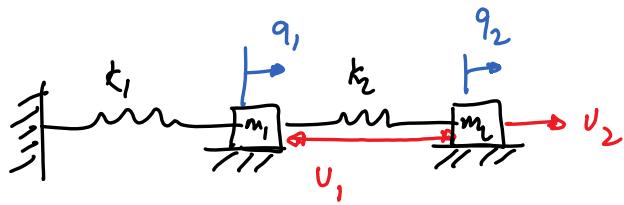


State Estimation



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

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\left(\frac{k_1}{m_1} + \frac{k_2}{m_1}\right) & \frac{k_2}{m_1} & 0 & 0 \\ \frac{k_2}{m_2} & -\frac{k_2}{m_2} & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \\ + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ -\frac{1}{m_1} & 0 \\ \frac{1}{m_2} & \frac{1}{m_2} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$x_1 = q_1 ; x_2 = q_2 ; x_3 = \dot{q}_1 ; x_4 = \dot{q}_2$$

$$u = -kx \quad \left\{ \text{Pole placement / LQR} \right.$$

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = -k \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix} \begin{array}{l} \text{to compute } k \\ \downarrow x_1 \end{array}$$

We need all 4 states for control.

This means we need 4 sensors (2 - position, 2 - velocity).

Since we position is related to velocity, we can get away with only 2 sensors and estimate the remaining 2. This will make the design cheaper.

y - sensor measurements

We will assume we have velocity sensors installed.

$$y = Cx$$
$$y = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \underline{x_3} \\ \underline{x_4} \end{bmatrix} = \begin{pmatrix} x_3 \\ x_4 \end{pmatrix}$$

$2 \times 1 \qquad \qquad \qquad 2 \times 4 \qquad \qquad \qquad \qquad \qquad 4 \times 1$

We want to estimate \hat{x}_1, \hat{x}_2 from measurements of \hat{x}_3, \hat{x}_4

Estimated state $\hat{x} = (\hat{x}_1, \hat{x}_2, \hat{x}_3, \hat{x}_4)$

$$\dot{x} = Ax + Bu \quad (\text{True})$$

$$\dot{\hat{x}} = A\hat{x} + Bu \quad (\text{Estimate})$$

$$e = x - \hat{x}$$

$$\begin{aligned}\dot{e} &= \dot{x} - \dot{\hat{x}} = Ax + Bu - A\hat{x} - Bu \\ &= A(x - \hat{x}) \\ &= Ae\end{aligned}$$

$$\dot{e} = Ae$$

This error depends on A (system dynamics)

If A is unstable e will also be unstable.

Luenberger Observer (Deterministic)

Consider the following estimator

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y})$$

error in measured state & estimate state
user-defined gain

$$\dot{\hat{x}} = A\hat{x} + Bu + L(cx - c\hat{x})$$

$$\dot{\hat{x}} = LCx + (A - LC)\hat{x} + Bu$$

$$e = x - \hat{x}$$

$$\dot{e} = \dot{x} - \dot{\hat{x}} = \underbrace{Ax + Bu}_{\substack{\uparrow \\ \{LCx + (A - LC)\hat{x} + Bu\}}} - \underbrace{(A - LC)x - (A - LC)\hat{x}}$$

$$\dot{e} = (A - LC)(x - \hat{x})$$

$$\Rightarrow \dot{e} = (A - LC)e$$

$$\dot{x} = (A - LC)x$$

We will choose L to place the eigenvalues of $A - LC$ far away on the -ive plane

Observability

A linear system is observable if and only if any initial state $x(0)$ can be reconstructed from the output $y(t)$ within a finite time $(t - \epsilon)$

$$Ob = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix}$$

observability matrix

rank (Ob) = n then the system is observable
 $< n$ then the system is NOT observable

import control

setup A, C

$Ob = \text{control. obsv}(A, C)$

`np.linalg.matrix_rank (A)`

Controllability / Observability Dual

① - $C_0 = [B, AB, \dots, A^{n-1}B]$

$$Ob = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{bmatrix}$$

$$Ob^T = [C^T \ (CA)^T \ ((CA^2))^T \ \dots \ (A^{n-1})^T]$$

② - $Ob^T = [C^T \ A^T C^T \ (A^2)^T C^T \ \dots \ (A^{n-1})^T C^T]$

$$\left. \begin{array}{l} C_0 \cong Ob^T \\ B = C^T \\ A = A^T \\ \uparrow \\ C_0 \end{array} \right\} \rightarrow Ob^T = \text{control. ctrl}(A^T, C^T)$$

$$\rightarrow C_0 = \text{control. ctrl}(A, B)$$

$$\textcircled{3} \quad \dot{x} = (A - BK)x \Rightarrow k = \text{place}(A, B, P)$$

$$\dot{e} = (A - LC)e$$

$$\hookrightarrow \dot{e}^T = (A - LC)^T c^T$$

$$\textcircled{4} \quad \dot{e}^T = (A^T - C^T L^T) e^T$$

User
Chosen

$$\begin{array}{lcl} x \leftrightarrow e & & \\ A \leftrightarrow A^T & & \left. \begin{array}{l} \\ \\ \end{array} \right\}^T = \text{place}(A^T, C^T, P) \\ B \leftrightarrow C^T \\ K \leftrightarrow L^T \end{array}$$

② Kalman Filter (Linear Quadratic Estimator)

[Stochastic system]

$$\dot{x} = Ax + Bu + Gw \quad \begin{matrix} \text{process noise} \\ \text{---} \end{matrix}$$

$$y = Cx + Du + v \quad \begin{matrix} \text{---} \\ \text{sensor noise} \end{matrix}$$

$$\left. \begin{array}{l} E(ww^T) = Q_e \\ E(vv^T) = R_e \\ E(wv^T) = N_e \end{array} \right\} \text{stochastic correlation}$$

Estimate \hat{x}

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + Bu + L(y - \hat{y}) \\ &= A\hat{x} + Bu + L(y - C\hat{x} - Du) \end{aligned}$$

Error dynamics

$$e = x - \hat{x}$$

$$\dot{e} = \dot{x} - \dot{\hat{x}}$$

$$\dot{e} = (A \dot{x} + Bu + Gw) - \underbrace{[A\hat{x} + Bu + L(y - (\hat{x} - Du))]}_{Cx + Du + v}$$

$$\dot{e} = \cancel{Ax} + \cancel{Bu} + Gw - \cancel{A\hat{x}} - \cancel{Bu} \dots$$

$$- \cancel{L} \left(\cancel{Cx} + \cancel{Du} + v - \cancel{C\hat{x}} - \cancel{Du} \right)$$

$$\dot{e} = (A - LC)e + Gw - Lv$$

↑ affected ↑ process noise ← sensor noise

To compute L we min $J = \lim_{T \rightarrow 0} \frac{1}{T} \int_0^T e^T e$

$$AP + PA^T - (PC^T + GN_e) R_e^{-1} (C P + N^T G) + G Q_e G^T = 0$$

Riccati equation

✓ $L, P, E = \text{control. lqe } (A, G, C, Q_e, R_e, N_e)$

stochasticity

Stochasticity

Linear Quadratic Gaussian (LQG)

