CPE 580

Fall 2008

Lecture 6 – Sensor Modeling

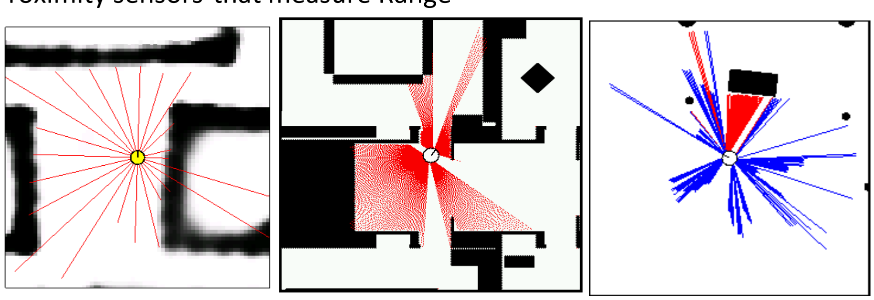
1 – Probabilistic Sensor Models

- There are many sensors used in robotics
  - Contact sensors: Bumpers
  - Internal sensors
  - Accelerometers (spring-mounted masses)
  - Gyroscopes (spinning mass, laser light)
  - Compasses, inclinometers (earth magnetic field, gravity)
  - Proximity sensors
  - Sonar (time of flight)
  - Radar (phase and frequency)
  - Laser range-finders (triangulation, tof, phase)
  - Infrared (intensity)
  - Visual sensors: Cameras
  - Satellite-based sensors: GPS
- All have uncertainty
  - **Demo X80 !**

- How can we model this uncertainty?
- How can we determine $p(z_t|x_t)$ that specifies the likelihood of a measurement z_t given a state x_t at time t
- Or we can write $p(z_t|x_t, m_t)$ where m_t is a map of the environment.
- Or, we can use the models z = Cx + delta, z = h(x) + delta

2 – Proximity Sensor Modeling

- Proximity sensors-that measure Range



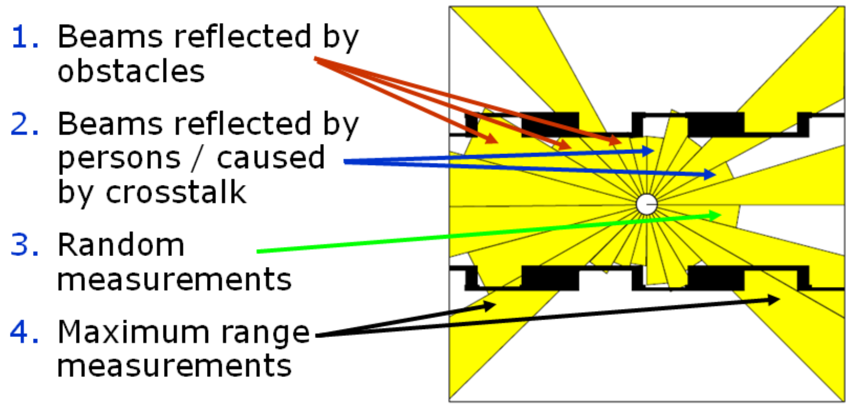
- First note you may have K different measurements in one time step

$$z = \{z_1, z_2, \ldots, z_K\}$$

- We assume that each of these measurements are independent

$$P(z \mid x, m) = \prod_{k=1}^{K} P(z_k \mid x, m)$$

- Next, consider all the different sources of measurements
- Measurement can be caused by …
  - a known obstacle.
  - cross-talk.
  - an unexpected obstacle (people, furniture, …).
  - missing all obstacles (total reflection, glass, …).

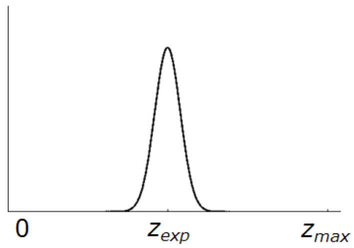


- Noise is due to uncertainty …
  - in measuring distance to known obstacle.
  - in position of known obstacles.
  - in position of additional obstacles.
  - whether obstacle is missed.

3 – Constructing a Proximity Sensor model

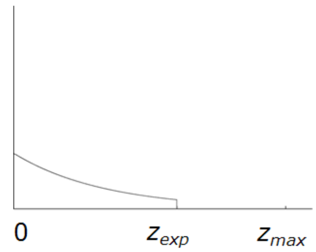
- Assume that with map we can get expected measurement z_{exp} or z^*
- Model each source of measurement individually, then sum

Measurement noise



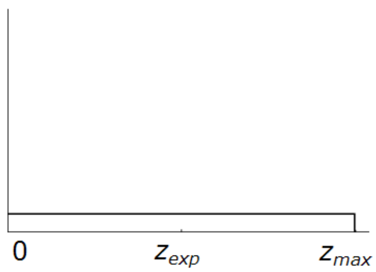
$$P_{hit}(z \mid x,m) = \eta \frac{1}{\sqrt{2\pi b}} e^{-\frac{1}{2}\frac{(z-z_{exp})^2}{b}}$$

Unexpected obstacles



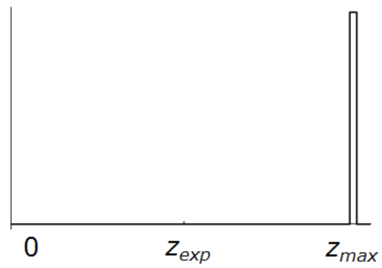
$$P_{unexp}(z \mid x,m) = \begin{cases} \eta \, \lambda \, e^{-\lambda z} & z < z_{exp} \\ 0 & otherwise \end{cases}$$

Random measurement



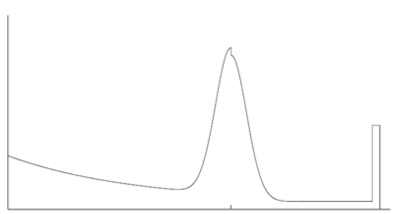
$$P_{rand}(z \mid x,m) = \eta \frac{1}{z_{max}}$$

Max range



$$P_{max}(z \mid x,m) = \eta \frac{1}{z_{small}}$$

- Resulting PDF



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

- How can we determine the alpha parameters?
  - α_{hit}, α_{unexp}, α_{max}, α_{rand}, b, and Lambda.

- We can use maximum likelihood
  - System Identification techniques?
  - Least Squares?
  - Table 6.2 from text

4 – Feature Based Measurement Models

- Consider the model z = h(x) + delta
- In this case $z^i_t = [r^i_t\ \phi^i_t\ s^i_t]^T$, where r is a range, ϕ is a bearing and s is a signature of the ith feature
- Consider the jth map feature is defined by $m^j = [mx^j\ my^j\ s^j]^T$
- Lets model this with respect to the robot pose [x y θ]

$$r^i_t = \text{sqrt}(\ (mx^j - x)^2 + (my^j - y)^2\ ) \quad + \quad \varepsilon(\sigma_r^2)$$

$$\phi^i_t = \text{atan2}(\ my^j - y,\ mx^j - x\ ) - \theta \quad + \quad \varepsilon(\sigma_\phi^2)$$

$$s^i_t = s^j \quad + \quad \varepsilon(\sigma_s^2)$$

- We can both calculate likelihood p(z|x,m)

Algorithm landmark_model_known_correspondence(z^i_t, c^i_t, x_t, m)

$j = c^i_t$
$r^{exp} = \text{sqrt}(\ (mx^j - x)^2 + (my^j - y)^2\ )$
$\phi^{exp} = \text{atan2}(\ my^j - y,\ mx^j - x\ ) - \theta$
$q = \text{prob}(r^i_t - r^{exp}, \sigma_r) * \text{prob}(\phi^i_t - \phi^{exp}, \sigma_\phi) * \text{prob}(s^i_t - s^j, \sigma_s)$
return q

- Note we could also do something like consider all bins.