Planning Under Uncertainty for Unmanned Aerial Vehicles (UAVs)

by Ryan Skeele
Advised by Geoff Hollinger

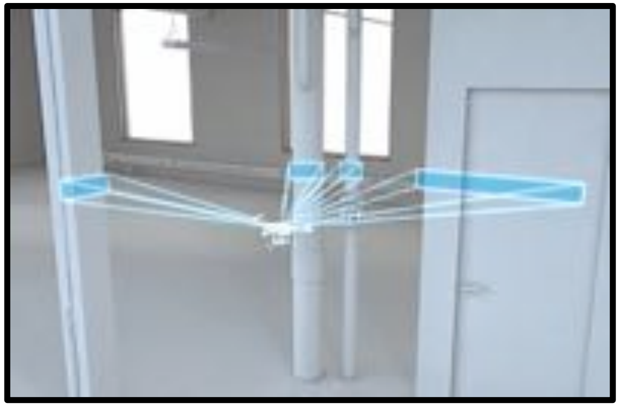
Thesis Defense for the Masters of Science in Robotics

UAVs Successfully Used for Many Tasks

UAVs Operate in Challenging Environments

The Challenges

The Challenges



- Precision **sensing** ability, and/or robust planning algorithms

- **Coordination** between UAVs, other robots, and humans become increasingly important

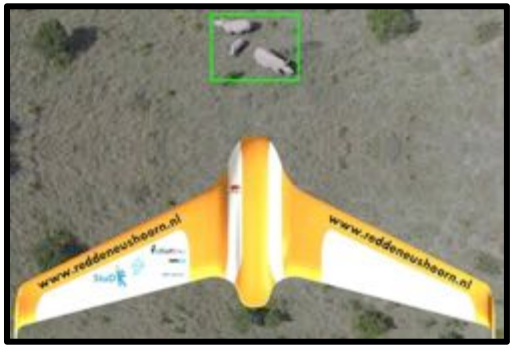
- **Planning** in unknown or dynamic areas

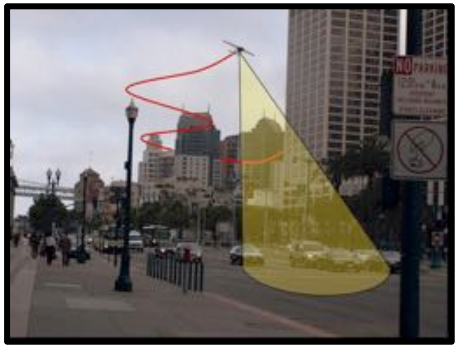
Three Main Research Areas

<u>Sensing</u>

<u>Planning</u>

<u>Coordinating</u>





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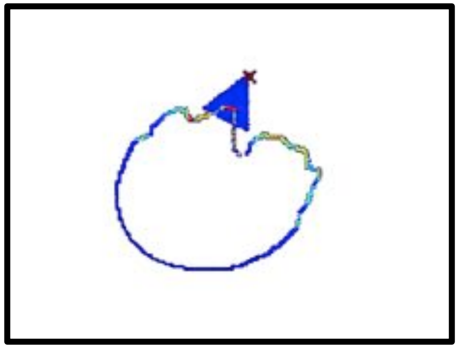
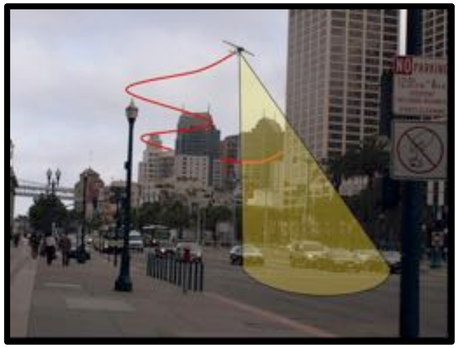
Outline

Sensing

Planning

Coordinating

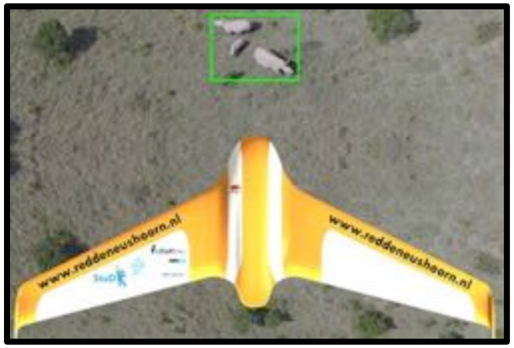


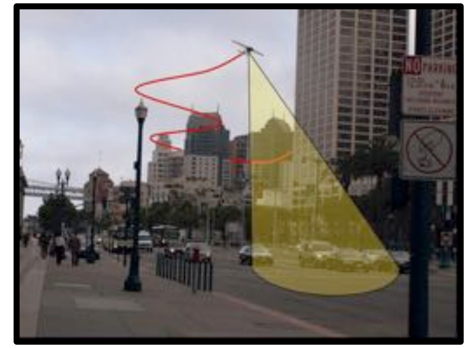


Related Work

Sensing

Coordinating





- “An Unmanned Aircraft System for Automatic Forest Fire Monitoring and Measurement,” Merino, et al. 2012.
- “Planning periodic persistent monitoring trajectories for sensing robots in gaussian random fields,” Lan & Schwager, 2013.

Sensing

- Sensing stationary targets is well studied
- Dynamic targets are tricky
- Used for environmental monitoring
- One of the most challenging monitoring problems is wildfires
- The uncertainty of where the fire will spread is challenging

Domain

Wildfires

- Dangerous for human pilots to get close
- Aerial sensing provides critical information
- Highly dynamic points of interest

*Taken from weathernetwork.com

Problem Formulation

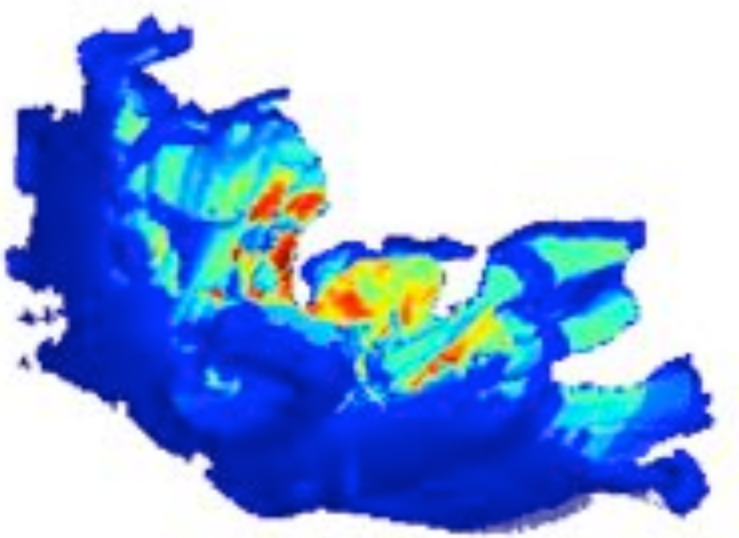
- Fireline intensity is crucial information
- Regions of high intensity are dangerous
- Identify regions as hotspots
- Minimize the max time that a hotspot is left unattended

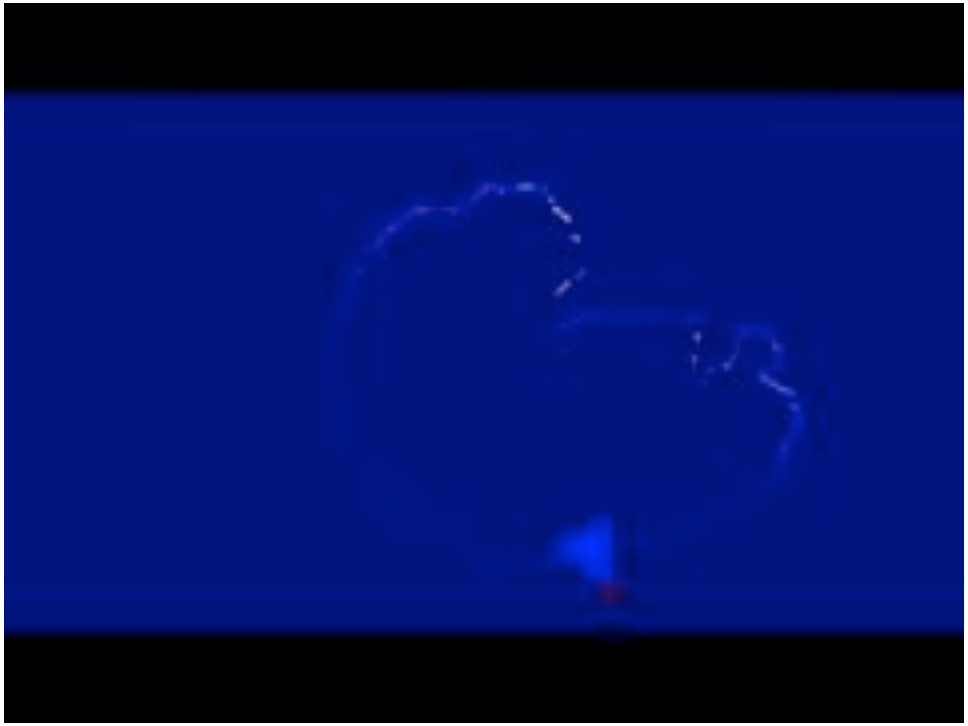
$$J(t) = \sum_{i=0}^{hotspots} \phi_i \,,$$

Where ϕ is max time untracked.

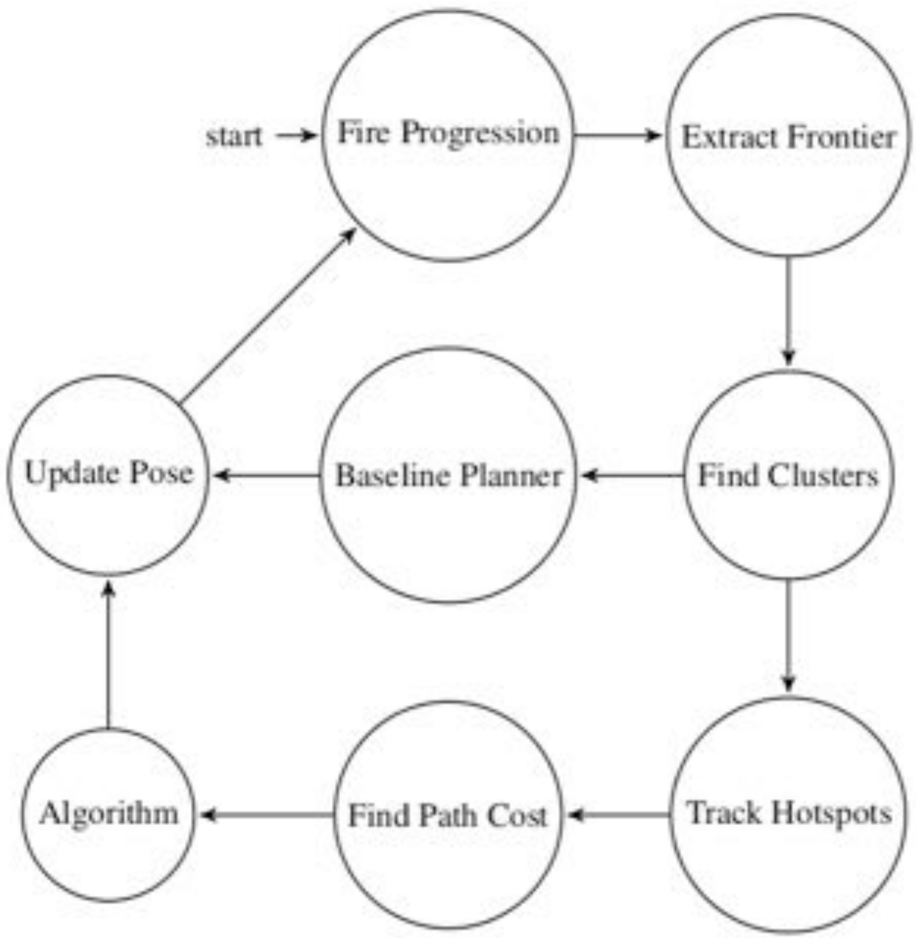
Simulation Environment

- FARSITE generates fire characteristics
- UAVs limited to flying around fire
- UAVs have sensing radius





Simulation Setup



State diagram of FLAME

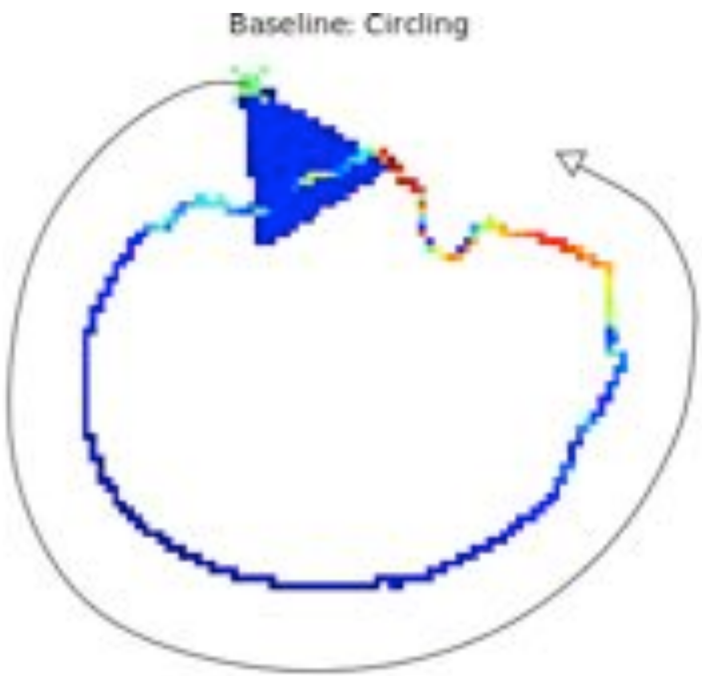
K-means clustering is run on a frontier filtered for the highest intensities. K is determined by

$$K = \sqrt{N/2}$$

where N is number of points of interest.

Algorithm: Baseline

- Periodic monitoring
- Minimizes time untracked of all points along the frontier
- Assumes no knowledge of fire

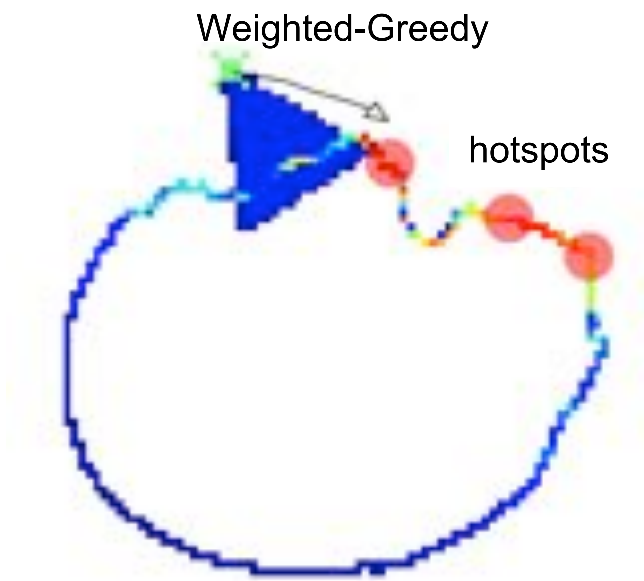


Algorithm: Clustered Weighted-Greedy

- Hotspot priority determined by time left untracked and distance from the UAV.

- A weighting parameter (α) is applied to the travel cost (C) of each hotspot (h) to combine with the time ($\mathcal{T}$) metric.

$$\mathcal{H} = \underset{h}{\operatorname{argmin}}\, \mathcal{T}_h - \alpha * \mathcal{C}_h$$



Simulation Results

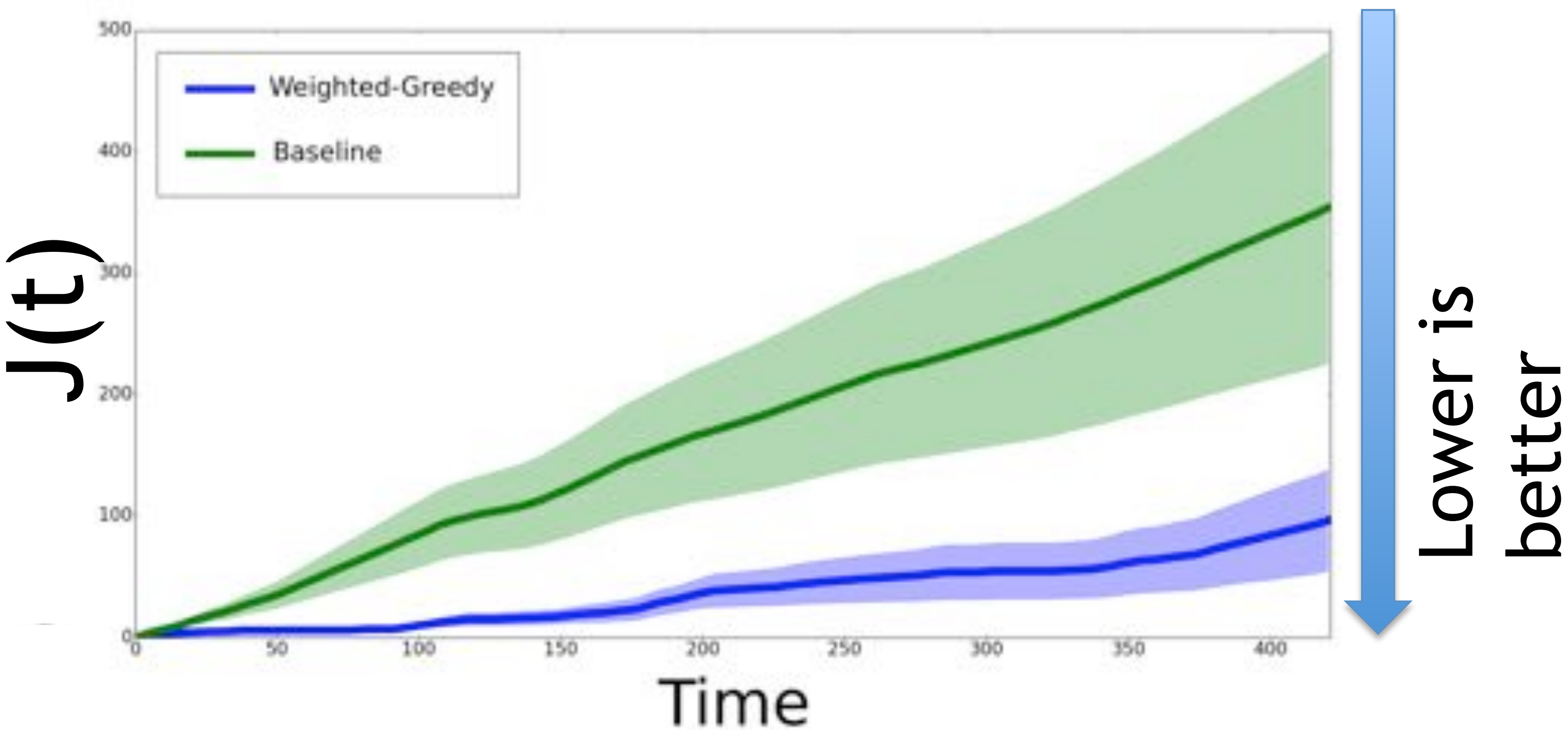
- Compare Baseline and Weighted-Greedy
- Three different hotspot thresholds used, (.25, .35, .45).
- Seven different fires

$$J(t) = \sum_{i=0}^{hotspots} \phi_i \, ,$$

Where ϕ is max time untracked.

Simulation Results

J(t) = sum of the max time untracked of all hotspots



Hotspot threshold = .25

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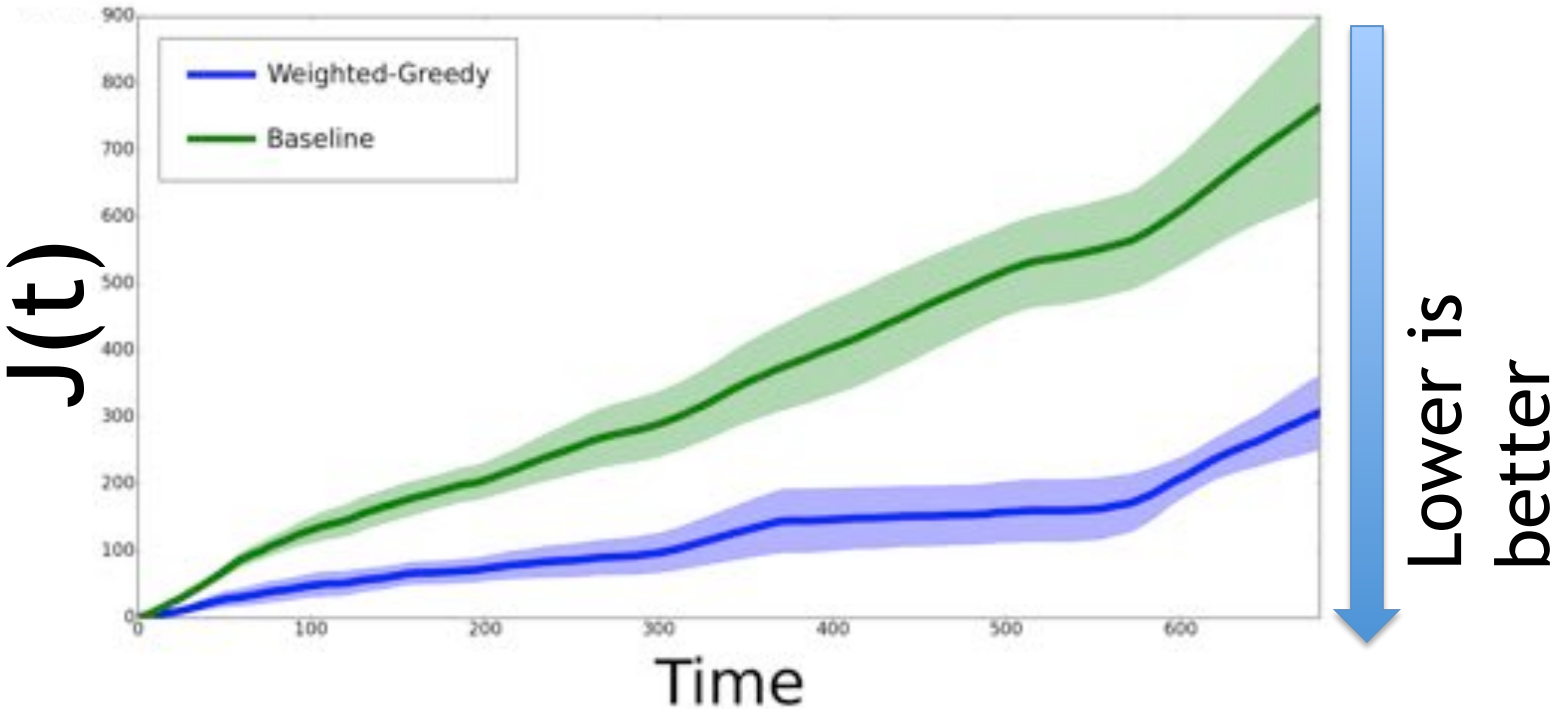
Simulation Results

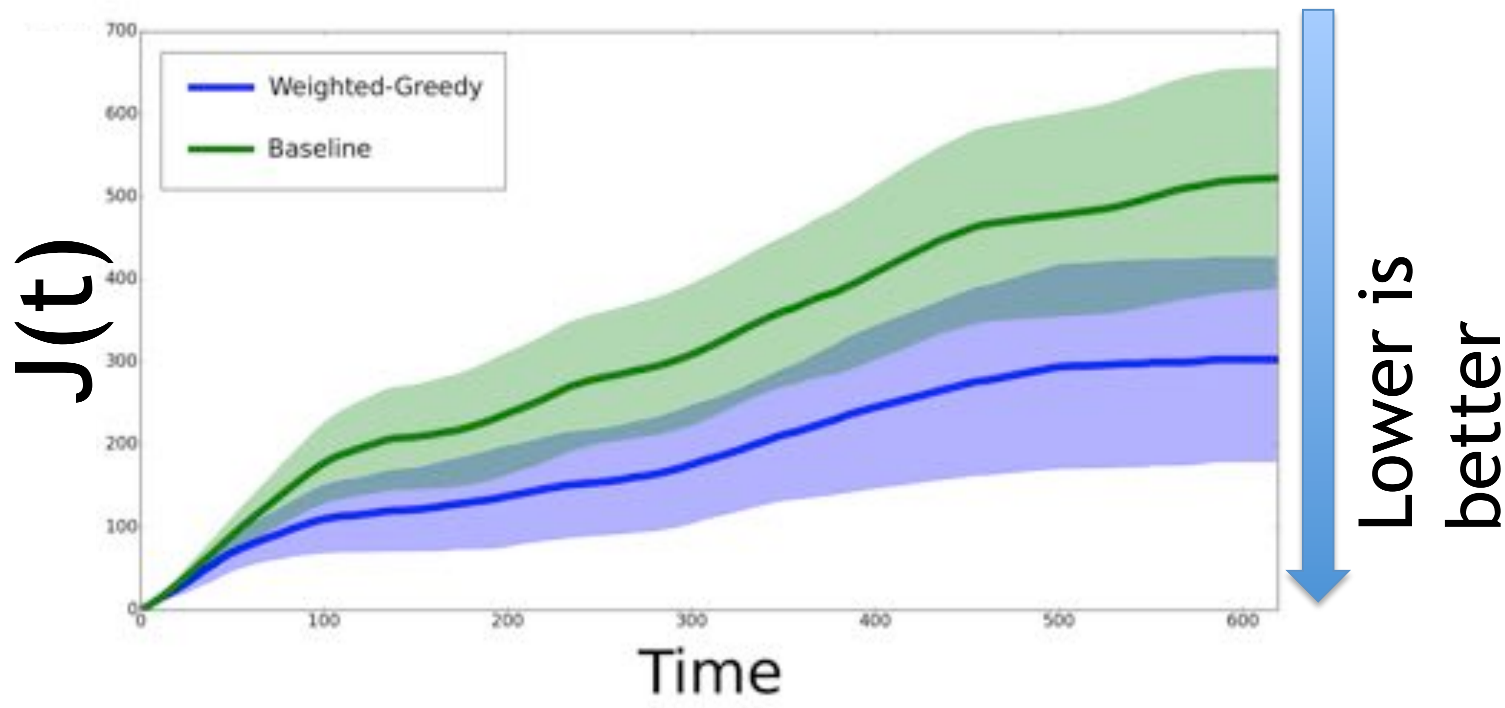
J(t) = sum of the max time untracked of all hotspots



Hotspot threshold = .35

Simulation Results

J(t) = sum of the max time untracked of all hotspots



Hotspot threshold = .45

Hardware Implementation

- FARSITE simulated fire
- Ground Station fed “live satellite data” from simulation
- Tethered IRIS+ Quadcopter
- 10 minute experiment

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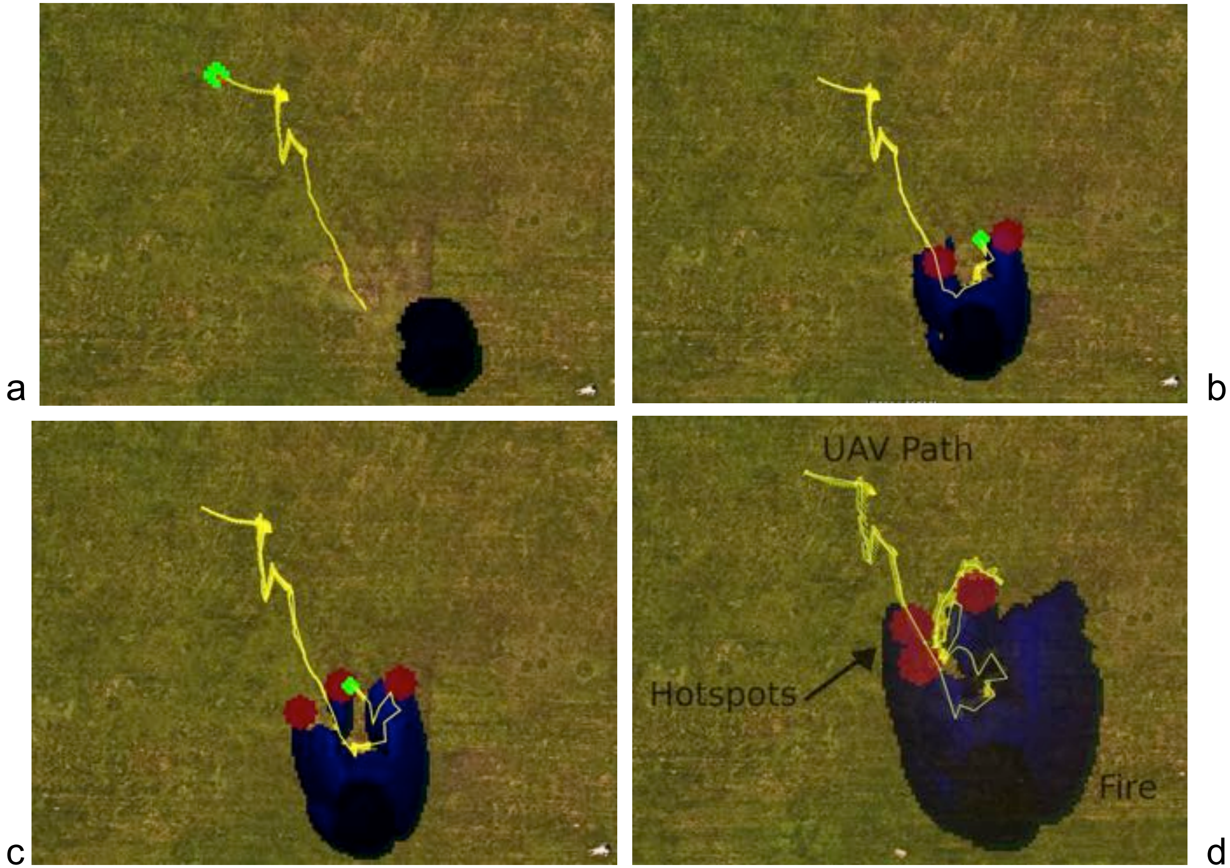
Hardware Implementation



GPS trajectory with fire

Discussion

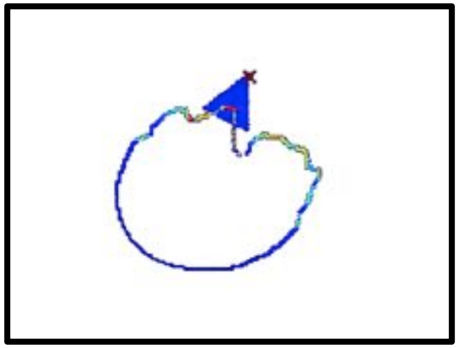
- Naive methods of monitoring the fire miss valuable information
- More sophisticated sensing provides better results
- Fewer hotspots do a worse job representing the frontier regions
- Possible to bring this technology to the real world
- Publication:
    - R. Skeele, and G. Hollinger. "Aerial Vehicle Path Planning for Monitoring Wildfire Frontiers." Field and Service Robotics, 2015.

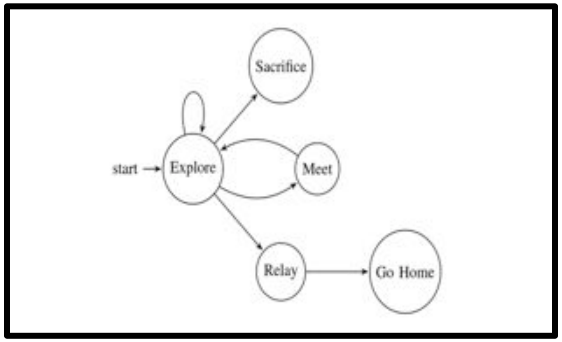
Outline

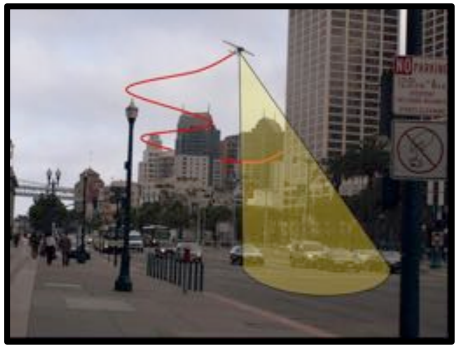
Sensing

Planning

Coordinating

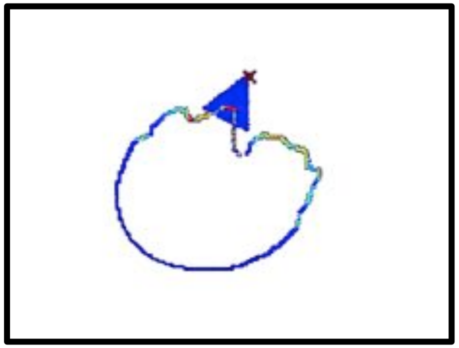




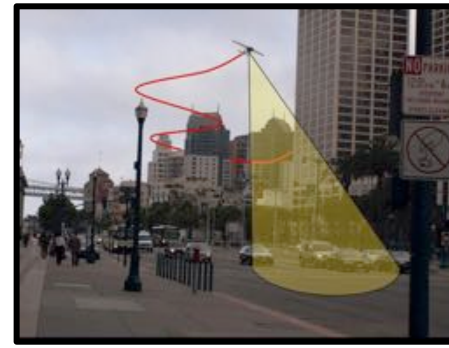


Related Work

<u>Sensing</u>



<u>Coordinating</u>



- “Multi-Robot Coordination with Periodic Connectivity,” Hollinger & Singh, 2010.
- “The Sensor-based Random Graph Method for Cooperative Robot Exploration,” Franchi et al., 2009.

Coordination

- Is task allocation among multiple systems
- Provide robustness and fault tolerance
- Operate effectively in groups or with humans
- Better efficiency
- Requires communication protocols
- Coordination is difficult if the space is unknown

Domain: Indoor Exploration

High-impact applications:

- Urban search and rescue
- Industrial inspection
- Military reconnaissance
- Underground mine rescue operations

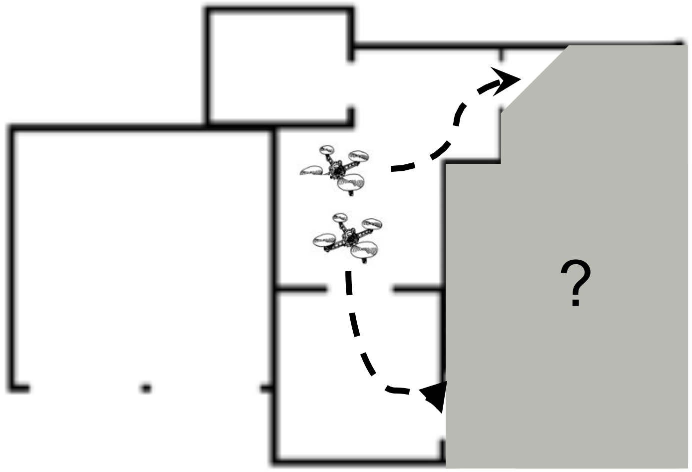
Key Challenges:

- Communication is uncertain
- Real robots have limited battery
- Planning through unknown maps

*Image from movie Indiana Jones

Problem Formulation

- Indoor environment represented in $\mathbb{R}^2$
- Multiple UAVs merge maps
- Maximize the map returned map to base station



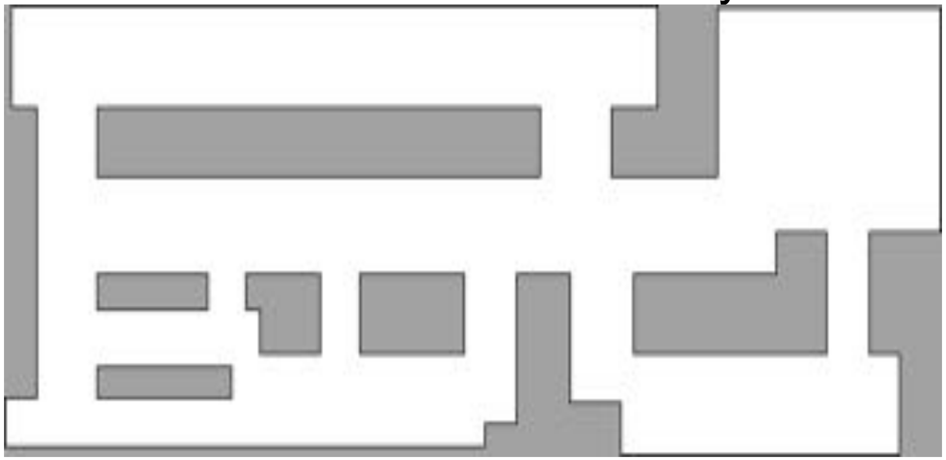
Maximize Area Mapped:

$$\mathcal{P} = \underset{\mathcal{P}\in\Psi}{\operatorname{argmax}}\, A_r(\mathcal{P}) \text{ s.t. } |\mathcal{P}_k| < B_K \ \forall k,$$

Area explored (A_r) with paths ($\mathcal{P}$) in the possible path space (Ψ), such that the path of each UAV (k) is less than the battery limit (B).

Simulation Setup

- UAVs are modeled as discs with omnidirectional sensors
- Kinodynamics of the vehicles are not considered
- Each UAV has a limited battery life
- Communication is constrained by distance and obstacles

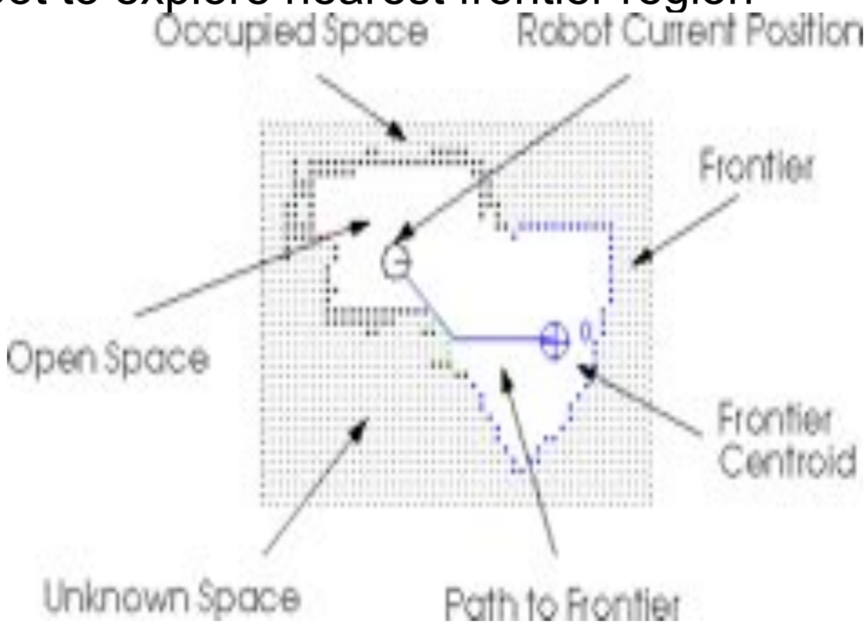


Complex Office Map (120m x 40m)

Simple Tunnel Map
(50m x 50m)

Algorithm: Baseline (Frontier Exploration)

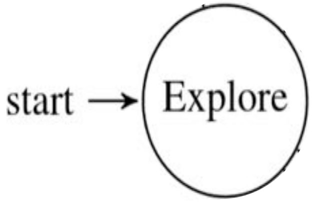
- Finds open cells next to unknown cells
- Uses blob detection to identify frontier regions
- Assigns robot to explore nearest frontier region



*Taken from robotfrontier.com

Algorithm: EMSR (Explore Meet Sacrifice Relay)

- Coordinates robots to share information
- Robust to unreliable communication
- Considers limited battery life



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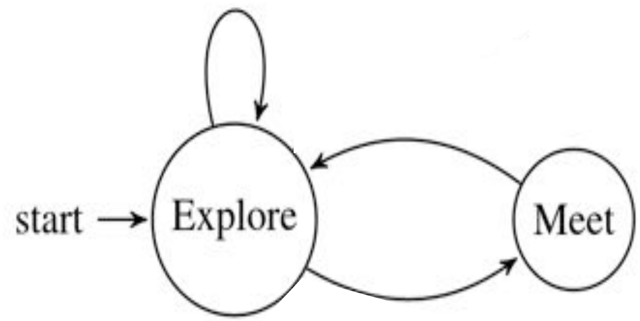

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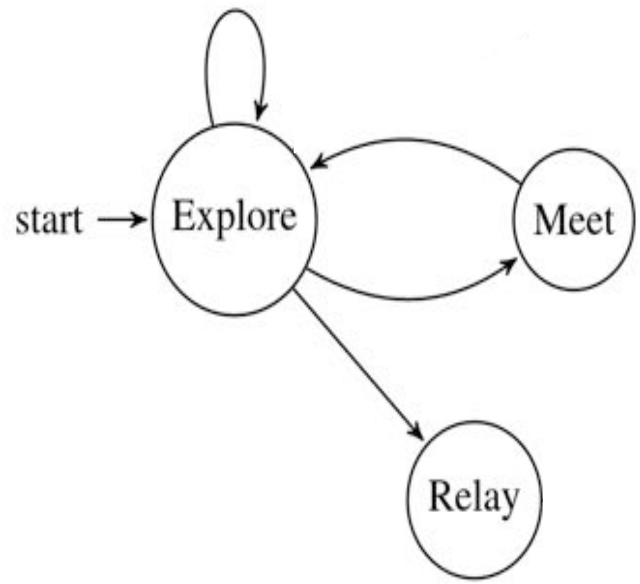

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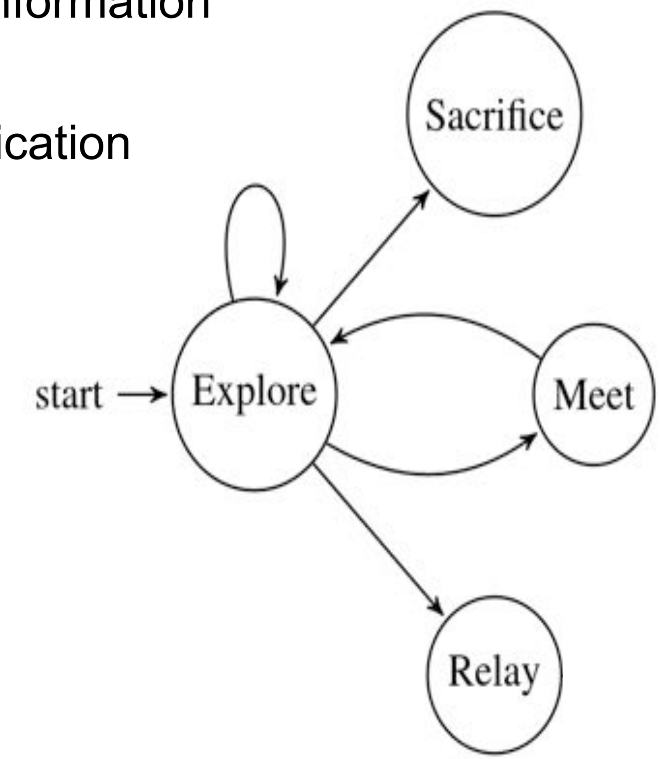

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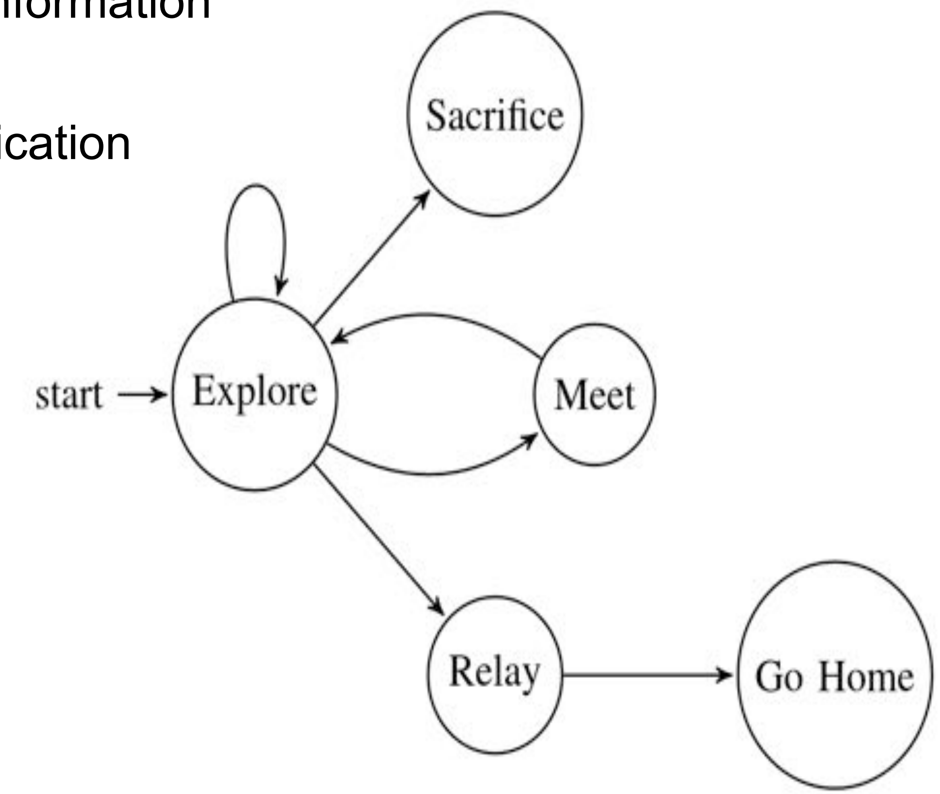
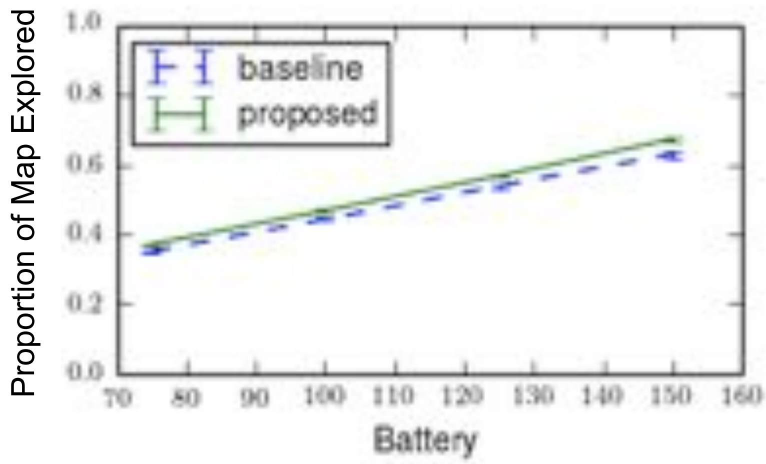


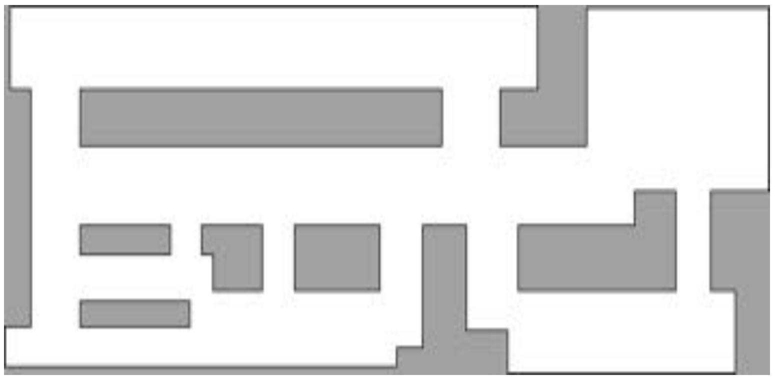
Simulation Results

- 200 Simulations
- Random Starting Point
- Speed 1 m/s

Simulation Results

2 UAVs

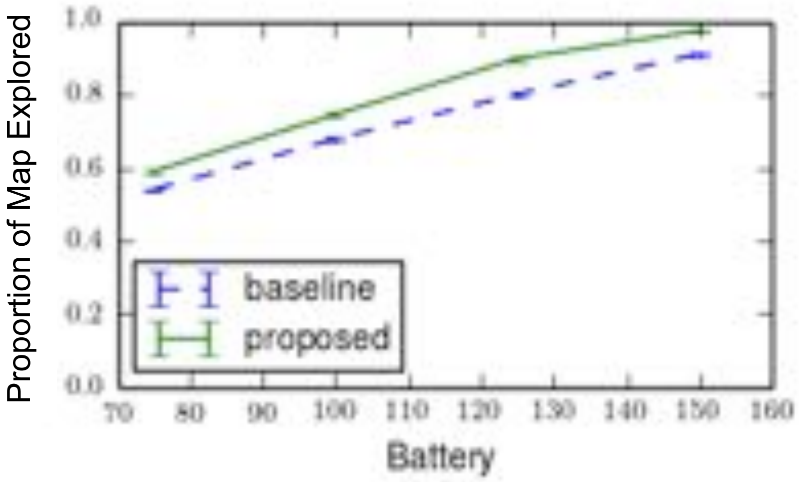


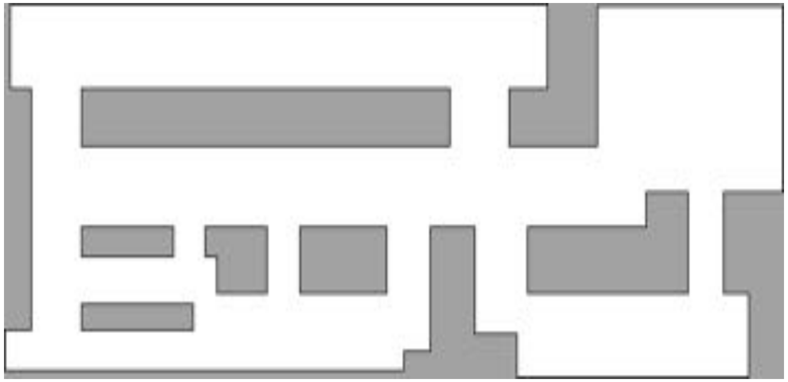


Complex Office Map (120m x 40m)

Simulation Results

4 UAVs

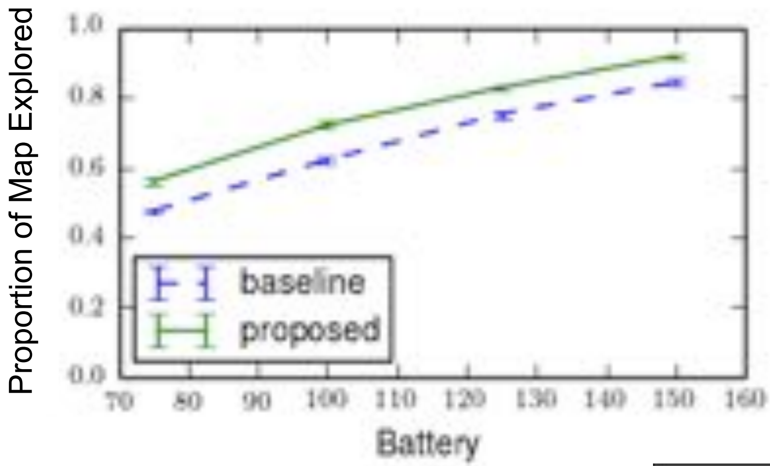


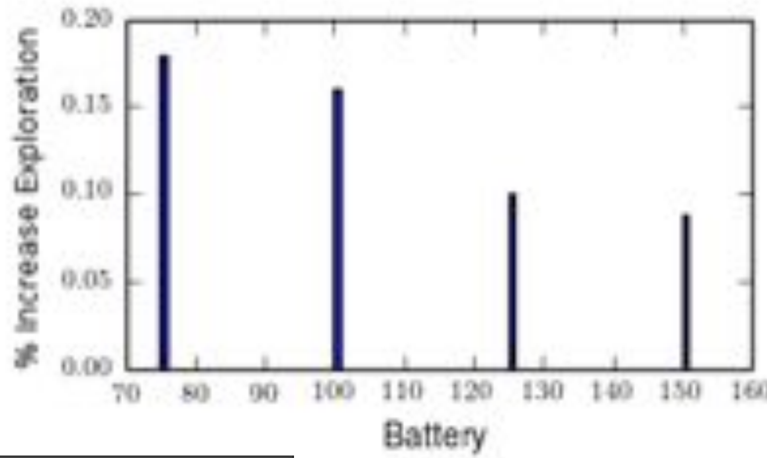


Complex Office Map (120m x 40m)

Simulation Results

8 UAVs in a simple tunnel

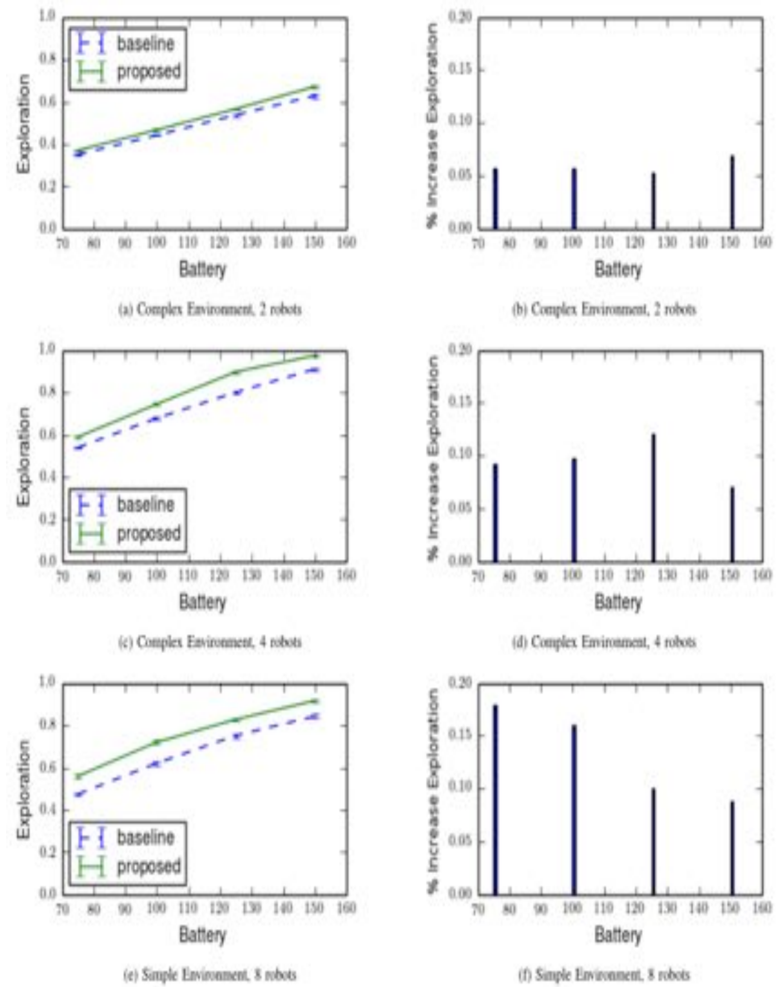




Simple Tunnel Map (50m x 50m)

Simulation Results

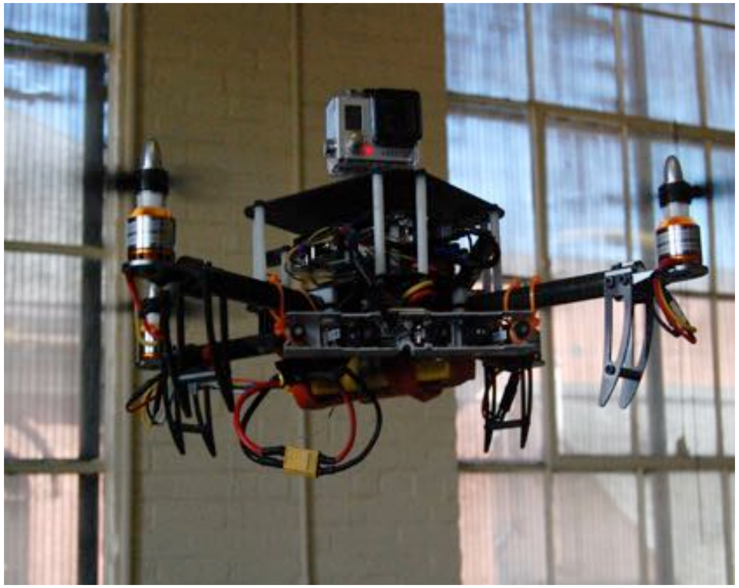
- Can use other exploration techniques with our state machine on top
- Improvements range from 5% to 18%
- Better results with a larger team



Average of 200 simulation runs, with random start points.

Hardware Testing

- Low cost platform, less than $1500
- Small enough to fit through doors
- Onboard vision and planning real time
- ROS planning and SLAM packages
- PX4 flight controller
- Xtion RGB-D Sensor



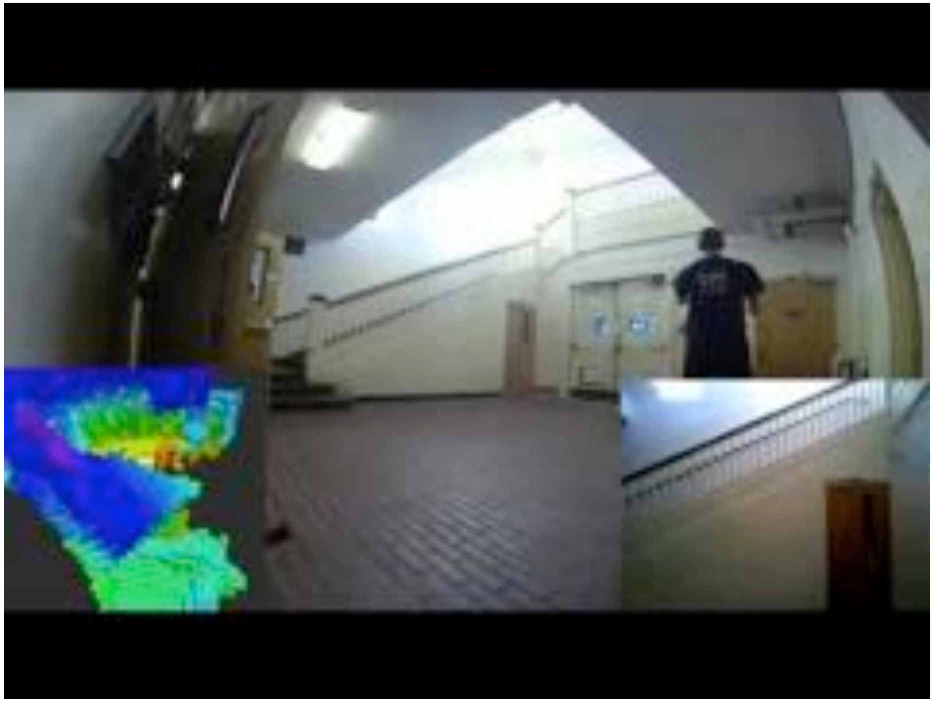
ROS

PX4 autopilot

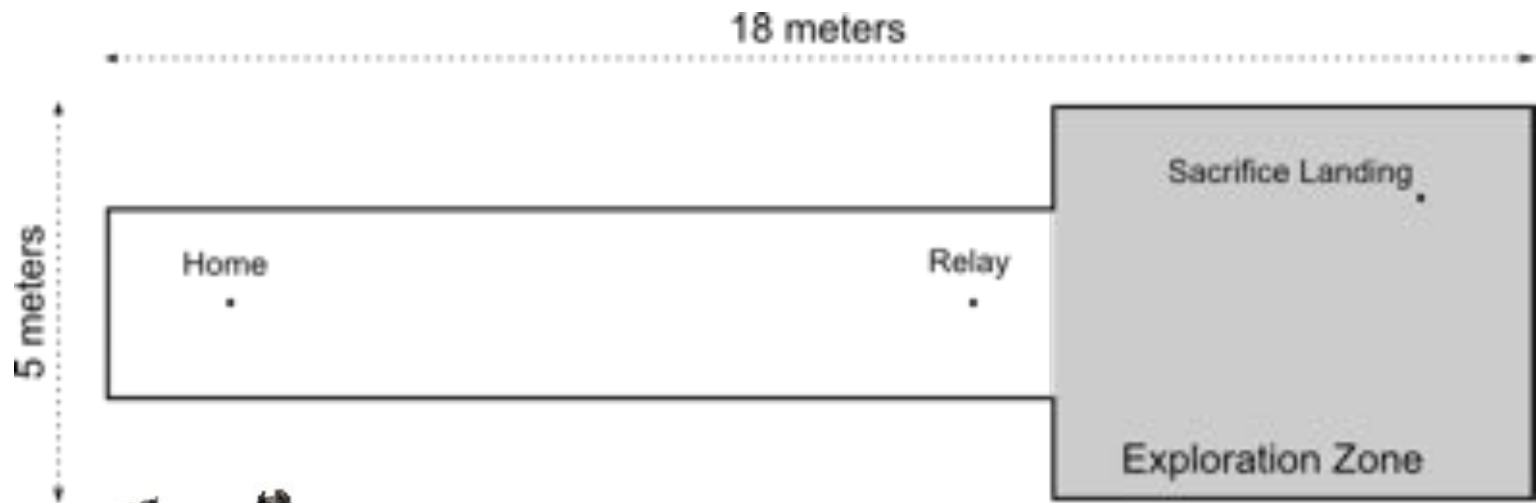
Hardware Testing

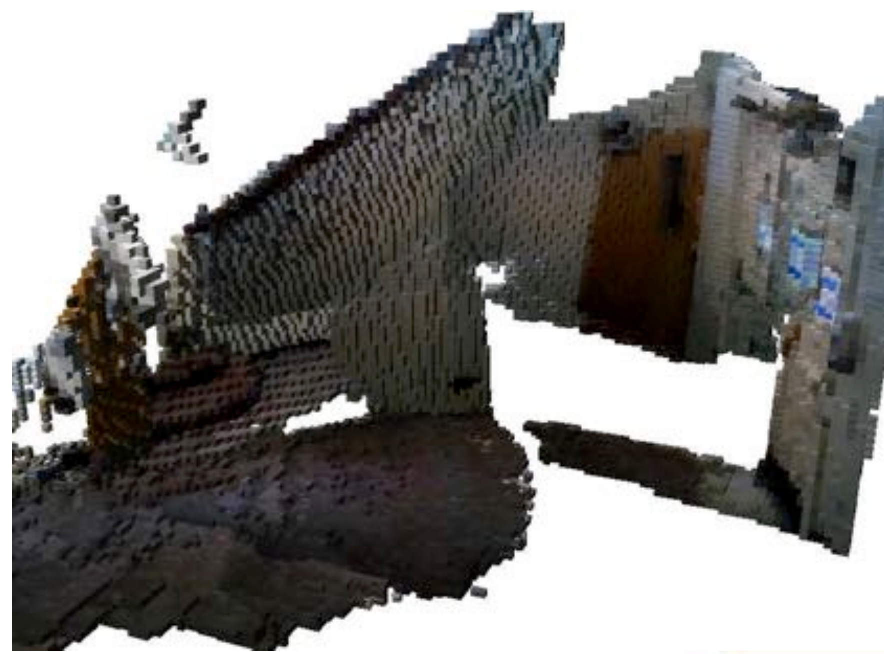
Demonstrated with two quadcopters

- Standard ROS-Packages for navigation
- Complete onboard autonomy
- Un-instrumented environment



Hardware Results





Discussion

- First looked at single vehicle constrained planning
- Coordinated exploration outperforms non coordinated methods
- Indoor exploration is feasible
- Publication:
    - K. Cesare, R. Skeele, S. Yoo, Y. Zhang, G. Hollinger, “Multi-UAV Exploration with Limited Communication and Battery.” IEEE International Conference on Robotics and Automation (ICRA), 2015.

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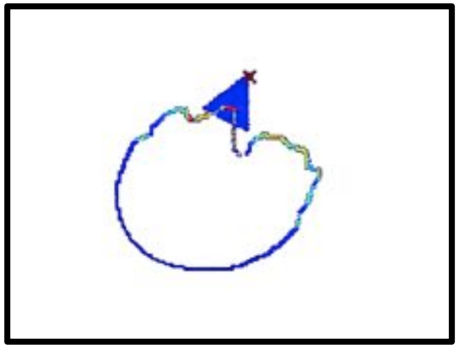
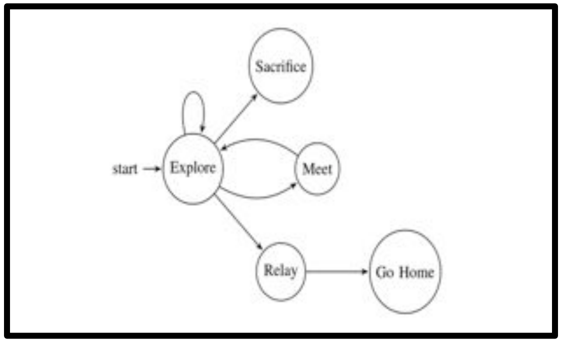
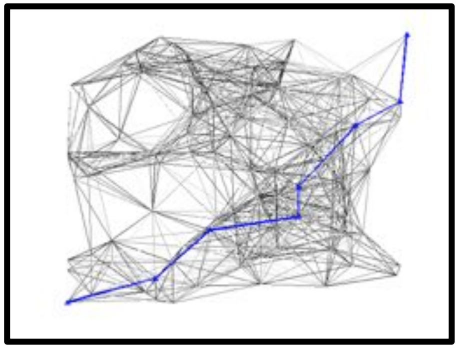
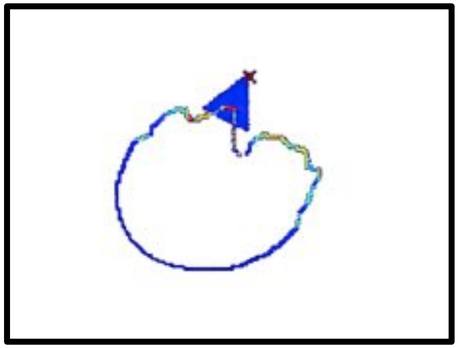




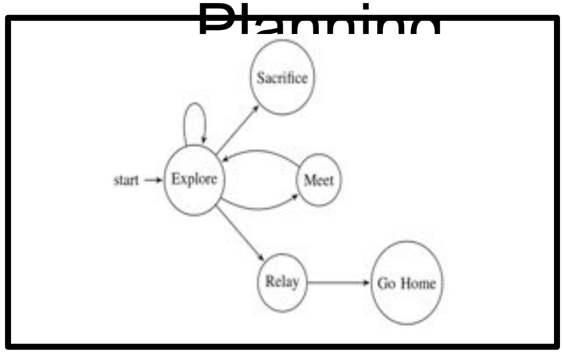


Related Work

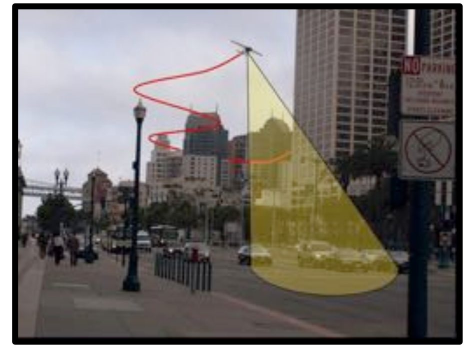
Sensing



Planning



Coordinating



- “Sampling-based Algorithms for Optimal Motion Planning,” Karaman & Frazzoli 2011.
- “The Stochastic Motion Roadmap: A Sampling Framework for Planning with Markov Motion Uncertainty,” Alterovitz, et al. 2007.
- “Planning Most-Likely Paths From Overhead Imagery,” Murphy & Newman, 2010.

Path Planning

- Trajectory optimization
- Waypoint navigation
- Graph based planning
- Discrete and sampling based planners

*Taken from wikipedia.com

Motivation

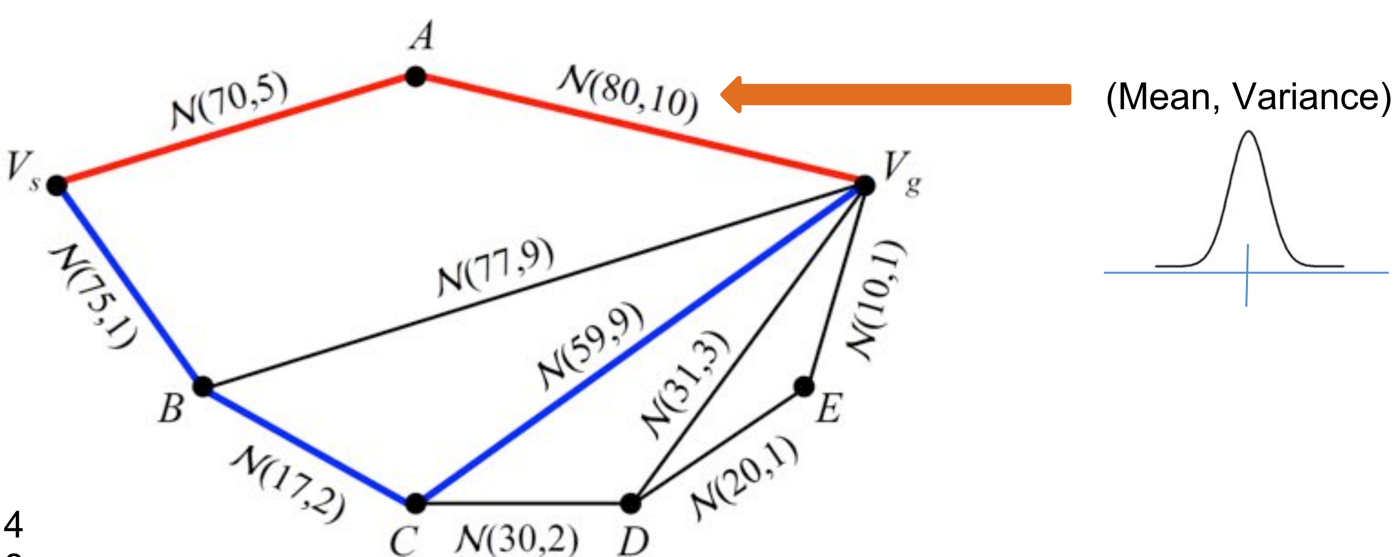
- Representing the world perfectly is impossible
- Graphs are a versatile representation of many domains
- Making reliable decisions is vital to future of robotics

Algorithm: Risk-Aware Graph Search (RAGS)

- Represent graphs using normal distributions of edge costs

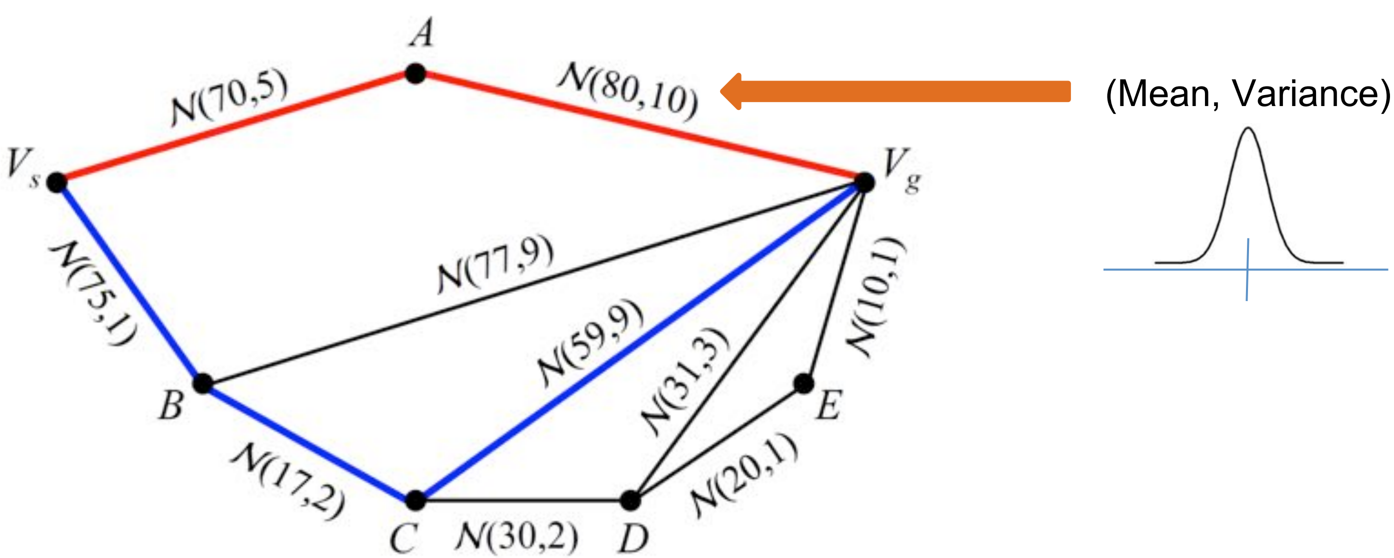
- Search through graph for paths to goal

- Traverse the graph along the path of least risk



Execution

- Red path represents A* planning over mean
- Blue paths represents RAGS
  - RAGS trades off the lower mean of Red against the path options of Blue.



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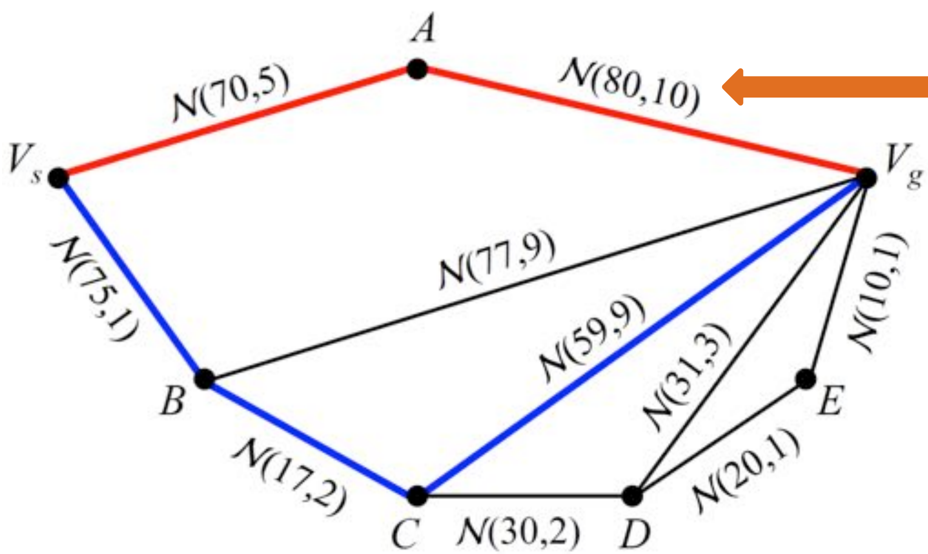
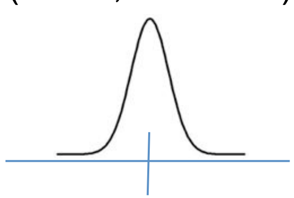


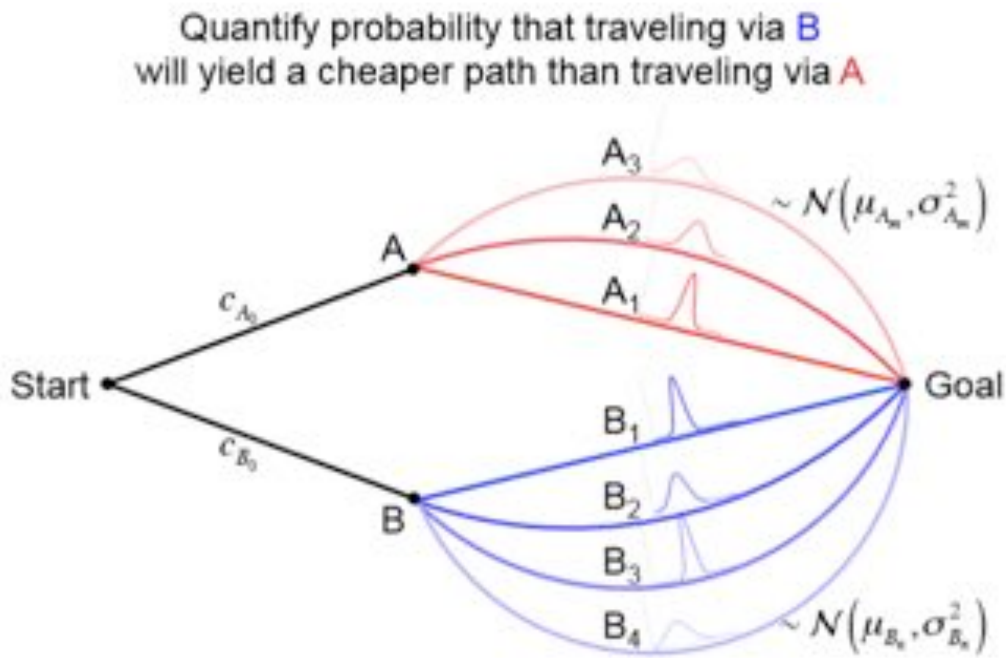
(Mean, Variance)



Probability of Better Path
At V_s -> A vs B = 41.85%
At B -> V_g vs C = 29.62%
At C -> D vs V_g = 47.16%

Quantifying Risk

- Current location has neighbor vertices
- Each vertex has child paths to the goal
- Integrate probabilities (of cost) over all child paths



Quantifying Risk

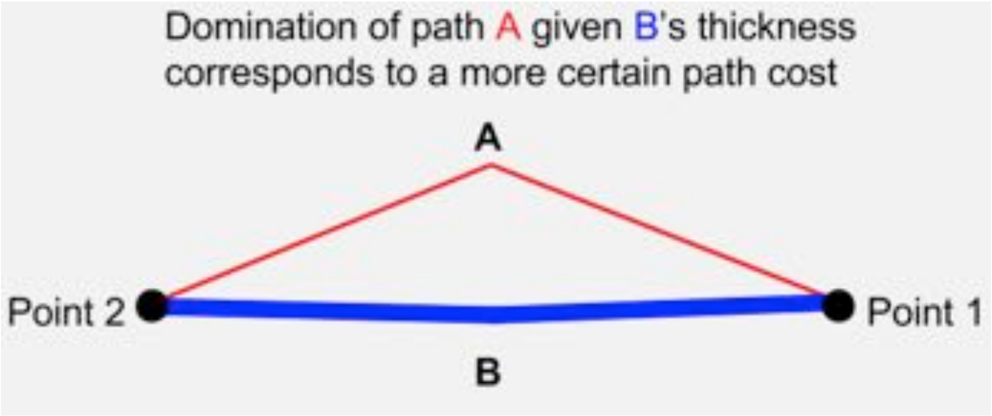
- Probability that the lowest-cost path in the set *A* is cheaper than the lowest-cost path in the set *B*
  - Becomes a relationship between mean, variance, and number of paths
  - Pairwise comparison of two neighbors
  - Provides local ordering

$$\boxed{P\left(C_{A_{min}} < C_{B_{min}}\right) = \int_{-\infty}^{\infty} P(C_{B_{min}} = x) \cdot P\left(C_{A_{min}} < x\right) dx}$$

Bounding

- Paths with both worse mean and variance are 'dominated'
- Bounding dominated paths reduces the computational complexity
- Partial ordering
  - Only non-dominated nodes are expanded

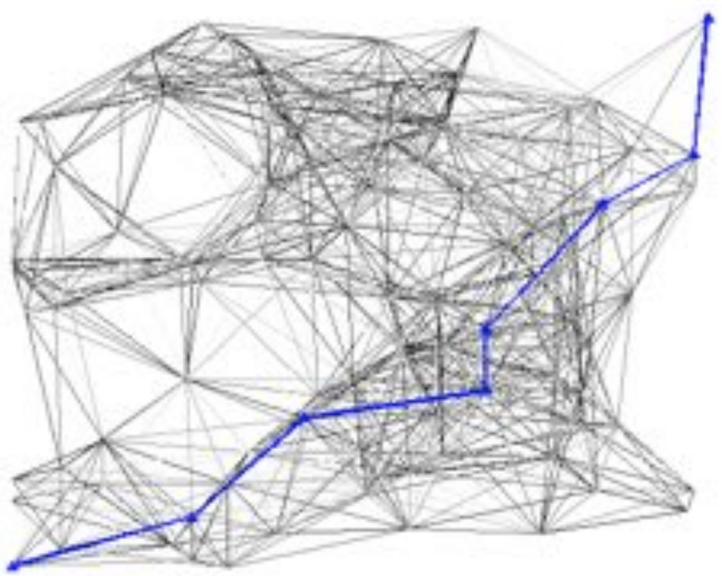
$$A < B \leftrightarrow (\mu_A < \mu_B) \wedge \left(\sigma_A^2 < \sigma_B^2\right)$$



Simulation Setup

Randomly generated graphs

- Final edge costs sampled from edge distributions
- Search from (0,0) to (100,100)
- Compared against A*, D*, and Greedy



Edge variances are represented in grayscale

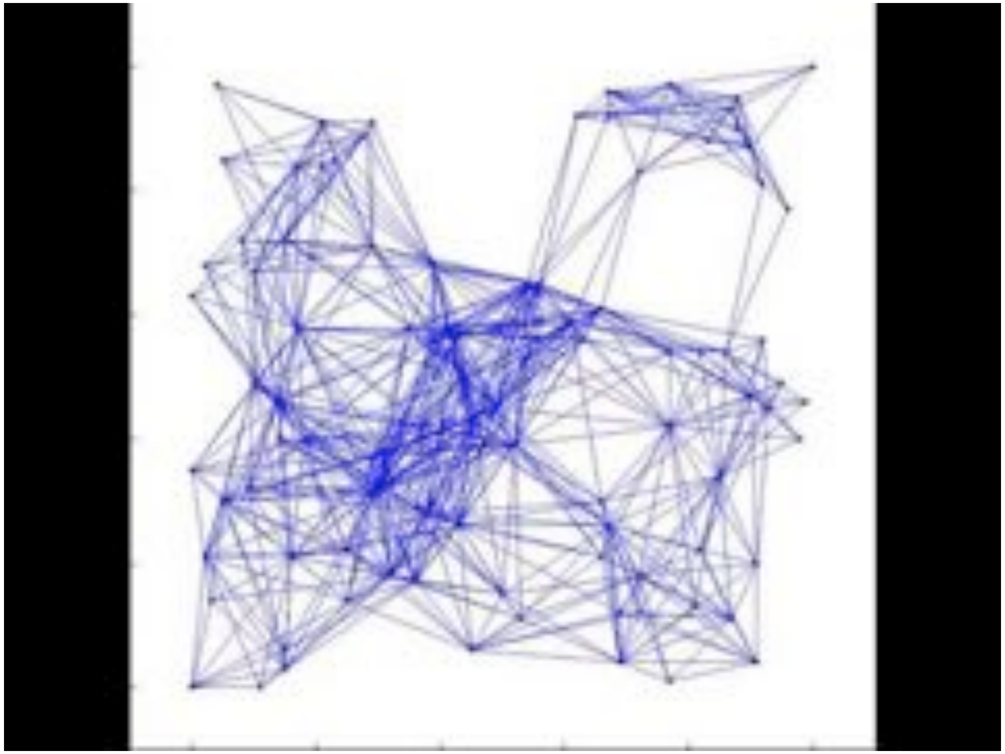
Example

The video shows

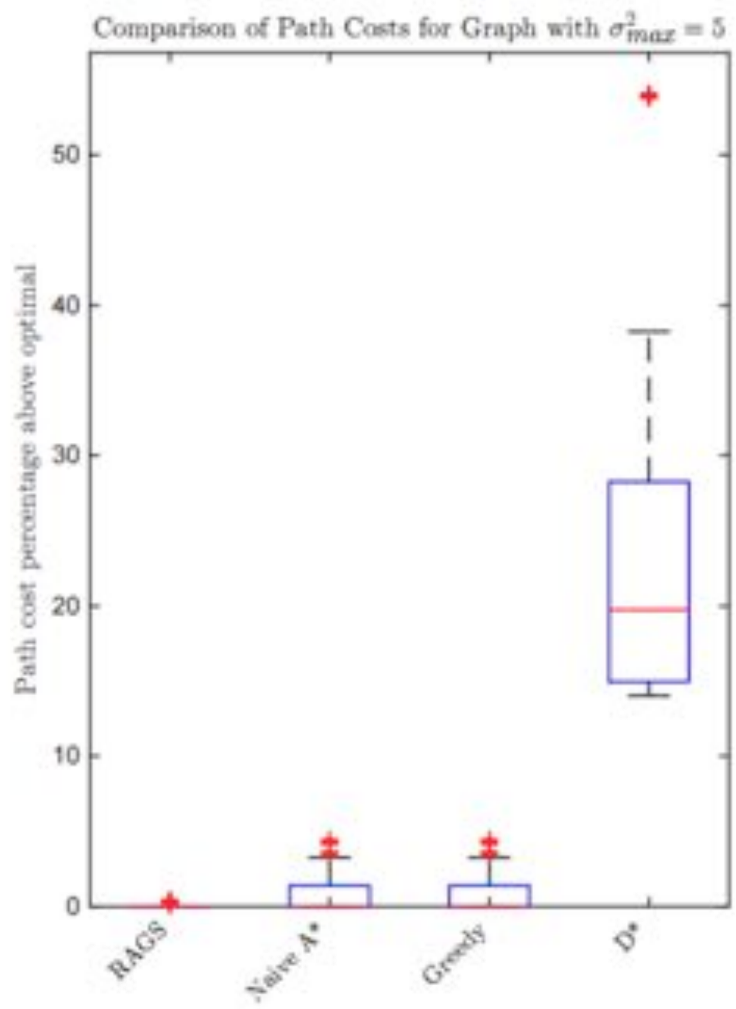
1. Generating a PRM (with edge means and variances)

2. Pruning the edges for non-dominated paths

3. Traversing the graph with risk-aware planning

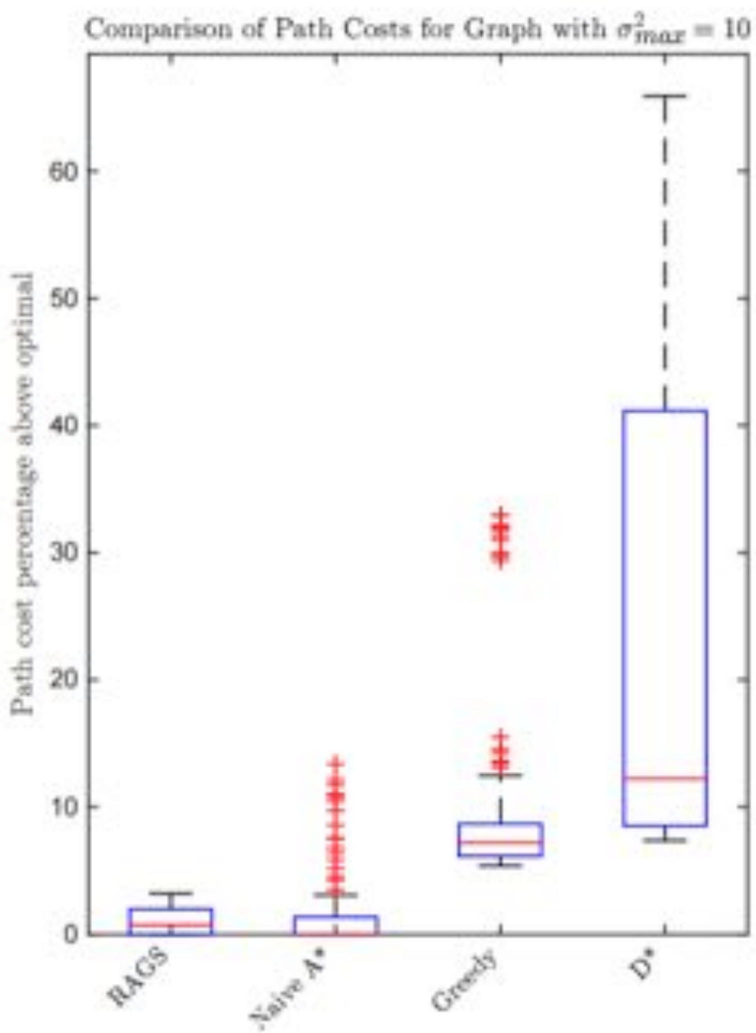


Simulation Results



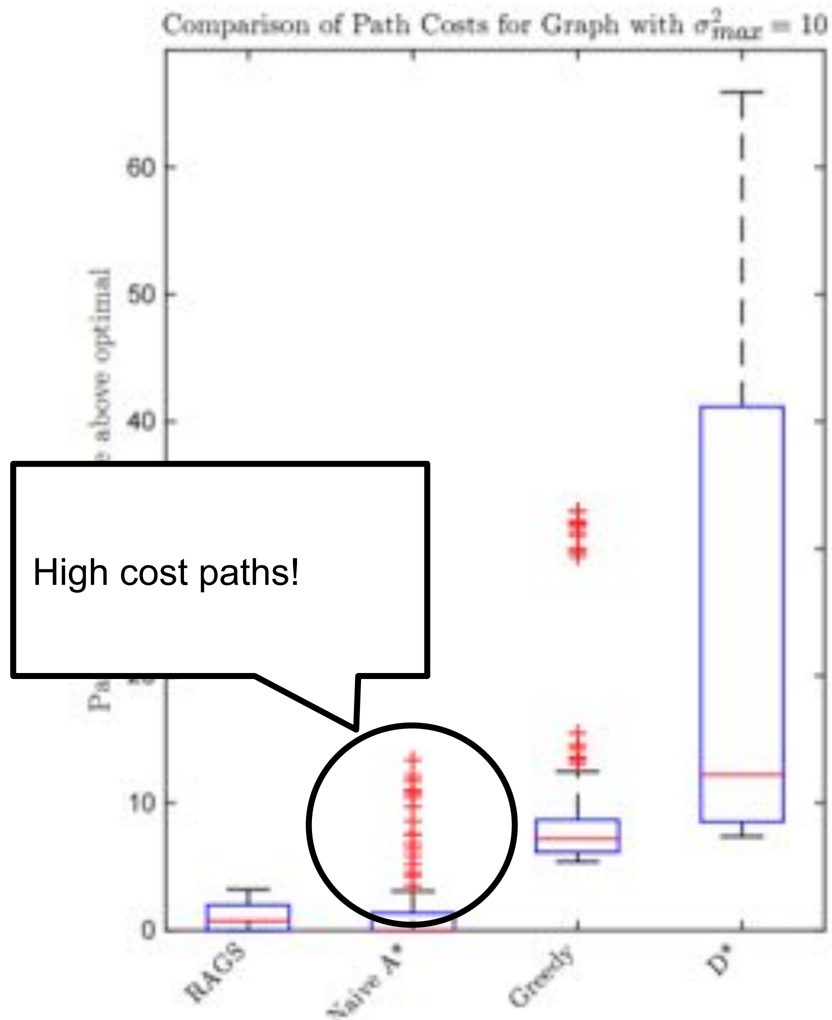
Lower is better

Simulation Results



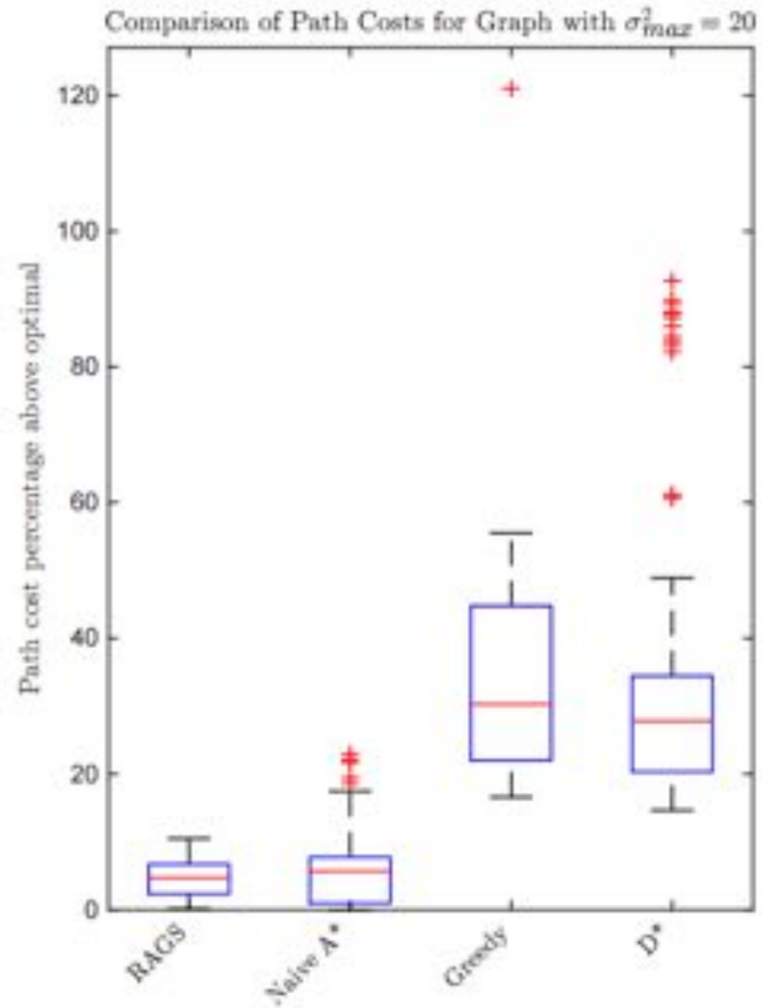
Lower is better

Simulation Results



Lower is better

Simulation Results



Lower is better

Experiments

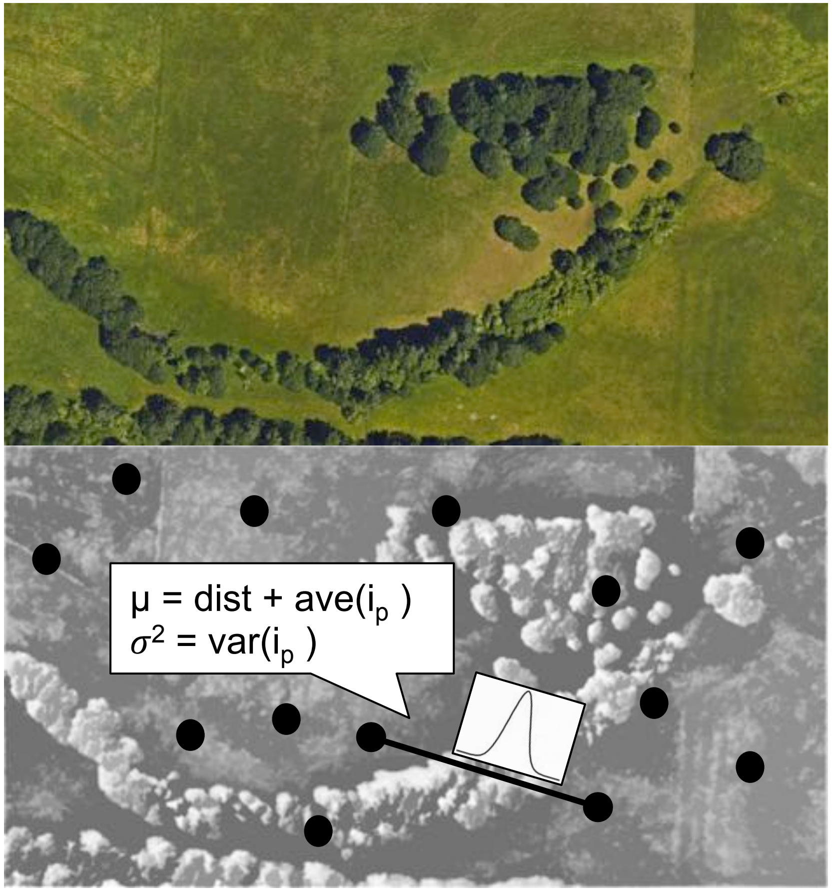
Satellite images for ground robot or low flying UAV

- Dataset of 64 images
  - tree clusters
  - man made structures
  - varying resolutions.
- Filtered to extract obstacles
- Edge variances taken from pixel intensities between vertices
- Mean values are Euclidean distance

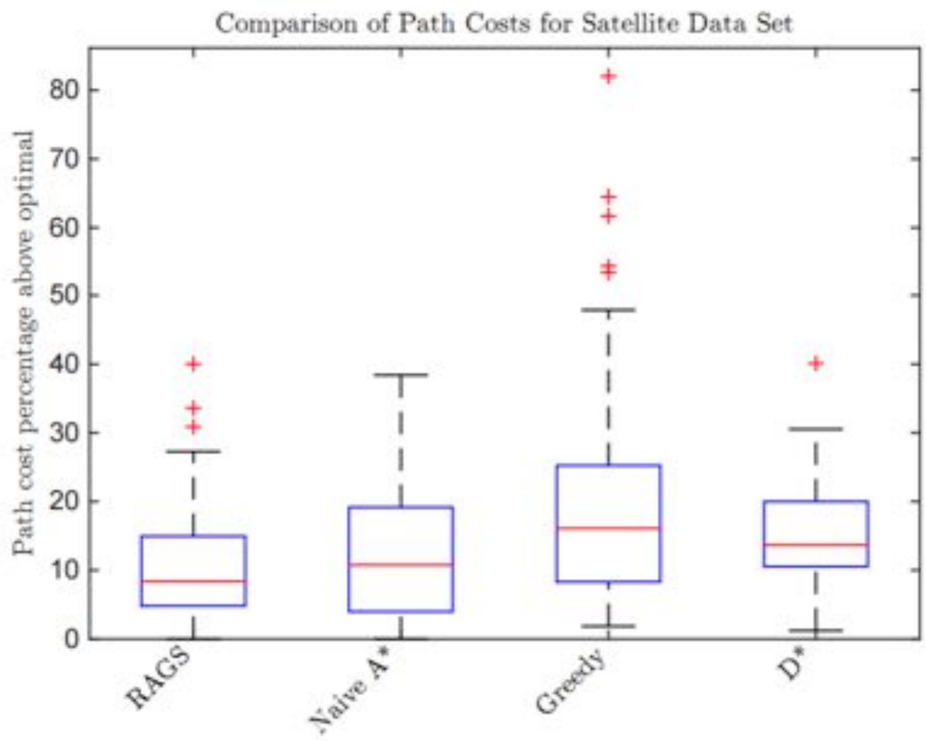
Experiments

- Dataset of 64 images
  - tree clusters
  - man made structures
  - varying resolutions.
- Filtered to extract obstacles
- Edge variances taken from pixel intensities between vertices
- Mean values are Euclidean distance plus pixel intensity

Satellite images for ground robot or low flying UAV



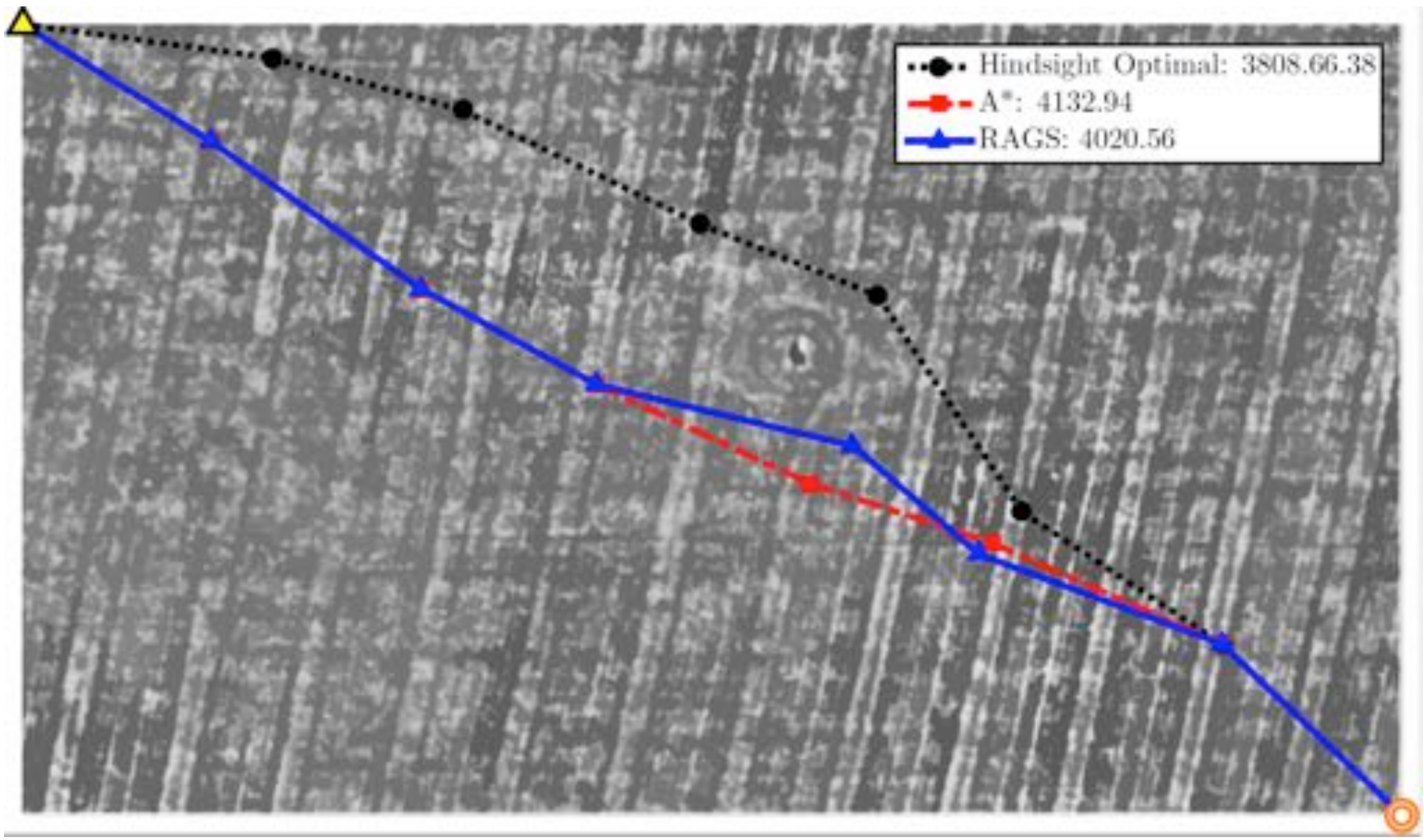
Experiments-Results



Example: Empty Field

Three distinct scenarios for analysis

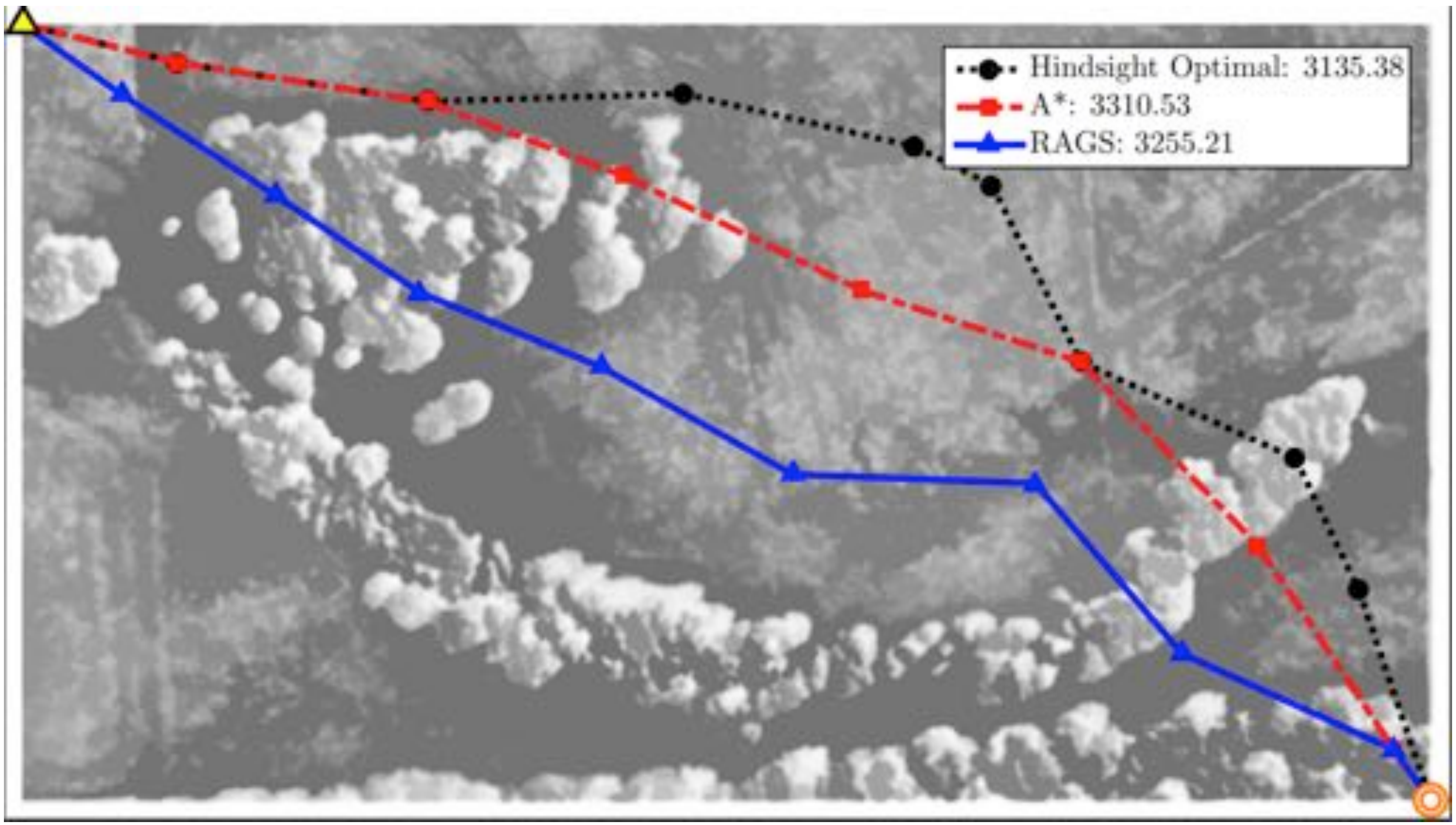
Similar trajectories through empty field.



Empty Field

Example: Sparse Tree Cluster

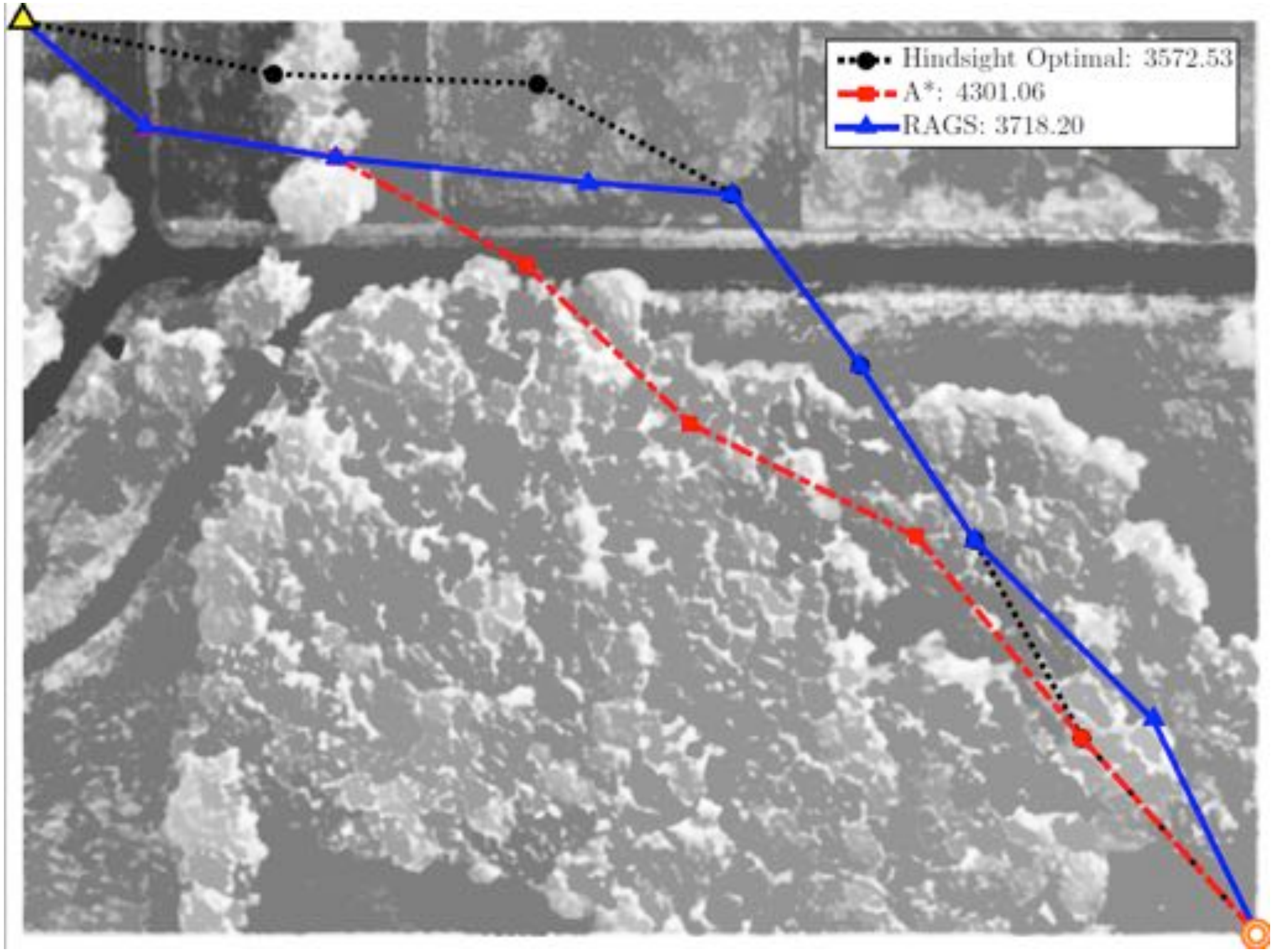
RAGS cuts through sparse cluster to take advantage of open space.



Sparse Tree Cluster

Example: Dense Obstacle

RAGS avoids narrow unlikely path through center of obstacle.



Large Dense Obstacle

Discussion

- Incorporating uncertainty accounts for unknowns in the real world

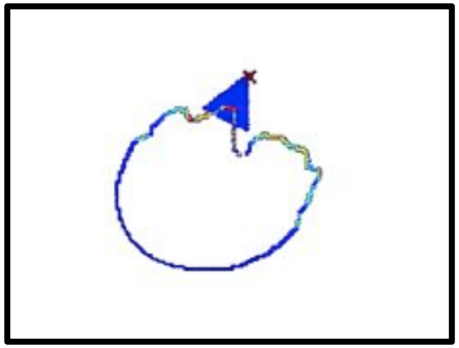
- Risk-aware planning provides robustness

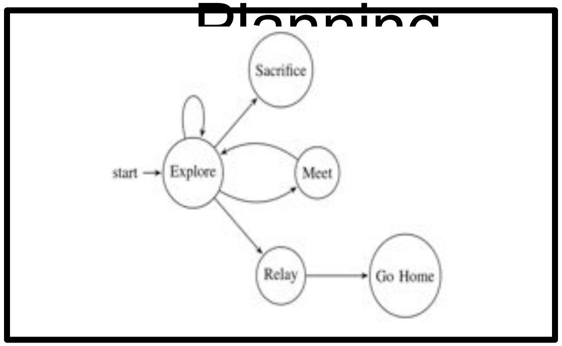
- Traditional search methods plan over mean cost risk outliers
- Publication:
    - R. Skeele, J. Chung, G. Hollinger, “Risk-Aware Graph Search”. IEEE International Conference on Robotics and Automation. Workshop on Beyond Geometric Constraints, 2015.
    - Submission planned: Workshop on the Algorithmic Foundations of Robotics (WAFR), 2016.

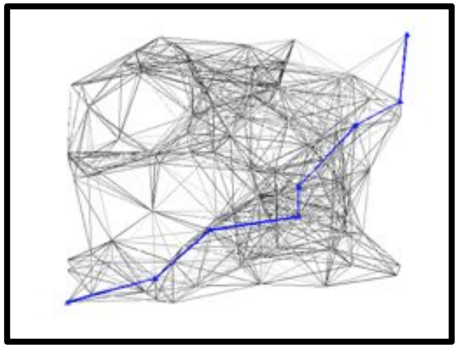
Oregon State UNIVERSITY

Summary of Contributions

Sensing | Planning | Coordinating







Sensing

- Monitored dynamic points of interest
- Leveraged realistic wildfire simulator for planning
- Demonstrated capability on hardware

Planning

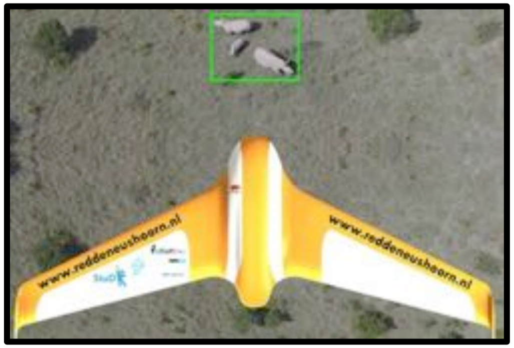
- Introduced coordination method for uncertain communication
- Simulated large teams of UAVs cooperatively exploring
- Developed low cost indoor autonomous quadcopters

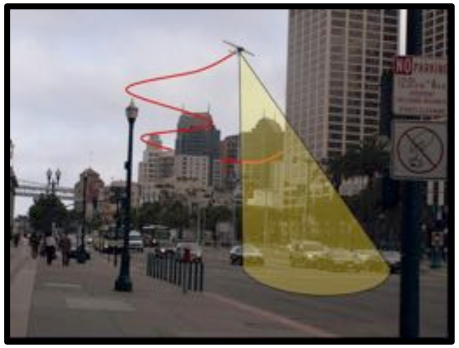
Coordinating

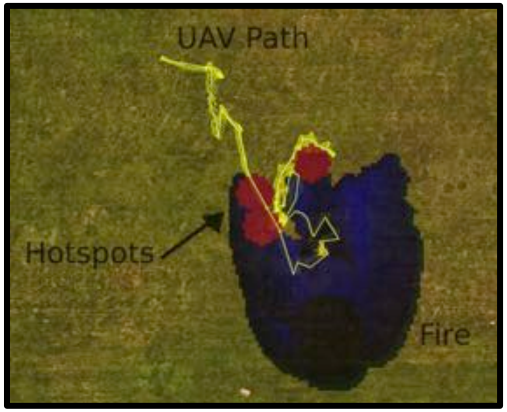
- Proposed risk-aware planning over uncertain costs
- Outperformed traditional search algorithms
- Demonstrated on satellite imagery

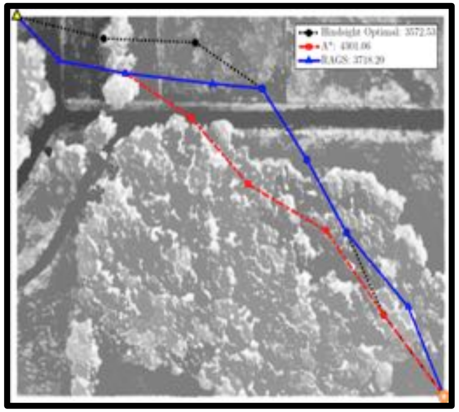
Summary of Contributions

Sensing **Planning** **Coordinating**









Future Work

- Gaussian process model of the fire frontier
  - Would give a continuous model of uncertainty
- Incorporate geometric knowledge of the environment to predict reconnection
  - Inference techniques on environment structure
- Informative path planning for RAGS

Acknowledgements

AIR FORCE RESEARCH LABORATORY

THE ROBOTICS INSTITUTE

NASA

Near Earth Autonomy

Office of Naval Research Science & Technology

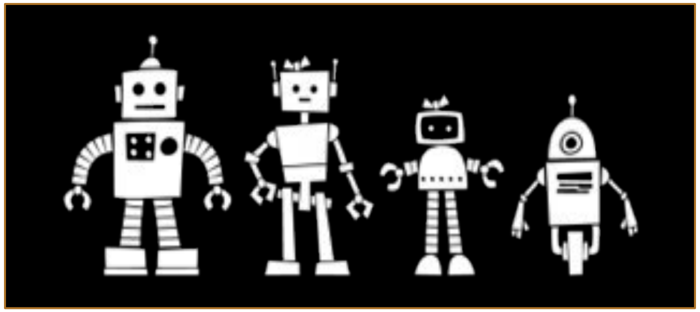
ONR

USN

Oregon State UNIVERSITY

Acknowledgements

Friends, Family



Special Thanks to:

Jen Jen Chung, Carrie Rebhuhn and the entire RDML

Thesis Committee

<u>Advisor</u>
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Autonomous Agents and Distributed Intelligence Lab

<u>GCR</u>
Fuxin Li

Artificial Intelligence, Machine Learning, and Data Science

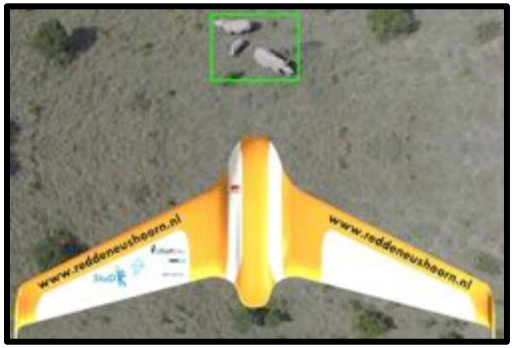
Oregon State University

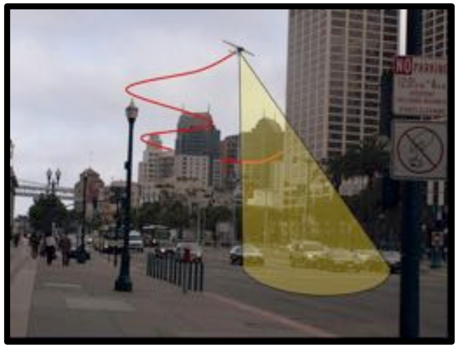
Questions?

Related Work

Sensing

Coordinating





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- "Planning periodic persistent monitoring trajectories for sensing robots in gaussian random fields," Lan & Schwager, 2013.

- "Multi-Robot Coordination with Periodic Connectivity," Hollinger & Singh, 2010.
- "The Sensor-based Random Graph Method for Cooperative Robot Exploration," Franchi et al., 2009.

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