Non-myopic data association aware BSP for robust active and passive inference

Shashank Pathak, Antony Thomas, Vadim Indelman
{shashank,antony.thomas,vadim.indelman}@technion.ac.il

ANPL Autonomous Navigation and Perception Lab

TECHNION Israel Institute of Technology

State of the art in belief space planning

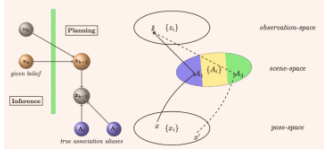
Assumes that the data association is given and perfect

Our contribution

We relaxed this assumption to incorporate ambiguous data association within belief space planning.

This resulted in a general framework for robust active and passive perception

Additionally, ambiguity is correctly accounted for where number of components in the belief may rise if needed so.

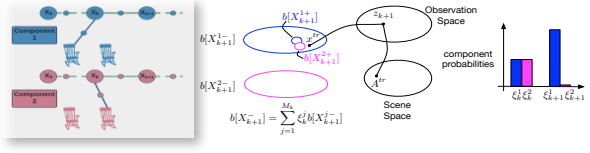


Approach

A general GMM belief is maintained (in the prior and the posterior)

The posterior is conditioned on each plausible scene that could have generated the observation

Weights of the components of the posterior are computed analytically within the BSP formulation (*details in the paper*)



Devising the algorithm

Usual belief space planning has: $\mathbb{P}(X_k|\mathcal{H}) = \mathbb{P}(x_0)\prod_{i=1}^{k}\mathbb{P}(x_i|x_{i-1},u_{i-1})\mathbb{P}(Z_i|x_i,A_i)$

$$J(u_k) = \mathop{\mathbb{E}}_{z_{k+1}}\{c(\mathbb{P}(X_{k+1}|\mathcal{H}^-_{k+1}, z_{k+1}))\}$$

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

In contrast, we consider all plausible scenes:

$$\mathbb{P}(z_{k+1}\,|\,\mathcal{H}^-_{k+1}) \equiv \sum_i \int_x \mathbb{P}(z_{k+1}, x, A_i\,|\,\mathcal{H}^-_{k+1}) \doteq \sum_i w_i$$

We show: $\mathbb{P}(A_i \mid z_{k+1}, \mathcal{H}^-_{k+1}) = \eta w_i \doteq \tilde{w}_i$

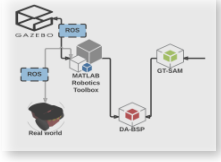
Consequently: $J(u_k) = \int_{z_{k+1}} (\sum_i w_i) \cdot c\left(\sum_i \tilde{w}_i b[X^{i+}_{k+1}]\right)$

Implementing the algorithm

GTSAM is used for efficient inference via factor graphs

To design arbitrary levels of ambiguity in the real world, **AprilTag** is used

Matlab toolbox for ROS as well as **Gazebo** are used as well



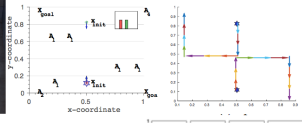
Comparing the algorithm

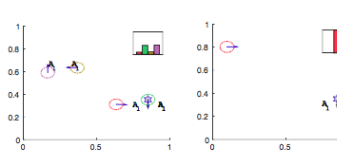
We compared our approach against algorithms that choose most-likely data associations using some deterministic heuristics (BSP-u and BSP-m).

Details in the paper.

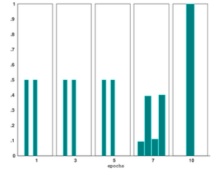
Results – explicit scenes (AprilTags as objects)

For a given trajectory, perform **data association aware** belief space planning in a **perceptually aliased** world





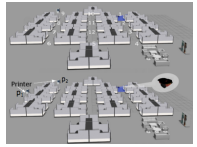
Epoch 7

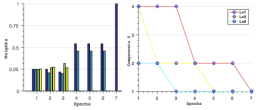


GMM weights of corresponding beliefs in DA-BSP. Epochs {1,3,5,7,10}.

Results – implicit scenes (laser scans as observations)

A **perceptually aliased** world in Gazebo simulator, with the robot equipped with laser scanner.





Most-likely association results in incorrect association

Algorithm	Epoch	$L=2$ t(s)	$(\eta_{fp}, \bar{m})$	DA	$L=4$ t(s)	$(\eta_{fp}, \bar{m})$	DA	Inference t(s)	$(\eta_{fp}, \bar{m})$	DA
DA-BSP	1	81.04	(0.25,4)	✓	307.95	(0.25,4)	✓	4.95	(0.25,4)	✓
	2	64.41	(0.27,4)	✓	97.60	(0.35,2)	✓	5.05	(0.25,4)	✓
	5	4.91	(0.51,2)	✓	8.56	(1,1)	✓	1.03	(0.49,2)	✓
	7	0.57	(1,1)	✓	0.57	(1,1)	✓	0.54	(1,1)	✓
		t(s)	η	DA	t(s)	η	DA	t(s)	η	DA
BSP-u	1	2.86	1	✓	4.84	1	✓	0.88	1	✓
	2	0.56	1	✓	0.91	0	×	0.32	1	✓
	5	0.54	1	✓	0.89	0	×	0.33	1	✓
	7	0.20	0	×	0.24	0	×	0.16	0	×

Summary

Incorporating data association within belief space planning affords a **general framework for active & passive perception**. It **scales** suitably well and **avoids** catastrophic inference by **correctly** accounting for uncertain associations.