January 23, 2015

Intelligent Vehicles exam
Simultaneous Localization and Mapping

Full Name : ________________________________

Question 1 (2 points)
"Boom! Boom!" An earthquake. The building is shaking vigorously. You wander around the building in search of an exit. Then, the lights go off. Pitch black darkness. You feel that your best bet for survival is to stay where you are and wait for your robot to come to rescue you. After a while, silence. Your robot finally enters the building and starts looking for you.

a) From a robotics point of view, explain why this is a problem in 2 or fewer sentences. (0.5 points)

b) Can the robot get to you and help you get out of this building safely? How? (Write the pseudo code algorithm). You will be given a map of an environment and a destination. You need to demonstrate that your robot can localize itself without knowing its starting pose and can go to the desired destination. (1 points)

c) Explain which step in the algorithm would use the sensor measurements. How would they be used? (0.5 points)

Question 2 (2 points)
Explain the different steps of Kalman filters. Divide them into prediction and correction and give an explanation on how the state and uncertainty evolves. (Not only equations please, your answer should include an intuitive explanation, pseudo code, ...)

Question 3 (2 points)
Extend the previous question with respect to EKF localization. What sensor data is typically used and where? What models of uncertainty need to be provided and where are they used? (Not only equations please, your answer should include an intuitive explanation, pseudo code, ...)

Question 4 (2 points)
4) Consider a world with only three possible robot locations: $X = \{x1 , x2 , x3 \}$. Consider a Monte Carlo localization algorithm which may use N samples among these locations. Initially, the samples are uniformly distributed over the three locations. (As usual, it is perfectly acceptable if there are less particles than locations.) Let Z be a Boolean sensor variable characterized by the following probabilities:

$$p(z \mid x1) = 0.8 \quad p(\neg z \mid x1) = 0.2$$
$$p(z \mid x2) = 0.4 \quad p(\neg z \mid x2) = 0.6$$
$$p(z \mid x3) = 0.1 \quad p(\neg z \mid x3) = 0.9$$

In other words, we have a high probability of observing $Z = z$ at location x1 , and a high probability of observing $Z = \neg z$ at location x3 . MCL uses these probabilities to generate particle weights, that are subsequently normalized and used in the resampling process. For simplicity, let us assume we only generate one new sample in the resampling process, regardless of N. This sample might correspond to any of the three locations in X. Thus, the sampling process defines a probability distribution over X. With $N = \infty$ this distribution would be equal to true posterior.

a) Based on the prior uniform distribution, calculate the true posterior $p(xi \mid z)$ for each of the locations
$X = \{x1 , x2 , x3 \}$.

Question 5 (2 points)
True or false?

a) Bayes filters assume conditional independence of sensor measurements taken at different points in time given the current and all past states. (0.5 points)

b) When the number of effective particles (Neff) in particle-filter SLAM is low, it is a good idea to perform resampling. (0.5 points)

c) In certain degenerate cases a particle filter could still work even with a single particle. (0.5 points)

d) The odometry estimate of a mobile robot's position can be improved by subsequently performing scan registration. (0.5 points)