CS 547: Sensing and Planning in Robotics

Lecture 7: Analysis of 'Monte Carlo Localization for Mobile Robots' by Dellaert et. al.

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Summary

- Monte Carlo Localization
- Representing the State Space
- Action Model
- Perception Model
- SIR theory
- Results

What is Different from the Markov Grid-based Localization?

- Representation of PDF is based on $samples$
- Leads to much less memory usage and faster computation

Monte Carlo Localization: Prediction Phase

- Propagate the dynamics of the system by using the action model

$$p(\mathbf{x}_k|Z^{k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1}, \mathbf{u}_{k-1})p(\mathbf{x}_{k-1}|Z^{k-1})d\mathbf{x}_{k-1}$$

$$Bel'(s) = \int P(s|s', a)Bel(s')ds'$$

Monte Carlo Localization: Update Phase

- Incorporate the measurement by using the perceptual (measurement) model

$$p(\mathbf{x}_k|Z^k) = \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|Z^{k-1})}{p(\mathbf{z}_k|Z^{k-1})}$$

$$Bel'(s) = \eta P(o|s) Bel(s)$$

Three Basic Ways of Representing $p(.)$ or $Bel(.)$

- Using values on a grid (last time)
- Using samples (this paper)
- Using a parametric form (next paper)

Representing and Propagating $p(.)$ Using Samples

- $p(\mathbf{x}_k|Z^k)$ is represented by a set of N random samples called $particles$ $S_k = (s_k^i; i = 1 \ldots N)$
- Prediction:
  - Apply motion model to each particle s_{k-1}^i from previous step as follows.
  - For each s_{k-1}^i draw one sample $s_k^{\prime i}$ from $p(\mathbf{x}_k|s_{k-1}^i, \mathbf{u}_{k-1})$
  - This results in a new set called S_k'
- S_k' approximates a random sample from $p(\mathbf{x}_k|Z^{k-1})$

Updating $p(.)$ Using Samples

- Update:
  - Incorporate measurement by weighting the particles in the set S'_k by the likelihood of $s_k^{'i}$ given $\mathbf{z}_k$.
  - Each weight m_k^i is given by $p(\mathbf{z}_k | s_k^{'i})$
  - Compute S_k by resampling N times from this weighted set.
- This results in picking more particles with higher likelihood, thus S_k approximates a random sample from $p(\mathbf{x}_k | Z^k)$

Results

- More accurate than grid-based Markov (data shown for both sonar and laser)
- Converges to accurate global localization quickly
- Accuracy increases with number of samples, then decreases