

# Design of a Fuzzy Adaptive PID Control System for Quadrotor UAVs

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Abstract: During flight operations, quadrotor UAVs are susceptible to interference from environmental factors such as wind gusts, battery depletion, and obstacles, which may compromise flight stability. This study proposes a fuzzy adaptive PID controller (Fuzzy PID) combining PID control with fuzzy logic to achieve self-adaptive adjustment of PID parameters in UAV flight control systems, thereby enhancing system robustness. A quadrotor UAV control model was developed in Simulink, and a Fuzzy PID control system was constructed by integrating fuzzy control logic for simulation and experimental validation. Test results demonstrate that UAVs governed by Fuzzy PID control exhibit faster regulation speed and improved stability when subjected to disturbances.

Keywords: Quadrotor UAV; Fuzzy PID; Robustness; Regulation speed

**Online publication:** 5 June, 2025

#### **1. Introduction**

With the advancement of technologies and the emergence of the low-altitude economy, quadrotor unmanned aerial vehicles (UAVs) have undergone rapid development, driving a transformative wave across industries. Quadrotor UAVs exhibit substantial market potential and expansive development prospects in military, civilian, and commercial domains.

Current research on quadrotor UAV algorithms is in a phase of rapid development with continuous groundbreaking achievements. The development of quadrotor UAVs primarily focuses on flight control systems, autonomous navigation, and multi-agent collaboration. For instance, the 'Kamikaze' UAV developed by Lockheed Martin employs hybrid control strategies combining PID control with adaptive control algorithms, enabling stable attitude maintenance during high-speed maneuvers <sup>[1]</sup>. Concurrently, research teams are exploring novel control theories such as Model Predictive Control (MPC) and deep learning to enhance decision-making autonomy <sup>[2–5]</sup>. China's DJI has integrated advanced attitude stabilization algorithms into its

'Phantom' and 'Mavic' series, delivering superior flight stability and precise hovering capabilities for users <sup>[6]</sup>.

Traditional PID control methods have significant limitations in addressing the control challenges of nonlinear dynamics, strong coupling, and environmental uncertainty in rotary wing unmanned aerial vehicle systems. Firstly, their fixed parameter structure is difficult to cope with dynamic conditions such as sudden wind disturbances and payload variations <sup>[7,8]</sup>; Secondly, the control model based on linearization assumption has theoretical deficiencies in dealing with the coupling effects between attitude channels <sup>[9,10]</sup>; Furthermore, the dependence on precise mathematical models severely restricts the robustness of the system <sup>[11]</sup>. To overcome these limitations, this study proposes a novel PID control architecture incorporating fuzzy inference mechanisms. By autonomously adjusting proportional, integral, and derivative parameters in real-time, the proposed Fuzzy PID hybrid controller significantly enhances control performance in complex operational environments <sup>[12]</sup>.

## 2. Design of Fuzzy PID control algorithm

## **2.1. Fuzzy control theory**

Fuzzy control theory, as an intelligent control methodology grounded in fuzzy mathematics, operates through three foundational components: Fuzzy set theory, linguistic variables, and fuzzy logic inference, collectively enabling effective control of complex systems. In practical engineering applications, fuzzy controllers are predominantly categorized into three canonical architectures: Mamdani-type, Larsen-type, and Takagi-Sugeno (T-S) type <sup>[13]</sup>. Given the inherent nonlinear dynamics, highly coupled characteristics, and environmental uncertainties inherent in unmanned aerial vehicle (UAV) systems, this study chooses a Mamdani-type fuzzy controller as the solution.

Fuzzy control, as an intelligent control method based on fuzzy mathematics theory, can be divided into three key steps in its core working principle: First, the precise input quantity is converted into a fuzzy quantity through fuzzy processing, then fuzzy inference is performed based on a preset fuzzy rule library, and finally the centroid method is used to achieve fuzzy operation, thereby generating precise control quantity output to the controlled object. The basic principle framework of this control process is shown in **Figure 1**.





## 2.2. Fuzzy PID hybrid control architecture

In the unmanned aerial vehicle control system, real-time flight attitude data is first collected through onboard sensors, and the deviation e and its rate of change ec between the current state and the expected state are calculated. Then, based on pre-defined membership functions and fuzzy subsets, the precise quantities e and ec are converted into fuzzy quantities E and EC. These fuzzy quantities are input into a fuzzy rule library for inference operations, and finally, the adjustment quantities. , , and of the PID parameters are output through deblurring processing to achieve dynamic optimization of the controller parameters. The system structure of the entire control process is shown in **Figure 2**.



Figure 2. Fuzzy PID control process

In the design of fuzzy control systems, the system deviation e and its rate of change ec are mapped to fuzzy language variables E and EC, respectively. Based on actual system requirements, the basic domain ranges of E and EC are determined to be [-3 3]. Define 7 fuzzy subsets for each language variable: Positive large (PB), median (PM), positive small (PS), zero (ZO), negative small (NS), negative medium (NM), and negative large (NB). The membership functions of each fuzzy subset in the domain are represented by trigonometric functions to ensure computational efficiency and real-time performance. Similarly, parameters , , and are also processed using the same fuzzification method to form a unified fuzzy subset , whose specific membership function distribution is shown in **Figure 3**.



Figure 3. Membership function diagram of transformation variables

The construction of a fuzzy rule library is the core component of a fuzzy reasoning system. In engineering practice, the establishment of fuzzy rules usually adopts two main methods: One is to establish a prior rule library based on control theory analysis and expert experience knowledge; The second is to use a large amount of experimental data and machine learning algorithms to mine and statistically analyze the input-output relationship, and then summarize it. In a Fuzzy PID control system based on the Mamdani inference mechanism, with system deviation e and its rate of change ec as input variables, and PID parameter adjustment  $K_p$ ,  $K_i$ , and  $K_d$  as output variables, the typical control rule can be expressed as <sup>[14]</sup>:

Rule 1: If (e is NB) and (ec is NB) then  $(K_p \text{ is PB})(K_i \text{ is NB})(K_d \text{ is PS})$ 

Rule 2: If (e is NB) and (ec is NM) then  $(K_p \text{ is PB})(K_i \text{ is NB})(K_d \text{ is NS})$ 

| The fuzzy logic reasoning rules for $\Delta K_a$ , $\Delta K_a$ , and $\Delta K_d$ are shown in <b>Tables 1</b> , 2, | and <b>3</b> . |
|--|----------------|
|--|----------------|

|              |              |    |    |    | EC |    |    |    |
|--------------|--------------|----|----|----|----|----|----|----|
| 1            | $\Delta K_p$ | NB | NM | NS | ZO | PS | PM | PB |
|              | NB           | PB | PB | PM | PM | PS | ZO | ZO |
|              | NM           | PB | PB | PM | PS | PS | ZO | NS |
|              | NS           | PM | PM | PM | PS | ZO | NS | NS |
| Е            | ZO           | PM | PM | PS | ZO | NS | NM | NM |
| $\downarrow$ | PS           | PS | PS | ZO | NS | NS | NM | NM |
|              | PM           | PS | ZO | NS | NM | NM | NM | NB |
|              | PB           | ZO | ZO | NM | NM | NM | NB | NB |

**Table 1.** Fuzzy reasoning table of  $\Delta K_p$ 

**Table 2.** Fuzzy reasoning table of  $\Delta K_i$ 

|              |              |    |    | ~  | EC |    |    |    |
|--------------|--------------|----|----|----|----|----|----|----|
| 1            | $\Delta K_i$ | NB | NM | NS | ZO | PS | PM | PB |
|              | NB           | NB | NB | NM | NM | NS | ZO | ZO |
|              | NM           | NB | NB | NM | NS | NS | ZO | ZO |
|              | NS           | NB | NM | NS | NS | ZO | PS | PS |
| Е            | ZO           | NM | NM | NS | ZO | PS | PM | PM |
| $\downarrow$ | PS           | NM | NS | ZO | PS | PS | PM | PB |
|              | PM           | ZO | ZO | PS | PS | PM | PB | PB |
|              | PB           | ZO | ZO | PS | PM | PM | PB | PB |

**Table 3.** Fuzzy reasoning table of  $\Delta K_d$ 

|   |              |    |    | <b>~</b> | EC |    |    |    |
|---|--------------|----|----|----------|----|----|----|----|
| ↑ | $\Delta K_d$ | NB | NM | NS       | ZO | PS | РМ | PB |
|   | NB           | PS | NS | NB       | NB | PB | NM | PS |
|   | NM           | PS | NS | NB       | NM | NM | NS | ZO |
|   | NS           | ZO | NS | NM       | NM | NS | NS | ZO |
| Е | ZO           | ZO | NS | NS       | NS | NS | NS | ZO |
| Ļ | PS           | ZO | ZO | ZO       | ZO | ZO | ZO | ZO |
|   | PM           | PB | NS | PS       | PS | PS | PS | PB |
|   | PB           | PB | PM | PM       | PM | PS | PS | PB |

## 2.3. Defuzzification processing

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For the obtained target object, we also need to blur it to make it correspond to the specific physical quantity. In Fuzzy PID mediation, we need  $K_p$ ,  $K_i$ , and  $K_d$ , so we need to get the  $K_p$ ,  $K_i$ , and  $K_d$  values we want according to

the results of fuzzy reasoning. We use the center of gravity method to calculate the quantized value of each output. The formula is as follows:

$$V_{O} = \frac{\sum_{i=0}^{n} M_{i} * F_{i}}{\sum_{i=0}^{n} M_{i}}$$
(1)

Where M is the membership degree and F is the fuzzy quantized value.

Because of the characteristics of the membership function we adopted, the sum of the calculated membership degrees in any direction is 1, so the denominator can be omitted. So the calculation of each object is actually a matrix operation. The formula is as follows:

$$K = \begin{bmatrix} M_{e1} & M_{e2} \end{bmatrix} \begin{bmatrix} F_a & F_b \\ F_c & F_d \end{bmatrix} \begin{bmatrix} M_{ec1} & M_{ec2} \end{bmatrix}^T$$
(2)

### **3. Simulation and experiments results**

#### **3.1. Simulation results**

#### **3.1.1. Building the test environment**

Based on the mechanism analysis of traditional PID control theory, this study adopts the MATLAB/Simulink simulation platform to construct the flight control system model. Given that the dynamic response of pitch and roll is the most significant among the UAV dynamics, and there is a strong coupling relationship between the two and the flight speed, the roll channel is selected as a typical research object, and a six-degree-of-freedom simulation model is established to verify the control performance. The simulation design is shown in **Figure 4**.



Figure 4. Fuzzy PID anti-interference simulation design diagram

#### 3.1.2. Functional testing

In the parameter configuration of the Fuzzy logic controller, the domain of the input/output variables is uniformly set to the normalized range of [-3,3]. To systematically evaluate the control performance of the UAV under extreme operating conditions, a multimodal disturbance test scheme is specially designed: Firstly, a step disturbance signal with an amplitude of 1.5 rad is applied at three time nodes of 6s, 10s and 15s to simulate sudden gusts of wind impacts; and secondly, a sinusoidal disturbance signal with a frequency of 0.5Hz and an amplitude of 1 rad is loaded at a sustained period of 20–30s to reproduce the complex airflow environment of the Continuous disturbance. By comparing and analyzing the dynamic response curves of the Fuzzy PID and traditional PID controllers in the pitch angle and roll angle channels (**Figure 5**), the differences in the anti-disturbance performance between the two control algorithms can be quantitatively evaluated.

According to the simulation comparison results in **Figure 5**, the following quantitative analysis conclusions can be drawn: Under the same PID parameter configuration conditions, the Fuzzy PID controller shows significant

dynamic performance advantages in the pitch and roll channels, and its regulation time (TS) averages 1.7s, which is about 43.3% shorter than the 3s response time of the traditional PID control; this phenomenon indicates that the Fuzzy PID algorithm has better adaptive regulation capability for the pitch/roll channel with stronger attitude angle coupling.



Figure 5. Comparison diagram of simulation tracking under strong interference of pitch angle

## **3.2. Experimental results**

#### 3.2.1. Fixed-axis testing

To establish a complete experimental data acquisition system and ensure the safety of the testing process, this study adopts a staged validation approach: Before carrying out the full-degree-of-freedom flight test, the fixed-axis constraint test is first implemented. A single axis (X/Y axis) of the UAV is fixed by a mechanical fixture, so that it carries out controlled motion in the remaining two planes of freedom, thus systematically evaluating the independent control performance of the Fuzzy PID controller on pitch and roll angles. The test scheme (**Figure 6**) can effectively isolate the multi-axis coupling effect and provide benchmark reference data for subsequent full-state flight control.



Figure 6. UAV Fuzzy PID control fixed axis test

The motion regulation test of Fuzzy PID and conventional PID for fuselage pitch angle is shown in Figure 7.



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#### **3.2.2. Flight test results**

After completing the fixed-axis constraint test and verifying the safety of the Fuzzy PID control system, this study enters the real-aircraft flight verification phase. In this phase, a full-degree-of-freedom flight test program is adopted, in which attitude control commands are sent to the on-board flight control via a 2.4 GHz wireless remote-control system to monitor the response speed and control accuracy of the UAV in the controlled area, and the Fuzzy PID flight control system is tested as shown in **Figure 8**.



Figure 8. Fuzzy PID flight test

Based on the real-time attitude information recorded by the flight test data acquisition system, this study compares and analyzes the pitch angle dynamic characteristics of the traditional PID and Fuzzy PID controllers, as shown in **Figure 9**.

Based on the comparative analysis of the dynamic response and convergence speed curves shown in **Figures 9** and **10**, the following quantitative conclusions can be drawn: The system TS of the traditional PID controller is  $2.5 \pm 0.2$ s, while the Fuzzy PID controller needs only  $1.6 \pm 0.1$ s to complete convergence, and the response speed is improved by 36%. In terms of control accuracy, Fuzzy PID strictly controls the steady state error within the range of  $\pm 0.5^{\circ}$ , which is a significant improvement over the  $\pm 1.2^{\circ}$  of traditional PID. The experimental data fully proves that the Fuzzy PID control algorithm shows dual advantages in UAV attitude control: On the one hand, the fuzzy inference mechanism realizes the reduction of convergence time; on the other hand, with the help of adaptive parameter adjustment, the fluctuation amplitude of the steady state error is significantly reduced, so that breakthroughs are achieved in the dimensions of both the dynamic response speed and the steady state control accuracy.



Figure 9. Comparison of pitch angle control tests



Figure 10. Comparison of error(e) convergence speed

## 4. Conclusion and future prospect

Based on the comparative analysis of the dynamic response and convergence speed curves shown in **Figures 9** and **10**, the following quantitative conclusions can be drawn: The system TS of the traditional PID controller is  $2.5 \pm 0.2$ s, while the Fuzzy PID controller needs only  $1.6 \pm 0.1$ s to complete convergence, and the response speed is improved by 36%. In terms of control accuracy, Fuzzy PID strictly controls the steady state error within the range of  $\pm 0.5^{\circ}$ , which is more than the traditional This study proposes an innovative UAV control strategy, which significantly improves the stability and dynamic response performance of the flight control system by organically integrating the multilevel digital filtering algorithm with the Fuzzy PID controller. In the experimental validation phase, a single-degree-of-freedom constrained test method is used to fix the UAV in a specific attitude axis (e.g., pitch axis) for a closed-loop control test. The test system adopts the USB 3.0 high-speed data interface to achieve real-time communication between the UAV and the ground control station, and the human-computer interactive interface to achieve visual monitoring of the attitude data. The experimental data show that the hybrid control scheme has the following advantages over the traditional PID control: (1) Dynamic response time is reduced by 36%; (2) steady state error is significantly reduced; and (3) anti-interference capability is effectively improved. These improvements significantly improve the flight control precision and stability of the UAV in complex environments significantly improved, laying a solid technical foundation for the realization of subsequent

autonomous flight missions.

## Funding

The 2023 Scientific and Technological Project in Henan Province of China (232102220098)

#### **Disclosure statement**

The authors declare no conflict of interest.

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