Data Association Aware Belief Space Planning (DA-BSP)

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We argue for incorporating data association within plan-infer framework of belief space planning (BSP). We show that 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.

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**:

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

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

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

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

- **computing (b)**:

$$\sum_i \mathbb{P}(X_{k+1} \mid \mathcal{H}^-_{k+1}, z_{k+1}, A_i) \cdot \mathbb{P}(A_i \mid \mathcal{H}^-_{k+1}, z_{k+1}) = \sum_i \tilde{w}_i b[X^{i+}_{k+1}]$$

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

Algorithm

Data association aware belief-space planning

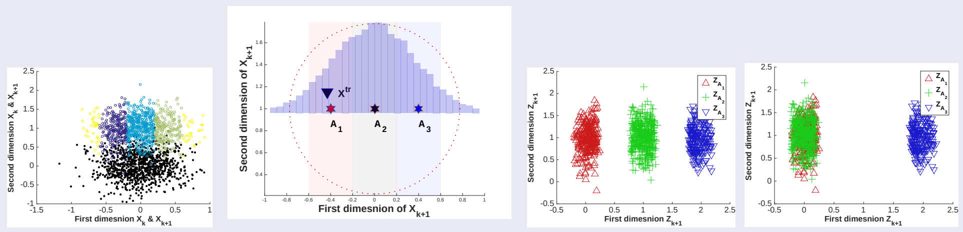
Input: Current belief $b[X_k]$ at step-k, history $\mathcal{H}_k$, action u_k, scenes $\{A_\mathbb{N}\}$, event likelihood $\mathbb{P}(A_i \mid \mathcal{H}_k, x)$ for each $A_i \in \{A_\mathbb{N}\}$

$b[X^-_{k+1}] \leftarrow b[X_k]\mathbb{P}(x_{k+1} \mid x_k, u_k)$
$\{z_{k+1}\} \leftarrow$ SimulateObservations($b[X^-_{k+1}], \{A_\mathbb{N}\}$)
$J \leftarrow 0$
for $\forall z_{k+1} \in \{z_{k+1}\}$ **do**
  $w_s \leftarrow 0$
  for $i \in [1 \ldots |A|]$ **do**
    ▷ compute weight
    $w_i \leftarrow$ CalcWeights($z_{k+1}, \mathbb{P}(A_i \mid \mathcal{H}^-_{k+1}, x), b[X^-_{k+1}]$)
    $w_s \leftarrow w_s + w_i$
    ▷ Calculate posterior belief given A_i
    $b[X^{i+}_{k+1}] \leftarrow$ UpdateBelief($b[X^-_{k+1}], z_{k+1}, A_i$)
  end for
  $\{\tilde{w}_i\} \leftarrow$ NormalizeWeights($\{w_i\}$)
  $c \leftarrow$ CalcCost($\{\tilde{w}_i\}, \{b[X^{i+}_{k+1}]\}$)
  $J \leftarrow J + w_s \cdot c$
end for
return J

end

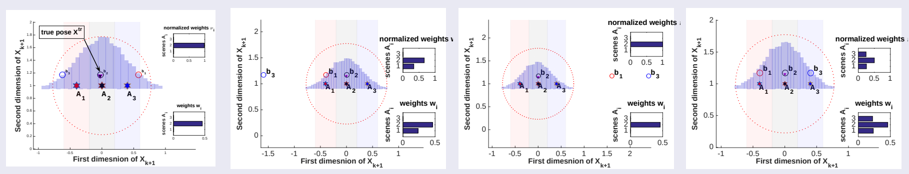
Experimental results

Abstract example

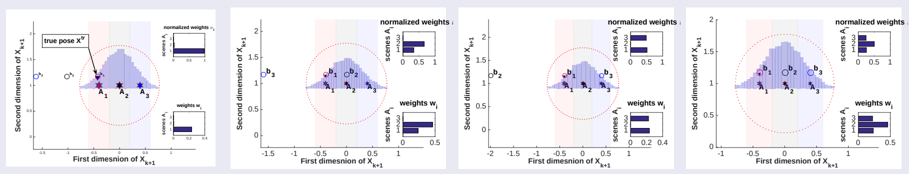


(a) Sampled viewpoints (b) Event likelihood $\mathbb{P}(A_i|x, \mathcal{H})\ \forall i$ (c) No aliasing (d) $\{A_1, A_3\}_{\text{aliased}}$

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 $\{x_{k+1}\}$ 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 $\{A_1, A_3\}_{\text{aliased}}$.



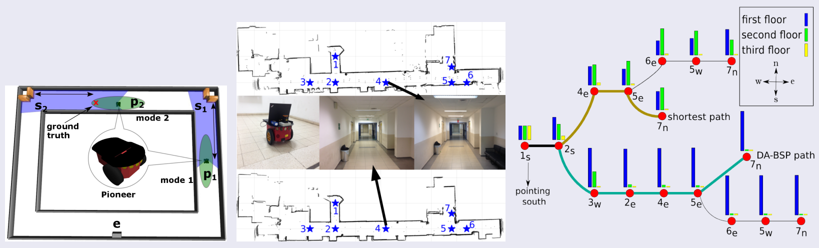
(a) No aliasing, $A^{tr} = A_1$, $A^{tr} = A_2$ (b) $\{A_1, A_2\}_{\text{aliased}}$, $A^{tr} = A_2$ (c) $\{A_1, A_3\}_{\text{aliased}}$, $A^{tr} = A_2$ (d) $\{A_1, A_2, A_3\}_{\text{aliased}}$, $A^{tr} = A_2$



(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.

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

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