CSE-571
Robotics

Fast-SLAM Mapping

1

Particle Representation

- A set of weighted samples

$$\mathcal{X} = \left\{ \left\langle x^{[i]}, w^{[i]} \right\rangle \right\}_{i=1,\ldots,N}$$

- Think of a sample as one hypothesis about the state
- For feature-based SLAM:

$$x = (\underbrace{x_{1:t}}_{\text{poses}}, \underbrace{m_{1,x}, m_{1,y}, \ldots, m_{M,x}, m_{M,y}}_{\text{landmarks}})^T$$

Courtesy: C. Stachniss

2

Dimensionality Problem

Particle filters are effective in low dimensional spaces as the likely regions of the state space need to be covered with samples.

$$x = (x_{1:t}, m_{1,x}, m_{1,y}, \ldots, m_{M,x}, m_{M,y})^T$$

high-dimensional

Courtesy: C. Stachniss

3

Can We Exploit Dependencies Between the Different Dimensions of the State Space?

$$x_{1:t}, m_1, \ \ldots, m_M$$

Courtesy: C. Stachniss

4

If We Know the Poses of the Robot, Mapping is Easy!

$$x_{1:t}, m_1, \ldots, m_M$$

Courtesy: C. Stachniss

5

Key Idea

$$x_{1:t}, m_1, \ldots, m_M$$

If we use the particle set only to model the robot's path, each sample is a path hypothesis. For each sample, we can compute an individual map of landmarks.

Courtesy: C. Stachniss

6

Rao-Blackwellization

- Factorization to exploit dependencies between variables:

$$p(a, b) \;=\; p(b \mid a)\, p(a)$$

- If $p(b \mid a)$ can be computed efficiently, represent only $p(a)$ with samples and compute $p(b \mid a)$ for every sample

Courtesy: C. Stachniss

7

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

poses map observations & movements

$$p(x_{0:t}, m_{1:M} \mid z_{1:t}, u_{1:t}) =$$

First introduced for SLAM by Murphy in 1999

K. Murphy, Bayesian map learning in dynamic environments, In Proc. Advances in Neural Information Processing Systems, 1999

Courtesy: C. Stachniss

8

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

poses, map, observations & movements

$$p(x_{0:t}, m_{1:M} \mid z_{1:t}, u_{1:t}) = p(x_{0:t} \mid z_{1:t}, u_{1:t})\; p(m_{1:M} \mid x_{0:t}, z_{1:t})$$

path posterior, map posterior

First introduced for SLAM by Murphy in 1999

K. Murphy, Bayesian map learning in dynamic environments, In Proc. Advances in Neural Information Processing Systems, 1999

Courtesy: C. Stachniss

9

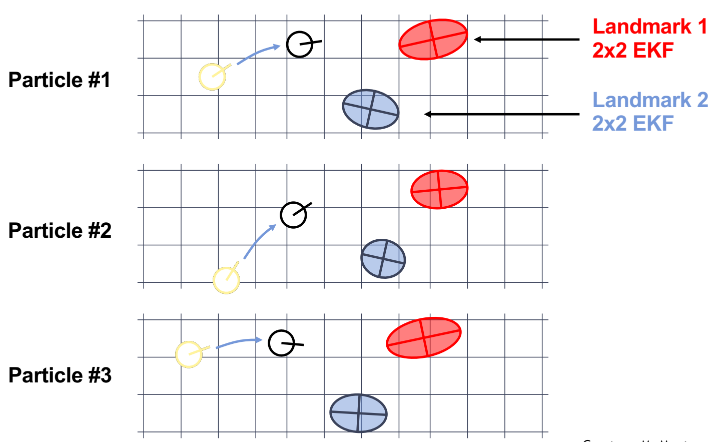
FastSLAM

- Proposed by Montemerlo et al. in 2002
- Each landmark is represented by a 2x2 EKF
- Each particle therefore has to maintain *M* individual EKFs

Particle 1	x, y, θ	**Landmark 1**	**Landmark 2**	**... Landmark *M***
Particle 2	x, y, θ	**Landmark 1**	**Landmark 2**	**... Landmark *M***
⋮				
Particle *N*	x, y, θ	**Landmark 1**	**Landmark 2**	**... Landmark *M***

10

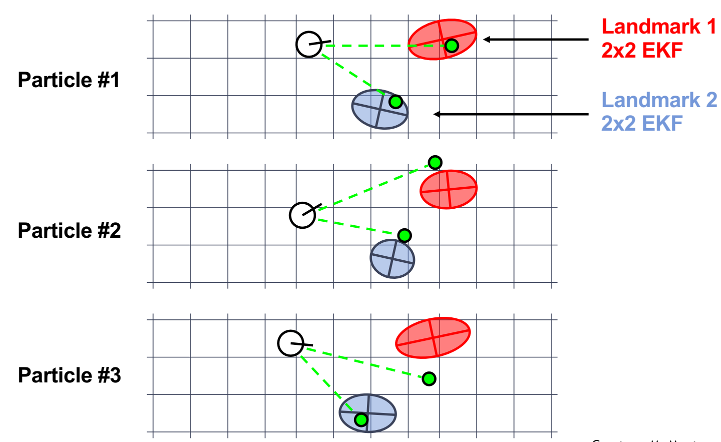
FastSLAM – Motion Update



Courtesy: M. Montemerlo

11

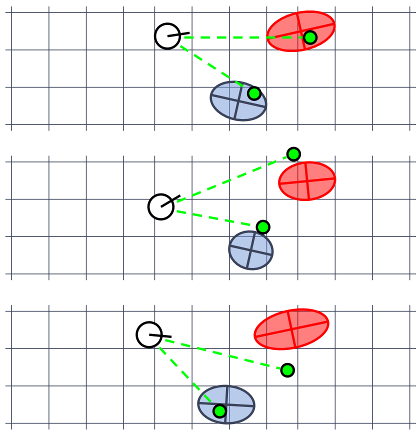
FastSLAM – Sensor Update



Courtesy: M. Montemerlo

12

FastSLAM – Sensor Update



Particle #1 — Weight = 0.8

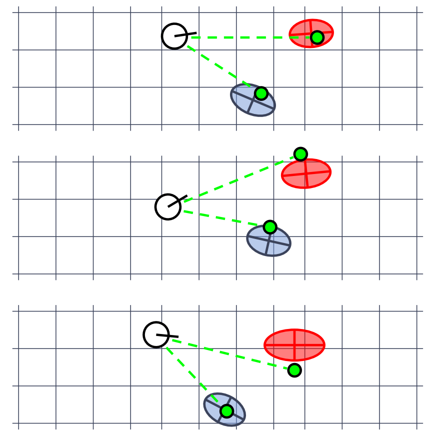
Particle #2 — Weight = 0.4

Particle #3 — Weight = 0.1

Courtesy: M. Montemerlo

13

FastSLAM – Sensor Update



Particle #1 — Update map of particle 1

Particle #2 — Update map of particle 2

Particle #3 — Update map of particle 3

Courtesy: M. Montemerlo

14

Key Steps of FastSLAM 1.0

- Extend the path posterior by sampling a new pose for each sample

  $$x_t^{[k]} \sim p(x_t \mid x_{t-1}^{[k]}, u_t)$$

- Compute particle weight

  exp. observation

  $$w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z_t - \hat{z}^{[k]})^T Q^{-1} (z_t - \hat{z}^{[k]})\right\}$$

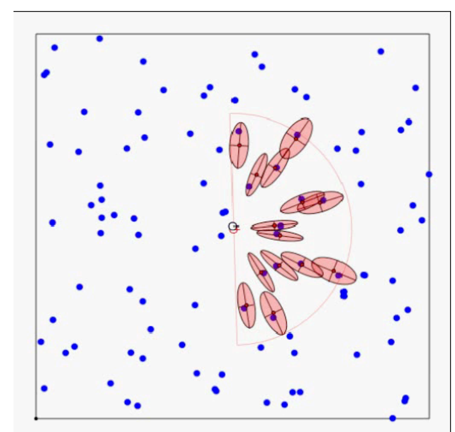
  innovation covariance

- Update belief of observed landmarks (EKF update rule)
- Resample

Courtesy: C. Stachniss

15

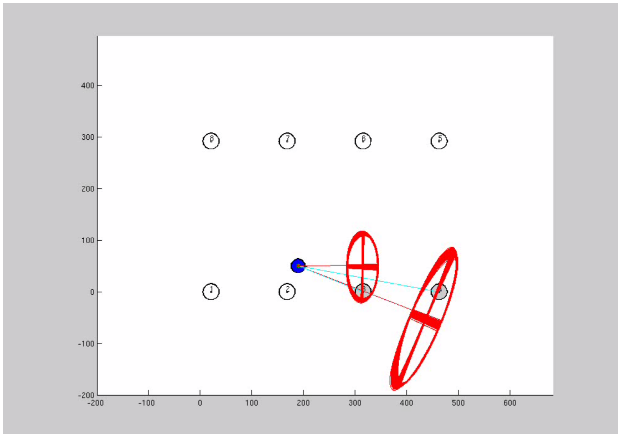
FastSLAM in Action



Courtesy: M. Montemerlo

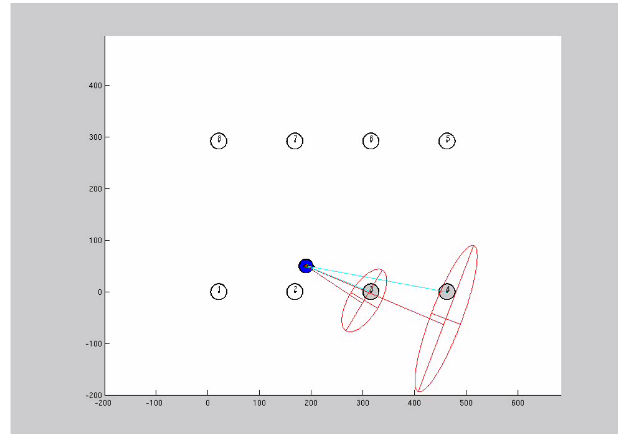
16

FastSLAM – Video – All Maps



17

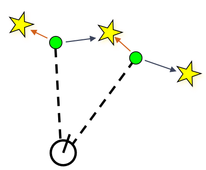
FastSLAM – Video – "Best" particle in terms of Cum Log Prob



18

Data Association Problem

- Which observation belongs to which landmark?



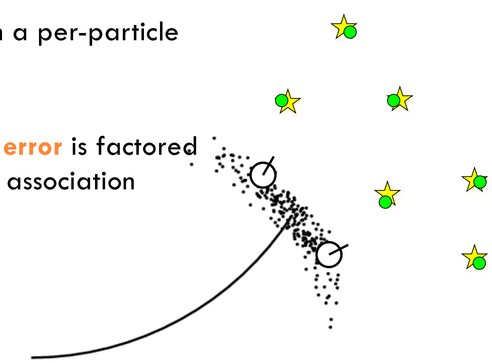
- More than one possible association
- **Potential data associations depend on the pose of the robot**

Courtesy: M. Montemerlo

19

Particles Support for Multi-Hypotheses Data Association

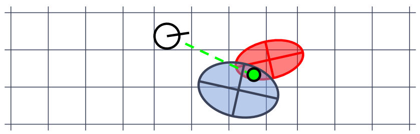
- Decisions on a per-particle basis
- Robot pose **error** is factored out of data association decisions



Courtesy: M. Montemerlo

20

Per-Particle Data Association



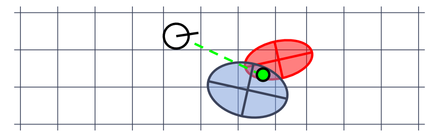
Was the observation generated by the **red** or by the **blue** landmark?

P(observation | red) = 0.3   P(observation | blue) = 0.7

Courtesy: M. Montemerlo

21

Per-Particle Data Association



Was the observation generated by the **red** or by the **blue** landmark?

P(observation | red) = 0.3   P(observation | blue) = 0.7

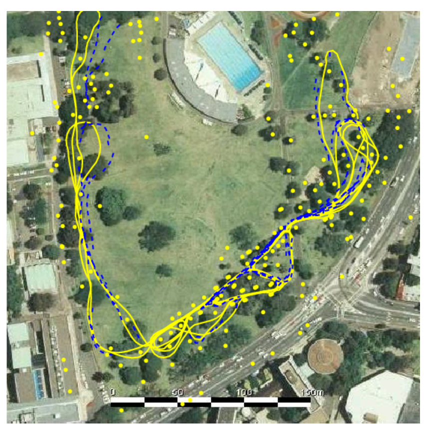
- Two options for per-particle data association
  - Pick the most probable match
  - Pick a random association weighted by the observation likelihoods
- If the probability for an assignment is too low, generate a new landmark

Courtesy: M. Montemerlo

22

Results – Victoria Park

- 4 km traverse
- < 2.5 m RMS position error
- 100 particles



Blue = GPS
Yellow = FastSLAM

Courtesy: M. Montemerlo

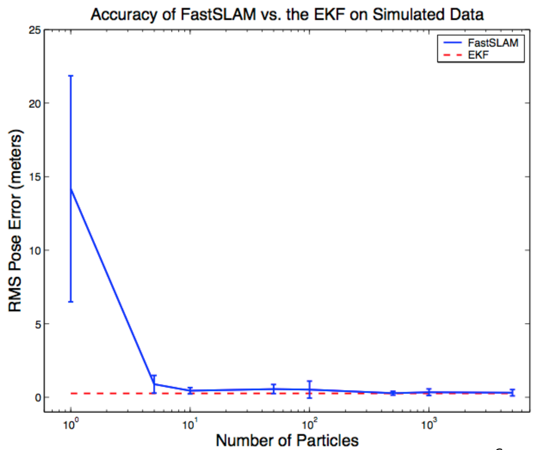
23

Results – Victoria Park (Video)

Courtesy: M. Montemerlo

24

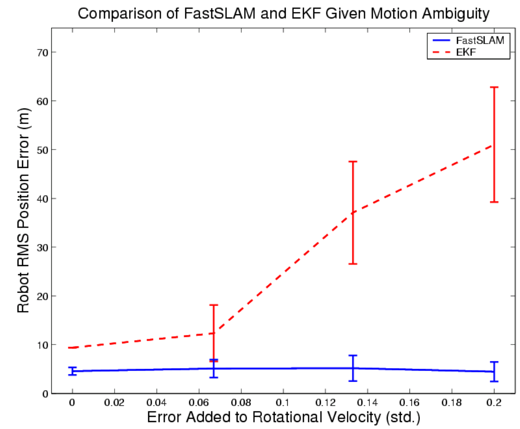
Results (Sample Size)



Courtesy: M. Montemerlo

25

Results (Motion Uncertainty)



Courtesy: M. Montemerlo

26

Techniques to Reduce the Number of Particles Needed

- Better proposals (put the particles in the right place in the prediction step).
- Avoid particle depletion (re-sample only when needed).

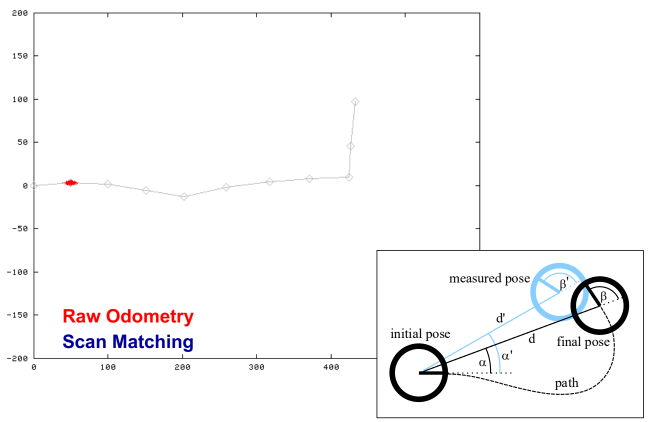
27

Generating better Proposals

- Use scan-matching to compute highly accurate odometry measurements from consecutive range scans.
- Use the improved odometry in the prediction step to get highly accurate proposal distributions.

28

Motion Model for Scan Matching



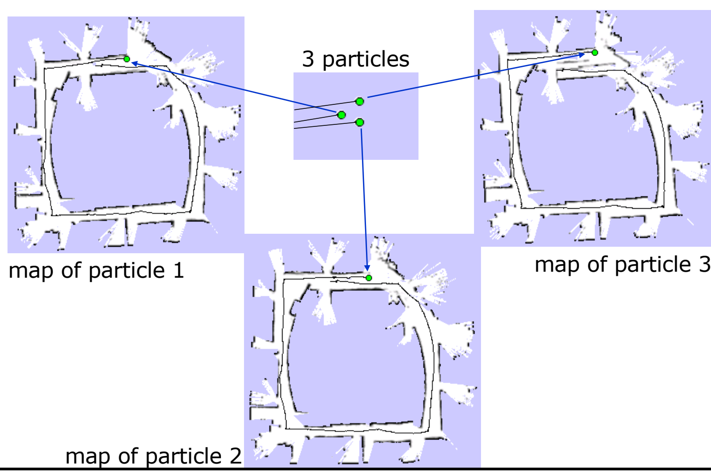
29

Rao-Blackwellized Mapping with Scan-Matching

Map: Intel Research Lab Seattle

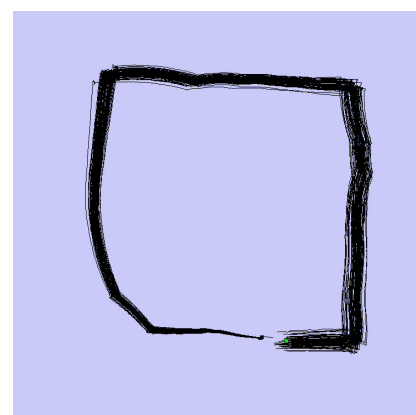
30

Loop Closure Example



31

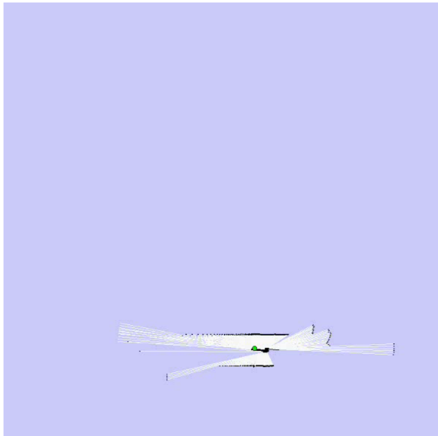
Rao-Blackwellized Mapping with Scan-Matching



Map: Intel Research Lab Seattle

32

Rao-Blackwellized Mapping with Scan-Matching



Map: Intel Research Lab Seattle

33

Example (Intel Lab)

- **15 particles**
- four times faster than real-time P4, 2.8GHz
- 5cm resolution during scan matching
- 1cm resolution in final map

Work by Grisetti et al.

34

Outdoor Campus Map

- **30 particles**
- 250x250m²
- 1.088 miles (odometry)
- 20cm resolution during scan matching
- 30cm resolution in final map

Work by Grisetti et al.

35

FastSLAM Summary

- Particle filter-based SLAM
- Rao-Blackwellization: model the robot's path by sampling and compute the landmarks given the poses
- Allow for per-particle data association
- Complexity $\mathcal{O}(N \log M)$

Courtesy: C. Stachniss

36

Literature

FastSLAM

- Thrun et al.: "Probabilistic Robotics", Chapter 13.1-13.3 + 13.8 (see errata!)
- Montemerlo, Thrun, Kollar, Wegbreit: FastSLAM: A Factored Solution to the Simultaneous Localization and Mapping Problem, 2002
- Montemerlo and Thrun: Simultaneous Localization and Mapping with Unknown Data Association Using FastSLAM, 2003

Courtesy: C. Stachniss

37