COMP7308 Introduction to unmanned systems 2021

Assignment 4

:

1 (50 points) Grid-map based localization

Robots encounter much uncertainties when operating in the real world. The uncertainties are contributed to from a number of factors, such as unpredictable environments, sensor limitations and robot actuations. For example, a robot moving through its environment will accumulate errors in odometry, gradually making it less certain of where it is.

A classic example of this problem is in robot localization, where a robot must estimate it's coordinates relative to an external reference frame. The robot is given a map of its environment, but in order to localize itself relative to this map it needs sensor input.

Grid localization uses a histogram filter to update the belief. Histogram filters decompose the state space into finitely many regions and represent each region as a single probability. The probabilistic paradigm represents the robot's momentary belief by a probability density function over the space of all locations i.e., grid cells. Formally, the belief, $bel(x_t)$ is the estimate of the robot's position in space, x_t at a given time t. This can be summarized by the equation below:

$$bel(x_t) = \{p_{k,t}\},$$

where $\{p_{k,t}\}$ is the set of probabilities over a robot positions x_k at time, t. For grid localization, we decompose the position into discrete cells. In the example below, we use a grid map which has been discretized into a $m \times n$ matrix.

The robot uses a sequence of 'moves' and 'senses' operations to gain a better understanding of where it is in the world. The robot's actions are defined as follows:

- Actions are denoted u_t
- The agent can move one step up, down, left or right.
- The agent cannot move out of the grid.
- Occasionally, the agent fails to move to the desired location. This occurs with a given probability, $actionFailsProb$, summarized formally in the motion model equation: $p(x_{k,t+1} \mid x_{k,t}, u_t)$, where $x_{k,t+1}$ is the position in the next time step after an action u_t.

The sensor model is as follows:

- Measurements are denoted as z_t
- We assume that each location on the grid is either 'free' or 'occupied'.

- The agent can sense if there is a cow in a cell with a given probability, $senseFailsProb$. This is expressed formally by the measurement model $p(z_t \mid x_{k,t})$, where the probability of measuring z_t given the current probabilities of being in a particular cell $x_{k,t}$.

(a) (10 points) Implement the grid-based localization code based on the provided starter code.

(b) (20 points) Try changing the probabilities that the sensor and action fail with different values. How does this affect the robot's understanding of where it is? Explain your observations.

(c) (20 points) In the `__init__` function in the `StateEstimator` class, try changing initial belief from being uniform over the entire grid map to being uniform over the free region in the occupancy map. How does this change the robot's understanding of where it is? Explain your observations.

2 (50 points) EKF-based mapping

We have mentioned in class that EKF-based mapping can be considered as a special case of EKF-based SLAM where the robot state x_t is given rather than estimated.

(a) (15 points) Please write down the EKF-based mapping for the cases when correspondence is known. You should get an algorithm of the similar form as the EKF-SLAM on page 37 of lecture 9.

(b) (15 points) Please write down the EKF-based mapping for the cases when correspondence is unknown. You should get an algorithm of the similar form as the EKF-SLAM on page 45 of lecture 9.

(c) (10 points) Write down the H_t^i matrix in these two cases.

(d) (10 points) In occupancy-based grid mapping, we mentioned that one important trick is assuming the occupancy states of different cells are conditionally independent. Do you think such independency is leveraged in EKF mapping that you get in (a) and (b)? Explain your judgement.