

Exercise 1:

Given,

$$x \sim N(\bar{x}, P)$$

$$H = \begin{pmatrix} 0 \\ 1 \end{pmatrix}^T = [0 \ 1]$$

$$\text{and } H^T = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\epsilon \sim N(0, R)$$

From Example 5.10 we know that if $x \sim N(\bar{x}, P)$ and $h(x) = Hx$, then the posterior distribution of x given an observed $y = y_{\text{obs}}$ is also gaussian with mean.

$$\begin{aligned} \bar{x}^a &= \bar{x} - P^a H^T R^{-1} (H\bar{x} - y_{\text{obs}}) \\ &= \bar{x} - P H^T \underbrace{(H P H^T + R)^{-1}}_{(a)} (H\bar{x} - y_{\text{obs}}) \end{aligned}$$

$$H = [0 \ 1] \text{ and } H^T = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Part (a) will be,

$$\begin{aligned} &P \begin{bmatrix} 0 \\ 1 \end{bmatrix} \left([0 \ 1] P \begin{bmatrix} 0 \\ 1 \end{bmatrix} + R \right)^{-1} ([0 \ 1] \bar{x} - y_{\text{obs}}) \\ &= \begin{bmatrix} 0 \\ P \end{bmatrix} (P + R)^{-1} ([0 \ \bar{x}] - y_{\text{obs}}) \\ &= \begin{bmatrix} 0 \\ P \end{bmatrix} \frac{1}{P+R} ([0 \ \bar{x}] - y_{\text{obs}}) \end{aligned}$$

Given that R tends to ∞ then $\frac{1}{P+R}$ will become

0 So part (a) will be 0.

$$\therefore \bar{x}^a = \bar{x}$$

Example 5.11 we can know that,

$$\bar{x}_j^a = \bar{x}_j - P_j H^T (H P_j H^T + R)^{-1} (H \bar{x}_j - y_{obs})$$

we already proof the second part is 0

so, for 1'st component $\bar{x}_1^a = \bar{x}_1$

and for 2'nd component $\bar{x}_2^a = \bar{x}_2$

Now, For covariance matrix,

$$\begin{aligned} P^a &= (P^{-1} + H^T R^{-1} H)^{-1} \\ &= P - P H^T (H P H^T + R)^{-1} H P \quad - [\text{Example 5.10}] \end{aligned}$$

$$H = \begin{bmatrix} 0 & 1 \end{bmatrix} \text{ and } H^T = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{aligned} P^a &= P - P \begin{bmatrix} 0 \\ 1 \end{bmatrix} \left(\begin{bmatrix} 0 & 1 \end{bmatrix} P \begin{bmatrix} 0 \\ 1 \end{bmatrix} + R \right)^{-1} \begin{bmatrix} 0 \\ 1 \end{bmatrix} P \\ &= P - \begin{bmatrix} 0 \\ P \end{bmatrix} (P + R)^{-1} \begin{bmatrix} 0 & P \end{bmatrix} \\ &= P - \begin{bmatrix} 0 \\ P \end{bmatrix} \frac{1}{P+R} \begin{bmatrix} 0 & R \end{bmatrix} \end{aligned}$$

Given that R tends to ∞ then $\frac{1}{P+R}$ will become 0

$$\therefore P^a = P$$

From Example 5.11 we know.

$$P_j^a = P_j - P_j H^T (H P_j H^T + R)^{-1} H P_j$$

The second part is 0,

so, for 1'st component $P_1^a = P_1$

and 2'nd component $P_2^a = P_2$

If we take a column vector $x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$

then $\bar{x}_1 = \begin{pmatrix} \bar{x}_1 x_1 \\ \bar{x}_1 x_2 \end{pmatrix}$ and $\bar{x}_2 = \begin{pmatrix} \bar{x}_2 x_1 \\ \bar{x}_2 x_2 \end{pmatrix}$

and the covariance matrix,

$$P_1^a = P_2^a = \begin{pmatrix} V[x_1] & \text{cov}(x_1, x_2) \\ \text{cov}(x_1, x_2) & V[x_2] \end{pmatrix}$$

$$\sigma_{\text{cov}} = \begin{pmatrix} \sigma_{x_1}^2 & \text{cov}(x_1, x_2) \\ \text{cov}(x_1, x_2) & \sigma_{x_2}^2 \end{pmatrix}$$