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Distributed SLAM in Multi-Robot Systems using Particle Filters

Outline

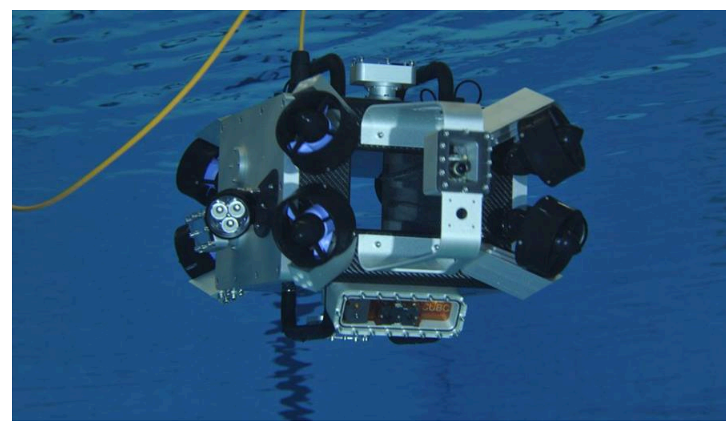
- Motivation
- The SLAM Problem
- Taxonomy and FastSLAM
- Towards Distributed Multi-Robot SLAM
- MRSLAM Approaches
- Discussion: Benefits & Problems
- Conclusion

Motivation

- Multiple robots for more efficient exploration and mapping
- Distributed techniques for higher robustness
- Applications in collaboration-based operations

[https://deliveryimages.acm.org/10.1145/2430000/2428574/figs/f1.jpg]

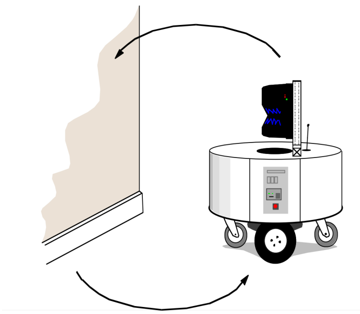
[https://www.army.mil/article/48456/robots_to_rescue_wounded_on_battlefield]



[https://blog.arduino.cc/wp-content/uploads/2016/06/13102905_1014622968612292_5004517645193876086_n.jpg]

Why Simultaneous Localisation and Mapping?

- Localization: estimating pose of robot requires a map
- Mapping: building environment map requires a pose estimate



[5]

- Chicken-or-Egg problem
- SLAM to the rescue - build map and locate robot at same time

Classical SLAM Problem

Given:

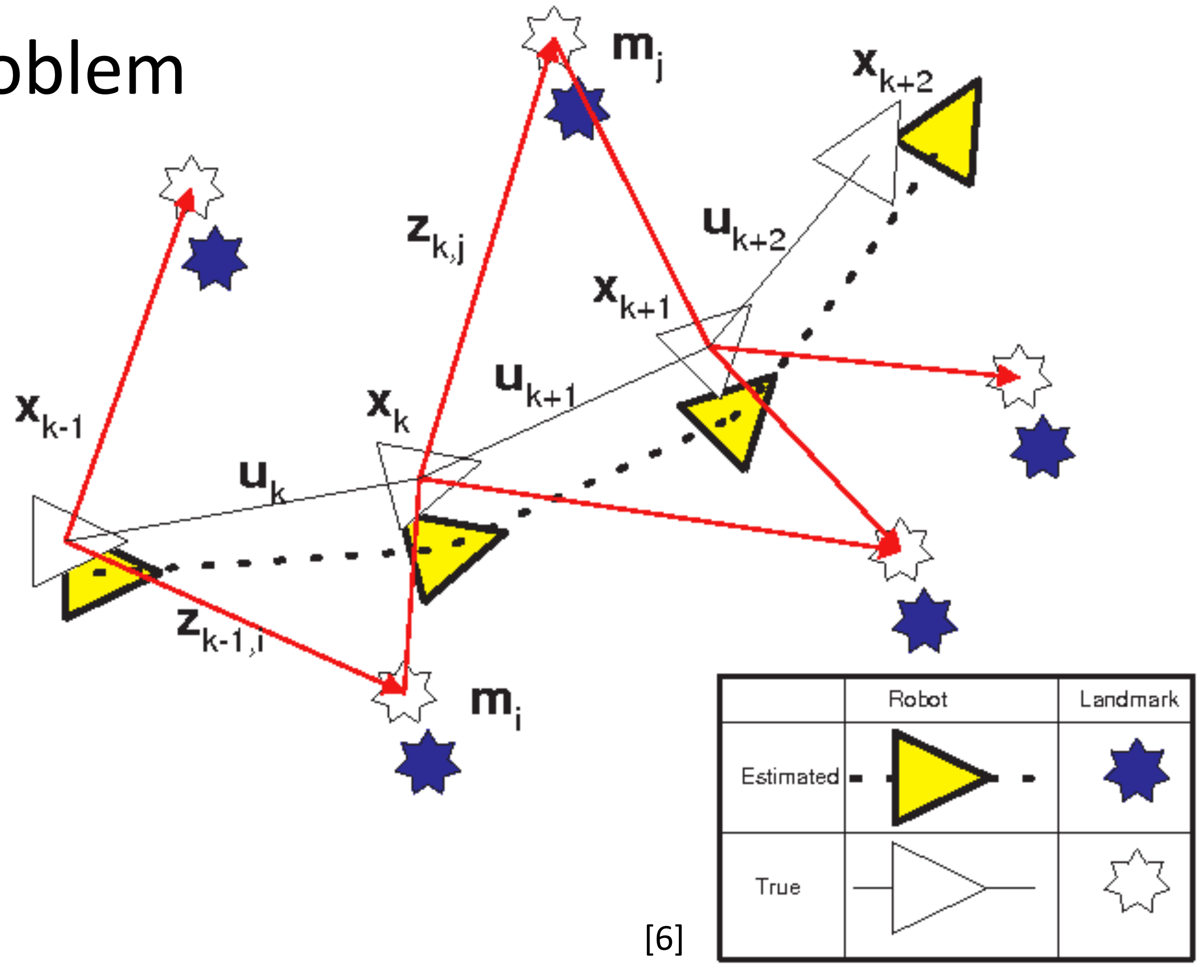
z: sensor observations
u: robot‘s controls

Wanted:

x: state of robot
m: map of environment

Posterior:

$$p(x_{1:t}, m | z_{1:t}, u_{1:t-1})$$

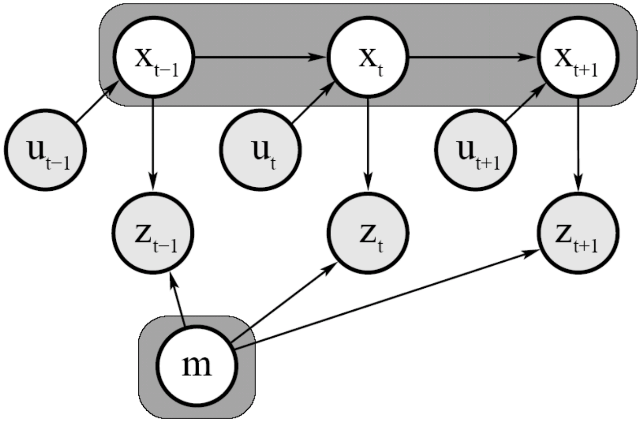


[6]

Full vs Online SLAM

Full SLAM estimates entire path (pose) and map

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t})$$



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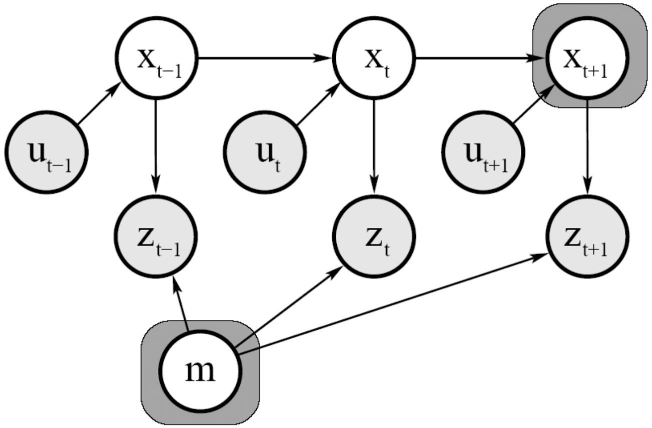
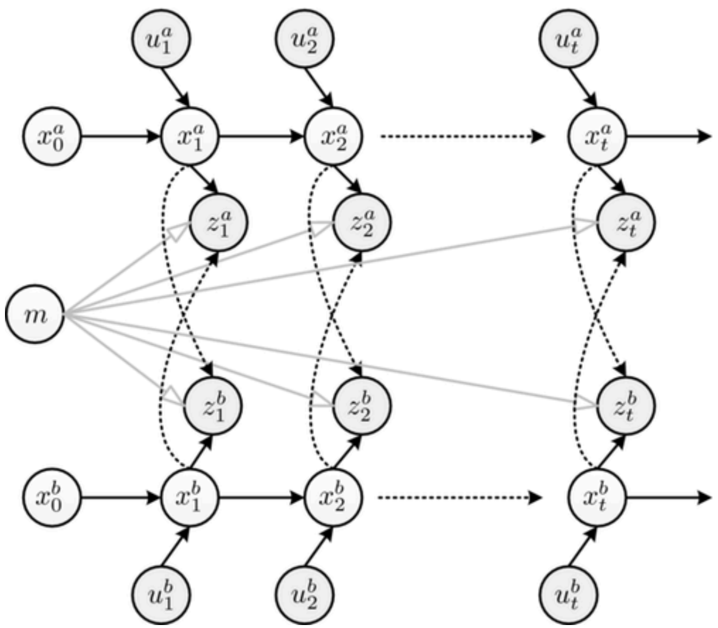
Online SLAM estimates most recent pose and map

$$p(x_t, m \mid z_{1:t}, u_{1:t}) = \int\int\cdots\int p(x_{1:t}, m \mid z_{1:t}, u_{1:t})\, dx_1\, dx_2 \ldots dx_{t-1}$$



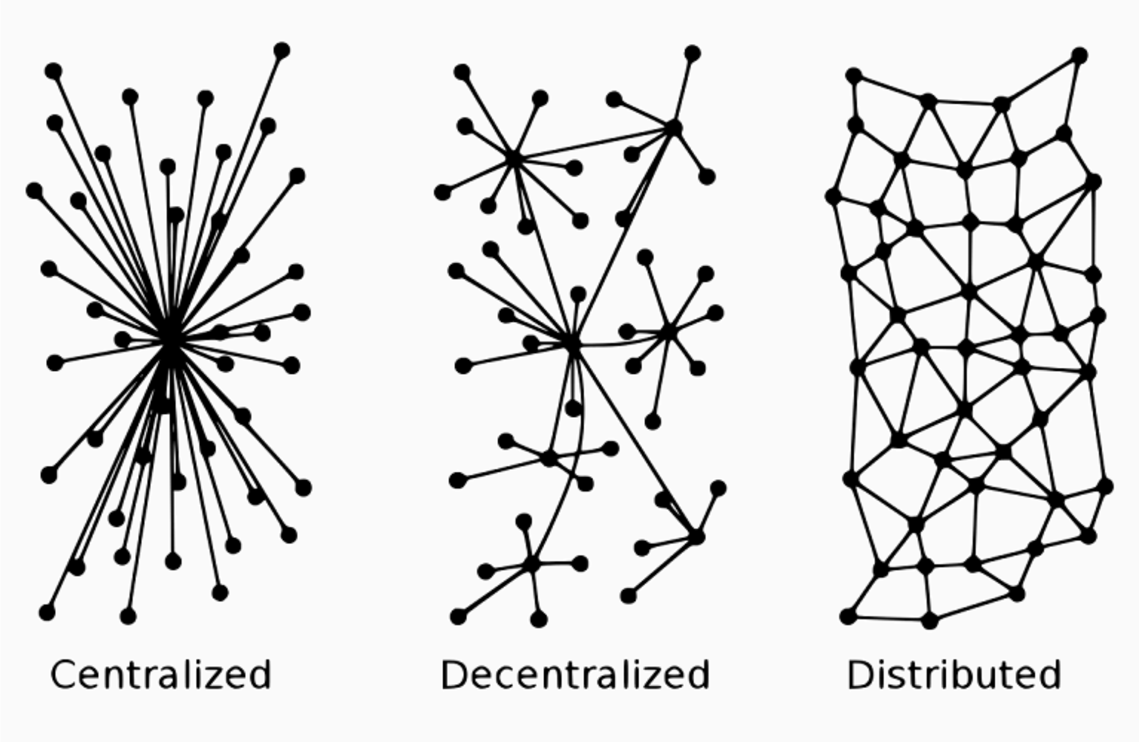
Multiple-Robot SLAM (MRSLAM)

Bayes Net for multiple-robot SLAM with two robots a and b [4]



$$p(x_{1:t}^a, x_{1:t}^b, m_t \mid z_{1:t}^a, z_{1:t}^b, u_{1:t}^a, u_{1:t}^b, x_0^a, x_0^b)$$

MRSLAM Communication Architectures



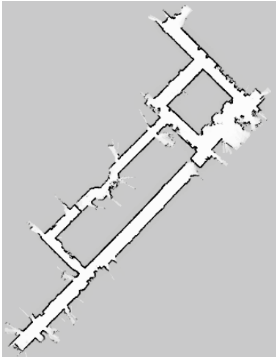
[http://www.truthcoin.info/images/cent-dec-dist.jpg]

Mapping in SLAM

Types of Maps

Grid-based

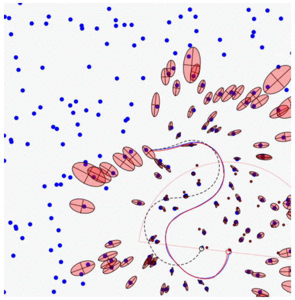
- Occupancy Grid
- Ideal for dense places



[5]

Feature-based

- Landmark based
- Ideal for sparse places

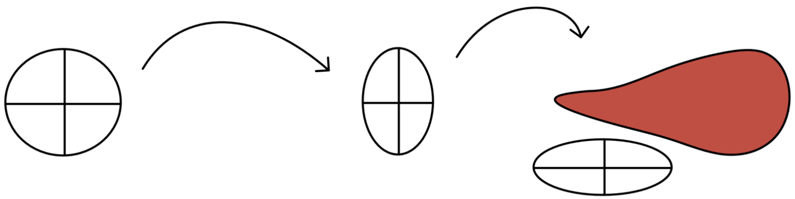


Localization in SLAM

Filtering Methods

Kalman Filter based

- Extended Kalman Filter
- High convergence
- Gaussian assumption



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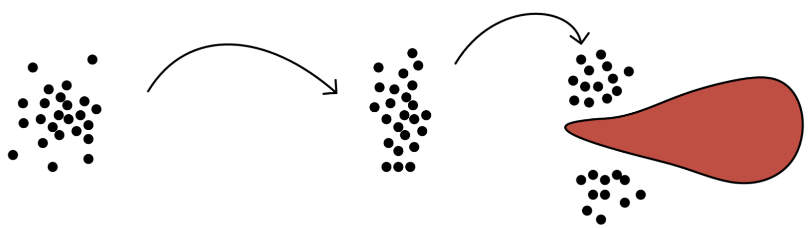
Particle Filter based

- FastSLAM
- Handle nonlinearities
- Growth in complexity



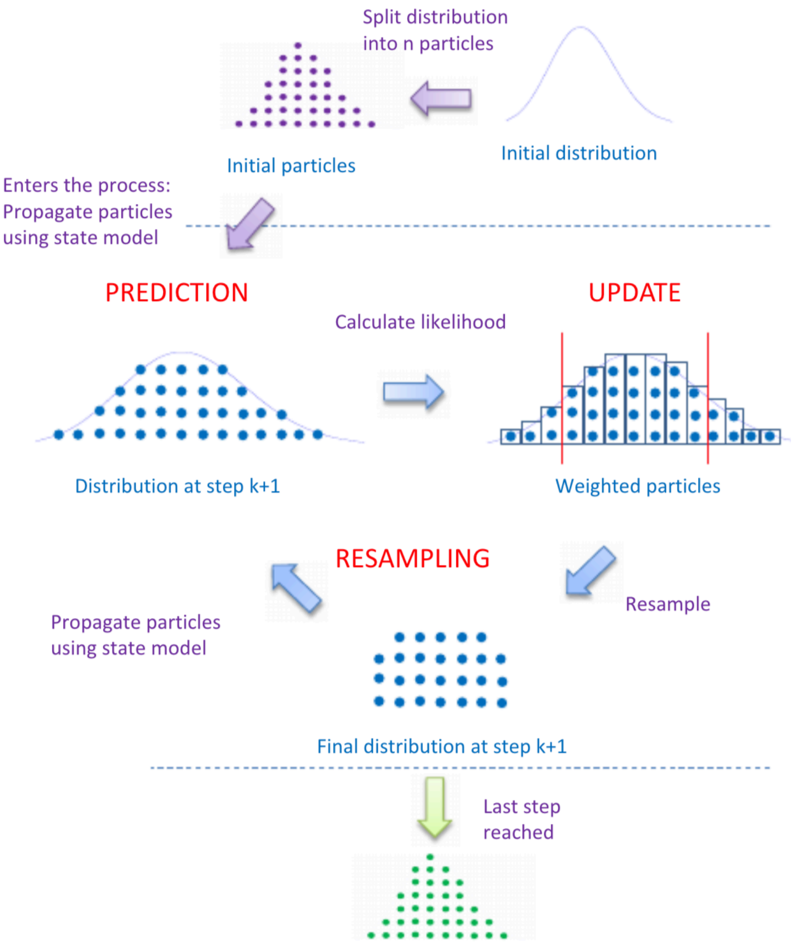
Particle Filter

- Motion Model

$$x_k = f(x_{k-1}, \vartheta_k, \nu_k)$$

- Observation Model

$$z_k = h(x_k, \mu_k)$$



[https://www.researchgate.net/figure/Particle-filter-principle_fig1_279866188]

FastSLAM

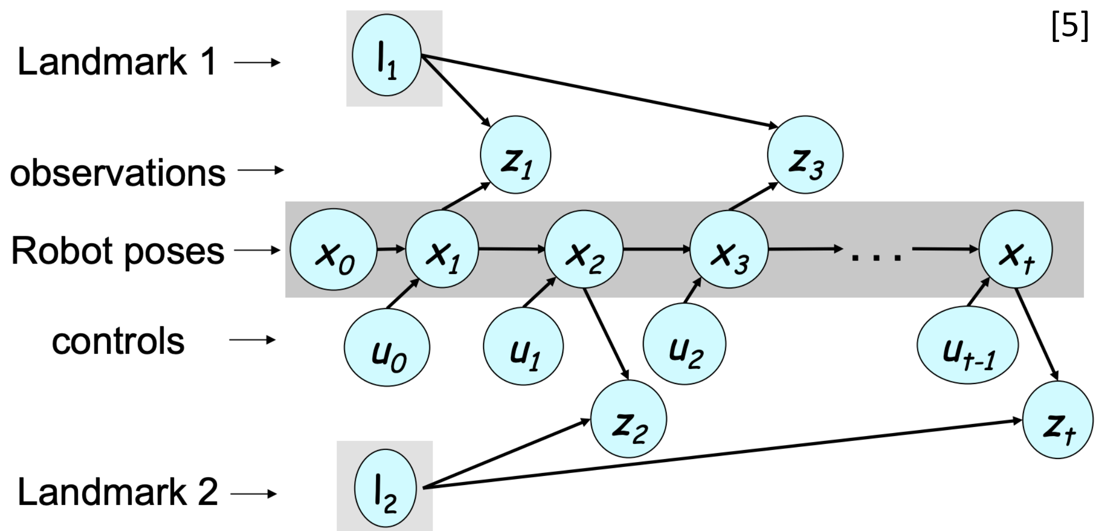
- Rao-Blackwellization
  - Common Particle Filter too inefficient for SLAM
  - Factored solution using Rao-Blackwell Particle Filter (RBPF)
- Multi-hypothesis for data association
- Landmark-based

$$
\begin{aligned}
& p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) \\
& \quad = p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot p(l_{1:m} \mid x_{1:t}, z_{1:t}) \\
& \quad = p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot \prod_{i=1}^{M} p(l_i \mid x_{1:t}, z_{1:t})
\end{aligned}
$$

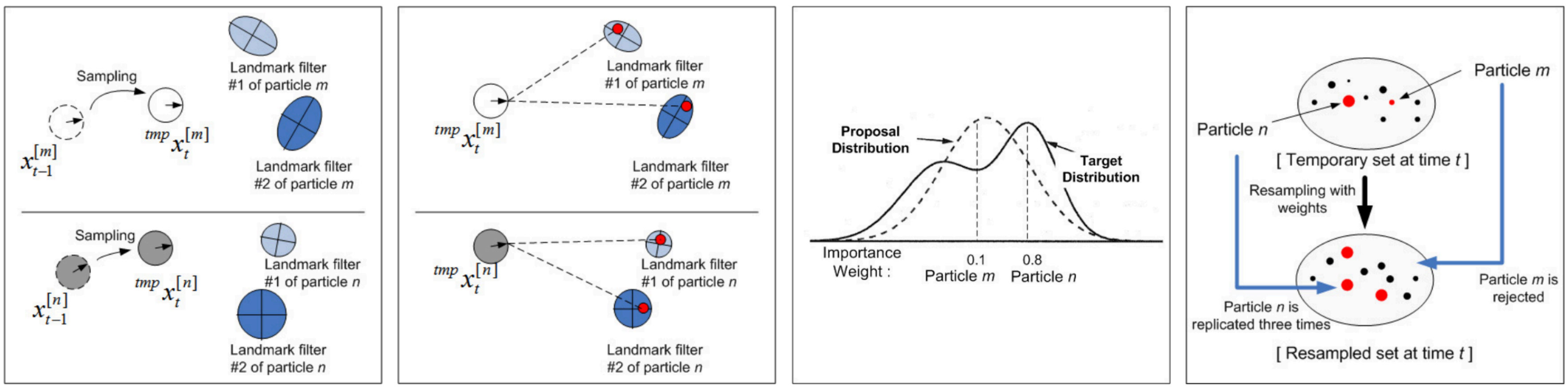
Path Posterior (localization)

Conditionally independent landmark positions

[5]



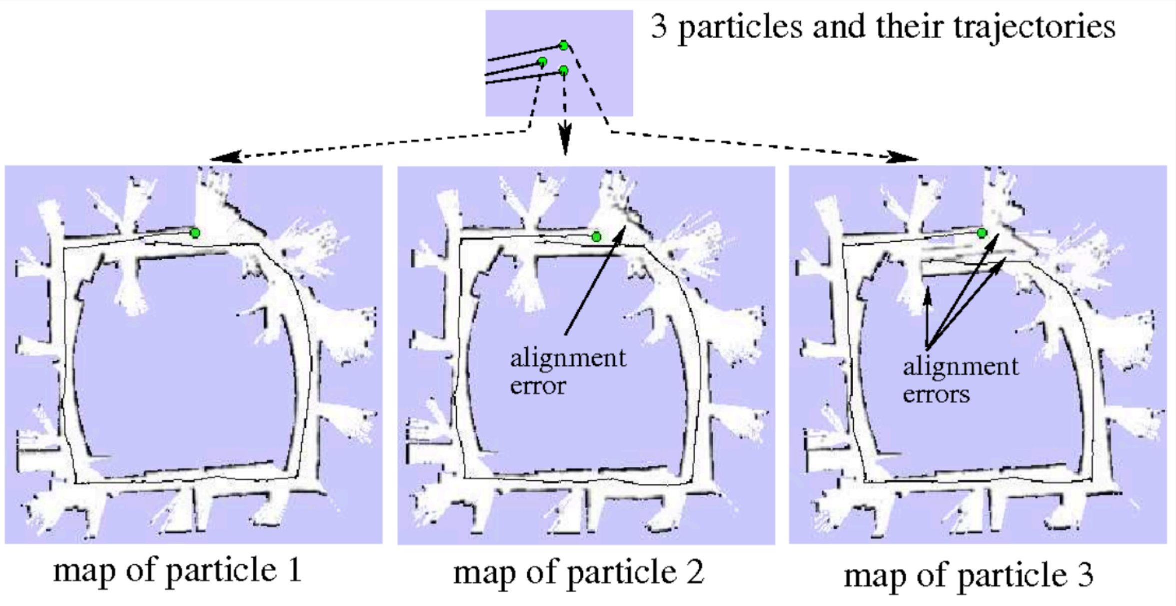
FastSLAM Algorithm



(a) Sampling (b) Measurement Update (c) Importance weight (d) Resampling

[9]

Grid based FastSLAM

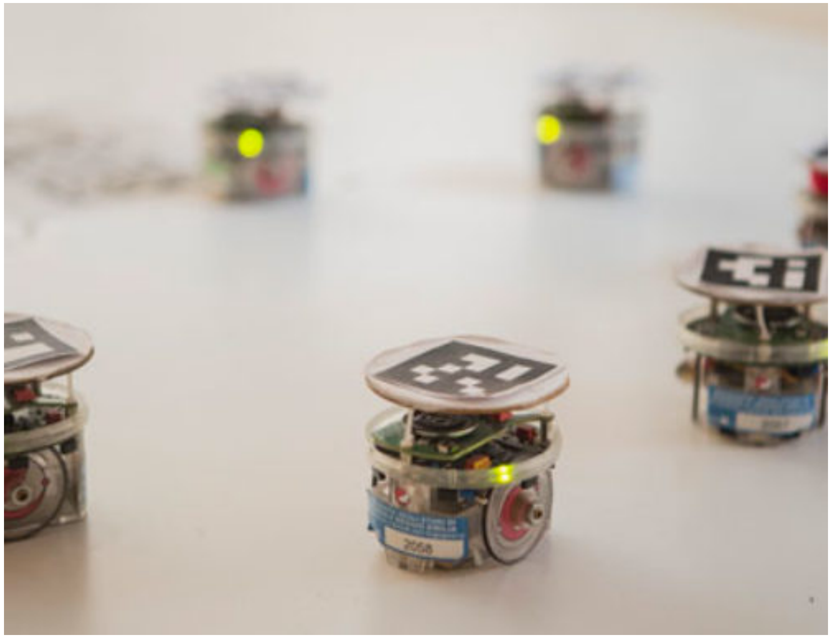


Three particles used within grid-based FastSLAM [8]

- Grid-based mapping also depends on poses
- Need fewer particles as each map is big
- Some approaches:
  - Improved Odometry
  - Improved Proposals

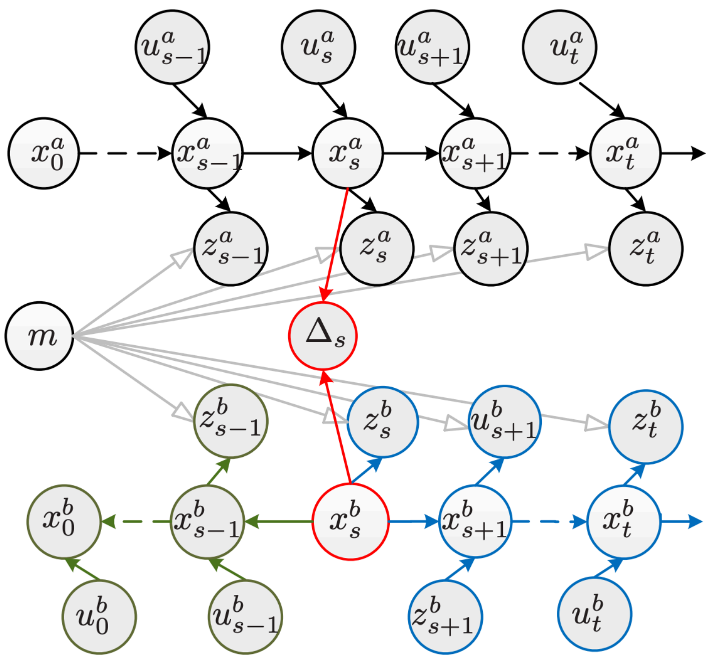
Towards MRSLAM

- Need and benefits
- Extending Classic SLAM to MRSLAM not straightforward
  - posterior estimation from data gathered by different robots
  - unreliable wireless sensing network
  - complexity and memory requirements
- Are the initial positions of the robots known?



[https://www.arscontrol.org/wp-content/uploads/2017/07/decentralized-control-of-multi-robot-systems-zoom-500x383.jpg]

MRSLAM Approach 1 (Howard, 2006)

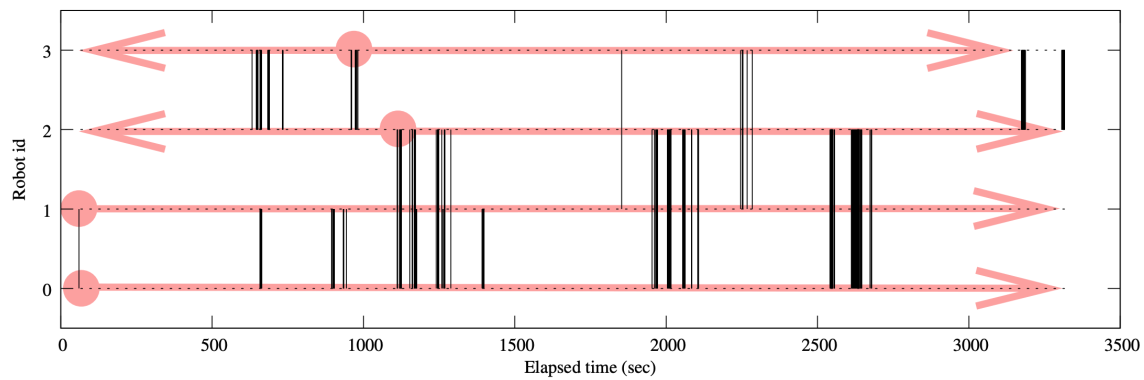


Bayes net for multi-robot SLAM with unknown initial poses [4]

- Online approach using RBPF
- Virtual Robots concept - integrate past measurements after encounters between robots
- Approaches for known and unknown initial poses
- Assumes support for time-reversed updates

Approach 1: Experiment

Four mapping robots [2]



Encounter diagram for multi-robot experiment [2]

Approach 1: Experiment Results

Combined map using multi-Robot SLAM algorithm [2]

Individual maps from two robots using single-Robot SLAM algorithm [2]

MRSLAM Approach 2 (Carlone, 2010)

P3-DX robots used for real test [1]

- Distributed grid-based RBPF
- Relative initial positions of robots unknown
- Fuses sensory information acquired by each teammate
- Short range communication technologies employable
- Assumes highly symmetric environment

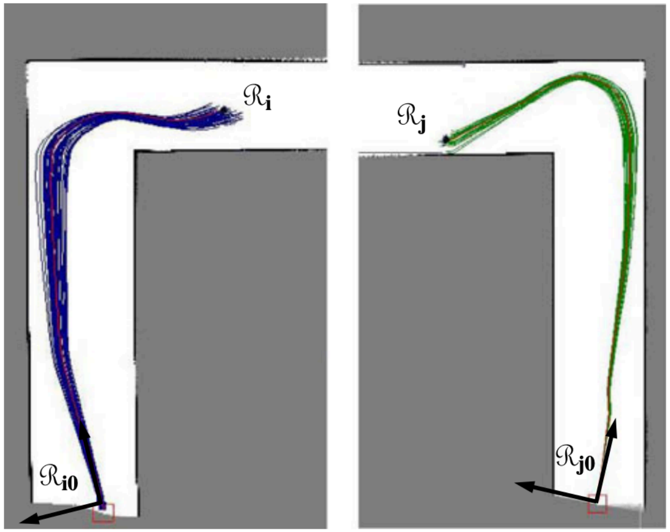
Approach 2 (contd.)

- $p(x_{1:t_{ij,1}}, m_i \mid d_{1:t_{ij,1}})$ **and** $p(x_{1:t_{ji,1}}, m_j \mid d_{1:t_{ji,1}})$

Robots i and j estimate posterior with

RBPF-SLAM pre rendezvous

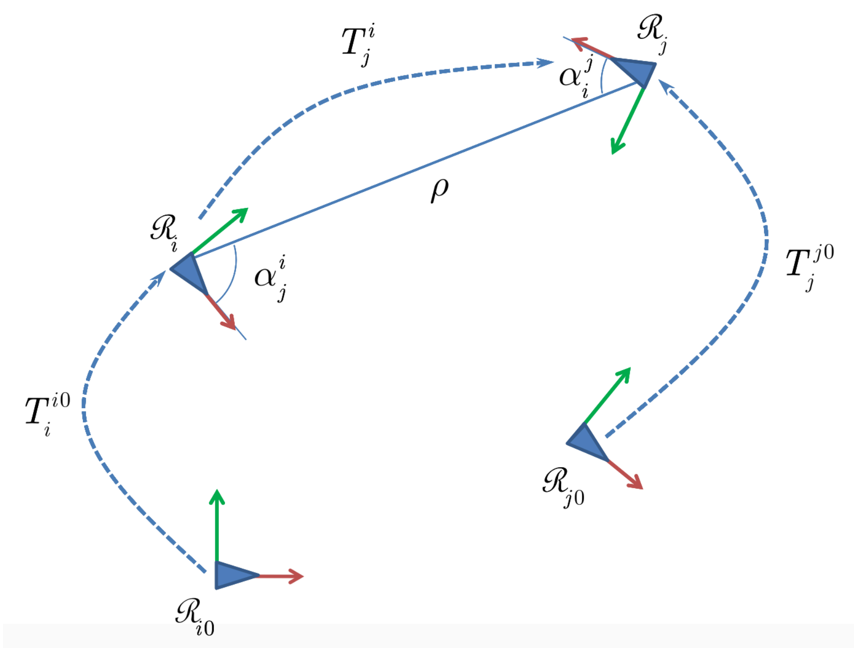
$d_{1:t_i} = \{z_{1:t_i}, u_{0:t_i-1}\}$ is the data



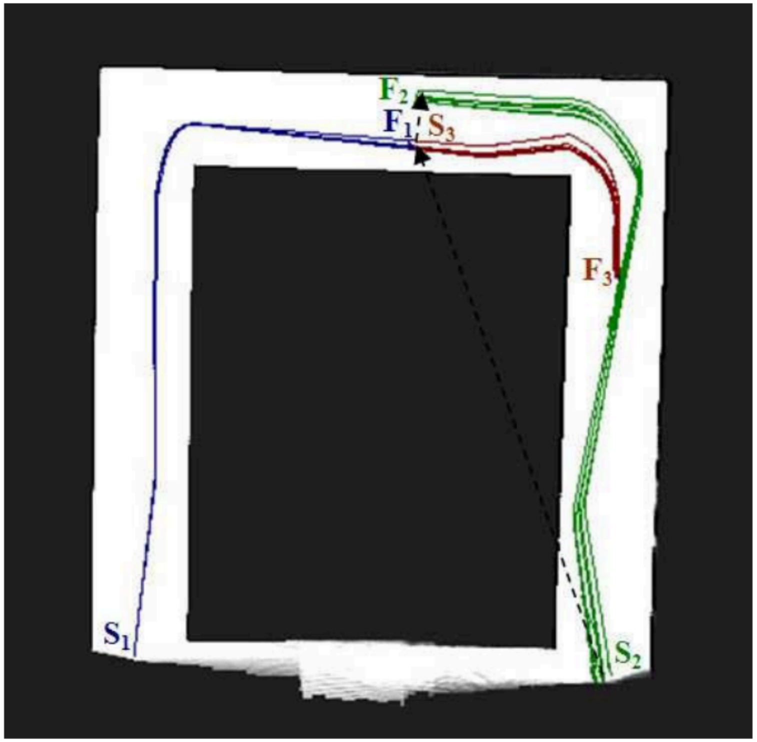
Single-robot FastSLAM before first rendezvous event [1]

- 3 Phase procedure at rendezvous
  - Data exchange between robots
  - Reference frame transformation
  - Estimation on virtual data

Approach 2 (contd.)

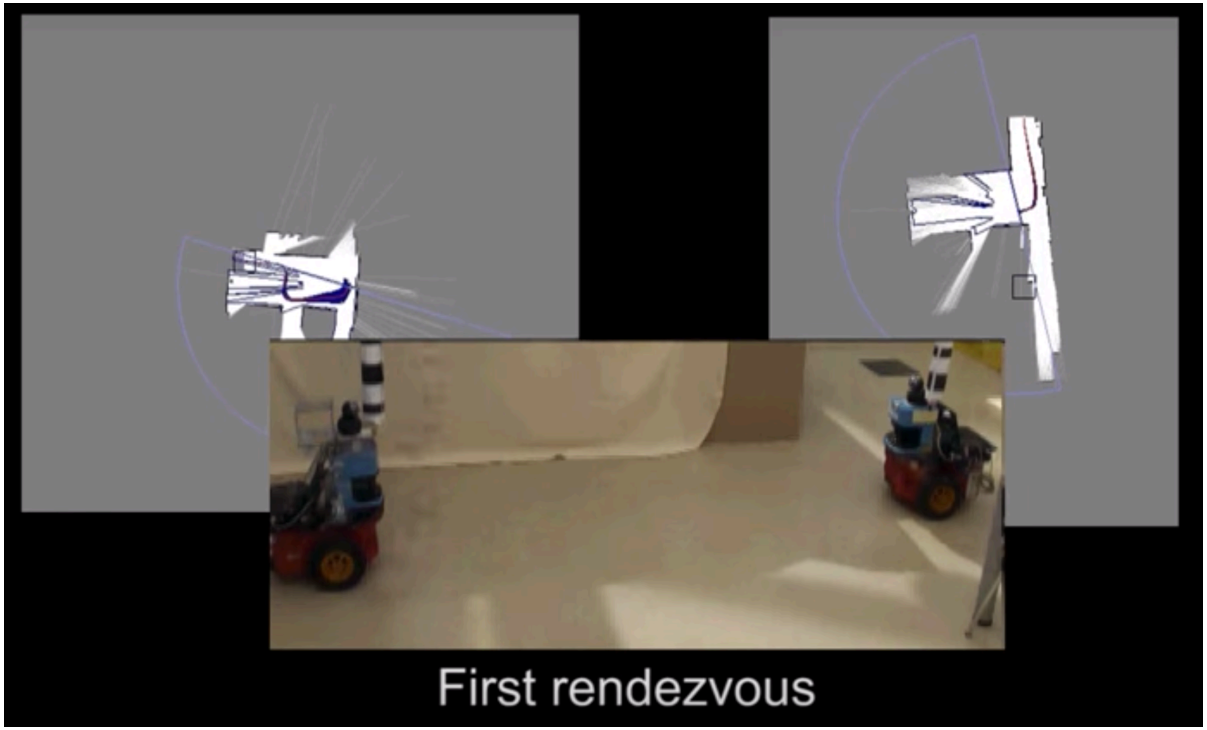


2nd Phase: Reference frame transformation [1]



3rd Phase: Estimation on virtual data after rendezvous [1]

Video Demo (Carlone, 2010)



[https://www.youtube.com/watch?v=UFm1pTsPqfk]

Discussion

Approach 1 (Howard, 2006)

- Maps and poses updated in real time
- Requires line-of-sight observations
- Uncertainty for relative poses not considered
- Only first encounter used

Approach 2 (Carlone, 2010)

- Short range communication technologies employable
- Reduces amount of data to be exchanged among robots
- Uncertainty for relative poses taken into account
- All encounters used

Conclusions

- Feasibility of Particle Filtering for SLAM
- Focus on Grid-Based RBPF approaches for MRSLAM
- Several works exist addressing varied challenges in MRSLAM

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Thank you for your attention!
Questions?