Probabilistic Qualitative Geometry SLAM

Roee Mor

Supervised by assoc. prof. Vadim Indelman

TECHNION
Israel Institute of Technology

ANPL
Autonomous Navigation and Perception Lab

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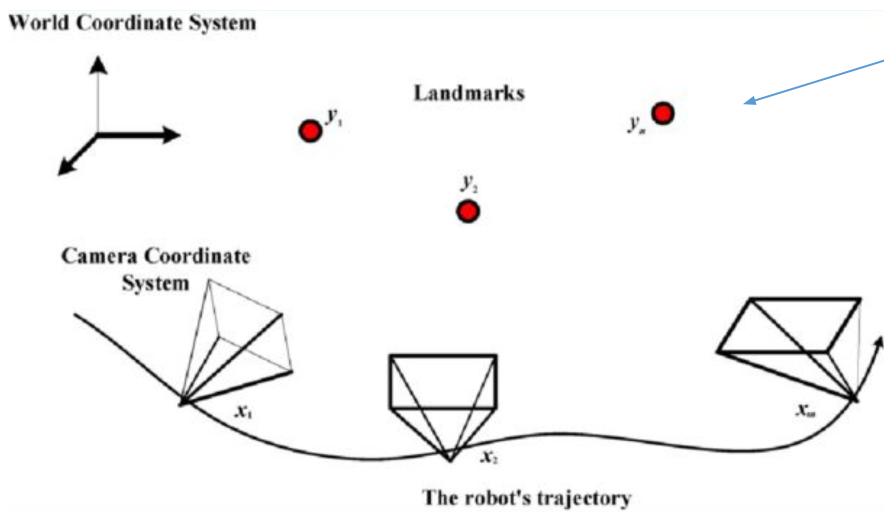
table of contents

Introduction

Introduction

- SLAM – simultaneous localization and mapping:

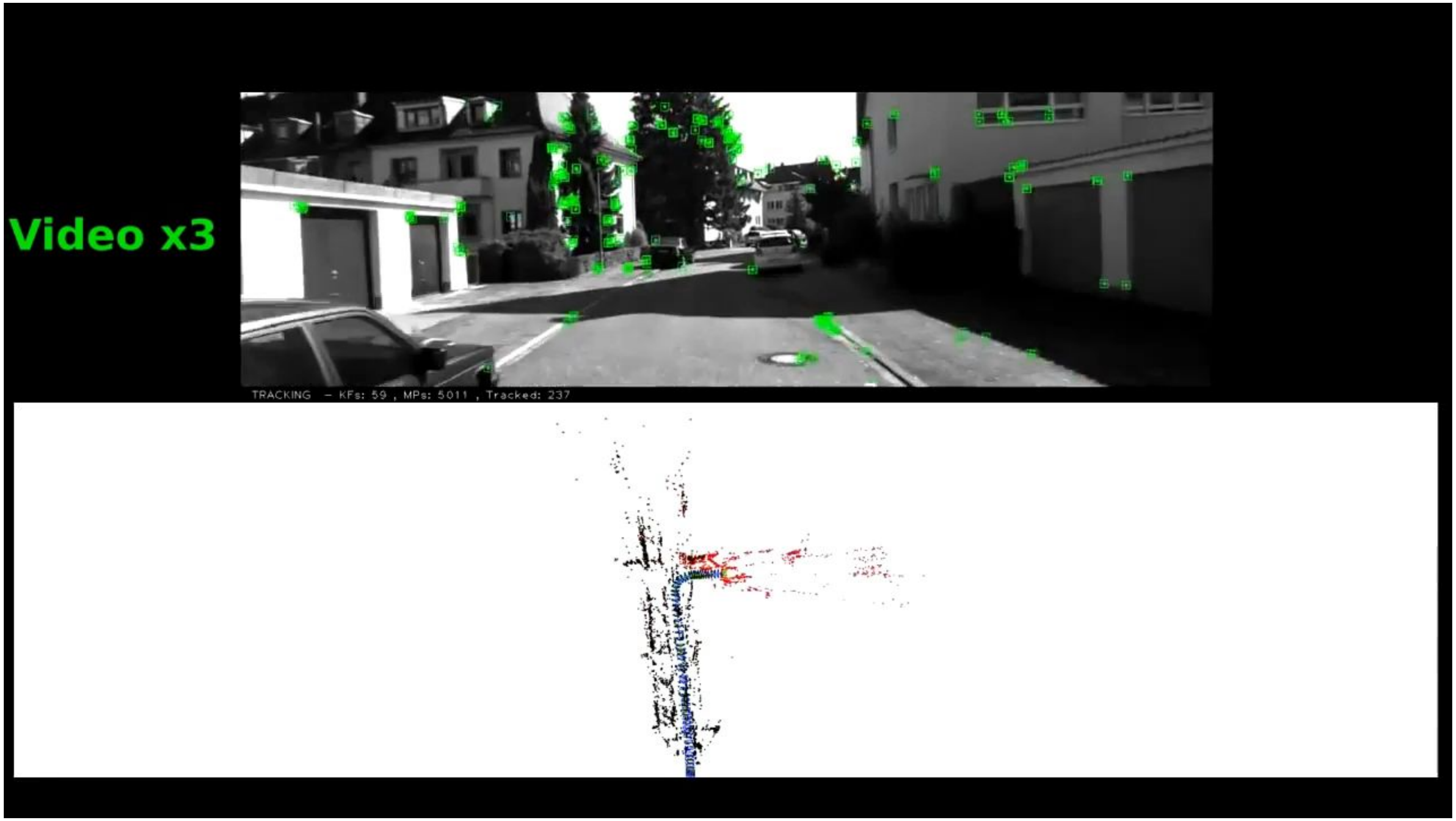


Landmark localization

Camera localization

Introduction

- SLAM – simultaneous localization and mapping:



Introduction

- SLAM – simultaneous localization and mapping:

Status:

- Well researched (also today), many open-source libraries
- Partial success in real world autonomous systems
- Online performance

Challenges:

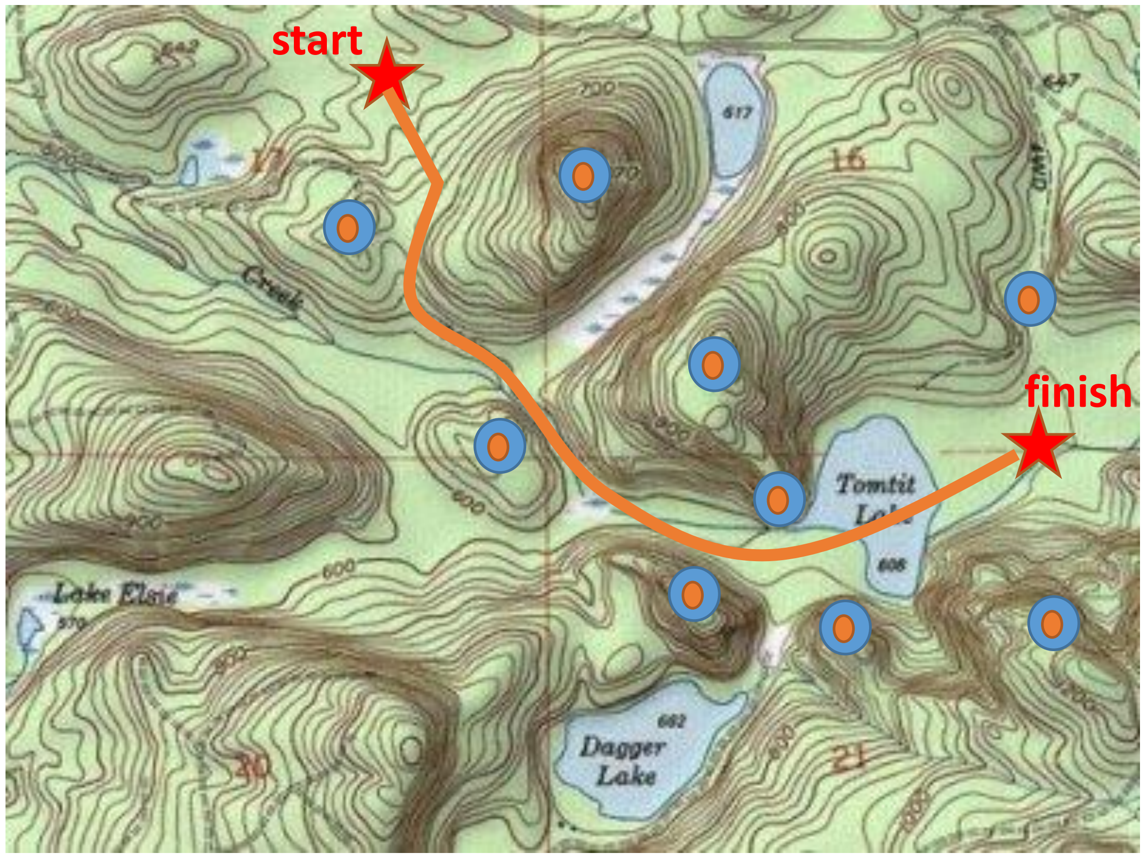
- Accumulated error (Linearization, Measurement noise, miss identification)
- High complexity – not real-time. Uses much power.

Motivation

Qualitative spatial reasoning – easier, and good enough

Human navigation:

- Landmark Relative path
- Qualitative geometry
- Local accurate navigation for minimal effort



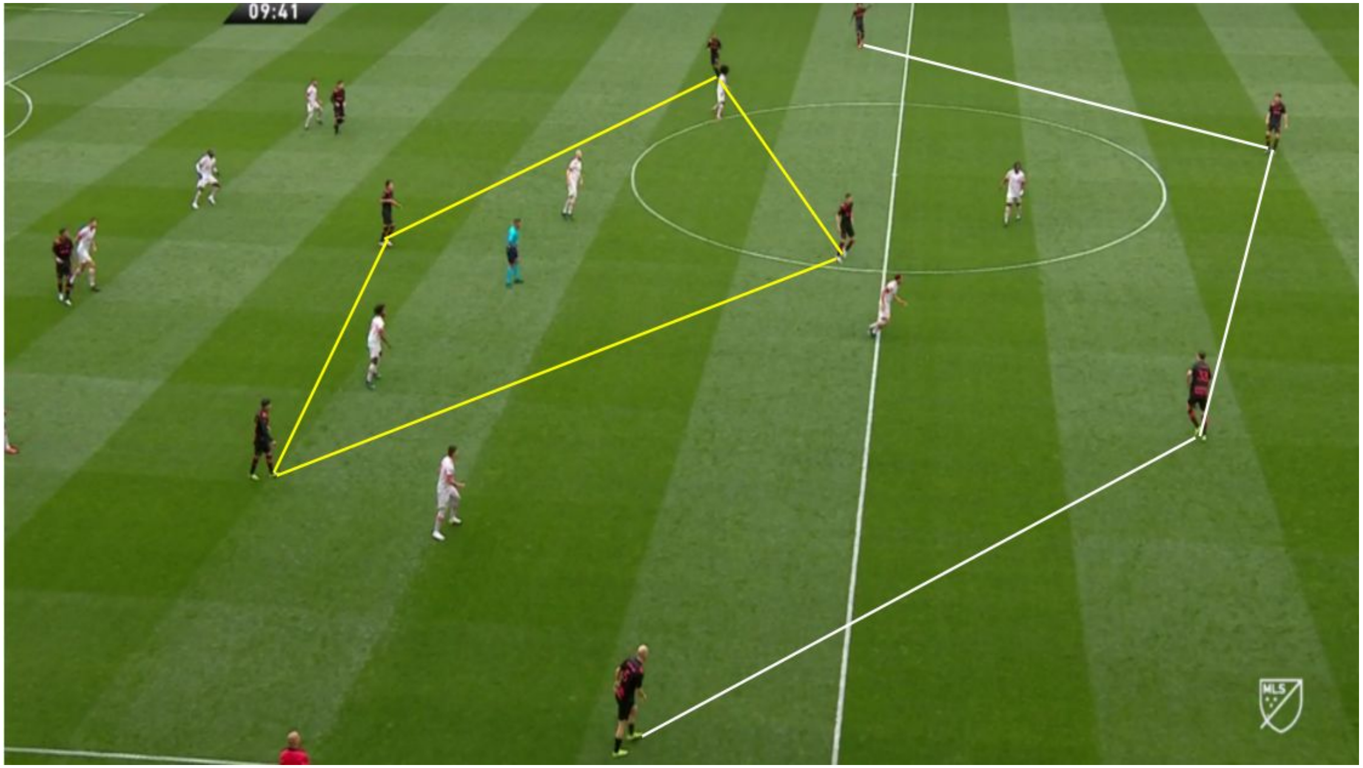
landmarks

Relative path

Qualitative path Vs metric path

Motivation

Qualitative spatial reasoning – easier, and good enough



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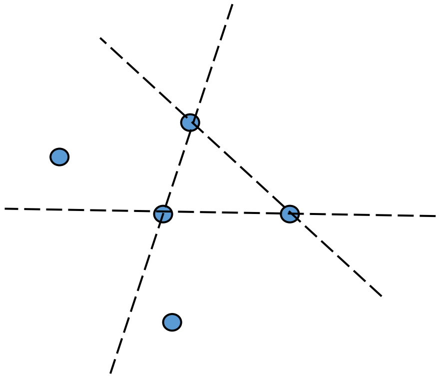
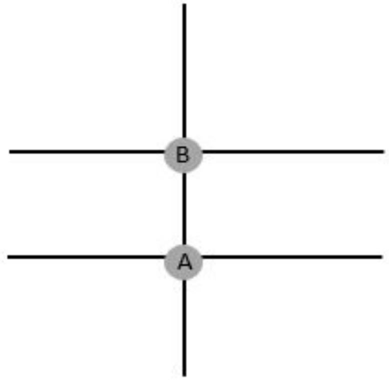
Motivation

Qualitative spatial reasoning – easier, and good enough

relative location
(no global frame)



qualitative localization
(qualitative geometric relations)

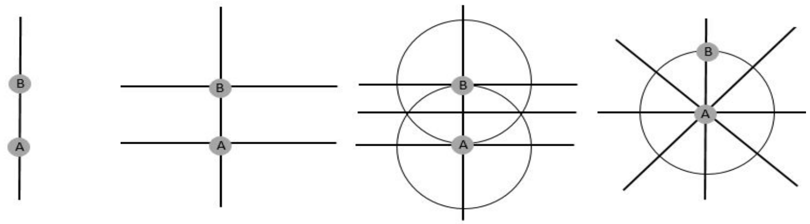


✔ less sensitive to noise
✔ No Long term error accumulation
✔ Low complexity

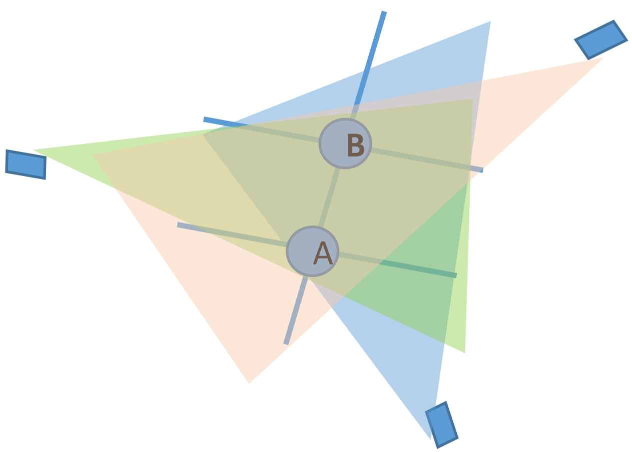
Concept Overview

Concept - Intuition

- Many small two-landmark relative frames of reference – no global frame
- Qualitative spatial partition instead of metric location



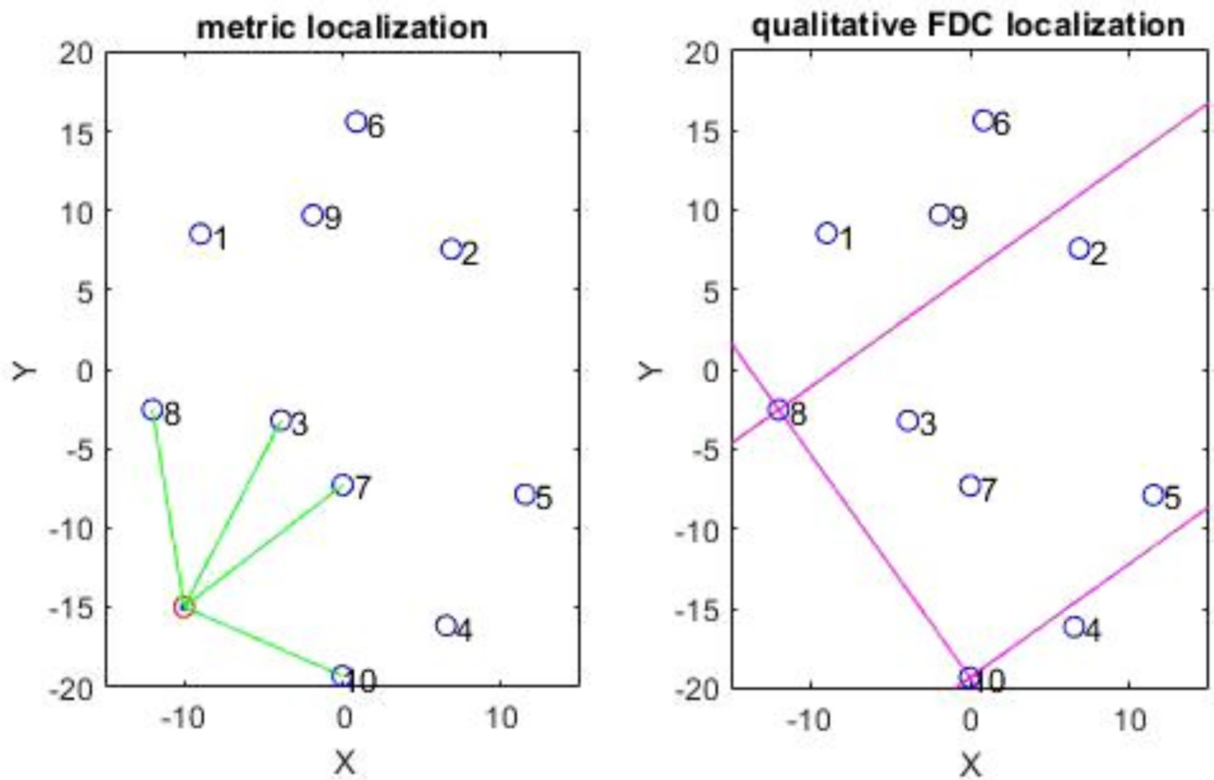
- Estimate state from landmark relative measurements



[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.

Concept - Intuition

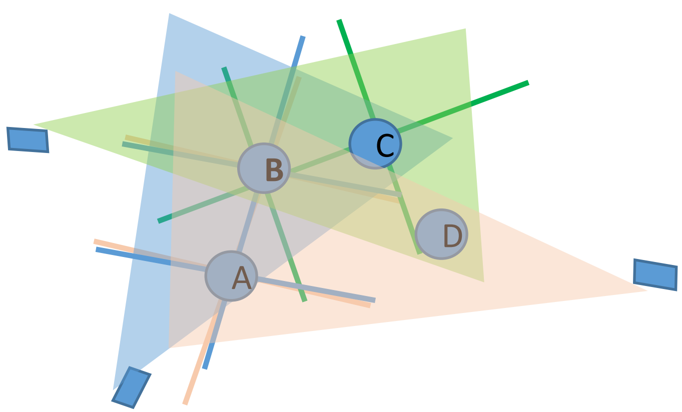
- Qualitative relational localization

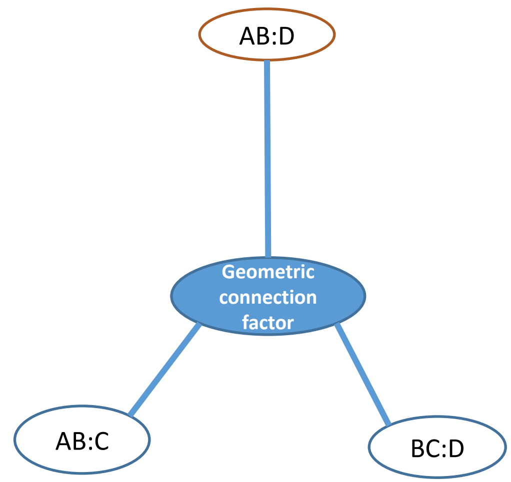


Concept - Intuition

- Qualitative relational mapping

Map -> connected graph of landmark triplets



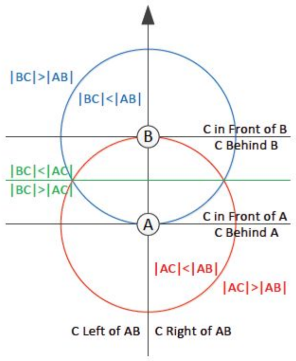


QSR related work

• Spatial Qualitative Reasoning (QSR) approaches:

<u>McClelland,2013</u>

- Typically assume data association is given
- Address mainly mapping, less localization
- Not probabilistic
- Extended double cross



(a) Region Boundaries

McClelland,2013, Qualitative relational mapping for planetary rovers

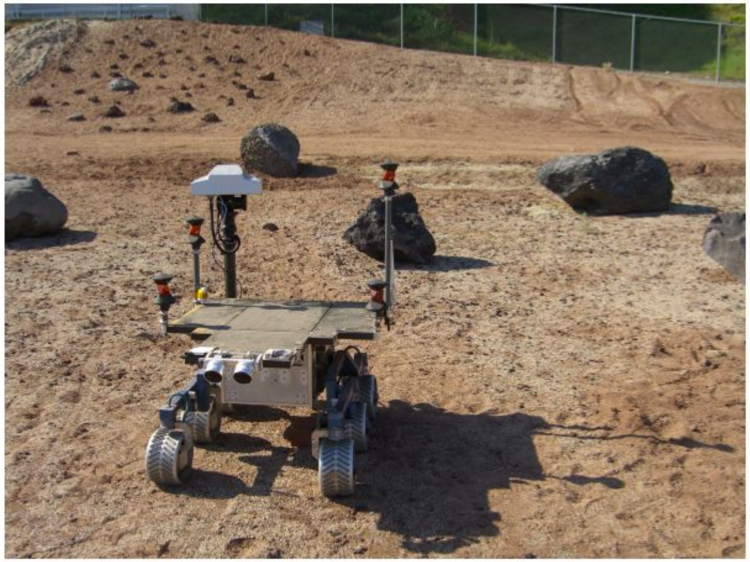


Image taken from McClelland,2013 [5]

QSR related work

- Spatial Qualitative Reasoning (QSR) approaches:

Padgett 2016+2017

- Probabilistic
- Passive + Active planning
- Not a full SLAM framework

Zilberman & Indelman 2022

- Composition in qualitative approaches (RA-L + ICRA 2022)
- Active planning (ongoing)

Padgett, 2016, Probabilistic qualitative mapping for robots
Zilberman, 2022, Incorporating Compositions in Qualitative

Contributions

<u>Our approach:</u> – probabilistic time and spatial dependent QSR:

- Full probabilistic SLAM framework:
    - Localization
    - mapping
- Incorporating Motion model
- Factor graph propagation

<u>publications:</u>

- IROS 2020
- Journal paper(in progress)
- Open-source repo (in progress)

Contributions

<u>Benefits Vs previous QSR work:</u>

- improve accuracy
- improve performance complexity
- estimate sets of landmarks that weren’t seen together

<u>Benefits Vs metric SLAM:</u>

- Low computation
- Robustness to noise / sensor quality
- Simpler computational process

Single Triplet
Qualitative Estimation

Our Approach – single triplet

Estimate each triplet separately:

- Landmark relative coordinate frames
- Small 3 landmark – multiple view SLAM problems

Fusing data:

- Build qualitative map and propagate data

Formulation

2D navigation:

- Metric state

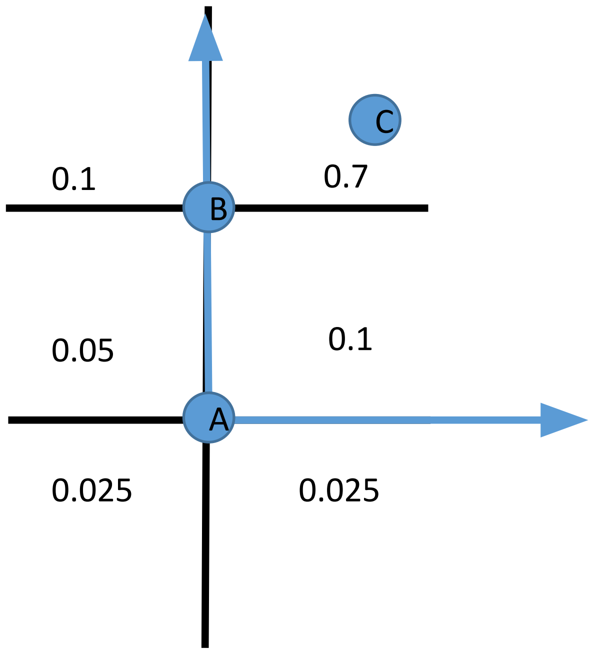
$X_{1:n}$ - Camera pose at times 1:n

$L^{AB:C}$ - Metric location of landmark C in AB frame

$H_n^{AB:C} = \{Z_1, \ldots, Z_n\}$ - All A,B,C measurements up to time n

- qualitative state probability: $\mathbb{P}(S^{AB:C} | H_n)$

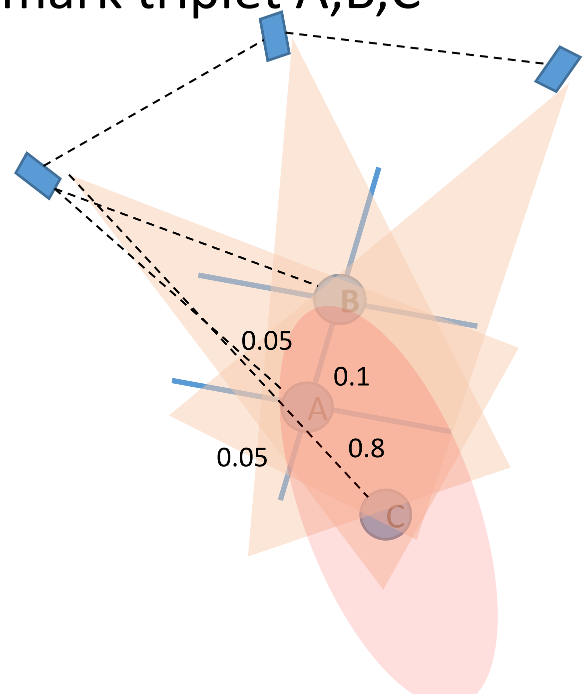
$S^{AB:C}$ - Qualitative state of landmark C in AB frame



Our Approach – single triplet

Estimation of a single landmark triplet:

- Measurements:
  - Azimuth to landmark triplet A,B:C
  - Heading between camera poses
- Metric SLAM For camera poses and landmark triplet A,B,C
  - Uses several separate camera poses
  - Incremental
- Integrate qualitative state probability



Our Approach – single triplet

- Probabilistic formulation

$$\mathbb{P}(S^{AB:C}=i|H_n^{AB:C}) = \underbrace{\int_{X_{1:n},L^{AB:C}}\cdots\int \mathbb{P}(L^{AB:C}|S^{AB:C}=i)}_{\text{Integrate over metric states}}\underbrace{\mathbb{P}(X_{1:n},L_C|H_n^{AB:C})}dL^{AB:C}dX_{1:n}$$

Metric SLAM

For landmark triplet

A,B,C

$$\mathbb{P}(X_{1:n}L^{AB:C}|H_n) = \frac{\mathbb{P}(Z_1|X_1,L^{AB:C})\mathbb{P}(X_1L^{AB:C})}{\mathbb{P}(Z_1)}\prod_{i=2}^{n}\frac{1}{\zeta_i}\underbrace{\mathbb{P}(Z_i|X_i,L^{AB:C})}_{\text{Measurement model}}\underbrace{\mathbb{P}(X_i|X_{i-1},a_{i-1})}_{\text{Motion model}}$$

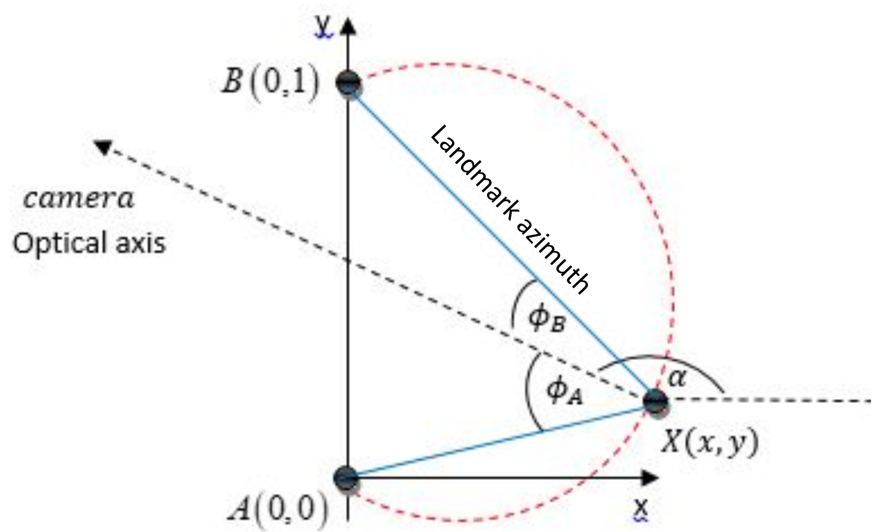
Our Approach – single triplet

Solving the 3 landmark SLAM problem:

- Non linear sample based SLAM approach
- Measurements
  - Measurements – azimuth to landmarks (φ)
  - Motion model – heading to next pose (Ψ)

Single view:

Camera on locus circle

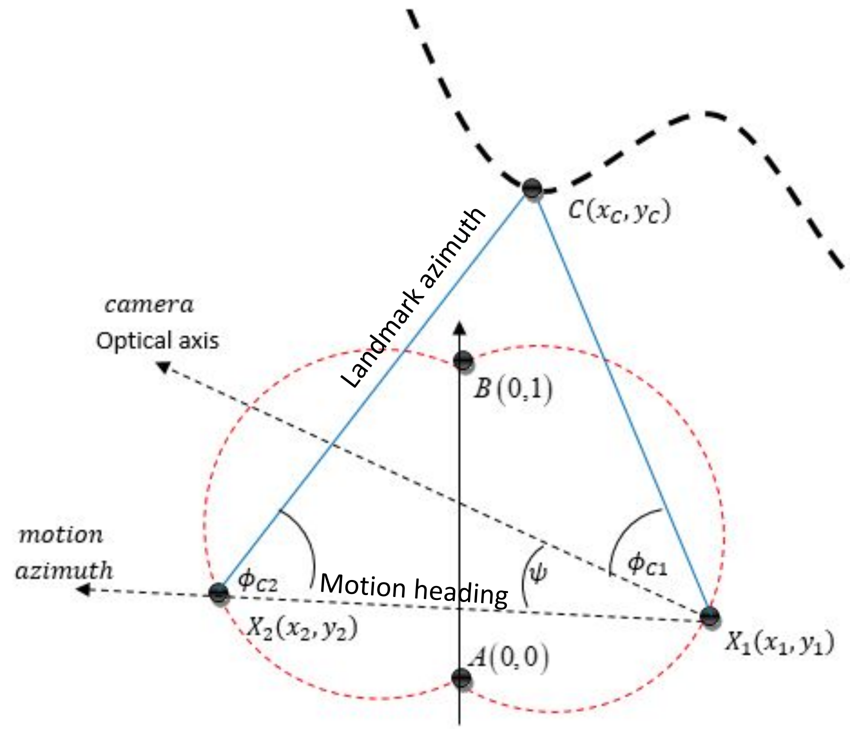


Our Approach – single triplet

Solving the 3 landmark SLAM problem:

<u>Two views:</u>

- Cameras on locus circles
- Landmark C can be triangulated to a curve

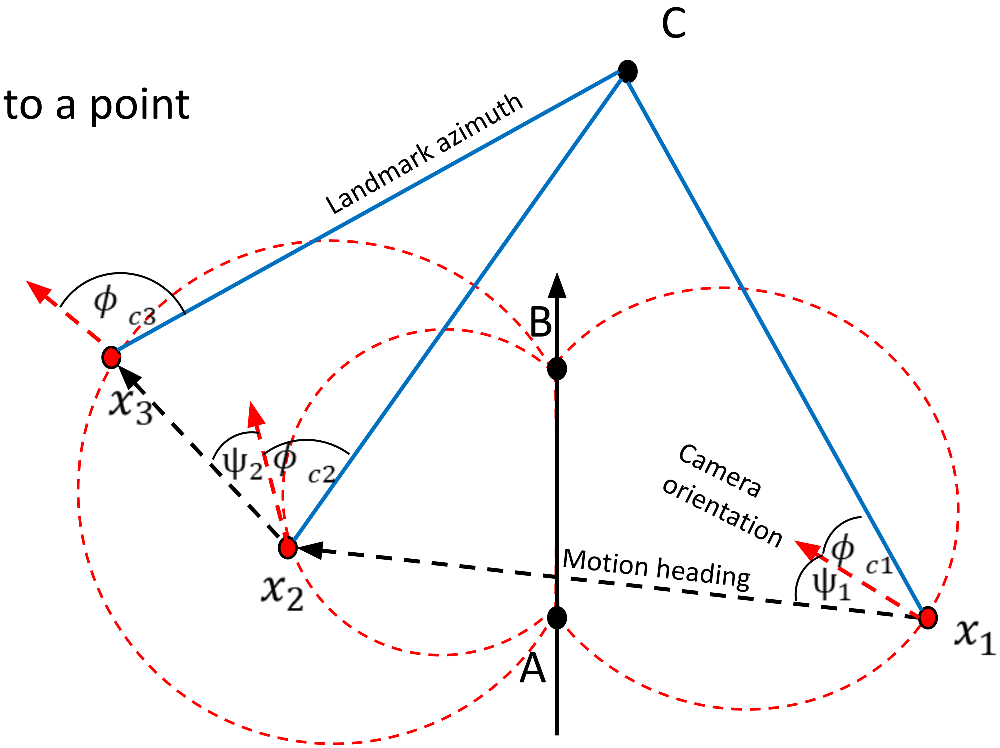


Our Approach – single triplet

Solving the 3 landmark SLAM problem:

<u>Three views or more:</u>

- Cameras on locus circles
- Landmark C can be triangulated to a point



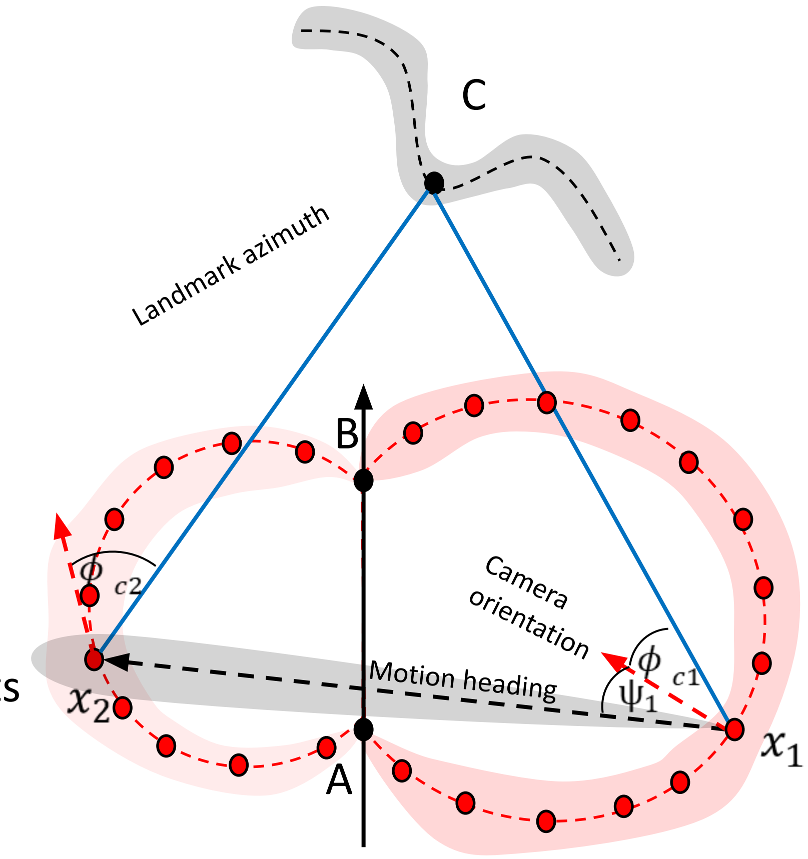
Our Approach – single triplet

Solving the 3 landmark SLAM problem:

- Non linear sample based SLAM approach
- A,B locus circle
- A,B azimuth measurements noise
- Motion heading noise

Number of samples:

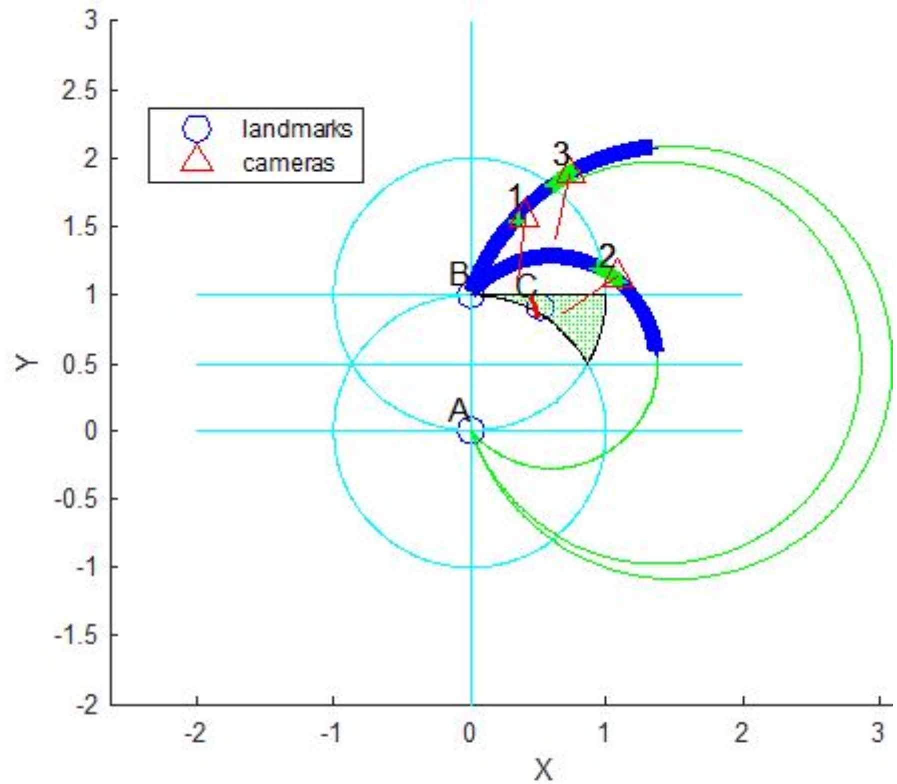
- Exponential in camera poses
- Practically reduces fast by consistency tests
- Very small for 3 camera poses or more
- Good for incremental algorithm



Our Approach – single triplet

Solving the 3 landmark SLAM problem:

- 3 view Simulation example



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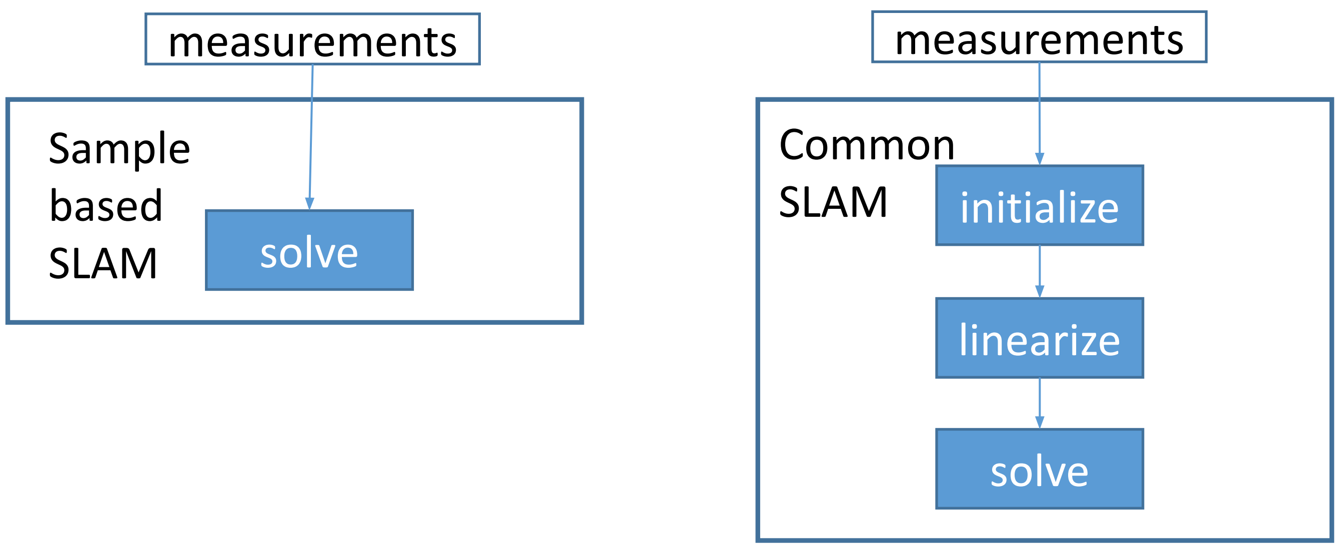
Our Approach – single triplet

Our approach Vs regular SLAM

- Non linear
  - no linearization errors
  - No need for linearization
  - No initialization process
- General - variables are not assumed to be Gaussian



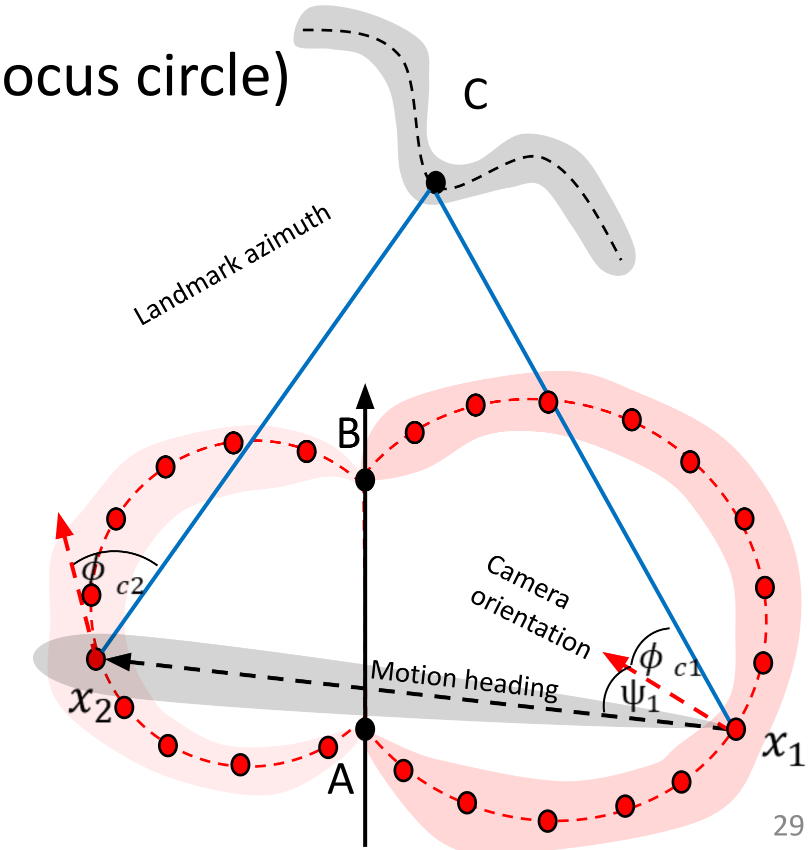
Our Approach – single triplet

Solving the 3 landmark SLAM problem – Fast approximation

Trying to capitalize on QSR coarse spatial partition

Fast solver variant:

- Sample only geometry (camera locus circle)
- No noise samples



Our Approach – single triplet

Single triplet results

single triplet EDC estimation results			
	baseline	ours	ours-fast
DMSE	0.39, 0.63, 0.71	**0, 0.16, 0.63**	0, 0.21, 0.62
geometric distance	0.28, 1.10, 2.30	**0, 0.25, 1.15**	0, 0.27, 1.16
Entropy	0.28, 0.66, 0.87	**0, 5e-3, 0.58**	0, 0.07, 0.64
time[sec]	26	18	**0.05**

Motion Model makes a difference!

Metrics:

- DMSE – probabilistic correctness
- Geometric distance – geometric correctness
- Entropy – distribution steepness
- GT rating – the position of the GT qualitative state when states are ordered by probability (1 – most probable)

$$DMSE = \sqrt{\sum_{i=1}^{m} (\mathbb{P}(s_i) - \mathbb{P}(s_{GT}))^2}$$

$$gmd = \sum_{i=1}^{m} \mathbb{P}(s_i)||c_i - c_{GT}||_2$$

$$e = -\sum_{i=1}^{m} \mathbb{P}(s_i) log(\mathbb{P}(s_i))$$

Baseline = padget

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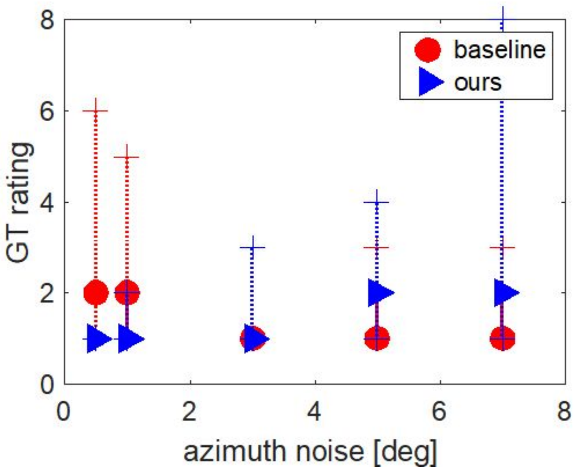
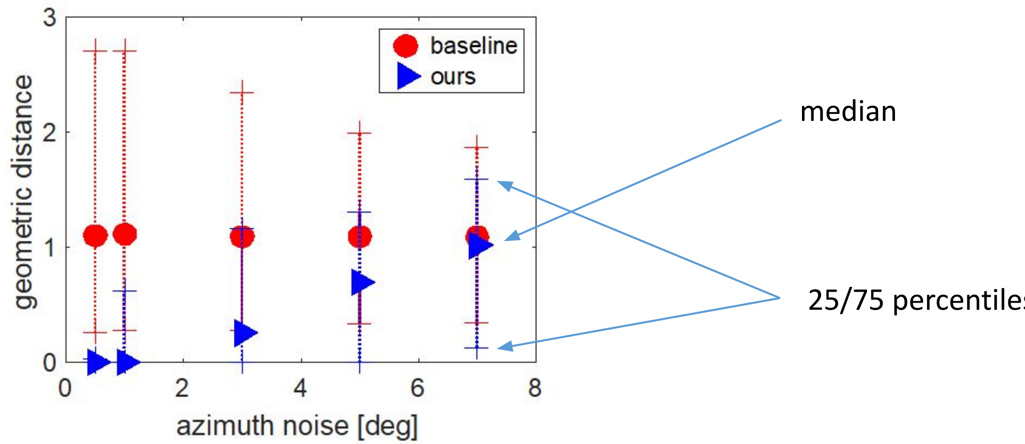
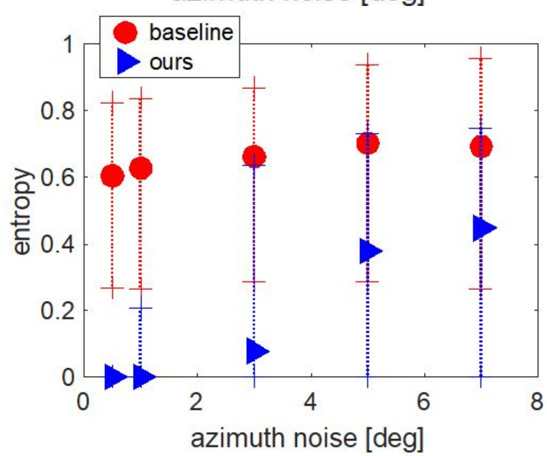
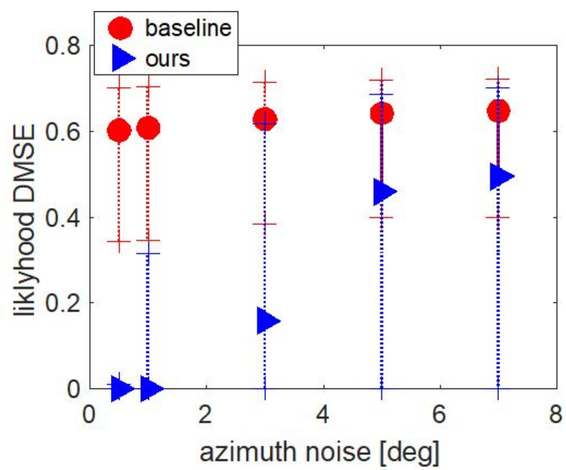
Results

Single triplet results









Motion Model makes a difference!

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Results

MRCLAM dataset

- Autonomous Space Robotics Lab (ASRL) at the University of Toronto
- Cylindrical landmarks
- Occlusions
- Sensors
  - Camera azimuth mesurements
  - Odometry

MRCLAM dataset EDC estimation		
	ours-fast	uniform
DMSE	0.03, 0.45, 0.69	0.97
gmd	5e-3, 0.27, 0.71	2.2
Entropy	4e-3, 0.38, 0.69	3
GT rating	1, 1, 2	-

median

25/75 percentiles

Autonomous Space Robotics Lab: MR.CLAM Dataset (utoronto.ca)

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Our Approach – single triplet

Conclusions

- Adding motion model:
  - Better performance
  - Better complexity (feasibility tests reduce samples faster)

- fast approximation
  - Much faster
  - Performance very close to full algorithm
  - uses qualitative inherent course spatial partition

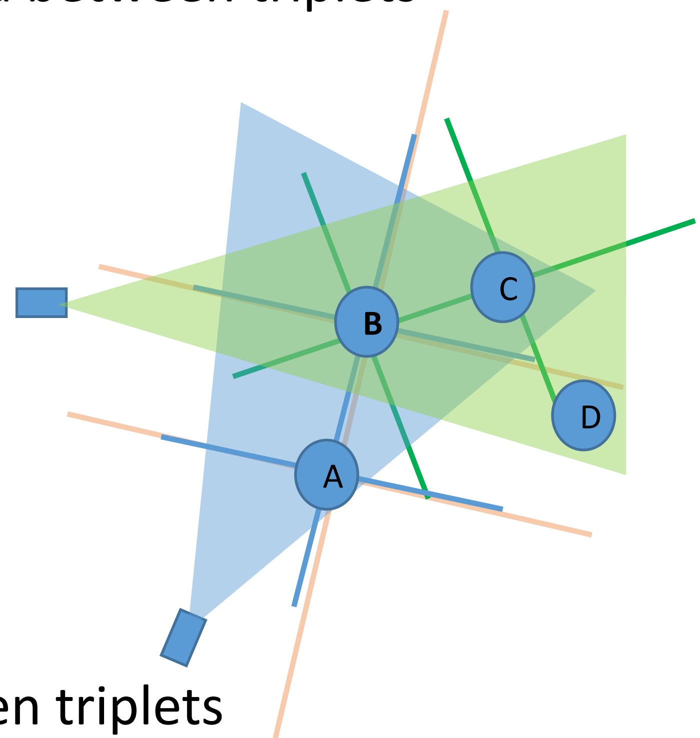
- General performance
  - Up-to azimuth measurement noise of 3deg – very close to GT
- (Published in IROS 2020)

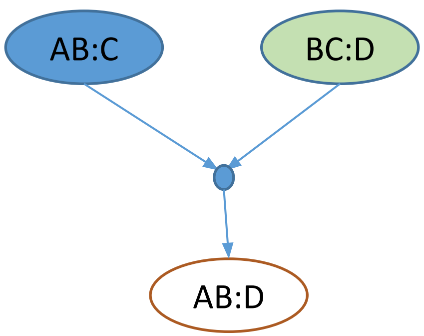
Qualitative Composition

Our Approach - composition

Novel probabilistic Composition:

- Propagate data between triplets





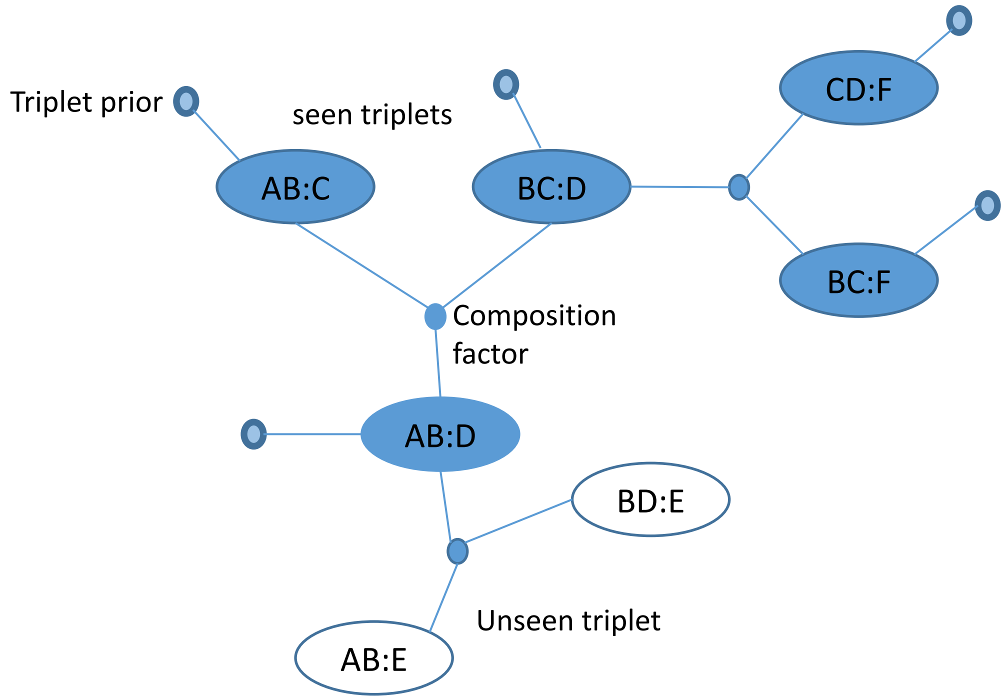
- Estimate unseen triplets
- Improve estimation

$$\mathbb{P}(S^t|\cancel{H^t}, H^{p1}, H^{p2}) = \sum_{s_i^{p1}} \sum_{s_j^t} p(S^t, s_i^{p1}, s_j^{p2}|\cancel{H^t}, H^{p1}, H^{p2})$$

Concept - Intuition

Composition:

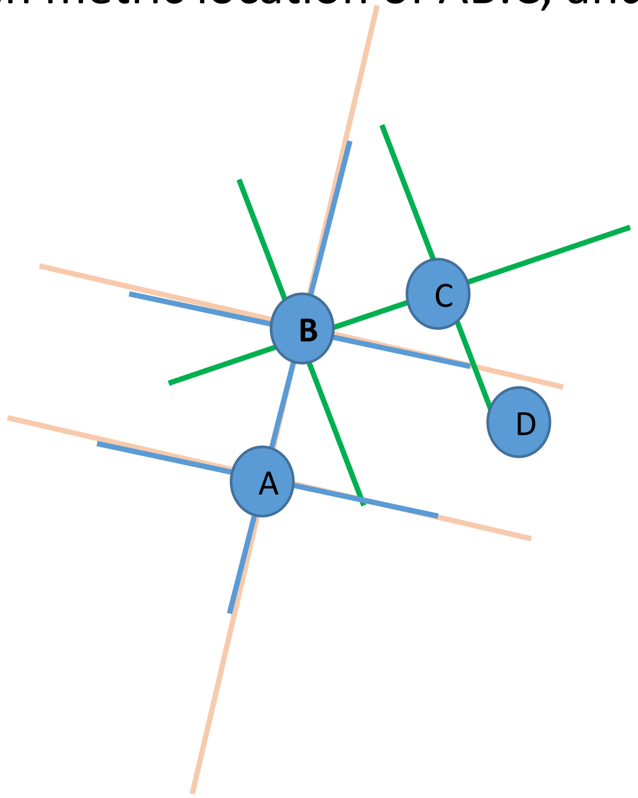
Qualitative map propagation by composition factor graph



Our Approach - composition

Composition:

- Calculate AB:D given metric location of AB:C, and BC:D



Our Approach - composition

Composition:

- Composition factor – pure qualitative approximation
  - Remember only qualitative state
  - Forget metric data

$$\mathbb{P}(L|s_i, H) \approx \mathbb{P}(L|s_i)$$

- Formulation:

AB:C = p1

BC:D = p2

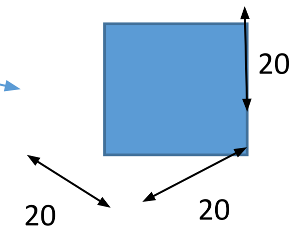
AN:D = t

Single triplet estimation

$$\mathbb{P}(S^t|H^{p1}, H^{p2}) \approx \sum_{s_i^{p1}} \sum_{s_j^{t}} \mathbb{P}(s_i^{p1}|H^{p1}) \mathbb{P}(s_j^{p2}|H^{p2}) \cdot$$

$$\iint_{L^{p1} \in s_i^{p1}, L^{p2} \in s_j^{p2}} \mathbb{P}(S^t|L^{p1}, L^{p2}) dL^{p1} dL^{p2}.$$

Calculate offline
Same for all factors



Our Approach - composition

Composition:

- Composition factor pure qualitative approximation:
  - Fast graph propagation
  - Very efficient in HW accelerators
  - Low memory consumption

- (Published in IROS 2020)

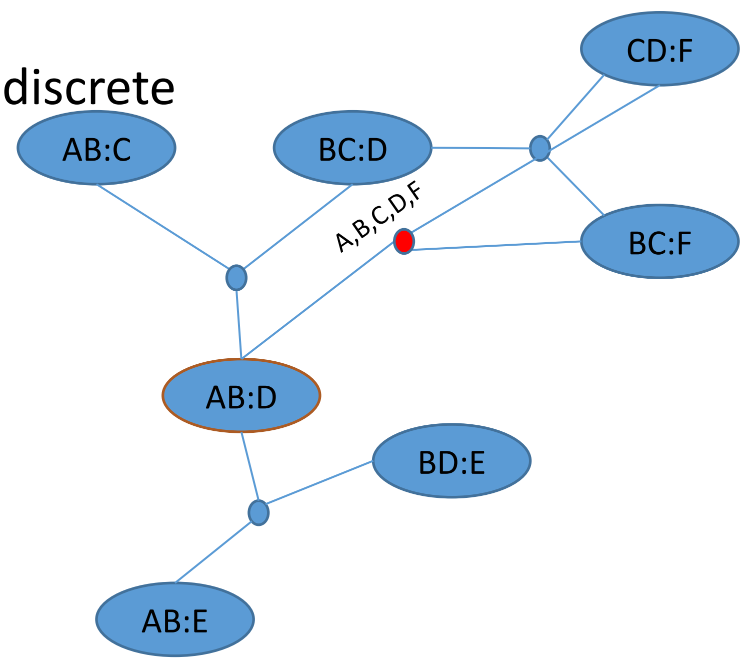
Factor Graph Propagation

Our Approach - composition

Factor graph propagation algorithm:

Accurate method :

- Elimination - trinary factors -> multiple node factor
- Calculation is exponential in number of nodes
- Runtime Not feasible
- Implemented in GTSAM-discrete

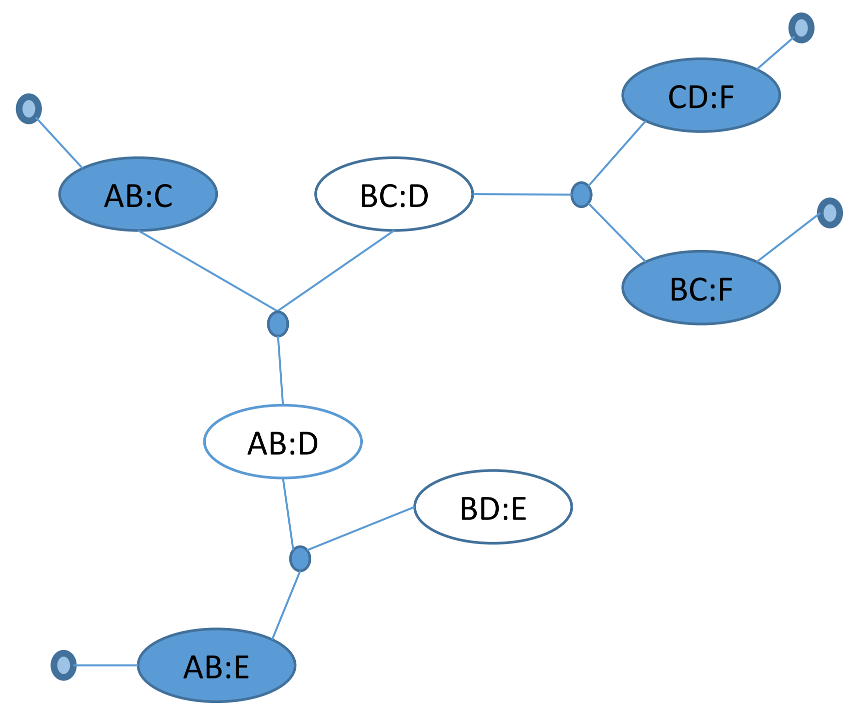


Our Approach - composition

Factor graph propagation:

Fast Approximated algorithm:

- Greedy – one most informative step
- Single best path
- One pass over each node



Our Approach - composition

Factor graph propagation:

<u>Information score (ISC):</u>

A metric to measure how informative is the probability distribution for a specific landmark triplet qualitative state:

- 0<ISC<1
- Higher is better (more informative)

$$ISC=\frac{H_{max}-H_n}{H_{max}-H_{min}}$$

H_n $= node\ entropy$
$H_{max} = uniform\ (max)\ entropy$
$H_{min} = perfect\ (min)\ entropy$

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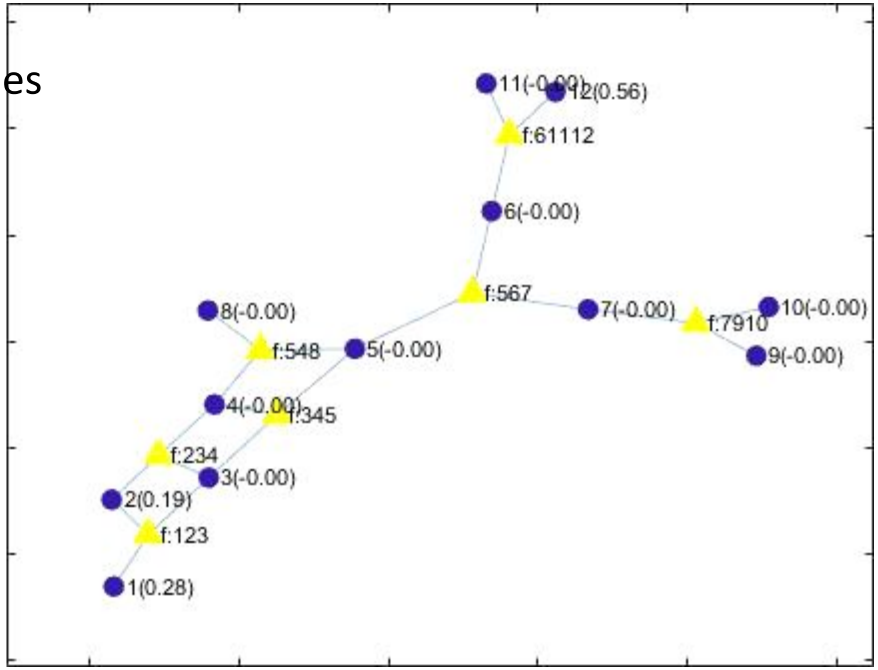
Our Approach - composition

Factor graph propagation:

Fast Approximated algorithm:

- Observed nodes = Source nodes
- Loop:
  - Propagate any factor that has 1 or 2 ‘done’ nodes
  - Calculate ISC for all newly calculated nodes
  - Keep best ISC node, and mark as ‘done’
- Break when no factor has 1 or 2 ‘done’ nodes



Example:

Fast Approximated algorithm:

- Node text: id (ISC)
- Priors on nodes 1,2,12
- Update order: 6,5,3,4,11,7,9,10,8

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Our Approach - composition

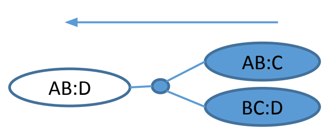
Factor graph propagation:

Composition level (CL):

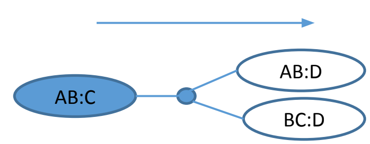
- A tool to study composition behavior in correlation to:
  - Graph topology
  - prior information

- Propagation in graph:
  - CL = ISC for observed nodes
  - Same graph propagation algorithm
  - ISC decay Factor:

$$ISC_{AB:D}=(1-\alpha^2)\frac{ISC_{AB:C}+ISC_{BC:D}}{2}$$



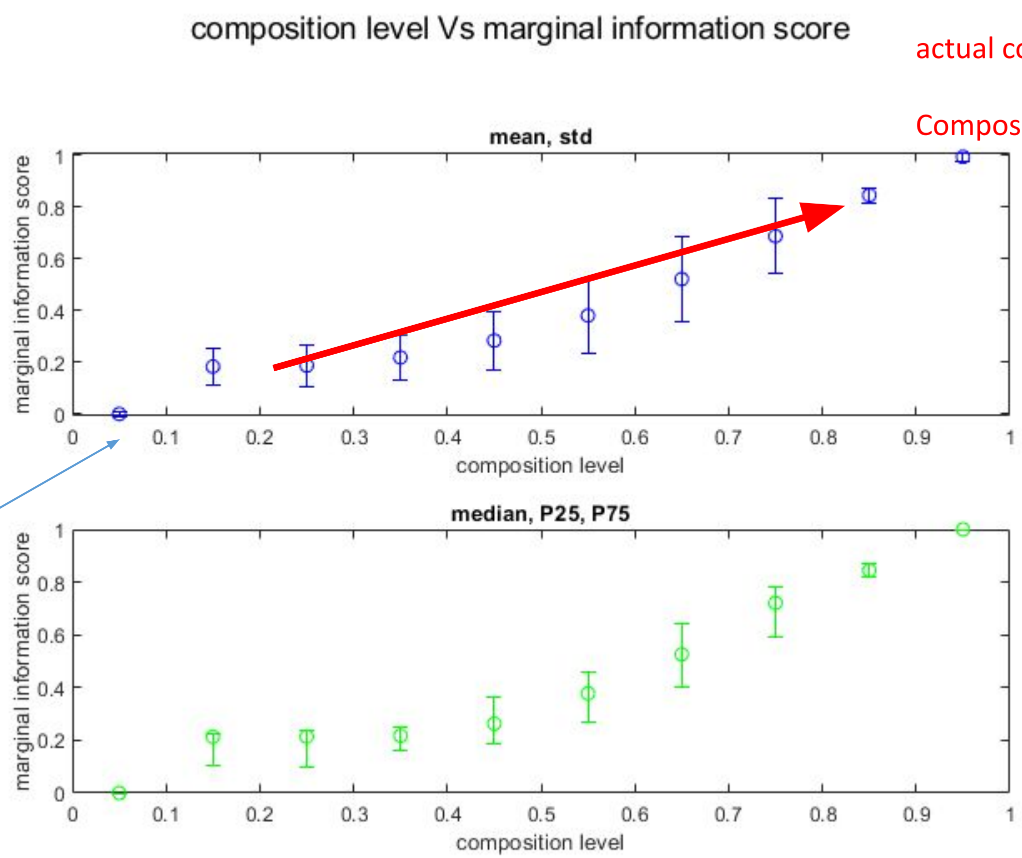
$$ISC_{AB:D}=ISC_{BC:D}=(1-\alpha)ISC_{AB:C}$$



α=0.5 - information decay factor

Our Approach - composition

Composition results:



actual composition informative
↕
Composition level informative

Marginal ICS Calculated by actual composition

ICS Calculated by "composition level" propagation

Our Approach – composition

Conclusions

- Composition propagates significant information
- Information propagated is correlated to graph topography (composition level)
- Might be practical for:
  - Estimating unseen nodes (for planning / landmark recognition)
  - Improving existing estimation

- (will be published soon)

Conclusions

Conclusions

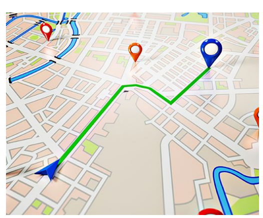
- Good Performance
  - Low measurement noise -> almost perfect results (up to 3°)
  - High measurement noise -> Better performance than state of the art (up to 7°)
- Low complexity (practical for low compute systems)
  - Good performance for fast approximation
- Good for fast active planning
  - Composition is fast and informative

future work

Rigorous

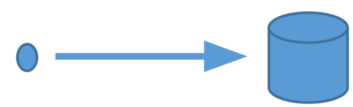
graph propagation

Active planning

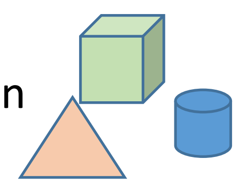


Multiple extensions

- Complex landmarks



- Data association



- 3D