

Announcements: 11/7/2023

- Guest lecture (11/09) - Attendance is mandatory
- We are doubling the F1-tenth Lab hours
- After Thanksgiving break F1-tenth supports (e.g. debugging the system) could be limited
- Utilized most of your time before/during the Thanksgiving break
- Most of the GEM slots are unutilized - utilize the slots

Midter2 Review Session: 11/7/2023**Topics:**

- Filtering
 - Bayes
 - Histogram/grid
 - Particle
 - MCL
- Search and Planning
 - Uniform
 - Greedy
 - A/A*/Hybrid A*
 - PRM
 - RRT/RRG

Practice Questions will be Released:

Visit office hours

Discrete Bayes Filtering Review:

we write the probability of a random variable X taking the value x as $P(X=x)$ or as $P(x)$ in short.

Sequence of states x_1, x_2, \dots, x_t , is written in short as $\mathbf{x}_{1:t}$

Sequence of measurements z_1, z_2, \dots, z_t , is written in short as $\mathbf{z}_{1:t}$

Sequence of control inputs u_1, u_2, \dots, u_t , is written in short as $\mathbf{u}_{1:t}$

Belief: Robot's knowledge about the state of the environment

True state is unknowable / measurable typically, so, robot must infer state from data

and we have to distinguish this inferred/estimated state from the actual state

We write the definition of Belief over state (x_t) in terms of conditional probability given measurements z_t and control u_t :

$$Bel(x_t) = P(x_t | z_{1:t}, u_{1:t})$$

We want to write $Bel(x_t)$ using $\overline{Bel}(x_t)$

$$Bel(x_t) = \eta \underbrace{P(z_t | x_t)} \overline{Bel}(x_t)$$

Where,

$$\overline{Bel}(x_t) = P(x_t | z_{1:t-1}, u_{1:t})$$

$$\eta = \text{normalization term} \\ \Rightarrow P(z_t | z_{1:t-1}, u_{1:t})$$

correction term:

$$P(z_t | \underbrace{x_t}_{\text{circled}}, z_{1:t-1}, u_{1:t})$$

Assuming that the measurement model is complete, then the correction term becomes

$$= P(z_t | x_t)$$

It's say we have three random variable X, Y, Z ,

$$P(X | Y, Z) = \frac{P(X, Y, Z)}{P(Y, Z)}$$

$$P(Y | X, Z) = \frac{P(X, Y, Z)}{P(X, Z)}$$

$$P(X | Y, Z) = \frac{P(Y | X, Z) P(X, Z)}{P(Y, Z)}$$

$$P(X | Z) = \frac{P(X, Z)}{P(Z)}$$

$$P(Y | Z) = \frac{P(Y, Z)}{P(Z)}$$

$$P(X | Y, Z) = \frac{P(Y | X, Z) P(X | Z) P(Z)}{P(Y | Z) P(Z)}$$

$$P(X | Y, Z) = \frac{P(Y | X, Z) P(X | Z)}{P(Y | Z)}$$

choose $X = x_t$

$Y = z_t$

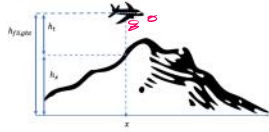
$Z = z_{1:t-1}, u_{1:t}$

$$\Rightarrow \frac{P(z_t | x_t, z_{1:t-1}, u_{1:t}) P(x_t | z_{1:t-1}, u_{1:t})}{P(z_t | z_{1:t-1}, u_{1:t})}$$

= η

Particle filtering

You are kidnapped in a plane with just an altitude map and you have to use particle filters to estimate your location.



The aircraft is flying parallel to the x-axis at a speed of 1 per unit time and keeping the same sea level altitude of $h_{plane} = 100$. Let the (unknown) horizontal location of the plane at time t be X_t . Below the aircraft is a mountain. You have a map (below) that gives the exact height h_x of the mountain at any position x . A noisy sensor mounted on the airplane measures the vertical distance h_t between plane and mountain at any time t . You are going to use m particles in your calculation initialized as in the table below. For calculating the importance factor W_t^m of the m^{th} particle, use:

$$W_t^m = \frac{1}{\sigma^2} \exp\left(-\frac{(h_{t,obs} - h_{t,m})^2}{\sigma^2}\right)$$

where x_m is the position of the m^{th} particle. Assume we do not resample particles.

Altitude map:

Position (x)	1	2	3	4	5	6	7	8	9	10
Mountain exact altitude (h_x)	15	23	32	29	25	23	10	10	8	5

a. Suppose you saw the sensor reading $h_t = 80$. Fill in the table to update the particle filter. Writing expressions will be adequate.

Particle number m	1	2	3	4	5
X_t^m	3	6	1	5	9
W_t^m	e^{-81}	e^{-16}	e^{-1}	e^{-9}	e^{-25}

$$n=5 \left(e^{-81} + e^{-16} + e^{-1} + e^{-9} + e^{-25} \right)$$

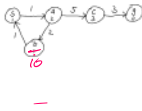
b. What is the estimated position \bar{X}_t at time t ? Just write down the equation; no need to calculate or simplify.

$$\bar{X}_t = \frac{1}{n} \left(4 \times e^{-81} + 7 \times e^{-16} + 3 \times e^{-1} + 6 \times e^{-9} + 10 \times e^{-25} \right)$$

a. Consider a search algorithm like A search in which the function $f(n) = (2-w)g(n) + wh(n)$ is used to choose the path that is expanded next. Recall, $g(n)$ is the cost to arrive at n and $h(n)$ is the cost-to-go heuristic. If the heuristic h is admissible, what kind of search does this algorithm perform for each of these values of w and why?

w	Type of search	Reasoning
$w = 0$	Uniform	
$w = 1$	A/A*	
$w = 2$	greedy	

b. Draw an example graph to illustrate why best-first search is incomplete. Draw the graph with the start and goal vertices, label the edge costs and the heuristic function values.



Cost	h
$\langle s \rangle$	0
$\langle a, s \rangle$	1
$\langle c, a, s \rangle$	2
$\langle b, a, s \rangle$	3
$\langle s, b, a, s \rangle$	4

c. (5 points) Write a run of the best-first search algorithm on the above graph to illustrate how it fails to find a path.

$\langle a, s, b, a, s \rangle$
 s (2)