FRTN10 Multivariable Control, Lecture 9

Automatic Control LTH, 2017

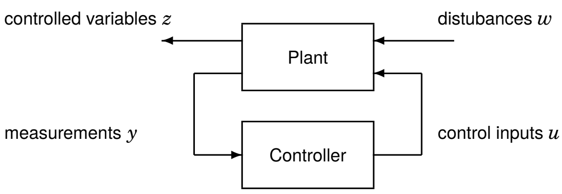
Course Outline

Lecture 9 – Outline

1. Dynamic programming
2. The Riccati equation
3. Optimal state feedback
4. Stability and robustness

Sections 9.1–9.4 + 5.7 in the book treat essentially the same material as we cover in lectures 9–11. However, the main derivation of the LQG controller in 9.A and 18.5 is different.

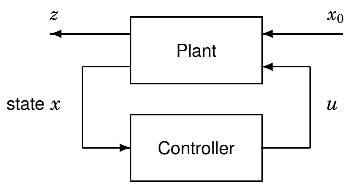
A general optimization setup



The objective is to find a controller that optimizes the transfer matrix $G_{zw}(s)$ from disturbances (and setpoints) w to controlled outputs z.

Lectures 9–11: Problems with analytic solutions
Lectures 12–14: Problems with numeric solutions

Today's problem: Optimal state feedback



Minimize $J = z^2 = \int_0^\infty \begin{pmatrix} x(t) \\ u(t) \end{pmatrix}^T \begin{pmatrix} Q_1 & Q_{12} \\ Q_{12}^T & Q_2 \end{pmatrix} \begin{pmatrix} x(t) \\ u(t) \end{pmatrix} dt$

subject to $\dot{x}(t) = Ax(t) + Bu(t), \quad x(0) = x_0$

$Q = \begin{pmatrix} Q_1 & Q_{12} \\ Q_{12}^T & Q_2 \end{pmatrix} > 0$ is a symmetric weighting matrix (design parameter)

Why linear-quadratic control?

- Simple, analytic solution
  - Quadratic cost function gives linear state feedback control law
- Always stabilizing
- Works for MIMO systems
- Guaranteed robustness (in the state feedback case)
- Foundation for more advanced methods like model-predictive control (MPC)

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Mini-problem

Determine u_0 and u_1 if the objective is to minimize

$$x_1^2 + x_2^2 + u_0^2 + u_1^2$$

when

$$x_1 = x_0 + u_0$$
$$x_2 = x_1 + u_1$$

Hint: Go backwards in time.

Solution to mini-problem

Break the problem into smaller parts that can be solved sequentially:

$$\min_{u_0,u_1}\{x_1^2+x_2^2+u_0^2+u_1^2\} = \min_{u_0}\Big\{x_1^2+u_0^2+\underbrace{\min_{u_1}\{x_2^2+u_1^2\}\,(x_1)}_{J_1(x_1)}\Big\}$$

$$J_1(x_1)=\min_{u_1}\{(x_1+u_1)^2+u_1^2\}=\min_{u_1}\Big\{2\big(u_1+\tfrac12 x_1\big)^2+\tfrac12 x_1^2\Big\}$$

$= \frac12 x_1^2$ with minimum attained for $u_1=-\frac12 x_1$

$$J_0(x_0)=\min_{u_0}\{(x_0+u_0)^2+u_0^2+J_1(x)\}=\min_{u_0}\Big\{\tfrac52\big(u_0+\tfrac35 x_0\big)^2+\tfrac35 x_0^2\Big\}$$

$= \frac35 x_0^2$ with minimum attained for $u_0=-\frac35 x_0$

Quadratic optimal cost

It can be shown that the optimal cost on the time interval $[t,\ \infty)$ is quadratic:

$$\min_{u[t,\infty)}\int_t^\infty \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix}^T Q \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix} d\tau = x^T(t)Sx(t), \qquad S=S^T>0$$

when

$$\dot x(t)=Ax(t)+Bu(t)$$

and

$$Q=\begin{pmatrix}Q_1 & Q_{12}\\ Q_{12}^T & Q_2\end{pmatrix}>0$$

Dynamic programming, Richard E. Bellman, 1957

An optimal trajectory on the time interval $[t,\ T]$ must be optimal also on each of the subintervals $[t,\ t+\epsilon]$ and $[t+\epsilon,\ T]$.

Dynamic programming in linear-quadratic control

Let $x_t=x(t), u_t=u(t)$. For a time step of length ϵ,

$$x(t+\epsilon)=x_t+(Ax_t+Bu_t)\epsilon \qquad \text{as } \epsilon\to 0$$

$$\begin{aligned} x_t^TSx_t &= \min_{u[t,\infty)}\int_t^\infty \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix}^T Q \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix} d\tau \\ &= \min_{u[t,\infty)}\left\{\begin{pmatrix}x_t\\u_t\end{pmatrix}^T Q \begin{pmatrix}x_t\\u_t\end{pmatrix}\epsilon + \int_{t+\epsilon}^\infty \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix}^T Q \begin{pmatrix}x(\tau)\\u(\tau)\end{pmatrix} d\tau\right\} \\ &= \min_{u_t}\Big\{(x_t^TQ_1x_t+2x_t^TQ_{12}u_t+u_t^TQ_2u_t)\epsilon \\ &\qquad + \big[x_t+(Ax_t+Bu_t)\epsilon\big]^T S\big[x_t+(Ax_t+Bu_t)\epsilon\big]\Big\} \end{aligned}$$

by definition of S. Neglecting ϵ^2 gives **Bellman's equation**:

$$0=\min_{u_t}\Big\{\big(x_t^TQ_1x_t+2x_t^TQ_{12}u_t+u_t^TQ_2u_t\big)+2x_t^TS\big(Ax_t+Bu_t\big)\Big\}$$

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Completion of squares

Suppose $Q_u>0$. Then

$$\begin{aligned} &x^TQ_xx+2x^TQ_{xu}u+u^TQ_uu \\ &=(u+Q_u^{-1}Q_{xu}^Tx)^TQ_u(u+Q_u^{-1}Q_{xu}^Tx)+x^T(Q_x-Q_{xu}Q_u^{-1}Q_{xu}^T)x \end{aligned}$$

is minimized by

$$u=-Q_u^{-1}Q_{xu}^Tx$$

The minimum is

$$x^T(Q_x-Q_{xu}Q_u^{-1}Q_{xu}^T)x$$

The Riccati equation

Completion of squares in Bellman's equation gives

$$\begin{aligned} 0 &= \min_{u_t}\Big\{\big(x_t^TQ_1x_t+2x_t^TQ_{12}u_t+u_t^TQ_2u_t\big)+2x_t^TS\big(Ax_t+Bu_t\big)\Big\} \\ &= \min_{u_t}\Big\{x_t^T[Q_1+A^TS+SA]x_t+2x_t^T[Q_{12}+SB]u_t+u_t^TQ_2u_t\Big\} \\ &= x_t^T\Big(Q_1+A^TS+SA-(SB+Q_{12})Q_2^{-1}(SB+Q_{12})^T\Big)x_t \end{aligned}$$

with minimum attained for

$$u_t=-Q_2^{-1}(SB+Q_{12})^Tx_t$$

The equation

$$0=Q_1+A^TS+SA-(SB+Q_{12})Q_2^{-1}(SB+Q_{12})^T$$

is called the *algebraic Riccati equation*

Jocopo Francesco Riccati, 1676–1754

Solving algebraic Riccati equations in Matlab

```
care  Solve continuous-time algebraic Riccati equations.

   [X,L,G] = care(A,B,Q,R,S,E) computes the unique stabilizing
   solution X of the continuous-time algebraic Riccati equation
                                   -1
      A'XE + E'XA - (E'XB + S)R  (B'XE + S') + Q = 0 .

   When omitted, R, S and E are set to the default values R=I,
   S=0, and E=I.  Beside the solution X, care also returns the
   gain matrix
               -1
         G = R  (B'XE + S')

   and the vector L of closed-loop eigenvalues (i.e.,
   EIG(A-B*G,E)).
```

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Linear-quadratic optimal control

Control problem:

Minimize $\int_0^\infty \Big(x^T(t)Q_1x(t) + 2x^T(t)Q_{12}u(t) + u^T(t)Q_2u(t)\Big)dt$

subject to $\dot{x}(t) = Ax(t) + Bu(t), \qquad x(0) = x_0$

Solution: Assume (A, B) controllable[1]. Then there is a unique $S > 0$ solving the algebraic Riccati equation

$$0 = Q_1 + A^TS + SA - (SB + Q_{12})Q_2^{-1}(SB + Q_{12})^T$$

The optimal control law is $u = -Lx$ with $L = Q_2^{-1}(SB + Q_{12})^T$.

The minimal cost is $x_0^TSx_0$.

[1] *stabilizable* is sufficient, see G&L

Remarks

Note that the optimal control law does not depend on x_0.

The optimal feedback gain L is static since we are solving an infinite-horizon problem.

(LQ theory can also be applied to finite-horizon problems and problems with time-varying system matrices. We then obtain a Riccati differential equation for $S(t)$ and a time-varying state feedback, $u(t) = -L(t)x(t)$)

Example: Control of an integrator

For $\dot{x}(t) = u(t)$, $x(0) = x_0$,

Minimize	$J = \int_0^\infty \{x(t)^2 + \rho u(t)^2\}\, dt$
Riccati equation	$0 = 1 - S^2/\rho \quad \Rightarrow \quad S = \sqrt{\rho}$
Controller	$L = S/\rho = 1/\sqrt{\rho} \quad \Rightarrow \quad u = -x/\sqrt{\rho}$
Closed loop system	$\dot{x} = -x/\sqrt{\rho} \quad \Rightarrow \quad x = x_0e^{-t/\sqrt{\rho}}$
Optimal cost	$J^* = x_0^TSx_0 = x_0^2\sqrt{\rho}$

What values of ρ give the fastest response? Why?

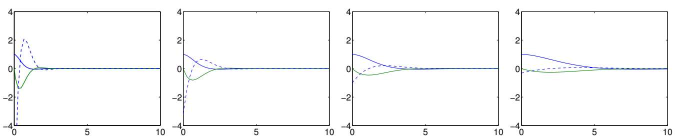
Solving the LQ problem in Matlab

```
lqr  Linear-quadratic regulator design for state space systems

[K,S,E] = lqr(SYS,Q,R,N) calculates the optimal gain matrix K
such that:

* For a continuous-time state-space model SYS, the state-
feedback law u = -Kx  minimizes the cost function

J = Integral {x'Qx + u'Ru + 2*x'Nu} dt

subject to the system dynamics  dx/dt = Ax + Bu

The matrix N is set to zero when omitted. Also returned are
the solution S of the associated algebraic Riccati equation
and the closed-loop eigenvalues E = EIG(A-B*K).
```

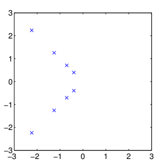
Example – Double integrator

$$A = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad Q_1 = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \quad Q_2 = \rho \quad x(0) = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

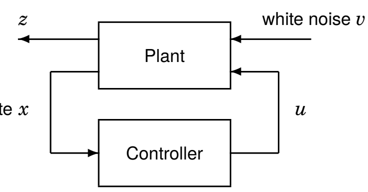
States and inputs (dotted) for $\rho = 0.01$, $\rho = 0.1$, $\rho = 1$, $\rho = 10$



Closed loop poles:
$s = 2^{-1/2}\rho^{-1/4}(-1 \pm i)$



Stochastic interpretation of LQ control



Minimize $J = \mathrm{E}\, z^2 = \mathrm{E}\left\{x^TQ_1x + 2x^TQ_{12}u + u^TQ_2u\right\}$

subject to $\dot{x}(t) = Ax(t) + Bu(t) + v(t)$

where v is white noise with intensity R. Same Riccati equation and solution S as in the deterministic case. The optimal cost is

$$J^* = \mathrm{tr}(SR)$$

where tr denotes matrix trace.

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Stability of the closed-loop system

Assume that

$$Q = \begin{pmatrix} Q_1 & Q_{12} \\ Q_{12}^T & Q_2 \end{pmatrix} > 0$$

and that there exists a solution $S > 0$ to the algebraic Riccati equation. Then the optimal controller $u(t) = -Lx(t)$ gives an asymptotically stable closed-loop system $\dot{x}(t) = (A - BL)x(t)$.

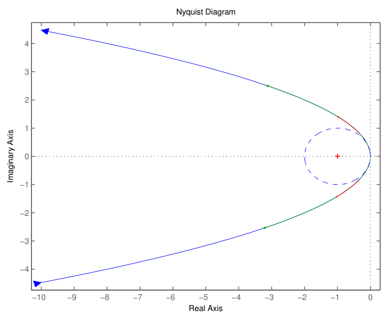
Proof:

$$\frac{d}{dt}x^T(t)Sx(t) = 2x^TS\dot{x} = 2x^TS(Ax + Bu)$$

$$= -\left(x^TQ_1x + 2x^TQ_{12}u + u^TQ_2u\right) < 0 \text{ for } x(t) \neq 0$$

Hence $x^T(t)Sx(t)$ is decreasing and tends to zero as $t \to \infty$.

Robustness of optimal state feedback



The distance from the loop gain $L(i\omega I - A)^{-1}B$ to -1 is never smaller than 1. This is always true(!) when $Q_1 > 0$, $Q_{12} = 0$ and $Q_2 > 0$ is scalar. The phase margin is at least $60°$ and the gain margin is infinite!

[For proof, see G&L Section 9.4]

Lecture 9 – summary

- We specify what "optimal" means using a quadratic cost function.
- Solving an algebraic Riccati equation gives the optimal state feedback law $u = -Lx$:

  $$0 = Q_1 + A^TS + SA - (SB + Q_{12})Q_2^{-1}(SB + Q_{12})^T \;\Rightarrow\; S$$
  $$L = Q_2^{-1}(SB + Q_{12})^{-1}$$

- The LQ controller has remarkable robustness properties.