Autonomous Online Perception and Navigation for Aerial Vehicles

Vadim Indelman

TECHNION
Israel Institute of Technology

ANPL
Autonomous Navigation and Perception Lab

Israel Robotics Meetup

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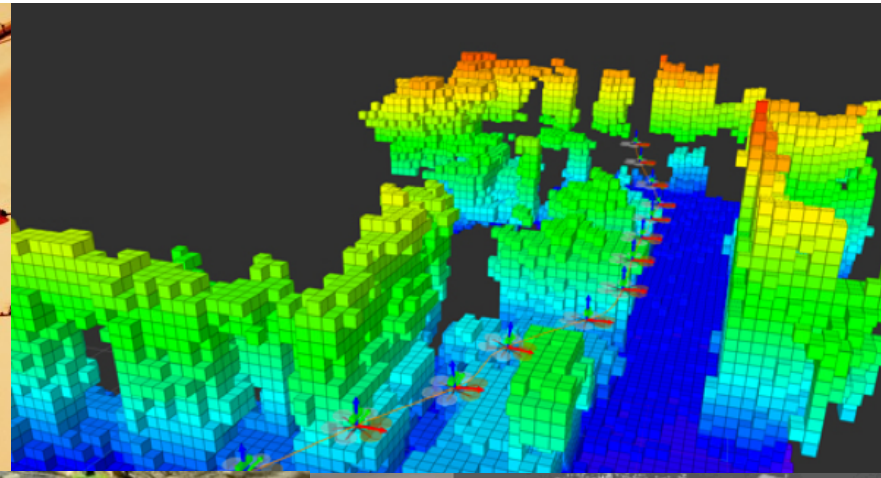
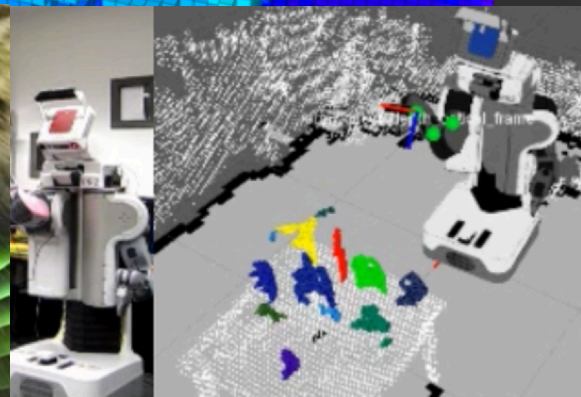
Introduction

- Autonomous operation in complex, uncertain and ambiguous scenarios
  - **Independent** of infrastructure and prior information
  - Within **static and dynamic** environments

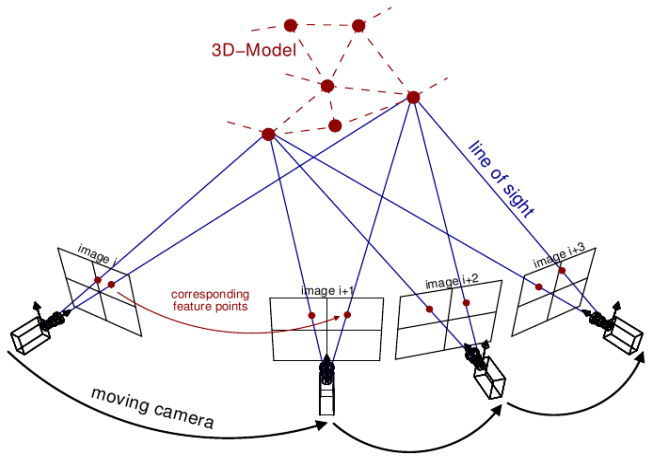


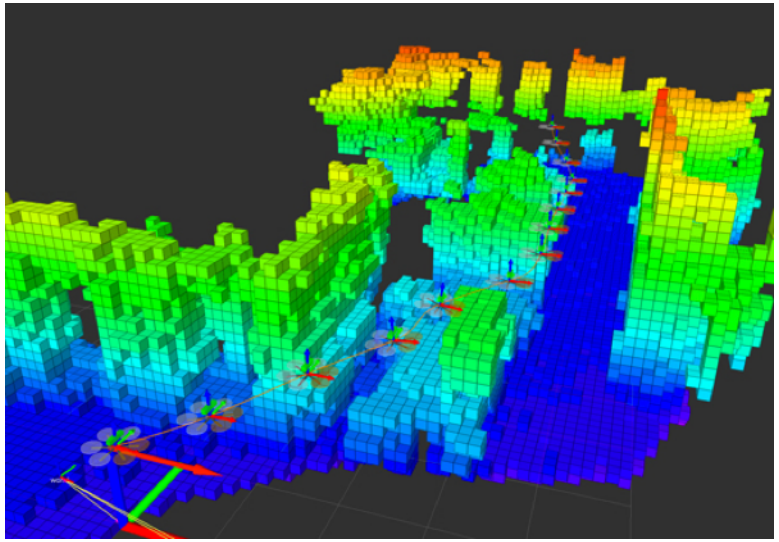


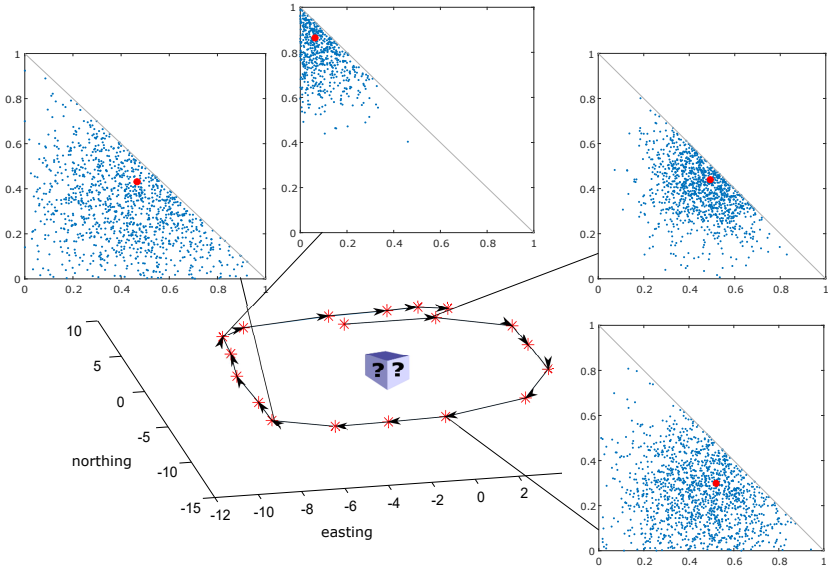
Introduction

Key required capabilities:

- **Perception and Inference**: Where am I? What is the surrounding environment?
- **Planning Under Uncertainty & Active Perception**: Decide next action(s) given partial, noisy data







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Perception & Inference ⟷ **Planning Under Uncertainty**

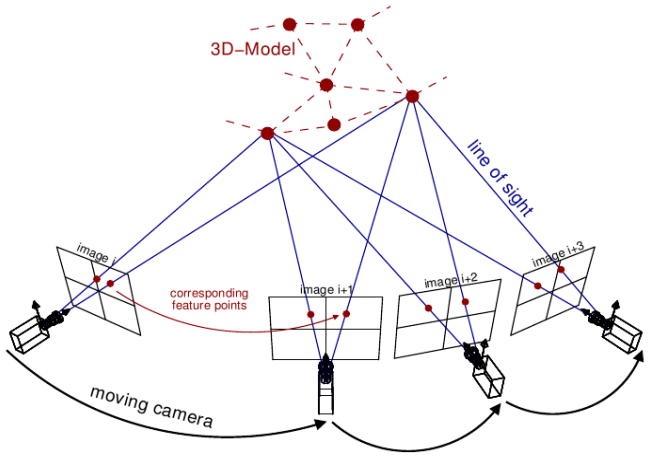
- Tight coupling with perception & inference
- <u>Related problems</u>: autonomous navigation, active SLAM, informative planning/sensing, etc.

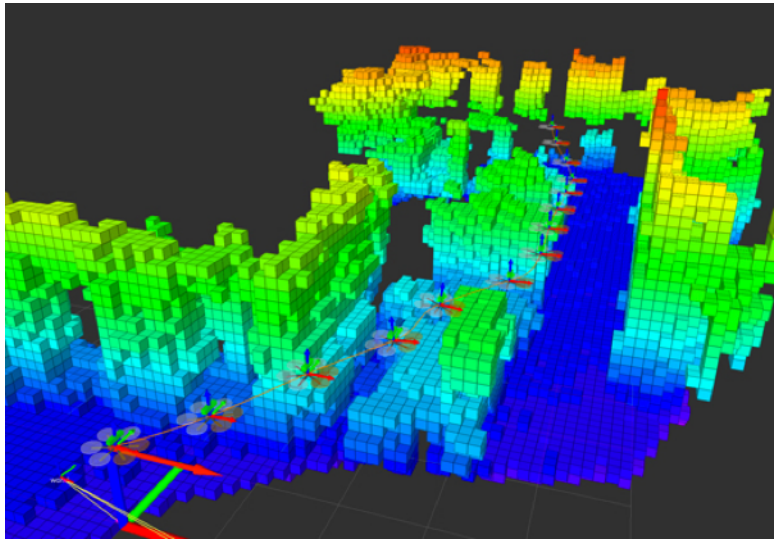
Perception & Inference

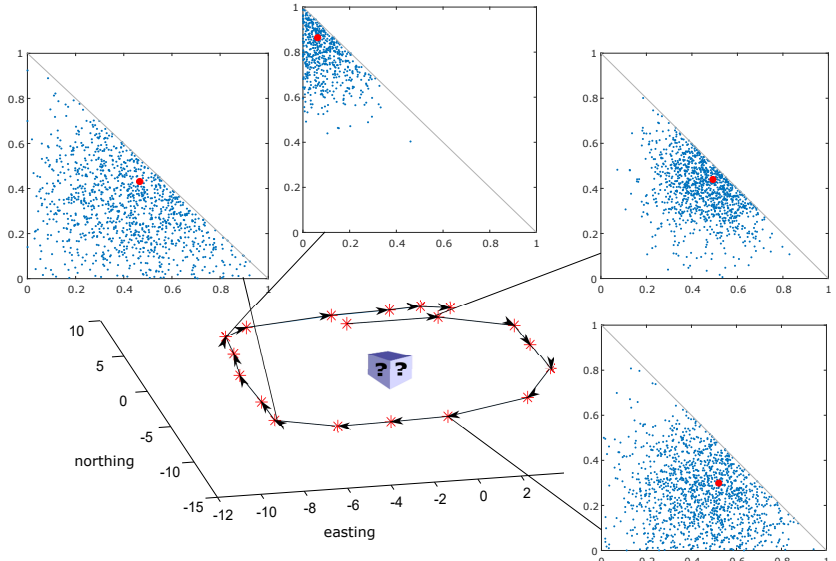
Perception and Inference

- **Key questions (given data obtained thus far)**:
  - Where am I?
  - What is the surrounding environment? (aspects: geometric/semantic; static/dynamic)

- What if neither is known?
  - Need to infer both robot pose and observed structure
  - **Robotics**: simultaneous localization and mapping (SLAM)
  - **Computer vision**: structure from motion, bundle adjustment



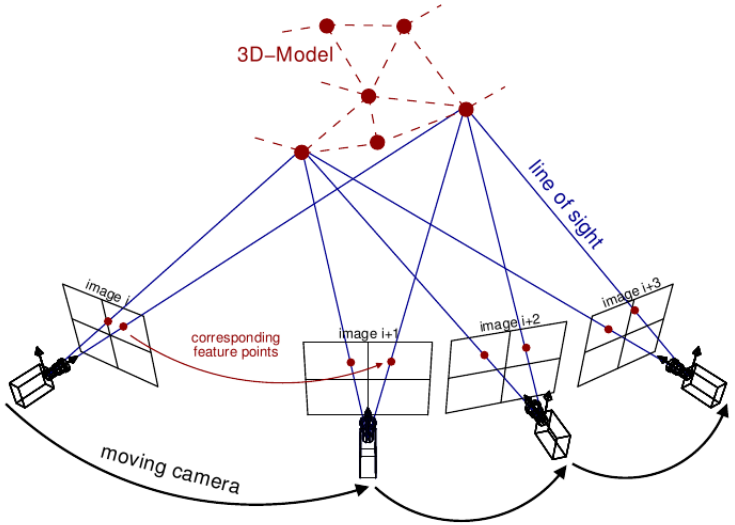


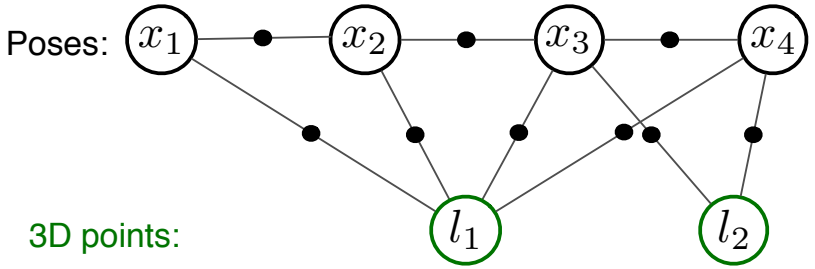


Perception and Inference

- State/variables at time k: $X_k \in \mathbb{R}^n$
- Posterior belief at time k: $b[X_k] \doteq \mathbb{P}(X_k \mid \underbrace{u_{0:k-1}, z_{1:k}}_{\doteq H_k})$ (history)
- Can be represented with graphical models, e.g. a factor graph
- Computationally-efficient maximum a posteriori inference e.g. [Kaess et al. 2012]

$$X_k \doteq \{\underbrace{x_0, \ldots, x_k}_{\text{Past \& current robot states}}, \underbrace{L_k}_{\text{Landmarks}}\}$$



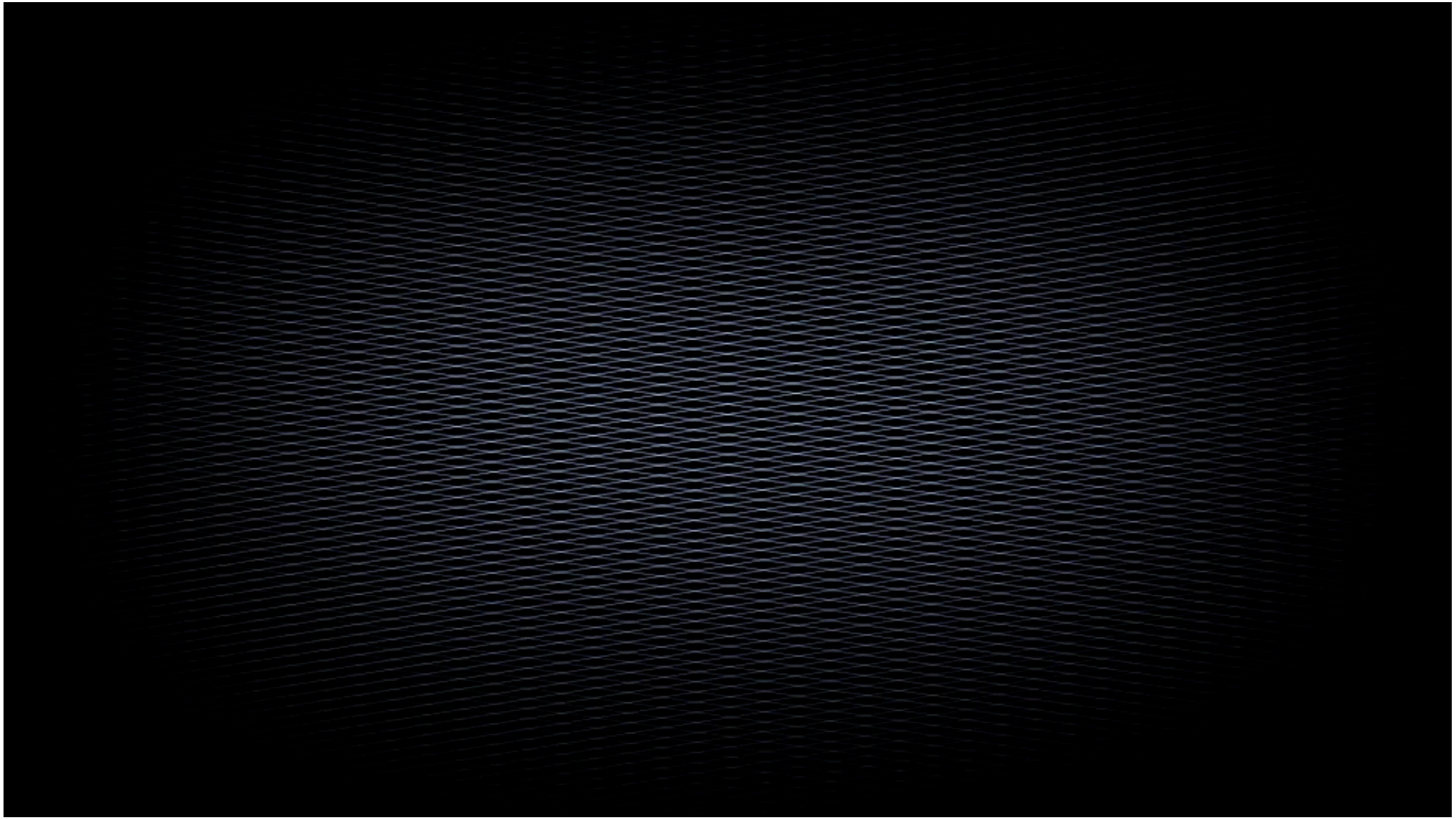


Incremental Light Bundle Adjustment

[Indelman, Richards, Dellaert, BMVC '12]

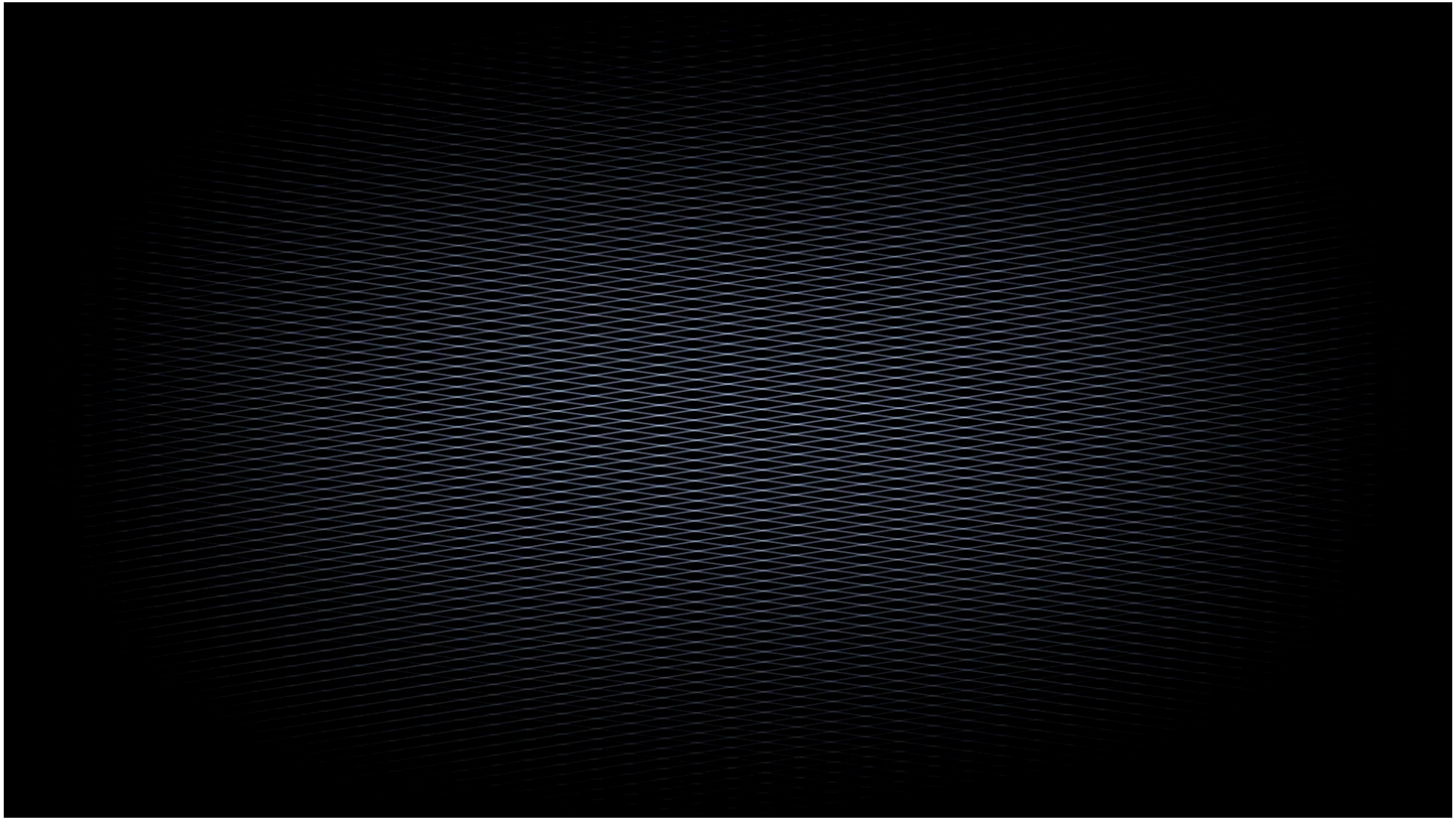
Key idea: (algebraically) eliminate 3D landmarks

RGBD Mapping



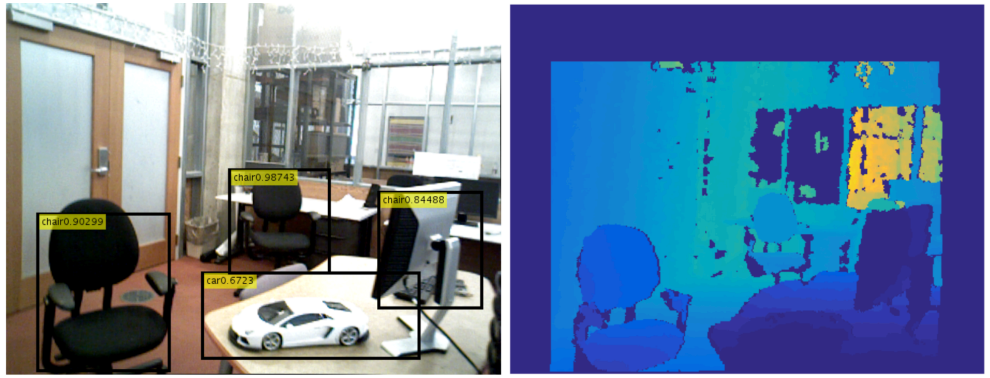
Collaborative Multi-Robot SLAM (2 Quads)

Key capability: improve performance by sharing information between robots and formulating multi-robot constraints

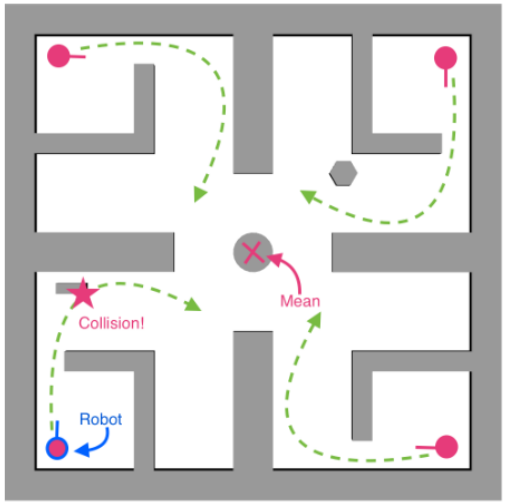


Ambiguous Environments

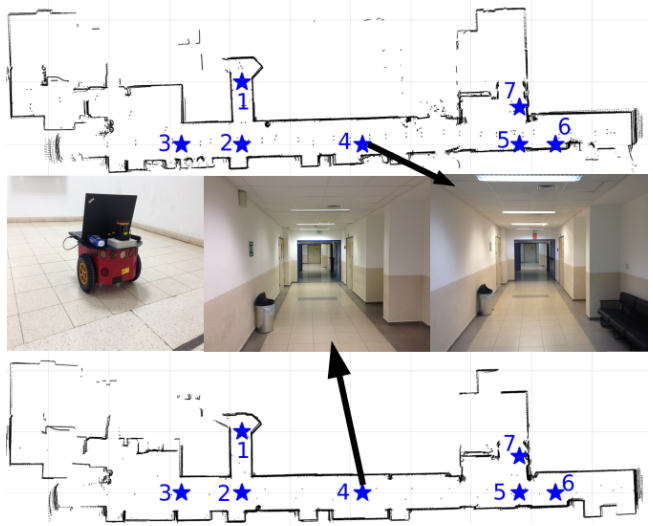
Angeli et al., TRO'08



Mu et al., IROS'16



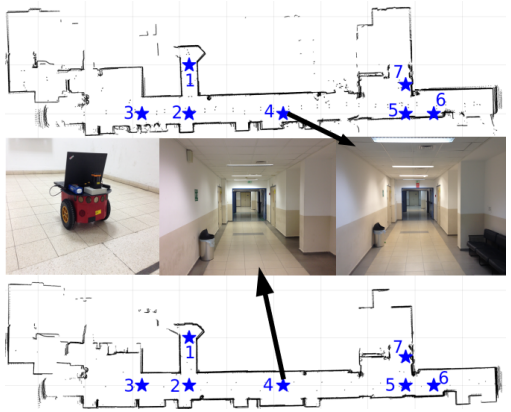
Agarwal et al., arXiv 2015



Pathak, Thomas, Indelnan, IJRR 2018

Ambiguous Environments

- Ambiguity can be due to (combination of):
  - Perceptually aliased scenes (two similar objects)
  - Limited/imperfect sensing (limited sensing range)



- Data association and SLAM/localization are inherently coupled
- Can we incorproate these aspects within **inference** and **decision making**?

Robust Perception – Ambiguous Scenarios

[Indelman, et al., CSM'16]

- Multi-robot collaborative localization and mapping – **distributed, online**
- **Robust perception** (cope with perceptual aliasing)

Autonomous Perception
(Planning Under Uncertainty, Belief Space Planning)

Perception & Inference ⟷ **Planning Under Uncertainty**

Belief Space Planning (BSP)

- Given partial and uncertain knowledge, determine: Next actions, given a task
- Tight coupling with perception & inference

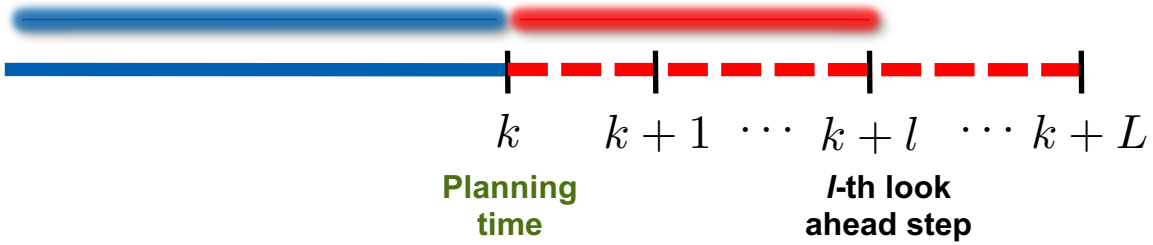
Perception & Inference ⟷ **Belief Space Planning**

- <u>Related problems</u>: autonomous navigation, active SLAM, informative planning/sensing, etc.

Belief Space Planning (BSP)

- Objective function ($u \doteq u_{k:k+L-1}$): $$J(u) \doteq \mathbb{E}\left[\sum_{l=1}^{L} c\left(b[X_{k+l}], u_{k+l-1}\right)\right]$$

- Belief at the l-th look-ahead step: $$b[X_{k+l}] \doteq \mathbb{P}(\underbrace{X_{k+l}}_{\text{Joint state at the } l\text{-th look ahead step}} \mid \underbrace{u_{0:k-1}, z_{0:k}}_{\text{Past actions \& observatinos}}, \underbrace{u_{k:k+l-1}, z_{k+1:k+l}}_{\text{Future actions \& observations}})$$



- Optimal (non-myopic) actions/control:

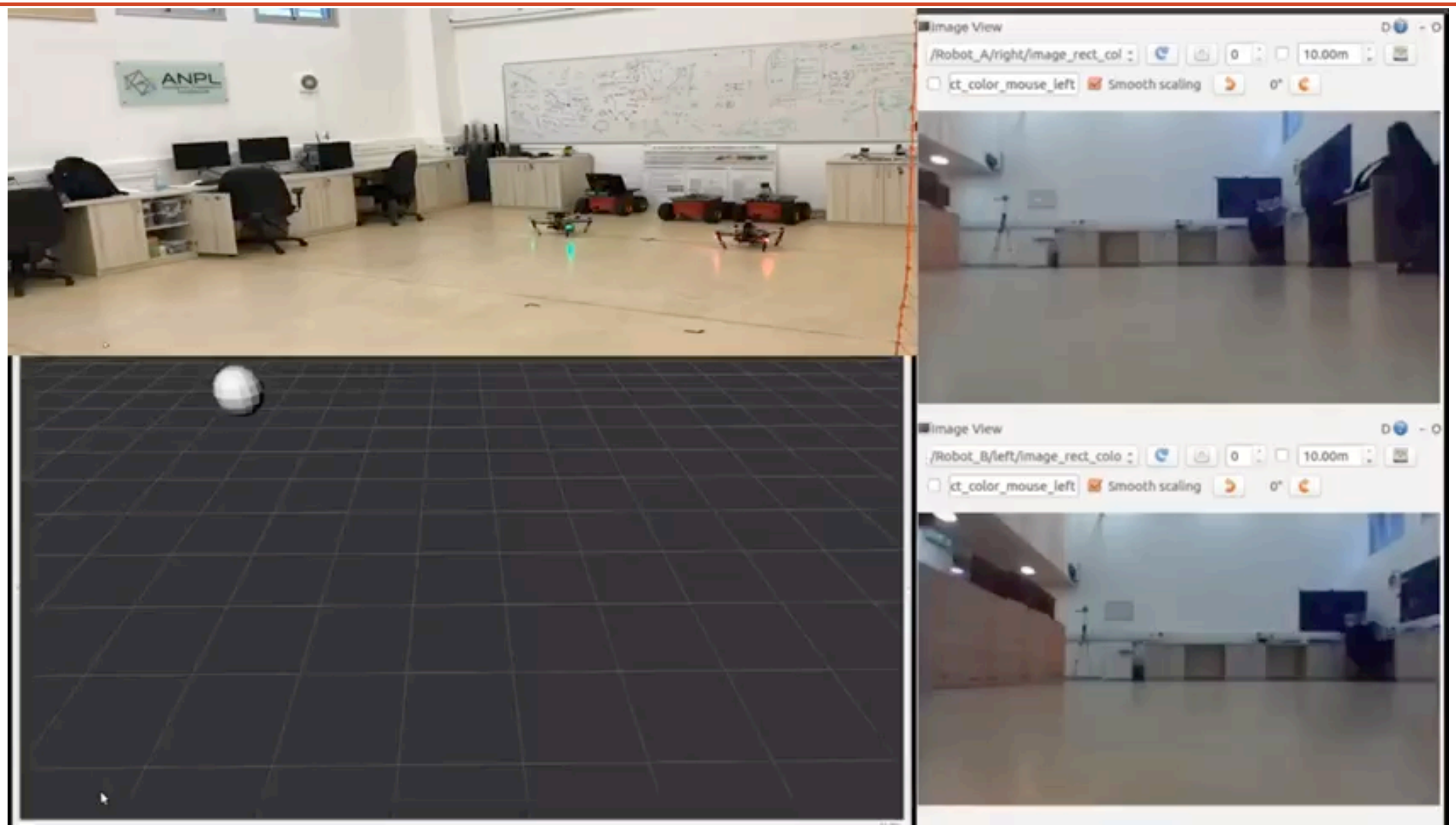
$$u^{\star} = \arg\min_{u} J(u)$$

Belief Space Planning (BSP)

$$J(u) \doteq \mathbb{E}\left[\sum_{l=1}^{L} c\left(b[X_{k+l}], u_{k+l-1}\right)\right]$$

- Finding an optimal solution is generally **computationally intractable**
- **Our focus - want to:**
  - Act autonomously, **online**, while accounting for different sources of uncertainty and ambiguity
  - Reliably operate in **uncertain, perceptually aliased** environments/scenarios

Collaborative SLAM & BSP on Quads



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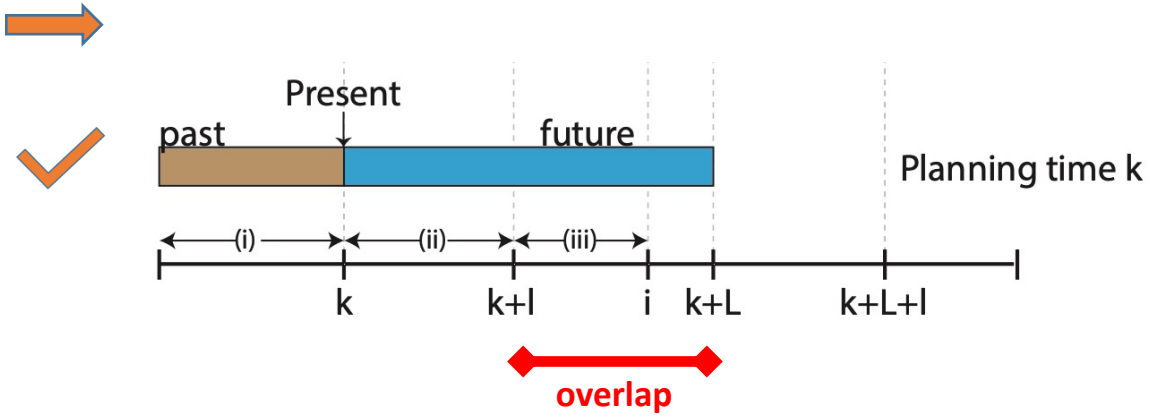
Incremental Belief Space Planning

[Farhi and Indelman, ICRA'19]

- **Key idea:**
  - Re-use calculations across successive planning sessions
  - Instead of calculating each planning session from scratch (state of the art)

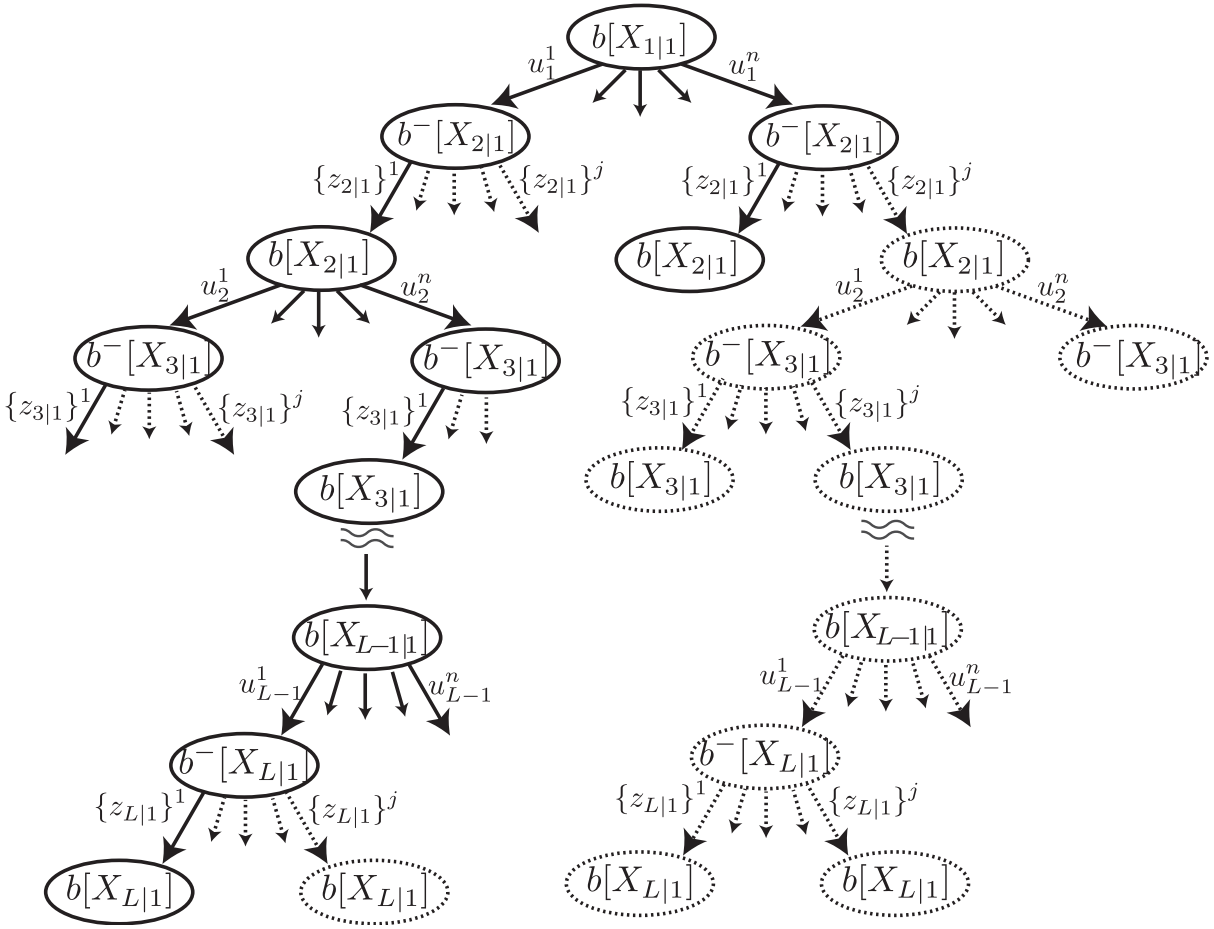
Calculations available



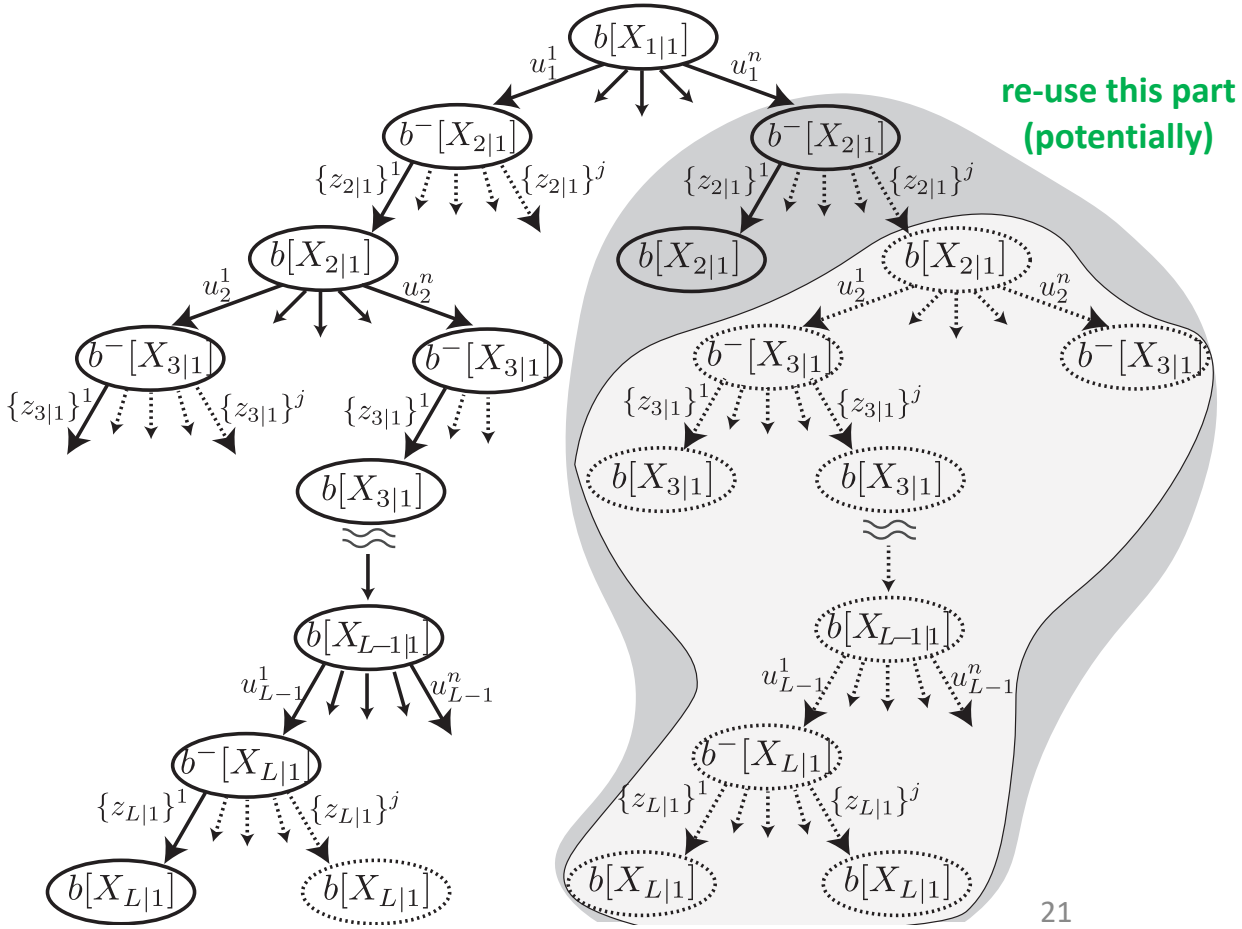
Incremental Belief Space Planning

[Farhi and Indelman, ICRA'19]

Planning time $k = 1$



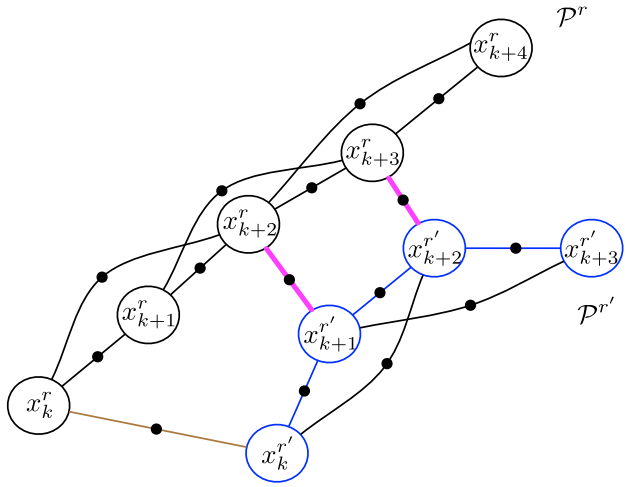
Planning time $k = 2$



Topological Belief Space Planning (t-BSP)

[Kitanov and Indelman, ICRA'18, arXiv'19]

- **Key idea**:
  - Design a metric of factor graph topology that is strongly correlated with entropy
  - Determine best action using that topological metric (instead of entropy)
  - **Does not require explicit inference, nor partial state covariance recovery**

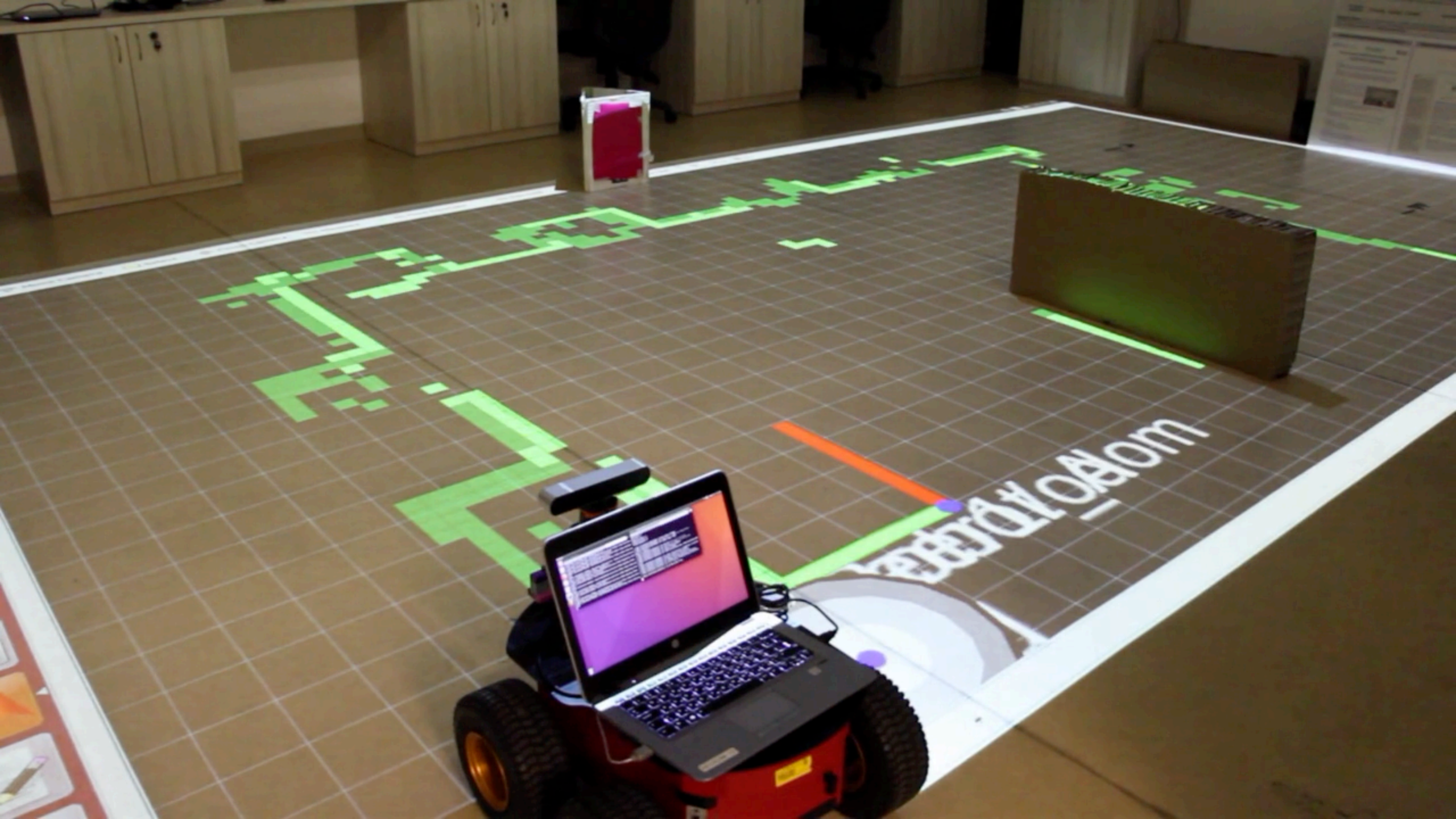


Factor graph for a 2-robot scenario, considering some specific candidate actions

Corresponding topology represented by a graph $G(\Gamma, E)$

topological metric $s(G)$

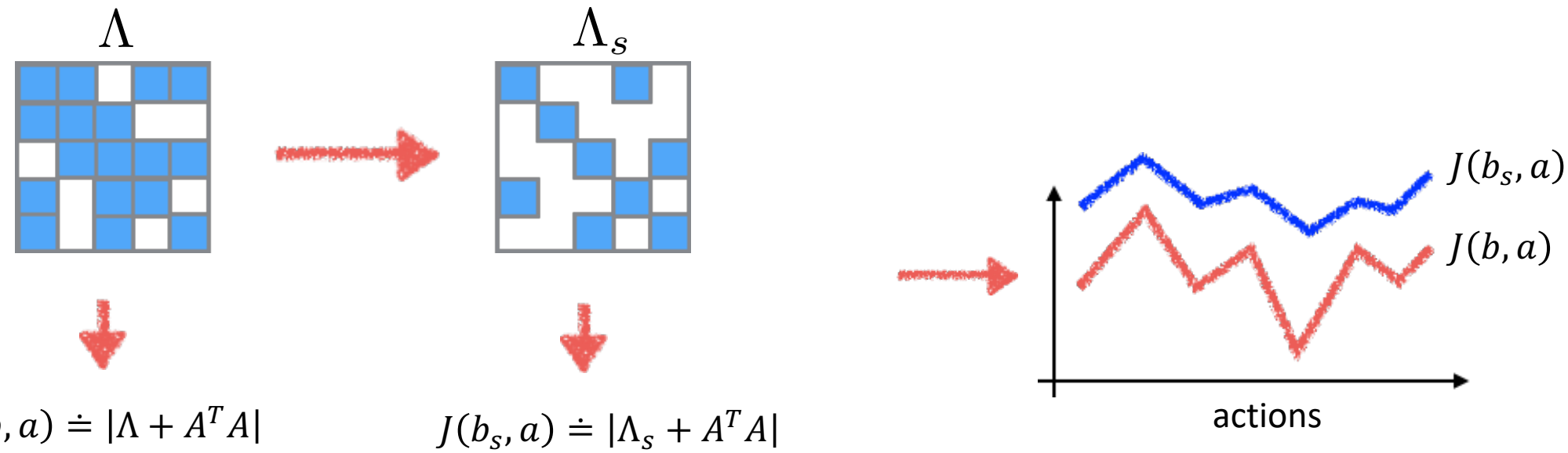
graph signature



Belief sparsification for BSP (s-BSP)

[Indelman RAL'16][Elimelech and Indelman, ICRA'17, IROS'17, ISRR'17, arXiv'19]

- Key Idea:
  - Find an appropriate **sparsified** information space (more generally, belief)
  - Perform decision making over that, rather the original, information space

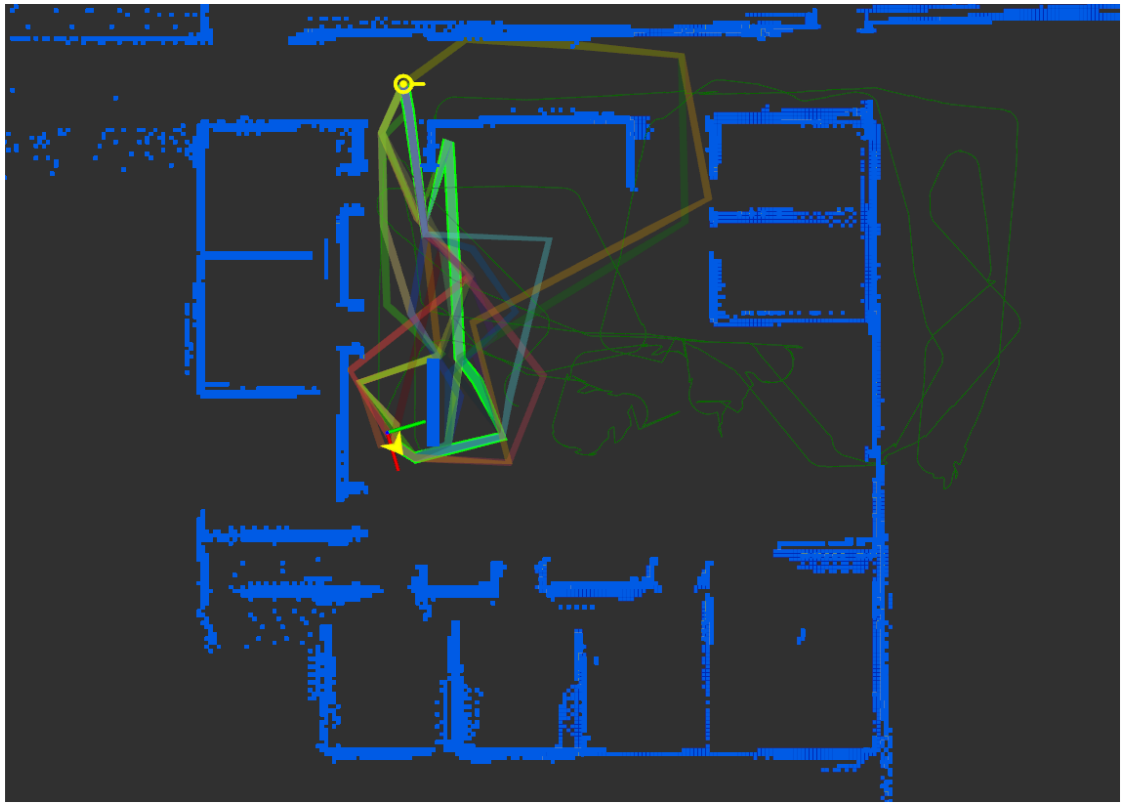


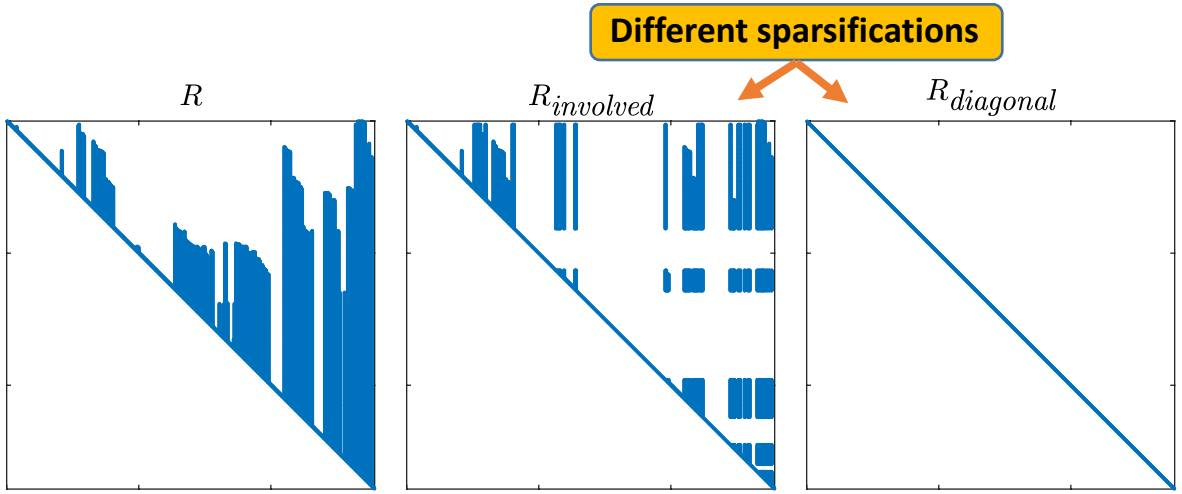
- Do we get the same performance (decisions), i.e. is it action consistent?
- If not, can we bound the loss?

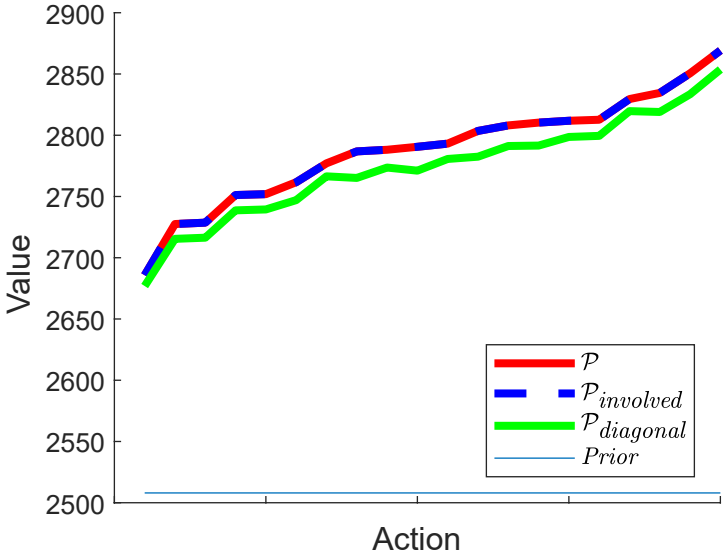
s-BSP: Gazebo Results

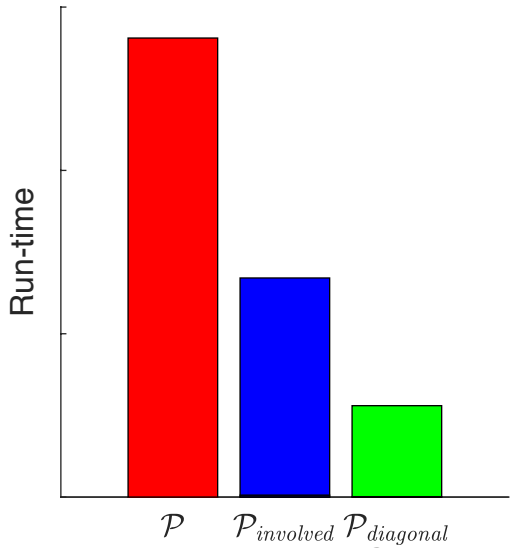
[Elimelech and Indelman, arXiv'19]

Candidate actions (trajectories)









Active Robust Perception

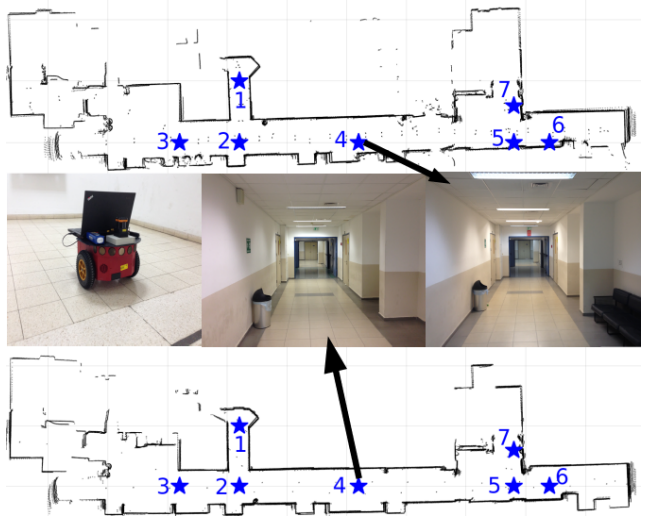
[Pathak, Thomas, Indelman, IJRR'18]

- What happens if the environment is ambiguous, perceptually aliased?
- BSP approaches typically assume data association is **given** and **perfect**! We **relax** this assumption

- Our Data Association Aware BSP (DA-BSP) algorithm considers both
  - **Ambiguous data association** (DA) due to perceptual aliasing, and
  - **Localization uncertainty** due to stochastic control and imperfect sensing

- Approach can be used for active disambiguation (for example)

Angeli et al., TRO'08

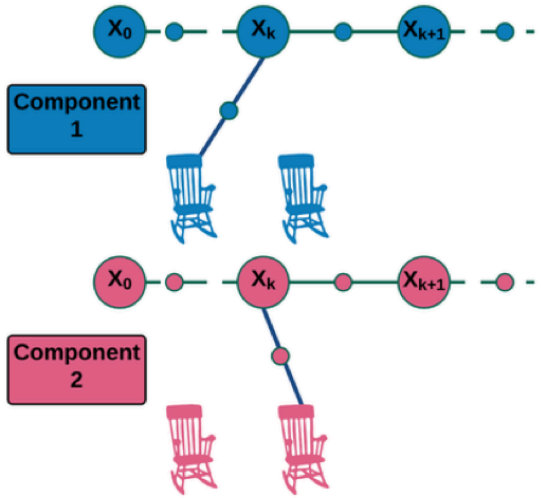


Approach Overview

[Pathak, Thomas, Indelman, IJRR'18]

- Belief is represented by a Gaussian Mixture Model (GMM)

$$b[X_k] = \mathbb{P}(X_k|\mathcal{H}_k) = \sum_{j=1}^{M_k} \underbrace{\xi_k^j}_{\text{Weight}} \underbrace{\mathbb{P}(X_k|\mathcal{H}_k, \gamma = j)}_{\text{Conditional multivariate Gaussian, represented by a factor graph}}$$



- **Main idea**: Reason within BSP how a GMM belief will evolve for different candidate actions

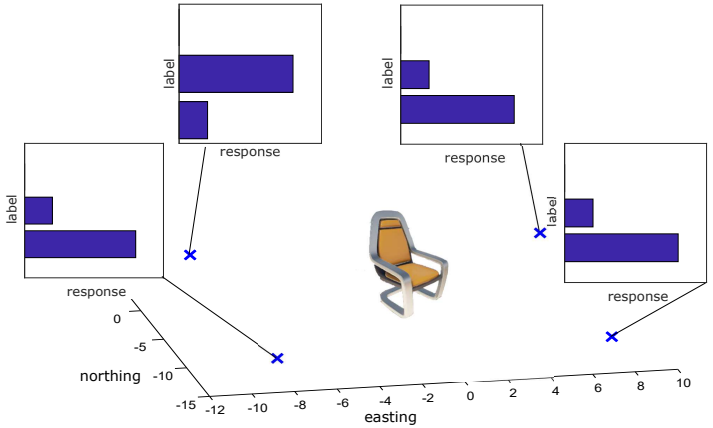
  - **Marginalize over possible data associations for future observations**
  - **Maintain & track data association hypotheses within inference and BSP**

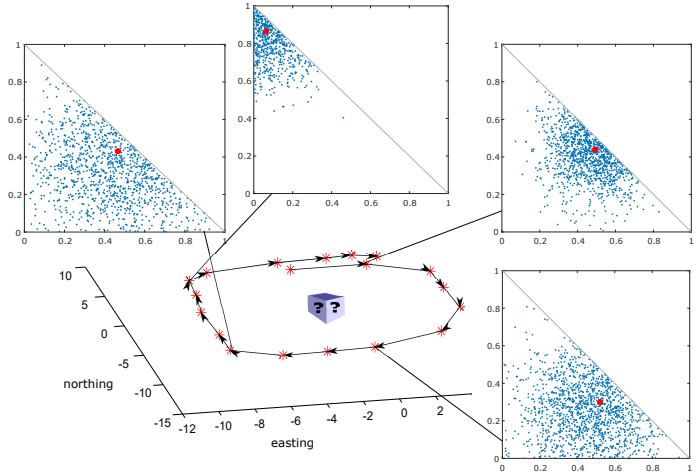
- Number of non-negligible modes can go down, and go up (!)

Extension to Semantic (Active) Perception

[Feldman and Indelman, ICRA'18, ARJ'19accepted; Tchuiev and Indelman, RAL'18; Tchuiev, Feldman and Indelman, IROS'19]

- Key challenge: operation in **perceptually aliased** environments
  - Ambiguous data association (e.g. different scenes/objects appear alike)
  - **Classification aliasing (ambiguous classification of a scene/object)**
- Ongoing work on semantic SLAM via a viewpoint-dependent classifier model
- Involves maintaining **hybrid** beliefs (continuous and discrete variables)





Summary

Autonomous Online Perception and Navigation for Aerial Vehicles

- Maintain and reason about **high-dimensional** beliefs
- Computational efficiency for online performance (both for inference & BSP)
- Robustness to ambiguous scenarios
- Collaboration between multiple (heterogenous) robots to enhance performance

More details:

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Autonomous Navigation and Perception Lab