Data Association Aware Belief Space Planning (DA-BSP)

Shashank Pathak, **Antony Thomas**, **Asaf Feniger** and **Vadim Indelman**
Autonomous Navigation and Perception Lab (ANPL) — Technion, IIT
Haifa 32000, Israel

In planning under uncertainty, when data association is incorporated within plan-infer framework of belief space planning (BSP), it results in a more general form of BSP capable of dealing with non-Gaussian beliefs, and perceptual aliasing, providing a framework for robust active perception and active disambiguation that avoids catastrophic failures.

Data-association in BSP

State of the art: Considers data association within BSP as given and perfect, typically through *maximum likelihood assumption*.

How to incorporate data association?

Maximum likelihood: assumes association corresponding to planner's nominal position is the correct one (e.g. [1], [2])

Passive robust inference: models association within passive inference via binary latent variables (e.g. [3])

Non-parametric inference: infers passively based on available data (e.g. [4])

Multiple hypothesis tracking: framing it as an MHT problem (e.g. [5])

Why care about data-association

- Data association may be ambiguous due to perceptual aliasing
- Incorrect data association may lead to catastrophic failures

[1] A. Kim and R.M. Eustice, IJRR 2014
Active visual SLAM for robotic area coverage: Theory and experiment.

[2] V. Indelman, L. Carlone F. Dellaert. IJRR 2015
Planning in the continuous domain: A generalized belief space approach for autonomous navigation in unknown environments

[3] N. Sunderhauf and P. Protzel. ICRA 2012
Towards robust back-end for pose graph slam

[4] E. Olson and P. Agarwal. IJRR 2013
Inference on network of mixtures for robust robot mapping

[5] S. Agarwal, A. Tamjidi, and S. Chakravorty. Preprint
Motion planning in non-gaussian belief spaces for mobile robots.

Data-association aware BSP

- **Approach**: Reason about possible associations within BSP.
- **Cost function**:

$$J(u_k) = \mathbb{E}\left\{c\left(b[X_{k+1}], u_k\right)\right\},$$

$$J(u_k) \doteq \int_{z_{k+1}} \overbrace{\mathbb{P}(z_{k+1} \mid \mathcal{H}^-_{k+1})}^{(a)}\ c\left(\overbrace{\mathbb{P}(X_{k+1} | \mathcal{H}^-_{k+1}, z_{k+1})}^{(b)}\right)$$

- **computing (a)**: For A_N data associations

$$\mathbb{P}(z_{k+1}|\mathcal{H}^-_{k+1}) \equiv \sum_i^{|A_{\mathbb{N}}|} \int_x \mathbb{P}(z_{k+1}, x, A_i \mid \mathcal{H}^-_{k+1}) \doteq \sum_i^{|A_{\mathbb{N}}|} w^i_{k+1}.$$

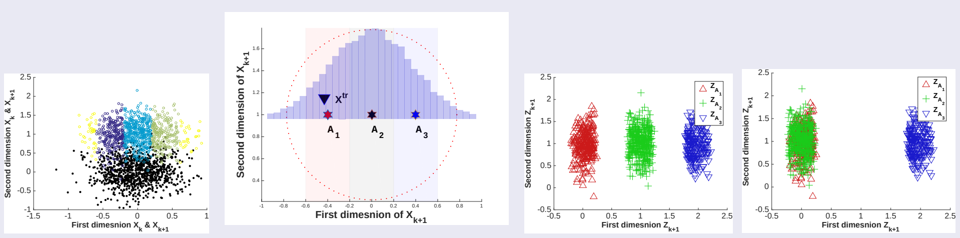
- **computing (b)**:

$$b[X_{k+1}] = \sum_{i=1}^{|A_{\mathbb{N}}|} \sum_{j=1}^{M_k} \xi^j_k \mathbb{P}(A_i \mid \mathcal{H}^-_{k+1}, z_{k+1}) b[X^{j+}_{k+1}|A_i].$$

with posterior conditioned on A_i: $b[X^{i+}_{k+1}] \doteq \mathbb{P}(X_{k+1} \mid \mathcal{H}^-_{k+1}, z_{k+1}, A_i)$.

Experimental results

Abstract example

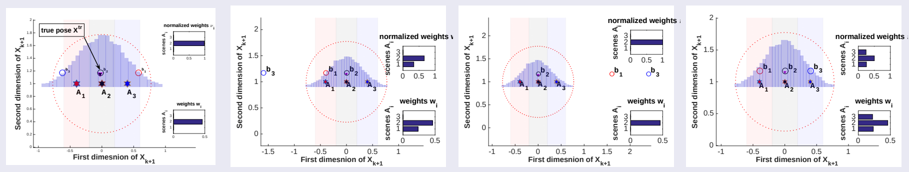


(a) Sampled viewpoints (b) Event likelihood $\mathbb{P}(A_i|x, \mathcal{H})\ \forall i$ (c) No aliasing (d) $\{A_1, A_3\}_{\text{aliased}}$

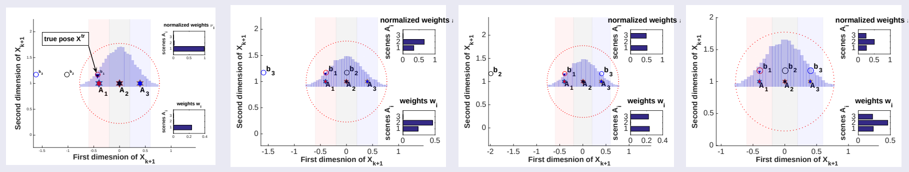
Figure: Pose and observation space. (a) black-colored samples $\{x_k\}$ are drawn from $b[X_k] \doteq \mathcal{N}([0,0]^T, \Sigma_k)$, from which, given control u_k, samples $\{x_{+1}\}$ are computed, colored according to different scenes A_i being observed, and used to generate observations $\{z_{k+1}\}$. (b) Stripes represent locations from which each scene A_i is observable, histogram represents distribution of $\{x_{k+1}\}$, which corresponds to $b[X^-_{k+1}]$. (c)-(d) distributions of $\{z_{k+1}\}$ without aliasing and when $\{A_1, A_3\}_{\text{aliased}}$.

Experimental results

Abstract example



(a) No aliasing, $A^{tr} = A_1$, $A^{tr}{=}A_2$ (b) $\{A_1, A_2\}_{\text{aliased}}$, $A^{tr}{=}A_2$ (c) $\{A_1, A_3\}_{\text{aliased}}$, $A^{tr}{=}A_2$ (d) $\{A_1, A_2, A_3\}_{\text{aliased}}$, $A^{tr}{=}A_2$



(e) No aliasing, $A^{tr} = A_1$ (f) $\{A_1, A_2\}_{\text{aliased}}$, $A^{tr}{=}A_1$ (g) $\{A_1, A_3\}_{\text{aliased}}$, $A^{tr}{=}A_1$ (h) $\{A_1, A_2, A_3\}_{\text{aliased}}$, $A^{tr}{=}A_1$

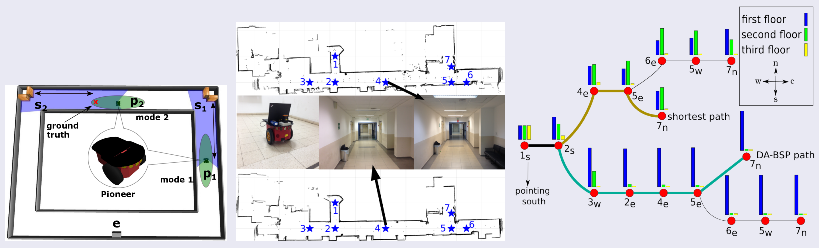
Figure: DA-BSP for a single observation z_{k+1}. Red-dotted ellipse denotes $b[X^-_{k+1}]$, while the true pose that generated z_{k+1} is shown by inverted triangle. Smaller ellipses are the posterior beliefs $b[X^{i+}_{k+1}]$. *Top row* x^{tr} is near center, observing A_2; *bottom row* x^{tr} is on the left, observing A_1. Columns represent different perceptual aliasing cases. Weights w_i and $\tilde{w}_i$, corresponding to each scene A_i are shown in the inset bar-graphs.

Comparison with state of the art

Table: Evaluating DA-BSP

config			cost		metrics	
			KL_u	Worst-Cov	modes	η_{da}
compare	DA-BSP	plan	2.60	5.48	21	**0.41**
		infer	8.14	5.08	4	**0.26**
	BSP	plan	-8.67	5.36	13	0.29
		infer	-4.35	2.95	2	0
	[5]	plan	-na-	-na-	-na-	-na-
		infer	-63.76	2.82	2	0
DA-BSP	bwd_1	plan	6571.29	28.74	48	0.08
		infer	6567.86	30.53	4	0.08
	fwd_1	plan	-1160.93	6.22	22	0.18
		infer	-1300.72	6.98	2	0.16
	fwd_2	plan	-166.03	0.66	2	1
		infer	-227.03	0.91	1	1

Real-world



(a) Counter-example (b) Real world (c) Partial decision tree

Figure: Using Pioneer robot in simulation and real-world. (a) a counter-example for hypothesis reduction in absence of pose-uncertainty in prior (b) two (of three) severely-aliased floors, and belief space planning for it (c) DA-BSP can plan for fully disambiguating path (otherwise sub-optimal) while usual BSP with *maximum likelihood* assumption can not

To wrap up

- Data association was incorporated within belief space planning (DA-BSP)
- DA-BSP is more general form of plan-infer framework of BSP
  - Other approaches are degenerate cases of it
  - Affords active disambiguation in a formal framework
  - Is a crucial step towards realistic long term planning & autonomy
- Parsimonious data association
  - Not all possible associations have significant weights
  - More effective strategies of pruning are currently explored

Funded by: **Israel Science Foundation (ISF) and Technion Autonomous System Program (TASP)**