Robot Mapping

FastSLAM – Feature-Based SLAM with Particle Filters

Gian Diego Tipaldi, Wolfram Burgard
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

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

1. Resampling: Draw sample \( i \) with probability \( w_t^{[i]} \) and repeat \( J \) times
Particle Representation

- A set of weighted samples
  \[ x = \{ (x[i], w[i]) \}_{i=1,...,N} \]

- Think of a sample as one hypothesis about the state

- For feature-based SLAM:
  \[ x = (x_{1:t}, m_1,x, m_1,y, \ldots, m_M,x, m_M,y)^T \]
  
  poses | landmarks
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.

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

$x_1 : t, m_1, \ldots, m_M$
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.
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

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

First introduced for SLAM by Murphy in 1999
Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

First introduced for SLAM by Murphy in 1999
Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

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

known

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

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

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**

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

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

First exploited in FastSLAM by Montemerlo et al., 2002
Rao-Blackwellization for SLAM

- Factorization of the SLAM posterior

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

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

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

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
  
  $x_0$  
  starting location, typically (0,0,0)  

  $x_1$  
  pose hypothesis at time $t=1$

  $x_2$  
  ...  

- 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
FastSLAM – Action Update

Particle #1

Particle #2

Particle #3

Landmark 1 2x2 EKF

Landmark 2 2x2 EKF

Courtesy: M. Montemerlo
FastSLAM – Sensor Update

Particle #1

Particle #2

Particle #3

Landmark 1
2x2 EKF

Landmark 2
2x2 EKF

Courtesy: M. Montemerlo
FastSLAM – Sensor Update

Particle #1

Particle #2

Particle #3

Weight = 0.8

Weight = 0.4

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
  \[ w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2} (z_t - \hat{z}^{[k]})^T Q^{-1} (z_t - \hat{z}^{[k]}) \right\} \]
- Update belief of observed landmarks (EKF update rule)
- Resample
FastSLAM 1.0 – Part 1

1: FastSLAM1.0_known_correspondence($z_t, c_t, u_t, \mathcal{X}_{t-1}$):  

2: \hspace{1cm} for \textit{k} = 1 to \textit{N} do  
3: \hspace{2cm} Let $\langle x^{[k]}_{t-1}, \langle \mu^{[k]}_{1,t-1}, \Sigma^{[k]}_{1,t-1} \rangle, \ldots \rangle$ be particle \textit{k} in $\mathcal{X}_{t-1}$  

4: \hspace{1cm} $x^{[k]}_t \sim p(x_t \mid x^{[k]}_{t-1}, u_t)$  

\hspace{1cm} // sample pose
FastSLAM 1.0 \_ known \_ correspondence \( z_t, c_t, u_t, \mathcal{X}_{t-1} \):

1: \textbf{for} \( k = 1 \) to \( N \) \textbf{do} \hfill \text{\// loop over all particles}

2: \hfill \text{Let } \left< x_{t-1}^{[k]}, \mu_{1,t-1}^{[k]}, \Sigma_{1,t-1}^{[k]} \right>, \ldots \text{ be particle } k \text{ in } \mathcal{X}_{t-1}

3: \hfill \text{sample pose}

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

5: \hfill j = c_t \hfill \text{\// observed feature}

6: \hfill \text{if feature } j \text{ never seen before}

7: \hfill \mu_{j,t}^{[k]} = h^{-1}(z_t, x_t^{[k]}) \hfill \text{\// initialize mean}

8: \hfill H = h'(\mu_{j,t}^{[k]}, x_t^{[k]}) \hfill \text{\// calculate Jacobian}

9: \hfill \Sigma_{j,t}^{[k]} = H^{-1} Q_t (H^{-1})^T \hfill \text{\// initialize covariance}

10: \hfill w_t^{[k]} = p_0 \hfill \text{\// default importance weight}

11: \hfill \text{else}
11: \textit{else}  \\
12: \ \ \ \langle \mu_{j,t}^{[k]}, \Sigma_{j,t}^{[k]} \rangle = \text{EKF-Update}(\ldots) \quad \text{// update landmark}  \\
13: \ \ \ \ 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\}  \\
14: \ \text{for all unobserved features } j' \text{ do}  \\
15: \ \ \ \langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j',t-1}^{[k]} \rangle \quad \text{// leave unchanged}  \\
16: \ \text{endfor}  \\
17: \endfor  \\
18: x_t = \text{resample} \left( \langle x_t^{[k]}, \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \rangle, \ldots, w^{[k]} \right)_{k=1,\ldots,N}  \\
19: \text{return } x_t
FastSLAM 1.0 – Part 2 (long)

```plaintext
11:  else
12:      \( \hat{z}^{[k]} = h(\mu^{[k]}_{j,t-1}, x_{t}^{[k]} \) \) // measurement prediction
13:      \( H = h'(\mu^{[k]}_{j,t-1}, x_{t}^{[k]} \) \) // calculate Jacobian
14:      \( Q = H \Sigma_{j,t-1}^{[k]} H^T + Q_t \) // measurement covariance
15:      \( K = \Sigma_{j,t-1}^{[k]} H^T Q^{-1} \) // calculate Kalman gain
16:      \( \mu_{j,t}^{[k]} = \mu_{j,t-1}^{[k]} + K(z_t - \hat{z}^{[k]} \) \) // update mean
17:      \( \Sigma_{j,t}^{[k]} = (I - K H)\Sigma_{j,t-1}^{[k]} \) // update covariance
18:      \( w^{[k]} = |2\pi Q|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (z_t - \hat{z}^{[k]} \right\}^T Q^{-1} (z_t - \hat{z}^{[k]} \) \} // importance factor
19:  endif
20:  for all unobserved features \( j' \) do
21:      \( \langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j,t-1}^{[k]} \rangle \) // leave unchanged
23:  endfor
24:  endfor
25:  \( x_t = \text{resample} \left( \langle x_t^{[k]}, \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \rangle, \ldots, w^{[k]} \right) \)
26:  return \( x_t \)
```
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

$$w^{[k]} = \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})}$$
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
  \[
p(x_{1:t} \mid z_{1:t-1}, u_{1:t}) = p(x_t \mid x_{t-1}, u_t) \quad \text{from } x_{t-1} \to \bar{x}_t \quad p(x_{1:t-1} \mid z_{1:t-1}, u_{1:t-1}) \quad \text{with } x_{t-1}
\]
The Importance Weight

\[ w^{[k]} = \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} = \frac{p(x_{1:t}^{[k]} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t) \cdot p(x_{1:t-1}^{[k]} \mid z_{1:t-1}, u_{1:t-1})} \]
The Importance Weight

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

$$= \frac{p(x^{[k]}_{1:t} \mid z_{1:t}, u_{1:t})}{p(x^{[k]}_t \mid x_{t-1}, u_t) \ p(x^{[k]}_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})}$$

Bayes rule + factorization
The Importance Weight

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

\[
= \frac{p(x^{[k]}_{1:t} \mid z_{1:t}, u_{1:t})}{p(x^{[k]}_{t} \mid x_{t-1}, u_t) \cdot p(x^{[k]}_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})}
\]

\[
= \frac{\eta \cdot p(z_t \mid x^{[k]}_{1:t}, z_{1:t-1}) \cdot p(x^{[k]}_{t} \mid x^{[k]}_{t-1}, u_t)}{p(x^{[k]}_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})}
\]
The Importance Weight

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

\[ \frac{\eta \ p(z_t | x_{1:t}^{[k]}, z_{1:t-1}) \ p(x_t^{[k]} | x_{t-1}^{[k]}, u_t)}{\ p(x_t^{[k]} | x_{t-1}^{[k]}, u_t)}\]
The Importance Weight

\[
\begin{align*}
\omega^{[k]} &= \frac{\text{target}(x^{[k]})}{\text{proposal}(x^{[k]})} \\
&= \frac{p(x^{[k]}_{1:t} \mid z_{1:t}, u_{1:t})}{p(x_t^{[k]} \mid x_{t-1}, u_t) \cdot p(x^{[k]}_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})} \\
&= \frac{\eta \cdot p(z_t \mid x^{[k]}_{1:t}, z_{1:t-1}) \cdot p(x^{[k]}_t \mid x^{[k]}_{t-1}, u_t)}{p(x^{[k]}_{1:t-1} \mid z_{1:t-1}, u_{1:t-1})} \\
&= \eta \cdot p(z_t \mid x^{[k]}_{1:t}, z_{1:t-1})
\end{align*}
\]
The Importance Weight

- Integrating over the pose of the observed landmark leads to

\[ w^{[k]} = \eta p(z_t \mid x^{[k]}_{1:t}, z_{1:t-1}) \]
\[ = \eta \int p(z_t \mid x^{[k]}_{1:t}, z_{1:t-1}, m_j) p(m_j \mid x^{[k]}_{1:t}, z_{1:t-1}) \, dm_j \]
The Importance Weight

- Integrating over the pose of the observed landmark leads to

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

\[ = \eta \int p(z_t \mid x_{1:t}^{[k]}, z_{1:t-1}) \ p(m_j \mid x_{1:t}^{[k]}, z_{1:t-1}) \ dm_j \]

\[ = \eta \int p(z_t \mid x_t^{[k]}, m_j) \ p(m_j \mid x_{1:t-1}^{[k]}, z_{1:t-1}) \ dm_j \]
The Importance Weight

- Integrating over the pose of the observed landmark leads to

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

- This leads to

\[ w[k] = \eta \int p(m_j \mid x_{1:t-1}^{[k]}, z_{1:t-1}) \cdot p(z_t \mid x_t^{[k]}, m_j) \, dm_j \]

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

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

- This leads to

\[
    w^{[k]} = \eta \underbrace{\int p(m_j \mid x^{[k]}_1:t-1, z_{1:t-1})}_{\mathcal{N}(m_j; \mu_j^{[k]}, \Sigma_j^{[k]})} \underbrace{p(z_t \mid x^{[k]}_t, m_j)}_{\mathcal{N}(z_t; \hat{z}^{[k]}, Q_t)} \, dm_j
\]

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

\[
    w^{[k]} \approx |2\pi Q|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (z_t - \hat{z}^{[k]})^T Q^{-1} (z_t - \hat{z}^{[k]}) \right\}
\]
FastSLAM 1.0 – Part 2

11: else
12: \[ \langle \mu_{j,t}^{[k]}, \Sigma_{j,t}^{[k]} \rangle = \text{EKF-Update}(\ldots) \quad \text{// update landmark} \]

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

14: endif
15: for all unobserved features \( j' \) do
16: \[ \langle \mu_{j',t}^{[k]}, \Sigma_{j',t}^{[k]} \rangle = \langle \mu_{j',t-1}^{[k]}, \Sigma_{j',t-1}^{[k]} \rangle \quad \text{// leave unchanged} \]
17: endfor
18: endfor
19: \( \mathcal{X}_t = \text{resample} \left( \langle x_t^{[k]}, \langle \mu_{1,t}^{[k]}, \Sigma_{1,t}^{[k]} \rangle, \ldots, w^{[k]} \rangle \right)_{k=1,\ldots,N} \)
20: 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
Per-Particle Data Association

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

\[ P(\text{observation}|\text{red}) = 0.3 \quad P(\text{observation}|\text{brown}) = 0.7 \]

Courtesy: M. Montemerlo
Per-Particle Data Association

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

\[
P(\text{observation|red}) = 0.3 \quad P(\text{observation|brown}) = 0.7
\]

- 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

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

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

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)

Accuracy of FastSLAM vs. the EKF on Simulated Data

- **RMS Pose Error (meters)**
- **Number of Particles**

Courtesy: M. Montemerlo
Results (Motion Uncertainty)

Comparison of FastSLAM and EKF Given Motion Ambiguity

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 \( \mathcal{O}(NM) \)

\[ N = \text{Number of particles} \]
\[ M = \text{Number of map features} \]
A Better Data Structure for FastSLAM

\[ \mu_1^{[k]}, \Sigma_1^{[k]} \]
\[ \mu_2^{[k]}, \Sigma_2^{[k]} \]
\[ \mu_3^{[k]}, \Sigma_3^{[k]} \]
\[ \mu_4^{[k]}, \Sigma_4^{[k]} \]
\[ \mu_5^{[k]}, \Sigma_5^{[k]} \]
\[ \mu_6^{[k]}, \Sigma_6^{[k]} \]
\[ \mu_7^{[k]}, \Sigma_7^{[k]} \]
\[ \mu_8^{[k]}, \Sigma_8^{[k]} \]

Courtesy: M. Montemerlo
A Better Data Structure for FastSLAM

Courtesy: M. Montemerlo
FastSLAM Complexity

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

$N = \text{Number of particles}$
$M = \text{Number of map features}$
Memory Complexity

Memory Usage of Log(N) FastSLAM vs. Linear FastSLAM – 100 Particles

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

- 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 $O(N \log M)$
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!)
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