A Review of Attitude Stability Optimisation Research for Quadrotor UAV Based on Fuzzy PID and Adaptive Control

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Abstract: This thesis reviews the research on applying fuzzy PID and adaptive control in attitude optimisation of quadrotor UAV, focusing on the fusion mechanism of these two control methods to enhance the control performance. The improvement methods of fuzzy PID controllers and adaptive control strategies are analysed, highlighting their complementary benefits. Fuzzy PID control has advantages in dynamically adjusting PID parameters, while adaptive control excels in responding to environmental changes. Integrating these two solutions can significantly improve the attitude control performance and stability of a quadrotor UAV in complex environments.

Keywords: Component; Quadcopter UAV; Adaptive Control; Fuzzy Algorithms; Attitude Optimisation

1. Introduction

Quadcopter UAV are widely used in agriculture, logistics, and other fields due to their simple structure and strong mobility. According to the research statistics of Hengzhou Cheng Si, the global FPV quadcopter drone market size is expected to be about 2.29 billion yuan in 2024, close to 6.54 billion yuan in 2031, and will continue to maintain a steady growth trend in the future[1]. However, the accident rate caused by unstable attitude control is gradually increasing, and more advanced control strategies are needed to increase the stability of the quadrotor UAV.

Attitude control of a quadrotor UAV is complex and easily affected by factors like airflow and flight environment. Traditional PID control struggles to meet high precision and stability requirements in these scenarios. Lopez-Sanchez et al. showed that the traditional PID control leads to an increase of 52% of the attitude angle error of the quadcopter UAV when the wind speed is greater than 6 m/s[2].

In contrast, Jiang et al. (2023) demonstrated that fuzzy PID reduces overshooting by 65% through dynamic parameter adjustment, showcasing its adaptability[3]. Fuzzy PID-based flight attitude control of quadrotor UAV can improve control accuracy and system stability. In addition, adaptive control algorithms have been widely studied in quadrotor UAV to improve control accuracy and stability by dynamically adjusting the controller parameters to adapt to the environmental changes[4].

Although fuzzy PID control and adaptive control, as intelligent control methods, have the advantages of self-adaptation, self-learning, and strong robustness, and can effectively deal with complex environments and uncertainties, the current research on the application of these two methods in the attitude optimisation of quadcopter UAV is still relatively limited. Many problems deserve to be explored in depth. For example, the fuzzy PID controller has the problem of high computational complexity, and the parameter adjustment may have hysteresis in high-speed flight or rapidly changing environment scenarios, thus affecting the control effect[5]. In addition, the attitude control method for small quadrotor uncrewed helicopters based on adaptive inverse control can cope with some faults to a certain extent. However, its fault-tolerance performance is still insufficient in complex fault scenarios[6].

In this study, fuzzy PID and adaptive control are combined to enhance the attitude control of a quadrotor UAV, which solves the limitations of traditional PID control in complex environments. It examines the evolution of UAV attitude control theory from traditional PID to adaptive and hybrid control methods. In this paper, various control techniques are compared, strategies combining fuzzy PID and adaptive control are studied, and the advantages and disadvantages of different control theories are compared in Table 1. In addition, this paper explores future research directions for technology fusion, optimization, and experimental validation.

2. Development of Attitude Control Theory for Quadrotor UAV.

The development of the quadrotor UAV attitude control theory reflects the continuous evolution of control strategies from traditional to intelligent. Early studies mostly used traditional PID control because of its simplicity and ease of implementation, but its limitations gradually became apparent in the complex dynamic environment and system uncertainty. In 2004, Bouabdallah et al. introduced linear-quadratic (LQ) control, which, in contrast to PID control, designs feedback controllers based on a more complete dynamics model and improves the response accuracy under significant angular deviation, but is insufficiently adaptive to model parameter Insufficient adaptability to model parameter changes and external perturbations。

In 2008, Mian and Wang proposed an inverse step-based nonlinear PID controller to introduce nonlinear PID to the attitude control domain[8]. In 2010, González-Vázquez and Moreno-Valenzuela proposed a stable time-scale separation theory based on a PID scheme, analysed the stability of a closed-loop system using the Lyapunov stability theory, and provided theoretical support for the application of linear PID control in quadrotor attitude control[9]. In the same year, Hoffmann et al. experimentally compared the robustness and anti-jamming ability of linear PID control with integral backstepping control, verifying the effectiveness of PID control in practical applications[10]. In 2012, Lee et al. for the first time rigorously demonstrated the stability of the PID controller for quadrotor attitude control through Lyapunov stability theory, and proposed a PID scheme for attitude control with a dynamic surface control method for altitude control, which ensures the consistent and ultimately bounded nature of the system signals[11]. In 2013, Luong Tuan and Won proposed the PID Sliding Mode Control, which improves the system's robustness to disturbances through a nonlinear design[12].In 2015, Lin et al. improved the backstepping control strategy by combining feedback linearisation with a linear PID inner loop, providing sufficient conditions for PID parameter selection[13].In the same year, Modirrousta and Khodabandeh designed an adaptive robust PID controller by combining integral backstepping control with adaptive terminal sliding mode[14].

With the deepening of research, intelligent control methods are gradually emerging. In 2016, Gao et al. designed fuzzy adaptive PID controllers to adjust the PID gain online through fuzzy logic, which improved the attitude tracking accuracy and robustness of the UAV[15]. In 2019, Rios et al. proposed a continuous sliding mode control strategy combined with a disturbance observer to achieve fast convergence of attitude errors[16]. In 2020, a team from Beijing University of Aeronautics and Astronautics designed an improved ADRC with nested inner and outer rings to optimise the expansion of the state observer and improve anti-jamming performance[17]. In 2022, Kang et al. combined MPC and PID to design lightweight MPC-PID controllers that balance control accuracy and computational efficiency[18]. In the same year, Ghasemi and Azimi introduced fuzzy logic and a nonlinear disturbance observer to design an adaptive fuzzy PID controller to improve attitude stability[19].

In recent years, breakthroughs have been made in applying deep learning techniques in attitude control.2023 Salzmann et al. used deep neural networks to replace traditional MPC's linear model to achieve high-precision nonlinear dynamics prediction [20].In 2024, Tan et al. adaptively adjusted their control strategy through an online learning mechanism to achieve autonomous attitude control in an unknown environment for the first time[21].In 2025, He et al. designed zero neural network observers to accurately estimate perturbations and solve the jitter problem of conventional sliding mode control[22].

In summary, as Figure 1 shows, the development process of the quadrotor UAV attitude control theory, which evolved from traditional PID control to nonlinear control, adaptive control, and intelligent control, provides theoretical and technical support for the stability and robustness of UAV in complex environments.

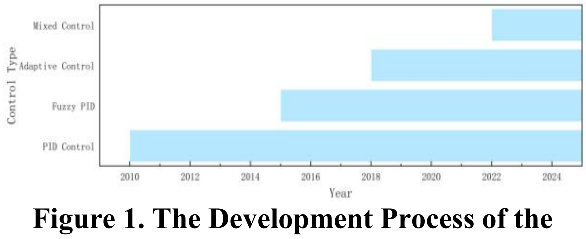

Figure 1. The Development Process of the Attitude Control Theory of the Quadrotor UAV

3. Mainstream Technology Comparison

3.1 Attitude Modelling of a Quadrotor UAV

The attitude motion of a quadrotor can be decomposed into positional motion (centre of mass translation) and attitude motion (rotation around the centre of mass). The attitude dynamics model is based on Euler's equations, which are mathematically described as

$$\begin{cases} \dot{\phi}=p+q\sin\phi\tan\theta+r\cos\phi\tan\theta \\ \dot{\theta}=q\cos\phi-r\sin\phi \\ \dot{\psi}=q\sin\phi\sec\theta+r\cos\phi\sec\theta \end{cases} \tag{1}$$

Where (ϕ, θ, ψ)are the roll, pitch, and yaw angles; and (p, q , r) are the angular velocities in the airframe coordinate system. According to the Newton-Euler formulation, the attitude dynamics equation can be expressed as

$$I\dot{\omega}+\omega\times I\omega=M-M_d \tag{2}$$

Where, $I\dot{\omega}$为 is the rotational inertia matrix, ωs is the angular velocity vector, M is the control moment, and M_d is the disturbance moment.

3.2 Fuzzy PID

In quadrotor UAV attitude control, fuzzy PID usually adopts a double closed-loop control structure, i.e., the inner loop controls the attitude (pitch, roll, and yaw angle), and the outer loop controls position[24]. The working principle is to take the system error e and the rate of change of the error ec as inputs, and dynamically adjust the three parameters(K_p,K_i,K_d), of the PID controller through the fuzzy rule, to achieve the precise control of the attitude of the quadrotor UAV.

$$\begin{cases} K_p=K_p+\Delta K_p \\ K_i=K_i+\Delta K_i \\ K_d=K_d+\Delta K_d \end{cases} \tag{3}$$

where, K_p , K_i, K_d are the proportional, integral, and differential parameters of the initial PID controller, ΔK_p ΔK_i ΔK_d is the parameter correction value calculated by the fuzzy controller

$$\begin{cases} \Delta K_p=F_1(e, ec) \\ \Delta K_i=F_2(e, ec) \\ \Delta K_d=F_3(e, ec) \end{cases} \tag{4}$$

where, F_i is the fuzzy inference function.

The affiliation function is designed using a combination of trigonometric and Gaussian forms, where the trigonometric function covers the main working intervals and the Gaussian function deals with boundary ambiguities. Based on Mamdani's "If $e$is A and $ec$is B, Then ΔK_p is C, ΔK_i is D, ΔK_d is E" the establishment of 49 rules of thumb (7×7 combinations)[3].

3.3 Adaptive Sliding Mode Control

Adaptive sliding mode control is another effective method for attitude control of quadrotor UAV, which is especially suitable for coping with system uncertainties and external disturbances. During the attitude adjustment process, adaptive sliding mode control estimates the uncertainties and disturbances in the system online by designing an adaptive law [25]. The basic principle is to construct an appropriate sliding mould surface, attract the system state to that sliding mould surface, and converge to the desired state along the sliding mould surface. The adaptive mechanism adjusts the control parameters in real time to adapt to system parameter changes and external perturbations so that the controller maintains good performance[26].

The slide mould surface is designed as a linear combination:

$$s=\lambda e+\dot{e} \tag{5}$$

Where λ is the sliding mode parameter, e is the error, and ė is the derivative of the error.

The control law contains the equivalent control term u_{eq} and the switching control term u_{sw}:

$$u=u_{eq}+u_{sw}=-I^{-1}(\omega\times I\omega+M_d)-K\cdot \mathrm{sat}(s/\Phi) \tag{6}$$

the equivalent control term: $u_{eq}=-I^{-1}(\omega\times I\omega+M_d)$, Compensating for nonlinear dynamics and perturbations

the switching control term: $u_{sw}=-K\cdot sat(s/\Phi)$, Jitter suppression based on saturation function (Φis boundary layer thickness)

Adaptive Law Dynamic Gain Adjustment:

$$\dot{K}=\gamma|s| \quad (\gamma>0) \tag{7}$$

Adaptive law dynamically adjusts the gain K>0 for enhanced robustness

γ is an adaptive gain adjustment parameter that controls the update rate of K.

Proof of Stability:

Selection of Lyapunov function

$$V=(1/2)s^2+\big(1/(2\gamma)\big)\tilde{K}^2\big(\tilde{K}=K-K_opt\big) \tag{8}$$

its derivative:

$$\dot{V}=s\cdot\dot{s}+(\tilde{K}\cdot\dot{K})/\gamma\leq-\eta|s| \tag{9}$$

he Lyapunov stability condition (η > 0) is satisfied, proving that the system is globally stable[27].

3.4 Fusion Control Research

3.4.1 Adaptive fuzzy terminal sliding mode control

Nekoukar and Dehkordi (2021) proposed a

fusion architecture combining adaptive fuzzy systems with terminal sliding mode control, which achieves state convergence and strong robustness in finite time[28]. At its core, it adopts a hierarchical design idea, where the upper layer determines the desired attitude angle through two PD controllers, and the lower layer regulates the rotor speed through terminal slip mode control. The control law of the architecture is expressed as

$u=u_1+u_2$

Here the equivalent control term u_1 is used to counteract the nonlinear dynamics of the system, expressed as:

$$u_1=\hat{g}^T\left[\varepsilon_0 I_m+\hat{g}\hat{g}^T\right]^{-1}\times\left(\beta^{-1}\gamma^{-1}\left|\dot{e}\right|^{2-\gamma}\operatorname{sign}(\dot{e})-\hat{f}+\ddot{X}_{ref}+K_1 s+K_2|s|^p\operatorname{sign}(s)\right) \tag{10}$$

The switching control term u_2 guarantees system stability and is defined as:

$$u_2=(s/|s^T|)\times[(\varepsilon_f+\varepsilon_g\|u_1\|+\|u_0\|)/\|s\|^2] \tag{11}$$

Where s is the sliding mould surface, $\hat{f}$, and $\hat{g}$ are the system dynamics estimates, K_1、K_2 are the control gains, and ε_0、ε_f、ε_g are small positive numbers.

3.4.2 Layered Converged Control Architecture

Layered fusion control divides the system into inner and outer control loops and achieves efficient control of complex systems through inner and outer loop synergy[27].

Upper level: fuzzy PID regulation of sliding mode parameters to optimise K and Φ

Lower level: sliding mode control to generate base control quantities

Fusion control law expressions:

$$u_{fusion}=\underbrace{F_{fuzzy}(e,ec)\cdot u_{smc}}_{\text{Parameter optimisation}}+\underbrace{\hat{d}}_{\text{Disturbance compensation}} \tag{12}$$

u_{fusion} is the fusion control output torque vector

$F_{fuzzy}(e,ec)$ is a fuzzy controller with inputs of error and rate of change of error and outputs of sliding mode parameter adjustment.

u_{smc} Foundation slipform control volume, calculated from the slipform surface.

$\hat{d}$ is a disturbance compensation term.

Under this architecture, the outer loop is responsible for robust attitude regulation, and the inner loop ensures fast angular velocity response, which work together to improve overall performance. The fuzzy controller adjusts the parameters of the sliding mode controller online through a rule base to adapt the system to different flight conditions. The disturbance observer improves the control robustness by predicting or estimating the compensation disturbance terms.

Table 1. Comparison of Attitude Control Theories for Quadrotor UAV

Controln methods	Advantage	Limitations
Traditional PID	Simple and easy to implement Low arithmetic Clear physical meaning of parameters	Fixed parameters Poor adaptability Poor effect on non-linear, coupled systems Weak anti-interference
Fuzzy PID	Adaptive parameter adjustment No need for accurate modelling Good performance for non-linear systems	Rule design is experience-dependent computationally intensive difficult to optimise parameters
Adapting control	Robust Good perturbation resistance Fast convergence Able to handle parameter uncertainty	Prone to jitter Difficult gain selection and realisation
Fusion control	Combining the strengths of each family Adaptability Robustness High control accuracy	Complex system High computational burden Difficult to debug parameters

4. Discussion & Future Directions

4.1 Existing Issues

4.1.1 Computational complexity and real-time challenges

Although the fusion of fuzzy PID and adaptive sliding mode control improves the control performance, the computational complexity increases significantly, which may lead to prolonged control cycles and affect the real-time system response. To solve this problem, optimisation can be carried out in several ways: Reducing the amount of fuzzy inference computation and simplifying the affiliation function through rule induction; separating computational tasks using multi-core processors to achieve computational load balancing; pre-calculating and storing commonly used fuzzy inference results and obtaining the control parameters quickly through interpolation at runtime, thus significantly reducing computational latency.

4.1.2 Sliding Mould Control of Jitter Problems

Although adaptive sliding mode control is robust, its high frequency switching characteristics often lead to control signal jitter [27]. The following measures can be taken to improve this problem: The continuous sliding mode control strategy proposed by Rios et al. (2019) smooths the control signal by replacing the traditional sign function with a continuous saturation function[16]. The boundary layer thickness is designed to be dynamically adjusted to reduce jitter while ensuring tracking accuracy; the combination of a high-order sliding mode observer and fuzzy logic-based gain adjustment estimates and compensates for system perturbations in real time and reduces the demand for control gain, thus suppressing jitter while maintaining tracking accuracy.

4.1.3 Parameter adjustment relies on expert experience

The design of fuzzy PID controllers and adaptive laws is highly dependent on expert experience, and the lack of a systematic approach to the shape of the affiliation function, the formulation of fuzzy rules, and the selection of adaptive gains leads to significant differences in controller performance.[24] To address this issue, the following methods can be used: Intelligent optimisation methods, such as particle swarm optimisation, genetic algorithm, or differential evolution, are automatically used to search for optimal control parameters. A system identification framework based on flight data is established. Fuzzy rules and affiliation functions are determined through experimental data analysis, and subjective experience dependence is reduced. Reinforcement learning algorithms are introduced to autonomously learn the optimal control strategy through interaction with the environment.

4.2 Trends in Technology Convergence:

4.2.1 Fuzzy PID combined with MPC

MPC can optimise the control sequence and cope with system constraints and perturbations by predicting the system's future behaviour. At the same time, fuzzy PID provides the ability to cope with model uncertainty through online parameter tuning. Combining the two forms, a closed-loop optimisation framework exploits MPC's predictive and fuzzy PID's adaptive nature. The lightweight MPC-PID control architecture proposed by Kang et al. (2022) demonstrates the advantages of this fusion: the MPC is responsible for generating the optimal control sequences, while the fuzzy PID performs the real-time tuning to ensure accurate tracking in the presence of external disturbances and model errors. Experiments show that the method reduces the tracking error by 40% under unknown disturbances while maintaining a low computational complexity[18].

4.2.2 Deep learning combined with adaptive

Deep neural networks can learn complex system dynamics and perturbation patterns with powerful nonlinear mapping capabilities to provide more accurate model predictions and compensation for adaptive control. This approach not only improves control accuracy but also reduces the reliance on accurate physical models. The neural network-enhanced MPC controller developed by Salzmann et al. (2023) reduces position tracking error by 82% compared to a conventional MPC by learning nonlinear dynamics in real time, while demonstrating greater robustness to model uncertainty[20].

4.2.3 Towards a two-tier optimisation framework based on hierarchical design

Hierarchical two-layer optimisation frameworks are gaining traction in quadrotor UAV control. This approach splits the control system into inner and outer loops, leveraging their synergy to manage complexity. The specific structure is shown in Figure 2, Hierarchical control architecture. The outer loop handles robust attitude regulation and optimal trajectory planning, while the inner loop ensures quick angular velocity response, jointly enhancing system performance. The MIMO Fuzzy Framework is crucial in overcoming traditional SISO fuzzy control limitations by considering system state variable couplings. A well-crafted fuzzy rule base enables it to manage multi-variable interactions for better control decisions. The adaptive predictive control framework, combining MPC and adaptive techniques, stands out in control theory. MPC predicts future states and optimises control sequences based on the system model, while adaptive mechanisms adjust model parameters and optimise the rolling horizon in real time. This integration preserves MPC's strengths and adds adaptive learning capabilities, making it highly suitable for quadrotor UAV with strong nonlinearity and uncertain parameters [24].

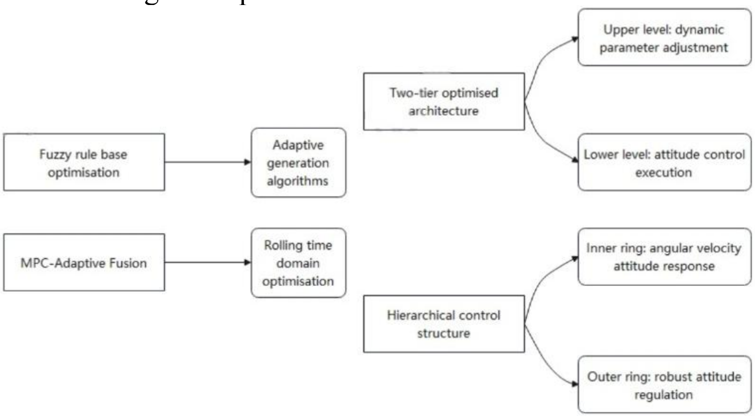

Figure 2. Hierarchical Control Architecture

4.3 Future Directions

4.3.1 Virtual debugging platform based on digital twins

Digital twin technology provides a new way to develop and test quadrotor UAV control algorithms. A parametric 3D model can be developed based on SolidWorks or MATLAB Multibody platform, integrating quadrotor multi-rigid body dynamics and aerodynamic effects, and generating a 3D turbulence database through CFD simulation. A virtual test environment is built based on ROS-Gazebo, which integrates the quadrotor dynamics model with real-time sensor simulation and realises two-way data interaction between the digital twin and the physical UAV with the help of Python API.

4.3.2 Brain-like computing chips enable real-time control

The neuromorphic computing chip mimics the structure and working principle of the human brain, providing a new hardware foundation for efficient intelligent control. The chip-based impulse neural network architecture implements asynchronous event-driven fuzzy logic computation, maps the fuzzy rule base into SNN synaptic connections, and reduces the fuzzy inference latency through chip-level parallelisation.

4.3.3 Combined with AI macro modelling

In the future, the quadcopter UAV control system will deeply integrate the AI big model to realise the intelligent autonomous flight of the UAV with its excellent data processing and predictive analysis capability, which can accurately predict the future state of the UAV, provide the basis for optimising the control strategy and generate intelligent control rules to improve the parameter adjustment accuracy of traditional control methods such as fuzzy PID and adaptive sliding mode control.

4.4 Research Constraints

This study mainly relies on literature review and theoretical analyses and lacks sufficient experimental data support. Because different studies use different hardware platforms, test environments and evaluation indexes, there is a lack of uniform quantitative standards for comparing the performance of various control methods, making it difficult to assess each control strategy's actual advantages and disadvantages objectively. Meanwhile, the theoretical model simplifies many nonlinear factors in the real system. This may lead to significant differences between the control effect and the simulation results in real flight. In addition, although the computational complexity issue was discussed, there is a lack of quantitative analysis of the resource consumption of different fusion control strategies on real embedded systems, which is especially important for small quadrotor UAVs with limited resources. Future research should enhance experimental validation, establish unified evaluation criteria, and consider engineering constraints in practical applications more comprehensively.

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