Robot Mapping

FastSLAM – Feature-Based SLAM with Particle Filters

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Particle Filter

- Non-parametric recursive Bayes filter
- Posterior is represented by a set of weighted samples
- Can model arbitrary distributions
- Works well in low-dimensional spaces
- 3-Step procedure
  - Sampling from proposal
  - Importance Weighting
  - Resampling

Particle Filter Algorithm

1. Sample the particles from the proposal distribution

$$x_t^{[j]} \sim \pi(x_t \mid \ldots)$$

2. Compute the importance weights

$$w_t^{[j]} = \frac{target(x_t^{[j]})}{proposal(x_t^{[j]})}$$

1. Resampling: Draw sample i with probability $w_t^{[i]}$ and repeat J times

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:

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

Dimensionality Problem

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

Higher dimensions -> more samples.

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

high-dimensional

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

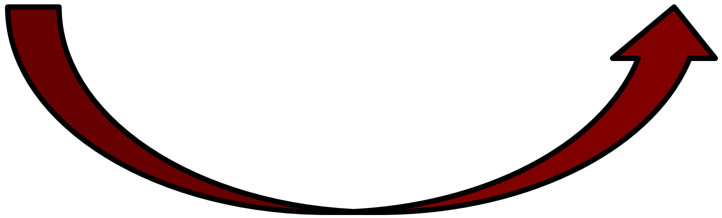
$$x_{1:t}, m_1, \ \ldots, m_M$$

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

$$\begin{tikzcd}\underline{x_{1:t},} \arrow[r, bend right] & \underline{m_1,\ \ldots,m_M}\end{tikzcd}$$

Key Idea

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



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.

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 in closed form, represent only $p(a)$ with samples and compute $p(b \mid a)$ for every sample

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

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

Rao-Blackwellization for SLAM

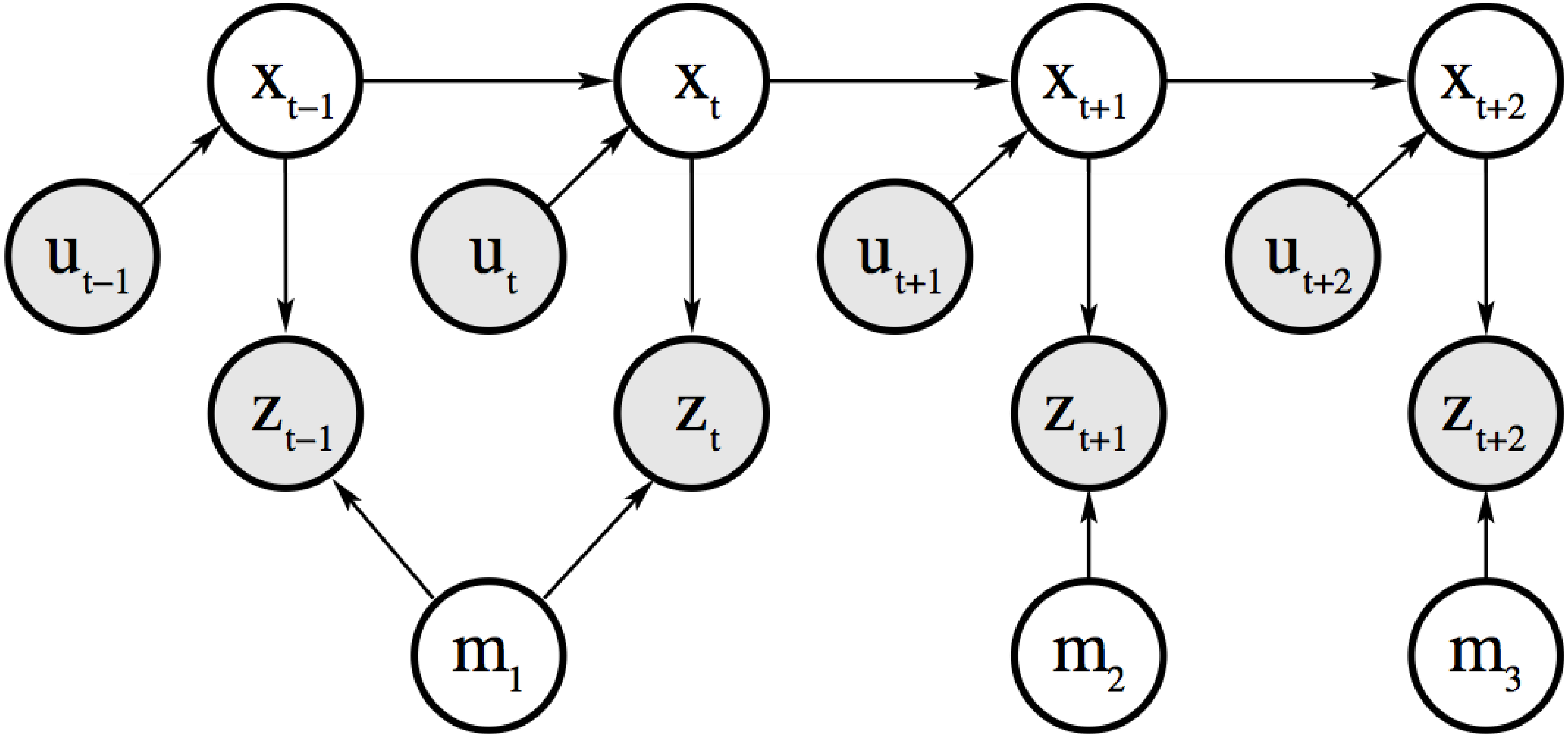
- Factorization of the SLAM posterior

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

How to compute this term efficiently?

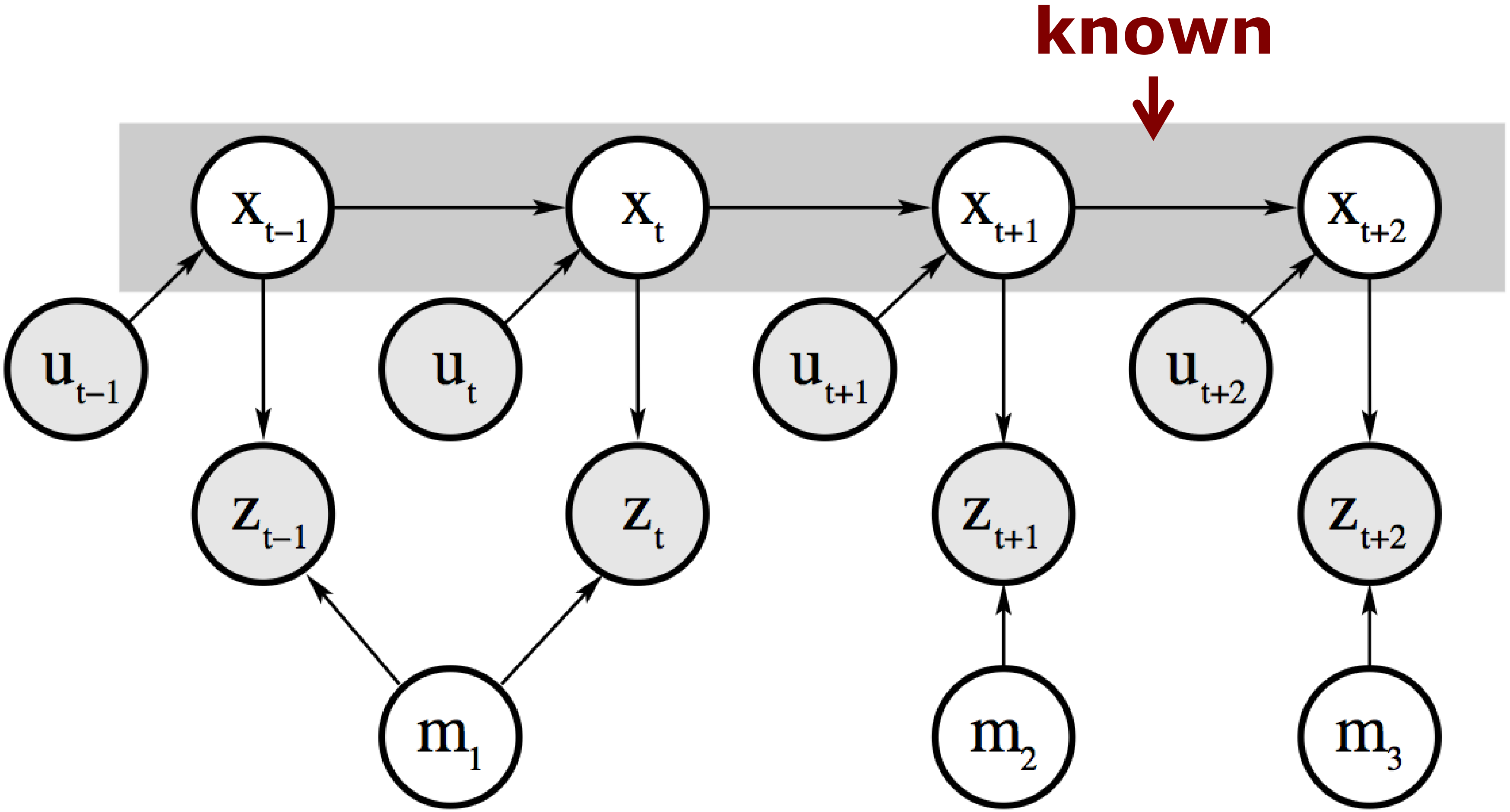
First introduced for SLAM by Murphy in 1999

Revisit the Graphical Model



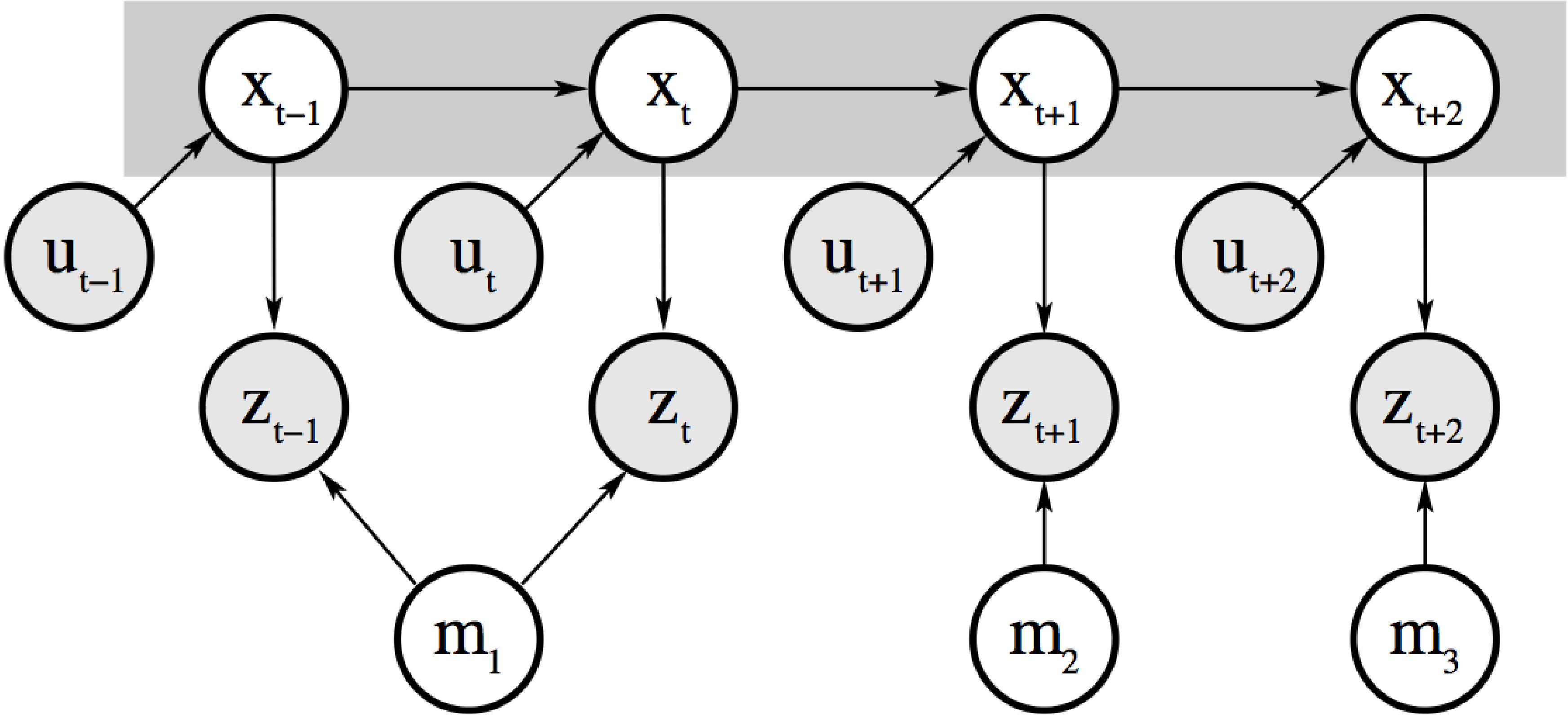
Courtesy: Thrun, Burgard, Fox

Revisit the Graphical Model



Courtesy: Thrun, Burgard, Fox

Landmarks are Conditionally Independent Given the Poses



Landmark variables are all disconnected (i.e. independent) given the robot's path

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

Landmarks are conditionally independent given the poses

First exploited in FastSLAM by Montemerlo et al., 2002

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

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

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

First exploited in FastSLAM by Montemerlo et al., 2002

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

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

$$p(x_{0:t} \mid z_{1:t}, u_{1:t}) \; \prod_{i=1}^{M} \underline{p(m_i \mid x_{0:t}, z_{1:t})}$$

2-dimensional EKFs!

First exploited in FastSLAM by Montemerlo et al., 2002

Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

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

$$\underbrace{p(x_{0:t} \mid z_{1:t}, u_{1:t})}_{\textbf{particle filter similar to MCL}} \; \prod_{i=1}^{M} \underbrace{p(m_i \mid x_{0:t}, z_{1:t})}_{\textbf{2-dimensional EKFs!}}$$

First exploited in FastSLAM by Montemerlo et al., 2002

Modeling the Robot's Path

- Sample-based representation for $p(x_{0:t} \mid z_{1:t}, u_{1:t})$
- Each sample is a path hypothesis

$$x_0 \qquad x_1 \qquad x_2 \qquad \ldots$$

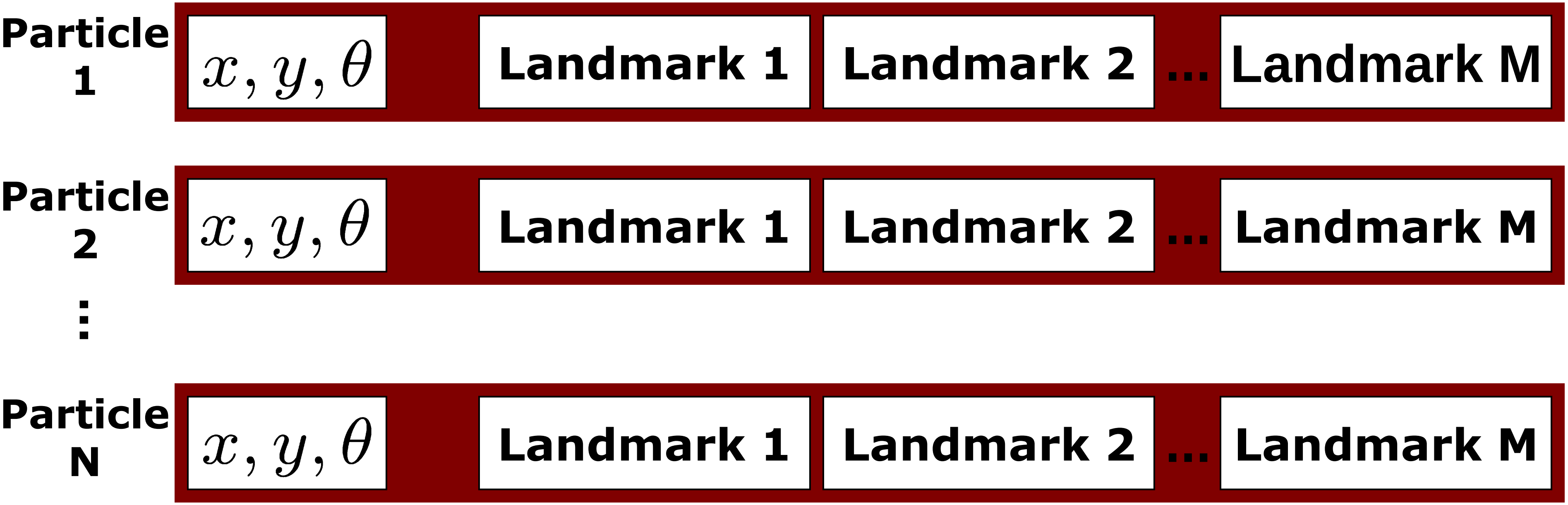
starting location,
typically (0,0,0)

pose hypothesis
at time t=1

- Past poses of a sample are not revised
- No need to maintain past poses in the sample set

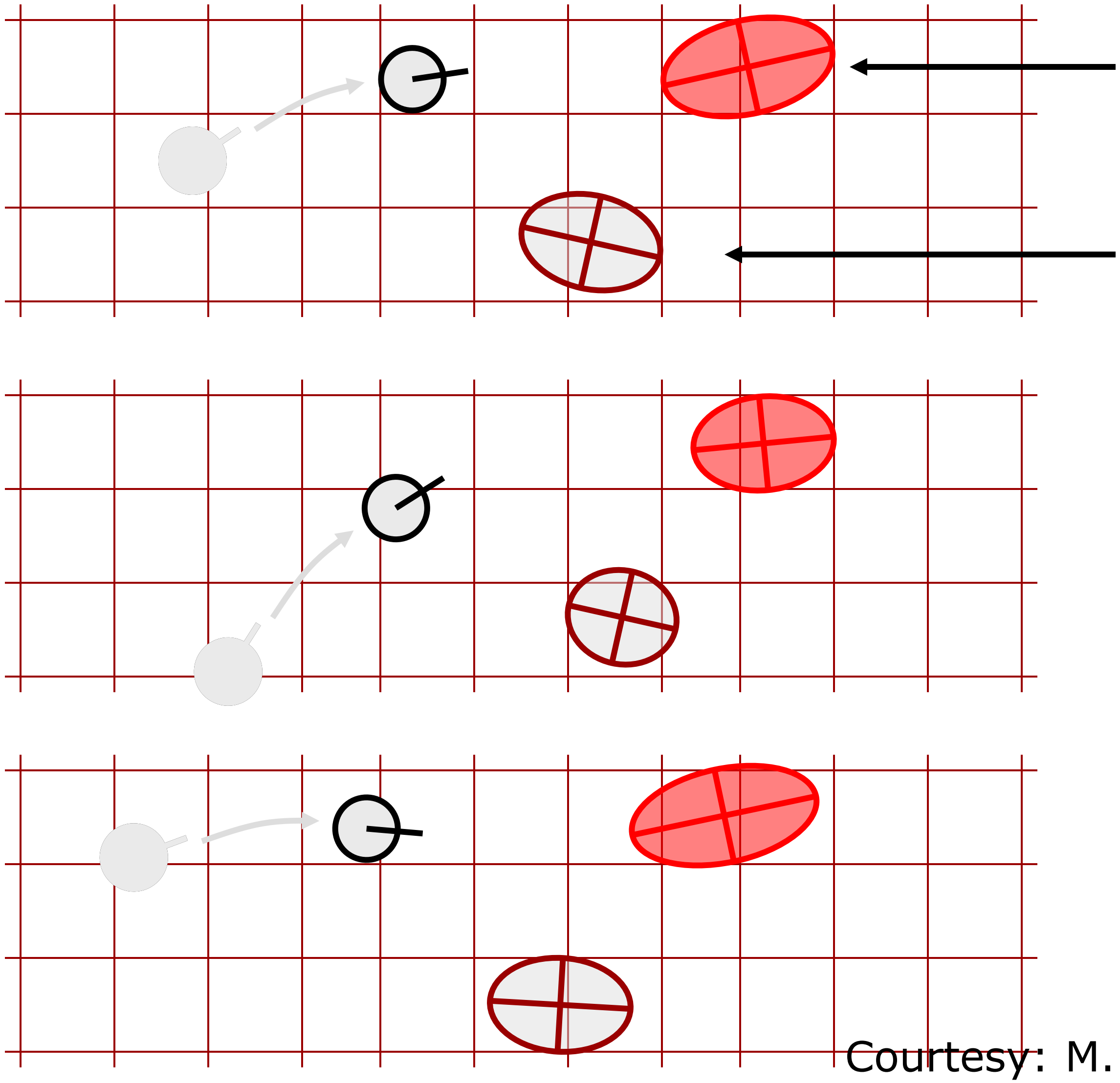
FastSLAM

- 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**

FastSLAM – Action Update



Particle #1

Landmark 1
2x2 EKF

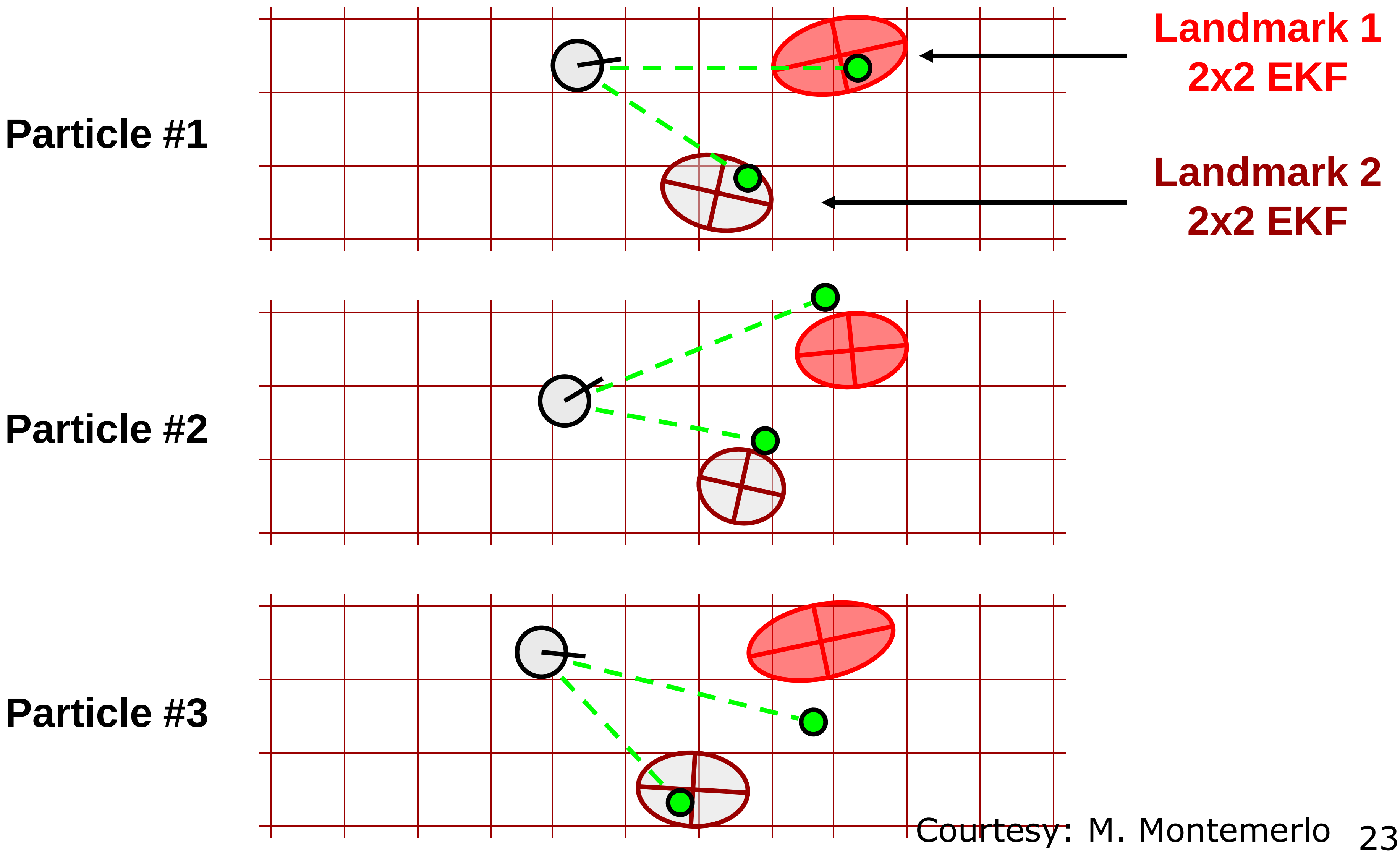
Landmark 2
2x2 EKF

Particle #2

Particle #3

Courtesy: M. Montemerlo

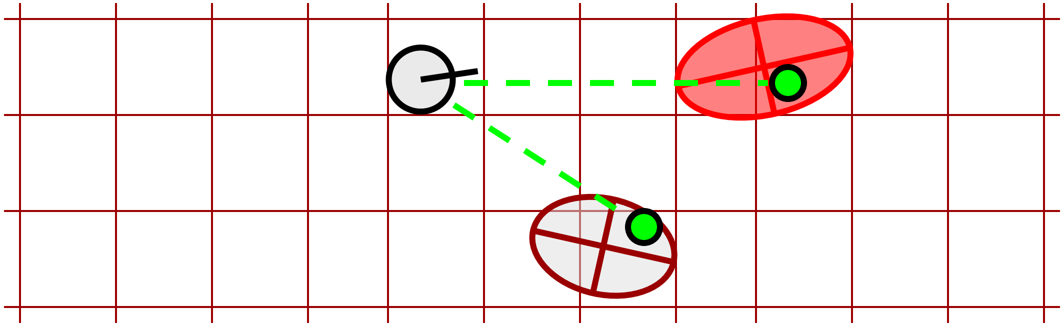
FastSLAM – Sensor Update



Courtesy: M. Montemerlo

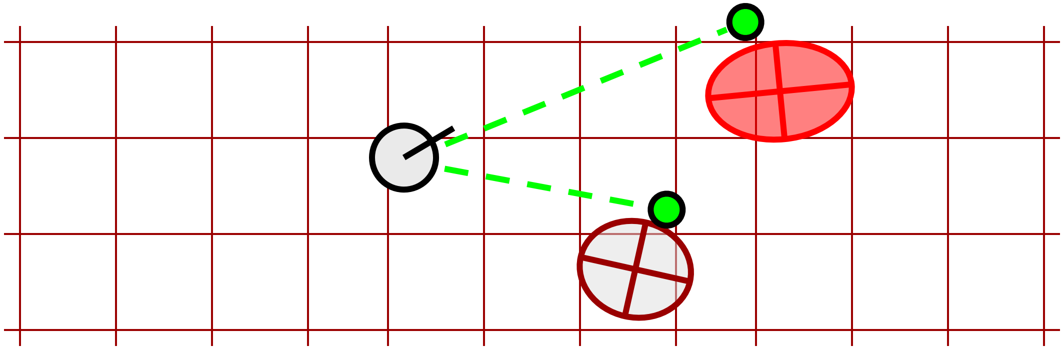
FastSLAM – Sensor Update

Particle #1



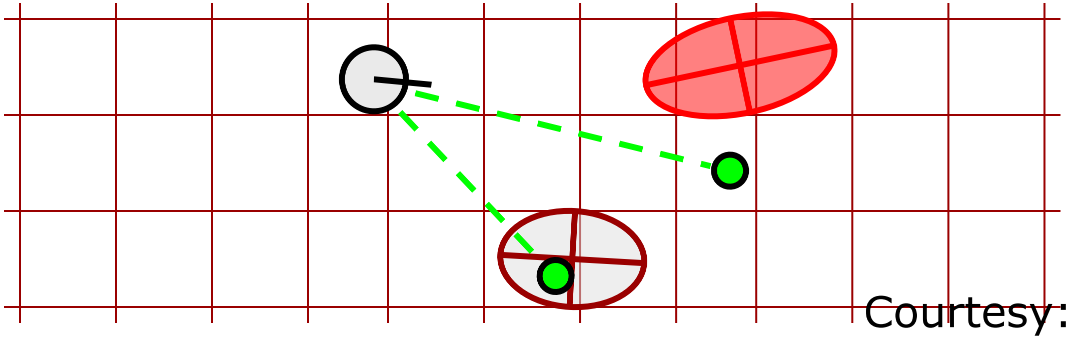
Weight = 0.8

Particle #2



Weight = 0.4

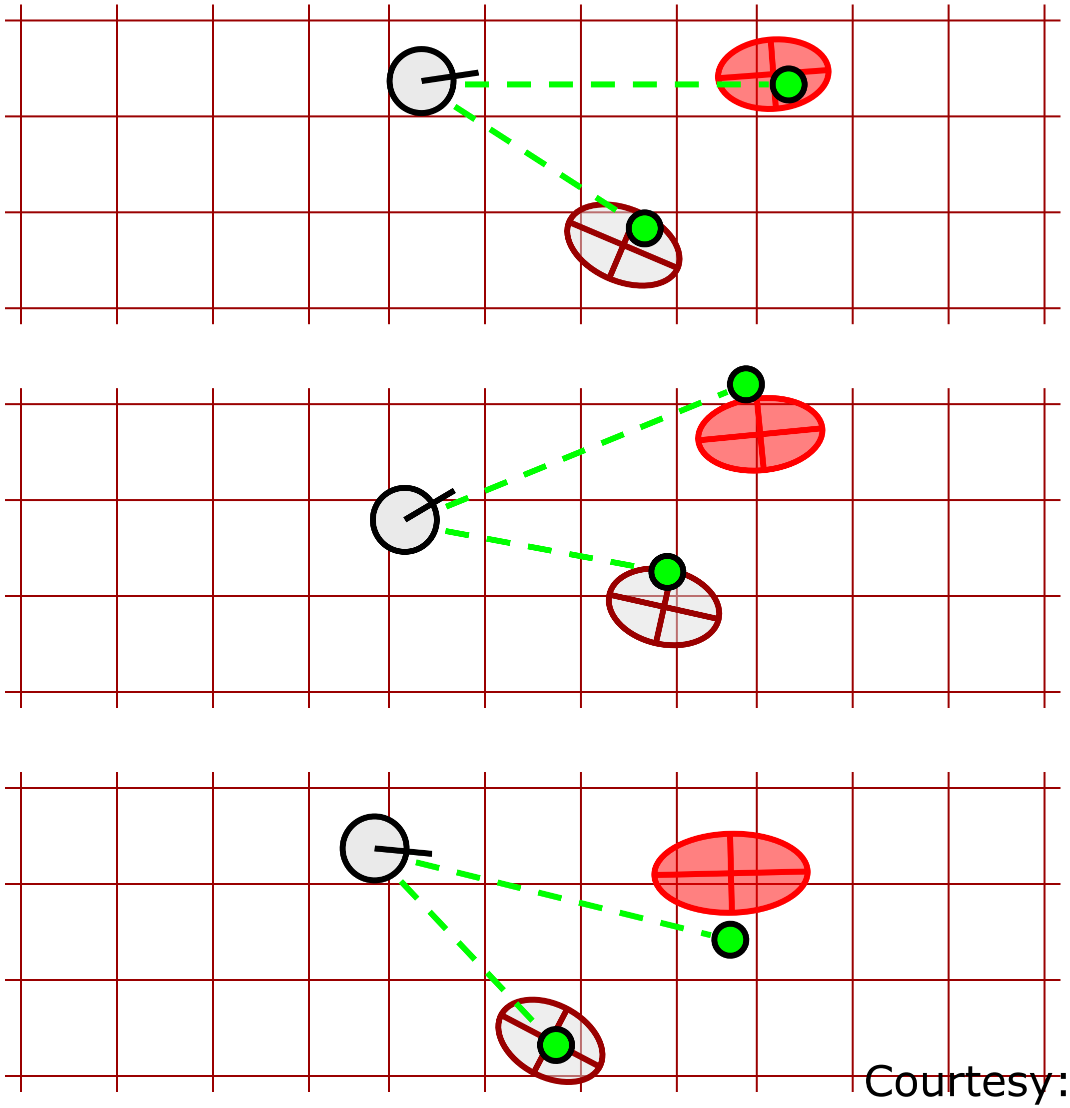
Particle #3



Weight = 0.1

Courtesy: M. Montemerlo

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

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

$$w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \ \exp\left\{-\frac{1}{2}(z_t - \hat{z}^{[k]})^T \underset{\underset{\textbf{measurement covariance}}{\uparrow}}{Q^{-1}} \ (z_t - \overset{\overset{\textbf{exp. observation}}{\downarrow}}{\hat{z}^{[k]}})\right\}$$

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

FastSLAM 1.0 – Part 1

```
**FastSLAM1.0_known_correspondence**($z_t, c_t, u_t, \mathcal{X}_{t-1}$):
    for $k = 1$ to $N$ do                                          // loop over all particles
        Let $\left\langle x_{t-1}^{[k]}, \left\langle \mu_{1,t-1}^{[k]}, \Sigma_{1,t-1}^{[k]} \right\rangle, \ldots \right\rangle$ be particle $k$ in $\mathcal{X}_{t-1}$
        $x_t^{[k]} \sim p(x_t \mid x_{t-1}^{[k]}, u_t)$                    // sample pose
```

FastSLAM 1.0 – Part 1

```
FastSLAM1.0_known_correspondence($z_t, c_t, u_t, \mathcal{X}_{t-1}$):
    for $k = 1$ to $N$ do                                                   // loop over all particles
        Let $\left\langle x_{t-1}^{[k]}, \left\langle \mu_{1,t-1}^{[k]}, \Sigma_{1,t-1}^{[k]} \right\rangle, \ldots \right\rangle$ be particle $k$ in $\mathcal{X}_{t-1}$
        $x_t^{[k]} \sim p(x_t \mid x_{t-1}^{[k]}, u_t)$                     // sample pose
        $j = c_t$                                                           // observed feature
        if feature $j$ never seen before
            $\mu_{j,t}^{[k]} = h^{-1}(z_t, x_t^{[k]})$                      // initialize mean
            $H = h'(\mu_{j,t}^{[k]}, x_t^{[k]})$                            // calculate Jacobian
            $\Sigma_{j,t}^{[k]} = H^{-1} \, Q_t \, (H^{-1})^T$              // initialize covariance
            $w^{[k]} = p_0$                                                 // default importance weight
        else
```

FastSLAM 1.0 – Part 2

```
        else
            $\langle \mu_{j,t}^{[k]}, \Sigma_{j,t}^{[k]} \rangle$ = EKF-Update(...)      // update landmark
            $w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} (z_t - \hat{z}^{[k]})^T Q^{-1} (z_t - \hat{z}^{[k]}) \right\}$
```

measurement cov. $Q = H\,\Sigma_{j,t-1}^{[k]}\,H^T + Q_t$ **exp. observation**

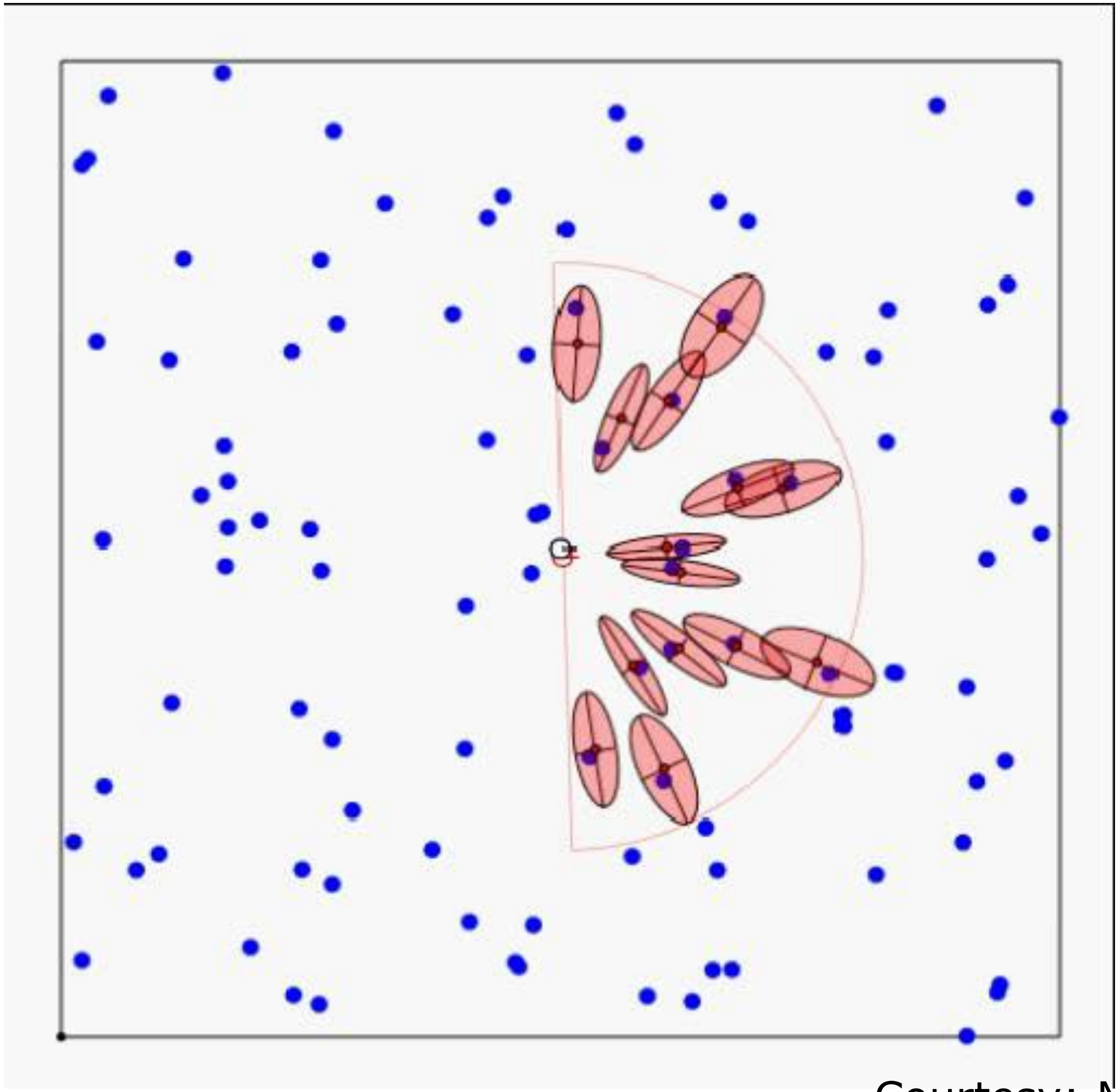
```
        endif
        for all unobserved features j' do
            $\langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j',t-1}^{[k]} \rangle$      // leave unchanged
        endfor
    endfor
    $\mathcal{X}_t = \text{resample}\left( \left\langle x_t^{[k]}, \left\langle \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \right\rangle, \ldots, w^{[k]} \right\rangle_{k=1,\ldots,N} \right)$
    return $\mathcal{X}_t$
```

FastSLAM 1.0 – Part 2 (long)

EKF update

```
        else
            $\hat{z}^{[k]} = h(\mu_{j,t-1}^{[k]}, x_t^{[k]})$                         // measurement prediction
            $H = h'(\mu_{j,t-1}^{[k]}, x_t^{[k]})$                             // calculate Jacobian
            $Q = H\ \Sigma_{j,t-1}^{[k]}\ H^T + Q_t$                          // measurement covariance
            $K = \Sigma_{j,t-1}^{[k]}\ H^T\ Q^{-1}$                            // calculate Kalman gain
            $\mu_{j,t}^{[k]} = \mu_{j,t-1}^{[k]} + K(z_t - \hat{z}^{[k]})$                // update mean
            $\Sigma_{j,t}^{[k]} = (I - K\ H)\Sigma_{j,t-1}^{[k]}$                      // update covariance
            $w^{[k]} = |2\pi Q|^{-\frac{1}{2}}\ \exp\left\{-\frac{1}{2}(z_t - \hat{z}^{[k]})^T\right.$
                                $\left.Q^{-1}\ (z_t - \hat{z}^{[k]})\right\}$   // importance factor
        endif
        for all unobserved features $j'$ do
            $\langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j',t-1}^{[k]} \rangle$         // leave unchanged
        endfor
    endfor
    $\mathcal{X}_t = \text{resample}\left(\left\langle x_t^{[k]}, \left\langle \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \right\rangle, \ldots, w^{[k]} \right\rangle_{k=1,\ldots,N}\right)$
    return $\mathcal{X}_t$
```

FastSLAM in Action



Courtesy: M. Montemerlo

The Weight is a Result From the Importance Sampling Principle

- Importance weight is given by the ratio of target and proposal in $x^{[k]}$
- See: importance sampling principle

$$w^{[k]} = \frac{\mathrm{target}(x^{[k]})}{\mathrm{proposal}(x^{[k]})}$$

The Importance Weight

- The target distribution is

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

- The proposal distribution is

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

- Proposal is used step-by-step

$$\begin{aligned} & p(x_{1:t} \mid z_{1:t-1}, u_{1:t}) \\ = \quad & \underbrace{p(x_t \mid x_{t-1}, u_t)}_{\text{from } \mathcal{X}_{t-1} \text{ to } \bar{\mathcal{X}}_t} \underbrace{p(x_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})}_{\mathcal{X}_{t-1}} \end{aligned}$$

The Importance Weight

$$\begin{aligned} w^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\ &= \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t)\; p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})} \end{aligned}$$

The Importance Weight

$$
\begin{aligned}
w^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\
&= \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t)\; p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}
\end{aligned}
$$

Bayes rule + factorization

The Importance Weight

$$
\begin{aligned}
w^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\
&= \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t)\; p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})} \\
&= \frac{\eta\, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1})\; p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)}{p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)} \\
&\quad \frac{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}
\end{aligned}
$$

The Importance Weight

$$
\begin{aligned}
w^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\
&= \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t)\; p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})} \\
&= \frac{\eta\, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1})\; \cancel{p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)}}{\cancel{p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)}} \\
&\quad \frac{\cancel{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}}{\cancel{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}}
\end{aligned}
$$

The Importance Weight

$$
\begin{aligned}
w^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\
&= \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t)\; p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})} \\
&= \frac{\eta\, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1})\; \cancel{p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)}}{\cancel{p(x_t^{[k]} \mid x_{t-1}^{[k]}, u_t)}} \\
&\quad \frac{\cancel{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}}{\cancel{p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})}} \\
&= \eta\, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1})
\end{aligned}
$$

The Importance Weight

- Integrating over the pose of the observed landmark leads to

$$
\begin{aligned}
w^{[k]} = & \\
= & \quad \eta\, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}) \\
= & \quad \eta \int p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}, m_j)\, p(m_j \mid x_{1:t}^{[k]}, z_{1:t-1})\, dm_j
\end{aligned}
$$

The Importance Weight

- Integrating over the pose of the observed landmark leads to

$$
\begin{aligned}
w^{[k]} = & \\
= \quad & \eta \, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}) \\
= \quad & \eta \int p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}, m_j) \, p(m_j \mid x_{1:t}^{[k]}, z_{1:t-1}) \, dm_j \\
= \quad & \eta \int p(z_t \mid x_t^{[k]}, m_j) \;\; p(m_j \mid x_{1:t-1}^{[k]}, z_{1:t-1}) \;\; dm_j
\end{aligned}
$$

The Importance Weight

- Integrating over the pose of the observed landmark leads to

$$w^{[k]} =$$

$$\begin{aligned} &= \eta \, p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}) \\ &= \eta \int p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}, m_j) \, p(m_j \mid x_{1:t}^{[k]}, z_{1:t-1}) \, dm_j \\ &= \eta \int \underbrace{p(z_t \mid x_t^{[k]}, m_j)}_{\mathcal{N}(z_t; \hat{z}^{[k]}, Q_t)} \, \underbrace{p(m_j \mid x_{1:t-1}^{[k]}, z_{1:t-1})}_{\mathcal{N}(m_j; \mu_{j,t-1}^{[k]}, \Sigma_{j,t-1}^{[k]})} \, dm_j \end{aligned}$$

The Importance Weight

- This leads to

$$w^{[k]} = \eta \int \underbrace{\underbrace{p(m_j \mid x^{[k]}_{1:t-1}, z_{1:t-1})}_{\mathcal{N}(m_j;\mu^{[k]}_{j,t-1},\Sigma^{[k]}_{j,t-1})}} \underbrace{p(z_t \mid x^{[k]}_t, m_j)}_{\mathcal{N}(z_t;\hat{z}^{[k]},Q_t)} \, dm_j$$

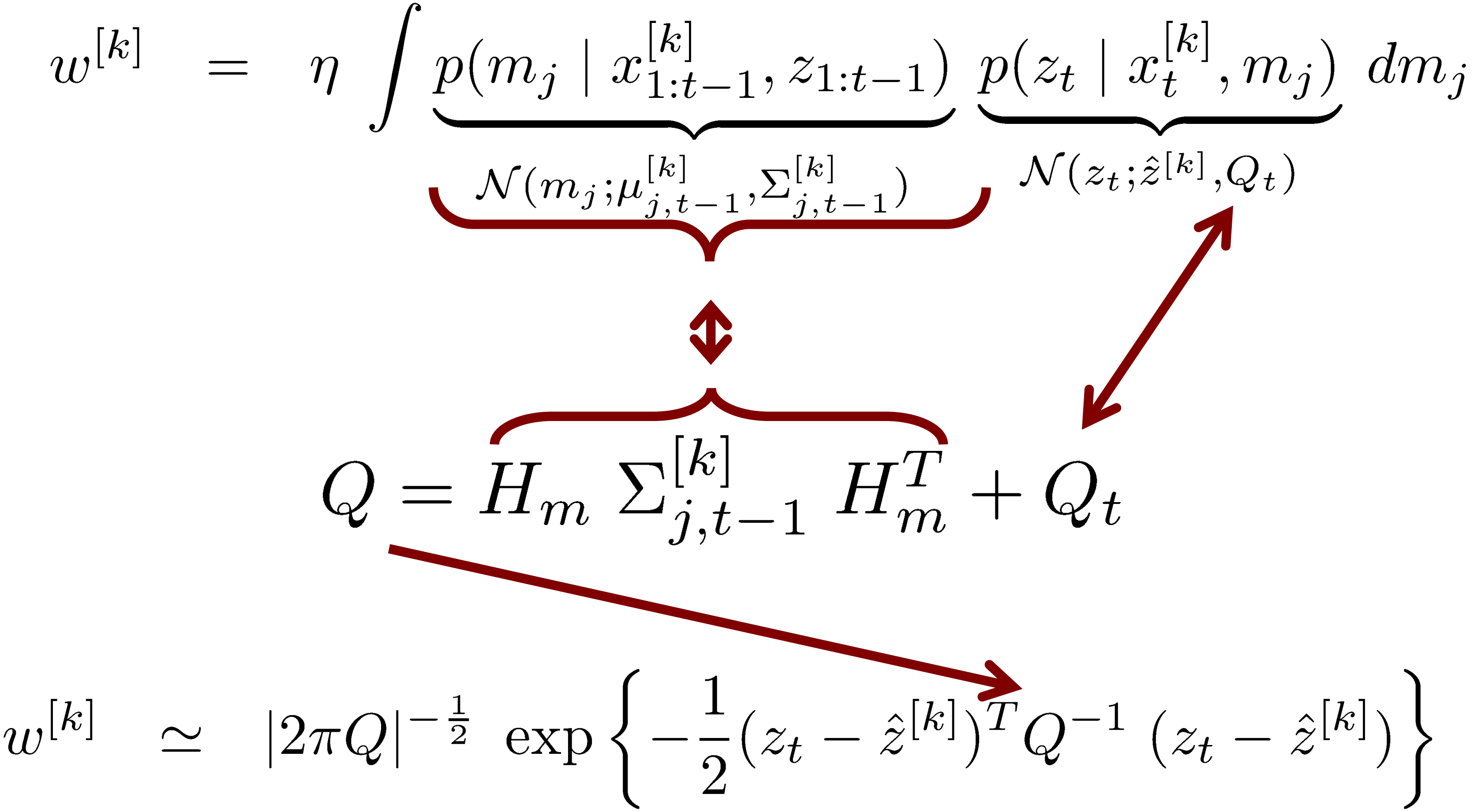
$$\Updownarrow$$

$$Q = \overbrace{H_m \, \Sigma^{[k]}_{j,t-1} \, H_m^T} + Q_t$$

measurement covariance (pose uncertainty of the landmark estimate plus measurement noise)

The Importance Weight

- This leads to



$$w^{[k]} = \eta \int \underbrace{p(m_j \mid x^{[k]}_{1:t-1}, z_{1:t-1})}_{\mathcal{N}(m_j;\mu^{[k]}_{j,t-1},\Sigma^{[k]}_{j,t-1})} \underbrace{p(z_t \mid x^{[k]}_t, m_j)}_{\mathcal{N}(z_t;\hat{z}^{[k]},Q_t)} \, dm_j$$

$$\Updownarrow$$

$$Q = H_m \, \Sigma^{[k]}_{j,t-1} \, H_m^T + Q_t$$

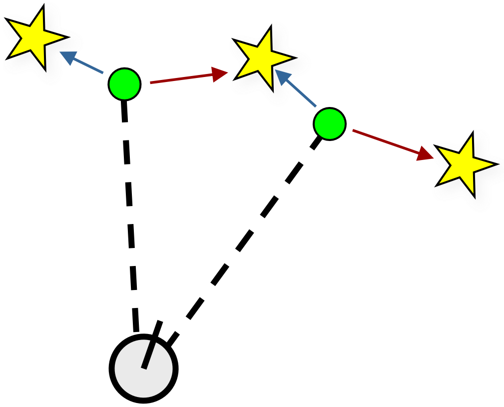
$$w^{[k]} \simeq |2\pi Q|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(z_t - \hat{z}^{[k]})^T Q^{-1} (z_t - \hat{z}^{[k]})\right\}$$

FastSLAM 1.0 – Part 2

```
        else
            $\langle \mu_{j,t}^{[k]}, \Sigma_{j,t}^{[k]} \rangle = \textit{EKF-Update}(\dots)$        // update landmark
        $\boxed{w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \ \exp\left\{-\frac{1}{2}(z_t - \hat{z}^{[k]})^T Q^{-1} \ (z_t - \hat{z}^{[k]})\right\}}$
        endif
        for all unobserved features $j'$ do
            $\langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j',t-1}^{[k]} \rangle$        // leave unchanged
        endfor
    endfor
    $\mathcal{X}_t = \text{resample}\left(\left\langle x_t^{[k]}, \left\langle \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \right\rangle, \dots, w^{[k]} \right\rangle_{k=1,\dots,N}\right)$
    return $\mathcal{X}_t$
```

Data Association Problem

- Which observation belongs to which landmark?

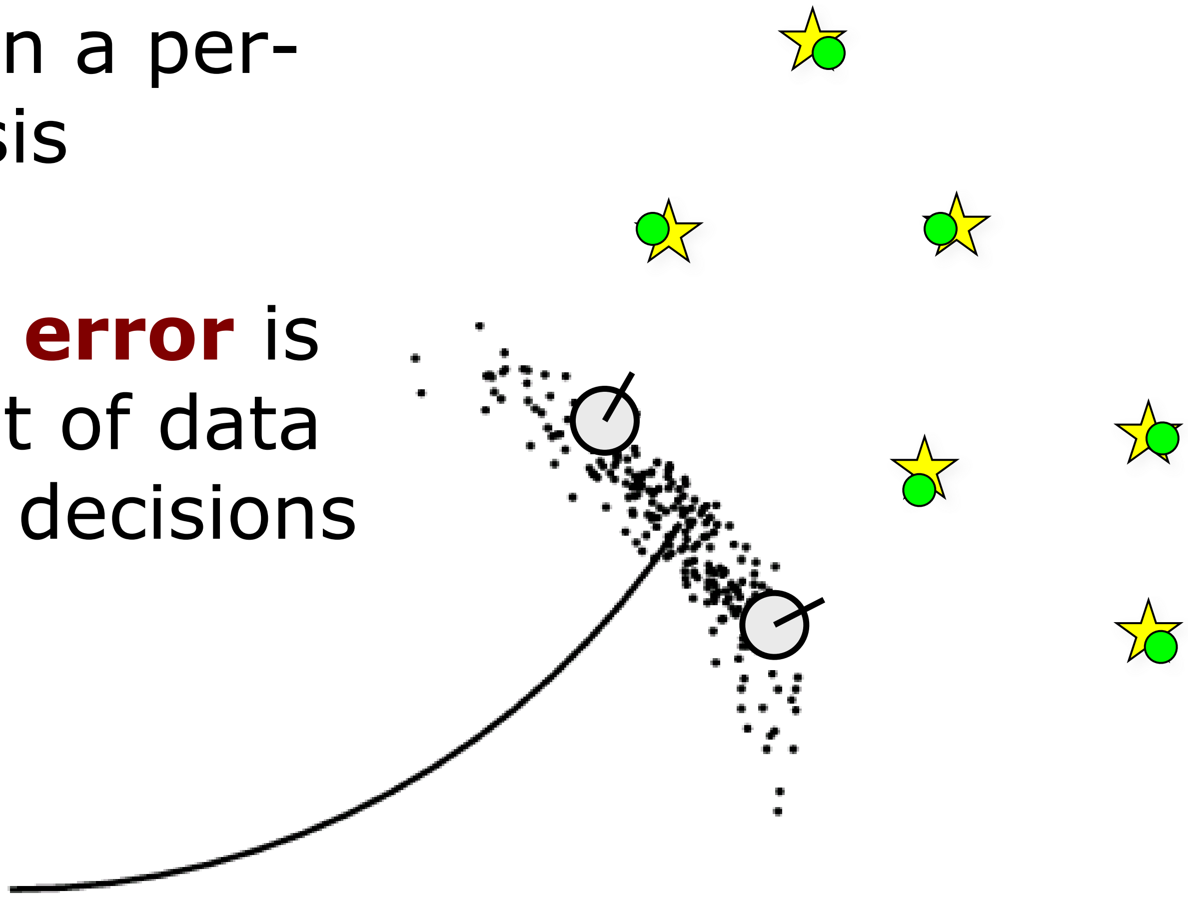


- More than one possible association
- **Potential data associations depend on the pose of the robot**

Courtesy: M. Montemerlo

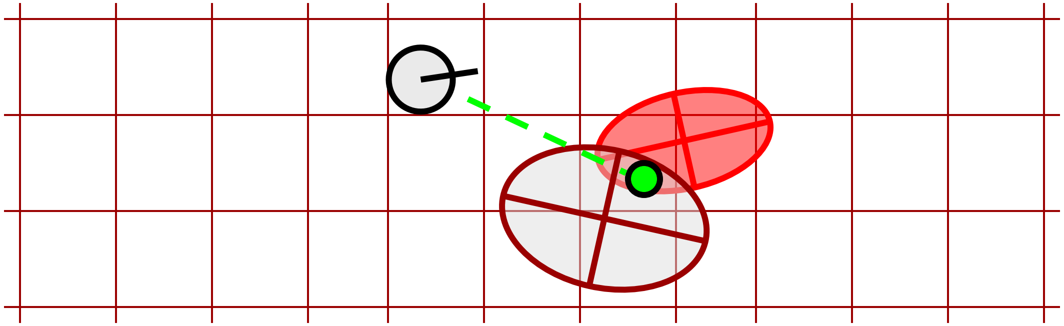
Particles Support for Multi-Hypotheses Data Association

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



Courtesy: M. Montemerlo

Per-Particle Data Association

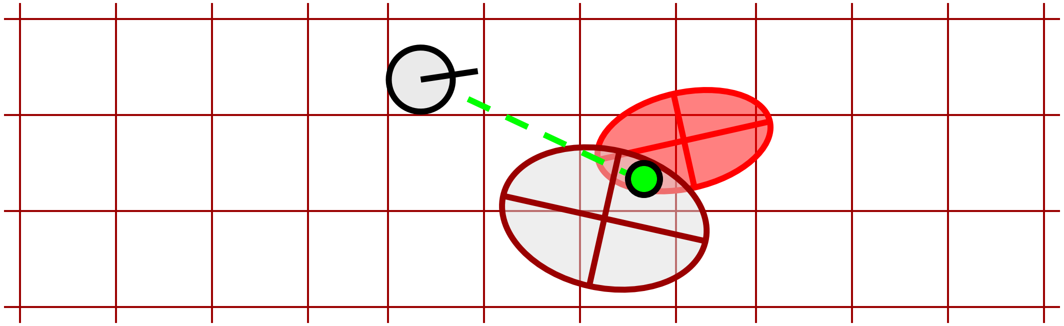


Was the observation generated by the **red** or by the **brown** landmark?

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

Courtesy: M. Montemerlo

Per-Particle Data Association



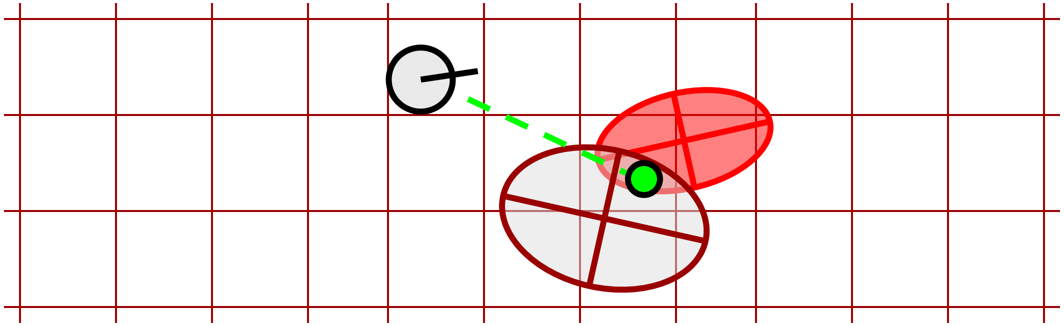
Was the observation generated by the **red** or by the **brown** landmark?

P(observation|red) = 0.3 P(observation|brown) = 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 for an assignment is too low, generate a new landmark

Courtesy: M. Montemerlo

Per-Particle Data Association



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

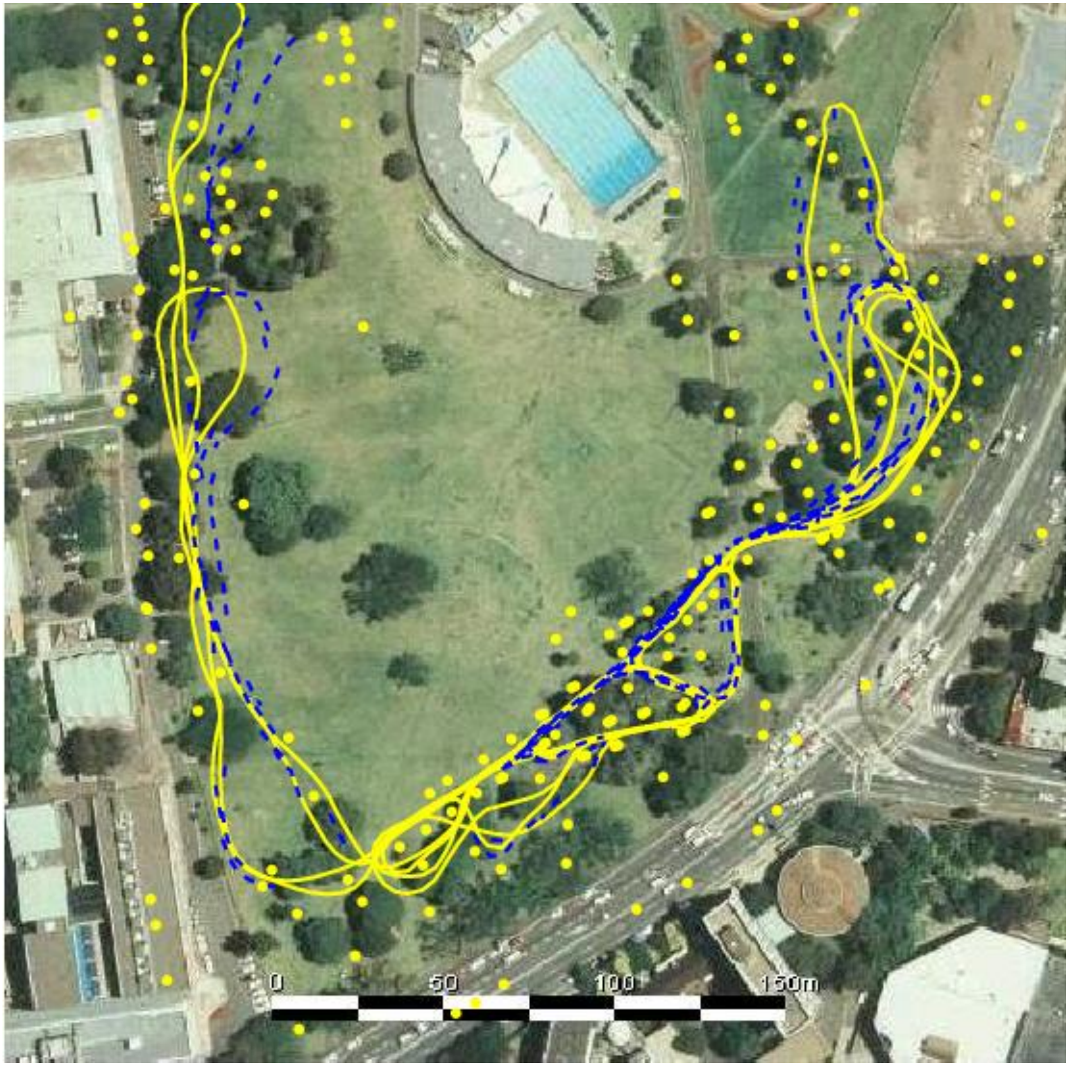
- Multi-modal belief
- Pose error is factored out of data association decisions
- **Simple but effective** data association
- Big **advantage of FastSLAM** over EKF

Courtesy: M. Montemerlo

Results – Victoria Park

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

Blue = GPS
Yellow = FastSLAM

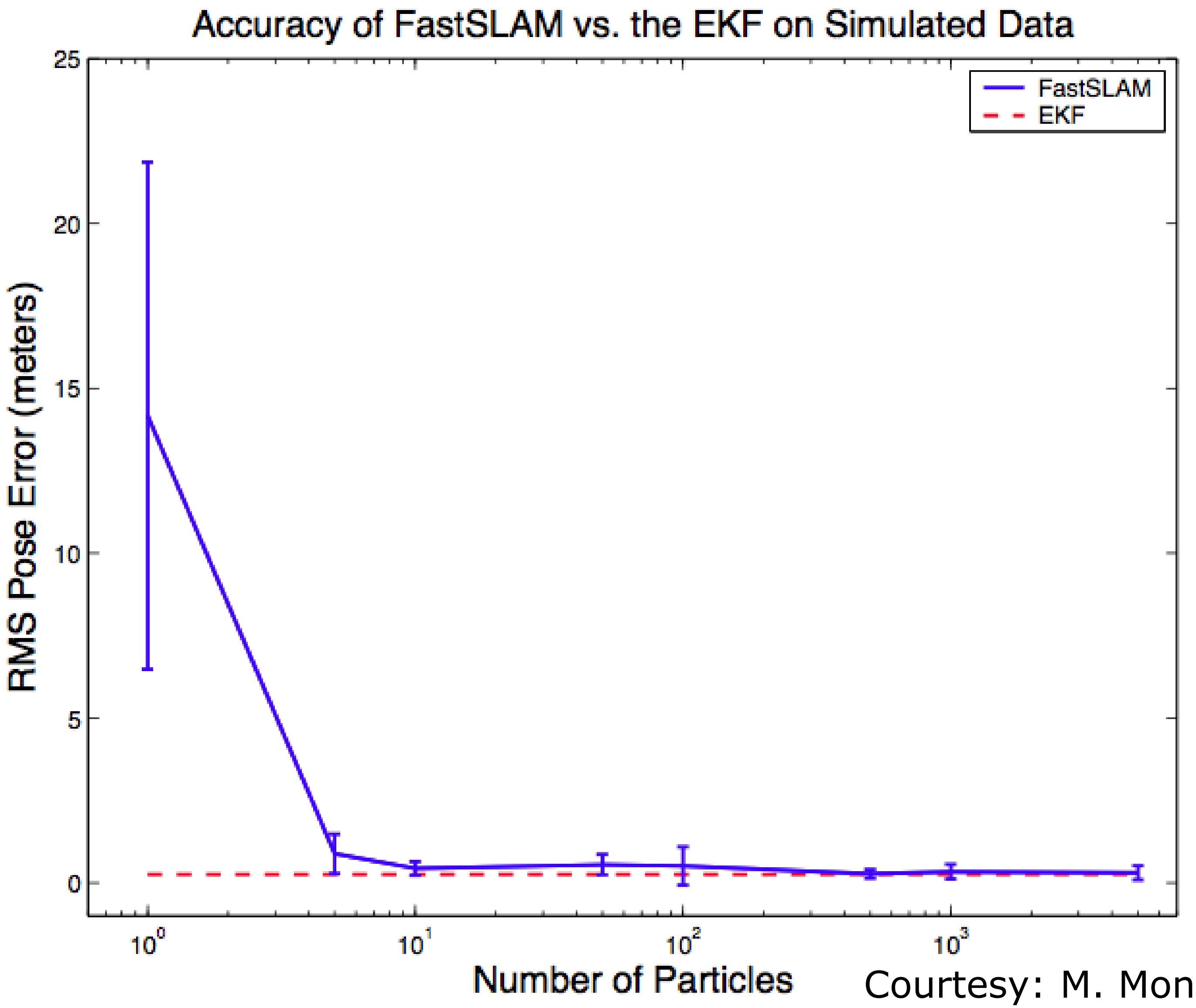


Courtesy: M. Montemerlo

Results – Victoria Park (Video)

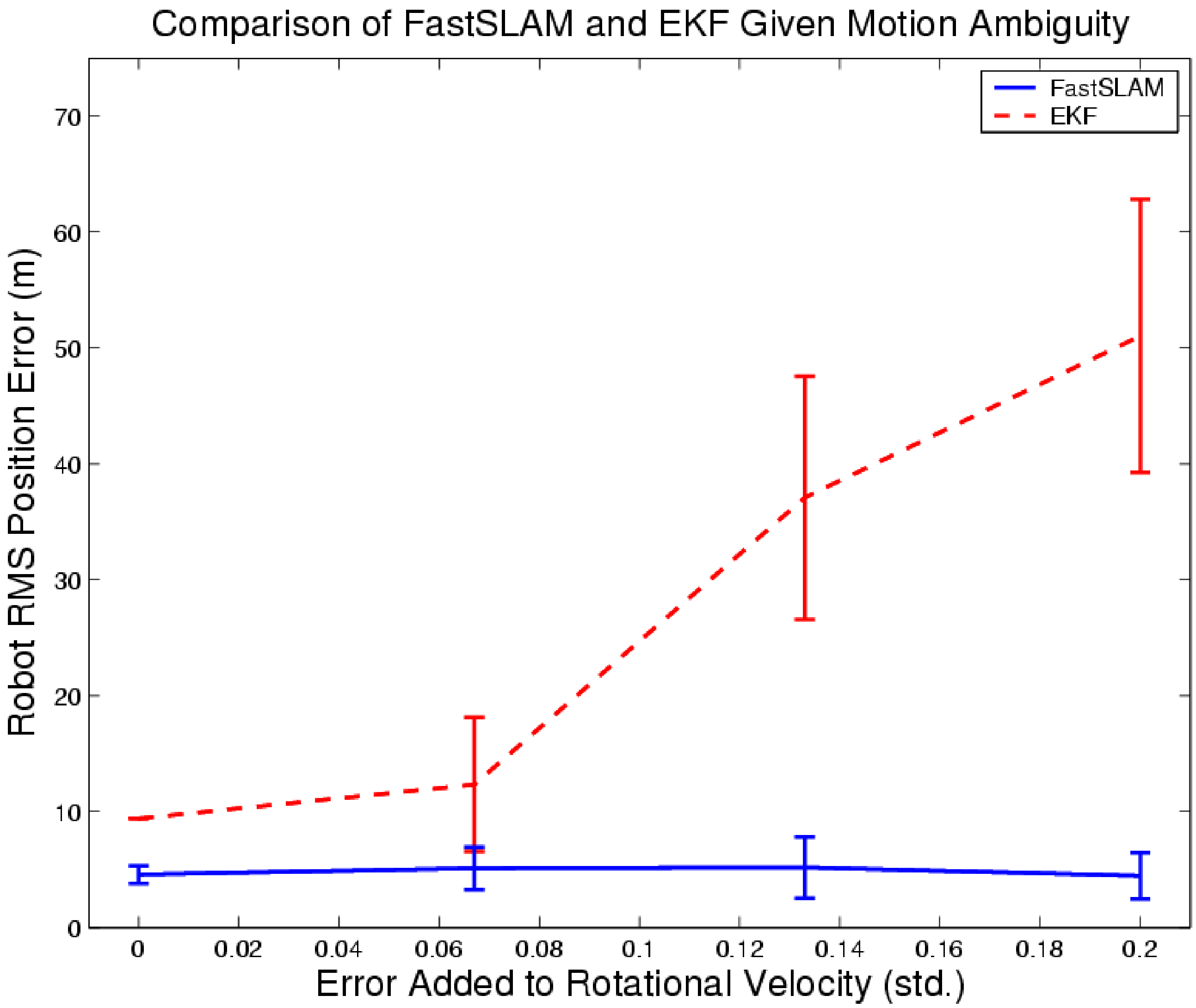
Courtesy: M. Montemerlo

Results (Sample Size)



Courtesy: M. Montemerlo

Results (Motion Uncertainty)



Courtesy: M. Montemerlo

FastSLAM 1.0 Summary

- Use a particle filter to model the belief
- Factors the SLAM posterior into low-dimensional estimation problems
- Model only the robot's path by sampling
- Compute the landmarks given the path
- Per-particle data association
- No robot pose uncertainty in the per-particle data association

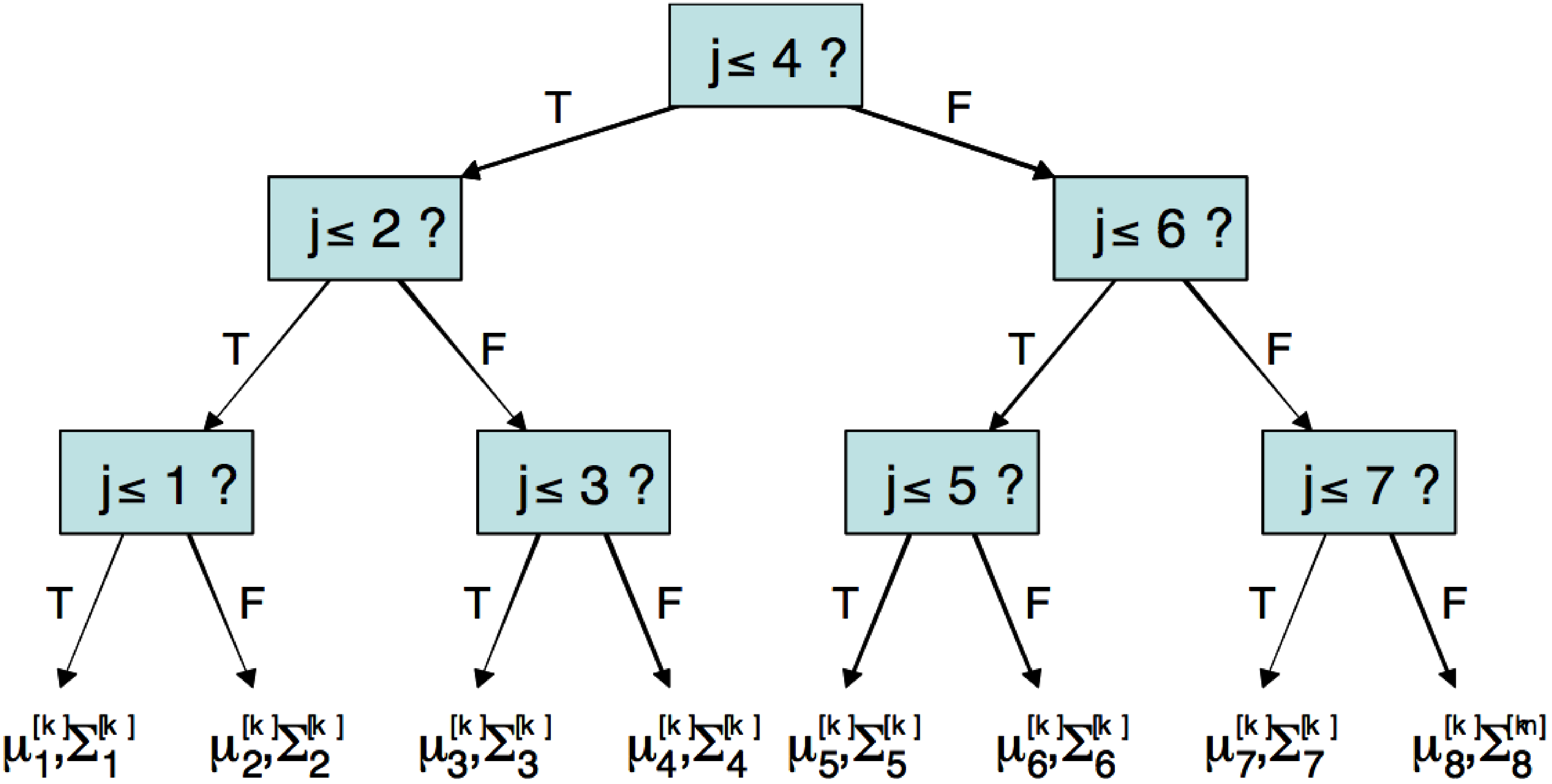
FastSLAM Complexity – Simple Implementation

- Update robot particles based on the control $\mathcal{O}(N)$
- Incorporate an observation into the Kalman filters $\mathcal{O}(N)$
- Resample particle set $\mathcal{O}(NM)$

$\mathcal{O}(NM)$

N = Number of particles
M = Number of map features

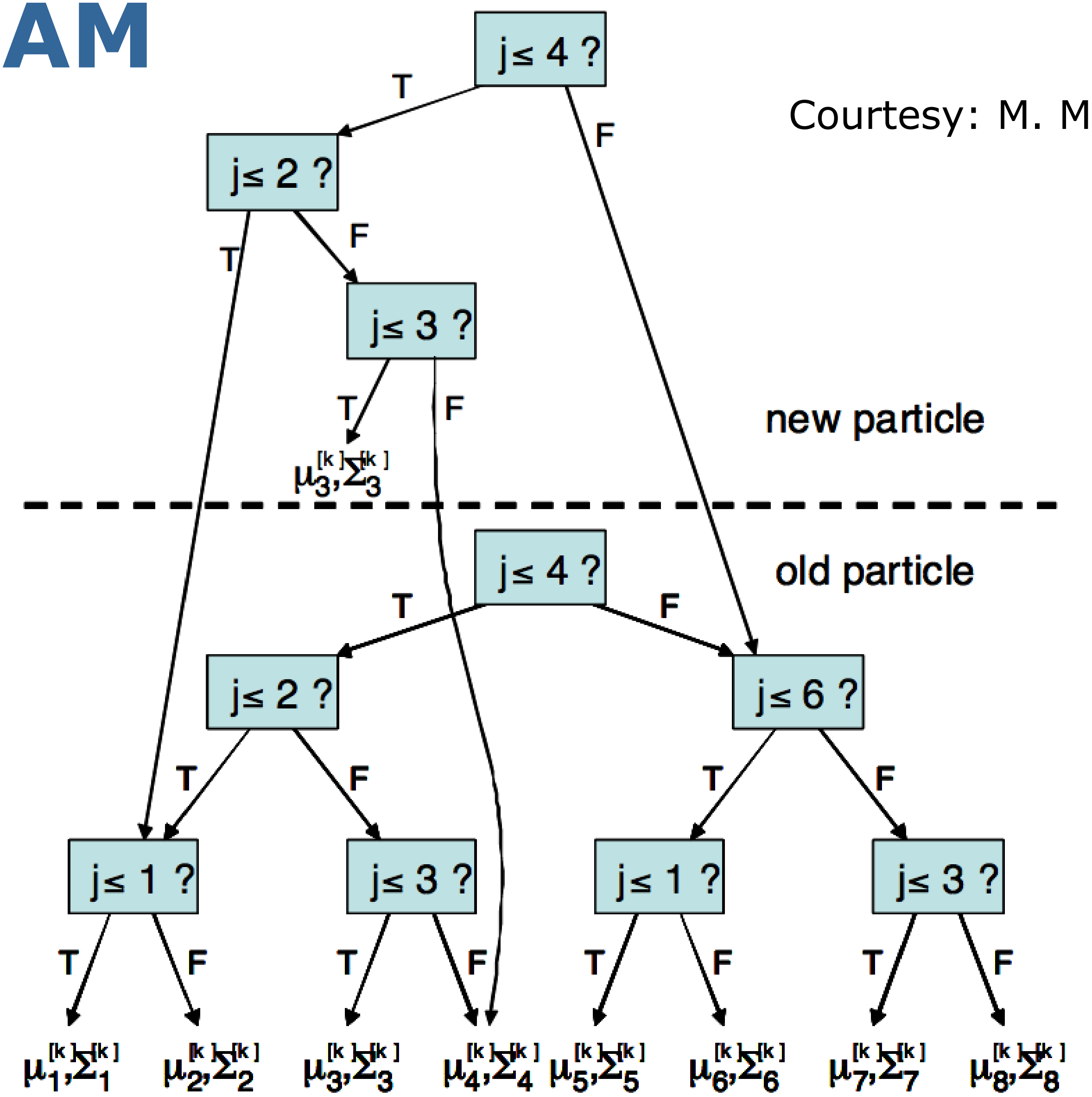
A Better Data Structure for FastSLAM



Courtesy: M. Montemerlo

A Better Data Structure for FastSLAM

Courtesy: M. Montemerlo



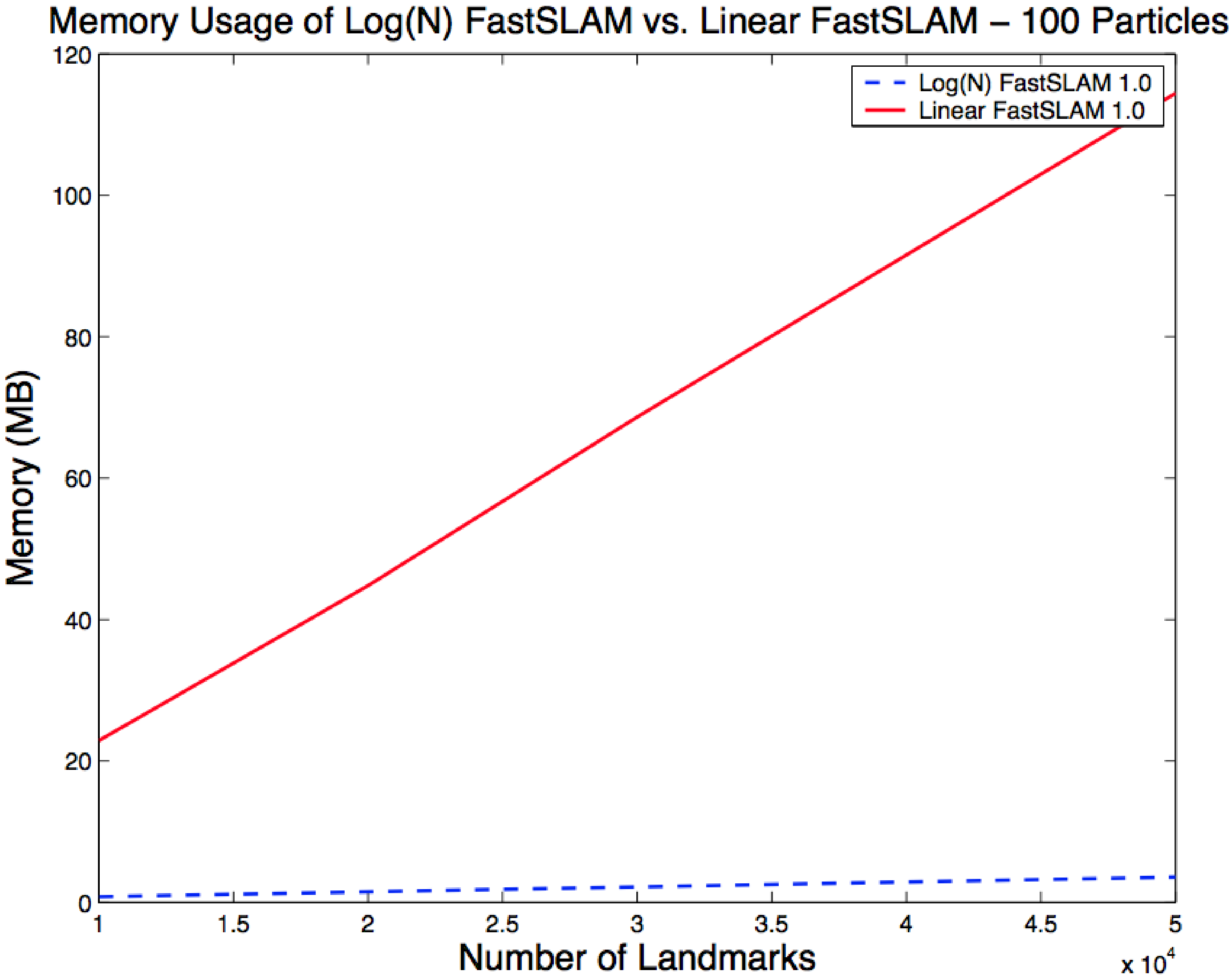
FastSLAM Complexity

Update robot particles based on the control	$\mathcal{O}(N)$
Incorporate an observation into the Kalman filters	$\mathcal{O}(N \log M)$
Resample particle set	$\mathcal{O}(N \log M)$

$$\mathcal{O}(N \log M)$$

N = Number of particles
M = Number of map features

Memory Complexity



Courtesy: M. Montemerlo

FastSLAM 1.0

- FastSLAM 1.0 uses the motion model as the proposal distribution

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

- **Is there a better distribution to sample from?**

[Montemerlo et al., 2002]

FastSLAM 1.0 to FastSLAM 2.0

- FastSLAM 1.0 uses the motion model as the proposal distribution

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

- FastSLAM 2.0 **considers also the measurements during sampling**
- Especially useful if an accurate sensor is used (compared to the motion noise)

[Montemerlo et al., 2003]

FastSLAM 2.0 (Informally)

- FastSLAM 2.0 samples from

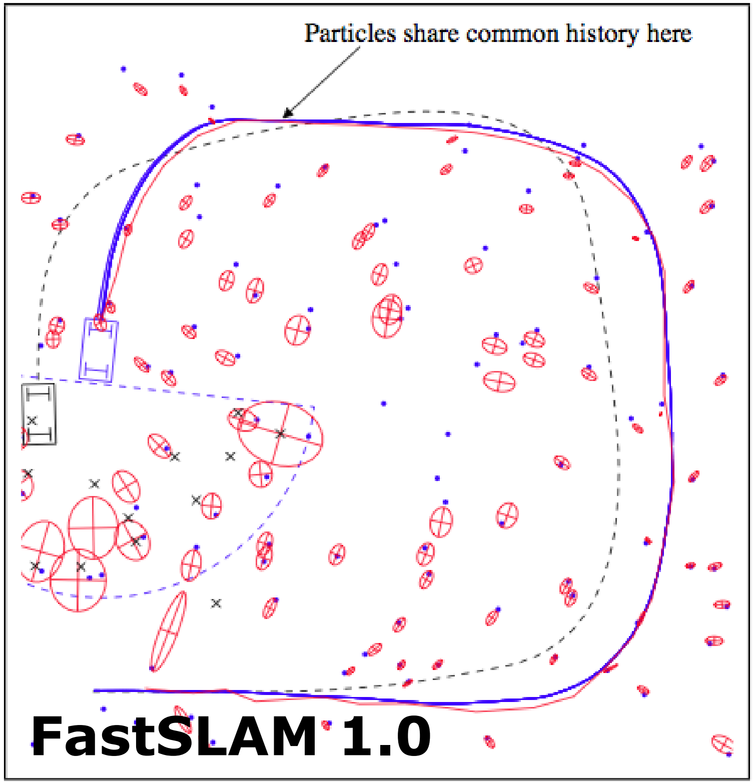
$$x_t^{[k]} \quad \sim \quad p(x_t \mid x_{1:t-1}^{[k]}, u_{1:t}, \underline{z_{1:t}})$$

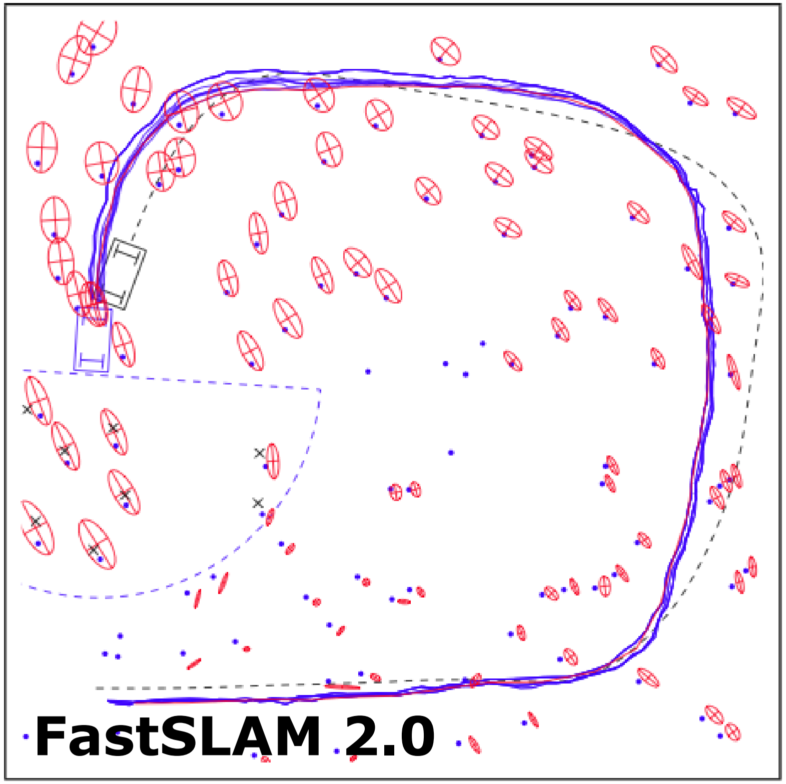
- Results in a more peaked proposal distribution
- Less particles are required
- More robust and accurate
- But more complex…

[Montemerlo et al., 2003]

FastSLAM Problems

- How to determine the sample size?
- Particle deprivation, especially when closing (multiple) loops





Courtesy: M. Montemerlo

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
- FastSLAM 1.0 and 2.0 differ in the proposal distribution
- Complexity $\mathcal{O}(N \log M)$

FastSLAM Results

- Scales well (1 million+ features)
- Robust to ambiguities in the data association
- Advantages compared to the classical EKF approach (especially with non-linearities)

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

Slide Information

- These slides have been created by Cyrill Stachniss as part of the robot mapping course taught in 2012/13 and 2013/14. I created this set of slides partially extending existing material of Edwin Olson, Pratik Agarwal, and myself.
- I tried to acknowledge all people that contributed image or video material. In case I missed something, please let me know. If you adapt this course material, please make sure you keep the acknowledgements.
- Feel free to use and change the slides. If you use them, I would appreciate an acknowledgement as well. To satisfy my own curiosity, I appreciate a short email notice in case you use the material in your course.
- My video recordings are available through YouTube:
  http://www.youtube.com/playlist?list=PLgnQpQtFTOGQrZ4O5QzbIHgl3b1JHimN_&feature=g-list

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