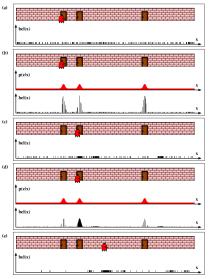
CS354

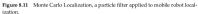
Nathan Sprague

December 12, 2022

Monte-Carlo Localization aka Particle Filter



Probabilistic Robotics. Thrun, Burgard, Fox, 2005





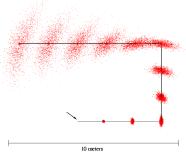
Particle Filter Algorithm

```
1: procedure PARTICLE_FILTER_FOR_LOCALIZATION(\mathcal{X}_{t-1}, u_t, z_t, m)
 2:
          Inputs
 3:
               \mathcal{X}_{t-1} – The previous set of particles
 4:
               u_t – The control signal
 5:
               z_t – The sensor value
               m – The map
 6:
 7:
          Output
 8:
               \mathcal{X}_t – The updated set of particles
 9.
          for m=0 to M-1 do
               x_t^{[m]} = \text{sample\_motion\_model}(u_t, x_{t-1}^{[m]})
10:
                                                                                                ▶ Predict
               w_t^{[m]} = \text{measurement\_model}(z_t, x_t^{[m]}, m)
11.
                                                                                                Correct
               \bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t \cup \{\langle x_t^{[m]}, w_t^{[m]} \rangle\}
12:
13.
          for m=0 to M-1 do
                                                                                          ▶ Resampling
               draw i with probability \propto w_t^{[i]}
14:
               \mathcal{X}_t = \mathcal{X}_t \cup \{\langle x_t^{[i]}, 1/M \rangle\}
15:
```

Based on Algorithm in Table 8.2 in Probabilistic Robotics. Thrun, Burgard, Fox, 2005

Sampling From the Motion Model

$$x_t^{[m]} \sim p(x_t \mid u_t, x_{t-1}^{[m]})$$



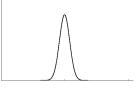
http://robots.stanford.edu/probabilistic-robotics/

Measurement Models for Laser Range Finders

$$w_t^{[m]} = p(z_t \mid x_t^{[m]}, m)$$

(Note that weights won't sum to one)

measurement noise:

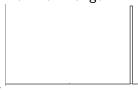


unexpected obstacles:



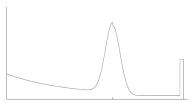
random measurement:

maximum range:



Measurement Models for Laser Range Finders

$$w_t^{[m]} = p(z_t \mid x_t^{[m]}, m)$$



$$P(z \mid x, m) = \begin{pmatrix} \alpha_{\text{hit}} \\ \alpha_{\text{unexp}} \\ \alpha_{\text{max}} \\ \alpha_{\text{rand}} \end{pmatrix}^{T} \cdot \begin{pmatrix} P_{\text{hit}}(z \mid x, m) \\ P_{\text{unexp}}(z \mid x, m) \\ P_{\text{max}}(z \mid x, m) \\ P_{\text{rand}}(z \mid x, m) \end{pmatrix}$$

http://robots.stanford.edu/probabilistic-robotics/

Issues

- Not a good idea to run the particle filter while the robot is stationary
 - Resampling will deplete the set of particles
- May not be necessary to resample on every update.

Extracting a Single State Estimate

Possibilities:

- Average over all particles
- Cluster the algorithms, average within the "best" cluster
- Something fancier...