Parsimonious, Risk-Aware, and Resilient Multi-Robot Coordination

Ph.D. Proposal Presentation

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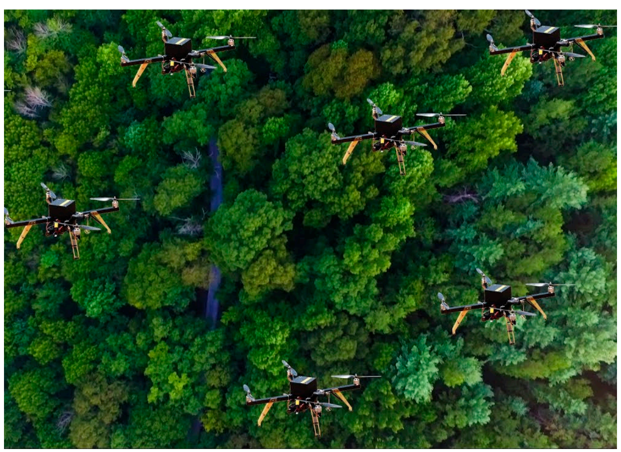
Multi-Robot Coordination

- Complete the task faster
- Achieve a better performance
- Perform multiple tasks collaboratively
- Have redundancy to failures and attacks



Forest search and rescue
web.mit.edu/spotlight

City surveillance
www.securitymagazine.com/surveillance

Warehouse order picking
www.youtube.com/watch?v=4sEVX4mPuto

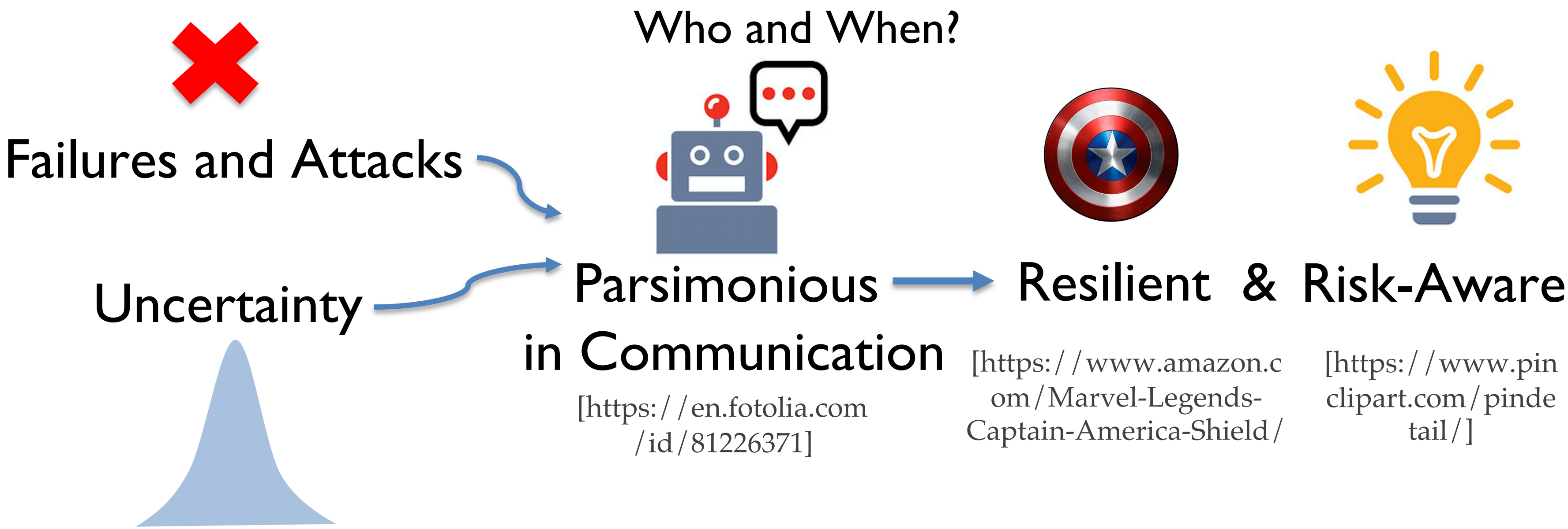
Challenges

- Communication
  - high energy consumption
  - not stable
  - not reliable
  - ...
- Safety
  - collision
  - failures
  - attacks
  - uncertainty
  - …
- Perception
  - sensing noise
  - limited sensing
  - local information
  - …
- Privacy
  - sensitive information
  - …
- Other…

Goals of this Thesis

Focus on challenges from **communication cost**, **failures**, **attacks**, the **uncertainty and changing conditions** in the environment

Final version: deploy multiple robots in real-world and



Contributions of this Thesis

Resilient coordination to counter worst-case failures
[ICRA+RA-L '19]

Risk-aware coordination to manage risk of performance loss
[WAFR '18]

Parsimonious communication strategies

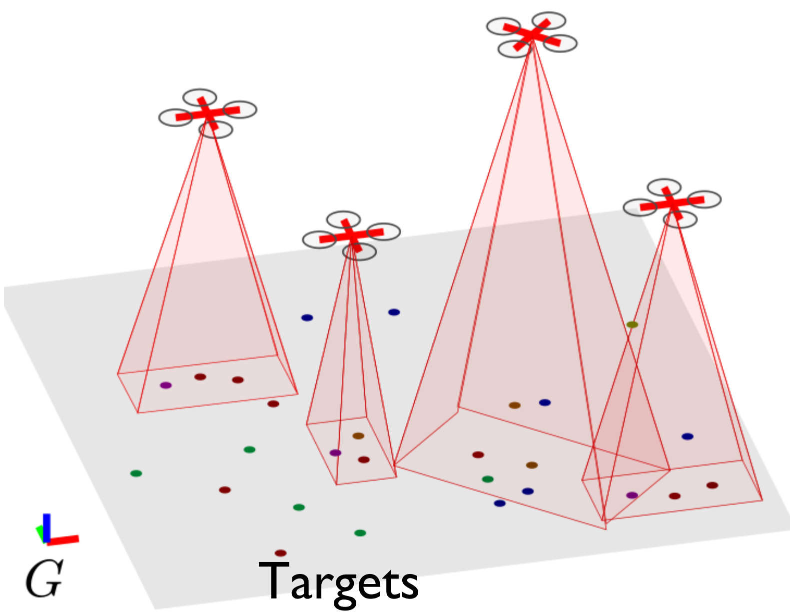
"who to communicate with" [T-RO '19]

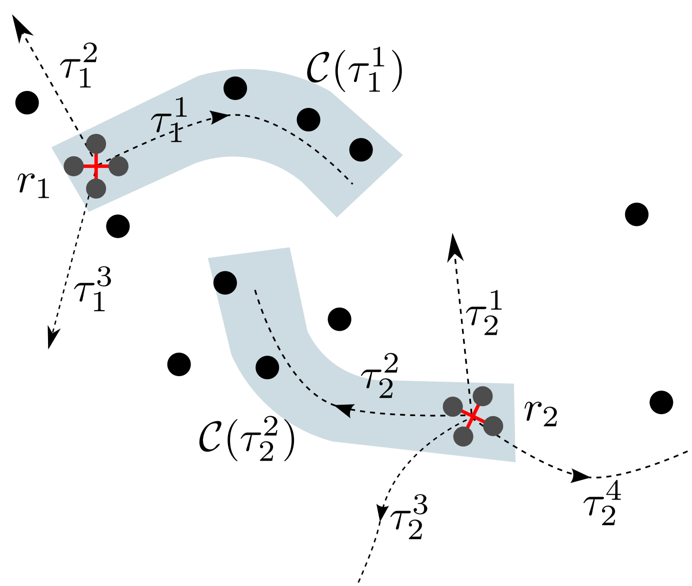
"when to communicate" [ICRA '17, T-ASE '18]

Proposed work: distributed resilient & online risk-aware coordination with parsimonious communication

Multi-Robot Target Tracking

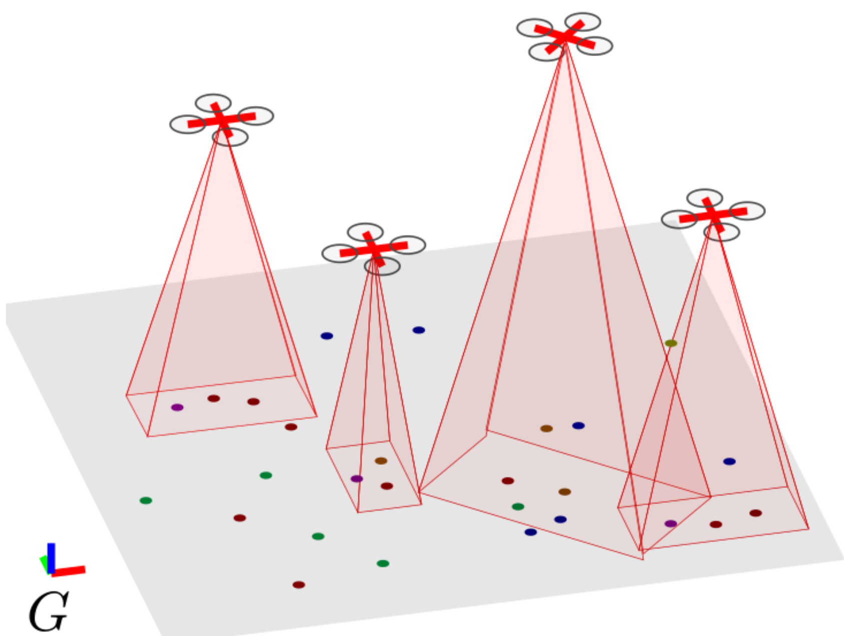
- Each robot has a tracking sensor (e.g., a camera)
- Each robot has a set of candidate trajectories from which it must choose one
- Each trajectory covers a number of targets

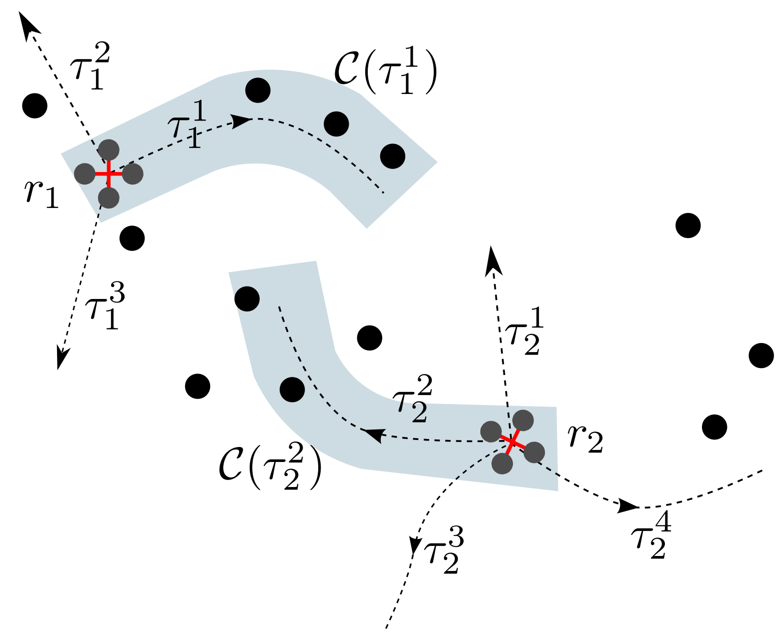




Submodular Objective

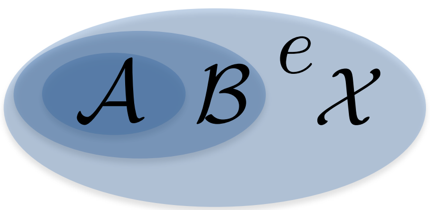
- $f(\mathcal{S})$: the number of targets covered by robots' selected trajectory set $\mathcal{S}$
- Maximize $f(\mathcal{S})$ with the constraint that each robot selects one trajectory





Submodular Function

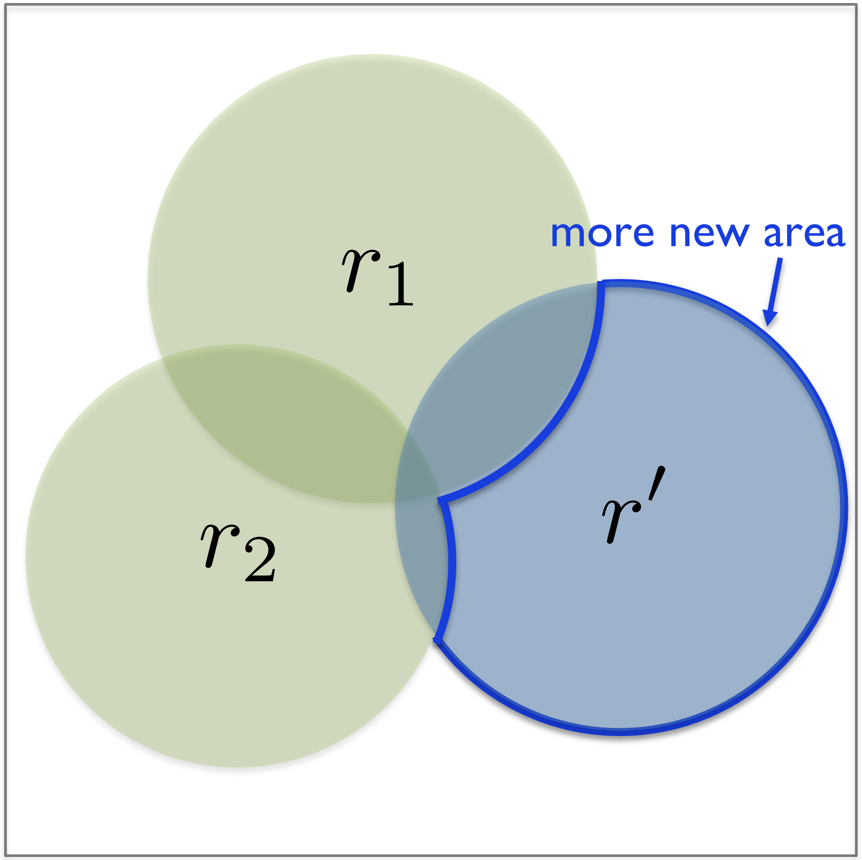
A *set* function $f : 2^{\mathcal{X}} \rightarrow \mathbb{R}$ is submodular if for every $\mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{X}$ and $e \in \mathcal{X} \backslash \mathcal{B}$ it holds



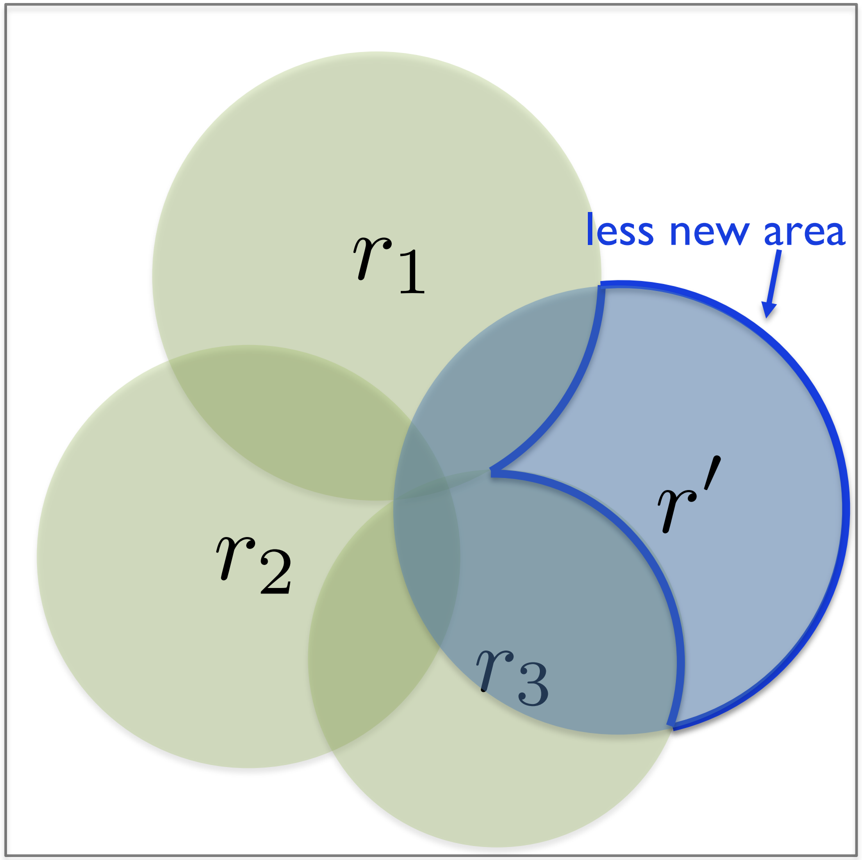
Marginal gain

$$f(\mathcal{A} \cup e) - f(\mathcal{A}) \geq f(\mathcal{B} \cup e) - f(\mathcal{B})$$

Diminishing Returns



Deploy r' after $\{r_1, r_2\}$



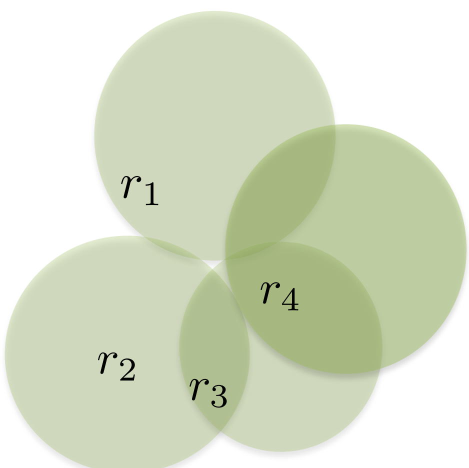
Deploy r' after superset $\{r_1, r_2, r_3\}$

Robot Coverage

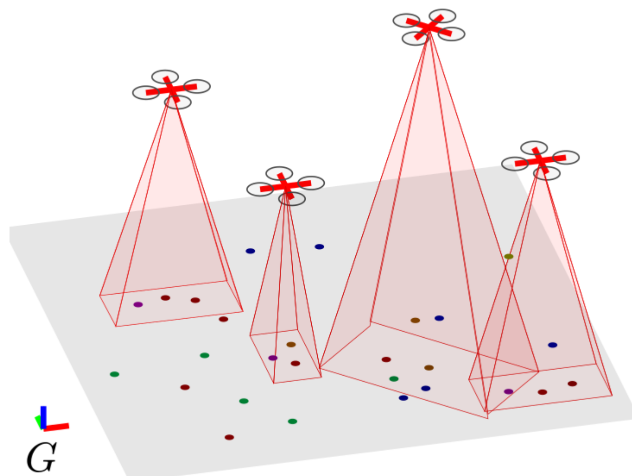
Submodular Maximization

$$\max\ f(\mathcal{S}),\ \text{s.t. } \mathcal{S} \subseteq \mathcal{X}$$

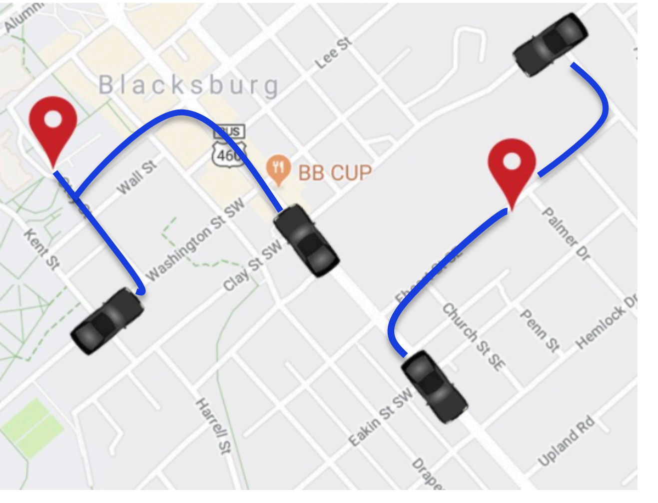
- NP-complete. There is no polynomial-time running algorithm that gives the optimal solution.



Robot coverage



Multi robot-target tracking



Redundant task assignment

Greedy Algorithm

$$\max \; f(\mathcal{S}), \;\; \text{s.t. } \mathcal{S} \subseteq \mathcal{X}$$

- Incrementally picks the element with the maximal marginal gain

$$f(\mathcal{S}^{\text{Greedy}}) \geq \frac{1}{2} f(\mathcal{S}^{\text{OPT}})$$

[Fisher et al., PC '1978]

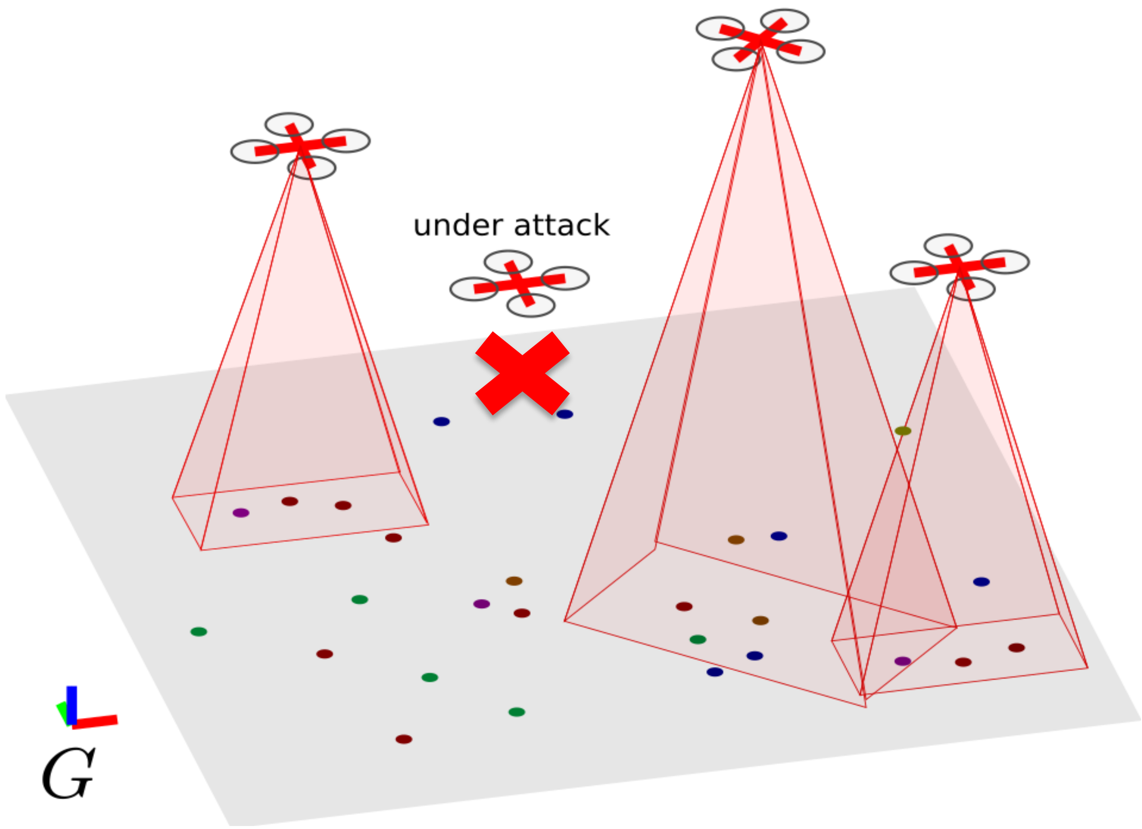
$k_f \in [0, 1]$ the curvature of function f

$$f(\mathcal{S}^{\text{Greedy}}) \geq \frac{1}{1 + k_f} f(\mathcal{S}^{\text{OPT}})$$

[Conforti & Gérard, DAM '1984]

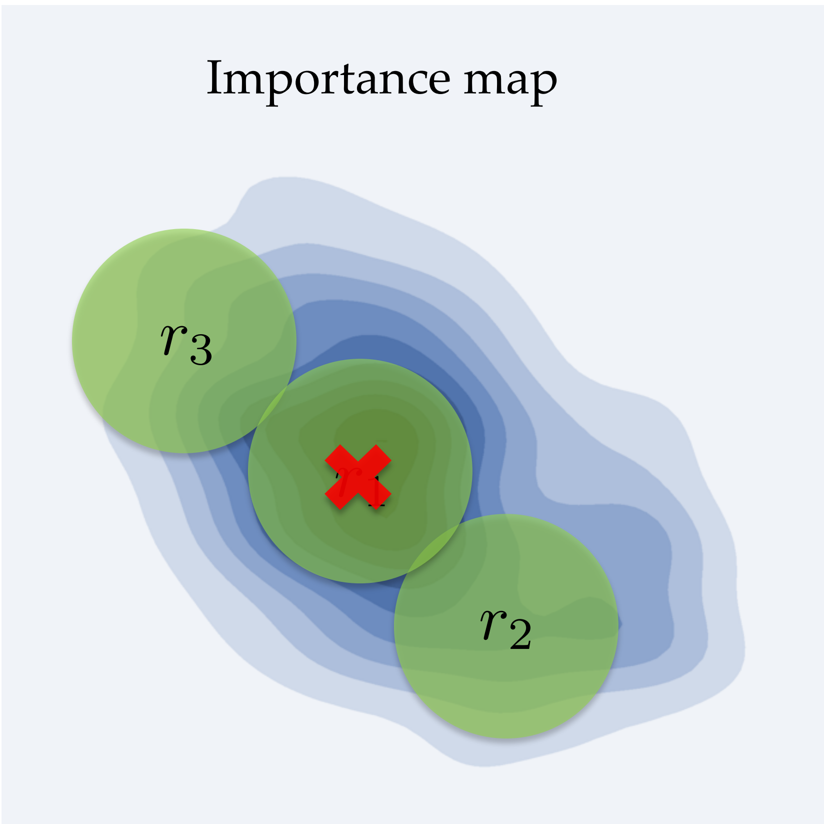
Adversarial Attacks

- Can we still guarantee the tracking performance by the greedy algorithm?

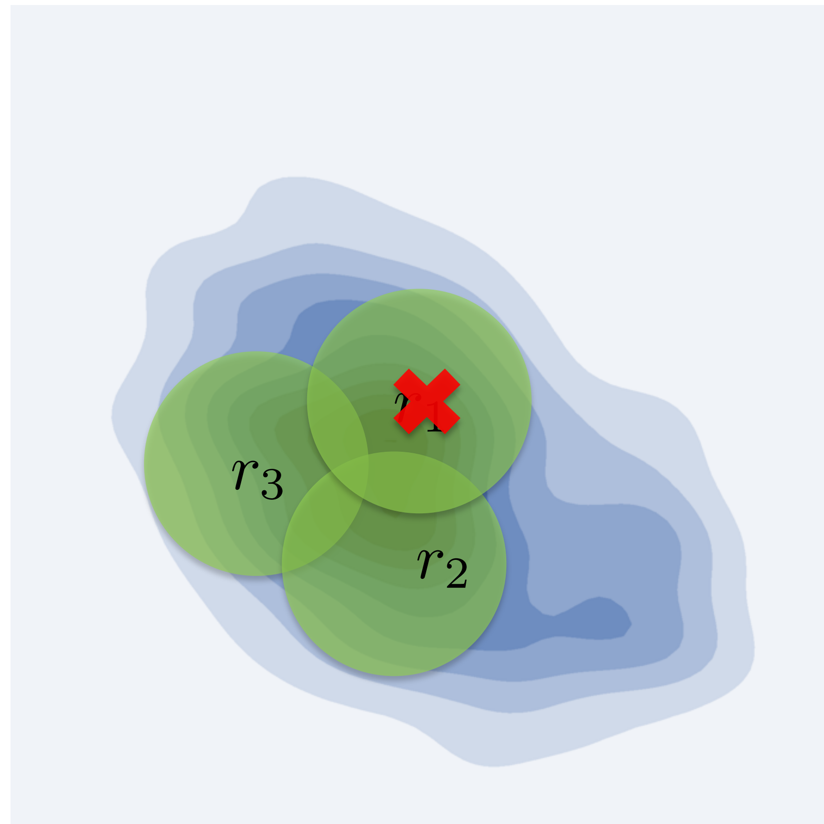


Greedy Is Not Resilient to Attacks

Greedy placement
reduce overlap



Resilient placement
want overlap



Target in the darker blue region is more important

Contributions of this Thesis

Resilient coordination to counter worst-case failures

[ICRA+RA-L '19]

Risk-aware coordination to manage risk of performance loss

[WAFR '18]

Parsimonious communication strategies

"who to communicate with" [T-RO '19]

"when to communicate" [ICRA '17, T-ASE '18]

Maximization with Worst-Case Attack

$$\max_{\mathcal{S} \subseteq \mathcal{X}} \; \min_{\mathcal{A} \subseteq \mathcal{S}} \; f(\mathcal{S} \setminus \mathcal{A})$$

$$s.t. \;\; |\mathcal{A}| = \alpha \leq N$$

- N robots, α attacks
- Worst case attack set, $\mathcal{A}$
- Maximize vs. Minimize

Contributions: Resilient Algorithm

- We present a resilient target tracking algorithm
- It gives a constant-factor approximation of the optimal
- It runs in polynomial time and as fast as the greedy algorithm

Resilient Tracking Algorithm: Oblivious + Greedy

- Step 1. *Oblivious decision*: Pick out the most profitable trajectory of each robot. Sort them, and select the top α ones

- Step 2. *Greedy decision*: Greedily select a trajectory for each of the remaining $N - \alpha$ robots

Provable Performance Guarantee

$$\frac{f(\mathcal{S} \setminus \mathcal{A}^\star(\mathcal{S}))}{f^\star} \geq \frac{1}{1+k_f} \max \left[1 - k_f, \frac{1}{1+\alpha}, \frac{1}{N-\alpha} \right]$$

- Constant-factor approximation of the optimal
- $k_f = 0$ → optimal solution
- If there is no attack, $\alpha = 0$, the ratio is $\frac{1}{1+k_f}$

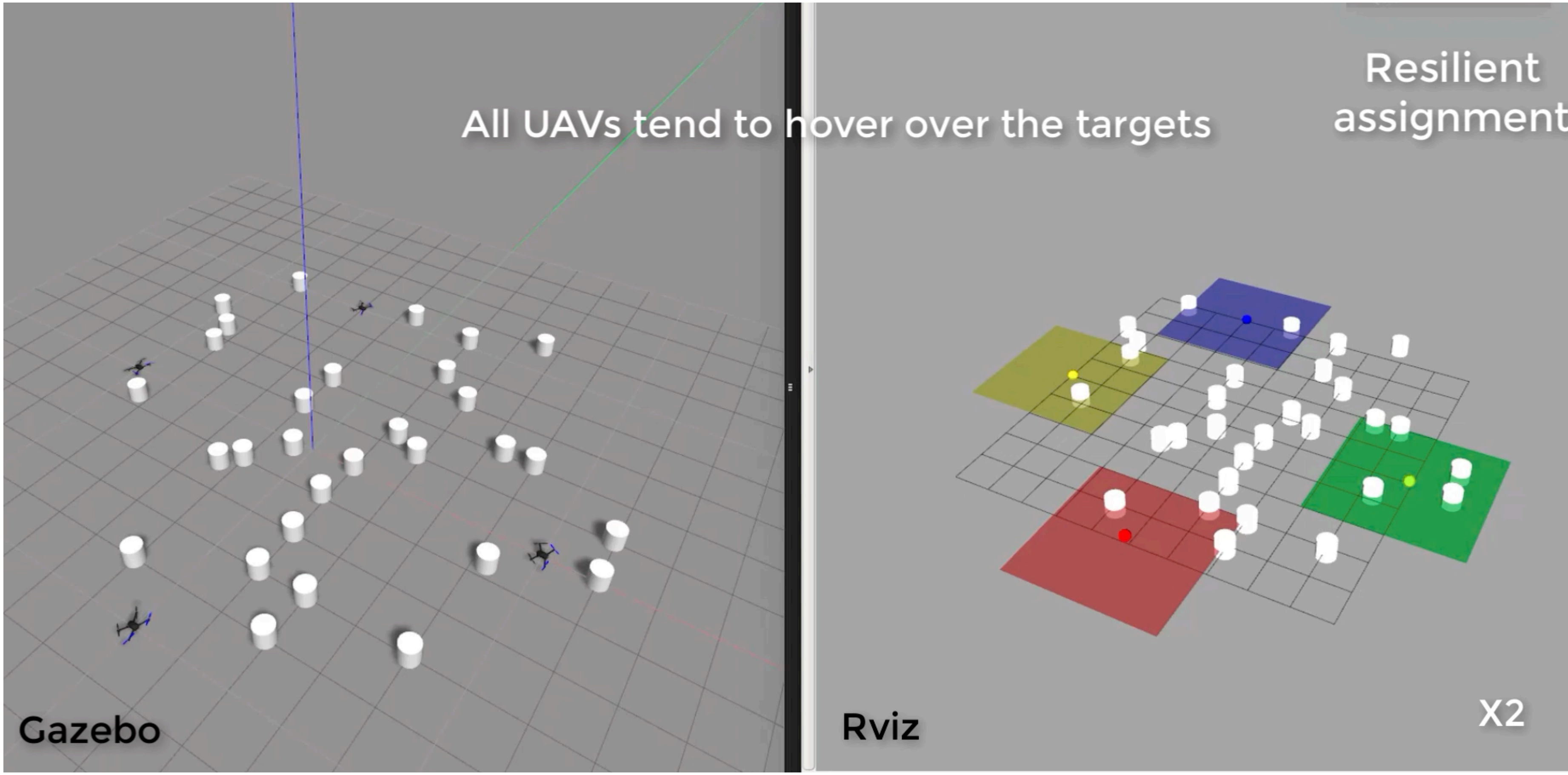
Runs in Polynomial Time

The number of candidate trajectories for each robot

$$O(N^2 \boxed{D}^2)$$

- As fast as the greedy algorithm
- Quadric in the number of robots N and the number of candidate trajectories D

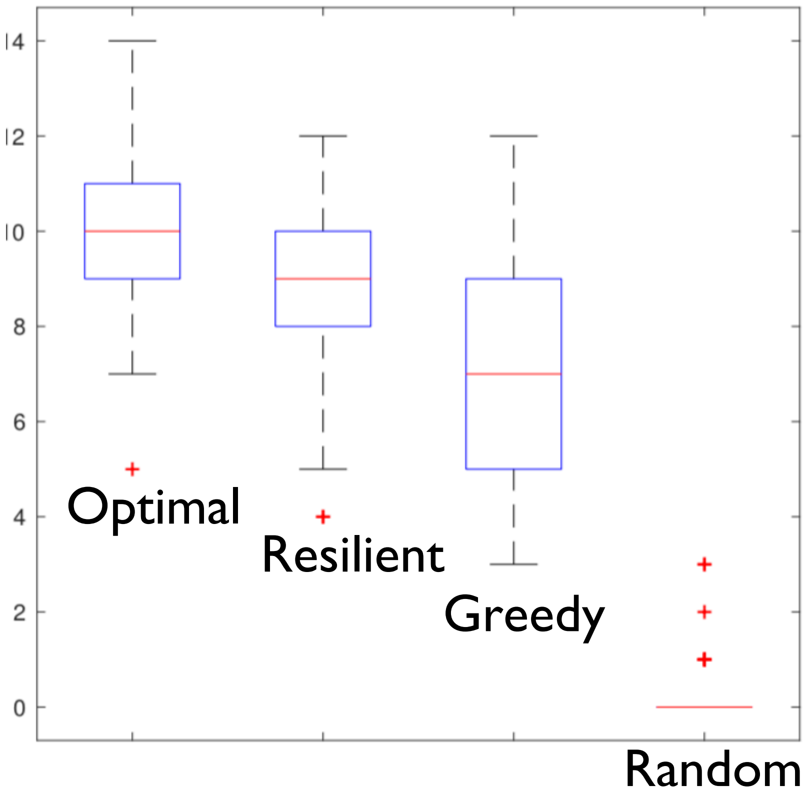
Resilient Target Tracking



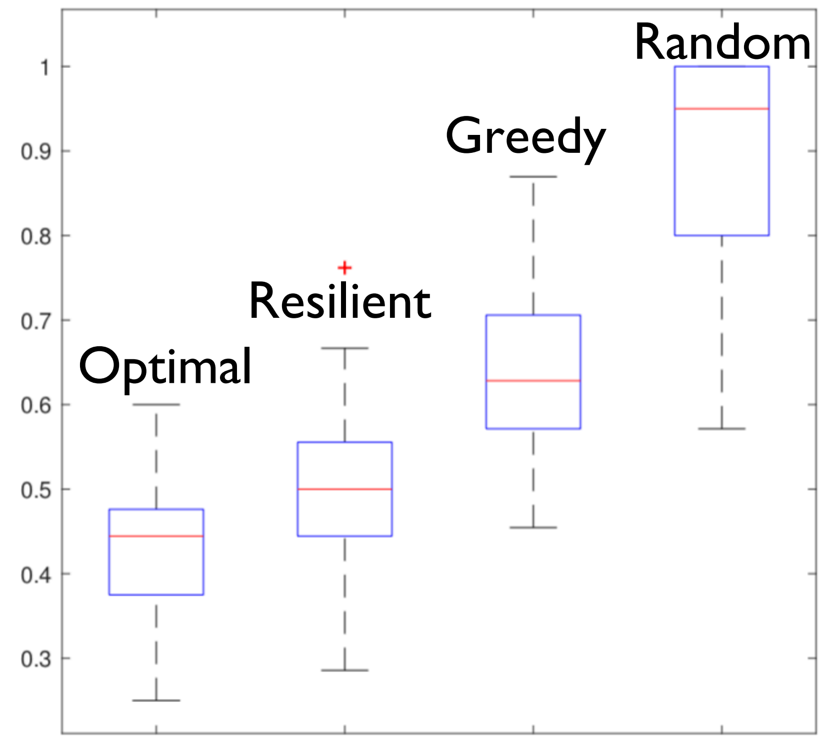
- 4 aerial robots track 30 ground targets
- 2 robots are attacked (their cameras are blocked) per round

Close-to-Optimal & Robust to No Attacks

Number of targets covered after attack



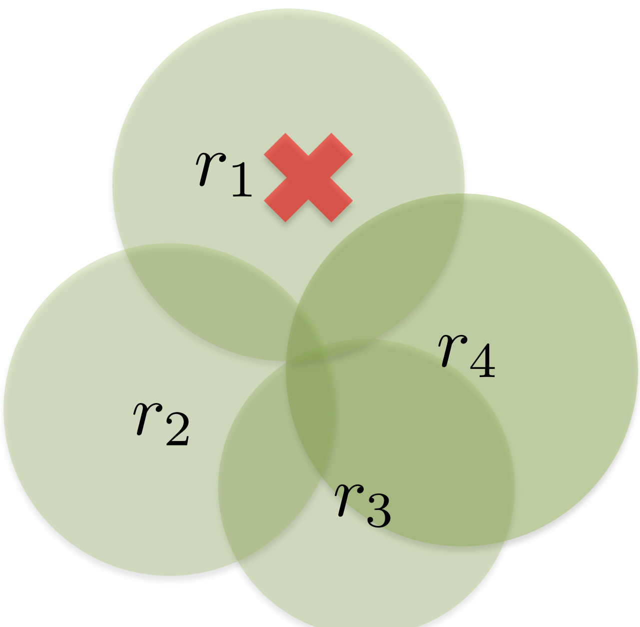
Adversary's attack rate



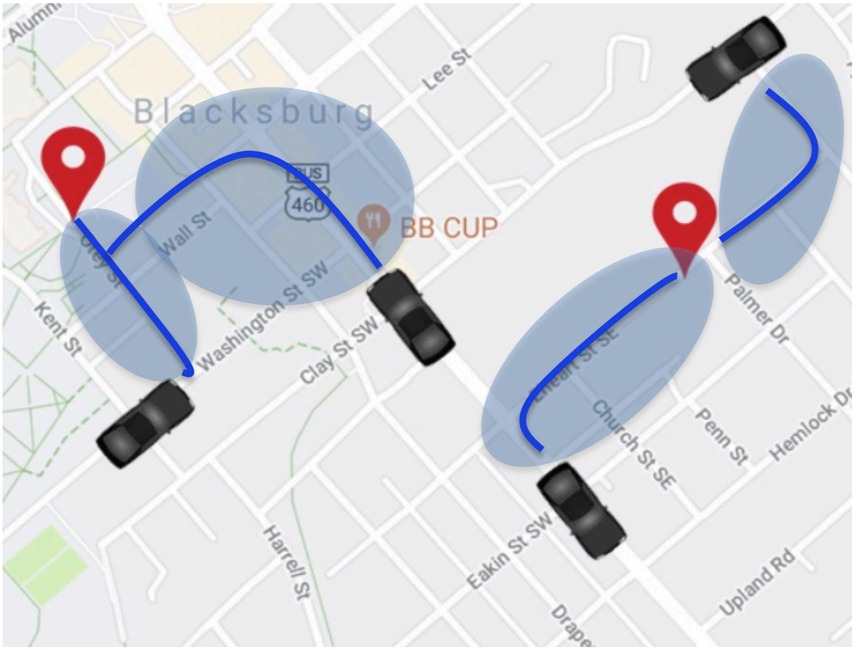
- Close-to "optimal", superior over "greedy" and "random"
- Resilient to attacks. *Attack rate:* $\dfrac{f(\mathcal{S}) - f(\mathcal{S} \setminus \mathcal{A}^\star(\mathcal{S}))}{f(\mathcal{S})}$

Random Failures and Uncertainty

$f(\mathcal{S})$ is a random variable



Robot random failure



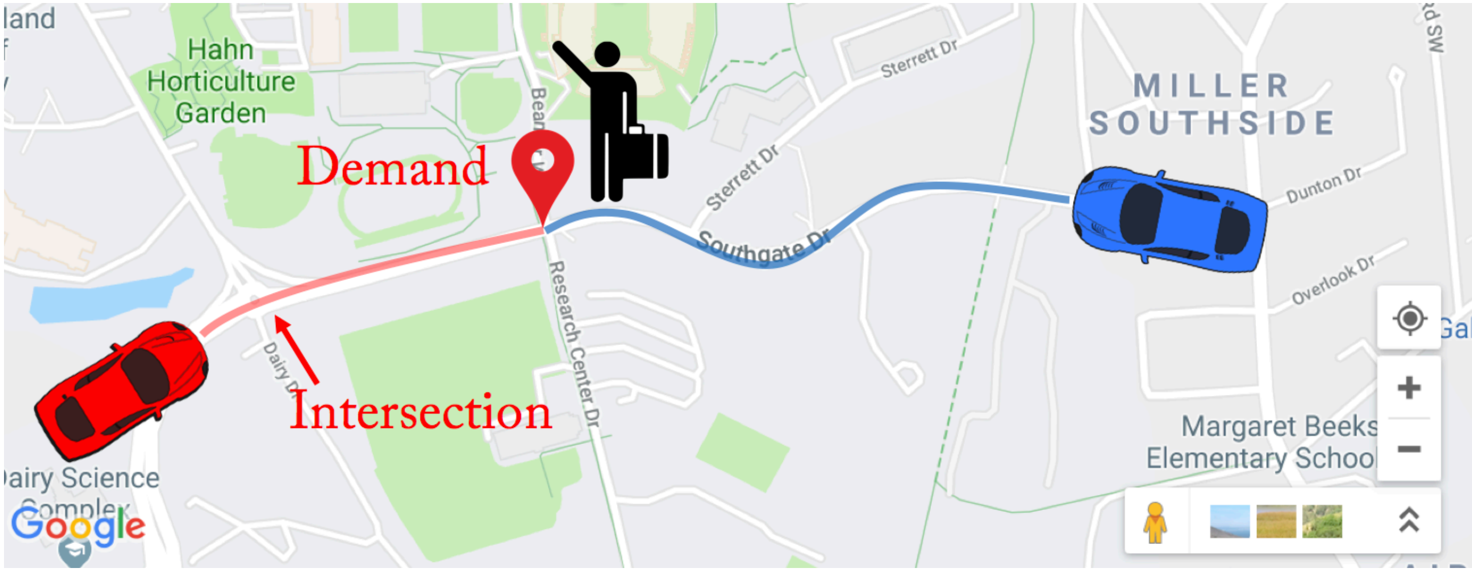
Uncertain travel time

Stochastic Submodular Function

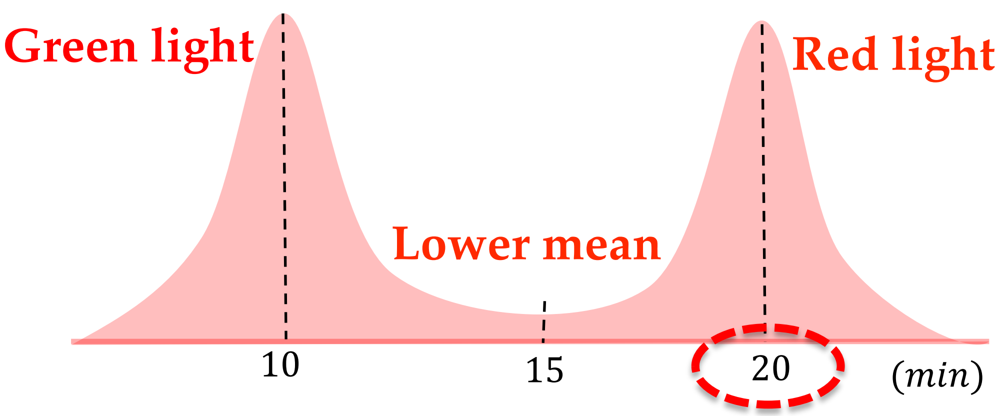
- $f(\mathcal{S}, y)$ is submodular in decision set $\mathcal{S}$
- $f(\mathcal{S}, y)$ is a random variable, the randomness is induced by y.

- Standard measure: Expectation $\mathbb{E}_y(f(\mathcal{S}, y))$
- Expectation is not risk-aware

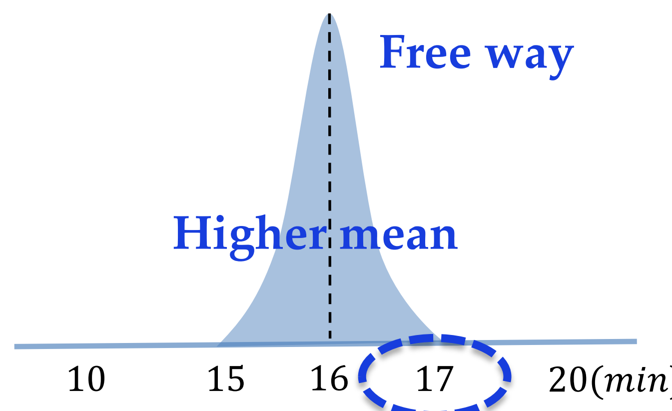
Risk-Aware Measure instead of Expectation



Which vehicle arrives first?



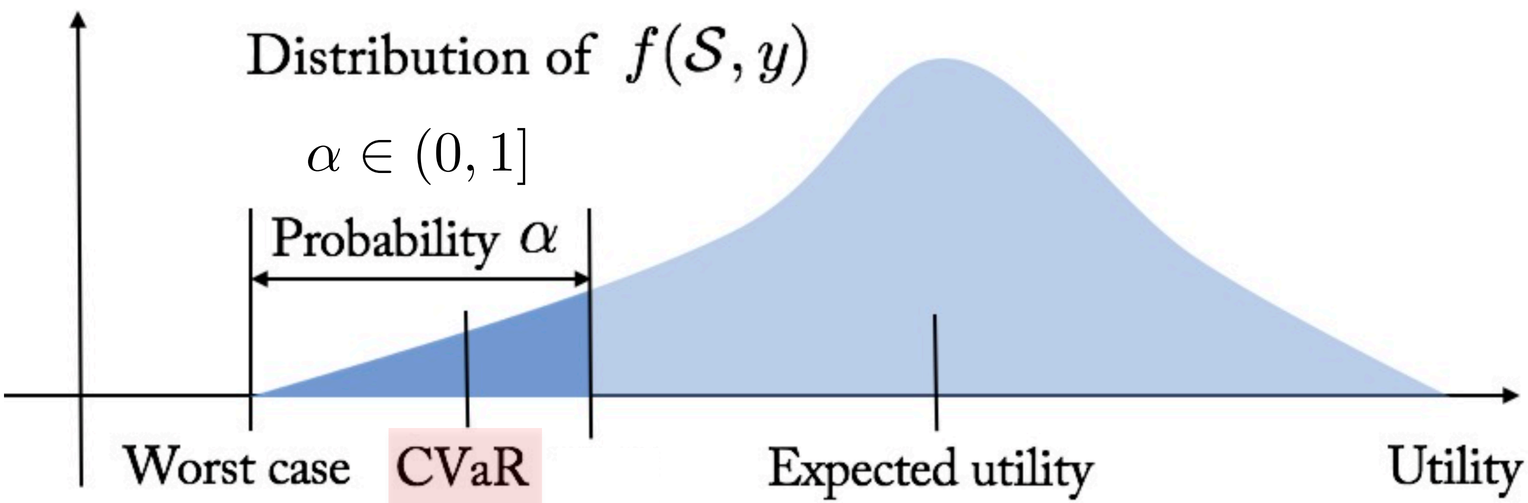
Travel time: Red vehicle



Travel Time: Blue vehicle

Conditional-Value-at-Risk

- CVaR is the expected performance in the worst $\alpha\%$ of cases



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Maximizing CVaR

- Optimization Problem:

$\mathrm{CVaR}_\alpha(\mathcal{S})$

$$\max \quad \tau - \frac{1}{\alpha}\mathbb{E}[(\tau - f(\mathcal{S}, y))_+]$$
$$s.t. \quad \mathcal{S} \subseteq \mathcal{X}, \tau \in [0, \Gamma]$$

α is risk level

y represents uncertainty

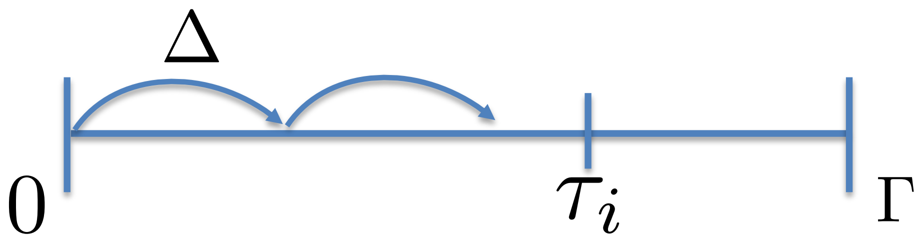
Γ is maximum value of $f(\mathcal{S})$

Contributions: risk-aware algorithm

- We present a *sequential greedy algorithm* (SGA)
- SGA gives a *bounded approximation* of the optimal
- SGA runs in *polynomial time*

Sequential Greedy Algorithm

- Sequentially search for τ from $[0, \Gamma]$



- For each τ_i, solve a subproblem by the greedy algorithm to select set: $\mathcal{S}_i^{\text{Greedy}}$

- Find $\mathcal{S}_i^{\text{Greedy}}$ that maximizes $\text{CVaR}_\alpha(\mathcal{S})$

Sequential Greedy Algorithm: Bounded Approximation

$$\mathrm{CVaR}(\mathcal{S}^{\mathrm{Greedy}}) \geq \frac{1}{1+k_f}(\mathrm{CVaR}(\mathcal{S}^{\mathrm{OPT}}) - \Delta) - \frac{k_f}{1+k_f}\Gamma(\frac{1}{\alpha} - 1)$$

Constant-factor

Approximation Error

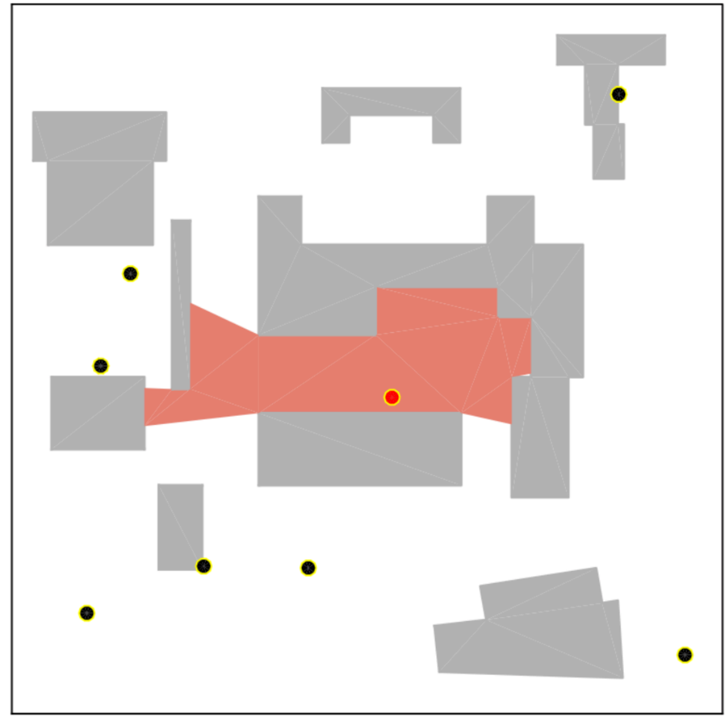
Δ is the user-defined searching separation for τ

Γ is the upper bound on τ

k_f is the curvature of $\mathrm{CVaR}_\alpha(\mathcal{S})$

Robust Environmental Monitoring

Part of campus



Top view

$$f(\mathcal{S}, y) = \text{area}\left(\bigcup_{i=1:M} A_i\right),$$

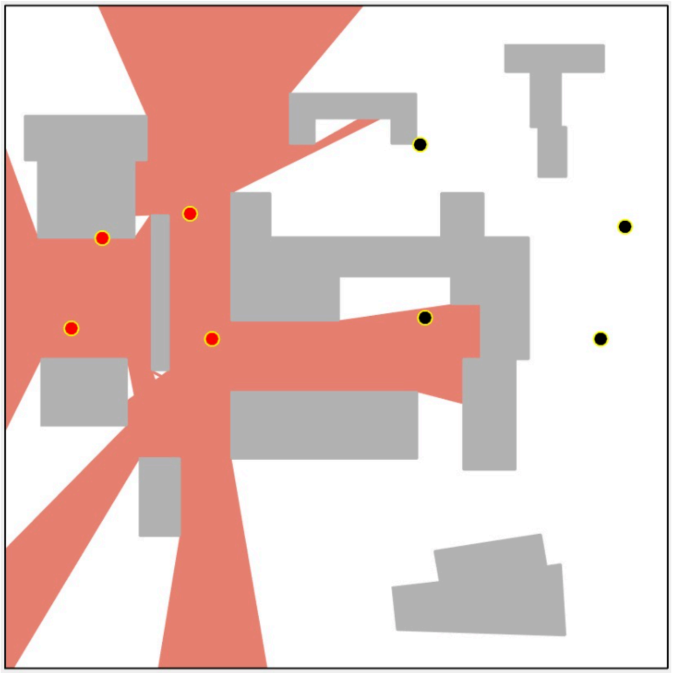
$$i \in \mathcal{S}, \mathcal{S} \subseteq \mathcal{I}.$$

Sensor $i \in \{1, ..., N\}$

A_i : random polygon

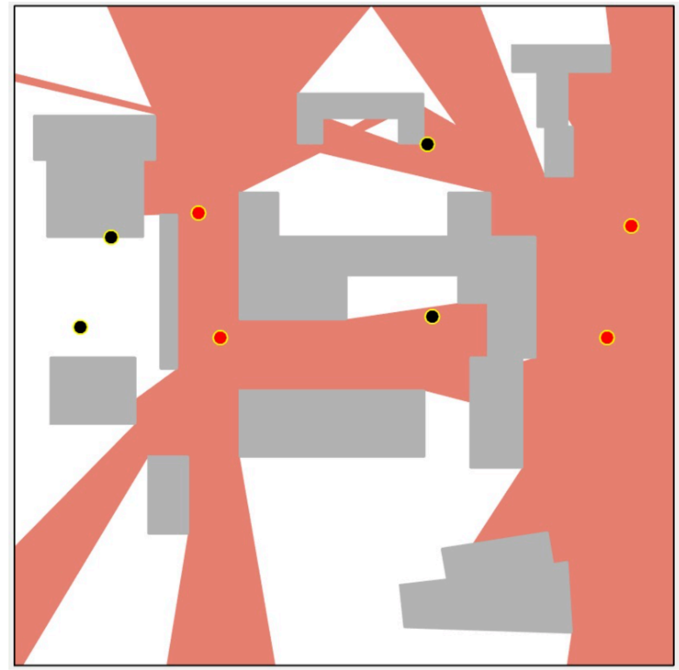
Low Risk vs. Expectation

Conservative



$\alpha = 0.1$

Riskier



$\alpha = 1, \text{expectation}$

- Compare *risk-averse* with *risk-neutral* → Lower visibility region VS Higher visibility region

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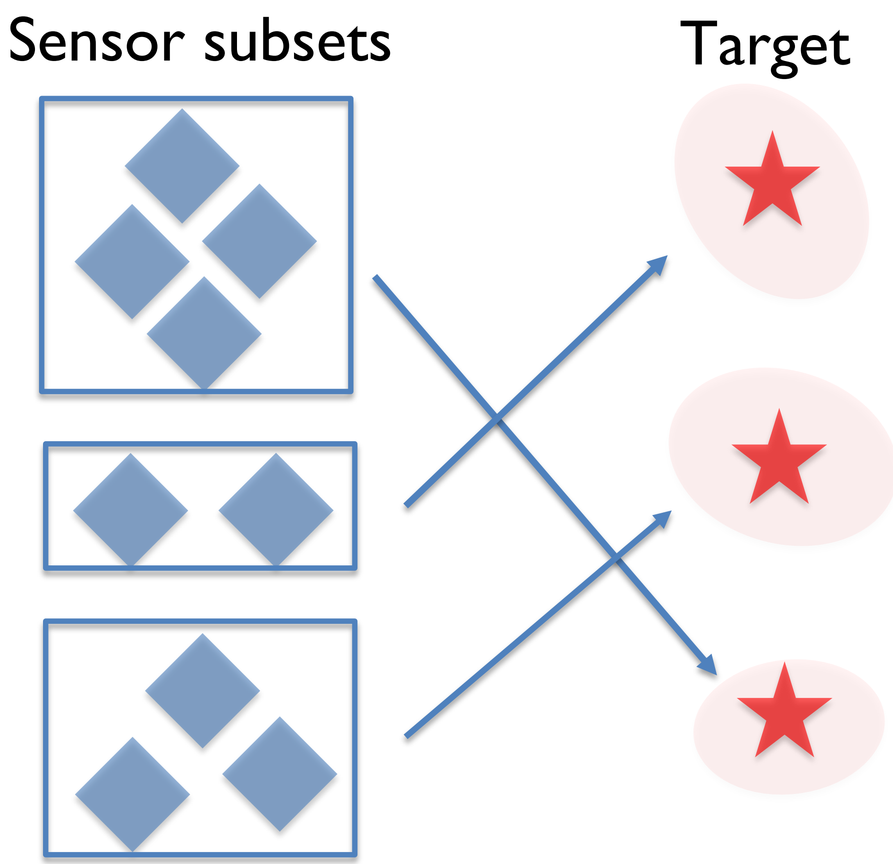
Who to Communicate with?

- Problem: assign sensor subsets to track targets
- Communication: sensors communicate within same subset
- Objective: reduce the uncertainty in targets' positions



Observability of Range Sensors

- Tracking quality: a number of measures on *sensor-target observability matrix*
- We prove certain observability measures are submodular (trace , rank, log det) or non-submodular (inverse cond)

$$O(p_{t_l}, u_{t_l}) \quad = \quad \begin{bmatrix} x_{t_l} - x_{s_1}, y_{t_l} - y_{s_1} \\ x_{t_l} - x_{s_2}, y_{t_l} - y_{s_2} \\ \vdots \\ x_{t_l} - x_{s_N}, y_{t_l} - y_{s_N} \\ u_{lx}, u_{ly} \end{bmatrix}$$

Trace, rank and log det of symmetric observability matrix

$$O^T(p_{t_l}, u_{t_l}) O(p_{t_l}, u_{t_l})$$

Inverse condition number of the observability matrix

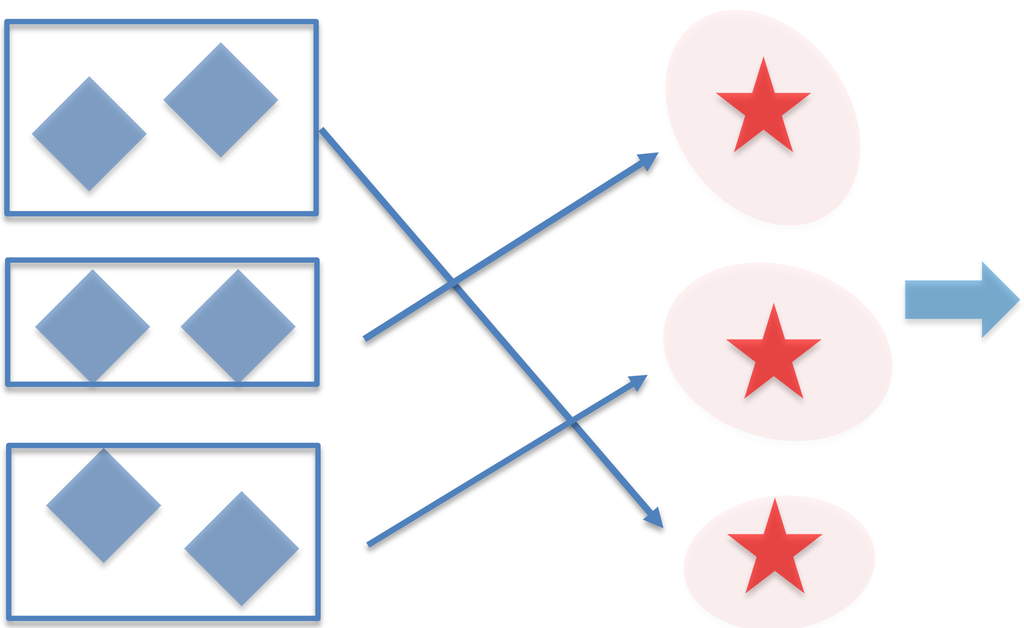
$$C^{-1}(O(p_{t_l}, u_{t_l})) = \frac{\sigma_{\min}(O(p_{t_l}, u_{t_l}))}{\sigma_{\max}(O(p_{t_l}, u_{t_l}))}$$

Contribution: Analysis of Greedy

- Assign sensor subsets with fixed size $n \geq 2$
- For **any** observability measure (not necessarily submodular)

$$f(\mathcal{S}^{\text{Greedy}}) \geq \frac{1}{n+1} f(\mathcal{S}^{\text{OPT}})$$

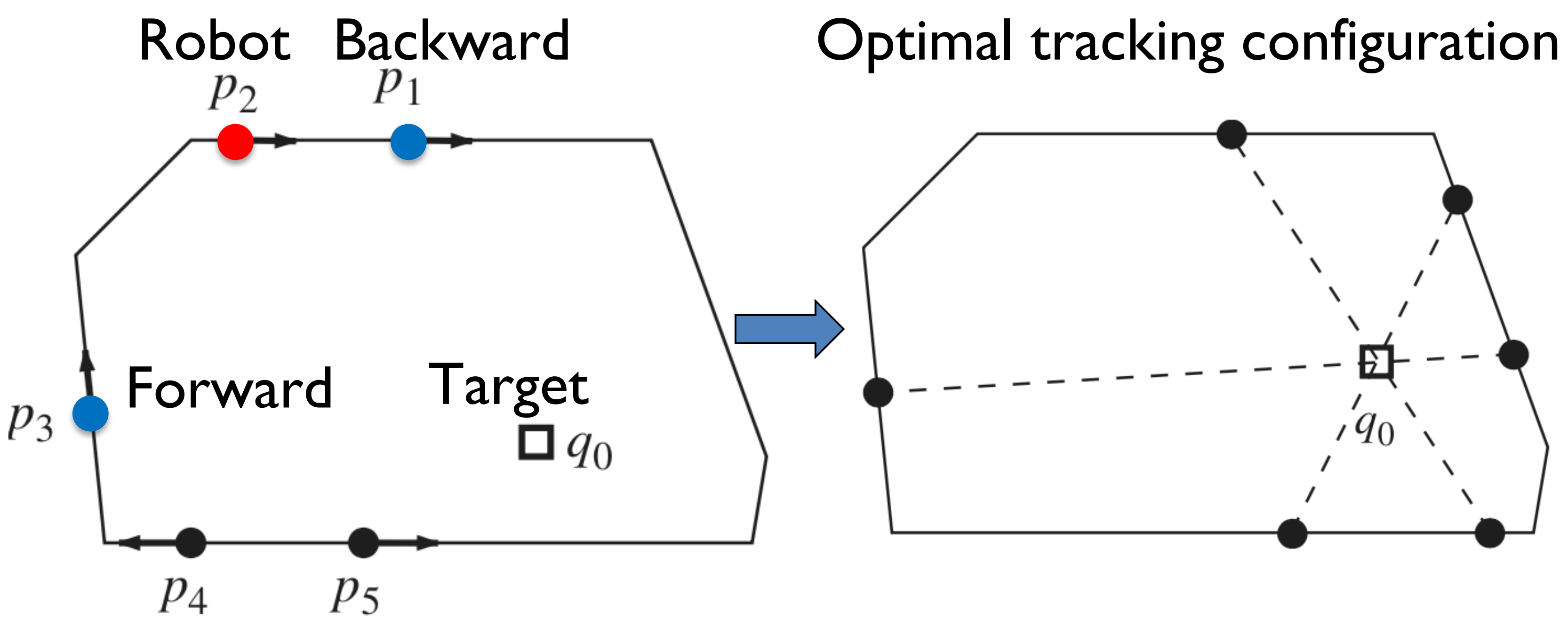
Sensor subsets with size 2



$$f(\mathcal{S}^{\text{Greedy}}) \geq \frac{1}{3} f(\mathcal{S}^{\text{OPT}})$$

Decentralized Target Tracking

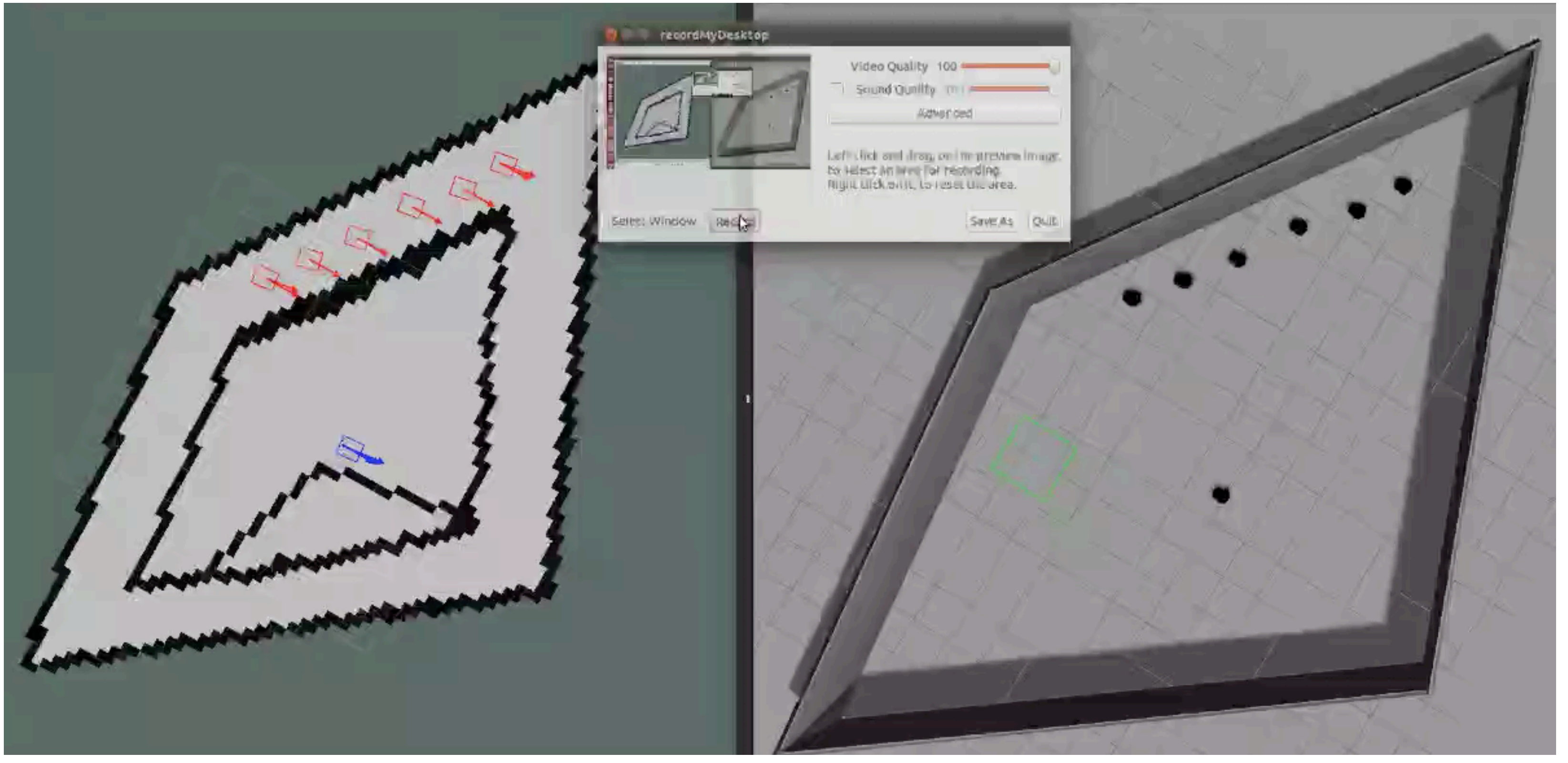
- Robots move on the convex boundary of the environment to track a target inside
- Communicates with backward and forward neighbors



[Martínez & Bullo. *Automatica '06*]

Contribution: Self-Triggered Strategy

- Prove *convergence* to the uniform distribution
- Communicate *when* certain conditions are violated
- Save *more than 30%* communication messages



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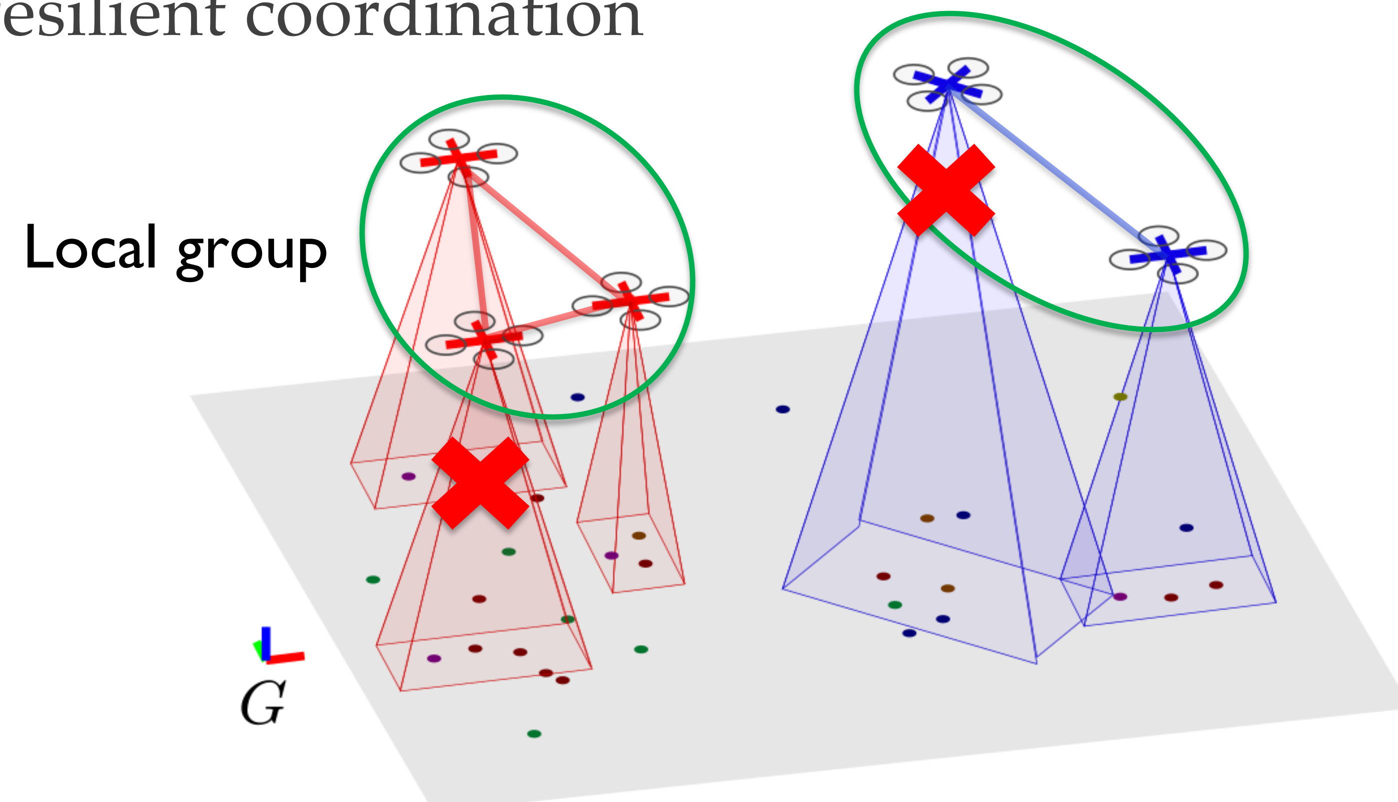
Future work: distributed resilient & online risk-aware coordination with parsimonious communication

Future Work: Distributed Resilient

- Problem: multi-target tracking with adversarial attacks and *limited communication range*
- Idea: *form local groups* & *perform in parallel* a resilient coordination



Future work: Online Risk-Aware

- Problem: reductant vehicle-demand assignment under travel time uncertainty
- Objective: minizine the total waiting time of all demand locations
- Question: *When to reschedule* the assignment: self-triggered

Work I have done

- Active Target Tracking with Self-triggered Communications, **Zhou** & Tokekar, ***ICRA ‘17***.
- Active Target Tracking with Self-triggered Communications in Multi-robot Teams, **Zhou** & Tokekar, ***T-ASE ‘18.***
- Sensor Assignment Algorithms to Improve Observability while Tracking Targets, **Zhou** & Tokekar, ***T-RO ‘19***.
- An Approximation Algorithm for Risk-averse Submodular Optimization, **Zhou** & Tokekar, ***WAFR ‘18***.
- Resilient Active Target Tracking With Multiple Robots, **Zhou**, Tzoumas, Pappas, & Tokekar, ***ICRA+RA-L ‘19***.
- Strategies to design signals to spoof Kalman filter, Zhang, **Zhou,** & Tokekar, ***ACC ’18.***
- A Minimax Tree Based Approach for Minimizing Detectability and Maximizing Visibility, Zhang, Smereka, Lee, Sung, **Zhou,** & Tokekar, ***ICRA ‘19.***

Thanks for listening!

Lifeng Zhou

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