ANPL Autonomous Navigation and Perception Lab

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Hypotheses Disambiguation in Retrospective

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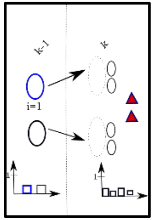
Motivation

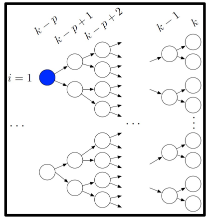
Relaxing the DA **(Data Association)** assumption can produce a Gaussian Mixture model (GMM) belief at a given time.

Current approaches in this field examine the state distribution at **current time.**

Our contribution

- ✓ Re-evaluation of **a strategic past event/point** using current information.
- ✓ Incremental calculation
- ✓ Past DA re-evaluation.
- ✓ Enhance hypotheses pruning





Problem formulation

Relaxing the DA assumption results in marginalization over possible associations.
Each i'th hypothesis is multiplied by a corresponding weight.

$$b[X_k] = \sum_{i=1}^{M_k} \underbrace{\mathbb{P}(\gamma_k = i \mid H_k)}_{w_k^i} \cdot \underbrace{\mathbb{P}(X_k \mid \gamma_k = i, H_k)}_{b^i[X_k]}$$

Our work wishes to re-evaluate the weight of a past i'th hypothesis given gathered information till current time.

$$w^i_{k-p|k} \triangleq \mathbb{P}(\gamma_{k-p} = i \mid H_k)$$

Approach

First, we performed our calculation for a single step, **i.e. p=1**.
Performing chain rule and marginalization yields,

$$w^i_{k-1|k} = \underbrace{\frac{\mathbb{P}(z_k \mid \gamma_{k-1} = i, H_k^-)}{\mathbb{P}(z_k \mid H_k^-)}}_{\text{update factor}} \cdot w^i_{k-1}$$

For the general case where we re-evaluate a hypothesis "p" steps from the robot's current time, we receive this following closed formula (m=k-p).

$$w^i_{m|k} = \underbrace{\left[\frac{\prod_{j=1}^{p} \mathbb{P}(z_{m+j} \mid \gamma_m, H^-_{m+j})}{\prod_{j=1}^{p} \mathbb{P}(z_{m+j} \mid H^-_{m+j})}\right]}_{\Psi_{m|k}} \cdot \underbrace{w^i_{m|m}}_{B}$$

In the paper we present an **incremental approach**, where we re-use previous step calculation in each current step.

Specific Data association re-evaluation

A specific DA probability can be described as,

$$\mathbb{P}(\beta_{k-p} \doteq c \mid H_{k-p})$$

In the paper, we suggested to summarize only those realizations that consider a specific DA from time k-p.

$$\mathbb{P}(\beta_{k-p} \doteq c \mid H_{k-p}) \doteq \sum_{i=1}^{M_{k-p}} w^i_{k-p} \mathbb{1}_{\{c\}}(i.r)$$

Therefore, in a direct form, weights re-evaluation will also update a specific DA re-evaluation

$$\mathbb{P}(\beta_{k-p} \doteq c \mid H_k) \doteq \sum_{i=1}^{M_{k-p}} w^i_{k-p|k} \mathbb{1}_{\{c\}}(i.r)$$

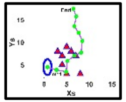
Implementation

The simulation setting is built on eight identical scattered landmarks.

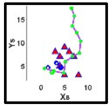
The simulation was built from two sections.

First, calculate the GMM at the end of the robot's trajectory.

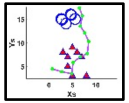
Second, perform re-evaluation a single step from the initial belief.



K = 0



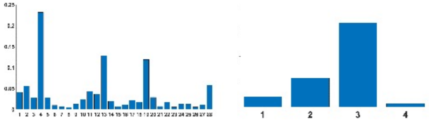
K = 1



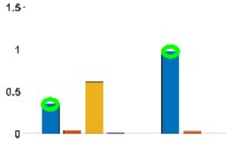
K = 10

Results

The figures below show ambiguous hypotheses at k=10, with or without merging.

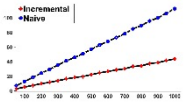


At the re-evaluation point, k=1, we can see that given current information allows us to perform full disambiguation .

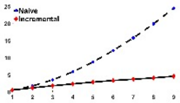


$w^i_{1|1}$ vs $w^i_{1|10}$

Run time analysis



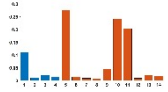
Runtime as a function of samples

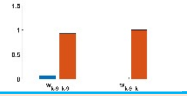


Runtime as a function of *p*

- ✓ Both show an **advantage to calculation re-use** approach.
- ✓ **Runtime as a function of *p*** in the incremental approach is small in one order than the Naïve approach.

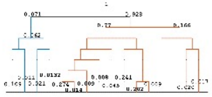
Enhanced pruning

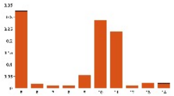




Current belief holds 14 hypotheses, 4 descendants of the blue hypothesis, and 10 of the orange one.

Performing re-evaluation at k=1, allows full disambiguation of the blue hypothesis.





Therefore, all its descents in the GMM hypothesis tree, can be pruned, specifically at current time.

Summary

- ✓ New information can have an impact on our ability to **disambiguate between past hypotheses**.
- ✓ Calculations **Incremental approach.**
- ✓ Weight re-evaluation can affect a specific DA evaluation, and currently known pruning abilities.