

Ubicomp CPD 2023

# SmoothLander:

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

Chenyu Zhao<sup>1</sup>, Haoyang Wang<sup>1</sup>, Jiaqi Li, Fanhang Man, Shilong Mu,  
Wenbo Ding, Xiao-Ping Zhang, Xinlei Chen

Tsinghua University



**TBSI**

清华-伯克利深圳学院  
Tsinghua-Berkeley Shenzhen Institute

# Landing of Quadrotors

Quadrotors need to land and take off during all kinds of tasks.



Delivery



Near crowd

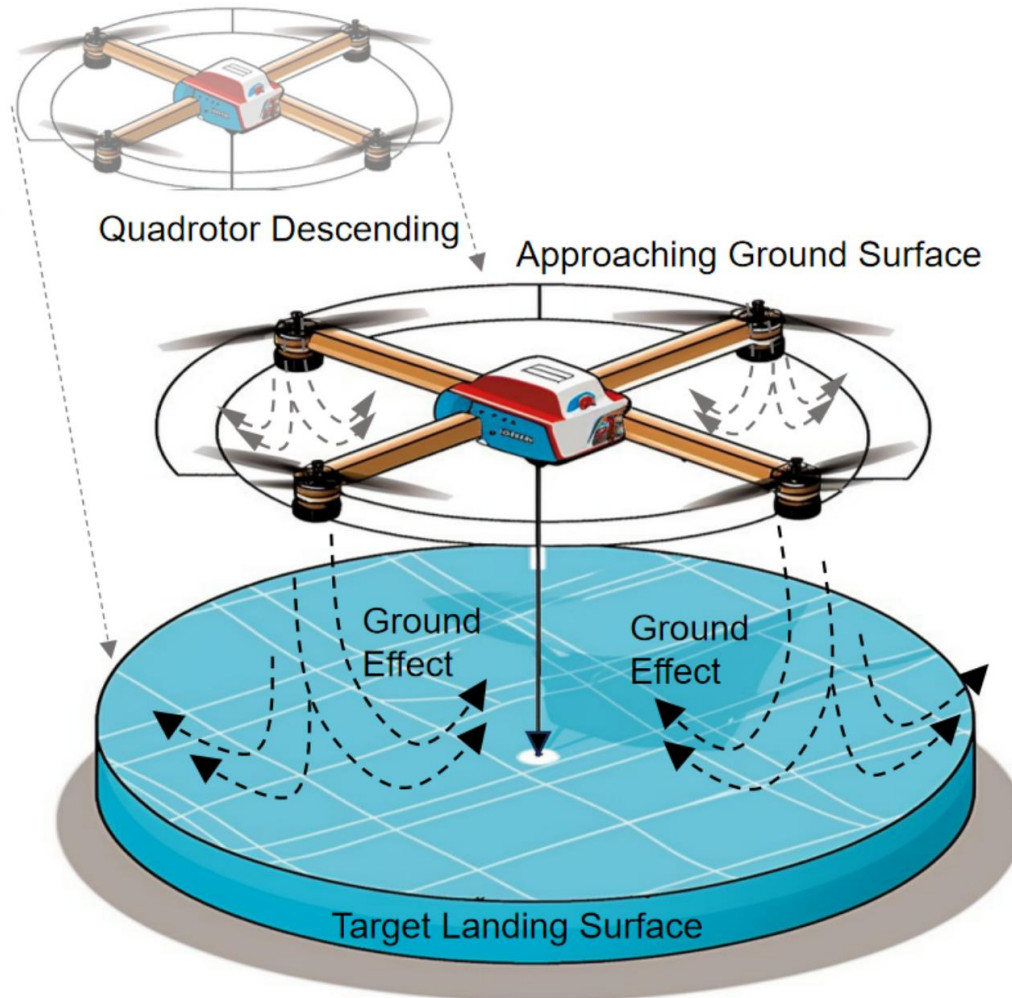


Equipment of high precision



Search and Rescue

# Ground Effect(GE) during landing of Quadrotors



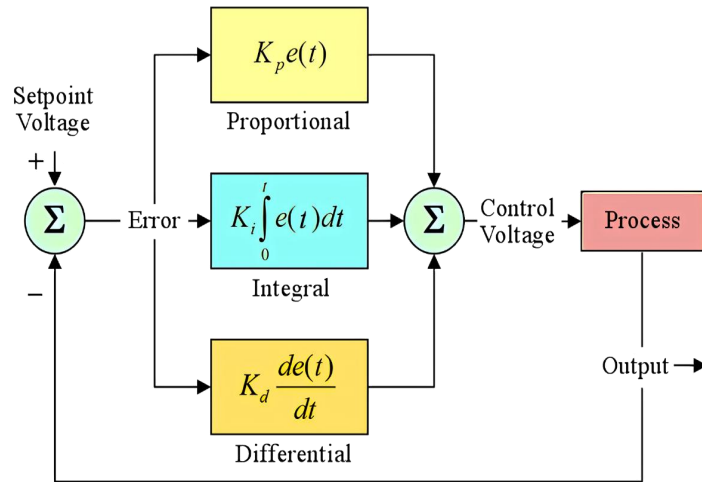
Then, this lift force may cause instability...

- Quadrotor collision
- Equipment damage
- .....

**Need a controller to land smoothly**

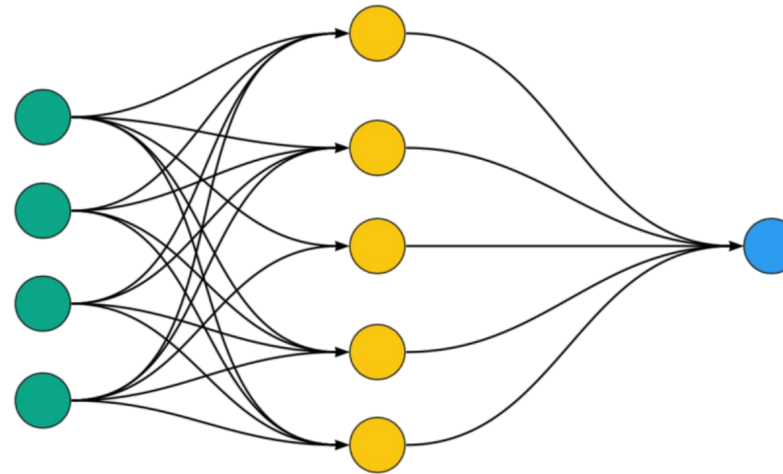
# Methods of alleviating Ground Effect

How to control the quadrotors to land smoothly and stably under the interference of the ground effect and control noise?



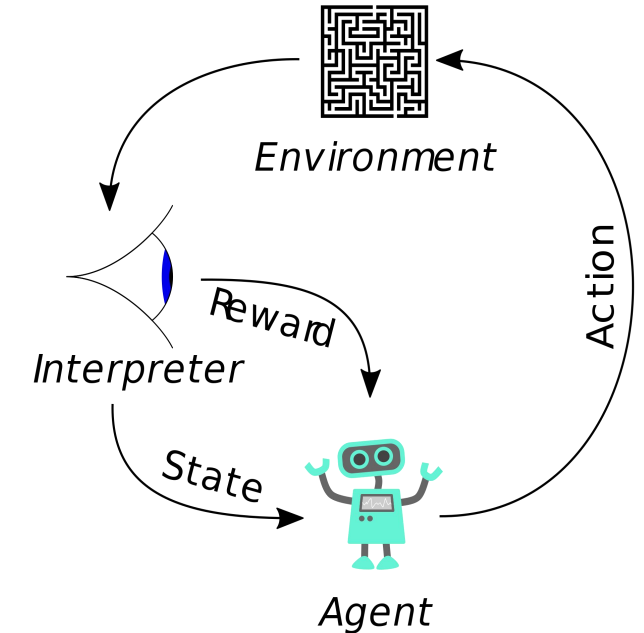
Self-adaptive PID

---Latency?



ANN

---Stability guarantee?

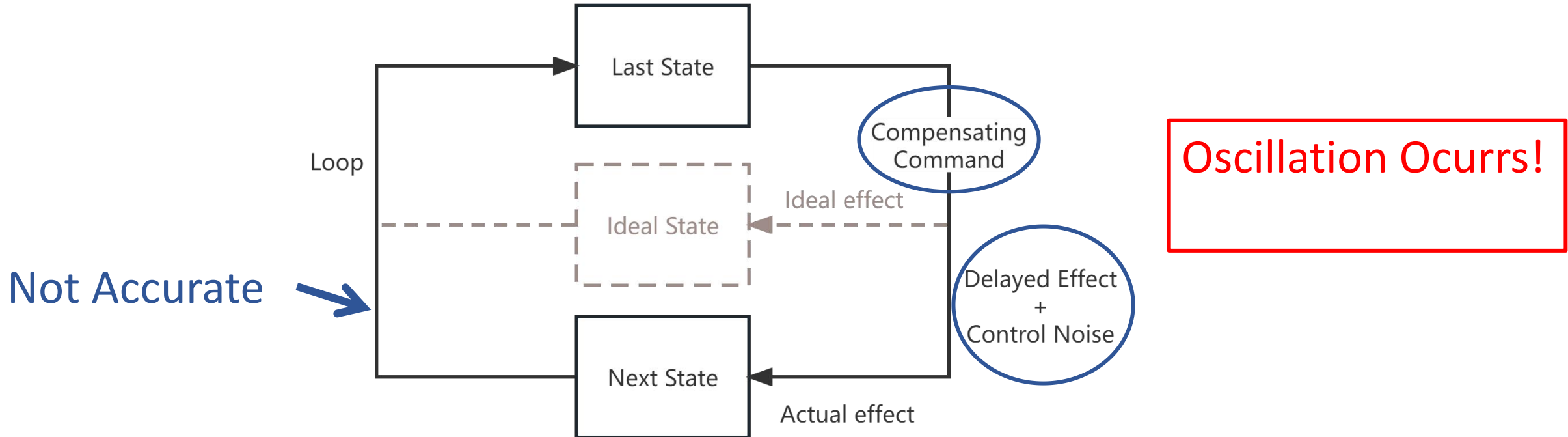


RL

---In-field influences?

# Two Challenges

C1: Delayed compensating time v.s. oscillation,  
and control noise v.s. control accuracy.



Solution:

- Use pre-trained RL to account for the **future** state changes.

# Two Challenges

C2: The lack of training data to learn the distribution and influence of GE.

- Large state space

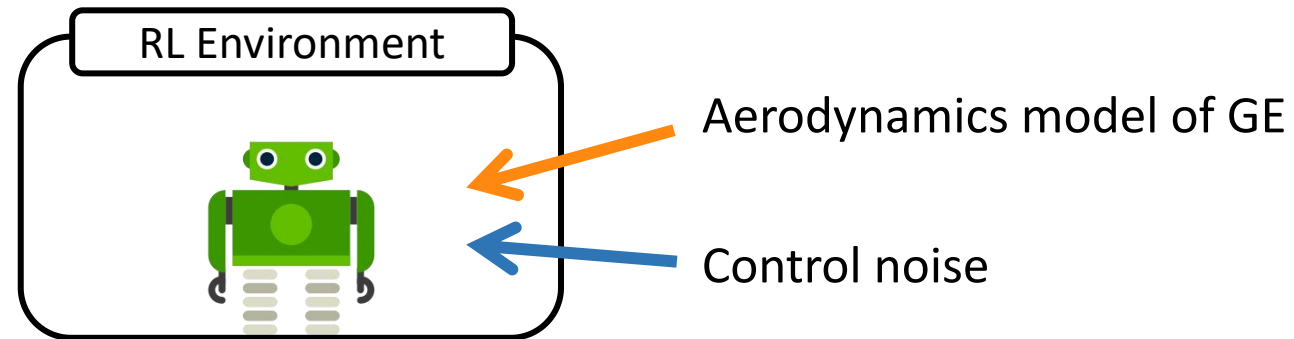


- High-dimensional transition matrix

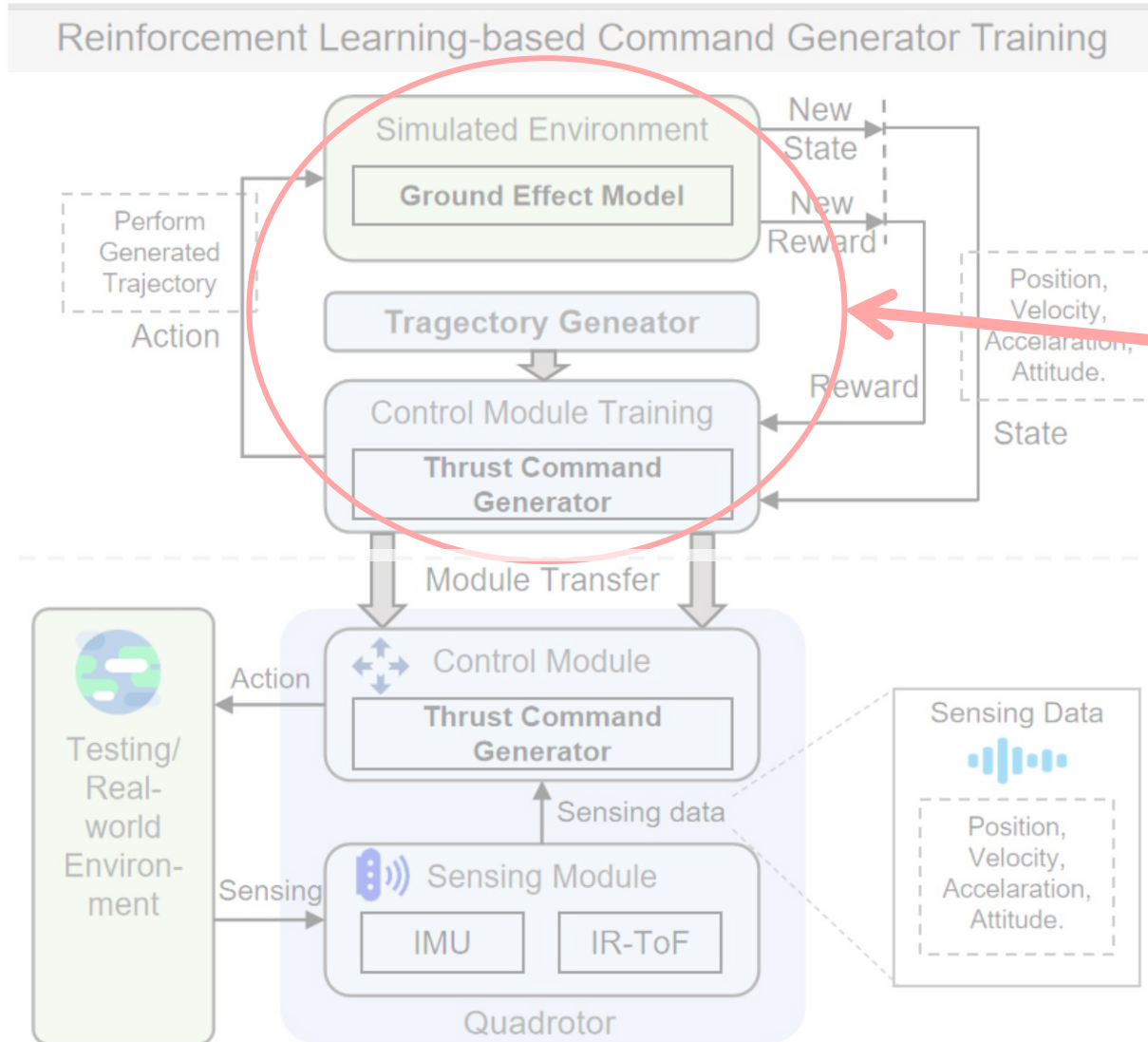
- Insufficient command-state pair data

Solution:

- Adding **physical-feature based model** of GE into training environment.



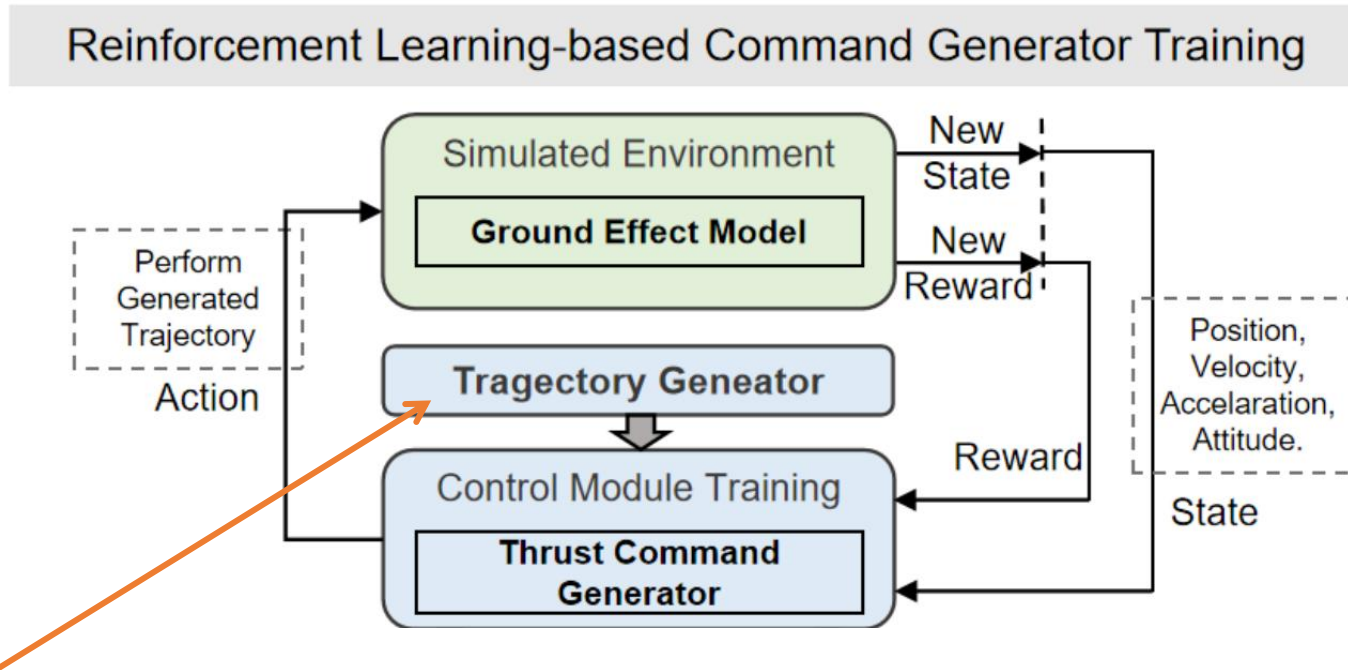
# System Design



Three key components of the system



# System Design



## Component 1: Trajectory Generator

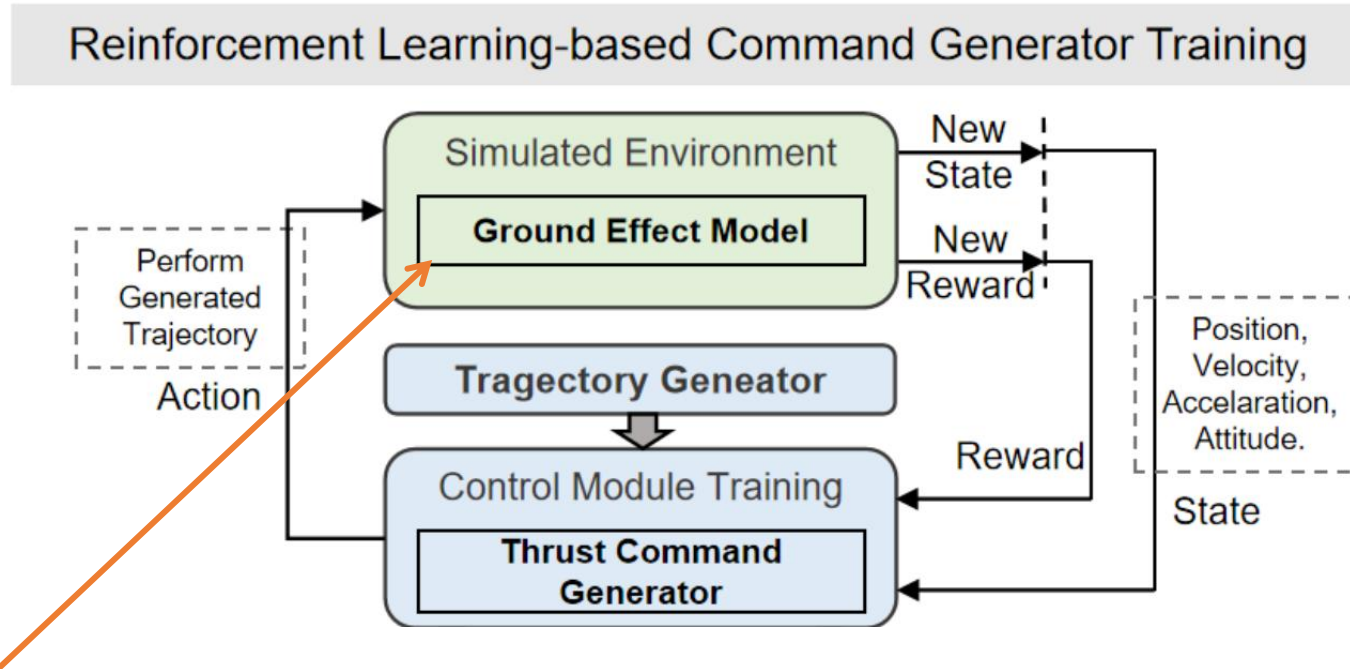
### From critical damping state

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

- Continuity in first two orders' derivatives
- Slow to approach final ground



# System Design



## Component 2: Ground Effect Modeling

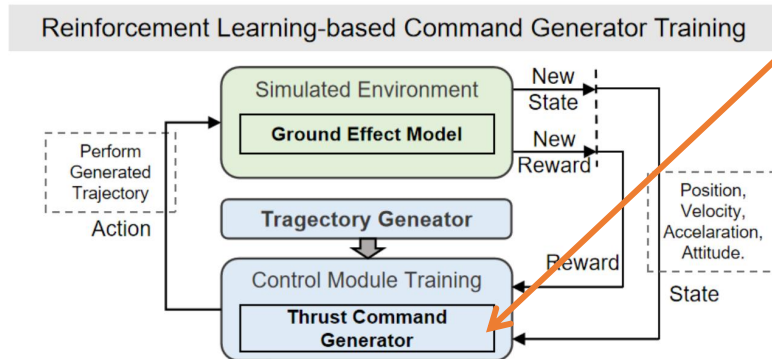
Ground Effect Model:

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

, which is validated experimentally on a real-world testbench

# System Design

## Component 3: Thrust Command Generator



$p$ : Position

$v$ : Velocity

$a$ : Acceleration

$\omega$ : Angular velocity

Reward:  $1/\text{sum}(\text{abs}(p - p_d))$

Action: Actuation command

Strategy: Commands - Certain states

---

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

---

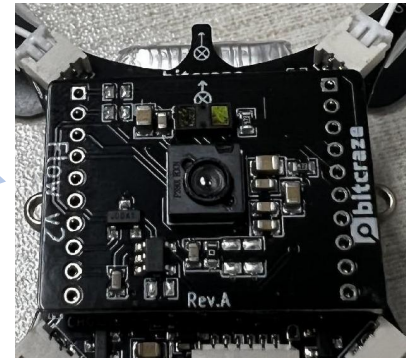
- 1: Randomly initialize a model  $\pi$
  - 2: **for** epoch=1:M **do**
  - 3:   randomly initialize  $p_t, v_t, a_t, \omega_t$ ;
  - 4:   **for**  $t = 0 : T - 1$  **do**
  - 5:     Quadrotor executes an action  $u_t = \pi(p_t)$ ;
  - 6:     Calculate  $f_u, f_w, \tau_u, \tau_w$ ;
  - 7:     Calculate  $a_{t+1}, v_{t+1}$ ; % according to Eq(1)
  - 8:     Calculate  $p_{t+1}$ ; % according to Eq(1)
  - 9:     Reward  $r_{t+1} = R(u_t, p_{t+1})$
  - 10:    Update the model  $\pi$  and the state  $p_{t+1}$
  - 11:   **end for**
  - 12: **end for**
-

# Evaluation Setup

Environment: in both **simulation** and **in-field** experiment, only in z-axis, based on Crazyflie 2.1, with configuration and data collected from the real world.



Crazyflie, only weights 33 grams



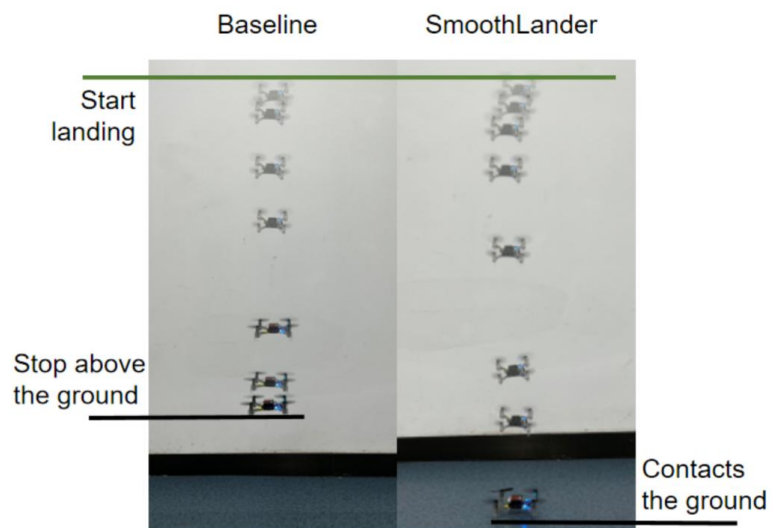
Mounted with a Flow Deck v2.

Baseline: A non-linear tracking controller **does not consider** outside wind.

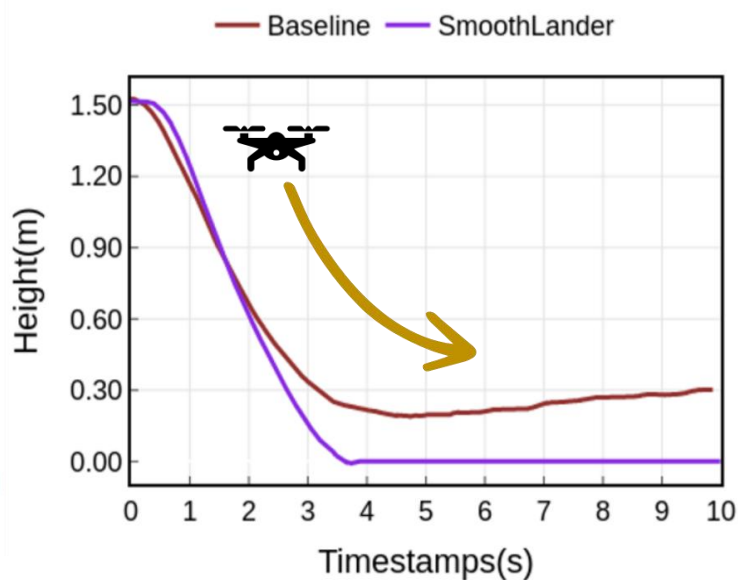
Metrics: Error between actual trajectory and designed trajectory.

# Performance

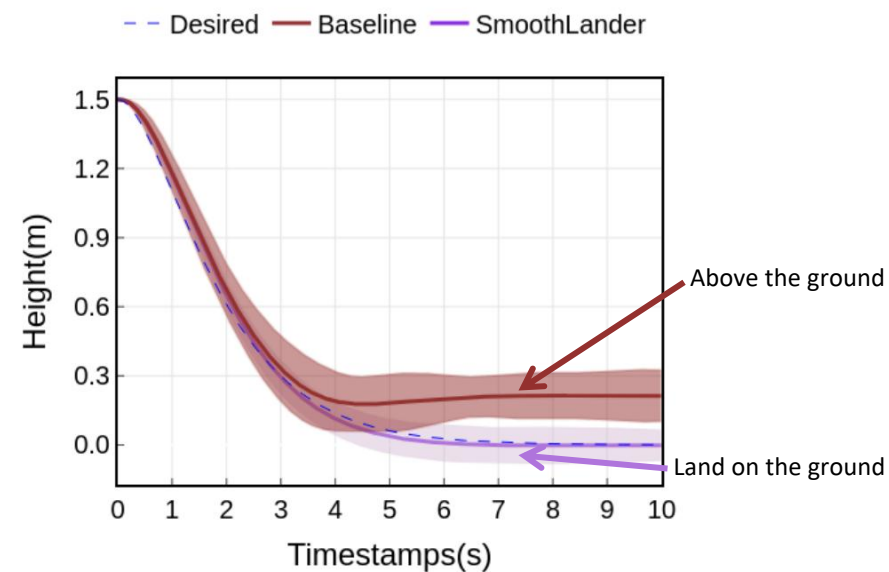
Resisting the upward lift from GE:



Clips of landing crazyflie



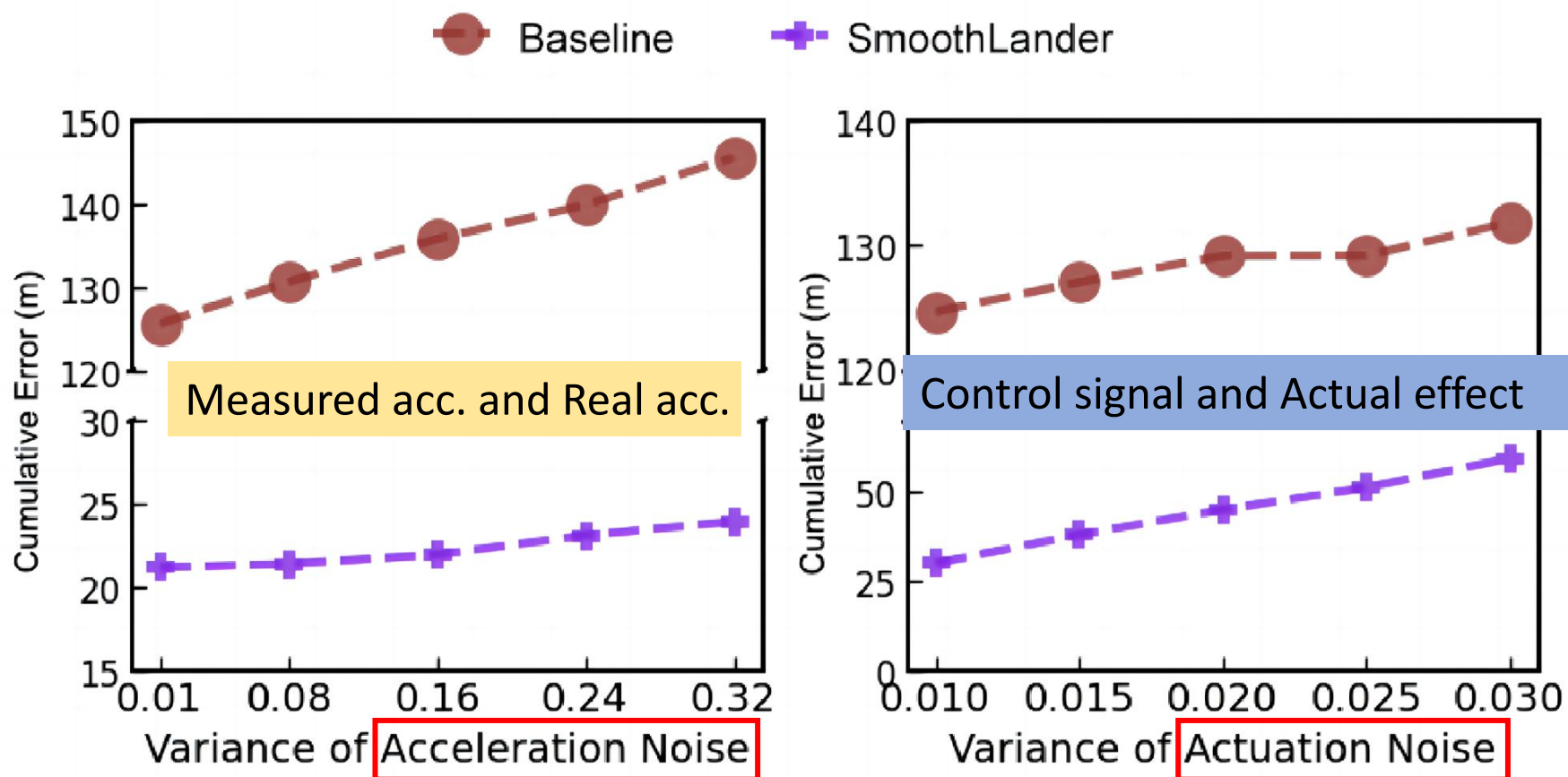
Trajectory of landing crazyflie



Trajectory of 100-time simulations

# Performance

Control noise reduction:



- As uncertainty of noise increasing, errors increase.
- Errors of ours are always lower than the Baseline.

# Summary of SmoothLander

- Design a RL-based landing control system by considering the **future interaction** with GE.
- Propose a physical feature-based method to **generate training data** in the RL.
- Evaluate the system through both physical feature-based **simulation** and **real-world** implementation.

# Thank You!

Presenter: Chenyu Zhao, TBSI  
Email: [zhaocy22@mails.tsinghua.edu.cn](mailto:zhaocy22@mails.tsinghua.edu.cn)