Probabilistic Qualitative Localization and Mapping

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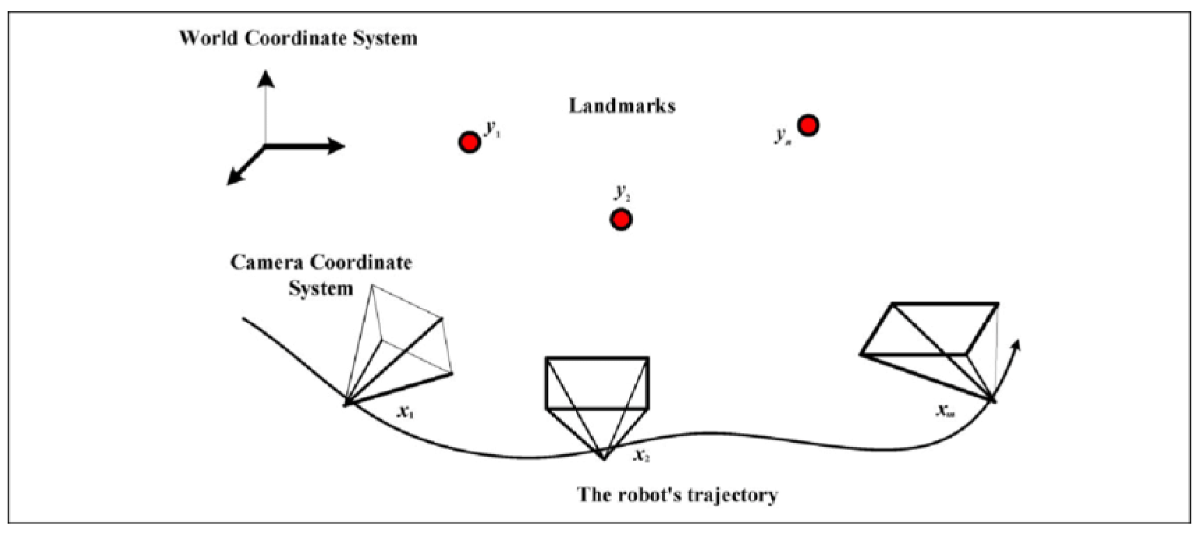
1. Introduction

- **SLAM** – simultaneous localization and mapping, applicable in many applications such as robotics, augmented \ virtual reality etc.



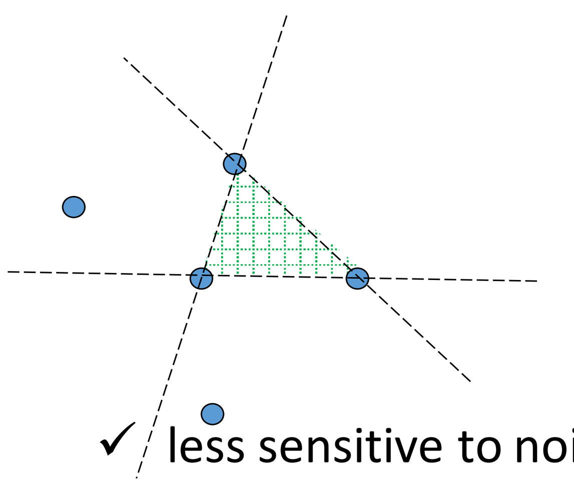
Challenges:

- Accumulated error (Linearization, Measurement noise)
- High complexity (Use many landmarks for filtering and outlier removal)
- long-term online operation in large scale environments

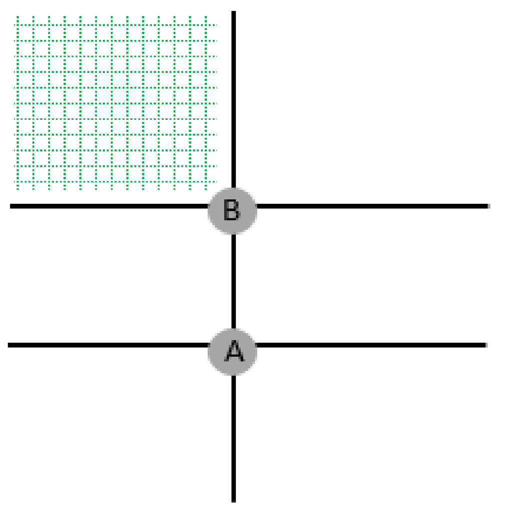
2. Motivation

- **Qualitative spatial reasoning** – easier, and good enough

relative location (no global frame)



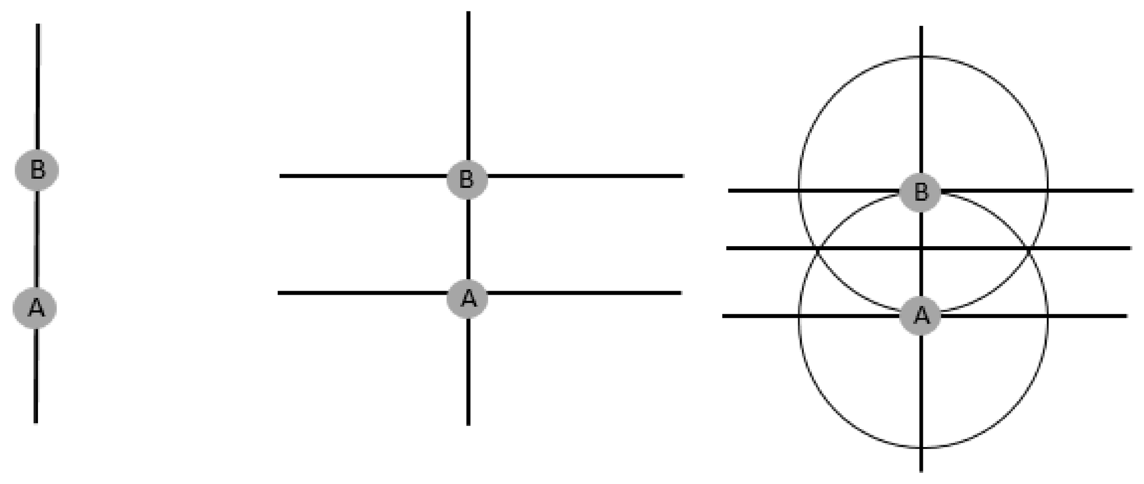
qualitative localization (qualitative geometric relations)



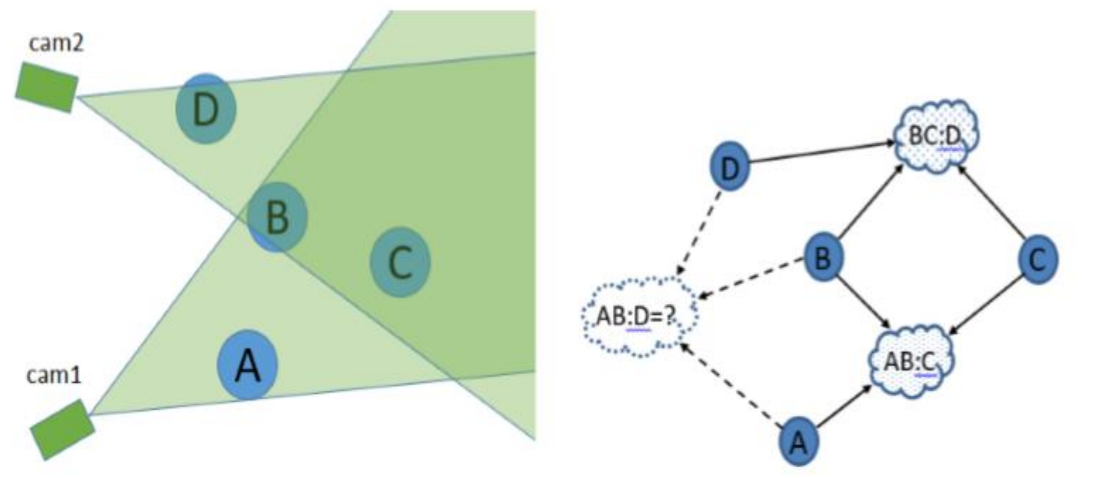
- ✓ less sensitive to noise (large scale, and
- ✓ Low complexity
- ✓ Small number of salient landmarks

3. Concept

Qualitative relational metrics instead of metric location



Map -> connected graph of landmark triplets



[1] Freksa 1992 . On the utilization of spatial structures for cognitively plausible and efficient reasoning.
[2] Schlieder 1993 Representing visible locations for qualitative navigation.
[3] Scivos 2004 The finest of its class: The natural pointbased ternary calculus lr for qualitative spatial reasoning

4. Related work

Spatial Qualitative Reasoning (QSR) approaches:

- Typically assume data association is given
- Address mainly mapping, less localization
- Partially address measurements time dependence
- Partially address measurement spatial dependence

[4] Padgett 2016 Probabilistic qualitative mapping for robots
[5] McClelland,2013 Qualitative relational mapping for planetary rovers

Image taken from McClelland,2013 [5]

5. Contributions

Our approach – probabilistic time and spatial dependent QSR:

- Full probabilistic qualitative localization and mapping framework
- Incorporates <u>motion model</u> (better model time and spatial dependence)
- <u>Composition</u> – qualitative spatial data propagation

These innovations improve performance (both in complexity and accuracy), as well as enable estimation of unseen sets of landmarks

6. Approach

1)

$$\mathbb{P}(S^C|H_n) = \int\cdots\int_{X_{1:n},L_C} \mathbb{P}(S^C|L_C)\mathbb{P}(X_{1:n},L_C|H_n)dL_C dX_{1:n}$$

Qualitative state of landmark C in AB frame Given measurements

Marginalize over metric camera poses and landmark location in relevance to each qualitative state

SLAM

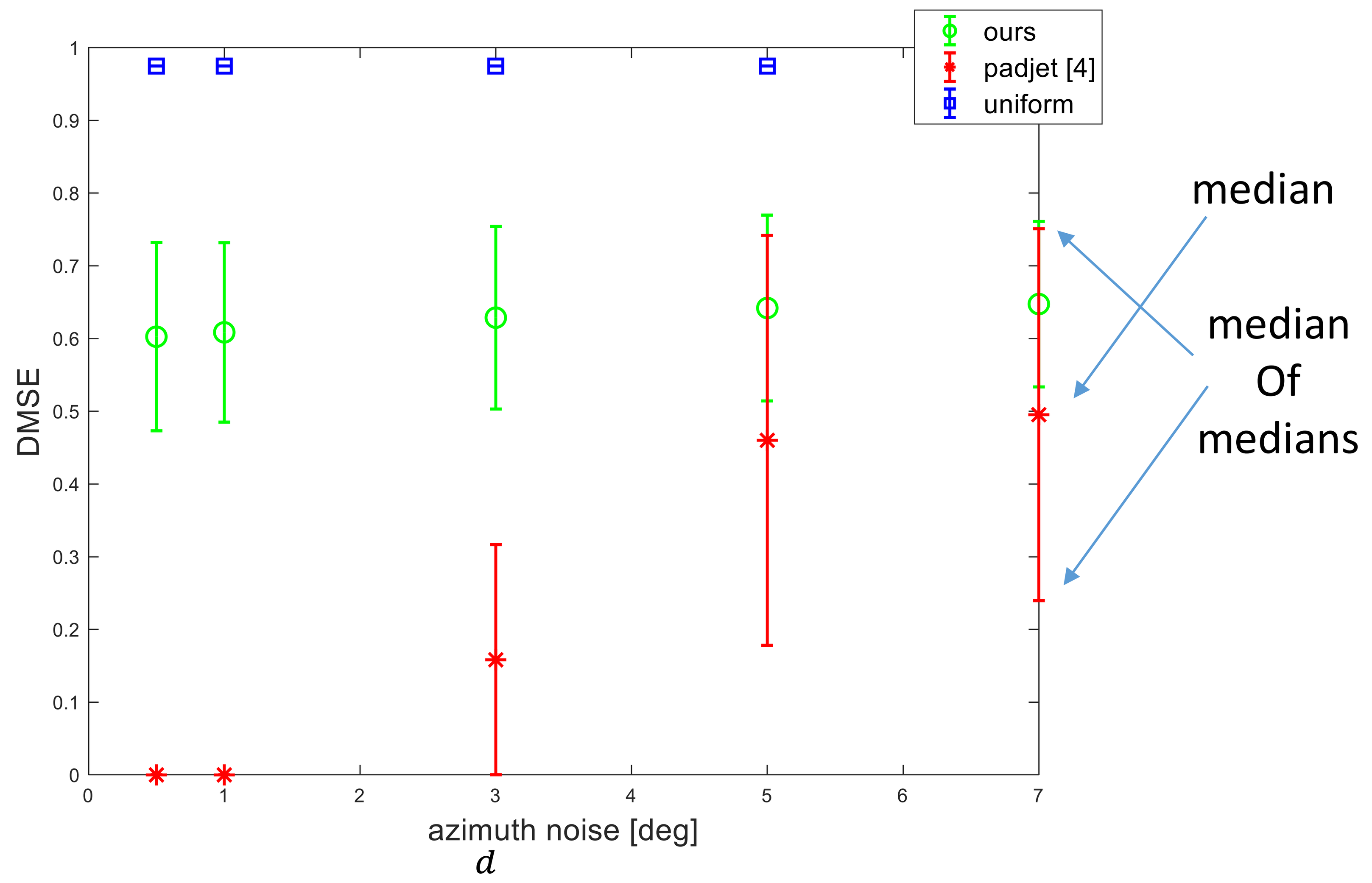
$$\mathbb{P}(X_{1:n},L_C|H_n) = \frac{\mathbb{P}(Z_1|X_1,L_C)\mathbb{P}(X_1,L_C)}{\mathbb{P}(Z_1)} \prod_{i=2}^{n} \frac{1}{\zeta_i} \underbrace{\mathbb{P}(Z_i|X_i,L_C)}_{\text{Measurement model}} \underbrace{\mathbb{P}(X_i|X_{i-1},a_{i-1})}_{\text{Motion model}}$$

- Solve for 3 landmarks and 3 views at a time
- Sampling based solution (no prior, no linearization, no local maxima)

2) Composition: $\mathbb{P}(S^{AB:D}|H^{AB:C},H^{BC:D}) \rightarrow$ Estimate qualitative state given other overlapping triplets

7. Results – MATLAB Simulation

Uniformly sampled scenarios:
(3 landmarks, 3 camera poses, different noise levels)



$$\text{DMSE} = \sum_{i=1}^{d} (P(S_i|H_n) - P(S_i|H_n)_{GT})^2$$

9. Conclusions

- Getting almost perfect results with low noise
- Better performance than state of the art for up to 7° measurement noise
- Low complexity (practical for low compute systems)
- We envision multiple extensions for future work such as active planning