

1 Occupancy Grid

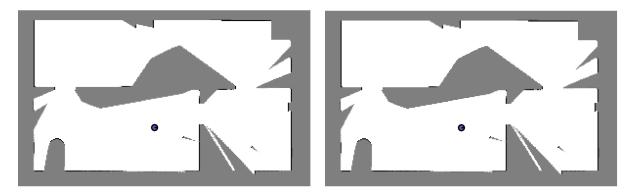


Figure 1: $\alpha = 0.1, \beta = 1$. Grids updated with absolute value (left) vs. trend (right)

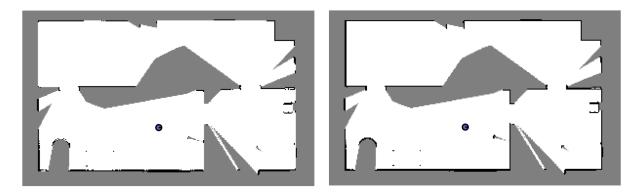


Figure 2: $\alpha = 10, \beta = 1$. Grids updated with absolute value (left) vs. trend (right)

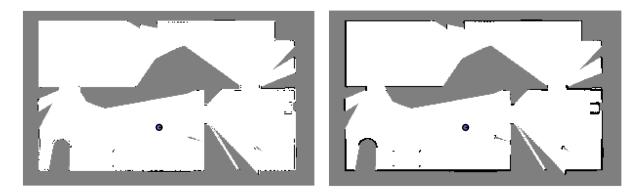


Figure 3: $\alpha = 100, \beta = 1$. Grids updated with absolute value (left) vs. trend (right)

The occupancy grids are iteratively updated by the laser scans at each time step. Each laser beam is divided into segments roughly the length of the grids, ranging from the closest to the furthest from the robot:

- The furthest laser segment is the obstacle, which blocked the laser beam from reaching further. We add α to the corresponding grid's log-odd value, indicating an increased probability that it is occupied.
- Conversely, all the other segments correspond to free space, and we therefore subtract β from their log-odd values.

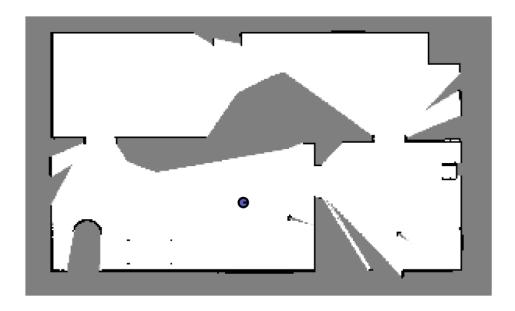


Figure 4: Output plot from to Question 1

While the algorithm is very straightforward, I tuned the α, β values and compared the results (fig.123). We can see that a smaller $\alpha : \beta$ ratio (fig.1) allows the free-space readings to easily override the previous occupancy reading, resulting in missing walls and obstacles. Conversely, a $\alpha : \beta$ The Picking a higher resolution for the rays, which are used to update the grid, reduced raggedness, but it decreased the number of walls in the map. Another issue that occurred is picking the correct alpha and beta, which is causing the missing walls in some parts of the map. A small alpha is easily overwritten by the beta values from the newer updates; a very large alpha has very inconsistent behavior, leaving large portions of the map without walls. Overall, the map is pretty accurate.

2 Noisy Wheel Odometry

In the beginning, the odometry estimate is slightly better the particle filter, as there is little drift in the odometry so far. Near the end of trajectory, the particle filter has trouble estimating the once again, though this time it is significantly lower than the odometry data. This is expected, the divergence of the odometry pose from the true path grows over distance travel. The growth in error for certain portions likely has to do with the ambiguity of the rooms and the limits of the laser, which caps at 5 meters. With similar features and only a single range value, it is easy for erroneous particles to have high weights. Perhaps with the full 640 angles of laser data, the particle filter will do much better.

The solution error is significantly lower in the beginning and end of the plot; it appears the solution model is more robust to changes in the location compared to my code. As I am using the same parameters,

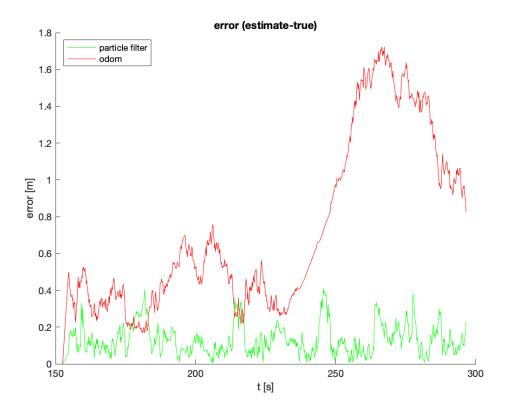


Figure 5: $\alpha = 10, \beta = 1$ with posterior update

provided by the model, the main difference should lie in the observation model. I estimated the expected sensor data from the particle using a ray extending from the laser scan pose, incrementally increasing the length of the ray and checking for obstacles.

Appendix I: Code for Occupancy Grid

```
1 % =======
2 % ass2_q1.m
3 % =======
_{5} % This assignment will introduce you to the idea of first building an
_{6} % occupancy grid then using that grid to estimate a robot's motion using a
7 % particle filter.
8 %
9 % There are two questions to complete (5 marks each):
     Question 1: code occupancy mapping algorithm
11 %
12 %
      Question 2: see ass2_q2.m
_{14} % Fill in the required sections of this script with your code, run it to
_{15} % generate the requested plot/movie, then paste the plots into a short report
_{16} % that includes a few comments about what you've observed. Append your
_{17} % version of this script to the report. Hand in the report as a PDF file
_{\rm 18} % and the two resulting AVI files from Questions 1 and 2.
20 % requires: basic Matlab, 'gazebo.mat'
22 % T D Barfoot, January 2016
23 %
24 clear all;
26 % set random seed for repeatability
27 rng(1);
29 % =======
30 % load the dataset from file
ground truth poses: t_true x_true y_true theta_true
34 % odometry measurements: t_odom v_odom omega_odom
             laser scans: t_laser y_laser
35 %
     laser range limits: r_min_laser r_max_laser
36 %
       laser angle limits: phi_min_laser phi_max_laser
39 load gazebo.mat;
42 % Question 1: build an occupancy grid map
44 %
_{45} % Write an occupancy grid mapping algorithm that builds the map from the
_{46} % perfect ground-truth localization. Some of the setup is done for you
47 % below. The resulting map should look like "ass2_q1_soln.png". You can
```

```
_{48} % watch the movie "ass2_q1_soln.mp4" to see what the entire mapping process
_{
m 49} % should look like. At the end you will save your occupancy grid map to
_{50} % the file "occmap.mat" for use in Question 2 of this assignment.
_{\rm 52} % allocate a big 2D array for the occupancy grid
                                  % resolution of occ grid
_{53} ogres = 0.05;
_{54} ogxmin = -7;
                                  % minimum x value
ogxmax = 8;
                                  % maximum x value
_{56} ogymin = -3;
                                  % minimum y value
                                  % maximum y value
ogymax = 6;
ognx = (ogxmax-ogxmin)/ogres; % number of cells in x direction
ogny = (ogymax-ogymin)/ogres; % number of cells in y direction
oglo = zeros(ogny,ognx); % occupancy grid in log-odds format
                                 % occupancy grid in probability format
ogp = zeros(ogny,ognx);
63 % precalculate some quantities
64 numodom = size(t_odom,1);
65 npoints = size(y_laser,2);
angles = linspace(phi_min_laser, phi_max_laser, npoints);
67 dx = ogres*cos(angles);
68 dy = ogres*sin(angles);
_{70} % interpolate the noise-free ground-truth at the laser timestamps
71 t_interp = linspace(t_true(1),t_true(numodom),numodom);
72 x_interp = interp1(t_interp,x_true,t_laser);
y_interp = interp1(t_interp,y_true,t_laser);
74 theta_interp = interp1(t_interp,theta_true,t_laser);
omega_interp = interp1(t_interp,omega_odom,t_laser);
77 % set up the plotting/movie recording
vid = VideoWriter('ass2_q1.avi');
79 open(vid);
80 figure(1);
81 clf;
82 pcolor(ogp);
83 colormap(1-gray);
shading('flat');
85 axis equal;
86 axis off;
87 M = getframe;
88 writeVideo(vid,M);
90 % Other variables and quantities
91 cos_angles = cos(angles);
92 sin_angles = sin(angles);
93 one = ones(1, npoints); % Just for homogenroes transformatiom
94 alpha = 10;
                              % log-odd of occupied cell (+)
95 beta = 1;
                             % log-odd of occupied free cell (-)
96
```

```
97 % loop over laser scans (every fifth)
98 for i=1:5:size(t_laser,1)
       % -----insert your occupancy grid mapping algorithm here-----
100
        if abs(omega_interp(i)) < 0.1</pre>
101 %
102 %
             continue;
103 %
         end
       % Step O. Preprocess the laser scans
       y_laser_t = y_laser(i,:);
                                                % Get the laser scans at time t
106
       y_laser_t(y_laser_t<r_min_laser) = NaN; % Remove all invalid values from</pre>
107
      the laser scan
       y_laser_t(y_laser_t>r_max_laser) = NaN;
108
      \% Step 1. Transform frames from laser -> robot (v) -> inertial (i) -> grid
      (g)
      % 1.1 laser -> robot (vehicle)
       x_v = y_laser_t .* cos_angles - 0.1; % Note laser is 10 cm behind origin
       of frame v's origin
       y_v = y_laser_t .* sin_angles;
114
       % 1.2 vehicle -> inertial
       robot_sin_i = sin(theta_interp(i));
                                               % Vehecle's current position/
116
      orientation in inertial frame
      robot_cos_i = cos(theta_interp(i));
                                               % Convention: x_,y_ for laser
117
      scanned "obstacle"
      robot_x_i = x_interp(i);
                                                %
                                                              robot_ for vehicle
118
      pose
      robot_y_i = y_interp(i);
119
       H_iv = [robot_cos_i -robot_sin_i robot_x_i; % Homogenous matrix defining
      the transformation
               robot_sin_i robot_cos_i robot_y_i;
                           0
                                         1];
       xy_i = H_iv*[x_v; y_v; one];
124
       % 1.3 inertial -> grid (i.e., distance -> grid index)
       robot_x_g = (robot_x_i-ogxmin)/ogres;
                                               % Scalars
126
       robot_y_g = (robot_y_i-ogymin)/ogres;
127
       x_g = (xy_i(1,:)-ogxmin)/ogres;
                                                % Arrays
128
       y_g = (xy_i(2,:)-ogymin)/ogres;
129
130
      % Step 2. Update the grid using ray tracking of each (j-th) laser ray, in
131
      log-odds form
132
       for j = 1:npoints
           if isnan(x_g(j)) \mid isnan(y_g(j)) % Only use valid measurements
               continue;
           end
136
           % 2.1 Break laser into segments (in x, y grids)
```

```
nsegments = round(y_laser_t(j)/ogres);
138
           segs_x_g = round(linspace(robot_x_g, x_g(j), nsegments));
139
           segs_y_g = round(linspace(robot_y_g, y_g(j), nsegments));
140
           % 2.2 Mark all segments up till the scanned obstacle as free (-beta)
                 and the obstacle as occupied (+alpha)
           for k = 1:nsegments-1
               oglo(segs_y_g(k), segs_x_g(k)) = oglo(segs_y_g(k), segs_x_g(k)) -
      beta:
146
           oglo(segs_y_g(nsegments), segs_x_g(nsegments)) = oglo(segs_y_g(
147
      nsegments), segs_x_g(nsegments)) + alpha;
       end
148
149
       % Step 3. Threshold the grids based on tendency (posterior vs. prior), in
      probability form
                 Only update those with increasing likelihood
152 %
         ogp = exp(oglo)./(1+exp(oglo));
       ogp_post = exp(oglo)./(1+exp(oglo));
       for y = 1:ogny
154
           for x = 1:ognx
               if ogp_post(y,x) > ogp(y,x) && ogp_post(y,x) >= 0.5
                    ogp(y,x) = ogp_post(y,x);
               elseif ogp_post(y,x) < ogp(y,x) && ogp_post(y,x) < 0.5 % Free</pre>
158
                    ogp(y,x) = ogp_post(y,x);
               end
160
           end
161
       end
162
       % -----end of your occupancy grid mapping algorithm-----
163
       % draw the map
165
       clf;
       pcolor(ogp);
       colormap(1-gray);
       shading('flat');
169
       axis equal;
       axis off;
       % draw the robot
       hold on;
174
       x = (x_interp(i)-ogxmin)/ogres;
       y = (y_interp(i)-ogymin)/ogres;
176
       th = theta_interp(i);
177
178
       r = 0.15/ogres;
       set(rectangle( 'Position', [x-r y-r 2*r 2*r], 'Curvature', [1 1]),'
      LineWidth', 2, 'FaceColor', [0.35 0.35 0.75]);
       set(plot([x x+r*cos(th)]', [y y+r*sin(th)]', 'k-'),'LineWidth',2);
180
181
       % save the video frame
182
```

```
M = getframe;
writeVideo(vid,M);

pause(0.1);

end

close(vid);
print -dpng ass2_q1.png

save occmap.mat ogres ogxmin ogxmax ogymin ogymax ogny oglo ogp;
```

Appendix II: Code for Particle Filtering

```
2 % ass2_q2.m
3 % =======
_{5} % This assignment will introduce you to the idea of first building an
_{6} % occupancy grid then using that grid to estimate a robot's motion using a
7 % particle filter.
8 %
9 % There are three questions to complete (5 marks each):
11 %
     Question 1: see ass2_q1.m
      Question 2: code particle filter to localize from known map
_{14} % Fill in the required sections of this script with your code, run it to
_{15} % generate the requested plot/movie, then paste the plots into a short report
_{16} % that includes a few comments about what you've observed. Append your
_{17} % version of this script to the report. Hand in the report as a PDF file
_{\rm 18} % and the two resulting AVI files from Questions 1 and 2.
20 % requires: basic Matlab, 'gazebo.mat', 'occmap.mat'
22 % T D Barfoot, January 2016
23 %
24 clear all;
26 % set random seed for repeatability
27 rng(1);
29 % =======
30 % load the dataset from file
ground truth poses: t_true x_true y_true theta_true
34 % odometry measurements: t_odom v_odom omega_odom
            laser scans: t_laser y_laser
35 %
     laser range limits: r_min_laser r_max_laser
36 %
      laser angle limits: phi_min_laser phi_max_laser
39 load gazebo.mat;
_{\rm 42} % load the occupancy map from question 1 from file
44 % ogres: resolution of occ grid
45 % ogxmin: minimum x value
46 % ogxmax: maximum x value
47 % ogymin: minimum y value
```

```
48 % ogymax: maximum y value
49 %
      ognx: number of cells in x direction
      ogny: number of cells in y direction
50 %
51 %
      oglo: occupancy grid in log-odds format
      ogp: occupancy grid in probability format
10ad occmap.mat;
56 % Question 2: localization from an occupancy grid map using particle filter
59 % Write a particle filter localization algorithm to localize from the laser
60 % rangefinder readings, wheel odometry, and the occupancy grid map you
_{61} % built in Question 1. We will only use two laser scan lines at the
_{62} % extreme left and right of the field of view, to demonstrate that the
_{63} % algorithm does not need a lot of information to localize fairly well. To
_{64} % make the problem harder, the below lines add noise to the wheel odometry
_{65} % and to the laser scans. You can watch the movie "ass2_q2_soln.mp4" to
66 % see what the results should look like. The plot "ass2_q2_soln.png" shows
_{67} % the errors in the estimates produced by wheel odometry alone and by the
68 % particle filter look like as compared to ground truth; we can see that
_{69} % the errors are much lower when we use the particle filter.
_{71} % interpolate the noise-free ground-truth at the laser timestamps
72 numodom = size(t_odom,1);
r<sub>3</sub> t_interp = linspace(t_true(1),t_true(numodom),numodom);
74 x_interp = interp1(t_interp,x_true,t_laser);
y_interp = interp1(t_interp,y_true,t_laser);
76 theta_interp = interp1(t_interp,theta_true,t_laser);
77 omega_interp = interp1(t_interp,omega_odom,t_laser);
_{79} % interpolate the wheel odometry at the laser timestamps and
_{80} % add noise to measurements (yes, on purpose to see effect)
s1 v_interp = interp1(t_interp, v_odom, t_laser) + 0.2*randn(size(t_laser,1),1);
82 omega_interp = interp1(t_interp,omega_odom,t_laser) + 0.04*randn(size(t_laser)
      ,1),1);
_{84} % add noise to the laser range measurements (yes, on purpose to see effect)
85 % and precompute some quantities useful to the laser
y_laser = y_laser + 0.1*randn(size(y_laser));
87 npoints = size(y_laser,2);
angles = linspace(phi_min_laser, phi_max_laser, npoints);
89 dx = ogres*cos(angles);
90 dy = ogres*sin(angles);
91 y_laser_max = 5; % don't use laser measurements beyond this distance
93 % particle filter tuning parameters (yours may be different)
94 nparticles = 200; % number of particles
v_{noise} = 0.2; % noise on longitudinal speed for propagating particle
```

```
% noise on lateral speed for propagating particle
96 u_noise = 0.2;
omega_noise = 0.04;
                         % noise on rotational speed for propagating particle
98 laser_var = 0.5<sup>2</sup>;
                         % variance on laser range distribution
99 w_gain = 10*sqrt( 2 * pi * laser_var ); % gain on particle weight
100 ogp_threshold = 0.5; % minimum probability reuired to declare that the grid
      is occupied
102 % generate an initial cloud of particles
x_particle = x_true(1) + 0.5*randn(nparticles,1);
y_particle = y_true(1) + 0.3*randn(nparticles,1);
theta_particle = theta_true(1) + 0.1*randn(nparticles,1);
107 % compute a wheel odometry only estimate for comparison to particle
108 % filter
x_odom_only = x_true(1);
y_odom_only = y_true(1);
theta_odom_only = theta_true(1);
112
_{113} % error variables for final error plots - set the errors to zero at the start
pf_err(1) = 0;
wo_{err}(1) = 0;
% set up the plotting/movie recording
vid = VideoWriter('ass2_q2.avi');
open(vid);
120 figure (2);
121 clf;
122 hold on;
pcolor(ogp);
124 set(plot( (x_particle-ogxmin)/ogres, (y_particle-ogymin)/ogres, 'g.'),'
      MarkerSize',10,'Color',[0 0.6 0]);
set(plot( (x_odom_only-ogxmin)/ogres, (y_odom_only-ogymin)/ogres, 'r.'),'
      MarkerSize',20);
x = (x_interp(1)-ogxmin)/ogres;
y = (y_interp(1)-ogymin)/ogres;
th = theta_interp(1);
r = 0.15/ogres;
set(rectangle( 'Position', [x-r y-r 2*r 2*r], 'Curvature', [1 1]),'LineWidth'
      ,2,'FaceColor',[0.35 0.35 0.75]);
set(plot([x x+r*cos(th)]', [y y+r*sin(th)]', 'k-'),'LineWidth',2);
132 set(plot( (mean(x_particle)-ogxmin)/ogres, (mean(y_particle)-ogymin)/ogres, 'g.
      '), 'MarkerSize', 20);
colormap(1-gray);
shading('flat');
135 axis equal;
136 axis off;
137 M = getframe;
138 writeVideo(vid,M);
139
```

```
140 % loop over laser scans
      for i=2:size(t_laser,1)
                 % update the wheel-odometry-only algorithm
                 dt = t_laser(i) - t_laser(i-1);
144
                 v = v_interp(i);
                 omega = omega_interp(i);
                 x_odom_only = x_odom_only + dt*v*cos( theta_odom_only );
                 y_odom_only = y_odom_only + dt*v*sin( theta_odom_only );
148
                 phi = theta_odom_only + dt*omega;
149
                 while phi > pi
                           phi = phi - 2*pi;
                 end
                 while phi < -pi
                           phi = phi + 2*pi;
154
                 end
                 theta_odom_only = phi;
157
                 % loop over the particles
                 for n=1:nparticles
159
                           % propagate the particle forward in time using wheel odometry
161
                           % (remember to add some unique noise to each particle so they
                           % spread out over time)
163
                           v = v_interp(i) + v_noise*randn(1);
164
                           u = u_noise*randn(1);
165
                           omega = omega_interp(i) + omega_noise*randn(1);
166
                           x_{particle}(n) = x_{particle}(n) + dt*(v*cos(theta_particle(n)) - u*sin(theta_particle(n)) + dt*(v*cos(theta_particle(n))) 
167
                  theta_particle(n) ));
                           y_{particle}(n) = y_{particle}(n) + dt*(v*sin(theta_particle(n)) + u*cos(
                  theta_particle(n) ));
                           phi = theta_particle(n) + dt*omega;
                           while phi > pi
170
                                     phi = phi - 2*pi;
                           end
172
                           while phi < -pi
                                     phi = phi + 2*pi;
174
                           end
                           theta_particle(n) = phi;
177
                           \% pose of particle in initial frame
178
                           T = [cos(theta_particle(n)) -sin(theta_particle(n)) x_particle(n); ...
179
                                        sin(theta_particle(n)) cos(theta_particle(n)) y_particle(n); ...
                                                           0
                                                                                                                   0
                                                                                                                                                                1];
                           % compute the weight for each particle using only 2 laser rays
                           % (right=beam 1 and left=beam 640)
184
                           w_particle(n) = 1.0;
185
                           for beam = 1:2
186
```

```
187
               \% we will only use the first and last laser ray for
188
               % localization
189
               if beam == 1 % rightmost beam
                    j = 1;
                elseif beam == 2 % leftmost beam
                    j = 640;
193
               end
194
195
               % -----insert your particle filter weight calculation here -----\
196
               % Step O. Rule out invalid scans and, if valid, prepare some
197
      variables
               laser_dist_measured = y_laser(i, j);
198
               if isnan(laser_dist_measured) || laser_dist_measured > y_laser_max
199
       || laser_dist_measured < r_min_laser</pre>
                    continue
200
               end
201
               laser_dist_segs = r_min_laser:ogres:laser_dist_measured;
                                                                                    %
      Breaks laser into segments of grid size
               x_particle_g = x_particle(n)-ogxmin;
203
               y_particle_g = y_particle(n)-ogymin;
204
               T_{lg} = T(1:2, 1:2) * [cos(angles(j)); sin(angles(j))];
                                                                                    %
205
      Transformation from laser dist to inertial frame
206
               % Step 1. Step from the pasticle to its furthest laser range and
207
      find the laser range w/ pose estimate
               for k = 1:length(laser_dist_segs)
208
                    laser_dist_estimated = laser_dist_segs(k);
209
                    likelihood = 1.0;
                    \% 1.1 Estimate laser distance based on particle position
                    laser_xy = T_lg * laser_dist_estimated; % Transform from laser
       -> robot -> inertial -> grid
214
                    x_g = round((x_particle_g + laser_xy(1))/ogres);
                                                                                    %
      Estimated obstacle location
                    y_g = round((y_particle_g + laser_xy(2))/ogres);
                                                                                    %
215
        given pose == particle && range = laser_dist_segs(k)
                   if x_g > size(ogp,2) \mid \mid y_g > size(ogp,1) \mid \mid isnan(x_g) \mid \mid
216
      isnan(y_g) || x_g<1 || y_g<1</pre>
                        break
                                                                                    %
217
      Stop if going out of map
                    end
218
219
                    % 1.2 Weight = (Gaussian) likelihood of measurement @ t, given
      map and current pose estimate (of particle)
                   if ogp(y_g, x_g) >= ogp_threshold
                                                                                    %
      If grid is occupied => estimated dist is right there
                        likelihood = normpdf(laser_dist_measured,
222
      laser_dist_estimated, laser_var);
```

```
break
223
                    end
224
               end
               \% Step 3. Update weight - multiplying it by each beam's weight gain
               w_particle(n) = w_particle(n) * likelihood * w_gain;
               % ----end of your particle filter weight calculation----
           end
230
231
       end
232
233
       % resample the particles using Madow systematic resampling
234
       w_bounds = cumsum(w_particle)/sum(w_particle);
       w_target = rand(1);
236
       j = 1;
       for n=1:nparticles
238
          while w_bounds(j) < w_target</pre>
              j = mod(j,nparticles) + 1;
          end
          x_particle_new(n) = x_particle(j);
          y_particle_new(n) = y_particle(j);
243
          theta_particle_new(n) = theta_particle(j);
244
          w_target = w_target + 1/nparticles;
245
          if w_target > 1
246
              w_target = w_target - 1.0;
247
              j = 1;
248
          end
       end
250
       x_particle = x_particle_new;
251
       y_particle = y_particle_new;
       theta_particle = theta_particle_new;
       % save the translational error for later plotting
       pf_err(i) = sqrt( (mean(x_particle) - x_interp(i))^2 + (mean(y_particle) -
      y_interp(i))^2 );
       wo_err(i) = sqrt( (x_odom_only - x_interp(i))^2 + (y_odom_only - y_interp(i))
257
      ))^2);
258
       % plotting
259
       figure(2);
260
       clf;
261
       hold on;
262
       pcolor(ogp);
263
       set(plot( (x_particle-ogxmin)/ogres, (y_particle-ogymin)/ogres, 'g.'),'
      MarkerSize',10,'Color',[0 0.6 0]);
       set(plot( (x_odom_only-ogxmin)/ogres, (y_odom_only-ogymin)/ogres, 'r.'),'
      MarkerSize',20);
       x = (x_interp(i)-ogxmin)/ogres;
266
       y = (y_interp(i)-ogymin)/ogres;
267
```

```
th = theta_interp(i);
268
       if ~isnan(y_laser(i,1)) & y_laser(i,1) <= y_laser_max</pre>
269
          set(plot([x x+y_laser(i,1)/ogres*cos(th+angles(1))]', [y y+y_laser(i,1)/
270
      ogres*sin(th+angles(1))]', 'm-'),'LineWidth',1);
271
       end
       if ~isnan(y_laser(i,640)) & y_laser(i,640) <= y_laser_max</pre>
          set(plot([x x+y_laser(i,640)/ogres*cos(th+angles(640))]', [y y+y_laser(i
       ,640)/ogres*sin(th+angles(640))]', 'm-'),'LineWidth',1);
274
       r = 0.15/ogres;
275
       set(rectangle( 'Position', [x-r y-r 2*r 2*r], 'Curvature', [1 1]),'
276
      LineWidth',2,'FaceColor',[0.35 0.35 0.75]);
       set(plot([x x+r*cos(th)]', [y y+r*sin(th)]', 'k-'), 'LineWidth',2);
277
       set(plot( (mean(x_particle)-ogxmin)/ogres, (mean(y_particle)-ogymin)/ogres,
278
       'g.'),'MarkerSize',20);
       colormap(1-gray);
279
       shading('flat');
       axis equal;
       axis off;
       % save the video frame
       M = getframe;
285
       writeVideo(vid,M);
286
287
       pause (0.01);
288
289
290 end
291
292 close(vid);
294 % final error plots
295 figure (3);
296 clf;
297 hold on;
298 plot( t_laser, pf_err, 'g-');
299 plot( t_laser, wo_err, 'r-');
300 xlabel('t [s]');
ylabel('error [m]');
302 legend('particle filter', 'odom', 'Location', 'NorthWest');
303 title('error (estimate-true)');
304 print -dpng ass2_q2.png
```