

MobiCom 2024



Foes or Friends: Embracing Ground Effect for Edge Detection on Lightweight Drones

Chenyu Zhao*, Ciyu Ruan*, Jingao Xu†, Haoyang Wang, Shengbo Wang, Jiaqi Li, Jirong Zha, Zheng Yang, Yunhao Liu, Xiao-Ping Zhang, Xinlei Chen†.



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†Xinlei Chen and Jingao Xu are the corresponding authors.

Drone Motivated Low-Altitude Economy in China



GDP in 2023

more than 10% of D.C.'s



no. of drones

35 times airliner worldwide



registered companies

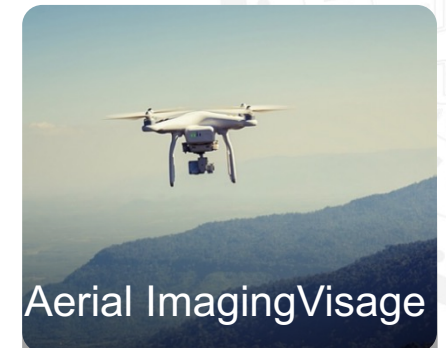
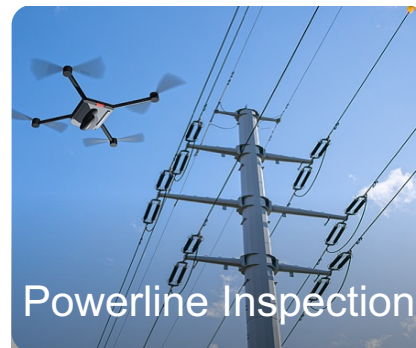
2 new companies per day



GDP at 2030

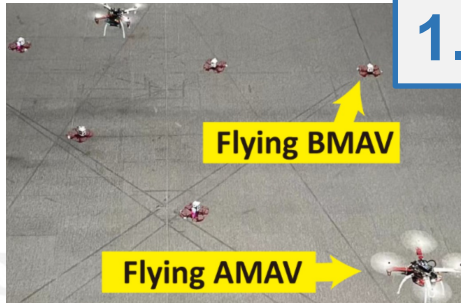
promising pillar industry

Applied in various fields



High Mobility and Large Scale

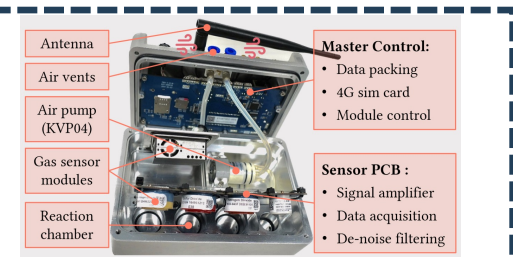
1. High Efficiency Collaboration



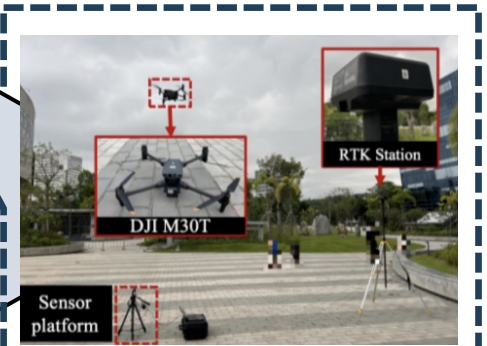
Heterogeneous drone swarm localization (INFOCOM'24)

Multi-UAV collaboration scheduling with exploration while exploitation (IoTJ)

High mobility sensing based on spatial-temporal physical knowledge (MobiSys'24)



Airport Side

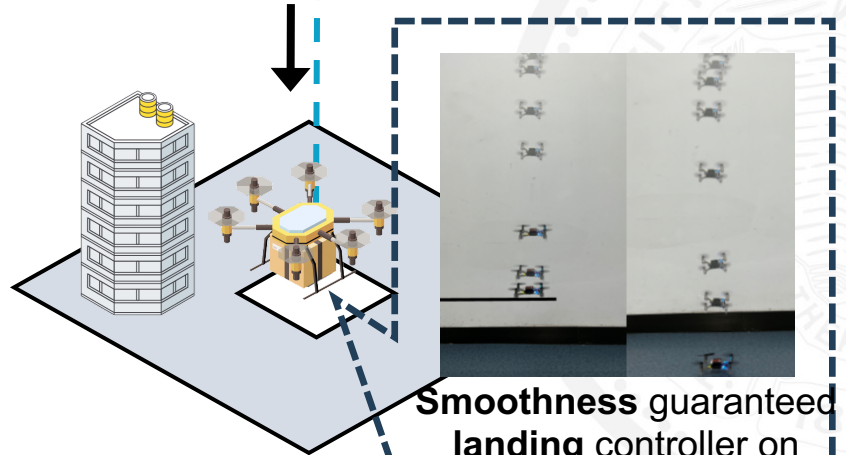


High frequency & low latency localization in 3D (in submission)

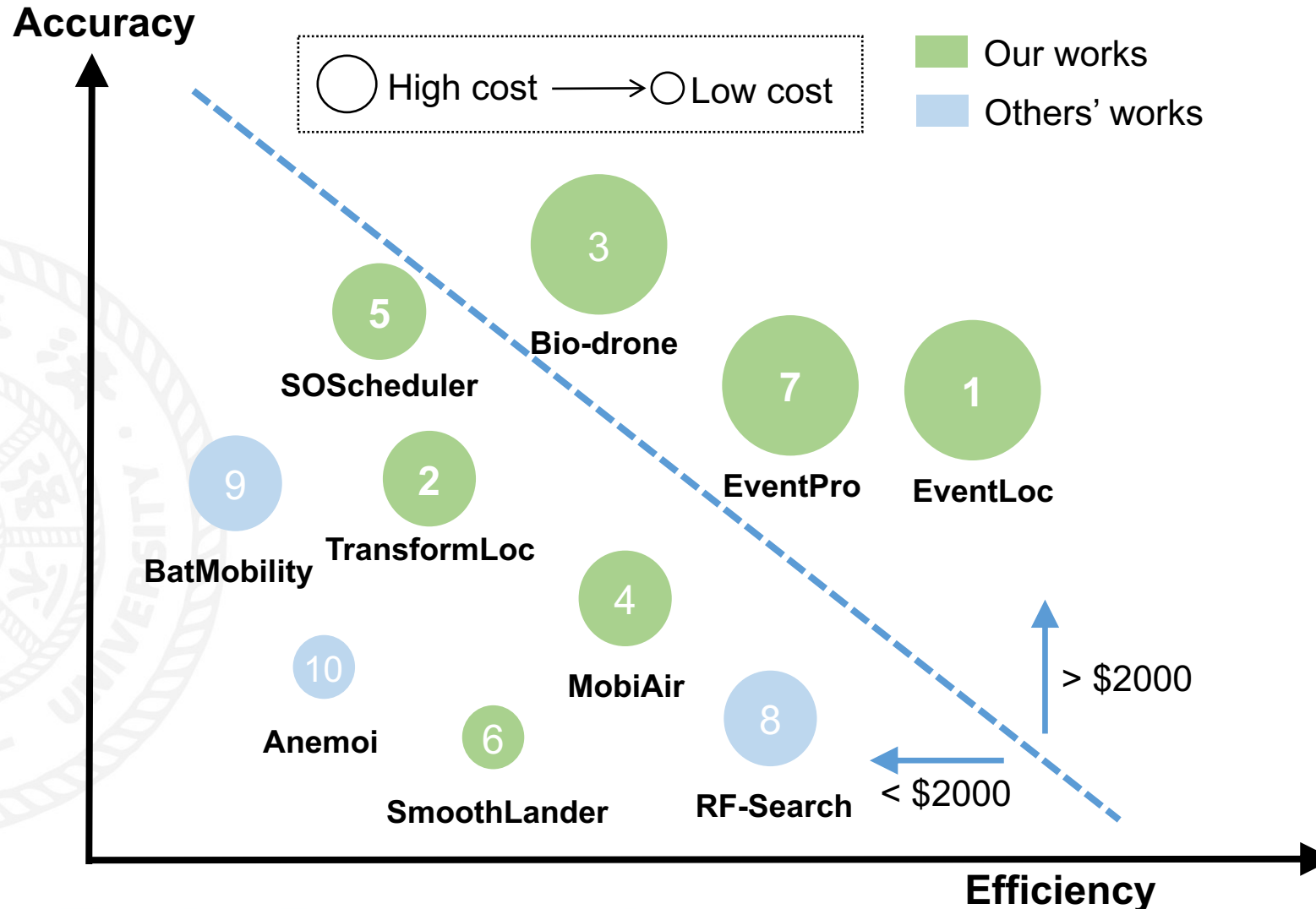


High accuracy & low latency obstacle avoidance (MobiCom'23)

2. High Mobility Sensing



High Mobility Sensing



[1] Wang H, et.al. EventLoc.

[2] Wang H, et al. TransformLoc: Transforming MAVs into Mobile Localization Infrastructures in Heterogeneous Swarms. INFOCOM'24.

[3] Xu J, et al. Taming event cameras with bio-inspired architecture and algorithm: A case for drone obstacle avoidance. MobiCom'23.

[4] Liu Y, et al. MobiAir: Unleashing Sensor Mobility for City-scale and Fine-grained Air-Quality Monitoring with AirBERT. MobiSys'24.

[5] Chen X, et al. SOScheduler: Toward Proactive and Adaptive Wildfire Suppression via Multi-UAV Collaborative Scheduling. IoTJ.

[6] Zhao C, et al. SmoothLander: A Quadrotor Landing Control System with Smooth Trajectory Guarantee Based on Reinforcement Learning. UbiComp'23.

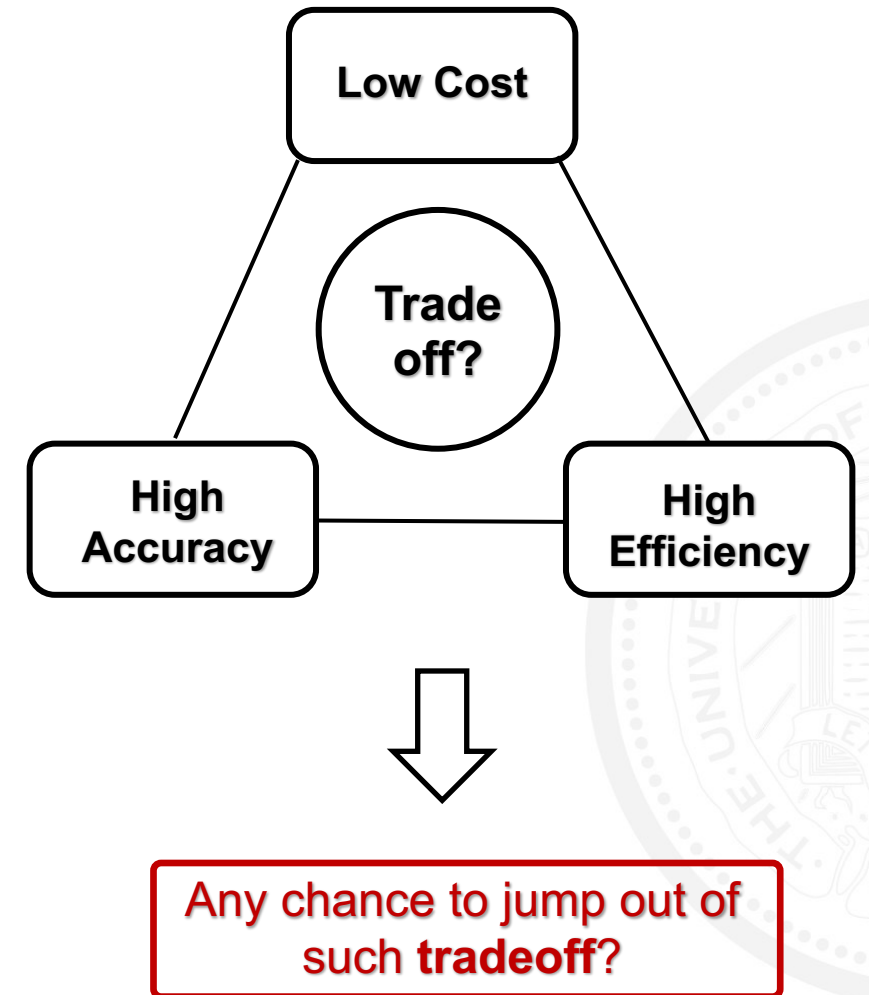
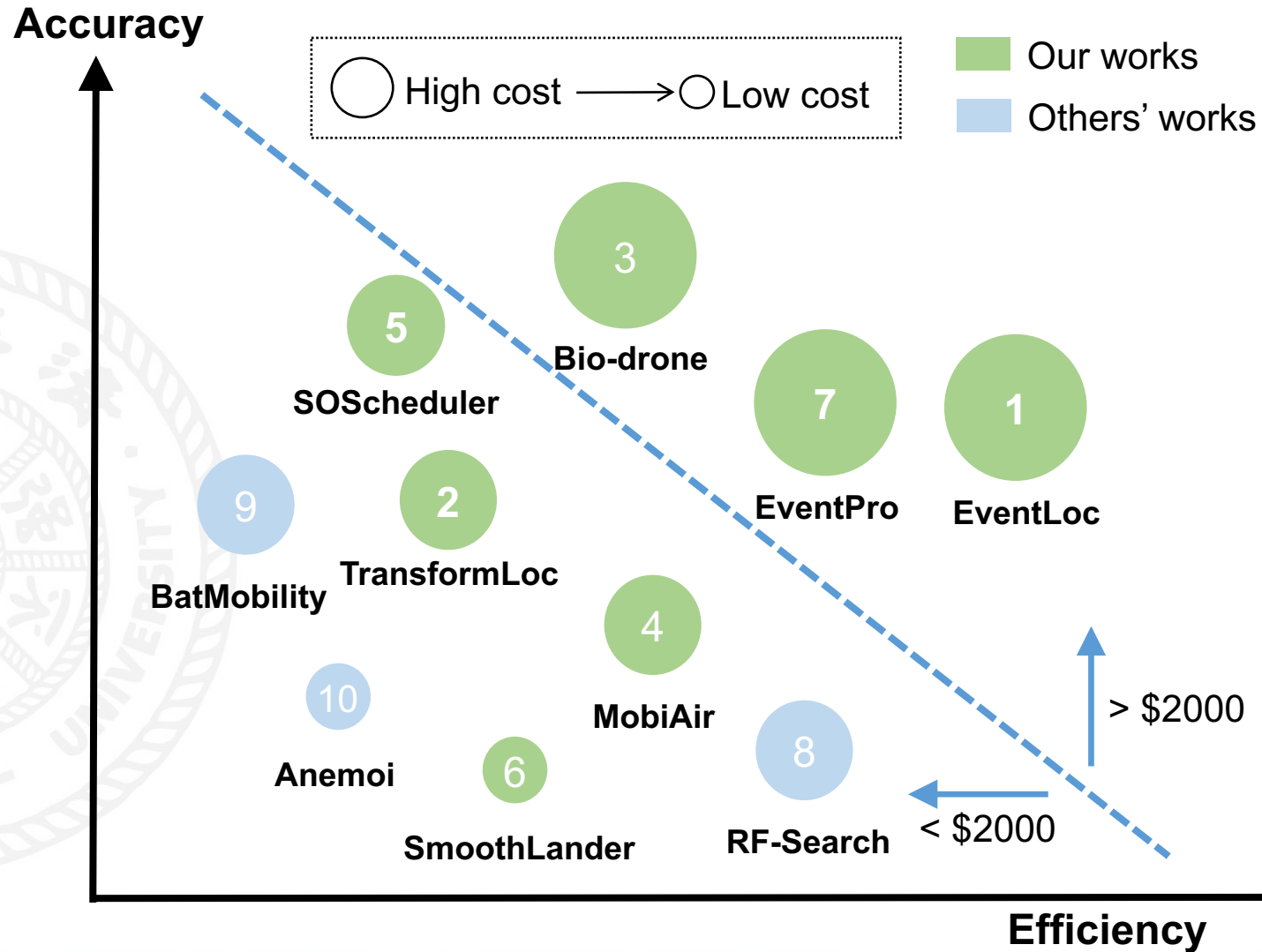
[7] Chen X, et.al. EventPro.

[8] Zhang, et al. RF-Search: Searching Unconscious Victim in Smoke Scenes with RF-enabled Drone MobiCom'23.

[9] Emerson Sie, et.al. BatMobility: Towards Flying Without Seeing for Autonomous Drones. MobiCom'23.

[10] Xia S, et.al. Anemoi: A Low-cost Sensorless Indoor Drone System for Automatic Mapping of 3D Airflow Fields

High Mobility Sensing





How to avoid the paradigm to continually add **sophisticated** sensors and/or design **sophisticated** algorithms?

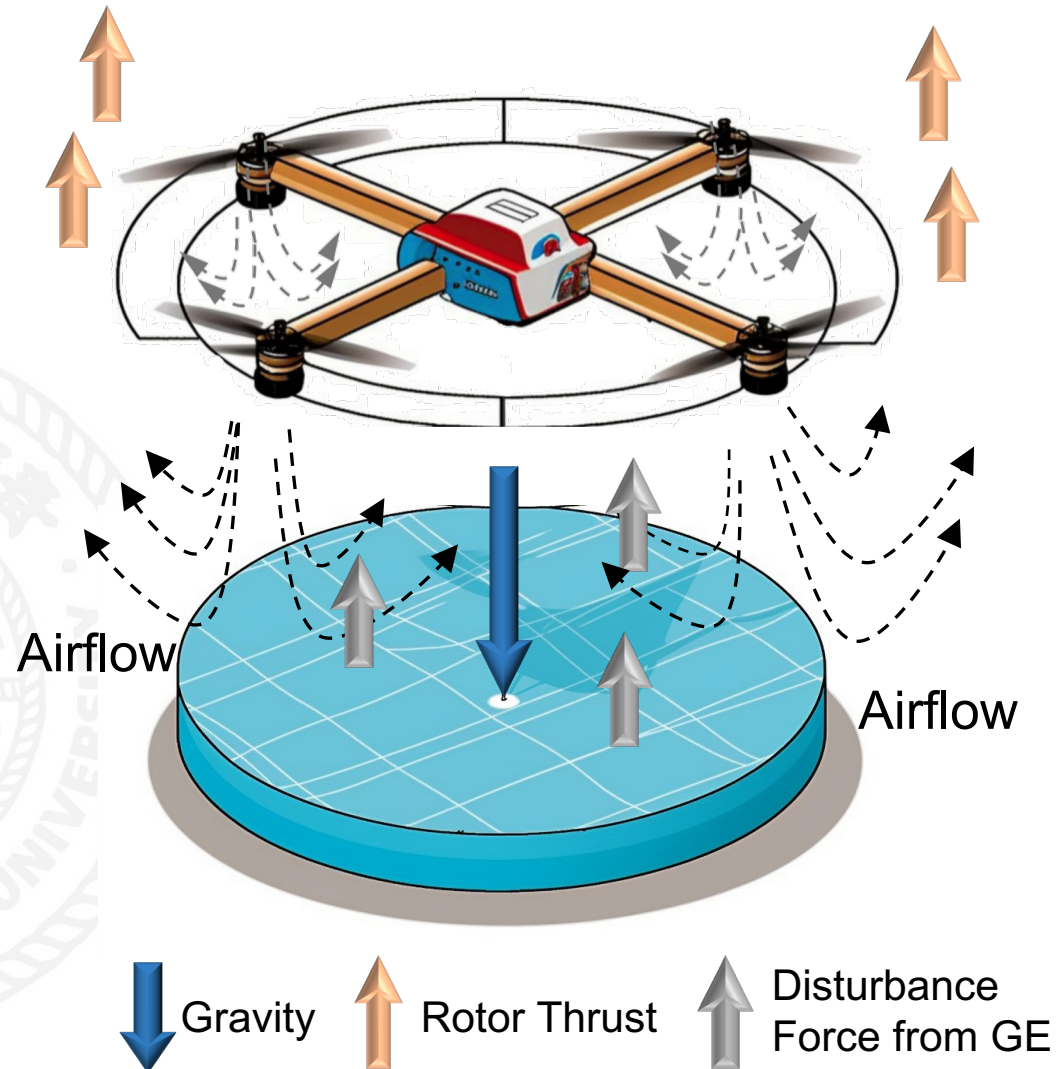
行有不得，反求诸己 -- 《孟子·离娄上》

If things do not work out, look within yourself for solutions



Drone itself is a **sophisticated** machine with Flight Control. Is there some opportunities to unlock additional sensing capabilities within these **sophisticated** machines?

Ground Effect (GE): Foe or Friend?

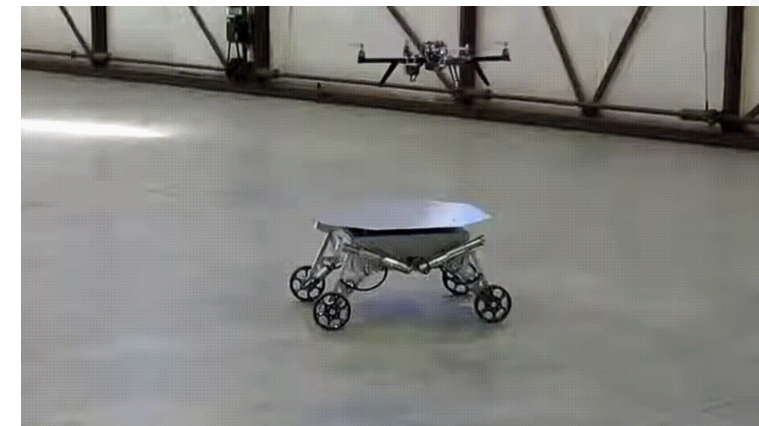


Foe?

- Landing Crash! Low Altitude Jittering!



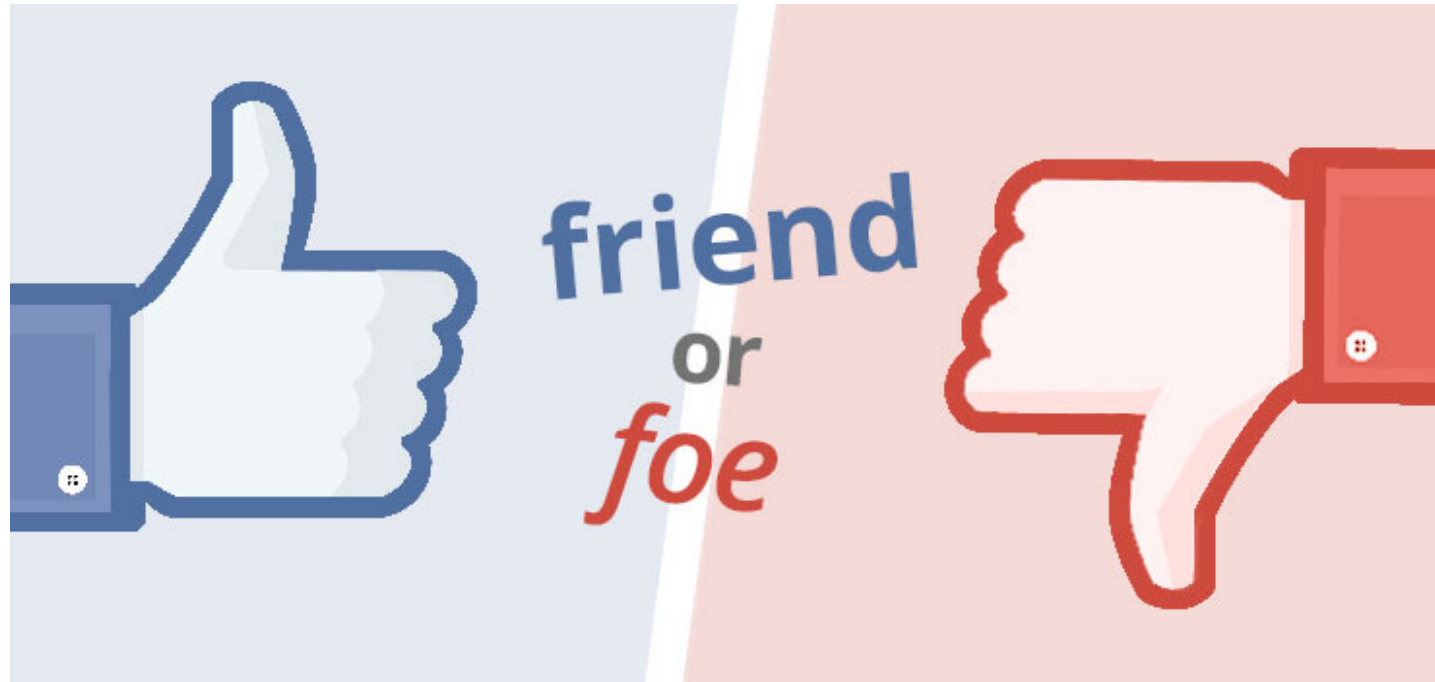
[1]



[2]

[1] <https://www.youtube.com/watch?app=desktop&v=66PmaluCvbU>[2] <https://www.youtube.com/watch?v=6UZjfsy1fJo>

Ground Effect As a **For** or a **Friend**?

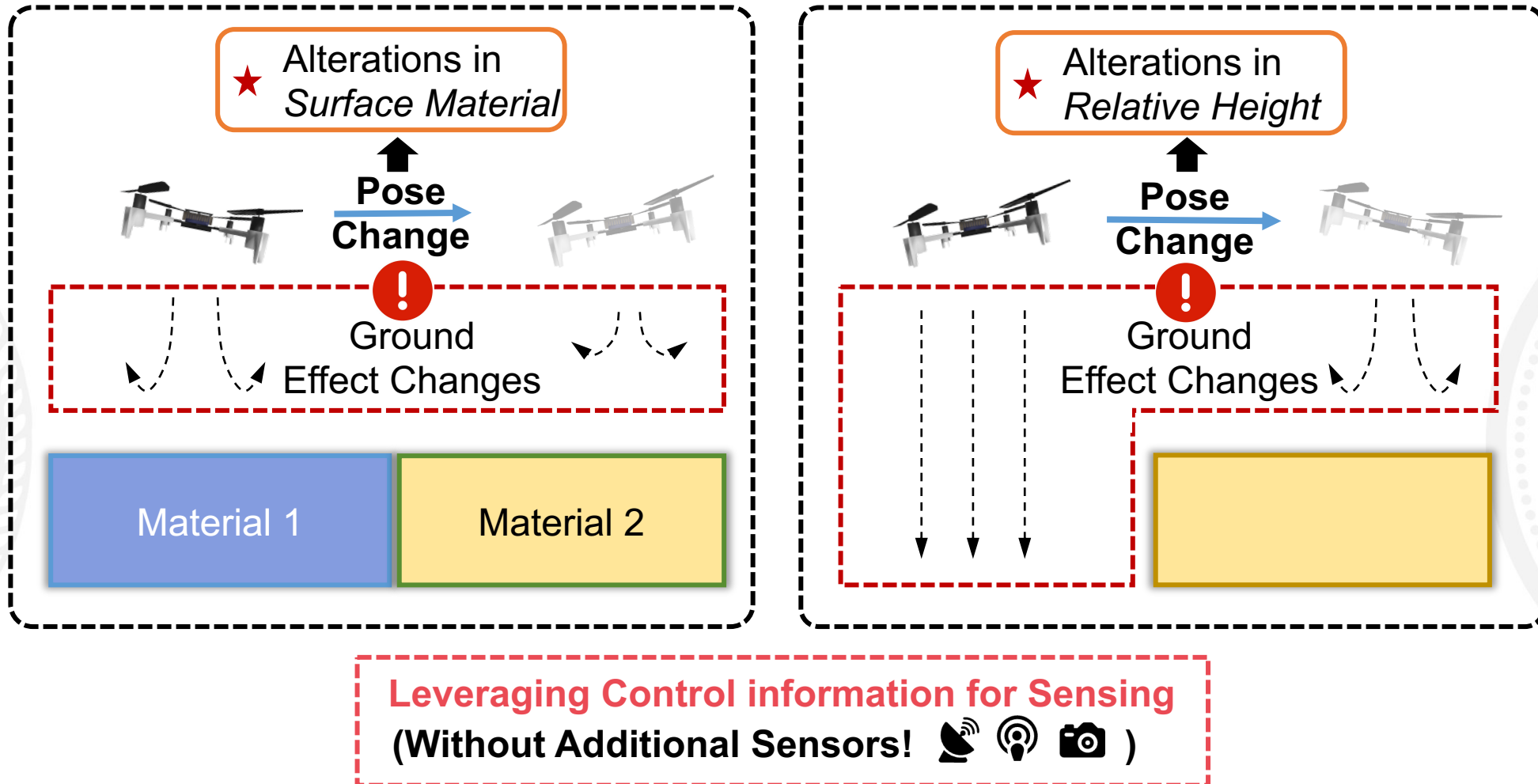


Ground Effect seems to reflect information of ground surface, especially the edge of a surface

As a Friend for Sensing?

Ground Effect As a Friend!

- New sensing modality for **Edge Detection!**



Ground Effect As a **Friend!**



But how to turn this idea into reality?



Challenges

C1: **Target Discrepancy** between sensing & flight control complicates GE profiling

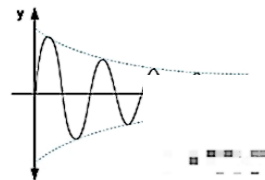
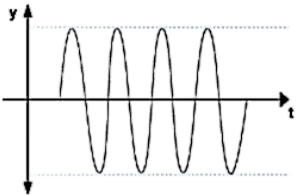
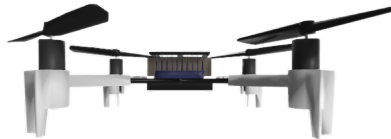
Sensing

CONFLICT

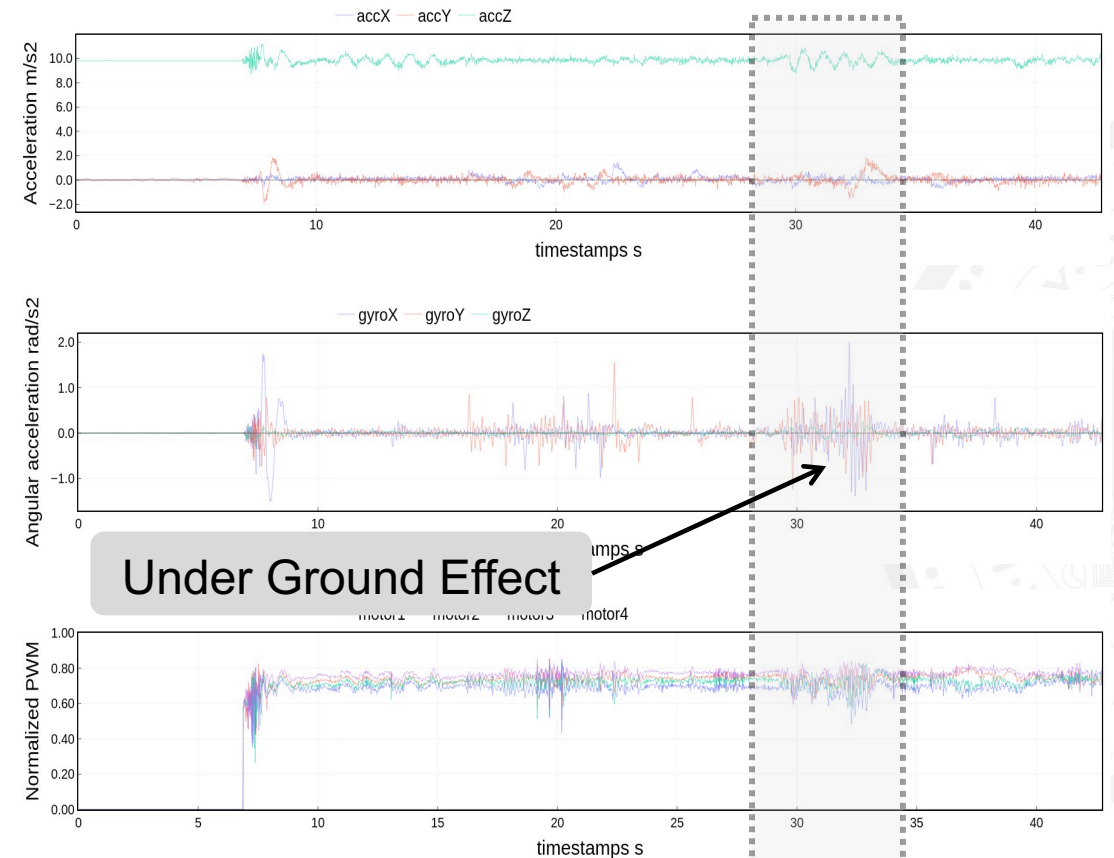
Flight Control

Capture GE
Detect & Highlight

Resist GE
Stabilize & Adjust

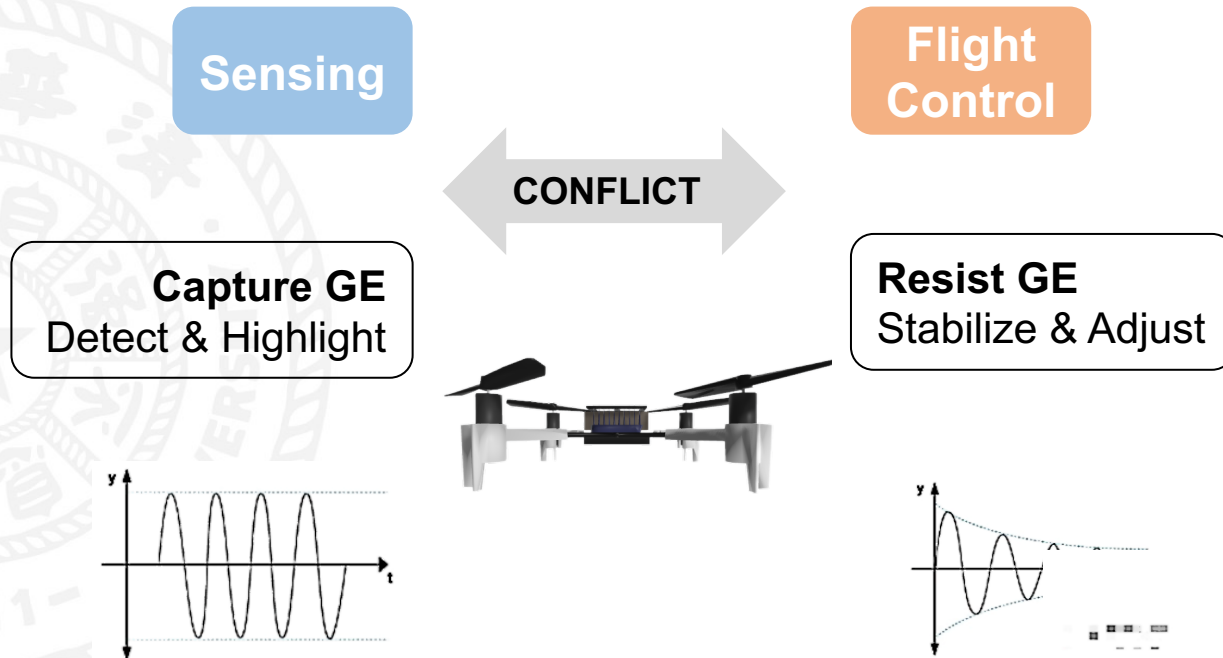


C2: **Noisy** sensing data hinders accurate GE detection

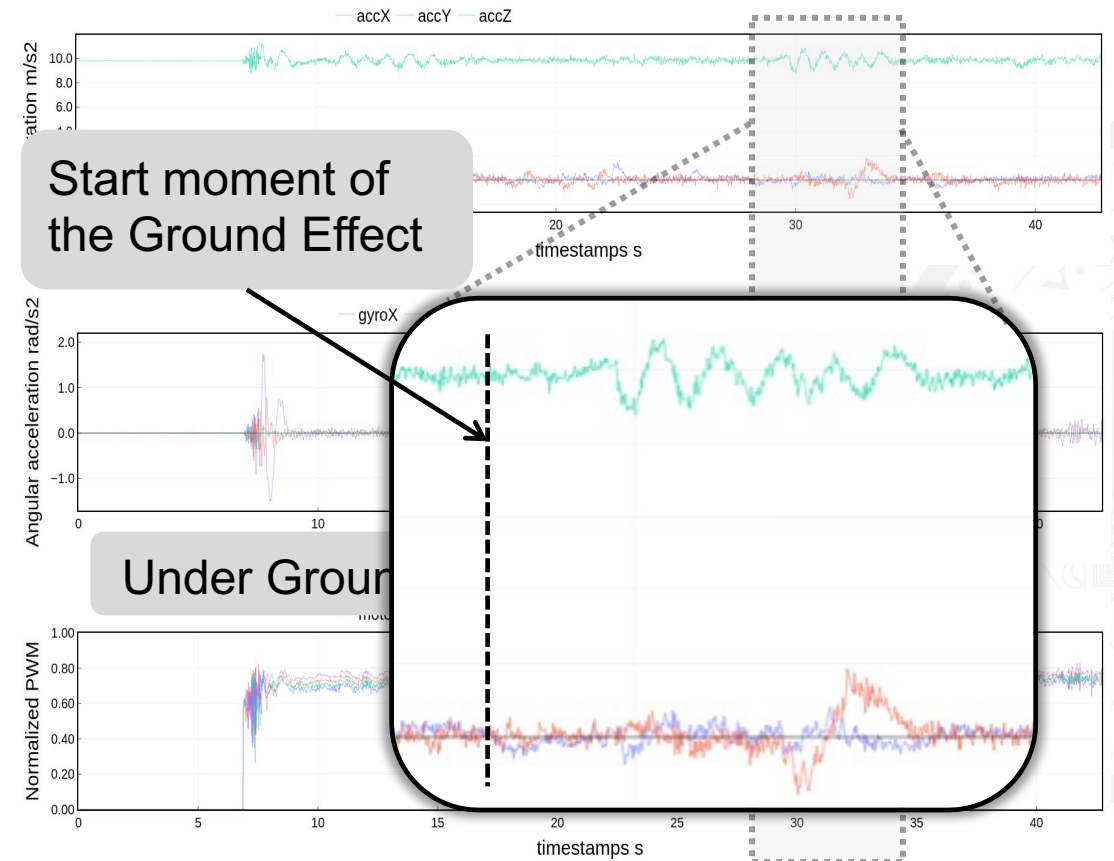


Challenges

C1: **Target Discrepancy** between sensing & flight control complicates GE profiling



C2: **Noisy** sensing data hinders accurate GE detection



Solutions: Theories, and Formulas

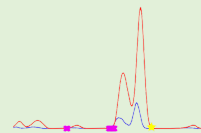
S1: Integrating **IMU data** and **Motor commands** for GE profiling

$$X(n) = \sum_{m=m1}^{m2} \sum_{k=0}^{N-1} x(k) \cdot w(k-m) e^{-j2\pi kn/N}$$

Fluctuation Components Feature Extraction



Cascaded Cross-Spectrum Feature Fusion



$$G_{xy}(f) = X(f)Y^*(f).$$

$$G_{xx}(f) = X(f)X^*(f).$$

$$|G_{xy}(f)|^2 = |G_{xx}(f)||G_{yy}(f)|.$$

$$|P_{ccs}(f)| = |X_1(f)X_2^*(f)X_3(f)\dots X_n^*(f)| \\ = \sqrt{|G_{x_1x_1}(f)||G_{x_2x_2}(f)|\dots|G_{x_nx_n}(f)|}.$$

$$ma = mg + Rf_u + f_w.$$

$$a = \dot{v}, v = \dot{p}.$$

$$J\dot{\omega} = J\omega \times \omega + \tau_u + \tau_w.$$

$$\dot{R} = RM(\omega).$$

$$H_0 = \begin{bmatrix} k_r & k_r & k_r & k_r \\ 0 & k_{rl} & 0 & -k_{rl} \\ -k_{rl} & 0 & k_{rl} & 0 \\ -c_Q & c_Q & -c_Q & c_Q \end{bmatrix}$$

Aerodynamics-Informed Double Phase Physical Filter

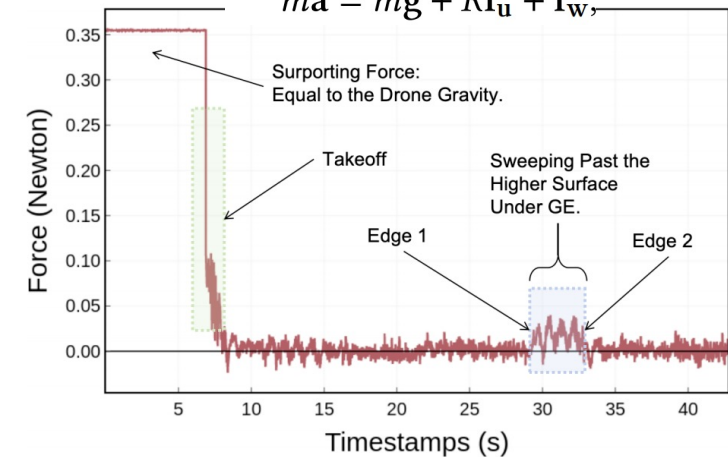


Physical Knowledge aided Network



Disturbance Force f_w

$$ma = mg + Rf_u + f_w.$$



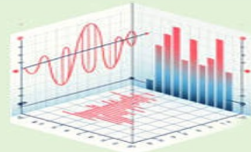
S2: Physical Knowledge embedded neural network

Solutions: Theories, and Formulas

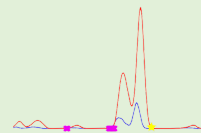
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Fluctuation Components Feature Extraction



Cascaded Cross-Spectrum Feature Fusion



$$G_{xy}(f) = X(f)Y^*(f).$$

$$G_{xx}(f) = X(f)X^*(f).$$

$$|G_{xy}(f)|^2 = |G_{xx}(f)||G_{yy}(f)|.$$

$$|P_{ccs}(f)| = |X_1(f)X_2^*(f)X_3(f)\dots X_n^*(f)| \\ = \sqrt{|G_{x_1x_1}(f)||G_{x_2x_2}(f)|\dots|G_{x_nx_n}(f)|}.$$

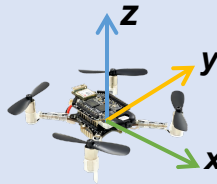
Physical Knowledge-aided Light-Weight Predictor

$$ma = mg + Rf_u + f_w, \\ a = \dot{v}, v = \dot{p}, \\ J\dot{\omega} = J\omega \times \omega + \tau_u + \tau_w,$$

$$\dot{R} = RM(\omega),$$

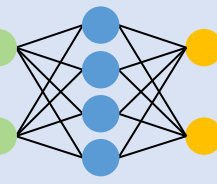
$$H_0 = \begin{bmatrix} k_T & k_T & k_T & k_T \\ 0 & k_T l_r & 0 & -k_T l_r \\ -k_T l_r & 0 & k_T l_r & 0 \\ -c_Q & c_Q & -c_Q & c_Q \end{bmatrix},$$

Aerodynamics-Informed Double Phase Physical Filter



Disturbance Force-Informed Loss Function

Physical Knowledge-aided Network



Loss Functions:

$$\mathcal{L}_F = \begin{cases} e^{|\hat{y}-1|} - 1, & \|f_w\| \geq T, \\ e^{|\hat{y}|} - 1, & \text{others.} \end{cases},$$

Disturbance Force-Informed Loss Function

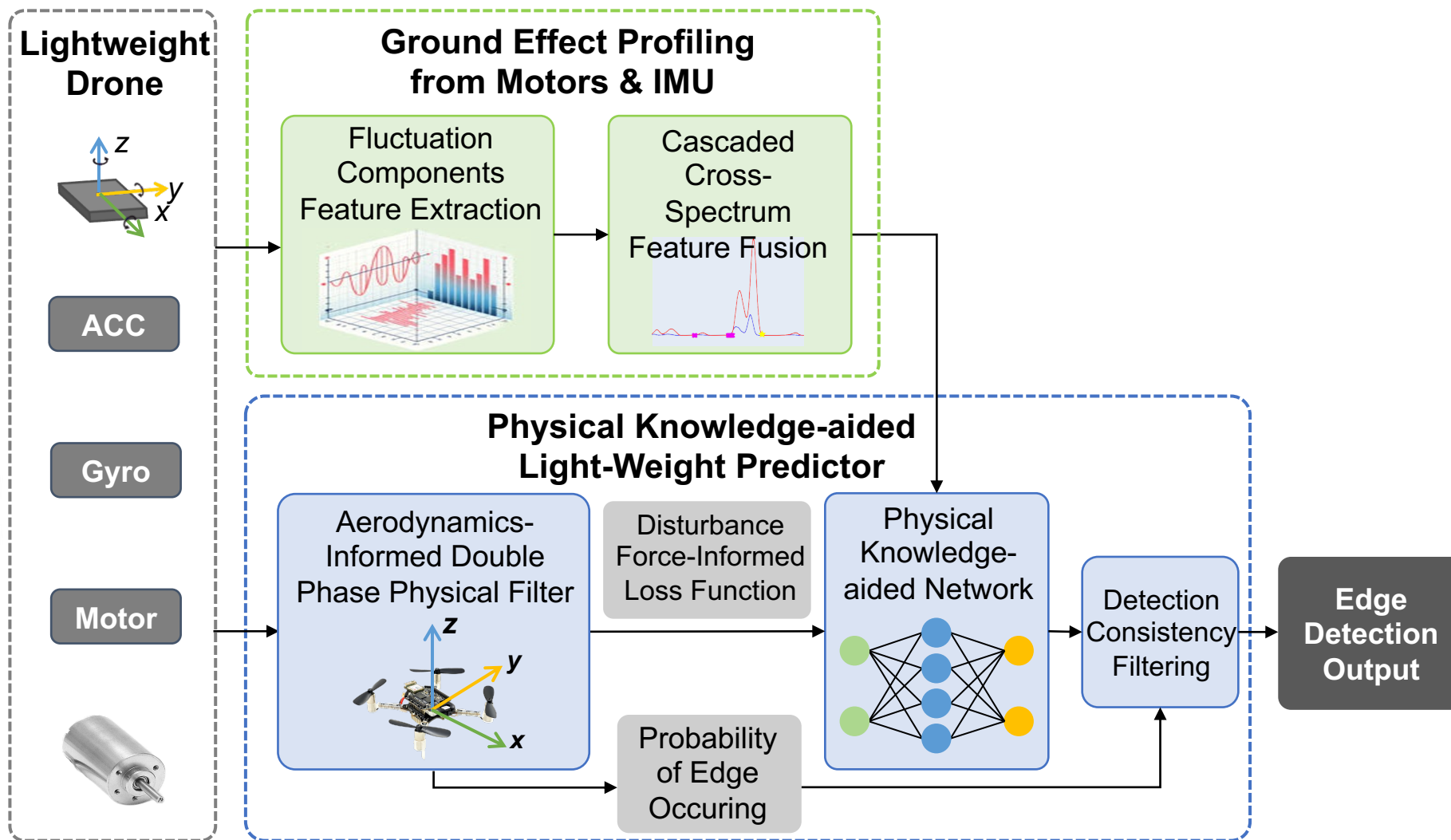
$$\mathcal{L}_S = -y \log \hat{y} - (1-y) \log(1-\hat{y}),$$

$$\mathcal{L} = \mathcal{L}_S + \lambda \cdot \mathcal{L}_F,$$

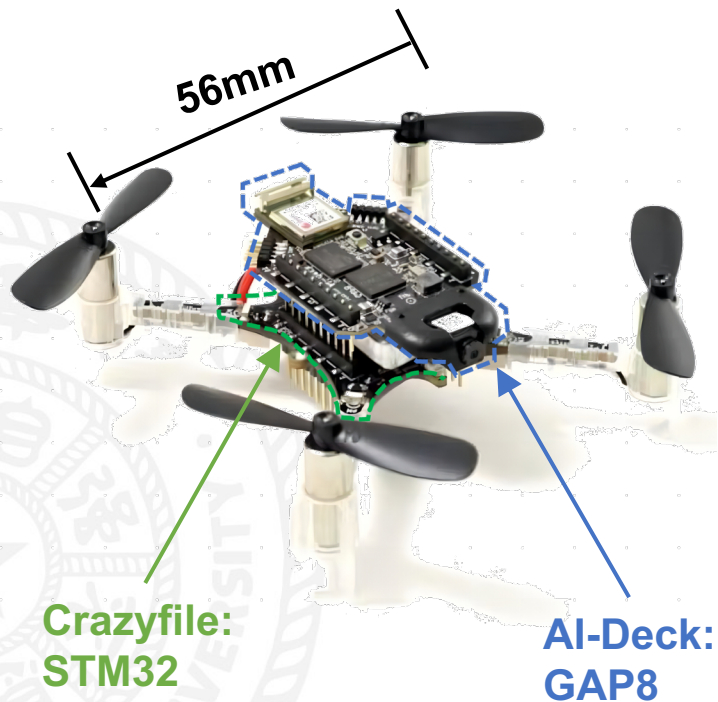
Total Loss

S2: **Physical Knowledge** embedded neural network for noise cancellation

AirTouch: Driven by Physical Knowledge & Data

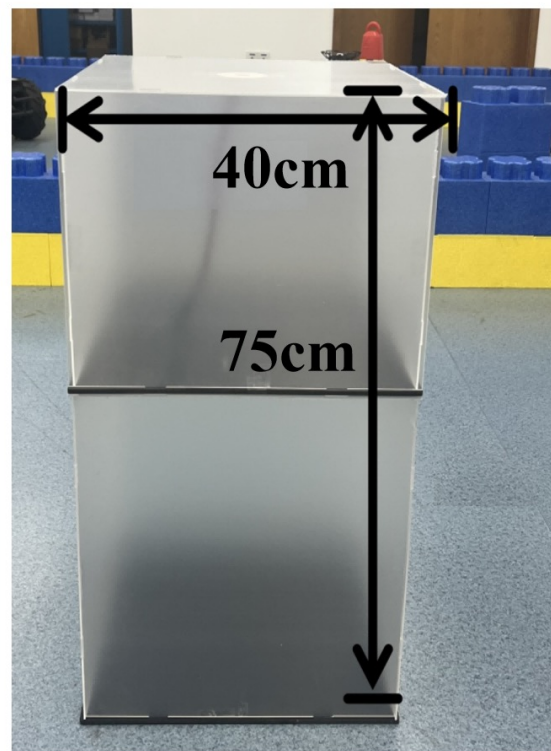


Experimental Setup and Performance

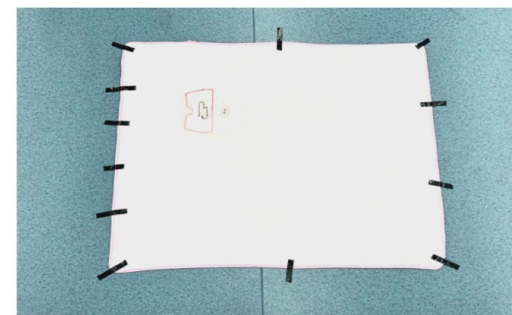


Weight: Only **36 g**
 Processor: 22.65 GOPS
 Memory: 512KB
 Sensors: IMU, Baro

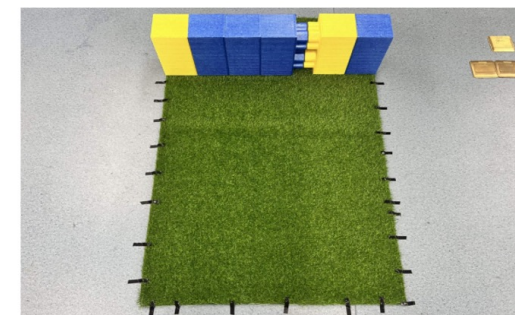
- Height change



- Material variation



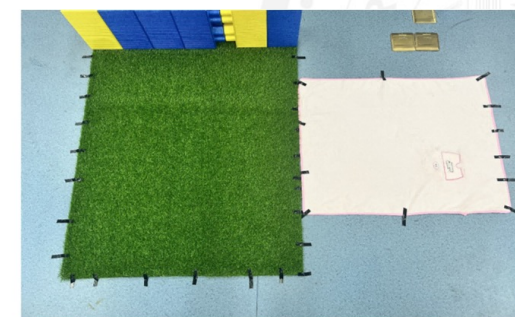
a. Mat & Cement



b. Grass & Cement



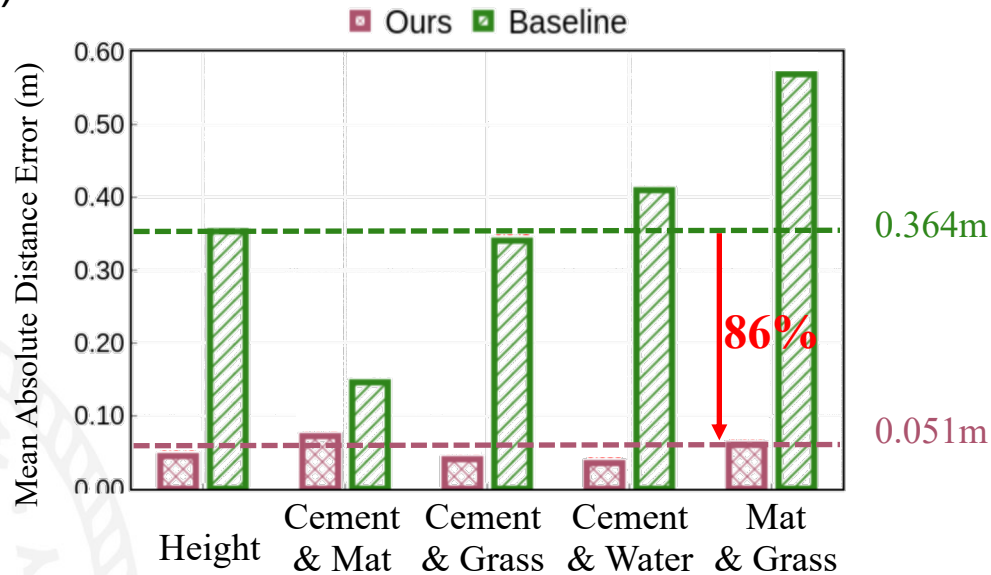
c. Water & Cement



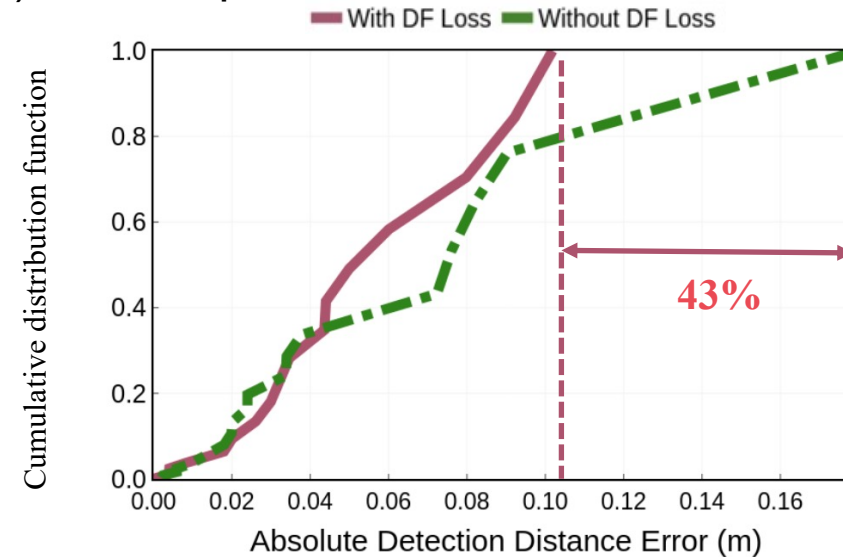
d. Grass & Mat

Performance

(1) Overall MAE reduces



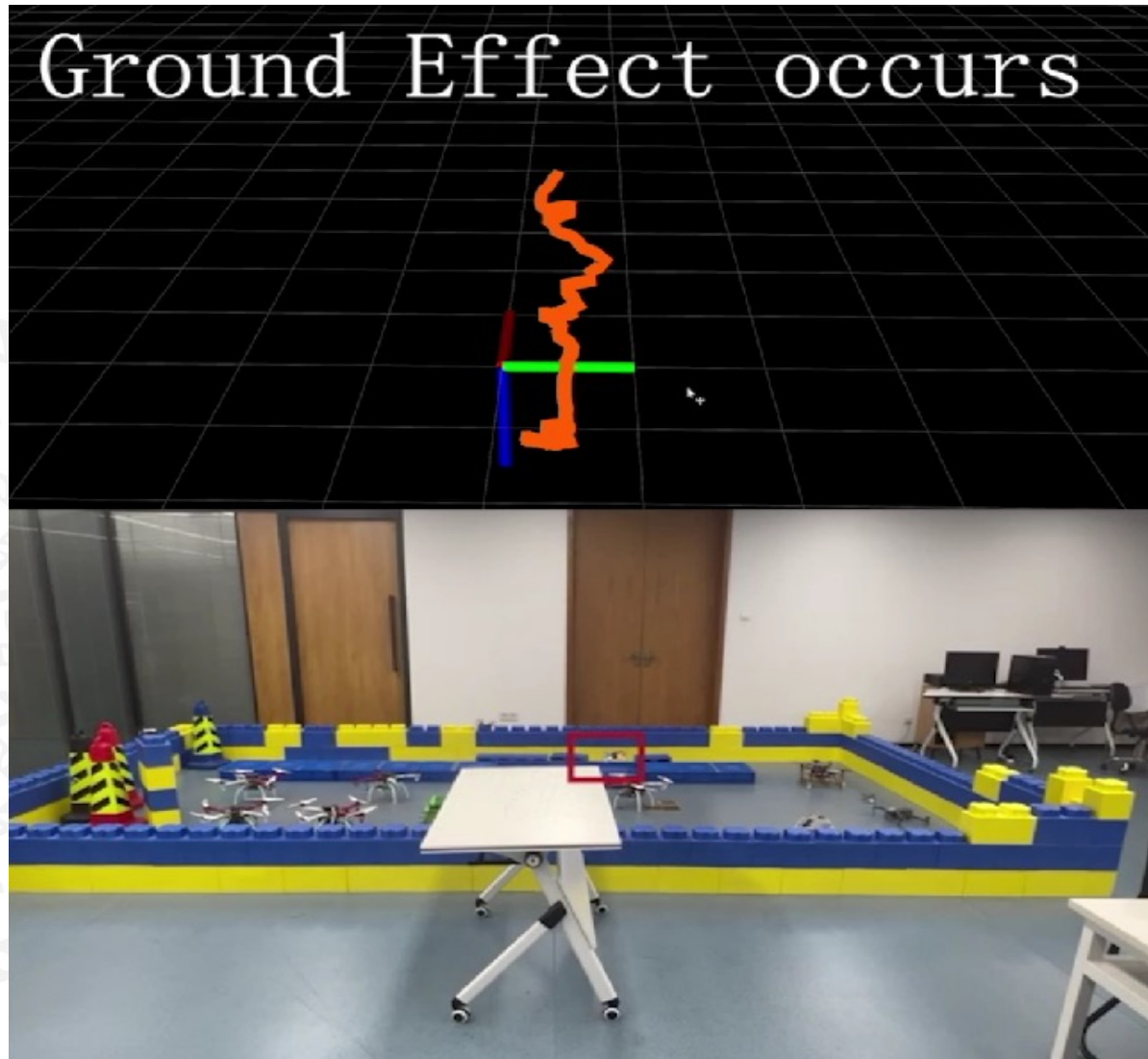
(2) DF loss provides improvement



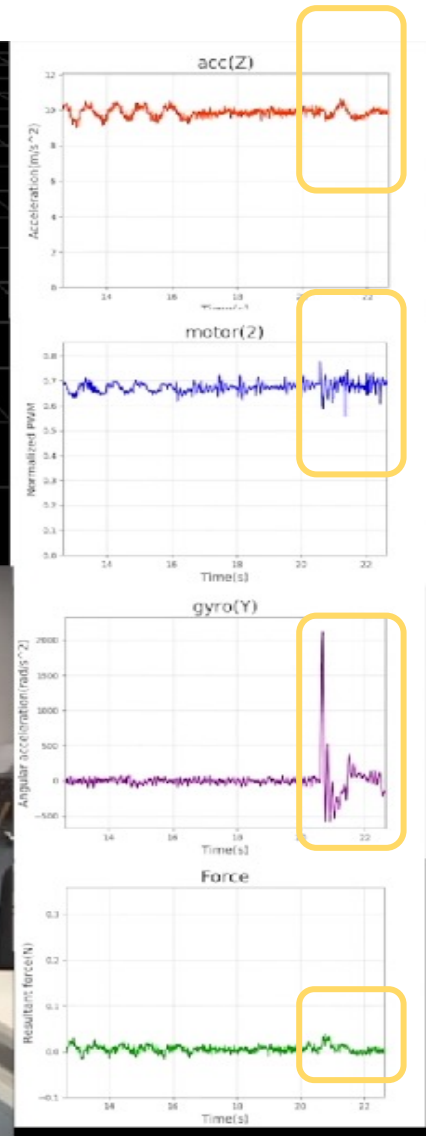
(3) Lightweight design

Items	Vision-based	AirTouch
FLOPs	3900 million	0.28 million — 0.007%
NN param size	58 KB	13KB — 22%
Memory per frame	Millions of bits	32K bits — Substantially less
Capability	Vulnerable in poor visual conditions	Works in low-light, similar texture

Demo and Conclusion



Variation in signals



Conclusion

- **AirTouch System:**
Ground Effect ->
Sensing Modality
- **Technical Points:**
GE profiling module;
Noise cancellation NN
with physical knowledge.
- **Evaluation:**
Error: 5.1cm (\downarrow 86%).
Power: 43mW.

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*Unify Sensing and Control for
Lightweight Drones!*

*These authors contributed equally to this research.

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