Distributed and Safe Autonomy for AI-enabled Multi-Robot Systems in Unstructured Environments

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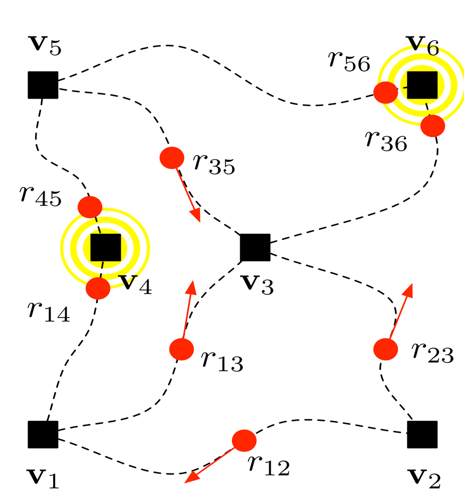
Motivation: Mobile robot teams operate in environments with unknown and possibly dynamic geometric and semantic structure that are often communication-denied. Successful mission planning in such unstructured environments requires (i) novel distributed coordination frameworks; (ii) a principled integration of AI-enabled perception with planning/control; (ii) adaptation to disruptive events (e.g., robot failures, adversarial environments); and (iv) learning-enabled controllers that can account for uncertainty in the system dynamics.

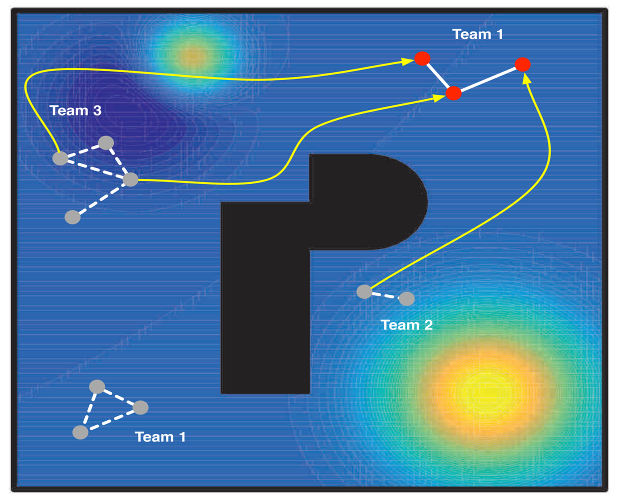
Distributed Multi-Robot Coordination in Communication-denied Environments

Problem: Design intermittent connectivity controllers for multi-robot systems.

Key Idea: Robots temporarily operate in disconnect mode to accomplish their tasks and occasionally return to connected configurations.

Next Steps: Relax the assumption of known environment. Currently, the robots know where to meet again.



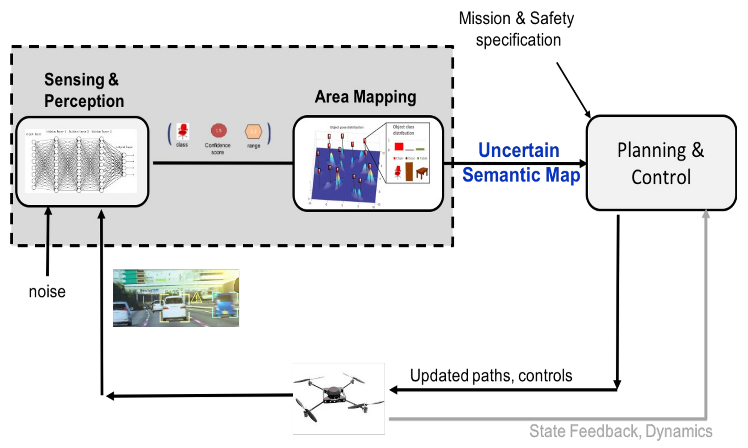


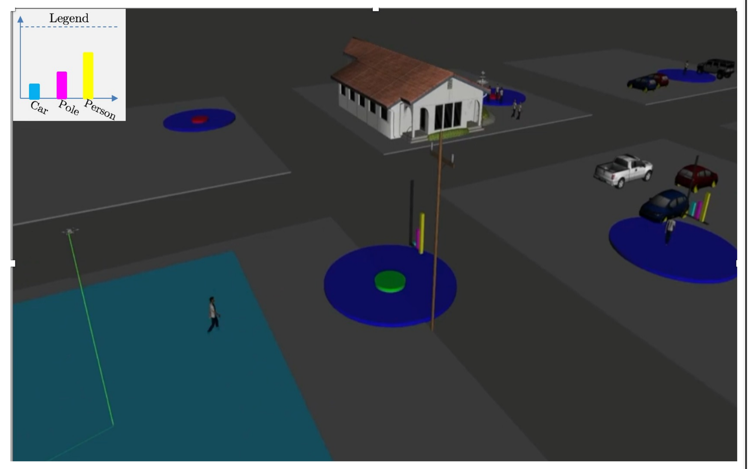
[TRO 2016, TAC 2017, TAC 2019, TRO 2019]

Perception-based Semantic Planning in Unknown and Dynamic Environments

Problem: Design perception-based controllers for multi-robot systems with semantic tasks in unknown/dynamic semantic worlds.

Key Idea: Sampling-based algorithm exploring robot motion space, mission space, and environmental uncertainty.





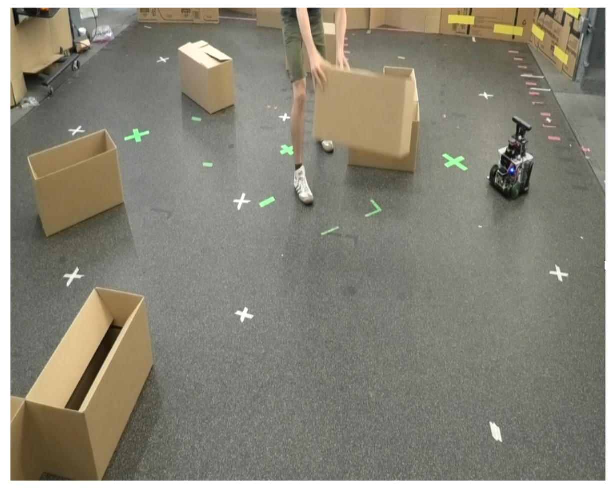
Next Steps: Robust planning to perceptual errors/failures (e.g., due to OOD data)

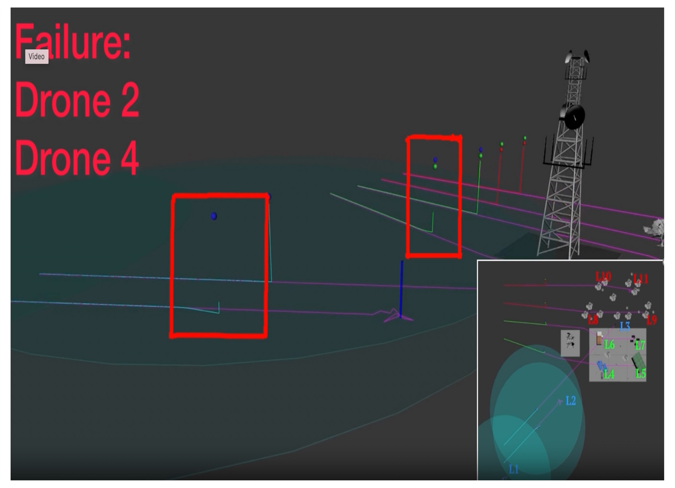
[RSS 2019, AURO 2021, TRO 2022, ICRA 2020-2023]

Robust Multi-Robot Planning to Disruptive Events

Problem: Design mission planners that can quickly adapt to (i) environmental changes and (ii) robot failures.

Key Idea: We focus on missions captured by Linear Temporal Logic (LTL) formulas. We leverage automaton representations of LTL missions and sampling-based planners to locally (i) re-plan when the environment changes; (ii) re-allocate tasks to robots when failures occur.





Next Steps: Adaption to dynamic missions and safety requirements.

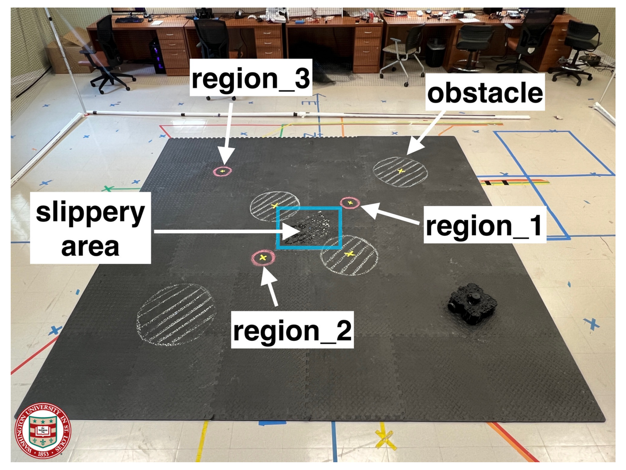
[ICRA 2020, 2021, 2022]

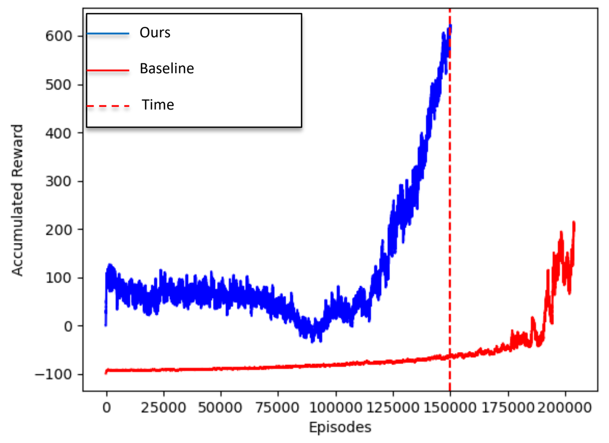
Provably Safe and Sample-Efficient Reinforcement Learning with Formal Specifications

Problem: Learn controllers that maximize the probability of satisfying mission and safety requirements expressed as Linear Temporal Logic (LTL) formulas in the presence of uncertainty in the dynamics and the environment.

Key Idea: Leverage automata theory to design `correct' rewards (safe learning) and guide exploration (sample-efficiency)

Next Steps: Consider high-dimensional states and tasks going beyond navigation (e.g., locomotion)





[CDC 2019, ICCPS 2019, IJRR 2020, IROS 2022, CDC 2023]

Broader Impacts:

- Applications to environmental monitoring, infrastructure inspection, and autonomous driving
- Established collaboration with the Institute of School Partnership at WashU to provide research experience to high school students and teachers
- Leading the undergraduate WashU robotics club.
- Designed new graduate classes at WashU on safe AI-enabled robotics.
- Promoting diversity in STEM (e.g., Women in CS programs at WashU)

2023 FRR & NRI Principal Investigators' Meeting
May 2-3, 2023