- Why multi-robot system?
 - Better global system performance
 - More abilities
 - More robustness
 - Lower cost
- What is multi-robot coordination?

A team of robots interacting with others to reach a common goal.



Kiva Systems





- Why building efficient multi-robot coordination is difficult?
 - Most problems are **NP-hard**:
 - Multi-robot Task Allocation
 - Resource allocation
 - Exploration

- Multi-robot Motion Planning
 - Routing
 - Trajectory planning



Wildfire monitoring



Multi-UAV path planning

- How to reduce the difficulty?
 - Reduce the environment space
 - Reduce the action space
 - Estimate a finite horizon of future



Outline

Known Environment with Global Communication:



Intelligent In-Orchard Bin-Managing System For Tree Fruit Harvest



Multi-robot Routing for Dynamic Information Gathering

Unknown Environment with Limited Communication:



Multi-UAV Explore, Map, and Search in Unknown Environments





Intelligent In-Orchard Bin-Managing System for Tree Fruit Harvest

(aka. the Bin-dog project)

Motivation

High labor demand of tree fruit(apple) harvest

Low productivity with inefficient bin management













6 October 1, 2015

Apple harvest in Prosser, WA.

Main Goal

To develop an intelligent bin-managing system supported by a robotic self-propelled fruit bin carrier





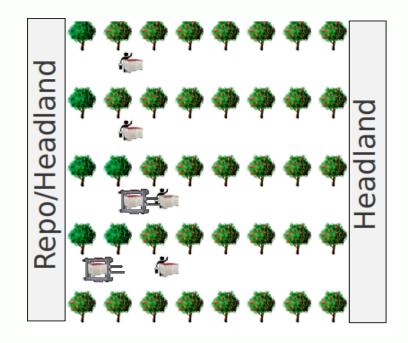
"Bin-dog", designed by Center for Precision & Automated Agriculture Systems, Washington State University



Simulation Environment

- 10 trees x 5 lanes
- Workers cost 2 steps to finish one tree
- Robots move 1 step per time when carrying a full bin, 2 steps otherwise.







Simulation Setup

 Groups of workers are initialized in the beginning of the lanes.

- No more apples?
 - Workers move to a new location.
 - Workers request a new bin.
- Robots choose which bin to pick up.
 - Robots wait if the target bin is not full yet.
- Robots choose where to carry a new bin to.



Algorithm: Baseline (Naive Greedy)

- Greedy, no coordination.
- Choose the closest full bin.
- Choose the earliest requested location.
- Choose the bin that will be filled faster.
 - Wait if the target bin is not full.
- Priority: other robots cannot see a chosen bin/request.

Not efficient!



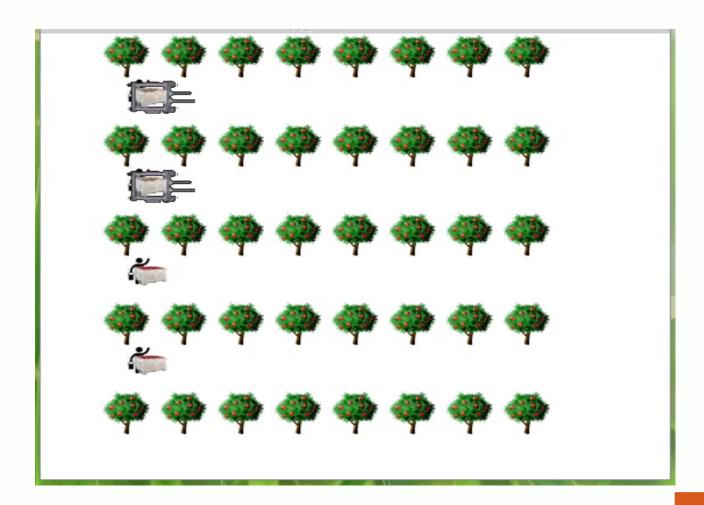
Algorithm: Auction-based

- Robots coordinate through auction.
 - Each robot makes plans to pick up a bin.
- Plan cost:

$$C = t_T + t_W$$

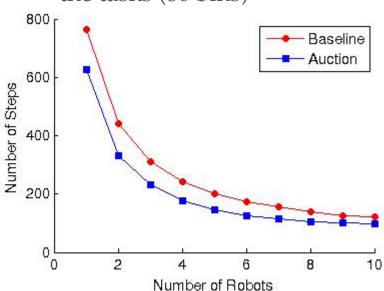
- t_T: the time required to reach target bin.
- t_w: the time required to wait for target bin to be full.
- The one with least cost wins the task

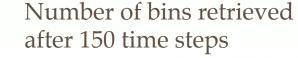
Simulation (Auction-based)

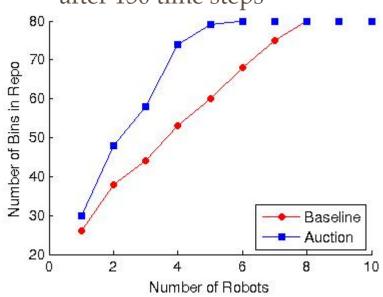


Results

Total steps cost to finish all the tasks (80 bins)











Higher is better



Extension

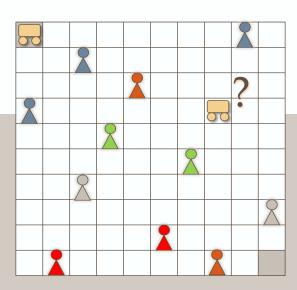
"Bin-dog" is interesting, but...

- Visit multiple points of interest one time?
- How to balance the workload between robots?
- Workers work in different speed?





Multi-Robot Routing for Information Gathering



Goal

Coordinate a team of robot to retrieve resources from a number of resource collectors in a static environment.

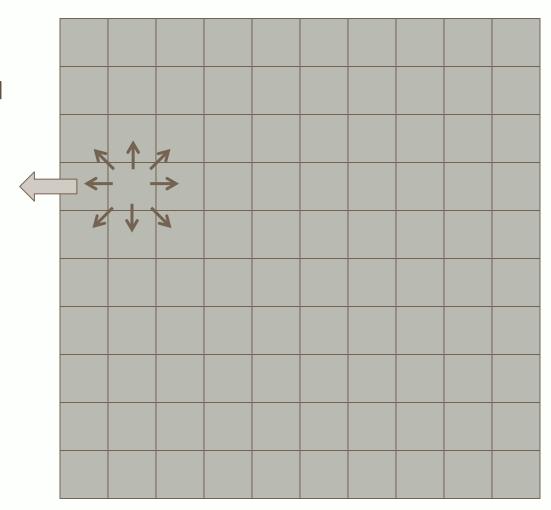






Informative map

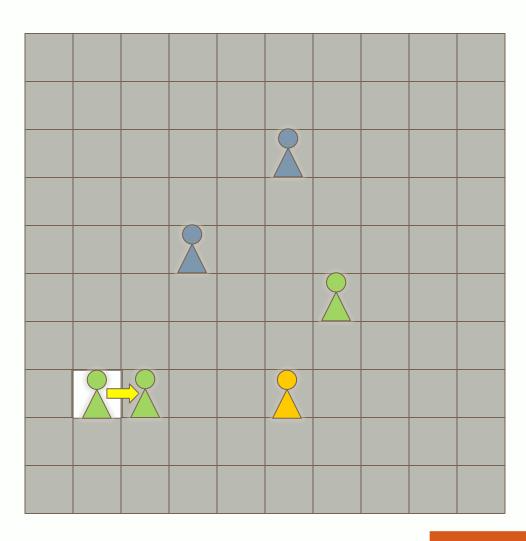
- 8-connected 2D grid
- No obstacles
- Each cell has a certain amount of information





Collectors:

- Collect information from each cell
- Move to a neighbor cell when finish
- Individual collecting rate
- Limited capacity, pause when full

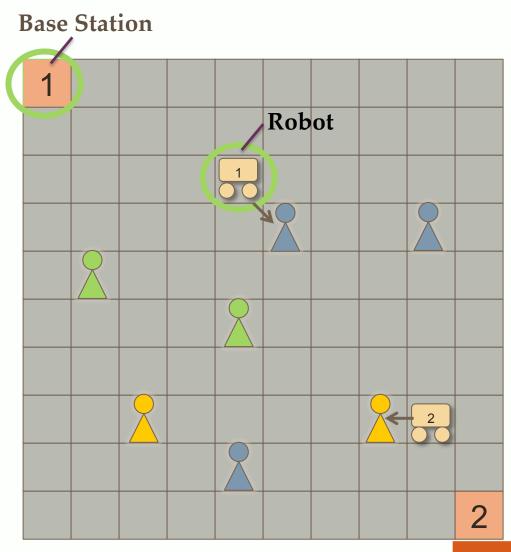




Robots

- Visit collectors to retrieve information
- Consistent speed
- Different base stations
- Limited capacity, go back if full

Robot can retrieve a portion of information from each collector



Problem Formulation

- Given:
 - n collectors
 - m robots
- Objective Function

$$arg\max(\neg p \downarrow i \in \Psi Info(R \downarrow i...m) - Idle(T \downarrow i...n)$$

Sub-problems

- Two sub-problems
 - Multi-robot Task allocation:
 - which collector should be assigned to which robot?
 - Multi-robot Motion Planning:
 - Visit the goal collectors in which order?
 - Retrieve how much information from a specific collector?



Algorithm: Sequential Auction with Greedy Path Planning

- Task Allocation: Sequential Auction
 - Sort the unassigned tasks (collectors) by urgency:

 $U \downarrow i$ = (collecting rate + current fullness)/distance

- Auction tasks based on urgency
- Cost of each robot:

 $c \downarrow i$ = total travel distance of current tasks + distance from last task to the auctioning task

Reassign if any robot idle



Demo: Sequential Auction with Greedy Path Planning

Be *exact* full after visit all assigned collectors

$$U \downarrow 1 > U \downarrow 2$$
$$T = 11$$

Information
Collected Estimation:

$$I = (r \downarrow 1 + r \downarrow 2) * T$$

+ CUR
Information

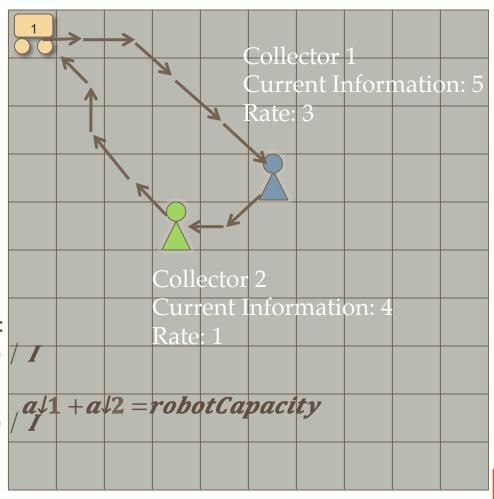
Retrieve for collector 1:

$$a \downarrow 1 = (r \downarrow 1 * T + cur \downarrow 1) / T$$

* robotCapacity

$$a \downarrow 2 = (r \downarrow 2 *T + cur \downarrow 1)$$

* robotCapacity



Algorithm: Sequential Auction with Greedy Path Planning

- Motion Planning: Greedy
 - Path Planning: 1-horizon greedy. Visit the most urgent collector first.
 - Information Gathering Planning
 - T: time *required* to travel the path.
 - Estimated information collected by collector *i*:

$$\Delta \downarrow i = content \downarrow i + T \times f \downarrow i$$

• Amount to take (Try to be *exact* full after visit all assigned collectors):

$$a\downarrow i = \Delta\downarrow i / \sum_{j=1}^{j} 1 |P| \otimes \Delta\downarrow j \times Robot Capacity$$

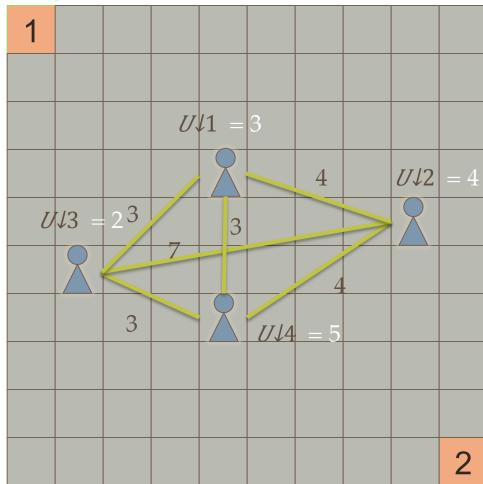


Algorithm: Distributed Sampling with RH-based Path Planning

- Task allocation: distributed sampling.
 - Goal: evenly distribute the workload to the robots



Create fully connected Graph *G*



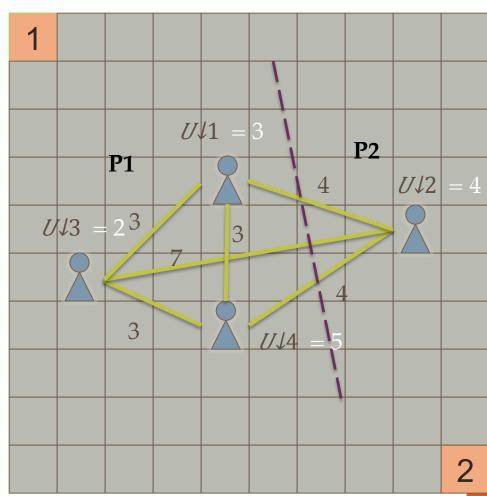
Random part it into *m* parts.

Cost(P1) = sum(

$$U \downarrow 1,3,4$$
)
+ sum(
 $E \downarrow 13,14,34$)
= 19

Cost(P2) = 4

$$Diff(P1, P2) = 15$$

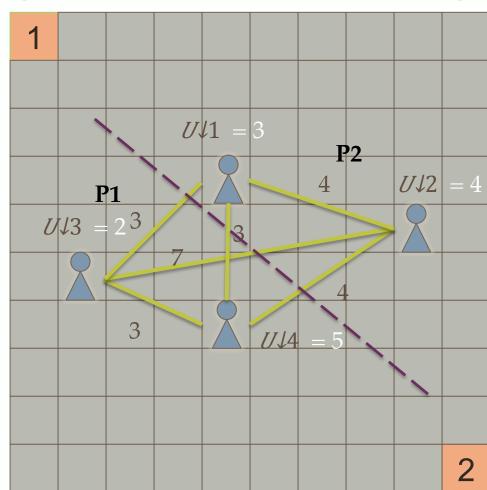


Balance by move the boundary nodes.

$$Cost(P1) = 10$$
$$Cost(P2) = 9$$

Diff(P1, P2) = 1 < previous Diff15

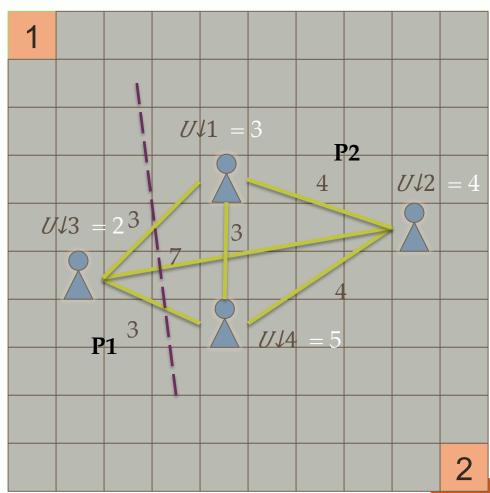
A better partition!



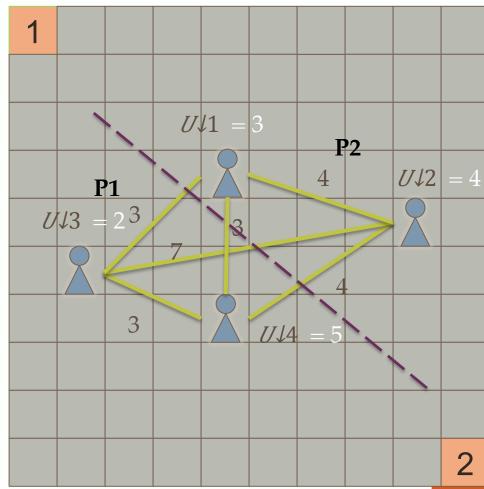
Balance by move the boundary nodes.

$$Cost(P1) = 2$$

 $Cost(P2) = 23$



Continue until converged



Workload Partition

Steps:

- Create a fully connected graph G = (V, E)
- *V* is the set of all nodes (collectors), *E* is the set of edges.
- Optimization problem:

$$\frac{\arg\min_{(G_i,G_j)} \ [\max_{i \in [1,m]} (\sum_{\forall a,b} (w_{v_a}^i + w_{e_b}^i)) - \min_{j \in [1,m]} (\sum_{\forall c,d} (w_{v_c}^j + w_{e_d}^j))]. }{\text{Time required}}$$
 to reach capacity Collector's fill rate

$$w \downarrow v \downarrow a = -t \downarrow v \downarrow a + f \downarrow v \downarrow a$$
$$w \downarrow e \downarrow b = length(e \downarrow b)$$



Proposed Algorithm: Distributed Sampling with RH-based Path Planning

Routing

- Receding Horizon-based routing.
- Look ahead h steps.
- Preferences of visiting a node V_i :

$$c \downarrow i = U \downarrow i / d \downarrow i$$

- $d_i = dist(R, v_i)$ if v_i is the first node in the path
- $d_i = dist(v_i, v_j)$ otherwise

Receding Horizon Path Planning

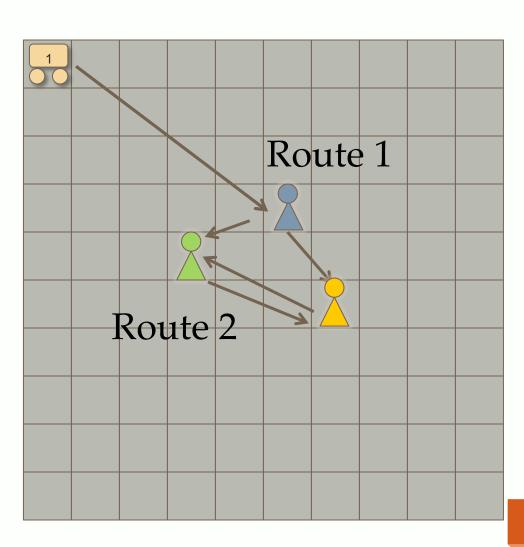
Find which collector to visit first

3-horizon planning

Route 1 Route 2

. . .

Route 6



Proposed Algorithm: Distributed Sampling with RH-based Path Planning

- Information Gathering Planning
 - T : time *required* to travel the path.
 - Estimated information collected by collector *i*:

$$\Delta \downarrow i = content \downarrow i + T \times f \downarrow i$$

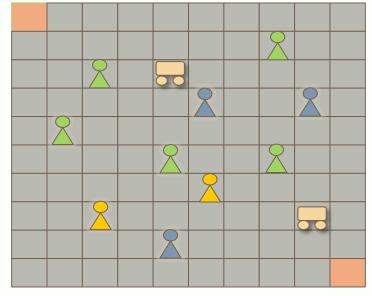
Amount to take (Try to be exact full after visit all assigned collectors):

$$a \downarrow i = \Delta \downarrow i / \sum_{j=1}^{j=1} |P| \otimes \Delta \downarrow j \times Robot Capacity$$



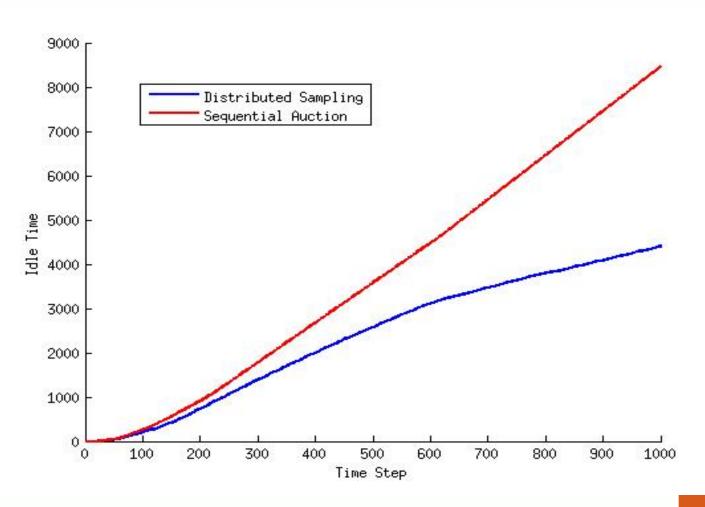
Simulation

- 10 x 10 cells. Each cell contains 200 units of information
- Collectors: 2 collectors with collecting rate 5, 3 collectors with rate 2, 5 collectors with rate 1.
- Capacity: Both robots and collectors have a capacity of 100 to store information.
- Robots start from different corners.



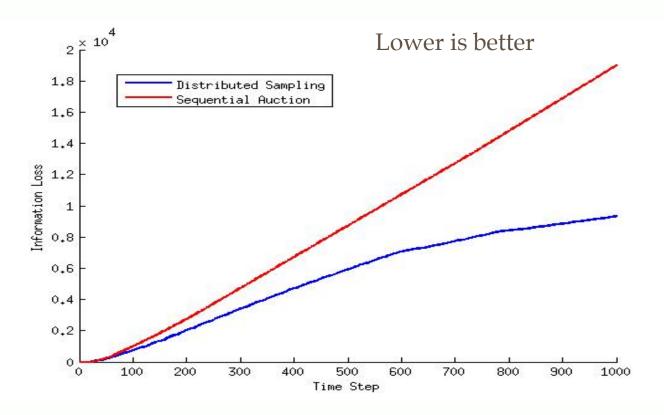


Idle Time (1000 steps)



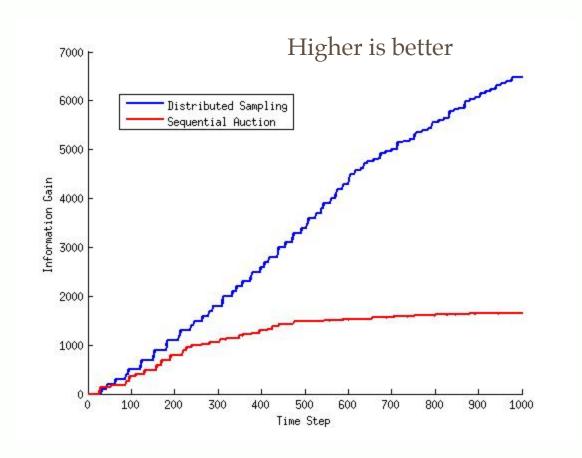


Information Loss (1000 steps)





Information Gain (1000 steps)





Extension

Known environment vs. Unknown environment

Certain vs. Uncertain

Global communication vs. Limited Communication

Centralized vs. Decentralized





Multi-UAV Explore, Map, And Search in Unknown Environments

Introduction











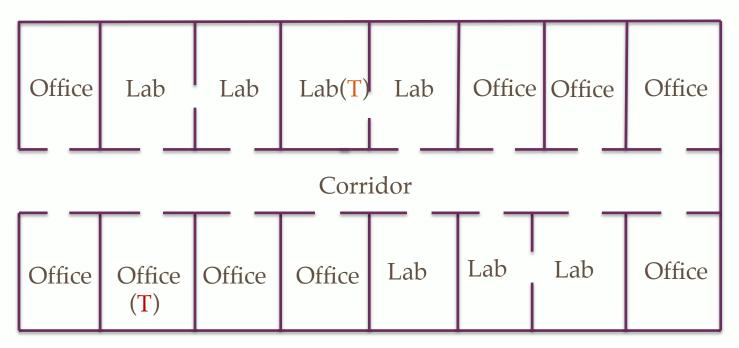
Goals

- An approach enable a team of UAVs simultaneously explore, map, and search in unknown environments.
- A mechanism controls the UAVs more focus on one or two subtasks (exploration, mapping and search).
- A communication scheme efficiently the human operators during the mission.



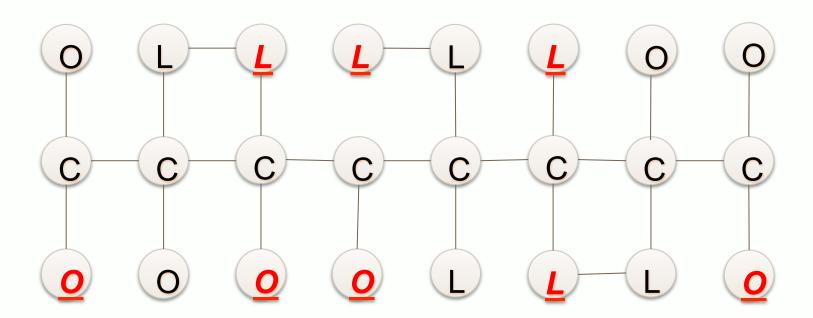
Problem Setup

- Environment
 - Indoor Environment with different types of rooms
 - Some rooms contain targets



Problem Setup

- Topological Representation
 - Model the environment as a graph with rooms as nodes





UAV Model

- Limited Battery Life
- Equipped with two types of sensors:
 - Observe the room type
 - Observe the target existence
 - Both of the sensors have noise
- Limited communication (disk model)



UAV Belief State

• Room type (assume UAVs know the all types of rooms) For room r, probability of room type:

$$P \downarrow r = [P \downarrow t1, P \downarrow t2, ...P \downarrow tn] (n = |R|)$$

$$\sum_{i} \hat{I} = 1$$

Target existence
 For room r, probability of target existence

$$P \downarrow t = [P \downarrow T, P \downarrow F]$$
$$P \downarrow T + P \downarrow F = 1$$



Priors

• Priors provide the probability of a specific type room contains a target.

| Office | Lab | Corridor |
|--------|-----|----------|
| 0.6 | 0.7 | 0.1 |



Bayesian Update

- Bayesian Update
 - $PR\uparrow t+1 T = P(T|R)/P(T) P(R\uparrow t)$
 - $PT\uparrow t+1 R = P(R|T)/P(R) P(T\uparrow t)$
- The posteriors become the new priors.

Reward Function

Robots choose one of the three actions:

Visit a neighbor node(exploring)

```
I \downarrow E = I \alpha \uparrow visited (I is the utility of first visit, 0 < \alpha < 1)
```

Observe for room type (mapping)

$$I \downarrow m = -\sum r \in R \uparrow @P \downarrow r \log P \downarrow r$$

Observe for target (search)

$$I \downarrow S = T \downarrow$$
, $T \in [0,1]$ (real utility gain)

$$I \downarrow S = P \downarrow T$$
, $P \downarrow T \in [0,1]$ (estimation)



Weighted Sub-goals

Weights are set up to more focus on one or two sub-tasks

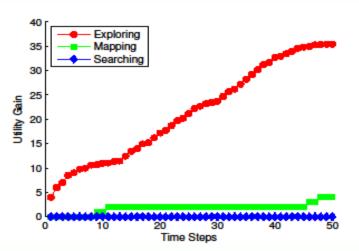
$$\omega = [\omega \downarrow e, \omega \downarrow m, \omega \downarrow s]$$

$$\omega \downarrow e + \omega \downarrow m + \omega \downarrow s = 1$$

How to apply:

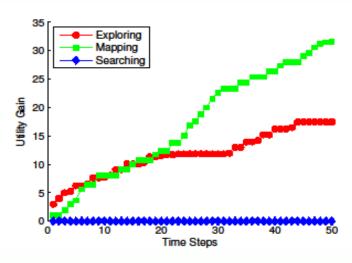
use ω times the estimated reward to generate new estimated reward





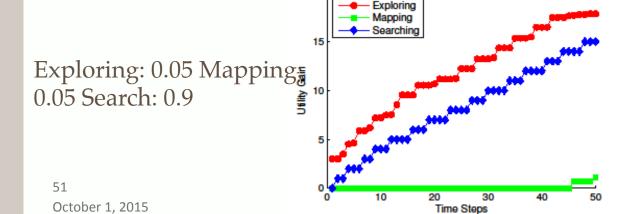
Exploring: 0.9 Mapping:

0.05 Search: 0.05



Exploring: 0.05 Mapping:

0.9 Search: 0.05



Oregon State

Communication Loss Constraint

A communication loss constraint S is set up that only allows each UAV lose a valid communication link with human operators no more than S steps.

Idea: Engage the human operators during the mission



Algorithm: Baseline

 Each UAV selects the action with the best estimated reward.

 Change if conflict with other UAVs with higher estimated reward for the same action.

 Have to select the goals without violate the constraint. Communicate with base station (human operators) at least every S steps.



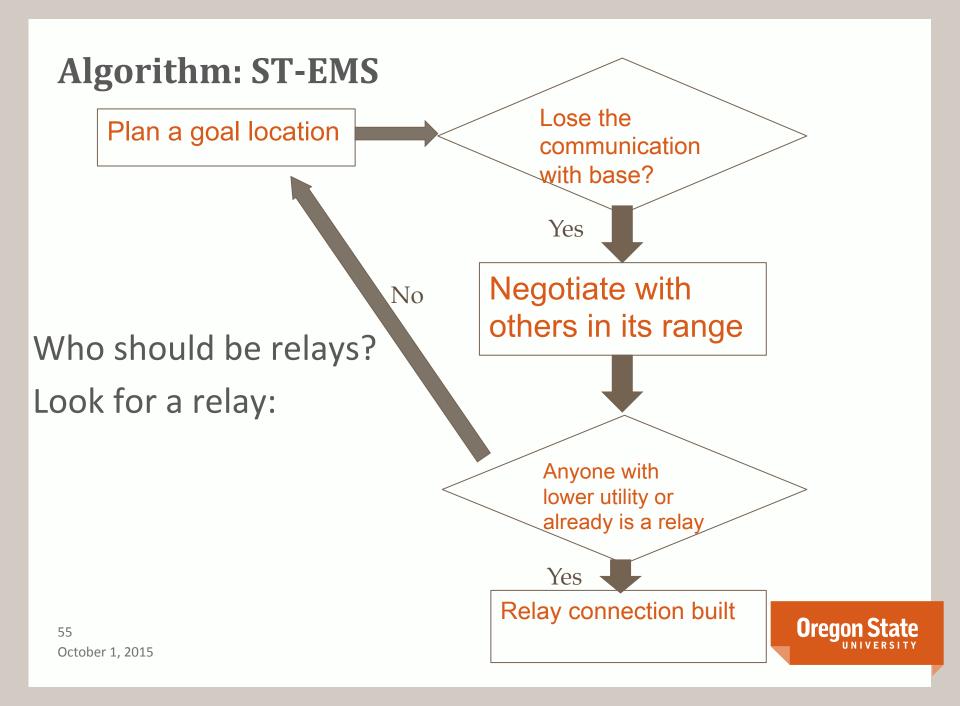
Algorithm: ST-EMS (Steiner Tree – Explore, Map, Search)

Explorer and Relay

• Explorer: explore, map, and search the environment base on the reward functions and weights.

 Relay: retrieve the explorer's information to base station so explorers have more freedom to fulfill the missions.



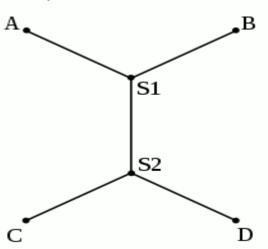


 Find relay locations: Steiner Minimum Tree with Minimum Steiner Points and bounded edge length(SMT-MSP)

Steiner Minimum Tree

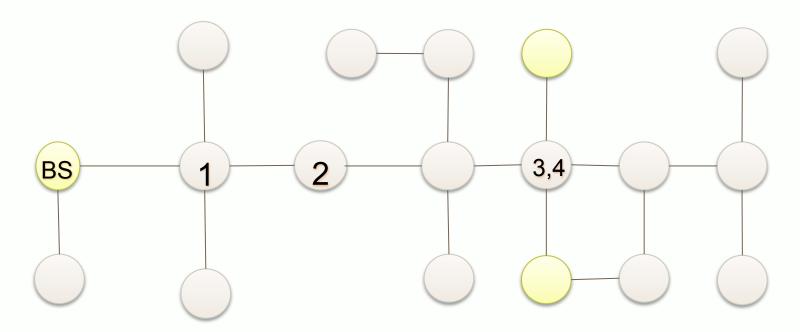
Given a set V of vertices, interconnect them by a graph of

shortest length



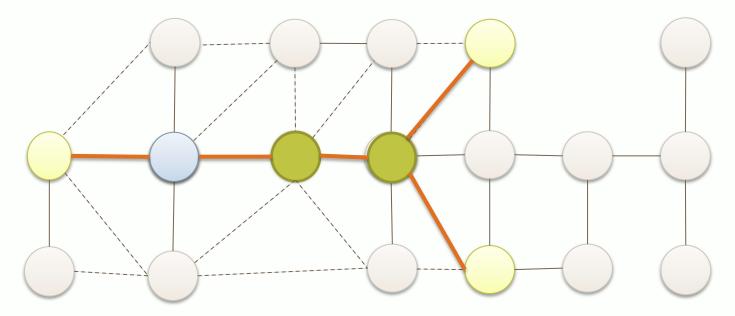


- SMT-MSP
 - Find the best relay locations

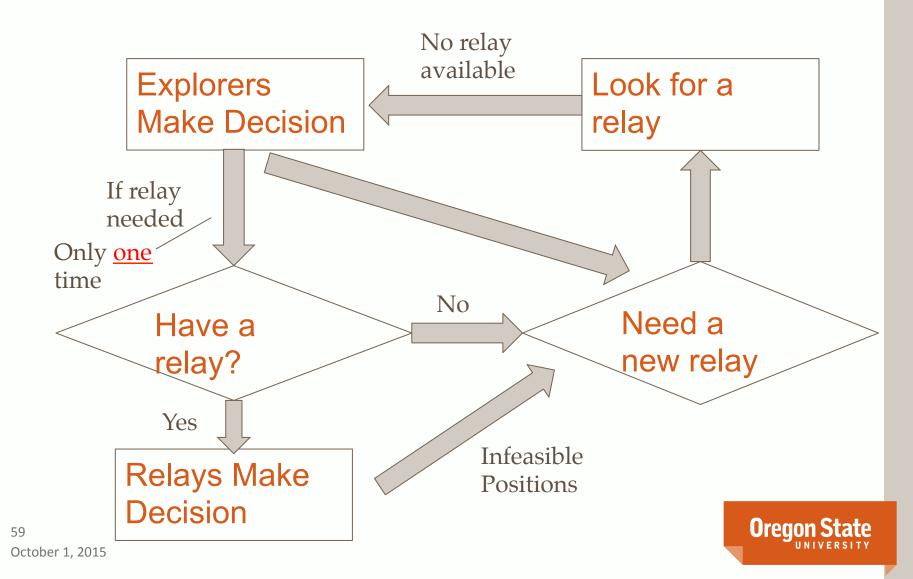




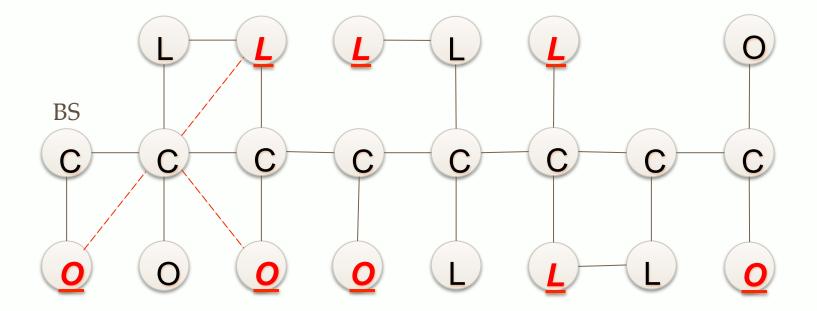
- SMT-MSP is NP-hard (Chen et. al, 2000)
- Greedy approximate(Du and Hu, 2008)



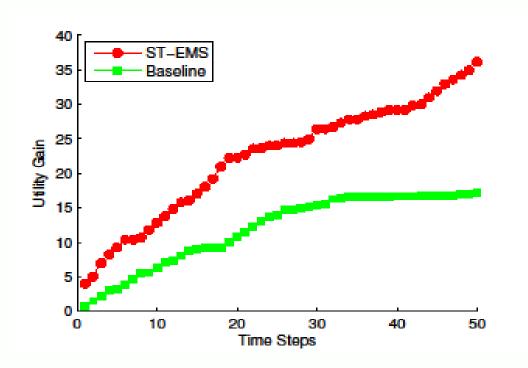




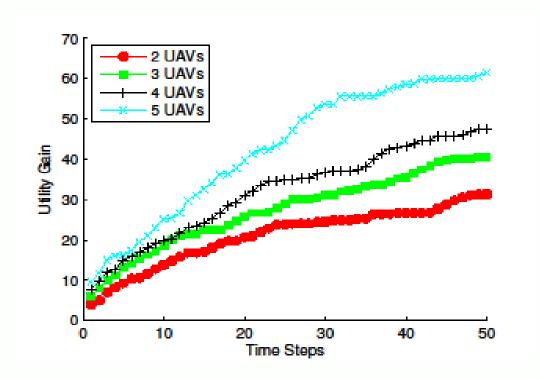
Simulation: Environment



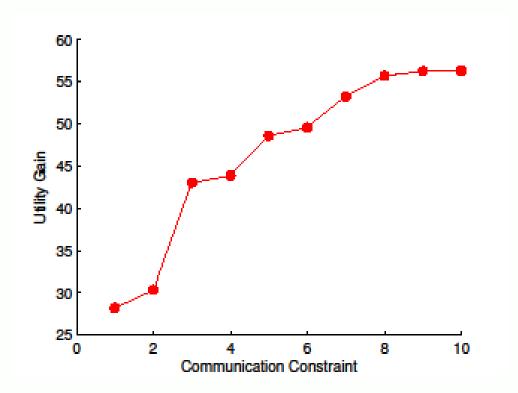
Total reward gain for both algorithms for 50 steps



• Scalability: total reward gain for 50 steps



Reward along with different communication loss constraint



Summary of Contributions

Known Environment with Global Communication:



An intelligent in orchard auction-based binmanagement system



Dynamic information gathering with even workload distribution and RH-based routing

Unknown Environment with Limited Communication:



Multi-UAV Explore, Map, and Search simultaneously with operator preferences and communication loss constraint



Conclusion

Multi-robot coordination is difficult because:

- Large state space
- Many action choices
- Dynamic environments

We approach them by:

- Estimating a finite horizon of future changes
- Each robot makes independent decisions while contributing to a common objective
- Underlying representation allows coordination



Future Work

- Improved future predictions
 - Environment, task, teammates
- Better task decomposition and allocation
 - More sophisticated partitioning, Steiner tree approximation
- Integration with human operators
 - Learning operator preferences across environments
- Implementation: orchard bin management, UAV exploration/ mapping/search



Acknowledgement







Center for Precision & Automated Agricultural Systems
World Preeminent, Washington Relevant

Washington State 🥳 University



Questions?

