

Online Submodular Coordination with Bounded Tracking Regret: Theory, Algorithm, and Applications to Multi-Robot Coordination

Zirui Xu, Hongyu Zhou, Vasileios Tzoumas

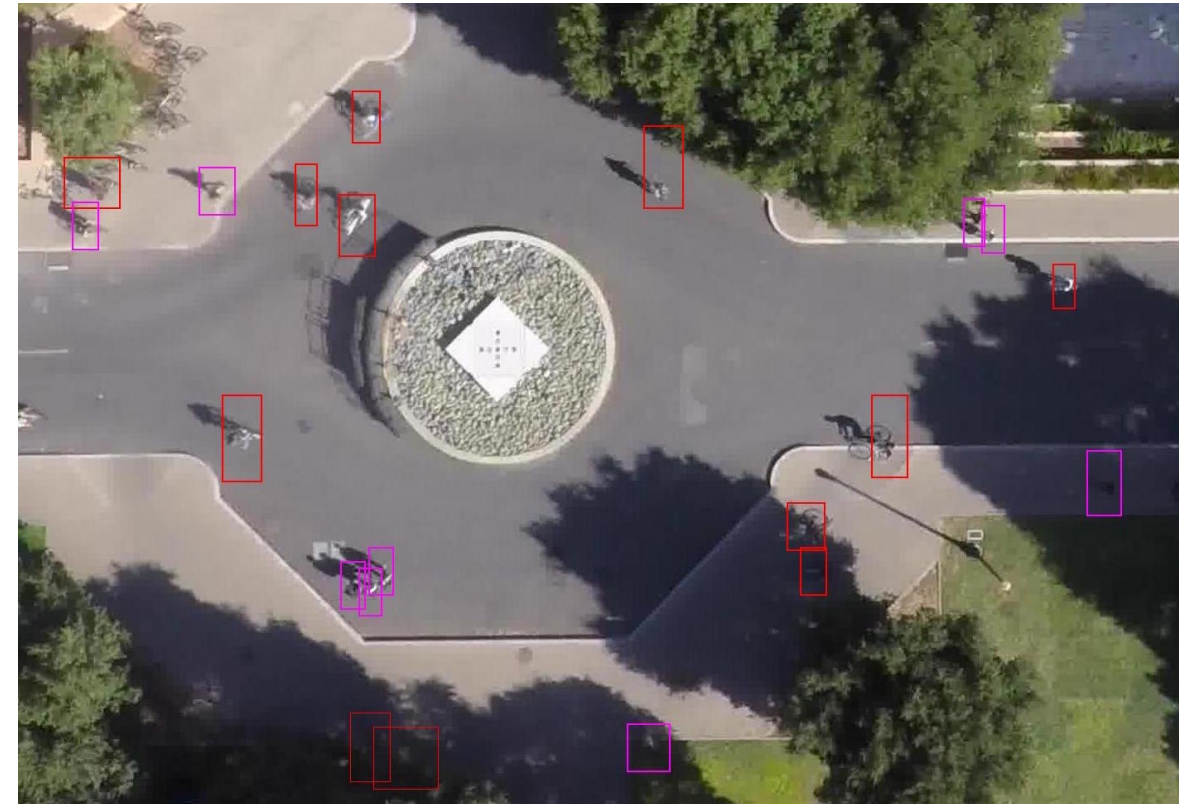


Multi-Robot Coordination Problems

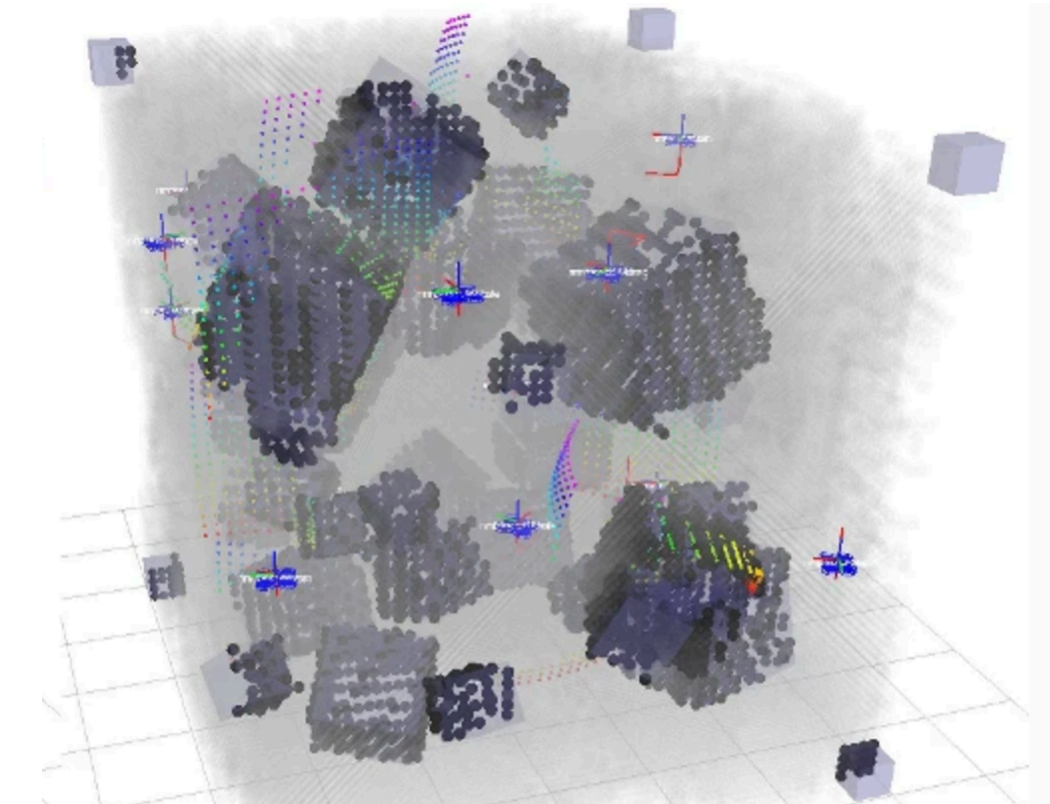
Environmental Monitoring



Target Tracking



Visual Mapping



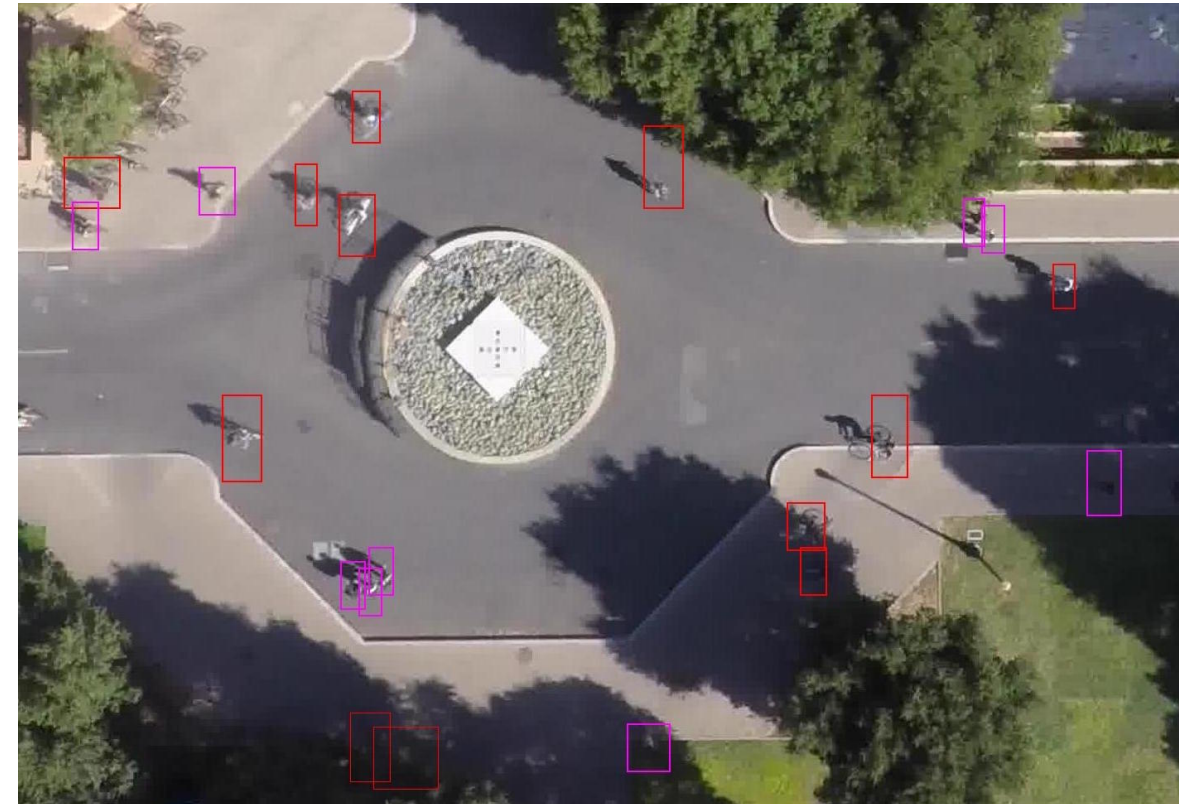
Goal: Robots need to coordinate their actions to complete complex tasks

Multi-Robot Coordination Problems

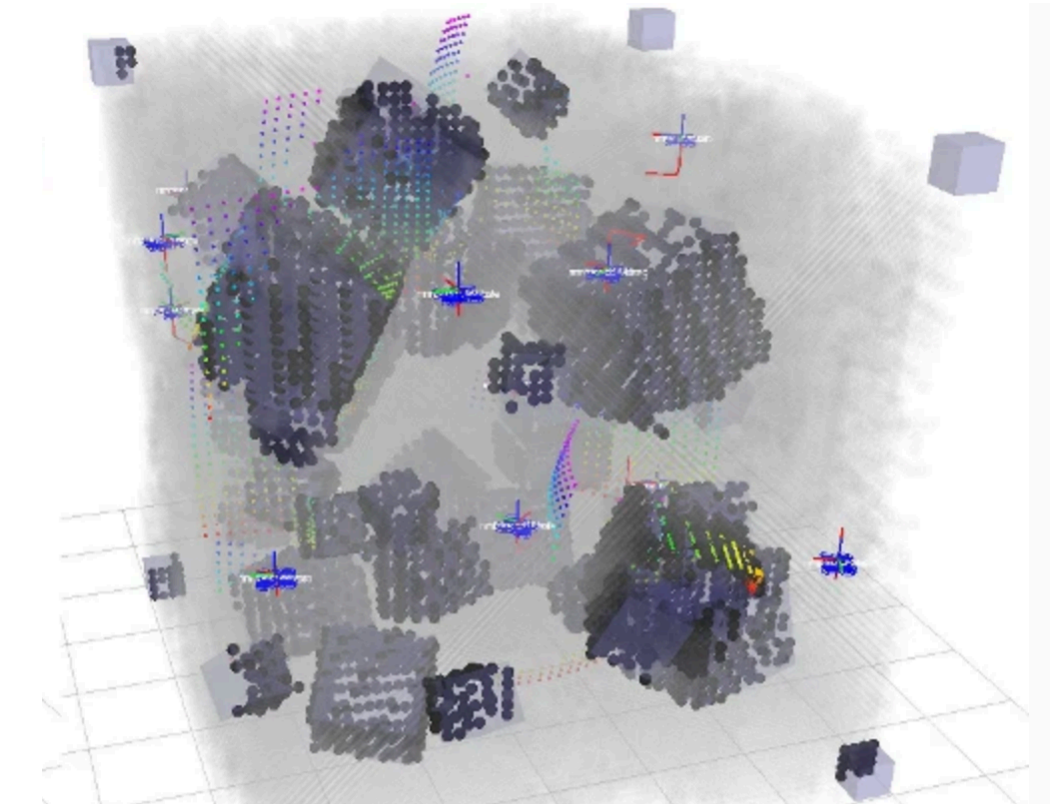
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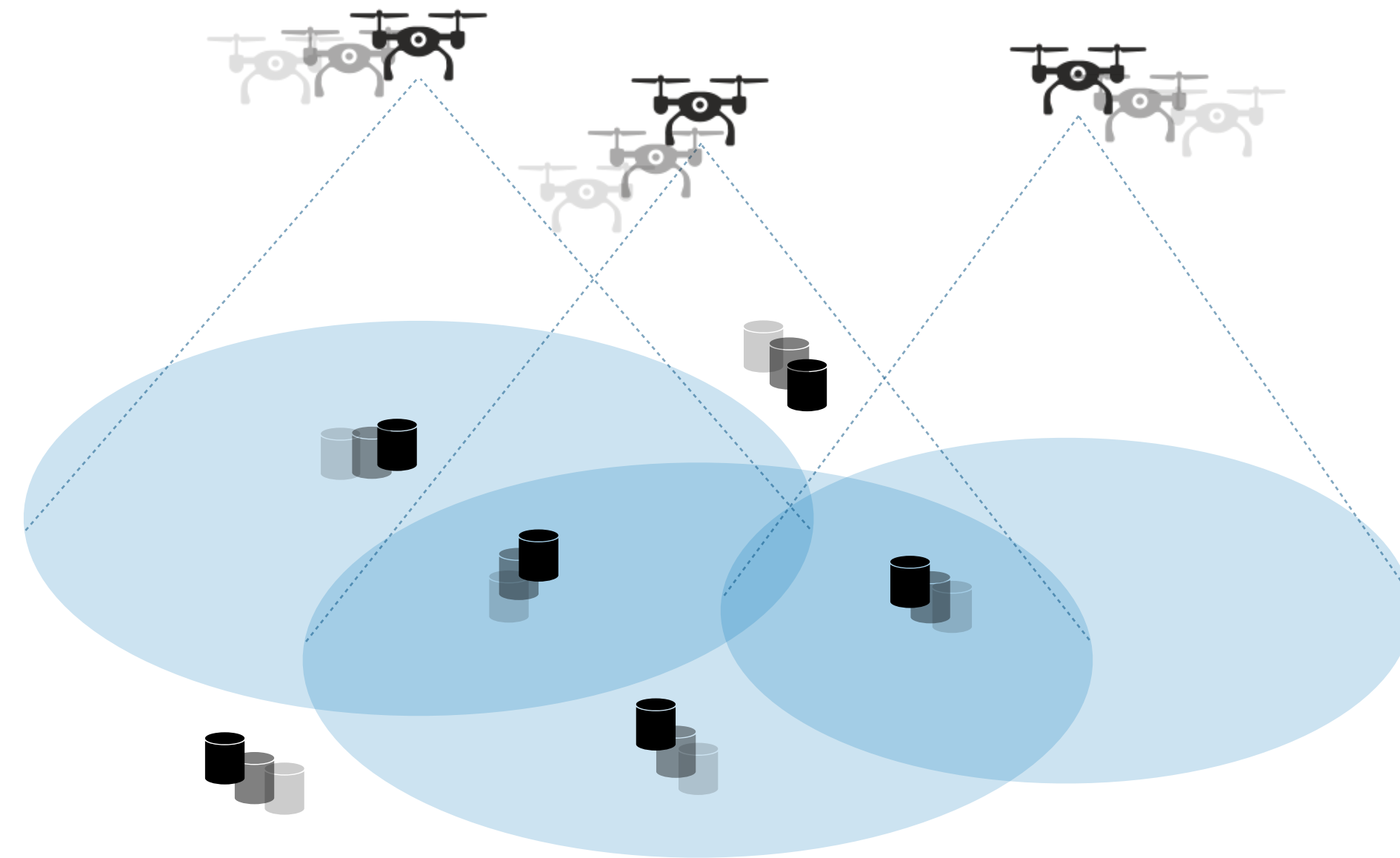
Goal: Robots need to coordinate their actions to complete complex tasks

Challenges: Such multi-robot information-gathering tasks are challenging because:

- I. Actions of different robots have **information overlap**.
- II. The environment can be **unpredictable**.

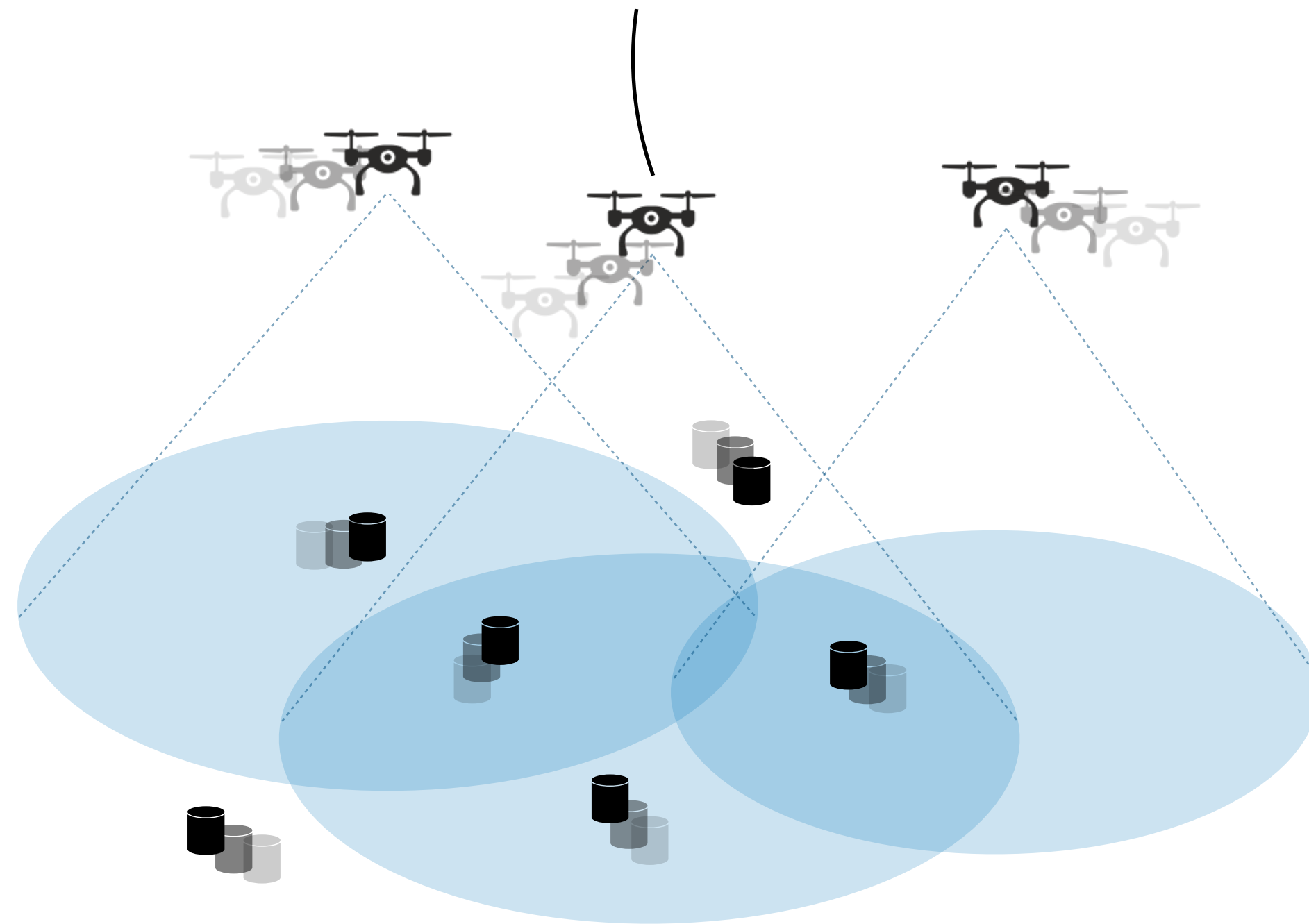
In-Depth Look of Challenges: Target-Tracking Case

Goal: Maximize the number of moving targets tracked by the drones' field of view

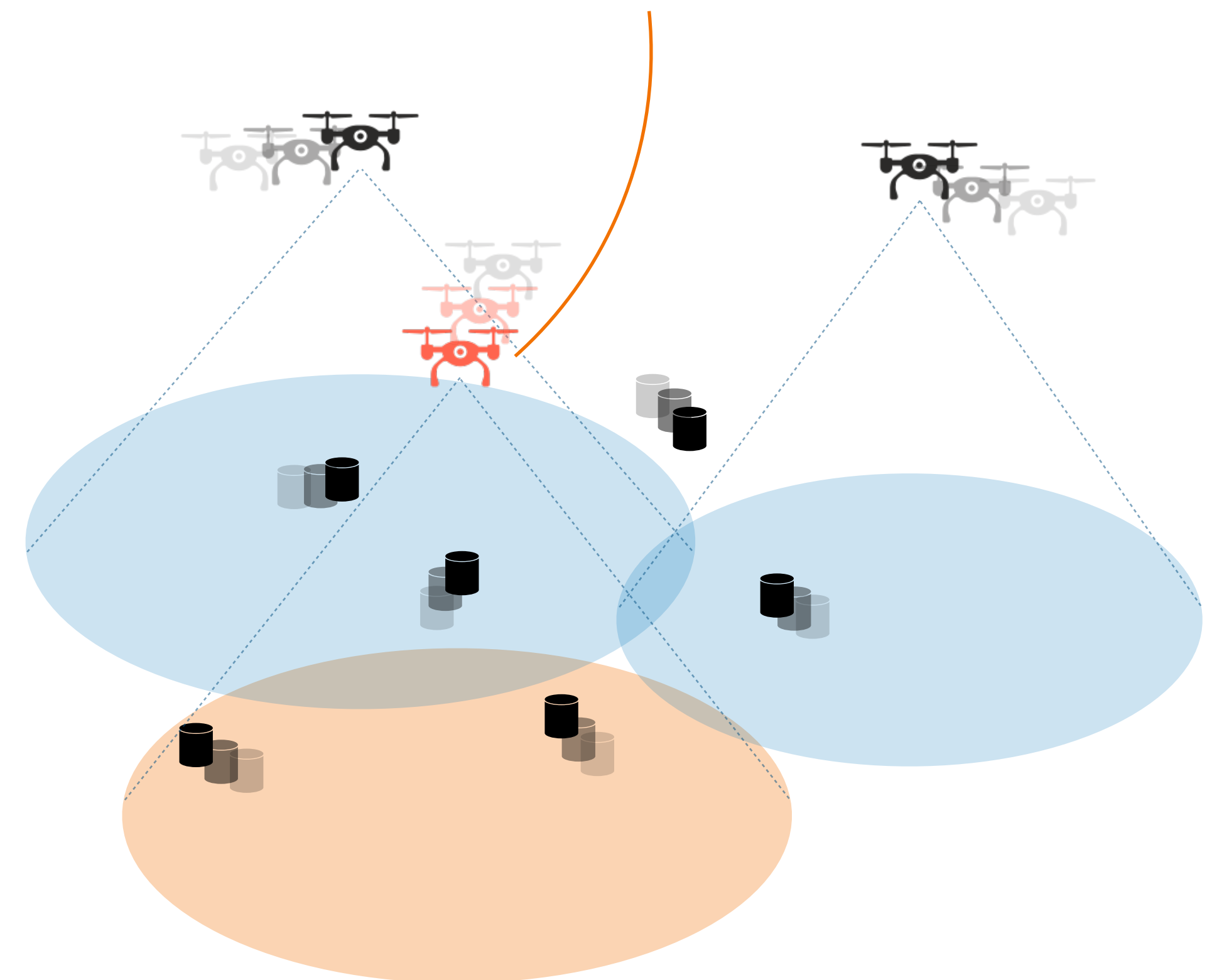


Challenge I (**Utility Overlap**): Compromises Actions' Effect

Using action 1: 4 targets tracked in total

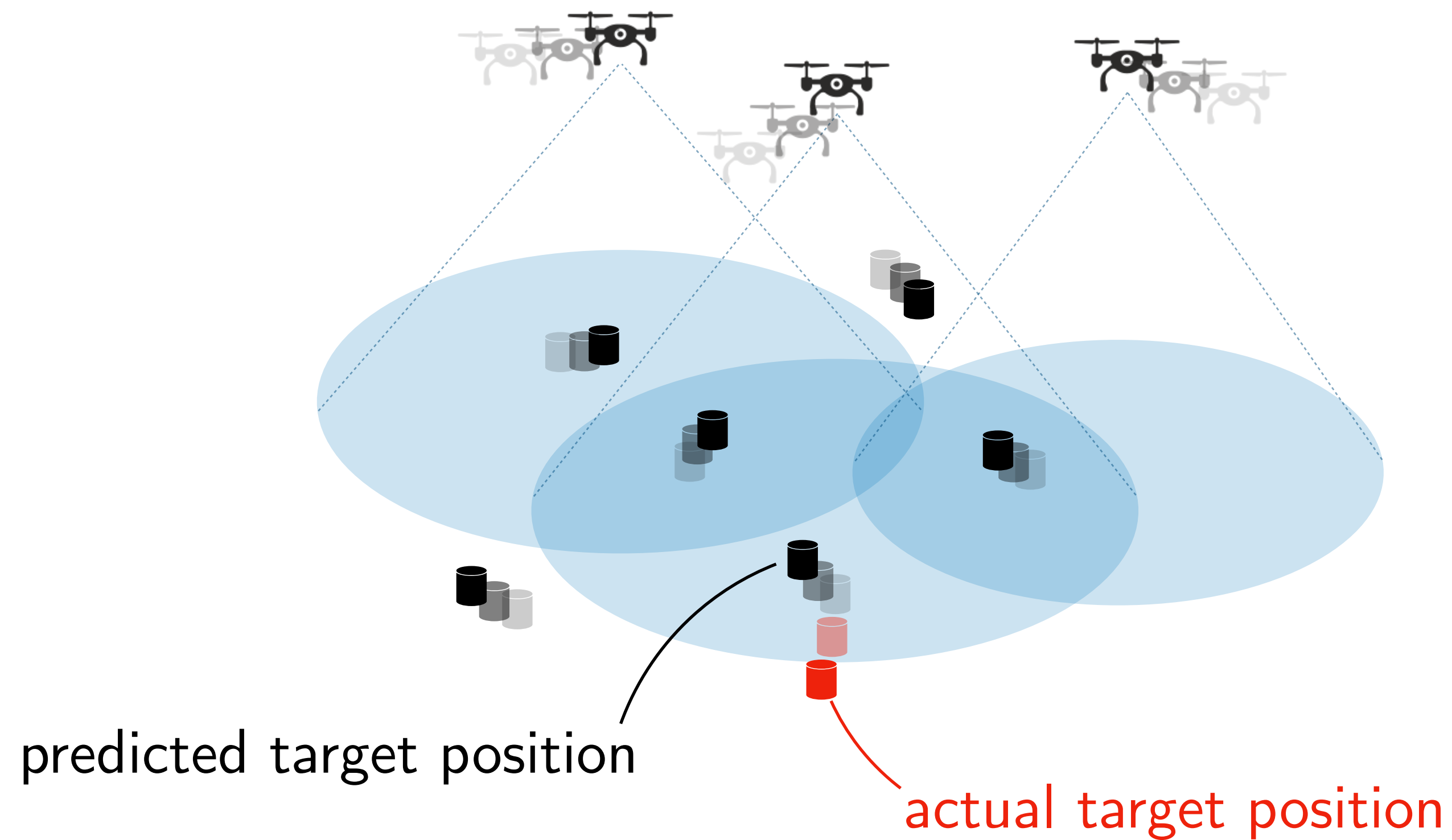


Using action 2: 5 targets tracked in total



To overcome Challenge I: Robots need to coordinate to minimize utility overlap

Challenge II (**Unpredictability**): Compromises Ability to Evaluate Actions A Priori



To overcome Challenge II: Robots need to select actions based on past information only

Current Coordination Paradigm Cannot Address the Challenges

Offline monotone submodular maximization with known environment:¹

Given:

- robots \mathcal{N}
- finite action sets $\mathcal{V}_i, \forall i \in \mathcal{N}$
- set function $f: 2^{\prod_{i \in \mathcal{N}} \mathcal{V}_i} \mapsto \mathbb{R}$

the robots \mathcal{N} select actions $\{a_i\}_{i \in \mathcal{N}}$ to solve

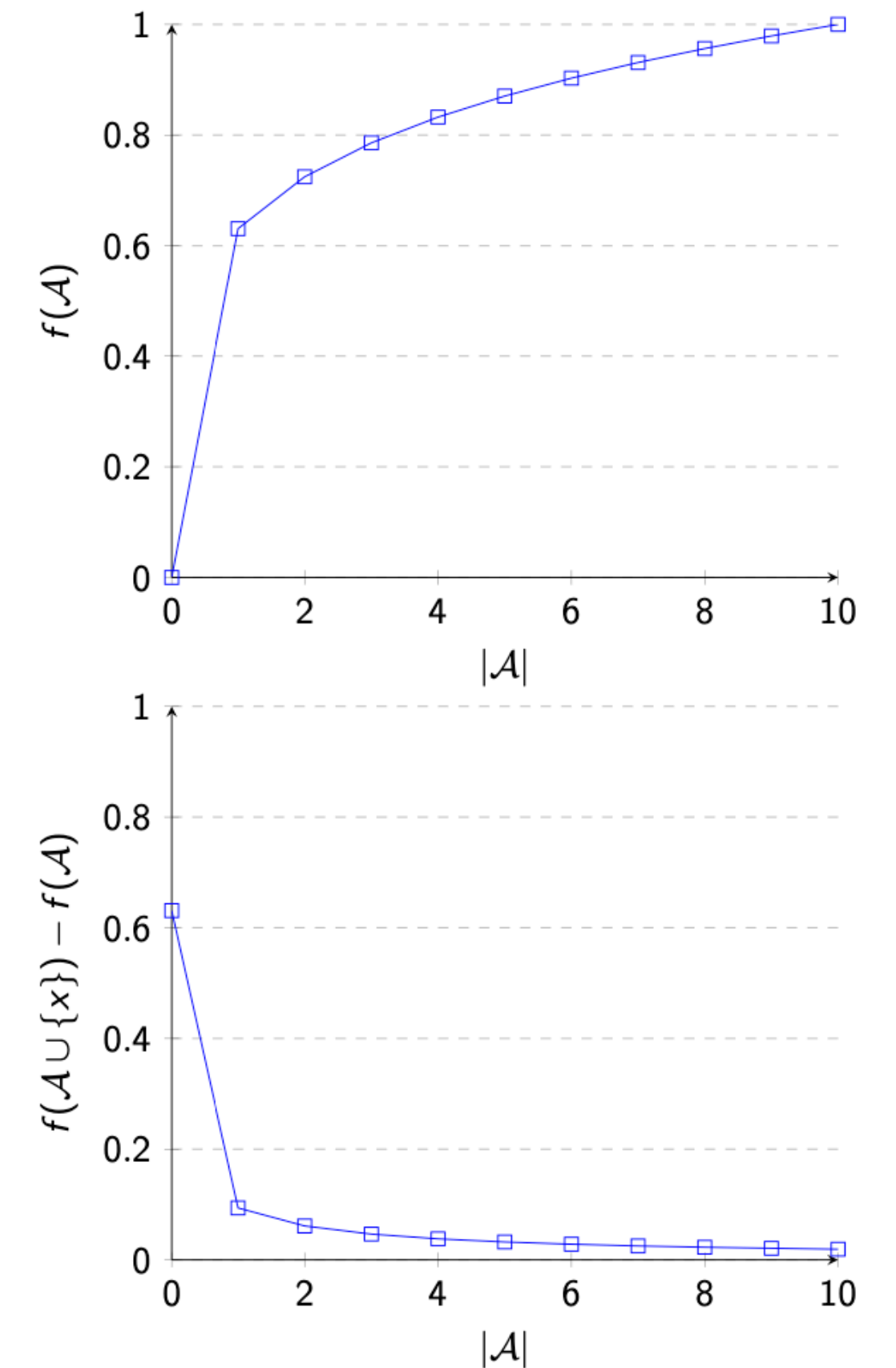
$$\max_{a_i \in \mathcal{V}_i, \forall i \in \mathcal{N}} f(\{a_i\}_{i \in \mathcal{N}})$$

known a priori

non-decreasing

submodular

(due to information overlap)



¹Atanasov; Bilmes; Bushnell; Calinescu; Chekuri; Clark; Corah; Gharesifard; Hassani; Hespanha; Iyer; Karbasi; Kia; Konda; Krause; Li; Marden; Martinez; Michael; Mirzasoleiman; Mokhtari; Pappas; Poovendran; Rezazadeh; Robey; Smith; Sundaram; Tokekar; ...

Problem (Online Submodular Coordination)

Given:

- time horizon T
- robots \mathcal{N}
- finite action sets $\mathcal{V}_i, \forall i \in \mathcal{N}$

at each time step $t \in [T]$, the robots \mathcal{N} select actions $\{a_{i,t}\}_{i \in \mathcal{N}}$ **online** to solve

$$\text{online feedback} \quad \max_{a_{i,t} \in \mathcal{V}_i, \forall i \in \mathcal{N}} f_t(\{a_{i,t}\}_{i \in \mathcal{N}}) \quad \text{non-decreasing submodular}$$

where f_t becomes known to the robots \mathcal{N} only once $\{a_{i,t}\}_{i \in \mathcal{N}}$ are executed

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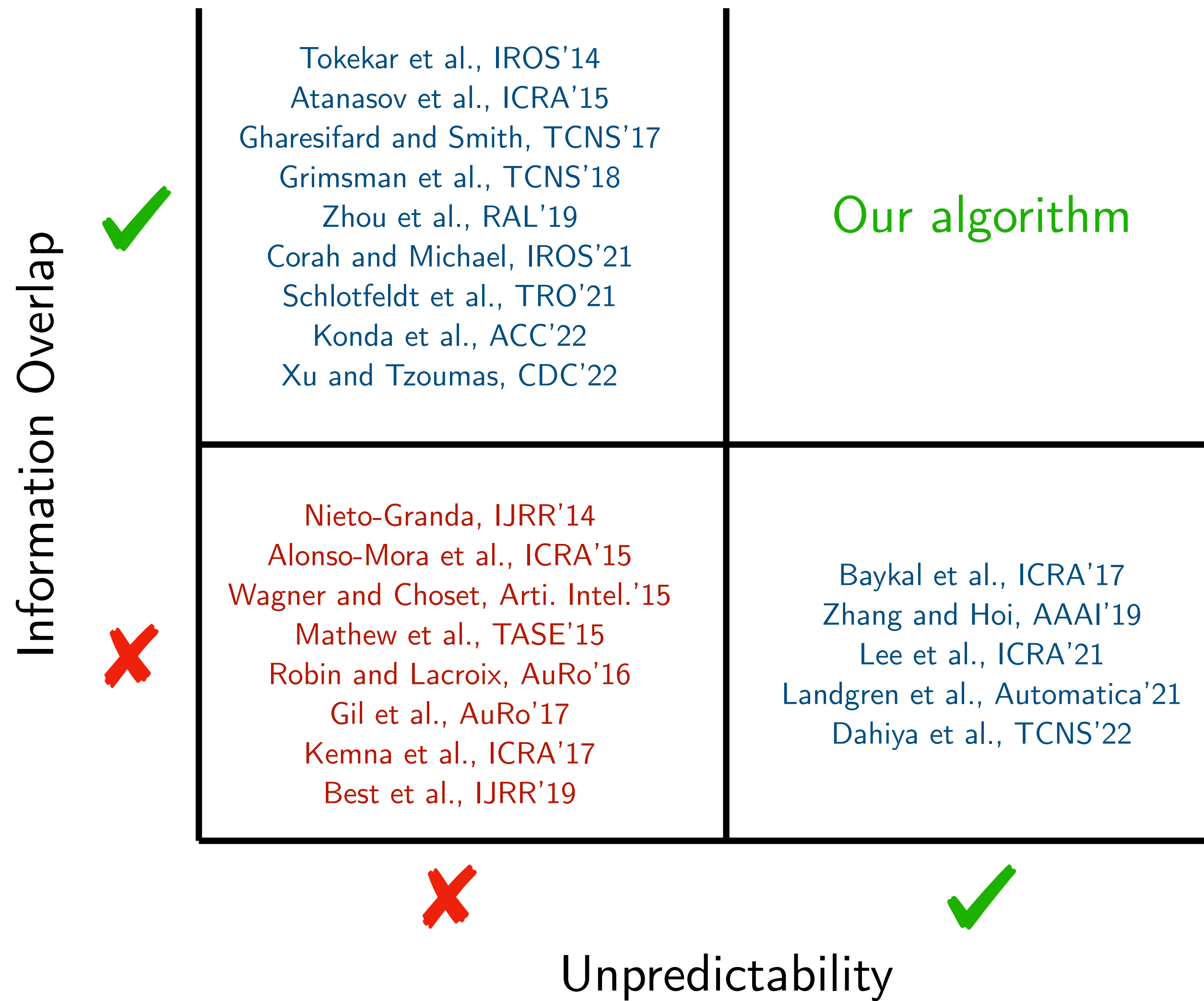
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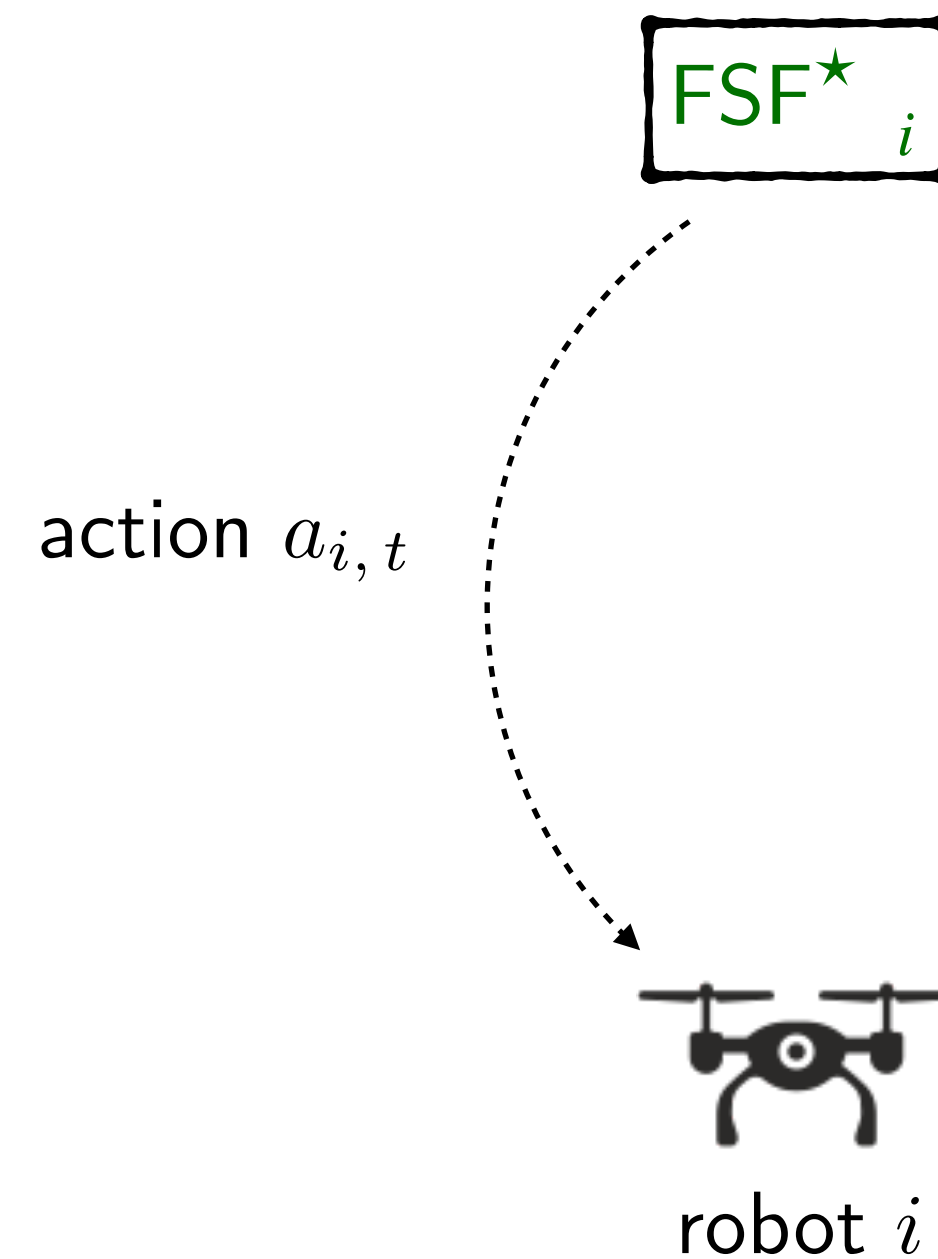
Difficulty: **NP-Hard** to achieve approximation bound better than $1/2$ even when f_t is known a priori

State of the Art



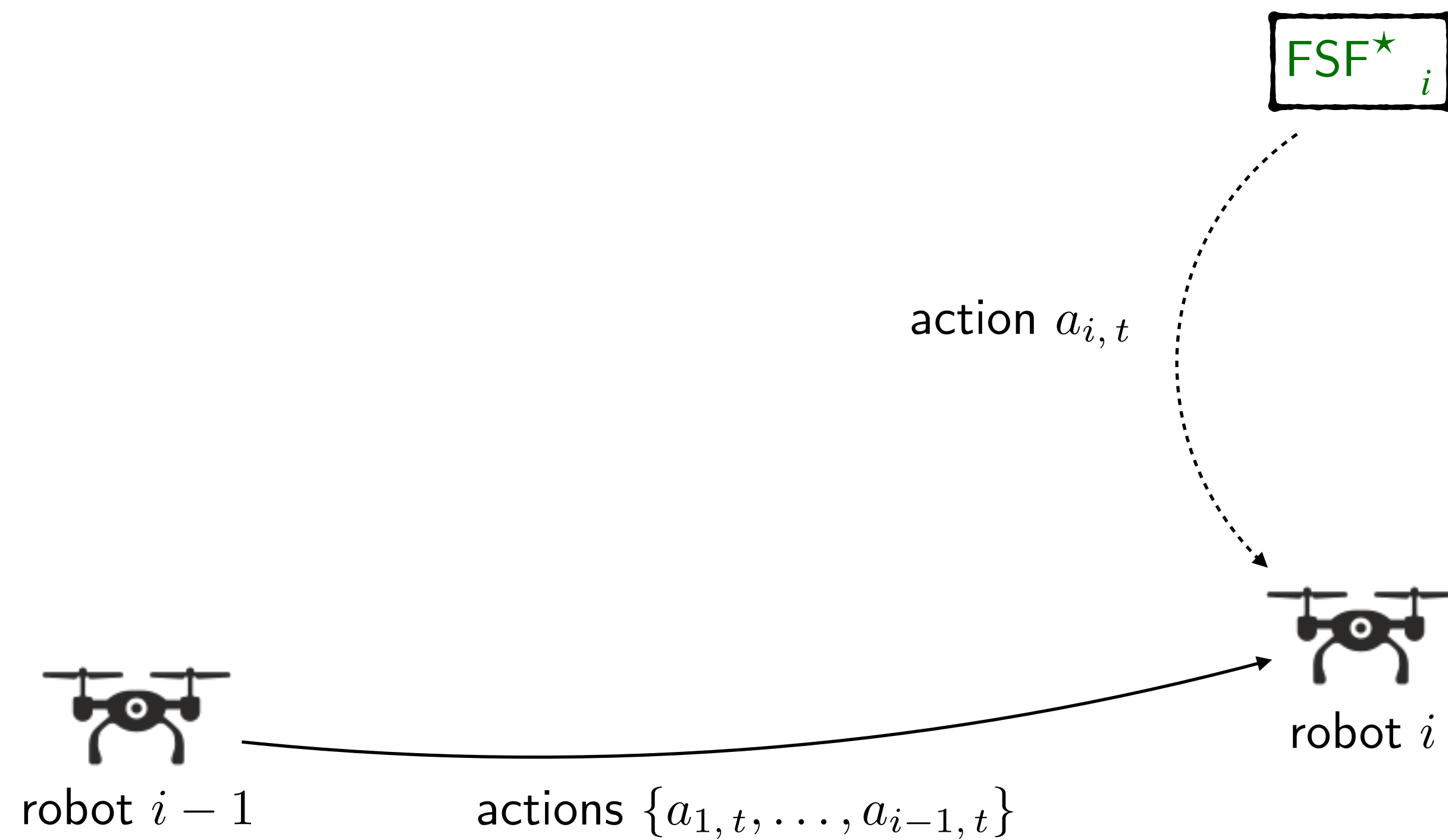
Our Algorithm: Online Sequential Greedy (OSG)

Step 1. Onboard algorithm FSF^* samples next action $a_{i,t}$ from probability distribution $p_t^{(i)}$ that is computed based on past rewards



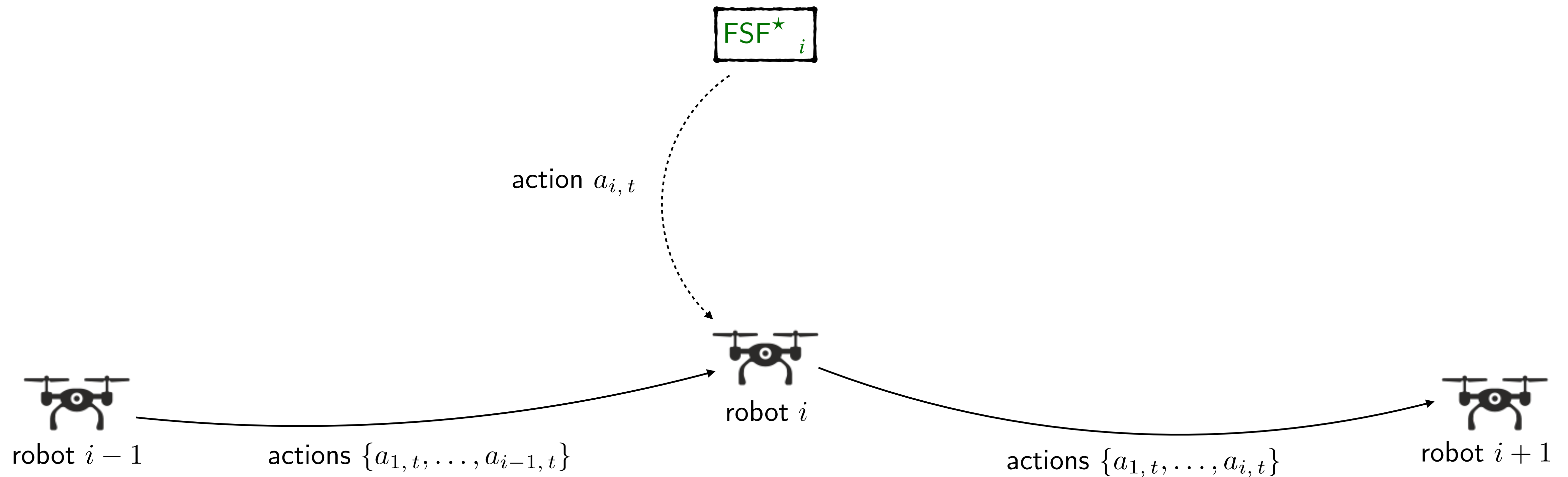
Our Algorithm: Online Sequential Greedy (OSG)

Step 2. Robot $i - 1$ sends actions $\{a_{1,t}, \dots, a_{i-1,t}\}$ to robot i



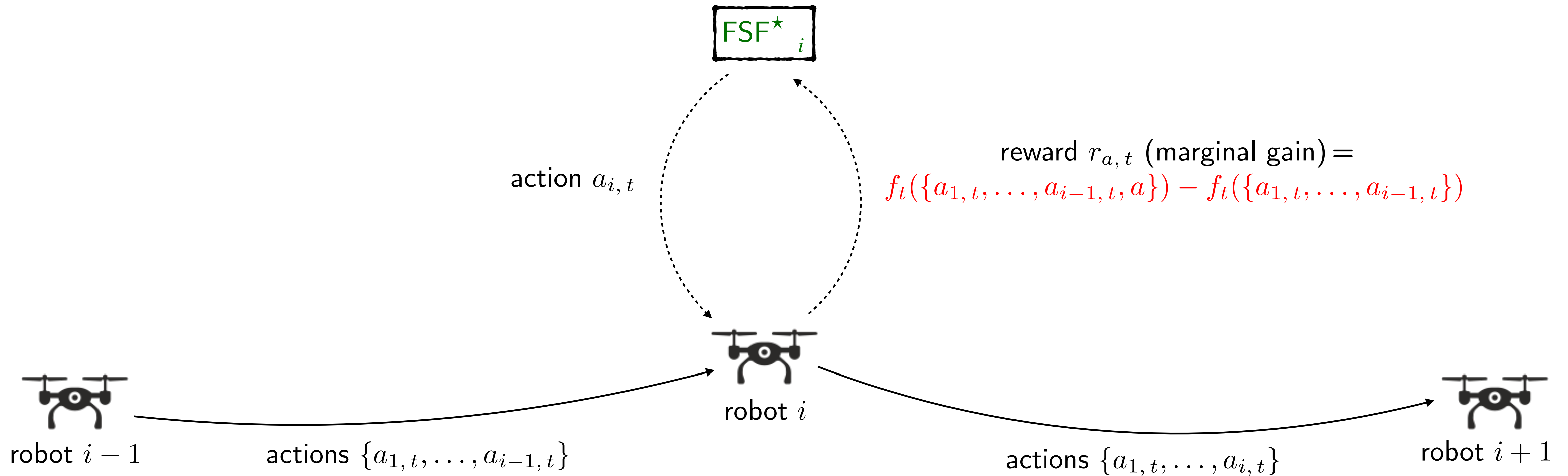
Our Algorithm: Online Sequential Greedy (OSG)

Step 3. Robot i sends actions $\{a_{1,t}, \dots, a_{i,t}\}$ to robot $i + 1$



Our Algorithm: Online Sequential Greedy (OSG)

Step 4. Robot i computes rewards $\{r_{a,t}\}_{a \in \mathcal{V}_i}$ (marginal gains) of all alternative actions \mathcal{V}_i and feeds them into FSF^* to update $p_t^{(i)}$



Computational complexity:

Theorem 1 (Sublinear Computational Complexity)

OSG requires each robot to perform $O(|\mathcal{V}_i|)$ function evaluation & $O(\log T)$ additions and multiplications per time step.

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Approximation performance:

Theorem 2 (Asymptotic 1/2 Near-Optimality*)

OSG instructs the robots to select actions that asymptotically achieve **1/2 near-optimal** coordination as the action-selection frequency increases.

Same performance as that of the near-optimal algorithm
Sequential Greedy for predictable environments

*Achievable in environments that cannot adapt to the action-selection frequency of the algorithm

Simulations on Multi-Target Tracking

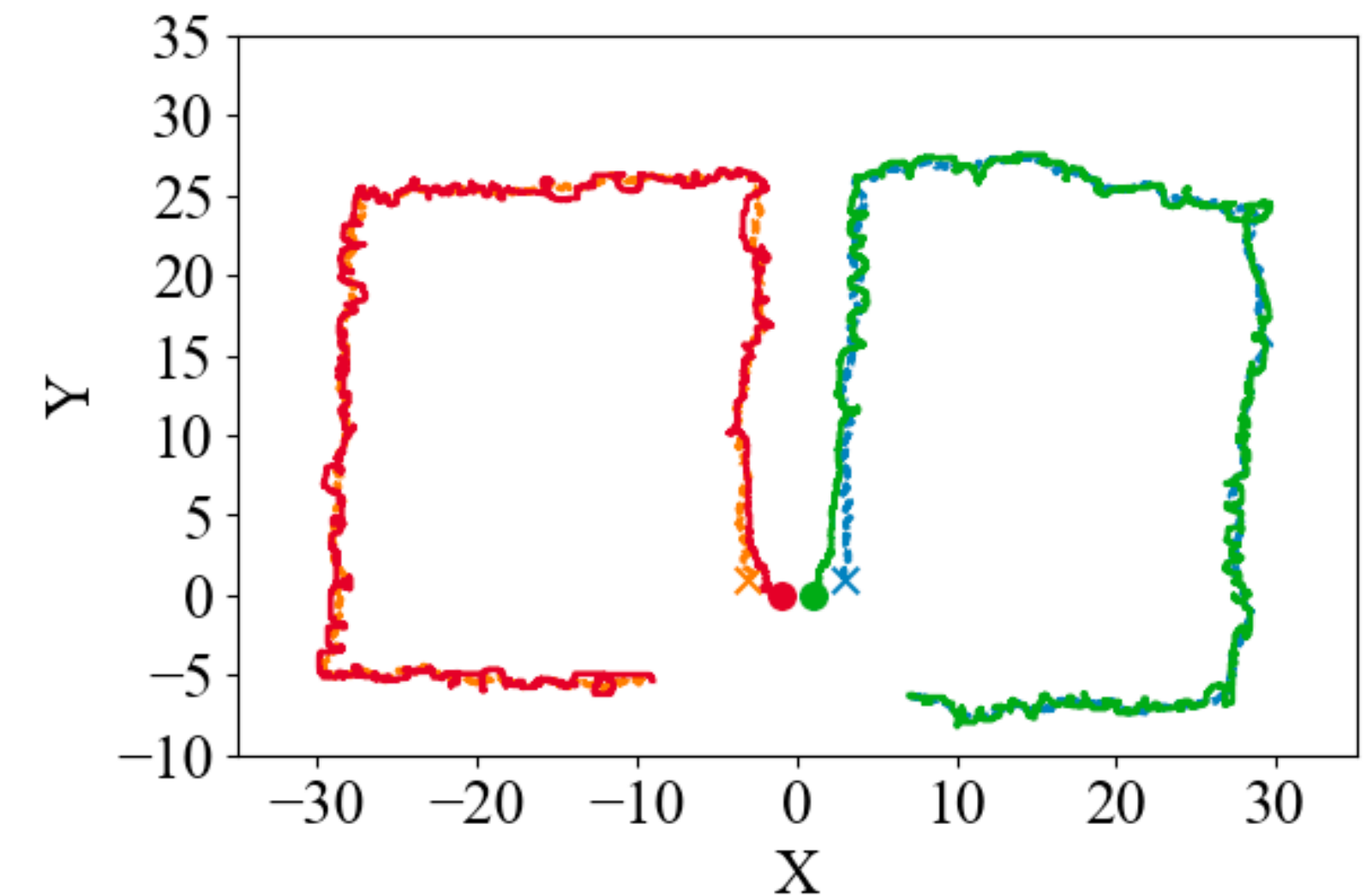
Goal: Minimize sum of distance from every target to its closest robot

Setup:

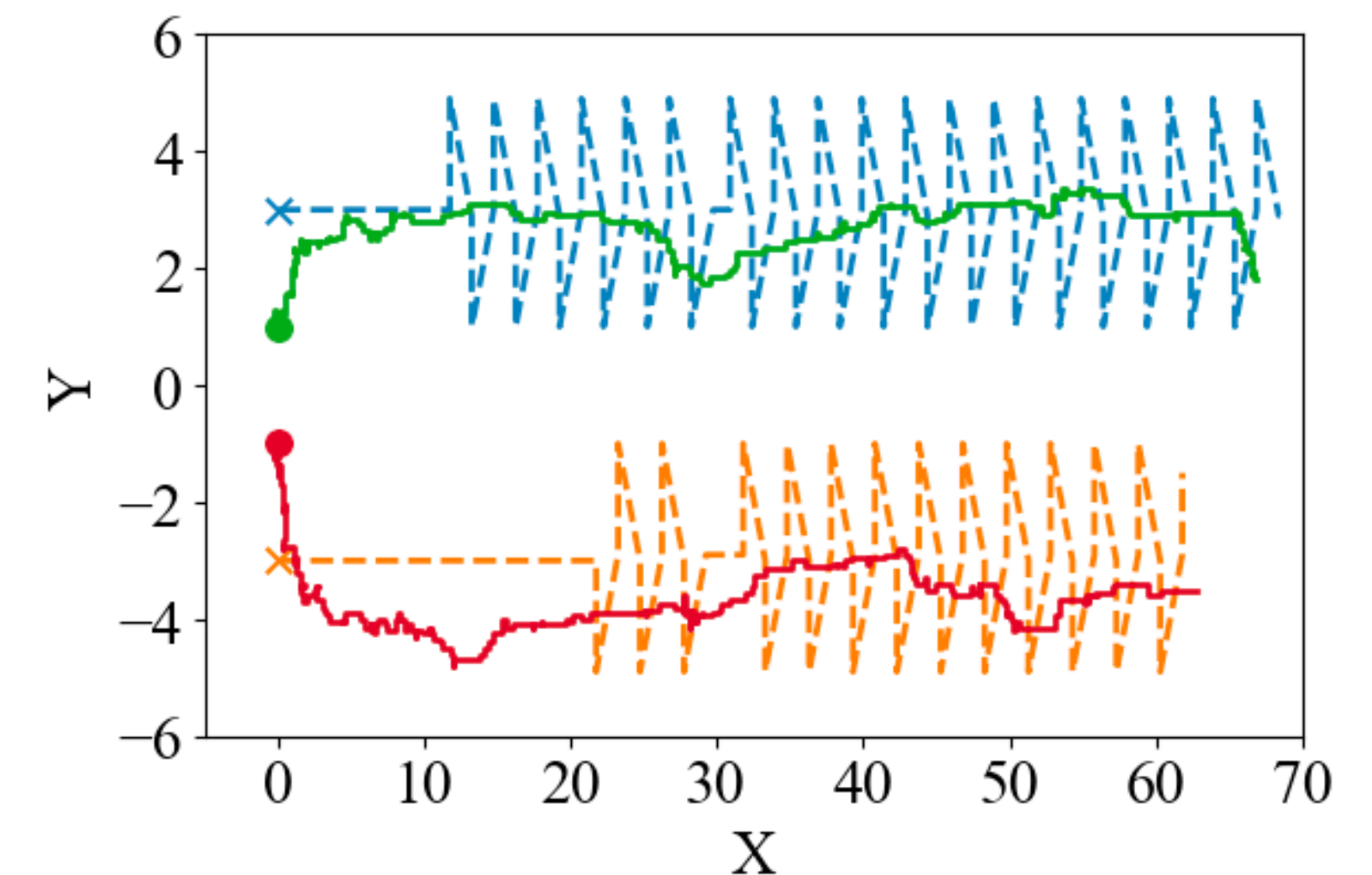
- The robots' field of view is unlimited
- The targets' future trajectories are **unknown to the robots**
- Two types of target trajectories:
 - Non-Adversarial: Pre-defined but corrupted with Gaussian noise
 - Adversarial: Adaptive to the robots' motion

Compared algorithm (SG-Heuristic): A heuristic algorithm selecting actions that **1/2** approximately

$$\max_{a_i \in \mathcal{V}_i, \forall i \in \mathcal{N}} f_{t-1}(\{a_i\}_{i \in \mathcal{N}})$$

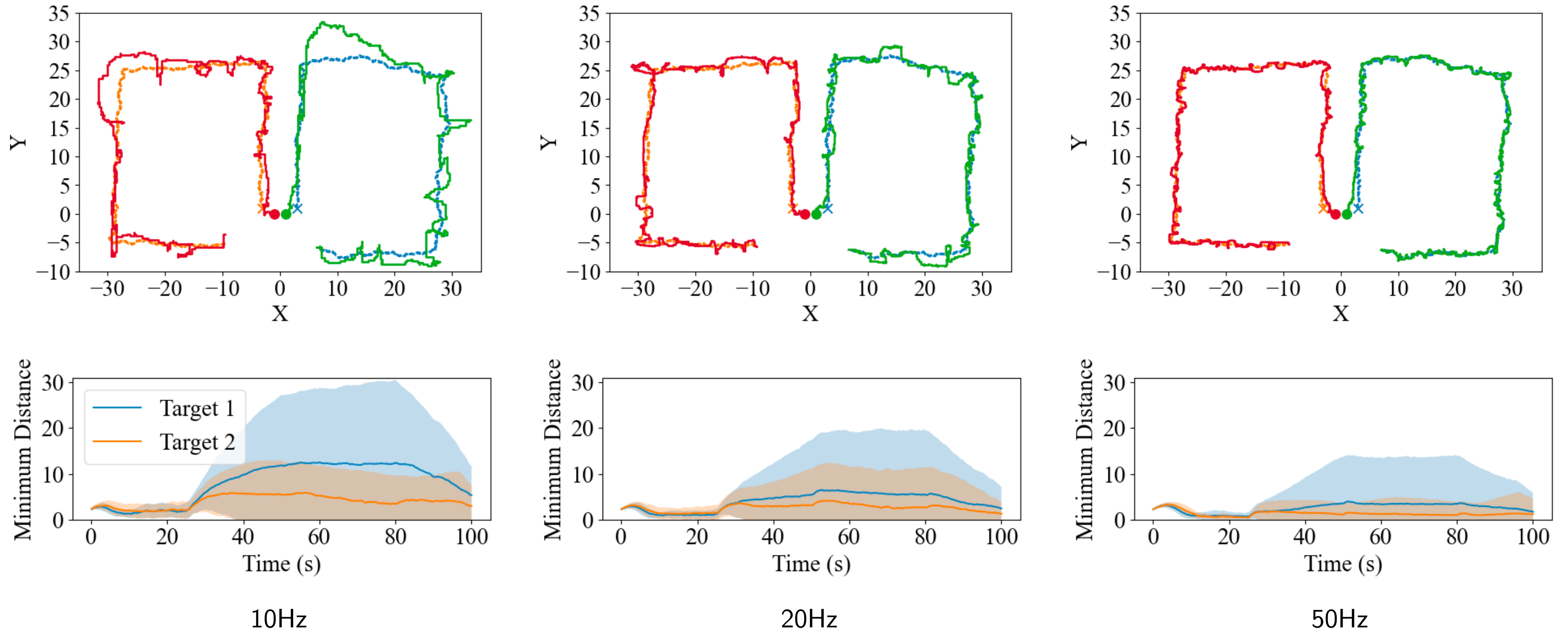


Non-Adversarial Target Motion



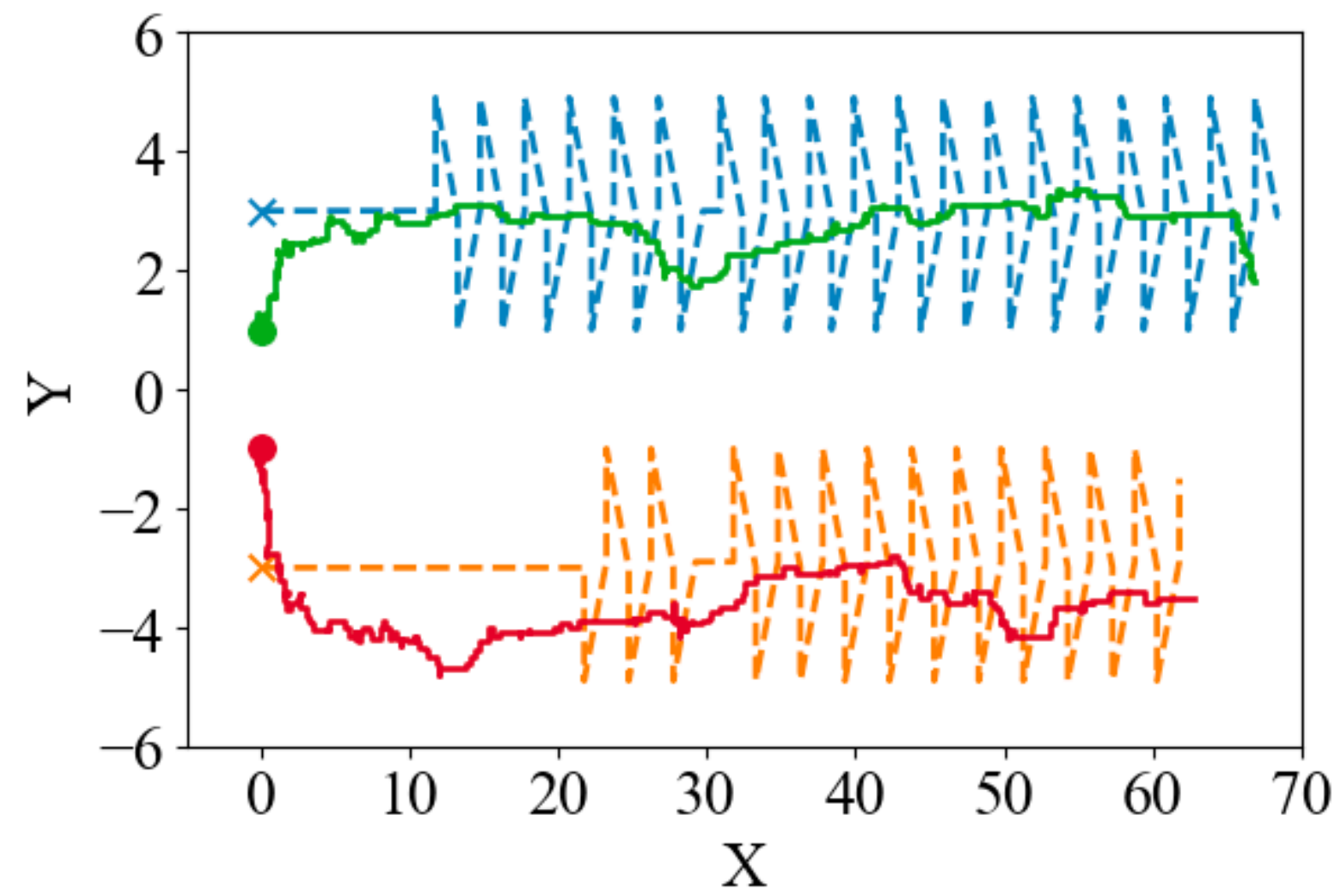
Adversarial Target Motion

Higher Action-Selection Frequency Improves Performance

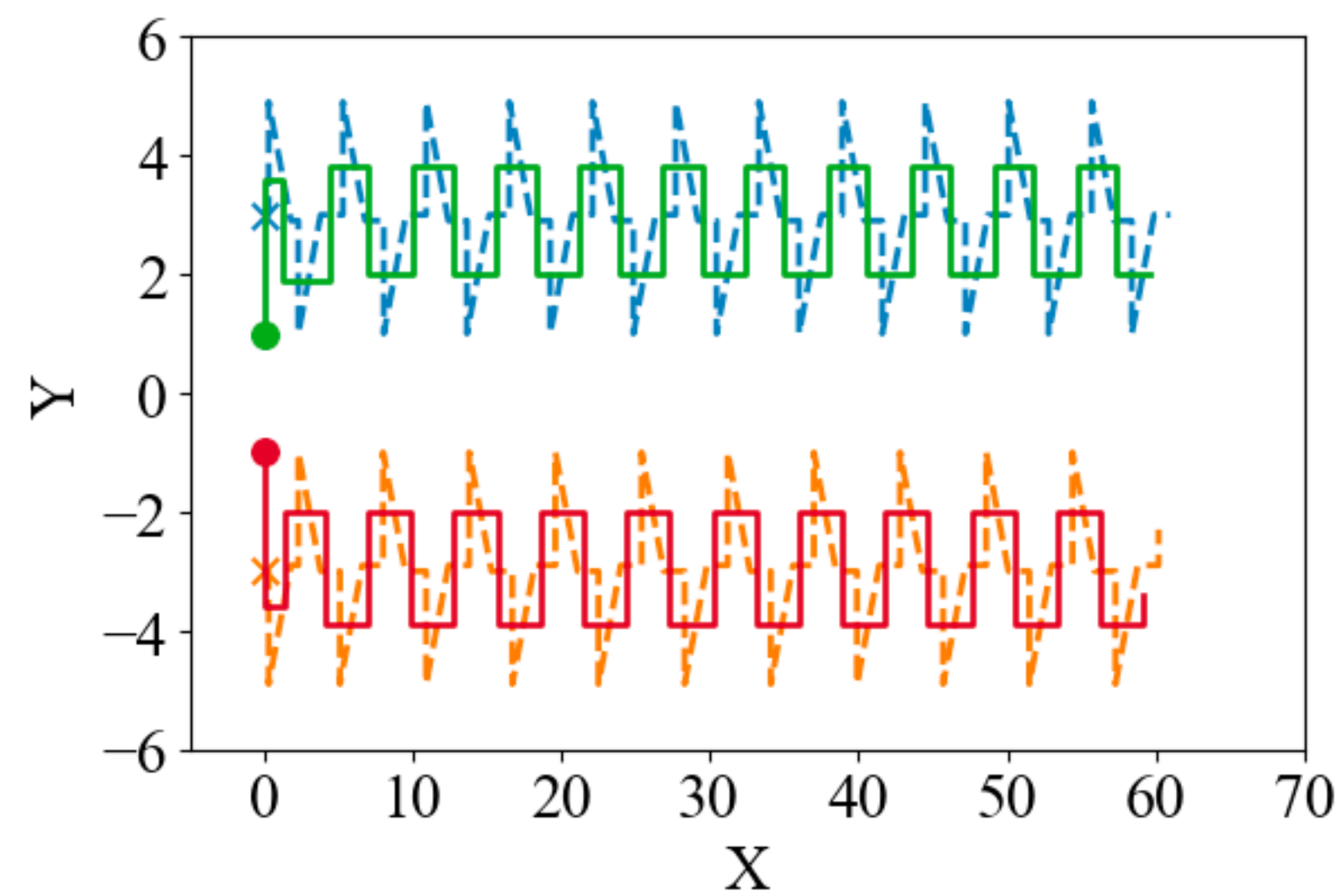


Total Minimum Target-Robot Distance: OSG with Different Action-Selection Frequencies in Non-Adversarial Scenarios

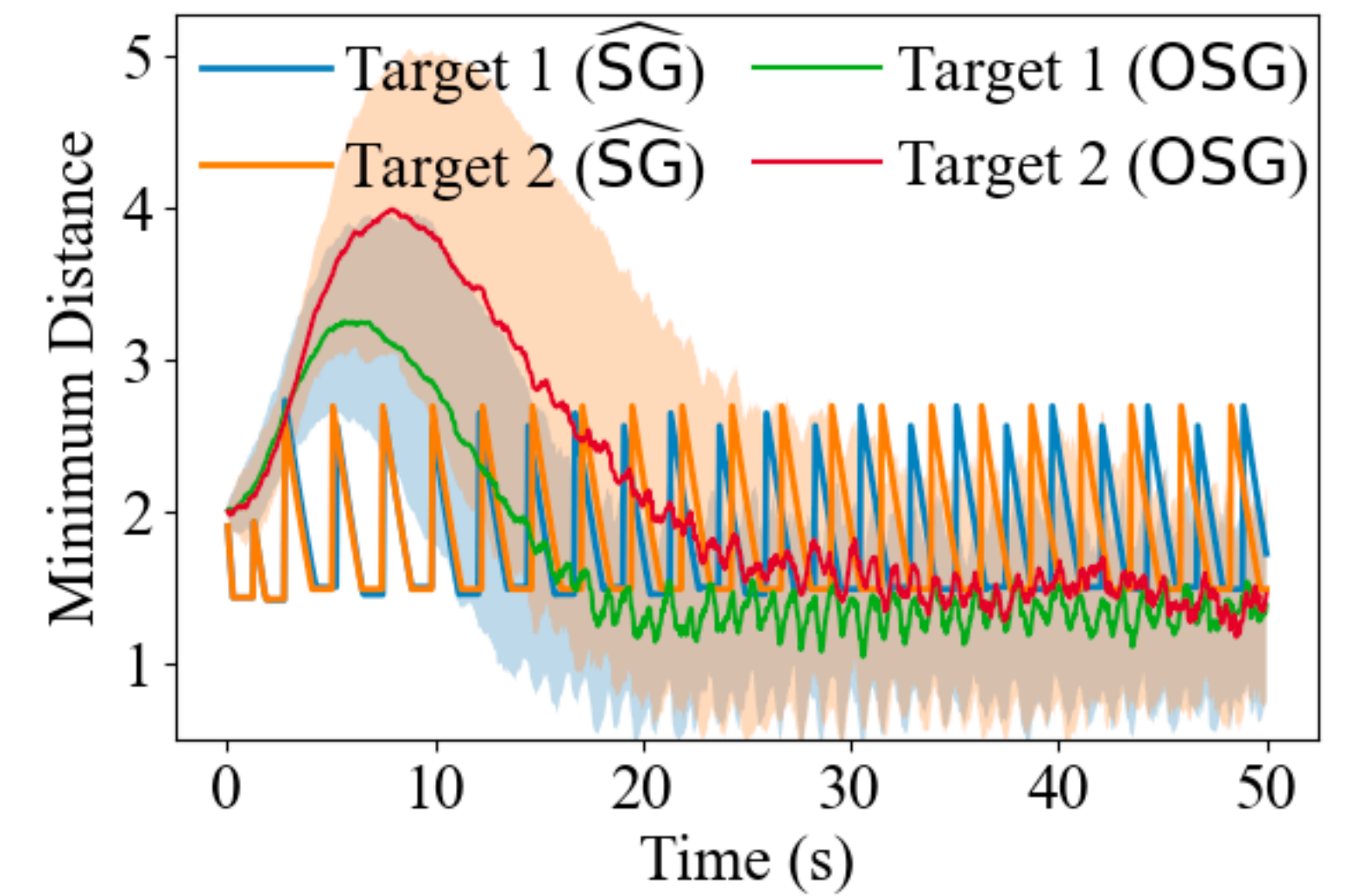
OSG Outperforms in Adversarial Scenarios



OSG



SG-Heuristic



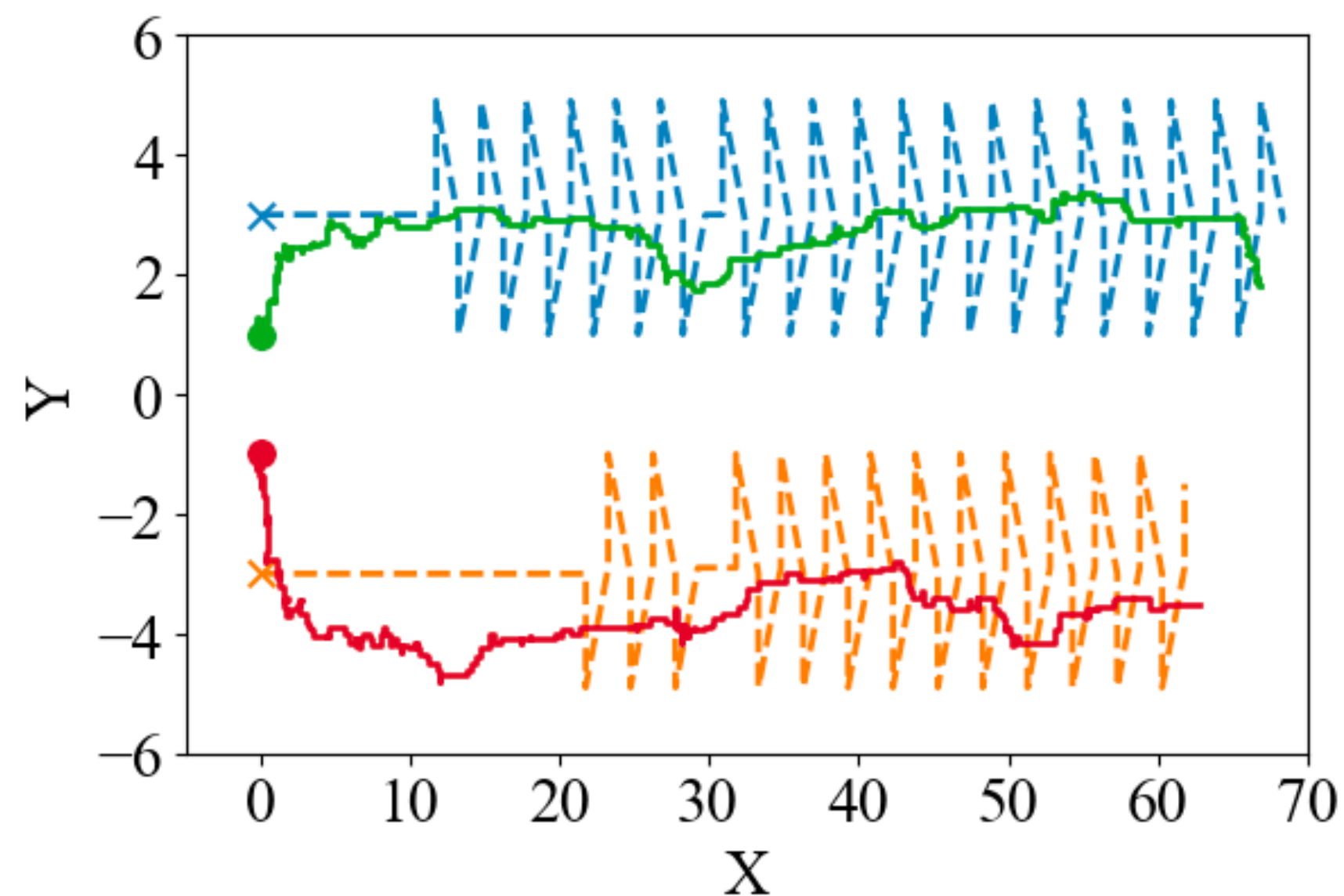
Minimum Distance: OSG vs. SG-Heuristic

Total Minimum Target-Robot Distance: OSG vs. SG-Heuristic in Adversarial Scenarios

Summary and Extensions

First coordination algorithm that achieves **bounded suboptimality guarantee** despite:

- *information overlap* among robot actions
- *completely unpredictable* future environment



Extensions:

- partial information feedback
- best of both worlds

Z. Xu, X. Lin, and V. Tzoumas, “Bandit submodular maximization for multi-robot coordination in unpredictable and partially observable environments,” in *Robotics: Science and Systems*, 2023