

13. JUL. 2016 < Model Based Estimation method

Bonus problem 10 & 11 >

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· BP 10. Luenberger observer

$$\begin{aligned} e[i+1] &= x[i+1] - \hat{x}[i+1] \\ &= Ax[i] + Bu[i] - \{ A\hat{x}[i] + L(y[i] - \hat{y}[i]) + Bu[i] \} \\ &= Ax[i] - A\hat{x}[i] - L(Cx[i] + Du[i] - (C\hat{x}[i] + Du[i])) \\ &= (A - LC)(x[i] - \hat{x}[i]) \\ &= \underline{(A - LC) e[i]} \end{aligned}$$

All eigenvalues of  $(A - LC)$  must have negative real parts to serve the purpose of a state estimator.

i.e.  $e(t) \rightarrow 0$  for  $t \rightarrow \infty$

$\rightarrow \hat{x}(t) \rightarrow x(t)$  for  $t \rightarrow \infty$

# BP. 11. Kalman Gain Derivation

1.  $P^+[k]$ , where  $P^+[k] = E[(x[k] - \hat{x}^+[k])(x[k] - \hat{x}^+[k])^T]$

$$\begin{aligned}\hat{x}^+[k] &= \hat{x}[k] + K[k](\hat{y}[k] - C_d \hat{x}[k] - D_d u[k]) \\ &= \hat{x}[k] + K[k](C_d x[k] + D_d u[k] + v[k] - C_d \hat{x}[k] - D_d u[k]) \\ &= \hat{x}[k] + K[k](C_d(x[k] - \hat{x}[k]) + v[k])\end{aligned}$$

$$P^+[k] = E[(x[k] - \hat{x}^+[k])(x[k] - \hat{x}^+[k])^T], \quad - \textcircled{1}$$

so we need  $(x[k] - \hat{x}^+[k])$ .

$$\begin{aligned}x[k] - \hat{x}^+[k] &= x[k] - \hat{x}[k] - K[k](C_d(x[k] - \hat{x}[k]) + v[k]) \\ &= I \cdot (x[k] - \hat{x}[k]) - K[k](C_d(x[k] - \hat{x}[k]) - K[k]v[k]) \\ &= (I - K[k]C_d)(x[k] - \hat{x}[k]) - K[k]v[k] \quad - \textcircled{2}\end{aligned}$$

now we plug in  $\textcircled{2}$  to  $\textcircled{1}$ ,

$$\begin{aligned}P^+[k] &= E[(I - K[k]C_d)(x[k] - \hat{x}[k]) - K[k]v[k])(I - K[k]C_d)(x[k] - \hat{x}[k]) - K[k]v[k])^T] \\ &= E[(I - K[k]C_d)(x[k] - \hat{x}[k])(x[k] - \hat{x}[k])^T(I - K[k]C_d)^T] \\ &= (I - K[k]C_d) E[(x[k] - \hat{x}[k])(x[k] - \hat{x}[k])^T] (I - K[k]C_d)^T \\ &\quad + K[k]R_k K[k]^T - K[k]v[k]v[k]^T K[k]^T \\ &= (I - K[k]C_d) P[k] (I - K[k]C_d)^T + K[k]R_k K[k]^T\end{aligned}$$



2. Kalman Gain matrix ( $K[k]$ ) which minimizes trace ( $P^+[k]$ )

$J = \text{trace}(P^+[k])$ , Necessary optimality conditions for

$$J \Leftrightarrow \frac{\partial J}{\partial K} = 0$$

$$\frac{\partial}{\partial K} P^+[k] = \frac{\partial}{\partial K} [(I - K[k]C_d) P^-[k] (I - C_d^T K[k]^T) + K[k] Q_k K[k]^T]$$

$$= (I - K[k]C_d) P^-[k] (-C_d^T) - (I - K[k]C_d) P^-[k]^T C_d^T + 2K[k] Q_k + K[k] Q_k^T$$

$$= 2 \{ (I - K[k]C_d) P^-[k] (-C_d^T) + K[k]^* Q_k \} = 0$$

$$\Leftrightarrow K[k] (-C_d P^-[k] (-C_d^T) + P^-[k] C_d^T) = 0$$

$$\Leftrightarrow K[k] = P^-[k] C_d^T (C_d P^-[k] C_d^T + Q_k)^{-1}$$

3.  $P^-[k+1] = E \{ (x[k+1] - \hat{x}[k+1]) (x[k+1] - \hat{x}[k+1])^T \}$

$$x[k+1] = A_d x[k] + B_d u[k] + w[k]$$

$$\hat{x}[k+1] = A_d \hat{x}[k] + B_d u[k]$$

$$x[k+1] - \hat{x}[k+1] = A_d (x[k] - \hat{x}[k]) + w[k]$$

$$P^-[k+1] = E \{ A_d (x[k] - \hat{x}[k]) (x[k] - \hat{x}[k])^T A_d^T +$$

$$+ A_d (x[k] - \hat{x}[k]) w[k]^T + w[k] (x[k] - \hat{x}[k])^T A_d^T + w[k] w[k]^T \}$$

$$= A_d E \{ (x[k] - \hat{x}[k]) (x[k] - \hat{x}[k])^T \} A_d^T + E \{ w[k] w[k]^T \}$$

$$= A_d P^+[k] A_d^T + R[k]$$