Midterm Exam CS226

Stanford CS226 Statistical Algorithms in Robotics, Winter 2006

Full Name: ______________________________

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Welcome to the CS223B Midterm Exam!

- The exam is 8 pages long. Make sure your exam is not missing any sheets. The exam has a maximum score of 50 points. You have 60 minutes.
- The exam is closed book, closed notes, closed cell phones, etc.
- Write your answers in the space provided. If you need extra space, use the back of the preceding sheet.
- Write clearly and be concise.
- All points will be manually counted before certification.

Question	Points
1 (20 max)	
2 (10 max)	
3 (20 max)	
total	

1 Rao-Blackwellized Filter 20pts

Suppose we have an existing (and working!) EKF implementation of feature-based localization for a mobile robot operating on a paved surface. Now suppose we operate the robot in outdoor terrain where the robot can face four very distinct surfaces: pavement (where the existing EKF works well), ice (where the wheels slip at random), water (where the robot floats), and mud (where the wheels frequently become stuck. Set up a Rao-Blackwellized EKF. *(Note: a simple yes/no is insufficient. Please explain your answers. And please keep things simple! This question is not about the dynamics of floating robots!)*

1. What is the state of the Rao-Blackwellized EKF?

2. In the Rao-Blackwellized EKF, what elements of the state would be implemented by particle filters, what elements by Kalman filters?

3. What modification would one have to apply to the EKF itself?

4. Suppose we know for a fact that the surface type remains constant throughout the robot's operation. What does this mean for the probabilistic models of the Rao-Blackwellized filter?

5. How would you compute the weight for resampling? (No equations please, just an intuitive explanation.)

6. Can the filter figure out the surface type? Will it?

7. Someone proposes to replace the particle filter by a histogram filter. Is this possible? Is this a good idea? Argue why / why not.

8. Obviously we can re-implement the EKF using FastSLAM. What would the mean for the basic filter? What variable would be represented by particles, what variables by Gaussians?

9. Should we replace the EKF by FastSLAM in this application? Argue why / why not.

10. Now suppose the terrain can changes over time, as the robot moves. Would this affect the state vector of the filter? If so, argue why and give the new state vector. If not, argue why not.

2 Multi-Robot GraphSLAM **10pts**

Suppose we run GraphSLAM for multiple robots. The robots can move along their x-, y-, and z axes, but in doing so they retain a fixed global (and known) orientation. Landmarks are points in 3-D, and the robots can measure Δx, Δy, and Δz to the landmarks. Suppose robots can see landmarks but they cannot see each other.

1. What would be an appropriate state vector? How many elements does it have? (Assume there are K robots, N landmarks, T time steps, and D total measurements.)

2. What would be the appropriate motion model? Be consise.

3. For GraphSLAM, would the robots be forced to exchange raw sensor measurements when building a joint map, or could they all retain their own local statistics and communicate those? If the latter, what statistics would that be?

4. Now suppose that robots can see each other. When one robot sees another, what would happen to the joint information matrix?

5. Could the robots still compute a local map after seeing each other? Argue why / why not.

3 True or False? 20pts

Correct answer is $+1$ point per question; a false answer results in -1 point.

- TRUE FALSE If two variables A and B are independent, then they remain independent given knowledge of any other variable C.
- TRUE FALSE If the posterior belief is unimodal, EKFs are the method of choice from the varius filters in the book.
- TRUE FALSE A particle filter that observes the position of a moving object can infer its velocity
- TRUE FALSE FastSLAM provides a sound solution to the data association problem in that each particle pursues its own data association
- TRUE FALSE The covariance matrix of EKF SLAM is rank deficient
- TRUE FALSE The Kalman gain K measures the amount of surprise of a specific sensor measurement
- TRUE FALSE In certain degenerate cases a particle filter could still work even with a single particle.
- TRUE FALSE A histogram filter approximates the posterior belief over a continuous space by a distribution over a finite decomposition of this space
- TRUE FALSE In occupancy grid maps, adding a large number has a stronger effect on the posterior probability than adding a small number
- TRUE FALSE The log-odds transform is invertible.
- TRUE FALSE Occupancy grid maps in log-odds form are numerically more stable than in probability form
- TRUE FALSE Given a GraphSLAM information matrix and vector, computing the map requires linear time so as long as the size of the largest loop is independent of N, the number of features in the map.
- TRUE FALSE Apply EKF to global localization, and assume the robot observes the range and bearing to four different landmarks in its very first sensor measurement (assuming known correspondence, and a map is available). EKF will then very likely succeed in globally localizing the robot.
- TRUE FALSE The information matrix is symmetric.
- TRUE FALSE In EKF SLAM, in the limit the robot can determine the exact locations of all landmarks with arbitrary accuracy
- TRUE FALSE Bayes filters assume conditional independence of sensor measurements taken at different points in time given the current and all past states.
- TRUE FALSE Bayes filters assume conditional independence of sensor measurements taken at different points in time given the current state (but not past states).
- TRUE FALSE The importance weight of a particle is the same (modulo some random noise) as the determinant of the covariance in a Kalman filter
- TRUE FALSE The update time of FastSLAM with known correspondence is in $O(N \log N)$.
- TRUE FALSE When implementing FastSLAM on a physical robot, it is always good to use at least 10,000 particles just to be sure