Research on Attitude Stability of Quadrotor UAV Based on Fuzzy Control

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Abstract: This research explores the attitude control of Unmanned Aerial Vehicles (UAVs) using fuzzy control theory. As UAV applications expand in military, agriculture, logistics, and surveying, traditional control methods like Proportional-Integral-Derivative (PID) often struggle with dynamic conditions, leading to reduced stability and mission success. Fuzzy control offers adaptability and the ability to handle nonlinearities, addressing uncertainties in UAV flight. By integrating fuzzy control, we achieve rapid and precise adjustments to UAV attitude, enhancing stability and response in complex environments. This study simplifies the control model, improves adaptability, and ensures flight safety through adaptive fuzzy rules. The findings provide new insights and practical solutions for advancing UAV flight control technology, establishing a foundation for broader UAV applications.

Keywords: Fuzzy Control; Attitude Control Of Quadrotor Uav; Pid Control

1. Introduction

Currently, significant research has been conducted on UAV PID control, yielding various results and effectively matching UAVs' complex operating conditions. Liu, L.Y. et al. leveraged the advantages of neural networks to simplify complex information into a model, combining conventional PID algorithms with RBF networks to achieve better control performance. However, this method faces challenges such as high computational complexity, parameter sensitivity, overfitting risks, integration difficulties, and potential impacts on real-time performance[1]. Zhang, L. designed a quadrotor UAV control system based on cascade PID control, offering higher stability and lower controller costs compared to traditional PID methods. However, it requires precise parameter adjustments and may suffer from reduced control accuracy due to nonlinearities, strong coupling, and disturbances[2]. Huang ,L.F. et al. proposed a PID-iterative learning UAV control strategy for high-precision trajectory tracking in repetitive motion scenarios. This method requires a good initial control strategy and is affected by system complexity and disturbances[3]. Feng, J.J. et al. introduced a fuzzy neural network-based UAV PID control system, combining fuzzy logic and neural networks to optimize PID control performance. Although this approach improves parameter accuracy, it faces difficulties in parameter selection, high computational complexity, and tuning challenges[4]. He, H.Y. et al. proposed a deep reinforcement learning-based algorithm using deep deterministic policy gradient (DDPG) for fixed-wing UAV longitudinal control, which reduces steady-state errors and offers faster tracking speed compared to PID controllers. However, this method demands high computational resources and may encounter local optima[5]. Yao, S. et al. presented a fuzzy position-type PID control algorithm for attitude control, using genetic algorithms for global optimization of fuzzy PID parameters. This approach maintains control advantages and reduces tuning effort but is limited by initial population selection and fitness function design, as well as the need for extensive knowledge in fuzzy control rule formulation[6]. The article proposed a dynamic PSO (Particle Swarm Optimization) algorithm that dynamically adjusts inertia weights based on the Euclidean distance between current and optimal particles and applies crossover to improve population diversity[7]. Another study introduced the ISSA (Improved Sparrow Search Algorithm) integrating piecewise chaotic mapping, dynamic inertia weights, and adaptive hybrid mutation strategies to enhance global search capabilities, applied to PID parameter optimization for quadrotor UAV models [8].

Zhao, Z.Y. studied the navigation attitude control system of unmanned ship based on fuzzy PID control, which improved the stability of unmanned ship in complex environment, but the complexity of the system increased the calculation burden[9]. Long, K. discusses a four-rotor delivery drone control system that uses fuzzy PID control to optimize flight stability and accuracy, but requires extensive debugging to achieve the best results[10]. The interval II fuzzy PID control method proposed by Wu, B. can improve the control performance of UAV in highly uncertain environment, but the design and implementation are complicated[11].

This paper applies fuzzy control algorithms to the study of UAV attitude control to improve stability and response speed in complex environments. By establishing the dynamics model of a quadrotor UAV, a fuzzy control-based attitude controller is designed to address the limitations of traditional PID control methods under dynamic conditions. To evaluate the feasibility of the control methods, simulations and experiments are conducted using Simulink software to compare the stability, responsiveness, and disturbance rejection capabilities of the quadrotor under both classical PID control and fuzzy control. The simulation results indicate that fuzzy control outperforms PID control, demonstrating improvements in response time, stability, accuracy, and disturbance rejection capabilities in the quadrotor control system.

2. Dynamics Model of Four-Rotor UAV

At this stage, it is essential to model the attitude of the quadrotor UAV's motion. This involves describing the changes in the aircraft's orientation in space, typically represented using Euler angles or quaternions. Attitude modelling must take into account the dynamics and mechanical characteristics of the aircraft, including the structure of the vehicle and the settings of the PID controller.

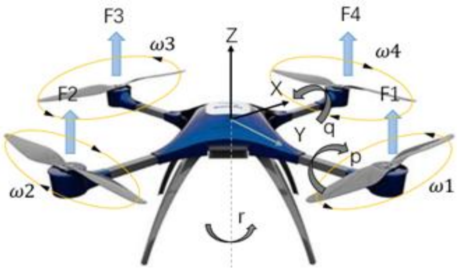


Figure1. Motion Model and Coordinate System of Four-Rotor UAV

The linear motion of the drone can be expressed as:

$$\dot{x} = v_x \tag{1}$$

$$\dot{y} = v_y \tag{2}$$

$$\dot{z} = v_z \tag{3}$$

$$m\dot{v}_x = F_t(\cos\Phi\cos\Psi\sin\theta + \sin\Phi\sin\Psi)m\dot{v}_y = F_t(\cos\Phi\sin\theta\sin\Psi - \cos\Psi\sin\Phi) \tag{5}$$

$$m\dot{v}_z = -mg + F_t\cos\Phi\cos\theta \tag{6}$$

The angular motion of the drone can be expressed as

$$\dot{\Phi} = p + (r\cos\Phi + q\sin\Phi)\tan\theta \tag{7}$$

$$\dot{\theta} = q\cos\Phi - r\sin\Phi \tag{8}$$

$$\dot{\Psi} = \frac{1}{\cos\theta}(r\cos\Phi + q\sin\Phi \tag{9}$$

$$I_x\dot{p} = \left(I_y - I_z\right)qr + \tau_p \tag{10}$$

$$I_y\dot{q} = (I_z - I_x)pr + \tau_q \tag{11}$$

$$I_z\dot{r} = \left(I_x - I_y\right)pq + \tau_r \tag{12}$$

3. The Design of Fuzzy Controller

Fuzzy control does not require knowledge of the internal structure, working principles, or mathematical models of the controlled object. Instead, it focuses on control experience and strategies, using fuzzy conditional language to formulate fuzzy rules through analysis and induction. The design of a fuzzy controller relies heavily on expert experience and theoretical knowledge to create a fuzzy rule base and fuzzy reasoning algorithms. Key aspects include determining the controller structure, establishing fuzzy rules, and selecting an appropriate reasoning algorithm, with the fuzzy rule base being central to the design. The design process involves identifying input and output variables, defining the membership functions of fuzzy subsets, establishing fuzzy rules, conducting fuzzy reasoning, calculating output values, and finally performing defuzzification. The main design steps of fuzzy controller are shown in Figure 2

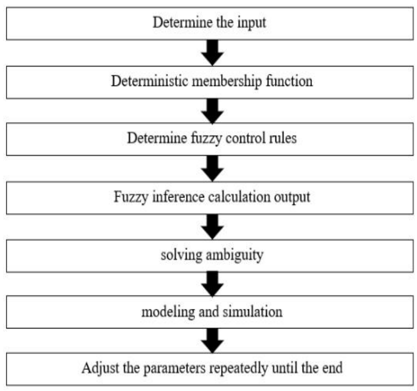


Figure 2. The Design Steps of Fuzzy Controller

3.1 The Input and Output Are Blurred

The selection of input variables is based on the system's characteristics and their relationships to output variables. In quadrotors, angle error (e) indicates the deviation from the desired flight attitude, while the rate of change of angle error (ec) provides insight into its trend. Together, these inputs allow the controller to adjust outputs dynamically, improving response and stability during flight experiments.

The four-rotor fuzzy controller has 2 input variables and 3 output variables, and the input is the Angle error e and the change rate ec, or angular velocity error e and angular velocity error change rate ec, the output is PID parameter change ΔKp, ΔKi, ΔKd.

Fuzzy control from the beginning of the input and output fuzzy processing to the final defuzzy are implemented in MATLAB; Using Fuzzy module, we choose Mamdani type fuzzy inference editor, and set up 2 input and 3 output variables respectively. The value is e, ec, kp, ki, and kd.

The fuzzy domain of input deviation e_1 and deviation rate of change ec_1 is taken [-1.5, 1.5]. Angle output values Kp_1 , Ki_1 , Kd_1 modulus. Paste domain is taken [0, 1.5]. Fuzzy subsets of input and output variables are all represented by [NB, NM, NS, ZO, PS, PM, PB]. Taking input variable error e as an example, NB indicates large negative error. NM indicates a large negative error; NS means that the negative error is small; ZO means the error is 0; PS positive error is small; PM means large positive error; PB indicates a large positive error.

3.2 Establishing Fuzzy Rules

The fuzzy rules are established based on the experience accumulated by operators during practical operations and the theoretical knowledge of experts, forming a fuzzy rule knowledge base. This base is used to determine the fuzzy relationships between the PID parameters ΔKp, ΔKi, ΔKd and the input deviation e, as well as the rate of change of the input deviation ec. After extraction and continuous refinement, these rules aim to achieve a good control effect on the quadrotor at different stages by optimizing the input variables. I refer to the definition of fuzzy control rules in reference [12].

Using the PID parameter adjustment method and integrating practical control experience with the relationship between parameters and control effects, fuzzy control rules have been established. Different combinations of the input variables e and ec correspond to different PID parameter control rules. Each input variable is assigned 7 linguistic fuzzy variables, resulting in a total of 49 fuzzy rules, with the adjustment rules for ΔKp, ΔKi, and ΔKd as follows:

1) If (e1 is NB) and (ec is NB) then (ΔKp1 is PB) (ΔKi1 is NB) (ΔKd1 is PS)
2) If (e1 is NM) and (ec is NB) then (ΔKp1 is PB) (ΔKi1 is NB) (ΔKd1 is NS)
3) If (e1 is NS) and (ec is NB) then (ΔKp1 is PM) (ΔKi1 is NM) (ΔKd1 is NB)
48) If (e1 is PM) and (ec is PB) then (ΔKp1 is NB) (ΔKi1 is PB) (ΔKd1 is PS)
49) If (e1 is PB) and (ec is PB) then (ΔKp1 is NB) (ΔKi1 is PB) (ΔKd1 is PB)

ΔKP		e						
		NB	NM	NS	ZO	PS	PM	PB
ec	NB	PB	PB	PM	PM	PS	ZO	ZO
	NM	PB	PB	PM	PS	PS	ZO	NS
	NS	PB	PM	PM	PS	ZO	NS	NS
	ZO	PM	PM	PS	ZO	NS	NM	NM
	PS	PS	PS	ZO	NS	NS	NM	NB
	PM	PS	ZO	NS	NM	NM	NM	NB
	PB	ZO	ZO	NM	NM	NM	NB	NB

Figure 3. ΔKp Fuzzy Rule Reasoning Table

ΔKI		e						
		NB	NM	NS	ZO	PS	PM	PB
ec	NB	NB	NS	NM	NM	NS	ZO	ZO
	NM	NB	NS	NM	NS	NS	ZO	ZO
	NS	NB	NM	NS	NS	ZO	PS	PS
	ZO	NM	NM	NS	ZO	PS	PM	PS
	PS	NS	NS	ZO	PS	PS	PM	PB
	PM	ZO	ZO	PS	PS	PM	PB	PB
	PB	ZO	ZO	PS	PM	PB	PB	PB

Figure 4. ΔKi Fuzzy Rule Reasoning Table

ΔKD		e						
		NB	NM	NS	ZO	PS	PM	PB
ec	NB	PS	NS	NB	NB	NB	NM	PS
	NM	PS	NS	NB	NM	NM	NS	ZO
	NS	ZO	NS	NM	NS	NS	NS	ZO
	ZO	ZO	NS	NS	NS	NS	NS	ZO
	PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
	PM	PB	NS	PS	PS	PS	PS	PB
	PB	PB	PM	PM	PS	PS	PS	PB

Figure 5. ΔKd Fuzzy Rule Reasoning Table

It can be edited by MATLAB fuzzy rule editor, and it can be deduced by fuzzy reasoning and unambiguousness to get the module paste value ΔKp, ΔKi, ΔKd.

As shown in Figure 5, when the fuzzy subset of input deviation e and deviation rate of change ec is different, the corresponding output control quantity ΔKp, ΔKi, ΔKd, is also different.

3.3 Fuzzy Reasoning and Defuzzification

After establishing the fuzzy rule base, fuzzy inference is performed on the input fuzzy quantities to obtain the corresponding fuzzy output quantities. Once the fuzzy output quantities are obtained, defuzzification is necessary to achieve control over the controlled variable. Both fuzzy inference and defuzzification processes are implemented in MATLAB. Fuzzy inference is used to adjust the PID parameters, thereby achieving online self-tuning of the parameter changes for Kp，Ki, Kd, as specified in equation (13).

$$\begin{cases} K_p = K_{p0} + \Delta K_p \\ K_i = K_{i0} + \Delta K_i \\ K_d = K_{d0} + \Delta K_d \end{cases} \tag{13}$$

Kp_0, Ki_0, and Kd_0 are the fundamental parameters of the PID controller, while ΔKp, ΔKi, and ΔKd are the online correction values obtained by the fuzzy controller based on the fuzzy control rules. The PID input parameters Kp, Ki, and Kd for the quadrotor drone system are the sum of the fundamental values and the online correction values.

In the parameter adjustment of drones based on fuzzy control, the parameters of the fuzzy controller (Kp, Ki, Kd) are dynamically adjusted through fuzzy inference and defuzzification processes. Based on the drone's real-time state (such as angle error and rate of change of error), the system utilizes a predefined fuzzy rule base to generate corresponding fuzzy output quantities. These fuzzy outputs are then converted into specific control parameters through defuzzification, enabling online self-tuning of the PID controller to enhance the drone's response speed and stability.

4. Simulation Experiment

4.1 Simulink Simulation Model of Quadrotor UAV

Using MATLAB Simulink platform, a detailed simulation model is constructed according to the dynamics principle and control strategy of the four-rotor UAV. Through modular design, each component of UAV and its interaction relationship are accurately simulated, which provides a solid foundation for the subsequent controller design and optimization.

The rotational dynamics of the UAV are shown in Figure 6, the Rotational - Kinematics is shown in Figure 7, and t translational dynamics of the UAV is shown in Figure 8

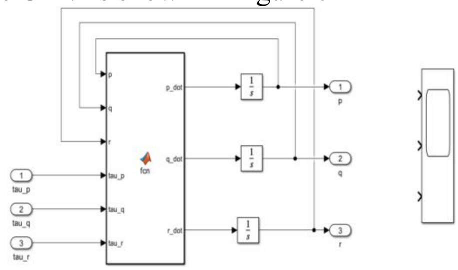


Figure 6. Rotational Dynamics Model of UAV

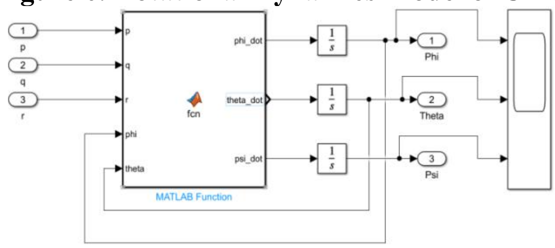


Figure 7. Rotational - Kinematics

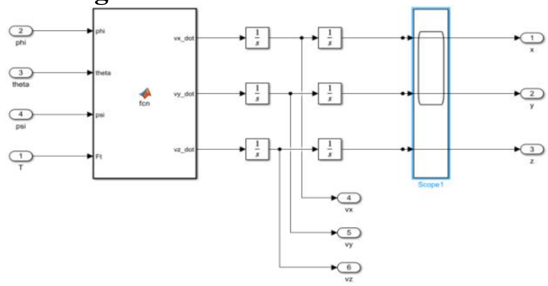


Figure 8. Translational Dynamics(Hybrid Frame)

4.2 Fuzzy Inference System

4.2.1 Fuzzy Inference System Editor

After opening MATLAB software, enter fuzzy in the main window and click Enter to start the fuzzy inference system editor. The fuzzy controller is Mamdani type, and the input and output variables of the controller are added. The fuzzy controller of the four-rotor UAV is a system with 2 inputs and 3 outputs, as shown in Figure 9.

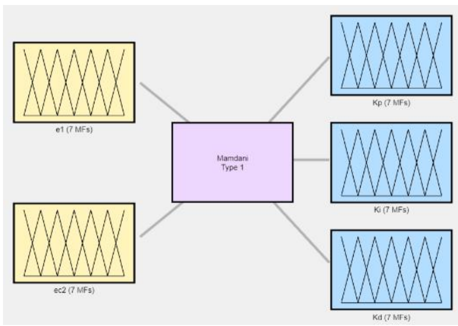


Figure 9. Two-Input, Three-Output Mamdani Fuzzy Inference Editor

4.2.2 Membership function editor

Double-click either of the 2 input and 3 output variables to enter the membership function editor and value the membership function range. The domain of Angle deviation e_1 and Angle deviation rate of change ec_1 is {-1.5,1.5}, as shown in Figure 10. The discourse domain of the outputs ΔKp1, ΔKi1, and ΔKd1 is {0,1.5}, as shown in Figure 11.

Name: e1

Range: [-1.5 1.5]

Number of MFs: 7

Name	Type	Parameters
NB	Triangular	[-2 -1.5 -1]
NM	Triangular	[-1.5 -1 -0.5]
NS	Triangular	[-1 -0.5 0]
ZO	Triangular	[-0.5 0 0.5]
PS	Triangular	[0 0.5 1]
PM	Triangular	[0.5 1 1.5]
PB	Triangular	[1 1.5 2]

Figure 10. Membership Function of Input

Name: Kp

Range: [0 1.5]

Number of MFs: 7

Name	Type	Parameters
NB	Triangular	[-0.25 0 0.25]
NM	Triangular	[0 0.25 0.5]
NS	Triangular	[0.25 0.5 0.75]
ZO	Triangular	[0.5 0.75 1]
PS	Triangular	[0.75 1 1.25]
PM	Triangular	[1 1.25 1.5]
PB	Triangular	[1.25 1.5 1.75]

Figure 11. Membership Function of Output

4.2.3 Fuzzy rule editor

Click View in Rule Editor at the upper right corner of the editor interface to pop up the fuzzy rule editor. According to the fuzzy rule combination, fuzzy rules for each variable are established. There are 49 fuzzy rule combinations in total, as shown in Figure 12.

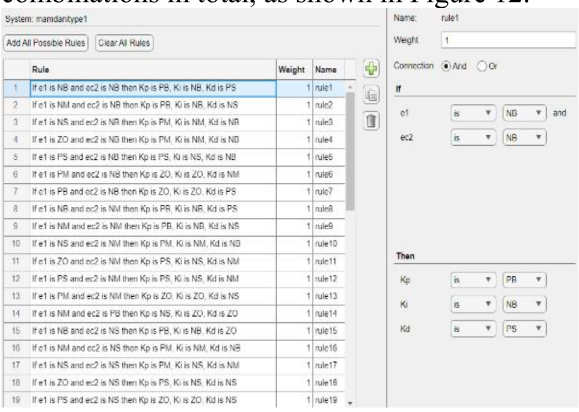


Figure 12. Fuzzy Rule Editing

4.2.4 Output Surface Observation Window

The output surface observation window is used to observe the relationship between the input variable and the output of the whole discourse domain. Output quantity control the curved surface diagram is shown in Figure 13.

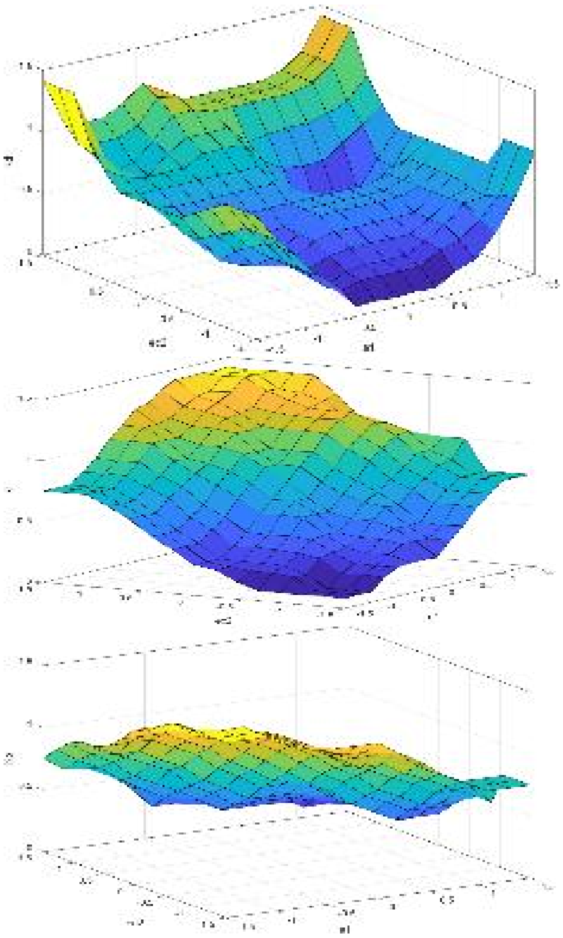
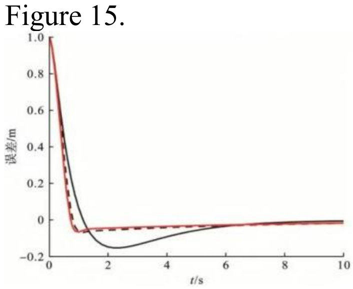


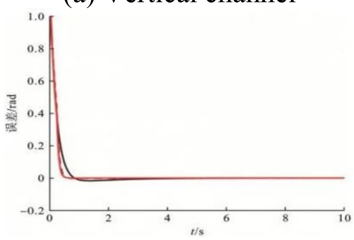
Figure 13. Output Control Surface Diagram

5. Experimental Result

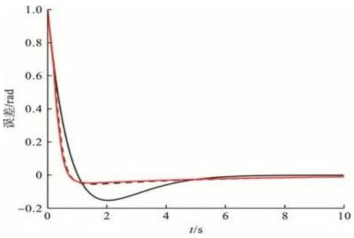
The simulation compared PID control algorithm and fuzzy control algorithm to verify the control effect of each channel, set the control system to add the input signal with the amplitude of 1, and the simulation time was 10 s. The control errors of the four channels of the four-rotor UAV are shown in Figure 15.



(a) Vertical channel



(b) Roll and pitch channels



(c) Yaw channel

Figure 14. Control errors of Different Channels

As can be seen from Figure 14, under the control of fuzzy controller, UAV has the advantages of short response time, fast adjustment speed, good stability and high robustness.

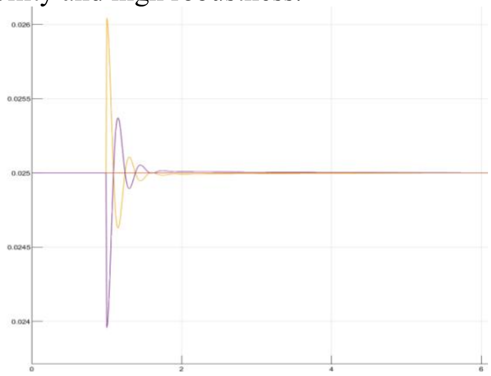


Figure 15. System Control Performance

6. Conclusion

Aiming at the shortcomings of traditional PID control, such as long response time and large overshoot, a new fuzzy controller is proposed in this paper. The control effect of the four channels of the four-rotor UAV is verified by MATLAB/Simulink simulation, and the PID control algorithm and fuzzy control algorithm are compared and analyzed. The simulation results show that the fuzzy control algorithm has faster response speed, higher steady-state accuracy and smaller overshoot, which shows better control ability.

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