Autonomous Online Perception and Navigation in Uncertain Environments

Vadim Indelman

TECHNION Israel Institute of Technology

ANPL Autonomous Navigation and Perception Lab

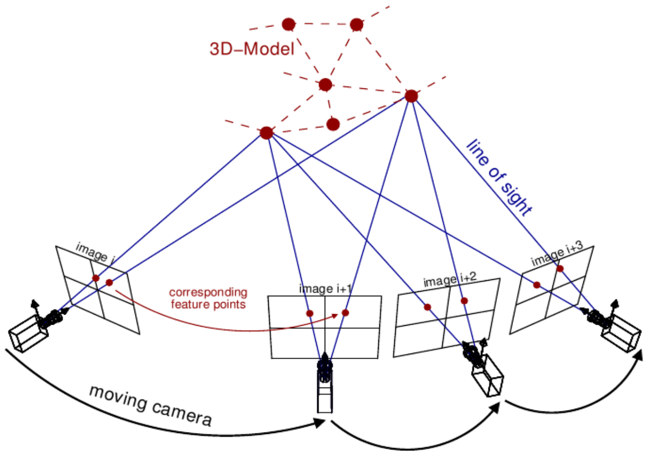
TCE Conference, Autonomous Systems, Technion

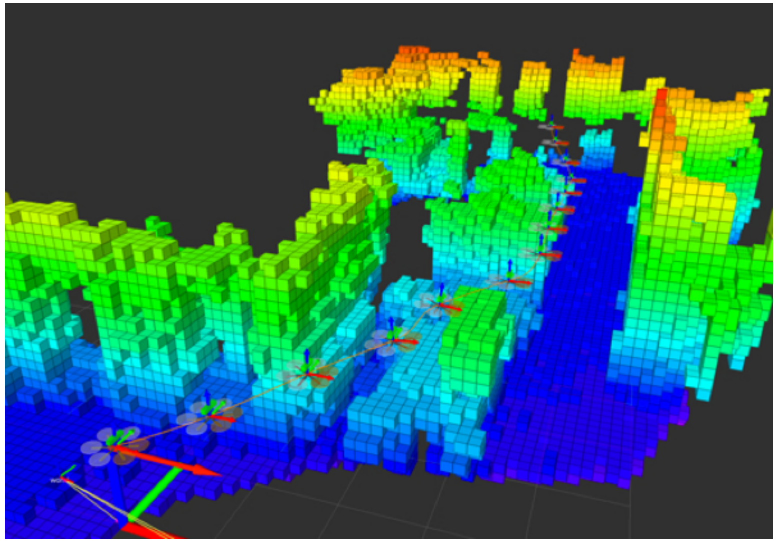
September 11, 2019

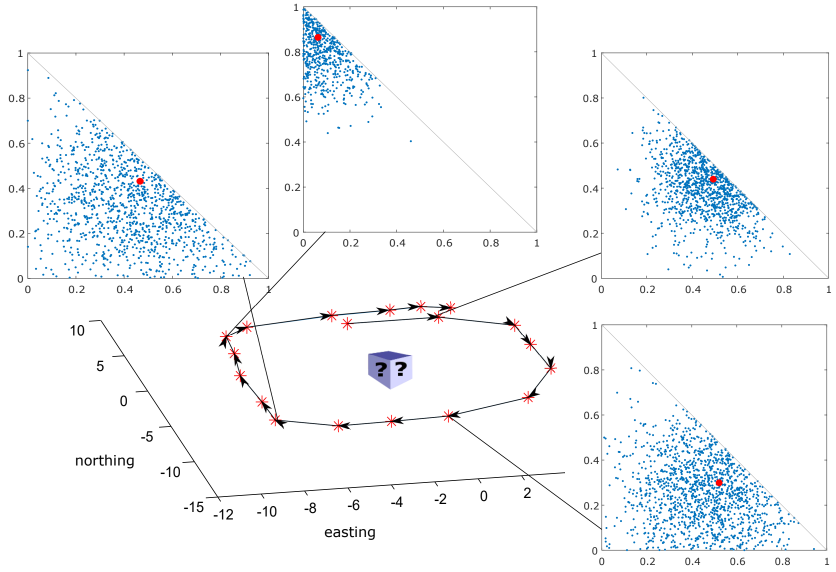
Introduction

Autonomous navigation and perception in uncertain/unknown environments:

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







Introduction

- **Belief space planning (BSP)** – determine optimal actions (policy) over the belief space with respect to a given objective, e.g. minimize state uncertainty
- A fundamental problem in robotics and AI
- Tight coupling with perception & inference

Perception & Inference ⟷ **Belief Space Planning**

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

Introduction – Models & Posterior Belief

- State at time k: $X_k \in \mathbb{R}^n$
- State transition and observation models: $\mathbb{P}(x_k \mid x_{k-1}, u_{k-1})$, $\mathbb{P}(z_k \mid X_k^{inv})$

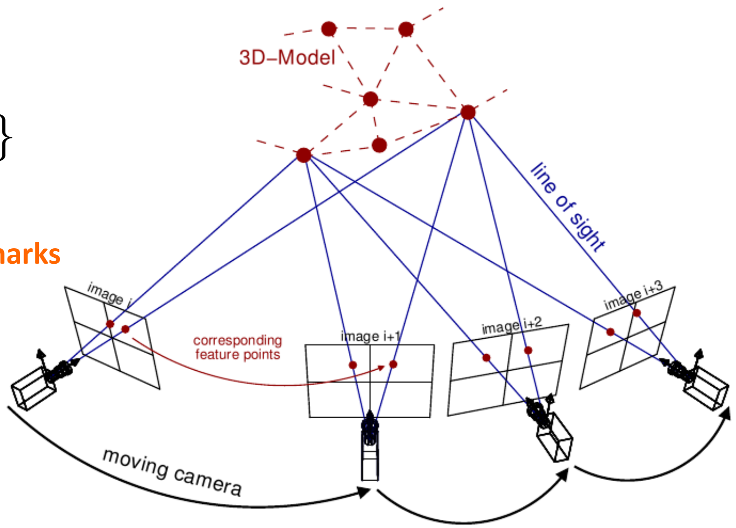
  $X_k^{inv} \subseteq X_k$: involved variables
- Posterior belief at time k: $b[X_k] \doteq \mathbb{P}(X_k \mid \underline{u_{0:k-1}, z_{1:k}})$

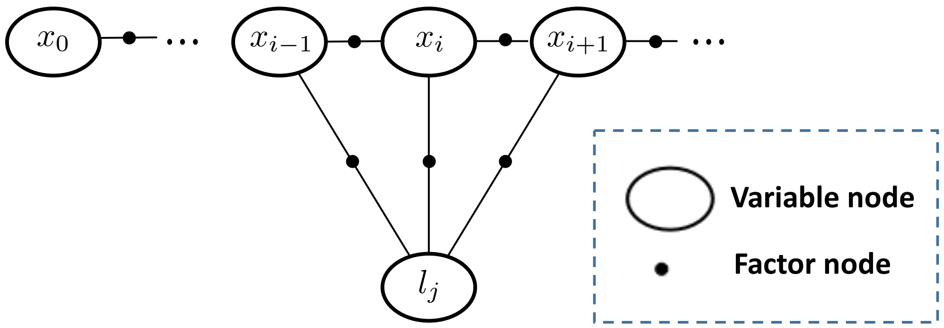
  $\doteq H_k$ (history)
- Can be represented with graphical models, e.g. a factor graph

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

Past & current robot states

Landmarks





Introduction - 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: $b\left[X_{k+l}\right] \doteq p\left(X_k | \underbrace{u_{0:k-1}, z_{0:k}}_{\text{history } H_k}, \underbrace{u_{k:k+l-1}, z_{k+1:k+l}}_{\text{future actions \& observations}}\right)$

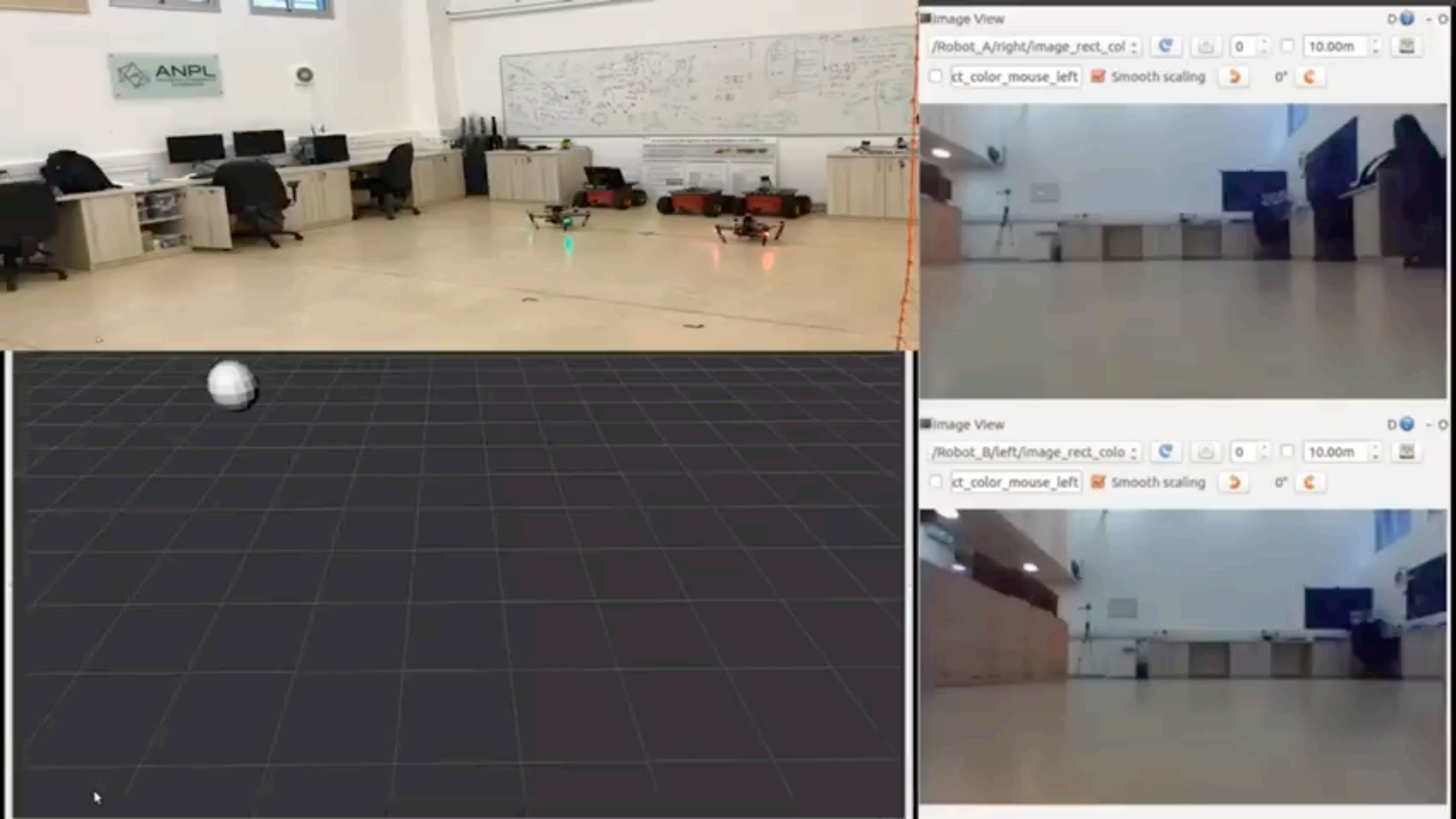
- Optimal (non-myopic) actions/control: $u^{\star} = \arg\min_{u} J\left(u\right)$

Introduction - Belief Space Planning (BSP)

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

- Belief space planning is an instantiation of POMDP
- Finding an optimal solution to POMDP 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


ANPL
Image View
/Robot_A/right/image_rect_col
0
10.00m
ct_color_mouse_left
Smooth scaling
0°
Image View
/Robot_B/left/image_rect_colo
0
10.00m
ct_color_mouse_left
Smooth scaling
0°

Agenda

Belief space planning (BSP) in high-dimensional state spaces:

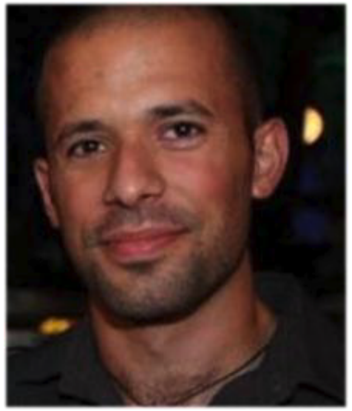
1. Computationally efficient BSP via calculation re-use
2. Simplification - action consistent and bounded BSP problem representations:
   - Topological perspective (t-BSP)
   - Sparsification perspective (s-BSP)
3. Active (semantic) perception in ambiguous environments – data association aware BSP

Agenda

Belief space planning (BSP) in high-dimensional state spaces:

1. **Computationally efficient BSP via calculation re-use**
2. Simplification - action consistent and bounded BSP problem representations:
   - Topological perspective (t-BSP)
   - Sparsification perspective (s-BSP)
3. Active (semantic) perception in ambiguous environments – data association aware BSP

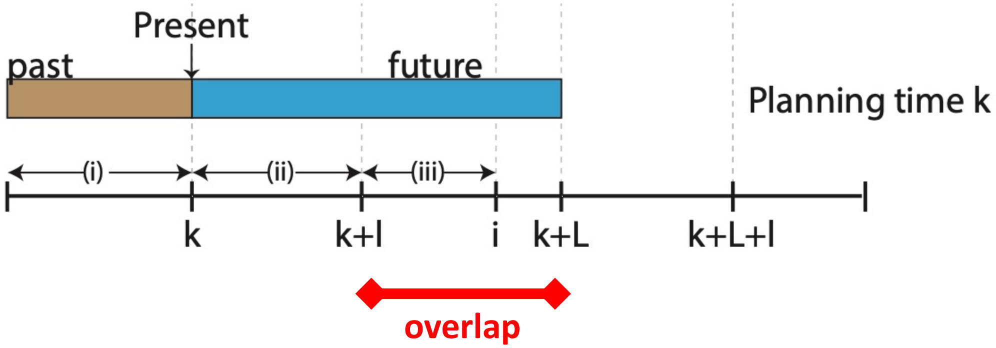
[Farhi and Indelman, ICRA'17, arXiv'19, ICRA'19]



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)



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

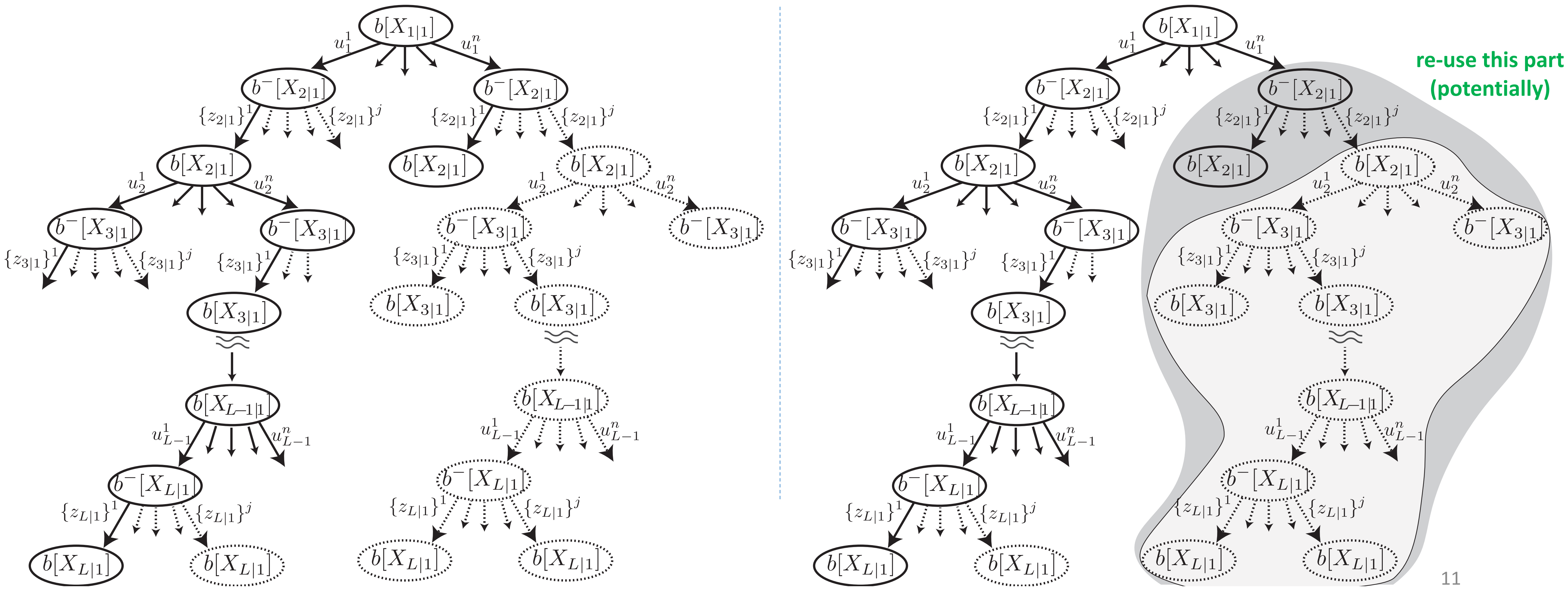
Calculations available

Incremental Belief Space Planning

[Farhi and Indelman, ICRA'19]

Planning time $k = 1$

Planning time $k = 2$



Incremental Belief Space Planning

[Farhi and Indelman, ICRA'19]

- Expectation related calculations from successive BSP sessions are similar
  - They **differ in new information from inference**, and the **sampled measurements**
- Incremental BSP uses **multiple importance sampling techniques** for selective re-sampling and selective measurement re-use from previous planning sessions
- Results in substantial reduction in computation time (e.g. x5), while statistically preserving accuracy

Planning time k:

$$J_k(u) \doteq \mathbb{E}\left[\sum_{i=k+1}^{k+L} c\left(b[X_{i|k}], u_{i-1|k}\right)\right] = \sum_{i=k+1}^{k+L} \int_{z_{k+1:i|k}} \mathbb{P}(z_{k+1:i} \mid H_k, u_{k:i-1})\, c\left(b[X_{i|k}], u_{i-1|k}\right) dz_{k+1:i|k}$$

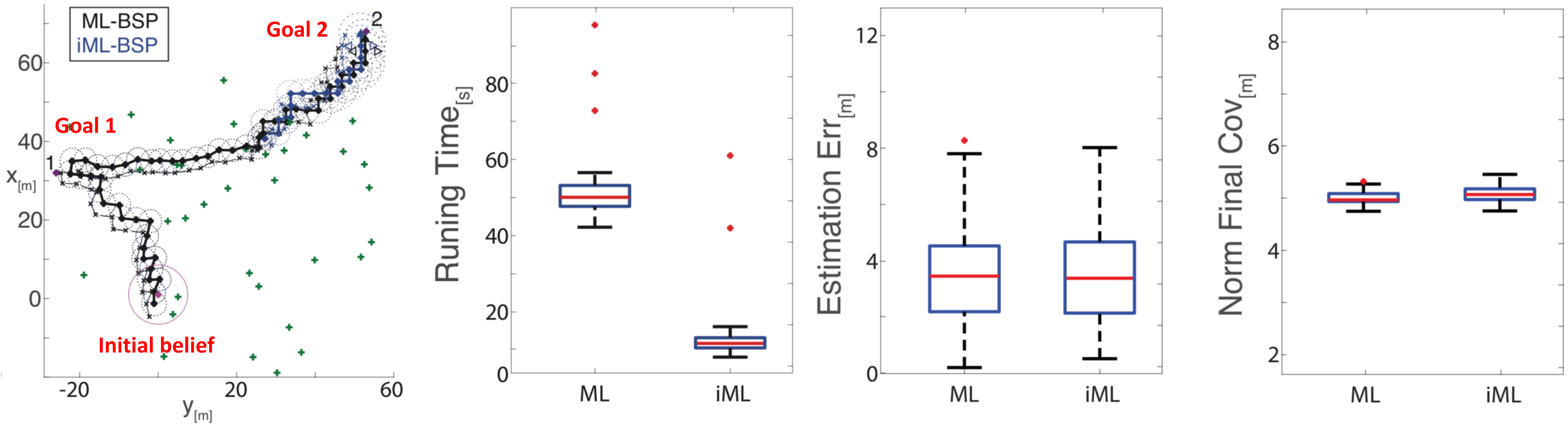
Planning time $k+l$:

$$J_{k+l}(u) \doteq \mathbb{E}\left[\sum_{i=k+l}^{k+l+L} c\left(b[X_{i|k+l}], u_{i-1|k+l}\right)\right] = \sum_{i=k+l}^{k+l+L} \int_{z_{k+l:i|k}} \mathbb{P}(z_{k+l:i} \mid \underline{H_{k+l}}, u_{k+l:i-1})\, c\left(b[X_{i|\underline{k+l}}], u_{i-1|k+l}\right) dz_{k+l}$$

Results: iML-BSP vs ML-BSP

ML-BSP: BSP with ML observations
(one sample per look ahead step)

Basic simulation – autonomous navigation in unknown environments:



Agenda

Belief space planning (BSP) in high-dimensional state spaces:

1. Computationally efficient BSP via calculation re-use
2. **Simplification - action consistent and bounded BSP problem representations:**
   - **Topological perspective (t-BSP)**
   - **Sparsification perspective (s-BSP)**
3. Active (semantic) perception in ambiguous environments – data association aware BSP

Simplification - Action Consistent & Bounded Approximations

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

Action Consistent & Bounded Approximations

[Elimelech and Indelman, ISRR'17]

- **Paradigm**: **generate and solve a simplified decision making problem, b_s, J_s , which has a minimal impact on the best-action selection**
- **Key observations**:
  - In decision making, only need to sort actions from best to worst
  - Changing reward values w/o changing order of actions does not change action selection

- **Action-consistent** representation b_s, J_s :

$$\forall a, a' \in \mathcal{A}: \quad J(b,a) < J(b,a') \iff J_s(b_s,a) < J_s(b_s,a')$$

$$J(b,a) = J(b,a') \iff J_s(b_s,a) = J_s(b_s,a')$$

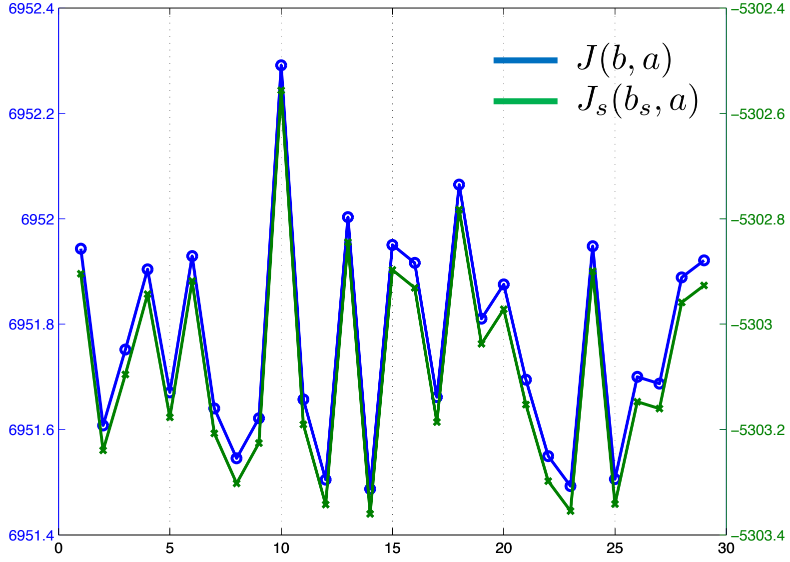


Image from Indelman RA-L'16

TECHNION Israel Institute of Technology

ANPL Autonomous Navigation and Perception Lab

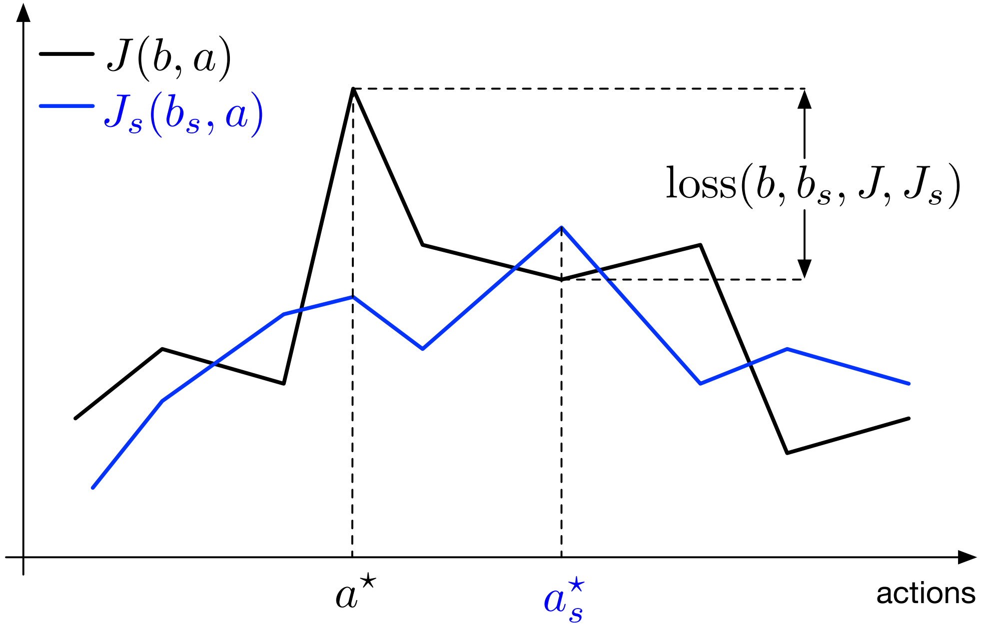
Action Consistent & Bounded Approximations

[Elimelech and Indelman, ISRR'17]

- Action consistency cannot be always guaranteed
- Sacrifice in performance - definition:

$$loss(b, b_s, J, J_s) \doteq J(b, a^*) - J(b, a_s^*)$$

with
$$a^* \doteq \underset{a \in \mathcal{A}}{\text{argmax}}\, J(b, a)$$
$$a_s^* \doteq \underset{a \in \mathcal{A}}{\text{argmax}}\, J_s(b_s, a)$$

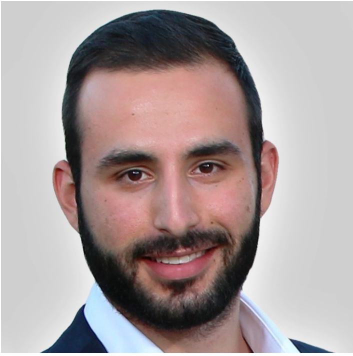


- Often possible to settle for a sub-optimal action, in order to reduce the solution complexity
- To provide performance guarantees, need tight bounds on $loss(b, b_s, J, J_s)$!

Perspectives

- **Belief sparsification for BSP (s-BSP)**

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



- **Topological BSP (t-BSP)**

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

<u>Setting</u>:

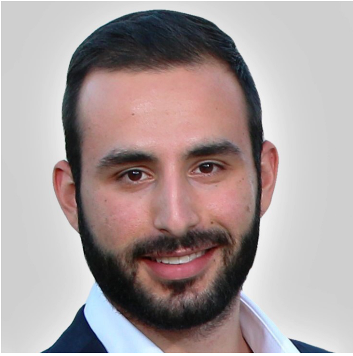
- High-dim. Gaussian beliefs
- Information-theoretic cost (entropy)
- ML observations (one sample per look ahead step)

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

Perspectives

- **Belief sparsification for BSP (s-BSP)**

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



- **Topological BSP (t-BSP)**

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

Setting:

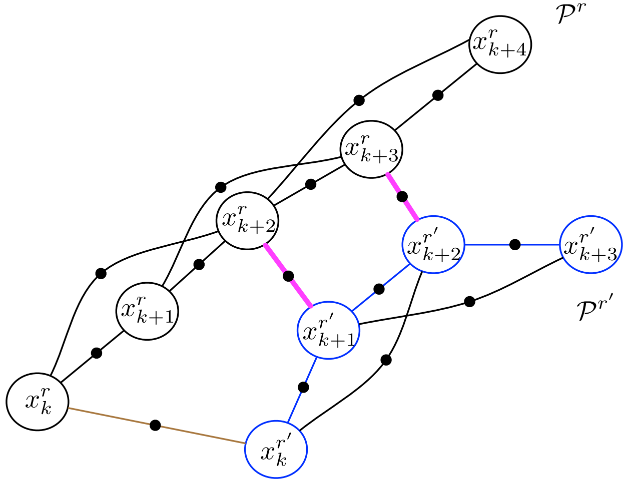
- High-dim. Gaussian beliefs
- Information-theoretic cost (entropy)
- ML observations (one sample per look ahead step)

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

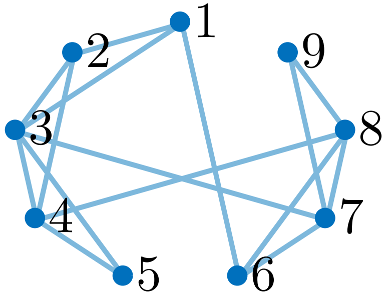
Topological Belief Space Planning (t-BSP)

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

- Topological properties of factor graphs dominantly determine estimation accuracy
  [Khosoussi et al. IROS'14, IJRR'17]
- **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

Topological Belief Space Planning (t-BSP)

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

<u>Metric Space</u>

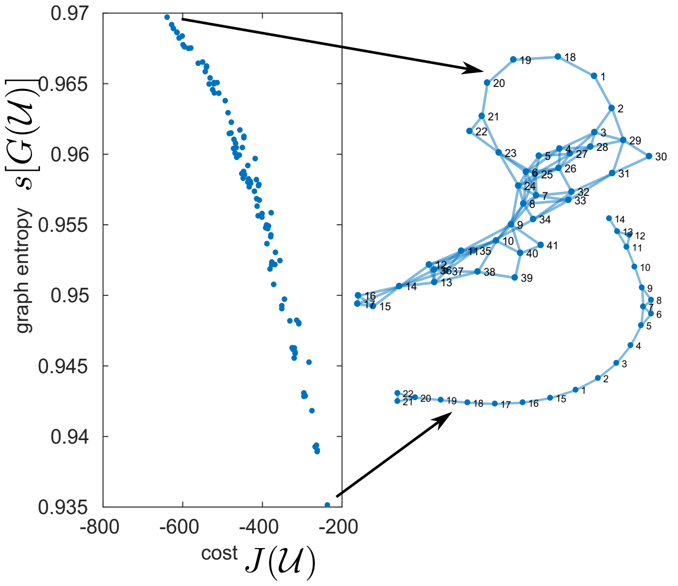
$$J(\mathcal{U}) = \frac{n}{2}\ln(2\pi e) + \frac{1}{2}\ln|\Sigma(X_{k+L})|$$

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

<u>Topological space</u>

$$s(G) = H_{VN}(G) \approx 1 - \frac{1}{|\Gamma|} - \frac{1}{|\Gamma|^2} \sum_{(i,j)\in E} \frac{1}{d(i)d(j)}$$

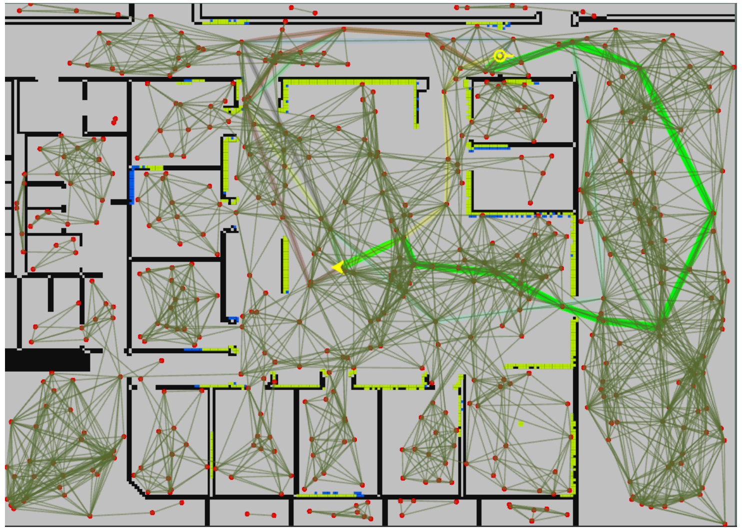
$$\hat{\mathcal{U}}^\star = \arg\max_{\mathcal{U}} s[G(\mathcal{U})]$$

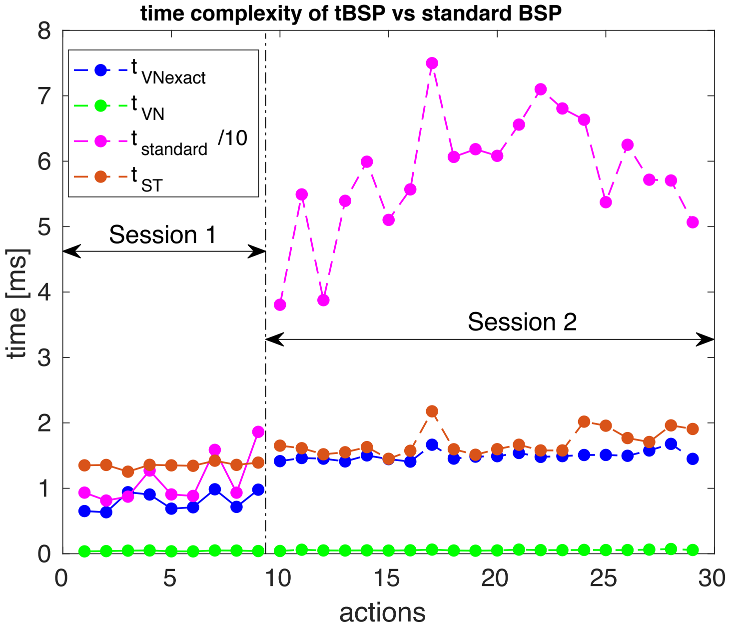


- Cheap to calculate, only a function of node degrees!
- Supports incremental calculations!
- Provided bounds on the error/loss $\left|J_k\left(\hat{\mathcal{U}}\right) - J_k\left(\hat{\mathcal{U}}^\star\right)\right|$

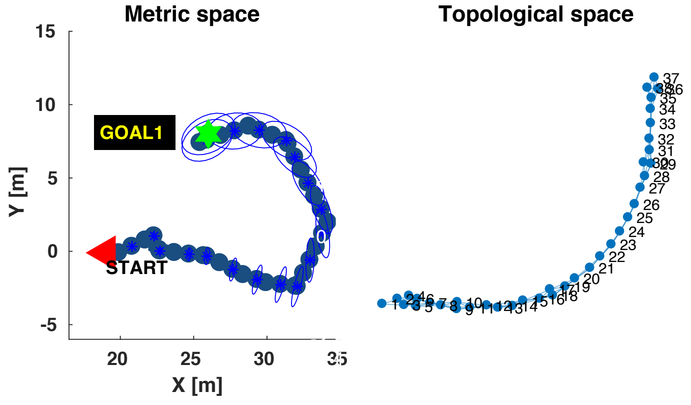
Topological and info-theoretic metrics are strongly correlated!

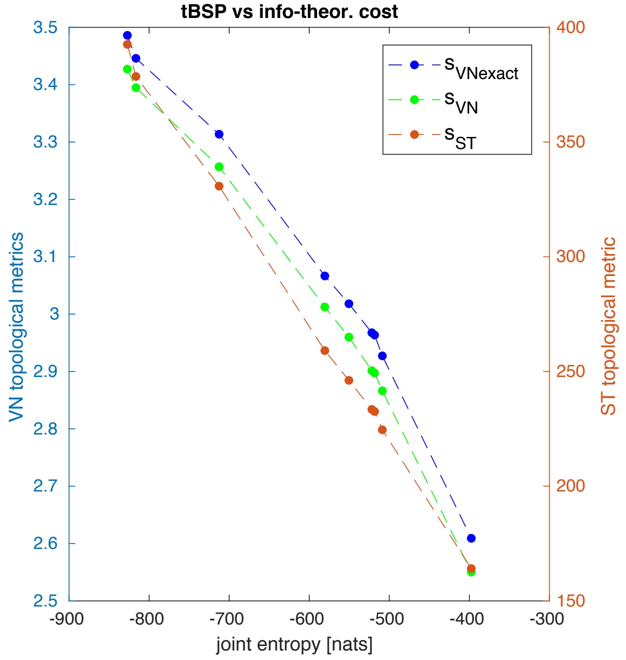
t-BSP: Gazebo Initial Results



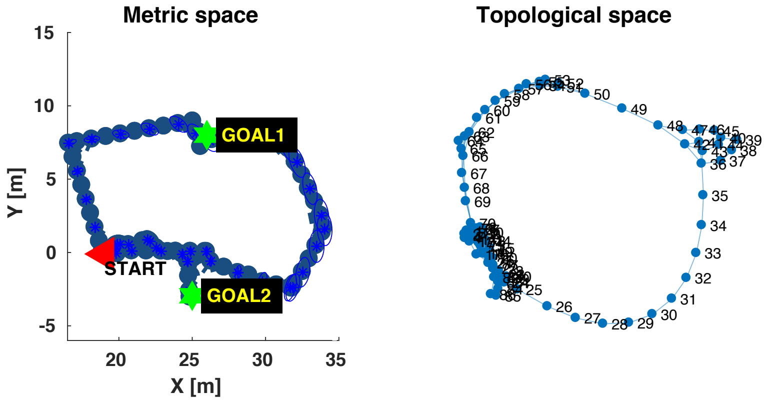


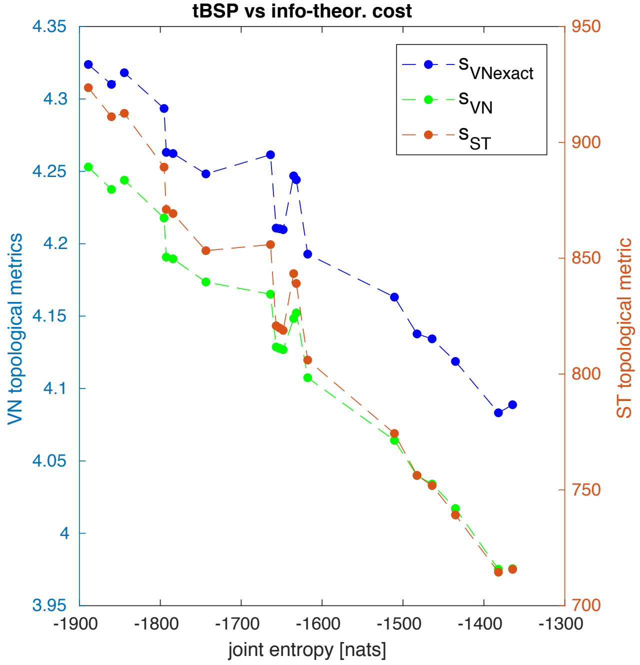
1st planning session (exploration)

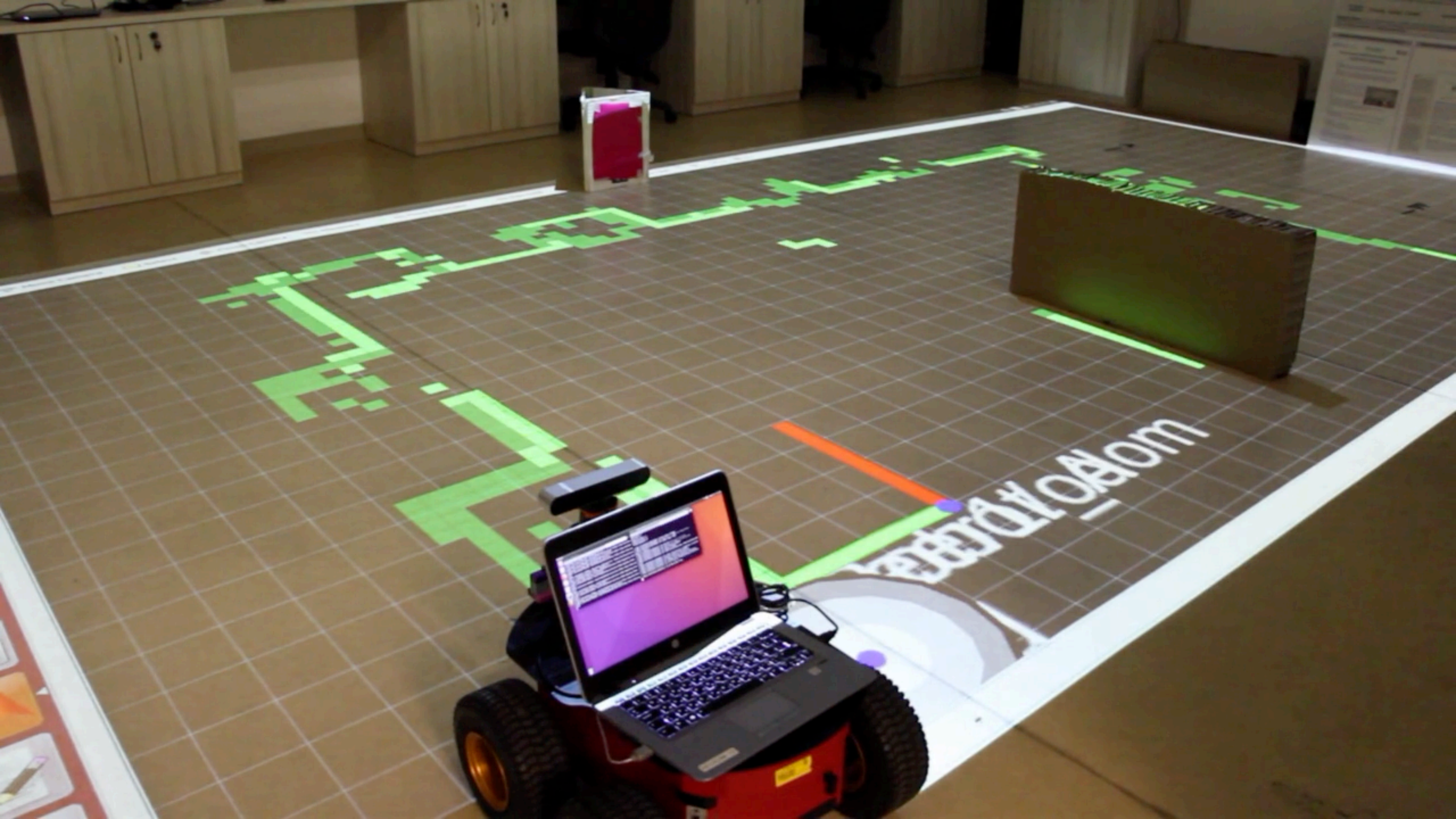




2nd planning session (exploitation, loop closures)







Perspectives

- **Belief sparsification for BSP (s-BSP)**

[Elimelech and Indelman, ICRA’17, IROS’17, ISRR’17, arXiv’19]

- **Topological BSP (t-BSP)**

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

<u>Setting</u>:

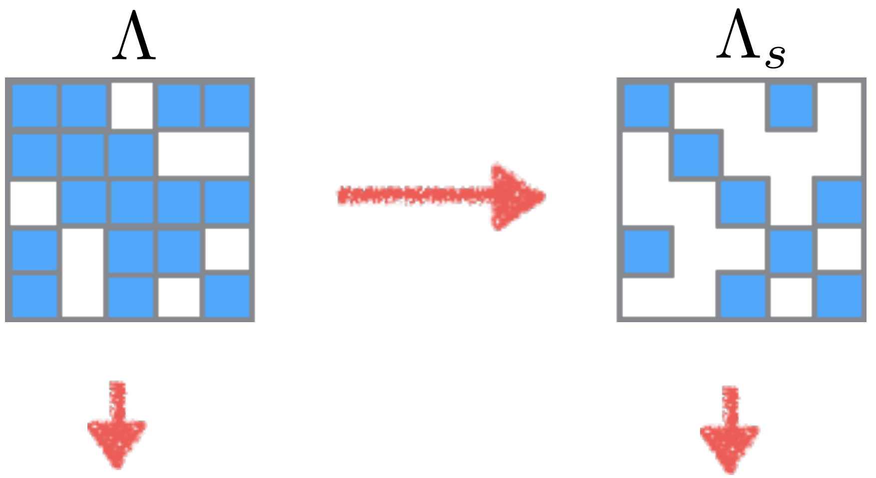
- High-dim. Gaussian beliefs
- Information-theoretic cost (entropy)
- ML observations (one sample per look ahead step)

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

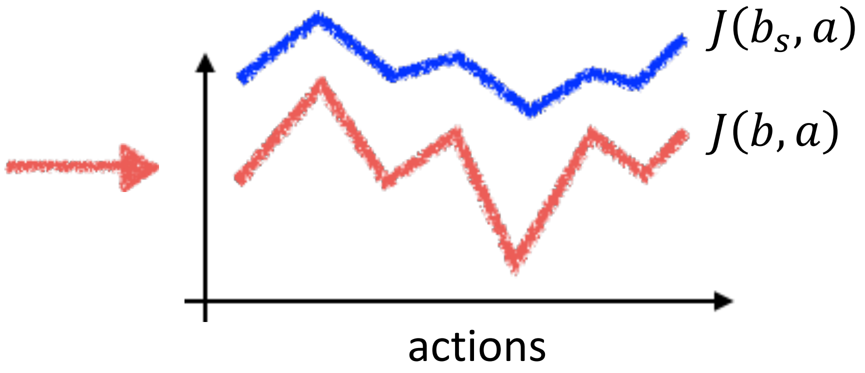
Belief sparsification for BSP (s-BSP): Key Idea

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

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



$J(b,a) \doteq |\Lambda + A^T A|$ $\quad$ $J(b_s,a) \doteq |\Lambda_s + A^T A|$

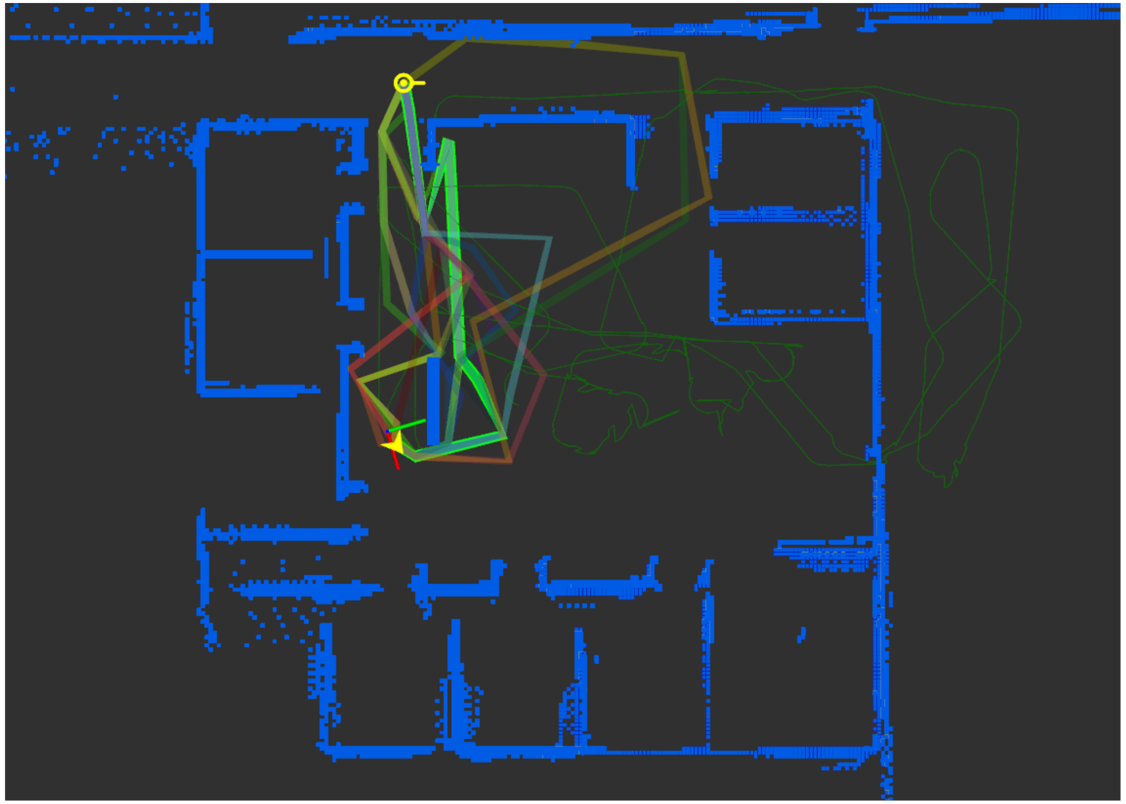


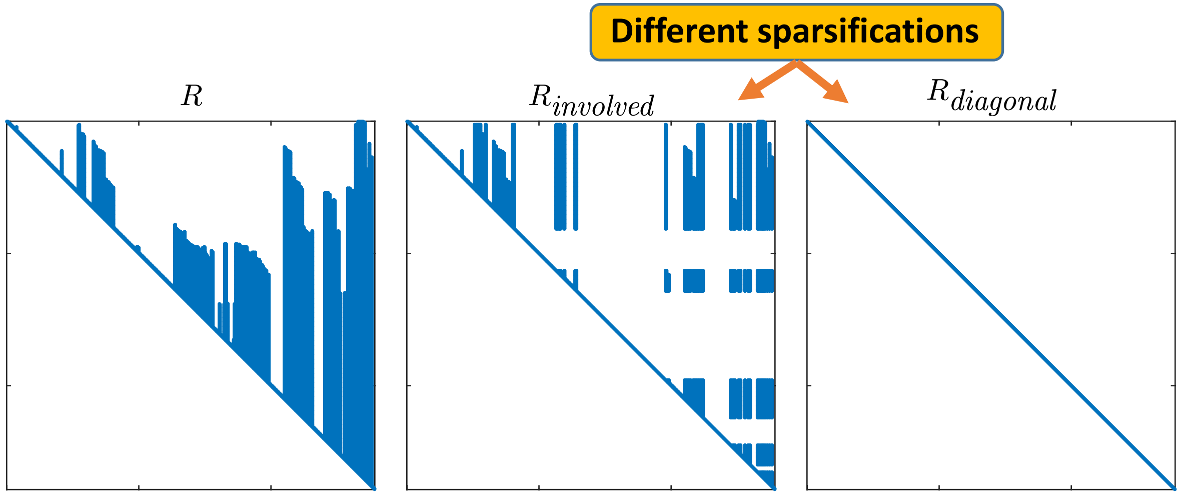
- Do we get the same performance (decisions), i.e. is it action consistent?
- If not, can we bound the loss?

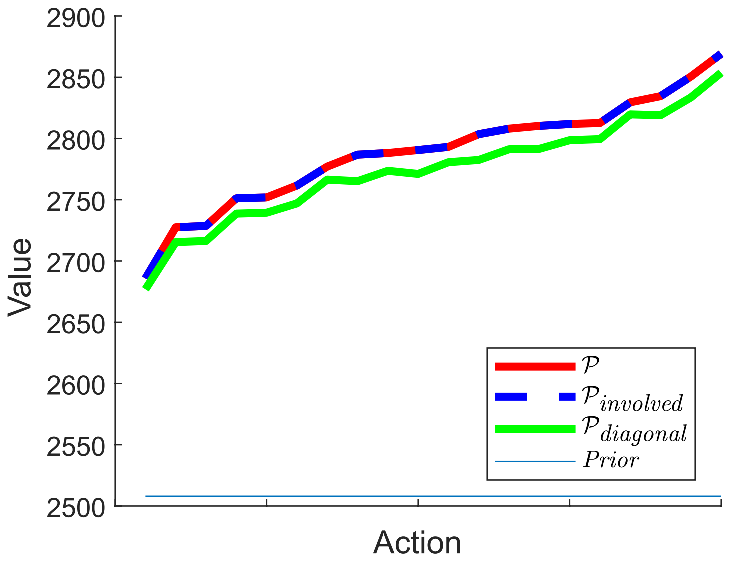
s-BSP: Gazebo Results

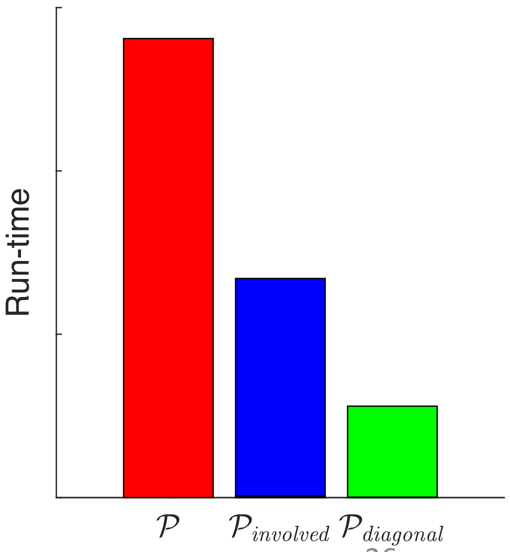
[Elimelech and Indelman, arXiv'19]

Candidate actions (trajectories)









Agenda

Belief space planning (BSP) in high-dimensional state spaces:

1. Computationally efficient BSP via calculation re-use
2. Simplification - action consistent and bounded BSP problem representations:
   - Topological perspective (t-BSP)
   - Sparsification perspective (s-BSP)
3. **Active (semantic) perception in ambiguous environments – data association aware BSP**

[Pathak, Thomas and Indelman, IJRR'18]

Active Robust Perception

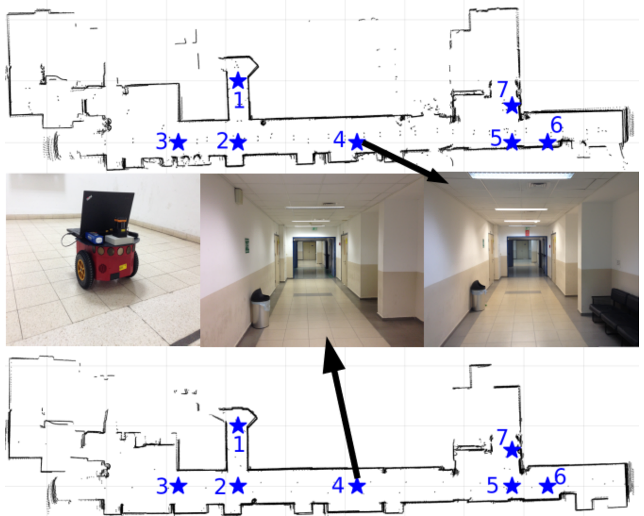
[Pathak, Thomas, Indelman, IJRR'18]

- 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

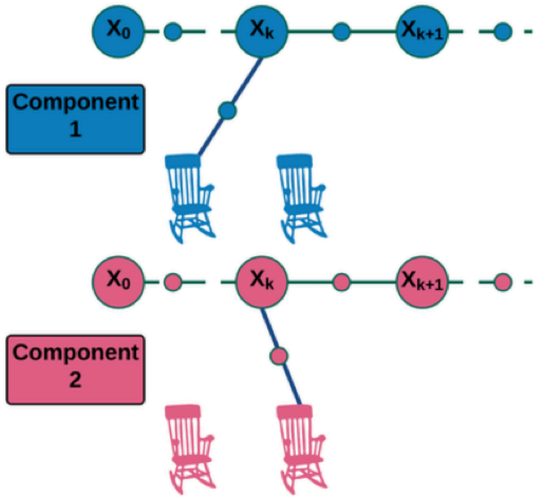


Approach Overview

[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 (!)

Approach Overview

[Pathak, Thomas, Indelman, IJRR'18]

$$J\left(u_k\right) \doteq \mathbb{E}\left\{c\left(b\left[X_{k+1}\right]\right)\right\} \equiv \int_{z_{k+1}} \boxed{p(z_{k+1}|\mathcal{H}_{k+1}^{-})} c\left(\boxed{p(X_{k+1}|\mathcal{H}_{k+1}^{-}, z_{k+1})} \right)$$

- **Marginalize over possible data associations**
- **Maintain & track data association hypotheses**

- Likelihood of a specific z_{k+1} to be captured

$$\underline{p(z_{k+1}|\mathcal{H}_{k+1}^{-})} \equiv \sum_j \int_x p(z_{k+1}, x, A_j|\mathcal{H}_{k+1}^{-}) \doteq \sum_j w_j$$

- Posterior *given* a specific observation z_{k+1}

$$\underline{b[X_{k+1}]} = \sum_j p(X_{k+1}|\mathcal{H}_{k+1}^{-}, z_{k+1}, A_j) p(A_j|\mathcal{H}_{k+1}^{-}, z_{k+1})$$
$$= \sum_j \tilde{w}_j b[X_{k+1}^{j+}] \qquad \tilde{w}_j = \eta w_j$$

Perceptual Aliasing Aspects

[Pathak, Thomas, Indelman, IJRR'18]

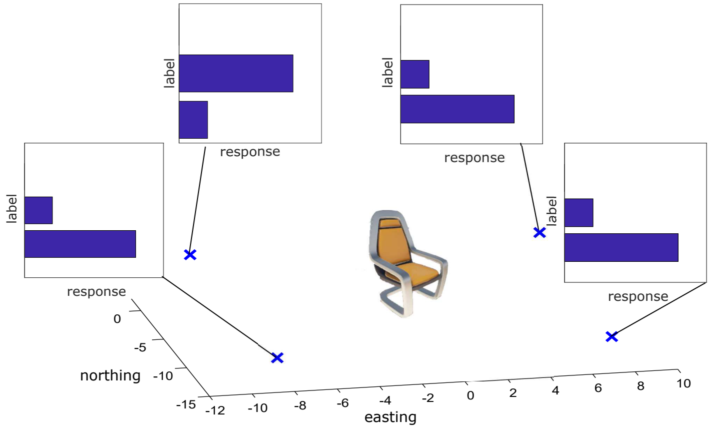
$$J(u_k) \doteq \int_{z_{k+1}} \underline{(\sum_j w_j)} c\left(\underline{\sum_j \tilde{w}_j b[X_{k+1}^{j+}]} \right)$$

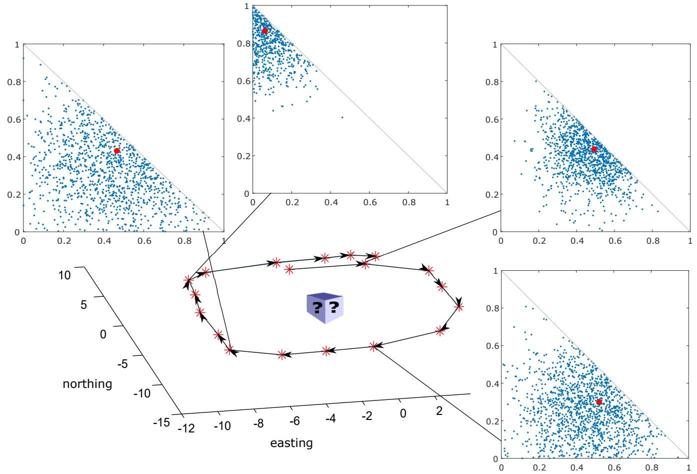
- No perceptual aliasing:
  - Only **one** non-negligible weight $\tilde{w}_j$
  - Reduces to state of the art belief space planning
- With perceptual aliasing:
  - Multiple non-negligible weights $\tilde{w}_j$, correspond to aliased scenes (given z_{k+1})
  - Posterior belief **becomes a mixture of pdfs (GMM)**
  - In practice, hypotheses pruning/merging is performed (**see IJRR'18 paper**)
- Approach can be used for **active disambiguation** (between DA hypotheses)

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

Belief space planning (BSP) in high-dimensional state spaces:

- Computationally efficient BSP via calculation re-use
- Simplification - action consistency & bounded approximations
  - s-BSP: belief sparsification for BSP
  - t-BSP: topological BSP
- Data association aware BSP: active (semantic) perception in ambiguous environments