	r
Time-driven	40,000	0.001	100%
Fixed threshold	14,595	0.001	36%
AETM	13,419	0.001	33%

Table 1 shows that the QUAV formation system under the proposed AETM requires fewer actual data transmissions than the fixed-threshold scheme. This demonstrates that the developed AETM can further reduce the communication burden while preserving satisfactory tracking performance, thereby improving network resource utilization.

5. Conclusions

This paper studies the adaptive event-triggered formation tracking control problem for the QUAV formation system in the presence of full-state constraints and unknown external disturbances. Firstly, the TGESO designed specifically for external disturbances not only overcome the initial peaking explosion problem of the traditional ESO, but also exhibits superior estimation accuracy and fast response performance. Moreover, based on the backstepping method, a formation tracking scheme is developed, enabling all state variables of each QUAV to track the corresponding trajectory signals of the virtual leader without violating the prescribed state constraints. Then, the AETM is adopted in the QUAV formation system, which reduces unnecessary transmission of network resources. Finally, the efficacy of the proposed adaptive event-triggered consensus control algorithm

is validated by means of numerical simulations. In the future, the parameter tuning method and the issues involved in real-flight experiments will be further investigated.

Author Contributions: Conceptualization, K.Y.; methodology, K.Y. and G.H.; investigation, L.L. and G.H.; writing—original draft preparation, L.L. and G.H.; writing—review and editing, T.L. and K.Y.; supervision, K.Y.; project administration, L.L. and C.C.; funding acquisition, T.L. and C.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grants 52572455 and 52572487, the Shanxi Province Higher Education Institutions Science and Technology Innovation Program Project under Grant 2024L374, the Lvliang City Introducing High-level Scientific and Technological Talents Key Research and Development Project under Grant 2024RC28, the Shaanxi Provincial Education Department Service Local Special Plan Project under Grant 24JC038, the Hubei Key Laboratory of Intelligent Robot under Grant HBIR202403, and the 2023 Youth Innovation Team of Shaanxi Universities.

Data Availability Statement: All data generated or analyzed are included in this study.

Acknowledgments: The authors thank the colleagues for their constructive suggestions and research assistance throughout this study.

Conflicts of Interest: The authors declare no conflict of interest.

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