Introduction to Mobile Robotics

SLAM - Landmark-based FastSLAM

(Slide courtesy of Mike Montemerlo)

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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-or-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 through an unknown, static environment

**Given:**
- The robot’s controls
- Observations of nearby features

**Estimate:**
- Map of features
- Path of the robot
Map Representations

Typical models are:

- Feature maps
- Grid maps (occupancy or reflection probability maps)
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 \(<x, y, \theta, \text{map}>\)
  - for landmark maps = \(<l_1, l_2, ..., l_m>\)
  - for grid maps = \(<c_{11}, c_{12}, ..., c_{1n}, c_{21}, ..., c_{nm}>\)

- **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?
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- 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)

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

Factorization first introduced by Murphy in 1999
Factored Posterior (Landmarks)

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

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

SLAM posterior

Robot path posterior

landmark positions

Does this help to solve the problem?

Factorization first introduced by Murphy in 1999
Mapping using Landmarks

Knowledge of the robot’s true path renders landmark positions conditionally independent.
Factored Posterior

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

Particle #1

Particle #2

Particle #3

Landmark #1 Filter

Landmark #2 Filter
FastSLAM – Sensor Update

Particle #1

Particle #2

Particle #3

Landmark #1

Landmark #2

Filter
FastSLAM – Sensor Update

Particle #1
Weight = 0.8

Particle #2
Weight = 0.4

Particle #3
Weight = 0.1
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

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

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

- Two options for per-particle data association
  - Pick the most probable match
  - Pick a random association weighted by the observation likelihoods
- If the probability 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 (Video)

Dataset courtesy of University of Sydney
Results – Data Association

Comparison of FastSLAM and EKF Given Motion Ambiguity

- FastSLAM
- EKF

Robot RMS Position Error (m)

Error Added to Rotational Velocity (std.)
FastSLAM Summary

- FastSLAM factors the SLAM posterior into low-dimensional estimation problems
  - Scales to problems with over 1 million features
- FastSLAM factors robot pose uncertainty out of the data association problem
  - Robust to significant ambiguity in data association
  - Allows data association decisions to be delayed until unambiguous evidence is collected
- Advantages compared to the classical EKF approach
- Complexity of $O(N \log M)$