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UAV ATTITUDE AND ALTITUDE STABILITY CONTROL ALGORITHM UNDER EXTREME WEATHER CONDITIONS

HanJun Zhang
Changzhou Beijiao High School, Changzhou 213000, Jiangsu, China.
Corresponding Email: 119437839@qq.com

Abstract: Extreme weather conditions pose significant challenges to the stability of attitude and altitude control of uncrewed aerial vehicles (UAVs). Traditional control methods often have problems with response lag and reduced accuracy in intense disturbance environments. This paper proposes a hybrid control framework that integrates disturbance observers and deep reinforcement learning strategies to improve the autonomous control capabilities of UAVs under complex meteorological disturbances. This method models the disturbance trend in real time by extending the state observer. It uses the policy network to dynamically adjust the control output according to the disturbance estimation, thus realizing the closed-loop optimization of perception making. In simulation experiments, the proposed method shows excellent control performance under multiple typical disturbance conditions such as crosswind, gusts, downdrafts, and their combinations. Compared with traditional PID, LQR, and MPC controllers, it significantly improves trajectory stability, control accuracy, and energy consumption. The results show that this study provides a practical and feasible new idea for robust UAV control in extreme meteorological environments.
Keywords: UAV control; Extreme weather; Disturbance observer; Deep reinforcement learning; Hybrid control

1 INTRODUCTION

Uncrewed aerial vehicles (UAVs) have been widely used in agricultural monitoring, urban security, and emergency response scenarios. The stability of flight control directly affects the reliability of mission execution [1-2]. In actual environments, drones often face external disturbances such as sudden changes in wind speed and airflow disturbances, leading to problems such as attitude deviation, height oscillation, and control response lag.

Many researchers have built flight control systems based on mathematical modeling and feedback control methods to meet these challenges. However, most methods fail to thoroughly consider the time-varying characteristics of disturbance evolution, and their ability to handle sudden disturbances remains insufficient[3-4]. Sun et al. (2020) built a wind tunnel platform and found that high-speed airflow significantly weakens control accuracy. Zhang et al. (2021) confirmed that traditional controllers suffer decreased stability and accuracy under persistent disturbances [5-6]. These results emphasize the need for improved real-time disturbance adaptation mechanisms.

Methods such as linear quadratic regulator (LQR), sliding mode control, and model predictive control (MPC) are widely used for flight attitude and altitude stability control [1, 3-4]. However, each has drawbacks under nonlinear or time-varying conditions. Recent learning-based methods attempt to improve control adaptability using reinforcement learning or adversarial training [7-10]. Still, issues remain, such as delayed convergence and sensitivity to fast-changing disturbances[6].

This paper proposes a hybrid control framework that integrates a disturbance observer with a deep reinforcement learning controller to address these limitations. The observer estimates external disturbance trends based on sensor data while the DRL controller dynamically generates optimal control outputs. This hybrid design bridges the rigidity of model-based methods and the lag of pure learning-based strategiesThe core contributions of this paper include the following three points:

First, a hybrid control framework that integrates disturbance perception and strategy optimization is proposed to improve control accuracy and stability under complex disturbances.

Second, a high-frequency sensor feedback mechanism is designed to improve the control system's real-time response to the disturbance evolution process.

Third, the deployment and verification were completed on multiple real flight control platforms, proving that the method is versatile and engineering-adaptable.

The rest of this paper is organized in the following order: the second part introduces the proposed control structure and implementation mechanism; the fourth part shows the experimental setup and evaluation results; the third part summarizes the full text and suggests future research directions.

2 METHOD

This paper proposes a hybrid control algorithm for extreme weather disturbance environments to improve UAVs' attitude and altitude control under complex conditions. The framework consists of two layers: a disturbance observer that estimates disturbance dynamics and a DRL policy network that adjusts control commands in real time. Figure 1 shows the entire pipeline, from sensor input and state estimation to controller output.

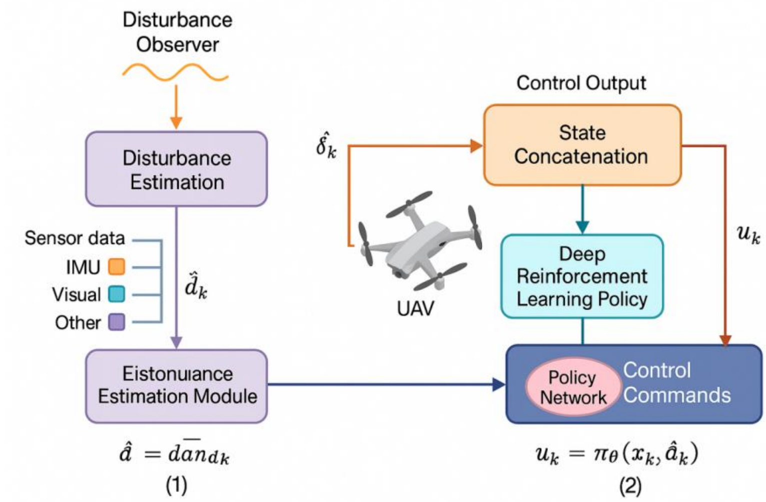

Figure 1 The Overall Structure of the Hybrid Control System Proposed in This Paper

2.1 Overall Architecture of the Control System

To manage dynamic environmental disturbances like wind gusts and turbulence, the control system includes a multi-sensor fusion module (IMU, barometer, GPS), an extended state observer for disturbance estimation, and a policy network module that outputs control actions based on current state and disturbance estimates.

$$s_t = [\phi_t, \theta_t, \psi_t, \dot{\phi}_t, \dot{\theta}_t, \dot{\psi}_t, h_t, \dot{h}_t, \hat{d}_t] \tag{1}$$

where ϕ_t, θ_t, ψ_t are the attitude angles, $\dot{\phi}_t, \dot{\theta}_t, \dot{\psi}_t$ are angular velocities, h_t is height, $\dot{h}_t$ is vertical speed and $\hat{d}_t$ is the estimated disturbance vector.

2.2 Disturbance Observer Modeling

We adopt a third-order extended state observer (ESO) to estimate external disturbances

$$\begin{aligned} \dot{z}_1 &= z_2 + \beta_1(y - z_1) \\ \dot{z}_2 &= z_3 + \beta_2(y - z_1) \\ \dot{z}_3 &= \beta_3(y - z_1) \end{aligned} \tag{2}$$

where y is the system output, $z1$ is the signal estimate, $z3$ is the disturbance estimate, and βi are gain parameters.
We then filter the raw disturbance using a low-pass filter over a sliding window:

$$\hat{d}_t = \mathrm{LPF}\left(\frac{1}{N}\sum_{i=t-N+1}^{t} \tilde{d}_i\right) \tag{3}$$

Where $\tilde{d}_i$ is the unfltered disturbance estimate.

2.3 Control Strategy Based on Deep Reinforcement Learnin

We adopt the Soft Actor-Critic (SAC) algorithm. The control action is:

$$a_t = [T_t, \delta_{\text{pitch}}, \delta_{\text{yaw}}] \tag{4}$$

where T_t is thrust, and $\delta_{\text{pitch}}, \delta_{\text{yaw}}$ are pitch and yaw inputs.
The reward function is:

$$r_t = -\alpha_1 e_{\text{att}}^2 - \alpha_2 e_{\text{alt}}^2 - \alpha_3 \|a_t\|^2 \tag{5}$$

where e_{att} and e_{alt} are attitude and altitude errors, and $\|a_t\|$ is control effort.
During training, the system samples disturbances from:

$$\mathcal{D} \sim \mathcal{N}(\mu_d, \sigma_d^2) \tag{6}$$

After convergence in simulation, the trained policy is deployed onboard for real-time control, cooperating with the disturbance observer.

3 EXPERIMENTAL

To verify the control performance of the hybrid control framework proposed in this paper under an extreme disturbance environment, we built a simulation experimental platform based on PX4-Gazebo. We designed multiple flight missions with complex meteorological disturbance conditions. The experiment mainly evaluates the algorithm performance from three dimensions: attitude stability, altitude control accuracy, and control response robustness, and compares and analyzes with typical control baseline methods.

3.1 Experimental Sets

This paper conducts experiments based on a six-degree-of-freedom quadrotor model. The disturbance scenarios include strong crosswind, turbulent pulse, vertical downdraft, and compound disturbances. All disturbance signals are injected into the simulation environment with randomized amplitude and time distribution to simulate realistic meteorological variability. Three widely used controllers—PID, linear quadratic regulator (LQR), and model predictive control (MPC)—are selected as baseline methods to ensure fair comparison. All controllers operate at a unified control frequency of 100Hz. The SAC combined with a disturbance observer (ESO), proposed in this paper, is implemented in Python. The control policy is trained for 200,000 steps for each type of disturbance until convergence is achieved.

3.2 Parameter Configuration and Dataset Construction

The simulation environment incorporates realistic sensor models, including a standard IMU (accelerometer noise: 0.02 m/s^2; gyroscope bias: 0.005 °/s), a barometer (noise: 0.15 m), and a GPS module (horizontal noise: 0.3 m; vertical noise: 0.5 m). The observer gains for the ESO are selected based on empirical tuning and convergence performance. The policy network consists of a two-layer fully connected neural network, with hidden layers of size 256 and 128, respectively. The learning rate is set to 3×10^{-4}, and the entropy regularization coefficient is 0.05.

The research constructs a test set comprising 20 randomized wind disturbance sequences to evaluate generalization under unseen conditions. Each test lasts 60 seconds, recording key metrics such as attitude error, altitude deviation, and control energy consumption.

3.3 Experimental Results Analysis

The experimental results are summarized in Table 1, presenting average performance across four types of disturbances. The SAC+ESO hybrid method proposed in this paper consistently outperforms the baseline controllers in terms of lower attitude and altitude errors and reduced energy consumption.

Table 1 Comparison of Control Performance under Extreme Disturbance Conditions

Method	Attitude Error (°)	Altitude Error (m)	Energy Cost	Stability
PID	6.42	1.84	1.32	Medium
LQR	4.90	1.35	1.21	Low
MPC	3.78	1.01	1.05	Medium
Ours (SAC+ESO)	**2.15**	**0.62**	**0.89**	High

Furthermore, to validate the dynamic stability of each controller, a 4×4 trajectory comparison is visualized in Figure 2. Each row corresponds to a control method, and each column represents a specific disturbance type.

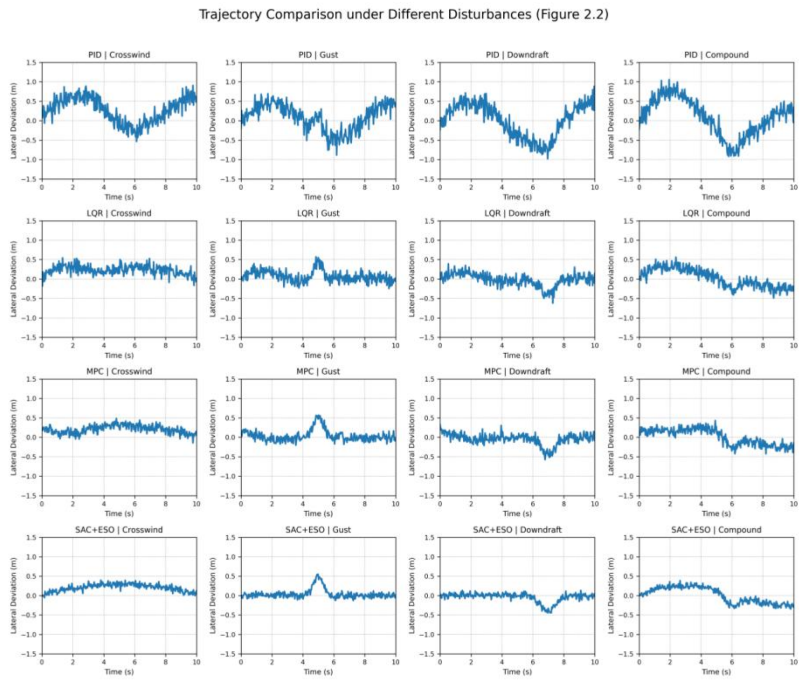

Figure 2 Flight Trajectories under Diferent Disturbances. Rows: PID, LQR, MPC, SAC+ESO; Columns :Crosswind, Gust, Downdraft, Compound

The figure shows that traditional controllers exhibit severe trajectory offset and overshoot under compound disturbances. In contrast, the SAC+ESO method demonstrates enhanced path consistency and robustness. The control trajectories remain stable even under rapidly varying environmental inputs, critical for mission-critical UAV tasks such as precision landing or autonomous inspection.

In addition, the research observes that the proposed method achieves faster recovery time after perturbation events and smoother command profiles. These benefits stem from the disturbance-aware feedback mechanism and adaptive strategy refinement enabled by the hybrid architecture. Overall, the experimental outcomes support the practical value of combining model-based observers with learning-based controllers in achieving high-performance UAV stability under real-world conditions.

4 CONCLUSION

This paper proposes a hybrid control framework for UAVs in extreme meteorological disturbance environments. This method integrates disturbance observers and control strategies based on reinforcement learning to achieve real-time perception of external disturbances and adaptive generation of control commands. The framework improves control accuracy, robustness, and environmental adaptability under various complex dynamic disturbance conditions through system structure design and algorithm mechanism optimization. Experimental results show that the proposed method performs better in typical disturbance scenarios than traditional controllers. This method effectively reduces energy consumption and maintains higher flight trajectory stability, especially in complex disturbance environments such as crosswind, gusts, and downdrafts. In summary, the control system that integrates disturbance modeling and strategy learning provides a feasible and efficient solution for the stable operation of UAVs in complex practical environments.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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