SmoothLander: A Quadrotor Landing Control System with Smooth Trajectory Guarantee Based on Reinforcement Learning

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ABSTRACT

The landing process of the quadrotors can be affected by the disturbance from the ground effect when approaching the landing surface. Such a disturbance significantly increases the chances of collision and jittering of the quadrotors, thereby posing threats to the safety of both the quadrotors and the mounted equipment. In light of this, we propose SmoothLander, an aerodynamics and reinforcement learning-based control system to stabilize the quadrotors under the influence of the ground effect and control noise. First, we design a landing trajectory for the quadrotor in accordance with aerodynamics. Then we design a reinforcement learning-based command generator to effectively optimize the quadrotor's landing behavior. We evaluate our control system through physical feature-based simulation and in-field experiments. The results show that our method can enable the quadrotor to land more smoothly and stably against control noise than the baseline.

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CCS CONCEPTS

• **Applied computing → Aerospace**; • **Computing methodologies → Reinforcement learning**; • **Computer systems organization → Sensors and actuators**.

KEYWORDS

Quadrotor, Ground Effect, Reinforcement Learning

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1 INTRODUCTION

As drone technology continues to mature, researchers and industries endue drones with more and more diverse applications and tasks, including large-scale urban sensing[10, 36], surveillance[6, 30], delivery[3, 8], disaster relief[12, 32], etc. The drones, such as quadrotors, can use loaded sensors or software algorithms to accurately locate themselves[7, 26], and then achieve highly stable hovering to execute predetermined tasks. However, the performance of landing for quadrotor is fairly unstable due to the phenomenon of

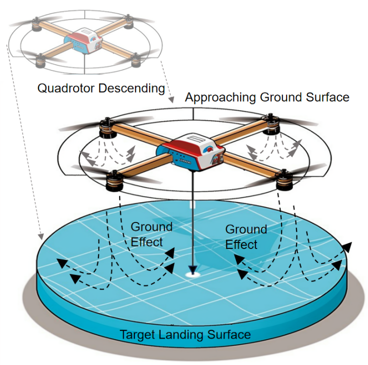


Figure 1: The quadrotor is affected by the ground effect in the landing process

ground effect(GE) and the control noise[28], as is illustrated in Fig.1. Such a phenomenon causes the quadrotor to experience an extra lift when close to a surface below due to the rebound airflow[23]. While this lift might be helpful to push the quadrotor to take off, it induces disturbance, compromising stability and smoothness during landing. Such disturbances might lead to jittering landings and pose threats to both the quadrotor and the mounted equipment[13].

Researchers have proposed traditional and learning-based methods to reduce the disturbance during low-height flight. Traditional methods include real-time adjustment through linear or self-adaptive control[20, 25], which can effectively compensate for the impact of ground effect[20]. However, due to the fact that the adjustment is triggered after experiencing turbulence[31], traditional methods always lead to delayed responses. Moreover, the ground effect is very intricate and subject to multiple influence factors including types of quadrotors, landing surface, natural wind, and control noise[28]. It is impractical to model for a large variety of conditions[14]. In the case of learning-based methods, artificial neural networks (ANN) have been applied to predict GE[15]. It was demonstrated that ANN methods significantly outperform a baseline nonlinear tracking controller in the cases of landing. However, these methods lack stability guarantees[23]. Reinforcement learning (RL) has been successfully applied to a wide range of control applications. It is a machine learning approach that focuses on an agent learning to make decisions or take actions in an environment to maximize a cumulative reward[17]. Also, RL has been employed for controlling quadrotors in landing tasks[16], showcasing exceptional landing performance[24, 33]. However, in-field wind influences and control noise is often neglected when utilizing RL for control.

The problem this paper tries to solve is: **how to control the quadrotors to land smoothly and stably under the interference of the ground effect and control noise?** This is a non-trivial problem and poses significant challenges. To address these challenges, this paper proposes SmoothLander, a reinforcement learning-based control system for compensating for GE and controlling noise during the landing process.

One of the two challenges **(C1)** is that: on the one hand, the quadrotor needs to adjust its thrust of four rotors based on its current state to compensate for the disturbance. On the other hand, the quadrotor may not return directly because the compensating commands do not consider the future GE caused by the adjustment. Thus, delayed compensating time is spent, and oscillation unavoidably occurs during this loop process. Additionally, control noise is difficult to precisely measure and filter in real time, further complicating the controller design. To tackle the challenge **(C1)**, we propose a reinforcement learning-based method for generating safe command sequences in advance under the interference of control noise and GE, without delayed adaption. The generated commands account for the future state changes from the combination of GE and thrust output. Leveraging the powerful modeling and searching capabilities of RL[18], our approach optimizes the quadrotor's control strategy to pre-generate control commands that follow a designed trajectory. This generated trajectory is proven to avoid oscillation and provide continuity, based on the features of a critical damping state in a second-order damping system.

The second challenge **(C2)** is the lack of training data for quadrotors to learn the distribution and influence of ground effect. This challenge arises because the quadrotor has a large state space and a high-dimensional transition matrix, caused by the highly dynamic nature of quadrotors' ground effect, making it hard to collect complete command-state pair data. To address the challenge **(C2)**, the reinforcement learning training environment includes an aerodynamics ground effect model and control noise distribution collected from the real world. The disturbance force influences from this physical GE model and control noise distribution help quadrotors learn how to compensate. We evaluate our method in both physical feature-based simulation and real-world environments. Results demonstrate that SmoothLander achieves smoother and more stable landings than the baseline.

The main contributions of this paper are as follows:

- Design a reinforcement learning-based landing control system, SmoothLander, for quadrotors to ensure smoothness and stability while compensating for the influence of the ground effect and control noise by considering the future interaction with GE, without the oscillation for adjusting.
- Propose a physical feature-based method to generate training data in the reinforcement learning environment for the quadrotor controller to learn the strategy of resisting GE.
- Evaluate the SmoothLander system through both physical feature-based simulation and real-world implementation on quadrotors. The results show that our method can enable the quadrotor to land smoothly and stably with light contacts.

The rest of this paper is organized as follows: Section 2 describes the problem definition. Section 3 represents our controller framework. Section 4 shows our experimental results and evaluation. In the last, Section 5 concludes this paper.

2 PROBLEM DEFINITION

In this section, we first introduce the background definitions of the landing system. Subsequently, we describe our objective for the landing system. Lastly, we formulize the problem of optimizing the landing controller system.

2.1 Key Definitions

The quadrotor can take off, land, and fly in a bounded free region, with a rigid floor surface where quadrotors can stay. Violent impacts or incline landing to the floor may cause hazardous collisions. As a flight agent, the quadrotor has states containing global position $\mathbf{p} = [p_x, p_y, p_z]^\top \in \mathbb{R}^3$, velocity $\mathbf{v} \in \mathbb{R}^3$, body angular velocity $\boldsymbol{\omega} \in \mathbb{R}^3$ and attitude rotation matrix $R \in SO(3)$. Then we can describe the following dynamics:

$$\begin{aligned} \dot{\mathbf{p}} = \mathbf{v}, \dot{\mathbf{v}} = \mathbf{a}, \quad m\mathbf{a} = m\mathbf{g} + R\mathbf{f_u} + \mathbf{f_w}, \\ R = RM(\boldsymbol{\omega}), \quad \mathbf{J}\dot{\boldsymbol{\omega}} = \mathbf{J}\boldsymbol{\omega} \times \boldsymbol{\omega} + \boldsymbol{\tau_u} + \boldsymbol{\tau_w}, \end{aligned} \tag{1}$$

where $\mathbf{a}$ is the acceleration, m and $\mathbf{g} = [0, 0, -g]$ are mass and gravity acceleration vector. $M(\cdot)$ indicates skew-symmetric mapping. $\mathbf{f_u} = [0, 0, T]^\top$ and $\mathbf{f_w}$ is the reflection force from four rotors thrust and unknown outside wind. $\mathbf{u} = [n_1^2, n_2^2, n_3^2, n_4^2]^T$ is the actuation signal, while n_1, n_2, n_3, n_4 are motor rotation speeds. Accordingly, $\boldsymbol{\tau_u}$ and $\boldsymbol{\tau_w}$ are the torques from four rotors and outside wind. The thrust $T = \mathbf{H_0 u}$ determines the motion of quadrotor, where $\mathbf{H_0}$ is a matrix containing k_T thrust coefficient, l_r the length of rotor arm, and c_Q torque coefficient. The critical factors in the quadrotor stable landing problem are disturbance force $\mathbf{f_w} = [f_{w,x}, f_{w,y}, f_{w,z}]^\top$ and disturbance torques $\boldsymbol{\tau_a} = [\tau_{a,x}, \tau_{a,y}, \tau_{a,z}]^\top$ from complicated aerodynamics interactions between quadrotors and environment. In general, the larger the rotor output power and the closer the drone is to the ground, the more effect the disturbance will have[1].

To be detailed, control noise existed in many processes, such as actuation noise $\boldsymbol{\sigma_a}$ in the process from control signal to rotor actual thrust output and acceleration noise $\boldsymbol{\sigma_u}$ caused by measurement and computing precision, two main components, with:

$$\mathbf{u_m} = \mathbf{u} + \boldsymbol{\sigma_u}, \quad \mathbf{a_m} = \mathbf{a} + \boldsymbol{\sigma_a}, \tag{2}$$

where $\mathbf{u_m}$ and $\mathbf{a_m}$ are the measured actuation signal and measured acceleration. In reality, these noises may cause unpredictable effects on the landing task.

2.2 Problem Formulation

In order to achieve a stable quadrotor landing, the trajectory and controller design are crucial factors for ensuring fast, smooth, and stable flights[35]. A desired trajectory $\mathbf{p_d}$ is designed to achieve a stable landing, followed by the design of a stabilized controller that compensates for disturbances caused by ground effect and control noise. The controller enables the quadrotor to follow the desired path during the landing task. **The optimization objective** of the system is to minimize the distance between the real-time position and the position along the desired trajectory, while ensuring the velocity and acceleration of the quadrotors meeting specific constraints during the entire landing process. **The main challenge** comes from uncertain mapping between actuation $\mathbf{u}$ and acceleration $\mathbf{a}$ under disturbances. We have the mathematical formulation of the stabilized controller problem as:

$$\arg\min_{\mathbf{u}} \|\mathbf{p}_{init} + \int_0^T (\mathbf{v}_{init} + \int_0^T \mathbf{a}\, dt)dt - \mathbf{p}_d(t)\|_2 \tag{3}$$

$$\begin{aligned} s.t. \quad & \mathbf{a}_{min} \le \mathbf{a} \le \mathbf{a}_{max} \\ & \mathbf{v}_{min} \le \mathbf{v} = \mathbf{v}_{init} + \int_0^T \mathbf{a}\, dt \le \mathbf{v}_{max} \end{aligned}$$

where $\mathbf{p}_d(t)$ and $\mathbf{v}_{init}$ are desired position of quadrotor's flight at time t and initial velocity, respectively. Acceleration $\mathbf{a}$ and velocity $\mathbf{v}$ are limited by the hardware constrain and the purpose of safety and smooth flight.

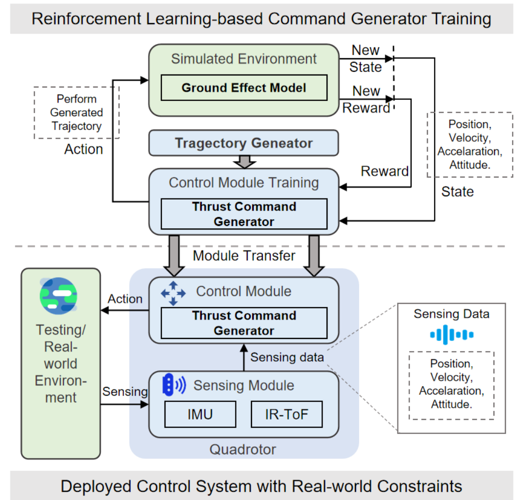


Figure 2: System Overview

3 SYSTEM DESIGN

In this section, the components and details of the control system will be introduced. The system comprises three main components: *Trajectory Generator*, *Ground Effect Modeling*, and *Thrust Command Generator*, as illustrated in Fig.2. The Trajectory Generator generates desired trajectories for quadrotors to follow, reducing the chances of oscillations and collisions. Ground Effect Modeling provides sufficient training data for quadrotors to learn the nature of ground effect within the RL environment. The Thrust Command Generator generates control commands to ensure that the quadrotor follows the designed trajectory while also compensating for GE and control noise, thereby ensuring smooth landing flights.

3.1 Trajectory Generator

Limited by the constraints of kino-dynamics for quadrotors, the trajectory must satisfy the requirements of a smooth and stable landing without oscillation, which can be guaranteed by a well-designed pre-defined trajectory. Therefore it should also be designed for quadrotors to achieve without extra help.

The motion of a quadrotor is subject to the constraints imposed by its kino-dynamics and physical hardware design[2], which necessitates that the trajectory adheres to these limitations. Specifically, to ensure smoothness and stability, the position and velocity sequence must maintain continuity without any glitches and ensure soft contact with the ground. In terms of operational constraints, the velocity and acceleration must not exceed the drone's performance limit. To ensure the safety, a deceleration buffer is necessary for the ending period to avoid collisions, oscillations, or heavy impact. To achieve these features, we refer to the critical damping state of a second-order damping system, which is a widely used design in control systems. The second-order damping system has three primary states: overdamping, underdamping, and critical damping. The first state takes a long time to return to the equilibrium position, and the second state oscillates around the desired position.

In contrast, the critical damping state ensures smoothness and a relatively quick return to the final stable position without oscillations. The smoothness, stability, and quick response of the critical damping state align with the requirements of the quadrotor landing trajectory. Thereby, following the model of the critical damping state in a second-order damping system, we design such trajectory $\mathbf{p}_d = [p_{d_x}, p_{d_y}, p_{d_z}]^\top \in \mathbb{R}^3$, as:

$$\mathbf{p}_d(t) = e^{(-Ct)}(1+Ct)(\mathbf{p}_{init} - \mathbf{p}_{end}) + \mathbf{p}_{end},\ t \in \mathbb{R}^+, \tag{4}$$

where $\mathbf{p}_{init} = [p_{init_x}, p_{init_y}, p_{init_z}]^\top \in \mathbb{R}^3$ is the initial position and $\mathbf{p}_{end} = [p_{end_x}, p_{end_y}, p_{end_z}]^\top \in \mathbb{R}^3$ is the destination of the quadrotor. Time t starts counting from 0 at the beginning of the task process and C controls the velocity of the flight.

It can be proved that $\mathbf{p}_d$ is continuous and smooth based on the continuity and smoothness of its first-order and second-order derivatives. Furthermore, this trajectory guarantees that the velocity and acceleration of the quadrotor remain bounded, as demonstrated by the maximum values of its derivatives. To prevent the quadrotor from receiving motion commands[27] that exceed its hardware design capabilities, we can constrain its motion by selecting an appropriate value for the constant C.

3.2 Ground Effect Modeling

The ground effect refers to the upward force created by the reflection of the downward wind generated by the quadrotor's rotors. During the landing process, this effect can be undesirable and its magnitude is strongly dependent on several factors, including the distance to the ground, the hardware configuration, and the current actuation of the rotors. The changing state of the quadrotor can cause variations in the magnitude of the disturbance forces induced by GE. To predict and compensate for this effect, it is crucial to have a precise model that provides prior knowledge to the quadrotor for self-adjustment. To address this issue, we adopt a model of the ground effect on the quadrotor based on[29], which is derived from the physical parameters of quadrotors and experimental results. This model can help to mitigate the impact of the ground effect during the landing process, which is:

$$\begin{aligned} T(n, p_z) = k_T n^2 / [\rho D^4 [1 - (D/4p_z)^2 - D^2 p_z / \sqrt{(d^2 + 4p_z^2)^3} \\ - (D^2/2)(p_z/\sqrt{(2d^2 + 4p_z^2)^3}\,) - 2D^2(p_z/\sqrt{(b^2 + 4p_z^2)^3})I_b]], \end{aligned} \tag{5}$$

where T is the actual thrust containing GE, ρ is the air density, D is the radius of the propeller, d and b are the distance between the closed two rotor axes and two diagonal rotor axes, and I_b is the empirical body lift coefficient. The last two terms of the denominator account for flow recirculation and the central body raise. The lift generated by the model considers the airflow velocity at the body's central position and modifies its impact using I_b. This model has been validated experimentally on a real-world testbench[28].

3.3 Thrust Command Generator

Designing a controller to generate stabilized thrust output for quadrotors to deal with control noise and coupled ground effect in advance using traditional methods is challenging. Although using reinforcement learning can satisfy these requirements, it introduces new challenges, such as generating safe actions and simulating

Algorithm 1 Learning a policy for the control of quadrotors based on reinforcement learning algorithm

Randomly initialize a model π
for epoch=1:M **do**
  randomly initialize $\mathbf{p}_t$, $\mathbf{v}_t$, $\mathbf{a}_t$,$\boldsymbol{\omega}_t$;
  for $t = 0 : T-1$ **do**
    Quadrotor executes an action $\mathbf{u}_t = \pi(\mathbf{p}_t)$;
    Calculate $\mathbf{f_u}$, $\mathbf{f_w}$, $\boldsymbol{\tau}_\mathbf{u}$, $\boldsymbol{\tau}_\mathbf{w}$;
    Calculate $\mathbf{a}_{t+1}, \mathbf{v}_{t+1}$;% *according to Eq(1)*
    Calculate $\mathbf{p_{t+1}}$;% *according to Eq(1)*
    Reward $\mathbf{r}_{t+1} = R(\mathbf{u}_t, \mathbf{p}_{t+1})$
    Update the model $\boldsymbol{\pi}$ and the state $\mathbf{p}_{t+1}$
  end for
end for

physical ground effect[19, 22]. To address these challenges, we adopt a changeable action space and physical feature-based ground effect model described in section 3.2 for our command generator.

Action Space: The action space for the thrust command generator is limited by the quadrotor's hardware design and must be within a safe region to prevent instability caused by excessive actuation commands or high velocities. Moreover, the velocity of the quadrotor must change slowly to ensure stability and prevent oscillations, and the velocity should be low when approaching the final destination to reduce the risk of collision or exceeding the hover position. To meet these requirements, the action space is constructed by adjusting based on the previous state.

State Space: The quadrotor is confined to a motion region within a free space Ω that includes a rigid ground boundary. The quadrotor's states are defined as $\mathbf{p}$, $\mathbf{v}$, $\mathbf{a}$, and $\boldsymbol{\omega}$.

Reward: The reward function is denoted as $R(\mathbf{u}, (\mathbf{p}_t, \mathbf{v}_t, \mathbf{a}_t, \boldsymbol{\omega}_t))$, to minimize the difference between the actual positions and the desired positions for the quadrotor to closely follow the desired trajectory. The function is defined in Eq(3).

4 EVALUATION

In this section, we test our method in both simulation and the real world, aiming to evaluate its effectiveness and performance. For simulation, our method is compared with a non-linear tracking controller in one-dimensional z-axis. We also implement our methods on Crazyflie 2.1 in the real world to test the performance.

4.1 Experimental Setup

Evaluation Metrics: The objective of the SmoothLander is to land with a smooth and stable trajectory under the interference from GE and control noise. Therefore, the error between the quadrotor's actual trajectory and its desired trajectory describes the performance of the SmoothLander controller in compensating for the ground effect.

Baseline: We compare our method with a nonlinear tracking controller that regards $\mathbf{f_w} \equiv 0$ in Eq(1). It tries to maintain a composite variable $\mathbf{s} = 0$, which is

$$\mathbf{s} = \dot{\mathbf{e}}_p + \Gamma \mathbf{e_p} = \dot{\mathbf{p}} - \mathbf{v}_r \tag{6}$$

where $\mathbf{e_p} = \mathbf{p} - \mathbf{p_d}$ is the tracking error, $\mathbf{v}_r$ is a reference velocity, Γ is a positive definite matrix. Thus, tracking the trajectory can be transformed to maintaining the velocity $\mathbf{v}$ to follow $\mathbf{v}_r = \dot{\mathbf{p}}_d - \Gamma \mathbf{e}_p$.

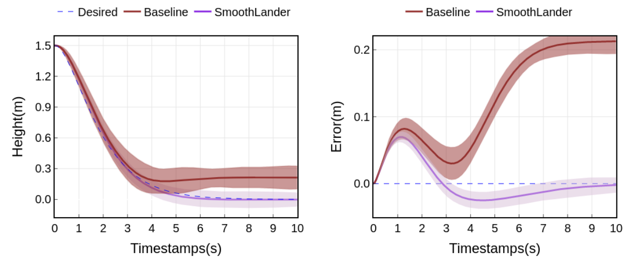
Experimental Setup: For both the simulation and real-world experiment, the environment is an open-air ground without any natural winds. The platform used is a nano-quadrotor, Crazyflie 2.1[4, 5], equipped with an infrared ToF distance sensor for flight height data collection. The command input is the actuation signal $\mathbf{u}$ generated from the Thrust Command Generator. To build a close-to-real model for simulation and real-world tests, we measured Crazyflie's mass m, rotor radius D, the distance between rotor axes d, diagonal length b, as well as air pressure ρ. Also, we tested the thrust constant k_T, actuation noise $\boldsymbol{\sigma_u}$, and acceleration noise $\boldsymbol{\sigma_a}$ from the real world. The control command rate, the attitude update rate, and the position estimation rate are all the same at 100Hz. The detailed experiment process is described in the next subsection.

4.2 System Performance

Overall Landing Performance: In this study, we conduct a landing simulation to evaluate the performance of SmoothLander. To assess the filtering of unwanted disturbances from the ground effect, we carry out 100 tests and compare the mean trajectories of the quadrotor using our method with those using the baseline. The experiments were conducted using the control noise of 0.01 for both acceleration and actuation noise variances. The quadrotor first ascends to an initial height of $p_z = 1.5(m)$ and then hovers at this height before initiating the landing process along the desired trajectory $\mathbf{p}_d$ with an initial zero-velocity, ultimately coming to a stop at ground level. As shown in Fig.3(a), Smoothlander successfully brings the quadrotor a low-velocity contact with the ground, while the baseline method struggles to approach the ground under the influence of the upward force. This demonstrates the efficacy of our reinforcement learning model in generating compensated control commands based on predicting the impact of GE to follow $\mathbf{p}_d$. In addition, we compare the mean absolute errors (MAE) between the simulated trajectory $\mathbf{p}$ and the desired trajectory $\mathbf{p}_d$, as shown in Fig.3(b). The results indicate that SmoothLander has smaller mean errors and smaller standard variances, indicating high-precision control and less fluctuation during the landing process.

Then we implement Smoothlander and baseline in the real world on a Crazyflie 2.1, which only controls the vertical power output with equal four rotors' thrust. The experiment is conducted identically to the simulation, with the same initial settings. The quadrotor using the baseline controller stops descending before reaching the final height, but Smoothlander contacts the ground steadily at last, as is shown in Fig.4. However, due to the high data variance of the low-cost sensors and the variable power output associated with the battery, the performance of the system is somewhat suppressed.

Control Noise Reduction Performance: We compare the performance of two methods under different levels of actuation noise and acceleration noise in a simulation. The mean cumulative position errors resulting from 100 simulations with varying noise variances are shown in Fig.5. As the variances increase, both methods experience growing mean errors due to the increasing uncertainty of the actions' effects. However, Smoothlander consistently exhibits smaller cumulative errors than the baseline, indicating its superior ability to filter control noise. This ability is likely attributed to the training process, during which our reinforcement learning model learns the noise distribution by interacting with the environment.



(a) Mean trajectory (b) Mean error

Figure 3: Mean trajectories and mean errors of landing simulations. (a)The lines indicate the mean trajectories of 100 simulations and the shadowed areas show the variances. (b)Mean errors compared with the desired trajectory are shown as lines and variances are shown with shadow area.

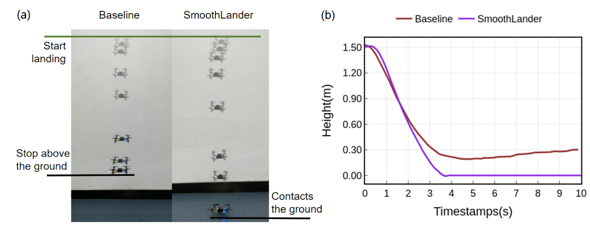


Figure 4: Landing performance in real-world experiments. (a)Landing Crazyflie. (b)Trajectories of landing. The quadrotor using baseline does not land on the ground as last, but using SmoothLander it does.

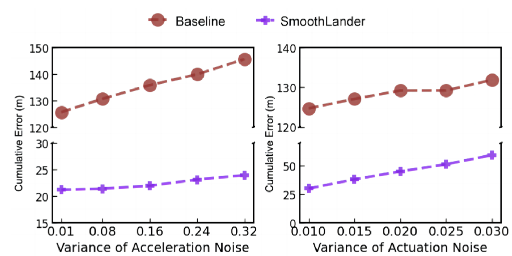


Figure 5: Trajectory errors with different noise variance. Although errors increase as the variance rises in both methods, SmoothLander always has much lower errors.

5 CONCLUSION

This paper proposes a landing control system, SmoothLander, designed to achieve smooth and stable flights even in the presence of ground effect interference and control noise. The system employs reinforcement learning to overcome the disturbance force from the ground effect and reduce control noise, thereby enabling more precise flights. Results from both physical feature-based simulations and in-field implementation tests demonstrate that SmoothLander outperforms the baseline in terms of landing performance. In the future, the system can help quadrotors provide smart living services[11, 21] based on advanced schedule algorithms[9, 34] and various sensors.

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