Multi-Robot Pose Graph Localization and Data Association from Unknown Initial Relative Poses

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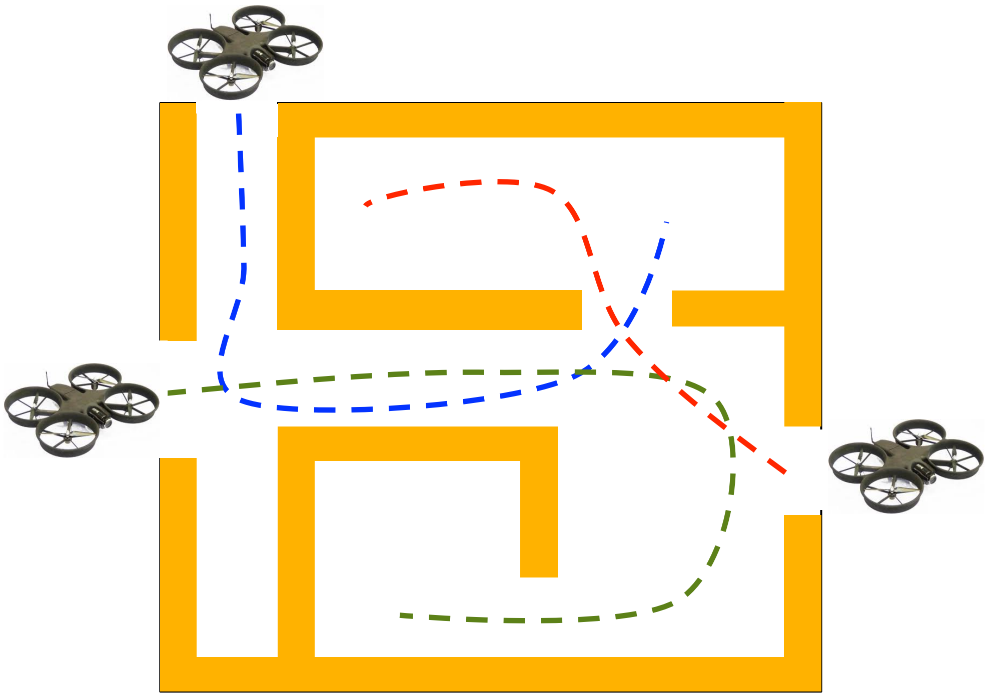
Collaborative Localization and Mapping

- Important in a variety of scenarios
  - Exploration in unknown/uncertain, dangerous environments
  - Search and rescue
  - Surveillance, tracking …

- Cooperative inference requires
  - Sharing relevant information (observations, marginals over variables of interest)
  - Correct interpretation (data association)
  - Robustness to outliers

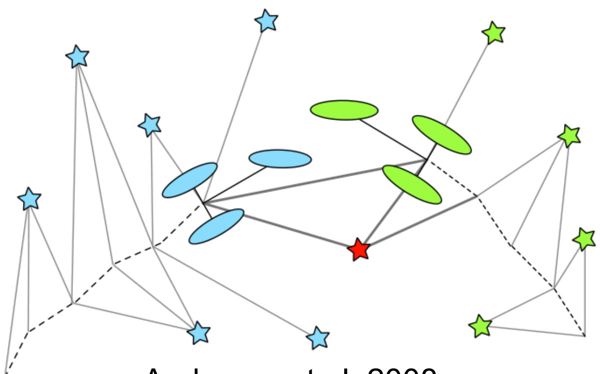
Motivating Scenario

- Robots/sensors are deployed in an environment (e.g. building)
- Initially unaware of each others' location
- How to establish collaboration and perform multi-robot localization?
  - Unknown multi-robot data association
  - Unknown initial relative poses between robots

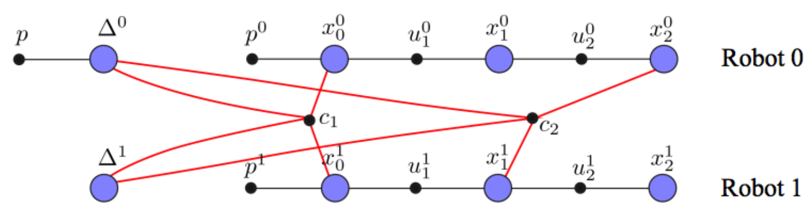


Related Work

- Known data association and common reference frames
  – Full SLAM [Howard et al. 2006], [Andersson et al. 2008]
  – Pose SLAM (direct, indirect) [Roumeliotis et al. 2002], [Kim et al. 2010], [Indelman et al. 2012]



Anderson et al. 2008



Kim et al. 2010

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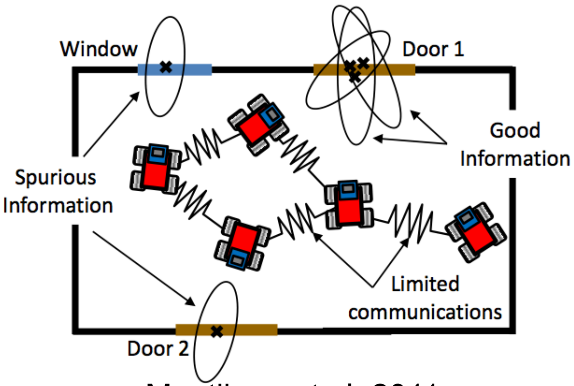
  - Pose SLAM (direct, indirect) [Roumeliotis et al. 2002], [Kim et al. 2010], [Indelman et al. 2012]
- Unknown multi-robot data association and common reference frame
  - Full SLAM [Montijano et al. 2011], [Cunningham et al. 2012]



Montijano et al. 2011

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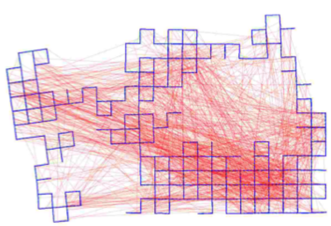
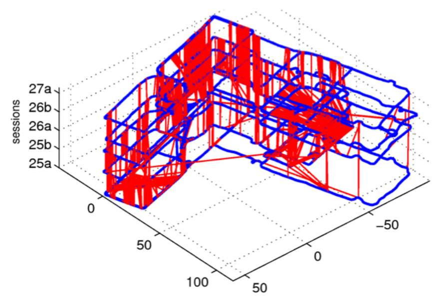
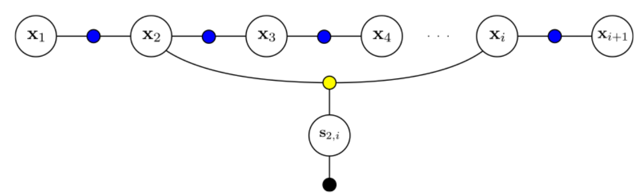
- Unknown multi-robot data association and common reference frame
  - Full SLAM [Montijano et al. 2011], [Cunningham et al. 2012]
- Robust graph optimization (**single** robot case – loop closures)
  - [Sunderhauf and Protzel 2012, 2013], [Latif et al. 2012], [Lee et al. 2013]



Lee et al. 2013



Latif et al. 2012



Sunderhauf and Protzel 2012, 2013

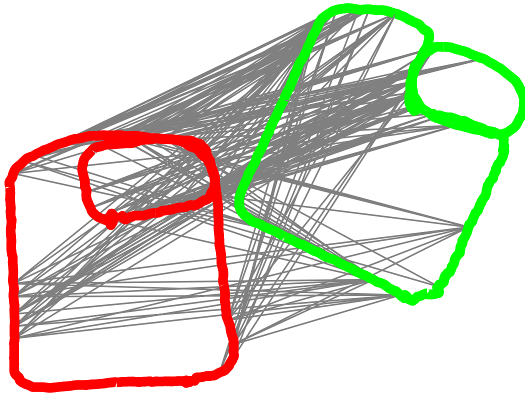
This Work

- Multi-robot framework with
  - **Unknown** multi-robot data association
  - **Unknown** initial relative poses between robots
  - **Pose SLAM** approach
- How to establish multi-robot data association when robots start operating from unknown locations?

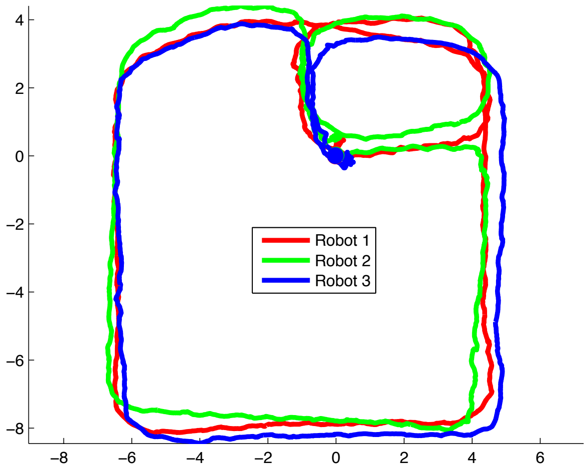
Multi-Robot Correspondences

- If **no** common reference frame is available, what information to share?
  - Robots share informative observations (e.g. laser scans)
  - Calculate candidate multi-robot relative pose constraints
    - Collect into set $\mathcal{F}$
    - Includes (many) outliers

Arbitrary common reference frame



Ground truth



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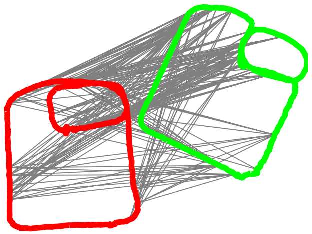
Probabilistic Formulation

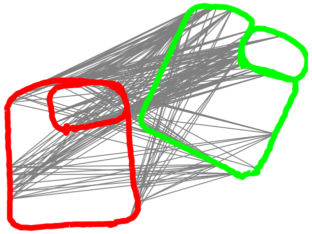
- Notations:
  - $\mathcal{F}$: Multi-robot correspondences set
  - $\mathcal{J}$: Latent variables to indicate inliers/outliers



- Joint pdf over robot trajectories **and** multi-robot data association:

$$p\left(X, \mathcal{J} | Z\right) \propto \underbrace{\prod_r p\left(X^r | Z^r\right)}_{\text{Only local measurements}} \underbrace{\prod_{(r_1, r_2, k, l) \in \mathcal{F}}}_{\text{Each multi-robot correspondence}} \underbrace{p\left(j_{k,l}^{r_1, r_2}\right)}_{\text{Data association}} \underbrace{p\left(u_{k,l}^{r_1, r_2} | x_k^{r_1}, x_l^{r_2}, j_{k,l}^{r_1, r_2}\right)}_{\text{Multi-robot measurement likelihood, given data association}}$$

Measurement likelihood



$$p\left(u_{k,l}^{r_1,r_2} | x_k^{r_1}, x_l^{r_2}\right) \propto \exp\left(-\frac{1}{2}\left\| err\left(u_{k,l}^{r_1,r_2}, x_k^{r_1}, x_l^{r_2}\right)\right\|_{\Sigma}^2\right)$$

with

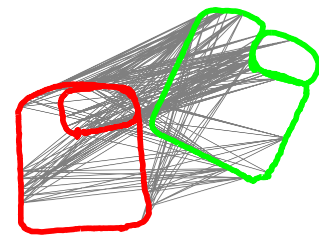
$$err\left(u_{k,l}^{r_1,r_2}, x_k^{r_1}, x_l^{r_2}\right) \doteq u_{k,l}^{r_1,r_2} \ominus h\left(x_k^{r_1}, x_l^{r_2}\right)$$

measured predicted

$$\doteq x_k^{r_1} \ominus \left(\underline{T_{r_2}^{r_1}} \oplus x_l^{r_2}\right)$$

Unknown!!

Measurement likelihood



$$p\left(u_{k,l}^{r_1,r_2} | x_k^{r_1}, x_l^{r_2}\right) \propto \exp\left(-\frac{1}{2}\left\| err\left(u_{k,l}^{r_1,r_2}, x_k^{r_1}, x_l^{r_2}\right)\right\|_{\Sigma}^2\right)$$

with

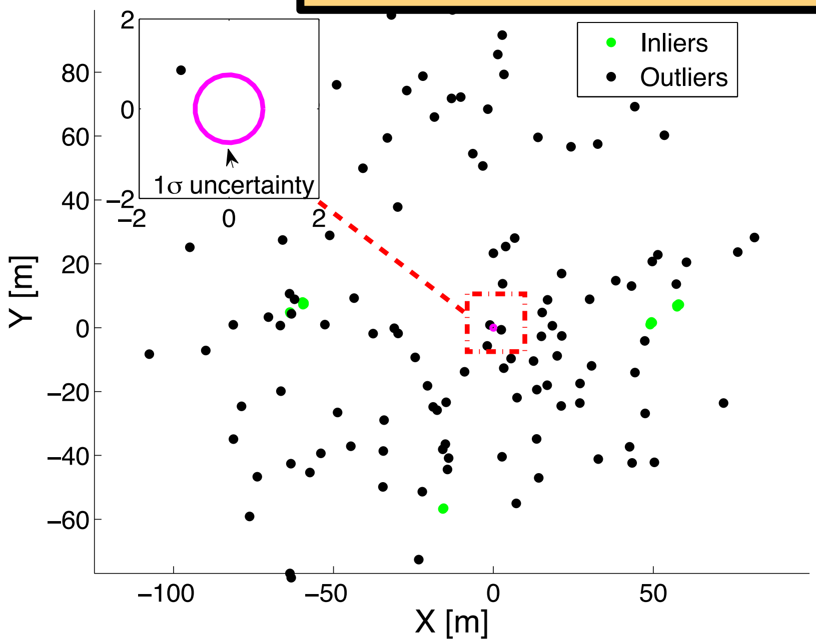
$$err\left(u_{k,l}^{r_1,r_2}, x_k^{r_1}, x_l^{r_2}\right) \doteq \underbrace{u_{k,l}^{r_1,r_2}}_{\text{measured}} \ominus \underbrace{h\left(x_k^{r_1}, x_l^{r_2}\right)}_{\text{predicted}}$$

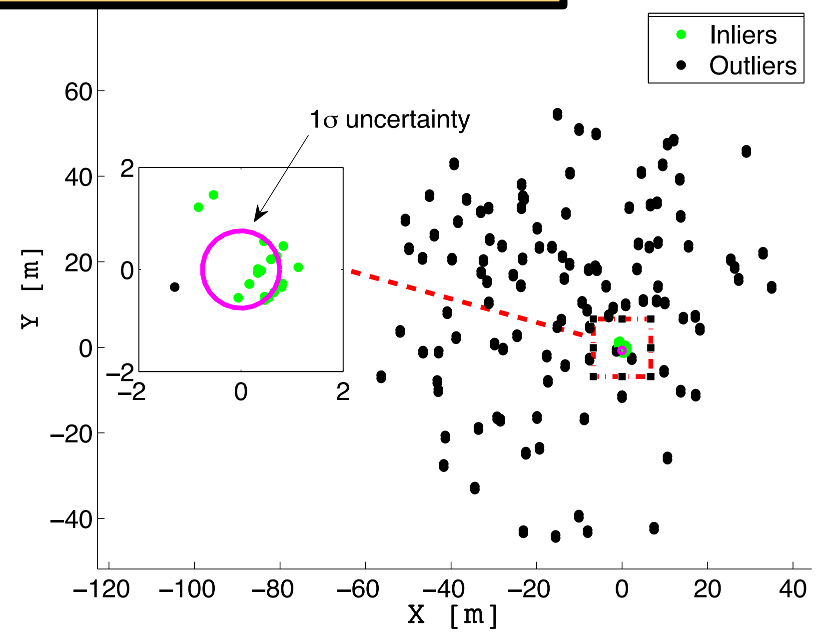
$$\doteq x_k^{r_1} \ominus \left(\underline{T_{r_2}^{r_1}} \oplus x_l^{r_2}\right)$$

Unknown!!

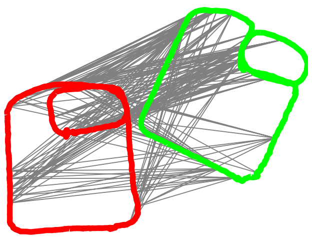
Error distribution for all correspondences:

Must <u>first</u> infer a common reference frame $T_{r_2}^{r_1}$!



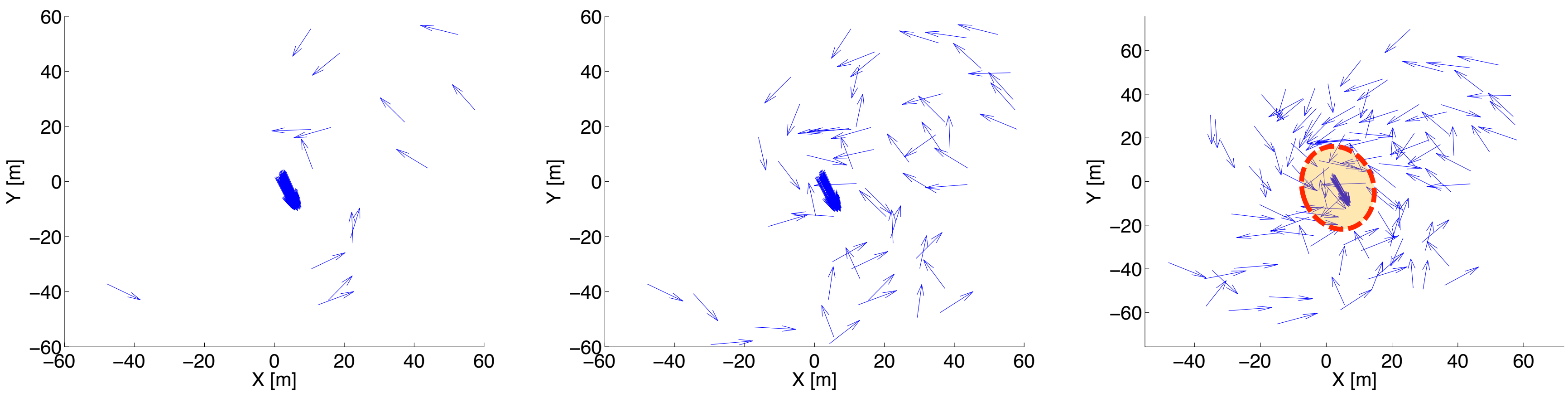


Key Observation



- Given robot local trajectories, relative initial pose can be calculated from each candidate multi-robot correspondence
  - **Only** inliers produce similar transformations
  - Objective: identify cluster

Initial relative pose between two robots (planar case: x, y, θ**)**
[synthetic data]



10% outliers 40% outliers 85% outliers

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Inference Over Common Reference Frame via EM

- MAP estimate of $T_{r_2}^{r_1}$ given robot local trajectories (using only local data):

$$\hat{T}_{r_2}^{r_1} = \arg\max_{T_{r_2}^{r_1}} p\left(T_{r_2}^{r_1} | \hat{X}^{SR}, Z\right) = \arg\max_{T_{r_2}^{r_1}} \sum_{\mathcal{J}} p\left(T_{r_2}^{r_1}, \mathcal{J} | \hat{X}^{SR}, Z\right)$$

  – $\mathcal{J}$: Latent binary variables to indicate inliers/outliers

Local trajectories

$$\hat{X}^r = \arg\max_{X^r} p\left(X^r | Z^r\right)$$

$$\hat{X}^{SR} \doteq \left\{\hat{X}^r\right\}_{r=1}^{R}$$

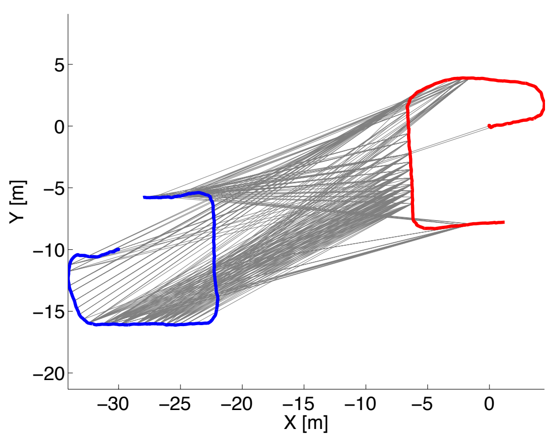
- EM formulation:

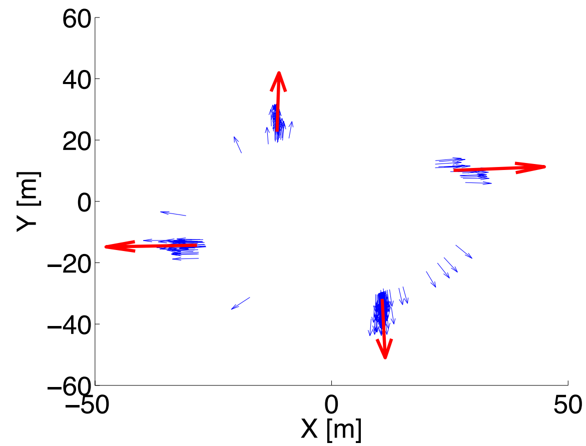
$$\hat{T}_{r_2}^{r_1} = \arg\max_{T_{r_2}^{r_1}} p\left(\mathcal{J} | \hat{T}_{r_2}^{r_1}, \hat{X}^{SR}, Z\right) \log p\left(T_{r_2}^{r_1}, \mathcal{J} | \hat{X}^{SR}, Z\right)$$

E step **M step**

Inference Over Common Reference Frame via EM (Cont.)

- Convergence only to **local** minima
- Therefore:
  - Start process from several initial guesses of $T_{r_2}^{r_1}$
  - Results in several locally-optimal solutions (inliers/outliers, estimated $T_{r_2}^{r_1}$)
  - Choose most likely solution (best support)
    - Ongoing research: model selection, sensitivity to perceptual aliasing





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Inference Over Robot Trajectories

- Once a common reference frame is established:
  - Multi-robot localization becomes possible
  - Robot trajectories can be expressed in the same frame
- Infer robot trajectories via EM (see paper for full derivation):

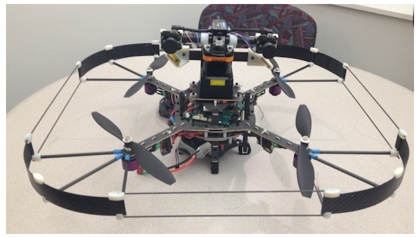
$$\hat{X} = \arg\max_{X} p\left(\mathcal{J}|\hat{X}, Z\right) \log p\left(X, \mathcal{J}|Z\right)$$

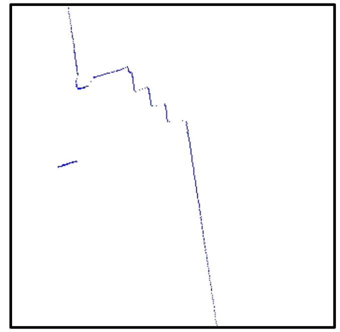
  - Identified common reference frame is used as **initial guess** within measurement likelihood

$$p\left(u_{k,l}^{r_1,r_2}|x_k^{r_1}, x_l^{r_2}\right) \propto \exp\left(-\frac{1}{2}\left\|err\left(u_{k,l}^{r_1,r_2}, x_k^{r_1}, x_l^{r_2}\right)\right\|_{\Sigma}^{2}\right)$$

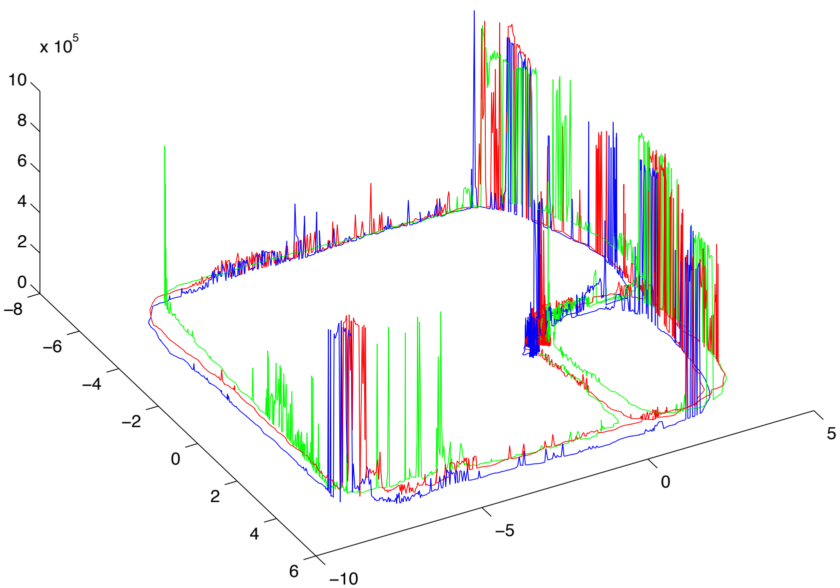
Results

Indoor navigation

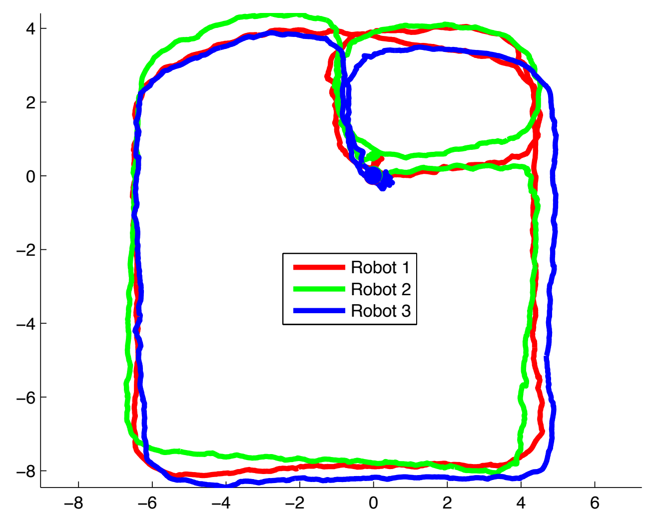




Shared salient laser scans

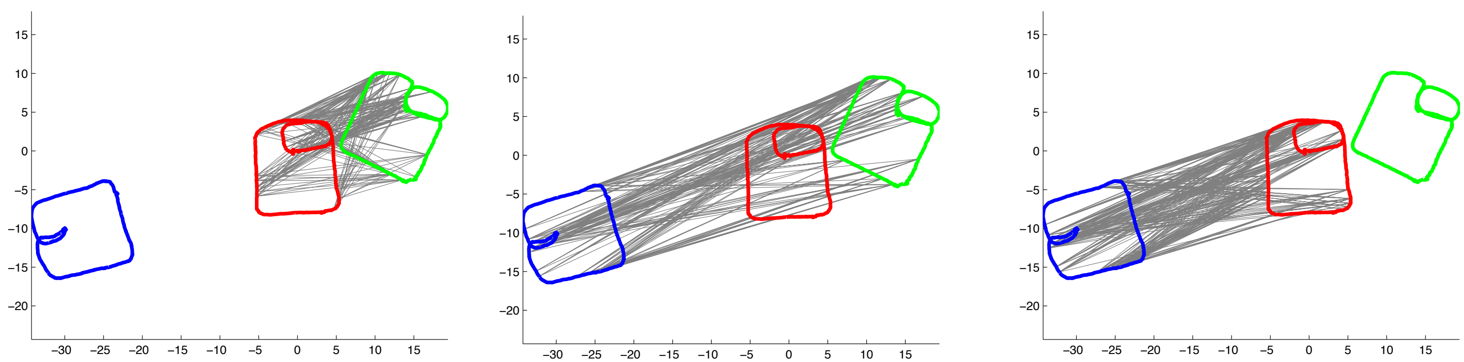


Ground truth



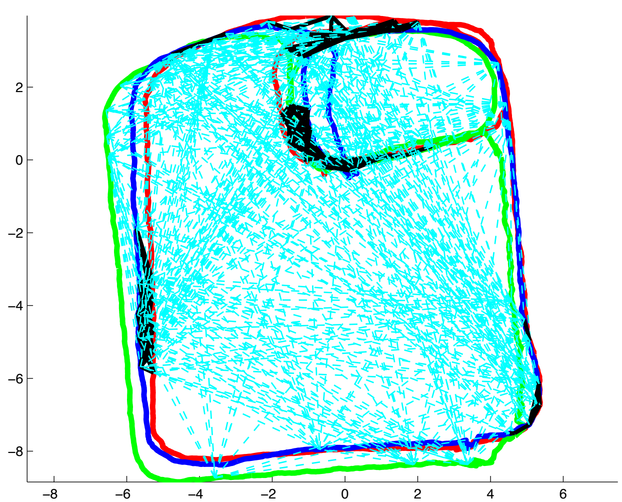
Results (Cont.)

Local trajectories of 3 robots; Arbitrary common reference frame

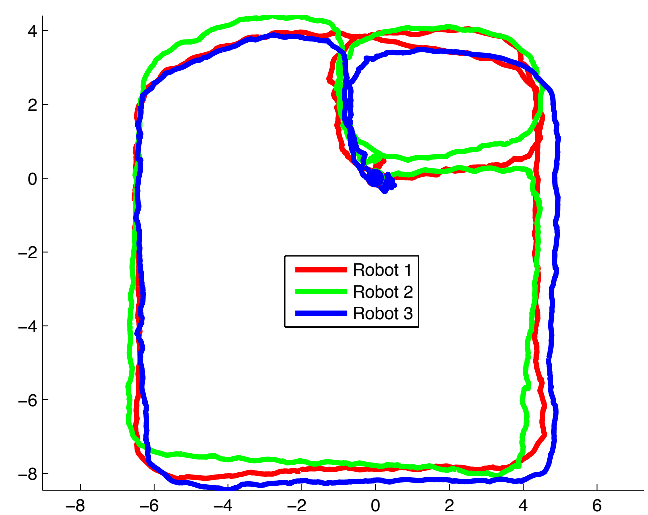


Inliers
Outliers

Estimated



Ground truth



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Conclusions and Future Work

- Collaborative inference from unknown initial poses and data association
  - Key observation (clusters for inlier correspondences)
  - EM approach to infer common reference frames and data association
  - Once established, EM approach for inference over robot poses
  - Extensive experimental study to appear in ISER 2014

Future Work

- Distributed and incremental framework
  - Perceptual aliasing
  - How to know when to make a decision?
- Vision sensors