Probabilistic Robotics

FastSLAM

The SLAM Problem

- SLAM stands for simultaneous localization and mapping
- The task of building a map while estimating the pose of the robot relative to this map

- Why is SLAM hard?
Chicken and egg problem:
a map is needed to localize the robot and
a pose estimate is needed to build a map

The SLAM Problem

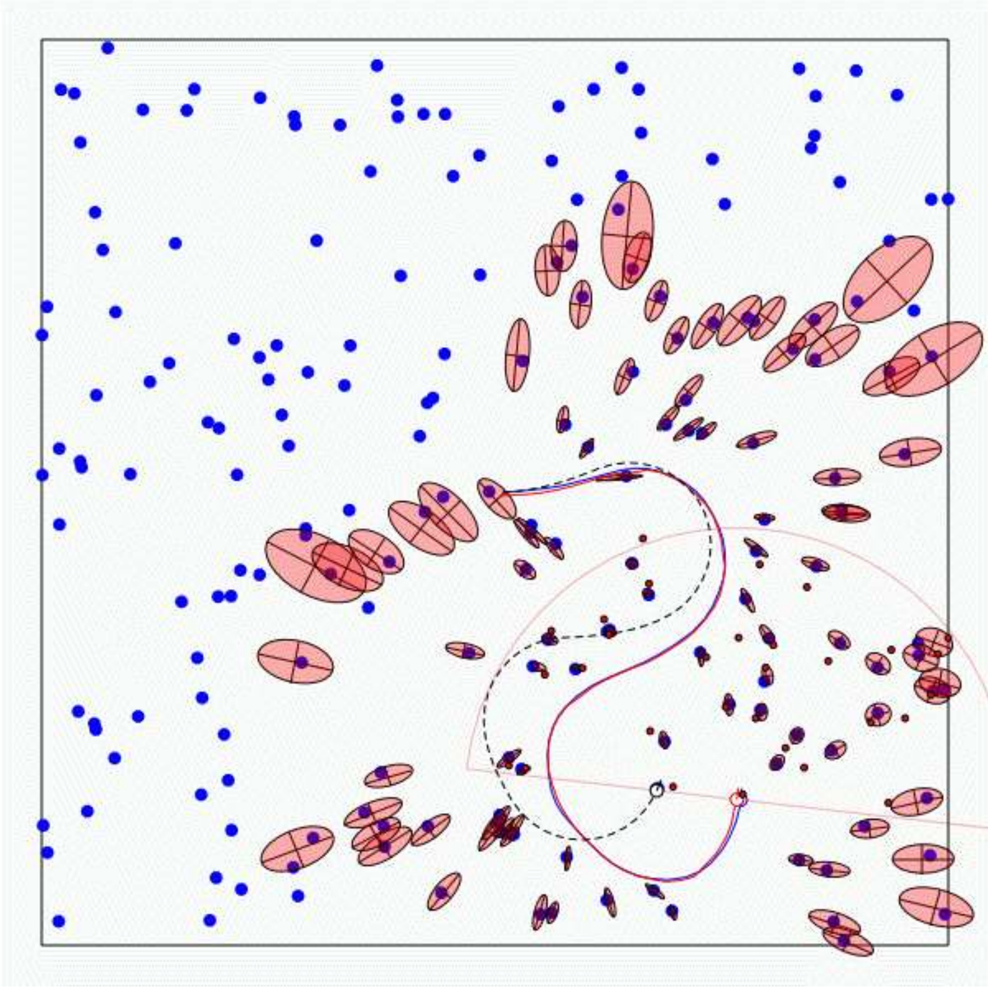
A robot moving though an unknown, static environment

Given:

- The robot's controls
- Observations of nearby features

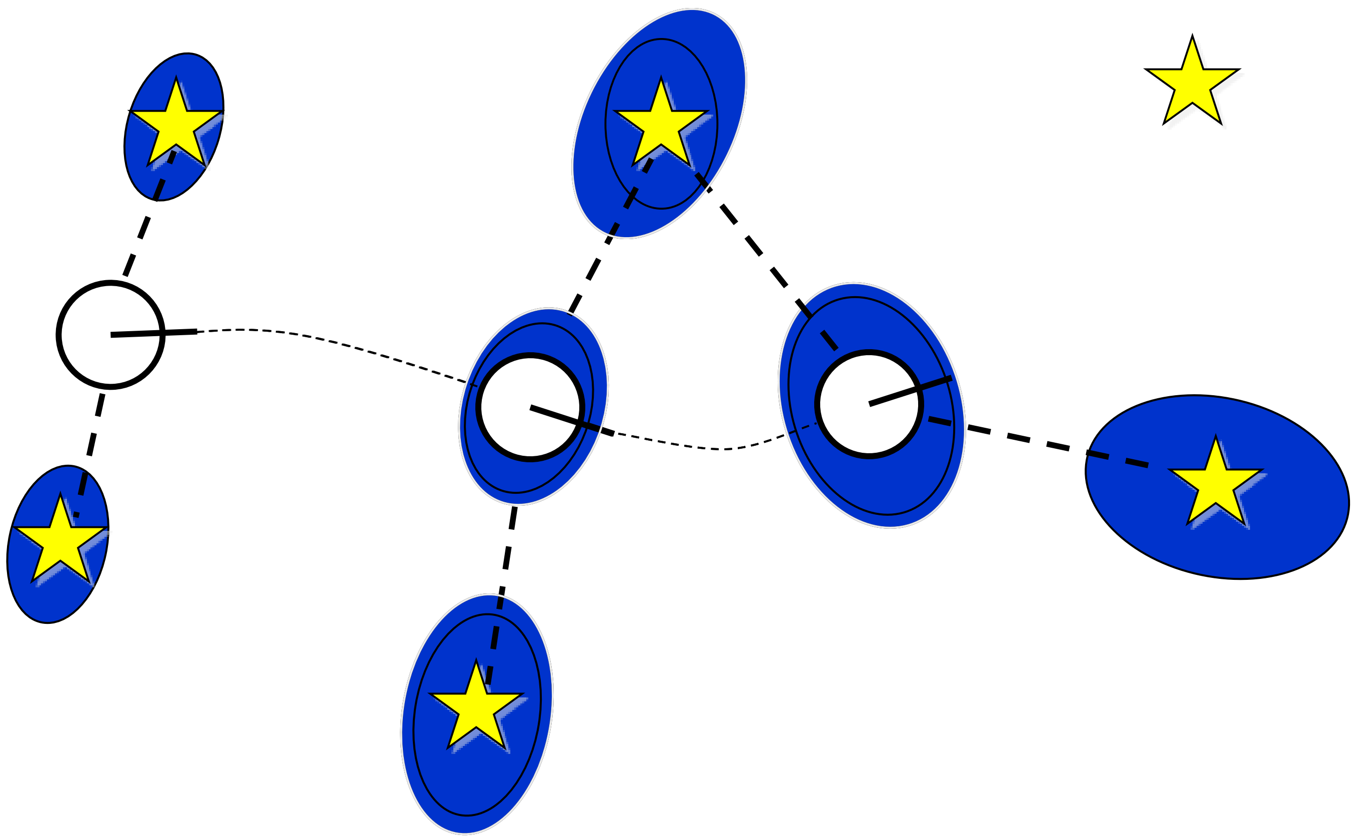
Estimate:

- Map of features
- Path of the robot



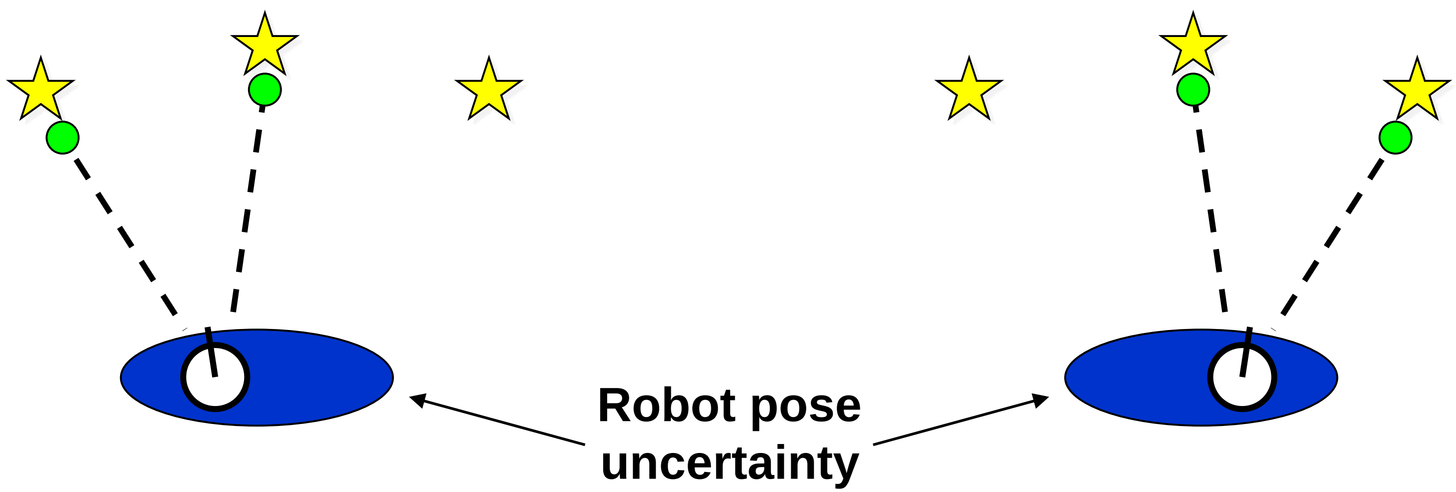
Why is SLAM a hard problem?

SLAM: robot path and map are both **unknown!**



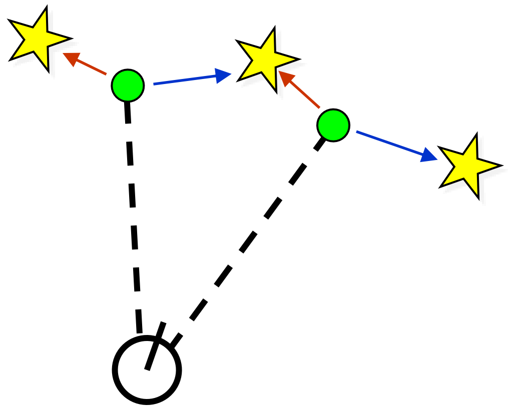
Robot path error correlates errors in the map

Why is SLAM a hard problem?



- In the real world, the mapping between observations and landmarks is unknown
- Picking wrong data associations can have catastrophic consequences
- Pose error correlates data associations

Data Association Problem



- A data association is an assignment of observations to landmarks
- In general there are more than $\binom{n}{m}$ (n observations, m landmarks) possible associations
- Also called "assignment problem"

Particle Filters

- Represent belief by random samples
- Estimation of non-Gaussian, nonlinear processes

- Sampling Importance Resampling (SIR) principle
  - Draw the new generation of particles
  - Assign an importance weight to each particle
  - Resampling

- Typical application scenarios are tracking, localization, …

Localization vs. SLAM

- A particle filter can be used to solve both problems

- Localization: state space $<x, y, \theta>$

- SLAM: state space $<x, y, \theta, map>$
  - for landmark maps = $<l_1, l_2, \ldots, l_m>$
  - for grid maps = $<c_{11}, c_{12}, \ldots, c_{1n}, c_{21}, \ldots, c_{nm}>$

- **Problem:** The number of particles needed to represent a posterior grows exponentially with the dimension of the state space!

Dependencies

- Is there a dependency between the dimensions of the state space?
- If so, can we use the dependency to solve the problem more efficiently?

Dependencies

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- If so, can we use the dependency to solve the problem more efficiently?

- In the SLAM context
  - The map depends on the poses of the robot.
  - We know how to build a map given the position of the sensor is known.

Factored Posterior (Landmarks)

poses map observations & movements

$$p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) =$$

$$p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot p(l_{1:m} \mid x_{1:t}, z_{1:t})$$

SLAM posterior

Robot path posterior

landmark positions

Does this help to solve the problem?

Factorization first introduced by Murphy in 1999

Factored Posterior (Landmarks)

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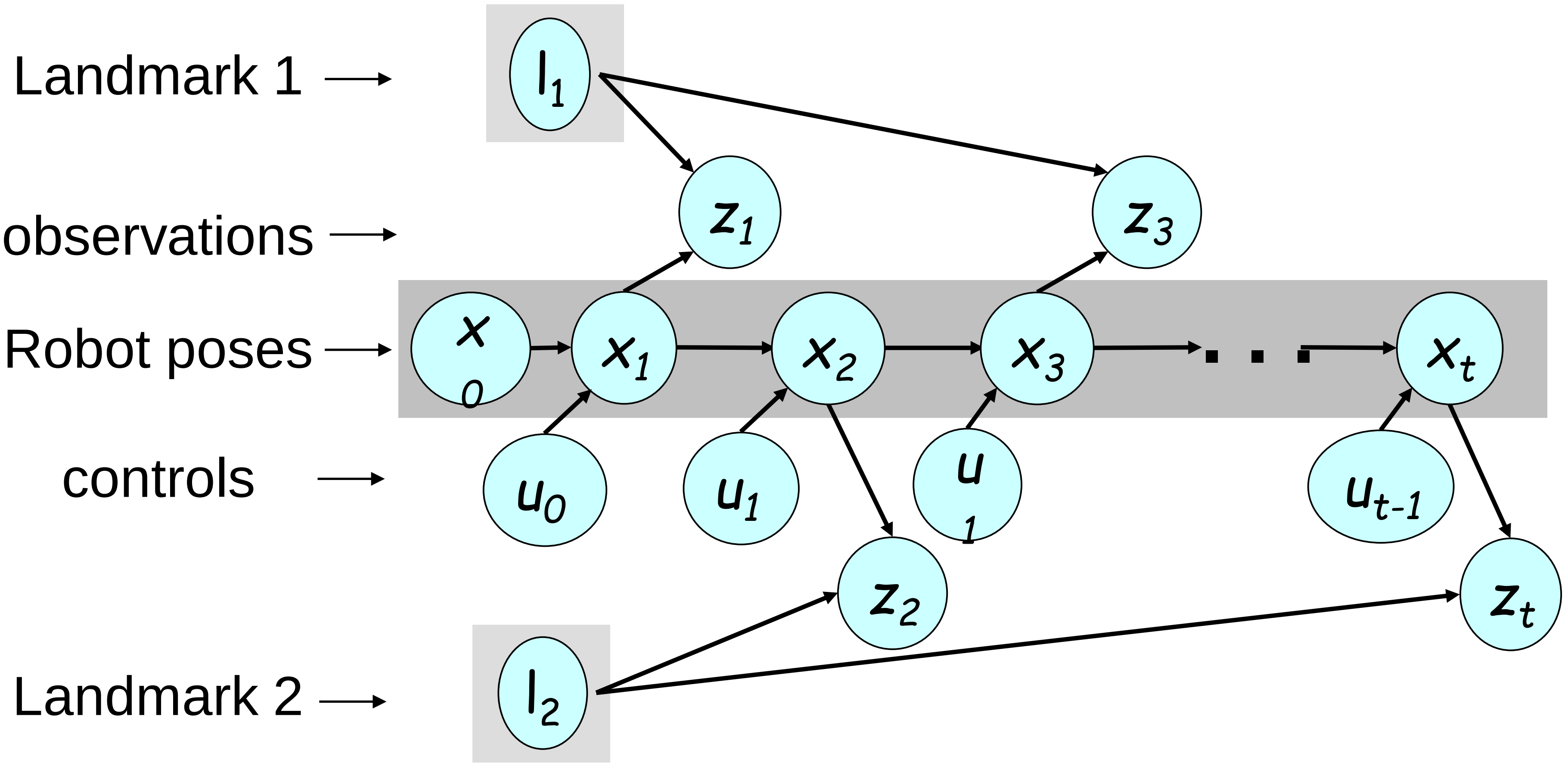
Factorization first introduced by Murphy in 1999

Mapping using Landmarks



Knowledge of the robot's true path renders landmark positions conditionally independent

Factored Posterior

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

Robot path posterior (localization problem)

Conditionally independent landmark positions

Rao-Blackwellization

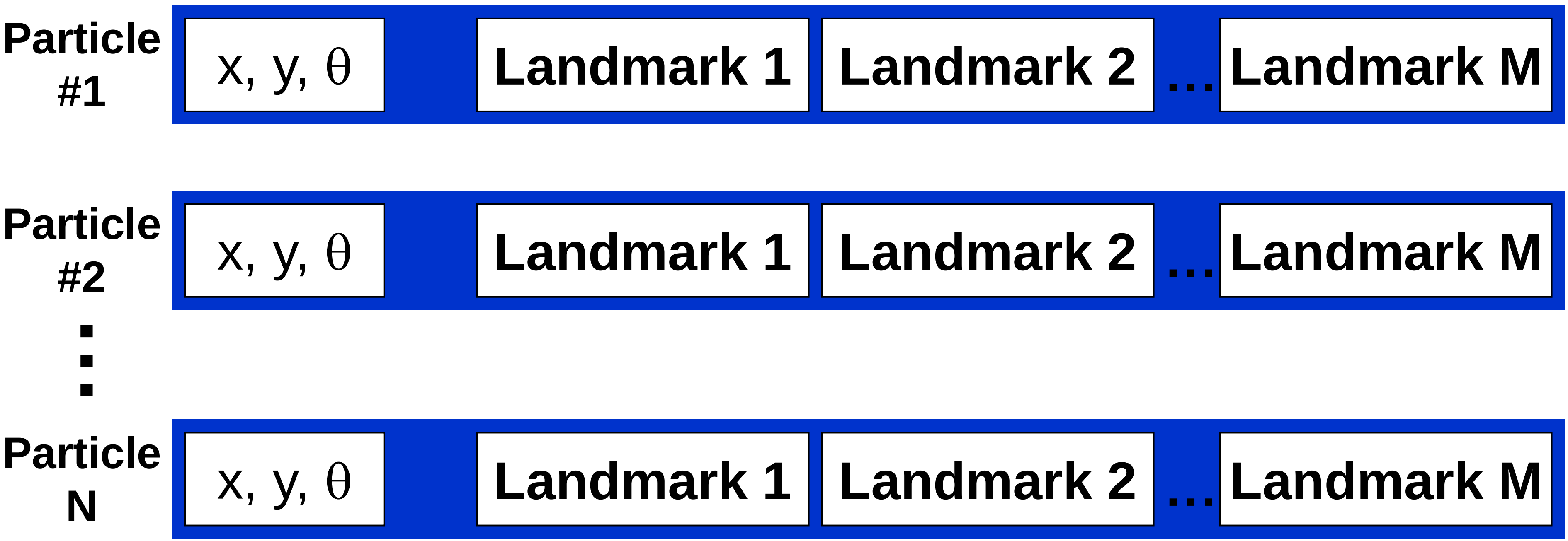
$$p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) =$$

$$p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot \prod_{i=1}^{M} p(l_i \mid x_{1:t}, z_{1:t})$$

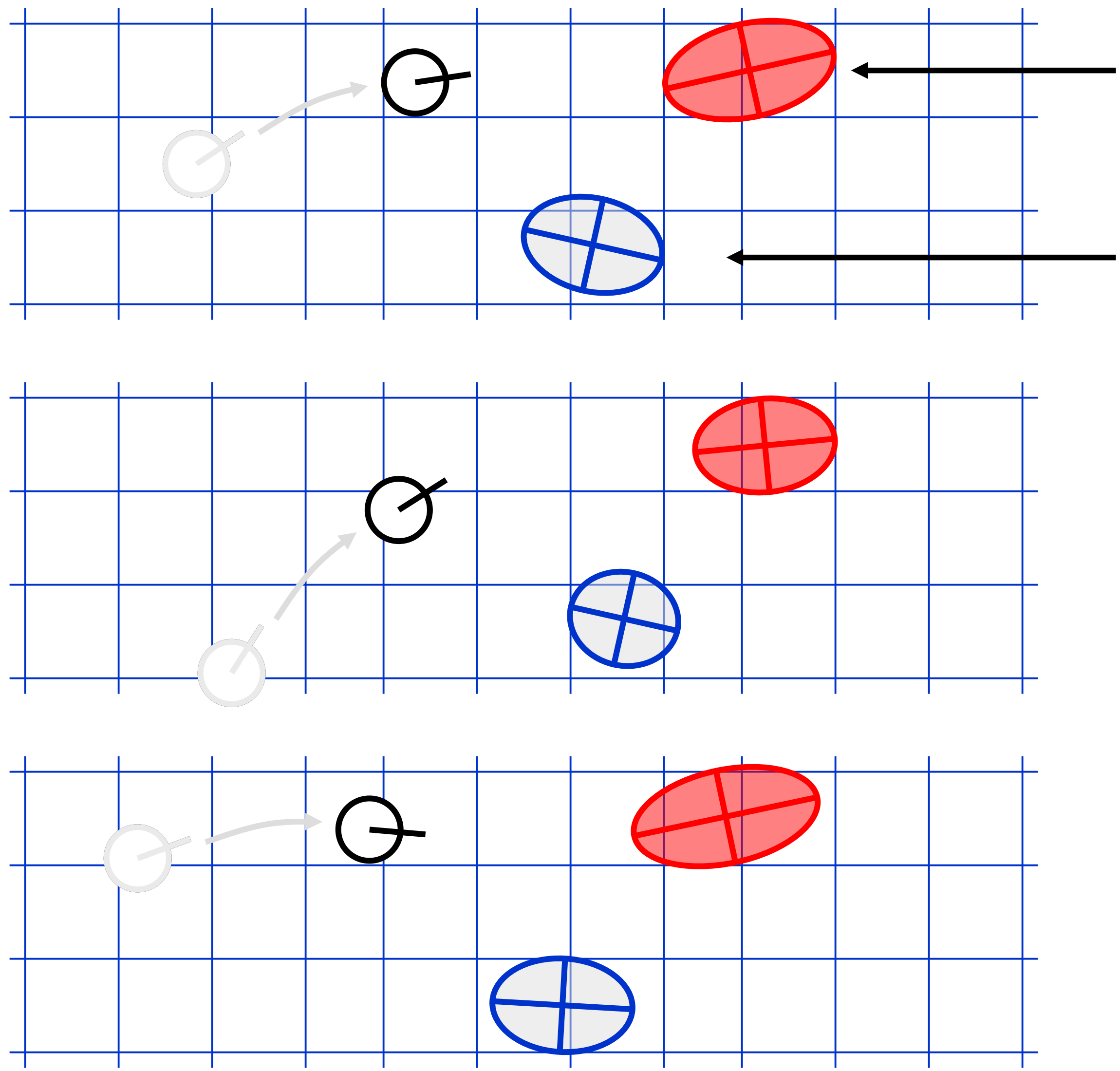
- This factorization is also called Rao-Blackwellization
- Given that the second term can be computed efficiently, particle filtering becomes possible!

FastSLAM

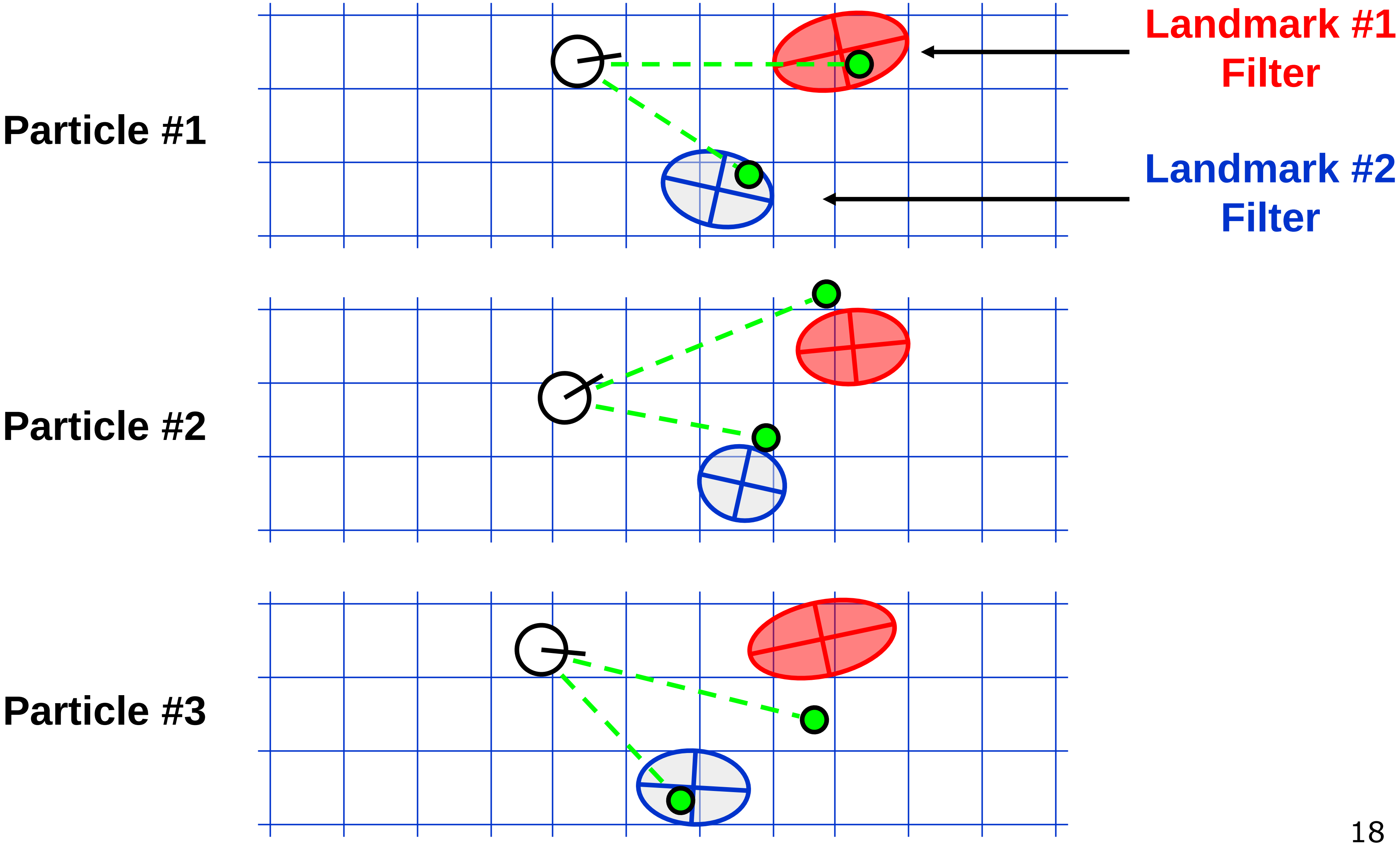
- Rao-Blackwellized particle filtering based on landmarks   [Montemerlo et al., 2002]
- Each landmark is represented by a 2x2 Extended Kalman Filter (EKF)
- Each particle therefore has to maintain *M* EKFs



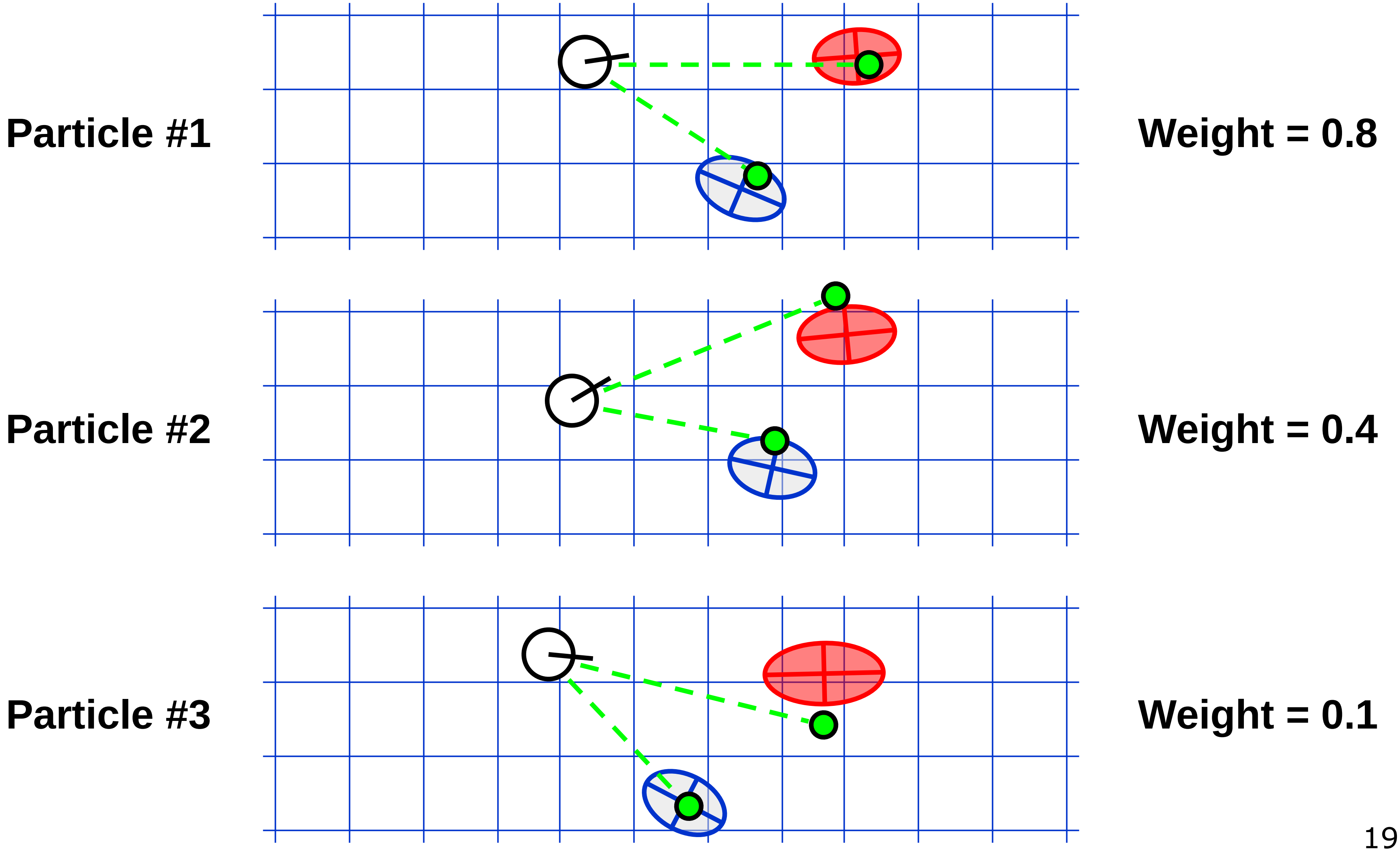
FastSLAM – Action Update



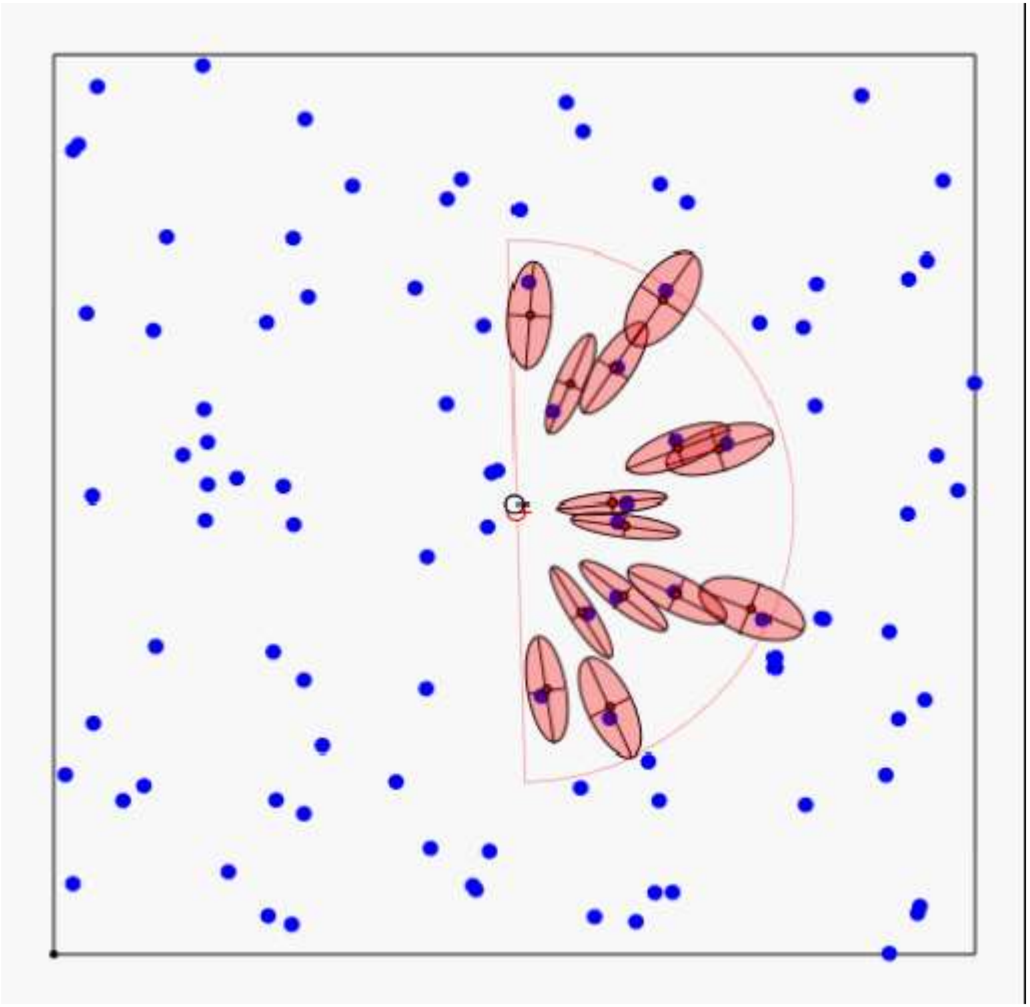
FastSLAM – Sensor Update



FastSLAM – Sensor Update



FastSLAM - Video



FastSLAM Complexity

- Update robot particles based on control u_{t-1}

  $O(N)$
  Constant time per particle

- Incorporate observation z_t into Kalman filters

  $O(N \cdot \log(M))$
  Log time per particle

- Resample particle set

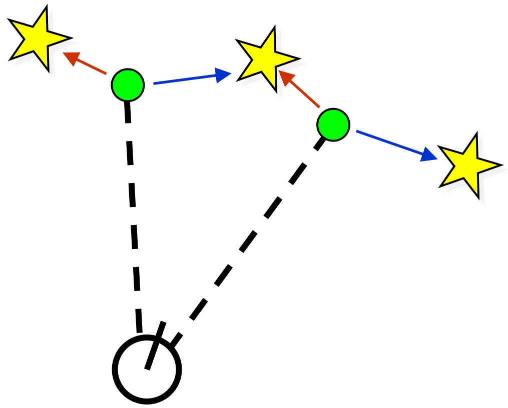
  $O(N \cdot \log(M))$
  Log time per particle

N = Number of particles
M = Number of map features

$O(N \cdot \log(M))$
Log time per particle

Data Association Problem

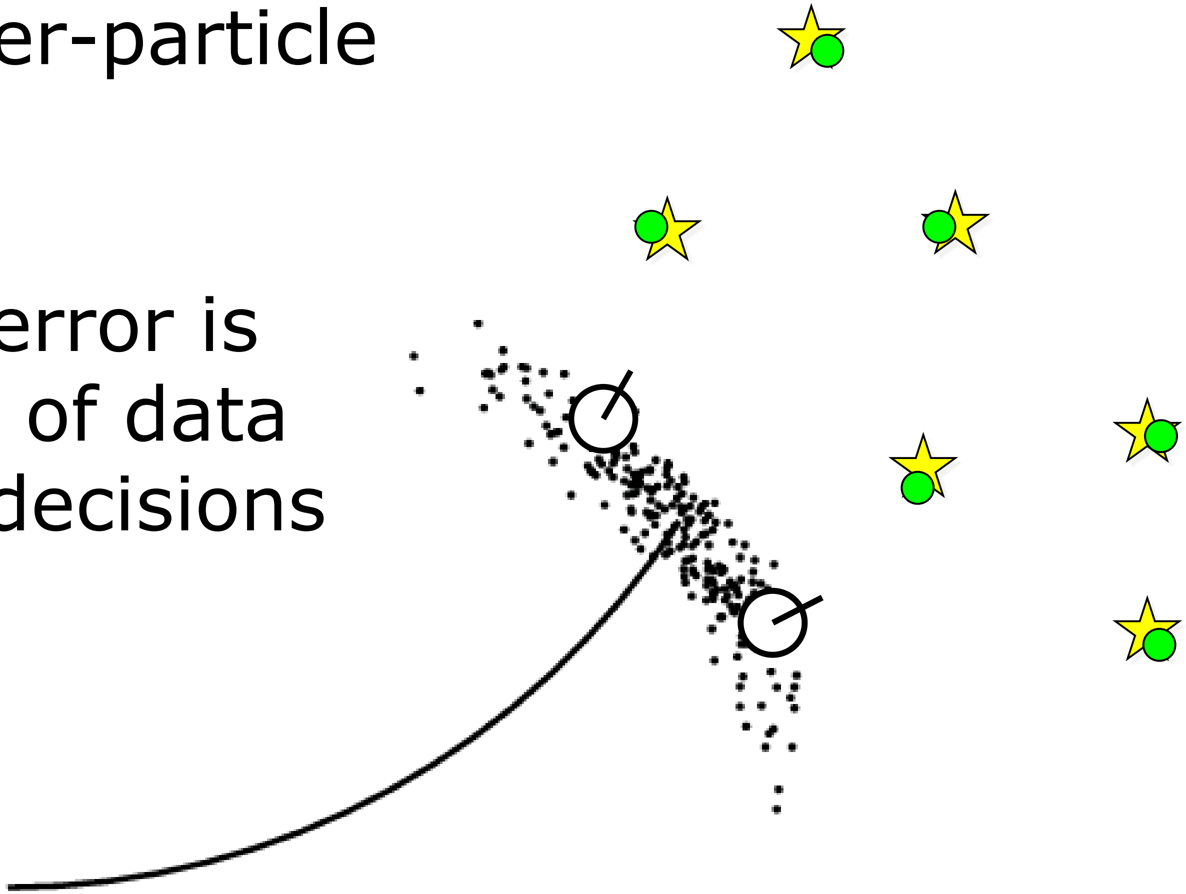
- Which observation belongs to which landmark?



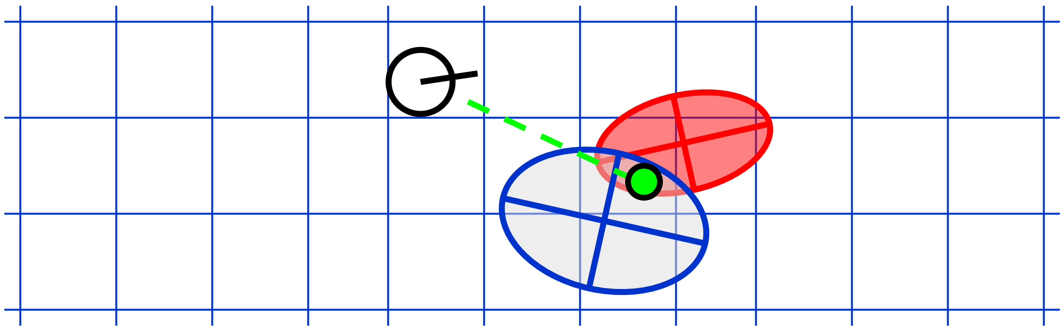
- A robust SLAM must consider possible data associations
- Potential data associations depend also on the pose of the robot

Multi-Hypothesis Data Association

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



Per-Particle Data Association



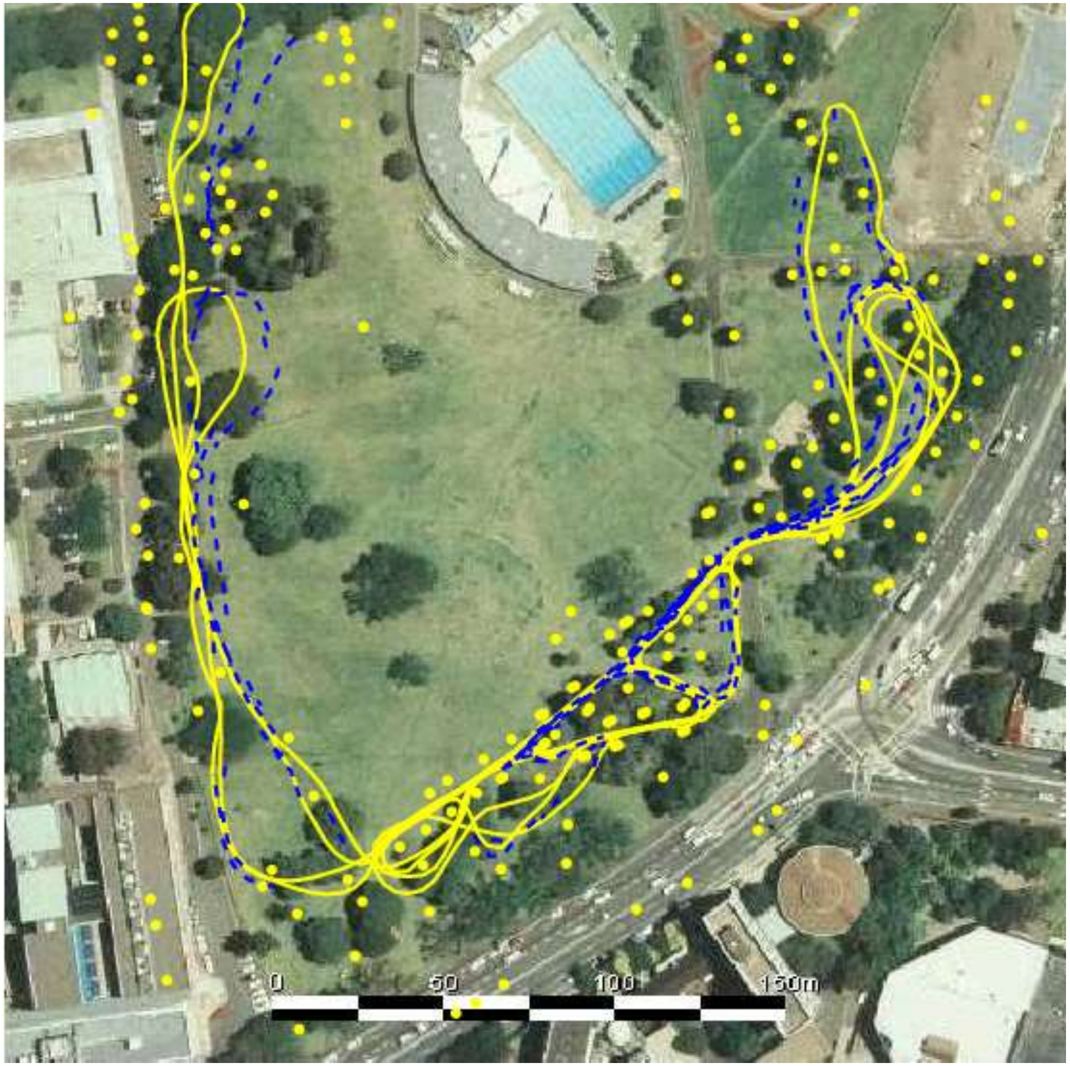
Was the observation generated by the red or the blue landmark?

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

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

Results – Victoria Park

- 4 km traverse
- < 5 m RMS position error
- 100 particles



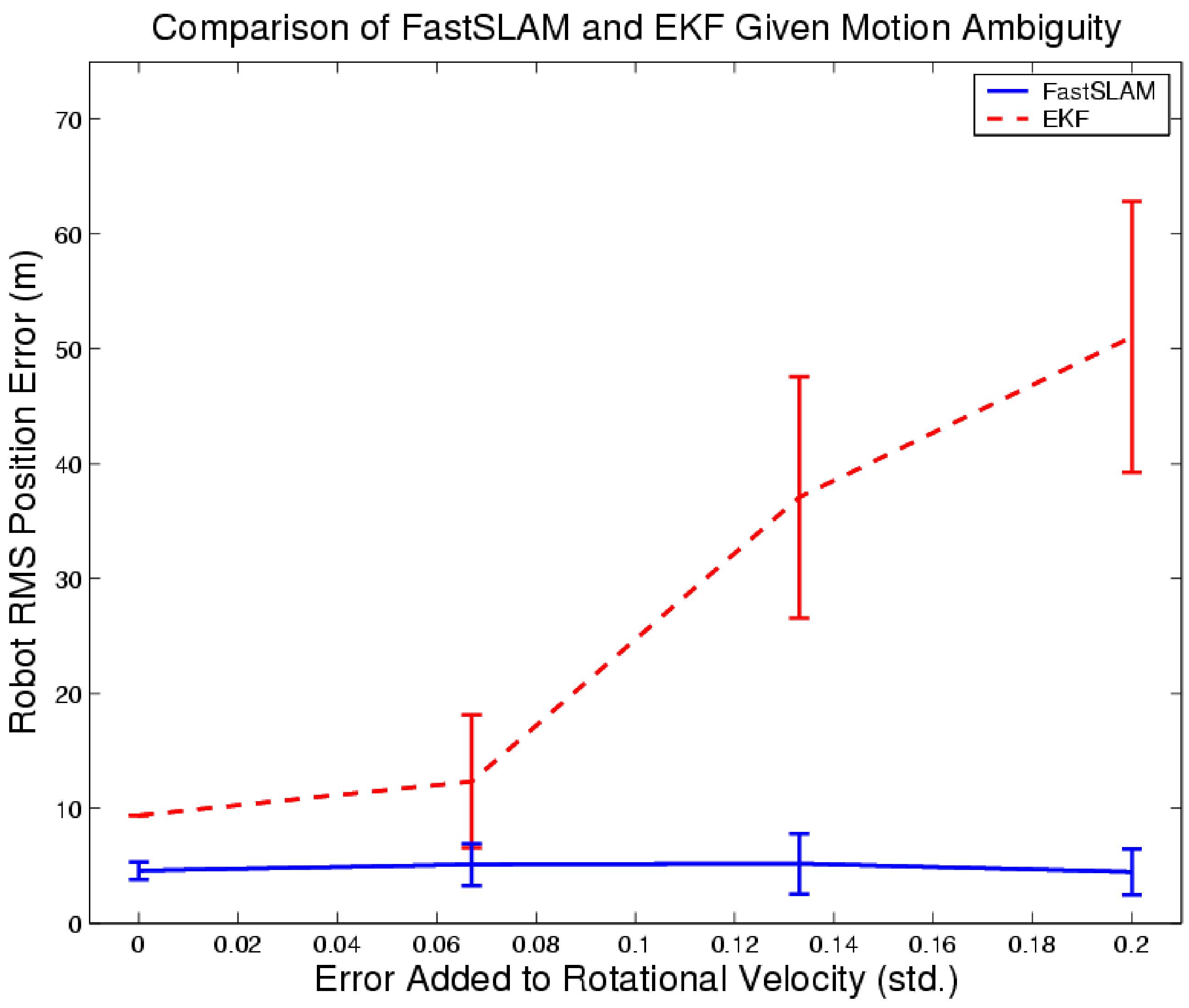
Blue = GPS
Yellow = FastSLAM

Dataset courtesy of University of Sydney

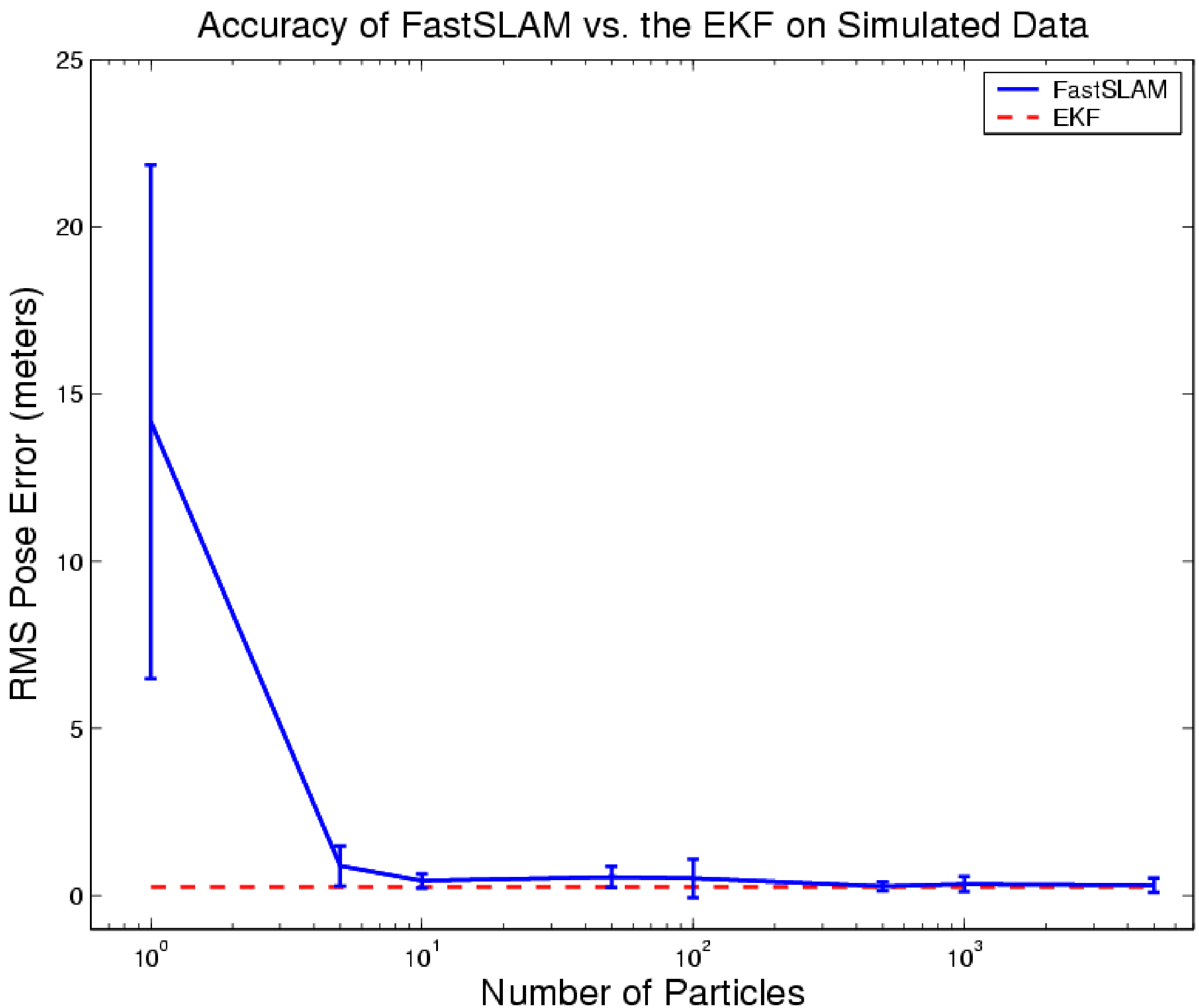
Results – Victoria Park

Dataset courtesy of University of Sydney

Results – Data Association



Results – Accuracy

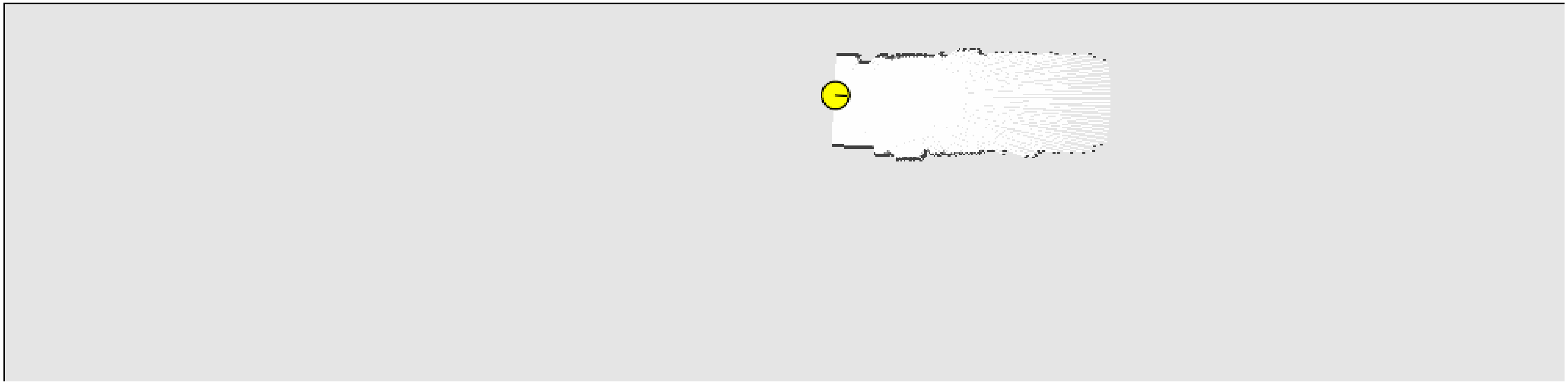


Grid-based SLAM

- Can we solve the SLAM problem if no pre-defined landmarks are available?
- Can we use the ideas of FastSLAM to build grid maps?
- As with landmarks, the map depends on the poses of the robot during data acquisition
- If the poses are known, grid-based mapping is easy ("mapping with known poses")

Mapping using Raw Odometry

Mapping with Known Poses



- Mapping with known poses using laser range data

Rao-Blackwellization

poses map observations & movements

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

$$p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot p(m \mid x_{1:t}, z_{1:t})$$

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SLAM posterior

Robot path posterior

Mapping with known poses

Factorization first introduced by Murphy in 1999

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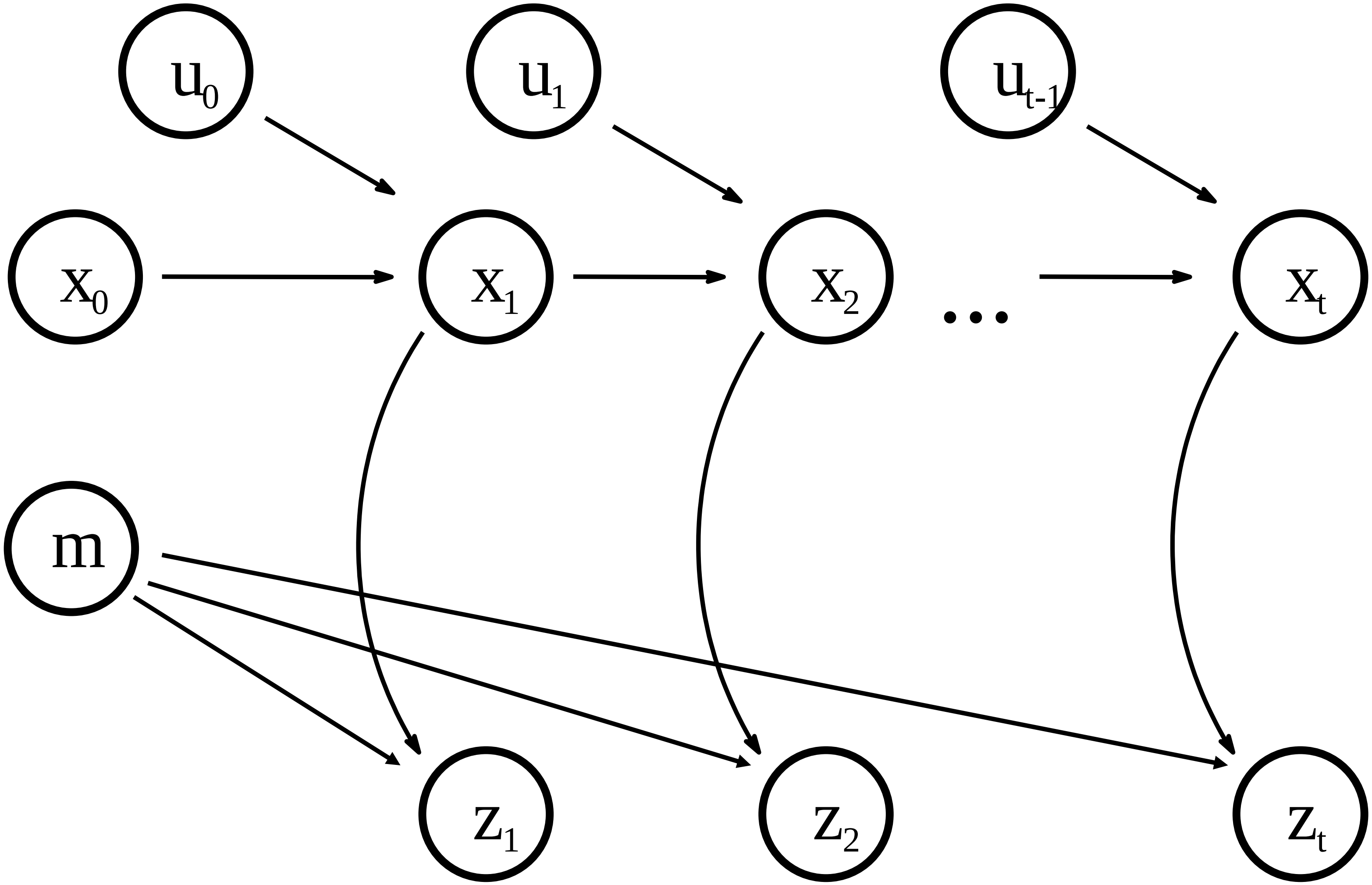
This is localization, use MCL

Use the pose estimate from the MCL part and apply mapping with known poses

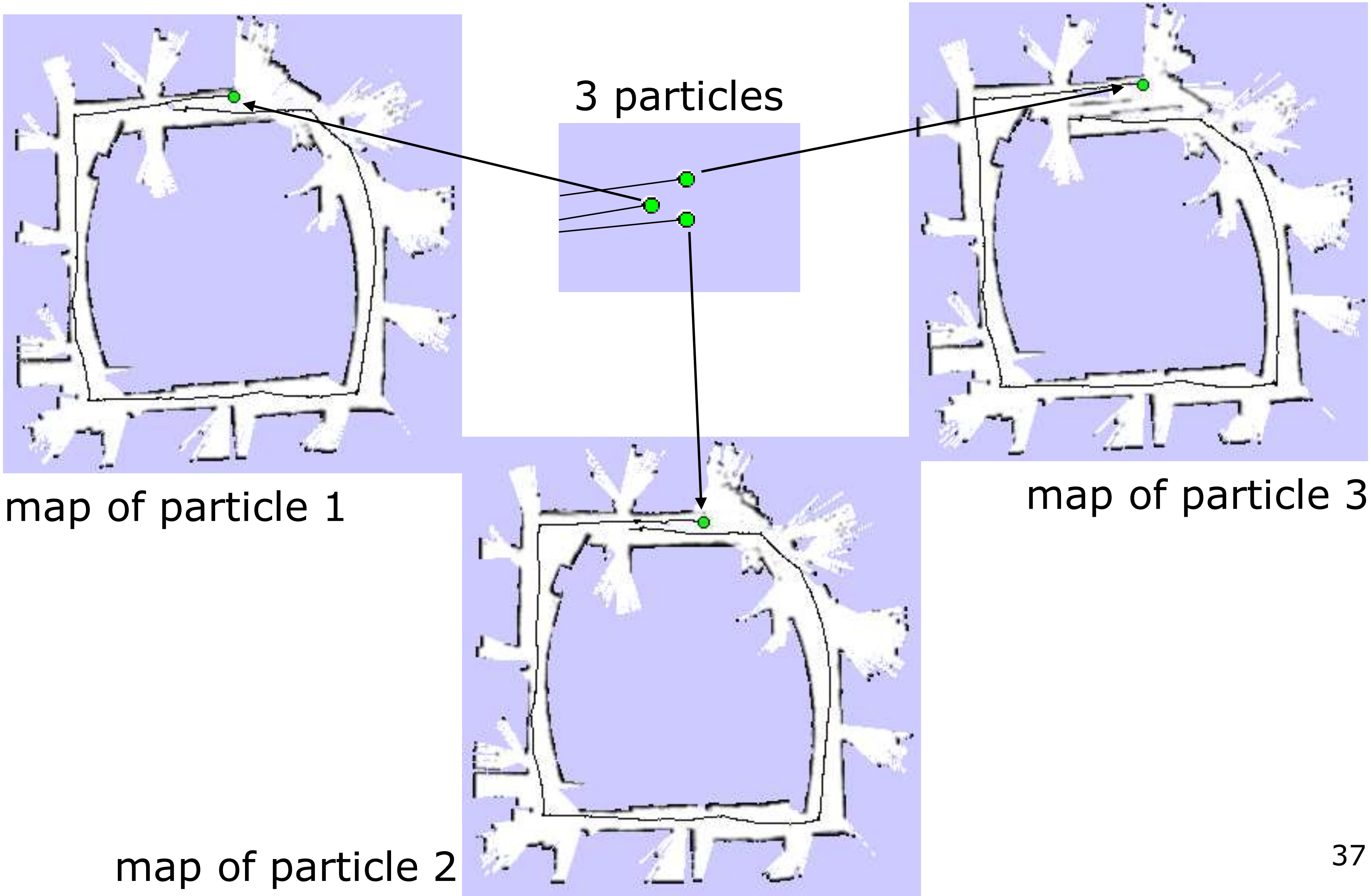
A Graphical Model of Rao-Blackwellized Mapping



Rao-Blackwellized Mapping

- Each particle represents a possible trajectory of the robot
- Each particle
  - maintains its own map and
  - updates it upon “mapping with known poses”
- Each particle survives with a probability proportional to the likelihood of the observations relative to its own map

Particle Filter Example



Problem

- Each map is quite big in case of grid maps
- Since each particle maintains its own map
- Therefore, one needs to keep the number of particles small

- **Solution**:
  Compute better proposal distributions!
- **Idea**:
  Improve the pose estimate **before** applying the particle filter

Pose Correction Using Scan Matching

Maximize the likelihood of the i-th pose and map relative to the (i-1)-th pose and map

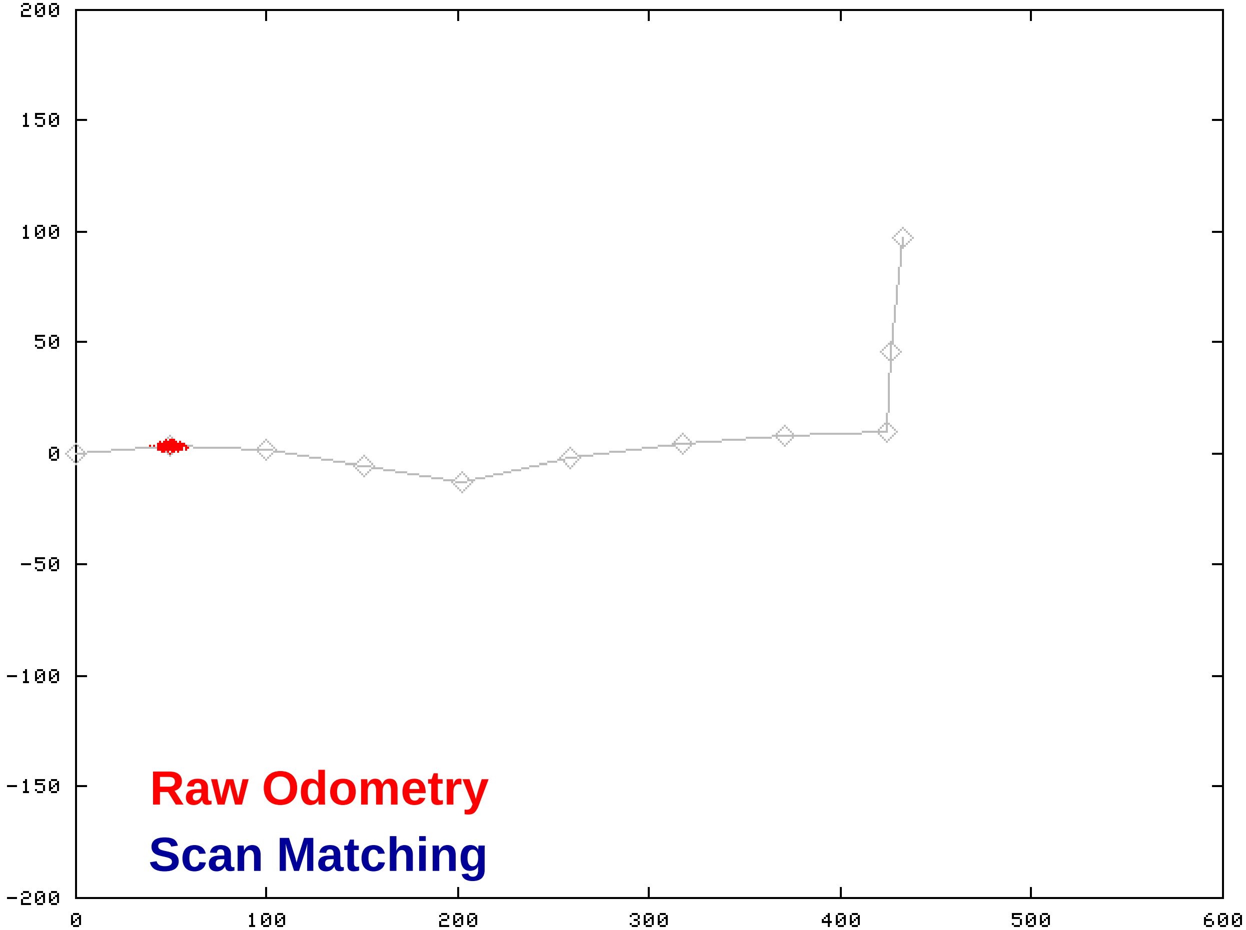
$$\hat{x}_t = \underset{x_t}{\arg\max} \left\{ p(z_t \mid x_t, \hat{m}_{t-1}) \cdot p(x_t \mid u_{t-1}, \hat{x}_{t-1}) \right\}$$

current measurement

robot motion

map constructed so far

Motion Model for Scan Matching



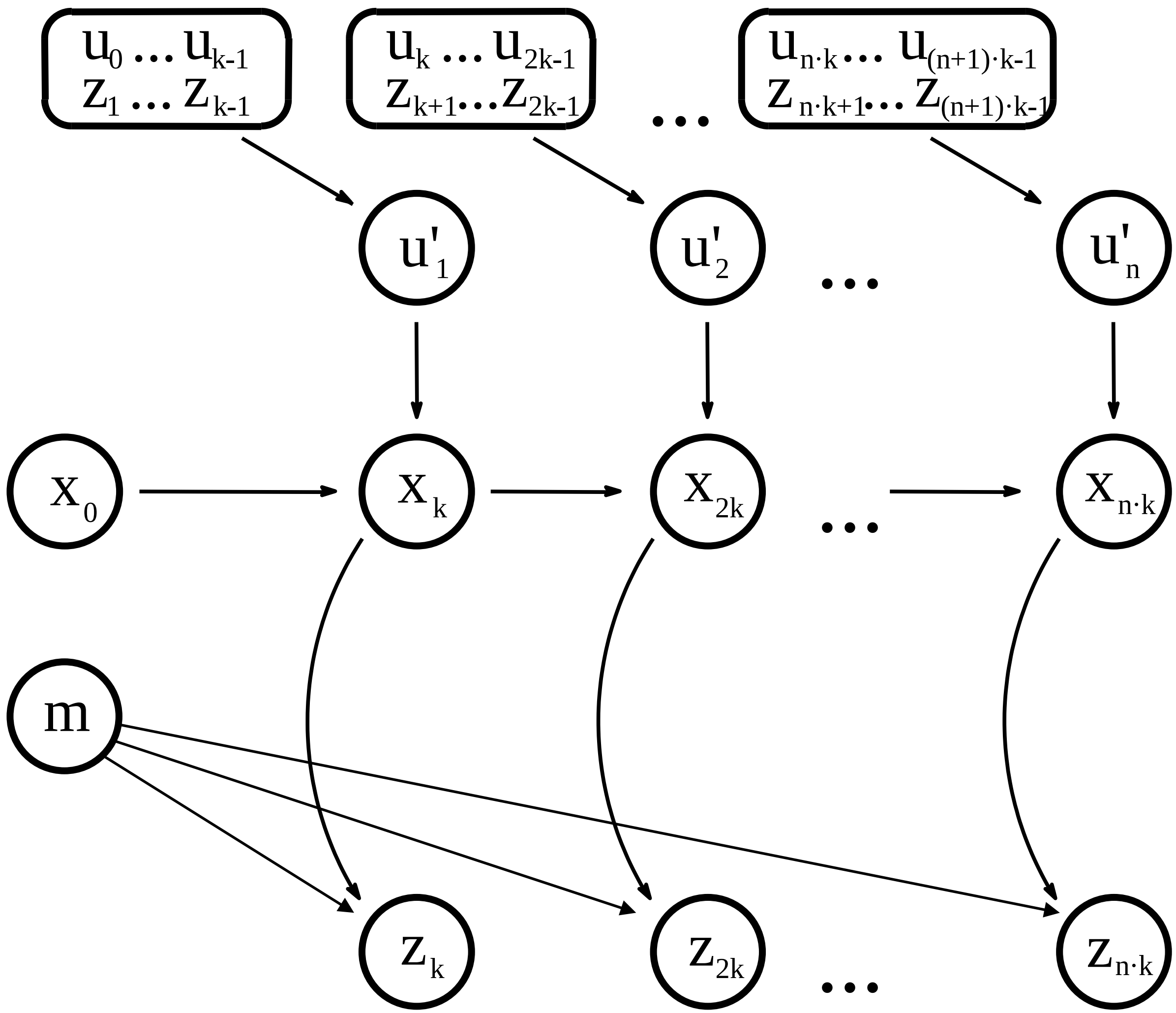
Mapping using Scan Matching

FastSLAM with Improved Odometry

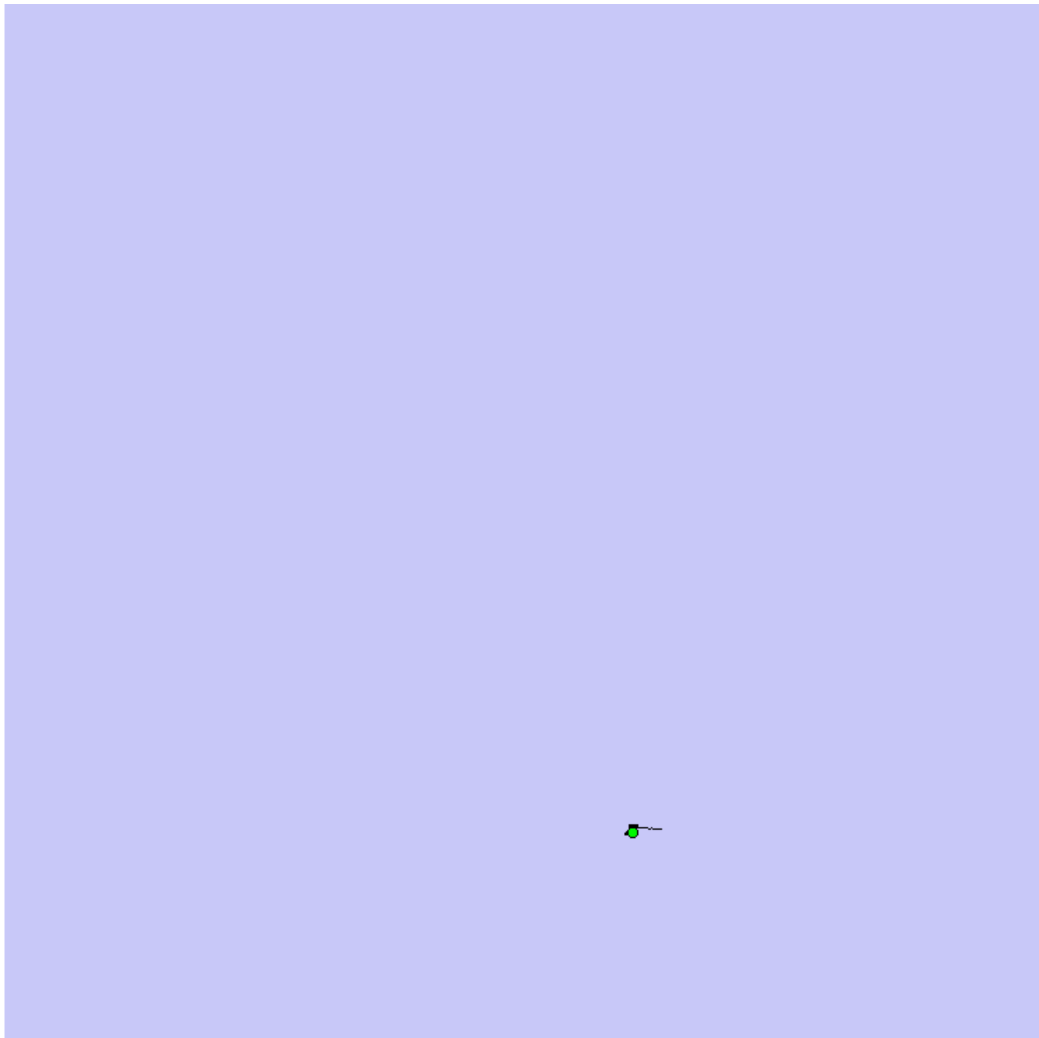
- Scan-matching provides a **locally consistent** pose correction
- Pre-correct short odometry sequences using scan-matching and use them as input to FastSLAM
- Fewer particles are needed, since the error in the input in smaller

[Haehnel et al., 2003]

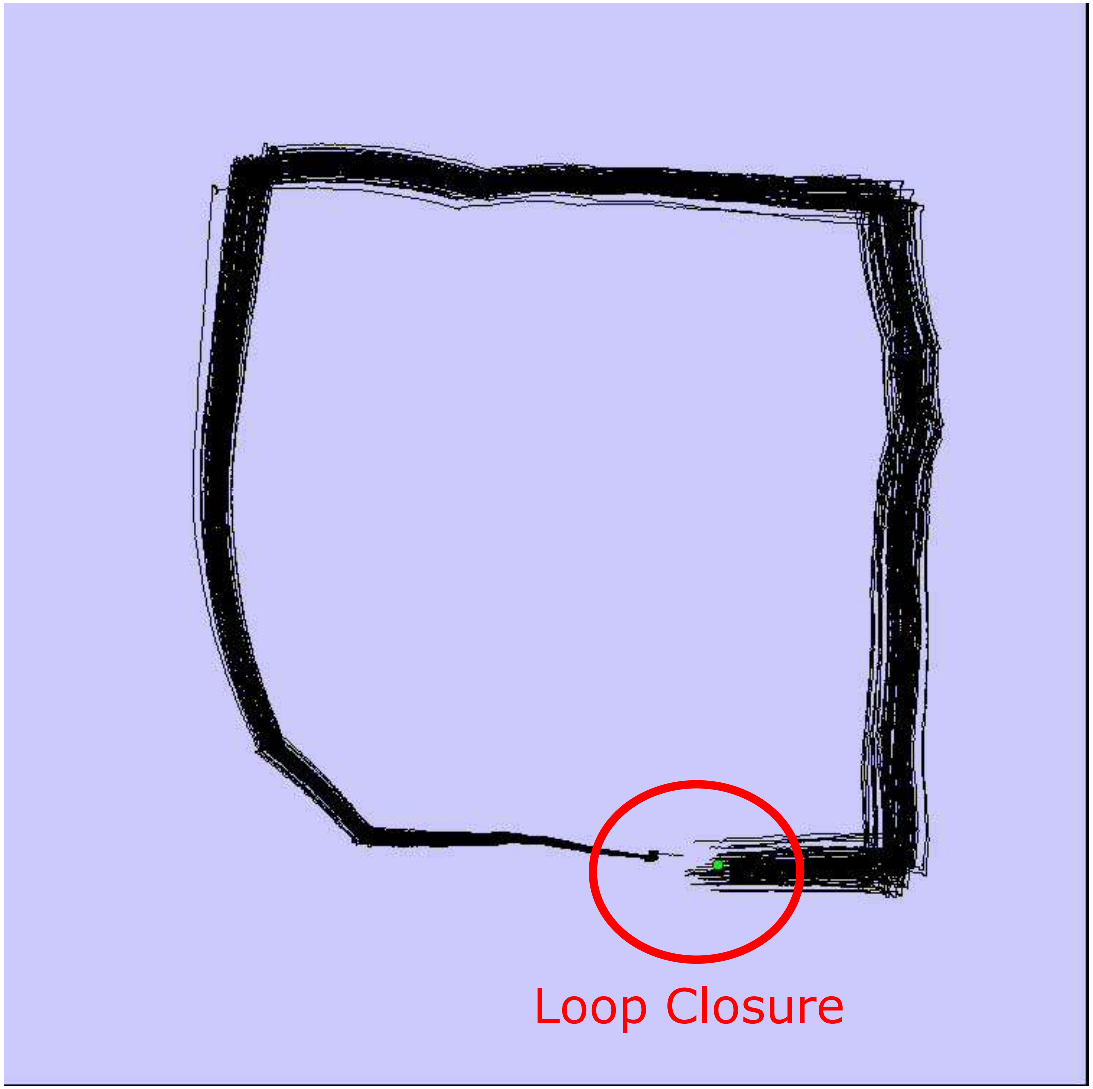
Graphical Model for Mapping with Improved Odometry



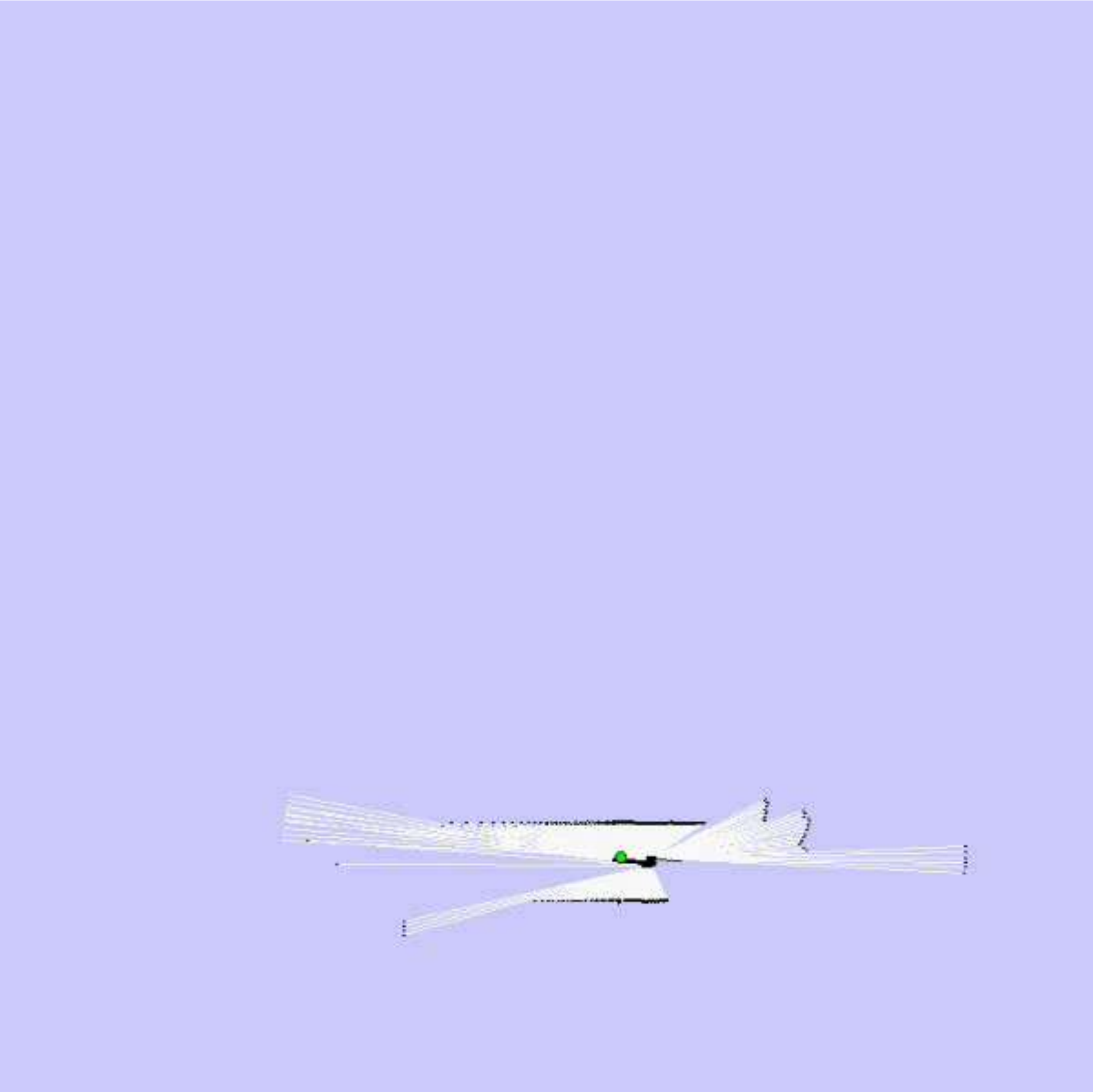
FastSLAM with Scan-Matching



FastSLAM with Scan-Matching



FastSLAM with Scan-Matching



Map: Intel Research Lab Seattle

Comparison to Standard FastSLAM

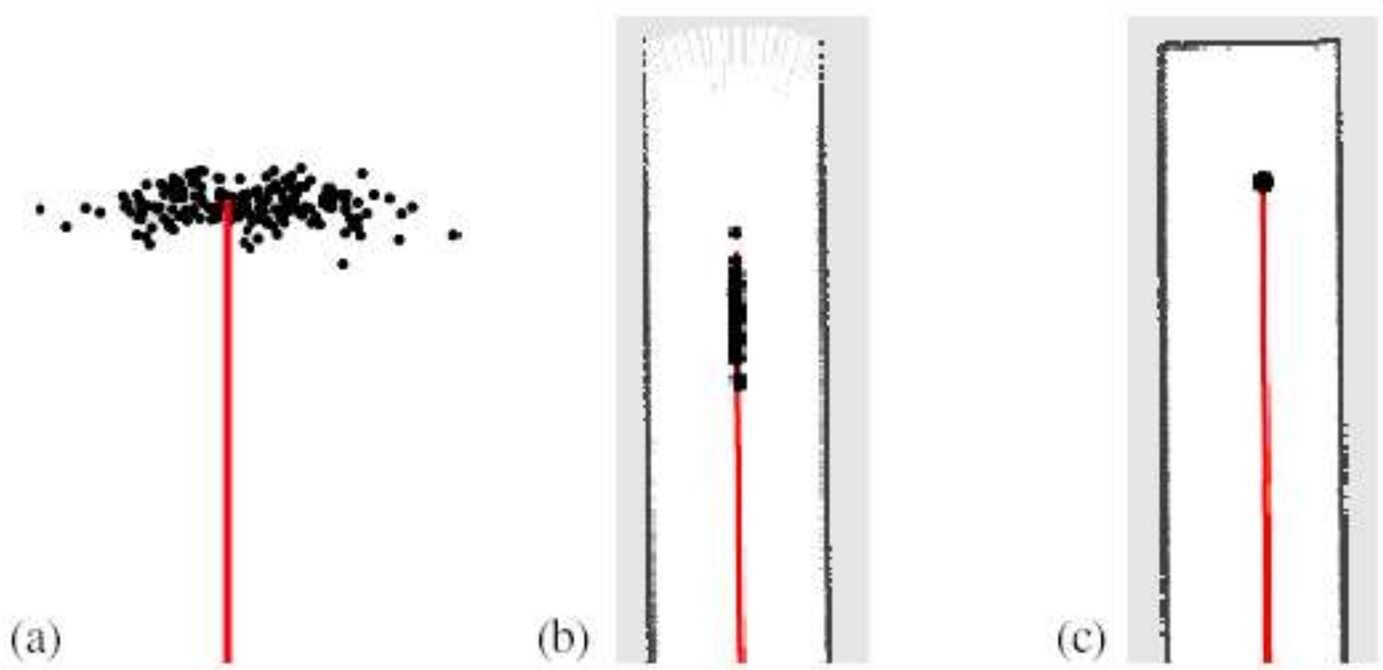
- Same model for observations
- Odometry instead of scan matching as input
- Number of particles varying from 500 to 2.000
- Typical result:

Further Improvements

- Improved proposals will lead to more accurate maps
- They can be achieved by adapting the proposal distribution according to the most recent observations
- Flexible re-sampling steps can further improve the accuracy.

Improved Proposal

- The proposal adapts to the structure of the environment



Selective Re-sampling

- Re-sampling is dangerous, since important samples might get lost (particle depletion problem)
- In case of suboptimal proposal distributions re-sampling is necessary to achieve convergence.
- Key question: When should we re-sample?

Number of Effective Particles

$$n_{eff} = \frac{1}{\sum_i \left(w_t^{(i)}\right)^2}$$

- Empirical measure of how well the goal distribution is approximated by samples drawn from the proposal
- n_{eff} describes "the variance of the particle weights"
- n_{eff} is maximal for equal weights. In this case, the distribution is close to the proposal

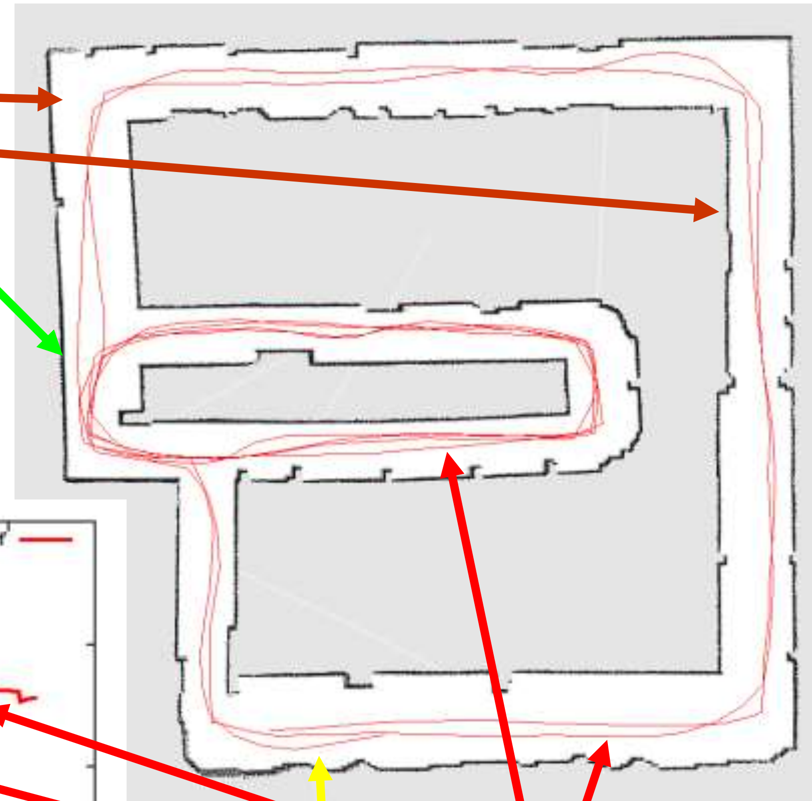
Resampling with Neff

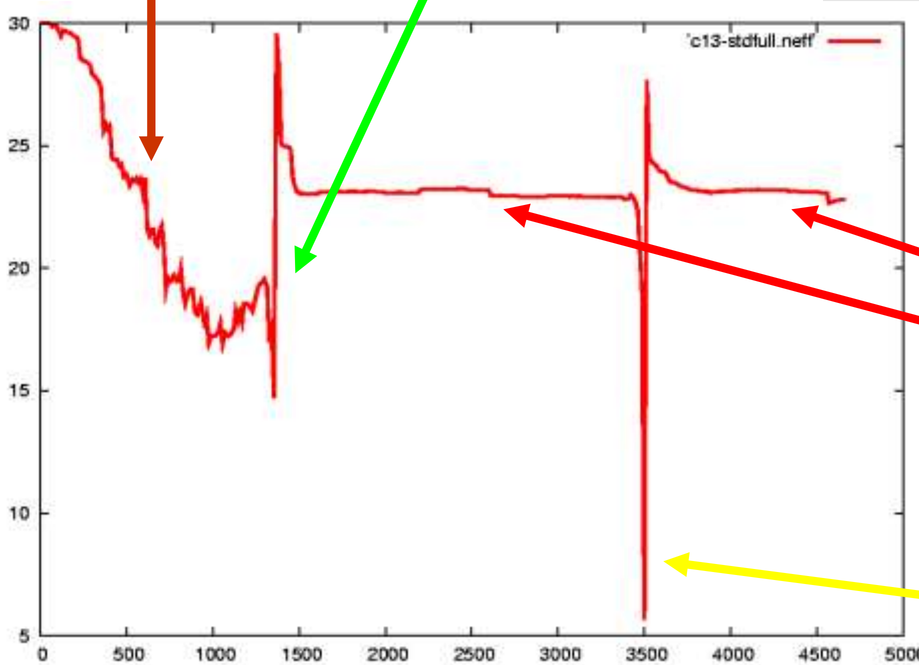
- Only re-sample when n_{eff} drops below a given threshold (n/2)
- See [Doucet, ’98; Arulampalam, ’01]

Typical Evolution of n_{eff}

visiting new areas

closing the first loop





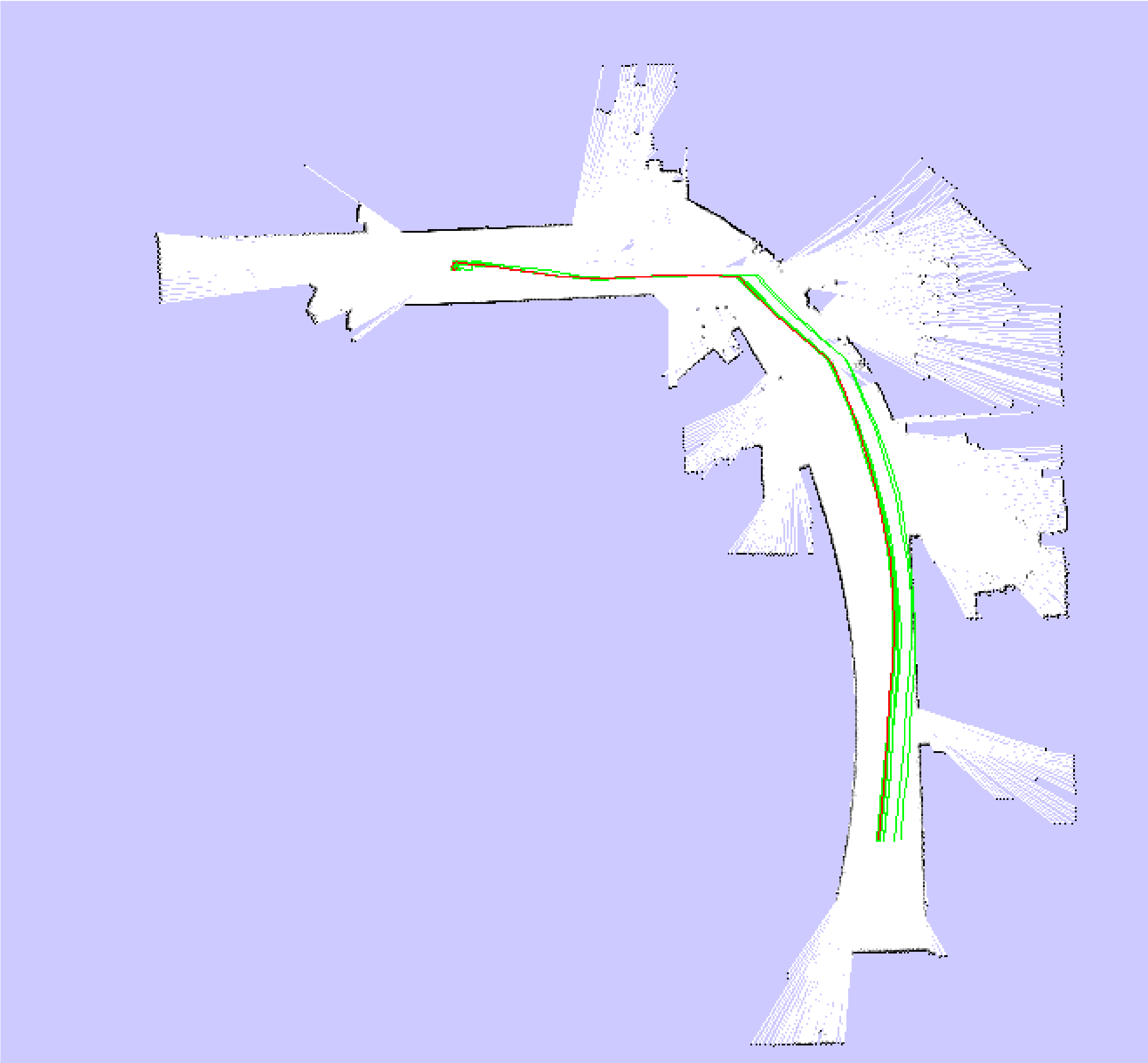
visiting known areas

second loop closure

Intel Lab

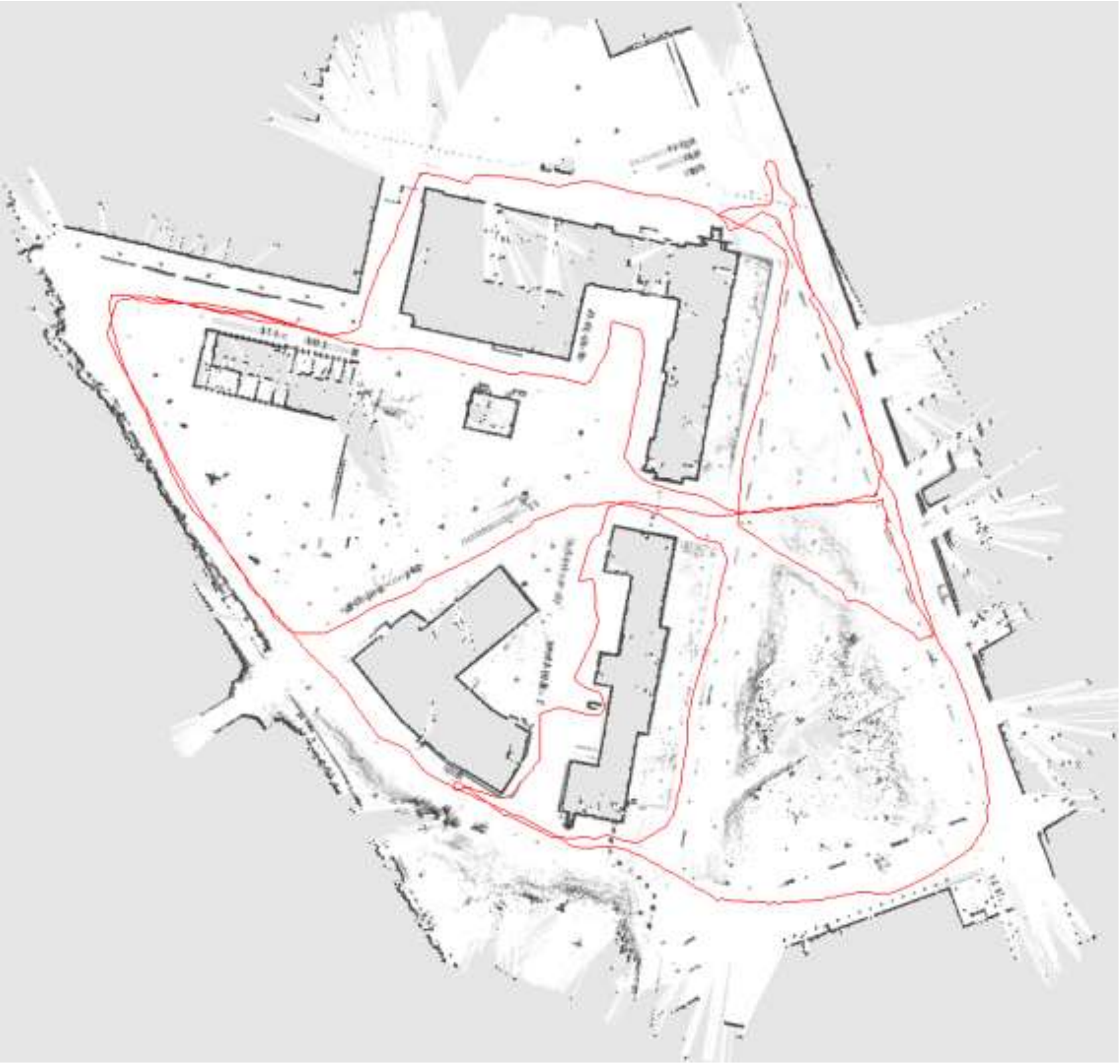
- **15 particles**
- four times faster than real-time P4, 2.8GHz
- 5cm resolution during scan matching
- 1cm resolution in final map

Intel Lab



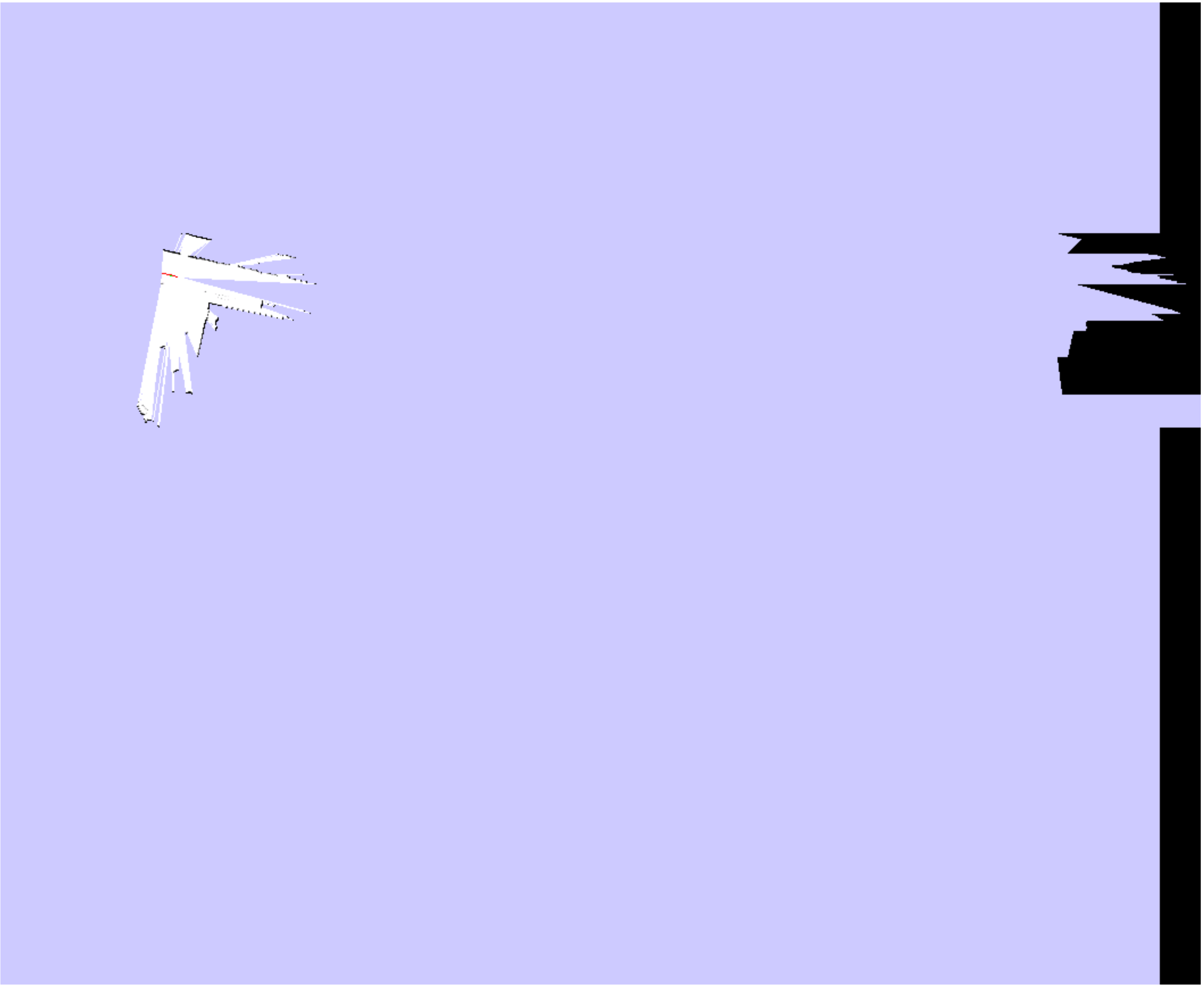
- **15 particles**
- Compared to FastSLAM with Scan-Matching, the particles are propagated closer to the true distribution

Outdoor Campus Map



- **30 particles**
- 250x250m^2
- 1.088 miles (odometry)
- 20cm resolution during scan matching
- 30cm resolution in final map

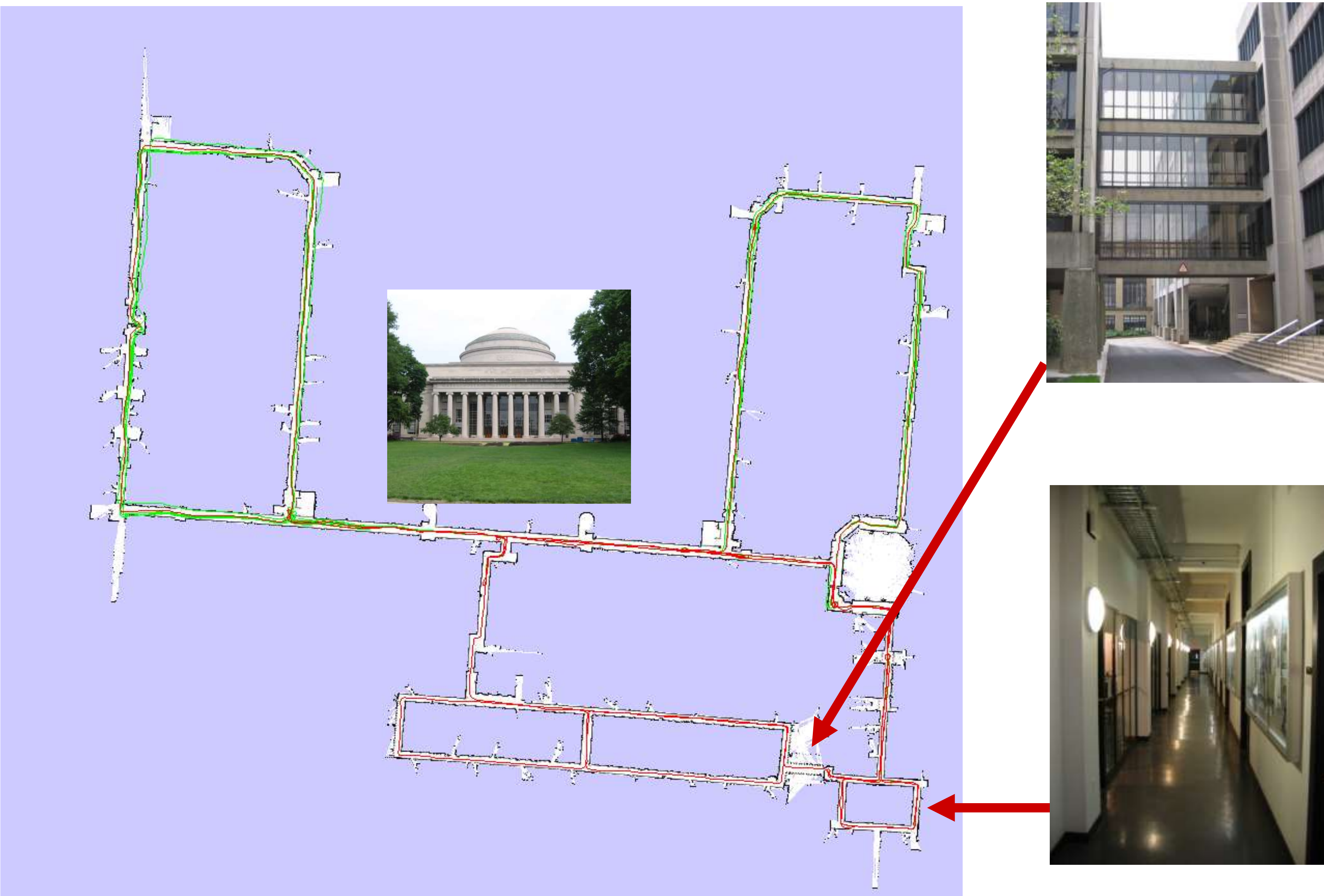
Outdoor Campus Map - Video



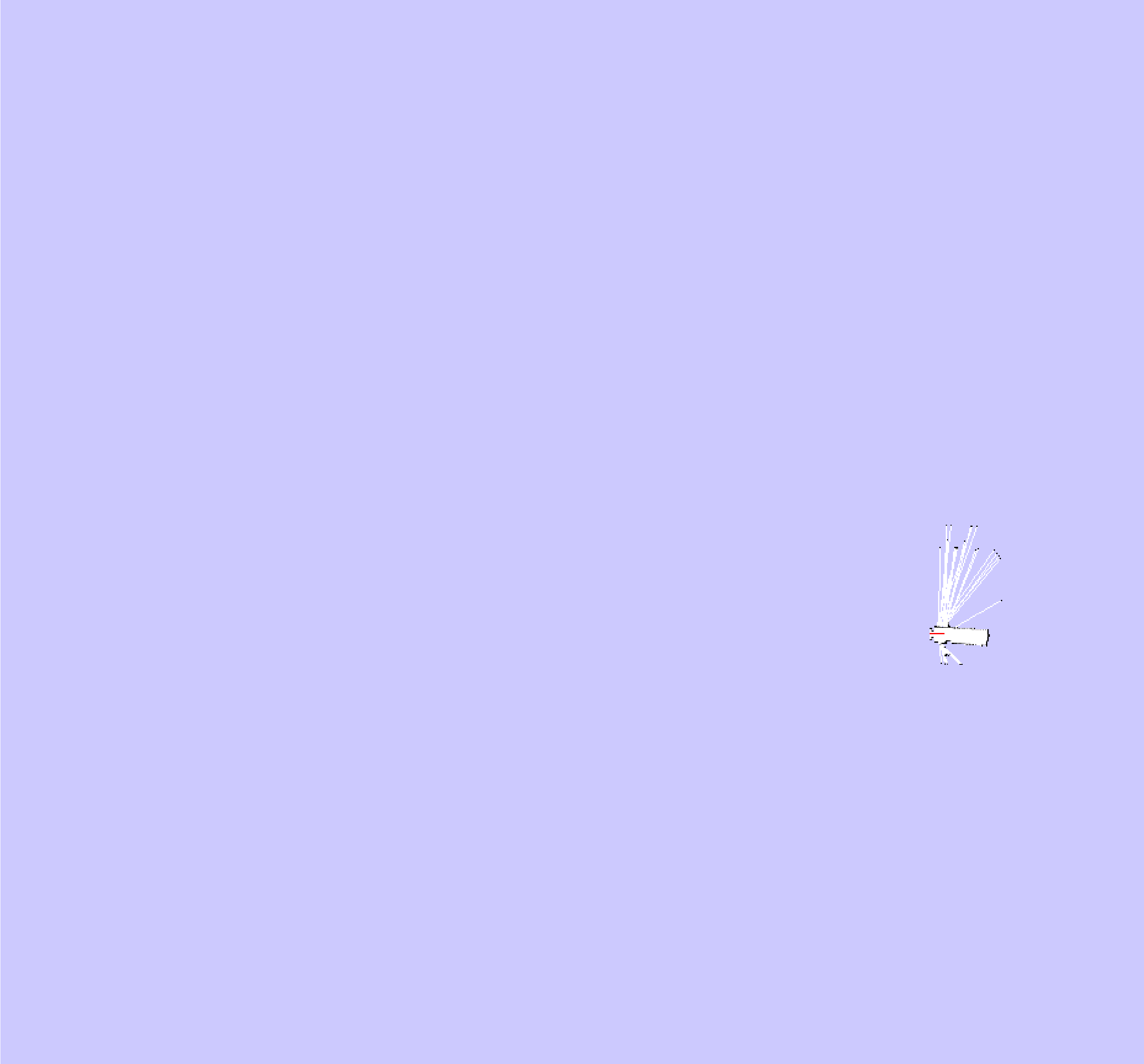
MIT Killian Court

- The **“infinite-corridor-dataset”** at MIT

MIT Killian Court



MIT Killian Court - Video



Conclusion

- The ideas of FastSLAM can also be applied in the context of grid maps
- Utilizing accurate sensor observation leads to good proposals and highly efficient filters
- It is similar to scan-matching on a per-particle base
- The number of necessary particles and re-sampling steps can seriously be reduced
- Improved versions of grid-based FastSLAM can handle larger environments than naïve implementations in "real time" since they need one order of magnitude fewer samples

More Details on FastSLAM

- M. Montemerlo, S. Thrun, D. Koller, and B. Wegbreit. FastSLAM: A factored solution to simultaneous localization and mapping, *AAAI02*
- D. Haehnel, W. Burgard, D. Fox, and S. Thrun. An efficient FastSLAM algorithm for generating maps of large-scale cyclic environments from raw laser range measurements, IROS03
- M. Montemerlo, S. Thrun, D. Koller, B. Wegbreit. FastSLAM 2.0: An Improved particle filtering algorithm for simultaneous localization and mapping that provably converges. IJCAI-2003
- G. Grisetti, C. Stachniss, and W. Burgard. Improving grid-based slam with rao-blackwellized particle filters by adaptive proposals and selective resampling, ICRA05
- A. Eliazar and R. Parr. DP-SLAM: Fast, robust simultanous localization and mapping without predetermined landmarks, IJCAI03