Probabilistic Estimation using Bayes Filters

MECH650 EECE 698 AMR Course

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1 Introduction and Problem Setup

In this exercise, you will develop a complete Bayesian filter for a simple mobile robot localization problem. You will learn to construct all components of the belief system and implement the recursive Bayes filter algorithm analytically.

1.1 Robot and Environment Description

Consider a simple mobile robot operating in a **1-dimensional corridor** of length 10 meters. The corridor is divided into **5 discrete cells**, each 2 meters wide, numbered from 0 to 4.

- **Robot State**: $x \in \{0, 1, 2, 3, 4\}$ (cell number)
- Robot Motion: Can move left (-1), stay (0), or right (+1) with some uncertainty
- Robot Sensor: Detects nearby walls with some noise
- Environment: Walls at both ends (cells 0 and 4 are near walls)

Cell 0	Cell 1	Cell 2	Cell 3	Cell 4
WALL				WALL
0-2m	2-4m	4-6m	6-8m	8-10m

Figure 1: 1D corridor with 5 discrete cells. Walls are present at cells 0 and 4.

2 Mathematical Framework

2.1 State Space and Notation

Define the following variables:

- \bullet $x_t =$
- \bullet $u_t = \underline{\hspace{1cm}}$
- ullet $z_t =$
- \bullet bel $(x_t) =$

2.2 Bayes Filter Components

The recursive Bayes filter requires three key components: the motion model, sensor model and prior belief, write the expresion and definition of each:

1. Motion Model: $p(___) = ___$

2. Sensor Model: $p(____) = ____$

3. **Prior Belief**: bel $(x_{t-1}) =$ ______

3 Task 1: Derive the Motion Model

The robot receives a control command $u_t \in \{-1, 0, +1\}$ but execution is imperfect:

• With probability 0.8: Robot moves as commanded

• With probability 0.1: Robot moves one step less than commanded

• With probability 0.1: Robot moves one step more than commanded

Example: For robot at cell 2 with command $u_t = +1$:

• $x_t =$ ____with probability ____(moves to cell 2)

• $x_t = \underline{\hspace{1cm}}$ with probability $\underline{\hspace{1cm}}$ (moves to cell 3)

• $x_t = \underline{\hspace{1cm}}$ with probability $\underline{\hspace{1cm}}$ (moves to cell 4)

Complete the motion model for $u_t = +1$ (robot cannot move outside cells 0-4):

$p(x_t x_{t-1},u_t=+1)$	$x_t = 0$	$x_t = 1$	$x_t = 2$	$x_t = 3$	$x_t = 4$
$x_{t-1} = 0$				0	0
$x_{t-1} = 1$					0
$x_{t-1} = 2$	0				
$x_{t-1} = 3$	0	0			
$x_{t-1} = 4$	0	0	0		

4 Task 2: Derive the Sensor Model

The robot has a **wall detector** with output $z_t \in \{0, 1\}$:

• In cells 0 and 4 (near walls): $P(z_t = 1 | x_t \in \{0, 4\}) = 0.9$

• In cells 1, 2, 3 (away from walls): $P(z_t = 1 | x_t \in \{1, 2, 3\}) = 0.2$

Complete the sensor model:

State	$p(z_t = 1 x_t)$	$p(z_t = 0 x_t)$
$x_t = 0$		
$x_t = 1$		
$x_t = 2$		
$x_t = 3$		
$x_t = 4$		

5 Task 3: Initialize Prior Belief

Assume the robot starts with uniform uncertainty about its location.

$$bel(x_0) = \begin{cases} \frac{1}{5} & \text{for } x_0 \in \{0, 1, 2, 3, 4\} \\ 0 & \text{otherwise} \end{cases}$$

Initial belief: $bel(x_0) = [\underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}]$ Verification: $\sum_{x_0} bel(x_0) = \underline{\hspace{1cm}}$

6 Task 4: Implement the Bayes Filter Algorithm

6.1 Bayes Filter Steps

The recursive Bayes filter consists of two steps:

Prediction Step (Motion Update):

$$\overline{\operatorname{bel}}(x_t) = \sum_{x_{t-1}} p(x_t | x_{t-1}, u_t) \cdot \operatorname{bel}(x_{t-1})$$

Update Step (Measurement Update):

$$bel(x_t) = \eta \cdot p(z_t|x_t) \cdot \overline{bel}(x_t)$$

where η is the normalization constant: $\eta = \frac{1}{\sum_{x_t} p(z_t|x_t) \cdot \overline{\text{bel}}(x_t)}$

6.2 Step-by-Step Example

Given:

- Initial belief: $bel(x_0)$
- Control input: $u_1 = +1$ (move right)
- Sensor measurement: $z_1 = 1$ (wall detected)

Step 1 - Prediction: Calculate $\overline{\mathrm{bel}}(x_1)$

For $\overline{\mathrm{bel}}(x_1=0)$:

$$\overline{\text{bel}}(x_1 = 0) = \sum_{x_0} p(x_1 = 0 | x_0, u_1 = +1) \cdot \text{bel}(x_0)$$

From the motion model table:

$$\overline{\text{bel}}(x_1 = 0) = p(x_1 = 0 | x_0 = 0, u_1 = +1) \cdot \text{bel}(x_0 = 0)$$
(1)

$$+p(x_1=0|x_0=1,u_1=+1)\cdot bel(x_0=1)$$
(2)

$$+\dots$$
 (3)

$$= \underline{} \cdot 0.2 + \underline{} \cdot 0.2 + 0 \cdot 0.2 + 0 \cdot 0.2 + 0 \cdot 0.2$$
 (4)

$$= (5)$$

Complete the remaining predictions:

•
$$\overline{\text{bel}}(x_1 = 1) = \underline{\hspace{1cm}}$$

$$\bullet \ \overline{\mathrm{bel}}(x_1=2) = \underline{\hspace{1cm}}$$

• $\overline{\operatorname{bel}(x_1=3)} = -$ • $\overline{\operatorname{bel}(x_1=4)} = -$ Step 2 · Update: Calculate bel (x_1) using $z_1=1$ For each state, multiply predicted belief by sensor likelihood: • $\operatorname{bel}(x_1=0) \propto p(z_1=1 x_1=0) \cdot \overline{\operatorname{bel}}(x_1=0) = -$ • $\operatorname{bel}(x_1=1) \propto p(z_1=1 x_1=1) \cdot \overline{\operatorname{bel}}(x_1=1) = -$ • $\operatorname{bel}(x_1=2) \propto -$ • $\operatorname{bel}(x_1=3) \propto -$ • $\operatorname{bel}(x_1=3) \propto -$ • $\operatorname{bel}(x_1=4) \propto -$ Step 3 · Normalization: Sum of unnormalized beliefs: $\sum_{x_1} \operatorname{bel}(x_1) = -$ Normalization constant: $\eta = \frac{1}{\operatorname{sum}} = -$ Final normalized belief: $\operatorname{bel}(x_1) = [-, -, -, -, -, -, -, -, -, -, -, -, -, -$	\bullet $\overline{\text{bol}}(x=3)$
Step 2 - Update: Calculate bel (x_1) using $z_1 = 1$ For each state, multiply predicted belief by sensor likelihood: • bel $(x_1 = 0) \propto p(z_1 = 1 x_1 = 0) \cdot \overline{\text{bel}}(x_1 = 0) = \underline{\hspace{1cm}} = \underline{\hspace{1cm}} = \underline{\hspace{1cm}}$ • bel $(x_1 = 1) \propto p(z_1 = 1 x_1 = 1) \cdot \overline{\text{bel}}(x_1 = 1) = \underline{\hspace{1cm}} = \underline{\hspace{1cm}} = \underline{\hspace{1cm}}$ • bel $(x_1 = 2) \propto \underline{\hspace{1cm}} = $	$\bullet \overline{\text{bel}}(x_1 = 3) = \underline{\hspace{2cm}}$
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• bel $(x_1 = 1) \propto p(z_1 = 1 x_1 = 1) \cdot \overline{\text{bel}}(x_1 = 1) = \underline{\hspace{1cm}} = \underline{\hspace{1cm}}$ • bel $(x_1 = 2) \propto \underline{\hspace{1cm}}$ • bel $(x_1 = 3) \propto \underline{\hspace{1cm}}$ • bel $(x_1 = 3) \propto \underline{\hspace{1cm}}$ • bel $(x_1 = 4) \propto \underline{\hspace{1cm}}$ Step 3 - Normalization: Sum of unnormalized beliefs: $\sum_{x_1} \text{bel}(x_1) = \underline{\hspace{1cm}}$ Normalization constant: $\eta = \frac{1}{\text{sum}} = \underline{\hspace{1cm}}$ Final normalized belief: bel $(x_1) = [\underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}, \underline{\hspace{1cm}}]$ 7 Task 5: Analysis and Key Insights 1. Recursive Nature: How does the Bayes filter use only the previous belief rather than the entire history of measurements? Answer: 2. Effect of Motion vs. Measurement: • How did the prediction step affect uncertainty? • How did the update step affect uncertainty? 3. Practical Applications: Name two robotics applications where Bayesian localization would be useful: 1	, ,
• bel $(x_1 = 2) \propto$	• bel $(x_1 = 0) \propto p(z_1 = 1 x_1 = 0) \cdot \overline{\text{bel}}(x_1 = 0) = \underline{\qquad} \cdot \underline{\qquad} = \underline{\qquad}$
• bel $(x_1 = 3) \propto$	• bel $(x_1 = 1) \propto p(z_1 = 1 x_1 = 1) \cdot \overline{\text{bel}}(x_1 = 1) = \underline{\qquad}$
• bel $(x_1 = 4) \propto$	• bel $(x_1=2) \propto \underline{\hspace{1cm}}$
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