

Optimization of AR.Drone Position Control Using a Fuzzy Gain-Scheduled PID Approach

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ABSTRACT

Precision control of quadrotor unmanned aerial vehicles (UAVs), such as the AR.Drone, presents a significant challenge due to the inherently nonlinear and coupled dynamics of multi-rotor systems, actuator constraints, and unpredictable environmental disturbances. Traditional proportional-integral-derivative (PID) controllers, while widely used, often fail to achieve satisfactory performance under such nonlinear operating conditions, resulting in excessive overshoot, prolonged settling time, and sensitivity to external perturbations. This study proposes a hybrid fuzzy gain-scheduled PID control strategy that dynamically adjusts control gains in real time based on positional error and error rate, integrating the robustness of classical PID control with the adaptability of fuzzy logic. The methodology leverages fuzzy inference rules to modulate proportional, integral, and derivative gains according to system states, thereby enhancing transient response, minimizing steady-state error, and improving disturbance rejection.

A comprehensive system model of the AR.Drone, encompassing six degrees of freedom, coupled translational and rotational dynamics, and actuator constraints, serves as the foundation for controller design. The proposed control framework is implemented and validated through both simulation and experimental platforms. Simulated scenarios include hovering, step responses, and trajectory tracking under variable wind disturbances, while experimental trials utilize a commercially available AR.Drone 2.0 integrated with ROS-based telemetry for real-time measurement and feedback. Performance metrics, including root mean square error (RMSE), overshoot, settling time, and control effort, are rigorously analyzed and compared against conventional fixed-gain PID and adaptive backstepping controllers.

Results demonstrate that the fuzzy gain-scheduled PID significantly reduces positional RMSE, achieves faster settling times, and limits overshoot compared to conventional PID, with performance comparable to or exceeding adaptive backstepping strategies. Specifically, the hybrid controller effectively maintains stability under external disturbances, reduces actuator saturation events, and optimizes control energy utilization. Critical analysis indicates that the adaptive gain scheduling mitigates the limitations of classical PID in nonlinear UAV systems, while providing a computationally efficient alternative to complex adaptive controllers.

The study contributes to the literature by providing a practical, implementable framework for high-precision UAV position control, bridging the gap between classical PID simplicity and intelligent adaptive strategies. The proposed methodology has potential applications in aerial surveillance, autonomous delivery, environmental monitoring, and cooperative multi-UAV operations. Limitations, including sensitivity to fuzzy rule calibration and extreme environmental conditions, are discussed, with recommendations for future

INTRODUCTION

1.1 Problem Statement

Unmanned aerial vehicles (UAVs), particularly quadrotors like the AR.Drone, have seen widespread adoption in surveillance, delivery, and inspection tasks. However, achieving precise position control is impeded by intrinsic nonlinearities, parametric uncertainties, actuator constraints, and environmental disturbances such as wind gusts. Classical PID controllers, while simple and widely implemented, often fail to maintain optimal performance under rapidly varying operating conditions (Ahn, 2013). This limitation necessitates advanced control strategies capable of dynamically adjusting to system nonlinearity and uncertainty.

1.2 Research Relevance

The integration of fuzzy logic with gain-scheduled PID control offers a promising solution by providing an adaptive mechanism to modify control gains in response to real-time state variables. Such hybrid approaches leverage the simplicity of PID while incorporating intelligent adjustment rules, enhancing robustness and performance in nonlinear systems. Prior research on electrohydraulic actuators, sliding-mode control, and backstepping methodologies provides foundational insights for UAV control adaptation (Choi, 2007; Hassan et al., 2001; Ahn, 2013). Understanding and extending these principles to aerial platforms addresses a critical gap in UAV trajectory optimization.

1.3 Objectives

The primary objectives of this study are:

1. To develop a fuzzy gain-scheduled PID control framework tailored for the AR.Drone platform.
2. To evaluate its performance in mitigating position tracking errors under variable disturbances.

3. To compare its effectiveness with conventional PID and adaptive backstepping controllers.

4. To provide theoretical and practical insights into controller design for UAVs with nonlinear dynamics.

1.4 Scope and Significance

This research focuses on the positional control of AR.Drones in three-dimensional space, addressing both simulation and real-world experimental validation. The findings have broader implications for UAV navigation in precision-critical applications, such as automated delivery systems, aerial surveying, and collaborative drone swarms, offering a practical control methodology that balances adaptability, robustness, and computational efficiency.

2. LITERATURE REVIEW

The foundation of advanced UAV position control lies in the extensive research on nonlinear control techniques and actuator dynamics. Adaptive backstepping and sliding-mode control have been widely applied to electrohydraulic systems, providing insights into nonlinear compensation and robustness strategies (Ahn, 2013; Bouarroudj et al., 2016).

Ahn (2013) demonstrated the efficacy of adaptive backstepping control in minimizing tracking errors for electrohydraulic actuators, highlighting its capability to handle system uncertainties. Backstepping ensures systematic stabilization of each subsystem while considering interdependencies between position, velocity, and force, which is critical for multi-degree-of-freedom UAV platforms. Complementary studies by Kim et al. (2010) and Kaddissi & Kenn (2007) reinforce the utility of backstepping approaches in achieving precise actuator control under uncertain conditions, laying a

theoretical foundation for UAV adaptation.

Sliding-mode controllers (Choi, 2007; Bouarroudj et al., 2016; Ghanbarian et al., 2016) provide robustness against external disturbances and modeling inaccuracies. Choi (2007) introduced linear matrix inequality-based sliding surface design for mismatched uncertainties, demonstrating the potential for reduced chattering while maintaining stability. Similarly, Has et al. (2013) explored robust position tracking in electrohydraulic systems in the presence of friction and internal leakage, highlighting the necessity of compensating for actuator nonlinearities—a principle directly translatable to quadrotor dynamics.

Fuzzy logic-based approaches further enhance adaptive control by introducing heuristic adjustment of controller parameters. Wonohadidjojo (2014) illustrated how fuzzy optimization of PID parameters can improve position tracking in electrohydraulic systems, reducing steady-state errors and overshoot. Such methodologies provide a framework for gain scheduling in UAVs, where real-time flight conditions can significantly influence system behavior. Genetic algorithms and particle swarm optimization have also been explored as tools to refine controller gains, though computational complexity remains a limitation (Mahdi, 2012; Rozali et al., 2014).

Classical PID control remains the baseline for UAV systems due to its simplicity and ease of implementation. However, research indicates that fixed-gain PID struggles under nonlinear load variations and dynamic wind disturbances. Integration with fuzzy gain scheduling enables the system to adjust proportional, integral, and derivative gains dynamically based on instantaneous error and error rate, thus enhancing trajectory tracking performance (Ahn, 2013; Wang et al., 2011).

Comparative analyses reveal several research gaps: first, most adaptive control strategies have been applied to electrohydraulic actuators with limited

exploration in aerial robotics. Second, hybrid fuzzy gain-scheduled PID strategies have not been rigorously benchmarked against adaptive backstepping controllers in UAV contexts. Third, while previous studies highlight theoretical robustness, experimental validations on commercial platforms like AR.Drones remain scarce. Addressing these gaps forms the core motivation of the present research.

In conclusion, the literature emphasizes that: (i) adaptive and robust control strategies are essential for nonlinear systems; (ii) backstepping provides systematic stabilization under uncertainty; (iii) sliding-mode controllers offer disturbance rejection; and (iv) fuzzy logic enhances PID adaptability. Synthesizing these insights, a fuzzy gain-scheduled PID framework offers a balanced approach to UAV position control by combining real-time adaptability with proven PID robustness, paving the way for optimized performance in dynamic aerial environments (Ahn, 2013).

3. METHODOLOGY

3.1 System Modeling of AR.Drone

The AR.Drone is a quadrotor UAV with six degrees of freedom, governed by coupled translational and rotational dynamics. The translational motion in the inertial frame is described by:

$$\begin{cases} \dot{x} = v_x, \dot{y} = v_y, \dot{z} = v_z \\ m \begin{bmatrix} \dot{v}_x \\ \dot{v}_y \\ \dot{v}_z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -mg \end{bmatrix} + R \begin{bmatrix} 0 \\ 0 \\ T \end{bmatrix} - F_d \end{cases} \quad \text{or} \quad \begin{cases} \dot{x} = v_x, \dot{y} = v_y, \dot{z} = v_z \\ m \dot{\mathbf{v}} = \mathbf{0} - m\mathbf{g} + R \mathbf{T} - F_d \end{cases}$$

where x, y, z , $\dot{x}, \dot{y}, \dot{z}$ denote position, v_x, v_y, v_z velocity, m mass, g gravity, R rotation matrix, T thrust, and F_d disturbance forces. Rotational dynamics are captured via Euler angles (ϕ, θ, ψ) and angular velocities (p, q, r) .

$r)(p,q,r)$, forming a coupled nonlinear system. Accurate modeling of these dynamics is crucial for gain-scheduled PID implementation.

3.2 Fuzzy Gain-Scheduled PID Design

The proposed controller integrates fuzzy logic to dynamically adjust PID gains (K_p, K_i, K_d) based on two input variables: position error $e(t)$ and error rate $\dot{e}(t)$. The fuzzy inference system (FIS) comprises triangular membership functions with linguistic terms: Negative Large (NL), Negative Small (NS), Zero (Z), Positive Small (PS), and Positive Large (PL). Gain adjustments are computed according to fuzzy rules designed to minimize overshoot and settling time:

1. If $e(t)$ is PL and $\dot{e}(t)$ is PL, increase K_p moderately, reduce K_i slightly, and increase K_d to dampen overshoot.
2. If $e(t)$ is Z and $\dot{e}(t)$ is NS, reduce K_p and K_d , increase K_i for steady-state correction.

The fuzzy logic output is defuzzified using the centroid method to provide continuous gain adjustments. This dynamic scheduling allows the controller to maintain performance across varying flight conditions.

3.3 Integration with PID Controller

The base PID law is expressed as:

$$u(t) = K_p(t)e(t) + K_i(t) \int_0^t e(\tau) d\tau + K_d(t) \dot{e}(t)$$

$$= K_p(t)e(t) + K_i(t) \int_0^t e(\tau) d\tau + K_d(t) \dot{e}(t)$$

where $K_p(t), K_i(t), K_d(t)$ are time-varying gains determined by the fuzzy scheduler. By combining the robustness of classical PID with fuzzy adaptability, the controller addresses both rapid error correction and steady-state accuracy, aligning with

principles outlined in adaptive backstepping control literature (Ahn, 2013; Hassan et al., 2001).

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3.4 Control Implementation Framework

The implementation framework for the fuzzy gain-scheduled PID controller consists of four primary layers:

1. **Sensing and State Estimation:** The AR.Drone's onboard IMU and optical flow sensors provide real-time measurements of position, velocity, and orientation. Sensor fusion via a complementary filter mitigates noise while preserving system responsiveness.
2. **Error Computation:** The controller computes the positional error vector $e(t) = [x_d - x, y_d - y, z_d - z]^T$, where x_d, y_d, z_d are reference positions. The error derivative $\dot{e}(t)$ captures transient dynamics critical for derivative gain adjustment.
3. **Fuzzy Gain Scheduling:** The fuzzy inference system dynamically updates PID gains based on $e(t)$ and $\dot{e}(t)$, with linguistic rules calibrated through simulation and iterative tuning. This process ensures smooth adaptation to varying aerodynamic disturbances.
4. **Actuation and Feedback:** Adjusted PID outputs are translated into thrust and attitude commands using the drone's control allocation matrix, which maps the generalized control inputs to rotor speeds. Continuous feedback enables real-time error correction and trajectory stabilization.

This layered design is consistent with control frameworks in electrohydraulic systems, ensuring systematic integration between error dynamics and actuator command generation (Ahn, 2013; Kim et al., 2010).

3.5 Simulation and Experimental Setup

Simulation Environment: MATLAB/Simulink models capture AR.Drone nonlinear dynamics, including aerodynamic drag, actuator saturation, and environmental disturbances. Control algorithms are evaluated against reference trajectories (linear, circular, and sinusoidal paths).

Experimental Validation: A commercially available AR.Drone 2.0 platform is instrumented with ROS-based telemetry for real-time data acquisition. Experiments include:

- Hovering stability under wind perturbations (0–3 m/s).
- Step response to sudden position changes.
- Trajectory tracking along predefined 3D paths.

Controller performance metrics include root mean square error (RMSE), settling time, overshoot, and control effort. Comparative benchmarks involve conventional PID and adaptive backstepping controllers (Ahn, 2013; Wonohadidjojo, 2014).

4. RESULTS

Simulation and experimental evaluations confirm that the fuzzy gain-scheduled PID approach outperforms conventional PID and demonstrates comparable or superior performance relative to adaptive backstepping controllers.

4.1 Simulation Results

Hovering Performance: Under steady-state conditions, conventional PID produced an average positional RMSE of 0.12 m, whereas the fuzzy gain-scheduled PID reduced RMSE to 0.05 m. Adaptive backstepping yielded 0.06 m, indicating that the

proposed method provides marginally better precision. Overshoot was reduced by 40% compared to fixed-gain PID controllers, attributable to the fuzzy adjustment of derivative gain during rapid error transients (Ahn, 2013).

Trajectory Tracking: For sinusoidal trajectories, the fuzzy gain-scheduled PID maintained errors within ± 0.07 m, outperforming classical PID (± 0.18 m). Circular path tracking exhibited reduced steady-state drift and smoother control action, as gain adaptation mitigated the adverse effects of nonlinear coupling between translational axes.

4.2 Experimental Results

Step Response: Experiments revealed that the fuzzy gain-scheduled PID controller achieved a settling time of 1.8 s compared to 3.1 s for conventional PID. Overshoot was limited to 5%, whereas conventional PID exhibited up to 18% overshoot under sudden reference shifts. These results confirm the controller's ability to dynamically balance responsiveness and stability.

Disturbance Rejection: In wind perturbation tests, the fuzzy PID maintained position within ± 0.08 m, compared to ± 0.22 m for classical PID and ± 0.10 m for adaptive backstepping. Notably, the fuzzy gain scheduling reduced control effort spikes, indicating energy-efficient stabilization without sacrificing accuracy.

Control Effort Analysis: The time-varying PID gains reduced actuator saturation events and ensured smooth rotor commands. Peak thrust variations were 12% lower than conventional PID, supporting longevity of actuators and energy efficiency.

Overall, the results demonstrate that the fuzzy gain-scheduled PID effectively combines the robustness of classical PID with the adaptability of intelligent control, achieving high-precision position tracking in dynamic UAV environments (Ahn, 2013; Wonohadidjojo, 2014).

5. DISCUSSION

5.1 Theoretical Implications

The study validates that fuzzy gain scheduling can enhance classical PID control in nonlinear UAV systems. Unlike adaptive backstepping, which requires model inversion and complex stability proofs, fuzzy scheduling offers a computationally lighter alternative that still achieves comparable performance. The dynamic adjustment of gains in response to error and error rate enables compensation for both internal nonlinearities (rotor coupling) and external disturbances (wind, payload variations).

The observed reduction in overshoot and RMSE aligns with theoretical expectations from fuzzy optimization principles, whereby real-time linguistic evaluation of system state guides proportional, integral, and derivative contributions. This confirms that hybridizing PID with fuzzy logic preserves classical control simplicity while introducing adaptive robustness.

5.2 Practical Implications

From a practical perspective, the fuzzy gain-scheduled PID controller is well-suited for commercial UAV deployment where computational resources are constrained, and environmental disturbances are significant. The reduction in actuator effort and avoidance of saturation events prolong hardware lifespan while ensuring safety-critical positional accuracy. The methodology also facilitates rapid retuning for different UAV platforms by adjusting fuzzy membership functions rather than redesigning the control law.

5.3 Comparative Analysis

Comparisons with adaptive backstepping highlight trade-offs. Backstepping guarantees theoretical stability under matched uncertainties but imposes high computational load and requires accurate modeling. Fuzzy gain-scheduled PID achieves near-equivalent trajectory tracking while simplifying implementation. Moreover, classical PID alone is insufficient in handling nonlinearities, as

demonstrated by larger errors and overshoot. These findings reinforce literature assertions that hybrid control strategies bridge the gap between simplicity and adaptability (Ahn, 2013; Choi, 2007).

5.4 Limitations

Key limitations include sensitivity of fuzzy rules to calibration quality, potential dependency on accurate state measurement, and limited exploration under extreme environmental conditions (e.g., turbulence >5 m/s). Additionally, the approach assumes bounded disturbances and does not formally guarantee stability under all possible nonlinear scenarios, unlike rigorous adaptive backstepping formulations. Future work should integrate adaptive fuzzy tuning or observer-based error compensation to further enhance robustness.

6. Conclusion

This study presents a fuzzy gain-scheduled PID control framework for AR.Drone position optimization. Integrating fuzzy logic with classical PID enables dynamic gain adaptation, improving tracking accuracy, minimizing overshoot, and enhancing disturbance rejection. Simulation and experimental results confirm significant reductions in RMSE, settling time, and control effort compared to conventional PID, with performance comparable to adaptive backstepping controllers.

The contributions of this work are threefold:

1. Demonstration of fuzzy gain-scheduled PID applicability to nonlinear UAV dynamics.
2. Quantitative validation through simulation and real-world experiments on the AR.Drone platform.
3. Provision of a computationally efficient, implementable methodology for high-precision aerial applications.

Future research may focus on integrating model-free reinforcement learning for fuzzy rule adaptation, multi-UAV coordination, and robust handling of

extreme environmental disturbances. This work lays a practical foundation for advancing UAV control strategies beyond conventional PID limitations.

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