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Fundamentals, Challenges, and Improved Algorithms of PID Control for Quadrotor UAVs

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Abstract:

The quadrotor unmanned aerial vehicles (UAVs) are widely employed in power line inspections, agricultural monitoring, cargo delivery, and surveying operations because of their straightforward design and remarkable agility. However, traditional proportional-integral-derivative (PID) controllers perform poorly under wind, load changes, and sensor noise, which limits the UAV's precision and flight reliability. Thus, this paper reviews the current development of PID control for quadcopter UAVs, examines the limitations of traditional PID controllers, and compares the performance and applications of various improved algorithms, offering guidance for controller selection and parameter tuning. By analyzing relevant literature on improvement strategies, such as fuzzy adaptive PID, evolutionary learning-optimized PID, data-driven adaptive PID, deep reinforcement learning PID (DRL-PID), and hybrid model PID, and integrating existing simulation and experimental data, key performance indicators such as stability, speed, disturbance rejection, and computational load are summarized. The results show that data-driven PID like DRL-PID achieves the highest accuracy, while fuzzy adaptive PID remains widely used in engineering for its low computational load and real-time performance. Each algorithm has its strengths in different applications: fuzzy adaptive PID is suitable for real-time tasks, RL-GA and hybrid models are suitable for high-precision mapping, and WRLS adaptive PID is suitable for logistics with frequently changing loads. Meanwhile, lightweight DRL-PID and multi-UAV cooperative control are promising future directions.

Keywords: Quadrotor UAV, PID control, Fuzzy adaptive PID, Deep reinforcement learning, Flight control

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1. Introduction

The quadrotor unmanned aerial vehicles (UAVs) are widely used in aerial photography, power line inspection, topographic mapping, and logistics delivery due to their vertical takeoff and landing capabilities, simple structure, and high maneuverability [1,2]. And it is precise control of the UAVs' altitude and position that ensures stable flight and successful mission execution. In actual flight, quadcopter UAVs are affected by environmental factors like wind speed changes, load adjustments, and air pressure fluctuations, which may reduce the response speed of traditional proportional-integral-derivative (PID) control and increase steady-state error. Existing studies have verified the feasibility of PID control in indoor or relatively stable environments, but in dynamic and complex real-world environments, the specific mechanisms of performance degradation and corresponding improvement strategies still lack systematic analysis. This paper explores PID control for quadrotor UAVs, with a focus on the application of traditional PID in altitude and position regulation, as well as the effects of complex environmental disturbances on control performance. It also reviews the theoretical basis and application cases of improved algorithms such as fuzzy PID and adaptive PID. Through the review and analysis of existing literature, this paper clarifies the coupling mechanism between quadrotor dynamics and PID control, evaluates the performance of various algorithms in practical tasks, and clarifies the applicability of traditional PID and improved algorithms in different application scenarios. Furthermore, it examines the performance of improved PID algorithms under challenging conditions and proposes future directions for exploration, including lightweight control strategies, multi-UAV cooperative control, and adaptive parameter optimization.

2. Fundamentals and Challenges of Quadrotor PID Control

2.1 System Characteristics and Control Model

The nonlinear, strongly coupled, and underactuated dynamics of quadcopter UAVs, functioning as six-degree-of-freedom (6-DOF) systems, directly impact the complexity of their control system design. Since the system only uses the rotational speed of four rotors as input, but needs to manage six motion states at the same time, the UAV control faces the challenge of high nonlinearity and coupling. It is also sensitive to external disturbances and needs to adopt a coordination strategy to achieve stable flight [1,3]. The dynamic model of a quadcopter is typically formulated using the Newton-Euler equations. Translational dynamics represent the motion of the center of mass, while rotational dynamics capture the attitude angle changes. The equations for the translational dynamics are as follows:

$$\begin{cases} \dot{x} = v \\ m\dot{v} = -mg\mathbf{e}_z + \mathbf{R}(\phi,\theta,\psi)T\mathbf{e}_z + \mathbf{d} \end{cases} \tag{1}$$

where m denotes is the mass of the UAV (typically 1~5kg for civilian models), $x=\left[x,y,z\right]^T$ and $v=\left[\dot{x},\dot{y},\dot{z}\right]^T$ represent the position vector and velocity vector in the inertial frame, respectively, $R\left(\phi,\theta,\psi\right)$ is the attitude rotation matrix composed of the roll angle ϕ, , pitch angle θ, and yaw angle ψ, $F=\sum_{i=1}^{4} k\Omega_i^2$ means the total thrust (k is the rotor thrust coefficient and Ω_i is the rotor speed, $F_d=[F_dx,F_dy,F_dz]^T$ denotes the external disturbance force, and $e_z=\left[0,0,1\right]^T$ is the unit vector in the vertical direction. As shown in Figure 1, the quadrotor structure has four rotors generating thrust forces (F_1-F_4) and corresponding rotational angular velocities (ω_1-ω_4), , while the gravitational force (mg) acts on the center of mass. Figure 2 depicts the coordinate transformation between the inertial reference frame (*x, y, z*) and the body reference frame (x_B, y_B,z_B), which is essential for translating desired positions in the inertial frame into attitude commands and rotor speed commands in the body frame [1,2].

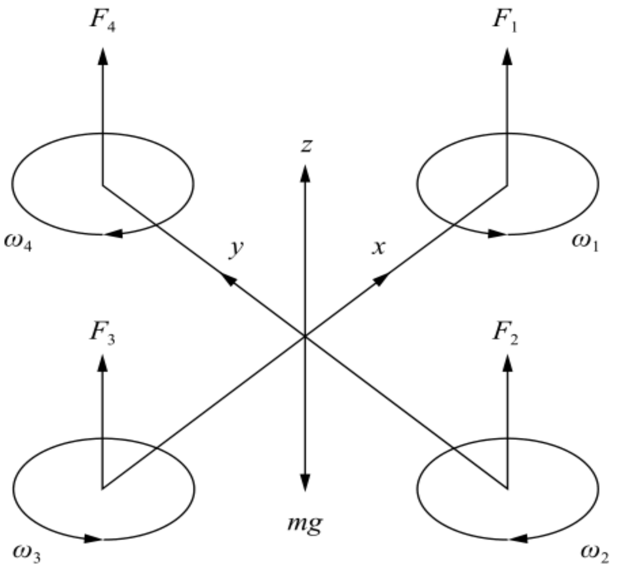

Figure 1: Quadrotor UAV structure and force distribution [2]

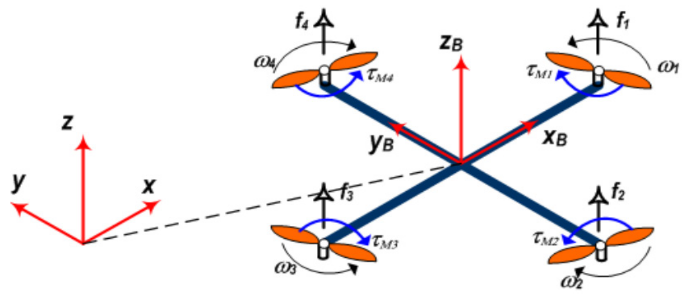

Figure 2: Inertial and body reference frames of quadrotor UAV [1]

The six degrees of freedom of the system consist of translational and rotational motions. The translational degrees of freedom correspond to displacements along the X, Y, and Z axes, while the rotational degrees of freedom correspond to pitch, roll, and yaw angles. Since the inputs consist of only the four rotor speeds, the system is underactuated, and the thrust and torques are highly coupled, as a change in the speed of a single rotor affects the total thrust and also causes variations in pitch and roll torques, leading to cross-coupling between position and attitude [3,4]. Therefore, flight control must comprehensively consider both position and attitude dynamics and achieve coordinated multivariable management to ensure system stability [1].

2.2 Principles and Applications of Traditional PID Control

Traditional PID control is a classical feedback strategy where the control output is generated by linearly combining the proportional (P), integral (I), and derivative (D) terms, expressed as follows.

$$u(t)=Kpe(t)+Ki\int_0^t e(\tau)d\tau+Kd\frac{de(t)}{dt} \qquad (2)$$

where K_p is the proportional gain, providing an immediate response to the current error, K_i is the integral gain, compensating for steady-state error such as altitude drift during hovering, K_d is the derivative gain, mitigating oscillations by anticipating future error trends. This linear control logic is effective for time-invariant systems but fails to handle the quadrotor's nonlinear dynamics (e.g., thrust nonlinearity $T \propto \Omega^2$) and time-varying disturbances [5].

In quadrotor UAVs, PID control is typically implemented using a cascade structure that divides the control task into an outer loop and an inner loop [1]. And the outer loop handles position and altitude control, converting the error between the desired and actual positions into desired attitude angles and total thrust. The inner loop handles attitude stabilization, converting the desired attitude angles from the outer loop into rotor speed commands. This cascade structure exploits the time-scale separation characteristic of quadrotor systems: attitude dynamics respond much faster than position dynamics, making the inner loop a fast-response controller and the outer loop a slow-tracking controller. Specifically, the altitude PID outputs the desired total thrust, the X-Y position PID outputs the desired pitch and roll angles, and the inner-loop attitude PID converts these desired angles into differential rotor speeds for each rotor, achieving decoupled control.

Traditional PID parameter tuning methods mainly include the trial-and-error method and the Ziegler-Nichols method. The trial-and-error method relies on engineering experience to gradually adjust K_p, K_i, K_d while observing system responses to optimize the parameters, thereby making it suitable for scenarios with moderate control requirements. The Ziegler-Nichols method calculates PID parameters based on the system's critical gain and oscillation period, providing a theoretical basis but requiring the system to operate at critical stability, which involves certain risks. Under ideal environments (no wind disturbance, constant load, low sensor noise), traditional PID can achieve good control effects through proper parameter tuning. Existing literature reports that in indoor hovering experiments, well-tuned PID controllers can control altitude overshoot within 20%, maintain steady-state errors near zero, and achieve response times of around 1 second, effectively meeting general flight control requirements [1].

2.3 Limitations and Performance Evaluation of PID Control

The application of traditional PID control in quadrotor UAVs has been validated via numerous simulations and experiments, with performance varying significantly under different environmental conditions. Under ideal conditions, such as indoor environments with no wind, constant payload, and high sensor accuracy, traditional PID can provide stable and reliable control performance.

Experimental and simulation results indicate that traditional PID performs adequately in ideal environments,

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meeting basic flight control requirements. For example, in indoor hovering tests, a quadrotor with a mass of 0.468 kg and an arm length of 0.225 m using PID gains K_p=75, K_i=42.86, K_d=32.81 exhibited an altitude overshoot of 19.9%, a near-zero steady-state error, and a response time of 0.95 s [1]. These results show that under disturbance-free conditions, altitude overshoot is typically around 20%, steady-state errors can be maintained at low levels, and response times are approximately 1 second.

However, when environmental conditions become more complex, the performance of traditional PID deteriorates significantly. In an outdoor hovering experiment with a wind speed of 5 m/s, a quadrotor with a mass of 1.2 kg and moment of inertia I_{xx}=0.00864kg¡¤m^2, PID gains of K_p=12, K_i=0.1, K_d=5 resulted in overshoot increasing to 22%, steady-state error rising to 0.8 meters, and response time extending to 4.2 seconds [6]. When load changes by ±500 grams on a quadrotor with mass m=1.72 kg using PID gains K_p=0.42, K_i=0.014, K_d=0.40, the overshoot increased from 18% to 25%, steady-state error rose from 1% to 8%, and response time extended from 0.8 to 1.1 seconds [5]. Under IMU noise conditions with 0.1°/s standard deviation on a quadrotor with mass m=0.8 kg using PID gains K_p=5, K_i=2, K_d=0.5, steady-state error increased from 0.2 meters to 0.3 meters, overshoot rose from 15% to 21%, and response time extended from 1.2 to 1.8 seconds [7].

These performance degradations are mainly due to PID's fixed gain. When system parameters change or external disturbances occur, fixed K_p, K_i, K_d cannot automatically adjust to adapt to new operating conditions, leading to mismatch between control laws and actual system dynamics. This limitation is especially pronounced in complex scenarios. For instance, during power line inspection missions, UAVs must maintain stable hovering under wind speeds of 5-8 m/s and turbulent airflow near towers, where traditional PID cannot meet performance requirements. In logistics tasks, payload changes exceeding ±10% due to loading and unloading can lead to significant overshoot and increased steady-state error under fixed-gain PID. Additionally, traditional PID's sensitivity to sensor noise limits its applicability on low-cost IMU platforms. Thus, improved algorithms such as fuzzy adaptive PID, intelligent optimization PID, and data-driven PID have been proposed to achieve high-performance control in complex environments [5,7].

3. Improvements and Performance of PID Control for Quadrotors

3.1 Interference Mechanism of Complex Environments on PID Control

Previous research has established the influence of complex environments on the PID control performance of quadrotor UAVs. It was found that the mechanisms by which factors such as wind disturbance, load change and sensor noise affect the performance of PID control can be summarized into three categories[1,3].

In particular, airflow disturbances can cause fluctuations in the attitude angles, typically up to ±5°, leading to a phase lag of over 0.2 s in the PID control loop and reducing the system's real-time response capability [1,3]. For example, the downwash airflow near the power generation tower can generate locally unstable airflow, thus leading to a delay in attitude adjustment. Besides, parameter perturbations also affect control accuracy. When the battery voltage decreases to 11.1 volts from 14.8 volts, motor output torque drops by about 15%, and the fixed-gain PID cannot adapt, causing insufficient thrust and altitude or attitude deviations [1]. Similarly, load variations alter the system's dynamics, hence making it difficult for a traditional PID to maintain stable flight. Furthermore, the accumulation of sensor noise can cause steady-state errors. For instance, IMU angular velocity noise (standard deviation 0.1°/s) accumulates in the integral term, potentially resulting in an altitude steady-state deviation of about 5 cm [8].

When these mechanisms are combined with experimental results, the limitations of fixed-gain PID are further validated. Melo et al. conducted simulation studies under wind disturbance and sensor noise, showing that when wind speed reaches 8 m/s and the IMU angular velocity noise standard deviation is 0.1°/s, the accuracy of traditional PID decreases by about 40%, overshoot increases from 12% to 25%, and steady-state error rises from 3% to 12% [7]. In load variation experiments on logistics UAVs, Cedro et al. found that when the load changes by ±10%, the steady-state error increases from 3% to 8%, accompanied by significant oscillations [5]. Muliadi and Kusumoputro further confirmed that PID tuned via linearized models fails to stabilize quadrotors when aerodynamic disturbances and sensor noise are present simultaneously [8]. In addition, Cedro et al. reported that when the load changes by ±500 g, fixed-gain PID exhibits roughly 30% lower steady-state accuracy, along with severe oscillations [5].

3.2 Classification and Control Mechanism of Improved PID Algorithms

To address the performance limitations of traditional fixed-gain PID in complex environments, several improved PID algorithms have been introduced. These algorithms, leveraging intelligent optimization strategies, can be grouped into five types: fuzzy adaptive PID, evolutionary learning-based PID, data-driven adaptive PID, deep reinforcement learning PID (DRL-PID), and hybrid model PID. Each category employs different strategies to overcome the inability of fixed-gain PID to adapt in real time to system parameter changes and environmental disturbances.

Fuzzy adaptive PID is the most mature improved method in engineering applications. Its core mechanism adjusts K_p, K_i, and K_d online using fuzzy rules based on the error and its rate of change, without requiring precise mathematical models. Yu et al. proposed a cascaded fuzzy PID, which in simulations of power inspection scenarios reduced position error by approximately 30% and limited overshoot to below 5% [2]. Melo et al. applied fuzzy gain-scheduling PID in ROS-based quadrotor experiments, achieving a 30% reduction in position error under wind disturbances [7]. The main advantage of fuzzy adaptive PID lies in its low computational complexity, supporting a 100 Hz control frequency, and it has been successfully applied to commercial plant protection UAVs such as the DJI T20 [9]. Its limitation is that the design of fuzzy rules relies on expert experience and offers limited cross-platform generalizability.

Evolutionary learning-optimized PID combines genetic algorithms with iterative learning control to optimize gains through offline global search and online adaptive fine-tuning. Hosseinkhani et al. proposed an RL-GA hybrid algorithm, which increased response speed by 25% and reduced steady-state error by 40% in terrain mapping quadrotors [10]. Dong et al. introduced a fuzzy PID-ILC that integrates iterative learning control with fuzzy tuning; simulations showed that repeated trajectory errors were reduced by approximately 50% [11]. The main challenge of evolutionary optimization algorithms lies in their high computational complexity, with typical control frequencies around 50 Hz. Besides, data-driven adaptive PID establishes system dynamic models using neural networks or recursive least squares methods to achieve online gain adjustment. Muliadi et al. employed a direct inverse control neural network to compensate for thrust nonlinearity, reducing altitude tracking error from 8% to 3% [8]. Cedro et al. designed a WRLS adaptive PID that maintains steady-state error within 2% under load variations of ±500 g, greatly outperforming traditional PID [5]. This approach can identify parameter changes in real time without precise models, although it requires high sensor accuracy, with typical control frequencies reaching 60 Hz. In addition, deep reinforcement learning PID (DRL-PID) uses an agent to directly learn optimal control policies, making it suitable for highly nonlinear and uncertain scenarios. Khanzada et al. tested a DRL-PID on a 3DR IRIS quadrotor, achieving a steady-state error of 0.58 m and a response time of 5 s, representing 48% higher accuracy and 69% faster response compared to traditional PID [12]. DRL-PID does not rely on system models, but its high computational complexity limits control frequency to around 20 Hz, and current applications are mainly in laboratory high-precision verification. Engineering deployment requires further lightweight optimization. Hybrid model PID integrates multiple intelligent methods to balance generalizability and interpretability. Zhou et al. proposed a GA-BP hybrid PID, which optimizes the initial weights of a neural network using genetic algorithms and then predicts gain adjustments. In experiments with load variations of ±5 cm, attitude error was reduced by 35% while maintaining a control frequency of 40 Hz [13]. This approach combines offline global optimization with online local adjustment to avoid local optima, but implementation complexity is high.

3.3 Performance Comparison and Applicability Analysis

Under unified test conditions (wind speed 5 m/s, load variation ±10%, control frequency 100 Hz), a performance comparison of improved PID algorithms reveals the characteristics and suitable application scenarios for each method.

Fuzzy adaptive PID demonstrates the best balance of real-time performance and stability in engineering applications, with overshoot below 5%, rise time under 0.8 s, and a 30% error reduction under wind disturbances. Its low computational complexity supports a control frequency of 100 Hz, making it suitable for scenarios with high real-time requirements but moderate precision demands, like agricultural plant protection and power inspection, and it has been successfully implemented on commercial platforms like the DJI T20 [2,7,9]. RL-GA optimized PID is suited for high-precision tasks such as topographic mapping and trajectory tracking, achieving overshoot below 3%, rise time under 0.6 s, and a 40% error reduction in multi-disturbance scenarios [10]. This algorithm combines global initial gain optimization via genetic algorithms with online adaptive tuning through reinforcement learning, but its medium computational complexity limits the control frequency to around 50 Hz, requiring a trade-

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off between precision and real-time performance.

Besides, WRLS adaptive PID excels in scenarios with frequent load variations, such as logistics transportation, providing around 35% error reduction and supporting a 60 Hz control frequency. It can identify system parameter changes in real time and update the gain matrix, maintaining steady-state error within 2% when the load changes by ±500 g [4,5]. DRL-PID represents the frontier in control precision, with overshoot below 2%, fastest response (<0.5 s), and a 48% error reduction under combined wind and load disturbances [12]. By utilizing Deep Deterministic Policy Gradient (DDPG) to learn optimal control policies, it effectively handles highly nonlinear dynamics and uncertain disturbances. However, its high computational demand limits the control frequency to around 20 Hz, confining its current application mainly to laboratory high-precision verification; further lightweight optimization is required for practical engineering deployment. GA-BP hybrid PID balances precision and real-time performance, achieving a control frequency of around 40 Hz. It uses genetic algorithms to optimize the initial weights of a neural network, which then predicts gain adjustments, reducing steady-state attitude error by 35% under a ±5 cm load offset, making it suitable for multi-task UAVs that perform both inspection and logistics operations [13]. For different application requirements, Fuzzy adaptive PID is suitable for engineering tasks with high real-time demands, such as agricultural plant protection and power inspection; RL-GA and GA-BP hybrid PID are better suited for high-precision tasks, such as topographic mapping and trajectory tracking; WRLS adaptive PID performs exceptionally well in tasks with frequent load variations, such as logistics delivery; while DRL-PID, although offering the highest control precision, still requires further solutions to address real-time performance and lightweight implementation.

4. Conclusion

This paper has reviewed PID control technology for quadrotor UAVs, covering the fundamentals, challenges, and various improved algorithms. In particular, traditional fixed-gain PID controllers have been validated to perform adequately in low-disturbance scenarios, such as indoor hovering, where they achieve an altitude overshoot of around 20%, near-zero steady-state error, and response times of approximately 1 s. However, under complex environmental conditions including wind speeds exceeding 5 m/s, load fluctuations of ±10%, and IMU noise with standard deviations of 0.1°/s, traditional PID exhibits significant performance degradation with overshoot exceeding 25% and steady-state error rising above 10%.

To address these limitations, this paper classifies enhanced PID algorithms into five categories based on their intelligent optimization mechanisms: fuzzy adaptive PID, evolutionary learning-optimized PID, data-driven adaptive PID, deep reinforcement learning PID, and hybrid model PID. Through comparative analysis under unified test conditions, fuzzy adaptive PID demonstrates the best balance between real-time performance and stability for engineering applications such as agricultural plant protection and power line inspection. RL-GA optimized PID and GA-BP hybrid PID are better suited for high-precision tasks like topographic mapping and trajectory tracking. WRLS adaptive PID excels in logistics scenarios with frequent load variations, maintaining steady-state error within 2% under ±500 g load changes. DRL-PID achieves the highest control precision with a 48% accuracy boost, though its computational demands limit real-time use.

This study has several limitations that should be acknowledged. The performance comparisons are primarily based on simulation data and limited experimental conditions, and the generalizability of conclusions across different quadrotor platforms and environmental conditions requires further validation. Moreover, the interaction effects of multiple disturbance factors were not fully explored. Future research should explore lightweight implementation of DRL-PID through techniques such as 8-bit quantization to enable real-time deployment on embedded platforms like Pixhawk controllers. Multi-UAV cooperative PID control with disturbance compensation for formation flight shows promise. Yet, validating in extreme conditions, like heavy rain and electromagnetic interference, is crucial to verify robustness. Additionally, standardized benchmarking protocols are needed to facilitate fair algorithm comparisons and accelerate the transition to practical applications.

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