

Towards Cooperative Multi-Robot Belief Space Planning in Unknown Environments

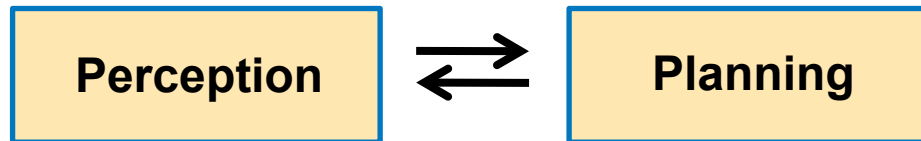
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Introduction

- Key components for autonomous operation include
 - **Perception**: Where am I? What is the surrounding environment?
 - **Planning**: What to do next?

Integrated planning and perception



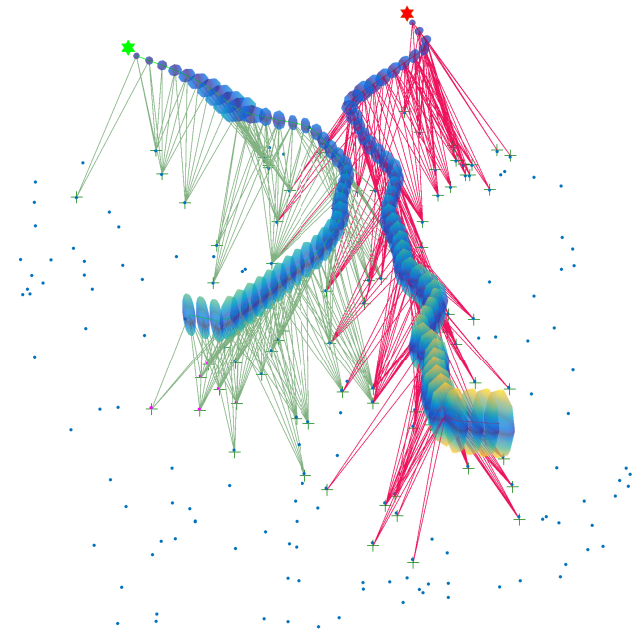
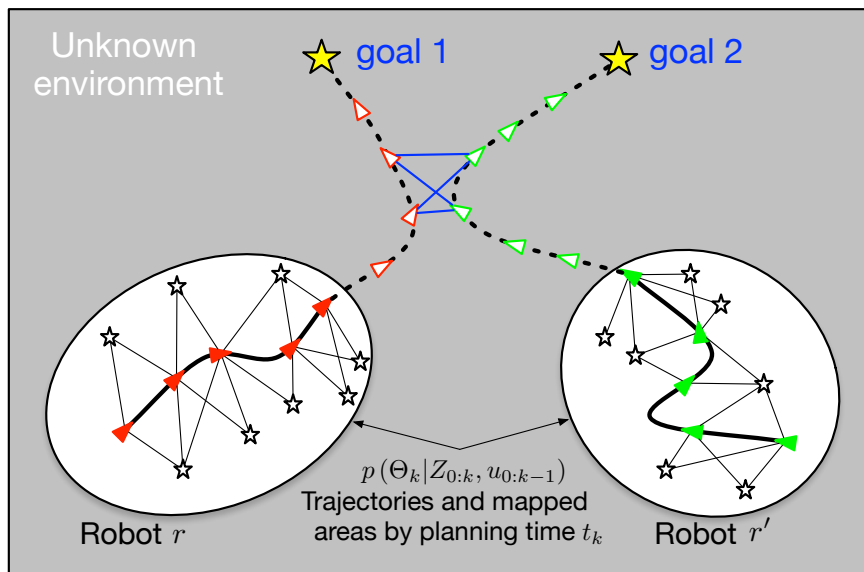
- Belief space planning - fundamental problem in robotics
- Computationally intractable to solve exactly (POMDP), approximate suboptimal approaches exist

Related Work – Belief Space Planning

- Existing approaches typically assume **environment/map is known**
[Prentice and Roy '09], [Miller et al. '09], [Platt et al. '10], [Van den Berg et al. '12], [Hollinger et al. '13]
- Recent research relaxes this assumption, **incorporates map uncertainty within the belief**
[Valencia et al. '12], [Kim and Eustice '13], [Indelman et al. '15]
- Still, planning reasons only in terms of **environment observed thus far**
- **This work:**
 - Incorporate reasoning regarding environments **unknown at planning time** into belief space planning
 - Multi-robot centralized framework
 - Autonomous navigation in unknown environments, as application

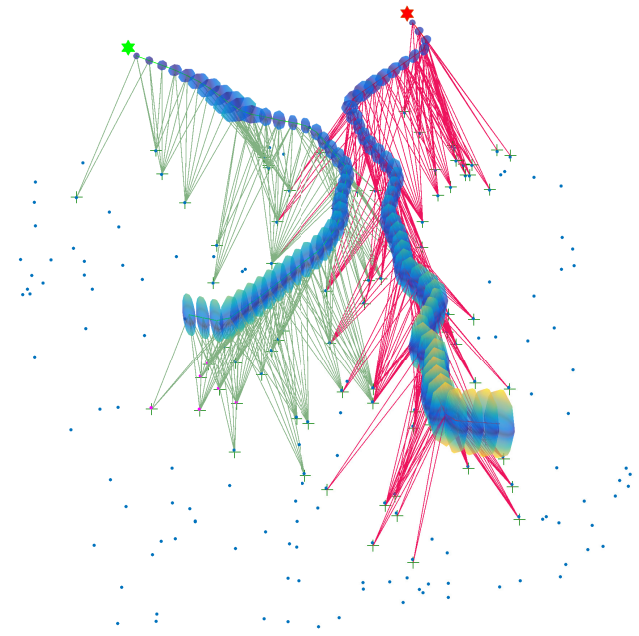
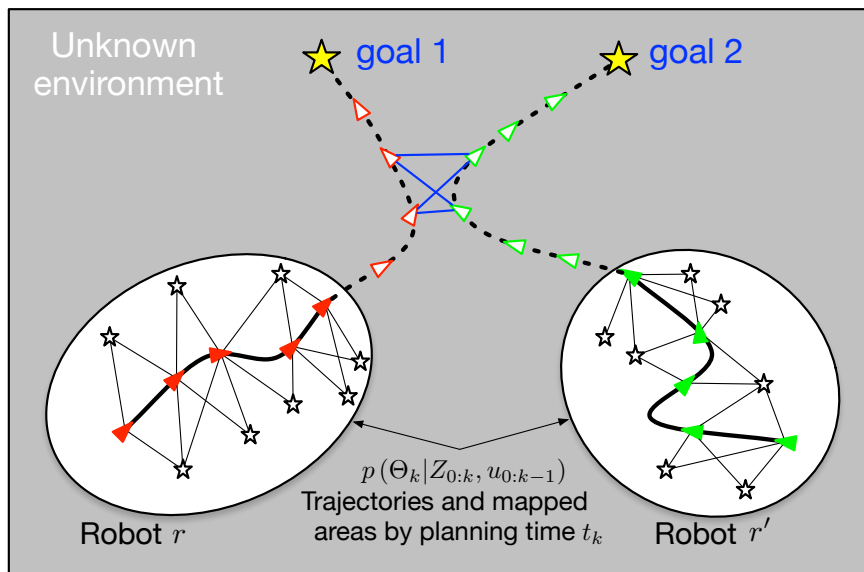
Contribution

- Framework for active collaborative state estimation while operating in unknown environments
- Key idea
 - Reason about future observations of environments that are **unknown at planning time** within multi-robot belief space planning
 - Incorporate into belief the corresponding **indirect** multi-robot constraints



Contribution

- Approach can be used to
 - Identify best robot trajectories among candidates generated by existing motion planning approaches
 - Refine nominal trajectories into locally optimal trajectories using direct trajectory optimization techniques
- Approach **does not require rendezvous** between robots (enhanced flexibility for the group)



Notations and Probabilistic Formulation

Single robot $r \in \{1, \dots, R\}$

- State transition and observation models:

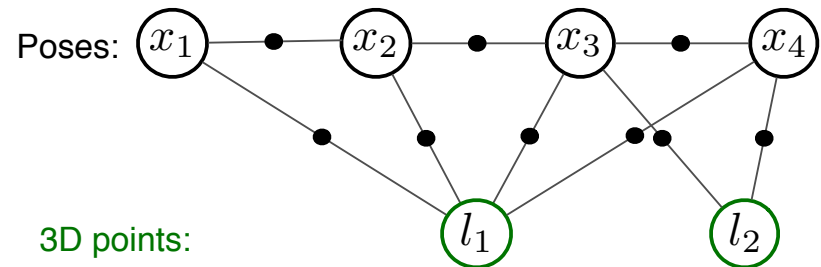
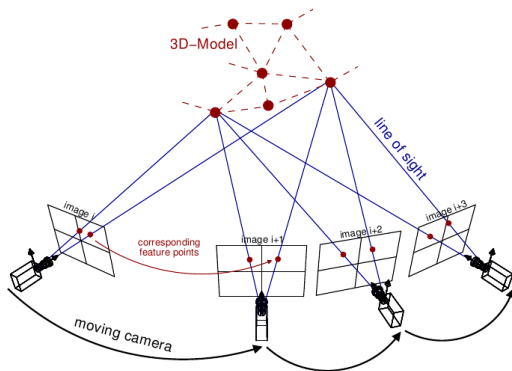
$$x_{i+1}^r = f(x_i^r, u_i^r) + w_i^r$$

$$z_{i,j}^r = h(x_i^r, l_j) + v_i^r$$

- Joint state: $\Theta_k^r \doteq X_k^r \cup L_k^r$, $X_k^r \doteq \{x_0^r, \dots, x_k^r\}$

- Joint probability distribution function (pdf) at planning time t_k :

$$p(\Theta_k^r | Z_{0:k}^r, u_{0:k-1}^r) \propto p(x_0^r) \prod_{i=1}^k [p(x_i^r | x_{i-1}^r, u_{i-1}^r) \underbrace{p(Z_i^r | \Theta_i^{r,o})}_{\doteq \prod_j p(z_{i,j}^r | x_i^r, l_j)}]$$



Notations and Probabilistic Formulation

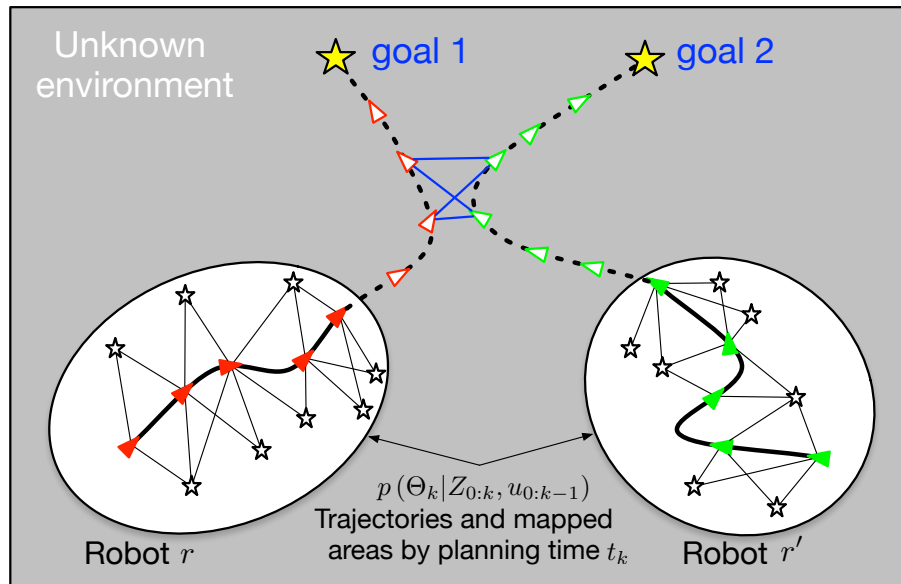
Multi-robot case

- Joint state for R robots:

$$\Theta_k \doteq X_k \cup L_k, \quad X_k \doteq \{X_k^r\}_{r=1}^R$$

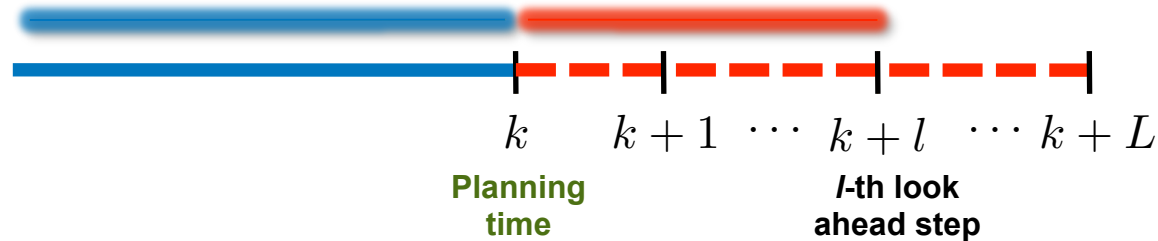
- Joint multi-robot pdf at planning time t_k

$$b(\Theta_k) \doteq p(\Theta_k | Z_{0:k}, u_{0:k-1}) \propto \prod_{r=1}^R p(\Theta_k^r | Z_{0:k}^r, u_{0:k-1}^r),$$



Multi-robot Belief Space Planning

- Multi-robot belief at a future time t_{k+l} : $b(\Theta_{k+l}) \doteq p(\Theta_{k+l} | Z_{0:k+l}, u_{0:k+l-1})$



- Multi-robot objective function:

$$J(u_{k:k+L-1}) \doteq \mathbb{E} \left[\sum_{l=0}^L c_l(b(\Theta_{k+l}), u_{k+l}) + c_L(b(\Theta_{k+L})) \right]$$

- Optimal controls for all R robots: $u_{k:k+L-1}^* = \arg \min_{u_{k:k+L-1}} J(u_{k:k+L-1})$

Evaluation of Candidate Paths

- Recall objective function $J(u_{k:k+L-1}) \doteq \mathbb{E} \left[\sum_{l=0}^L c_l (b(\Theta_{k+l}), u_{k+l}) + c_L (b(\Theta_{k+L})) \right]$
- Need to evaluate objective function for each candidate path
- Involves inference over beliefs from different time instances

$$b(\Theta_{k+l}) \equiv p(\Theta_{k+l} | Z_{0:k+l}, \underline{u_{0:k+l-1}}) = N(\Theta_{k+l}^*, I_{k+l})$$

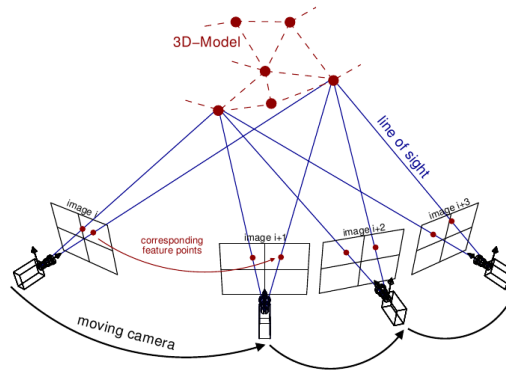


different for each path

Multi-Robot Belief

- Recall - Joint probability distribution function (pdf) at planning time t_k :

$$p(\Theta_k^r | Z_{0:k}^r, u_{0:k-1}^r) \propto p(x_0^r) \prod_{i=1}^k [p(x_i^r | x_{i-1}^r, u_{i-1}^r) \underbrace{p(Z_i^r | \Theta_i^{ro})}_{\doteq \prod_j p(z_{i,j}^r | x_i^r, l_j)}]$$



- Recursive formulation of a multi-robot belief at the l -th look ahead step:

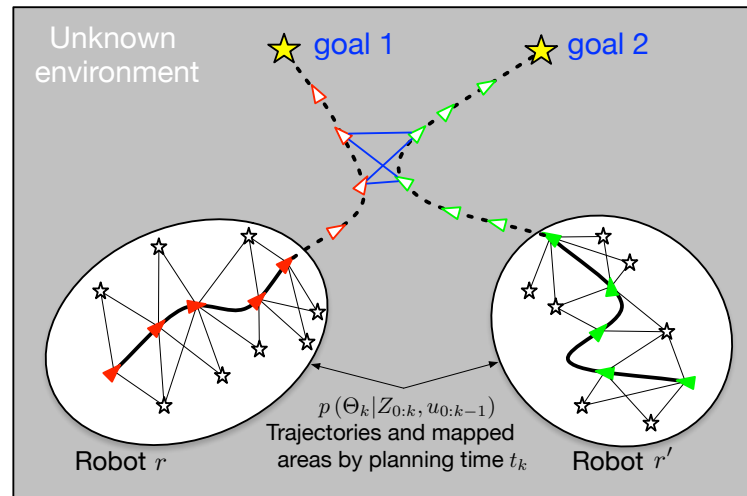
$$b(\Theta_{k+l}) = \eta b(\Theta_{k+l-1}) \prod_{r=1}^R p(x_{k+l}^r | x_{k+l-1}^r, u_{k+l-1}^r) p(Z_{k+l}^r | \Theta_{k+l}^{ro})$$

Incorporating Future Multi-Robot Constraints

- **Recall** - Key idea:

- Reason about future observations of environments that are unknown at planning time within multi-robot belief space planning
- Incorporate into belief indirect multi-robot constraints that correspond to these future observations

- **How?**



Incorporating Future Multi-Robot Constraints

- If we knew landmarks $L_{k+l,k+j}^{r,r'}$ will be observed from poses x_{k+l}^r and $x_{k+j}^{r'}$

$$p\left(x_{k+l}^r, x_{k+j}^{r'}, L_{k+l,k+j}^{r,r'} \mid z_{k+l}^r, z_{k+j}^{r'}\right) \propto p\left(z_{k+l}^r \mid x_{k+l}^r, L_{k+l,k+j}^{r,r'}\right) p\left(z_{k+j}^{r'} \mid x_{k+j}^{r'}, L_{k+l,k+j}^{r,r'}\right)$$

$$p\left(z_{k+l}^r, z_{k+j}^{r'} \mid x_{k+l}^r, x_{k+j}^{r'}\right) \propto \int p\left(x_{k+l}^r, x_{k+j}^{r'}, L_{k+l,k+j}^{r,r'} \mid z_{k+l}^r, z_{k+j}^{r'}\right) dL_{k+l,k+j}^{r,r'}$$

- But, what if environment is unknown?
- Recall passive framework (robot actions are determined):
 - Assume a mutual scene will be observed from some poses x_i^r and $x_j^{r'}$
 - Match between observations (image, laser scans) to get constraint $z_{i,j}^{r,r'}$
 - Measurement likelihood: $p(z_{i,j}^{r,r'} \mid x_i^r, x_j^{r'}) \propto \exp\left(-\frac{1}{2} \|z_{i,j}^{r,r'} - g(x_i^r, x_j^{r'})\|_{\Sigma_v}^2\right)$

Incorporating Future Multi-Robot Constraints

- Can we do the same in our (active) case?
 - Assume an unknown scene will be observed from future poses x_{k+l}^r and $x_{k+j}^{r'}$
 - Let $z_{k+l,k+j}^{r,r'}$ denote an unknown constraint calculated by matching the corresponding observations
 - Measurement likelihood is then

$$p\left(z_{k+l,k+j}^{r,r'} | x_{k+l}^r, x_{k+j}^{r'}\right) \propto \exp\left(-\frac{1}{2} \|z_{k+l,k+j}^{r,r'} - g\left(x_{k+l}^r, x_{k+j}^{r'}\right)\|_{\Sigma_v^{MR}}^2\right)$$

- $z_{k+l,k+j}^{r,r'}$ can be treated as random variable
- Taking a maximum-likelihood assumption, actual value is not important for belief inference

Incorporating Future Multi-Robot Constraints

- How to know two future poses mutually observe a scene?
 - Answer is scenario-specific
 - Can use
 - Indicator function $\gamma(x^r, x^{r'})$, as e.g. in [1]
 - Simpler criteria, e.g. if two poses are sufficiently nearby
 - Statistics (note: only used for planning, not for estimation)

[1] D. Levine, B. Luders, and J. P. How. Information-theoretic motion planning for constrained sensor networks. *Journal of Aerospace Information Systems*, 10(10):476–496, 2013.

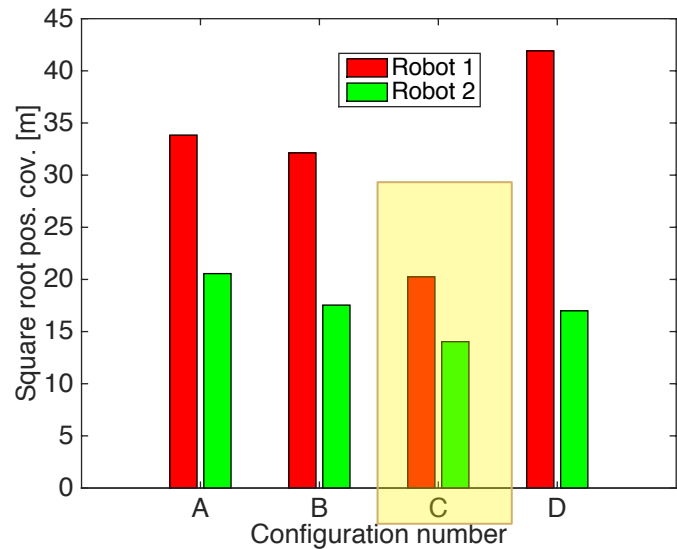
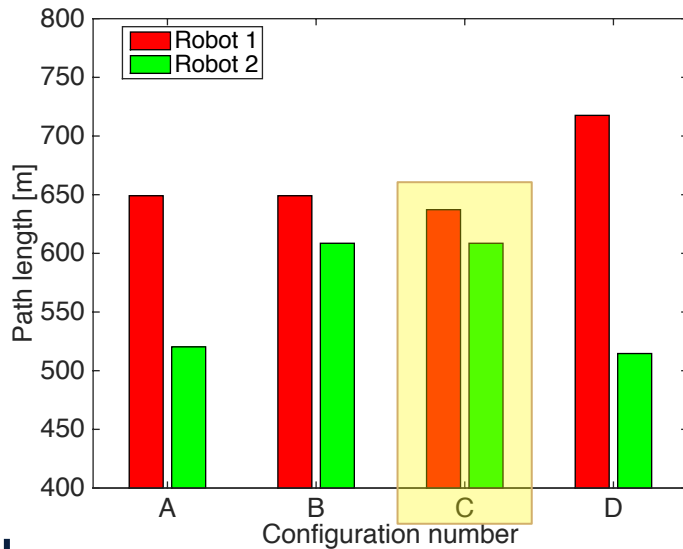
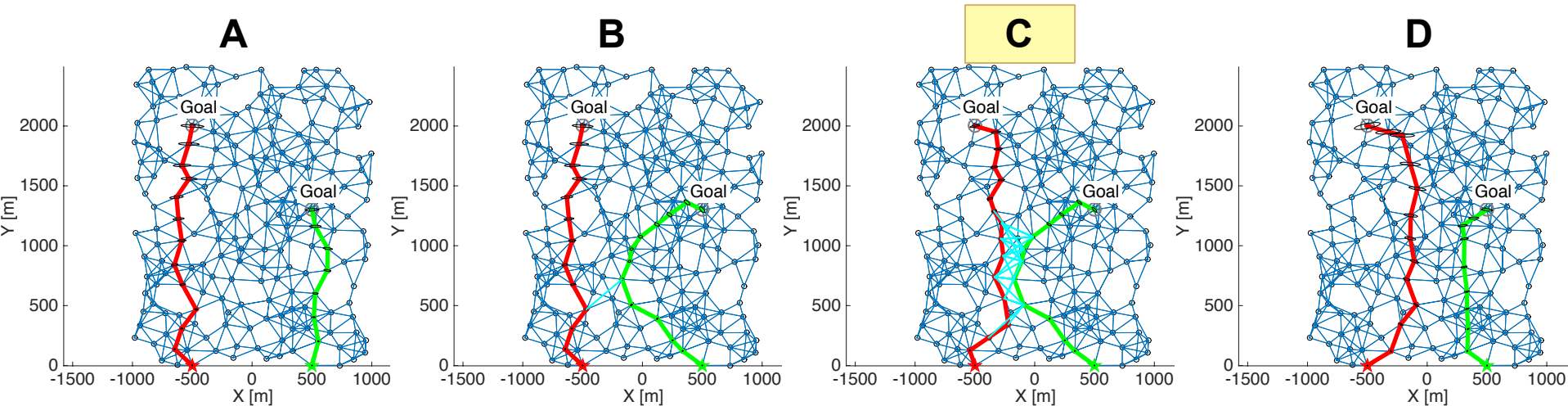
Recursive Formulation of a Multi-Robot Belief

- Plugging-in, final expression for a future time t_{k+l}

$$b(\Theta_{k+l}) = \eta b(\Theta_{k+l-1}) \prod_{r=1}^R \left[p(x_{k+l}^r | x_{k+l-1}^r, u_{k+l-1}^r) \prod_{l_j \in \Theta_{k+l}^{ro}} p(z_{k+l,j}^r | x_{k+l}^r, l_j) \right. \\ \left. p(z_{k+l,k+l-1}^r | x_{k+l}^r, x_{k+l-1}^r) \cdot \prod_j p(z_{k+l,k+j}^{r,r'} | x_{k+l}^r, x_{k+j}^{r'}) \right].$$

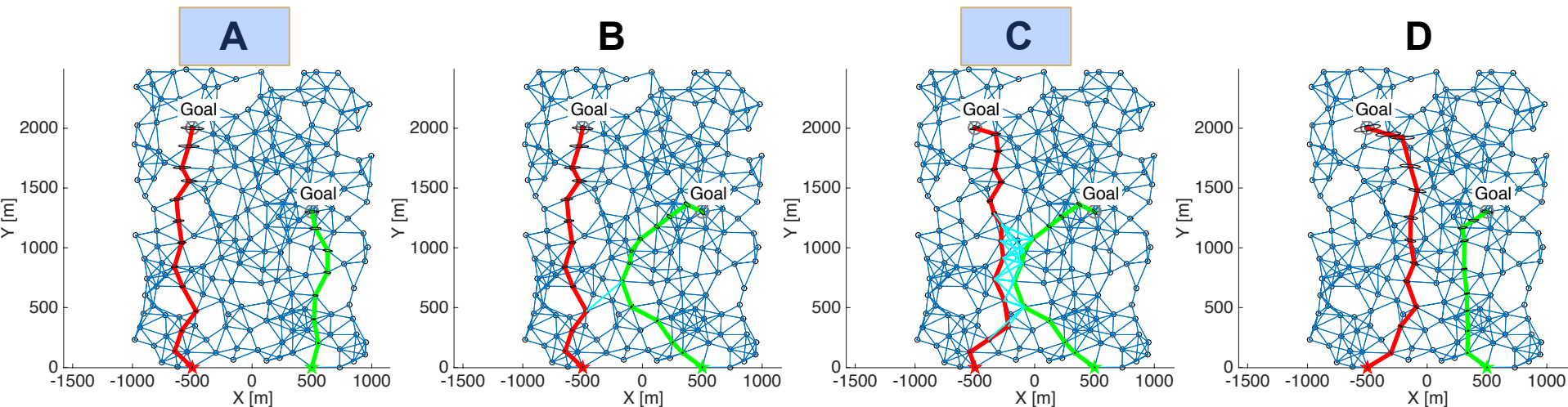
Preliminary Evaluation

- Objective function $J = \sum_{r=1}^R [\kappa^r t_{goal}^r + (1 - \kappa^r) tr(\Sigma_{goal}^r)]$
- PRM

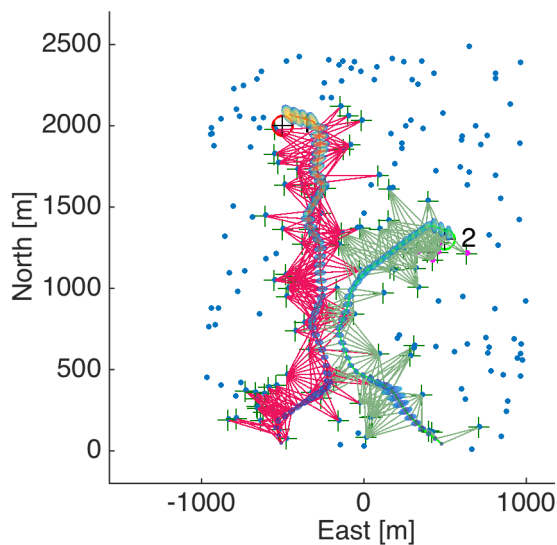
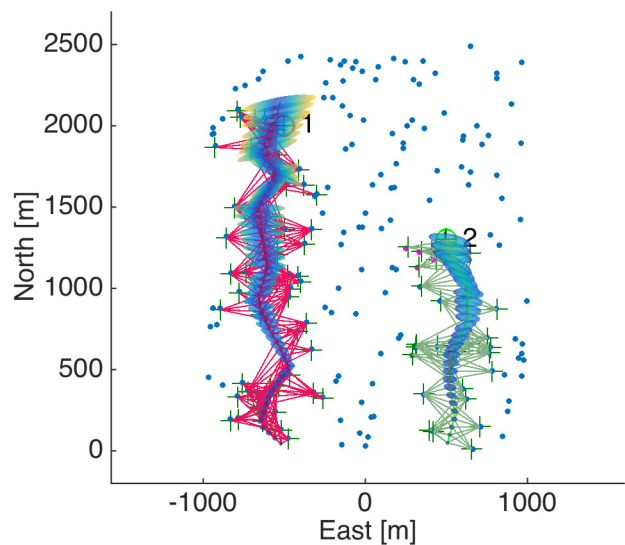


Preliminary Evaluation

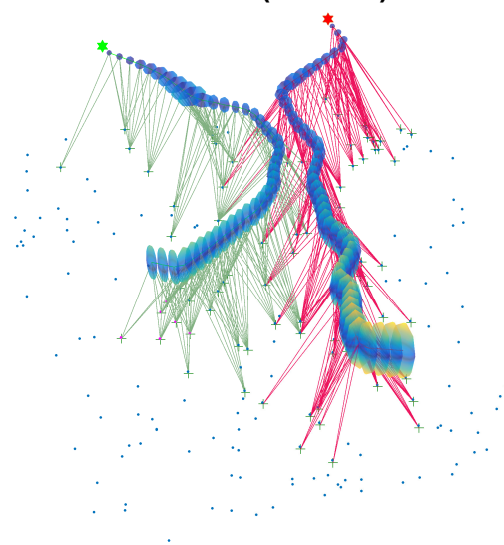
- Objective function $J = \sum_{r=1}^R [\kappa^r t_{goal}^r + (1 - \kappa^r) tr(\Sigma_{goal}^r)]$
- PRM



Path execution:



3D view (rotated)



Conclusions and Future Work

- Collaborative multi-robot belief space planning in unknown environments
- Contribution:
 - Incorporate within the belief constraints that represent multi-robot mutual observations of unknown environments
 - Enhanced flexibility to the group - rendezvous are no longer necessary
 - Concept can be used both within sampling based and direct trajectory optimization approaches
- Future work includes:
 - Extensive evaluation
 - Distributed/decentralized framework