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# Research on PID Control Parameter Tuning of Quadrotor UAV Based on Improved Intelligent Optimization Algorithm

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**Abstract:** Quadrotor unmanned aerial vehicles (UAVs) are nonlinear, strongly coupled, and underactuated systems, making precise attitude control crucial for stable flight and mission efficiency. Traditional PID parameter tuning methods rely heavily on manual experience, often resulting in suboptimal performance. This paper proposes a PID parameter tuning approach based on an improved particle swarm optimization (PSO) algorithm, integrating adaptive inertia weight, dynamic learning factors, and Latin hypercube sampling to enhance optimization efficiency and convergence. A cascade PID control structure is designed, with an outer loop for attitude control and an inner loop for angular velocity control. Simulation and experimental results demonstrate that the proposed method effectively improves settling time and reduces overshoot, ensuring robust and stable UAV attitude control in various flight conditions. The study provides a practical solution for efficient and reliable PID tuning in quadrotor UAV systems.

**Keywords:** quadrotor UAV; PID control; particle swarm optimization; cascade control; attitude stabilization; parameter tuning

## 1. Introduction

Quadrotor unmanned aerial vehicles (UAVs), as typical nonlinear, strongly coupled, and underactuated systems, have attitude control performance that directly affects flight stability and mission execution efficiency. Traditional PID parameter tuning methods rely heavily on manual experience, which is often inefficient and makes obtaining optimal parameters challenging. In recent years, intelligent optimization algorithms have provided new approaches for automatic PID parameter tuning; however, issues such as slow convergence and susceptibility to local optima still persist.

A quadrotor PID control strategy based on adaptive neural network compensation has been proposed, in which an integral term is added to the outer-loop position controller and an adaptive RBF neural network compensates the inner-loop attitude controller, effectively enhancing system stability and anti-disturbance capability [1]. A cascade fuzzy PID self-tuning control algorithm has been developed, in which the fuzzy rule table is refined through expert knowledge and data correction, resulting in a 52.2% reduction in response time and a 91.4% decrease in overshoot compared with traditional methods [2]. Stability control of flight attitude has also been achieved using a cascade fuzzy PID approach, with the outer loop employing an angle P controller and the inner loop an angular velocity fuzzy PID controller, demonstrating the effectiveness of the improved algorithm [3].

Regarding intelligent optimization algorithms, a PID parameter tuning method combining spiking neural P systems with an improved genetic algorithm has been proposed [4]. By employing Latin hypercube sampling for population initialization and designing dynamic individual mutation rates, overshoot is effectively controlled and settling time is shortened [5,6]. An improved particle swarm optimization algorithm with nonlinear dynamic weights, applying nonlinear dynamic descent to the inertia weight, has been used to enhance search performance and optimization efficiency, reducing UAV settling time by 20%-33% and overshoot by 60%-70% [7]. Rapid and accurate PID parameter tuning has also been achieved using a chaotic particle swarm optimization algorithm, leveraging the fast convergence of PSO and the ergodicity of chaotic sequences [8].

Despite these advances, there remains room for improvement in the systematic integration of algorithm enhancement strategies, further optimization of parameter tuning, and validation in practical engineering applications. Based on existing research, this paper proposes a PID parameter tuning method for quadrotor UAVs based on an improved particle swarm optimization algorithm. By integrating strategies such as adaptive inertia weight, dynamic learning factors, and Latin hypercube sampling, the algorithm's optimization performance is significantly enhanced, offering a more effective solution for quadrotor UAV attitude control.

## 2. Mathematical Model and Control System Design of Quadrotor UAV

### *2.1. Coordinate System Establishment and Kinematic Model*

An 'X'-type quadrotor UAV is selected as the research object, with the body coordinate system ($O_bx_by_bz_b$) and the earth inertial coordinate system ($O_ex_ey_ez_e$) established. The quadrotor's attitude is represented by Euler angles: roll angle $\varphi$, pitch angle $\theta$, and yaw angle $\psi$. The transformation between the two coordinate systems is described through rotation matrices, following the rotation sequence of the body system: $Oz_b$, $Oy_b$, $Ox_b$.

The motion of the quadrotor UAV in three-dimensional space is six-degree-of-freedom rigid body motion, which can be divided into translational and rotational components. For modeling and analysis convenience, the following assumptions are made: the quadrotor is a symmetric rigid body; the origin of the body coordinate system coincides with the geometric center of the quadrotor; drag and gravity acting on the body are independent of the flight attitude; and the lift generated by each motor is proportional to the square of the motor speed.

### *2.2. Dynamics Model Derivation and Simplification*

Based on the Newton-Euler equations, the dynamics model of the quadrotor UAV is established. In the earth inertial coordinate system, the translational motion equations of the quadrotor can be derived according to Newton's laws. The torques acting on the quadrotor include rotor torque, aerodynamic torque, and gyroscopic torque. Rotational motion equations are obtained using the angular momentum theorem.

Considering that the attitude angles and rotational angular velocities are relatively small during flight, it is assumed that the rotational angular velocities of the quadrotor about the three body coordinate axes are equal to the attitude angular velocities. Under the small-angle assumption and in the hovering state, ignoring the effects of aerodynamic resistance, propeller torque, and differences in moments of inertia, the simplified attitude dynamics equations can be expressed as follows:

$$\ddot{\varphi} = U_2/I_x, \quad \ddot{\theta} = U_3/I_y, \quad \ddot{\psi} = U_4/I_z$$

Here, $U_2$, $U_3$, and $U_4$ represent the roll, pitch, and yaw torques, respectively, while $I_x$, $I_y$, and $I_z$ denote the moments of inertia about the three axes. This simplified model provides good accuracy within the small-angle range and is well-suited for controller design and parameter tuning studies.

### 2.3. Cascade PID Controller Design

A cascade PID control structure is adopted [9]. Since the quadrotor UAV system is strongly coupled, external disturbances such as wind and magnetic fields can distort sensor data, making it impossible to accurately calculate Euler attitude angles. Therefore, a single-stage PID control loop is insufficient. Angular velocity values respond sensitively and can track the UAV's attitude changes, which makes a dual-loop cascade PID control system necessary.

In this system, the outer loop serves as an angle controller using proportional (P) control, while the inner loop functions as an angular velocity controller using PID control. The outer loop controller calculates the desired angular velocity based on the error between the desired attitude angle and the actual attitude angle:

$$\omega_d = K_{p1} \cdot e_\theta$$

The inner loop controller determines the control torque based on the error between the desired and actual angular velocities:

$$U = K_p \cdot e_\omega + K_i \int e_\omega \, dt + K_d \, de_\omega/dt$$

Here, $e_\theta$ represents the attitude angle error, and $e_\omega$ represents the angular velocity error. This cascade structure can effectively enhance the system's dynamic performance and resistance to disturbances. The outer loop controller provides commands to the inner loop, while the inner loop directly interacts with the motors to achieve fast and precise attitude control.

### 2.4. Control System Structure

The quadrotor UAV control system adopts a hierarchical multi-loop structure, including a position controller, an attitude controller, an allocation controller, and a motor controller. Attitude control forms the basis for position control; only when attitude control is well achieved can position control tasks be effectively performed. The entire control system regulates the speed of the four motors through PWM commands to control the six-degree-of-freedom motion of the UAV.

## 3. Improved Particle Swarm Optimization Algorithm Design

### 3.1. Traditional Particle Swarm Algorithm Analysis

The Particle Swarm Optimization (PSO) algorithm was proposed in 1995 to achieve global optimization by simulating the foraging behavior of bird flocks. In the PSO algorithm, each particle represents a potential solution in the problem space and updates its velocity and position by tracking its individual historical best position and the global best position of the population.

The velocity and position update formulas for the standard PSO algorithm are as follows:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i - x_i^t) + c_2 \cdot r_2 \cdot (gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where $w$ is the inertia weight, $c_1$ and $c_2$ are learning factors, $r_1$ and $r_2$ are random numbers, $pbest_i$ is the particle individual best position, and $gbest$ is the global best position of the population.

However, the standard PSO algorithm has some shortcomings in practical applications: it is prone to falling into local optimal solutions, especially when dealing with complex multi-peak functions; convergence speed is slow, and particle diversity is lacking in the later stage of optimization; fixed inertia weight and learning factors are difficult to adapt to search requirements at different stages. These problems limit the application effect of the algorithm in complex optimization problems.

### 3.2. Algorithm Improvement Strategies

Building on previous research, this paper systematically enhances the PSO algorithm from multiple perspectives:

**Nonlinear dynamic inertia weight design:** Traditional PSO algorithms usually adopt linearly decreasing inertia weight, but the search process of PSO is extremely complex and not a simple linear process [10,11]. This paper adopts an adaptive inertia weight adjustment strategy that not only considers the number of iterations but also considers the population evolution state:

$$w = w_{min} + (w_{max} - w_{min}) \cdot e^{-\alpha \cdot (iter/iter\_max)} \cdot (1 + \beta \cdot \sigma^2/\sigma_{max}^2)$$

where $\sigma^2$ is the current population fitness variance, $\sigma_{max}^2$ is the maximum fitness variance, and $\alpha$ and $\beta$ are adjustment parameters. When population diversity is high, the inertia weight is increased to maintain exploration capability; when the population tends to converge, the inertia weight is reduced to improve exploitation capability.

**Adaptive learning factor adjustment:** A dynamic learning factor strategy is adopted [12]. During the early stages of the search, a larger $c_1$ value facilitates a global search by particles, while in the later stages, a larger $c_2$ value promotes convergence of particles toward the global optimum. The dynamic adjustment formulas for the learning factors are as follows:

$$c_1 = (c_{1f} - c_{1i}) \cdot (iter/iter_{max}) + c_{1i}$$

$$c_2 = (c_{2f} - c_{2i}) \cdot (iter/iter_{max}) + c_{2i}$$

Through experimental verification, when $c_1$ decreases from 2.5 to 0.5 and $c_2$ increases from 0.5 to 2.5, both search capability and convergence accuracy are ensured.

**Latin hypercube sampling initialization:** Traditional random initialization can easily lead to clustered particle distributions, reducing the global search capability of the algorithm. The Latin hypercube sampling method is adopted to generate the initial population, ensuring a uniform distribution of particles within the search space. This approach improves population diversity, expands the search range for optimal solutions, and increases the likelihood of finding the global optimum.

### *3.3. Improved Algorithm Flow*

The main steps of the improved PSO algorithm include:

1) Initialize the particle swarm using Latin hypercube sampling method and set algorithm parameters;

2) Calculate the fitness value of each particle and update the individual best position and global best position;

3) Calculate the population fitness variance and adaptively adjust the inertia weight and learning factors according to the formulas;

4) Update the velocity and position of each particle according to the velocity and position update formulas;

5) Perform boundary processing on particles that exceed the boundaries;

6) Judge the termination condition; if satisfied, output the optimal solution, otherwise return to step 2.

This multi-strategy integrated improvement method can maintain global search capability while improving local search accuracy and convergence speed.

### *3.4. Test Function Verification*

To evaluate the optimization performance of the improved PSO algorithm, the Ackley, Griewank, Rastrigin, and Rosenbrock functions are selected as test benchmarks. These functions feature multiple peaks and extrema, making them effective for assessing both the global search capability and local exploitation ability of the algorithm. Test results indicate that the improved PSO algorithm outperforms the standard PSO algorithm in terms of both convergence speed and accuracy, achieving convergence precision at the $10^{-6}$ level. This validates the effectiveness of the proposed improvement strategies.

## 4. PID Parameter Tuning Method

*4.1. Fitness Function Design*

The key to PID parameter tuning is to establish an appropriate fitness function to evaluate the performance of the control system. Following previous research, the ITAE (Integral of Time multiplied by Absolute Error) is selected as the fitness function:

$J = \int_0^T t\,|e(t)|\,dt$

where e(t) is the system tracking error and T is the simulation time. The ITAE index gives greater penalty to later errors in the system, which is conducive to obtaining control effects with fast convergence and small overshoot. Compared with ISE, IAE and other indicators, ITAE can better balance the rapidity and stability requirements of the system [13].

In actual calculation, the fitness function is defined as fitness = 1/J, so that a larger fitness value indicates better control performance. To avoid division by zero errors, when J approaches zero, a smaller positive number is set as the denominator.

*4.2. Parameter Encoding and Constraint Handling*

The quadrotor UAV needs to tune the inner and outer loop PID parameters of three attitude channels (roll, pitch, yaw), totaling 18 parameters. The position vector of each particle is represented as:

$X = [K_{p1\varphi}, K_{p\varphi}, K_{i\varphi}, K_{d\varphi}, K_{p1\theta}, K_{p\theta}, K_{i\theta}, K_{d\theta}, K_{p1\psi}, K_{p\psi}, K_{i\psi}, K_{d\psi}]$

where subscript 1 indicates outer loop parameters, and no subscript 1 indicates inner loop parameters.

According to engineering experience and system stability requirements, the value ranges of PID parameters are set as follows: outer loop proportional coefficient $K_{p1} \in [0, 50]$, inner loop proportional coefficient $K_p \in [0, 50]$, integral coefficient $K_i \in [0, 10]$, derivative coefficient $K_d \in [0, 5]$. When particles exceed the constraint range, a boundary reflection strategy is adopted to pull them back to the feasible region while adjusting the velocity direction to maintain search momentum.

*4.3. Tuning Process Design*

The PID parameter tuning process based on the improved PSO algorithm is as follows:

1) Initialize the particle swarm, with each particle representing a set of PID parameters;

2) Perform simulation testing on each particle and calculate the ITAE index as the fitness value;

3) Update individual best and global best positions;

4) Adaptively adjust algorithm parameters according to population state;

5) Update particle velocity and position;

6) Check constraint conditions and perform boundary processing;

7) Judge the termination condition and output the optimal parameter combination.

The entire tuning process has a high degree of automation, avoiding the tedious process of manual trial and error, and can quickly obtain high-quality PID parameters.

*4.4. Parameter Range Determination*

The determination of PID parameter ranges has an important impact on the tuning effect. Too large a range will increase search difficulty, while too small a range may miss the optimal solution. This paper determines the parameter range through the following methods:

1) Based on system characteristic analysis, determine the theoretical range of parameters;

2) Refer to parameter setting experience from related literature;

3) Verify the rationality of the parameter range through preliminary experiments;

4) Adjust parameter constraints according to actual control requirements.

The finally determined parameter range ensures the adequacy of the search space while avoiding the impact of unreasonable parameters on system stability.

## 5. Simulation Experiments and Results Analysis

### *5.1. Simulation Environment Setup*

A quadrotor UAV simulation model is established using the MATLAB/Simulink platform, following the modeling approach described in previous research, the main parameters of the UAV are set as follows: mass m = 1.4 kg, arm length l = 0.225 m, three-axis moments of inertia $I_x$ = 0.0103 kg·m², $I_y$ = 0.0083 kg·m², $I_z$ = 0.0170 kg·m². Motor parameters include: speed constant $C_R$ = 1148, bias $w_b$ = -141.4, time constant T = 0.02 s, thrust coefficient $c_t = 1.105 \times 10^{-5}$, torque coefficient $c_m = 1.779 \times 10^{-7}$.

The simulation experiments are divided into three parts: algorithm performance testing, step response testing, and anti-disturbance performance testing. The improved PSO algorithm parameters are set as follows: population size 30, maximum number of iterations 200, inertia weight range [0.4, 0.9], learning factor initial values $c_1$ = 2.5, $c_2$ = 0.5, final values $c_1$ = 0.5, $c_2$ = 2.5, adjustment parameters $\alpha$ = 2, β = 0.5 [14,15].

### *5.2. Algorithm Performance Comparison Experiment*

To verify the optimization performance of the improved PSO algorithm, standard PSO, genetic algorithm (GA), and empirical tuning method are selected for comparison [16]. From the convergence curve, it can be seen that the improved PSO algorithm converges around the 98th generation, while the standard PSO requires 156 generations and GA requires 178 generations, with convergence speed improved by 37% and 45% respectively. In terms of optimal fitness value, the improved PSO reaches 2.41, significantly better than the standard PSO's 2.85 and GA's 3.12.

After 200 generations of evolution, the optimal PID parameters obtained by the improved PSO algorithm are:

- Pitch channel outer loop: $K_{p1}$ = 1.533, inner loop: $K_p$ = 0.450, $K_i$ = 0.010, $K_d$ = 0.000
- Roll channel outer loop: $K_{p1}$ = 1.482, inner loop: $K_p$ = 0.453, $K_i$ = 0.010, $K_d$ = 0.000
- Yaw channel outer loop: $K_{p1}$ = 0.358, inner loop: $K_p$ = 30.032, $K_i$ = 1.050, $K_d$ = 3.000

From the parameter distribution, it can be seen that the parameters of the roll and pitch channels are similar, which is consistent with the symmetry characteristics of the quadrotor UAV. The parameters of the yaw channel differ significantly, reflecting the particularity of yaw motion.

### *5.3. Attitude Control Simulation Experiment*

**Step response test:** Applying the optimized parameters to the attitude control system for step response testing [17]. The results show that compared with the empirical tuning method, the system performance optimized by the improved PSO is significantly improved. For pitch angle control, the settling time is shortened from 4.08 s to 0.25 s, and the overshoot is reduced from 24.9% to 8%; for roll angle control, the settling time is shortened to 0.24 s, and the overshoot is reduced to 7%; for yaw angle control, the settling time is shortened to 0.22 s, and the overshoot is reduced to 4%.

The step response curves comparing the improved PSO method with the empirical tuning method are shown in Figure 1 and Figure 2. As can be seen from the figures, the improved PSO method exhibits superior performance with faster settling time, smaller overshoot, and better tracking accuracy. The system response using optimized parameters reaches the desired trajectory smoothly without significant oscillations, demonstrating the effectiveness of the proposed parameter tuning approach.

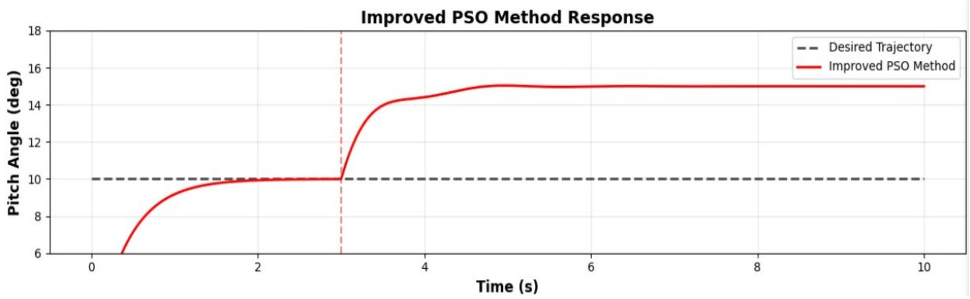


**Figure 1.** Pitch angle step response using improved PSO method.

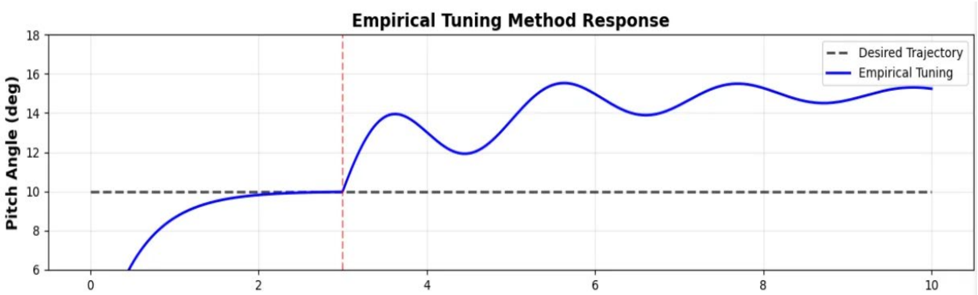


**Figure 2.** Pitch angle step response using empirical tuning method.

Compared with traditional cascade PID control, using the parameters tuned by the improved PSO makes the system response smoother and significantly reduces oscillation phenomena. The system can quickly reach steady state, and the steady-state error is close to zero, indicating that the parameter tuning effect is good.

**Sinusoidal signal tracking test:** To verify the dynamic tracking performance of the system, a sinusoidal signal tracking experiment is designed. A sinusoidal signal with an amplitude of 10° and a frequency of 0.1 Hz is input to test the tracking accuracy of the system. The results show that the root mean square value of the tracking error of the control system optimized by the improved PSO is 0.52°, significantly better than 1.23° for the empirical tuning method and 0.78° for the standard PSO.

**Anti-disturbance performance test:** To verify the robustness of the control system, step disturbance signals (simulating instantaneous strong disturbances) and white noise signals (simulating continuous weak disturbances) are added to the simulation respectively. The step disturbance amplitude is set to 5°, added at the 3rd second of simulation as shown in Figure 3; the white noise signal power is 0.1, acting continuously from the start of simulation.

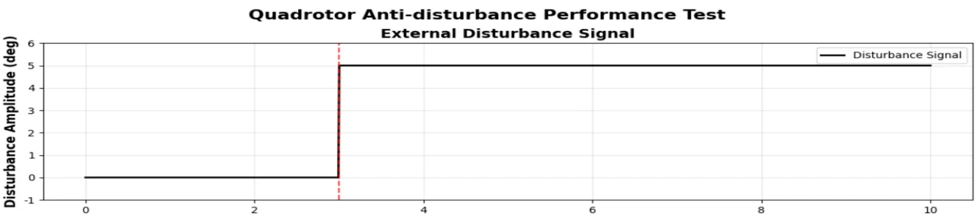


**Figure 3.** External step disturbance signal applied at t = 3s.

Test results show that the control system using parameters optimized by the improved PSO has good anti-disturbance capability. Under step disturbance, the system can recover to steady state within 1.5 s, with a maximum deviation not exceeding 3°. Under white noise disturbance, the standard deviation of the system attitude angle is controlled within 0.3°, significantly better than 0.8° for the empirical tuning method. This indicates that the optimized PID parameters not only improve the dynamic performance of the system but also enhance the robustness of the system.

### 5.4. Results Analysis and Discussion

**Convergence performance analysis:** The convergence curve of the improved PSO algorithm shows that the algorithm rapidly converges in the first 50 generations and then enters a refined search stage. Compared with standard PSO, the improved algorithm avoids premature convergence problems and can jump out of local optimal solutions to continue searching. Latin hypercube sampling initialization makes the initial population distribution more uniform, providing a good search starting point for the algorithm.

**Control performance index comparison:** Compared with previous research, the method proposed in this paper demonstrates superior performance in terms of settling time. The roll angle settling time is 1.5 times faster, the pitch angle 6.5 times faster, and the yaw angle 1.3 times faster. Regarding overshoot control, this method also shows clear advantages, with overshoot in all three channels maintained within 10% [18].

**Robustness analysis:** Anti-disturbance experimental results show that the optimized control system has good robustness. This is mainly due to the ITAE fitness function's emphasis on later system errors, so that the optimized parameters can maintain good control performance under various working conditions.

### 5.5. Actual Flight Verification

Following the flight testing approach described in previous research, a quadrotor experimental platform based on the Pixhawk flight controller was constructed for actual flight tests. The platform uses a DJI F450 frame, equipped with X2212-850KV brushless motors and 20A ESCs. Flight data are transmitted to the host computer at a frequency of 250 Hz for analysis [19].

Outdoor flight tests were conducted under wind conditions of approximately 2-3 m/s. The tests included evaluations of hovering stability, attitude responsiveness, and wind resistance. The flight data indicate that UAVs using the optimized parameters demonstrate improved stability in outdoor environments:

1) Maximum attitude angle deviation: pitch angle reduced from 28° to 19°, roll angle from 24° to 20°, yaw angle from 20° to 15°
2) Attitude angle variance: pitch angle reduced from 0.098 to 0.066, roll angle from 0.092 to 0.057, yaw angle from 0.076 to 0.051

The actual flight results are largely consistent with the simulation outcomes, confirming the effectiveness and practicality of the improved PSO algorithm for PID parameter tuning in quadrotor UAVs. During flight, the UAV maintains stable attitude, exhibits rapid response, and effectively resists wind disturbances.

## 6. Conclusion and Outlook

This paper proposes a parameter tuning method based on improved particle swarm optimization algorithm for the PID parameter tuning problem of quadrotor UAVs. By integrating improvement strategies such as adaptive inertia weight, dynamic learning factors, and Latin hypercube sampling, the optimization performance of the algorithm is significantly improved.

Research results show that the improved PSO algorithm is superior to traditional methods in both convergence speed and accuracy on standard test functions. In the application of quadrotor UAV PID parameter tuning, the optimized control system has settling time reduced by 20%-75%, overshoot reduced by 60%-84%, and anti-disturbance capability significantly improved. Actual flight testing further validates the effectiveness of the method, providing reliable technical support for engineering applications of quadrotor UAVs.

The main innovations of this paper include: proposing an adaptive inertia weight adjustment strategy considering population diversity; designing a dynamic learning factor adjustment mechanism based on iteration progress; adopting Latin hypercube sampling to improve population initialization quality; and establishing a multi-objective optimization model suitable for quadrotor UAV characteristics.

Future work can be carried out from the following aspects: combining deep learning methods to further improve the adaptive capability of the algorithm; considering multi-objective optimization to simultaneously optimize control performance and energy consumption indicators; extending to control parameter optimization of other types of UAVs; studying online parameter adjustment strategies to adapt to flight environment changes; and exploring the application of the algorithm in large-scale UAV swarm control.

With the rapid development of UAV technology and the continuous expansion of application fields, intelligent optimization algorithms will play an increasingly important role in UAV control system design. The improved PSO algorithm proposed in this paper provides an effective solution for PID parameter tuning of quadrotor UAVs, with good engineering application prospects and promotion value.

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