Autonomous Mobile Robots (AUMR6Y, Fall 2013)
Examination: Localization, Planning & Navigation

Friday December December 20th, 13:00-15:00, G3.02

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Question 1

Consider a robot that operates in a triangular environment with three types of landmarks, as illustrated in Figure 1:

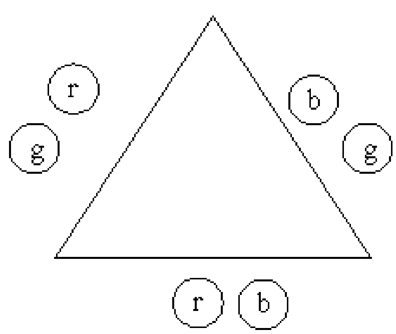

Figure 1: A triangular environment

Each side of the triangle is categorized as a location and each location has two different landmarks, each with a different color. Let us assume that in every round the robot can only inquire about the presence of one landmark type: either the one labeled ”r”, the one labeled ”g” or the one labeled ”b”.

(a) Suppose that robot first fires the detector for ”b” landmarks and moves clockwise to the next location. What would be the optimal landmark detector to use next?

(b) How would the answer change if the robot moved counterclockwise to the next location?

(c) What would your answer be if there is a 10% chance that the move is unsuccesful and the robot stays at the same location?

Question 2

Consider how a robot moves from one frontier to another in frontier-based exploration. What are the advantages and disadvantages of explicitly planning a path between frontier centroids versus using a set of purely reactive behaviors consisting move-to-goal & avoid obstacles?

Question 3

Consider an environment with the shape of a snailshell as depicted in Fig. 2. What will happen when you apply the Rao-Blackwellized particle filter algorithm in such an environment? Consider robots with accurate/weak odometry and with accurate/noisy sensors. Give an sketch for all the nominal and the four extreme cases.

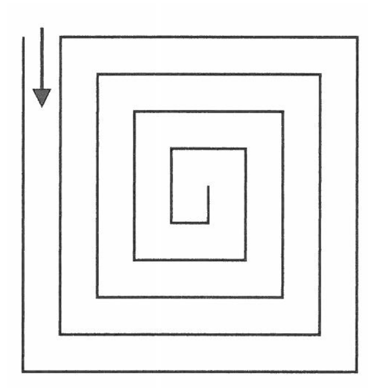

Figure 2: An environment in the form of a snailshell

Question 4 [1]

The *extended Kalman filter localization* algorithm in Fig. 3 depends on a multivariate Gaussian representation of uncertainty in the motion model $g()$ and measurement model $h()$.

Algorithm Extended_Kalman_filter($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$):

$\bar{\mu}_t = g(u_t, \mu_{t-1})$

$\bar{\Sigma}_t = G_t \, \Sigma_{t-1} \, G_t^T + R_t$

$K_t = \bar{\Sigma}_t \, H_t^T (H_t \, \bar{\Sigma}_t \, H_t^T + Q_t)^{-1}$

$\mu_t = \bar{\mu}_t + K_t(z_t - h(\bar{\mu}_t))$

$\Sigma_t = (I - K_t \, H_t) \, \bar{\Sigma}_t$

return μ_t, Σ_t

Figure 3: The Extented Kalman Filter Algorithm (Courtesy Thrun *et al* [1])

Noise enters the equations through the addition of a (hopefully) small factor. It is important to understand that this is always an approximation: real systems never experience zero-mean white Gaussian noise. For an *extended Kalman filter* this approximation is made with an first-order Taylor expansion. For each of the noise sources below, briefly describe how the zero-mean white Gaussian noise assumption fails for a *classical Kalman filter*, and to what extend the EKF approximation solves this problem.

- odometry error in a differentially steered wheeled robot due to a mismatch in wheel size
- odometry error in a wheeled robot due to wheel slippage
- sonar errors due to multipath reflections
- temperature dependent drift in a rate gyro

References

[1] S. Thrun, W. Burgard and D. Fox, *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*, The MIT Press, September 2005, ISBN 0-262-20162-3.

[1] Question 1 and 4 orginate from the book 'Probabilistic Robotics' by Sebastian Thrun *et al*. Question 2 originates from 'Introduction to AI Robotics' by Robin Murphy. Question 3 originates from 'Principles of Robot Motion' by Howie Choset *et al*.