CR MCQ Final

Table of Contents

Some Notes:

- For some of the questions (especially those involving equations), our colleagues were not able to reconstruct the given choices.
- Problem questions were possibly spread out across more than one MCQ
- The slides reference often contains something that closely matches the solution, not always the solution itself.
- Questions in pink marked with [] are degrees ambiguous, you may pretend the given solution by the authors is only a suggestion. Some of these were recolored to teal as a result of the degree of ambiguity being too small.
- For some of these questions, the Underthinking Hypothesis will be applied. It assumes that the professor made the questions from the slides without pondering much about the other choices he has put and without realizing that some of them might be valid under overthinking scenarios

I. Introduction to Cognitive Robotics

Q1. Probabilistic robotics…………………………

A. perception by state estimation
B. action by utility optimization
C. models uncertainty in actions and measurements using calculus probability theory
D. All
E. None

Reference Slide: 27

Q2. Causal reasoning is ………………….
A. Easier to calculate than diagnostic
B. Estimates target Probability
C. Calculates probability of effect given the cause.
D. All of the above
E. None of the above

Reference Slide: 42

Q3. The equation for incorporating measurements (Bayes recursive update rule):

$$P(x|z_1, z_2, \dots, z_n) = \eta_{1:n} \prod_{i=1}^{n} [P(z_i|x_i)]\, P(x)$$

Reference Slide: 45

Q4. Welding robotics in automotive industry are……………………

A. Cognitive Robotics
B. Traditional Robotics

Comment: Welding in automotive industry is a controlled process that's well understood.

Reference Slide: 9

Q5. Cognitive robotics can deal with …………… In dynamic real-world environments

A. Unpredictable
B. Predictable
C. Well-understood

D. All of the above

E. None of the above

Comment: Unpredictable follows by the underthinking hypothesis. The overthinking hypothesis suggests that D should be true since by logic if A holds then so should B and C.

Reference Slide: 11

Q6.

A robot is equipped with an unreliable door detector that outputs either "Door" or "NoDoor".

If there is a door in front of the robot, it indicates "Door" with a probability of 0.9. However, if there is no door in front of the robot, the detector also indicates "Door" with a probability of 0.2

Before observing the detector, the prior belief of the robot about a door being in front of it is 0.6.

What is the posterior probability of a door being in front of the robot when the detector outputs "NoDoor"?

Comment:

Given is $P(Z = D|X = D) = 0.9$ and $P(Z = D|X = \bar{D}) = 0.2$ and $P(X = D) = 0.6$

Wanted is $P(X = D|Z = \bar{D})$

Apply Bayes Rule (Expanded)

$$P(X = D|Z = \bar{D}) = \frac{P(Z = \bar{D}|X = D)P(X = D)}{\sum_x P(Z = \bar{D}|X = x)P(X = x)}$$

$$= \frac{P(Z = \bar{D}|X = D)P(X = D)}{P(Z = \bar{D}|X = D)P(X = D) + P(Z = \bar{D}|X = \bar{D})P(X = \bar{D})}$$

$$= \frac{(1 - 0.9)(0.6)}{(1 - 0.9)(0.6) + (1 - 0.2)(0.4)} = \frac{3}{19}$$

Reference Slide: 43

Q7.

1. A special-purpose robot is equipped with a vacuum unit to clean the floor. The robot has a binary sensor to detect whether a floor tile is clean or dirty.

- However, neither the cleaning unit nor the sensor are perfect.

2. From previous experience, you know that the robot succeeds in cleaning a dirty floor tile with a probability of $P(x_{t+1} = clean\,|x_t = dirty) = 0.6$, where x_t is the state of the floor tile at time t and x_{t+1} is the resulting state after the action has been applied.

3. Activating the cleaning unit when the tile is clean will never make it dirty.

4. Assume the robot always cleans at every time t (i.e., the transition probabilities model the fact that the robot is cleaning the floor tile).

5. The probability that the sensor indicates that the floor tile is clean although it is dirty is $P(z_t = clean\,|x_t = dirty) = 0.2$ and the probability that the sensor correctly detects a clean tile is $P(z_t = clean\,|\,x_t = clean) = 0.6$

6. Assume a prior distribution at time t as $P(x_t = clean) = c$, where $0 < c < 1$.

Unfortunately, you have no knowledge about the current state of the floor tile. However, after cleaning the tile, the robot's sensor indicates that it is clean. Compute $P(x_{t+1} = clean\,|z_{t+1} = clean)$ i.e., the probability that at time t + 1, the floor tile is now clean given that the sensor indicates it is clean.

Use Bayes Rule:

$$P(x_{t+1} = C\,|z_{t+1} = C) = \frac{P(z_{t+1} = C|x_{t+1} = C)P(x_{t+1} = C)}{\sum_{x_{t+1}} P(z_{t+1} = C|x_{t+1})P(x_{t+1})}$$

$$= \frac{P(z_{t+1} = C|x_{t+1} = C)P(x_{t+1} = C)}{P(z_{t+1} = C|x_{t+1} = C)P(x_{t+1} = C) + P(z_{t+1} = C|x_{t+1} = D)P(x_{t+1} = D)}$$

- From 5, $P(z_{t+1} = C|x_{t+1} = C) = 0.6$ and $P(z_{t+1} = C|x_{t+1} = D) = 0.2$ (these are properties of the sensor regardless to any timestep)
- Now we only need $P(x_{t+1} = C)$. Which the probability of the floor being clean in $t + 1$ given that the robot attempted to clean in t, as defined in 2.
- Since $P(x_{t+1} = C\,|x_t = D) = 0.6$ is given in 2, $P(x_{t+1} = C|x_t = C) = 1.0$ is given in 3 and the prior probability before cleaning $P(x_t = clean) = c$ as given in 6, we can find $P(x_{t+1} = C)$ by using total probability as follows:

$$P(x_{t+1} = C) = P(x_{t+1} = C|x_t = C)P(x_t = C) + P(x_{t+1} = C|x_t = D)P(x_t = D)$$
$$= c + 0.6(1 - c) = 0.6 + 0.4c$$

Thus,

$$P(x_{t+1} = C\,|z_{t+1} = C) = \frac{0.6(0.6 + 0.4c)}{0.6(0.6 + 0.4c) + 0.2(1 - (0.6 + 0.4c))} = \frac{1.5c + 2.25}{c + 2.75}$$

II. Bayes & Kalman Filter

Q1. Kalman gain ……………………………….

A. Measure how much we trust the sensor

B. if σ_{obs} = 0, then $K = 1$

C. if σ_{obs}= ∞, then $K = 0$

D. All

E. None

Comment:

$$k_t = \frac{\bar{\Sigma}_t C_t^T}{C_t \bar{\Sigma}_t C_t^T + Q_t}$$

Indeed, as Q $(i.e., \sigma_{obs}^2)$ approaches 0 or 1, K_t approaches 1 or 0 respectively (assuming $C = 1$). The higher is the Kalman gain the more we trust our sensor because this implies it has less uncertainty.

Reference Slide: 38

Q2. In the Kalman filter, …………….

A. Motion model is applied first

B. Sensor model is applied first

C. Order is not important.

Comment: In Bayes filter in general, there is no specific order that has to be followed. In real life, prediction and correction calls are arbitrarily interleaved depending on how often sensors or actions are "published" on the relevant topic.

Reference Slide: 18

Q3. Kalman Filter …………………………….

A. Assumes gaussian world

B. Can handle nonlinear systems

C. Assume arbitrary distributions

D. All

E. None

Comment: Without extensions, it cannot be applied to nonlinear systems and it can't work with arbitrary distributions (generally).

Reference Slide: 24

Q4. According to Markov assumption …………………… //Mainstream version

A. Current measurement depends only on the previous state

B. Current state depends only on the previous state

C. Current measurement depends only on the current action

D. All

E. None

Comment: The Markov assumption says that if we know the current state, then the past and future are independent. This leads to:

$P(z_t|x_{0:t}, z_{1:t-1}, u_{1:t}) = P(z_t|x_t)$ // current measurement depends only on current state

Here we know x_t so z_t (future) is independent of $x_{0:t-1}, z_{1:t-1}, u_{1:t}$ (the past of x_t)

$P(x_t|x_{0:t-1}, z_{1:t-1}, u_{1:t}) = P(x_t|x_{t-1}, u_t)$ // current state depends only on previous state & action

Here we know x_{t-1} so x_t (future) is independent of $x_{0:t-2}, z_{1:t-1}, u_{1:t-1}$ (the past of x_{t-1}).

Reference Slide: 15

Q4. According to Markov assumption …………………… //Credit version

A. Measurement likelihood depends on state and current map

Comment: The choices were different compared to mainstream but they were not remembered except for the one above which was suggested as the correct choice. Indeed, $P(z_t|x_{0:t}, z_{1:t-1}, u_{1:t}, m) = P(z_t|x_t, m)$

Q5. In Kalman prediction correction cycle ……………………

A. The new belief is between the old belief and the belief plus the measurement
B. The predicted uncertainty is smaller than the old uncertainty since we incorporate new actions
C. The correction step moves the mean using the action
D. All
E. None

Reference Slides: -

Comment: Whether we think that A is referring to the value of the belief or the mean, the statement does not hold. The opposite of B is obviously true and in C the correction step does not use the action and can be done without an action.

[Can skip this] To show that A doesn't hold if the value is the belief, observe that if the old belief is p then the new belief is expected to be $p - c_1$ and and the belief after correction is expected to be $p + c_2$ but $p < p - c_1 < p + c_2$ does not hold. To show that it doesn't hold if the value is the mean observe that $\mu_{t-1} < \mu_{t-1} + c < \mu_{t-1} + c \pm \epsilon$ is also not guaranteed to hold as the ϵ introduced by correction can move the mean after or before its predicted state depending on which better explains the measurement.

Q6. Suppose a stationary robot has a noisy distance sensor which reports distances to a wall with standard deviation $\boldsymbol{\sigma_{sensor}} = \mathbf{3m}$ (Gaussian noise).

Suppose the Gaussian robot belief about its distance to the wall is 10m with $\boldsymbol{\sigma_{belief}} = \mathbf{1m}$ before making a measurement.

What should the belief of the robot about the wall distance be after incorporating a measurement of 11 m distance?

Comment:

Given is $Q = 3^2$ and $\bar{\mu} = 10$ and $\bar{\Sigma} = 1^2$ and $z = 11$ and $C_t = 1$ (since what's being measured and the state are the same type of quantity)

A. Compute Kalman gain:

$$k_t = \frac{\bar{\Sigma}_t C_t^T}{C_t \bar{\Sigma}_t C_t^T + Q_t} = \frac{1}{1+9} = 0.1$$

B. Compute the Corrected Mean:

$$\mu_t = \bar{\mu}_t + k_t(z_t - C_t\bar{\mu}_t) = 10 + 0.1(11 - 10) = 10.1$$

C. Compute the Standard Deviation:

$$\Sigma_t = (I - K_t C_t)\,\bar{\Sigma}_t = (1 - 0.1) * 1 = 0.9$$

$$\sigma_t = \sqrt{0.9}$$

Reference Slide: 38

III. Kalman Filter Extensions

Q1. EKF is ……………………..

A. Approximate to two Taylors terms
B. Slower than UKF by constant factor because it needs sampling
C. Can work with nonlinear processes as long as they can be linearized
D. All
E. None

Reference Slide: 41

Comment: EKF is approximate to one Taylor term only and is faster than UKF by a constant factor. It extends the Kalman filter to work with nonlinear motion and sensor models.

IV. Motion Models

Q1. ………….. is an inherited uncertainty.

A. Robot motion
B. Sensor measurements
C. EKF
D. None
E. All

Reference Slide: -

Comment: Uncertainty in motion propagates (gets inherited) through time due to its accumulative nature. Since the choice EKF exists we can rule out sensor measurements, but anyway the covariance gets directly updated on through R, Q only sets the Kalman gain.

Q2. Odometry model motion has .... elementary motions

A. Two

B. Three

C. Four

D. Five

Comment: They are Rotation, Translation and Rotation. In this we have used the Underthinking Hypothesis to avoid choosing Two.

Reference Slide: 14

Q3. possible source of motion uncertainty in wheeled robot..................

A. Bump

B. Uncalibrated joints

C. Uncalibrated manipulators

D. All

E. None

Reference Slide: 14

Comment: Has no explicit answer in the slides but wheeled robots seem to involve joints and motion uncertainty would be increases if they are uncalibrated. When the professor mentioned wheel encoders in the lecture, he said "this doesn't just apply to wheels".

Q3. possible source of motion uncertainty in wheeled robot ....

A. Bad light Conditions

B. Uncalibrated joints

C. Uncalibrated manipulators

D. All

E. None

Reference Slide: 12

Comment: Motor encoders rely on counting light interruptions by disk falling on photo sensors.

V. Probabilistic Sensor Models

Q1. Physical interpretation of a max range measurement ....

A. Beam wasn't reflected back

B. Bean hit an unknown obstacle.

C. All

D. None

Reference Slide: 15

Comment: Max range measurements happen when no object within the range was reached or when the beam fails to reflect to the right sensor (or when it fails*).

Q2. Sensor not affected by rain or fog:

A. Lidar

B. Sonar

C. Camera

D. All of the above

E. None of the above

Reference Slide: -

Comment: Rain affects LIDAR due to reflection and refraction, and causes noise for Sonar and Camera is obviously affected by rain and fog. It's more obvious for Sonar that depends on sound waves and cameras which need clear vision.

Q3. If a robot observes a landmark L1 at a distance of 6m and with a degree 90 counterclockwise of his heading, then he observes a landmark L2 at a distance of 8 m and the angle to the landmark is unknown. The distance between the two landmarks is 10m. The robot can be in ………………. locations

A. 1

B. 2

C. 3

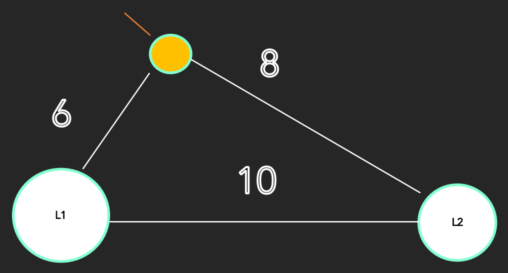
D. 4

E. None

Comment: Consider any two points 10m apart from each other. Draw a circle of radius 8m from one of them and a circle of radius 6m from the other, you are guaranteed to find two intersections (two possible robot locations).

Alternatively, consider two landmarks separated by 10m in any two locations

If the robot is 6m away from the first and 10m away from the second then the three must for a right-angled triangle. This is one of them and the other would reflect the robot about the 10m long line.



Q4. Ultrasonic sensor is affected by ……………….
A. Beam reflected by obstacles
B. Max range measurement
C. Crosstalk
D. All of the above
E. None

Reference Slide: 14

Comment: The first choice is a little bit ambiguous but B and C definitely hold.

VI. Non-Parametric Filters

Q1. To solve the kidnapped robot problem……………….
A. Insert a fixed number of random samples periodically.
B. Apply scan matching
C. Insert a number of random samples proportional to the number of particles.
D. All
E. None

Reference Slide: 56

Comment: We didn't cover anything that relates scan matching to the kidnapped robot problem, its purpose is to improve odometry. A is explicit in the slides and C should be okay because the professor mentioned it while explaining A (a number of random samples proportional to J is a fixed number of samples.

VII. Mapping with Known Poses

Q1. Occupancy maps
A. represents the material
B. Each cell represents the reflectance and the map represents material such as glass
C. Each cell states the occupancy probability and can converge to 0 or 1
D. All
E. None

Reference Slide: 13

Comment: As was shown later in the same slideset (65), the probability converges eventually for occupied objects regardless to the degree of reflectance (doesn't represent glass).

Q2. Mapping is used for ……………………….
A. Navigation
B. Motion calibration
C. Industrial factories

D. All
E. None

Reference Slide: 3

Comment: Mapping has nothing to do with calibration and A is mentioned in the slides (path planning)

Q3. pose correction is vital to mapping

A. True
B. False

Reference Slide: 8 (Next Slideset)

Comment: Mapping assumes known poses and correction is vital to make that assumption hold.

VIII. Simultaneous Localization and Mapping (SLAM)

Q1. In SLAM ....

A. Mapping is done first
B. Mapping and localization accuracy depend on each other.
C. Localization and mapping are sequential
D. All
E. None

Reference Slide: 27

Comment: They are "simultaneously" done (in the interleaving sense) and their errors are correlated.

IX. FastSLAM

Q1. landmark based fast SLAM Rao Blackwellization equation

$$P(x_{0:t}, m_{1:M} | z_{1:t}, u_{1:t}) = P(x_{0:t} | z_{1:t}, u_{1:t}) P(m_{1:M} | x_{0:t}, z_{1:t})$$

Q2. Data association is ....

A. Tracking different hypothesis to associate landmarks to them in EKF SLAM
B. Linking observations to landmarks
C. Not an issue for single mode
D. None

Reference Slide: 28

Comment: Data association is defined by B and is an issue for single mode (such as EKF) as wrong data association can cause divergence.

Q3. Scan matching is used to ....

A. Correct the odometry before using it in FastSLAM prediction step.
B. Maximize likelihood of the current pose relative to the previous pose and map.
C. Apply local consistent pose corrections.
D. All.
E. None

Reference Slide: 17 (C), 10 (B), 53 [Next Slideset] (A)

X. Grid-Based FastSLAM

Q1. Particle depletion ....
A. Can cause important samples to be lost by chance
B. Results in redundant samples
C. Can be solved by selective resampling
D. All
E. None

Reference Slide: 27 (C)
Comment: Suppose we had samples A, B, C with probabilities 1/3, 1/3, 1/3 then when resampling gives us A, A, A we have introduced redundancy and possibly have lost important samples (B, C)

XI. Path Planning and Collision Avoidance

Q1. A velocity is admissible if ....
A. The robot is able to stop before colliding with an obstacle
B. Are reachable by acceleration within time period t

Reference Slide: 7
Comment: Follows by the definition

Q2. A* disadvantages ....
A. Don't respect robot kinematics
B. Overestimates distances to obstacles
C. Doesn't consider the goal
D. Its randomness makes the path not optimal
E. None

Reference Slide: 37
Comment: None of A, B, C or D hold. Refer to the slideset for A.

Q3. What is the step that does not exist in the 5D path planning algorithm?
A. Use A* to find a path in the $<x, y>$-space using the updated grid map
B. A* search in the full 5D $<x, y, \theta, v, \omega>$-configuration space

C. Use heuristic navigation function to drive fast in the right direction
D. Find a trajectory by planning in this restricted $<x, y, \theta, v, \omega>$-space using 2D value iteration as heuristic
E. None

Reference Slide: 40

Comment: B is definitely false since we don't search in the full 5D space. C was mentioned for DWA only in the slides (no specific heuristic for 5D A* was set) but its more valid than B.

Q4. Collision avoidance depends mainly on ....

A. Map
B. Sensor data
C. Motion commands
D. All
E. None

Reference Slide: 4

Comment: Sensor data is what helps it spot dynamic obstacles.

XII. ROS

Q1. ROS is open-source meta-OS used for hardware abstraction and makes robot software easier development

A. True
B. False

Comment: As defined on ROS wiki here

Q2. ROS bags are used to replay experiments

A. True
B. False

Comment: As defined on ROS wiki here