

# Feedback control and state estimation

Master Lab in Autonomous driving - Motion planning and control

Paolo Falcone

Dipartimento di Ingegneria "Enzo Ferrari"

Università di Modena e Reggio Emilia



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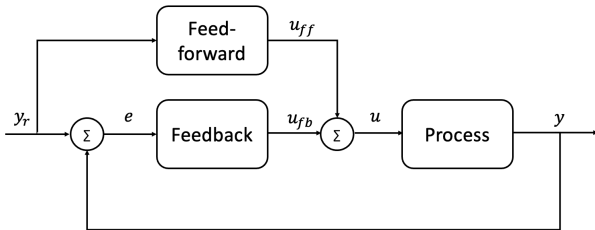
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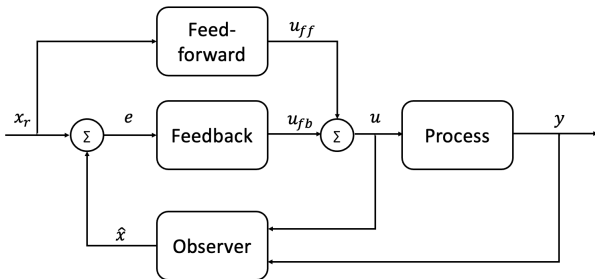
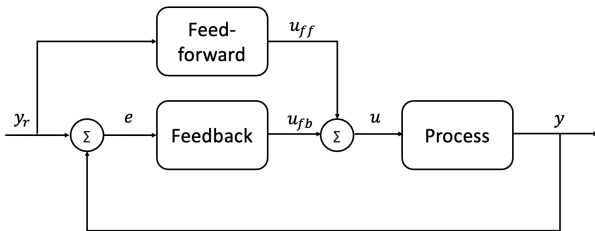
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- State estimation. The Kalman filter
- Integral action

# A general control structure



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How do we design  $K$ ?

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$K$  is to be designed such that the roots of  $p(s)$  are placed as desired.

# Pole placement. Example

Consider the double integrator

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$K_r = k_1$  leads to unitary steady state gain. That is,  $y(t) = r, t \rightarrow \infty$ .

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The feedback gain is given by

$$K = [p_1 - a_1 \quad p_2 - a_2 \quad \dots \quad p_n - a_n] \tilde{W}_r W_r^{-1},$$
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with

$$W_r = [B \quad AB \quad A^2 B \quad \dots \quad A^{n-1} B],$$
$$\tilde{W}_r = \begin{bmatrix} 1 & a_1 & a_2 & \dots & a_{n-1} \\ 0 & 1 & a_1 & \dots & a_{n-1} \\ \vdots & & & & \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix}^{-1}$$

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**Step 3.** Calculate the characteristic polynomials and equate the coefficients of equal powers of  $s$  to the desired polynomials

$$p(s) = s^n + p_1s_{n-1} + \dots + p_{n-1}s + p_n$$

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The *objective* or *criterion* or *cost function*  $V_N$  is given by

$$\begin{aligned} V_N(x(0), u(0:N-1)) &= \sum_{i=0}^{N-1} (x^\top(i)Qx(i) + u^\top(i)Ru(i)) + x^\top(N)P_fx(N) \\ &= \sum_{i=0}^{N-1} l(x(i), u(i)) + l_f(x(N)) \end{aligned} \quad (2)$$

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Remark 2: The first term  $x^\top(0)Qx(0)$  in the objective is really redundant but is kept for notational convenience.

# Batch solution

Repeated use of  $x^+ = Ax + Bu$  gives

$$\begin{bmatrix} x(1) \\ x(2) \\ \vdots \\ x(N) \end{bmatrix} = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^N \end{bmatrix} x(0) + \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ A^{N-1}B & A^{N-2}B & \cdots & B \end{bmatrix} \begin{bmatrix} u(0) \\ u(1) \\ \vdots \\ u(N-1) \end{bmatrix} \quad (3)$$



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or, with a more compact notation,

$$x = \Omega x(0) + \Gamma u \quad (4)$$

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The LQ criterion (2) can now be written

$$\begin{aligned} V_N(x(0), u) &= x^\top(0) Q x(0) + x^\top \bar{Q} x + u^\top \bar{R} u \\ &= x^\top(0) Q x(0) + (\Omega x(0) + \Gamma u)^\top \bar{Q} (\Omega x(0) + \Gamma u) + u^\top \bar{R} u \\ &= u^\top (\Gamma^\top \bar{Q} \Gamma + \bar{R}) u + 2x^\top(0) \Omega^\top \bar{Q} \Gamma u + x^\top(0) (Q + \Omega^\top \bar{Q} \Omega) x(0) \end{aligned} \quad (5)$$

where  $\bar{Q} = \text{diag}(Q, \dots, Q, P_f)$  and  $\bar{R} = \text{diag}(R, \dots, R)$ .

# Dynamic programming solution to the LQ problem

Sequence of optimal control laws (*control policy*):

$$u^0(k; x) = K(k)x, \quad k = 0, \dots, N-1$$

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Riccati equation:

$$P(k-1) = Q + A^\top P(k)A - A^\top P(k)B(R + B^\top P(k)B)^{-1}B^\top P(k)A, \quad P(N) = P_f$$

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Optimal cost-to-go (from time  $k$  to time  $N$ ):

$$V_{k \rightarrow N}^0(x) = x^\top P(k)x$$

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The latter equation is called the *algebraic Riccati equation*. The optimal cost is given by

$$V_\infty^0(x(0)) = x^\top(0)Px(0)$$

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The eigenvalues of the closed-loop system are the roots of the characteristic polynomial

$$|sI - A + BK| \cdot |sI - A + LC|.$$

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$$|sI - A + BK| \cdot |sI - A + LC|.$$

That is, if the system is *reachable* and *observable* the control and observer dynamics can be arbitrarily assigned (*separation principle*).



# The Kalman filter

System model:

$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) + w(k), & x(0) &\sim \mathcal{N}(x_0, P_0), w \sim \mathcal{N}(0, Q) \\y(k) &= Cx(k) + v(k), & v &\sim \mathcal{N}(0, R)\end{aligned}$$

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State estimator:

Correction:  $\hat{x}(k|k) = \hat{x}(k|k-1) + L(k)[y(k) - C\hat{x}(k|k-1)], \hat{x}(0|0) = x_0$

Prediction:  $\hat{x}(k+1|k) = A\hat{x}(k|k) + Bu(k)$

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State estimation error covariance update (note that  $P(k) \widehat{=} P(k|k-1)$ ):

Estimation error:  $P(k|k) = P(k) - P(k)C^T[CP(k)C^T + R]^{-1}CP(k), P(0|0) = P_0$

Prediction error:  $P(k+1) = AP(k|k)A^T + Q$

# Stationary Kalman filter

System:

$$\begin{aligned}x^+ &= Ax + Bu + w, \quad w \sim \mathcal{N}(0, Q) \\ y &= Cx + v, \quad v \sim \mathcal{N}(0, R)\end{aligned}$$

If the pair  $(C, A)$  is observable and  $Q, R > 0$ , then the Kalman filter gain  $L(k)$  and the prediction error covariance  $P(k)$  converge to the solution of the (filtering) algebraic Riccati equation

$$\begin{aligned}L &= PC^T[CPC^T + R]^{-1} \\ P &= APA^T - APC^T[CPC^T + R]^{-1}CPA^T + Q\end{aligned}$$