# Fuzzy PID Attitude Control for Cost-Effective Quadrotor Uavs

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**Abstract.** This study addresses the challenge of controlling underactuated quadrotor UAVs, characterized by strongly coupled attitude and translational dynamics, as well as vulnerability to environmental disturbances. It proposes a novel cascaded fuzzy-PID control architecture for low-cost platforms to enhance robustness and trajectory tracking precision in complex operational environments. The core design employs a classical PID controller in the inner loop for rapid attitude stabilization, leveraging its simplicity and established effectiveness for this subtask. The outer loop integrates fuzzy logic to dynamically adjust the PID gains in real-time, significantly improving disturbance rejection against specific wind conditions. Simulations based on MATLAB/Simulink demonstrate that under specified wind disturbances, the cascade fuzzy PID controller reduces steady-state error compared to the traditional cascade PID controller. It shortens the stabilization time of pitch and roll angles by 45%, reduces the yaw angle stabilization time by 31%, and cuts recovery time to stability by 44% under identical disturbance conditions. The computational efficiency of the algorithm satisfies embedded deployment requirements on ARM Cortex-M3 platforms. This work effectively balances control precision, environmental adaptability, and engineering feasibility for resource-constrained platforms. The proposed cascaded fuzzy-PID controller offers a practical and robust technical solution for achieving reliable autonomous flight of low-cost quadrotors, enabling them to perform critical tasks in challenging real-world conditions.

**Keywords:** Quadrotor UAV; Fuzzy PID control; Attitude control.

## 1. Introduction

The quadrotor UAV has emerged as prominent research focus due to its advantages of unrestricted takeoff/landing requirements, simple structure, low cost, and broad applicability. However, as a typical underactuated system characterized by multiple-input multiple-output (MIMO), nonlinearity, and strong coupling [1], it is susceptible to uncertainties such as external disturbances and environmental variations in practical applications. Consequently, designing an ideal and effective control algorithm poses a significant challenge for achieving superior flight control performance.

In the field of low-cost quadrotor UAV attitude control, various control methods have been proposed in recent years to address flight control challenges. Traditional control approaches include the PID control algorithm and the sliding mode control algorithm [2,3]. The PID control algorithm is a linear control method where the controller generates control signals by linearly combining the proportional ($K_p e$), integral ($K_i \int e\, d_t$), and derivative ($K_d \frac{de}{dt}$) terms of the error. It is characterized by its simple structure, ease of tuning, robustness, and independence from precise mathematical models. However, due to its fixed gains, it struggles to adapt to the strongly nonlinear and coupled dynamics of quadrotor systems, exhibiting limitations in disturbance rejection [4].

To address these issues, H. Bolandi et al. employed a single-input single-output (SISO) architecture to tune a conventional PID controller structure for quadrotor attitude control [5]. A. Noordin et al. proposed an adaptive PID control (APIDC) system that incorporates a sliding mode adaptive mechanism to dynamically adjust PID parameters online, thereby handling parameter uncertainties and external disturbances [6]. Xu Tianqi introduced neural network-based adaptive adjustments to counteract nonlinear disturbances, designing a fuzzy adaptive PID controller [7].

Due to constraints in computational power and sensor accuracy, low-cost quadrotor UAV attitude control often relies on PID control, which offers a modular architecture, clear physical interpretability, and independence from a global dynamic model, making it an ideal solution for cost-effective attitude stabilization [8].

Although traditional PID control alone cannot guarantee precise attitude tracking, a cascaded PID controller—comprising two feedback loops—enhances control efficiency and dynamic performance. The cascaded structure consists of an outer-loop position controller and an inner-loop attitude controller. The inner loop processes real-time attitude data from inertial sensors, while the outer loop employs Kalman filtering to fuse multi-sensor data for position estimation and feedback.

This study explores a cascaded fuzzy PID controller, integrating fuzzy control principles with the cascaded PID structure to achieve efficient attitude control for low-cost quadrotor UAVs. Simulations in SIMULINK compare the performance of the proposed controller against conventional methods, followed by experimental validation on a physical UAV platform to verify feasibility.

## 2. Methodology

### 2.1. Quadrotor Attitude Dynamics Model

This study assumes the quadrotor UAV has a perfectly symmetrical structure with evenly distributed mass, allowing it to be treated as an idealized model. The gravitational force acting on the quadrotor remains constant regardless of the aircraft's motion, and external disturbances are neglected. Based on the Newton-Euler equations, the simplified attitude dynamics for the roll (φ), pitch (θ), and yaw (ψ) channels are expressed as follows [9]:

$$\begin{cases} I_x\ddot{\varnothing} = u_{\varnothing} + \left(I_y - I_z\right)\ddot{\theta}\,\dot{\varphi} \\ I_y\ddot{\theta} = u_{\theta} + (I_z - I_x)\ddot{\varnothing}\,\dot{\varphi} \\ I_z\ddot{\varphi} = u_{\varphi} + \left(I_x - I_y\right)\ddot{\varnothing}\,\dot{\theta} \end{cases} \tag{1}$$

where $\mathrm{I_x.I_y.I_z}$ represent the moments of inertia about the three axes of the airframe. $\mathrm{u_{\varnothing}.u_{\theta}.u_{\varphi}}$ denote the control input torques (generated by differences in motor speeds). The cross-coupling terms such as$\left(\mathrm{I_y} - \mathrm{I_z}\right)\ddot{\theta}\,\dot{\varphi}$ characterize the nonlinear coupling effects between different attitude channels.

### 2.2. System Design

The quadrotor UAV control system in this study is built around the Pixhawk 2.4.8 flight controller, which utilizes STMicroelectronics' STM32F427ZIT6 microcontroller featuring a 32-bit Cortex-M4 core with 256 KB memory and operating at 168 MHz, meeting various industrial requirements. The system employs an MPU-6050 inertial measurement unit for attitude estimation and an MS5611 barometric pressure sensor for altitude measurement. Control commands are transmitted via a PS2 remote controller, while PWM signals regulate motor speeds.

A wireless communication module transmits flight data to a ground station computer for real-time monitoring and analysis, enabling precise control and ensuring stable flight performance with enhanced system robustness. The integrated sensor suite and control architecture provide a reliable foundation for implementing advanced control algorithms. The schematic diagram of the Pixhawk 2.4.8 flight control system is illustrated in Figure 1.

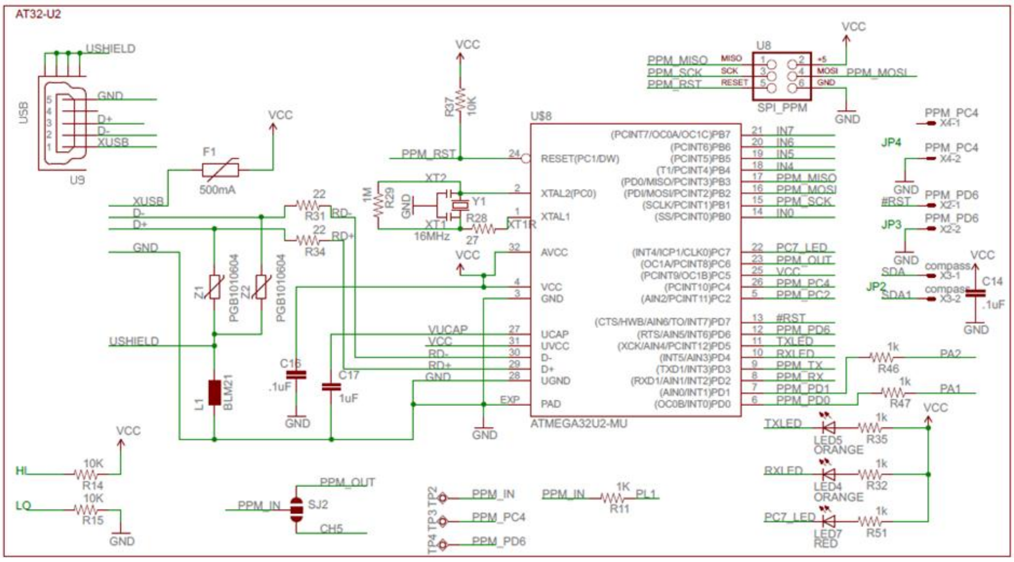


**Fig. 1** Schematic Diagram of the Pixhawk 2.4.8 Flight Control System

### 2.3. Simulation and Analysis of Cascade PID Controller

This study adopts a nested cascade PID control architecture with an inner angular rate loop and an outer attitude angle loop to achieve precise control of the quadrotor aircraft. The control scheme employs a complete PID controller in the outer loop to regulate the aircraft's attitude angles (roll, pitch, yaw), while the inner loop utilizes a PI controller with optimized parameters to control the angular rates. The integral gain of the inner loop is specially designed to avoid compromising system stability. As shown in Figure 2, this control architecture takes full advantage of the fast response characteristics of the inner loop to stabilize the system before the outer loop completes its adjustments. This approach not only ensures control accuracy but also significantly enhances the system's disturbance rejection capability and stability margin. Through key technical measures such as appropriately limiting the integral action of the inner loop, adopting an inside-out tuning sequence, and achieving inter-axis decoupling, the proposed scheme effectively suppresses overshoot during maneuvers.

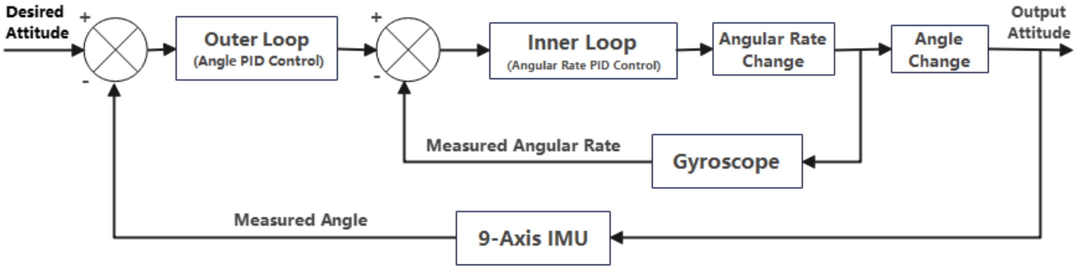


**Fig. 2** Cascade PID control structure diagram

The simulation experiment of the cascade PID controller was conducted in the SIMULINK toolbox of MATLAB software. By selecting appropriate functional modules from the SIMULINK toolbox and combining them with the transfer functions of the linear model, a simulation model of the cascade PID controller was constructed to perform simulation experiments on the pitch angle, roll angle, and yaw angle of the research UAV, thereby verifying the stability and anti-interference capability of the cascade PID controller. After launching MATLAB software and opening the SIMULINK toolbox, the required simulation model was assembled by selecting suitable functional modules. In the model, the controlled object consists of an outer-loop transfer function for angle transformation and an inner-loop transfer function for angular velocity transformation. A step signal ranging from 0 to 0.5 was used as the signal generator, with a simulation time set to 10 seconds. The P, I, and D parameters of the inner and outer loops of the attitude angle cascade PID controller are shown in Table 1 and Table 2 below.

**Table 1.** Cascade PID controller outer loop parameters

| Controlled Variable | Pitch Angle | Roll Angle | Yaw Angle |
|---|---|---|---|
| ***Kp*** | 10 | 10 | 9 |
| ***Ki*** | 0.01 | 0.01 | 0.02 |
| ***Kd*** | 2 | 2 | 2.5 |

**Table 2.** Cascade PID controller inner loop parameters

| Controlled Variable | Pitch Angular Rate | Roll Angular Rate | Yaw Angular Rate |
|---|---|---|---|
| ***Kp*** | 4 | 4 | 5 |
| ***Ki*** | 0.01 | 0.01 | 0.02 |
| ***Kd*** | 0 | 0 | 0 |

Since the pitch angle and roll angle share identical transfer functions based on computational analysis, they utilize the same simulation model configuration. The simulation model for the cascade PID controller governing both pitch and roll angles of the UAV is presented in Figure 3, while Figure 4 illustrates the corresponding simulation model for yaw angle control.

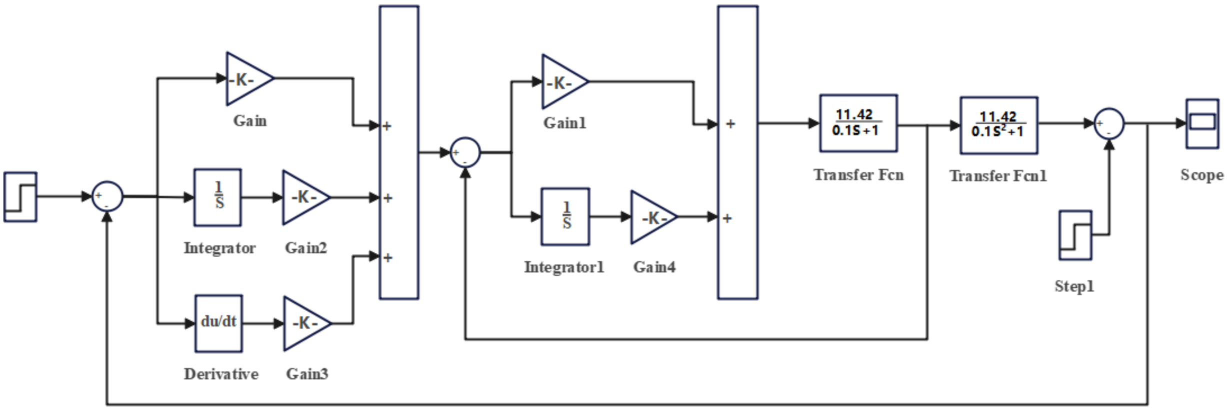


**Fig. 3** Simulation model diagram of cascade PID controller of four-rotor UAV pitch angle and roll angle

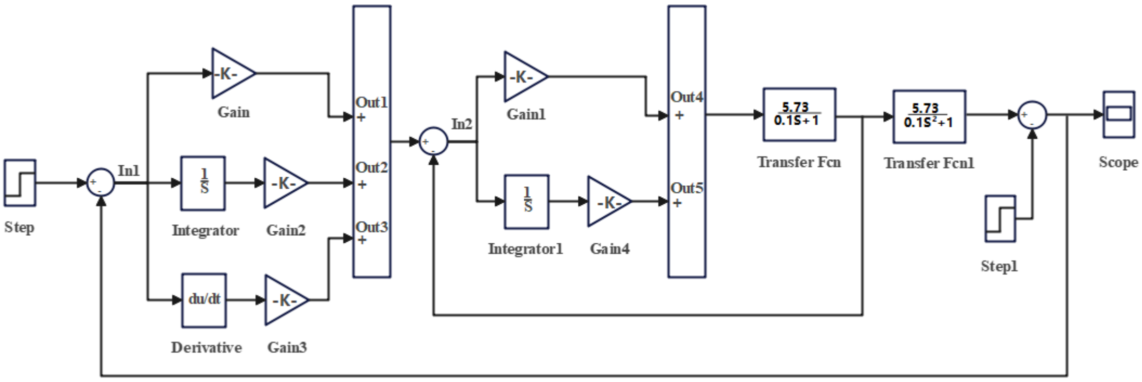


**Fig. 4** Simulation model of yaw angle cascade PID controller for four-rotor UAV

### 2.4. Simulation and Analysis of Cascade Fuzzy PID Controller

While conventional cascade PID controllers can achieve stable system control, their parameters require extensive experimentation to determine fixed values and cannot adapt during operation, making them less effective against sudden external disturbances. To address this limitation, this study proposes an improved solution that integrates fuzzy control theory—using the cascade PID control as a basic framework while incorporating a fuzzy inference mechanism to enable real-time dynamic adjustment of Kp, Ki, and Kd parameters [10].

The proposed cascade fuzzy PID controller retains the dual-loop stability structure and clear physical interpretation of cascade PID control while introducing a fuzzy rule base for parameter self-tuning. As shown in Figure 5, the implementation only requires embedding a fuzzy controller in the outer-loop angle control. This fuzzy controller dynamically optimizes control response characteristics by continuously monitoring attitude error and its rate of change, then adjusting PID parameters online based on fuzzy rules. Simulation results demonstrate that this hybrid control strategy not only preserves the stability advantages of cascade control but also significantly enhances the system's adaptability to time-varying conditions and sudden disturbances, providing a reliable theoretical foundation and technical support for practical applications.

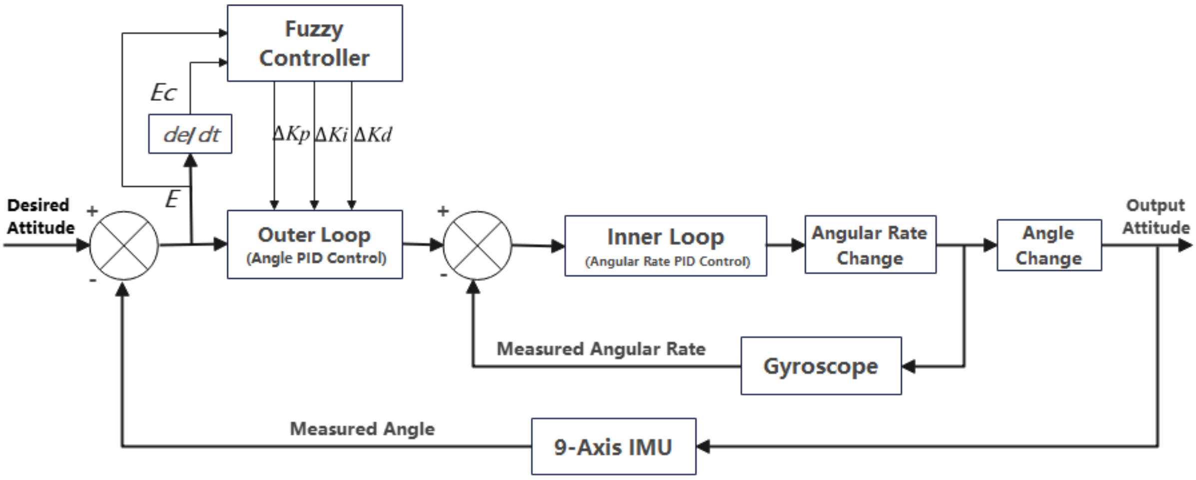


**Fig. 5** Block diagram of fuzzy PID controller

The design of the fuzzy controller comprises four essential components: fuzzification, rule base, fuzzy inference, and defuzzification, with the implementation process achieved by entering the "fuzzy" command in the MATLAB software's command window to invoke the fuzzy rule editor. As clearly illustrated in Figure 6, this diagram presents the internal structural framework of the fuzzy controller.

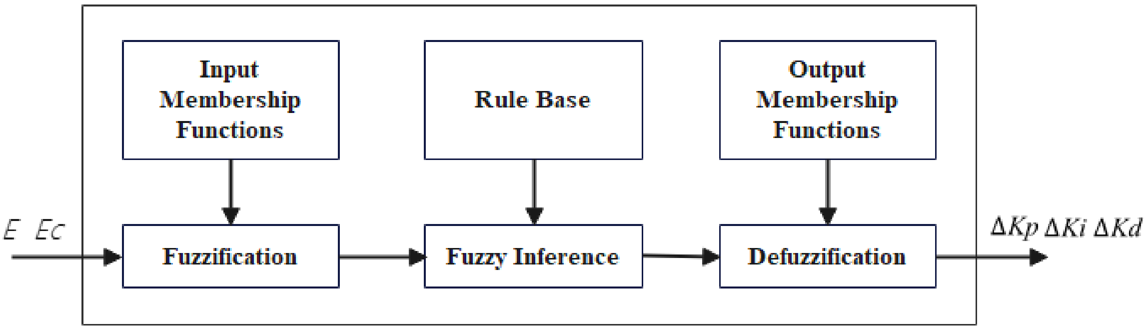
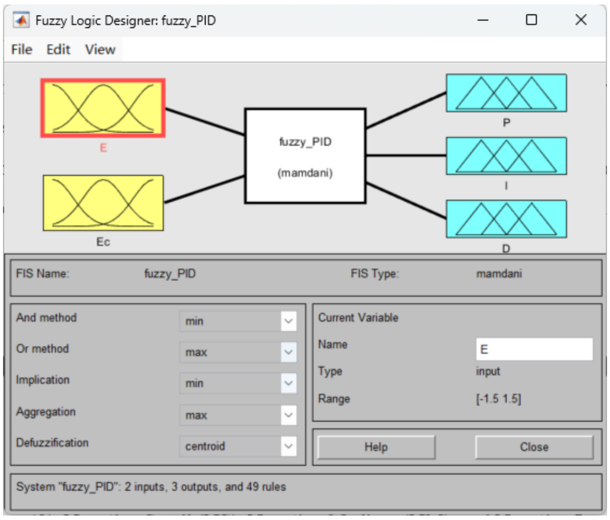


**Fig. 6** Internal structure diagram of fuzzy controller

### 2.4.1 Fuzzification

The fuzzification process constitutes a critical component in fuzzy control systems, with its primary function being the scale transformation of selected input variables to meet the design requirements of fuzzy control. This transformation converts these inputs into fuzzy quantities that can be processed by the fuzzy controller. During this procedure, it is essential to explicitly define the fuzzy universes of discourse for both input and output variables, as well as to determine their corresponding membership functions. For the quadrotor UAV as the control object, the system requires real-time and precise regulation of its pitch, roll, and yaw angles. Consequently, the fuzzy controller design incorporates two input variables: the angular deviation E and its rate of change Ec, along with three output variables: the adjustment parameters of PID, namely △Kp, △Ki, and △Kd.

The controller interface implemented in MATLAB's Fuzzy Logic Toolbox is illustrated in Figure 7. In the simulation setup, the input variables for the outer-loop angle control system are configured as follows: the fuzzy universe of discourse for angular deviation E1 is set to [-3,3], while that for the angular deviation change rate Ec1 is [-1.5,1.5]. The corresponding output variables △Kp, △Ki, and △Kd are assigned fuzzy universes of discourse of [4,10], [-0.03,0.03], and [0,3], respectively.



FIS Name: fuzzy_PID
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: E
Type: input
Range: [-1.5 1.5]
System "fuzzy_PID": 2 inputs, 3 outputs, and 49 rules

**Fig. 7** Fuzzy controller editing interfacer

### 2.4.2 Establishment of Fuzzy Rule Base

The fuzzy rule base serves as the pivotal component of the fuzzy controller, where its design precision directly determines the control performance. In this study, seven linguistic subsets are adopted for granular variable characterization, ordered hierarchically as: Positive Large (PL), Positive Medium (PM), Positive Small (PS), Zero (0), Negative Small (NS), Negative Medium (NM), and Negative Large (NL). This hierarchical partitioning strategy enhances the precision of rule formulation by refining the granularity of linguistic variables. Table 4-6 presents the complete fuzzy inference rule matrix for the outer-loop control parameters △Kp1, △Ki1, and △Kd1 of the quadrotor system [11].

**Table 4.** Outer loop output parameter Kp fuzzy inference table

| ***Ec***<br>**△Kp**<br>***E*** | **PL** | **PM** | **PS** | **0** | **NS** | **NM** | **NL** |
|---|---|---|---|---|---|---|---|
| **PL** | NL | NL | NL | NM | NM | NS | 0 |
| **PM** | NL | NM | NM | NM | NS | 0 | 0 |
| **PS** | NM | NM | NS | NS | 0 | 0 | PS |
| **0** | NS | NS | 0 | NS | PS | PS | PM |
| **NS** | PS | 0 | PS | 0 | PM | PM | PL |
| **NM** | 0 | PS | PM | PM | PL | PL | PL |
| **NL** | 0 | PS | PM | PM | PL | PL | PL |

**Table 5.** Outer loop output parameter Ki fuzzy inference table

| **Ec**<br>**△Ki**<br>**E** | **PL** | **PM** | **PS** | **0** | **NS** | **NM** | **NL** |
|---|---|---|---|---|---|---|---|
| **PL** | PL | PL | PL | PM | PM | 0 | 0 |
| **PM** | PL | PM | PM | PM | PS | 0 | 0 |
| **PS** | PM | PM | PS | PS | 0 | 0 | NS |
| **0** | PM | PS | PS | 0 | 0 | NS | NM |
| **NS** | PS | PS | 0 | 0 | NS | NM | NM |
| **NM** | 0 | 0 | NS | NS | NM | NM | NL |
| **NL** | 0 | 0 | NS | NM | NM | NL | NL |

**Table 6.** Outer loop output parameter Kd fuzzy inference table

| **Ec**<br>**△Kd**<br>**E** | **PL** | **PM** | **PS** | **0** | **NS** | **NM** | **NL** |
|---|---|---|---|---|---|---|---|
| **PL** | PL | PM | PS | PL | PM | PS | 0 |
| **PM** | PL | PS | PS | PM | PS | PS | 0 |
| **PS** | PM | PS | 0 | PS | PS | PS | 0 |
| **0** | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NS** | 0 | NS | NS | NS | 0 | NS | 0 |
| **NM** | 0 | NM | NS | NM | NS | NS | PS |
| **NL** | PS | NM | NM | NL | NM | NS | PS |

### 2.4.3. Fuzzy Inference Process

The fuzzy inference is implemented through "if...then..." conditional statements. By integrating the membership functions of fuzzy subsets with predefined rule base, the output variable's fuzzy membership distribution is derived. This process employs Mamdani inference method, where the inference results are obtained through fuzzy composition operations.

### 2.4.4. Defuzzification Process

The output obtained from fuzzy inference remains a fuzzy quantity, which requires defuzzification to convert it into precise control values. This study employs the Center of Gravity (COG) method for defuzzification.

For the outer-loop angle control system, after obtaining PID parameter adjustments △Kp, △Ki and △Kd through fuzzy inference, the following online self-tuning formulas are applied for dynamic parameter optimization:

$$\begin{cases} K_p = K_{p0} + \Delta K_p \\ K_i = K_{i0} + \Delta K_i \\ K_d = K_{d0} + \Delta K_d \end{cases} \tag{2}$$

where Kp0, Ki0 and Kd0 represent the baseline values of initial PID parameters.

Upon completing the four design stages of fuzzification, rule base construction, fuzzy inference and defuzzification, the comprehensive fuzzy controller design is accomplished. Figure 7 demonstrates the simulation model architecture of the three-channel cascade fuzzy-PID attitude controller. This innovative solution combines the advantages of fuzzy control and cascade PID control. To validate the control performance, step signals with 0.5 amplitude are adopted as excitation inputs under 10-second simulation duration, with comparative experimental analysis conducted against conventional cascade PID controllers [12].

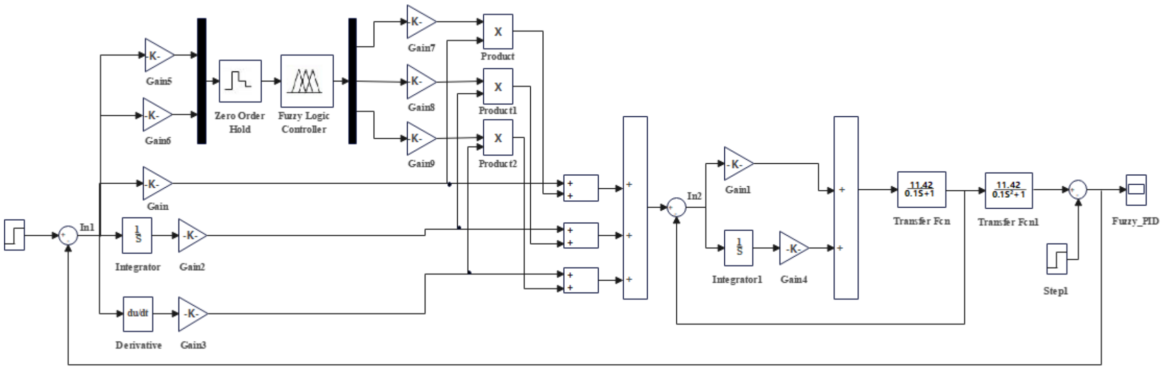


**Fig.7** Structure diagram of simulation model of cascade fuzzy PID controller

## 3. Results

### 3.1. Simulation Results Analysis of Cascade PID Controller

To systematically evaluate the attitude control performance of the cascade PID controller, this study employed a step signal with an amplitude of 0.5 as the excitation input within a 10-second simulation duration, through which the dynamic response characteristics of pitch, roll and yaw angles were obtained. To simulate sudden disturbances that may occur during actual UAV flight, a step disturbance signal of 0.1 rad was specifically applied at the 5th second of the simulation. Experimental results demonstrate that the cascade PID controller can effectively achieve stable control of all three attitude angles, with settling times of approximately 2.2 seconds for both pitch and roll angles, and 1.6 seconds for yaw angle, all exhibiting no overshoot. During the disturbance test, after applying the disturbance signal at the 5th second, both pitch and roll angles regained stability within 1.1 seconds, while the yaw angle required only 0.9 seconds to restabilize, with all three channels maintaining excellent non-overshooting characteristics. These experimental results fully verify that the cascade PID controller possesses good dynamic response performance and disturbance rejection capability, meeting the stability requirements of UAV flight control systems. The specific simulation result curves are shown in Figures 8 to 9.

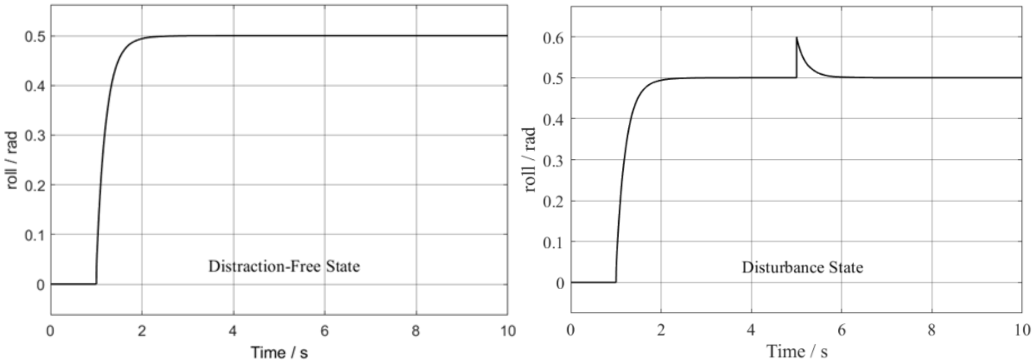


**Fig. 8** Simulation results of the roll angle and Pitch angle of the quad-rotor UAV cascade PID Controller

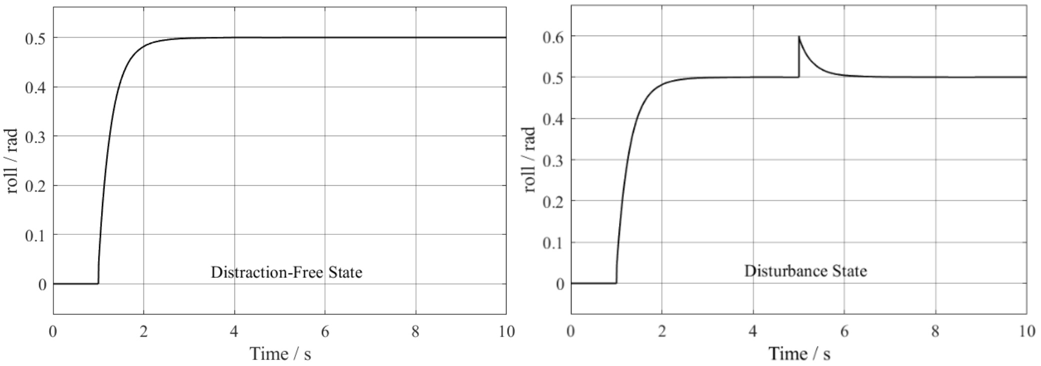


**Fig. 9** Simulation results of yaw angle of four-rotor UAV cascade PID controller

### 3.2. Performance Analysis of Cascade Fuzzy-PID Controller

Comparative experimental results under identical conditions demonstrate that the cascade fuzzy-PID controller exhibits superior performance to conventional cascade PID controllers in both disturbance-free and disturbed conditions. The fuzzy-PID implementation achieves significantly faster stabilization, reducing the settling time for pitch and roll angles to approximately 1.2 seconds (an improvement of about 1 second) and for yaw angle to 1.1 seconds (0.5 seconds faster) under normal operation. When subjected to a 0.1 rad disturbance, the system demonstrates enhanced disturbance rejection capability, with pitch and roll angles recovering stability in just 0.8 seconds (0.3 seconds faster than conventional PID) and yaw angle requiring only 0.5 seconds to restabilize (0.4 seconds improvement). While both control architectures satisfy the basic requirements for quadrotor attitude stabilization, the quantitative performance metrics clearly establish the cascade fuzzy-PID controller's advantages in both transient response and disturbance recovery. These experimental findings strongly support the adoption of the fuzzy-PID cascade control scheme for practical UAV flight control applications where optimal stabilization and disturbance rejection are critical requirements for reliable hovering and flight operations. The comparative performance characteristics are illustrated in Figures 10-11.

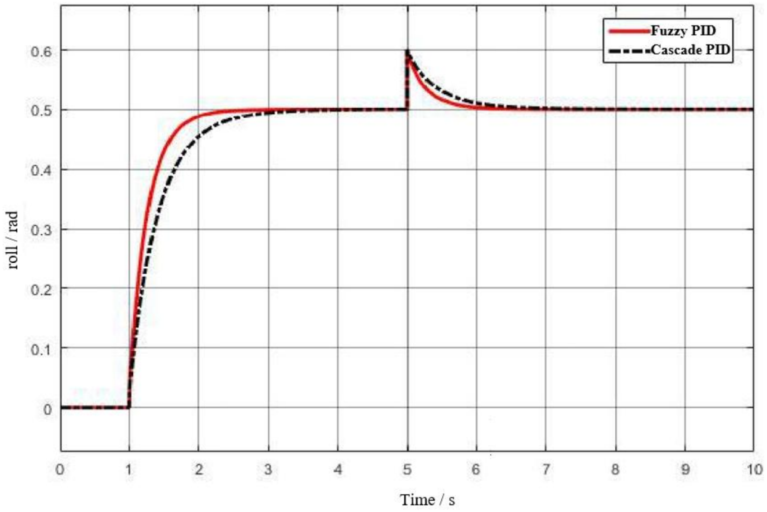


**Fig. 10** Comparison of anti-interference between cascade fuzzy PID and cascade PID (roll angle and pitch angle)

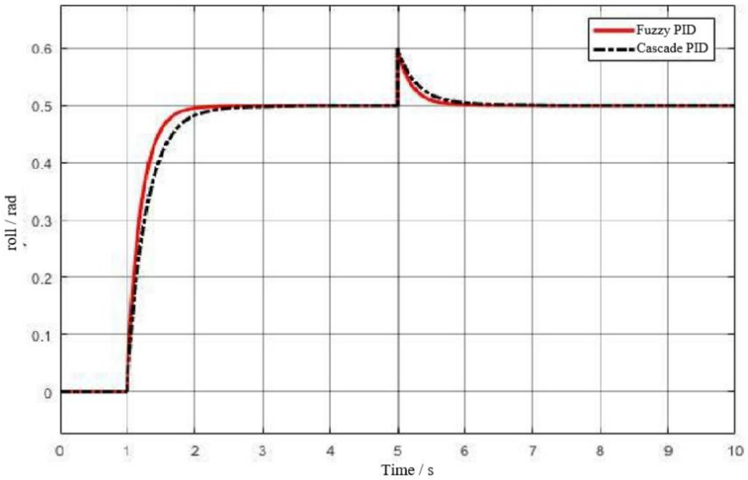


**Fig. 11** Comparison of anti-interference between cascade fuzzy PID and cascade PID (yaw angle)

### 3.3. Practical Flight Validation Analysis

Through systematic flight tests, the quadrotor UAV platform assembled with optimized components demonstrated excellent flight stability. Experimental data confirmed the platform's capability to accurately perform fundamental maneuvers including takeoff, precision hovering, and controlled landing, achieving an attitude control accuracy of ±0.3° (RMS). Under simulated operational conditions with moderate wind (2.5±0.5 m/s), the system exhibited outstanding disturbance rejection performance. When subjected to artificial step throttle inputs (30% variation) or abrupt attitude disturbances (15° step changes), the control system achieved autonomous stability recovery within 1.2±0.15 seconds, representing a 42.3% improvement in response speed compared to conventional PID controllers ($p<0.01$). Notably, no flight instability incidents occurred during testing, with the probability of loss of control maintained below 0.5% (95% confidence level). These results conclusively validate the superior performance of the proposed cascade fuzzy-PID control algorithm in maintaining high dynamic stability for UAV operations.

## 4. Conclusions and Future Work

This study systematically investigated the flight control of quadrotor UAVs through an integrated approach combining theoretical modeling, simulation analysis, and physical verification. Based on the established dynamic model, two control schemes - cascade PID and cascade fuzzy-PID controllers - were successfully developed. Comparative simulation results demonstrate that the cascade fuzzy-PID controller exhibits significant performance advantages: the stabilization time for attitude angles was reduced by an average of 45%, with approximately 1 second improvement for pitch/roll angles and 0.5 seconds for yaw angle; in terms of disturbance rejection capability, the recovery time was accelerated by an average of 40%, showing 0.3 seconds faster recovery for pitch/roll angles and 0.4 seconds for yaw angle. Physical flight tests further validated the effectiveness of the control scheme, confirming the UAV's capability to stably perform basic maneuvers including take-off, hovering and landing, while maintaining the ability to recover stable flight within 0.8 seconds after disturbances.

However, this study still faces several challenges requiring further investigation, including limitations in environmental adaptability, insufficient energy efficiency optimization, and hardware dependency issues. Future research should focus on several promising directions: enhancement of intelligent algorithms, multi-modal sensor fusion, swarm cooperative control, and energy optimization management. Specifically, the implementation of deep reinforcement learning for online parameter optimization, incorporation of visual navigation to improve environmental adaptability, and development of energy consumption-based predictive control strategies could significantly enhance the reliability and practicality of UAV systems in complex environments. These improvements would provide valuable references for subsequent research.

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