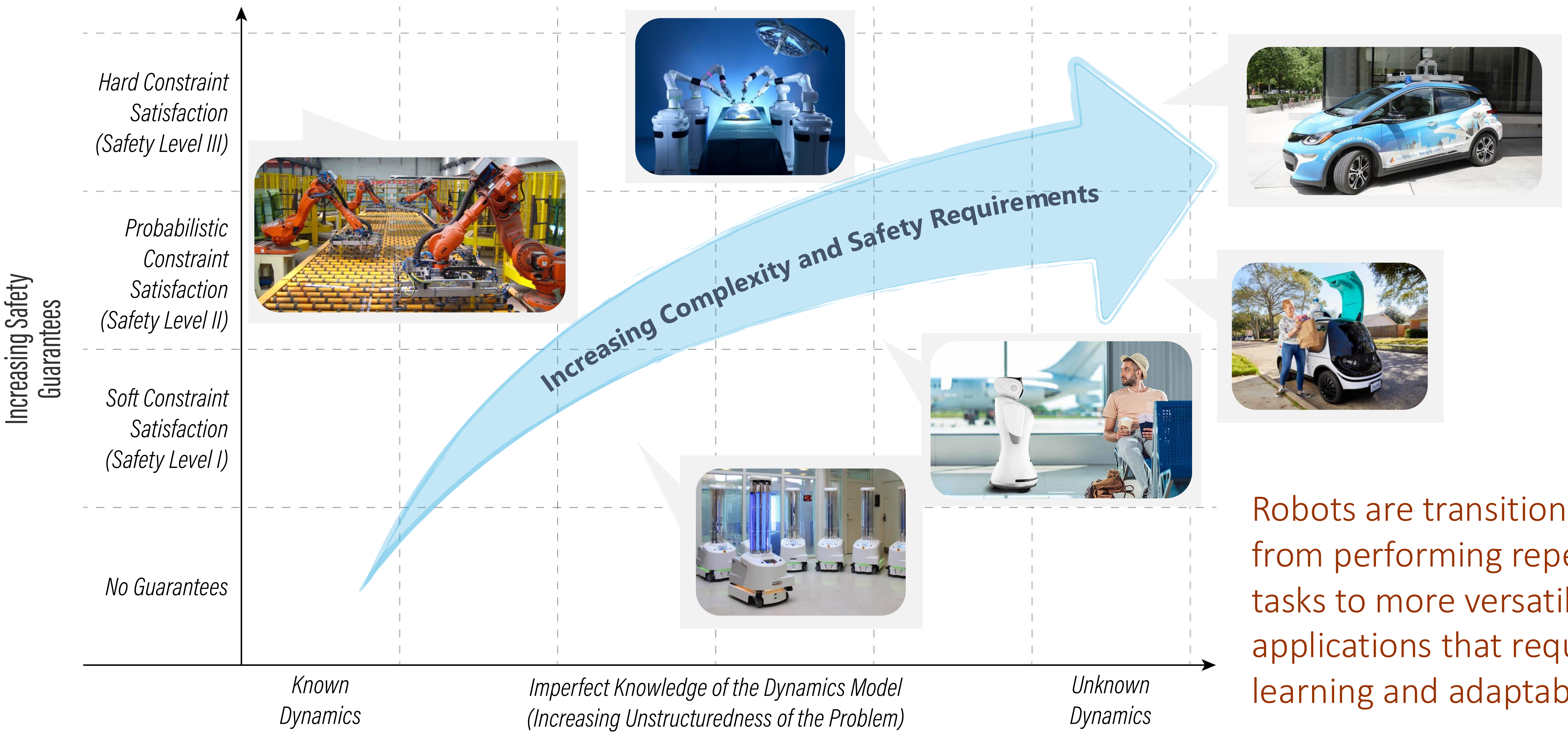
Safe Decision-Making for Aerial Swarms

From Reliable Localization to Efficient Coordination

RSS 2024 Workshop on Aerial Swarm Tools and Applications
July 19, 2024

SiQi Zhou (on behalf of Prof. Angela P. Schoellig)
Chair of Safety, Performance and Reliability for Learning Systems
Technical University of Munich

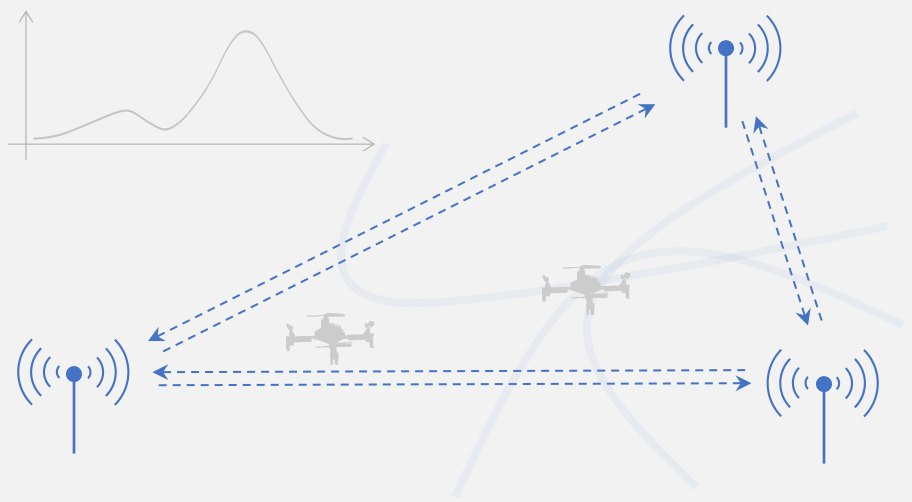
A Spectrum of Real-World Robot Applications



Robots are transitioning from performing repetitive tasks to more versatile applications that require learning and adaptability

Talk Overview

Part I
Robust Range-Based Methods
for
Reliable Aerial Swarm
Localization



Part II
Control Theoretic Approaches
for
Efficient Swarm Coordination

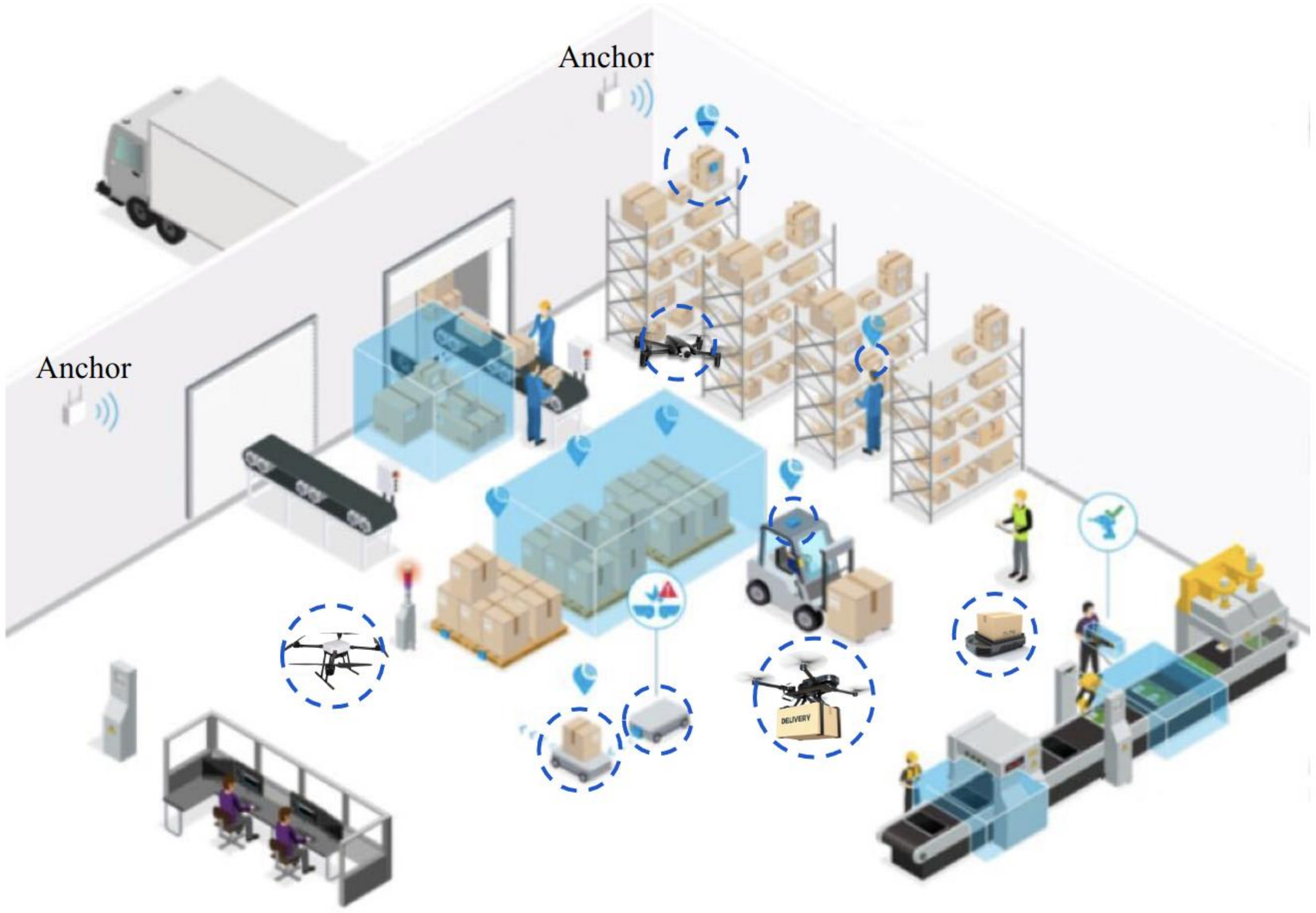
Part III
Simulation Tools and Datasets
for
Scaling Up Swarming Tasks

UWB for Portable and Reliable Indoor Localization

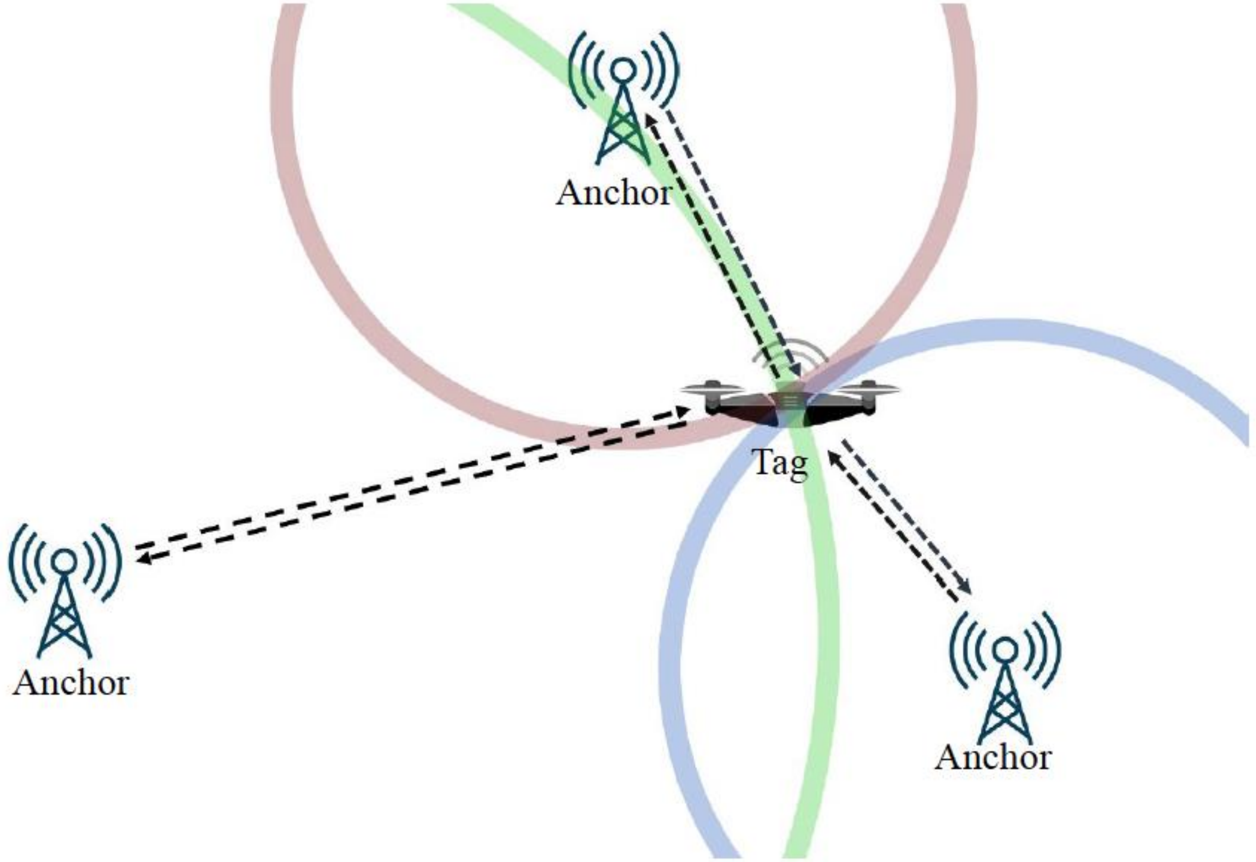
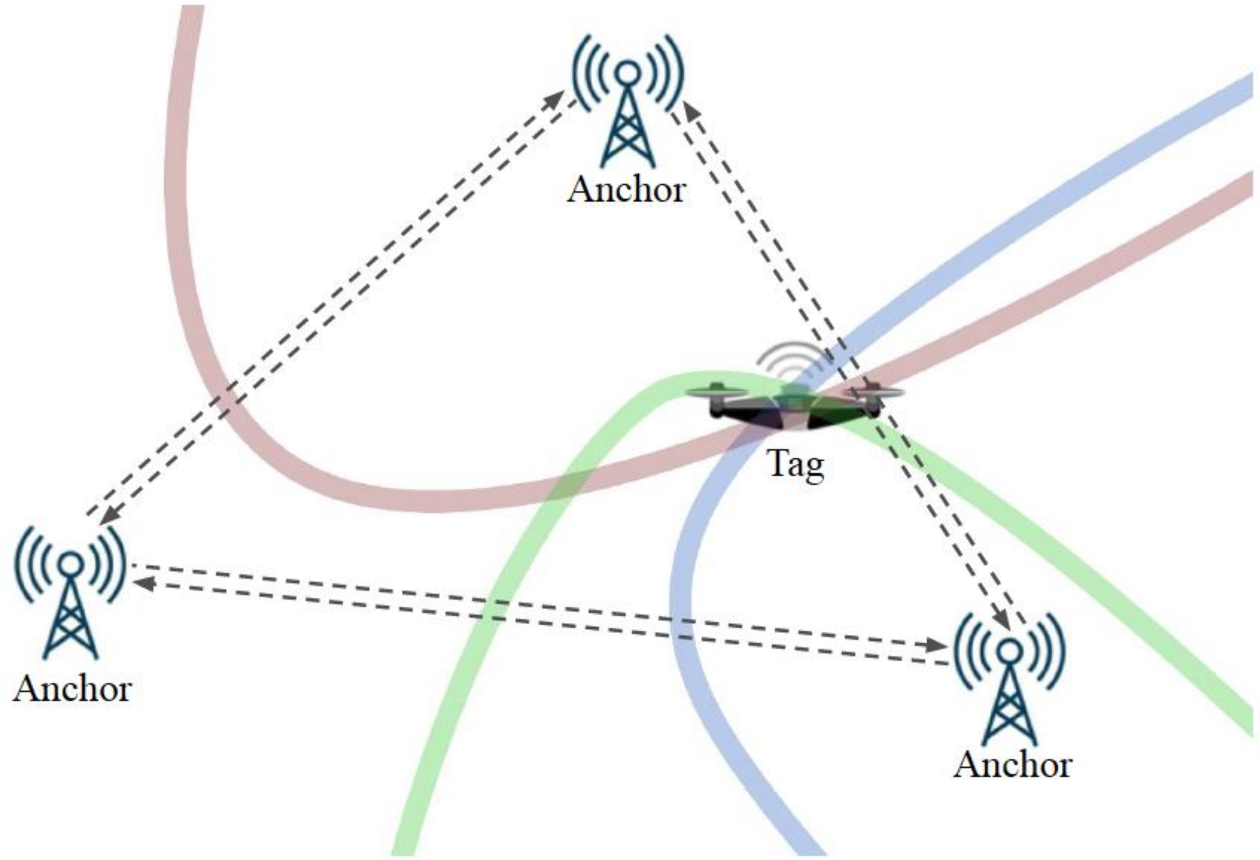
Accurate, robust, and scalable indoor localization is a crucial enabling technology for many robot applications

- warehouse management
- industrial inspection
- long-term monitoring tasks

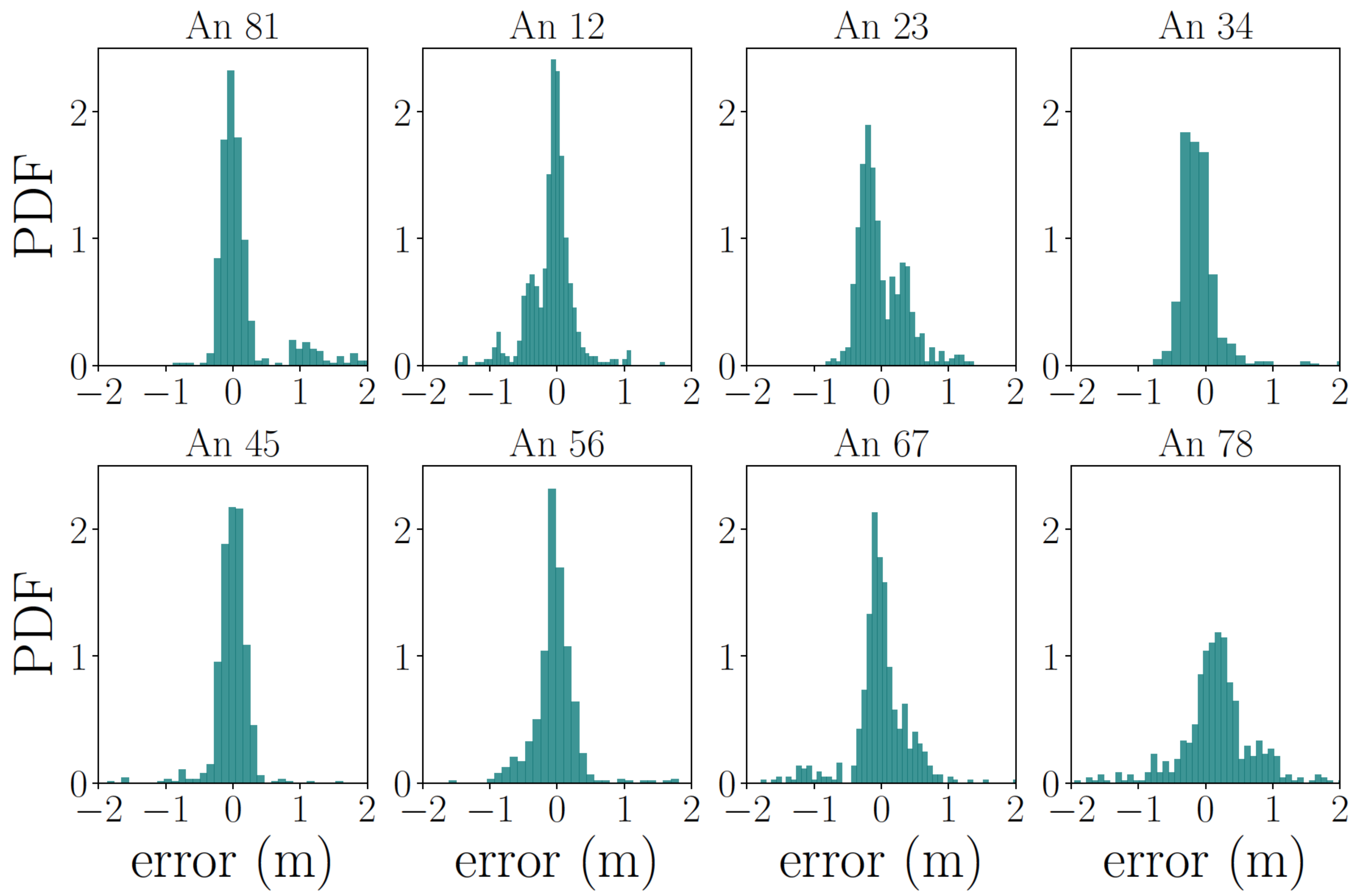
Ultra-wideband (UWB) radio technology, with its ability to provide high-accuracy time of arrival (TOA) measurements, has emerged as a promising indoor positioning solution.



Two Modes of Operation

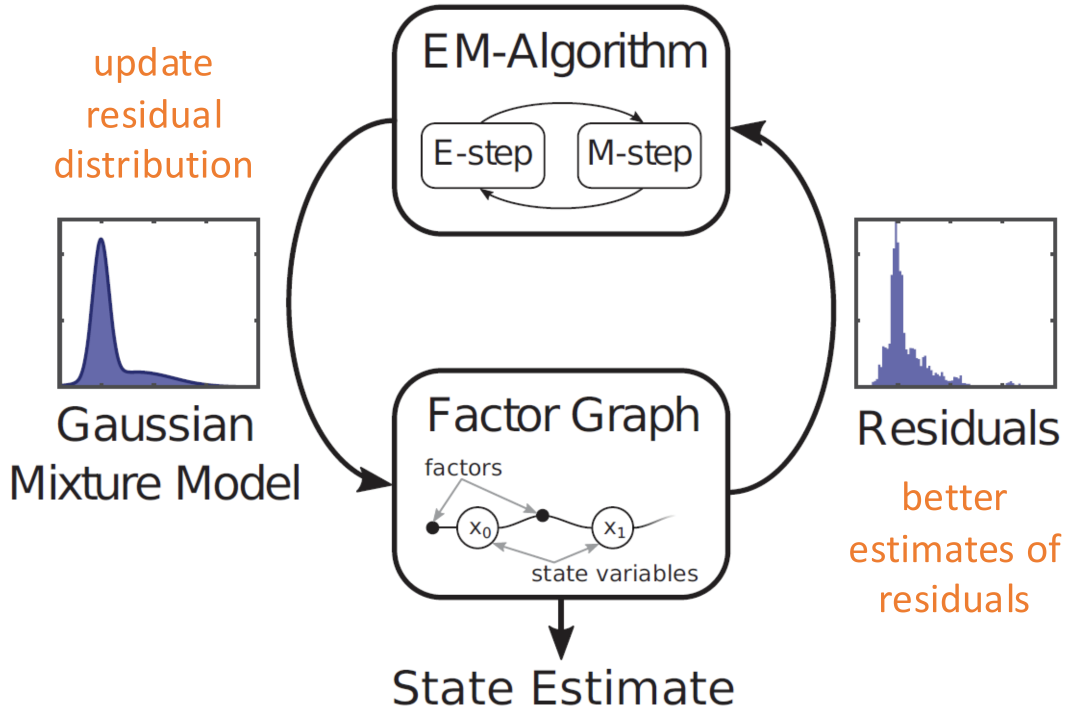
Two-Way Ranging (TWR)	Time Difference of Arrival (TDOA)
	
UWB tag communicates with anchors and acquires range measurements through two-way communication.	UWB tags receive signals from anchors passively and compute the difference in distance as TDOA measurements.

Challenges Hindering Reliable Localization

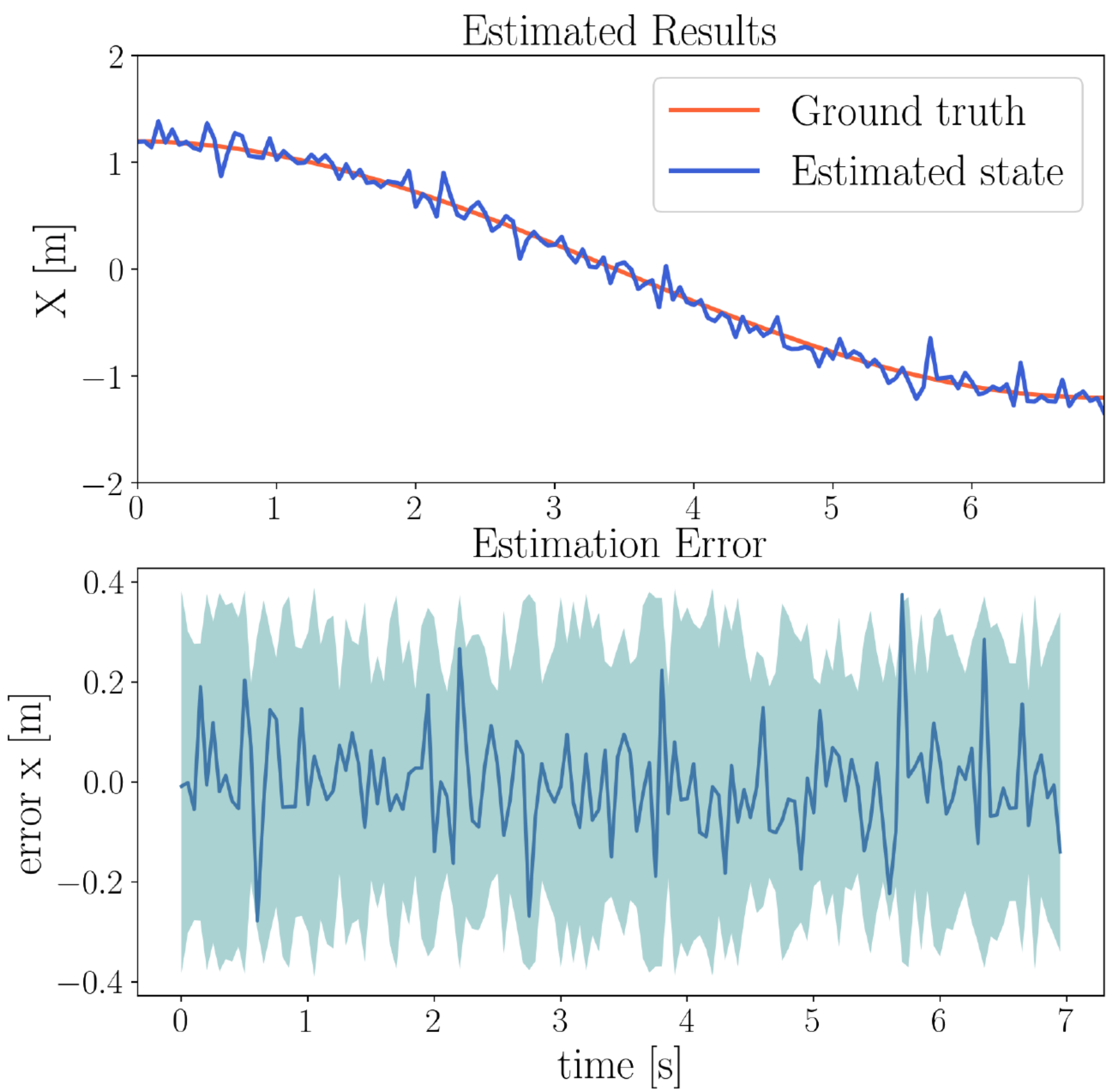


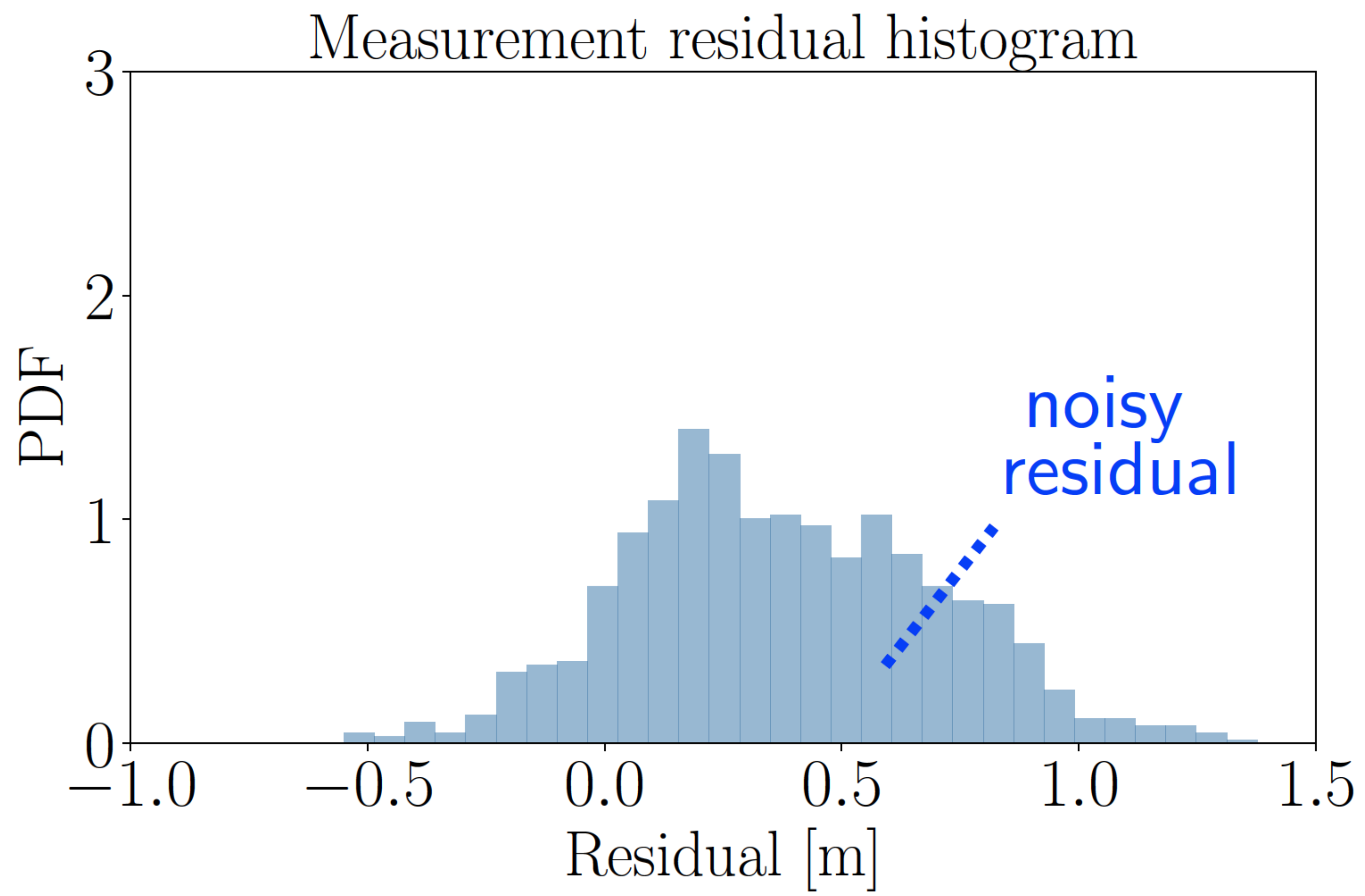
UWB measurement errors demonstrate biased and non-Gaussian distributions in dynamic and cluttered environments.

Idea: Gaussian Mixture Models



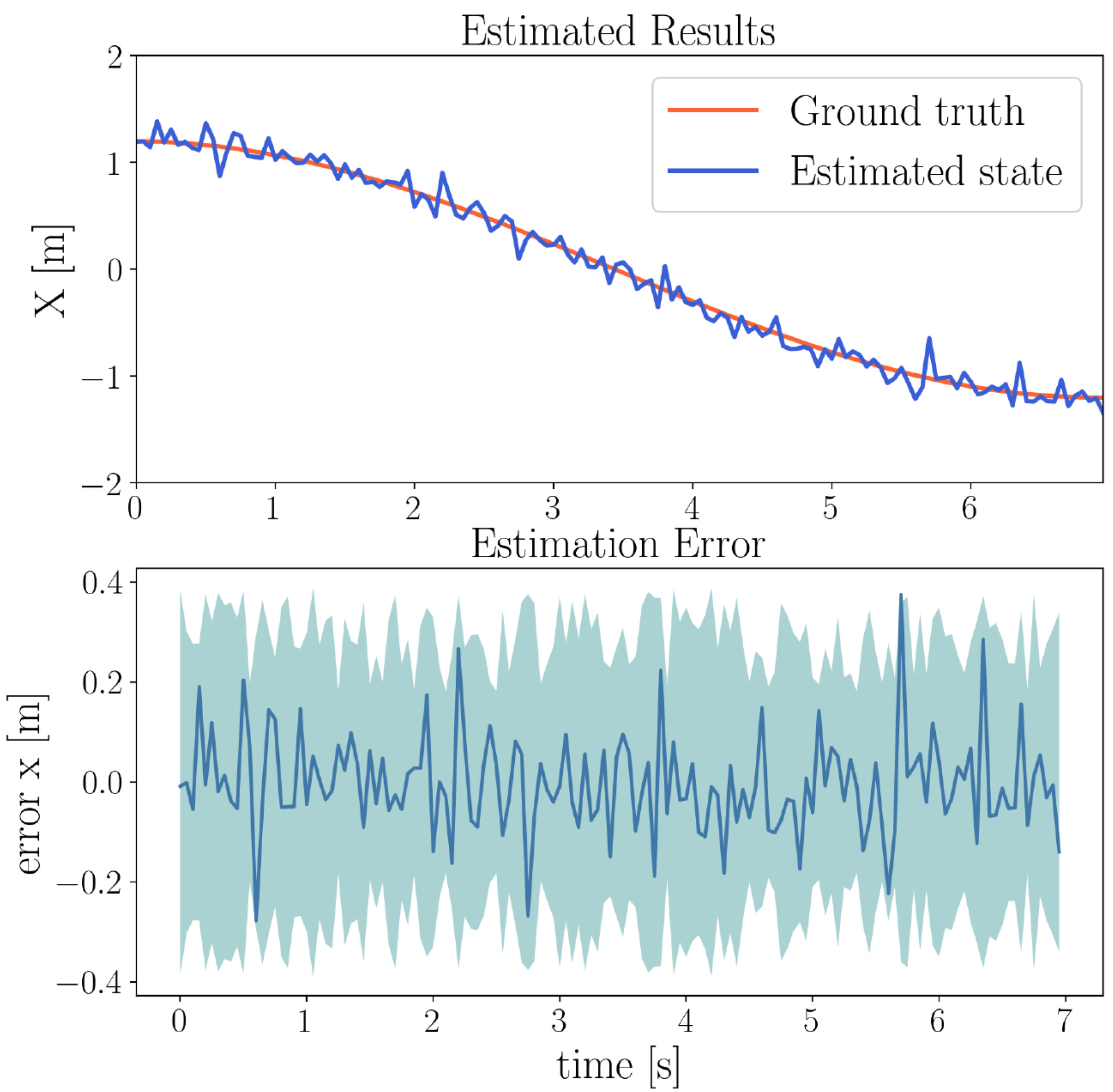
Limitations of Existing Methods

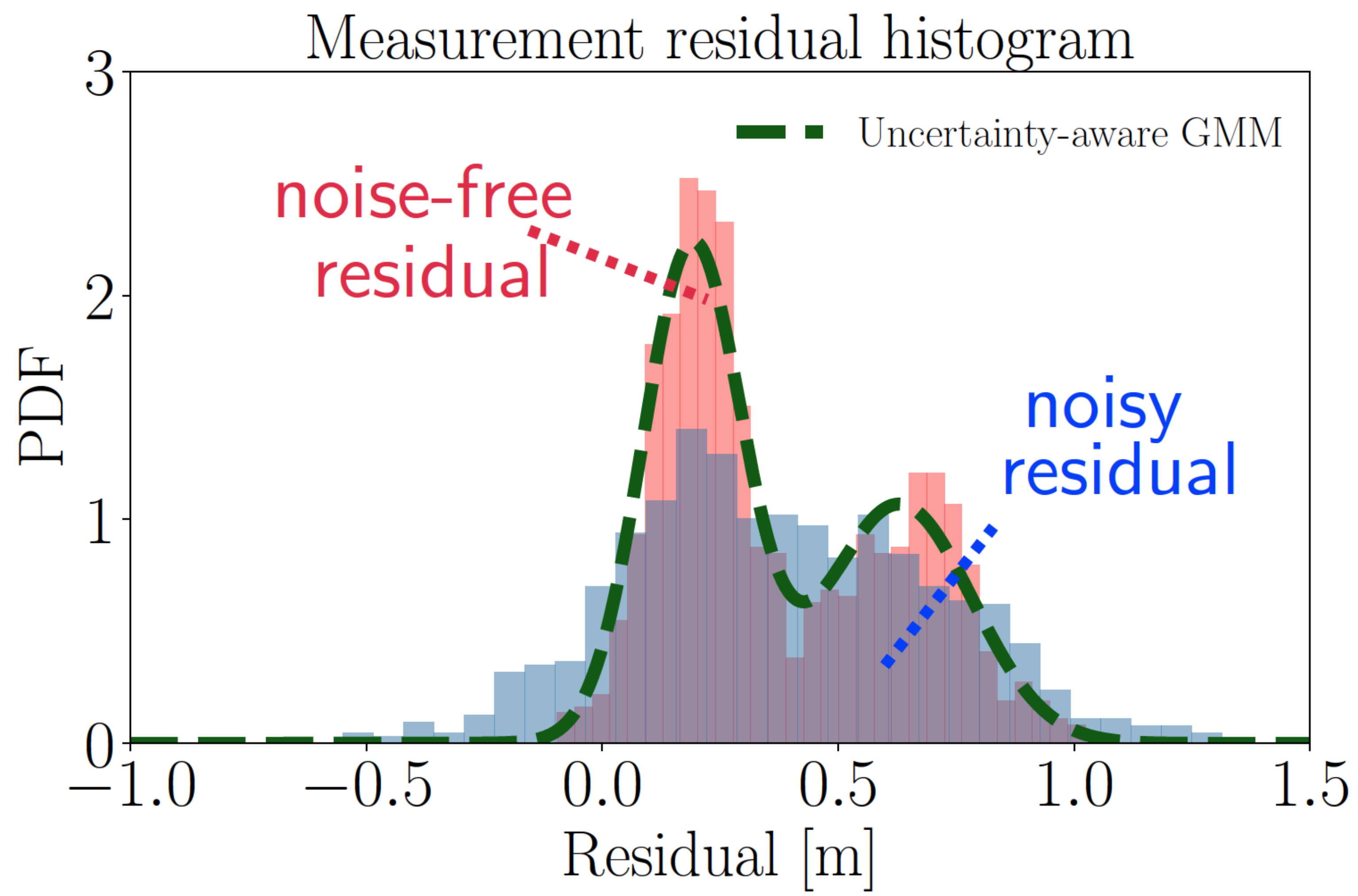




residuals computed based on the mean of the estimated state

Limitations of Existing Methods





residuals computed based on the ground-truth state estimates

Methodology

We apply a similar variational inference approach, originally used in motion segmentation, to incorporate the residuals' uncertainties into the GMM noise model learning. The variational distributions of the hyperparameters are computed through maximizing the evidence lower bound.

The key insight of this approach is to incorporate the residuals' uncertainties when evaluating the responsibilities in the variational E step.

Methodology

We propose a bi-level optimization algorithm for joint localization and uncertainty-aware noise model learning

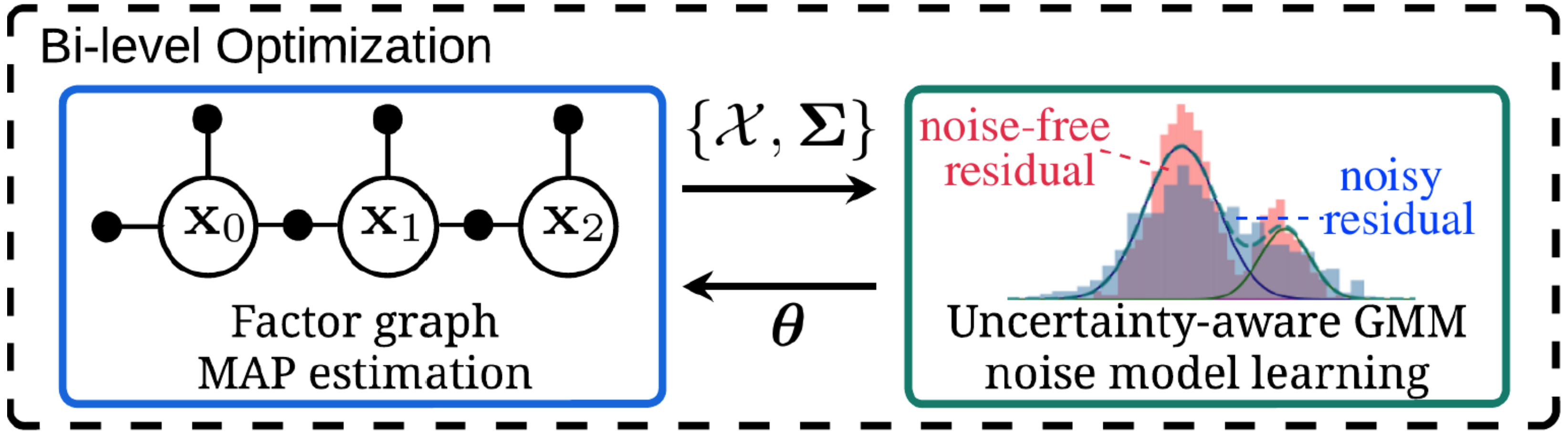
- Inner loop

$$\hat{\mathcal{X}} = \arg\max_{\mathcal{X}} \; p(\mathcal{X}, \mathcal{U}, \mathcal{D} \mid \boldsymbol{\theta})$$

- Outer loop

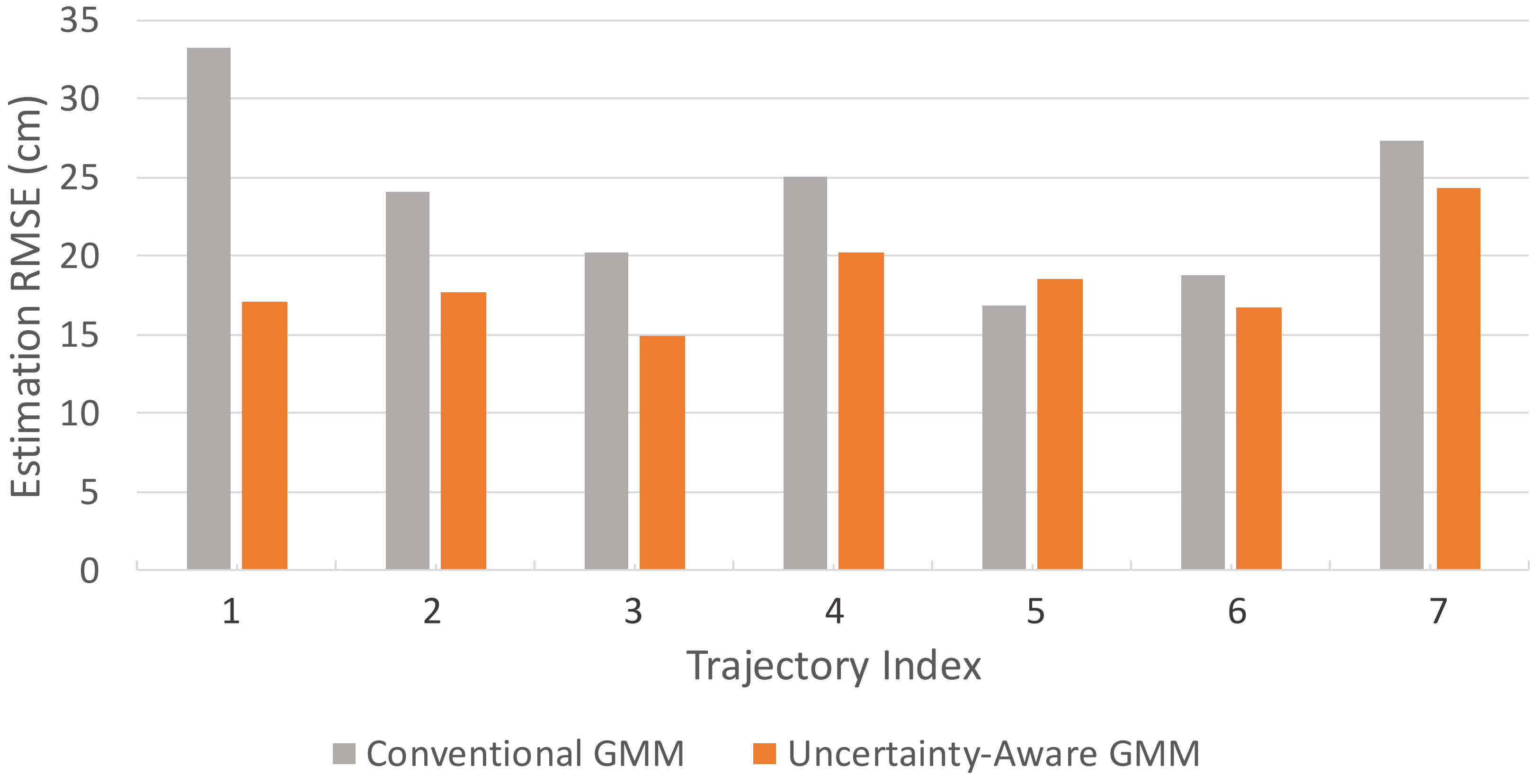
$$\hat{q}(\boldsymbol{\theta}) = \arg\max_{q(\boldsymbol{\theta})} \; \mathcal{L}(q(\boldsymbol{\theta} \mid \mathcal{X}, \Sigma))$$

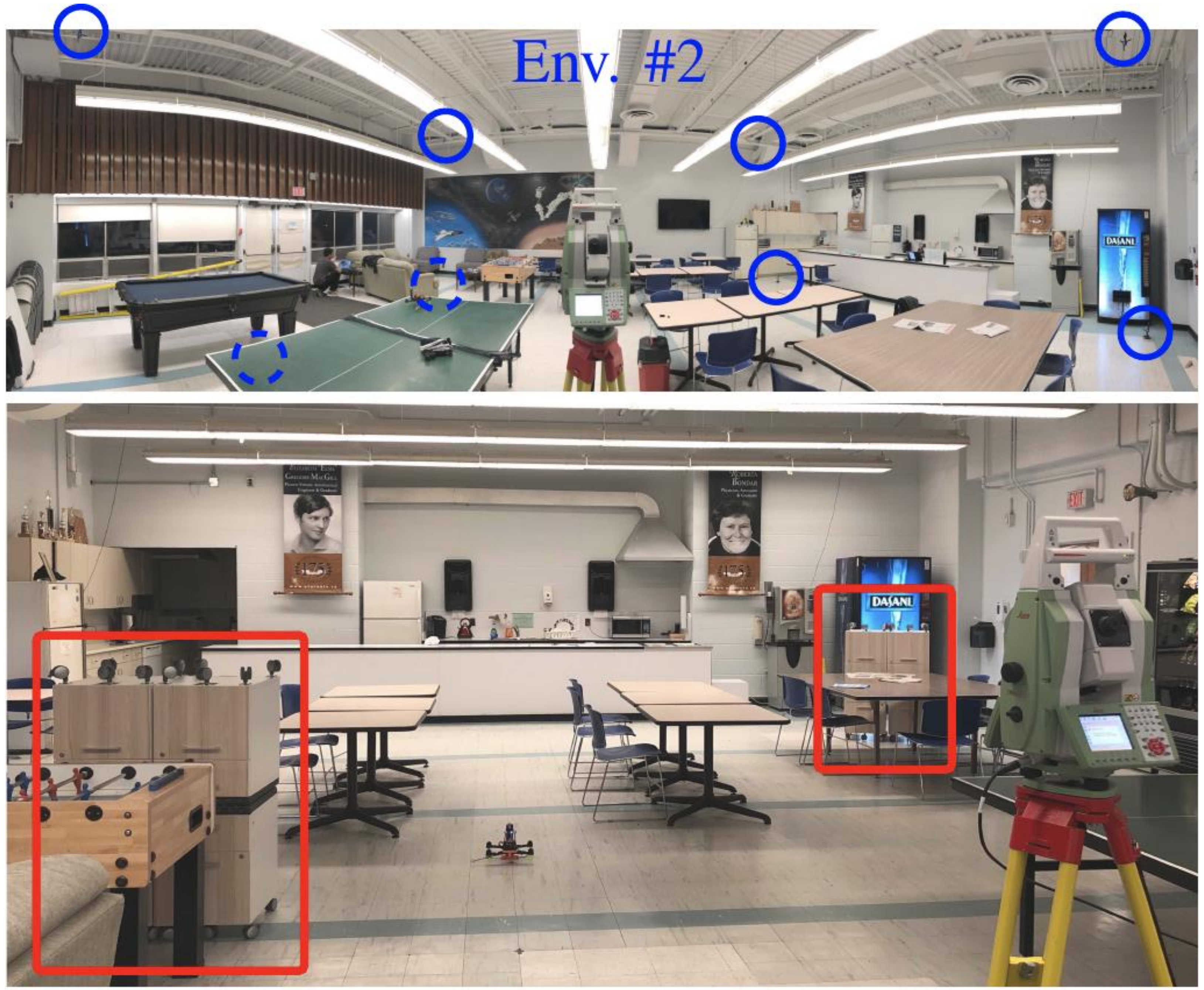
$$\hat{\boldsymbol{\theta}} = \mathbb{E}_{\boldsymbol{\theta}}[\hat{q}(\boldsymbol{\theta})]$$



Uncertainty-Aware GMM

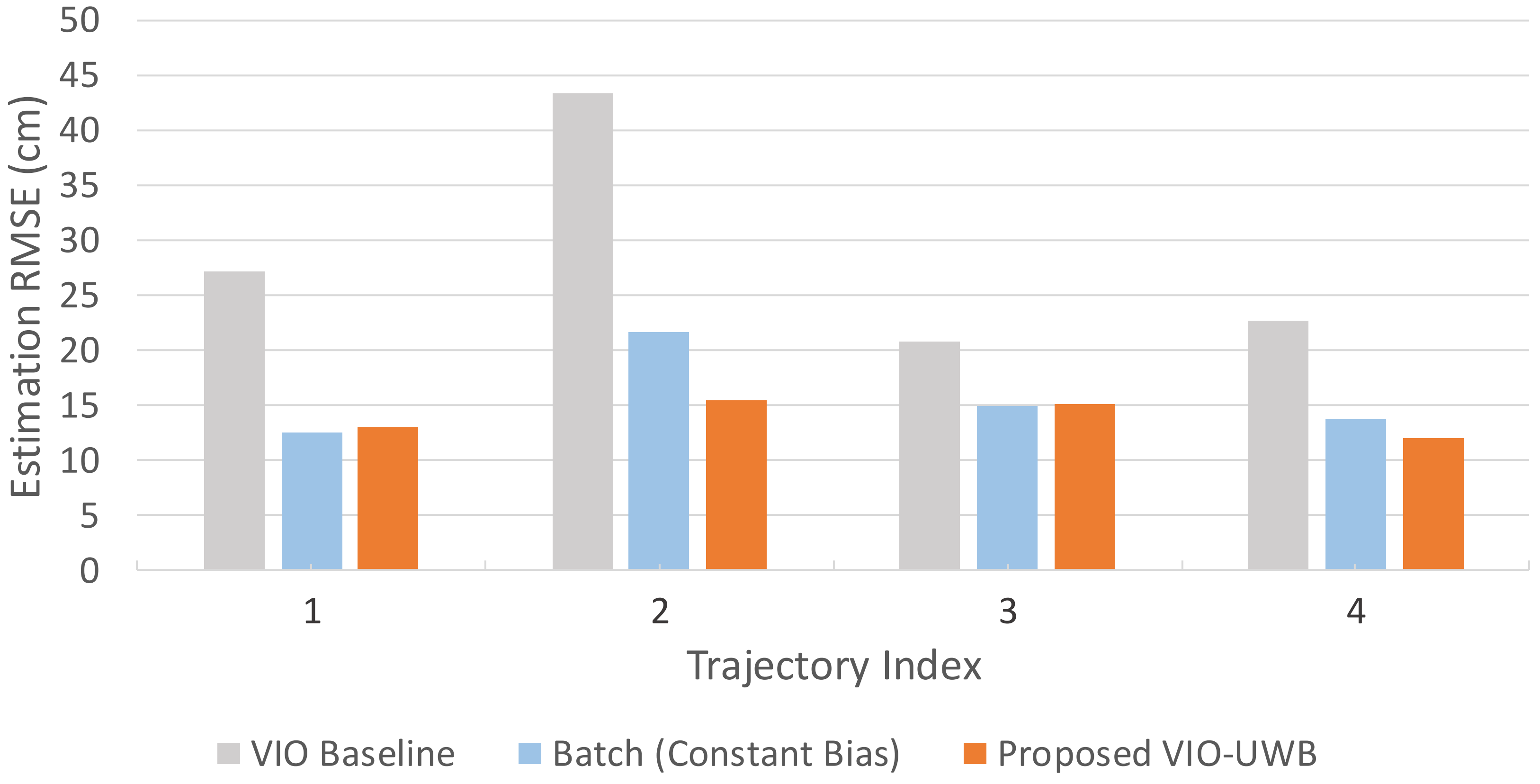
Our proposed method still achieves an average of 18.49 cm localization accuracy, leading to 19.11% error reductions compared to conventional GMM approach.

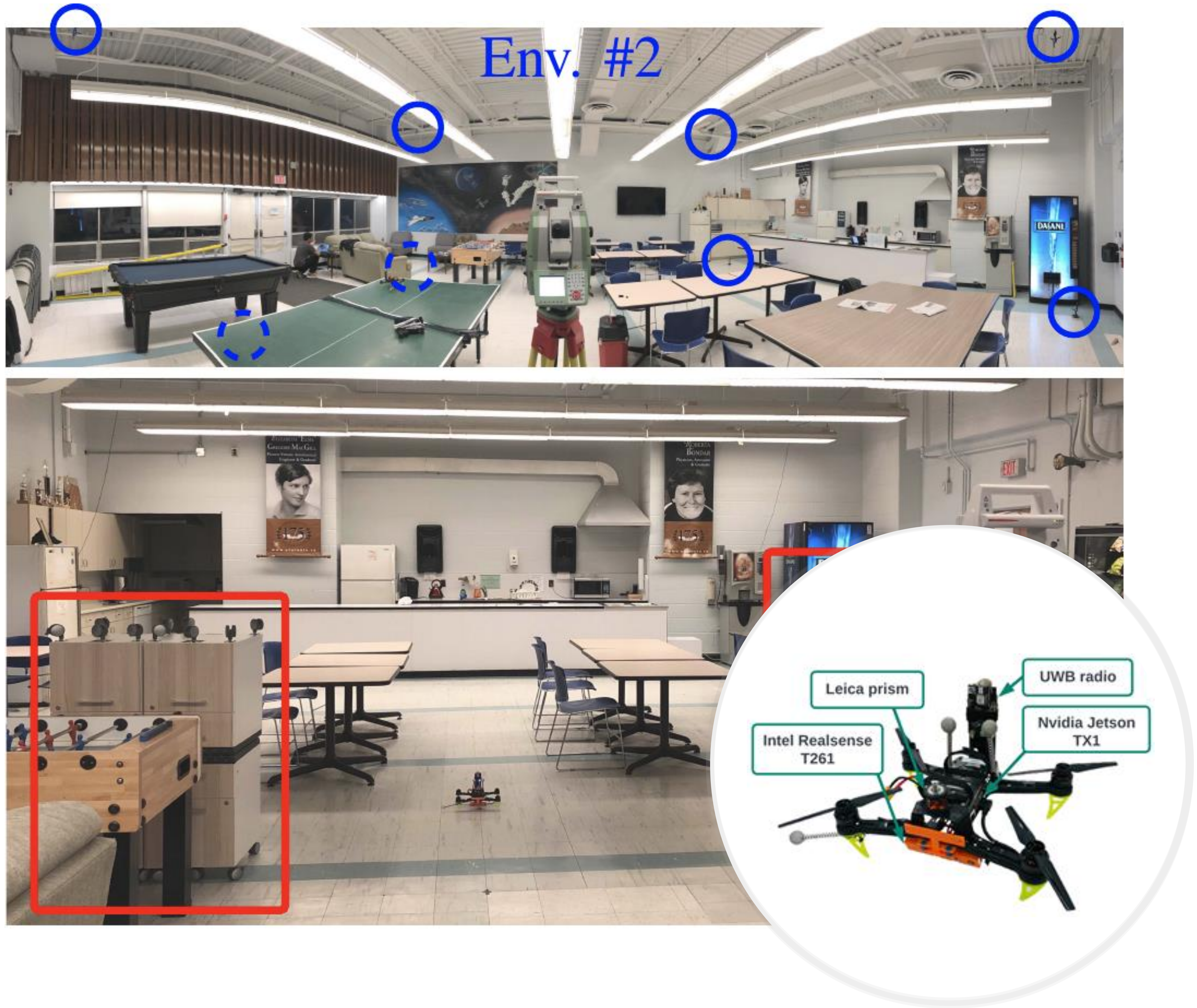




Range-Visual-Inertial-Aided Localization and Navigation

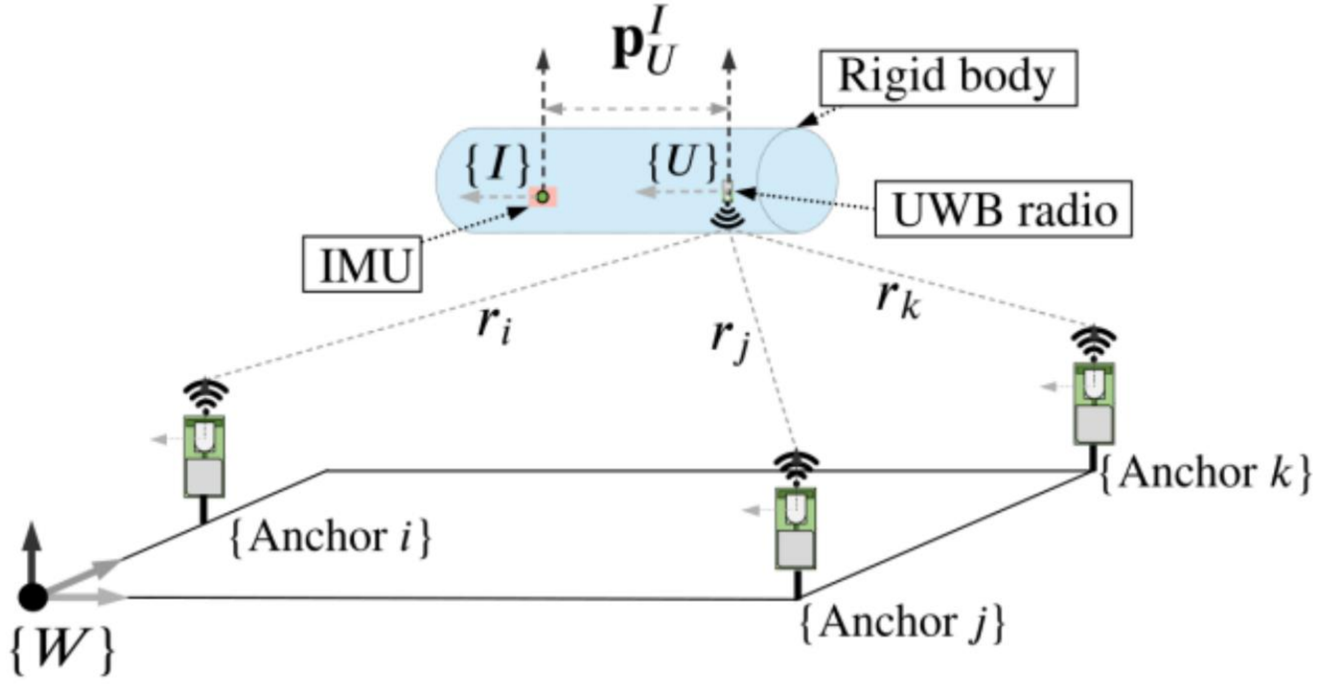
Further fusing UWB and VIO for localization achieves higher accuracy in cluttered environments with off-the-shelf sensors.

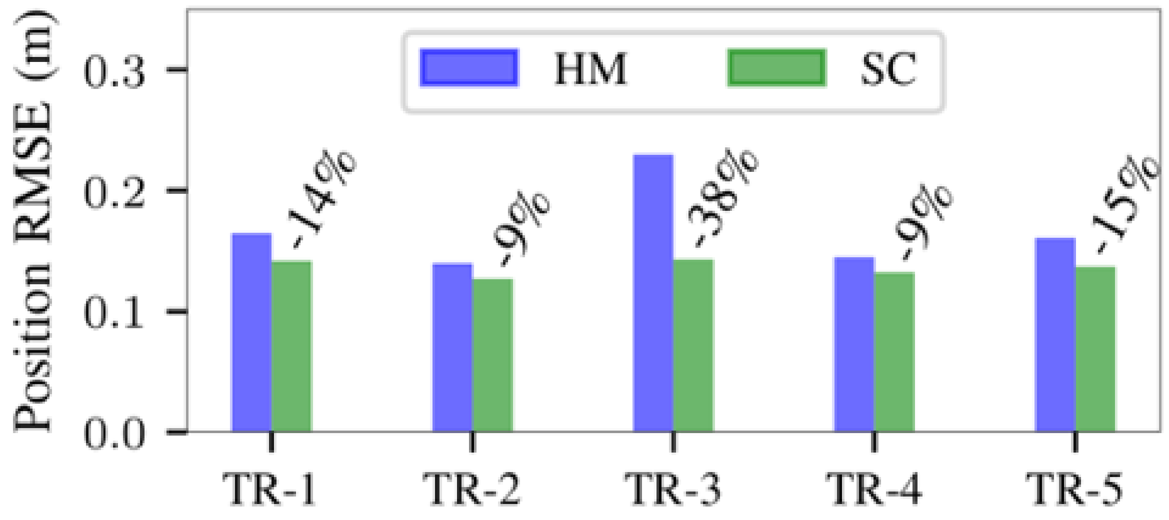




Online Spatio-Temporal Calibration

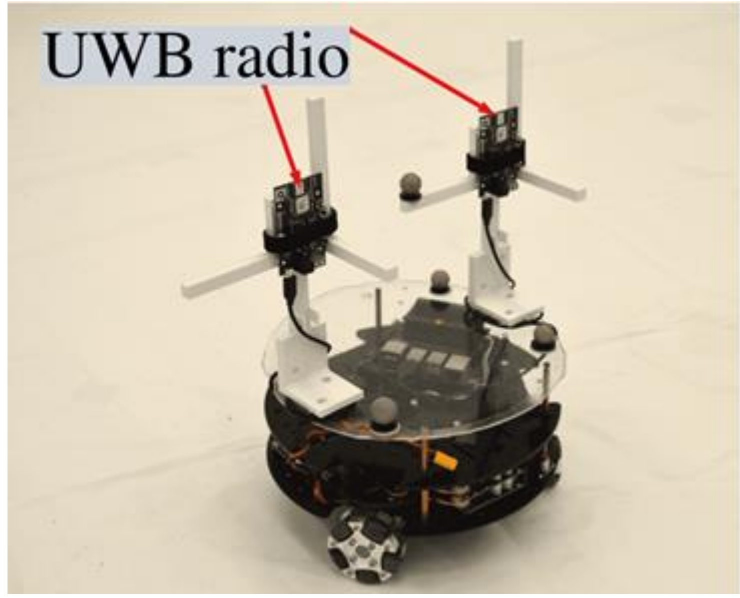
- Accurate positioning requires multi-modal sensor fusion and calibration of position and time offsets.
- Sensors are generally not collocated
- Sensors have different latencies
- Temporal and spatial offsets can be **calibrated online** as long as the required **identifiability and observability conditions** are met.





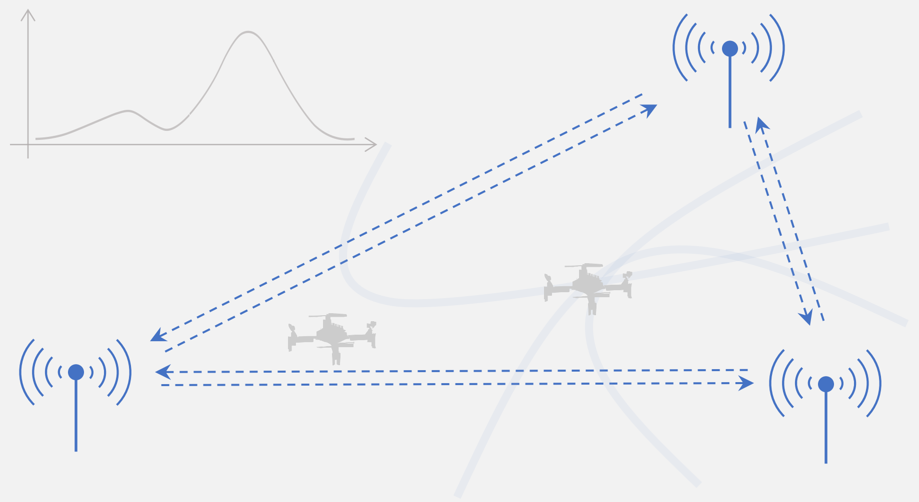
Multiagent Relative Localization and Pose Estimation

- Localization multiple aerial robots by measuring inter-robot distance.
- Use multiple UWB tags to estimate initial pose and trajectory.



UWB-Based Localization for Aerial Swarms

Part I
Robust Range-Based Methods for Reliable Aerial Swarm Localization



- UWB for portable and reliable indoor localization
- Uncertainty-aware GMM model learning algorithm for improved localization performance in cluttered scenes
- Fusing VIO and spatio-temporal calibrations further reduce localization errors
- Scaling to multiagent systems

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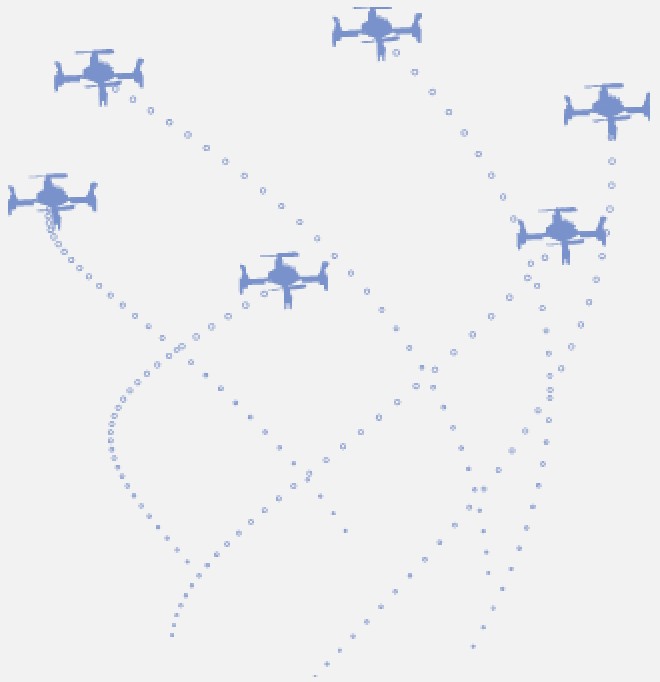


Part III
Simulation Tools and Datasets
for
Scaling Up Swarming Tasks

F. Augugliaro, A. P. Schoellig, and R. D'Andrea, "Dance of the Flying Machines" | Video https://youtu.be/NRL_1ozDQCA?si=MrpwBvNS2D3SNOFI

Trajectory of Aerial Swarm Research from the Lab

Dancing to the Music

Schoellig, Angela P., et al. "So you think you can dance? Rhythmic flight performances with quadrocopters." Controls and Art: Inquiries at the Intersection of the Subjective and the Objective (2014): 73-105. [pdf, website]

Du, Xintong, et al. "Fast and in sync: Periodic swarm patterns for quadrotors." *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2019. [pdf]

Prior Work: Primitive-based motion planning frameworks for "dancing to the music," where motion parameters are **designed by experts**

Idea: Use large language model (LLM) to facilitate choreography design through language

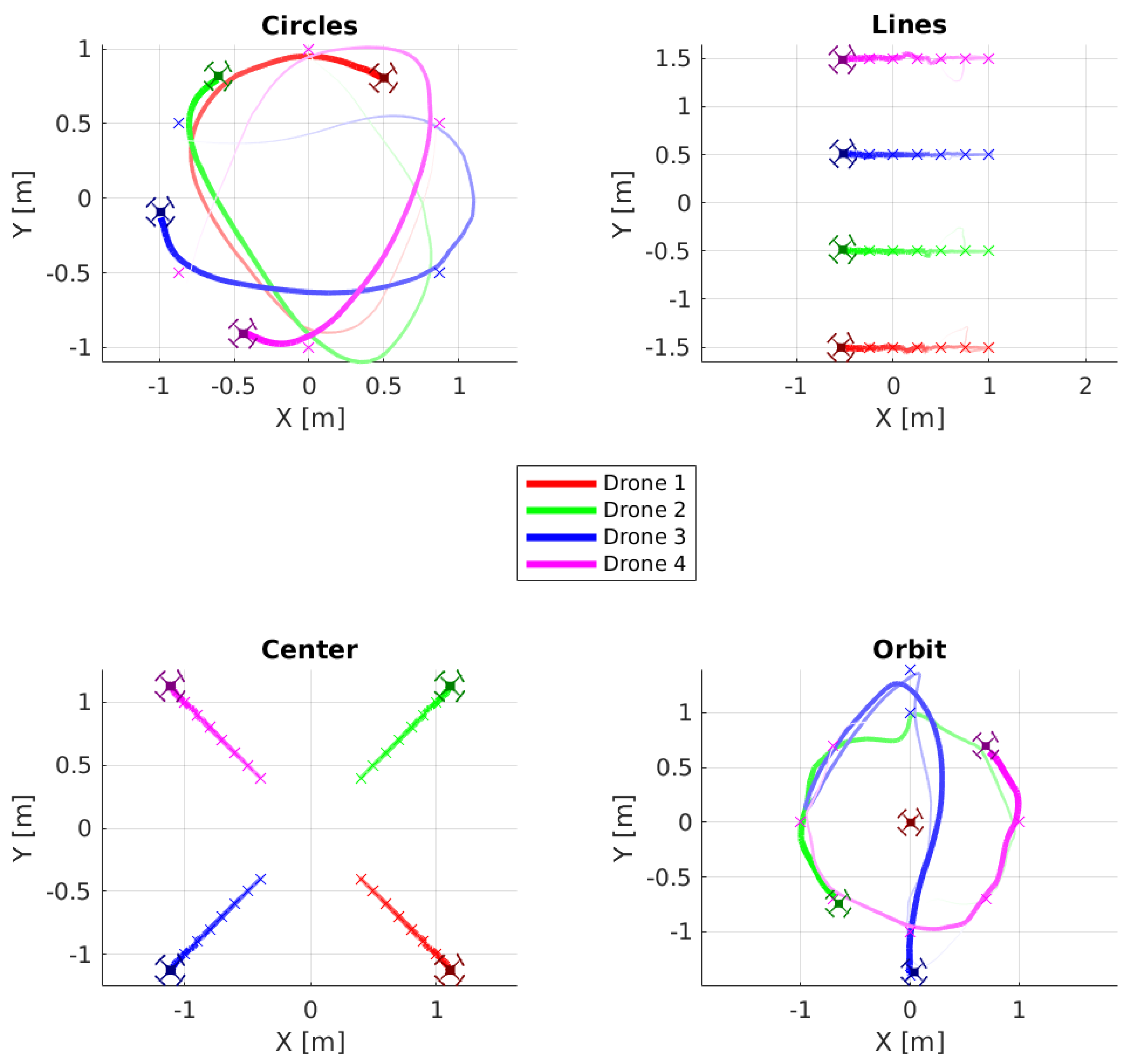
Luis, Carlos E., and Angela P. Schoellig. "Trajectory generation for multiagent point-to-point transitions via distributed model predictive control." *IEEE Robotics and Automation Letters* 4.2 (2019): 375-382. [pdf]

Luis, Carlos E., Marijan Vukosavljev, and Angela P. Schoellig. "Online trajectory generation with distributed model predictive control for multi-robot motion planning." *IEEE Robotics and Automation Letters* 5.2 (2020): 604-611. [pdf]

Adajania, Vivek K., et al. "AMSwarm: An Alternating Minimization Approach for Safe Motion Planning of Quadrotor Swarms in Cluttered Environments." *IEEE International Conference on Robotics and Automation (ICRA)*, 2023. [pdf]

Swarm Trajectory Generation

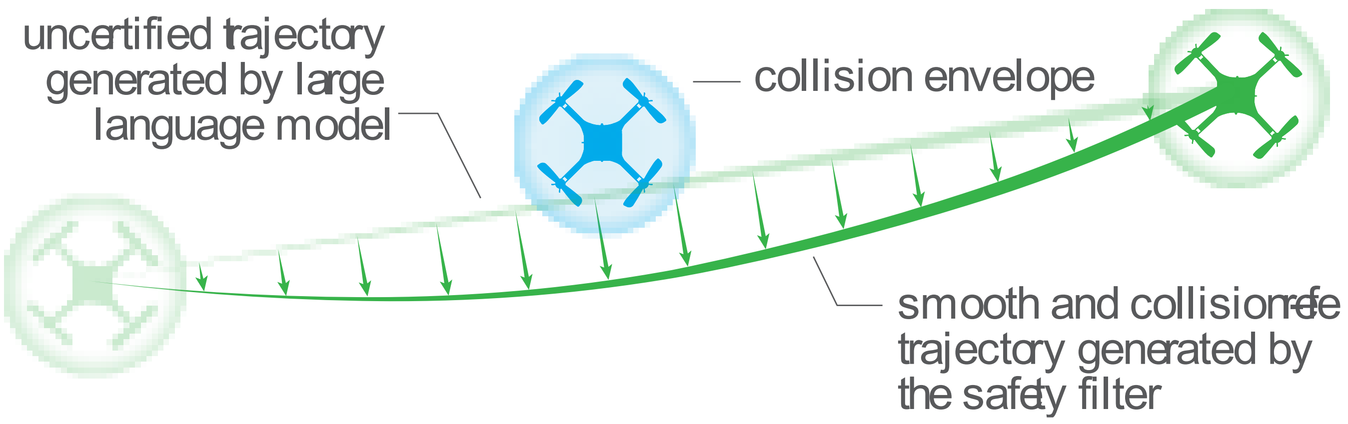
Capabilities of LLMs



Pro: Interpretating qualitative instructions and allowing specifications of behaviors through intuitive instructions

Con: Difficult to guarantee feasibility and safety of generated choreographies (especially for large swarms)

Safety Filter: Encode prior knowledge via optimization-based trajectory generation



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Du, Xintong, et al. "Fast and in sync: Periodic swarm patterns for quadrotors." *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2019. [pdf]

Safety Filter: Distributed optimization problems for individual agents to account for actuation constraints, smoothness, and motion of other agents

Luis, Carlos E., and Angela P. Schoellig. "Trajectory generation for multiagent point-to-point transitions via distributed model predictive control." *IEEE Robotics and Automation Letters* 4.2 (2019): 375-382. **[pdf]**

Luis, Carlos E., Marijan Vukosavljev, and Angela P. Schoellig. "Online trajectory generation with distributed model predictive control for multi-robot motion planning." *IEEE Robotics and Automation Letters* 5.2 (2020): 604-611. **[pdf]**

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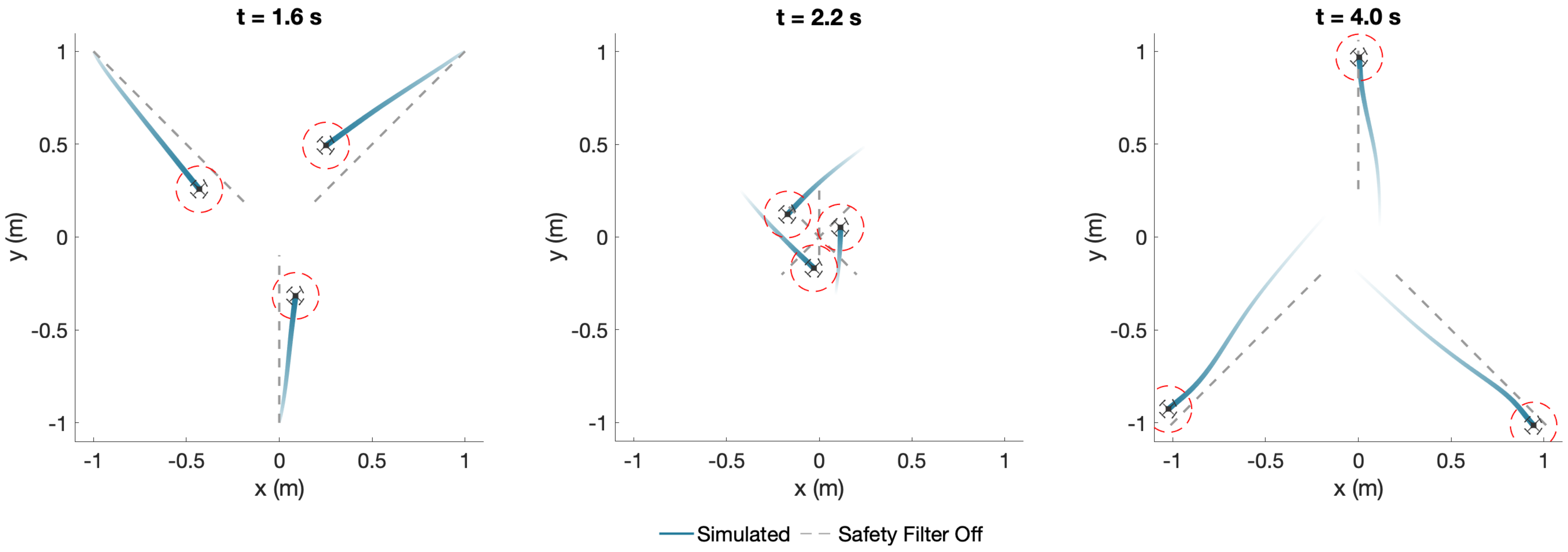
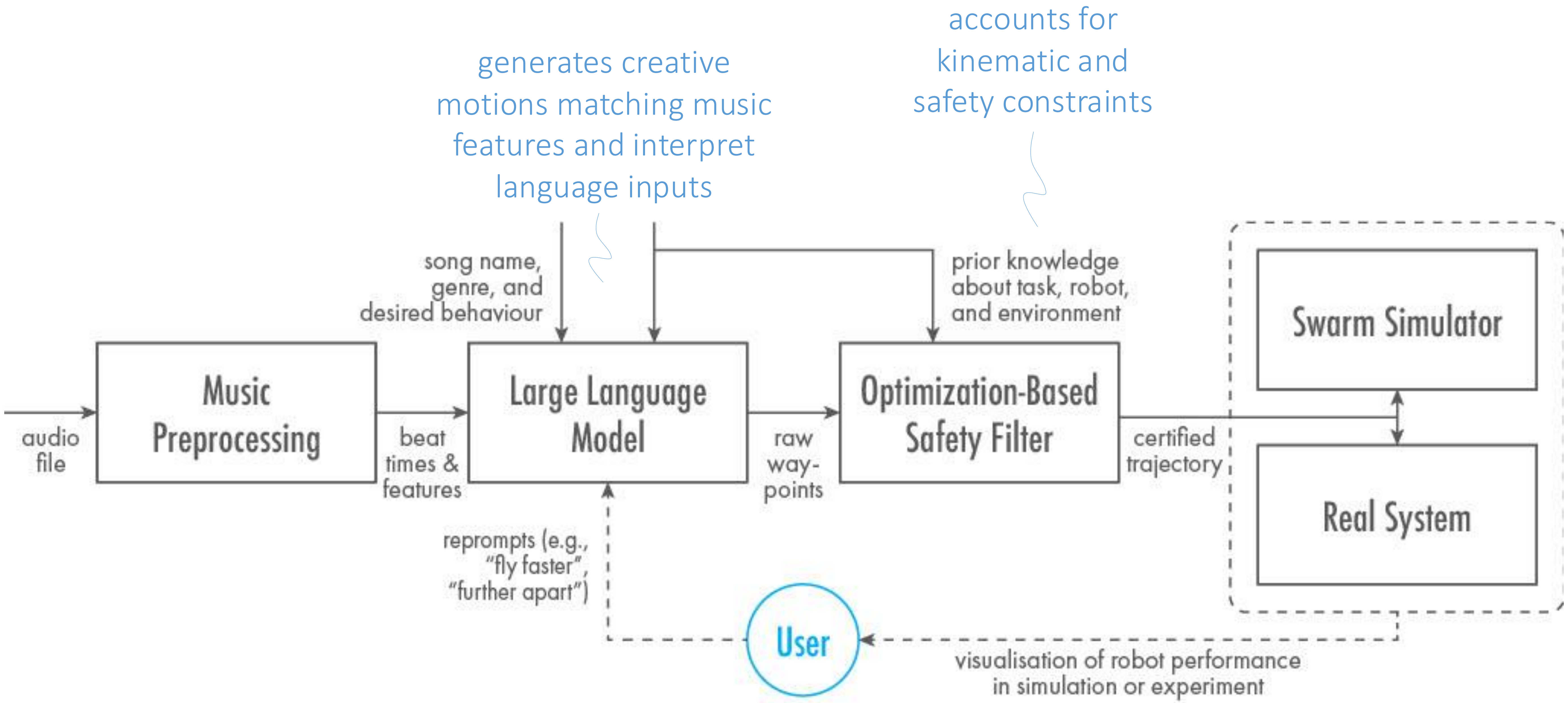
Swarm Trajectory Generation

AMSwarm Safety Filter: Illustration



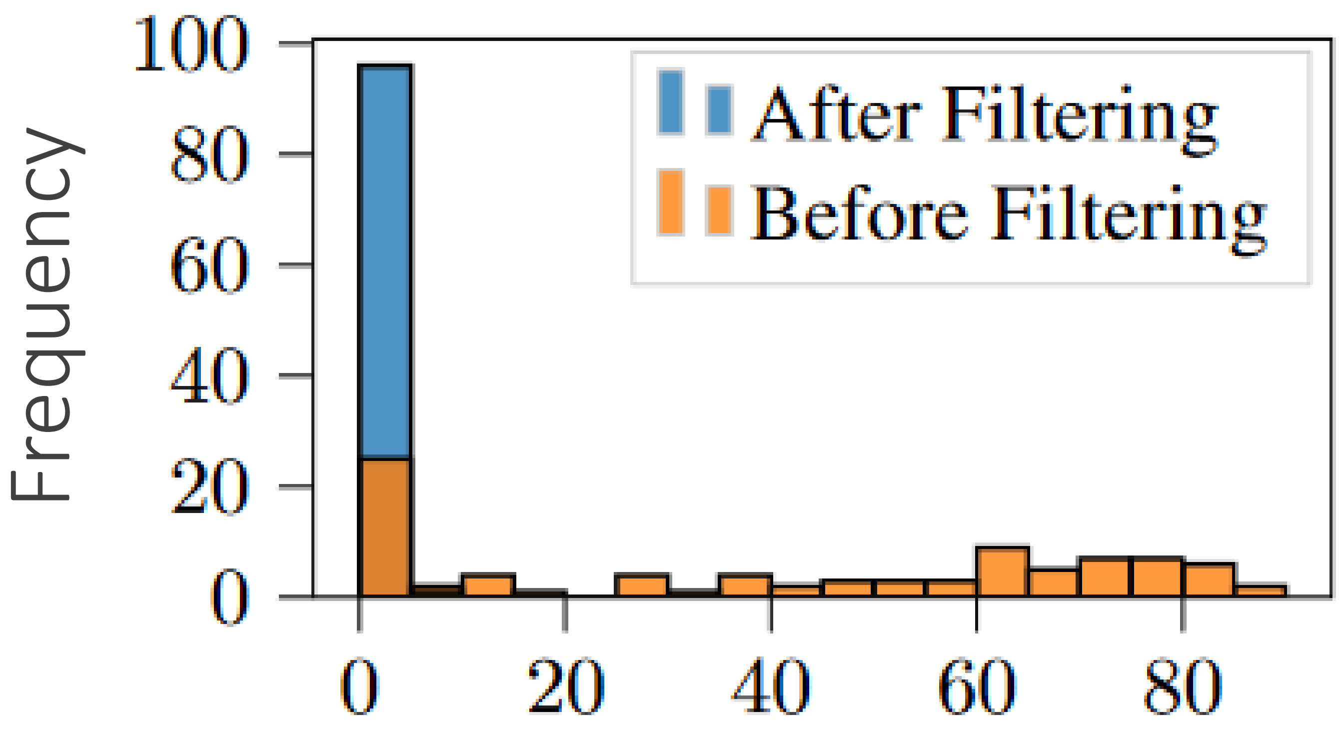
Swarm-GPT: An Interactive Choreography Interface



M. Schuck, B. Sprenger, A. Jiao, T. P. Patel, S. Khurana, A. Korol, L. Brunke, V. K. Adajania, U. Culha, S. Zhou, and A. P. Schoellig
Swarm-GPT: Combining Large Language Models with Safe Motion Planning for Robot Choreography Design

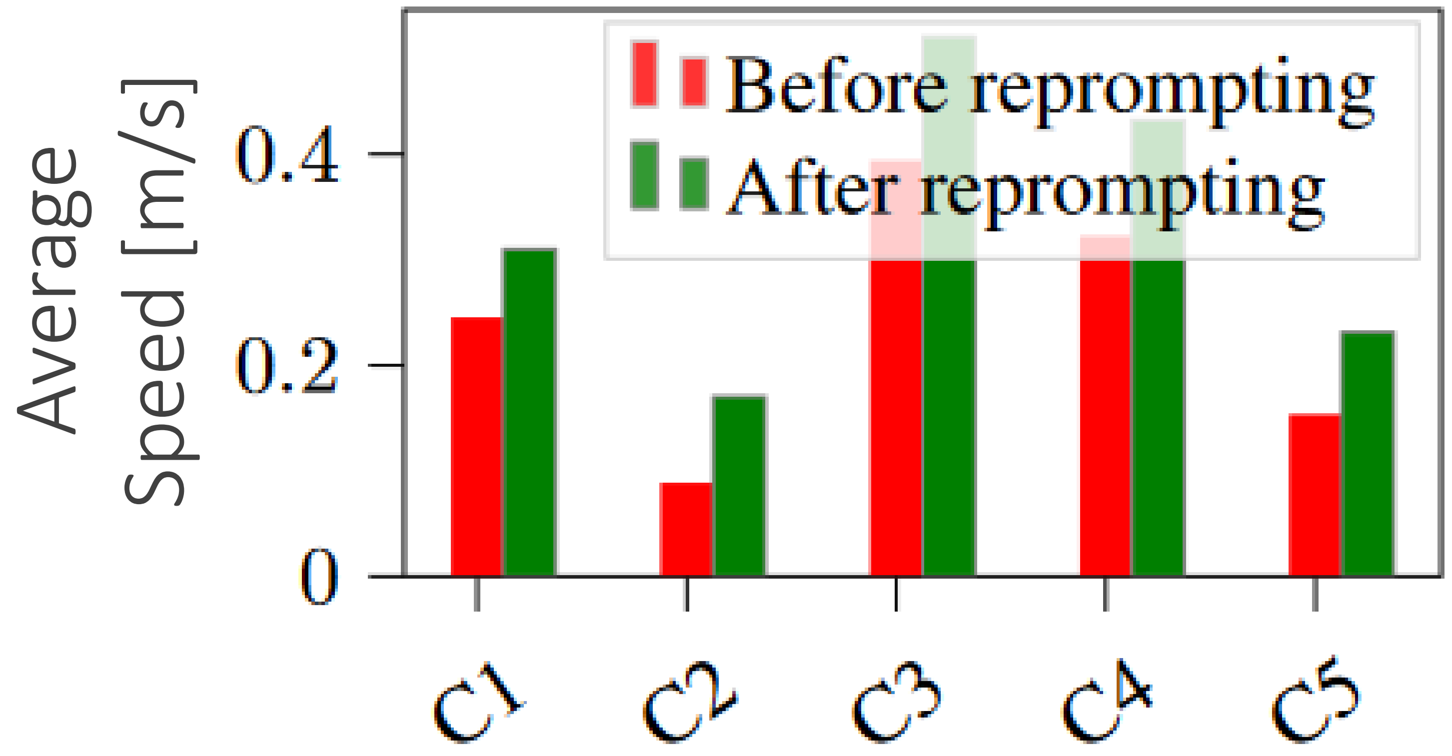
Swarm-GPT: Results

Number of collisions before and after the safety filter is applied



Percent of Trajectory with Collisions [%]

Average speeds after the drones are instructed to “fly faster”

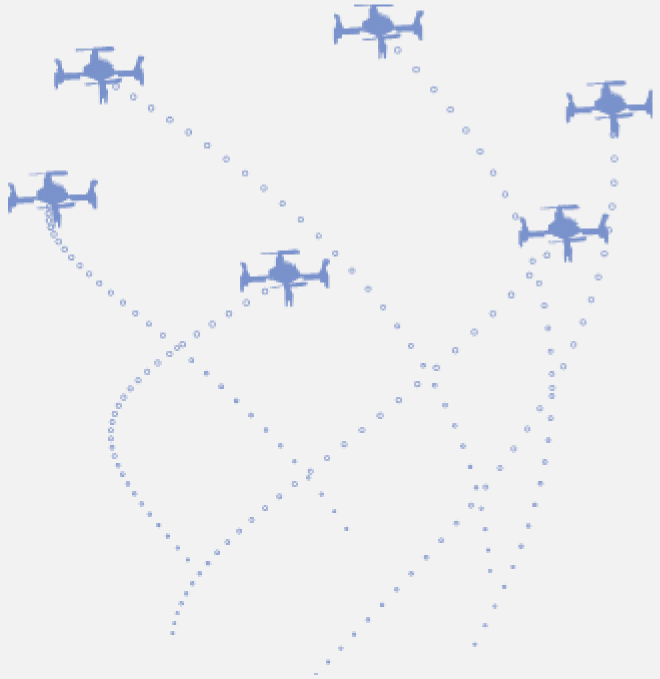


Choreography Index

"Here Comes the Sun"

Safe and Intuitive Multiagent Motion Planning

Part II
Control Theoretic Approaches
for
Efficient Swarm Coordination



- Leveraging our prior knowledge optimization-based methods for safe multiagent motion planning
- Incorporating language models for intuitive interactions
- Seamlessly combining the two gives non-experts the ability to program robots

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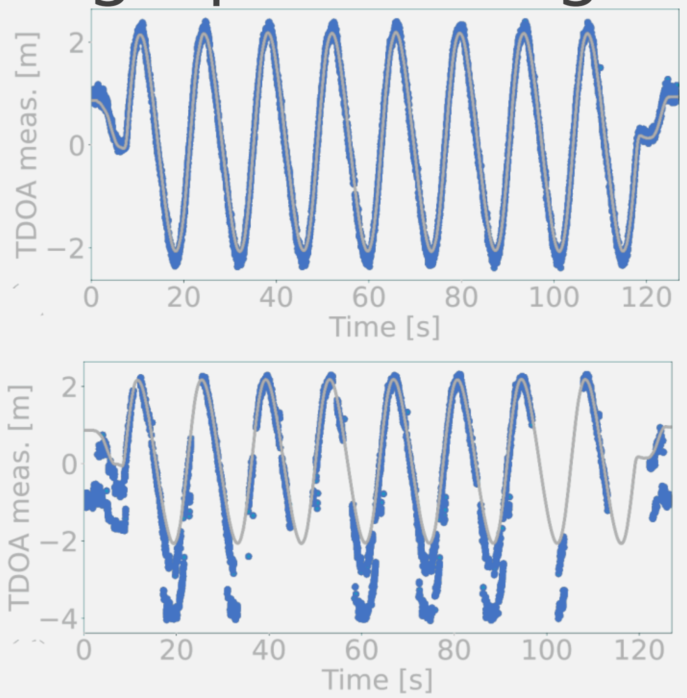
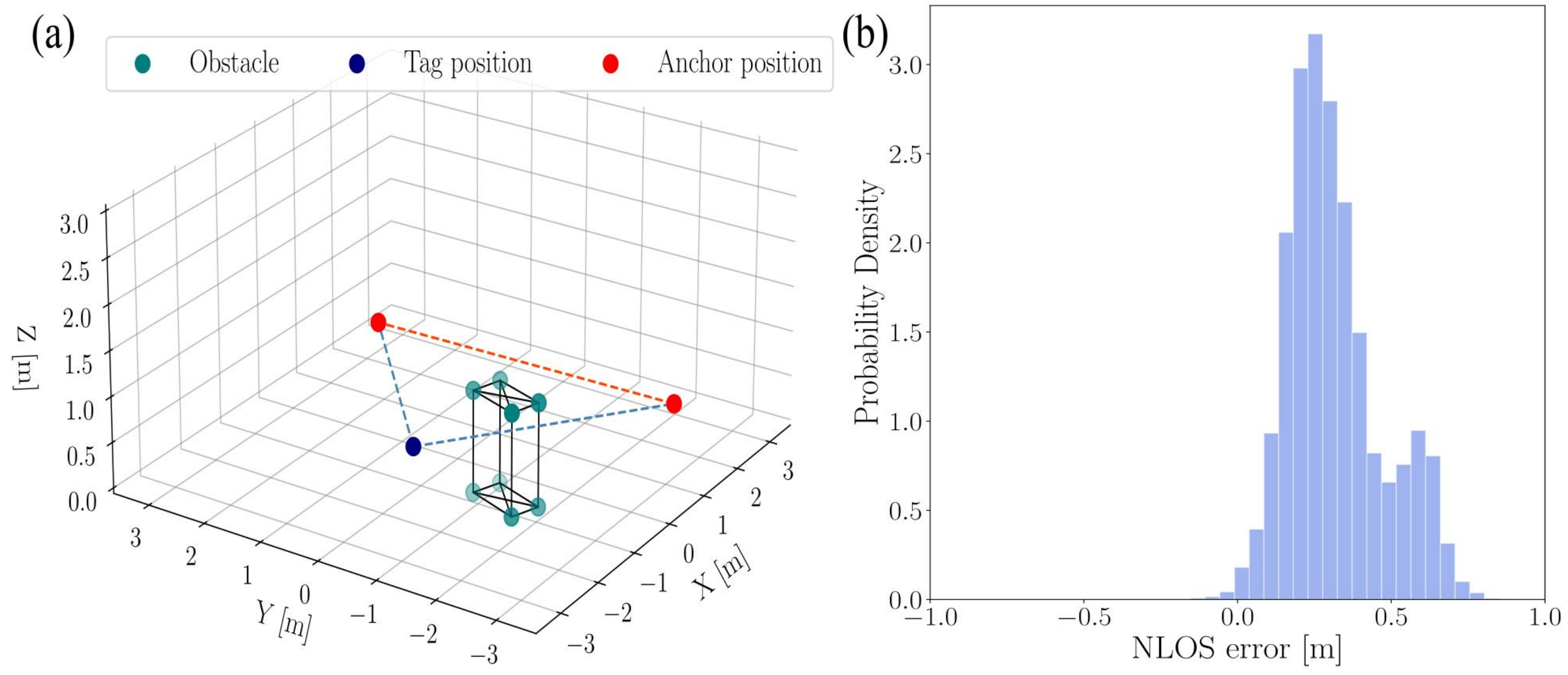


UTIL Dataset: Overview

- Designed a variety of identification experiments in line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios
- Two UWB anchors and one Crazyflie nano-quadrotor equipped with an UWB tag are placed on wooden structures
- A millimeter-level accurate motion capture system measures the poses of the tag and the anchors for ground truth data

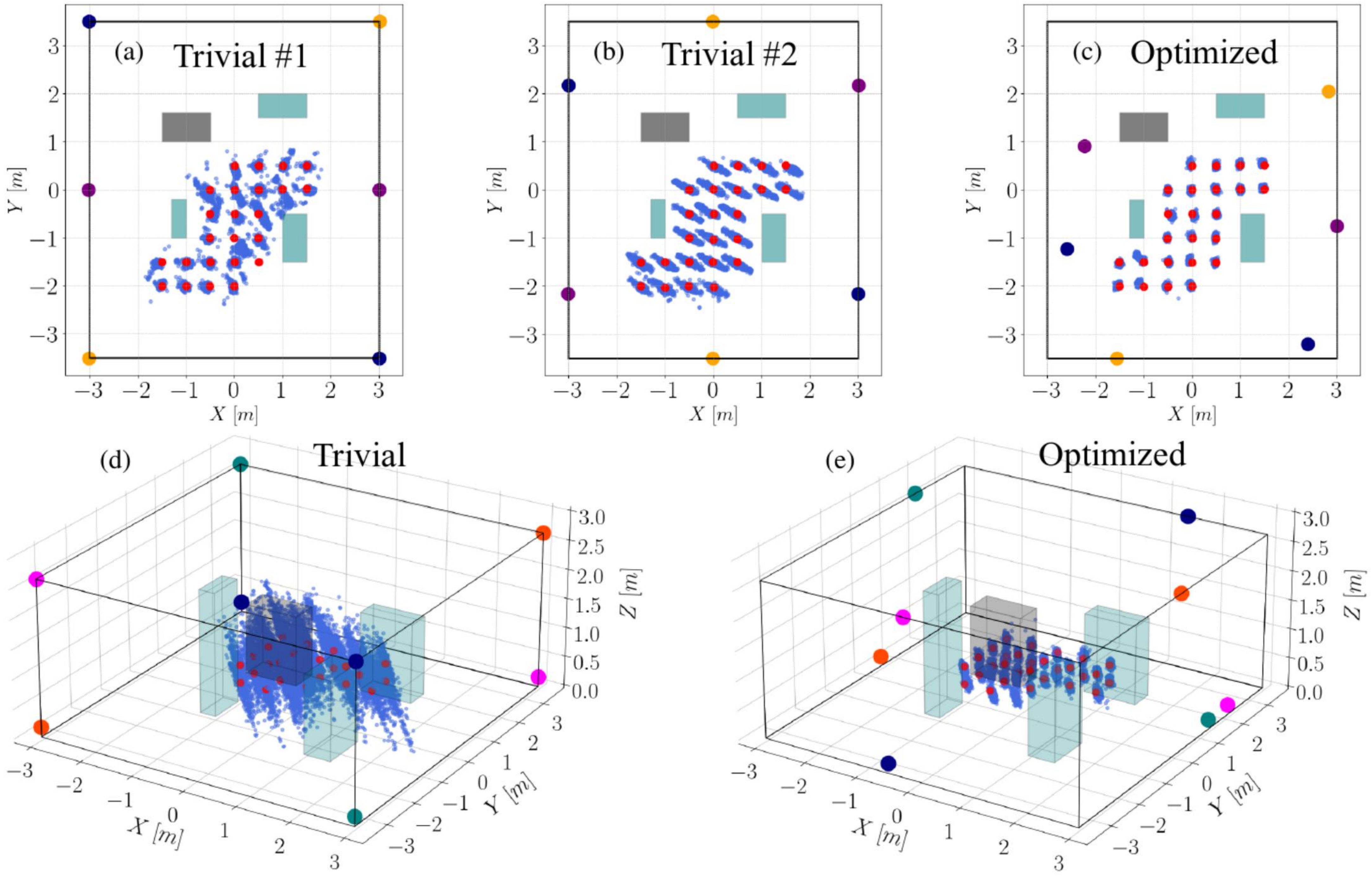
https://utiasdsl.github.io/util-uwb-dataset/



UTIL Dataset: Optimizing Sensor Placement

NLOS experiments

- Modeling and optimizing sensor placements can significantly reduce the variance of range measurements
- RMSE error can be reduced up to 76% in 3D settings



W. Zhao, A. Goudar, X. Qiao, and A. P. Schoellig
Finding the Right Place: Sensor Placement for UWB Time Difference of Arrival Localization in Cluttered Indoor Environments

gym-pybullet-drones

An open-source environment for <u>the reinforcement learning of single and multi-agent quadcopter control</u>

Based on the widely available and open-source <u>Bitcraze Crazyflie hardware and software stack</u>

Design Principles:

- <u>Flexibility</u> (multiple use cases in one Python pkg)
- <u>Ease-of-use</u> (low-friction installation and 1st use)

Integrations:

- PyBullet Physics
- Farama Found. Gymnasium
- DLR <u>Stable-baselines3</u> 2.0
- Betaflight SITL
- CFFirmware (WIP)

gym-pybullet-drones Public

PyBullet Gym environments for single and multi-agent reinforcement learning of quadcopter control

Python ☆ 929 280

J. Panerati, H. Zheng, S. Zhou, J. Xu, A. Prorok, and A. P. Schoellig
Learning to Fly---a Gym Environment with PyBullet Physics for Reinforcement Learning of Multi-agent Quadcopter Control

gym-pybullet-drones

Installation

Tested on Intel x64/Ubuntu 22.04 and Apple Silicon/macOS 14.1.

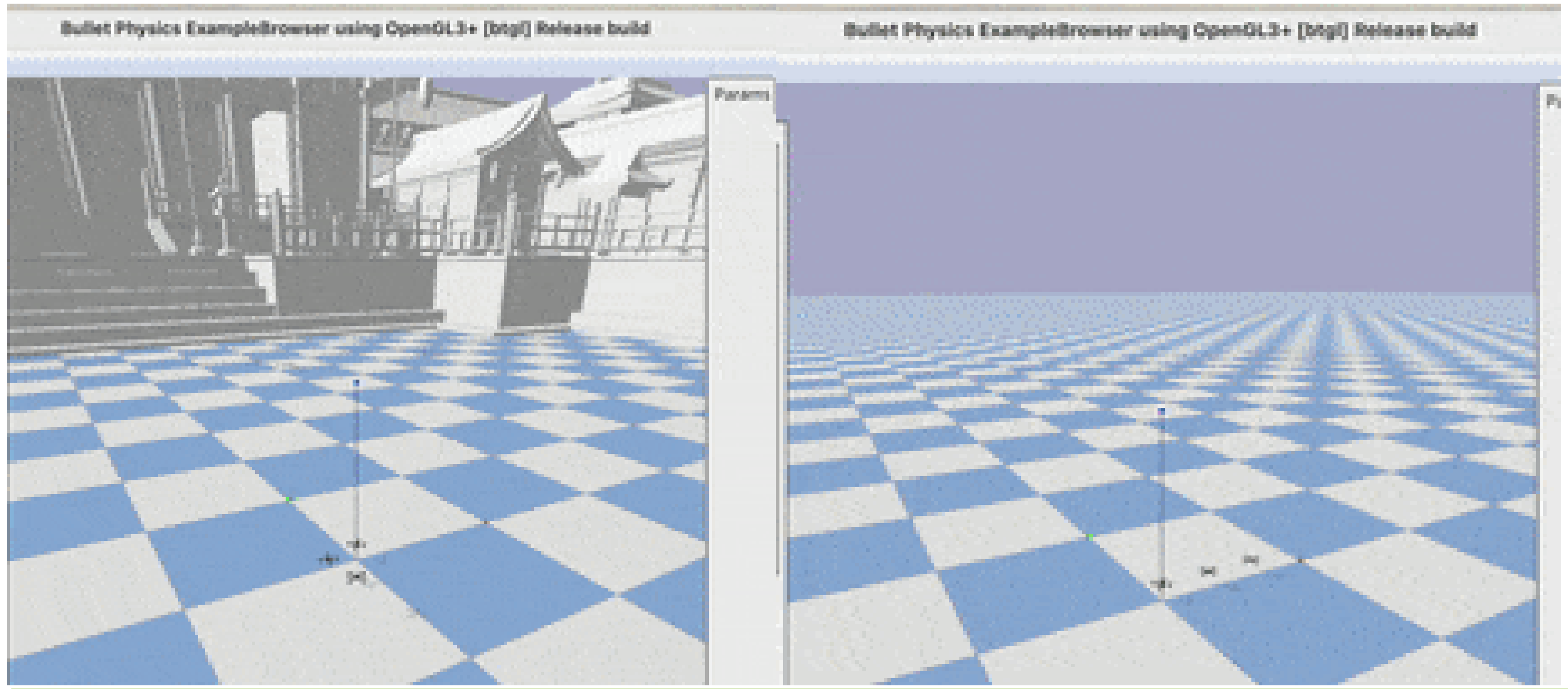
```
git clone https://github.com/utiasDSL/gym-pybullet-drones.git
cd gym-pybullet-drones/

conda create -n drones python=3.10
conda activate drones

pip3 install --upgrade pip
pip3 install -e . # if needed, `sudo apt install build-essential` to install `gcc` and builc
```

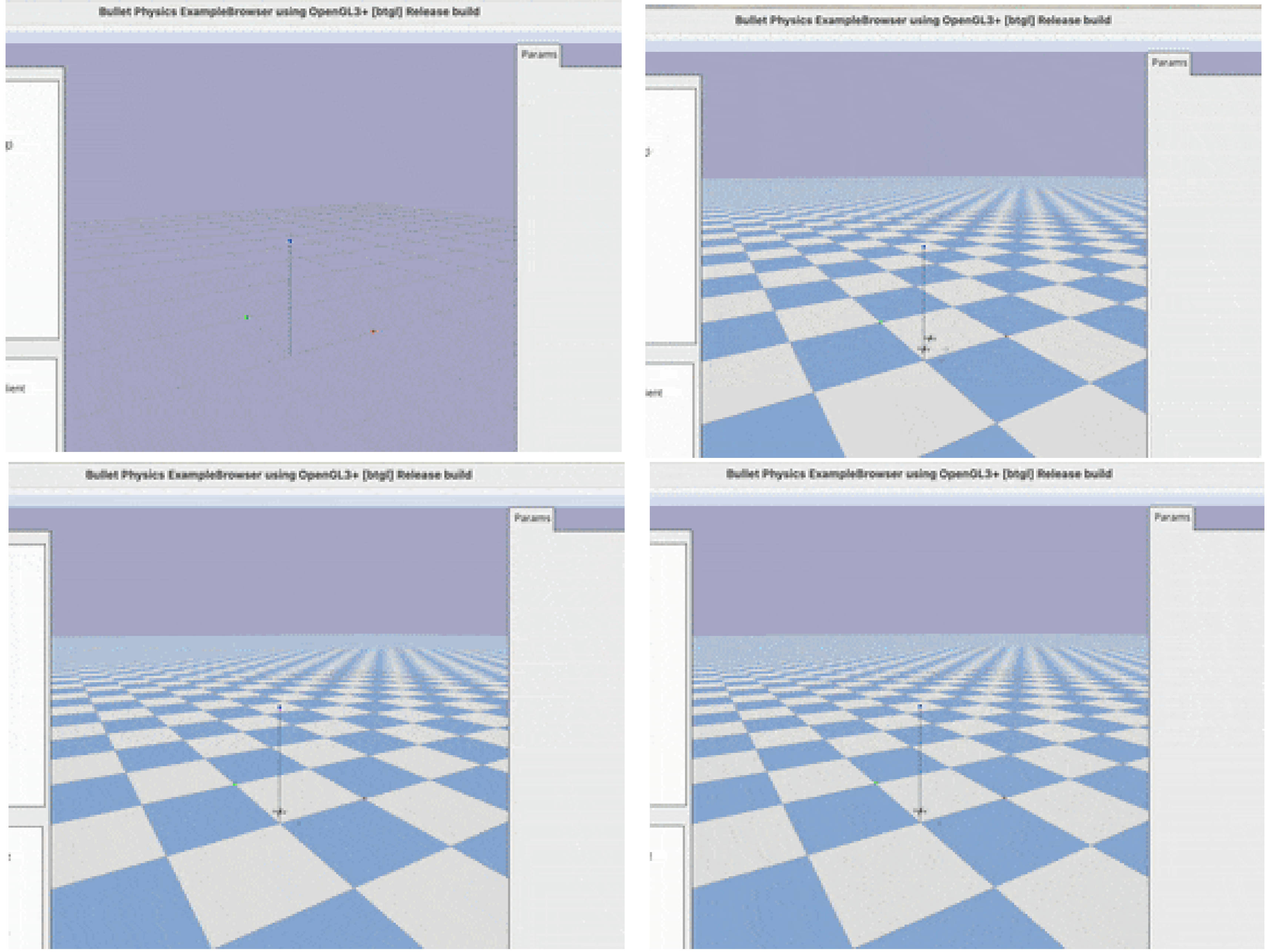
PID control examples

```
cd gym_pybullet_drones/examples/
python3 pid.py # position and velocity reference
python3 pid_velocity.py # desired velocity reference
```



Reinforcement learning examples (SB3's PPO)

```
cd gym_pybullet_drones/examples/
python learn.py # task: single drone hover at z == 1.0
python learn.py --multiagent true # task: 2-drone hover at z == 1.2 and 0.7
```



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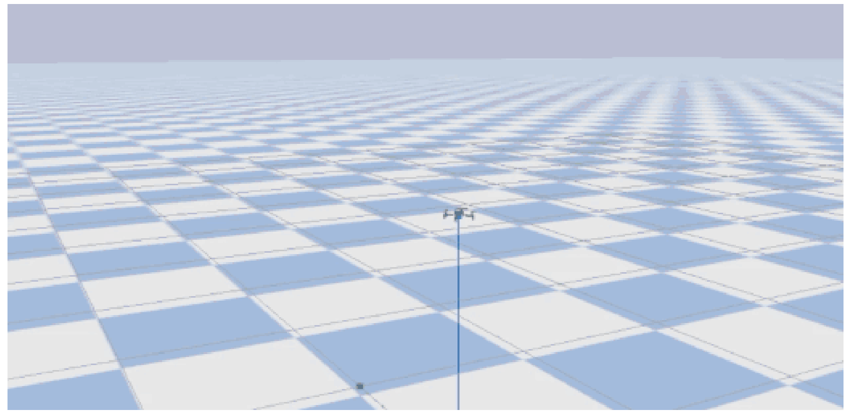
safe-control-gym: a Unified Benchmark Suite

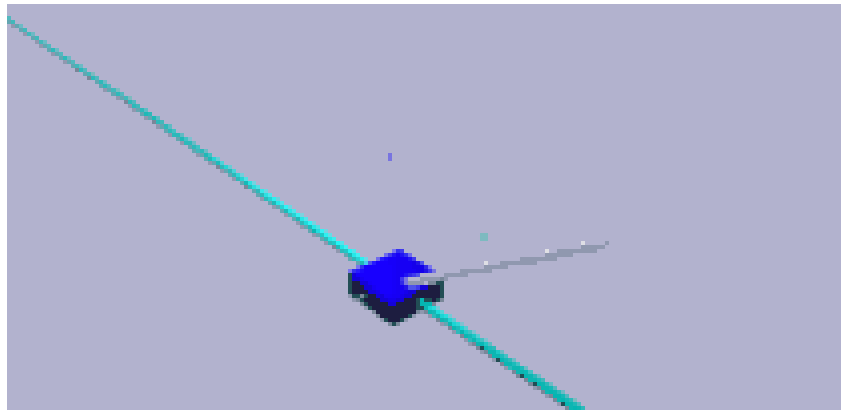
Components

- Open-source physics-engine Bullet
- Compatibility with OpenAI Gym
- CasADi as a symbolic framework
- YAML-based configuration system
    - For portability and reproducibility

Test Environments

- Three environments (cartpole, 1D quadrotor, and 2D quadrotor)
- Two tasks (stabilization and trajectory tracking) with increasing difficulty





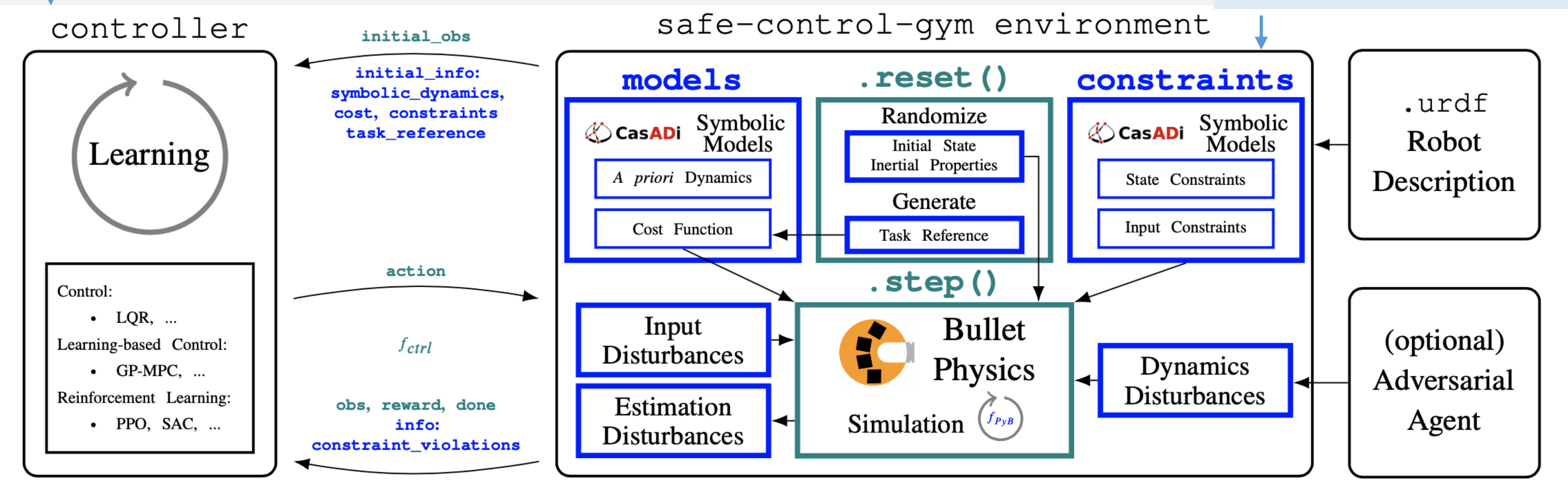
safe-control-gym: a Unified Benchmark Suite

safe-control-gym
https://github.com/utiasDSL/safe-control-gym

gym architecture

Software Architecture

symbolic prior dynamics, cost, and constraints



LQR	GP-MPC	Robust Adversarial RL
Iterative LQR	Soft Actor Critic	MPC Safety Filter
Linear MPC	Proximal Policy Optimization	Control Barrier Certification

Related Discussions
(from Recent Workshops)

Safety Definitions and Requirements for Real-World Applications

Opportunities and Challenges in Developing Robot Learning Algorithms

Benchmark, Challenges, Evaluation to Bridge the Gap Between Theory and Practice

Z. Yuan, A. W. Hall, S. Zhou, L. Brunke, M. Greeff, J. Panerati, and A. P. Schoellig
safe-control-gym: a Unified Benchmark Suite for Safe Learning-based Control and Reinforcement Learning in Robotics

safe-control-gym: a Unified Benchmark Suite

3 Environments

- Cartpole
- 1D Quadrotor
- 2D Quadrotor

2 Tasks (for each system)

- Stabilization to fixed points
- Tracking given trajectories

10+ Implemented Algorithms

- PID
- Linear Quadratic Regulator (LQR)
- Model-predictive control (MPC)
- RL agents (PPO, SAC)
- *your algorithm…*

safe-control-gym Public

PyBullet CartPole and Quadrotor environments—with CasADi symbolic a priori dynamics—for learning-based control and RL

Python 445 96

`Repo: https://github.com/utiasDSL/safe-control-gym`

Related Publications (* Equal Contribution)

[1] L. Brunke*, M. Greeff*, A. W. Hall*, Z. Yuan*, S. Zhou*, J. Panerati, and A. P. Schoellig, “Safe learning in robotics: From learning-based control to safe reinforcement learning,” *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 5, 2021. [pdf]

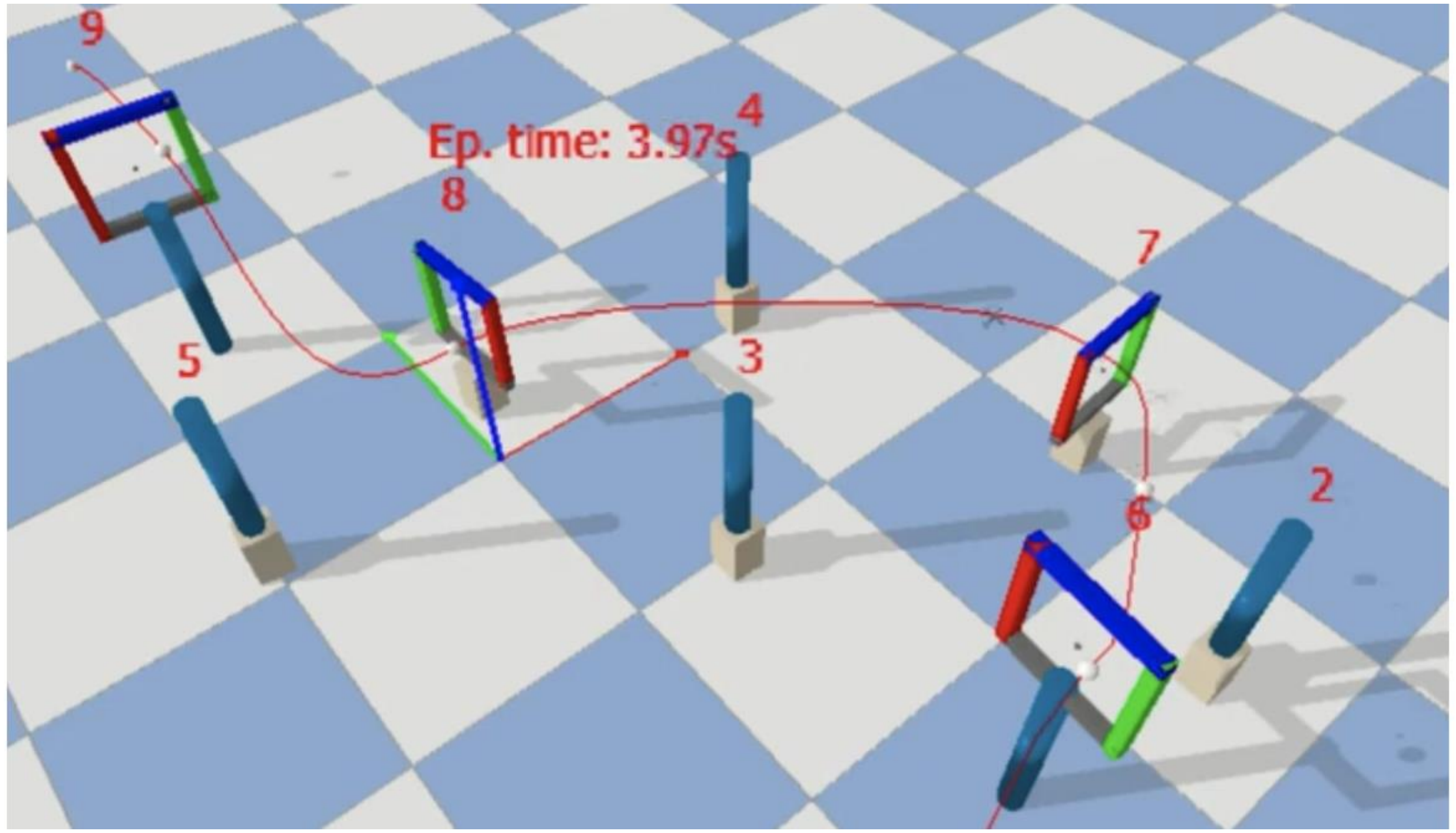
[2] Z. Yuan, A. W. Hall, S. Zhou, L. Brunke, M. Greeff, J. Panerati, and A. P. Schoellig, "Safe-control-Gym: A unified benchmark suite for safe learning-based control and reinforcement learning in robotics," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11142-11149, 2022. [pdf]

IROS Safe Robot Learning Competition and Beyond

Objective: design a controller/planner for a Crazyflie 2.x quadrotor to safely slalom through a set of gates and reach a target

Challenge: uncertainties in the robot dynamics (e.g., mass and inertia) and the environment (e.g., wind, position of the gates).

Participants were encouraged to explore both control and reinforcement learning approaches (e.g., robust, adaptive, predictive, learning-based and optimal control, and model-based/model-free RL).

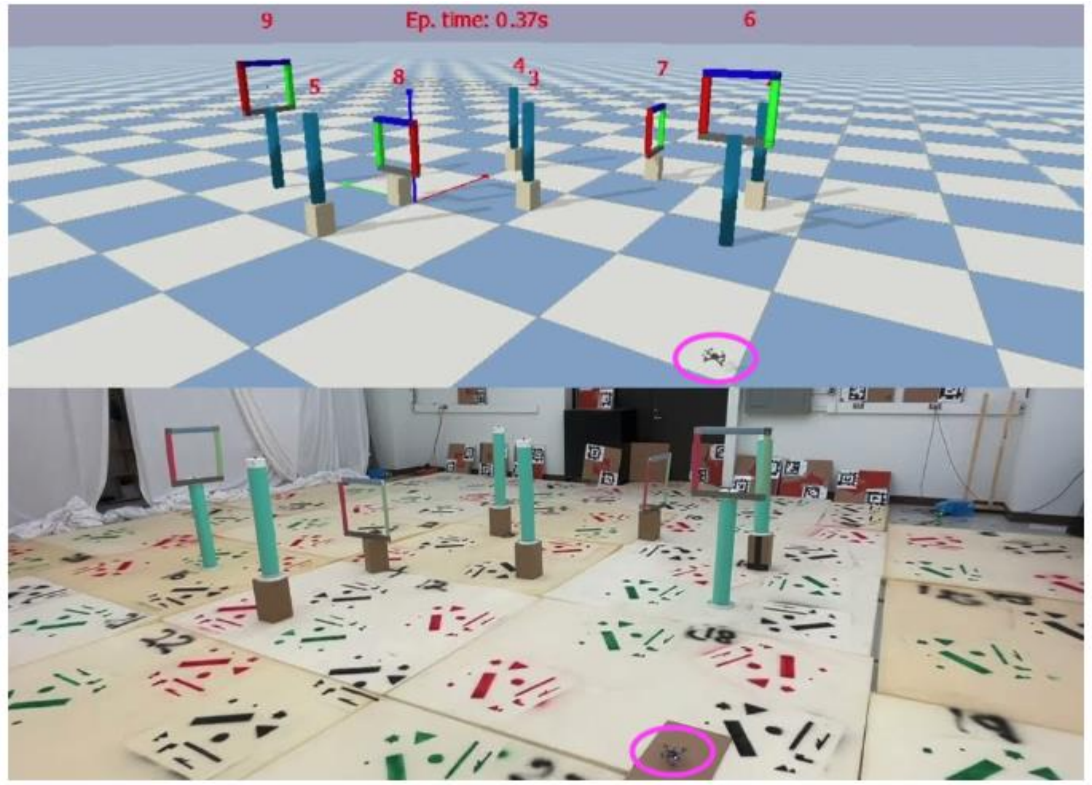


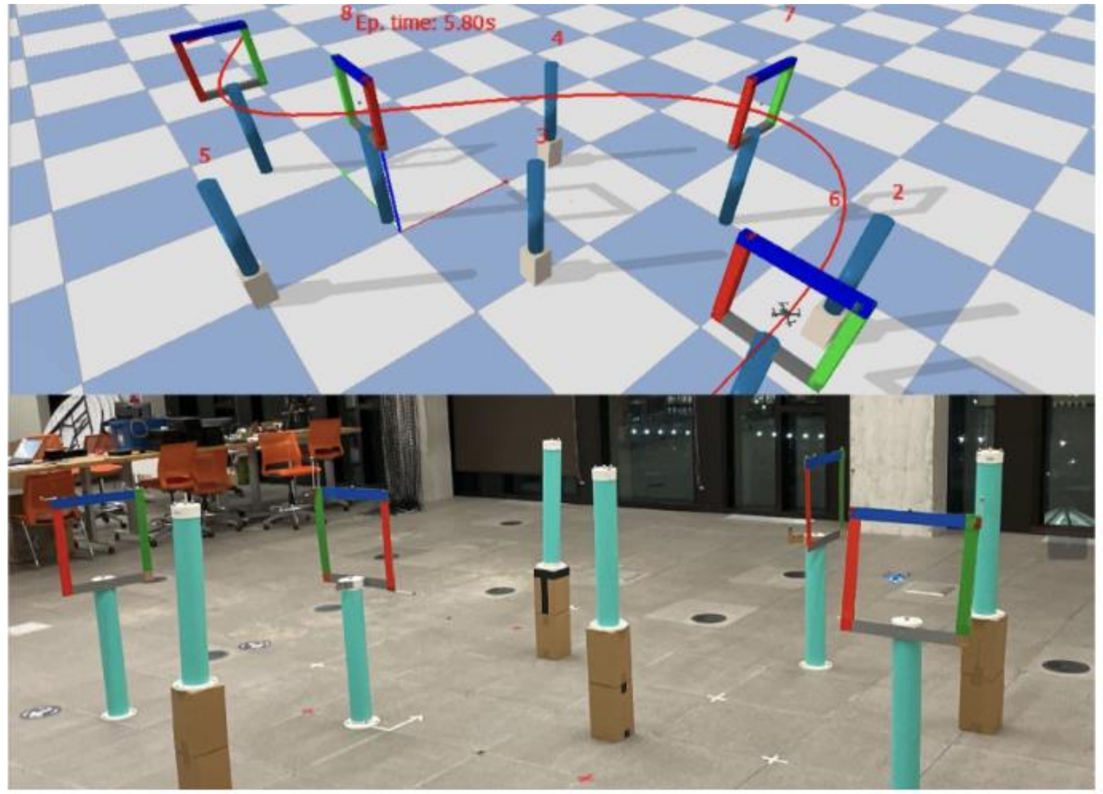
[1] Teetaert S, Zhao W, Xinyuan N, Zahir H, Leong H, Hidalgo M, Puga G, Lorente T, Espinosa N, Carrasco JA, Zhang K. A Remote Sim2real Aerial Competition: Fostering Reproducibility and Solutions' Diversity in Robotics Challenges. arXiv preprint arXiv:2308.16743. 2023 Aug 31.

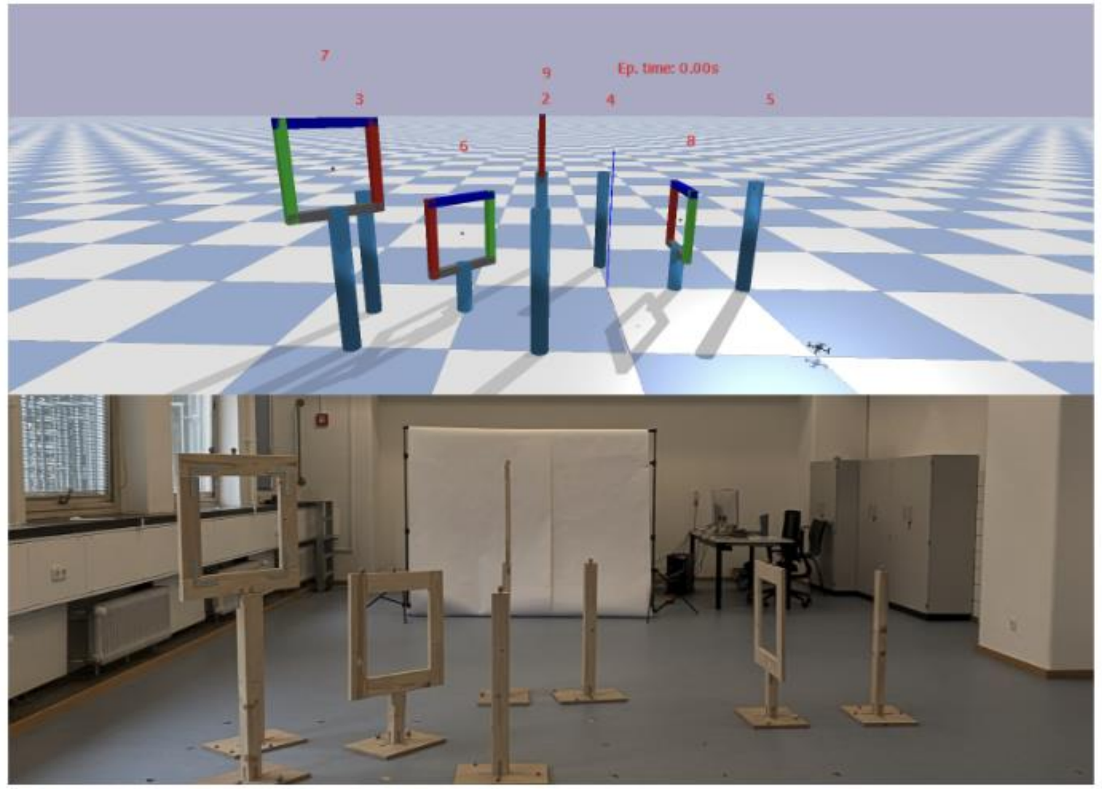
IROS Competition Code Base | https://github.com/utiasDSL/safe-control-gym/tree/beta-iros-competition

IROS Safe Robot Learning Competition and Beyond

Evaluation Scenario	Constraints	Rand. Inertial Properties	Randomized Obstacles, Gates	Rand. Between Episodes	Notes
level 0	**Yes**	*No*	*No*	*No*	Perfect knowledge
level 1	**Yes**	**Yes**	*No*	*No*	Adaptive
level 2	**Yes**	**Yes**	**Yes**	*No*	Learning, re-planning
level 3	**Yes**	**Yes**	**Yes**	**Yes**	Robustness
sim2real	**Yes**	Real-life hardware	**Yes**, injected	*No*	Sim2real transfer

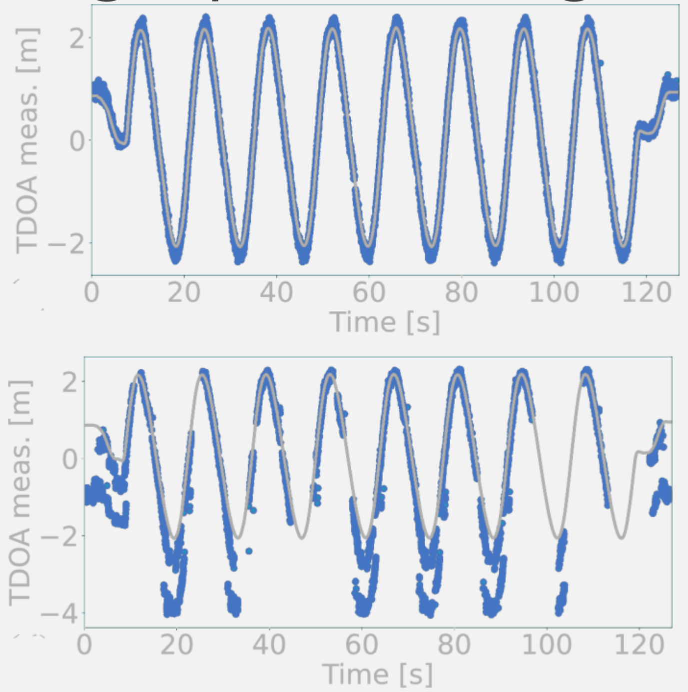






A World of Abundant Data

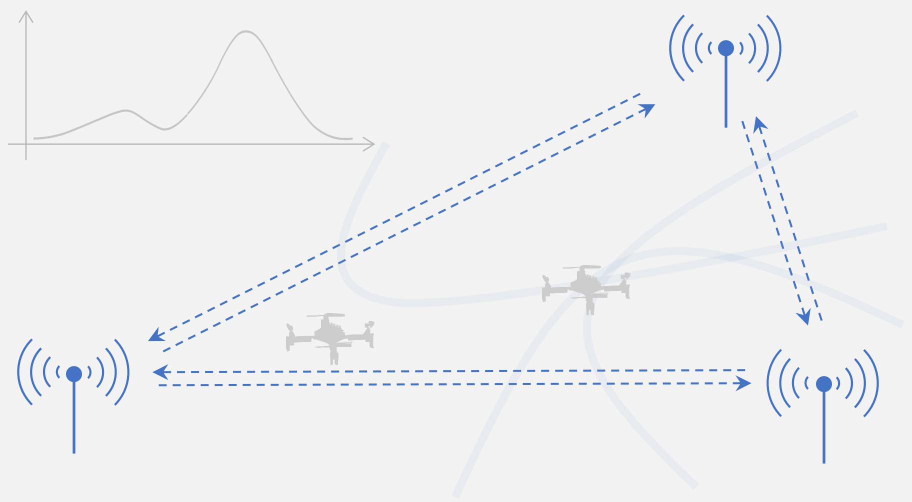
Part III
Simulation Tools and Datasets for
Scaling Up Swarming Tasks



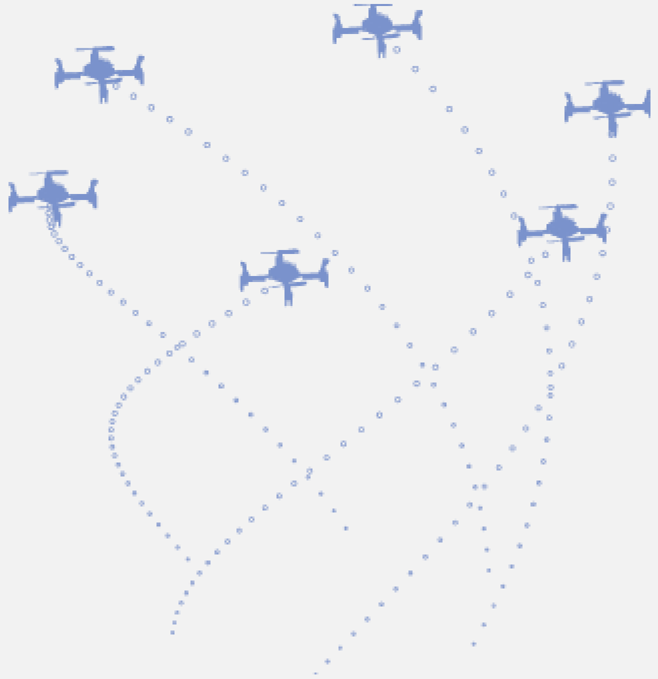
- UTIL dataset facilitating reliable estimation algorithm design in real-world cluttered environments
- gym-pybullet-drones providing abundant simulation data for learning complex tasks
- safe-control-gym bridging the gap between learning-based control and safe reinforcement learning
- sim2real aerial competition fostering reproducibility and solutions' diversity in robotics challenges

Safe Decision-Making for Aerial Swarms

Part I
Robust Range-Based Methods
for
Reliable Aerial Swarm
Localization



Part II
Control Theoretic Approaches
for
Efficient Swarm Coordination



Part III
Simulation Tools and Datasets
for
Scaling Up Swarming Tasks