TEAM-CoSTAR at DARPA SubTerranean Challenge: Collaborative Autonomous Robots to Explore Extreme and High-risk Terrains

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Government sponsorship acknowledged.

Outline

- Part 1: Planetary Cave Exploration and JPL technologies
- Part 2: TEAM-CoSTAR at DARPA Subterranean Challenge
- Part 3: Robust and risk-aware autonomy
  - Information-control-based perspective
- Part 4: Conclusion

Part 1: Planetary Cave Exploration

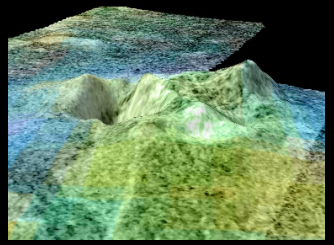
Cave Exploration: Scientific Value

- More than 200 lunar and 2000 Martian cave-related features have been identified.

- **Titan cryovolcanos**
  - Most pristine, earth-like environment in the solar system, with chance of finding pre-biotic chemistry
- **Potential environment for future human exploration**
  - Expected stable, UV-shielding environment and potential to act as volatile traps may make caves ideal habitats for future human exploration (e.g. Boston et al., 2007; Boston et al., 2010)
- **Astrobiology interest**
  - Stable physio-chemical environments, may trap volatiles, enhance secondary mineral precipitation and microbial growth, preserve biosignatures, and provide record of past climate (e.g. Boston et al., 2001; Leveille and Datta, 2010; Northup et al., 2011)
- **Volcanic processes**
  - Petrology informs lava temperature and cooling history, would lead into insight into Martian magmatic processes and differentiation (e.g. Ashley et al., 2011; Kerber et al., 2016)

Unaltered record of lava freezing sequence

Cave as extraterrestrial human habitat

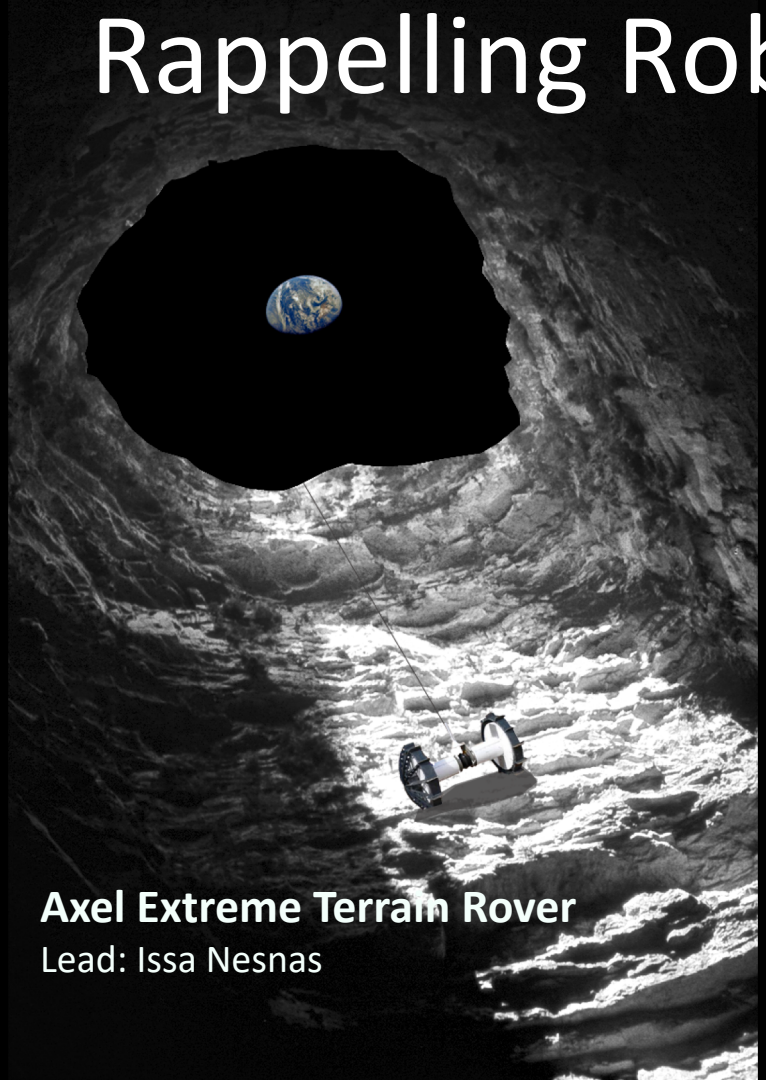

Sotra Patera cryovolcano on Titan

Cave Exploration: Technological Value

- Representative environments for extreme terrains
  - Mobility-wise
  - Perception-wise
  - Autonomy and communication-wise

- Various Mobility Systems at JPL for Robotic Operations in SubT environments
  - Rappling Robots
  - Climbing Robots
  - Flying and racing Drones
  - Modular Robots
  - CoSTAR Robots

Rappelling Robots



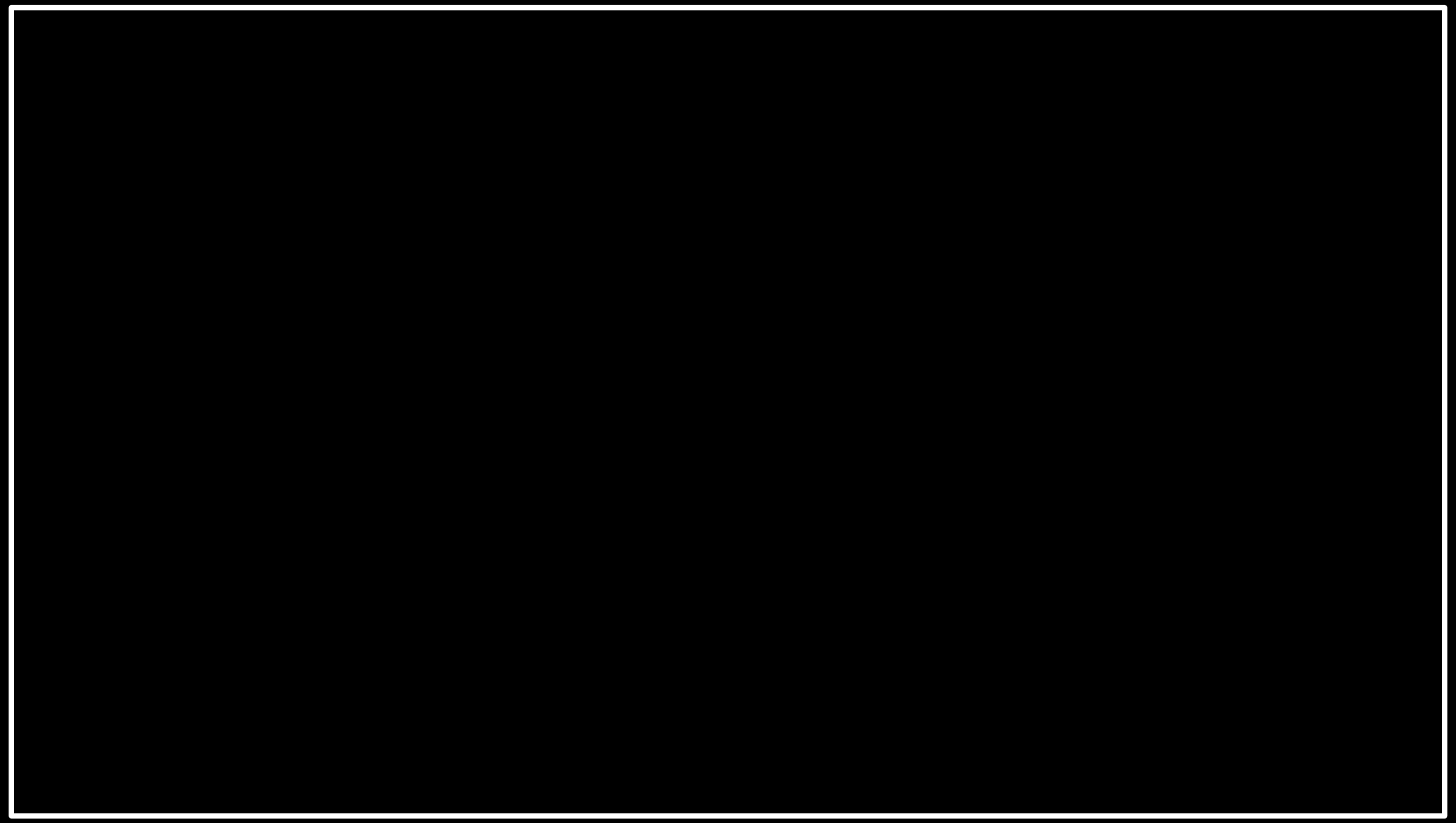
Axel Extreme Terrain Rover

Lead: Issa Nesnas

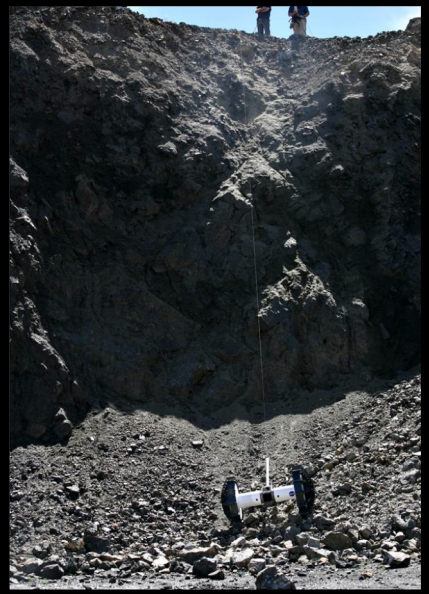
MOON DIVER

Artist concept

Axel robot on extreme terrains



Traversing Extreme Terrain



Climbing Robots

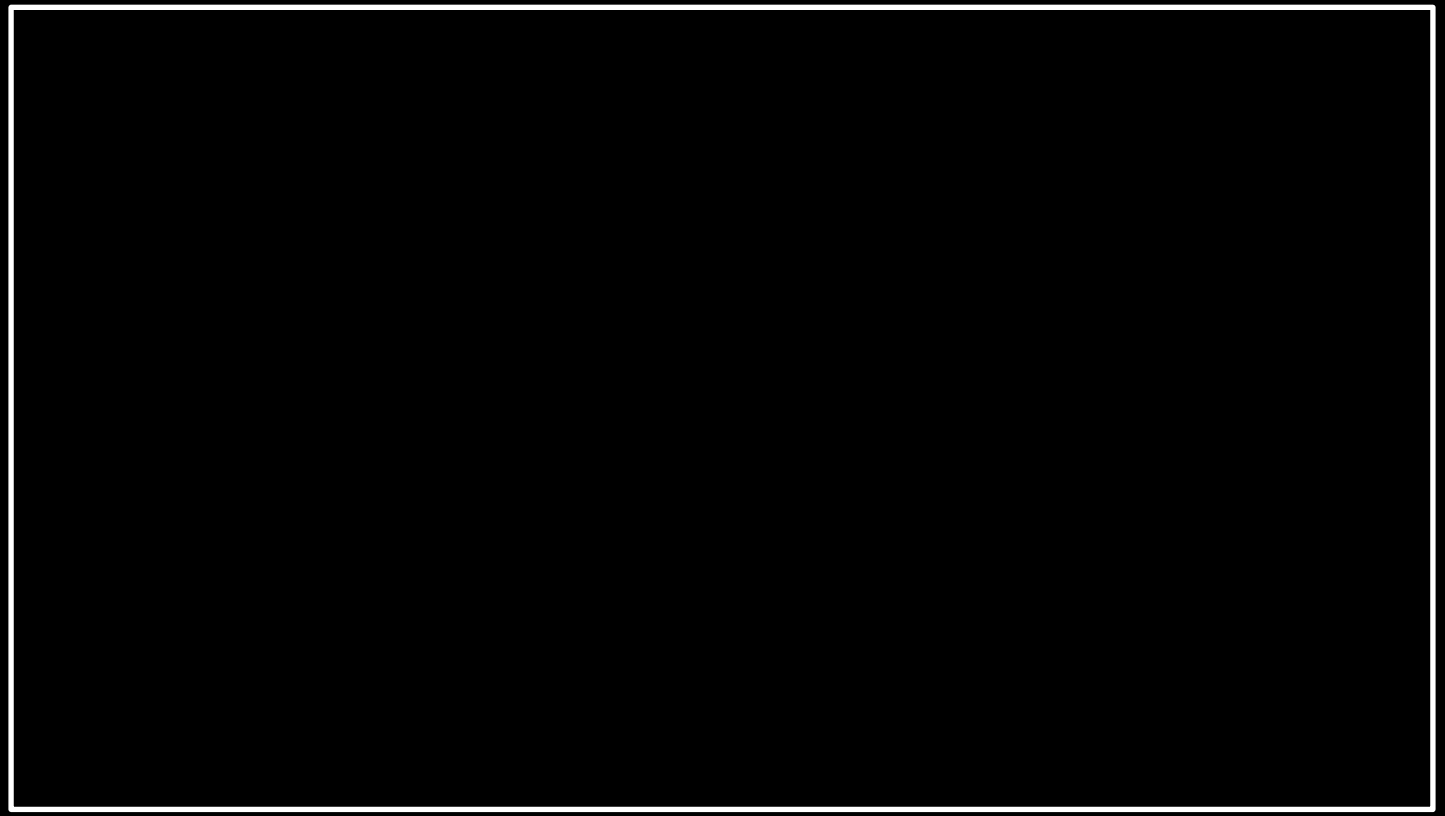
Axel Extreme Terrain Rover

Lead: Aaron Parness

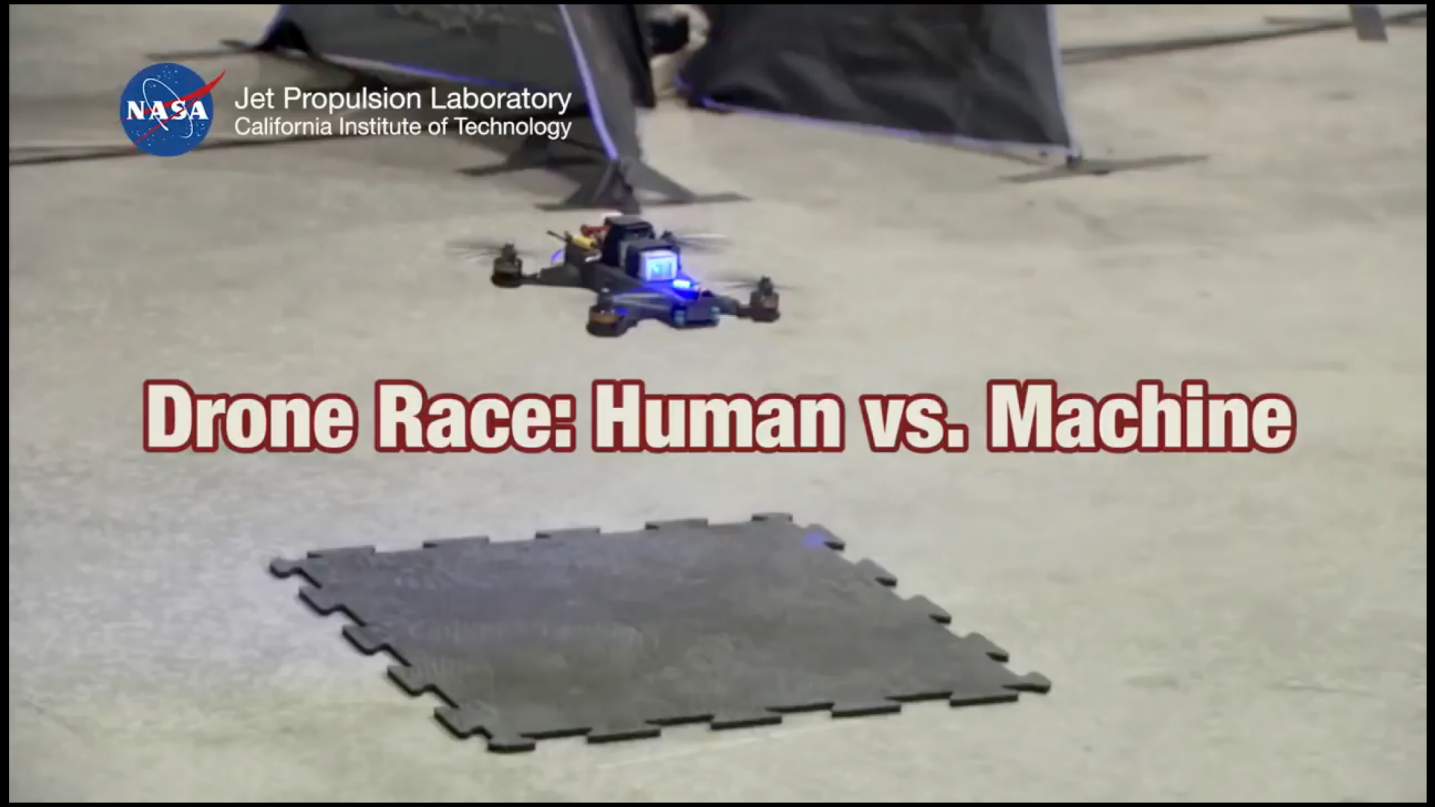
Ali Agha, UCLA, Feb 7th, 2019

Climbing Robots

Flying: Mars Helicopter

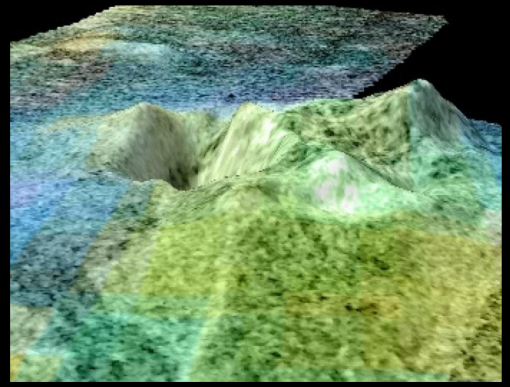


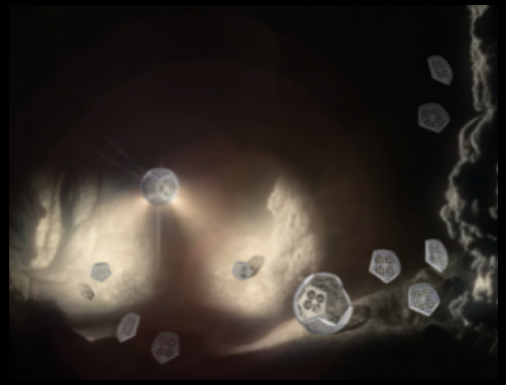
Robust Localization

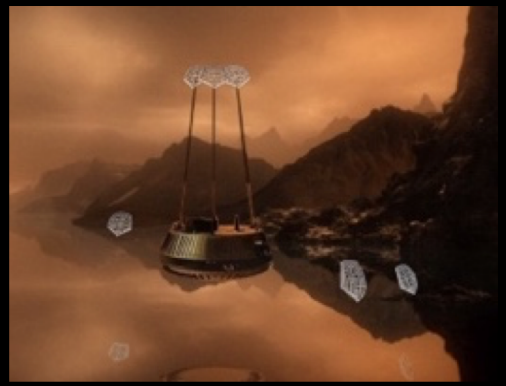


Tango Project
Lead: Robert Reid

Shapeshifter: Modular systems







Artist concept

Artist's concept. © 2018 California Institute of Technology. Government sponsorship acknowledged.

Part 2: TEAM-CoSTAR at DARPA Subterranean Challenge

Past: Series of DARPA challenges

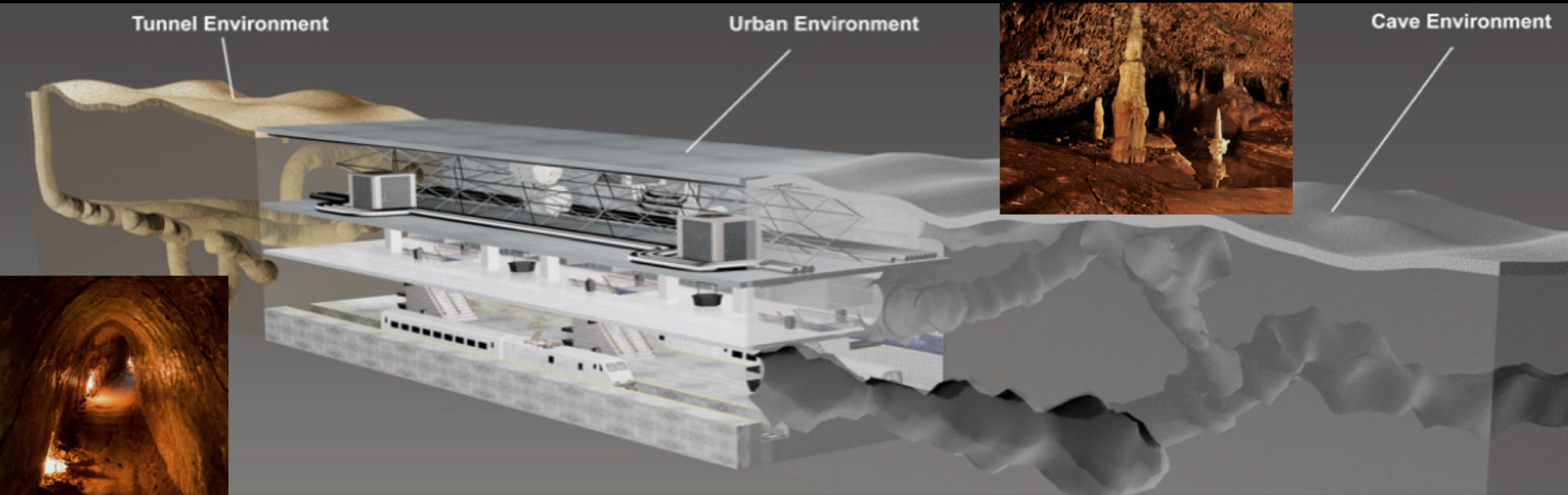
- Setting ambitious goals, making way for novel approaches that might otherwise seem too risky to pursue. [from DARPA website]
  - Realizing advancing the cutting-edge technologies

- Robotics-relevant examples: have catalyzed advances in autonomy and changes the course of research/funding in the U.S. (for driving and manipulation).

- In DARPA challenge teams are large with many institutions and collaborators.

Present: Darpa Subterranean (SubT) Challenge

Objectives: to revolutionize technologies needed for exploring subterranean environments (tunnel, cave, lava tubes, pit craters, etc.) using a swarm of robots
Scope: only 6 teams are selected worldwide (DARPA awarded each ~$4.5M/3yrs).
Duration: 4 competitions throughout a 3 year effort
Scoring: cm-level mapping of km-long cave network/find objects
Challenges: Mobility, Perception, Autonomy, Communication



Very Aggressive Schedule

Project Started

Sep 1, 2018

November

JPL Tests in Mueller Tunnel

DARPA Single-robot Qualification

Dec 21, 2018

February

JPL Tests at Galvez Tunnel

A critical practice run set up by DARPA

DARPA SubT Integration Exercise (STIX)

April

May

DARPA Qualification round

DARPA Tunnel Competition

August 2019

YEAR 2 & 3
void/submerged Caves
(multi km-long)

Challenges and Thrusts:

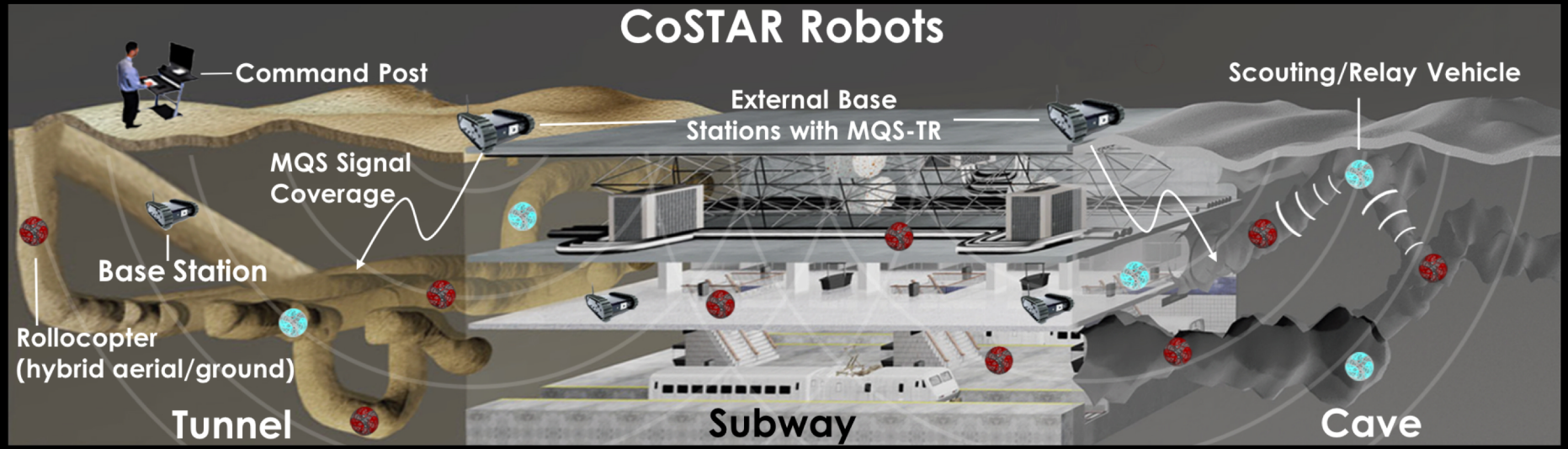
Thrust 1: Cross-domain Mobility
Thrust 2: Extreme Navigation
Thrust 3: Resilient Communication
Thrust 4: Multi-robot Situational Awareness
Thrust 5: Verifiable Autonomy
Thrust 6: Mission planning, AI, and machine learning

CoSTAR-bots

Collaborative SubTerranean Autonomous Resilient robots

NASA-JPL, Caltech, MIT

subt.jpl.nasa.gov



Thrust 1: Cross-domain Mobility
Thrust 2: Extreme Navigation
Thrust 3: Resilient Communication
Thrust 4: Multi-robot Situational Awareness
Thrust 5: Verifiable Autonomy
Thrust 6: Mission planning, AI, and machine learning

Mobility Challenges:

1) 8Km long SubT env
2) 60-90 min operation
3) Large climbs/drops/vertical shafts
4) Passages as narrow as 1m in diameter

Thrust 1: Cross-domain Mobility
Thrust 2: Extreme Navigation
Thrust 3: Resilient Communication
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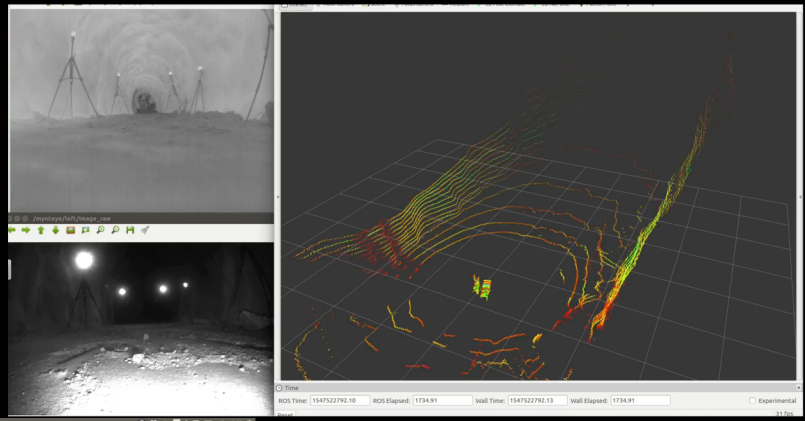
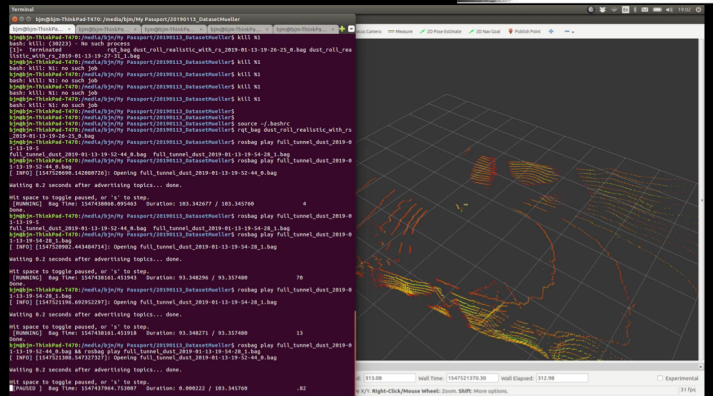
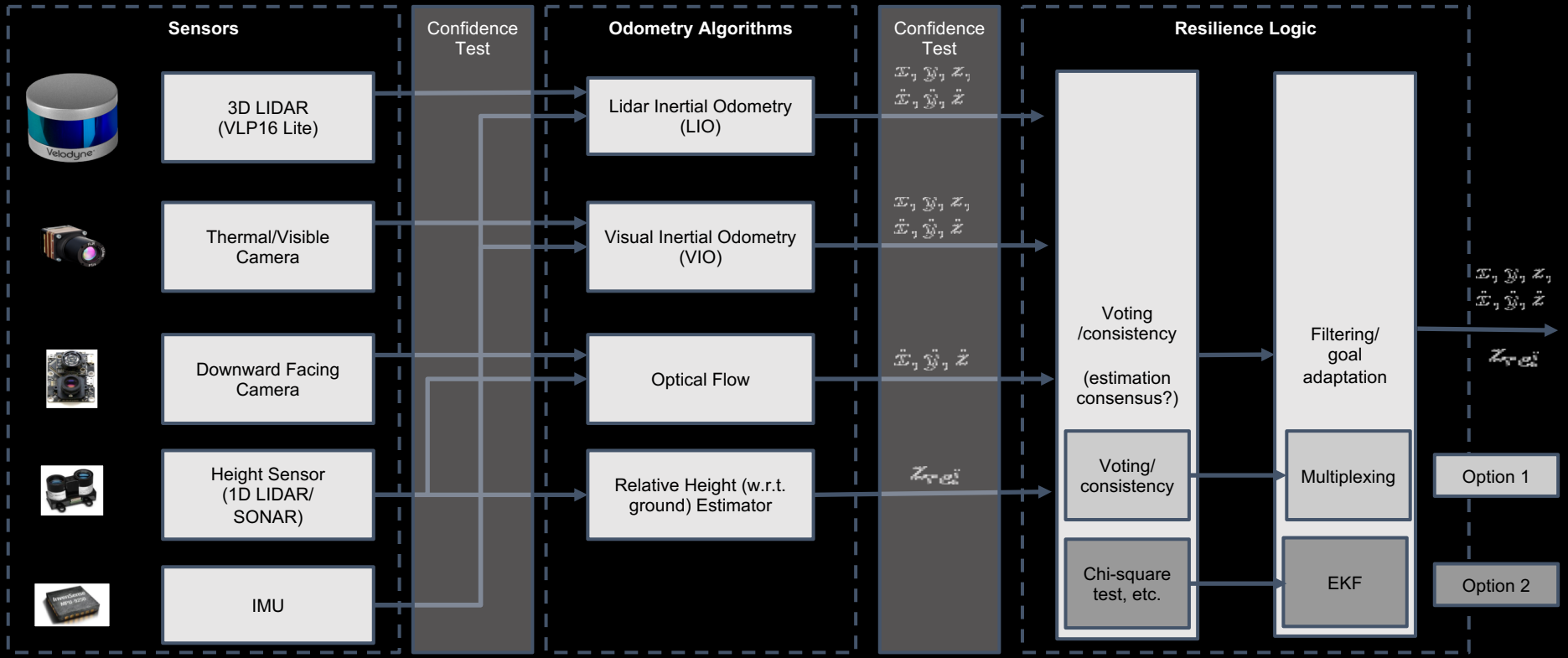


Localization Challenges:

1) Dark
2) Dust/fog/smoke
3) High-dynamic range
4) Lightweight
5) Robust (handle texture-poor environments)
6) High-frequency



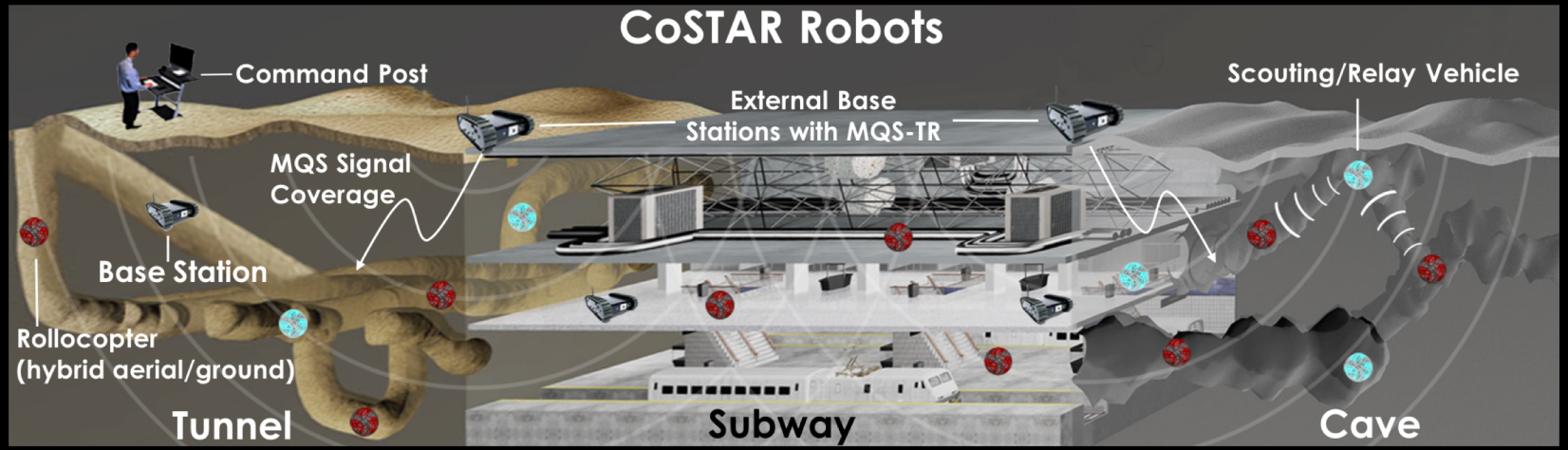
Confidence tests and resiliency logic



Thrust 1: Cross-domain Mobility
Thrust 2: Extreme Navigation
Thrust 3: Resilient Communication
Thrust 4: Multi-robot Situational Awareness
Thrust 5: Verifiable Autonomy
Thrust 6: Mission planning, AI, and machine learning

Comm and perception Challenges:

1) several-km long subsurface voids
2) Multipath environment generating unpredictable link qualities
3) Requirement on a few seconds of delay
4) high-bandwidth for multi-agent decision making
5) Very large scale decentralized SLAM with cm-level accuracy and with lots of loop closures
6) lightweight



Thrust 1: Cross-domain Mobility
Thrust 2: Extreme Navigation
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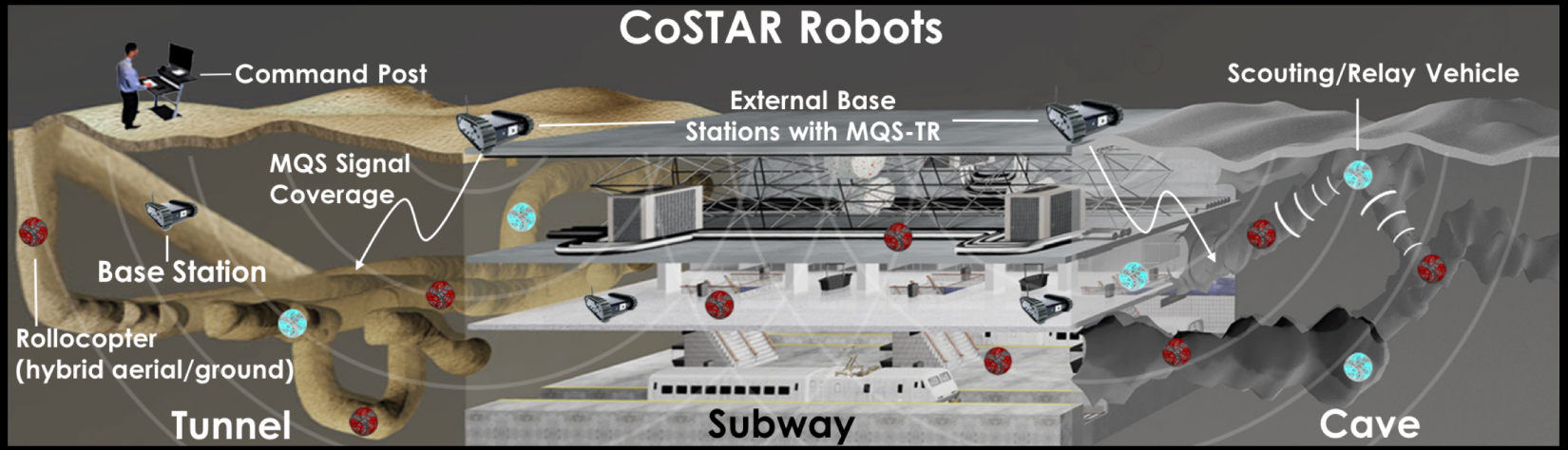
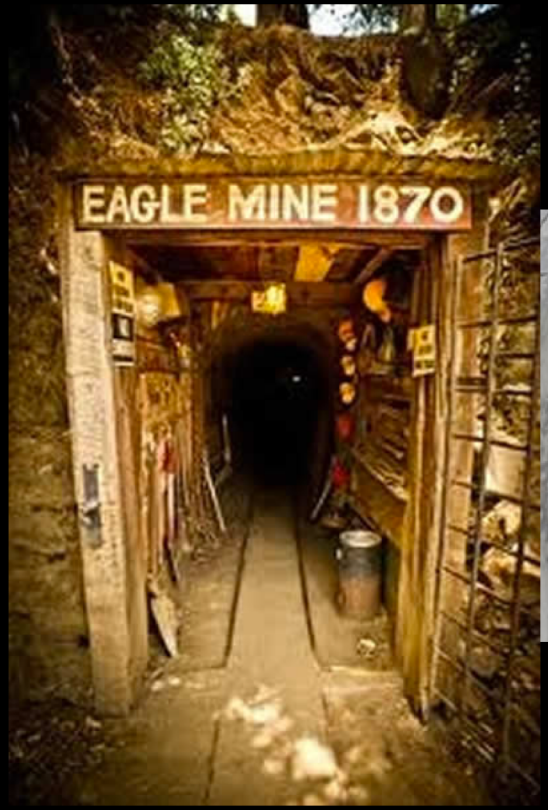
Autonomy and ML challenges:

1) Multi-agent operations for an extended period without human intervention in a fully unknown environment
2) Losing full/partial capability/health of an agent
3) Modeling and balancing high-level mission risk and low-level mobility risks
4) Semantic understanding and object detection in perceptually-degraded environments



Testing location

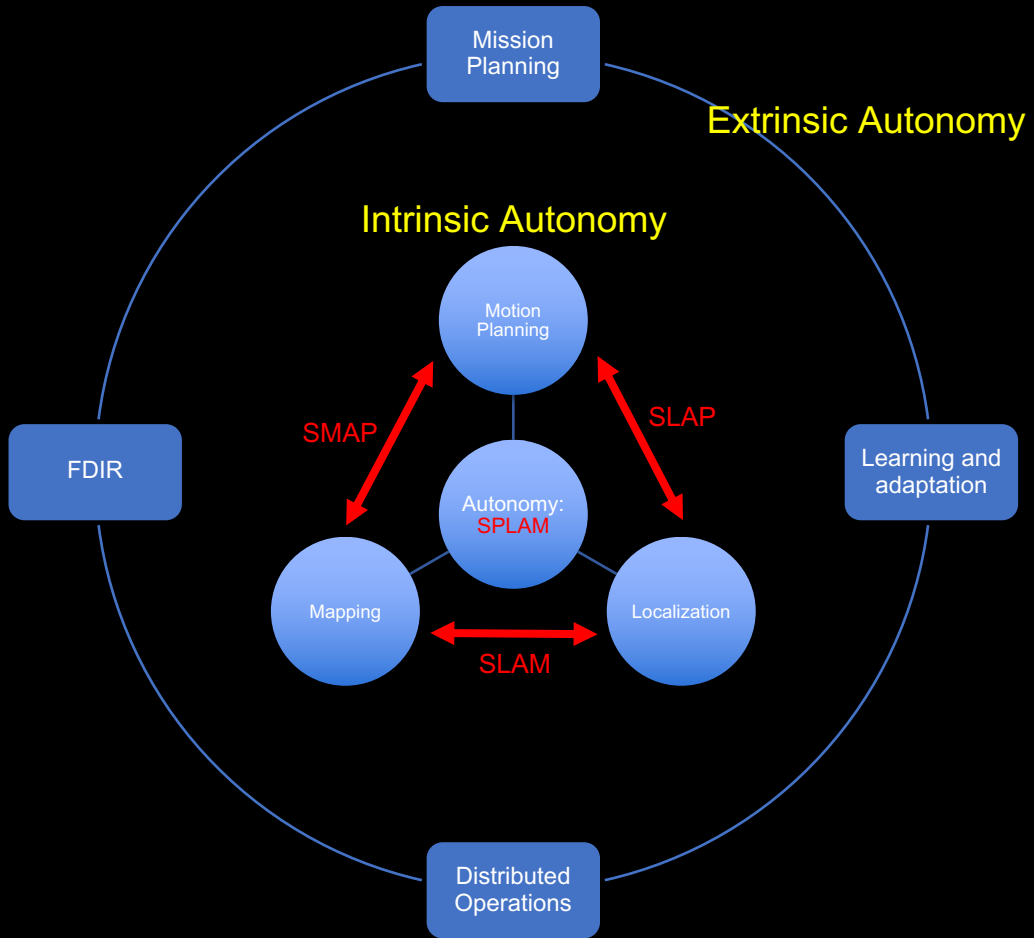
- Mueller tunnel
- Eagle mine



Part 3:
Robust and risk-aware autonomy; Information-control perspective

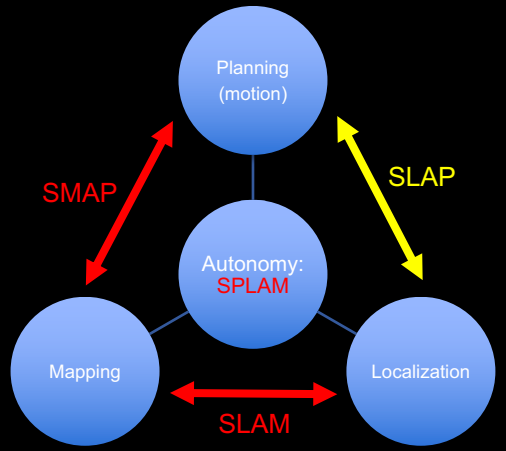
CoSTAR Autonomy Architecture

- Real-world applications
- Resilience/Robustness
- Reason over uncertainty
- Accurate risk prediction
- Integrated perception/planning



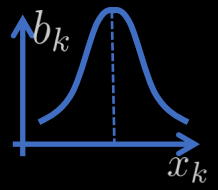
SLAP: Simultaneous Localization and Planning

- Risk-aware SLAP under uncertainty

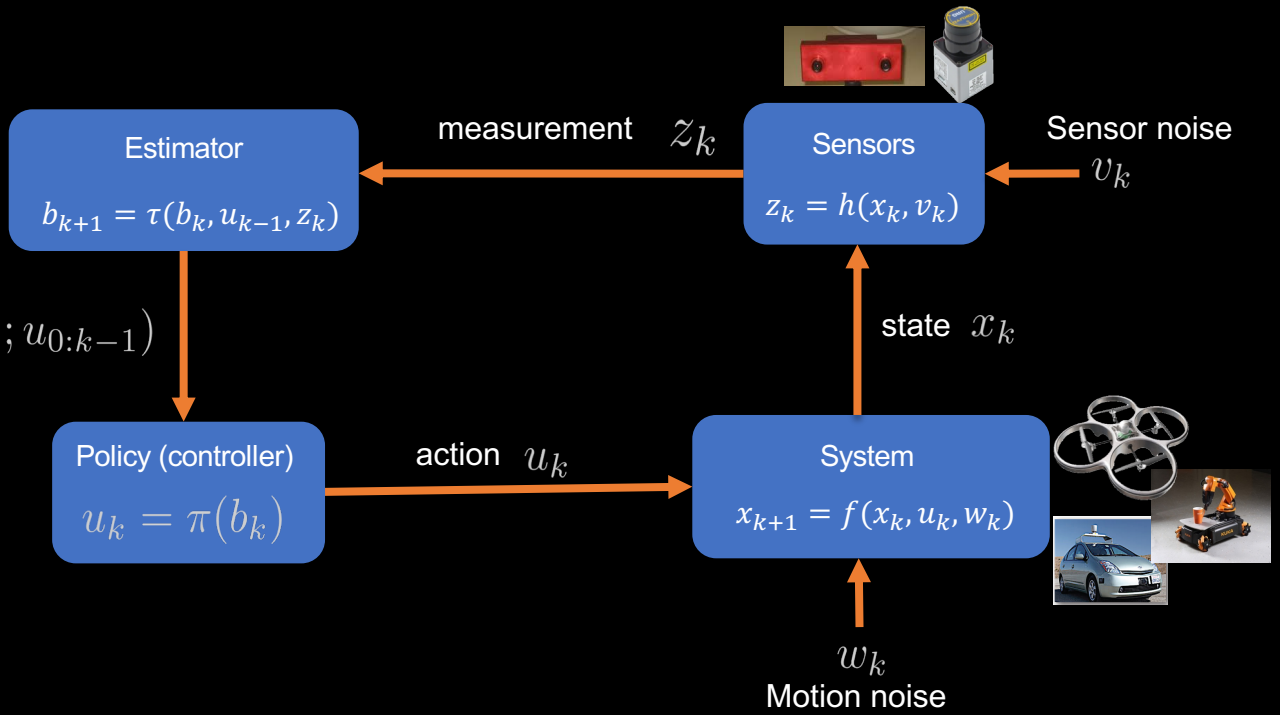


Joint Inference and Control

Information-state (Belief)



$$b_k = p(x_k | z_{0:k}; u_{0:k-1})$$



Stochastic Control with Imperfect Measurements

- Cost per stage $c(b, u)$ [captures the desired behavior]
- Cost-to-go: $$J^{\pi}(b_0) = \mathbb{E}\left[\sum_{k=0}^{\infty} c(b_k, u_k) | u_k = \pi(b_k)\right]$$
- POMDP (Partially-Observable Markov Decision Process):

$$\pi^* = \arg\min_{\pi \in \Pi} J^{\pi}(b_0)$$

- Constraints set!

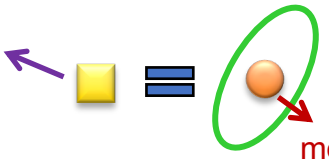
intractable over continuous spaces

Traditional POMDPs

$b_i = (\hat{x}_i^+, P_i)$

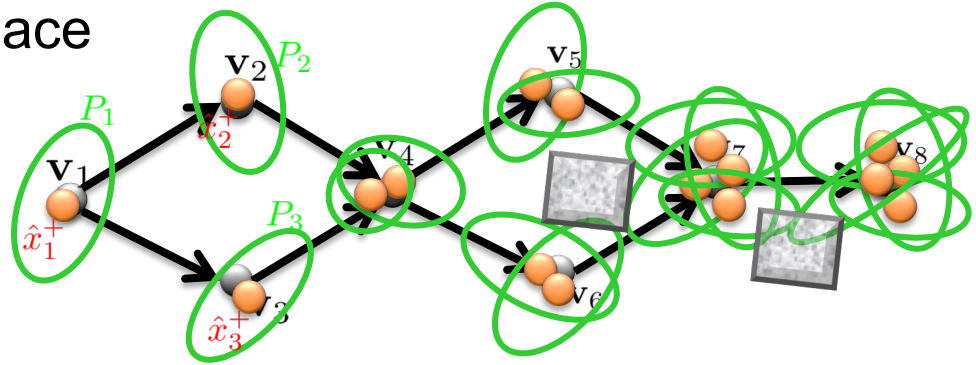
covariance

Gaussian belief

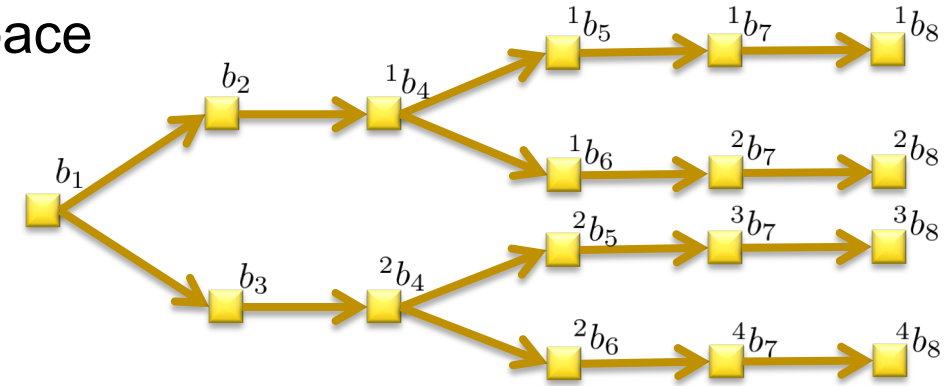


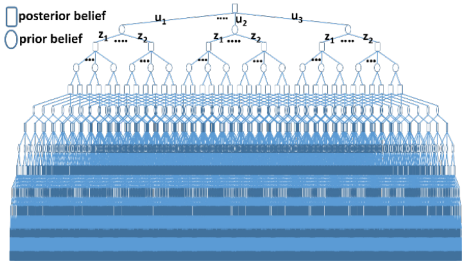
mean

State space



Belief space

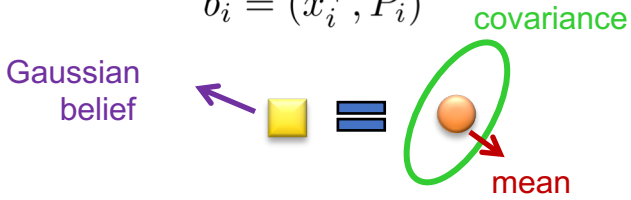




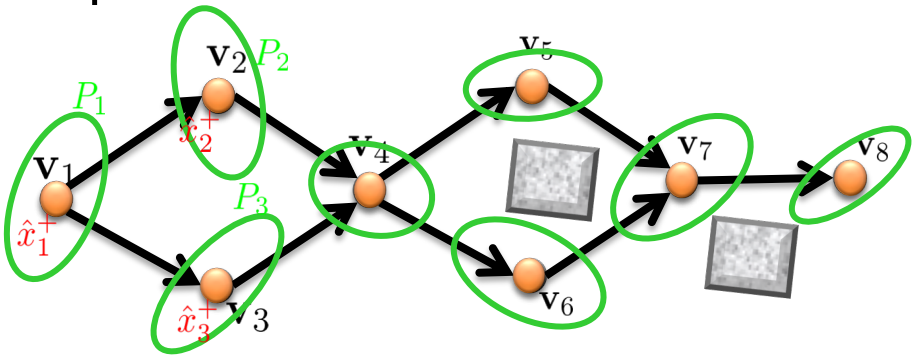
1) Tree (grows exp.)
2) No feedback
3) Simple constraint

Feedback-based Information Roadmaps

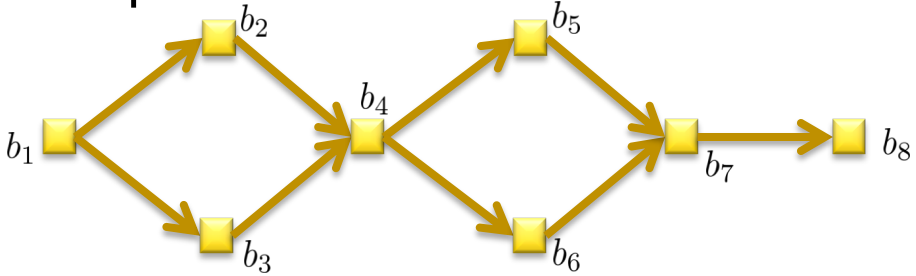
$b_i = (\hat{x}_i^+, P_i)$

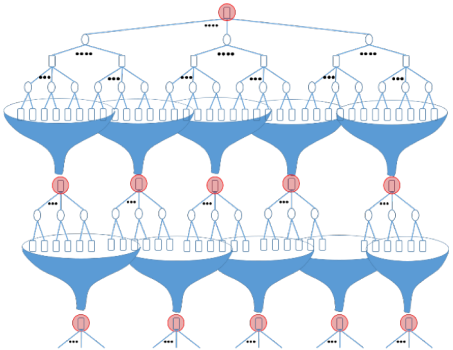


State space



Belief space



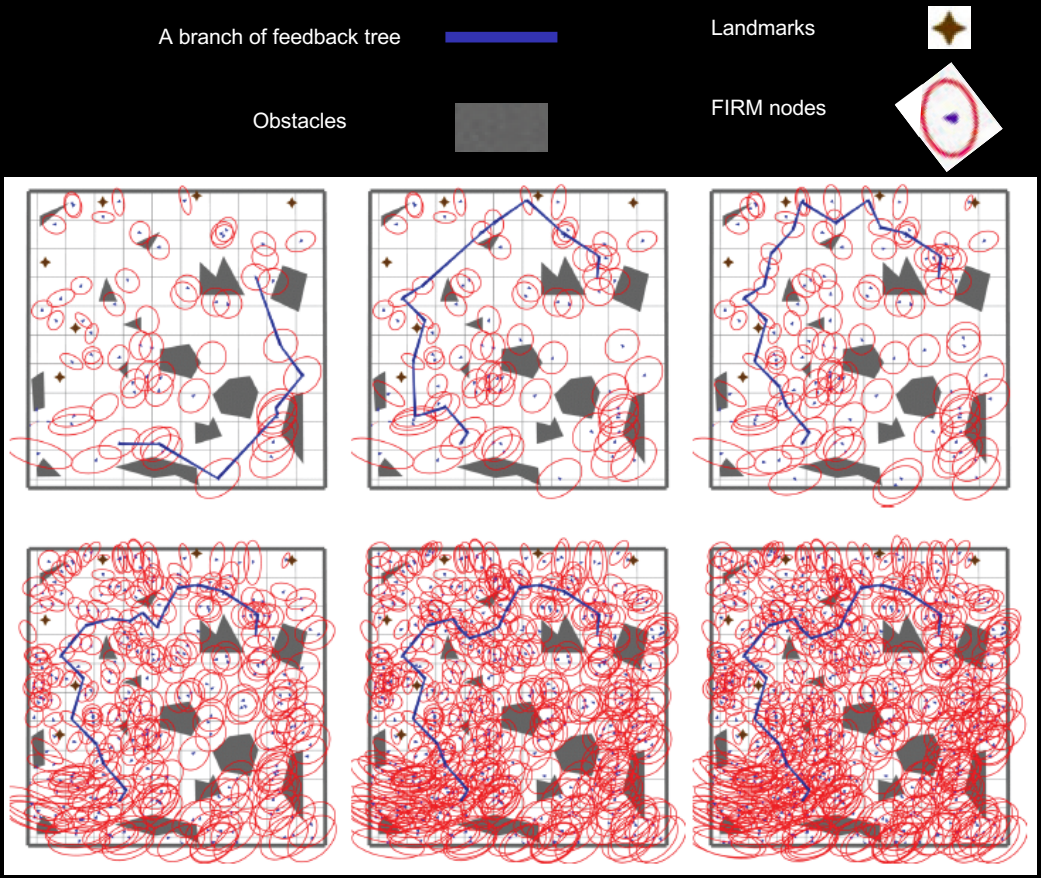


1) Graph (grows linearly)
2) Feedback (switching controller) -> robust
3) Constraints

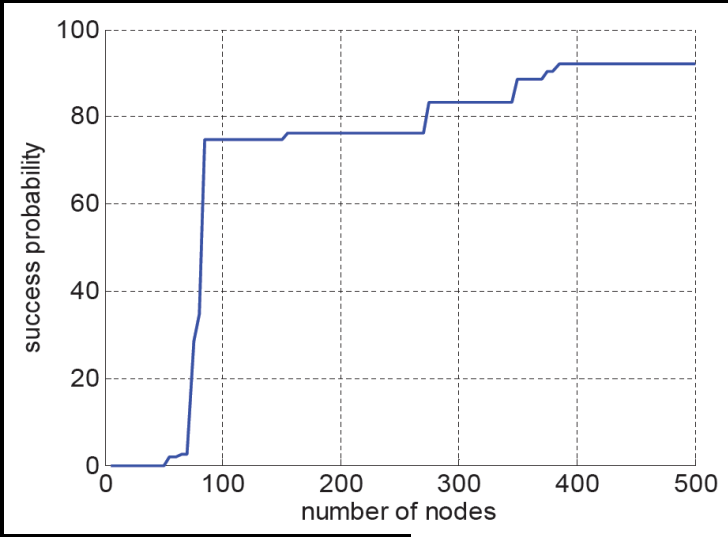
Graph in belief space; Feedback-based information RoadMap (FIRM)

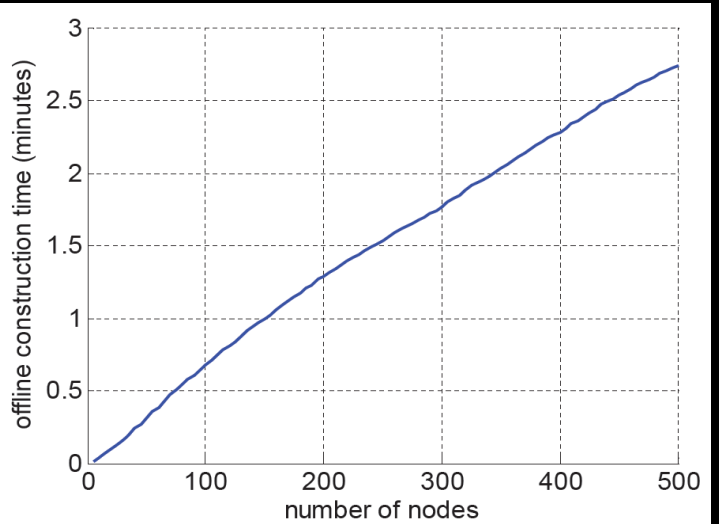
Agha, Chakravorty Amato, "FIRM: Sampling-based Feedback Motion Planning Under Motion Uncertainty and Imperfect Measurements," *IJRR*'14.

Offline graph construction



Offline graph construction





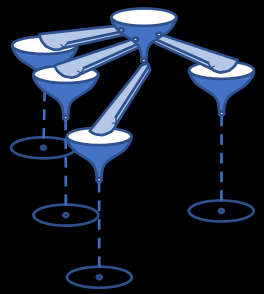
Reduction in comp. complexity

$$O(Nk^N)$$

$$\Downarrow$$

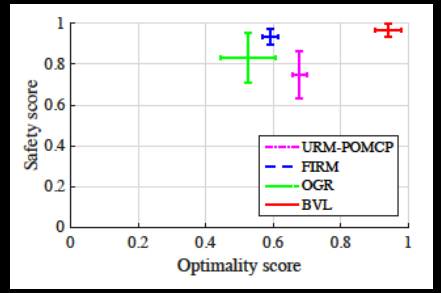
$$O(Nk)$$

FIRM++



- Local rollout-based optimization

Agha, et al.,"SLAP: Simultaneous Localization and Planning for Physical Mobile Robots via Enabling Dynamic Replanning in Belief Space," TRO 2018 .



- Bi-directional value learning

Sung, Agha, et al.,"Bi-directional value learning for risk-aware planning in stochastic systems," Under review.

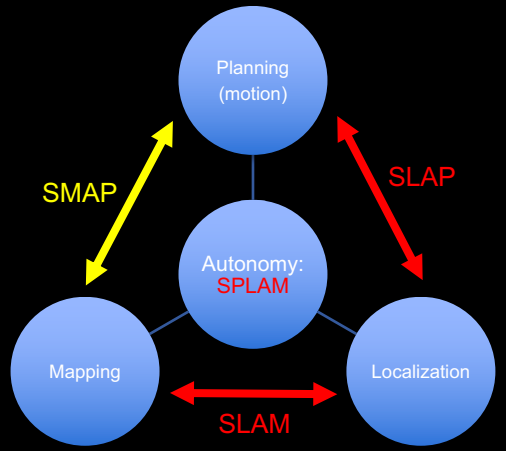
- Decentralized POMDPs

Omidshafiei, Agha, et al, "Decentralized Control of Partially Observable Markov Decision Processes using Belief Space Macro-actions," *IJRR'2017.*

Overview:

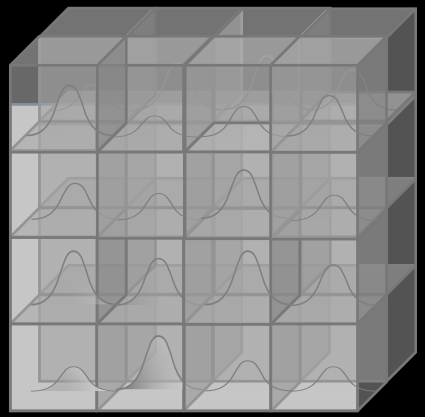
SMAP: Simultaneous Mapping and Planning

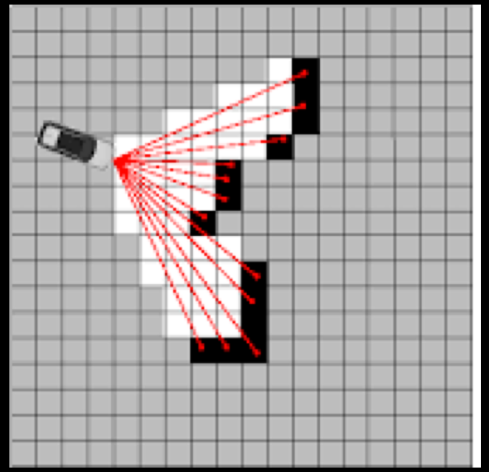
- Risk-aware SMAP under uncertainty



Confidence-rich mapping

- A planning-oriented representation of the environment

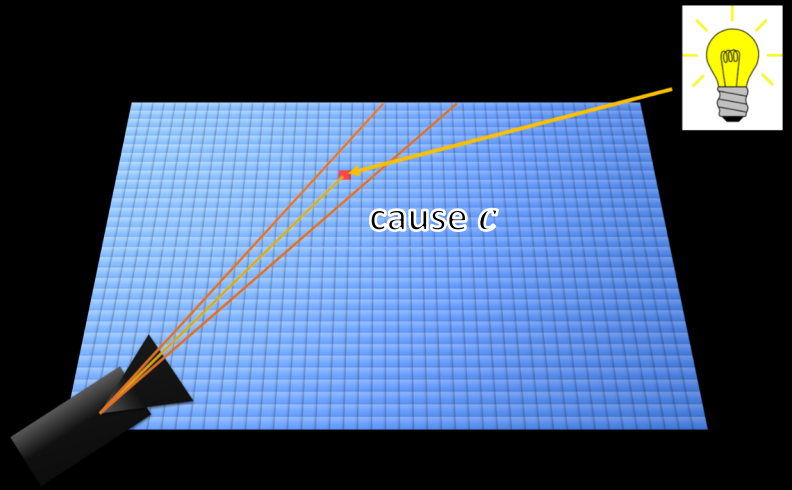




Agha, Heiden, Hausman, Sukhatme, "**Confidence-rich 3D Grid Mapping**," *IJRR* 2019.

- Voxel independence assumption
- Unreliable representation of confidence

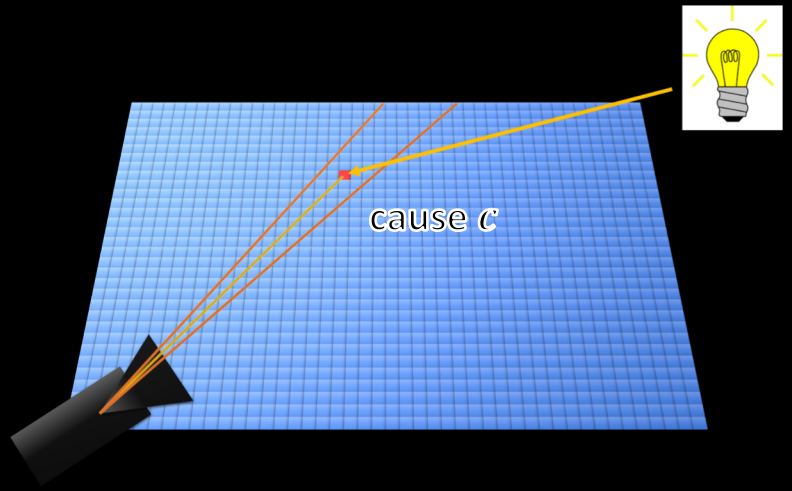
Sensor-Cause Model



$$p(c|b^m) = \Pr(B^c, R^c|b^m) = \widehat{m}^c \prod_{l=1}^{c^l-1}\left(1 - \widehat{m}^{g(l,x)}\right)$$

$$b_k^{m^i} = p\left(m^i \middle| z_{0:k}, x_{0:k}\right) = \tau(b_k^{m^i}, x_k, z_k)$$

Sensor-Cause Model



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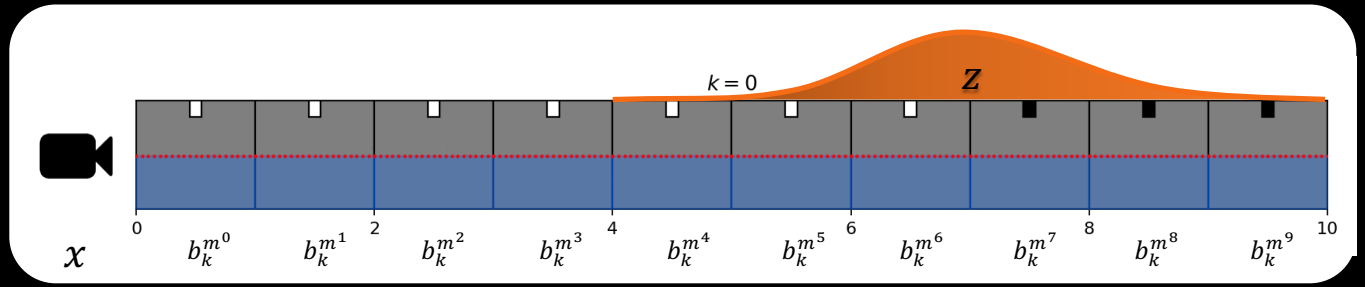
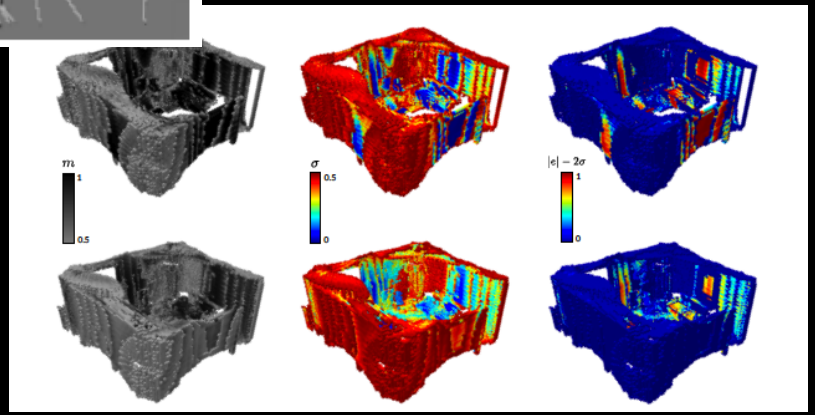
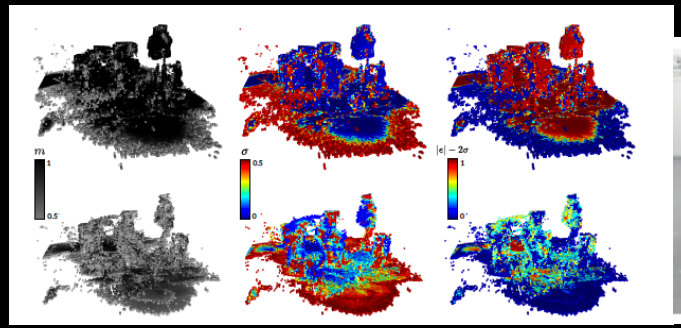


Results on DataSets

Inconsistency I_c	log-odds	CRM
albert-b-vision	984.777	**716.211**
ICL-NUIM	2871.180	**1307.793**
EuRoC MAV	645.750	**434.598**
USC Intel Drone	6344.294	**1196.418**

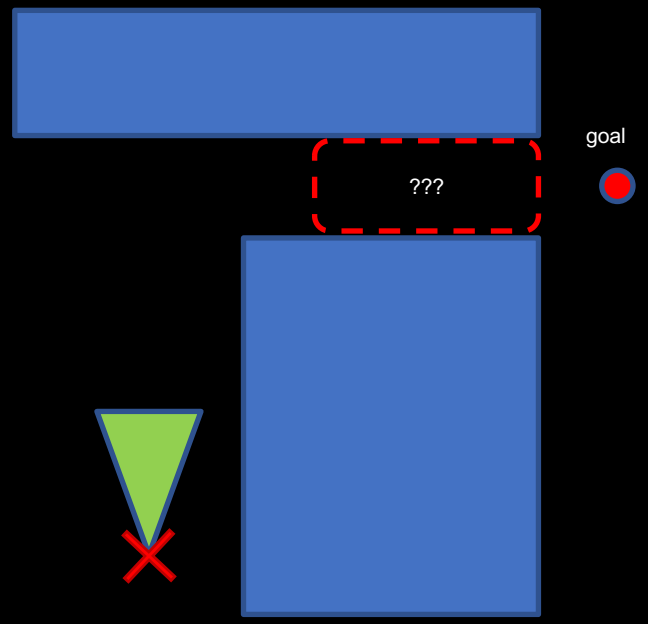




Agha, Heiden, Hausman, Sukhatme, "**Confidence-rich 3D Grid Mapping**," *IJRR* 2019.

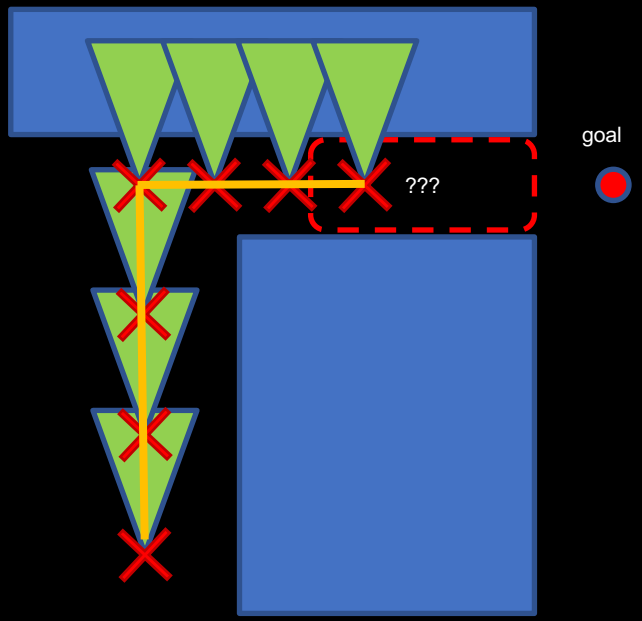
SMAP: induced behavior

- Go from start to goal
  - While minimizing time and
  - Collision probability



SMAP: induced behavior

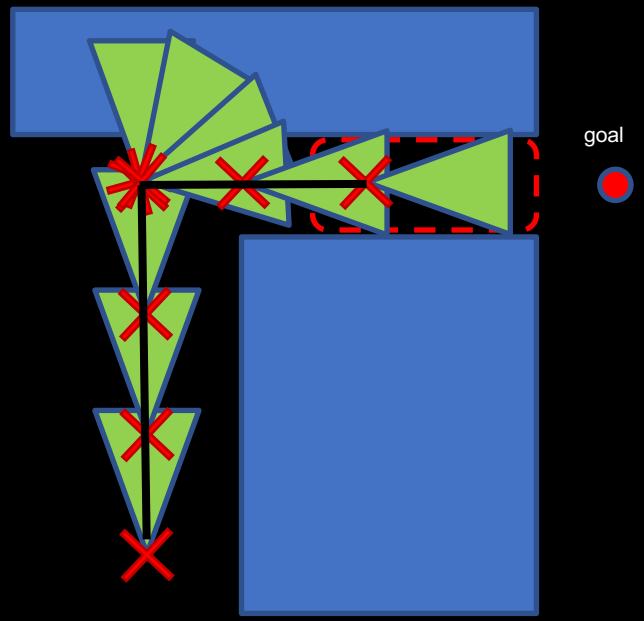
- Without SMAP
  - Without considering uncertainty and perceptual capabilities



- Fast and risky

SMAP: induced behavior

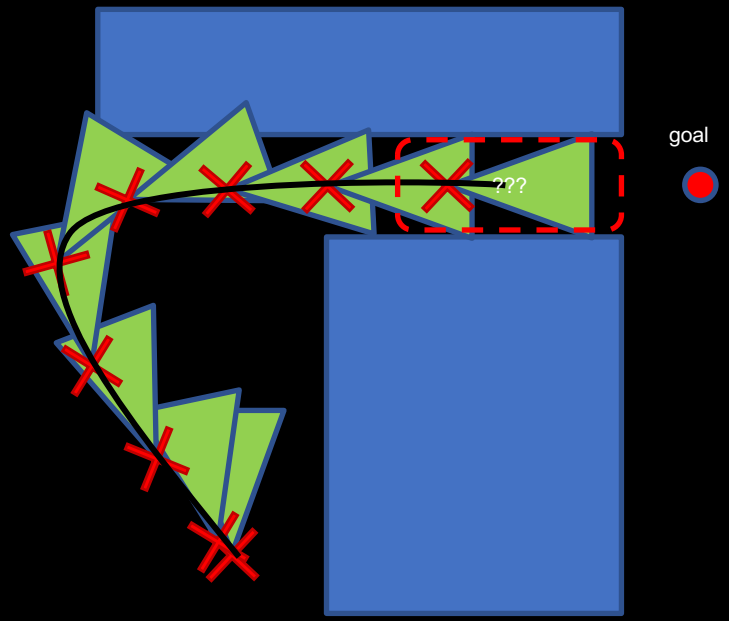
- Without SMAP
- Safe but slow



SMAP

- Risk-aware and fast

- Predict map evolution
- Incorporate predicted sensory measurements into planning



$$\text{Risk} = \mathbb{E}[R(\mathbf{x})] - \kappa\sigma[R(\mathbf{x})]$$

Reduction in re-planning stops up to 70%

Speed-up in traversal time up to 34%

Heiden, Hausman, Sukhatme, Agha, "Planning High-speed Safe Trajectories in Confidence-rich Map," IROS 2017.

Conclusion

- Exploring planetary caves offers high-value science return.

- CoSTAR
  - Lots of challenges and lots of research opportunities

- Resilience/Robustness ⟺ More accurate risk evaluation

  Integrated perception/planning ⟺ Information control

Thank you!