Homogeneous and Heterogeneous Multi-Robot Coverage

Guillaume Sartoretti

Assistant Professor, National University of Singapore

Multi-Agent Ergodic Coverage

- Many search and surveillance applications have prior information, e.g., target distributions, information from scouting missions, satellite images, etc.

- Coverage tasks benefit greatly from high cooperation levels in the team, e.g., to distribute agents, avoid redundant work, or even leverage individual agent capabilities/synergies.

- Ergodic coverage offers a unique and natural means to tackle homogeneous and heterogeneous coverage problems in the presence of prior knowledge.

Outline

- Homogeneous Teams
  - Reminder on SA Ergodic Planning
  - Sequential MA Planning
  - Examples

- Heterogeneous Teams
  - Spectral-Based Distribution
  - Systematic Investigation

Background on Ergodic Trajectory Optimization

- Reminder: we seek paths that minimizes the Ergodic metric

$$\boldsymbol{\Phi}(\gamma, \xi) = \sum_{k=0}^{m} \alpha_k \left(c_k(\gamma(t)) - \xi_k \right)^2$$

$m = 100$

Number of Fourier coefficients

$$\alpha_k = \sqrt{(1 + k^2)^{-(d+1)}}$$

normalizing coefficients

$\gamma = [x_0, \ldots, x_{T-1}]$

Robot trajectory

$\xi(x)$

Utility function

$$c_k(\gamma(t)) = \frac{1}{T} \sum_{t=0}^{T-1} F_k(x_t)$$

Time-averaged trajectory statistics

$$\xi_k = \int_X F_k(x) \xi(x) dx$$

Utility distribution

[1] Mathew, G., Mezìc, I.: Metrics for ergodicity and design of ergodic dynamics for multi-agent systems. Physica D: Nonlinear Phenomena 240(4), 432–442 (2011)

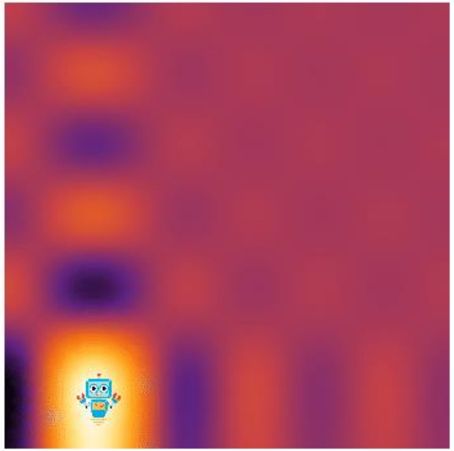
Background on Ergodic Trajectory Optimization

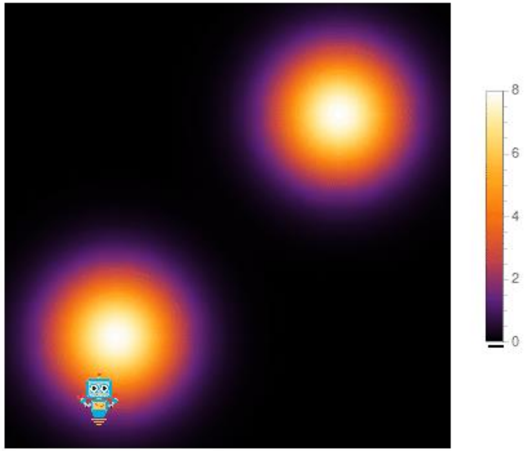
- Find controls that minimize the Ergodic metric

$$\boldsymbol{u}^* = \arg\min_u \boldsymbol{\Phi}(\gamma, \xi)$$

- subject to dynamic constraints

$$\text{subject to } \dot{\boldsymbol{q}} = f(\boldsymbol{q}(t), \boldsymbol{u}(t))$$

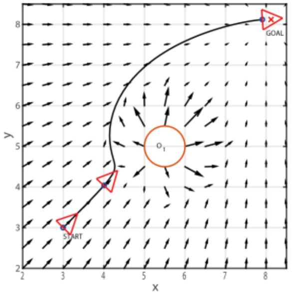




[1] Mathew, G., Mezić, I.: Metrics for ergodicity and design of ergodic dynamics for multi-agent systems. Physica D: Nonlinear Phenomena 240(4), 432–442 (2011)

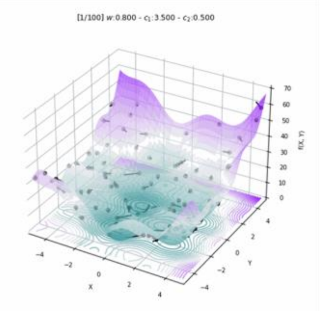
Stochastic Trajectory Optimization

- Deterministic vs Stochastic trajectory optimization
- Example of DTO: Artificial Potential Field, A*, etc.
- Example of STO: Rapidly exploring random tree, Particle swarm optimization, simulated annealing, Bayesian optimization, etc.



APF [4]

RRT [5]


PSO[6]

- In our case, we use sampling-based cross-entropy planning [3]

[3] Kobilarov, M. (2012). Cross-Entropy Randomized Motion Planning. Robotics: Science and Systems VII, 153.
[4] Fedele, G. (2018). Obstacles avoidance based on switching potential functions. Journal of Intelligent & Robotic Systems, 90, pp.387-405.
[5] LaValle, Steven M. (1998). Rapidly-exploring random trees: A new tool for path planning. Technical Report (TR 98–11).
[6] Axel Thevenot. https://towardsdatascience.com/particle-swarm-optimization-visually-explained-46289eeb2e14

Sampling-based Cross-Entropy Ergodic Planning

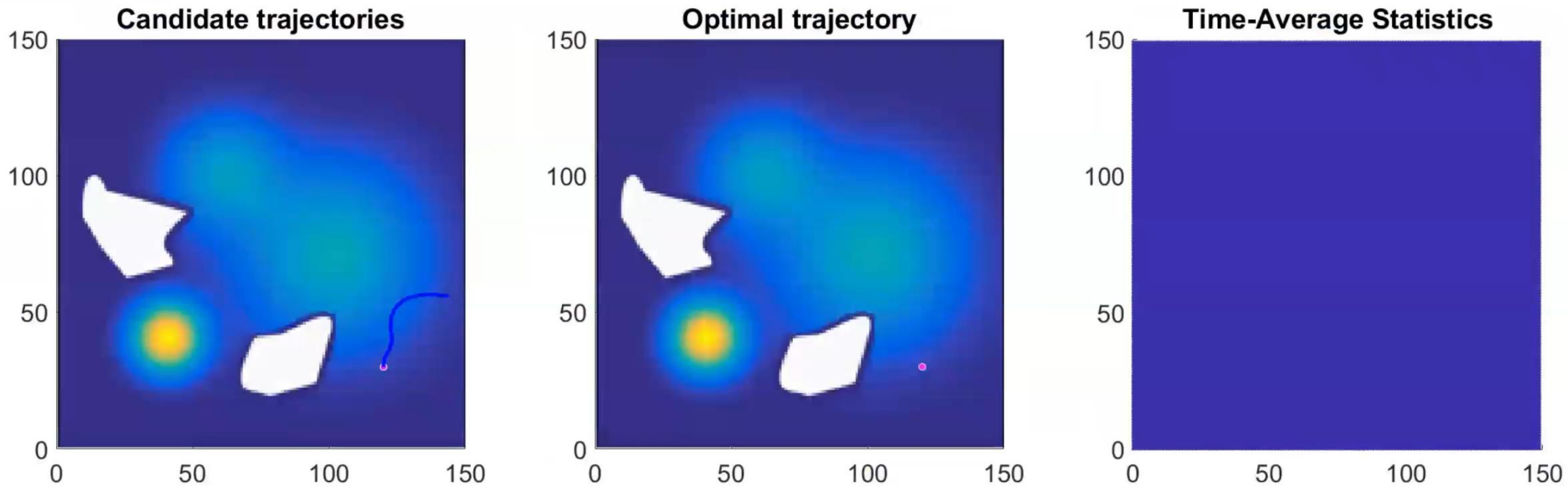
- Dubins car model with state $q = (x, y, \theta)$ of coordinates and orientation
$$\dot{x} = u\, cos\theta, \quad \dot{y} = u\, sin\theta, \quad \dot{\theta} = v$$

- Define primitives based on forward velocity v and turning rate w (based on the agent's dynamics)
  - straight lines (constant velocity v, and w = 0)
  - arcs of radius v/w (v,w ≠ 0)

- Importance sampling and evaluation on ergodicity at each timestep
  - Starting from the previous ending position
  - Sample a set of trajectories, each a sequence of primitives ($z = [v_1, w_1, v_2, w_2, \dots, v_n, w_n]$)
  - Calculate Ergodicity and update sampling distribution using elite trajectories
  - Iterate above steps until converge

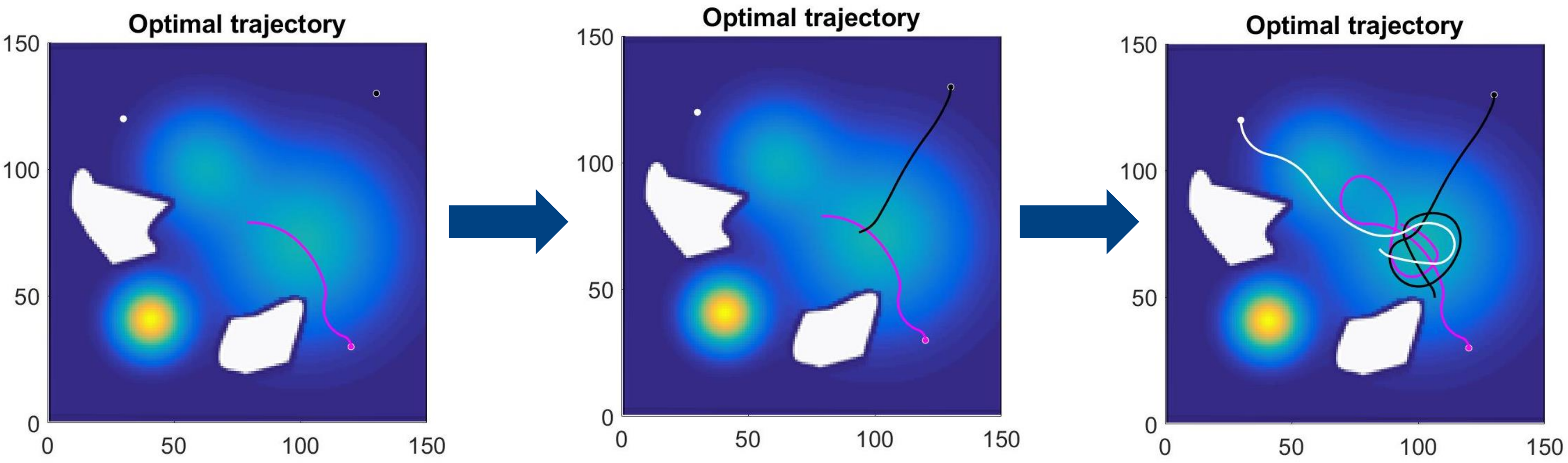
[3] Kobilarov, M. (2012). Cross-Entropy Randomized Motion Planning. Robotics: Science and Systems VII, 153.

Single agent Cross-Entropy Ergodic Planning



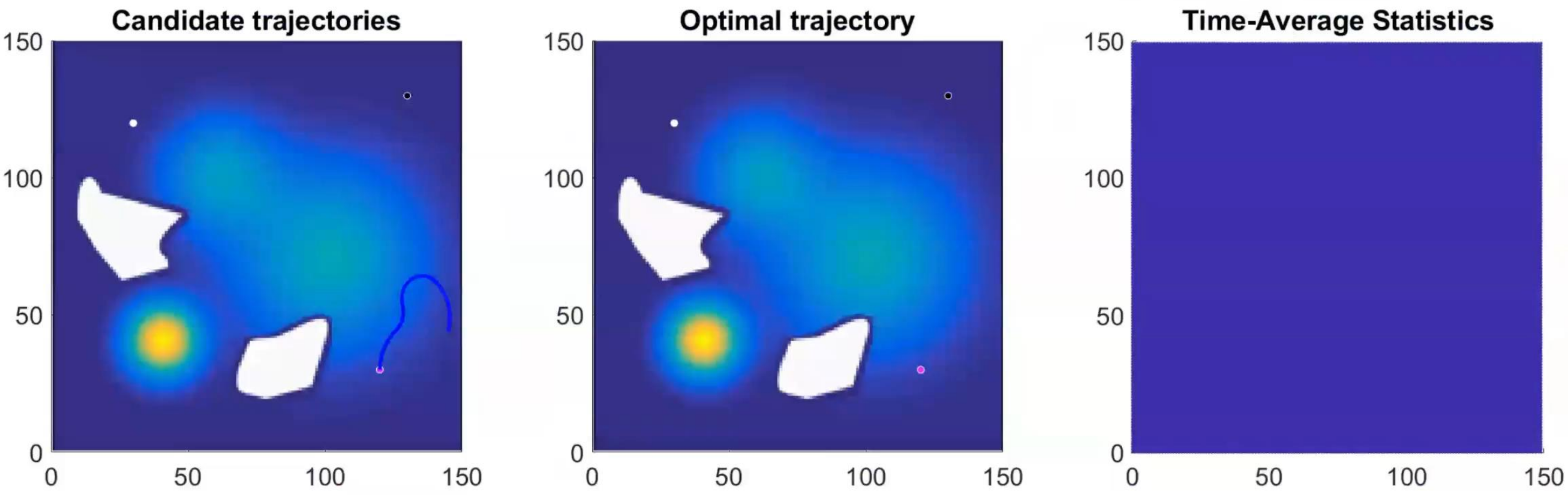
Homogeneous Multi-Agent Ergodic Planning

- Sequential MA Ergodic planning: For each agent
  - get current time accumulated statics conditioned on all previous planned agents
  - plan a current optimal trajectory (using SA planner)
  - renormalize time accumulated statics for the next decision agent



Agent 1's trajectory | Agent 2's trajectory | After several iterations

Multi agent Cross-Entropy Ergodic Planning



Outline

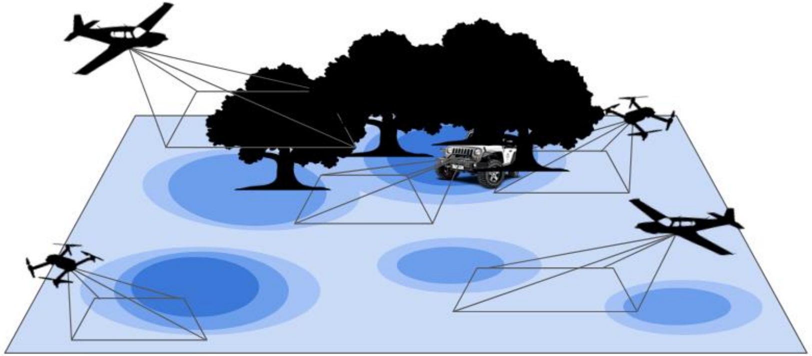
- Homogeneous Teams
  - Reminder on SA Ergodic Planning
  - Sequential MA Planning
  - Examples

- Heterogeneous Teams
  - Spectral-Based Distribution
  - Systematic Investigation

Cooperation in Heterogeneous Teams

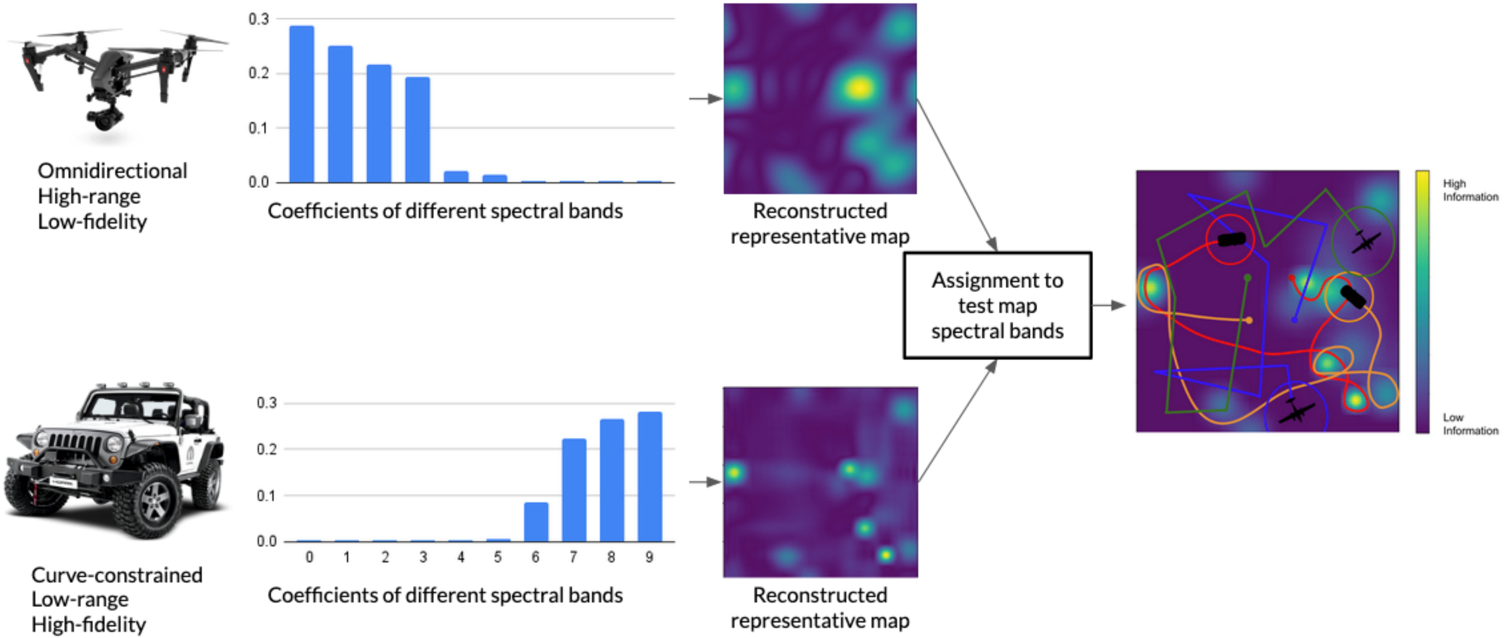
https://medium.com/@oluwafemidiakhoa/the-convergence-of-human-ambition-and-artificial-intelligence-c45f8e7371bf

https://www.nasaspaceflight.com/2021/03/nasa-preparing-ingenuity-enabling-future-missions/



Heterogeneous Ergodic-Based Distribution

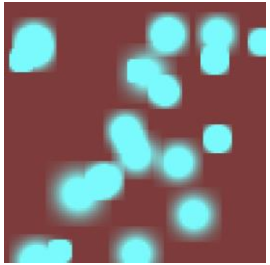
- Key Idea: Let agents identify/leverage their own capabilities
  - Distribution of heterogeneous agents directly in the spectral domain
  - Spectral bands encode information at different scales, matching their individual motion/sensing capabilities

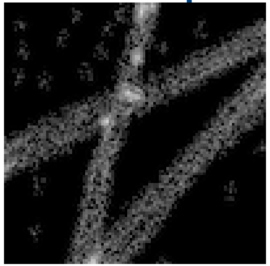


*Guillaume Sartoretti, Ananya Rao, & Howie Choset. Spectral-based Distributed Ergodic Coverage for Heterogeneous Multi-Agent Search. DARS 2021 (**Best Paper Award**).*

Simulation results

- Fixed, randomly generated search problems over Gaussian-based and road network information maps

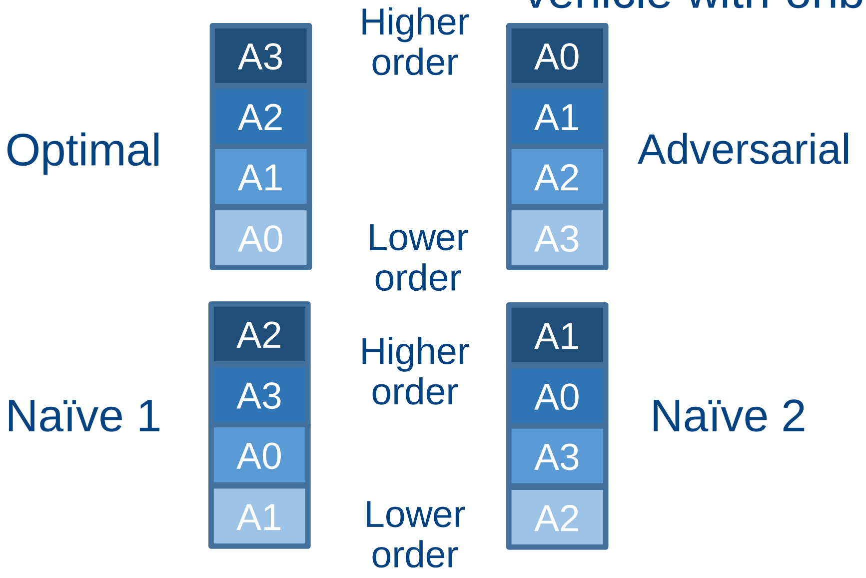




- Teams: mix of agents with different Gaussian sensor footprints
- Cross-entropy planner, based on path primitives

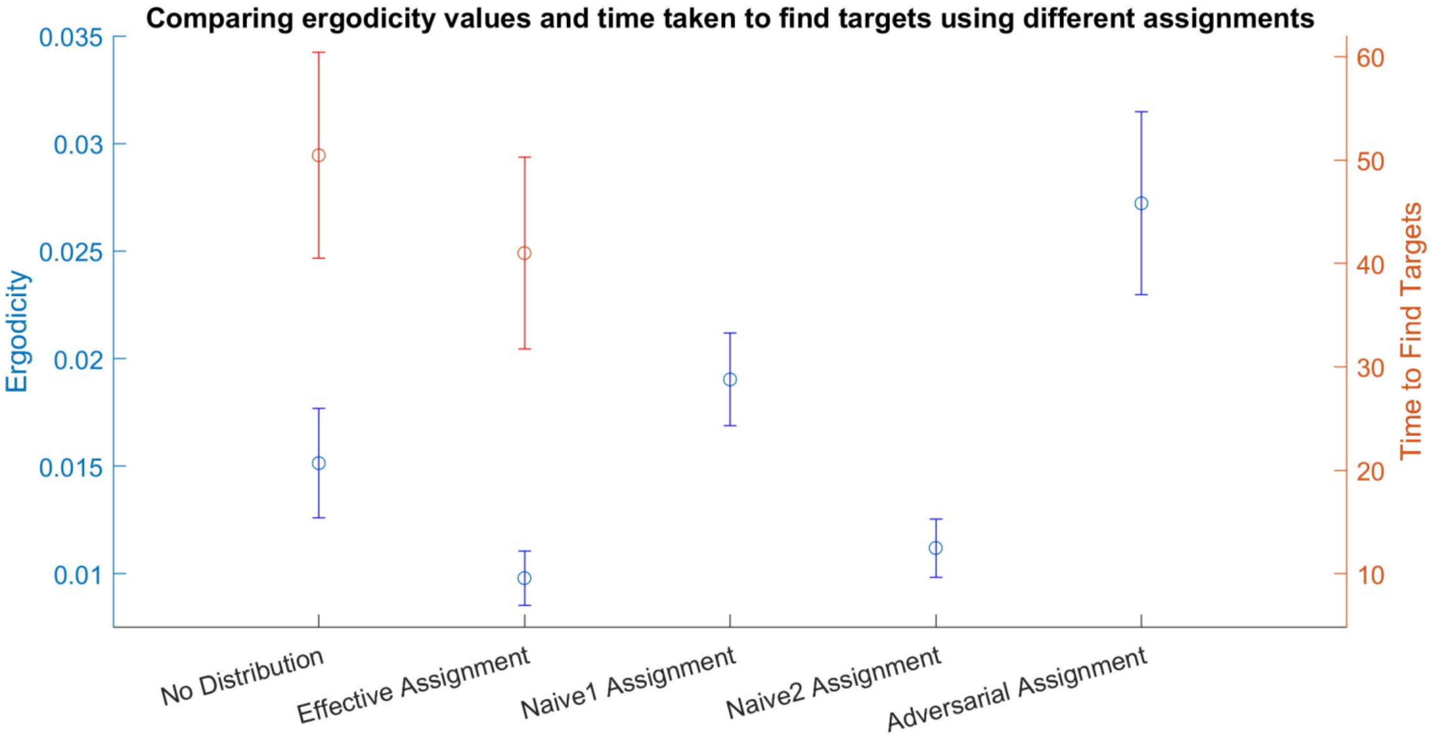
Agent Types and Assignments

- A0: low-fidelity, high-range sensor, omnidirectional motion model (e.g., UAV flying at high altitude)
- A2: high-fidelity, low-range sensor, omnidirectional motion model
- A1: low-fidelity, high-range sensor, curve-constrained motion model
- A3: high-fidelity, low-range sensor, curve-constrained motion model (e.g., ground vehicle with onboard LiDAR)

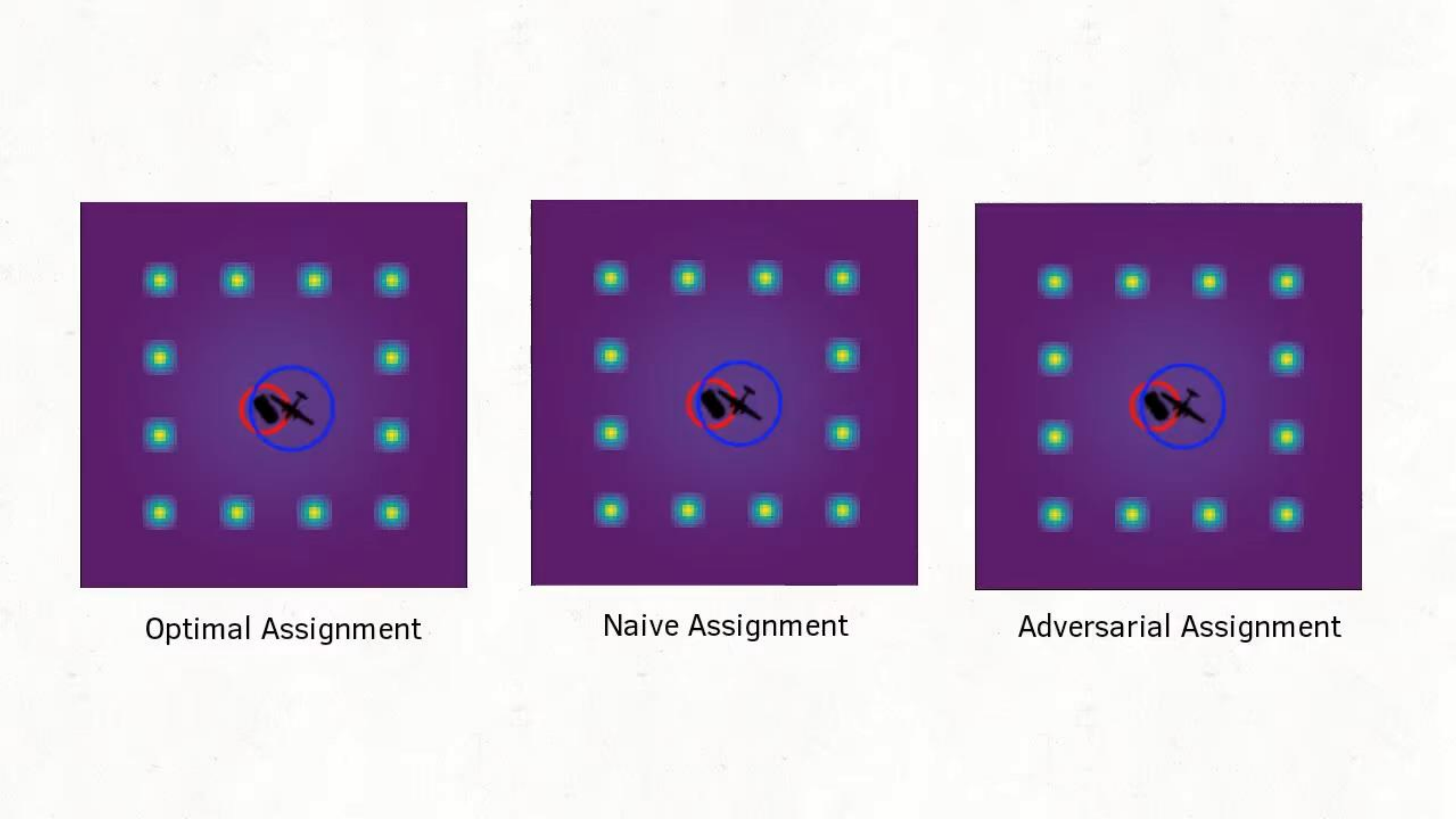


Simulation results

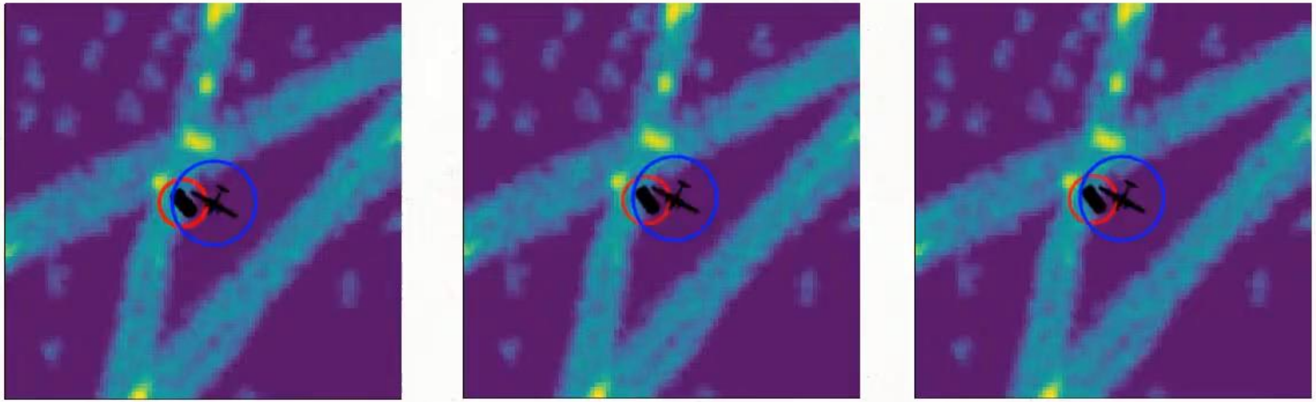
- 40% improvement in coverage efficiency, 15% in time to find all targets



Simulation results



Simulation results



Optimal Assignment | Naive Assignment | Adversarial Assignment

Summary

- Multi-Agent Coverage benefits from high cooperation to help distribute agents, avoid redundant work, and even leverage individual capabilities/synergies within the team

- Single-Agent Ergodic Planning can be naturally extended to offer these advantages
  - Sequential planning
  - Joint Planning feasible, but more expensive (cannot scale well)
  - Heterogeneous distribution of the agents in spectral domain

- Interesting note: paths with lower Ergodicity often correlate with better time to find discrete targets (in addition to better balancing exploration/exploitation of prior information).