Advaned Robot Navigation: Lecture 7
Lecture Notes

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September 29, 2023

1 Recap

- EKF robot starting position is [0,0]
- Landmark uncertainty is added onto the robot position uncertainty.
- Full SLAM is generating the whole path/trajectory.
- Online SLAM is only based on the last robot position.

1.1 EKF SLAM

- EKF SLAM is a very big problem. This problem scales quadraticly, since the both a row and a column is added each time the robot finds a new landmark.
- The problem of data association is vary big in EKF SLAM.
- The state vector becomes very big and the covariance matrix becomes very big.
- EKF is **assuming** that everything is distributed with a gaussian, and that the motion and measurement model is linear.

2 Particle filter SLAM

- Instead of a gaussian distribution of the motion- and measurement model, it is non-parametric, which entails that we do not assume anything about the distributiuon of the models.
- The particle's probability of being the robot position, is based on its weight.

For each particle we update:

- Compare the particle's predictions of measurements with the actual measurements. If it is closer to the actual measurments, it gets a higher weight.
- Normalise the weights.

- Add noise to the particles, grap the percentage of highest weight, and generate the new particles wich all have equal weight.
- It is assumed that the new equal weights are 0. The most important thing is that they have equal weight.

At timestep t_0 we randomly pick $N = 3$ states represented as

$$x_0 = x_0^{[1]}, x_0^{[2]}, x_0^{[3]} \tag{1}$$

Where all $x_0^{[i]}$'s have equal weights.
We measure, and then update:

- Emprically recover the sensor model.

compute the $P(x_t|z_1)$.

Problem: The number of particles to represent the exterior grows exponentially?? check up on the logarithmic scaling, which i read.

2.1 Decomposition

You can factor the posteerior landmarks.

$$p(x_{0:t}, m_{0:\ldots}) \tag{2}$$

3 Graph based SLAM

Soft constraints between the landmarks.
Given the robot path, the landmarks are independent. This entails that the landmarks does not move together, they are independent of each other.

4 Rao-Blackwellization Paricle filter

Key koncept: Decrease the number of particles while maintainng accuracy.
Partition state nodes $Z(t)$ into $R(t)$ and $X(t)$ such that:

- $P(R_{1:t}) =$

Partition into robot path and the conditionally independent particles.
For each particle we have a map.
We only have particles for the robot position, and then a map corresponding to that particle. This reduces the number of particles immensly. e.g. Each landmark contains 10 landmarks. This is te general case, which can then be applied to the particle filter.
We give weights to each particle, based on the map that they have. The map is the landmarks. Each particle have a map of all the landmarks, and based on the precision of these landmarks, we give a weight.
Applying the EKF for each landmark position. This is FastSLAM

5 Wrapup

EKF data association is difficult becuase both the robot and the landmarks are added. In particle filters, we assume that the pose of the robot is known in each particle. Therefore it is easier to do data association.
This is called **pr particle data association**
pr particle data association:

- Pick the most probable match
- Pick the random associateed weight by observation likelihoods

If the probality is too low, generate a new landmarks. Becuase if we associate a landmark with other landmarks, and the probaililty of that being the landmark, then it does not make sense to associate it with that landmark. Then assume that you have seen a new landmark.

6 Open Challenges in SLAM

- Perception problem
- Multirobot SLAM
- Dynamic maps
- Sensitivity to incorrect data association
- Visual SLAM

For Markov Decision process, we need further background. Therefore the self study is important.

note Instead of using the entire robot path, in practice it is enough to use only the previous path position.