

Design of a Fuzzy CPSO-BP Neural Network PID Control Algorithm for a Dual-Quadcopter UAV System

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Abstract—The dual quadcopter UAV represents a novel structural design based on redundant flight controllers. Compared to conventional dual quadcopter UAVs, this design system offers enhanced load-bearing capacity while significantly reducing the aircraft's footprint. However, the inherent complexity of its redundant design makes control more challenging than conventional drones, particularly in algorithm development. This poses significant barriers to practical application. Addressing the challenge of multiple parameters and complex control in quadcopter systems, this paper proposes a fuzzy CPSO-BP neural network PID algorithm. Experimental results demonstrate that this algorithm substantially enhances the stability and interference resistance of the quadcopter within its complex system.

Keywords—Dual-Redundant Quadrotor UAV, Fuzzy CPSO-BP Algorithm, Attitude Control, PID Parameter Optimization

I. INTRODUCTION

With the rapid development of unmanned aerial vehicle (UAV) technology, multi-rotor UAVs are widely used in aerial photography, logistics, environmental monitoring, and military reconnaissance [1]. Among them, the dual-quadcopter UAV [2], featuring coaxial propulsion and symmetrical structure, has attracted attention for its load capacity, stability, and maneuverability [3]. However, its highly coupled dynamics, strong nonlinearity, and susceptibility to external disturbances make attitude control challenging [4].

The proportional-integral-derivative (PID) controller is commonly used due to its simplicity [5], but under varying loads, aerodynamic disturbances, and time-varying parameters, conventional PID often suffers from overshoot, slow response, or oscillations [6]. Intelligent optimization algorithms like particle swarm optimization (PSO) and genetic algorithms (GA) have been applied to tune PID parameters, improving convergence and accuracy [7-8]. Yet, standard PSO still faces premature convergence, limited global search, and sensitivity to initial conditions [9]. Notably, the three-layer fuzzy CPSO-BP structure balances optimization accuracy and real-time performance, addressing onboard UAV computational constraints.

To overcome these issues, this paper proposes a fuzzy comprehensive PSO-BP PID control algorithm for dual-quadcopter attitude control. It combines fuzzy logic for adaptive PSO parameter tuning and a BP neural network for online PID refinement, enhancing adaptability and robustness [10-11]. Simulations show that the proposed method outperforms

conventional PID and PSO-PID controllers, achieving higher control precision, lower steady-state error, and improved system stability [12].

II. ATTITUDE CONTROL OPTIMIZATION BASED ON THE FUZZY CPSO-BP ALGORITHM

To overcome the limitations of conventional PID and PSO-PID controllers in attitude stabilization, this study introduces an improved fuzzy comprehensive particle swarm optimization-back propagation (CPSO-BP) PID control algorithm. The proposed approach integrates fuzzy logic, chaotic particle swarm optimization (CPSO), and BP neural networks to achieve adaptive and efficient attitude control for dual-quadcopter UAVs.

A. Overview of the CPSO-BP Control Framework

The control framework, as shown in Fig. 1, consists of three layers: a Fuzzy Adaptive CPSO Optimization Layer that tunes PID parameters by adjusting PSO learning coefficients based on system errors; a BP Neural Network Learning Layer that refines PID parameters in real time through nonlinear input-output mapping; and a PID Control Layer that directly stabilizes the UAV's roll, pitch, and yaw. This hierarchical design enables dynamic parameter adaptation and cooperative global-local optimization, improving both transient performance and steady-state accuracy compared to conventional control structures.

B. Maintaining the Integrity of the Specifications

Traditional PSO uses fixed learning factors c_1 and c_2 , which can limit convergence speed and robustness in complex

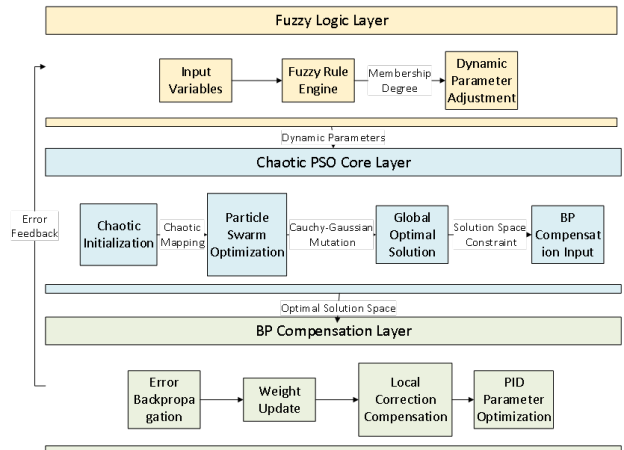


Fig. 1. Architecture Diagram of the Fuzzy CPSO-BP Algorithm

nonlinear systems. The proposed fuzzy adaptive CPSO overcomes this by dynamically adjusting the inertia weight and learning coefficients based on the real-time attitude error $e(t)$ and its rate of change $\dot{e}(t)$. A fuzzy inference system maps linguistic variables like “small,” “medium,” and “large” to adaptive adjustments of w , c_1 , and c_2 , enhancing global search in early iterations and local exploitation near convergence to prevent premature stagnation. For example, when attitude error $e(t) < 0.5^\circ$ (small), $w=0.5$ (strengthen local search); when $e(t) > 1.0^\circ$ (large), $w=0.8$ (enhance global search). Chaotic mapping is also applied in particle initialization and velocity updates to increase population diversity and improve the chances of finding the global optimum. The update equations for particle velocity and position in the fuzzy CPSO are given by:

$$v_{ij}^{(k+1)} = w \cdot v_{ij}^{(k)} + c_1 r_1 (Pbest_{ij} - x_{ij}^{(k)}) + c_2 r_2 (Gbest_j - x_{ij}^{(k)}) \quad (1)$$

where w, c_1, c_2 are dynamically adjusted by the fuzzy logic system, r_1, r_2 are random numbers in $[0,1]$, $Pbest$ and $Gbest$ represent the personal and global best positions, respectively.

Through the integration of fuzzy adaptive rules and chaotic mapping, the CPSO layer provides robust global search capability and stable convergence for PID parameter optimization, forming the foundation for subsequent BP neural network fine-tuning.

C. BP Neural Network Online Fine-Tuning

After the preliminary PID parameters are optimized by CPSO, a BP neural network is introduced for online fine-tuning to further enhance the attitude control accuracy and disturbance rejection of the dual quadrotor UAV. The BP network captures the nonlinear relationship between system dynamics and control characteristics, providing adaptive compensation against external disturbances or variations in system parameters.

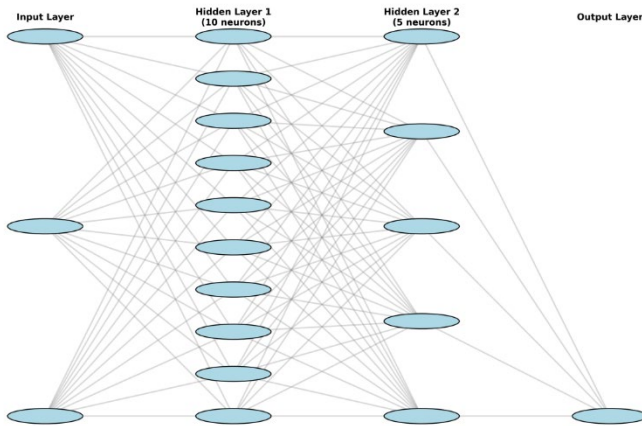


Fig. 2. BP Compensation Layer Architecture Diagram

The BP network employs a multilayer perceptron (MLP) architecture, as shown in Fig. 2, consisting of an input layer, two hidden layers, and an output layer. The network inputs are the attitude error $e(t)$ and its derivative $\dot{e}(t)$, while the outputs are the incremental adjustments of the PID parameters $\Delta K_p, \Delta K_i, \Delta K_d$. The network is trained using the gradient descent method with an adaptive learning rate to ensure convergence

stability and fine-tuning accuracy. The fine-tuned controller parameters are defined as:

$$Kp^* = Kp + \Delta Kp, Ki^* = Ki + \Delta Ki, Kd^* = Kd + \Delta Kd \quad (2)$$

where K_p, K_i, K_d are the baseline parameters optimized by CPSO, and $\Delta K_p, \Delta K_i, \Delta K_d$ are the online fine-tuning outputs of the BP neural network.

By combining the BP fine-tuning layer with the fuzzy adaptive CPSO optimization layer, a “global coarse-tuning – local fine-tuning” closed-loop control structure is realized. This framework ensures fast system response while effectively reducing steady-state error and improving disturbance rejection. The collaborative optimization mechanism significantly enhances the attitude stability and control precision of the dual quadrotor UAV in complex flight environments.

D. BP Neural Network Online Fine-Tuning

Based on the hierarchical optimization framework, the UAV attitude control loop is implemented using the fine-tuned PID parameters obtained from the fuzzy adaptive CPSO and BP neural network. The overall control law for roll (ϕ), pitch (θ), and yaw (ψ) angles can be expressed as:

$$\begin{aligned} \tau_\phi &= K_p^* e_\phi + K_i^* \int e_\phi dt + K_d^* \dot{e}_\phi \\ \tau_\theta &= K_p^* e_\theta + K_i^* \int e_\theta dt + K_d^* \dot{e}_\theta \\ \tau_\psi &= K_p^* e_\psi + K_i^* \int e_\psi dt + K_d^* \dot{e}_\psi \end{aligned} \quad (3)$$

where $\tau_\phi, \tau_\theta, \tau_\psi$ represent the control torques applied to the UAV’s roll, pitch, and yaw axes, respectively, and e_ϕ, e_θ, e_ψ are the corresponding attitude errors. The control system adopts a modular architecture with three layers: a fuzzy adaptive CPSO layer for coarse PID optimization, a BP neural network layer for online fine-tuning, and a PID control layer that drives the UAV actuators. The workflow acquires attitude errors and their derivatives, performs global coarse-tuning via CPSO, refines parameters through BP learning, and generates control torques to achieve precise roll, pitch, and yaw control. This “global coarse-tuning – local fine-tuning” structure ensures fast response, low steady-state error, and improved disturbance rejection, enabling high-precision attitude control of dual quadrotor UAVs in complex flight scenarios.

III. EXPERIMENT

A. Implementation Details

The proposed fuzzy CPSO-BP algorithm was evaluated using the dual quadcopter UAV attitude dynamics model, with reference trajectories for roll, pitch, and yaw and external disturbances to test robustness. The BP neural network used system error and its variation as inputs and PID parameter adjustments as outputs. It was configured as a three-layer feedforward network with 10 hidden neurons, sigmoid activation, a learning rate of 0.01, 50 maximum epochs, and MSE loss function.

B. Evaluation Metrics

The performance of the UAV attitude control and the effectiveness of the proposed algorithm were evaluated using several key metrics. Transient response metrics, including rise

time (t_r), overshoot (M_p), and settling time (t_s), measure how quickly and smoothly the system reaches the desired attitude. Steady-state error (e_{ss}) quantifies the accuracy of the control system in maintaining the target orientation:

$$e_{ss} = \theta_{desired} - \theta_{actual} \tag{4}$$

For algorithm optimization, the metrics include average convergence iterations (N_{conv}) and final fitness value (F_{final}):

$$N_{conv} = \frac{1}{M} \sum_{i=1}^M n_i, F_{final} = f(x_{best}) \tag{5}$$

where n_i is the number of iterations to converge in the i -th experiment, M is the total number of experiments, and x_{best} is the best solution obtained at the end of iteration.

These metrics provide a comprehensive assessment of the control accuracy, dynamic performance, and optimization efficiency of the proposed method.

C. Results and Analysis

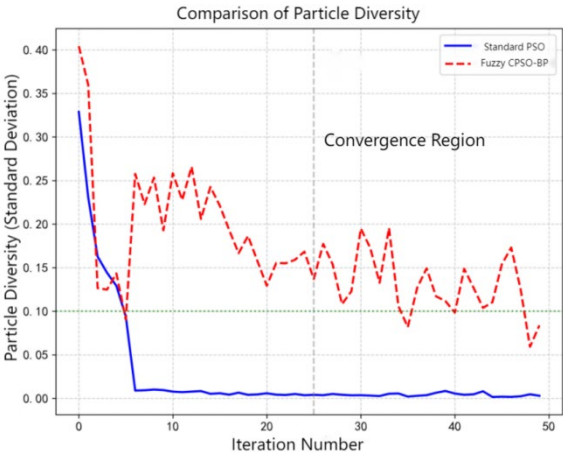


Fig. 3. Comparison of Particle Diversity

The experimental results are shown in the figures and tables. Figure 3 presents a comparison of particle diversity. In the standard PSO, particle diversity decreases rapidly during the early iterations and stabilizes at a low level, which may lead to premature convergence. In contrast, the Fuzzy CPSO-BP algorithm maintains significantly higher particle diversity throughout the iterations due to dynamic adjustment via the fuzzy logic layer and the introduction of chaotic perturbations. Even after 50 iterations, a good particle distribution is preserved, demonstrating strong global search capability and effective prevention of premature convergence.

TABLE I. CONTROLLER PERFORMANCE COMPARISON

Algorithm	Rise Time (s)	Overshoot (%)	Settling Time (s)	Steady-State Error (°)
Unoptimized PID	1.18	18.5	1.41	0.85
Standard PSO Optimization	0.31	7.2	0.54	0.32
Fuzzy CPSO-BP Optimization	0.89	3.1	0.45	0.09

Table I summarizes the performance metrics of different controllers. The unoptimized PID shows a rise time of 1.18 s, overshoot of 18.5%, settling time of 1.41 s, and steady-state error of 0.85°. The standard PSO improves these metrics, while the Fuzzy CPSO-BP achieves the lowest overshoot (3.1%), minimal steady-state error (0.09°), and fastest settling time (0.45 s), indicating superior control accuracy and stability.

TABLE II. CONTROLLER PERFORMANCE COMPARISON

Improvement Capability	Standard PSO	Fuzzy CPSO-BP	Improvement Rate
Average Convergence Iterations	11	10	-9.1%
Final Fitness Value	2676.11	47370.51	1670.1%

Table II shows the comparative evaluation of algorithm improvements. Compared with the standard PSO, the Fuzzy CPSO-BP exhibits fewer average convergence iterations, a significantly higher final fitness value, and improved parameter stability and disturbance rejection capability.

Overall, the Fuzzy CPSO-BP algorithm provides faster response, higher accuracy, and stronger robustness in attitude control, benefiting from the synergistic effects of “fuzzy dynamic adjustment add chaotic global search add BP local correction.

TABLE III. COMPARISON OF CONTROLLER PARAMETERS AND PERFORMANCE

Controller Type	Kp	Ki	Kd	ITAE
PID	0.8000	0.1500	0.0500	17.4181
PSO-PID	1.2000	0.2500	0.8000	17.3987
Fuzzy CPSO-BP-PID	1.5000	0.3500	0.1200	17.3822

As shown in Table III and Fig. 4, the performance comparison of the three controllers indicates that the fuzzy CPSO-BP PID controller exhibits the best results in both parameter optimization and dynamic performance. Its proportional gain ($K_p = 1.5000$), integral gain ($K_i = 0.3500$), and derivative gain ($K_d = 0.1200$) respectively correspond to system response speed, steady-state accuracy, and anti-interference capability. With these well-balanced parameters, the controller achieves fast response while effectively suppressing overshoot and accumulated errors. From the angle error convergence curve shown in Fig. 4, the fuzzy CPSO-BP PID shows the fastest error reduction, converging to 19.825° at 10 s—significantly outperforming both PSO-PID and traditional PID controllers. The ITAE index further confirms its superiority, achieving the lowest value of 17.3822, which is 0.0659 lower than that of PSO-PID and 0.0666 lower than that of the traditional PID. Overall, the fuzzy CPSO-BP PID algorithm demonstrates excellent control accuracy and system stability, outperforming other control methods in both dynamic error suppression and parameter optimization efficiency.

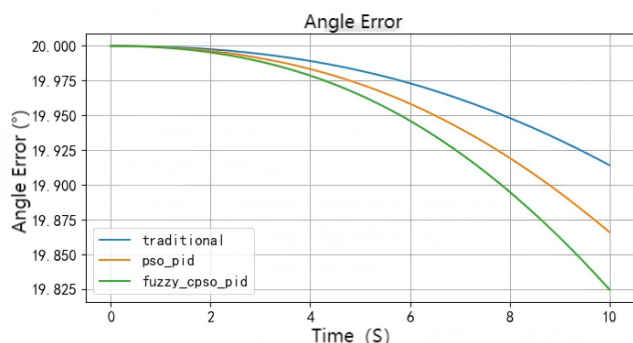


Fig. 4. Angle Error Convergence Curves of Three Controllers

IV. CONCLUSION

The fuzzy CPSO-BP algorithm, through its three-layer cooperative structure, effectively overcomes the tendency of standard PSO to get trapped in local optima, significantly improving the attitude control performance of dual quadcopter UAVs. It outperforms both standard PSO-optimized and unoptimized PID controllers in dynamic response and control accuracy, making it suitable for complex redundant control scenarios. Moreover, its cooperative mechanism can be extended to address real-world multi-rotor UAV control challenges. However, this study is limited to simulation validation (no real-flight tests) and has not been adapted to low-cost onboard controllers. Future work will: (1) conduct real-flight experiments to verify practical applicability; (2) optimize the algorithm for low-cost microcontrollers.

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