

Kalman filter

Consider

$$x(t+1) = A(t)x(t) + B(t)u(t)$$

$$y(t) = C(t)x(t) + D(t)w(t)$$

where

$$E\{u(t)u^T(s)\} = Q\delta(t-s), \quad E\{w(t)w^T(s)\} = R\delta(t-s)$$

$$E\{u(t)w^T(s)\} = 0$$

Denote $H_t(y) = \text{span}\{y_1(0), \dots, y_m(0), \dots, y_1(t), \dots, y_m(t)\}$

$$\hat{x}(t) = E^{H_{t-1}(y)} x(t)$$

$$\hat{x}_y(t) = E^{H_t(y)} x(t)$$

$$\tilde{x}(t) = x(t) - \hat{x}(t)$$

$$P(t) = E\{\tilde{x}(t)\tilde{x}(t)^T\}$$

We have derived: (by orthogonal projection)

Measurement update: $\hat{x}_y(t) = \hat{x}(t) + K(y(t) - C(t)\hat{x}(t))$

where $K = P(t)C^T(t)(C(t)P(t)C^T(t) + D(t)R D^T(t))^{-1}$

— Kalman gain

Time update:

$$\hat{x}(t+1) = A \hat{x}_t(t) \quad (\hat{x}(t+1) = E^{-H_t(y)} x(t+1))$$

$$\Rightarrow \hat{x}(t+1) = A(t) \hat{x}(t) + AK(y(t) - C(t) \hat{x}(t))$$

$$\text{Now let } P_t(t) = E \{ (x(t) - \hat{x}_t(t)) (x(t) - \hat{x}_t(t))^T \}$$

$$\Rightarrow P_t(t) = P(t) - P(t) C^T (C P(t) C^T + D R D^T)^{-1} C P(t)$$

$$\text{Denote } P(t+1) = E \{ (x(t+1) - \hat{x}(t+1)) (x(t+1) - \hat{x}(t+1))^T \}$$

$$\tilde{x}(t+1) = x(t+1) - \hat{x}(t+1)$$

\Rightarrow

$$\tilde{x}(t+1) = A \tilde{x}(t) - AKC \tilde{x}(t) - AKDw + Bv$$

$$\left\{ \begin{array}{l} P(t+1) = (A - AKC) P(t) (A - AKC)^T + \\ \quad AKD R D^T K^T A^T + B Q B^T \\ P(0) = P_0 \end{array} \right.$$

Since our measurement starts at $t=0$

$$\hat{x}(0) = E^{-H_{-1}(y)} x(0) = 0.$$

$$\Rightarrow \underline{P_0 = E \{ x(0) x(0)^T \}}$$

Kalman filter for continuous time systems

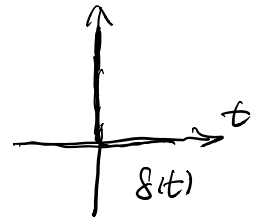
Consider

$$\begin{aligned}\dot{x}(t) &= A(t)x(t) + B(t)v(t), & x \in \mathbb{R}^n \\ y(t) &= C(t)x(t) + D(t)w(t) & y \in \mathbb{R}^m \\ x(0) &= x_0\end{aligned}$$

Where x_0 , $v(t)$, and $w(t)$ are uncorrelated.

$$E \left\{ \begin{bmatrix} v(t) \\ w(t) \end{bmatrix} \begin{bmatrix} v(s) \\ w(s) \end{bmatrix}^T \right\} = \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \delta(t-s)$$

where $\int_{-t_0}^{\infty} f(t) \delta(t) dt = f(0)$



Bottom line: find the "best" estimator

$\hat{x}(t)$ for $x(t)$ based on $y(t)$.

Recall
$$\begin{aligned}\dot{\hat{x}}(t) &= A\hat{x} + L(y(t) - C\hat{x}) \\ &= (A - LC)\hat{x}(t) + Ly(t)\end{aligned}$$

an observer can be viewed as a linear system with $y(t)$ as the input.

$$\Rightarrow \int_0^t G(t,s) y(s) ds$$

Duality between control and observation

Define

$$\dot{z} = -A^T z + C^T u$$

$$z(T) = a$$

$$\frac{d}{dt} (z^T(t) x(t)) = z^T B u(t) - u^T D w(t) + u^T y$$

$$a^T x(T) - z(0)^T x(0) = \int_0^T (\quad) dt$$

$$a^T x(T) - \int_0^T u^T y dt = z(0)^T x(0) + \int_0^T (z^T B u - u^T D w) dt$$

$$\begin{aligned} E \left\{ \left(a^T x(T) - \int_0^T u^T y dt \right)^2 \right\} \\ = z(0)^T P_0 z(0) + \int_0^T (z^T \tilde{Q} z + u^T \tilde{R} u) dt \end{aligned}$$

Where, $\tilde{Q} = B Q B^T$, $\tilde{R} = D R D^T$

\Rightarrow Find u s.t.

$$\left\{ \begin{array}{l} \min z(0)^T P_0 z(0) + \int_0^T (z^T \tilde{Q} z + u^T \tilde{R} u) dt \\ \dot{z} = -A^T z + C^T u \\ z(T) = a \end{array} \right.$$

Recall that for

$$\min \quad x^T(T) S x(T) + \int_0^T (x^T Q x + u^T R u) dt$$

$$\dot{x} = Ax + Bu$$

$$x(0) = x_0$$

$$u^* = -R^{-1} B^T P(t) x$$

$$\text{where} \quad \dot{P} = -A^T P - PA + PBR^{-1}B^T P - Q$$

$$P(T) = S$$

we can let $\bar{t} = T - t$

$$\Rightarrow \quad u^* = \tilde{R}^{-1} C^T P(\bar{t}) z(\bar{t})$$
$$= (P C^T \tilde{R}^{-1})^T z(\bar{t}) = K^T z$$

$$K = P(\bar{t}) C^T \tilde{R}^{-1}$$

$$\begin{cases} \dot{P} = AP + PA^T - PC^T \tilde{R}^{-1} C P + \tilde{Q} \\ P(0) = P_0 \end{cases}$$

we plugin u^* :

$$\dot{z} = -A^T z + C^T (P C^T \tilde{R}^{-1})^T z$$

$$= -(A - P C^T \tilde{R}^{-1} C)^T z$$

$$= -(A - KC)^T z$$

$$z(T) = u$$

Recall if $\underline{\Phi}(t,s)$ is the
state transition matrix for $A(t)$,
then $\underline{\Phi}^T(s,t)$ is the state transition
matrix for $-A^T(t)$

$$\left(\frac{\partial \underline{\Phi}(t,s)}{\partial s} = -\underline{\Phi}(t,s)A(s) \right)$$

Now let $\underline{\Phi}(t,s)$ be the state transition
matrix for $A(t) - K(t)C(t)$

$$z(t) = \underline{\Phi}^T(0,t) z(0)$$

$$\Rightarrow z(T) = \underline{\Phi}^T(0,T) z(0)$$

$$z(0) = (\underline{\Phi}^T(0,T))^{-1} z(T) = \underline{\Phi}^T(T,0) z(T)$$

$$\Rightarrow z(t) = (\underline{\Phi}^T(T,0) \underline{\Phi}^T(0,t))^{-1} z(T)$$

$$= \underline{\Phi}^T(T,t) z(T)$$

$$= \underline{\Phi}^T(T,t) a$$

$$\Rightarrow \boxed{w^* = K^T(t) \underline{\Phi}^T(T,t) a}$$

(Some writing got erased accidentally)

$\Rightarrow \int_0^t \Phi(t,s) K(s) y(s) ds$ gives
the best estimator.

$$\begin{aligned}\Rightarrow \dot{\hat{x}}(t) &= (A(t) - K(t)C(t))\hat{x}(t) + K(t)y(t) \\ &= A(t)\hat{x}(t) + K(t)(y(t) - C(t)\hat{x}(t)) \\ \hat{x}(0) &= 0\end{aligned}$$