

Technion – Israel Institute of Technology



HW1

Autonomous Navigation and Perception

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April 5, 2022

Question 1 – filtering and smoothing

Consider models:

$$p(x_{k+1} | x_k, a_k), p(z_k | x_k)$$

And prior:

$$p(x_0)$$

a. Recursive formulation for posterior over x_k (filtering)

$$\begin{aligned} p(x_k | a_{0:k-1}, z_{1:k}) &\stackrel{\text{bayes}}{=} \frac{p(z_k | x_k, a_{0:k-1}, z_{1:k-1}) \cdot p(x_k | a_{0:k-1}, z_{1:k-1})}{p(z_k | a_{0:k-1}, z_{1:k-1})} = \\ &\quad \{\text{denoting } \eta_k = p(z_k | a_{0:k-1}, z_{1:k-1})\} \\ &\stackrel{\text{indep.}}{=} \eta_k p(z_k | x_k) \cdot p(x_k | a_{0:k-1}, z_{1:k-1}) = \\ &\stackrel{MR}{=} \eta_k p(z_k | x_k) \int p(x_k | x_{k-1}, a_{0:k-1}, z_{1:k-1}) \cdot p(x_{k-1} | a_{0:k-1}, z_{1:k-1}) dx_{k-1} = \\ &\stackrel{\text{indep.}}{=} \eta_k \underbrace{p(z_k | x_k)}_{\text{observation model}} \underbrace{\int \underbrace{p(x_k | x_{k-1}, a_{k-1})}_{\text{motion model}} \cdot \underbrace{p(x_{k-1} | a_{0:k-1}, z_{1:k-1})}_{\text{posterior on } x_{k-1}} dx_{k-1}}_{\sim \text{weighted integration for motion to } x_k} \end{aligned}$$

b. Smoothing - recursive

We developed in the previous section:

$$p(x_{0:k} | a_{0:k-1}, z_{1:k-1}) = \eta_k p(z_k | x_k) \cdot p(x_{0:k-1} | a_{0:k-1}, z_{1:k-1})$$

Instead of marginalizing, we will apply the chain rule:

$$\begin{aligned} p(x_{0:k} | a_{0:k-1}, z_{1:k-1}) &= \eta_k p(z_k | x_k) \cdot p(x_k | a_{0:k-1}, z_{1:k-1}, x_{0:k-1}) \cdot p(x_{0:k-1} | a_{0:k-1}, z_{1:k-1}) = \\ &\stackrel{\text{indep.}}{=} \eta_k p(z_k | x_k) \cdot p(x_k | x_{k-1}, a_{k-1}) \cdot p(x_{0:k-1} | a_{0:k-2}, z_{1:k-2}) \end{aligned}$$

c. Smoothing – full solution

From the recursive formulation in the previous section, we can deduce the following:

$$p(x_{0:k} | a_{0:k-1}, z_{1:k-1}) = p(x_0) \prod_k \eta_k p(z_k | x_k) \cdot p(x_k | x_{k-1}, a_{k-1})$$

Question 2 – Occupancy grid and mapping

Given the map:

$$M = \{m_i\}, m \in \{\text{free}, \text{occ}\}$$

We denote:

$$p(m) = p(m = \text{free})$$

We also assume an inverse observation model: $p(m | z, x)$

a. Find posterior $p(m|z_{1:k}, x_{1:k})$

$$\begin{aligned}
 p(m|z_{1:k}, x_{1:k}) &\stackrel{\text{bayes}}{=} \frac{p(z_k|x_{1:k}, z_{1:k-1}, m) \cdot p(m|x_{1:k}, z_{1:k-1})}{p(z_k|x_{1:k}, z_{1:k-1})} = \\
 &\stackrel{\text{indep.}}{=} \frac{P(z_k|x_k, m) \cdot P(m|x_{1:k-1}, z_{1:k-1})}{P(z_k|x_{1:k}, z_{1:k-1})} = \\
 &\stackrel{\text{bayes}}{=} \frac{\frac{p(m|x_k, z_k) \cdot p(z_k|x_k)}{p(m|x_k)} \cdot p(m|x_{1:k-1}, z_{1:k-1})}{p(z_k|x_{1:k}, z_{1:k-1})} = \\
 &= \frac{p(m|x_k, z_k) \cdot p(z_k|x_k) \cdot p(m|x_{1:k-1}, z_{1:k-1})}{p(z_k|x_{1:k}, z_{1:k-1})P(m|x_k)} =
 \end{aligned}$$

$$\begin{aligned}
 \{\text{Assuming: } P(m|x_k) = P(m) \text{ and denoting } \eta_k &= \frac{P(z_k|x_k)}{P(z_k|x_{1:k}, z_{1:k-1})}\} \\
 &= \eta_k \frac{p(m|x_k, z_k) \cdot p(m|x_{1:k-1}, z_{1:k-1})}{p(m)}
 \end{aligned}$$

As m has a binary state:

$$p(\neg m|z_{1:k}, x_{1:k}) = \eta_k \frac{p(\neg m|x_k, z_k) \cdot p(\neg m|x_{1:k-1}, z_{1:k-1})}{p(\neg m)}$$

b. Log-odds ratio $l(m)$

$$\text{odds}(m) = \frac{p(m)}{p(\neg m)} = \frac{p(m)}{1 - p(m)}$$

$$l(m) = \log(\text{odds}(m)) = \log\left(\frac{p(m)}{1 - p(m)}\right)$$

$$\begin{aligned}
 \text{odds}(m|z_{1:k}, x_{1:k}) &= \frac{p(m|z_{1:k}, x_{1:k})}{p(\neg m|z_{1:k}, x_{1:k})} = \frac{\eta_k \frac{p(m|x_k, z_k) \cdot p(m|x_{1:k-1}, z_{1:k-1})}{p(m)}}{\eta_k \frac{p(\neg m|x_k, z_k) \cdot p(\neg m|x_{1:k-1}, z_{1:k-1})}{p(\neg m)}} = \\
 &= \frac{p(\neg m)}{p(m)} \cdot \frac{p(m|x_k, z_k)}{p(\neg m|x_k, z_k)} \cdot \frac{p(m|x_{1:k-1}, z_{1:k-1})}{p(\neg m|x_{1:k-1}, z_{1:k-1})} = \\
 &\stackrel{\text{binary state}}{=} \frac{1 - p(m)}{p(m)} \cdot \frac{p(m|x_k, z_k)}{1 - p(m|x_k, z_k)} \cdot \frac{p(m|x_{1:k-1}, z_{1:k-1})}{1 - p(m|x_{1:k-1}, z_{1:k-1})}
 \end{aligned}$$

Hence:

$$\begin{aligned}
 l_k(m|z_{1:k}, x_{1:k}) &= \log(\text{odds}(m|z_{1:k}, x_{1:k})) = \\
 &= \log\left(\frac{1 - p(m)}{p(m)} \cdot \frac{p(m|x_k, z_k)}{1 - p(m|x_k, z_k)} \cdot \frac{p(m|x_{1:k-1}, z_{1:k-1})}{1 - p(m|x_{1:k-1}, z_{1:k-1})}\right) =
 \end{aligned}$$

$$\begin{aligned}
&= \log\left(\frac{1-p(m)}{p(m)}\right) + \log\left(\frac{p(m|x_k, z_k)}{1-p(m|x_k, z_k)}\right) + \log\left(\frac{p(m|x_{1:k-1}, z_{1:k-1})}{1-p(m|x_{1:k-1}, z_{1:k-1})}\right) \\
&= \log\left(\frac{p(m|x_k, z_k)}{1-p(m|x_k, z_k)}\right) - \log\left(\frac{p(m)}{1-p(m)}\right) + l_{k-1}(m|x_{1:k-1}, z_{1:k-1})
\end{aligned}$$

c. Posterior over M_k

$$\begin{aligned}
p(M_k|z_{1:k}, x_{k:1}) &= p(\{m_i\}_{i=1}^k | z_{1:k}, x_{1:k}) = \\
&\quad \{\text{Assuming independence between cells } \{m_i\}\} \\
&= \prod_i p(m_k^i | z_{1:k}, x_{1:k}) = \\
&\quad \{\text{Using section a}\} \\
&= \prod_i \eta_k \frac{p(m_k^i | x_k, z_k) \cdot p(m_k^i | x_{1:k-1}, z_{1:k-1})}{p(m_k^i)}
\end{aligned}$$

Hands On

We successfully installed *Julia* with the required packages to run and debug the attached code, producing the following image:

