Computationally Efficient and Robust Belief Space Planning in High-Dimensional State Spaces

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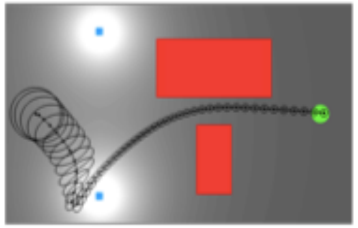
Introduction

- 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

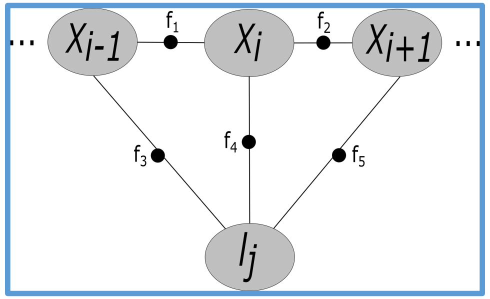
Perception & Inference ⟷ **Belief Space Planning**

- Related problems: (multi-robot) informative planning/sensing, sensor deployment, active SLAM, autonomous navigation, graph sparsification etc.



Introduction – Posterior Belief

- State vector $X_k \in \mathbb{R}^n$ at time t_k
- Posterior joint pdf can be represented by a factor graph
- Factors $F_i = \{f_i^1, \ldots, f_i^{n_i}\}$ for $0 \le t_i \le t_k$



$$p\left(X_k | H_k\right) \propto \prod_{i=0}^{k} \prod_{j=1}^{n_i} f_i^j \left(X_i^j\right) \qquad H_k \doteq \{u_{0:k-1}, z_{0:k}\}$$

history

- Maximum a Posteriori (MAP) inference:

$$\underbrace{b\left[X_k\right]}_{\text{belief}} \doteq p\left(X_k | H_k\right) = N\left(X_k^\star, \Sigma_k\right) = N^{-1}\left(\eta_k^\star, \Lambda_k\right)$$

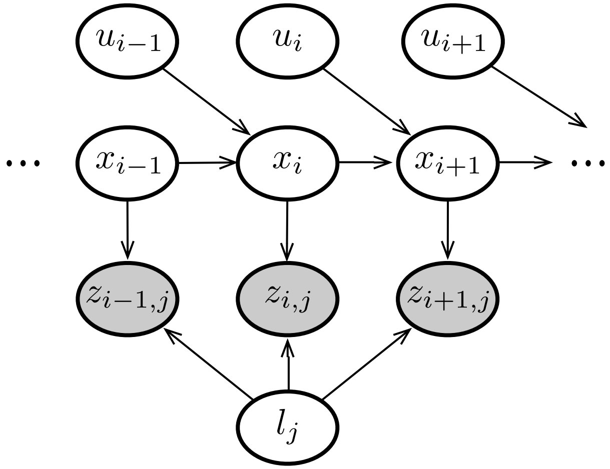
- Usually (square root) information form is used, admits comp. efficient

controls

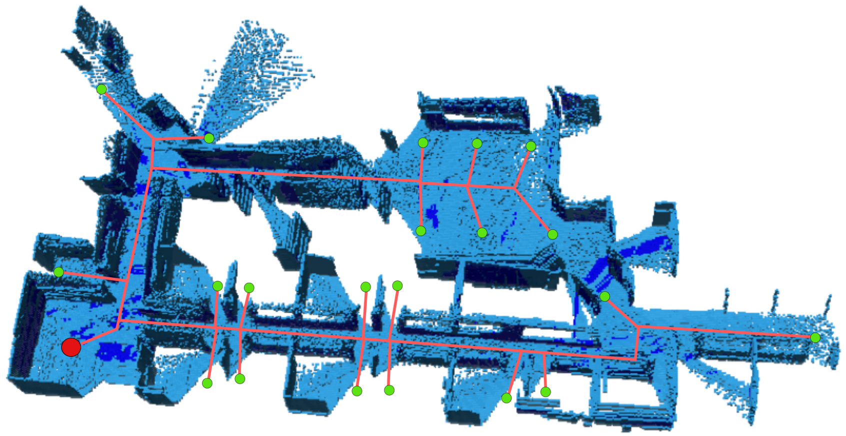
states/poses

observations

World model
(e.g. 3D points)



Belief Space Planning (BSP)



- Consider a set of candidate actions $\mathcal{A} \doteq \{a_1, a_2, \ldots, a_N\}$
- For each (non-myopic) action $u_{k:k+L-1} \doteq a_i \in \mathcal{A}$
  - Belief at the l-th look-ahead step

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

  - Given new factors and variables (if any), can be expressed as: $b[X_{k+l}] \propto b[X_k] \prod_{i=k+1}^{k+l} \prod_{j=1}^{n_i} f_i^j \left(X_i^j\right)$

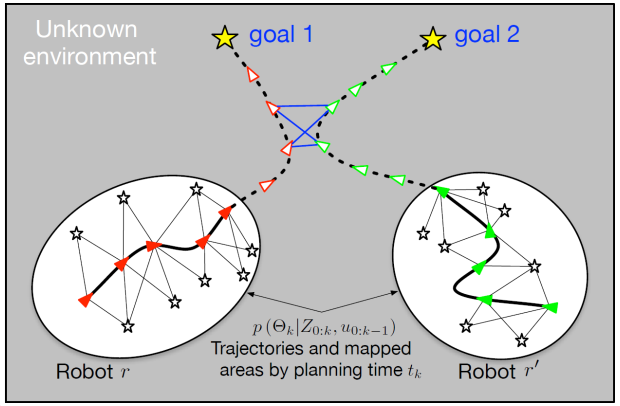
- Objective function (e.g. **entropy**) : $J(u_{k:k+L-1}) \doteq \mathbb{E}\left\{ \sum_{l=1}^{L} c_l \left(b[X_{k+l}], u_{k+l}\right) \right\}$

Multi-robot BSP

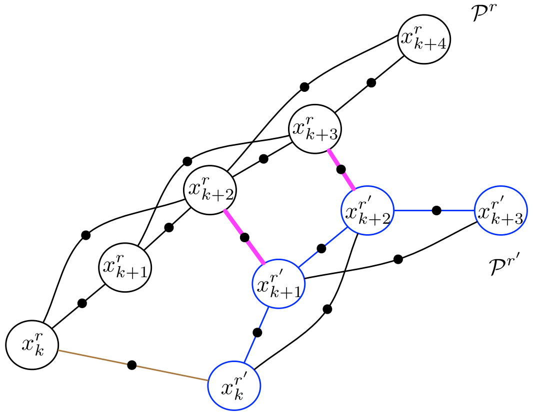
- Each robot r has its own discrete set of candidate actions $\mathcal{A}^r$
- Multi-robot joint belief for a specific candidate action permutation $P \doteq \left\{ P^r, P^{r'}, \ldots \right\}$

$$b[\mathrm{P}] = \underbrace{p(X_k \mid \mathrm{Z}_{0:k}, \mathrm{U}_{0:k-1})}_{\text{Current joint belief}} \prod_{r=1}^{R} \left[\underbrace{\prod_{l=1}^{L(\mathrm{P}^r)} p(x^r_{v_l} \mid x^r_{v_{l-1}}, u^r_{v_{l-1}}) \cdot p(Z^r_{v_l} \mid X^r_{k+l})}_{\text{Local information}} \underbrace{\prod_{\{i,j\}} p(z^{r,r'}_{i,j} \mid x^r_{v_i}, x^{r'}_{v_j})}_{\text{Multi-robot observations}} \right]$$

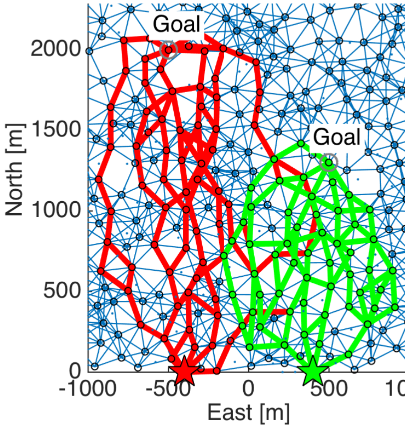
Multi robot future observations/constraints



Corresponding factor graph



Candidate actions



Challenges Include

- Calc. a globally optimal solution involves evaluating J(.) for **all** action permutations
  - **Comp. intractable** ($|\mathcal{A}|^R$)
- Belief is over a high-dimensional state – **comp. expensive** to evaluate **each** cost $c_l\left(b\left[X_{k+l}\right], u_{k+l}\right)$
  - Involves propagating posterior belief for each action
  - Calc. of entropy is $O(N^3)$
  - Expensive also for focused case (reduce uncertainty of only some variables)
- Requires correct data association (e.g. loop closures, multi-robot constraints)
  - **Challenging** in presence of **ambiguity**

Agenda

Belief space planning in high-dimensional state spaces:

1. Computationally efficient information-theoretic BSP by re-using calculations and avoiding explicit belief propagation
2. Action consistent and bounded BSP problem representations:
   - Topological perspective (t-BSP)
   - Sparsification perspective (s-BSP)
3. Active perception in ambiguous environments – data association aware BSP

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Belief space planning in high-dimensional state spaces:

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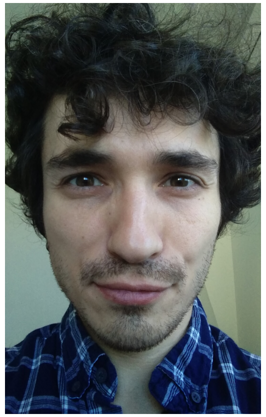
BSP via factor graphs, the matrix determinant lemma, and re-use of calculation (rAMDL)

[Kopitkov and Indelman, IJRR'17]



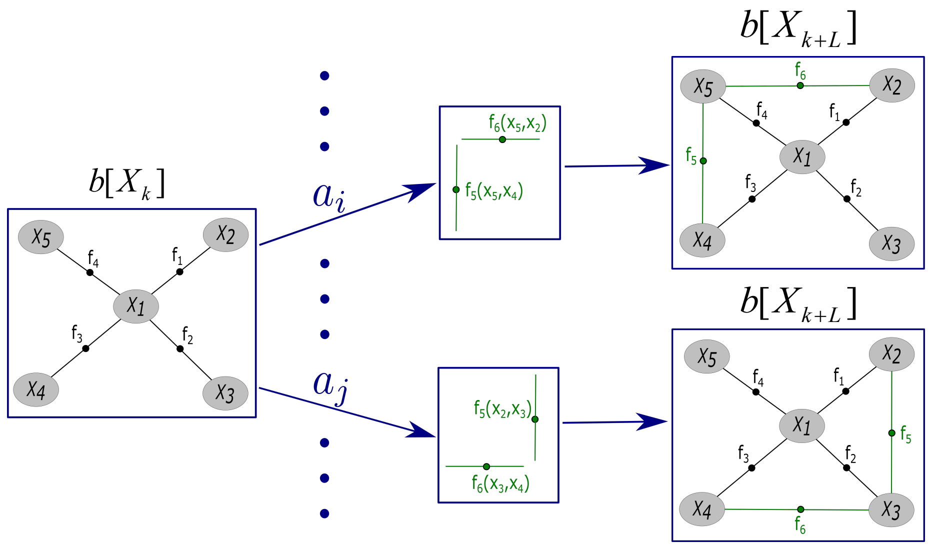
Objective & Key Idea

[Kopitkov and Indelman, IJRR'17]

- Consider an information-theoretic cost (e.g. entropy, info. gain)
- Existing approaches:
  - Propagate posterior belief for **each** action $a \in \mathcal{A}$
  - Calculate determinants of large matrices, $O(N^3)$
    (reduced complexity in presence of sparsity)

$$J_{\mathrm{H}}(a) = dim.const - \frac{1}{2}\ln\left|\Lambda_{k+L}\right|$$

$$J_{IG}(a) = \frac{1}{2}\ln\frac{\left|\Lambda_{k+L}\right|}{\left|\Lambda_{k}\right|}$$



- <u>Our objective</u>: want to avoid explicitly calculating $|\Lambda_{k+L}|$
- Key ideas: (i) use (augmented) matrix determinant lemma
  (ii) re-use calculations between cand. actions

Posterior Information Matrix

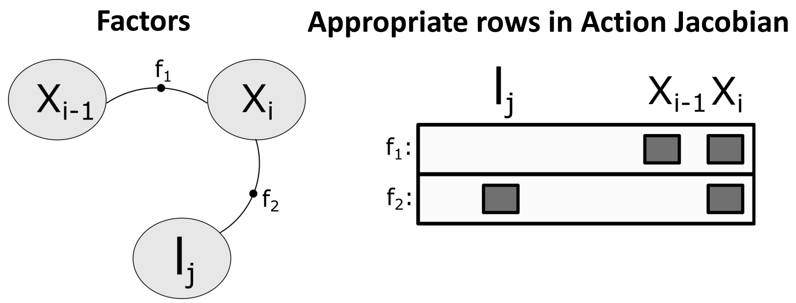
[Kopitkov and Indelman, IJRR'17]

Our objective: want to avoid explicitly calculating $|\Lambda_{k+L}|$

- For each action $a \in \mathcal{A}$:

Posterior belief $$b[X_{k+L}] \propto b[X_k] \prod_{l=k+1}^{k+L} \prod_{j=1}^{n_l} f_l^j(X_l^j)$$

Posterior info. matrix $$\Lambda_{k+L} = \Lambda_k + A^T \cdot A$$



- A is a **sparse** Jacobian matrix of **new** factors, with dimension $m \times N$
- Typically number of ***involved*** variables is very small

Matrix Determinant Lemma (MDL)

[Kopitkov and Indelman, IJRR'17]

- We use MDL to reduce calculations:

$$\left|\Lambda_k + A^T \cdot A\right| = \left|\Lambda_k\right| \cdot \left|I_m + A \cdot \Sigma_k \cdot A^T\right|$$

where $\Sigma_k \equiv \Lambda_k^{-1} \in \mathbb{R}^{n \times n}$ $\quad A \in \mathbb{R}^{m \times n}$

- Applying it to unfocused not-augmented BSP (see IJRR'17 paper):

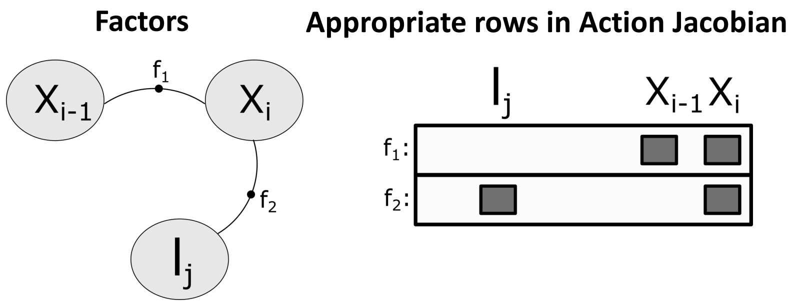
$$J_{IG}(a) = \frac{1}{2} \ln \left| I_m + {}^I\!A \cdot \Sigma_k^{M,{}^I\!X} \cdot ({}^I\!A)^T \right|$$

(Instead of $|\Lambda_k + A^T \cdot A|$)

where:

${}^I\!A$ is a partition of A with all non-zero columns

$\Sigma_k^{M,{}^I\!X}$ is a prior marginal covariance of *involved* variables ${}^I\!X$



Matrix Determinant Lemma (MDL)

[Kopitkov and Indelman, IJRR'17]

$$J_{IG}(a) = \frac{1}{2} \ln \left| I_m + {}^{I}\!A \cdot \Sigma_k^{M,{}^{I}\!X} \cdot ({}^{I}\!A)^T \right|$$

- We can **avoid** posterior propagation and calc. of determinants of **large** matrices
- Calculation of action impact **does not** depend on N, **given** $\Sigma_k^{M,{}^{I}\!X}$
- Calculation complexity depends on m and $dim({}^{I}\!X)$, typically very cheap

- We propose **re-use of calculation**:
  - Only **few entries** from the prior covariance are actually required!
  - Different candidate actions often **share** many **involved** variables ${}^{I}\!X$
  - Combine variables involved in all candidate actions into set $X_{All} \subseteq X_k$
  - Perform one-time calculation of $\Sigma_k^{M,X_{All}}$ (depends on N)
  - Calculate $J_{IG}(a)$ for each action, using $\Sigma_k^{M,X_{All}}$

Extensions

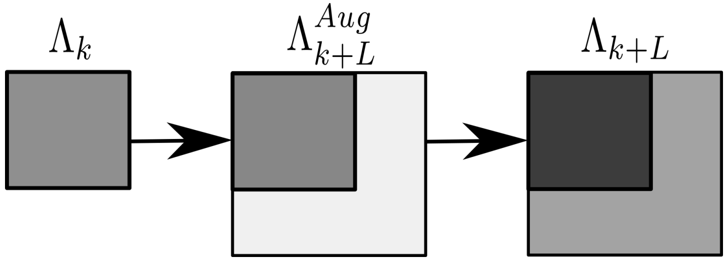
[Kopitkov and Indelman, IJRR'17]

- Approach has been extended to support other BSP problem types (**see IJRR'17 paper**)

BSP problem type	Non-Augmented	Augmented
Unfocused	✓	✓
Focused (reduce uncertainty only of some states)	✓	✓

- Focused: $$J_{IG}^{F}(a) = \frac{1}{2}\ln\left|I_m + {}^{I}A \cdot \Sigma_k^{M,{}^{I}X} \cdot ({}^{I}A)^T\right| - \frac{1}{2}\ln\left|I_m + {}^{I}A^U \cdot \Sigma_k^{{}^{I}X^U|F} \cdot ({}^{I}A^U)^T\right|$$

- For augmented case (e.g. active SLAM), Matrix Determinant Lemma (MDL) **cannot** be used!
  - We extended MDL to an augmented case (AMDL), details in the paper

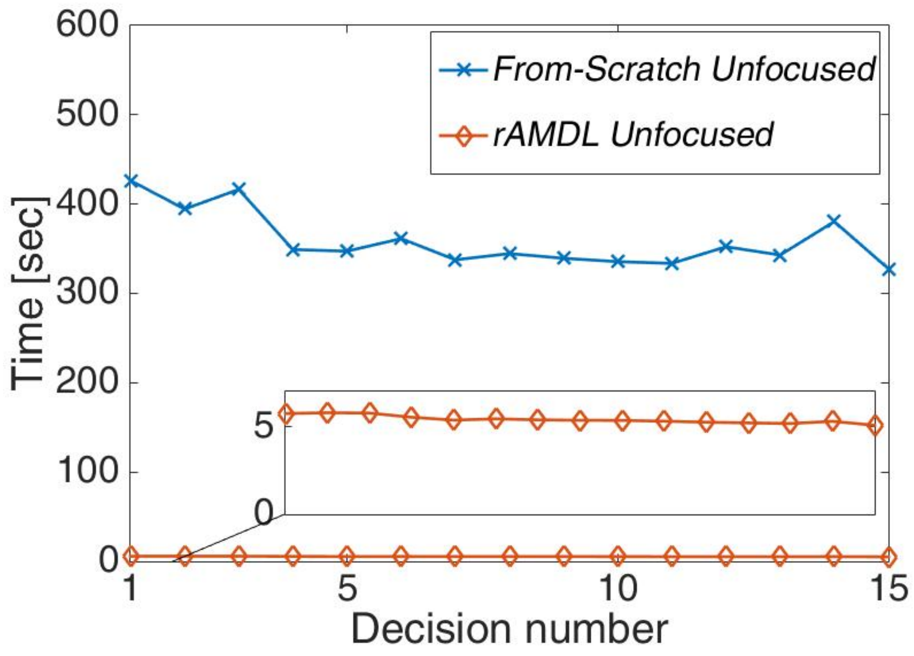


$$\Lambda_{k+L} = \Lambda_{k+L}^{Aug} + A^T \cdot A$$

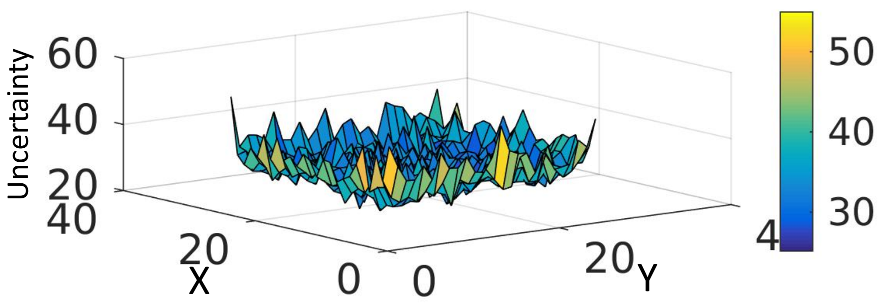
Results – Unfocused, Non-Augmented - Sensor Deployment

[Kopitkov and Indelman, IJRR’17]

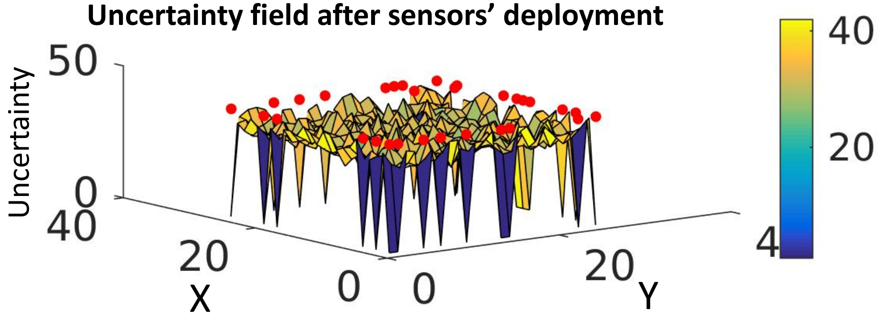
- Significant time reduction in *Unfocused* case



Uncertainty field (dense prior information matrix)



Uncertainty field after sensors’ deployment

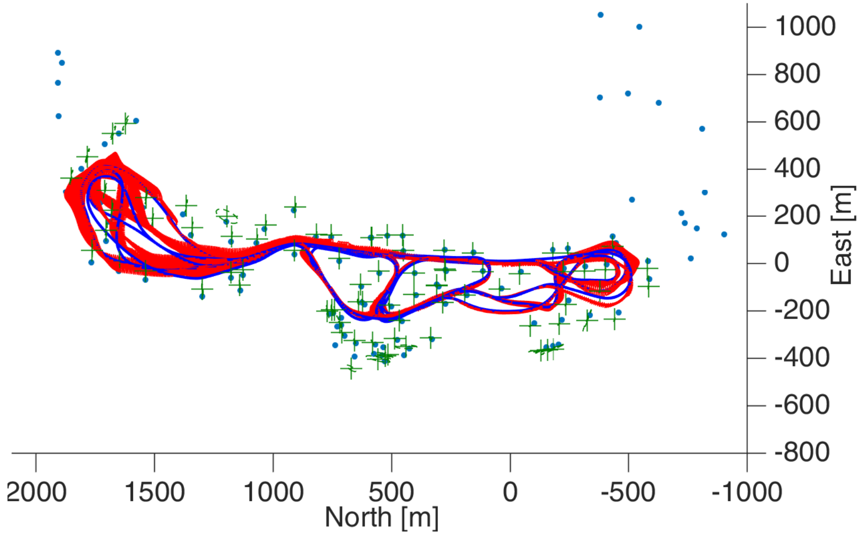


Results – Focused, Augmented – SLAM – Viktoria Park

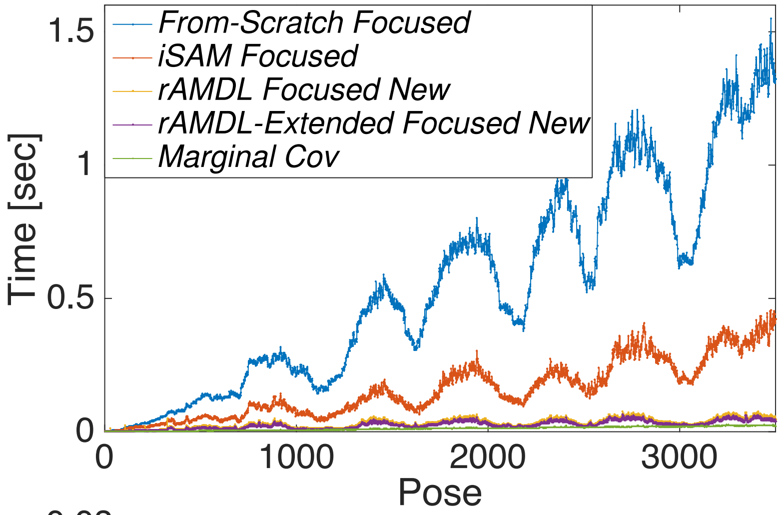
[Kopitkov and Indelman, IJRR'17]

- Significant time reduction in *Focused* case – focus on **last robot pose**

Dataset

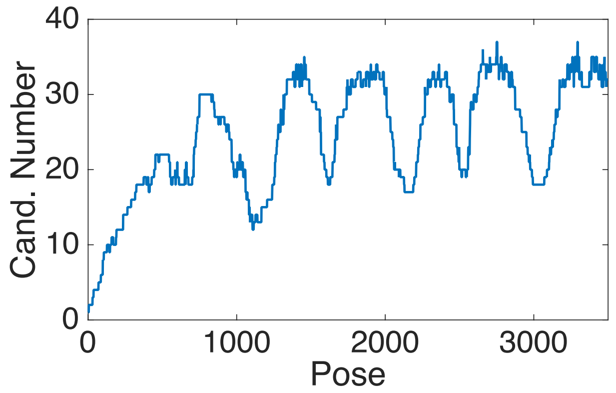


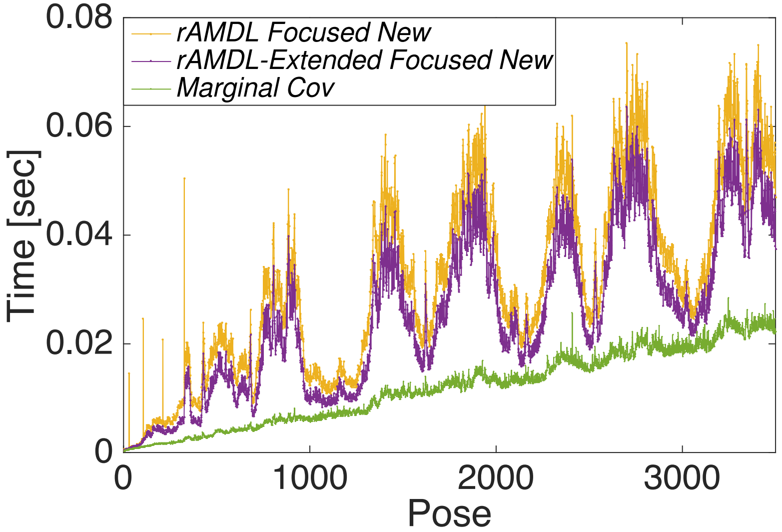
Running time of planning



Zoom-in

Number of candidate actions





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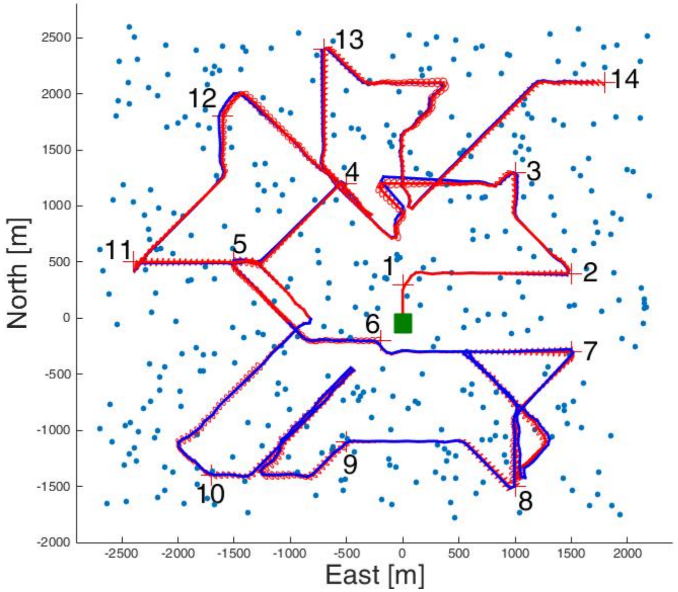
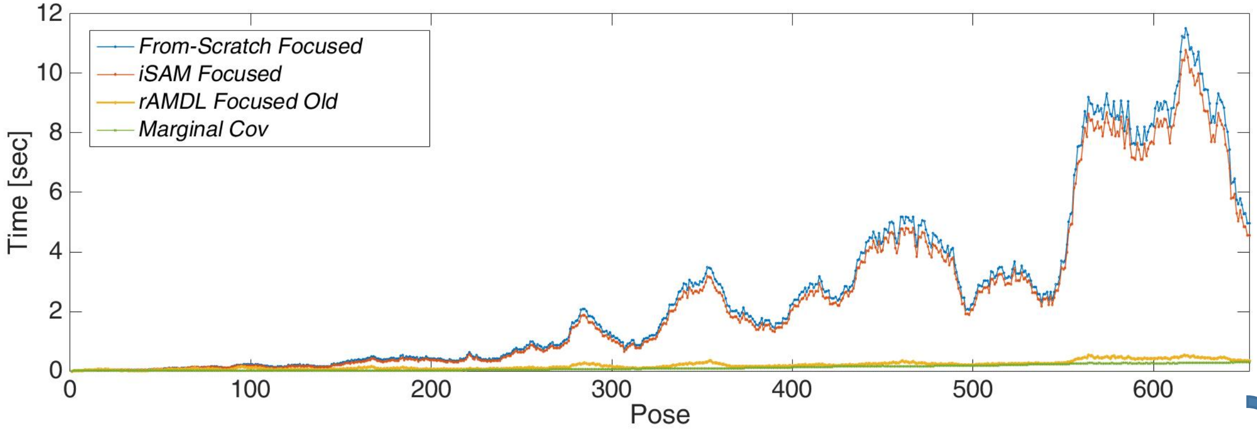
Results – Focused, Augmented – SLAM – Simulation

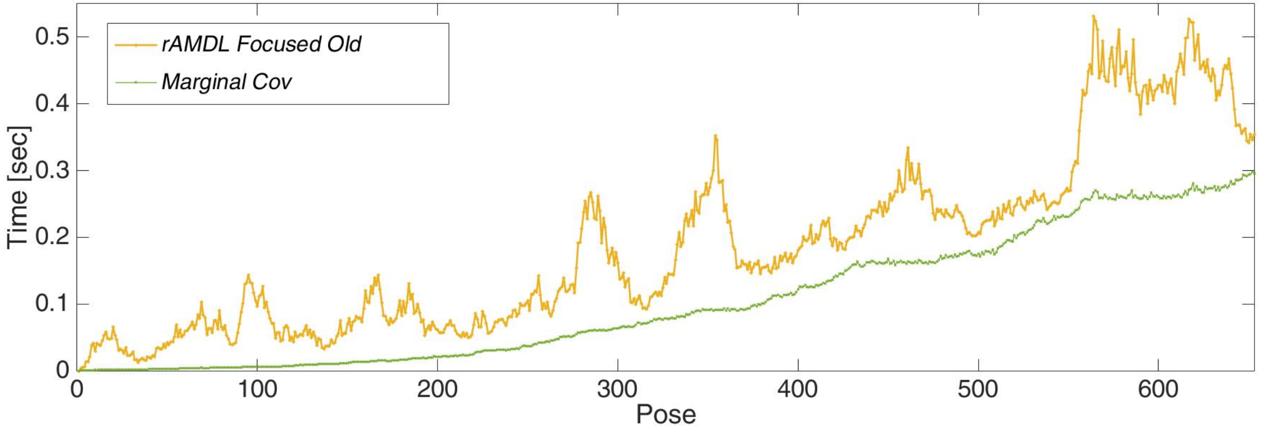
[Kopitkov and Indelman, IJRR'17]

- Significant time reduction in *Focused* case – focus on **mapped landmarks**





Zoom-in



rAMDL - Summary

[Kopitkov and Indelman, IJRR'17]

- We address all 4 BSP problem types:

BSP cases	Non-Augmented	Augmented
Unfocused	✓	✓
Focused	✓	✓

- **No need** for posterior belief propagation
- **An exact** solution
- **Avoid** calculating determinants of large matrices
- Calculation **Re-use**
- Per-action evaluation **does not depend on state dimension**, given marginal prior covariances
- Still requires a **one-time** recovery of marginal covariances of involved variables

Agenda

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   - **Topological perspective (t-BSP)**
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Action Consistent & Bounded Approximations

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

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 :

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

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

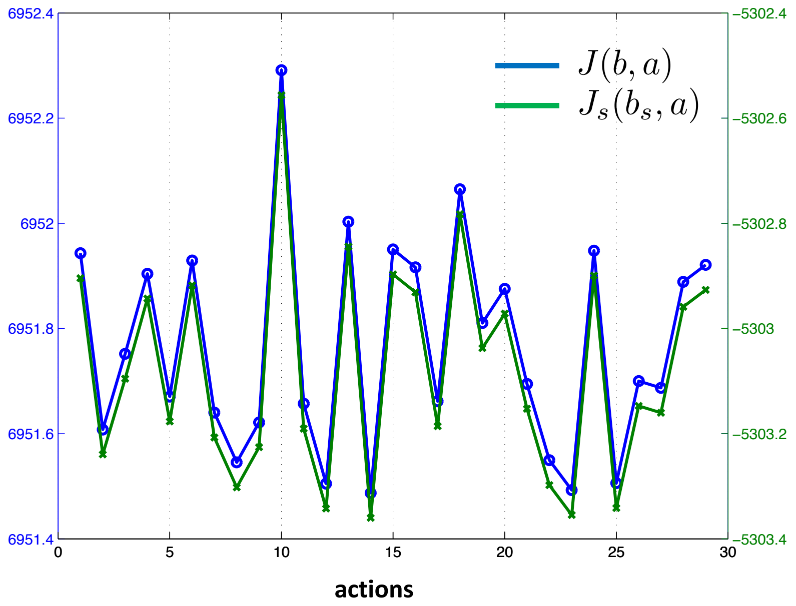

Image from Indelman RA-L'16

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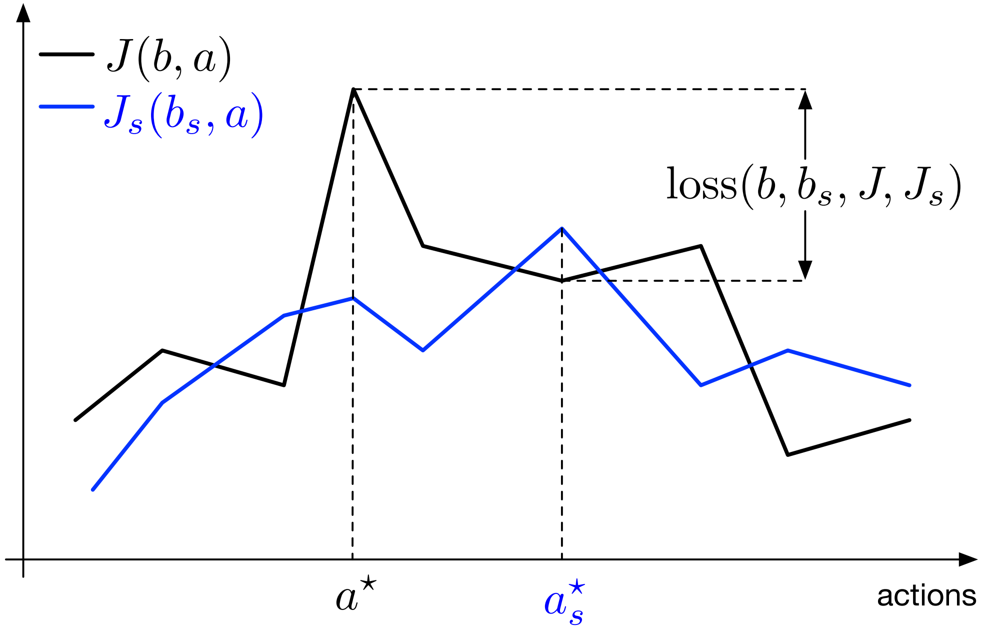
Action Consistent & Bounded Approximations

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



- Often possible to settle for a sub-optimal action, in order to reduce the solution complexity
- 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]

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

[Kitanov and Indelman, ICRA’18]

Perspectives

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

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

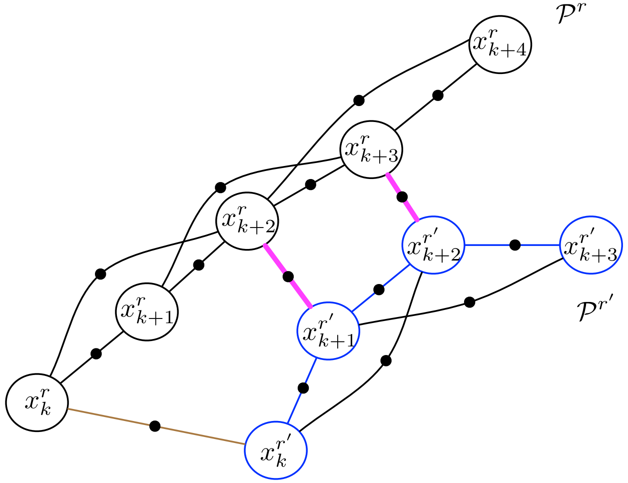
- **Topological BSP (t-BSP)**

[Kitanov and Indelman, ICRA'18]

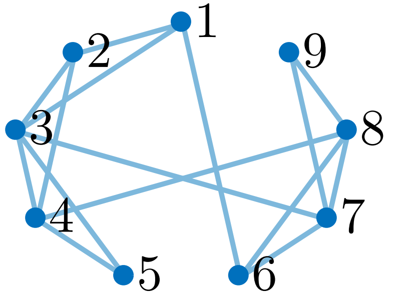
Topological Belief Space Planning (t-BSP)

[Kitanov and Indelman, ICRA’18]

- 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 $G(\Gamma, E)$

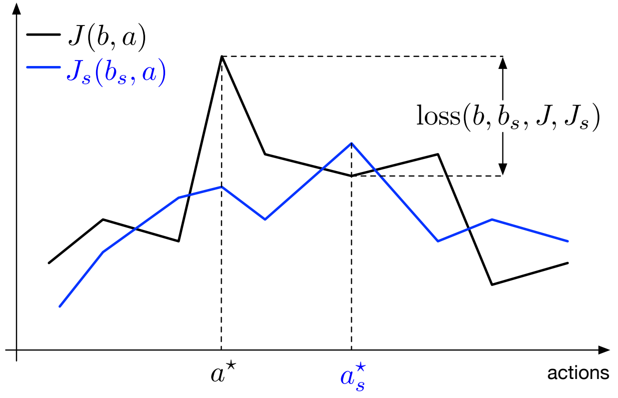
topological metric $s(G)$

graph signature

Topological Belief Space Planning (t-BSP)

[Kitanov and Indelman, ICRA'18]

- Relation to action-consistent & bounded approximations framework:
  - b_s - Factor graph topology
  - J_s - Graph signature $s(G)$



- Two graph signatures currently considered in t-BSP:
  - Von Neumann entropy of G (VN) which is further simplified with a function of graph node degrees *d*

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

Cheap to calculate, only a function of node degrees!

  - Signature based on the number of spanning trees of G (ST)

$$s(G) = \frac{3}{2}\tau(G) + \frac{|\Gamma|}{2}[\ln |\Omega_w| - \ln(2\pi e)]$$

Topological Belief Space Planning (t-BSP)

[Kitanov and Indelman, ICRA'18]

Metric Space

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

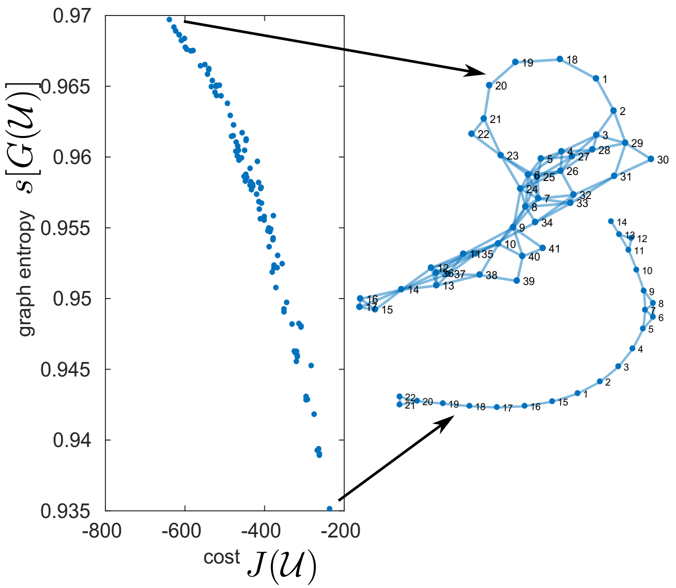
$$\mathcal{U}^\star = \arg\min_{\mathcal{U}} J(\mathcal{U})$$

Topological space

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

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

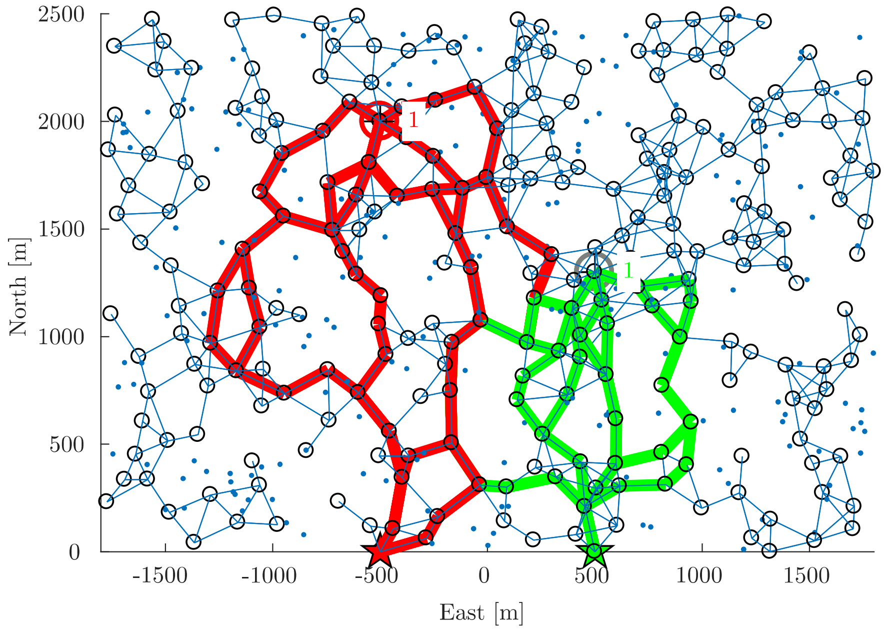
Topological and info-theoretic metrics are strongly correlated!



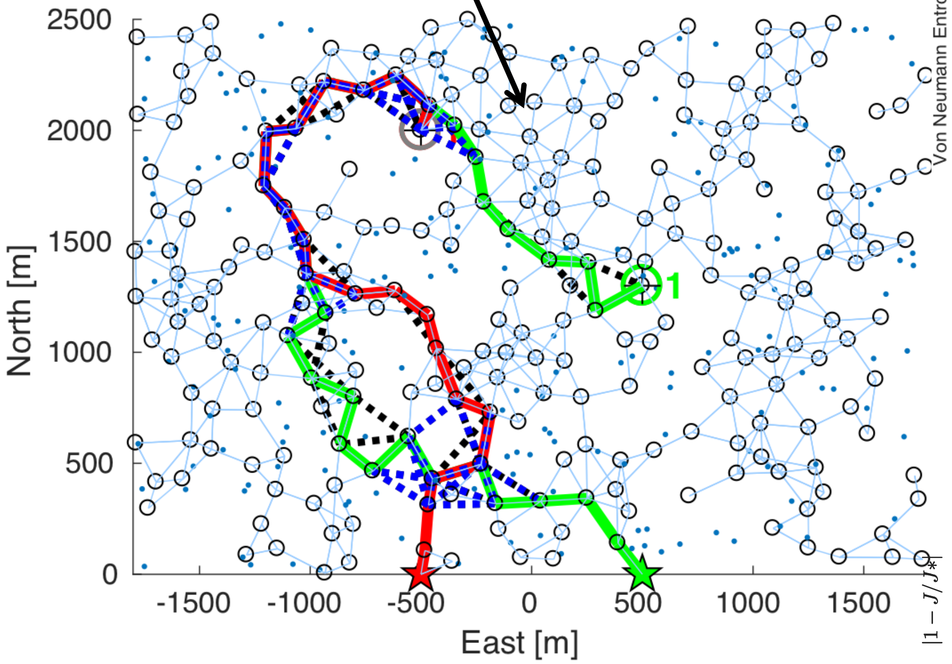
t-BSP: Application to Multi-Robot BSP

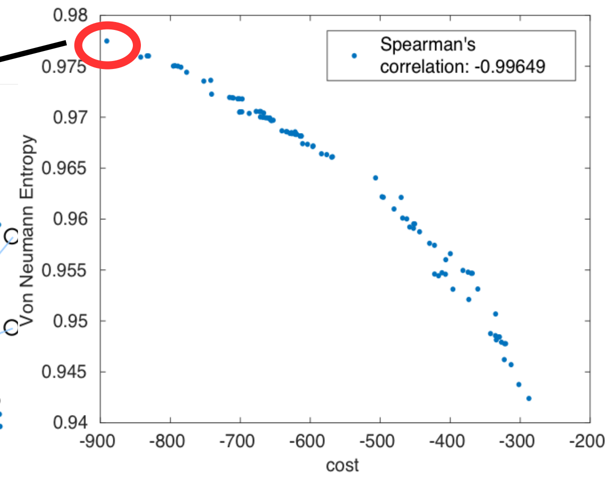
[Kitanov and Indelman, ICRA'18]

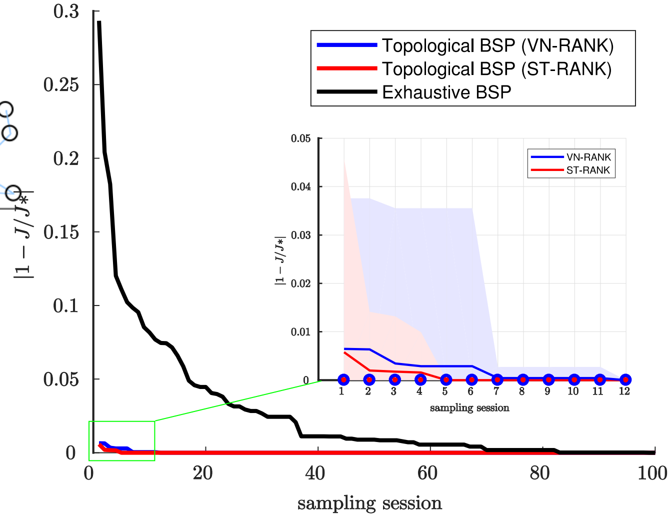
Candidate paths of two robots (red and green) generated on top of PRM in a single planning session:



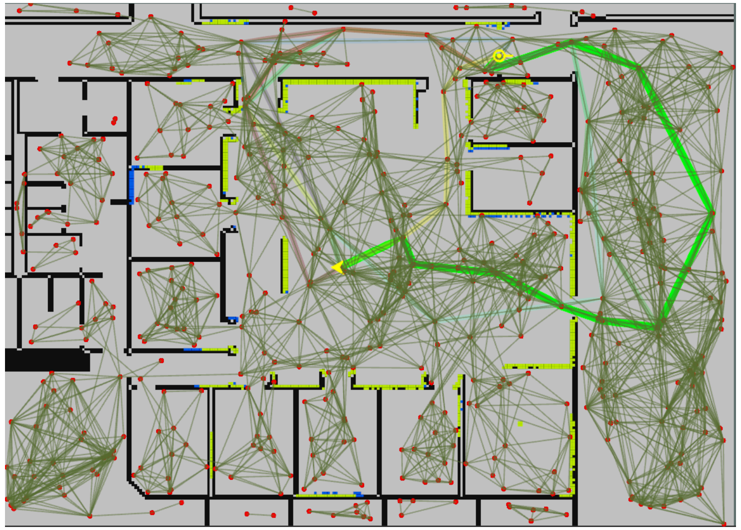
Optimal paths found

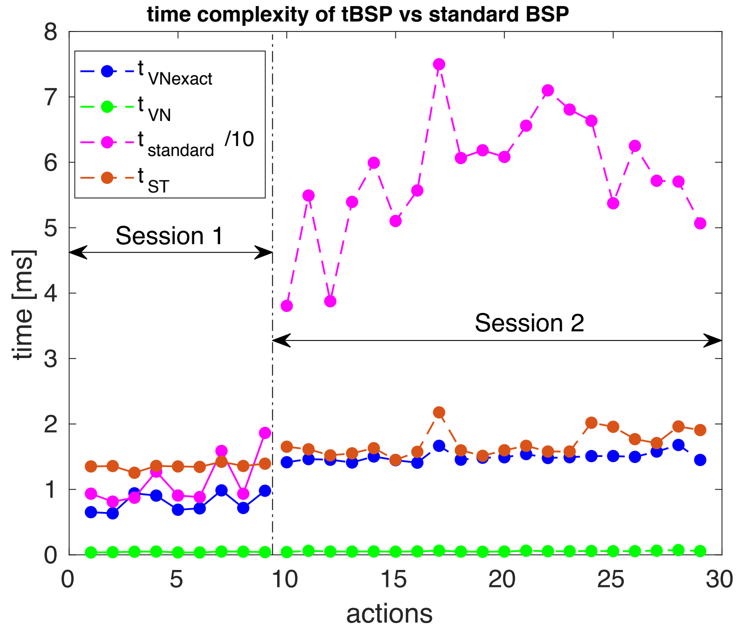




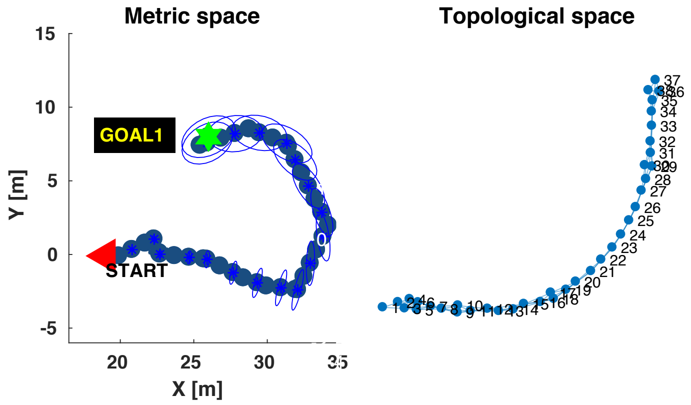


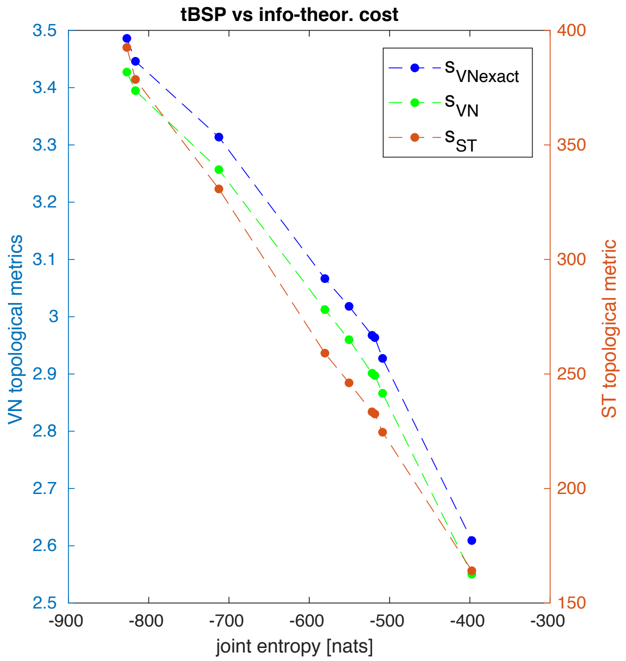
t-BSP: Gazebo Initial Results



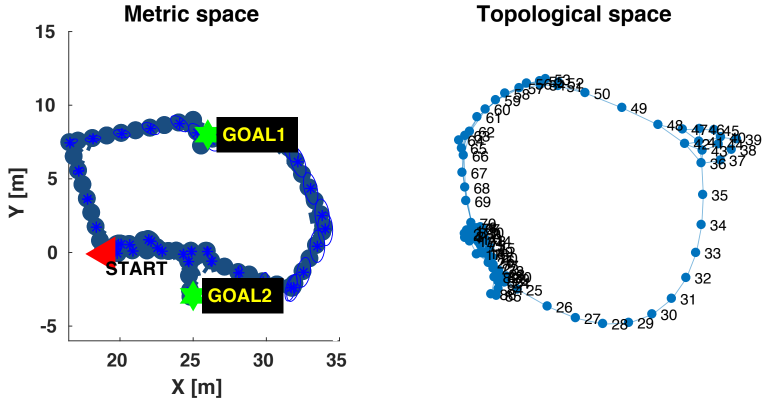


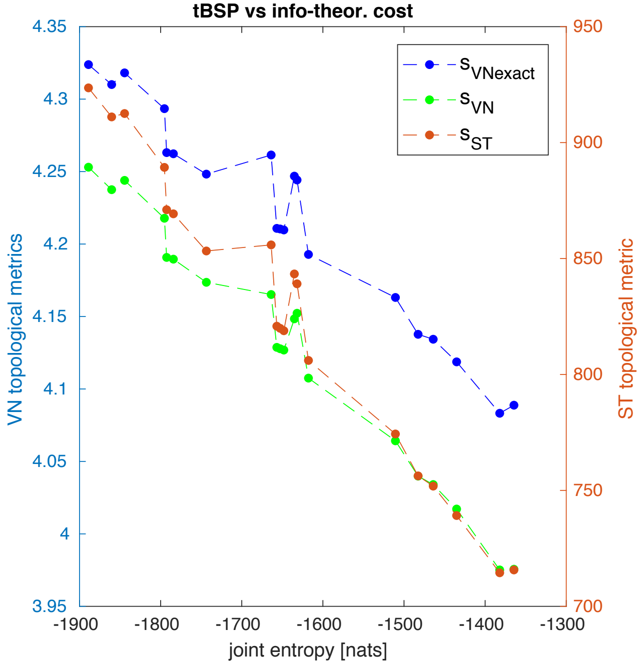
1st planning session (exploration)





2nd planning session (exploitation, loop closures)





Perspectives

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

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

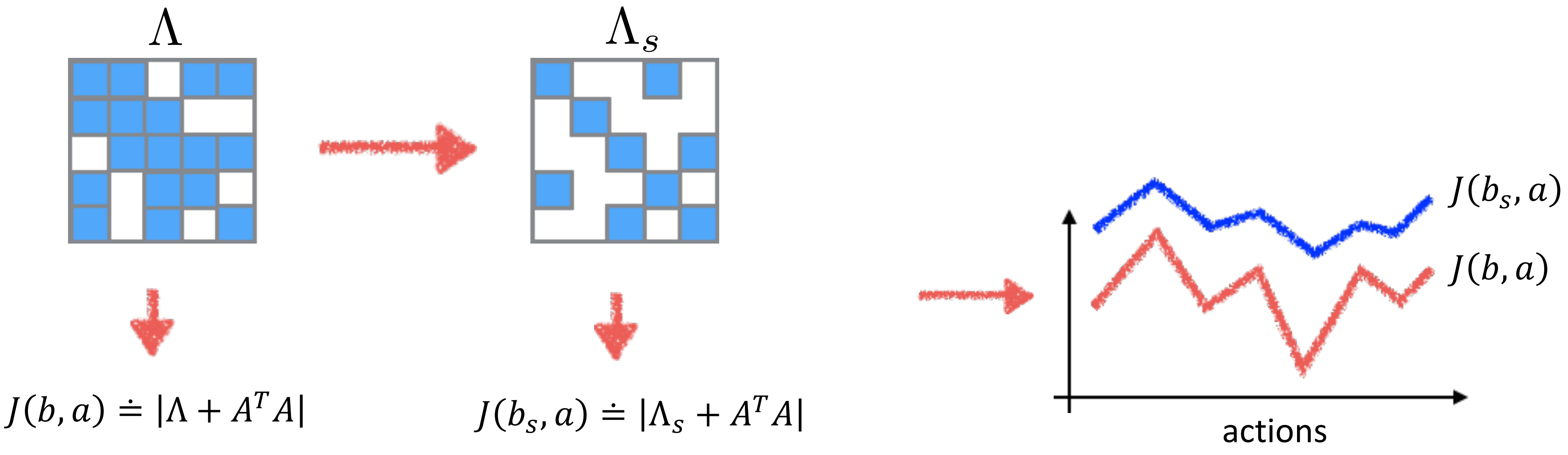
- **Topological BSP (t-BSP)**

[Kitanov and Indelman, ICRA'18]

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

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

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

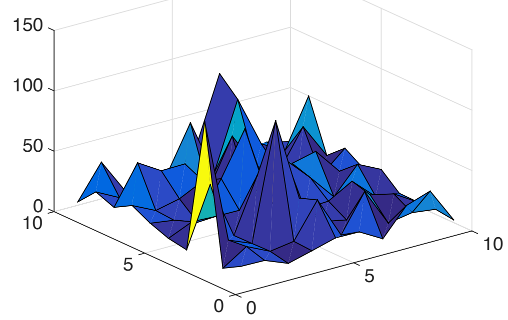


- Do we get the same performance (decisions), i.e. is it action consistent?
- If not, can we bound the loss?

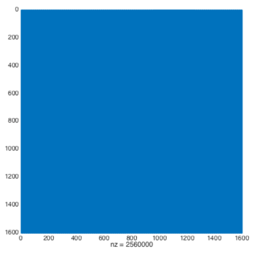
s-BSP: Initial Results – Sensor Deployment

- **Objective**: deploy k sensors in an $N \times N$ area
- **Motivating example: extreme** sparsification – drop **all** off-diagonal terms
- Action consistency is **guaranteed** **[Indelman RA-L'16]** for a restricted problem setting (myopic, single-row measurement Jacobians)

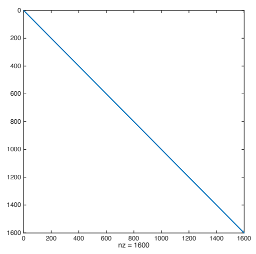
Prior uncertainty field:

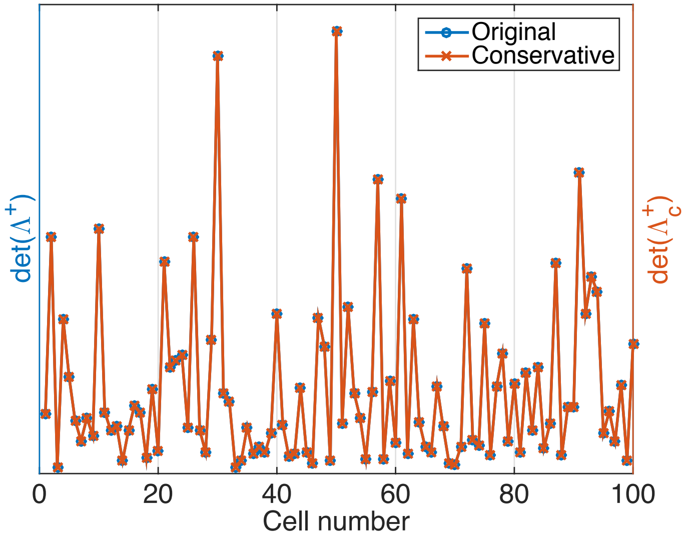


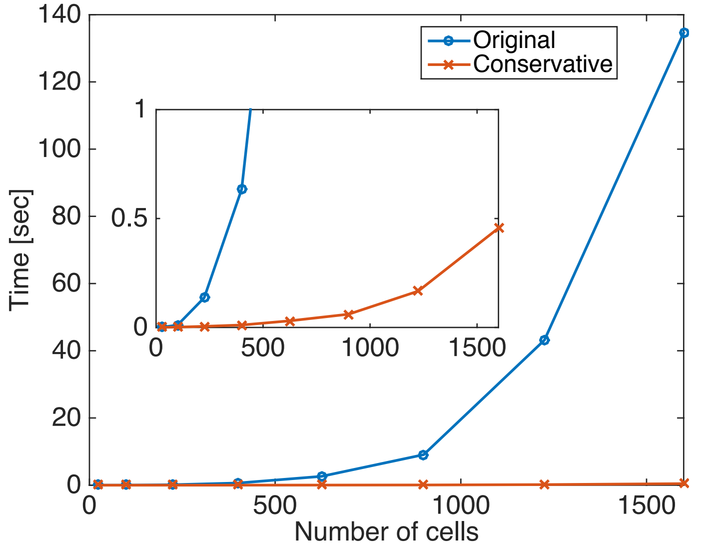
Λ



Λ_s



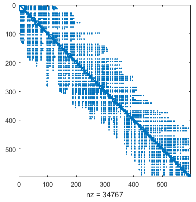




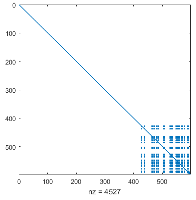
s-BSP: Initial Results - Active SLAM

- Active full SLAM scenario – navigation to a goal in an unknown environment
- LIDAR sensor – range-bearing observations of surrounding landmarks
- Primitive actions – star-pattern search of best progression angle (20 actions)
- Results considering 3 sparsity levels:
  (i) **original**, (ii) **sparsification of uninvolved variables**, (iii) **sparsification of all variables (diag. info. matrix)**

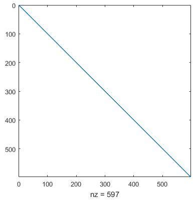
(i)

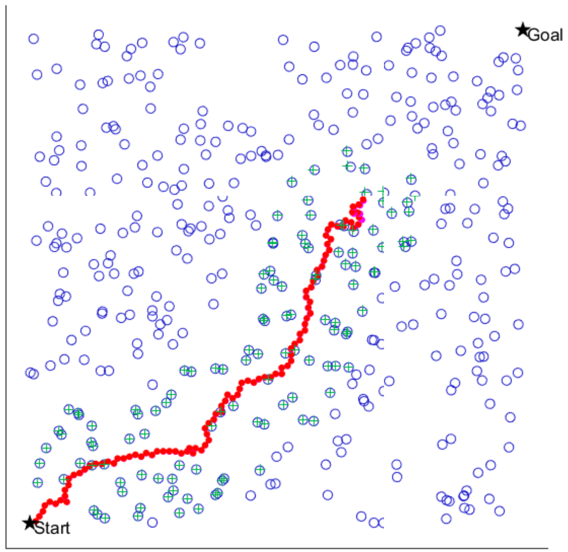


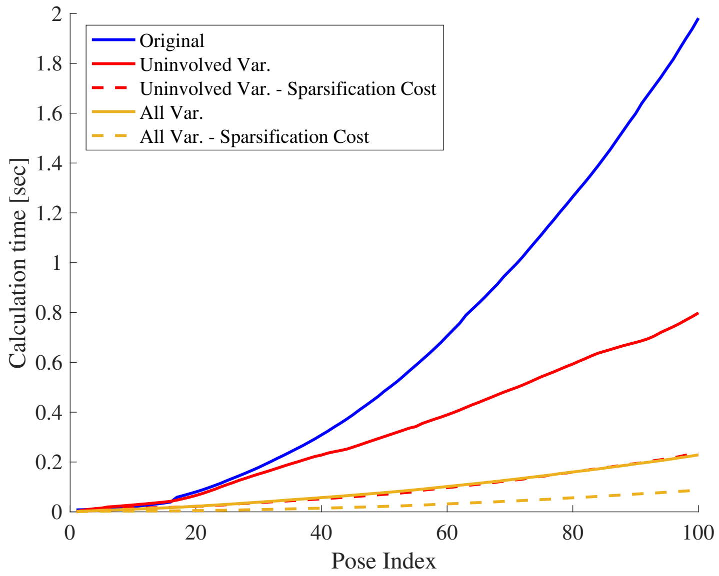
(ii)

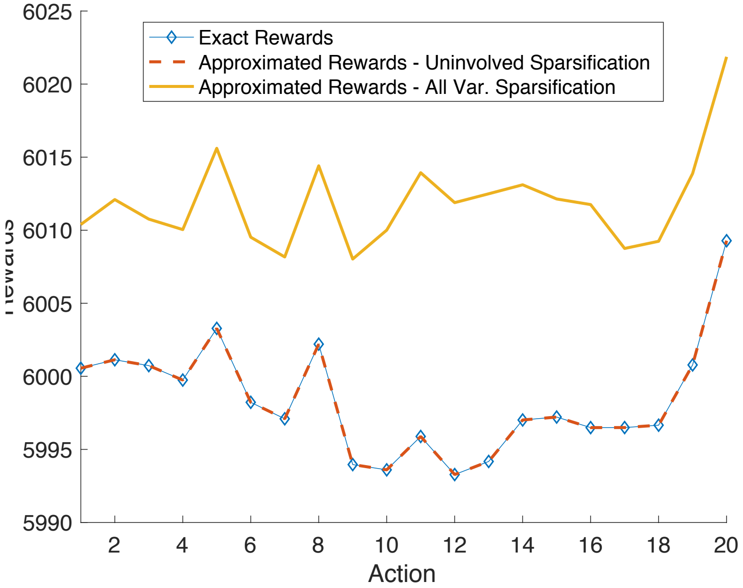


(iii)









Agenda

Belief space planning in high-dimensional state spaces:

1. Computationally efficient information-theoretic BSP by re-using calculations and avoiding explicit belief propagation
2. Action consistent and bounded BSP problem representations:
   - Topological perspective (t-BSP)
   - Sparsification perspective (s-BSP)
3. **Active perception in ambiguous environments – data association aware BSP**

[Pathak, Thomas, 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)

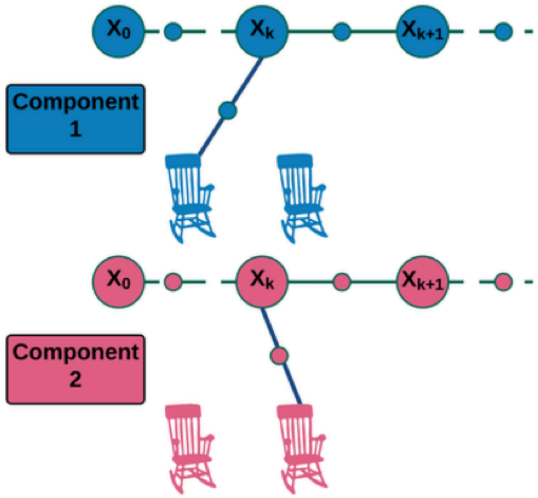
Angeli et al., TRO'08

Approach Overview

[Pathak, Thomas, Indelman, IJRR'18]

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

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



Pathak et al., IJRR'18

- **Main idea**: Reason how a GMM belief will evolve for different candidate actions
- Number of 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}

$$\underline{b[X_{k+1}]} = \sum_j p(X_{k+1}|\mathcal{H}_{k+1}^{-}, z_{k+1}, A_j)p(A_j|\mathcal{H}_{k+1}^{-}, z_{k+1})$$

$$= \sum_j \tilde{w}_j b[X_{k+1}^{j+}] \qquad \tilde{w}_j = \eta w_j$$

Approach Overview

[Pathak, Thomas, Indelman, IJRR'18]

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

- Posterior belief

$$b[X_{k+1}] = \sum_{j}^{\{A_{\mathbb{N}}\}} p(X_{k+1}|\mathcal{H}_{k+1}^{-}, z_{k+1}, A_j)p(A_j|\mathcal{H}_{k+1}^{-}, z_{k+1})$$

- In other words
  - Observation is given, hence, **must** capture **one** (unknown) scene
  - Which one? Consider all possible scenes

Approach Overview

[Pathak, Thomas, Indelman, IJRR'18]

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

- Likelihood of a specific z_{k+1} to be captured
- Marginalize over all scenes A_j and viewpoints x_{k+1}

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

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

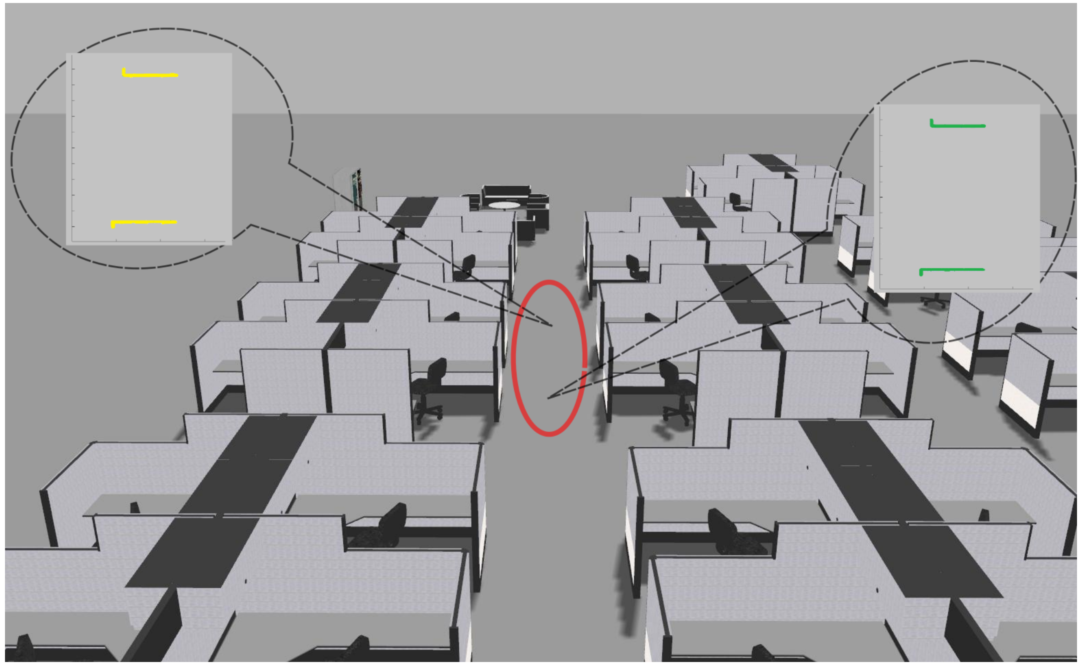
- With perceptual aliasing:
  - Multiple non-negligible weights $\tilde{w}_j$, correspond to aliased scenes (given z_{k+1})
  - Posterior **becomes a mixture of pdfs (GMM)**
  - In practice, hypotheses pruning/merging is performed (**see IJRR'18 paper**)

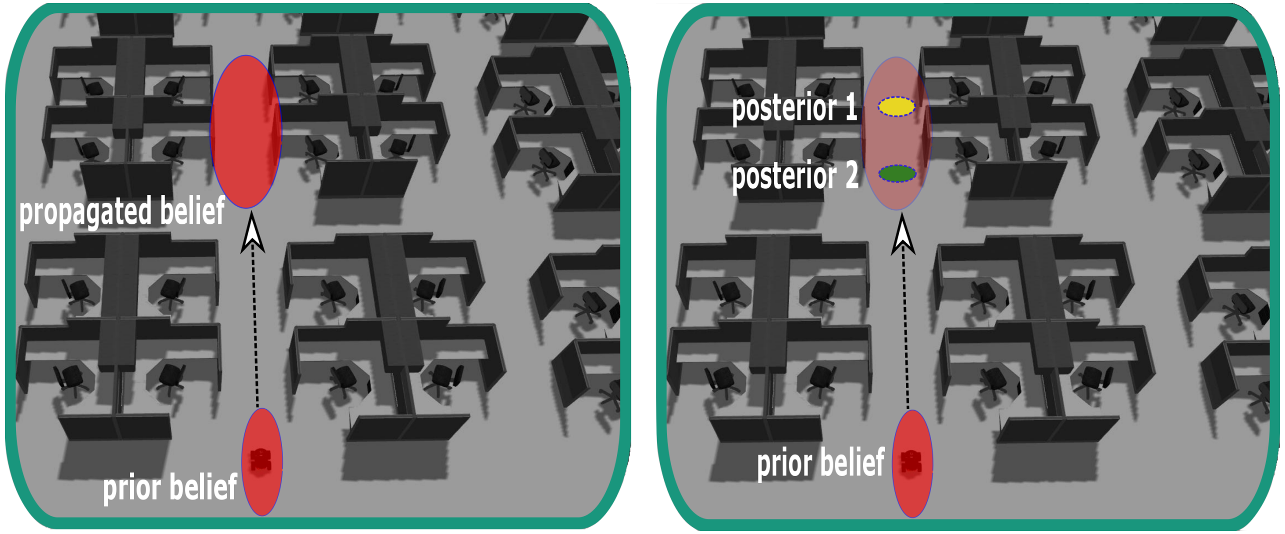
- Approach can be used for **active disambiguation** (between DA hypotheses)

Number of GMM Components Can Increase

[Pathak, Thomas, Indelman, IJRR'18]

- Gazebo simulation

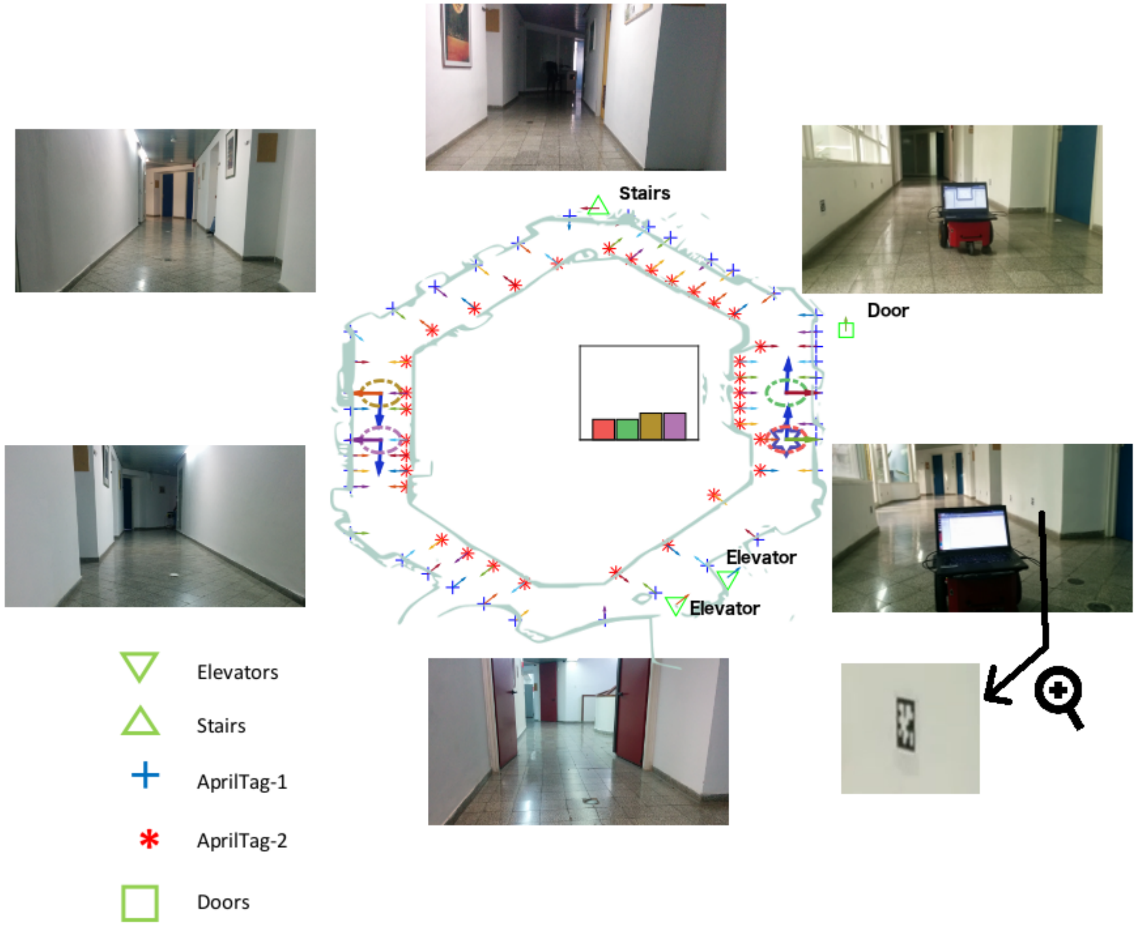


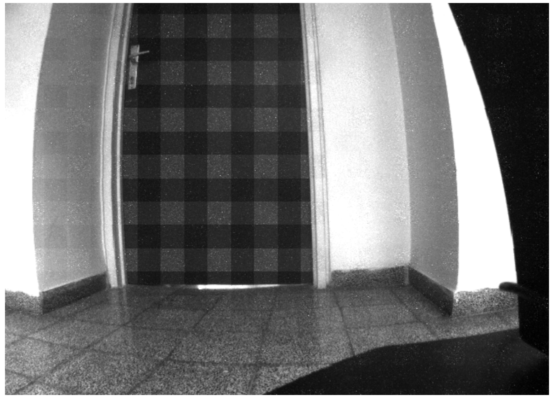


Real Experiment with April Tags

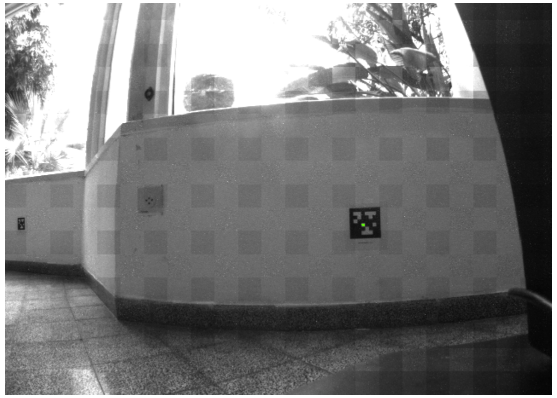
[Pathak, Thomas, Indelman, IJRR’18]

- Octagonal world with a known map
- April Tags used to simulate aliasing environment and for localization





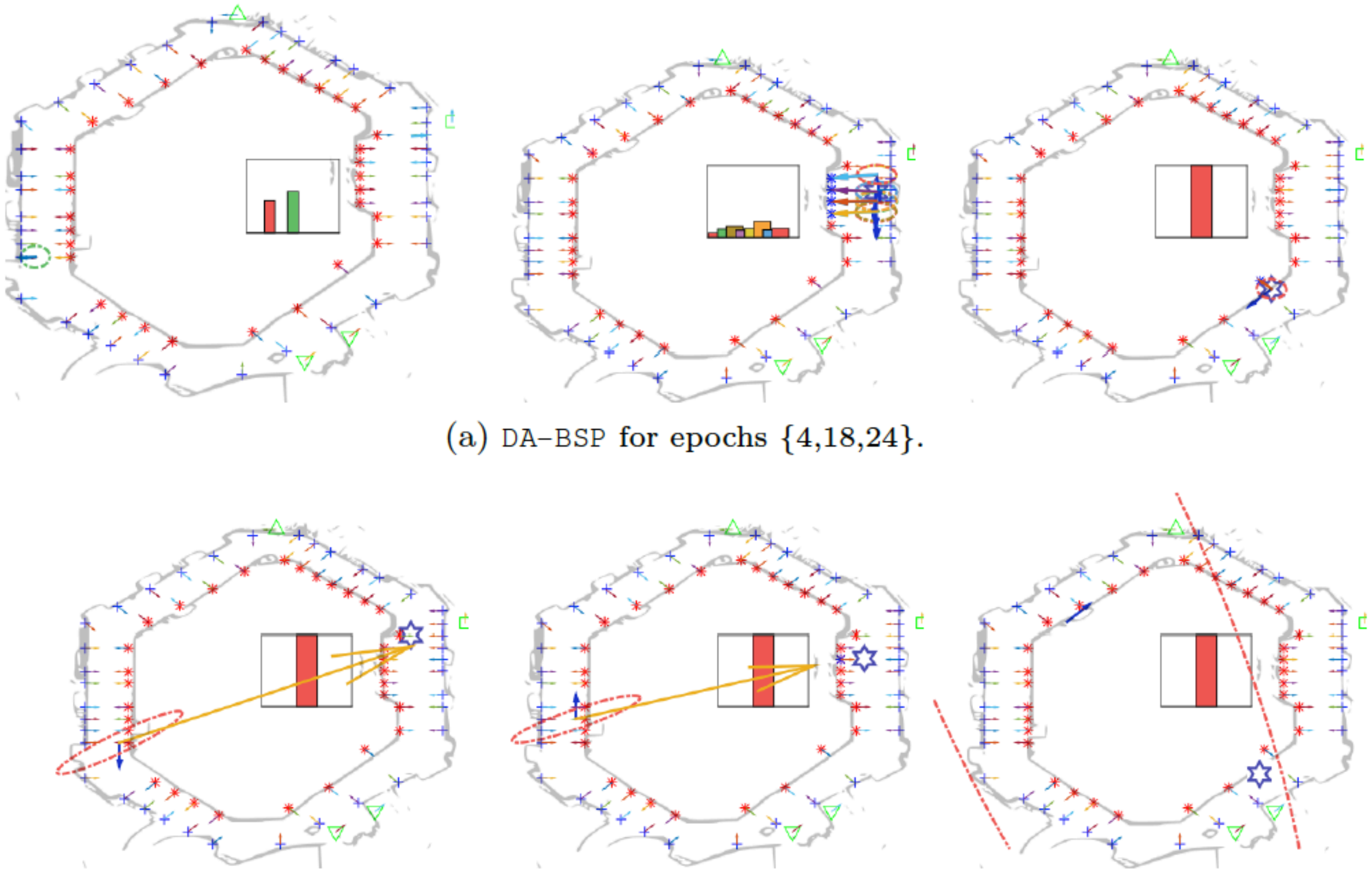
No object detected



An object detected

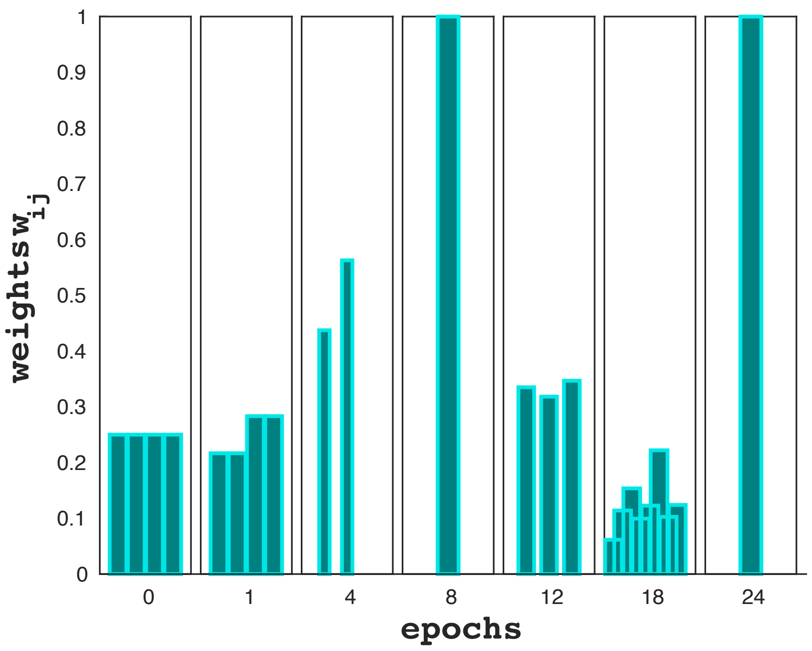
Real Experiment with April Tags

[Pathak, Thomas, Indelman, IJRR'18]



(a) DA-BSP for epochs {4,18,24}.

(b) BSP-uni for epochs {4,18,24}

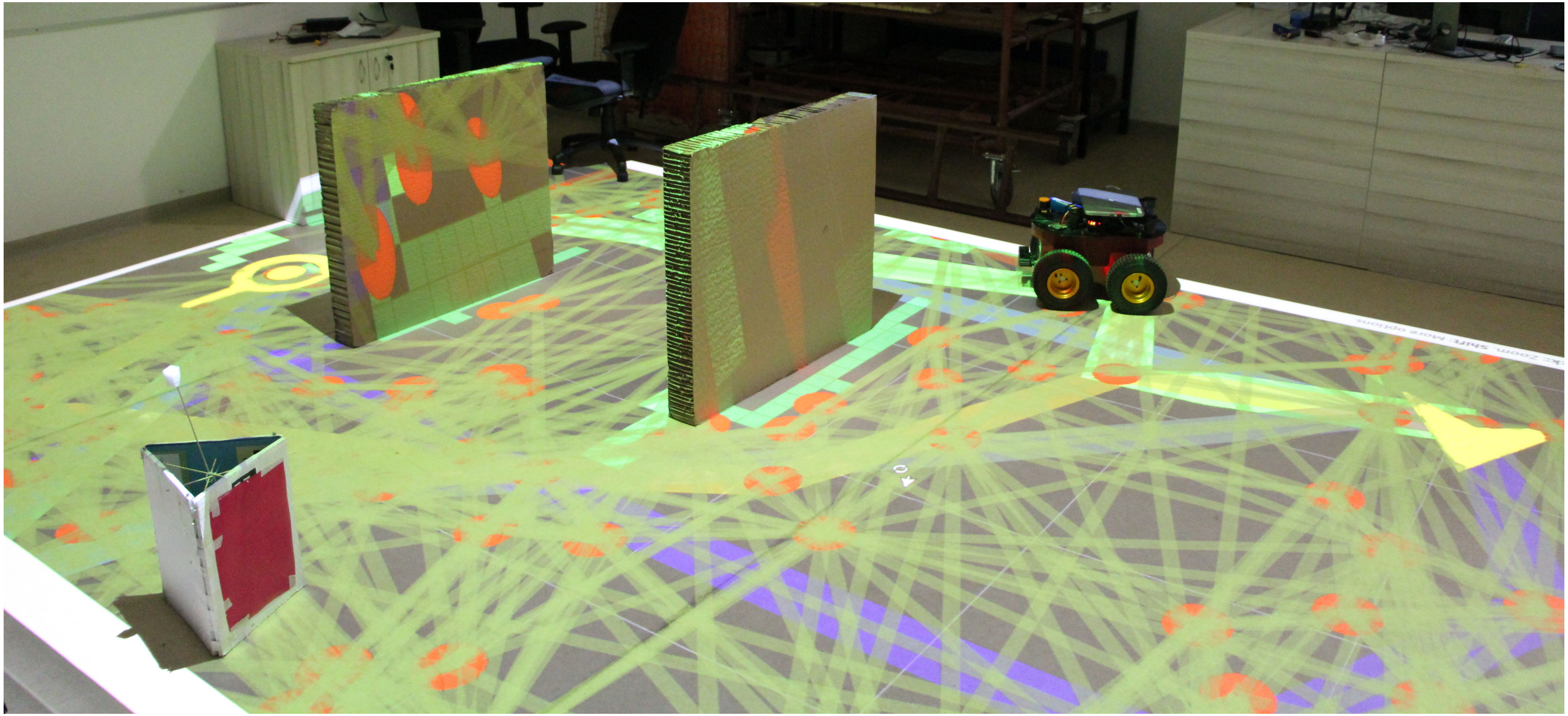


DA-BSP - Summary

[Pathak, Thomas, Indelman, IJRR'18]

- **Data association aware belief space planning (DA-BSP)**
  - Considers **data association** within BSP
  - Relaxes typical assumption in BSP that DA is **given** and **correct**
  - Approach in particular suitable to handle scenarios with **perceptual aliasing** and **localization uncertainty**
  - Unified framework for **robust active** and **passive perception**

Experiments at ANPL – In Process



Summary

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

- rAMDL: Computationally efficient BSP in high dim. state spaces
- Action consistency & bounded approximations
  - s-BSP: belief sparsification for BSP
  - t-BSP: topological BSP
- Active perception in ambiguous environments: Data association aware BSP