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Abstract

This paper presents an event-triggered cascade active disturbance rejection control (CADRC) approach for quadrotor trajectory tracking. The proposed method decouples the system into position and velocity subsystems, with dedicated extended state observers (ESOs) and controllers designed for each subsystem to achieve accurate estimation and compensation of system nonlinearities, coupling effects, and external disturbances. To further optimize computational resource utilization, a hybrid event-triggering mechanism incorporating both static and dynamic thresholds is developed. This mechanism updates system states and control commands only at triggering instants, significantly reducing computational overhead. Additionally, an online self-tuning method based on particle swarm optimization (PSO) is introduced to enhance controller adaptability. Simulation results validate the robustness and efficiency of the proposed approach.

Keywords: quadrotor UAV, trajectory tracking, cascade active disturbance rejection control, event-triggered mechanism, particle swarm optimization, extended state observer

1 Introduction

With the rapid advancement of unmanned aerial vehicle (UAV) technologies, quadrotors have demonstrated vast application potential across military [1, 2] and civilian [3, 4] domains due to their unique flight performance characteristics. As a vertical take-off and landing (VTOL) platform capable of stationary hovering and agile maneuvering, quadrotor systems exhibit superior environmental adaptability compared to fixed-wing UAVs, enabling the execution of complex missions within confined and challenging airspace. However, quadrotors are inherently underactuated systems with strongly coupled nonlinear dynamics. Addressing model uncertainties, inter-channel coupling effects, and nonlinearities to achieve stable control has become a focal point in current international research.

In the domain of traditional control methods, PID control [5, 6] has dominated early UAV control systems due to its simple structure and ease of implementation. PID control exhibits poor adaptability to nonlinear and strongly coupled systems, making it difficult to handle complex disturbances. To address this limitation, researchers have introduced sliding mode control (SMC) [7, 8]. The SMC controller demonstrates strong robustness against systems with parametric uncertainties. Modern control methods, such as adaptive control [9, 10] and model predictive control (MPC) [11, 12], have gradually gained attention. Adaptive control possesses the ability to actively adjust to dynamic systems, making it suitable for systems with uncertainties. During the control process, it continuously modifies its own parameters to adapt to variations in the controlled plant. However, adaptive control requires a mathematical model where the system structure is known, and uncertainties are limited to unknown parameters. MPC, rooted in optimization theory, is well-suited for constrained control problems. Nevertheless, its performance heavily depends on model accuracy.

From an implementation perspective, the constrained computational resources onboard UAV platforms necessitate stringent requirements for both real-time performance and computational efficiency in control algorithms. Current mainstream control methods typically employ fixed-frequency time-triggered mechanisms, which, while simple to implement, incur significant unnecessary computational and communication overhead during periods of stable flight conditions.

Event-triggered control (ETC) has emerged as an innovative control strategy and gained significant attention in the field of UAVs [13–15]. Unlike conventional time-triggered control (TTC), which operates with fixed sampling intervals and offers straightforward implementation, ETC presents a more resource-efficient alternative particularly valuable for systems with limited computational and communication capabilities. Rather than executing control updates periodically, this approach dynamically determines update instants based on real-time system state evaluations. Importantly, these efficiency improvements are achieved while maintaining guaranteed closed-loop stability, thereby optimizing resource utilization without compromising system performance [16, 17].

Active disturbance rejection control (ADRC), developed by Han in the 1990s [18], employs an extended state observer (ESO) to estimate and compensate disturbances in real time. Unlike conventional methods, ADRC requires no precise system model and demonstrates exceptional robustness and disturbance rejection capabilities.

Recent years have seen remarkable progress in ADRC theory. The observer design has evolved from nonlinear to linear ESO [19, 20] for easier tuning, with advanced variants like adaptive [21, 22], fuzzy [23, 24] and neural network [25] ESOs achieving better disturbance estimation. Researchers have also developed hybrid approaches by integrating ADRC with SMC [26], MPC [27] and adaptive control [28], significantly enhancing system performance. Furthermore, intelligent parameter tuning methods using grey wolf optimization [29] and reinforcement learning [30] have greatly improved practicality in real-world applications of ADRC.

This study focuses on the trajectory tracking control of quadrotor UAVs, with the main research contents outlined as follows:

1. A cascaded active disturbance rejection control (CADRC) scheme is proposed, where the system is decoupled into position and velocity subsystems. Separate ESOs and controllers are designed for each subsystem.
2. A hybrid event-triggering mechanism incorporating both static and dynamic thresholds is developed. This approach enables system state and control command updates only at triggered instants, significantly reducing computational resource consumption.
3. To enhance control system adaptability, an online self-tuning method based on particle swarm optimization (PSO) is introduced for automatic controller parameter adjustment.

2 Modeling

Quadrotor UAVs represent a typical underactuated and strongly coupled nonlinear system. Accurate modeling of such systems forms the basis for effective control. To accurately characterize the motion of quadrotor, the system structure is illustrated in Fig. 1.

Two coordinate systems are established: the body-fixed frame $B(O_b, X_b, Y_b, Z_b)$ and the inertial frame $E(O_e, X_e, Y_e, Z_e)$. During quadrotor motion, the inertial frame remains stationary as an absolute reference. The body-fixed frame varies with changes in quadrotor attitude. The inertial frame facilitates intuitive description of kinematic states such as UAV position and velocity. Conversely, the body-fixed frame proves more suitable for analyzing dynamic effects including aerodynamic forces and propulsion moments. Coordinate vector transformations between these frames are implemented through rotation matrices. These matrices are typically computed following the conventional sequence: yaw first, then pitch, and finally roll. The rotation matrices for yaw angle ψ , pitch angle θ , and roll angle ϕ are respectively given by:

$$R_\psi = \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}, R_\theta = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}, R_\phi = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \phi & -\sin \phi \\ 0 & \sin \phi & \cos \phi \end{bmatrix} \quad (1)$$

The transformation matrix from the body-fixed frame B to the inertial frame E , denoted as R_{B-E} , can be derived by exploiting the orthogonality property of rotation

matrices:

$$R_{B-E} = R_{E-B}^T = (R_\phi \cdot R_\theta \cdot R_\psi)^T$$

$$= \begin{bmatrix} \cos \psi \cos \theta & \cos \psi \sin \theta \sin \phi - \sin \psi \cos \phi & \cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi \\ \sin \psi \cos \theta & \sin \psi \sin \theta \sin \phi + \cos \psi \cos \phi & \sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi \\ -\sin \theta & \cos \theta \sin \phi & \cos \theta \cos \phi \end{bmatrix} \quad (2)$$

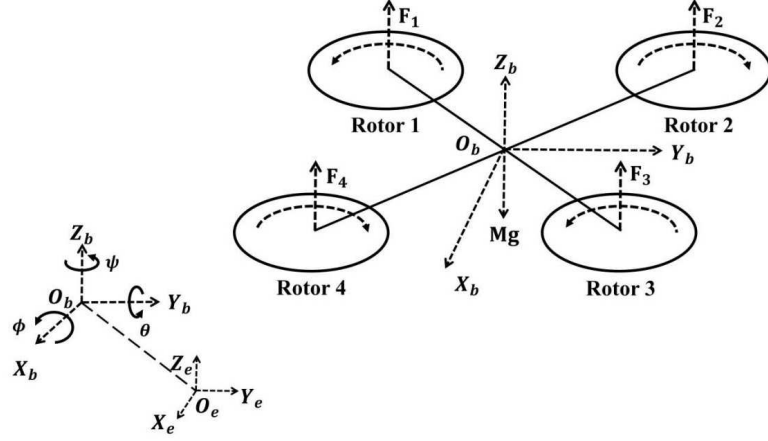


Fig. 1 Structure diagram of the Quadrotor.

In the modeling process, the following assumptions are adopted:

Assumption 1. The quadrotor UAV is modeled as a rigid body, neglecting elastic deformation during flight.

Assumption 2. The quadrotor UAV is considered a symmetric rigid body with uniformly distributed mass, where the center of gravity coincides with the origin of the body-fixed frame.

The gravitational force acting on the quadrotor in the inertial frame is expressed as:

$$M_e = [0 \ 0 \ Mg]^T \quad (3)$$

where M denotes the total mass of the quadrotor airframe, and g represents the gravitational acceleration constant.

The lift force acting on the quadrotor in the body-fixed frame is given by:

$$F_b = [0 \ 0 \ F_l]^T = \left[0 \ 0 \ \sum_{i=1}^4 F_i \right]^T \quad (4)$$

where F_l denotes the total lift force generated by all rotors, and $F_i (i = 1, \dots, 4)$ represents the individual lift force produced by the i^{th} rotor.

By combining Eq. (2) and (4), the expression of the lift force in the inertial frame can be derived as:

$$F_e = [F_x \ F_y \ F_z]^T = R_{B-E} F_b = F_l \begin{bmatrix} \cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi \\ \sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi \\ \cos \theta \cos \phi \end{bmatrix} \quad (5)$$

During flight, the aerodynamic drag acting on the quadrotor can be expressed in the following form:

$$F_a = [k_a \dot{x} \ k_a \dot{y} \ k_a \dot{z}]^T \quad (6)$$

where k_a denotes the aerodynamic drag coefficient.

For the quadrotor system, the moment expression is formulated as:

$$\tau = \begin{bmatrix} \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} = \begin{bmatrix} l(-F_1 + F_2 + F_3 - F_4)/\sqrt{2} \\ l(F_1 + F_2 - F_3 - F_4)/\sqrt{2} \\ k_c(F_1 - F_2 + F_3 - F_4) \end{bmatrix} \quad (7)$$

where l represents the length of the rotor arms, and k_c denotes the moment coefficient.

Based on Assumption 2, the moment of inertia matrix of the unloaded quadrotor can be derived as:

$$J = \begin{bmatrix} J_x & 0 & 0 \\ 0 & J_y & 0 \\ 0 & 0 & J_z \end{bmatrix} \quad (8)$$

The dynamic model of the quadrotor UAV is derived as:

$$\begin{cases} \ddot{x} = (F_x - k_a \dot{x})/M \\ \ddot{y} = (F_y - k_a \dot{y})/M \\ \ddot{z} = (F_z - k_a \dot{z})/M - g \\ \ddot{\phi} = \tau_x/J_x + \dot{\theta}\dot{\psi}(J_y - J_z)/J_x \\ \ddot{\theta} = \tau_y/J_y + \dot{\phi}\dot{\psi}(J_z - J_x)/J_y \\ \ddot{\psi} = \tau_z/J_z + \dot{\phi}\dot{\theta}(J_x - J_y)/J_z \end{cases} \quad (9)$$

By introducing virtual control variables U_1, U_2, U_3, U_4 in the control system, defined as:

$$[U_1 \ U_2 \ U_3 \ U_4]^T = [F_l \ \tau_x \ \tau_y \ \tau_z]^T \quad (10)$$

and combining with Eq. (4) and (7), the control input of the UAV can be derived as:

$$\begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \end{bmatrix} = \begin{bmatrix} F_l \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ -\frac{l}{\sqrt{2}} & \frac{l}{\sqrt{2}} & \frac{l}{\sqrt{2}} & -\frac{l}{\sqrt{2}} \\ \frac{l}{\sqrt{2}} & \frac{l}{\sqrt{2}} & -\frac{l}{\sqrt{2}} & -\frac{l}{\sqrt{2}} \\ k_c & -k_c & k_c & -k_c \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{bmatrix} \quad (11)$$

By combining Eq. (9) and (11), the control model for the quadrotor UAV with variable payload can be derived as:

$$\begin{cases} \ddot{x} = [U_1(\cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi) - k_a \dot{x}] / M \\ \ddot{y} = [U_1(\sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi) - k_a \dot{y}] / M \\ \ddot{z} = [U_1(\cos \theta \cos \phi) - k_a \dot{z}] / M - g \\ \ddot{\phi} = U_2 / J_x + \dot{\theta} \dot{\psi} (J_y - J_z) / J_x \\ \ddot{\theta} = U_3 / J_y + \dot{\phi} \dot{\psi} (J_z - J_x) / J_y \\ \ddot{\psi} = U_4 / J_z + \dot{\phi} \dot{\theta} (J_x - J_y) / J_z \end{cases} \quad (12)$$

3 Controller Design

3.1 Cascade ADRC Design with Event-Triggered Mechanism

Due to the physical structure of quadrotor, the control system is decoupled into an outer-loop position control and an inner-loop attitude control, with the controller architecture illustrated in Fig. 2.

Position control is achieved indirectly through attitude adjustment of the UAV. The system implements three sub-controllers in both the position and attitude loops, with parameters optimized via PSO. To address the motion characteristics of quadrotor, the sub-controllers are further stratified into position controllers and velocity controllers, constructing a CADRC controller.

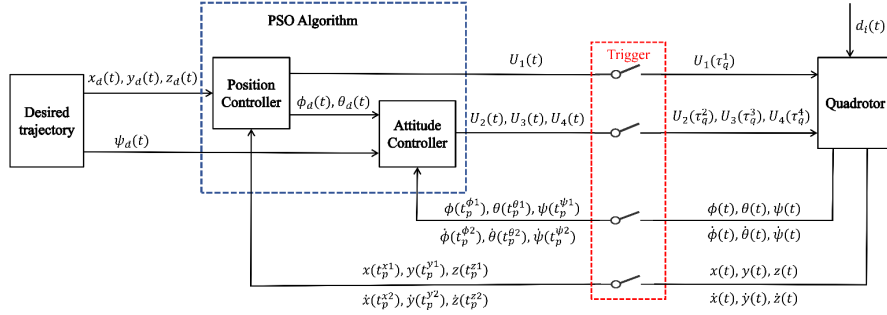


Fig. 2 A dual-loop CADRC framework based on event-triggered mechanism for the quadrotor.

Taking the altitude channel Z as an example, by introducing a new virtual control variable $h_z = z_2$, the dynamic relationship can be reformulated as:

Position Subsystem: $S_{z1} : \dot{\chi}_{z1} = h_z + \omega_{z1}$;

Velocity Subsystem: $S_{z2} : \dot{\chi}_{z2} = U_z + \omega_{z2}$

where ω_{z1} and ω_{z2} represent the disturbances and system nonlinearities in the two subsystems, respectively.

The design of CADRC comprises two key steps:

Step 1: For the subsystem S_{z1} , the ESO can be formulated as:

$$\begin{cases} \dot{\hat{\alpha}}_{z1} = \hat{\alpha}_{z2} + h_z + l_{z1}(\rho_{z1} - \hat{\alpha}_{z1}) \\ \dot{\hat{\alpha}}_{z2} = l_{z2}(\rho_{z1} - \hat{\alpha}_{z1}) \end{cases} \quad (13)$$

where $\hat{\alpha}_{zi}(i = 1, 2)$ are estimates of the state variable $\alpha_{zi}(i = 1, 2)$, and the design of the observer gain $l_{zi}(i = 1, 2)$ is required to satisfy the matrix $A_{z1} = \begin{bmatrix} -l_{z1} & 1 \\ -l_{z2} & 0 \end{bmatrix}$ being a Hurwitz matrix. The variable ρ_{z1} represents the sampled value of system state $z_1(t)$ at the event triggering instant t_p^{z1} for observer (13). This value serves as the state estimate for the current control cycle.

The event-triggering mechanism for this observer is designed as follows:

$$\begin{cases} \rho_{z1}(t) = z_1(t_p^{z1}), t \in [t_p^{z1}, t_{p+1}^{z1}) \\ t_{p+1}^{z1} = \inf \{t > t_p^{z1} \mid |z_1(t) - \rho_{z1}(t)| > \gamma_{z1}\} \end{cases} \quad (14)$$

The virtual control variable h_z is designed as follows:

$$h_z = k_{z1}(z_d - \hat{\alpha}_{z1}) - \hat{\alpha}_{z2} \quad (15)$$

where k_{z1} represents the tunable controller parameter.

Step 2: For the subsystem S_{z2} , the ESO can be formulated as:

$$\begin{cases} \dot{\hat{\beta}}_{z1} = \hat{\beta}_{z2} + \sigma_z + l_{z3}(\rho_{z2} - \hat{\beta}_{z1}) \\ \dot{\hat{\beta}}_{z2} = l_{z4}(\rho_{z2} - \hat{\beta}_{z1}) \end{cases} \quad (16)$$

where $\hat{\beta}_{zi}(i = 1, 2)$ denotes the estimated values of the state variables $\beta_{zi}(i = 1, 2)$. The observer gains $l_{zi}(i = 3, 4)$ must be designed such that the matrix $A_{z2} = \begin{bmatrix} -l_{z3} & 1 \\ -l_{z4} & 0 \end{bmatrix}$ is Hurwitz. The variable ρ_{z2} represents the sampled value of system state $z_2(t)$ at the event-triggering instant t_p^{z2} for observer (16).

The event-triggering mechanism for this observer is designed as follows:

$$\begin{cases} \rho_{z2}(t) = z_2(t_p^{z2}), t \in [t_p^{z2}, t_{p+1}^{z2}) \\ t_{p+1}^{z2} = \inf \{t > t_p^{z2} \mid |z_2(t) - \rho_{z2}(t)| > \gamma_{z2}\} \end{cases} \quad (17)$$

The observer triggering thresholds γ_{z1} and γ_{z2} are designed as fixed values.

The virtual control variable U_z is derived through the following design formulation:

$$U_z = k_{z2}(h_z - \hat{\beta}_{z1}) - \hat{\beta}_{z2} \quad (18)$$

where k_{z2} denotes the tunable controller gain.

The control design for the x and y channels in the position controller follows a similar approach to the Z channel. In these channels, the control variables U_x and U_y are computed by the controller based on the desired displacement values x_d and y_d .

In the position controller, the sampled values of virtual control variables U_x , U_y , U_z and yaw angle ψ at the event-triggering instant t_p^ψ are utilized to compute the desired roll and pitch angles ϕ_d , θ_d and The control variable U_1 :

$$\phi_d = \arctan \left(\cos \theta(t_q^\theta) \frac{U_x \sin \psi(t_p^\psi) - U_y \cos \psi(t_p^\psi)}{U_z} \right) \quad (19)$$

$$\theta_d = \arctan \left(\frac{U_x \cos \psi(t_p^\psi) + U_y \sin \psi(t_p^\psi)}{U_z} \right) \quad (20)$$

$$U_1 = \frac{U_z}{\cos \phi(t_q^\phi) \cos \theta(t_q^\theta)} \quad (21)$$

The variables σ_x , σ_y , and σ_z are computed based on the sampled values of control variable $U_1(t)$. The event-triggering mechanism for this controller is designed as follows:

$$\left\{ \begin{array}{l} \sigma_1(t) = U_1(\tau_q^1), t \in [\tau_q^1, \tau_{q+1}^1) \\ \sigma_x(t) = \sigma_1(t) (\cos \psi(t_p^\psi) \sin \theta(t_p^\theta) \cos \phi(t_p^\phi) + \sin \psi(t_p^\psi) \sin \phi(t_p^\phi)) \\ \sigma_y(t) = \sigma_1(t) (\sin \psi(t_p^\psi) \sin \theta(t_p^\theta) \cos \phi(t_p^\phi) - \cos \psi(t_p^\psi) \sin \phi(t_p^\phi)) \\ \sigma_z(t) = \sigma_1(t) \cos \phi(t_p^\phi) \cos \theta(t_p^\theta) \\ \tau_{q+1}^1 = \inf \left\{ t > \tau_q^1 \mid |U_1(t) - \sigma_1(t)| > M_1^1 e^{-M_2^1 \hat{e}_t} \right\} \end{array} \right. \quad (22)$$

where M_1^1 represents the threshold extremum factor and M_2^1 denotes the error sensitivity factor. The controller triggering threshold is determined by the trajectory estimation error $\hat{e}_t$ through the following relation:

$$\hat{e}_t = \sqrt{(\hat{\alpha}_{x1} - x_d)^2 + (\hat{\alpha}_{y1} - y_d)^2 + (\hat{\alpha}_{z1} - z_d)^2} \quad (23)$$

Remark 1. For quadrotor systems exhibiting strong coupling dynamics, the tracking error should be evaluated as a three-dimensional trajectory deviation. The event-triggered mechanism prevents real-time state measurements in Eq. (23). The ESO estimates are consequently employed for both event-triggering conditions (14), (17) and trajectory tracking error computation.

The attitude channel control design follows a similar approach to the position channel. The controller event-triggering mechanism differs slightly from Eq. (22). Taking the roll channel as an example, its event-triggering mechanism is formulated as:

$$\left\{ \begin{array}{l} \sigma_2(t) = U_2(\tau_q^2), t \in [\tau_q^2, \tau_{q+1}^2) \\ \tau_{q+1}^2 = \inf \left\{ t > \tau_q^2 \mid |U_2(t) - \sigma_2(t)| > M_1^2 e^{-M_2^2 |\hat{\alpha}_{\phi 1} - \phi_d|} \right\} \end{array} \right. \quad (24)$$

3.2 Online Self-Tuning of CADRC Parameters based on Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm finds optimal solutions by simulating collective behaviors observed in biological groups such as bird flocks or fish schools. This study develops an ADRC strategy with online parameter self-tuning based on PSO. The cascade subcontroller requires tuning for six parameters $[l_1, l_2, l_3, l_4, k_1, k_2]$, while the complete quadrotor control system involves 36 tunable parameters in total.

Introducing observer bandwidth and controller bandwidth simplifies the parameter tuning process. The controller parameters can be systematically determined through the following bandwidth-based relationships:

$$l_1 = \omega_{o1}^2, l_2 = 2\omega_{o1}, l_3 = \omega_{o2}^2, l_4 = 2\omega_{o2}, k_1 = \omega_c^2, k_2 = 2\omega_c \quad (25)$$

In both attitude and position controllers, the sub-controllers exhibit control objectives of comparable magnitude. Consequently, identical parameter sets can be employed for both attitude and position control. This simplification reduces the total number of tunable parameters from thirty-six to six, with three parameters allocated for attitude control and three for position control, while maintaining guaranteed control effectiveness. The parameters to be adjusted are $[\omega_{oa1}, \omega_{oa2}, \omega_{ca}, \omega_{op1}, \omega_{op2}, \omega_{cp}]$.

Remark 2. During the controller parameter tuning process, the quadrotor cannot derive displacement control inputs directly from the reference trajectory, but requires indirect adjustment through desired attitude values. The six controllers function as a coupled system when acting on the controlled plant, which inherently constrains individual sub-controller tuning.

In the PSO, each particle maintains its own position and velocity vectors, which are updated according to the following rules:

$$V_i^{t+1} = wV_i^t + c_1r_1(P_{besti} - X_i^t) + c_2r_2(G_{best} - X_i^t) \quad (26)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (27)$$

where i indexes particles in the swarm, V_i^t and X_i^t denote the velocity and position of particle i at iteration t . Each particle tracks its historical best position P_{besti} , while G_{best} represents the global optimum. The algorithm employs an inertia weight w , acceleration constants c_1 and c_2 , along with uniformly distributed random numbers $r_1, r_2 \in [0, 1]$. Through iterative updates of these particle states, the algorithm efficiently explores the solution space.

In the PSO algorithm, adjusting the inertia weight w enables appropriate solutions for different optimization problems. Typically, larger w values facilitate global exploration, allowing particles to search broader regions of the solution space. Conversely, smaller w values emphasize local refinement, promoting faster convergence toward optimal solutions. This study implements a linear decreasing inertia weight strategy to dynamically adjust w , with the update rule formulated as:

$$w = w_{ini} - \frac{t}{t_{max}}(w_{ini} - w_{fin}) \quad (28)$$

where w_{ini} and w_{fin} denote the initial and final values of the inertia weight, respectively, while t_{max} specifies the maximum number of iterations.

The fitness function directly determines optimization effectiveness by quantitatively evaluating particle quality. While an overly complex design may reduce iteration counts, the computational overhead can compromise overall efficiency. Therefore, fitness function design must balance guidance capability with computational efficiency.

For trajectory tracking objectives, the tracking error between the quadrotor and its reference trajectory serves as the key performance metric. For quadrotor systems operating in three-dimensional space, the trajectory tracking error is mathematically defined as:

$$e_q = \sqrt{(x - x_d)^2 + (y - y_d)^2 + (z - z_d)^2} \quad (29)$$

In quadrotor flight control, attitude stability and trajectory tracking accuracy hold equal importance. To quantitatively evaluate oscillation severity in attitude angles, this study employs standard deviation as the performance metric. Taking the roll angle ϕ as an example, its standard deviation is computed as:

$$s_\phi = \sqrt{\frac{1}{n} \sum_{i=1}^n (\phi_i - \bar{\phi})^2} \quad (30)$$

where n denotes the sample size and $\bar{\phi}$ represents the sample mean.

The fitness function designed in this study is formulated as:

$$Y = a \int_0^t \tau e_q(\tau) d\tau + b (s_\phi + s_\theta + s_\psi) \quad (31)$$

where a and b represent positive weighting coefficients, and s_ϕ , s_θ , and s_ψ denote the standard deviations of roll, pitch, and yaw angles, respectively. The function design incorporates time as an error weighting factor. Under this formulation, the fitness function output Y exhibits an inverse correlation with controller performance—lower Y values indicate superior control effectiveness.

Remark 3. Quadrotors require flight control systems that simultaneously satisfy both trajectory tracking precision and attitude stability requirements. Simulation results demonstrate that omitting attitude angle constraints in the fitness function design leads to rapid trajectory convergence at the expense of pronounced high-frequency attitude oscillations, ultimately degrading actual flight performance.

To enable online self-tuning via the PSO algorithm, the following event-triggering mechanism is implemented:

$$\begin{cases} \omega_{(\cdot)} = \omega_{oa}, \omega_{ca}, \omega_{op}, \omega_{cp} \\ \omega_{(\cdot)}(t) = \omega_{(\cdot)}(t_p), t \in [t_p, t_{p+1}) \\ t_{p+1} = \inf \{t > t_p + \bar{t} | e_q(t) > \gamma_p\} \end{cases} \quad (32)$$

where t_p denotes the triggering instant for parameter adaptation, while t_{p+1} represents the subsequent triggering instant. The minimum triggering interval $\bar{t}$ and

designed constant threshold γ_p collectively prevent Zeno behavior through enforced time separation.

The integration of PSO for online parameter tuning in CADRC proceeds through the following steps:

Step 1: Initialize the particle swarm when either first-time operation occurs, or tracking error exceeds the threshold while maintaining the minimum triggering interval;

Step 2: Execute PSO to determine globally optimal parameters through iterative computation;

Step 3: Update controller parameters and compute real-time tracking error.

4 Stability Analysis

4.1 Convergence Analysis of the Cascade Extended State Observer

The estimation error of the Cascade Extended State Observer (CESO) is formally defined as $\tilde{\alpha}_i = \alpha_i - \hat{\alpha}_i$, $\tilde{\beta}_i = \beta_i - \hat{\beta}_i$, ($i = 1, 2$). Combining Eqs. (13) and (16), the dynamics of the estimation error system can be derived as:

$$\begin{cases} \dot{\tilde{\alpha}}_1 = \dot{\alpha}_1 - \dot{\hat{\alpha}}_1 = -l_1 \tilde{\alpha}_1 + \tilde{\alpha}_2 - l_1 (\rho_1 - \alpha_1) \\ \dot{\tilde{\alpha}}_2 = \dot{\alpha}_2 - \dot{\hat{\alpha}}_2 = -l_2 \tilde{\alpha}_1 + \dot{\omega}_1 - l_2 (\rho_1 - \alpha_1) \end{cases} \quad (33)$$

$$\begin{cases} \dot{\tilde{\beta}}_1 = \dot{\beta}_1 - \dot{\hat{\beta}}_1 = -l_3 \tilde{\beta}_1 + \tilde{\beta}_2 - l_3 (\rho_2 - \beta_1) \\ \dot{\tilde{\beta}}_2 = \dot{\beta}_2 - \dot{\hat{\beta}}_2 = -l_4 \tilde{\beta}_1 + \dot{\omega}_2 - l_4 (\rho_2 - \beta_1) \end{cases} \quad (34)$$

Define $\delta_1 = \rho_1 - \alpha_1$, $\delta_2 = \rho_2 - \beta_1$. The system (33), (34) can be written as:

$$\begin{cases} \dot{\tilde{\alpha}} = A_1 \tilde{\alpha} - B_1 \delta_1 + B_3 \dot{\omega}_1 \\ \dot{\tilde{\beta}} = A_2 \tilde{\beta} - B_2 \delta_2 + B_3 \dot{\omega}_2 \end{cases} \quad (35)$$

where:

$$\begin{aligned} \dot{\tilde{\alpha}} &= \begin{bmatrix} \dot{\tilde{\alpha}}_1 \\ \dot{\tilde{\alpha}}_2 \end{bmatrix}, \dot{\tilde{\beta}} = \begin{bmatrix} \dot{\tilde{\beta}}_1 \\ \dot{\tilde{\beta}}_2 \end{bmatrix}, A_1 = \begin{bmatrix} -l_1 & 1 \\ -l_2 & 0 \end{bmatrix}, A_2 = \begin{bmatrix} -l_3 & 1 \\ -l_4 & 0 \end{bmatrix} \\ B_1 &= \begin{bmatrix} l_1 \\ l_2 \end{bmatrix}, B_2 = \begin{bmatrix} l_3 \\ l_4 \end{bmatrix}, B_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{aligned}$$

Before proceeding with the proof, we state the following assumption:

Assumption 3. All external disturbances and unmodeled dynamics, along with their time derivatives, are uniformly bounded. Specifically, there exist positive constants $\bar{\omega}_i > 0$ such that $\|\dot{\omega}_i\| \leq \bar{\omega}_i$.

Theorem 1. Consider the quadrotor system (12), equipped with the ESOs (13), (16) and event-triggered mechanisms (14), (17). There exist observer gains l_i ($i = 1, 2, 3, 4$) such that all estimation errors converge to an arbitrarily small compact set.

Proof. For the coupled estimation error dynamics of the quadrotor system, consider the composite Lyapunov function:

$$V_1 = \tilde{\alpha}^T P_1 \tilde{\alpha} + \tilde{\beta}^T P_2 \tilde{\beta} \quad (36)$$

The matrices P_1 and P_2 are symmetric positive-definite and satisfy $A_i^T P_i + P_i A_i = -I$ ($i = 1, 2$). The time derivative of V_1 is:

$$\begin{aligned} \dot{V}_1 &= \dot{\tilde{\alpha}}^T P_1 \tilde{\alpha} + \tilde{\alpha}^T P_1 \dot{\tilde{\alpha}} + \dot{\tilde{\beta}}^T P_2 \tilde{\beta} + \tilde{\beta}^T P_2 \dot{\tilde{\beta}} \\ &= (A_1 \tilde{\alpha} - B_1 \delta_1 + B_3 \dot{\omega}_1)^T P_1 \tilde{\alpha} + \tilde{\alpha}^T P_1 (A_1 \tilde{\alpha} - B_1 \delta_1 + B_3 \dot{\omega}_1) \\ &\quad + (A_2 \tilde{\beta} - B_2 \delta_2 + B_3 \dot{\omega}_2)^T P_2 \tilde{\beta} + \tilde{\beta}^T P_2 (A_2 \tilde{\beta} - B_2 \delta_2 + B_3 \dot{\omega}_2) \\ &= \tilde{\alpha}^T (A_1^T P_1 + P_1 A_1) \tilde{\alpha} - 2\tilde{\alpha}^T P_1 B_1 \delta_1 + 2\tilde{\alpha}^T P_1 B_3 \dot{\omega}_1 \\ &\quad + \tilde{\beta}^T (A_2^T P_2 + P_2 A_2) \tilde{\beta} - 2\tilde{\beta}^T P_2 B_2 \delta_2 + 2\tilde{\beta}^T P_2 B_3 \dot{\omega}_2 \end{aligned} \quad (37)$$

Given that $|\dot{\omega}_i| \leq \bar{\omega}_i$ and the triggering condition enforces $\delta_i \leq \gamma_i$ ($i = 1, 2$), Eq. (37) can be derived:

$$\begin{aligned} \dot{V}_1 &\leq -\|\tilde{\alpha}\|^2 + 2\|\tilde{\alpha}\| (\|P_1 B_3\| \bar{\omega}_1 - \|P_1 B_1\| \gamma_1) \\ &\quad - \|\tilde{\beta}\|^2 + 2\|\tilde{\beta}\| (\|P_2 B_3\| \bar{\omega}_2 - \|P_2 B_2\| \gamma_2) \end{aligned} \quad (38)$$

Let:

$$\begin{aligned} c_1 &= \|P_1 B_3\| \bar{\omega}_1 - \|P_1 B_1\| \gamma_1 \\ c_2 &= \|P_2 B_3\| \bar{\omega}_2 - \|P_2 B_2\| \gamma_2 \end{aligned}$$

When the errors satisfy $\|\tilde{\alpha}\| > c_1$ and $\|\tilde{\beta}\| > c_2$, the $\dot{V}_1$ fulfills $\dot{V}_1 \leq 0$, indicating convergence of the ESO estimation errors. The errors $\tilde{\alpha}$ and $\tilde{\beta}$ are uniformly ultimately bounded. Their convergence thresholds can be arbitrarily adjusted by properly tuning the observer gains l_i ($i = 1, 2, 3, 4$), allowing the error bounds to be constrained within any prescribed compact set.

4.2 Stability Analysis of Control Systems

Assumption 4. The reference signal v and its derivative $\dot{v}$ are bounded.

Let v_1 and v_2 represent v and $\dot{v}$, respectively. The controller tracking errors are defined as $e_1 = \alpha_1 - v_1$ and $e_2 = \beta_1 - h$. By combining Eqs. (15), (18) with the estimation error dynamics, the tracking error system dynamics can be derived as follows:

$$\begin{aligned} \dot{e}_1 &= \dot{\alpha}_2 - v_2 = \alpha_2 + h - v_2 \\ &= k_1(v_1 - \hat{\alpha}_1) + v_2 - \hat{\alpha}_2 + \alpha_2 - v_2 \\ &= -k_1 e_1 + k_1 \tilde{\alpha}_1 + \tilde{\alpha}_2 \end{aligned} \quad (39)$$

$$\begin{aligned} \dot{e}_2 &= \dot{\beta}_2 - \dot{h} = \beta_2 + \sigma - \dot{h} \\ &= k_2(h - \hat{\beta}_1) + h - \hat{\beta}_2 + \beta_2 - \dot{h} + [U(\tau_q) - U(t)] \\ &= -k_2 e_2 + k_2 \tilde{\beta}_1 + \tilde{\beta}_2 + [U(\tau_q) - U(t)] \end{aligned} \quad (40)$$

where $[U(\tau_q) - U(t)]$ represents the error introduced by the event-triggered mechanism of the controller.

Theorem 2. Consider the quadrotor system described by Eq. (12), equipped with the controller (18) and subject to event-triggered mechanisms (22) and (24). There exist controller gains k_1 and k_2 that guarantee bounded tracking errors.

Proof. The Lyapunov function is defined as:

$$V_2 = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 \quad (41)$$

The time derivative is given by:

$$\begin{aligned} \dot{V}_2 &= e_1 \dot{e}_1 + e_2 \dot{e}_2 \\ &= e_1 (-k_1 e_1 + k_1 \tilde{\alpha}_1 + \tilde{\alpha}_2) + e_2 \left(-k_2 e_2 + k_2 \tilde{\beta}_1 + \tilde{\beta}_2 + [U(\tau_q) - U(t)] \right) \\ &= -k_1 e_1^2 + k_1 e_1 \tilde{\alpha}_1 + e_1 \tilde{\alpha}_2 - k_2 e_2^2 + k_2 e_2 \tilde{\beta}_1 + e_2 \tilde{\beta}_2 + e_2 [U(\tau_q) - U(t)] \end{aligned} \quad (42)$$

By applying Young's inequality, we obtain:

$$\begin{aligned} k_1 e_1 \tilde{\alpha}_1 &\leq \frac{v_1 e_1^2}{2} + \frac{k_1^2 \tilde{\alpha}_1^2}{2v_1}, \quad e_1 \tilde{\alpha}_2 \leq \frac{v_2 e_1^2}{2} + \frac{\tilde{\alpha}_2^2}{2v_2} \\ k_2 e_2 \tilde{\beta}_1 &\leq \frac{v_3 e_2^2}{2} + \frac{k_2^2 \tilde{\beta}_1^2}{2v_3}, \quad e_2 \tilde{\beta}_2 \leq \frac{v_4 e_2^2}{2} + \frac{\tilde{\beta}_2^2}{2v_4} \\ e_2 [U(\tau_q) - U(t)] &\leq \frac{v_5 e_2^2}{2} + \frac{[U(\tau_q) - U(t)]^2}{2v_5} \end{aligned} \quad (43)$$

where $v_i (i = 1, \dots, 5)$ are positive constants. Substituting Eq. (43) into (42) yields:

$$\dot{V}_2 = -\kappa_1 e_1^2 - \kappa_2 e_2^2 + \Pi \quad (44)$$

where:

$$\begin{aligned} \kappa_1 &= k_1 - \frac{v_1}{2} - \frac{v_2}{2} \\ \kappa_2 &= k_2 - \frac{v_3}{2} - \frac{v_4}{2} - \frac{v_5}{2} \\ \Pi &= \frac{k_1^2 \tilde{\alpha}_1^2}{2v_1} + \frac{\tilde{\alpha}_2^2}{2v_2} + \frac{k_2^2 \tilde{\beta}_1^2}{2v_3} + \frac{\tilde{\beta}_2^2}{2v_4} + \frac{[U(\tau_q) - U(t)]^2}{2v_5} \end{aligned} \quad (45)$$

Theorem 1 guarantees the boundedness of the state variables $\tilde{\alpha}$ and $\tilde{\beta}$. Furthermore, by design of the event-triggering mechanisms, $[U(\tau_q) - U(t)]$ is bounded. Through proper selection of control gains k_1 and k_2 to ensure $\kappa_1 > 0$ and $\kappa_2 > 0$, all tracking errors are uniformly ultimately bounded, and the closed-loop system achieves asymptotic stability.

4.3 Analysis of the Zeno Phenomenon

The Zeno phenomenon, which refers to the occurrence of infinitely many triggering events within a finite time interval, must be rigorously excluded in the proposed ETC

scheme. Since both the observer and controller incorporate event-triggered mechanisms, a formal proof is required to demonstrate that the designed triggering conditions prevent Zeno behavior.

Theorem 3. For the quadrotor system described by Eq. (12) with event-triggering mechanisms (14), (17), (22), and (24), there exist strictly positive parameters that guarantee the exclusion of Zeno behavior in the closed-loop system.

Proof. For the event-triggered mechanism in the observation channel, the triggering mechanisms for velocity and position states follow similar designs. Taking the z -axis as an example, the actual system output $z_1(t)$ is differentiable and satisfies $|\dot{z}_1(t)| \leq L$, where L is a finite positive constant. Let $\Delta t_1 = t - t_p^{z_1}$. Then, the following holds:

$$|z_1(t) - z_1(t_p^{z_1})| \leq L\Delta t_1 \quad (46)$$

When the event-triggering mechanism is satisfied, the following holds:

$$|z_1(t) - z_1(t_p^{z_1})| > \gamma_{z_1} \quad (47)$$

Consequently, it can be derived that:

$$\begin{aligned} L\Delta t_1 &> \gamma_{z_1} \\ \Delta t_1 &> \frac{\gamma_{z_1}}{L} = \iota_1 \end{aligned} \quad (48)$$

The event-triggering mechanism guarantees a strictly positive minimum inter-event interval, denoted by ι_1 , which ensures the exclusion of Zeno behavior in the observer's event-triggered scheme.

For the event-triggering mechanism of control channel, consider U_2 as an example. The controller output is differentiable and satisfies $|\dot{U}_2(t)| \leq K$, where K is a finite positive constant. Let $\Delta t_2 = t - \tau_q^2$. Then, the following results hold:

$$|U_2(t) - U_2(\tau_q^2)| \leq K\Delta t_2 \quad (49)$$

When the event-triggering mechanism is met, the following holds:

$$|U_2(t) - U_2(\tau_q^2)| > M_1^2 e^{-M_2^2 |\hat{\alpha}_{\phi_1} - \phi_d|} \quad (50)$$

Thus, we obtain the following result:

$$\begin{aligned} K\Delta t_2 &> M_1^2 e^{-M_2^2 |\hat{\alpha}_{\phi_1} - \phi_d|} \\ \Delta t_2 &> \frac{M_1^2}{K} e^{-M_2^2 |\hat{\alpha}_{\phi_1} - \phi_d|} = \iota_2 \end{aligned} \quad (51)$$

By Theorems 1 and 2, the term $|\hat{\alpha}_{\phi_1} - \phi_d|$ is bounded, and consequently $e^{-M_2^2 |\hat{\alpha}_{\phi_1} - \phi_d|}$ remains bounded. This guarantees the existence of a strictly positive minimum inter-event interval ι_2 , which precludes Zeno behavior in the event-triggered mechanism of controller.

5 Simulation Experiments

The effectiveness and robustness of the proposed CADRC approach were verified through MATLAB simulations, with a conventional ADRC controller serving as the baseline for comparison. The simulation was configured with a 20-second duration and a fixed step size of 0.01 seconds. The quadrotor's initial position and attitude were set to zero values $[x \ y \ z \ \phi \ \theta \ \psi]^T = [0 \ 0 \ 0 \ 0 \ 0 \ 0]^T$. The parameter configurations for the quadrotor system, PSO algorithm, and event-triggered mechanism are presented in Table 1.

The drone executes a simplified urban patrol mission comprising four phases (total duration: 20 seconds) before returning to its origin:

Phase 1 ($t \leq 5 \text{ s}$): Simultaneous constant-velocity flight along x and z axes at 3 m/s each.

Phase 2 ($5 \text{ s} < t \leq 10 \text{ s}$): Constant-velocity flight along y -axis at 3 m/s.

Phase 3 ($10 \text{ s} < t \leq 15 \text{ s}$): Reverse constant-velocity flight along x -axis at -3 m/s.

Phase 4 ($15 \text{ s} < t \leq 20 \text{ s}$): Reverse constant-velocity flight along y -axis at -3 m/s.

With the desired yaw angle $\psi_d = 0^\circ$ maintained throughout, the quadrotor completes this rectangular trajectory cycle while tracking the prescribed path. The system incorporates zero-mean Gaussian noise with a standard deviation of 1 as external disturbances in both the attitude and position control channels.

Table 1 The parameters for the quadrotor system, particle swarm optimization algorithm (PSO), and event-triggered mechanism.

Quadrotor System		PSO		Event-Triggered Mechanism	
Notation	Value	Notation	Value	Notation	Value
M	2.5 (kg)	n	50	γ_1	0.01
l	0.6 (m)	d	4	γ_2	0.03
g	9.8 (m/s ²)	w_{ini}	0.8	M_1^1	5
k_c	0.06 (N·m/m ²)	w_{fin}	0.2	M_1^2/M_1^3	1000
k_a	0.02 (N·m/m ²)	c_1/c_2	2	M_1^4	10
J_x	1.4 (kg·m ²)	max_iter	15	M_2	10
J_y	1.4 (kg·m ²)	γ_p	0.15		
J_z	2.8 (kg·m ²)	$\underline{t}$	2		

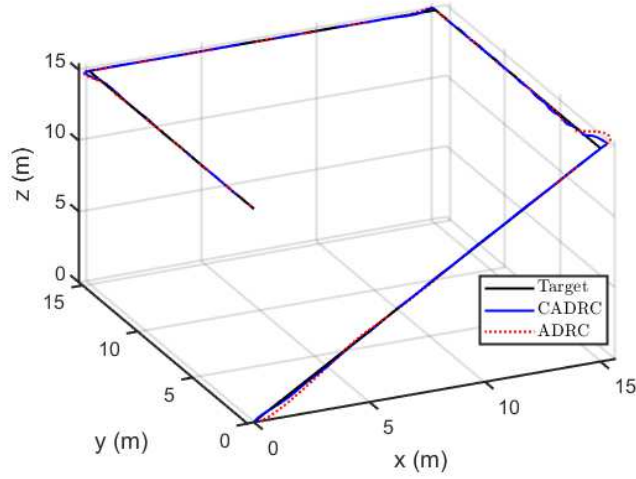


Fig. 3 Quadrotor 3D trajectory tracking.

Figure 3 presents the 3D trajectory tracking performance of the quadrotor during the simplified urban patrol mission. The simulation results demonstrate effective tracking of the predefined rectangular trajectory across all four flight phases. A comparative analysis between the CADRC and conventional ADRC methods reveals superior trajectory adherence during transitional phases where motion direction changes occur, with the proposed CADRC algorithm exhibiting closer alignment to the desired path. Notably, the CADRC controller maintains high tracking precision even under sensor noise conditions, thereby validating the robustness of the control strategy.

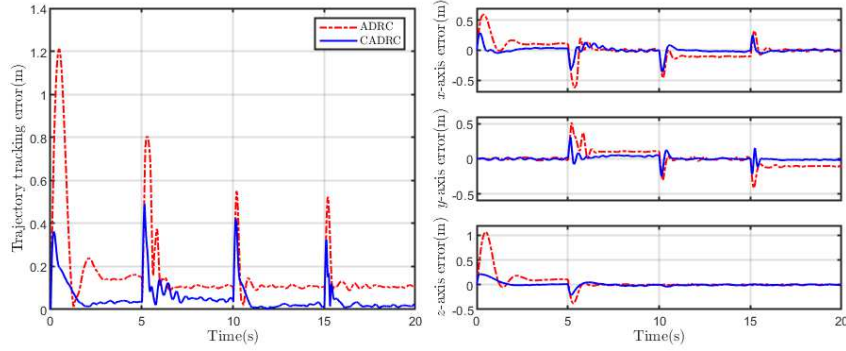


Fig. 4 The trajectory tracking errors of the quadrotor.

Figure 4 presents the trajectory tracking error characteristics of the quadrotor UAV. A comparative analysis of the error curves between the ADRC and CADRC control strategies reveals that, consistent with the results shown in Figure 3, the CADRC

controller demonstrates superior transient response performance during trajectory switching phases. Specifically, the CADRC generates smaller overshoot compared to the conventional ADRC controller while maintaining consistently lower tracking errors throughout the entire control process. The proposed CADRC method achieves a 65.3% reduction in root-mean-square (RMS) error compared to conventional ADRC, with measured values of 0.092 versus 0.265 respectively. This quantifies the superior tracking precision of the cascaded event-triggered architecture.

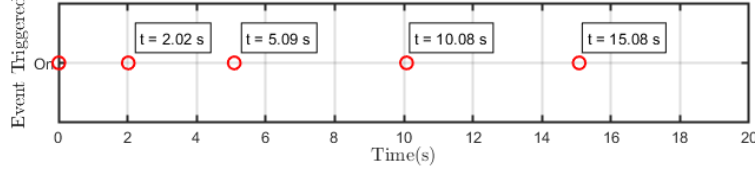


Fig. 5 The event-triggered instant of PSO algorithm.

As shown in Figure 5, the PSO algorithm triggered parameter adjustments at five distinct time instants: initial startup ($t = 0$ s), $t = 2.02$ s, $t = 5.09$ s, $t = 10.08$ s, and $t = 15.08$ s. These parameter updates were activated when abrupt transitions in the quadrotor's reference trajectory caused instantaneous increases in tracking error, thereby satisfying the event-triggering conditions.

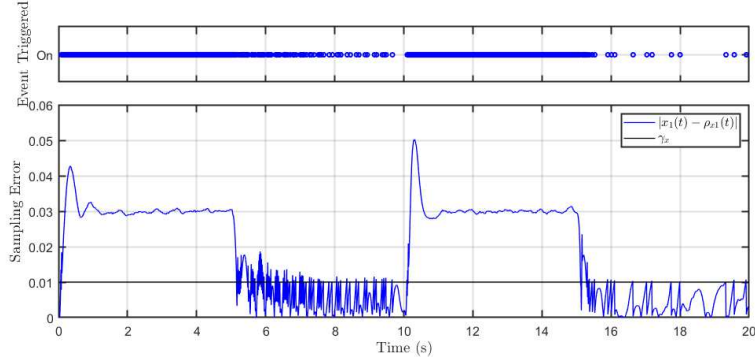


Fig. 6 The instant and sampled error of the observation event triggering mechanism.

Taking the displacement along the x -axis as an example, we analyze the event-triggered mechanism of observer. Figure 6 illustrates both the triggering instants and corresponding thresholds for the x -axis observation channel. The results demonstrate that the observer performs state sampling and data transmission only when the sampling error between measured and actual values exceeds the predefined threshold. Compared to continuous triggering approaches, this event-triggered strategy achieves a 43.45% reduction in data transmission frequency.

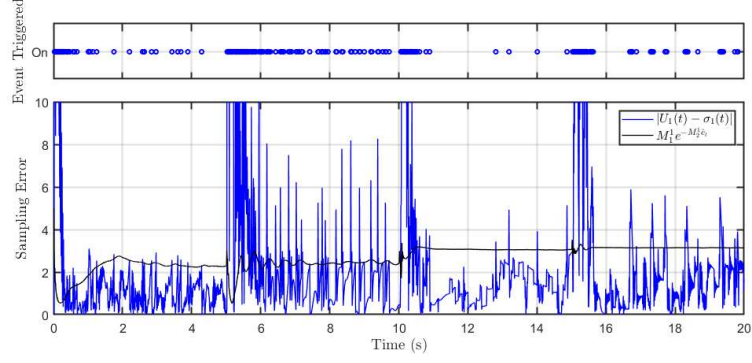


Fig. 7 The instant and sampled error of the control event triggering mechanism.

Figure 7 presents the event-triggering instants and corresponding thresholds for control input U_1 . When correlated with the error curves in Figure 4, a clear adaptive thresholding strategy emerges: the triggering threshold decreases during periods of larger tracking errors to prioritize control accuracy, while adopting higher thresholds when errors diminish to reduce triggering frequency. This time-varying event-triggered mechanism achieves a 84.05% reduction in data transmission compared to fixed-threshold approaches.

The simulation results demonstrate that the event-triggered CADRC approach outperforms conventional ADRC in both trajectory tracking precision and computational efficiency. The cascaded control structure effectively decouples position and velocity regulation, while the event-triggering mechanism significantly reduces system resource utilization without compromising performance. Furthermore, the PSO-based online parameter tuning enhances the controller's adaptability to external disturbances.

6 Conclusion

This study addresses the trajectory tracking control problem for quadrotor by proposing a CADRC method with event-triggered mechanisms. Through hierarchical system design, we independently construct ESOs and controllers for both position and velocity subsystems, achieving precise disturbance estimation and compensation while enhancing control accuracy. The incorporation of event-triggered mechanisms ensures system state and control signal updates only when necessary. Simulation results demonstrate significant reductions in data transmission volume for both observation and control channels, substantially lowering computational resource consumption without compromising performance.

Compared to conventional ADRC, the cascaded structure of CADRC exhibits stronger robustness against dynamic payload variations and external disturbances. Furthermore, the online parameter tuning via PSO enhances the controller's adaptive capability, enabling rapid adjustment to system parameter changes. Theoretical analysis confirms the method's stability and guarantees the absence of Zeno behavior in the event-triggered mechanism.

Future work will investigate fault-tolerant control strategies for actuator failures during flight. We plan to integrate fault detection and diagnosis techniques into the quadrotor system to improve operational reliability during mission execution.

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Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author Contributions

Xin Chen: Xin Chen conceptualized the cascade active disturbance rejection control (CADRC) framework integrated with the event-triggered mechanism. He designed the hierarchical control architecture, formulated the theoretical foundation, and drafted the manuscript. Kai Chen: Kai Chen implemented the simulation platform using MATLAB, developing the software for control algorithms and performing formal analysis of trajectory tracking performance. He validated the robustness of the proposed method under external disturbances and contributed to data curation. Fuhua Qiang: Fuhua Qiang derived the quadrotor dynamics model, decoupled the system into position and velocity subsystems, and conducted parameter configuration for simulation experiments. He assisted in investigating the system's response under varying flight conditions. Yongke Sun: Yongke Sun was responsible for visualization, generating key results such as 3D trajectory plots and error comparisons. He provided computational resources and contributed to reviewing and editing the manuscript, particularly in enhancing the clarity of graphical presentations. Xin Lai: Xin Lai supervised the research progress. He provided critical feedback during manuscript revision and ensured alignment with industrial application requirements.

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