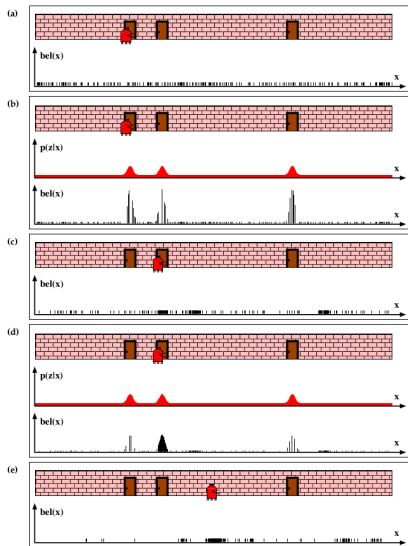


# CS354

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# Monte-Carlo Localization aka Particle Filter



Probabilistic Robotics. Thrun, Burgard, Fox, 2005

Figure 8.11 Monte Carlo Localization, a particle filter applied to mobile robot localization.

# Particle Filter Algorithm

- 1: **procedure** PARTICLE\_FILTER( $\mathcal{X}_{t-1}, u_t, z_t$ )
- 2:     **Inputs**
- 3:          $\mathcal{X}_{t-1}$  – The previous set of particles
- 4:          $u_t$  – The control signal
- 5:          $z_t$  – The sensor value
- 6:     **Output**
- 7:          $\mathcal{X}_t$  – The updated set of particles
  
- 8:      $\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
- 9:      $M = |\mathcal{X}_{t-1}|$
- 10:    **for**  $m = 0$  to  $M - 1$  **do**
- 11:        sample  $x_t^{[m]} \sim p(x_t | u_t, x_t^{[m]})$  ▷ Predict
- 12:         $w_t^{[m]} = p(z_t | x_t^{[m]})w_{t-1}^{[m]}$  ▷ Correct
- 13:         $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t \cup \{ \langle x_t^{[m]}, w_t^{[m]} \rangle \}$
- 14:    **for**  $m = 0$  to  $M - 1$  **do** ▷ Resampling
- 15:        draw  $i$  with probability  $\propto w_t^{[i]}$
- 16:         $\mathcal{X}_t = \mathcal{X}_t \cup \{ \langle x_t^{[i]}, 1/M \rangle \}$

# Sampling From the Motion Model

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

# Measurement Models for Laser Range Finders

- $p(z_t | x_t^{[m]})$

- Not a good idea to run the particle filter while the robot is stationary
  - Resampling will deplete the set of particles
- If we've resampled, the  $w_{t-1}^{[m]}$  term in:  $w_t^{[m]} = p(z_t | x_t^{[m]})w_{t-1}^{[m]}$  will be the same for every particle.
  - Could use  $w_t^{[m]} = p(z_t | x_t^{[m]})$  instead.
- 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...