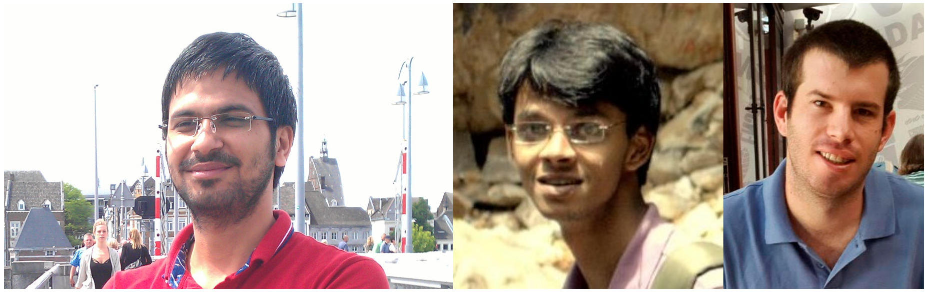
TECHNION
Israel Institute
of Technology

Autonomous Navigation
and Perception Lab (ANPL)

Towards Robust Autonomous Navigation in Perceptually Aliased GPS-deprived Environments

Vadim Indelman

Collaborators: Shashank Pathak, Antony Thomas, Asaf Feniger



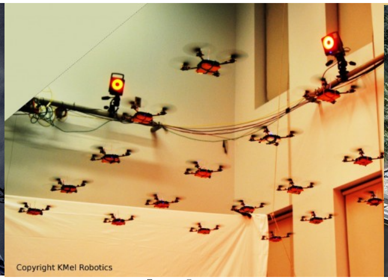
IAAC workshop “Navigation Systems and Applications”, February 2016

Introduction

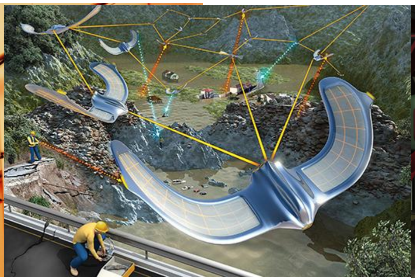
- **Autonomous navigation involves:**
  - **Inference (estimation)**: **Where am I?**
  - **Perception**: **What is the environment perceived by sensors?**
    e.g.: What am I looking at? Is that the same scene as before?
  - **Planning**: **What is the next best action(s) to realize a task?**
    e.g.: where to look or navigate next?

Inference	Perception	Planning

Urban
IROS 2013 workshop

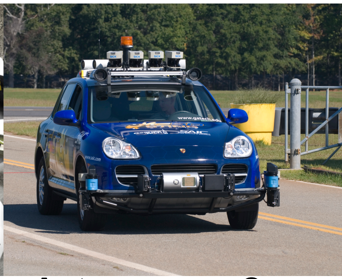


Indoor
Upenn



Aerial sensor network
EPFL

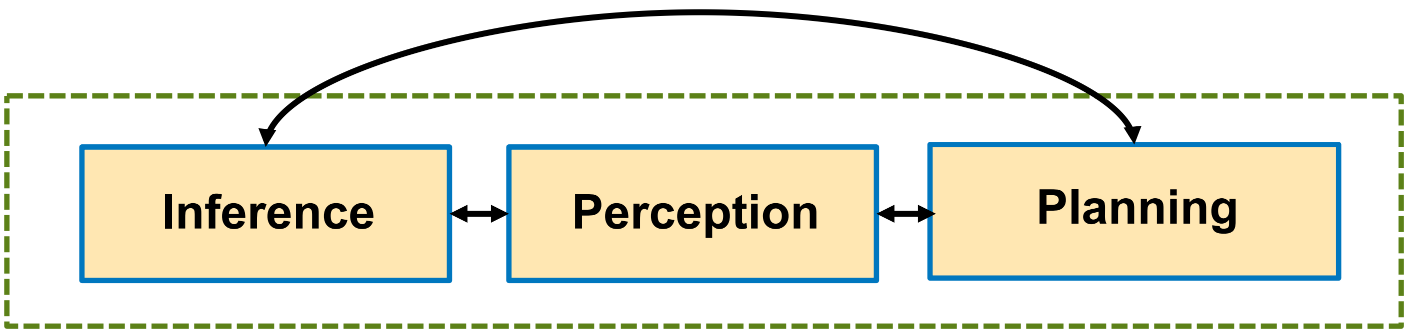
Humanoids
DARPA Challenge



Autonomous Cars
Georgia Tech

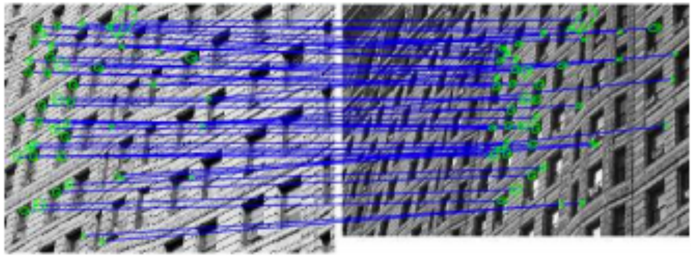
Introduction - Belief Space Planning

- Belief space planning and decision making under uncertainty
  - Determine best action(s) while accounting for different sources of uncertainty (stochastic control, imperfect sensing, uncertain environment)
  - Fundamental problem in robotics and AI



Motivation

- What happens if the environment is ambiguous, perceptually aliased?
  - Identical objects or scenes
  - Objects or scenes that appear similar for some viewpoints
- Examples:
  - Two corridors that look alike
  - Similar in appearance buildings, windows, …
- What if additionally, we have localization (or orientation) uncertainty?



Noury et al., AVC'10

Images from Angeli et al.,TRO'08

Motivation

- What happens if the environment is ambiguous, perceptually aliased?
  - Identical objects or scenes
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- Examples:
  - Two corridors that look alike
  - Similar in appearance buildings, windows, …
- What if additionally, we have localization (or orientation) uncertainty?

- Data association is particularly challenging
- Incorrect assocation (*wrong* scene) can be catastrophic
- **Can we incorproate these aspects within decision making?**

Contribution

- We develop a belief space planning (BSP) algorithm, considering both
  - **Ambiguous data association** due to perceptual aliasing, and
  - **Localization uncertainty** due to stochastic control and imperfect sensing
- Our approach - **Data association aware belief space planning (DA-BSP):**
  - Relaxes common assumption in BSP regarding known and perfect DA
  - To that end, we incorporate reasoning about DA within BSP

Relation to Prior Work

- **Belief space planning (BSP) approaches**:
  - Typically assume data association (DA) to be given and perfect
  - We relax this assumption by incorporating reasoning about DA into BSP

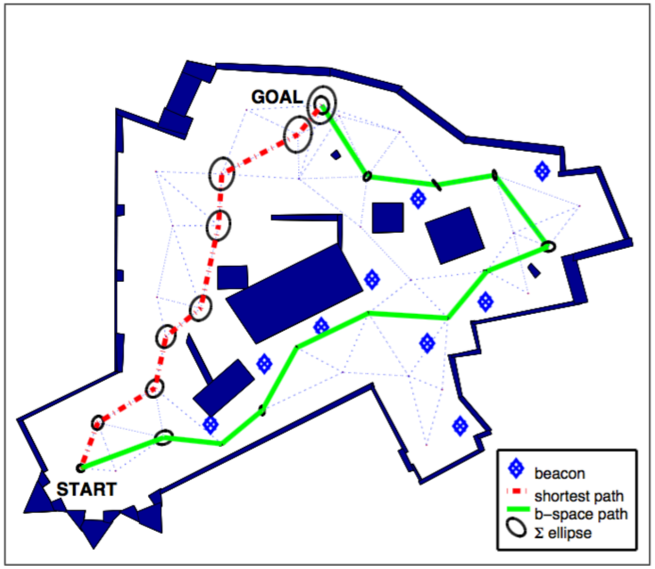


Image from Prentice et al., IJRR'09

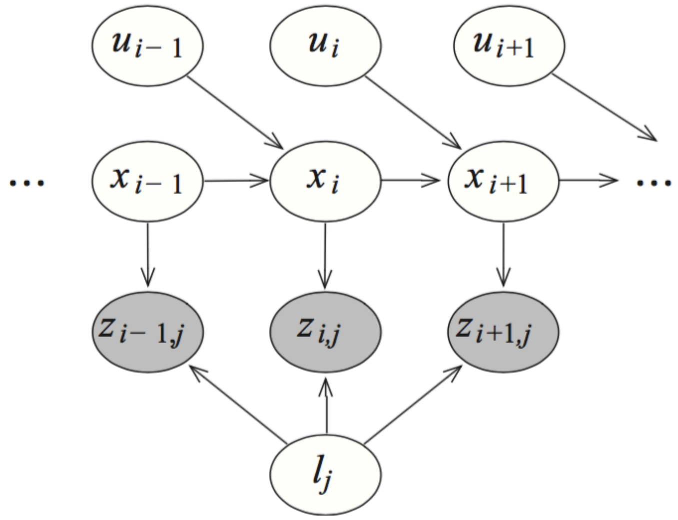
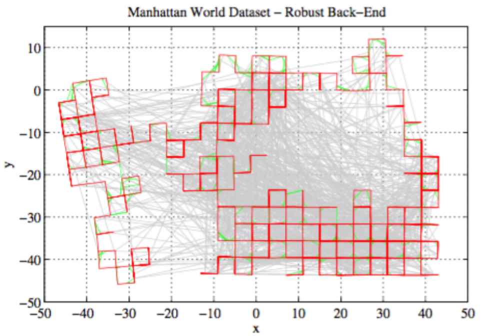
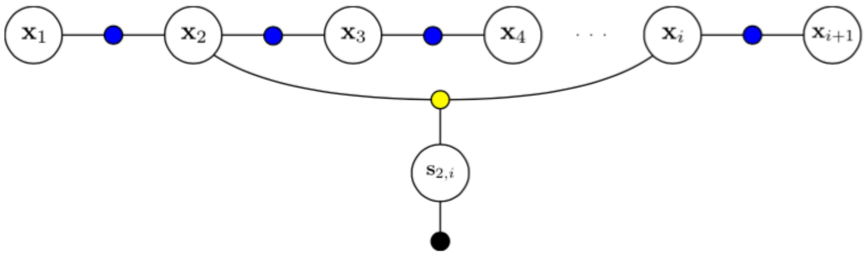


Image from Indelman et al., IJRR'15

Relation to Prior Work

- **Robust graph optimization approaches**:
  - Attempt to be resilient to incorrect data association (outliers overlooked by front-end algorithms, e.g. RANSAC)
  - Only consider the **passive** case (actions/controls are given)
  - In contrast, we consider the **active** case (belief space planning)

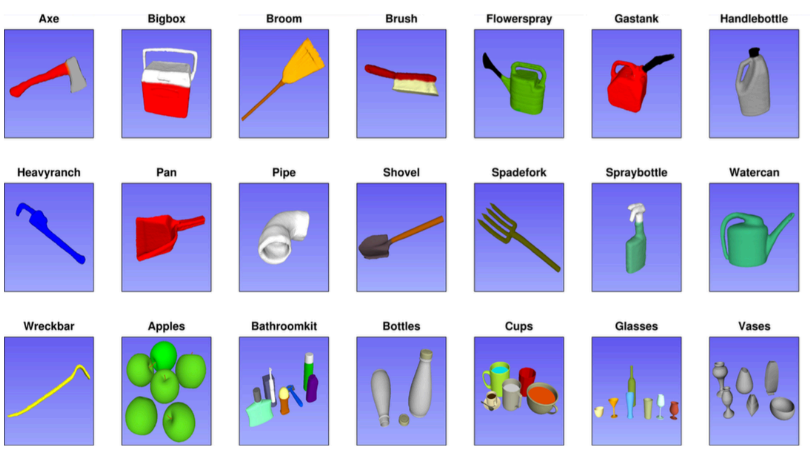


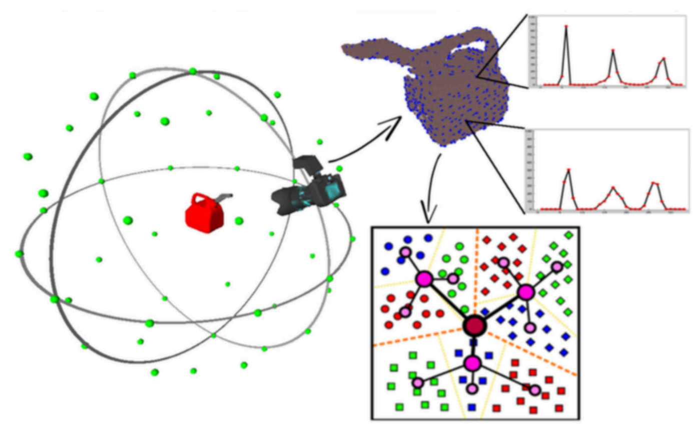


Images from Sünderhauf et al., ICRA'12

Relation to Prior Work

- **Active hypothesis disambiguation, active object classification**
  - Approaches aim to find sequence of future viewpoints to determine the correct hypothesis
  - Assume sensor is perfectly localized, belief is only about the hypotheses
  - Our approach considers both localization uncertainty and data association aspects within the belief



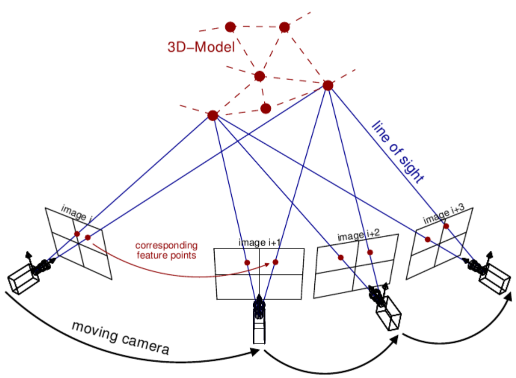


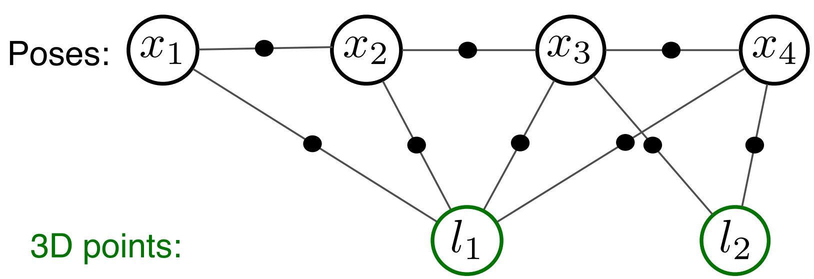
Images from Atanasov et al., TRO'14

Formulation

- Consider a robot operating in a partially known environment
- The robot takes observations of different scenes or objects as it travels (e.g. images, laser scans)
- These observations are used to infer random variables of interest (e.g. robot pose)

- For example, visual SLAM: $$p\left(X_k|\mathcal{Z}_k,\mathcal{U}_{k-1}\right) = priors \cdot \prod_{i=1}^{k} p\left(x_i|x_{i-1},u_{i-1}\right)p\left(z_i|X_i^o\right)$$





Formulation

- Motion model: $p(x_{i+1}|x_i, u_i)$ $\quad x_{i+1} = f(x_i, u_i) + w_i \quad w_i \sim \mathcal{N}(0, \Sigma_w)$
- Observation model: $p(z_k|x_k, A_i)$ $\quad z_k = h(x_k, A_i) + v_k \quad v_k \sim \mathcal{N}(0, \Sigma_v)$

i-th scene or object

- Belief at current time k: $b[X_k] \doteq p(X_k|u_{0:k-1}, z_{0:k})$

- Belief at a *future* time k+1, given control: $b[X_{k+1}] \doteq p(X_{k+1}|u_{0:k}, z_{0:k+1})$
- Objective function (single look ahead step):

$$J(u_k) \doteq \underset{z_{k+1}}{\mathbb{E}} \{c(p(X_{k+1}|u_{0:k}, z_{0:k+1}))\} \equiv \underset{z_{k+1}}{\mathbb{E}} \{c(b[X_{k+1}])\}$$

- Optimal control: $u_k^\star \doteq \underset{u_k}{\arg\min}\, J(u_k)$

Formulation

$$J(u_k) \doteq \underset{z_{k+1}}{\mathbb{E}} \{c(p(X_{k+1}|u_{0:k}, z_{0:k+1}))\} \equiv \underset{z_{k+1}}{\mathbb{E}} \{c(b[X_{k+1}])\}$$

- Given: a candidate action(s) and $b[X_k]$
- Reason about a future observation z_{k+1} (e.g. an image) to be obtained once this action is executed
- Consider all possible values such an observation can assume (expectation)
- For each case, calculate cost over posterior belief

- Write expectation explicitly:

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

$$\mathcal{H}^-_{k+1} \doteq \{u_{0:k}, z_{0:k}\}$$

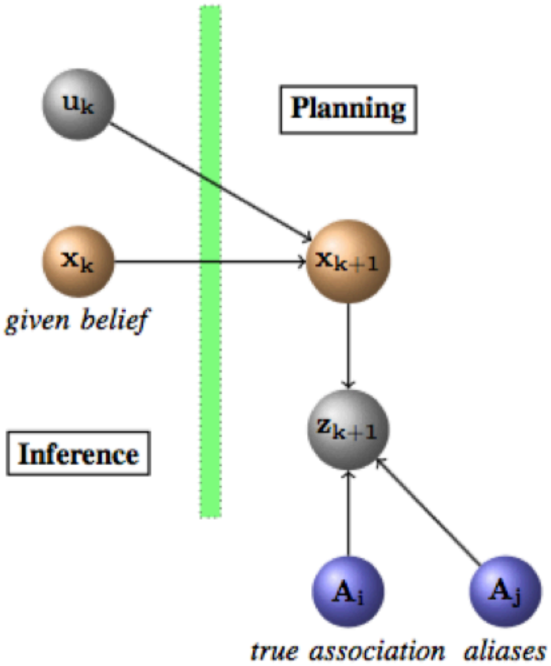
Formulation

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

- Known and perfect data association means:

$$b[X_{k+1}] = \eta \mathbb{P}(X_k | \mathcal{H}_k) \mathbb{P}(x_{k+1} | x_k, u_k) \mathbb{P}(z_{k+1} | x_{k+1}, A_i).$$

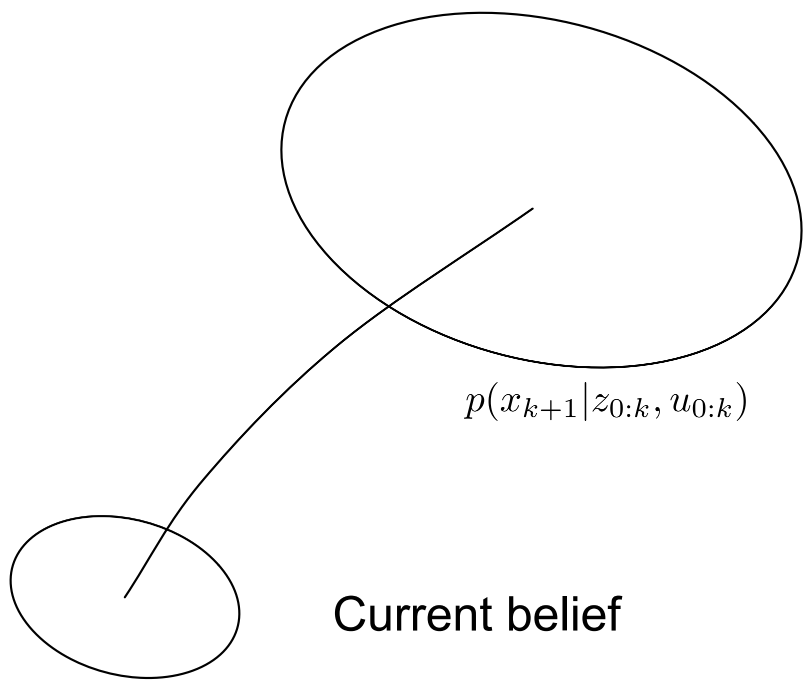
  - Scene/object Ai is **known** and **correct**
  - Typical assumption in belief space planning



Concept

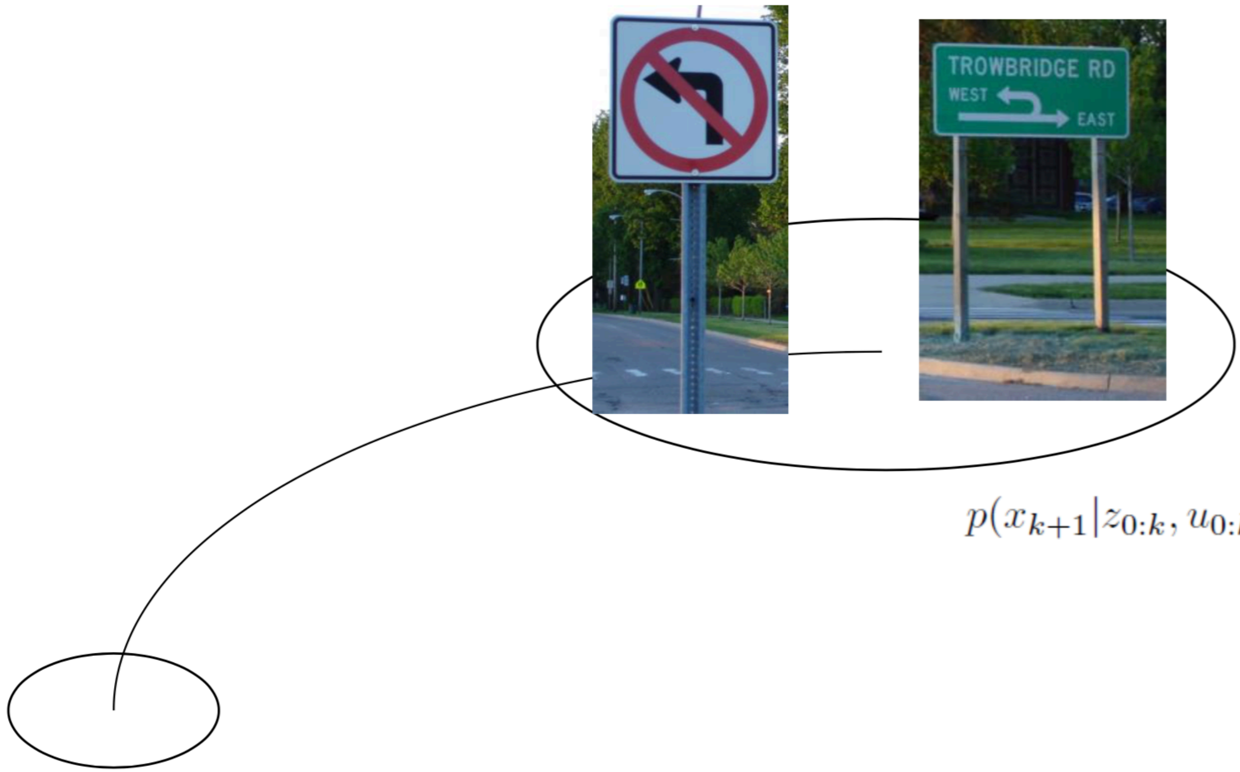
$$J(u_k) \doteq \int_{z_{k+1}} \overbrace{\mathbb{P}(z_{k+1} \mid \mathcal{H}^{-}_{k+1})}^{(a)} \; c\left(\overbrace{\mathbb{P}(X_{k+1} | \mathcal{H}^{-}_{k+1}, z_{k+1})}^{(b)} \right)$$

- However, it is unknown from what actual pose x_{k+1} future observation will be acquired z_{k+1}
- Robot pose x_{k+1} can be anywhere within $b[x^{-}_{k+1}] \doteq p(x_{k+1}|z_{0:k}, u_{0:k})$



Concept - Intuition

Distinct scenes

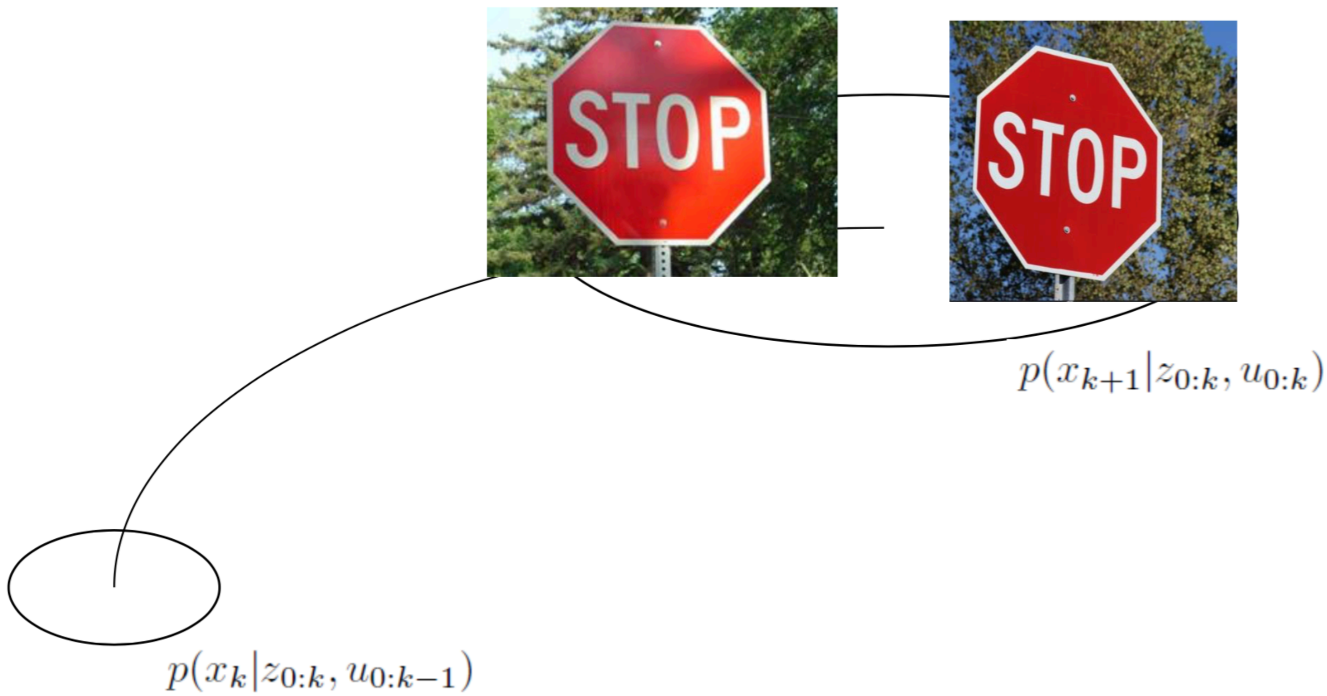


$p(x_{k+1}|z_{0:k}, u_{0:k})$

$p(x_k|z_{0:k}, u_{0:k-1})$

Concept - Intuition

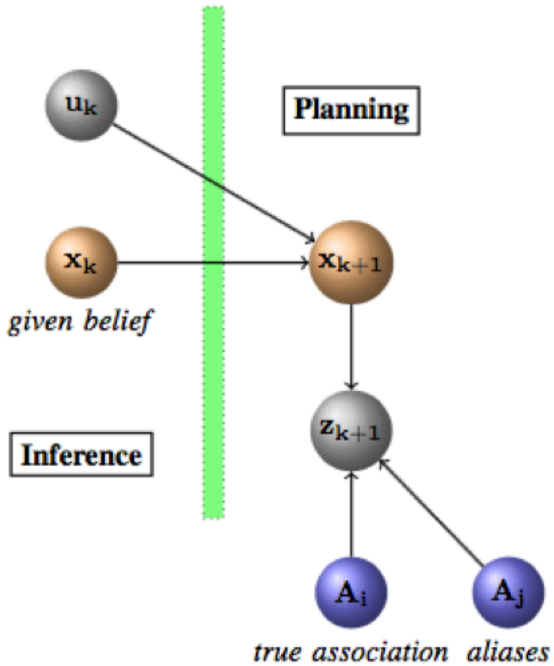
Perceptually aliased scenes

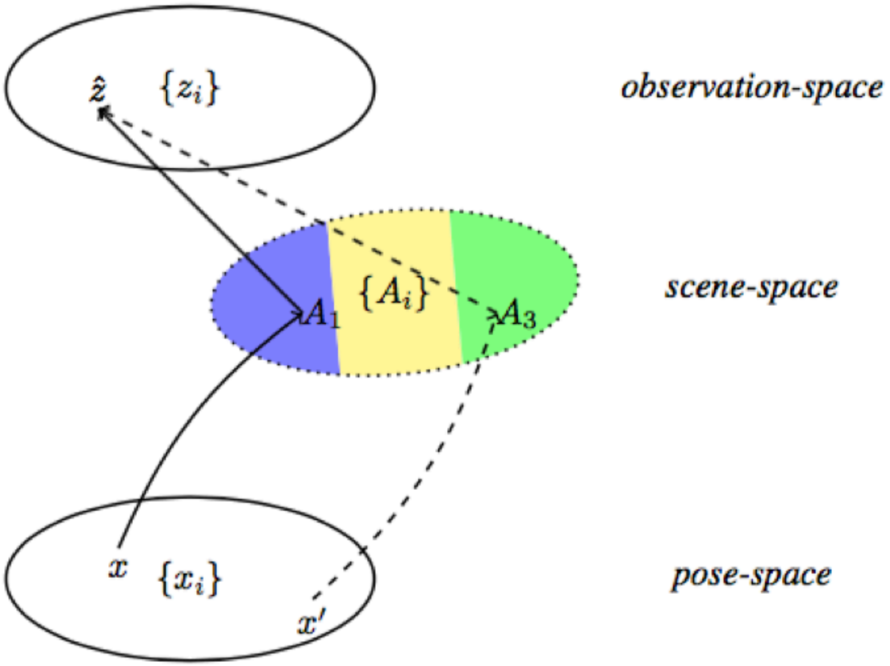


Concept

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

- In presence of perceptual aliasing, the **same observation** could be obtained from **different poses** viewing **different scenes**





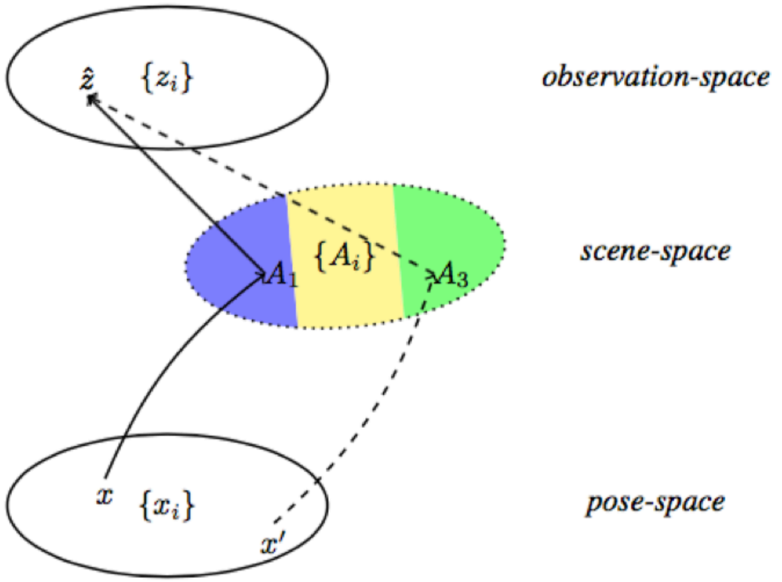
How to capture this fact within belief space planning?

Key Idea

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

- Reason about possible scenes (or objects) that each possible future observation z_{k+1} *could* be generated from

- Re-interpret terms (a) and (b), as:
  - (a): likelihood of a specific z_{k+1} to be captured
  - (b): posterior *given* that specific z_{k+1}



More details in the next slide(s)

Key Idea

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

- **(a)**: likelihood of a specific z_{k+1} to be captured
  - Consider a given environment map/model, and a partitioning to scenes:

$$\{A_{\mathbb{N}}\} = \{A_1, A_2, \ldots\}$$

  - Consider from what scene(s) observation z_{k+1} *could* be generated
  - Calculate corresponding likelihood for each A_i
    (while accounting for all viewpoints x_{k+1} according to $b[x_{k+1}^{-}]$)
    - Treat as weight w_i
  - Sum up all weights:

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

Key Idea

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

- <u>**(b)**: posterior *given* a specific observation z_{k+1}.</u>
  - Observation is given, hence, **must** capture **one** (unknown) scene A_i
  - Which one? Consider all possibilities

$$\sum_i \mathbb{P}(X_{k+1} \mid \mathcal{H}_{k+1}^{-}, z_{k+1}, A_i) \cdot \underline{\mathbb{P}(A_i \mid \mathcal{H}_{k+1}^{-}, z_{k+1})}$$

Posterior, given A_i — normalized weight $\tilde{w}_i$

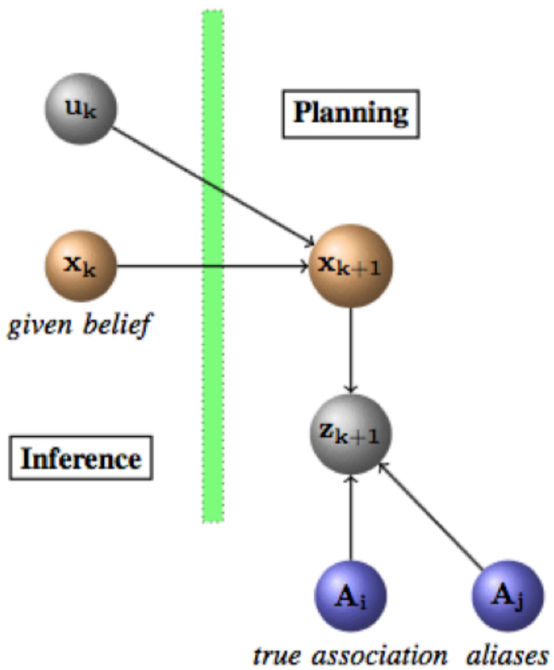
- Thus:

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

Perceptual Aliasing Aspects

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

- No perceptual aliasing:
  - Only **one** non-negligible weight $\tilde{w}_i$
  - Corresponds to the true scene A_i
  - Reduces to state of the art belief space planning
- With perceptual aliasing:
  - Multiple non-negligible weights $\tilde{w}_i$
  - Correspond to aliased scenes, given z_{k+1}
  - Posterior **becomes a mixture of pdfs**
  - Can now reason about **active disambiguation**

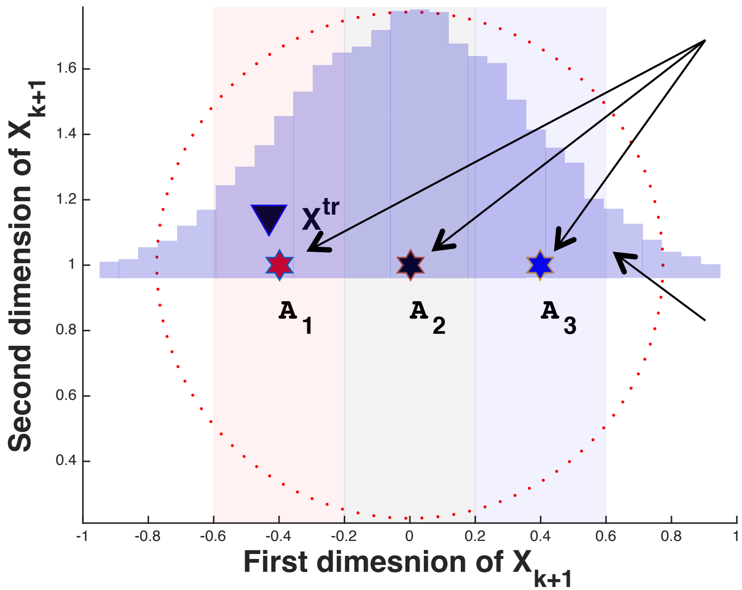


Basic Example

- Consider a simplified world of only 3 scenes $\{A_1, A_2, A_3\}$
- Control aliasing by modifying parameter s_i in observation function

$$h(x, A_i) = h_i(x) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \cdot (x - x_i) + s_i$$

- Simulate future observations $\{z_{k+1}\}$ via sampling



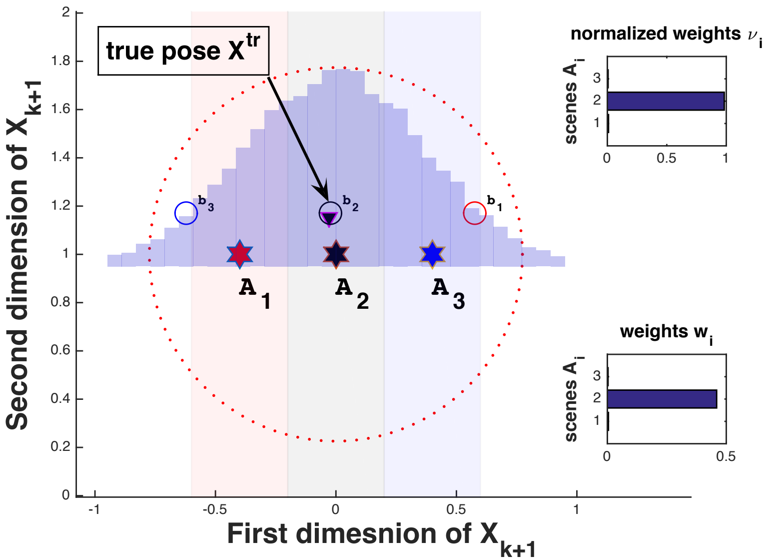
Scenes/objects

Stripes: viewpoints from which each scene is observable

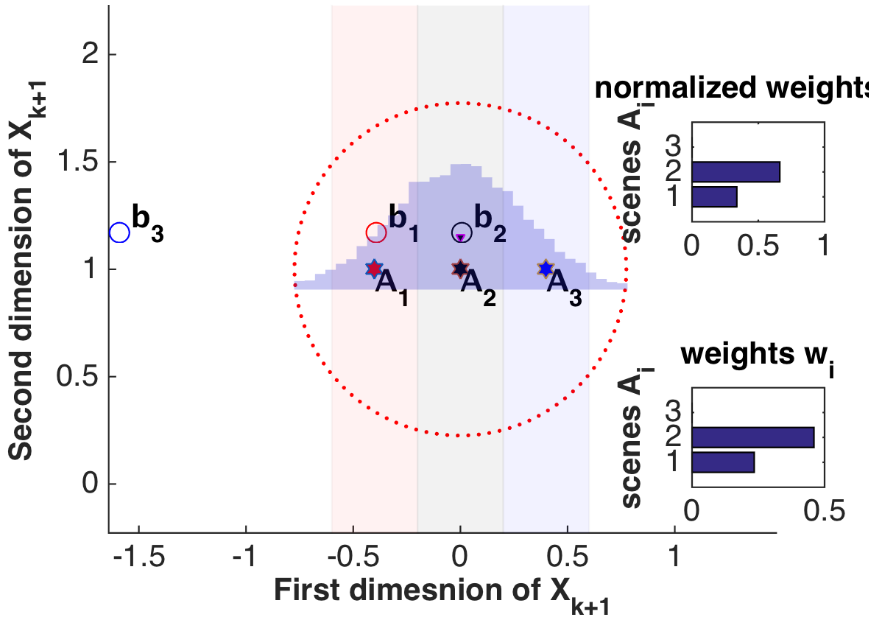
Histogram over samples representing propagated belief $b[x^-_{k+1}]$

Basic Example

No Aliasing, **true** scene is A2

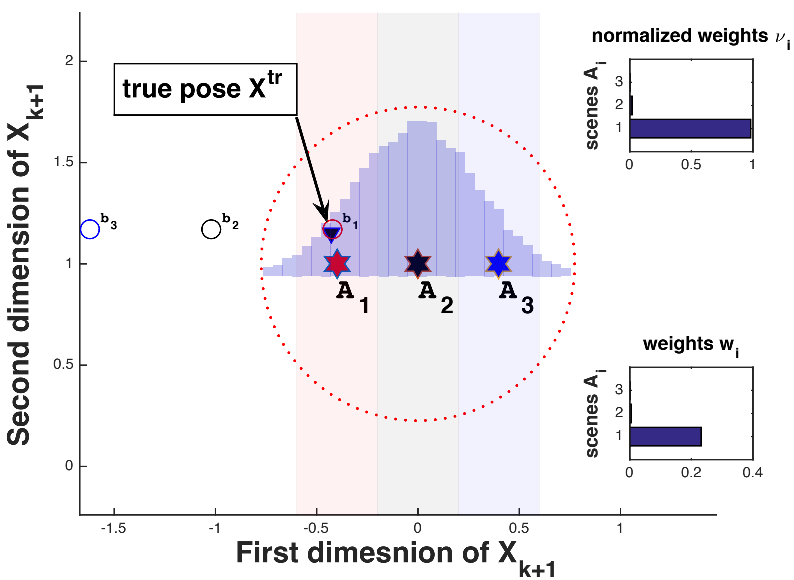


A1 and A2 are aliased, **true** scene is A2

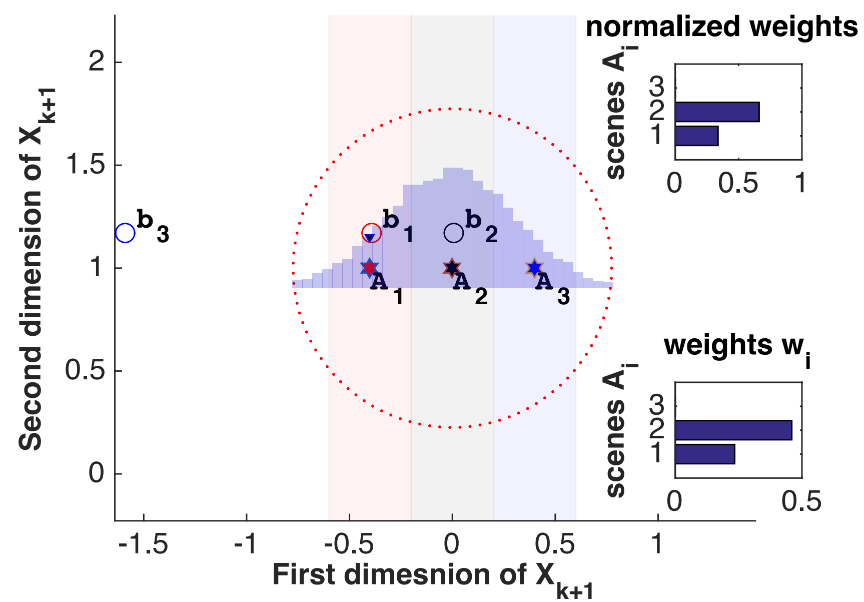


Basic Example

No Aliasing, **true** scene is A1



A1 and A2 are aliased, **true** scene is A1



Gazebo Example: Active Disambiguation

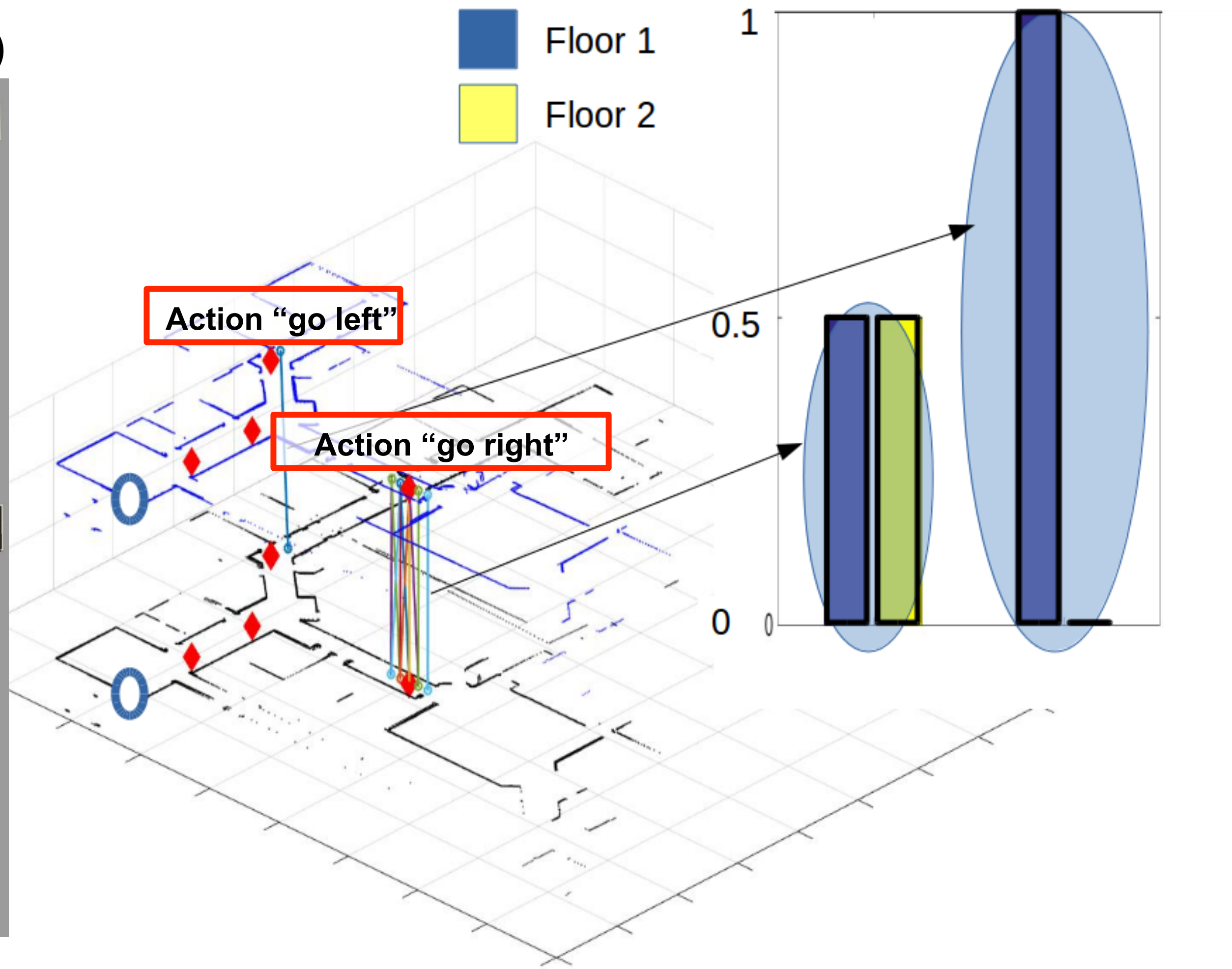
- **Scenario**:
  - Indoor navigation in a 2-story building
  - Two floors are **roughly identical**, except for the upper left corridor
  - Setup: map is given, laser sensor
  - Robot is uncertain on what floor it is
- **Goal**: disambiguate situation, i.e. determine correct floor

Gazebo Example: Active Disambiguation

Figure shows inter-floor ICP matches, for each candidate action

Floor maps (assumed given)

% of successful matches per floor



Conclusions

- **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
  - Ongoing research
  - Numerous applications

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