Robotics
Exercise 8

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January 10, 2017

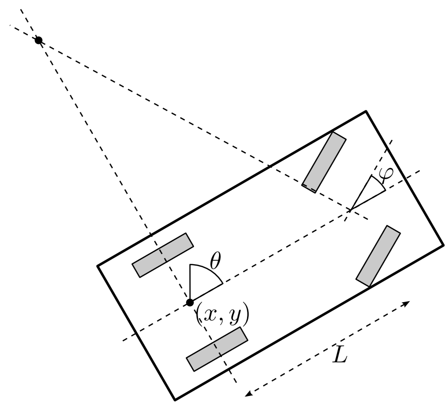
1 Particle Filtering the location of a car

You are going to implement a particle filter. Download the code framework here:
https://ipvs.informatik.uni-stuttgart.de/mlr/16-Robotics/e08-code.tbz2
Unpack the code such that the folder structure is 'robotics15/share/teaching/RoboticsCourse/particle_filter/main.cpp'
The motion of the car is described by the following:

State $q = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix}$ **Controls** $u = \begin{pmatrix} v \\ \varphi \end{pmatrix}$

Sytem equation $\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} v \ \cos\theta \\ v \ \sin\theta \\ (v/L) \ \tan\varphi \end{pmatrix}$

$\dot{x} = v \ \cos\theta$
$\dot{y} = v \ \sin\theta$
$\dot{\theta} = (v/L) \ \tan\varphi$
$|\varphi| < \Phi$



The `CarSimulator` simulates the described car (using Euler integration with step size 1sec). At each time step a control signal $u = (v, \phi)$ moves the car a bit and Gaussian noise with standard deviation $\sigma_{\text{dynamics}} = .03$ is added to x, y and θ. Then, in each step, the car measures the relative positions of m landmark points (green cylinders), resulting in an observation $y_t \in \mathbb{R}^{m\times 2}$; these observations are Gaussian-noisy with standard deviation $\sigma_{\text{observation}} = .5$. In the current implementation the control signal $u_t = (.1, .2)$ is fixed (roughly driving circles).

a) Odometry (dead reckoning): First write a particle filter (with $N = 100$ particles) that ignores the observations. For this you need to use the cars system dynamics (described above) to propagate each particle, and add some noise σ_{dynamics} to each particle (step 3 on slide 08:24). Draw the particles (their x, y component) into the display. Expected is that the particle cloud becomes larger and larger.

b) Next implement the likelihood weights $w_i \propto P(y_t|x_t^i) = \mathcal{N}(y_t|y(x_t^i), \sigma) \propto e^{-\frac{1}{2}(y_t - y(x_t^i))^2/\sigma^2}$ where $y(x_t^i)$ is the (ideal) observation the car would have if it were in the particle possition x_t^i. Since $\sum_i w_i = 1$, normalize the weights after this computation.

c) Test the full particle filter including the likelihood weights (step 4) and resampling (step 2). Test using a larger ($10\sigma_{\text{observation}}$) and smaller ($\sigma_{\text{observation}}/10$) variance in the computation of the likelihood.

2 Bayes Basics

a) Box 1 contains 8 apples and 4 oranges. Box 2 contains 10 apples and 2 oranges. Boxes are chosen with equal probability. What is the probability of choosing an apple? If an apple is chosen, what is the probability that it came from box 1?

b) The blue M&M was introduced in 1995. Before then, the color mix in a bag of plain M&Ms was: 30% Brown, 20% Yellow, 20% Red, 10% Green, 10% Orange, 10% Tan. Afterward it was: 24% Blue , 20% Green, 16% Orange, 14% Yellow, 13% Red, 13% Brown.

A friend of mine has two bags of M&Ms, and he tells me that one is from 1994 and one from 1996. He won't tell me which is which, but he gives me one M&M from each bag. One is yellow and one is green. What is the probability that the yellow M&M came from the 1994 bag?

c) The Monty Hall Problem: I have three boxes. In one I put a prize, and two are empty. I then mix up the boxes. You want to pick the box with the prize in it. You choose one box. I then open *another* one of the two remaining boxes and show that it is empty. I then give you the chance to change your choice of boxes—should you do so?

d) Given a joint probability $P(X, Y)$ over 2 binary random variables as the table

	Y=0	Y=1
X=0	.06	.24
X=1	.14	.56

What are $P(X)$ and $P(Y)$? Are X and Y independent?