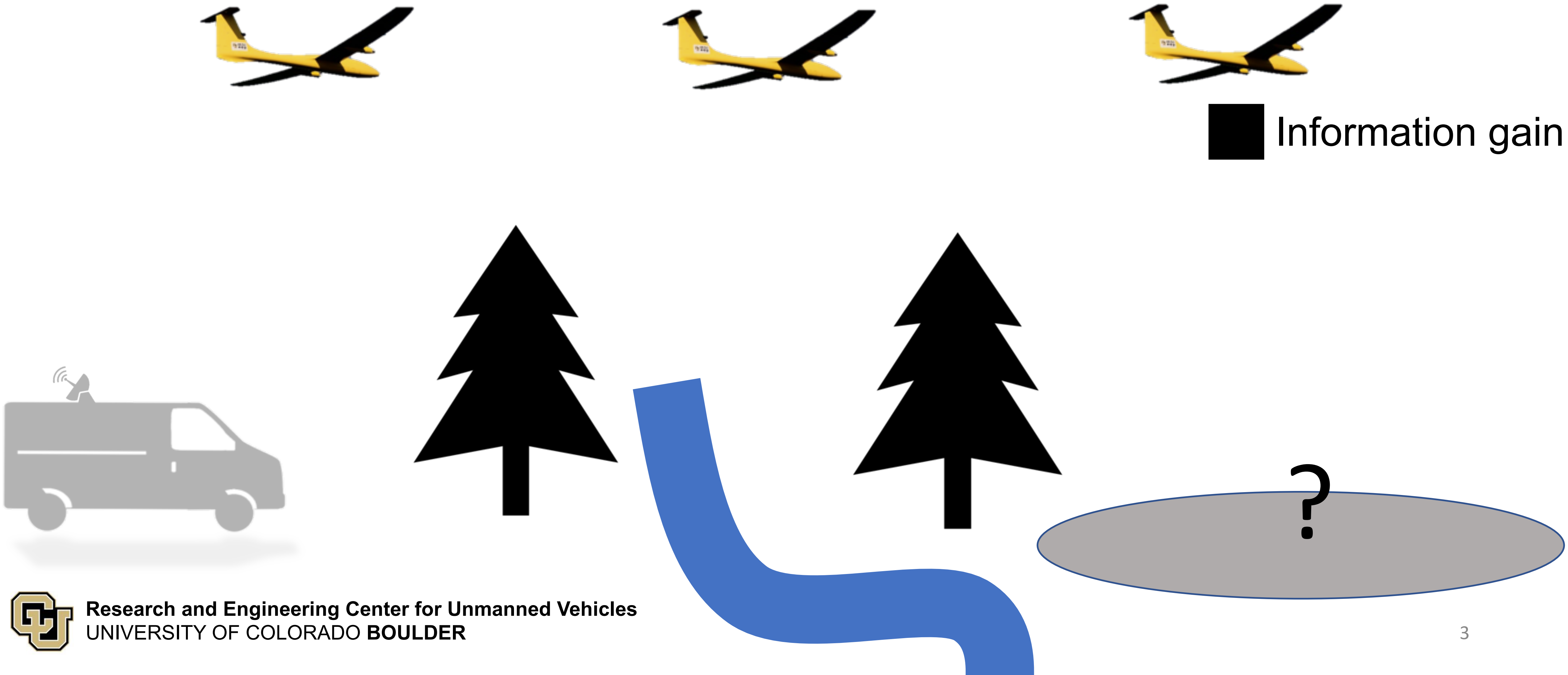
A Distributed, Greedy Planner for Multiple sUAS using Expected Downstream Information Gain

John M. C. Jackson
PhD Student
Smead Aerospace, CU Boulder
2020 AIAA SciTech Exposition

Motivation for Networked sAUS

Images from OnyxStar, CGTN

sUAS Mission Example



Planning for Networked sUAS

- Sequential planning – first, then second, then third, etc.
  - Does nots scale to number of vehicles
  - Agents have complete knowledge

- Parallel planning – plan at every step, uncertain of what neighbors may do
  - Lacks complete knowledge about what neighbors will do
  - Scales massively

- In both cases: collect information, maintain comms

Problem Statement

Problem – Design a planner for a network of sUAS such that

1) information is collected on a target, while
2) maintaining a communication route to the base

Solution – A distributed, greedy planner that maximizes the expected downstream information gain

Focus: The Information Utility

Expected Downstream Information Gain

- Used to define a utility for optimization
- Expected – Best estimate of future values based on states
- Information Gain – Measure of quality of data collected
- Downstream – Communication hierarchy

Expected Information Gain

- Amount of information an agent expects from neighbors
- Defined using gradient of the sensor model

Communication Model

- Binary erasure model – messages go through or don't

[redacted]

Communication Event Random Variable
0 or 1

[redacted]

Expectation of Communication Event
P(success)

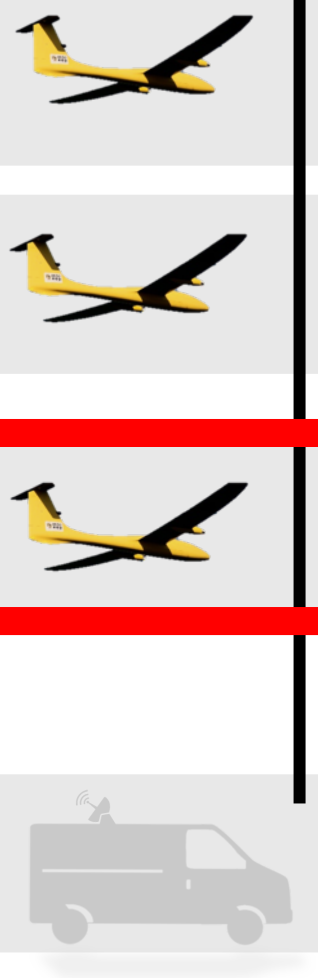
E[Info Received] = P(success) x E[Info Sent]

Comm-Aware Information Gain

- Agents predict the expected information received at a future position

Communication Hierarchy

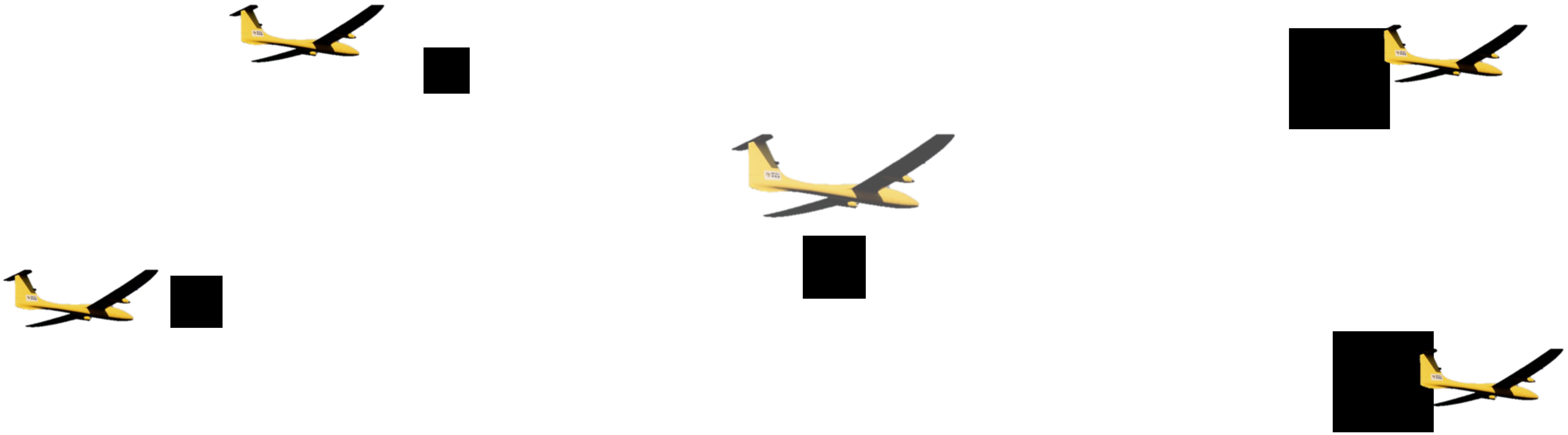
Agent		Comm Order
C		3
B	Downstream / Upstream	2
A		1
Base		0



Downstream Information Gain

Downstream Agents

Upstream Agents



Downstream Information gain

- Putting it all together gives the expected downstream information gain

$$\downarrow\text{Info} = P(\downarrow) \times (\text{Self Info} + \uparrow\text{Info})$$

P(↓) – probability of communication with closest downstream neighbor

Agent w/ no sensors becomes relay

Simplified Algorithm

- Each agent in parallel:
  - Receives messages from neighbors
  - Takes its own sensor measurements
  - Calculate best action for downstream information gain in next step
  - Execute, and repeat

Simulation Details

- Homogenous network of fixed wing sUAS (Dubin's car)

$$u' = 0.5 u_k \Delta T$$

$$x_{k+1} = x_k + \Delta T sinc(u') \mathrm{v}_g \cos(\psi_k + u')$$

$$y_{k+1} = x_k + \Delta T sinc(u') \mathrm{v}_g \sin(\psi_k + u')$$

$$\psi_{k+1} = \psi_k + \Delta T u_k$$

- Small control space (move right, speed, etc.)
- Obstacle-free environment

Simulation Details

- RF-emmittor sensor model

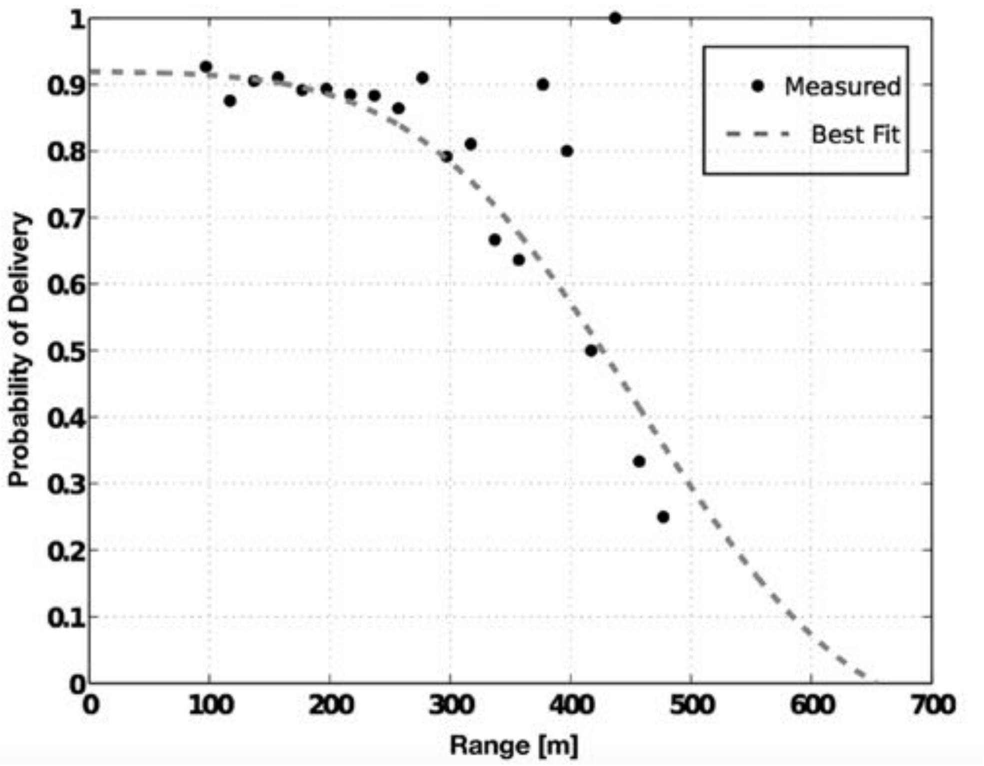
$$h(r) = 10 \log 10 \frac{k_0}{r^\alpha}$$

$$I_r = \nabla_r h(r)^T \mathbf{R}^{-1} \nabla_r h(r)$$

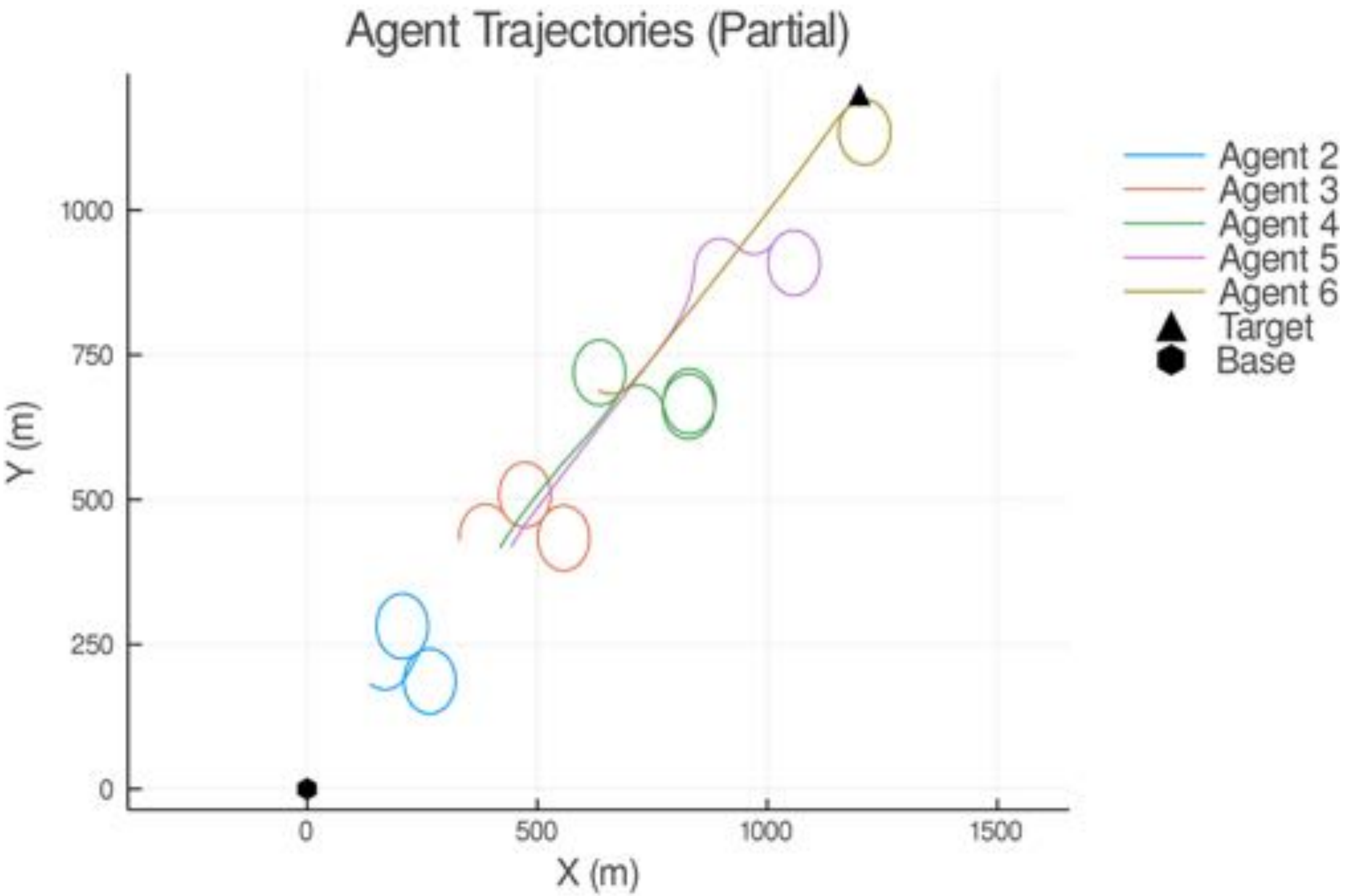
- Communication from flight experiment

$$\downarrow I^i = \downarrow \beta^i (\hat{I}^i + \uparrow I^i)$$

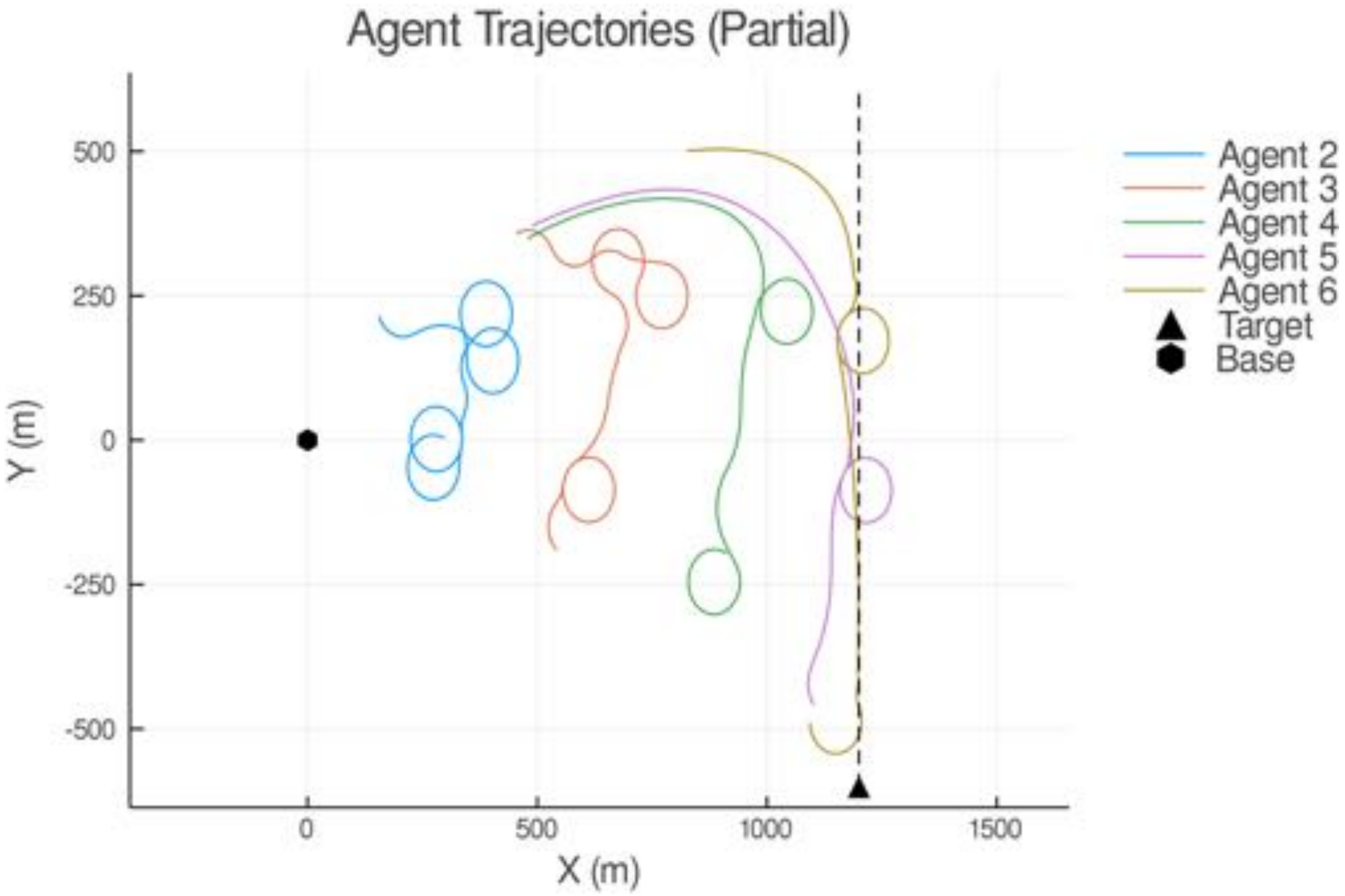
- Assumes a good estimator is available



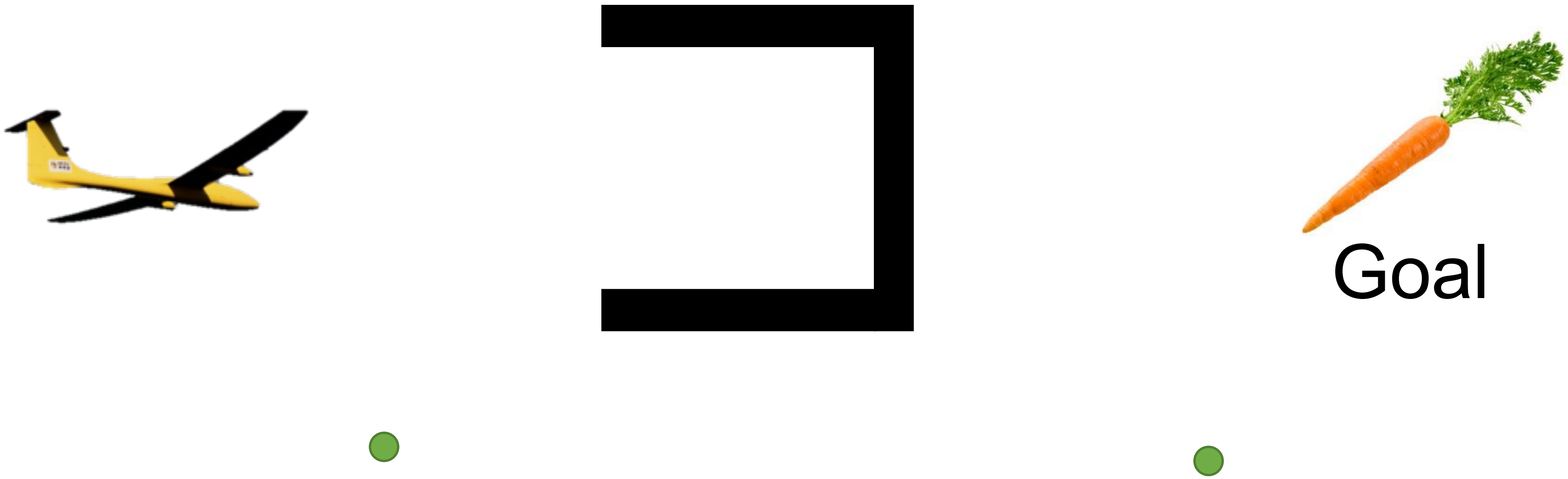
Static Target



Moving Target

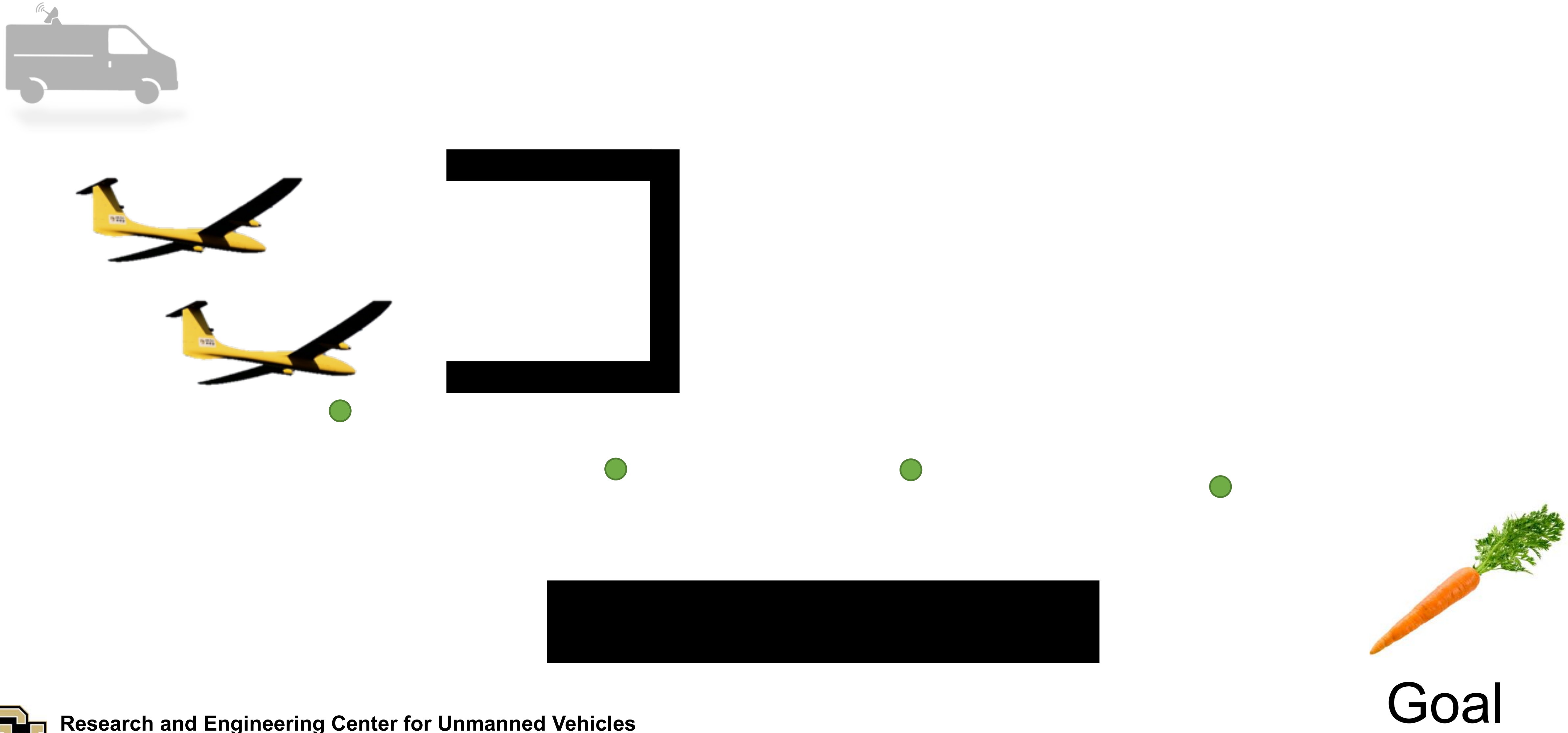


With Obstacles

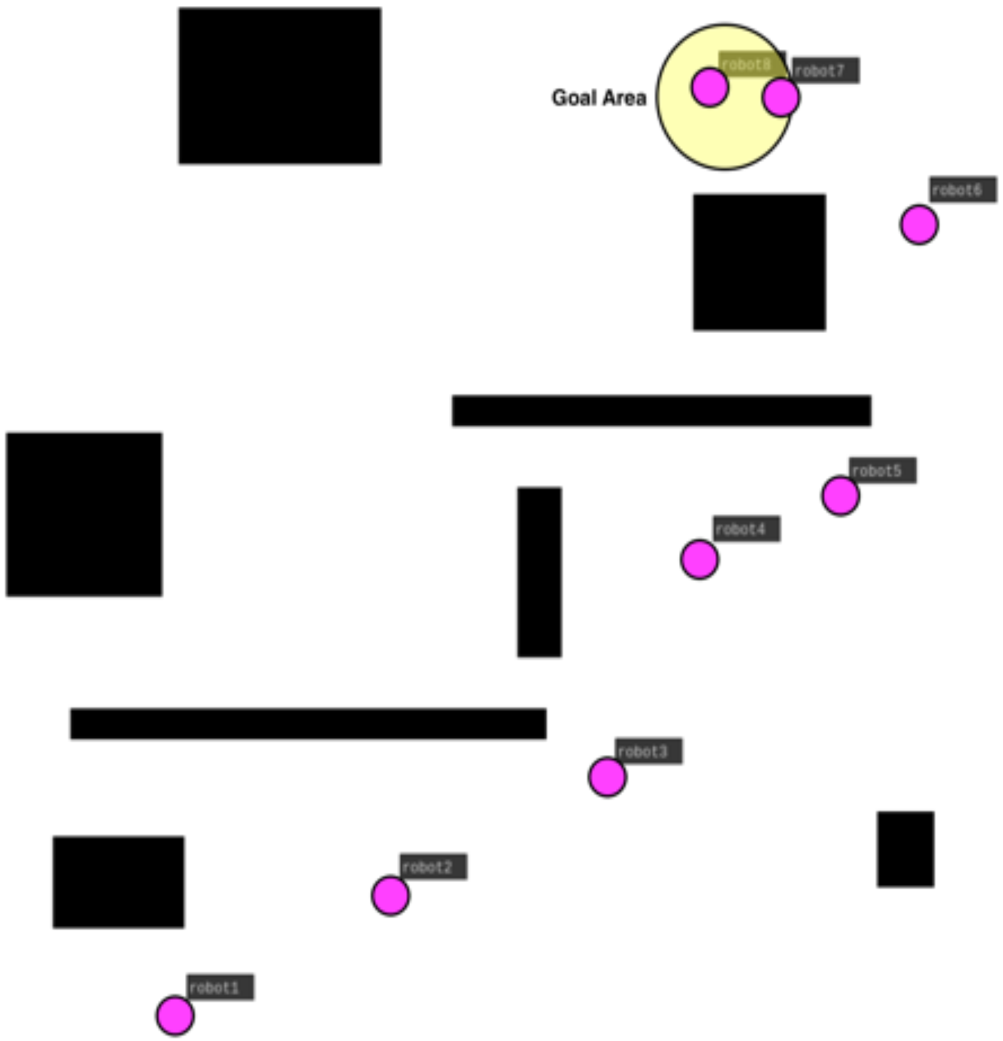


- Greedy planners don’t work with obstacles
- Workaround using a discrete path and treat them as pseudo targets

With Multiple sUAS



Simulation Result



Future Work

- Communication not always maintained
  - Assumption that neighbors don’t do anything, easy to implement
- Inherently handles heterogenous network of agents
  - Though dynamic communication ordering would be nice
- Information is “duplicated” – need to account for mutual information for multitarget tracking

Conclusions

- Use communication model and sensor model to define expected information gain
- Downstream information gain is a useful utility for missions which require connections to base or other nodes in network
- Simple simulations show it is conceptually sound

Thank you for listening!