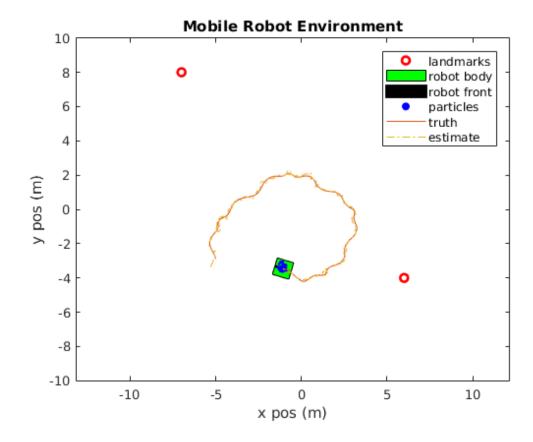
```
% Homework 4 Autonomous Two-wheel robot Particle Filter
% Jesse Wynn
% October 10, 2017
clc
clear
close all
% time params
Ts = 0.1; % sec
t = 0:Ts:20;
% commanded velocity
v_c = 1 + 0.5 * cos(2 * pi * (0.2) * t);
w_c = -0.2 + 2 * cos(2 * pi * (0.6) * t);
% input noise
alpha_1 = 0.1;
alpha_4 = 0.1;
alpha_2 = 0.01;
alpha_3 = 0.01;
alpha_5 = 0.01;
alpha_6 = 0.01;
input_noise = [alpha_1, alpha_2, alpha_3, alpha_4, alpha_5, alpha_6];
% measurement noise
sigma r = 0.1;
sigma_phi = 0.05;
% landmark locations
landmarks = [6, -7, 6]
             4, 8, -4];
num landmarks = size(landmarks);
num_landmarks = num_landmarks(2);
% number of particles
M = 1000;
% initialize a bunch of random particles
Chi_t_prev = zeros(3, M);
% = 100 give them random x locations on the interval [-10 10]
Chi_t_prev(1,:) = -10 + (10 - (-10)).*rand(M,1);
% give them random y locations on the interval [-10 10]
Chi_t_prev(2,:) = -10 + (10 - (-10)).*rand(M,1);
% give them random headings on the interval [min_heading max_heading]
min_heading = pi/4;
\max_{heading} = 3*pi/4;
```

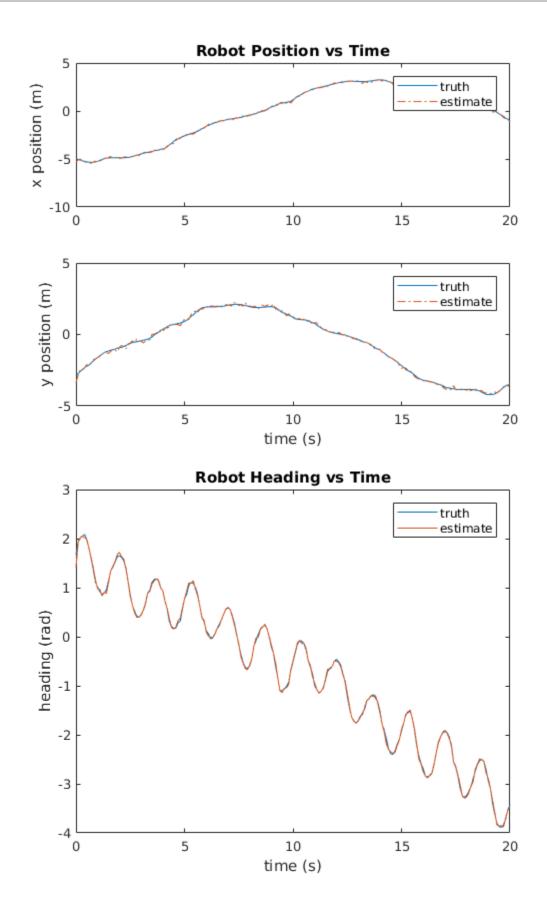
```
Chi_t_prev(3,:) = min_heading + (max_heading -
 min heading).*rand(M,1);
% allocate space for holding data
x_true = zeros(1,length(t));
y_true = zeros(1,length(t));
theta_true = zeros(1,length(t));
Chi_bar_t = zeros(4,M);
W_t = zeros(1,M);
Chi_t = zeros(3,M);
range = zeros(length(t), num landmarks);
bearing = zeros(length(t),num_landmarks);
x_{est} = zeros(1, length(t));
y_est = zeros(1,length(t));
theta_est = zeros(1,length(t));
Sigma_x = zeros(1, length(t));
Sigma_y = zeros(1,length(t));
Sigma_theta = zeros(1,length(t));
% robot initital conditions
x = -5i
y = -3;
theta = pi/2;
% plot the first time
first = 0;
drawRobot(x,y,theta,landmarks, Chi_t_prev, first);
first = 1;
pause(0.5)
% loop through each time step
for i = 1:length(t)
    % implement velocity motion model from Table 5.3 (this gives us
 truth)
    v_hat = v_c(i) + randn*sqrt(alpha_1*(v_c(i))^2 +
 alpha 2*(w c(i))^2;
    w_hat = w_c(i) + randn*sqrt(alpha_3*(v_c(i))^2 +
 alpha_4*(w_c(i))^2;
    gamma_hat = randn*sqrt(alpha_5*(v_c(i))^2 + alpha_6*(w_c(i))^2);
    x = x - (v_hat/w_hat)*sin(theta) + (v_hat/w_hat)*sin(theta +
 w hat *Ts);
    y = y + (v_hat/w_hat)*cos(theta) - (v_hat/w_hat)*cos(theta +
 w hat*Ts);
    theta = theta + w_hat*Ts + gamma_hat*Ts;
    % save off the true state data for plotting
    x_{true}(i) = x;
    y_{true}(i) = y;
    theta_true(i) = theta;
```

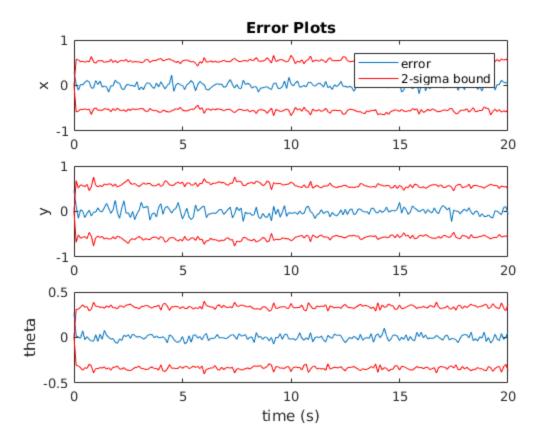
```
% simulate range and bearing measurements to landmarks
   range(i,1) = norm([x; y] - landmarks(:,1)) + randn*sigma_r;
measurement + noise
   range(i,2) = norm([x; y] - landmarks(:,2)) + randn*sigma_r;
   range(i,3) = norm([x; y] - landmarks(:,3)) + randn*sigma_r;
   bearing(i,1) = atan2(landmarks(2,1) - y, landmarks(1,1) - x) -
theta + randn*sigma phi; % measurement + noise
   bearing(i,2) = atan2(landmarks(2,2) - y, landmarks(1,2) - x) -
theta + randn*sigma_phi; % maybe sqrt
   bearing(i,3) = atan2(landmarks(2,3) - y, landmarks(1,3) - x) -
theta + randn*sigma phi;
   % control input at time t
   u = [v_c(i); w_c(i)];
   % measurement for all three landmarks at time t
   z t = [range(i,:);
          bearing(i,:)];
   % BEGIN particle filter (Monte Carlo Localization) algorithm
   % from table 8.2
   for m = 1:M
       % pass each particle through the motion model
       Chi_t(:,m) = sample_motion_model(u, Chi_t_prev(:,m),
input_noise, Ts);
       % assign a weight to each particle based on the current
measurement.
       W_t(m) = measurement_model(z_t, Chi_t(:,m), landmarks,
[sigma_r, sigma_phi]);
       % augment the state of each particle with its associated
weight
       % Chi_bar_t(:,m) = [Chi_t(:,m); W_t(m)]; % instead of doing
this, just pass Chi_t and W_t into LVS
   end
   % use the low variance sampler to resample particles (particles
with
   % highter weight are more likely to be chosen and some will be
chosen
   % more than once.
   % first, normalize the weights
   W t = W t./sum(W t);
   % then pass particles and weights to the LVS
   Chi_t_prev = LVS(Chi_t, W_t);
   % END particle filter algorithm
```

```
% update the plot
    drawRobot(x,y,theta,landmarks, Chi t prev, first)
    pause(0.01)
    % estimates and error bounds
    x_{est(i)} = mean(Chi_t_prev(1,:));
    y_{est(i)} = mean(Chi_t_prev(2,:));
    theta est(i) = mean(Chi t prev(3,:));
    Sigma_x(i) = std(Chi_t_prev(1,:));
    Sigma_y(i) = std(Chi_t_prev(2,:));
    Sigma_theta(i) = std(Chi_t_prev(3,:));
end
% plots
plot(x_true, y_true, x_est, y_est,'-.')
legend('landmarks','robot body','robot
front', 'particles', 'truth', 'estimate')
figure(2), clf
subplot(2,1,1)
plot(t,x_true, t, x_est, '-.')
title('Robot Position vs Time')
ylabel('x position (m)')
legend('truth','estimate')
subplot(2,1,2)
plot(t,y_true, t, y_est, '-.')
ylabel('y position (m)')
xlabel('time (s)')
legend('truth','estimate')
figure(3), clf
plot(t,theta_true,t,theta_est)
title('Robot Heading vs Time')
xlabel('time (s)')
ylabel('heading (rad)')
legend('truth','estimate')
figure(4), clf
subplot(3,1,1)
plot(t,x_true - x_est,t,2*sqrt(Sigma_x),'r',t,-2*sqrt(Sigma_x),'r')
title('Error Plots')
ylabel('x')
legend('error','2-sigma bound')
subplot(3,1,2)
plot(t,y_true - y_est,t,2*sqrt(Sigma_y),'r',t,-2*sqrt(Sigma_y),'r')
ylabel('y')
subplot(3,1,3)
plot(t,theta true -
 theta_est,t,2*sqrt(Sigma_theta),'r',t,-2*sqrt(Sigma_theta),'r')
ylabel('theta')
```

xlabel('time (s)')







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