Lecture 4 : Linear Quadratic Optimal Control II

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Outline

- \blacktriangleright Regulator Problem
- \triangleright Solution of the Time-Varying Riccati Equation
- \blacktriangleright The Infinite-Time Regulator Problem

Solution of the Finite-time Regulator

Regulator problem

Consider the system

$$
\dot{x} = A(t)x(t) + B(t)u(t), \qquad x(t_0) = x_0
$$

The performance index is

$$
V(x(t_0), u(\cdot), t_0) = \int_{t_0}^T (u^T R u + x^T Q x) dt + x^T(T) M x(T),
$$

where $A(t)$, $B(t)$ assumed continuous, the $Q(t) \geq 0$ and $R(t)$ have continuous entries, be ϵ symmetric, and be positive definite. The optimum performance index is $V^*(x(t_0),t_0)$.

To solve the problem can be done in two steps:

- ▶ show that if $V^*(x(t), t)$ exists, it must be of the form $x^T(t)P(t)x(t)$, where $P(t) ≥ 0$.
- **►** show that if $V^*(x(t), t)$ exists, it satisfies the so called Riccati Differential equations.

Solution of the Finite-time Regulator Proof

Show that V^* must be of the quadratic form x^TPx .

▶ the function $V^*(x)$ is a quadratic form if and only if it is continuous in x and

$$
V^*(\lambda x) = \lambda^2 V^*(x) \quad \text{for all real } \alpha
$$

$$
V^*(x_1) + V^*(x_2) = \frac{1}{2}(V^*(x_1 + x_2) + V^*(x_1 - x_2)).
$$

▶ Let u_x^* denotes the optimal control when the initial state is *x*. Since the plant model is linear and the performance index quadratic in *x*, we have

$$
V(\lambda x, \lambda u_x^*, t) = \lambda^2 V^*(x, t) \quad \text{and} \quad V^*(\lambda x, t) = \lambda^2 V(x, \frac{1}{\lambda} u_{\lambda_x}^*, t)
$$

 \blacktriangleright Because the optimum is minimal, we also have

$$
V^*(\lambda x,t)\leq V(\lambda x,\lambda u^*_x,t)\qquad \text{ and }\qquad \lambda^2 V^*(x,t)\leq \lambda^2 V(x,\frac{1}{\lambda}u^*_{\lambda x},t).
$$

▶ Combining all together (to show both are equal.)

Solution of the Finite-time Regulator Proof

- **►** The two inequalities imply that $V^*(x,t)$ satisfies the condition one.
- \blacktriangleright Similar reasoning gives the inequality

$$
V^*(x_1, t) + V^*(x_2, t) = \frac{1}{4} \left[V^*(2x_1, t) + V^*(2x_2, t) \right]
$$

$$
\leq \frac{1}{4} \left[V(2x_1, u_{x_1+x_2}^* + u_{x_1-x_2}^*, t) + V(2x_2, u_{x_1+x_2}^* - u_{x_1-x_2}^*, t) \right]
$$

by linearity

$$
= \frac{1}{2} \left[V(x_1 + x_2, u_{x_1 + x_2}^*, t) + V(x_1 - x_2, u_{x_1 - x_2}^*, t) \right]
$$

=
$$
\frac{1}{2} \left[V^*(x_1 + x_2, t) + V^*(x_1 - x_2, t) \right]
$$

▶ By using the controls $u^*_{x_1}$ and $u^*_{x_2}$, we establish the following inequality in a like manner:

$$
\frac{1}{2}[V^*(x_1+x_2,t)+V^*(x_1-x_2,t)] \le V^*(x_1,t)+V^*(x_2,t)
$$

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Solution of the Finite-time Regulator

Proof

▶ This is trivial to show that $V^*(x(t), t)$ is continuous in $x(t)$. It is follows that it has the form

$$
V^*(x(t),t) = x^T(t)P(t)x(t)
$$

for some matrix *P*(*t*).

- ▶ The Positive semidefiniteness follows from the fact that $V^*(x(t), t)$ cannot be negative.
- \blacktriangleright $P(t)$ is symmetric. If it is not, one can replace it by the symmetric matrix $\frac{1}{2}(P+P^T)$ without altering the value of *V ∗*.

Matrix Riccati Equation

The second step we show that the matrix $P(t)$ satisfies a particular matrix differential equation, the Riccati Differential Equation (RDE).

 \blacktriangleright the first form of the HJB equation

$$
\frac{\partial V^*}{\partial t}(x(t),t) = -\min_{u(t)} \left(l(x,u,t) + \left[\frac{\partial V^*}{\partial x} \right]^T f(x,u,t) \right)
$$

 \blacktriangleright for the linear regulator problem, we have

$$
l(x, u, t) = x^T Q x + u^T R u
$$
 and $V^* = x^T P x$ for some $P(t)$.

- In Thus, we have $f(x, u, t) = Ax + Bu$
- \blacktriangleright Since *t* and $x(t)$ are considered separately, we have

$$
\frac{\partial V^*}{\partial x} = 2x^T(t)P(t) \quad \text{ and } \quad \frac{\partial V^*}{\partial t} = x^T(t)\dot{P}(t)x(t)
$$

Matrix Riccati Equation

 \blacktriangleright in the special case of the regulator problem

$$
x^T \dot{P} x = - \min_u \left[x^T Q x + u^T R u + 2x^T P A x + 2x^T P B u \right]
$$

 \blacktriangleright By completing the square:

$$
u^{T}Ru + x^{T}Qx + 2x^{T}PAx + 2x^{T}PBu = (u + R^{-1}B^{T}Px)^{T}R(u + R^{-1}BPx) + x^{T}(Q - PBR^{-1}B^{T}P + PA + A^{T}P)x
$$

Because the matrix $R(t)$ is positive definite, the equation is minimized by setting

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

$$
x^{T}\dot{P}x = -x^{T}(PA + A^{T}P - PBR^{-1}B^{T}P + Q)x.
$$

Since the equation holds for all x , we have the celebrated matrix Riccati Equation

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

Matrix Riccati Equation

A boundary condition for the Riccati Equation follows from the boundary condition for the HJB equation

$$
V^*(x(T),T) = x^T(T)P(T)x(T) = x^T(T)Sx(T) \qquad \text{or} \qquad P(T) = S
$$

where *S* is the penalty on the final state vector introduced previously. In conclusion

 \blacktriangleright \bar{u} is the optimal control input at time *t*, thus solving the Riccati equation and substituting the solution $P(t)$ back the optimal controller in the form of linear, time-varying state feedback

$$
u^*(t) = F(t)x(t)
$$

$$
F(t) = -R^{-1}B^T P(t).
$$

Consider the Riccati differential equation

$$
-\dot{P}(t) = P(t)A + A^T P(t) - P(t)BR^{-1}B^T P(t) + Q,
$$

with boundary condition $P(T) = S$. Note that in the last lecture we consider only a constant matrix *P* .

First, we show that the Riccati equation can be solved by solving the linear system

$$
\begin{bmatrix} \dot{X}(t) \\ \dot{Y}(t) \end{bmatrix} = \begin{bmatrix} A & -BR^{-1}B^T \\ -Q & -A^T \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}, \qquad \begin{bmatrix} X(T) \\ Y(T) \end{bmatrix} = \begin{bmatrix} I \\ S \end{bmatrix},
$$

where *X*(*t*) and *Y* (*t*) are square matrices of the same size as *A*. Having solved the above system for *X* and *Y* , one can compute the solution of the Riccati equation as

$$
P(t) = Y(t)X^{-1}(t).
$$

This can be proved as

$$
\frac{dP}{dt} = \frac{dYX^{-1}}{dt} = Y\frac{dX^{-1}}{dt} + \frac{dY}{dt}X^{-1}.
$$

Differentiate both sides of $X(t)X^{-1}(t) = I$ we have

$$
\frac{dX^{-1}}{dt}=-X^{-1}\frac{dX}{dt}X^{-1}
$$

Substituting this result to get

$$
\begin{split} \frac{dYX^{-1}}{dt} &= -YX^{-1}\frac{dX}{dt}X^{-1} + \frac{dY}{dt}X^{-1} \\ &= -YX^{-1}(AX - BR^{-1}B^TY)X^{-1} + (-QX - A^TY)X^{-1} \\ &= -YX^{-1}AXX^{-1} - A^TYX^{-1} + YX^{-1}BR^{-1}B^TYX^{-1} - QXX^{-1} \end{split}
$$

Comparing with the Riccati equation, it is clear that $P(t) = Y(t)X^{-1}(t)$.

Hamiltonian matrix

The matrix

$$
H = \begin{bmatrix} A & -BR^{-1}B \\ -Q & -A^T \end{bmatrix}
$$

is called the *Hamiltonian matrix* and plays an important role in the linear quadratic optimization. It has a property that if *λ* is an eigenvalue of *H*, then so is *−λ*. This can be proved as

$$
H = -JH^TJ^{-1} \qquad \text{where} \qquad J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix}
$$

If *H* has no eigenvalue on the imaginary axis there exists a nonsingular transformation *U* such that

$$
U^{-1}HU=\begin{bmatrix} \Lambda_s & 0 \\ 0 & \Lambda_u \end{bmatrix},
$$

where Λ*s* is a matrix whose eigenvalues are the stable eigenvalues of *H*, and Λ*u* is a matrix with the unstable eigenvalues of *H*.

Hamiltonian matrix

Partitioning *U* as

$$
U = \begin{bmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \end{bmatrix},
$$

the the columns of $\begin{bmatrix} U_{11} & U_{21} \end{bmatrix}^T$ span the eigenvalue space corresponding to the stable eigenvalues of H , whereas the columns of $\begin{bmatrix} U_{12} & U_{22} \end{bmatrix}^T$ span the eigenvalue space corresponding to the unstable eigenvalues. Applying the transformation

> [*X Y* $\Big] = U \Big[\frac{\tilde{X}}{\tilde{Y}} \Big]$ *Y*˜ $\begin{bmatrix} \hat{X} & \hat{X} \end{bmatrix}$ $\dot{\tilde{Y}}$] $=\begin{bmatrix} \Lambda_s & 0 \\ 0 & \Lambda \end{bmatrix}$ $0 \Lambda_u$ $\overline{}$ $\overline{\$ *Y*˜]

The solution at time *T* can be computed in terms of the solution at time *t* as

$$
\tilde{X}(T) = e^{\Lambda_s (T-t)} \tilde{X}(t)
$$

$$
\tilde{Y}(T) = e^{\Lambda_u (T-t)} \tilde{Y}(t)
$$

Hamiltonian matrix

From $X(T) = I$ and $Y(T) = S$, we have

$$
I = U_{11}\tilde{X}(T) + U_{12}\tilde{Y}(T)
$$

$$
S = U_{21}\tilde{X}(T) + U_{22}\tilde{Y}(T)
$$

 $Definition G = -(U_{22} - SU_{12})^{-1}(U_{21} - SU_{11})$ we obtain

$$
\tilde{Y}(T) = G\tilde{X}(T).
$$

Evaluating *X*(*t*) and *Y* (*t*) , we have

$$
X(t) = (U_{11} + U_{12}e^{-\Lambda_u(T-t)}Ge^{\Lambda_s(T-t)})e^{-\Lambda_s(T-t)}\tilde{X}(T)
$$

$$
Y(t) = (U_{21} + U_{22}e^{-\Lambda_u(T-t)}Ge^{\Lambda_s(T-t)})e^{-\Lambda_s(T-t)}\tilde{X}(T).
$$

The Riccati differential equation is

$$
P(t) = Y(t)X^{-1}(t)
$$

=
$$
(U_{21} + U_{22}e^{-\Lambda_u(T-t)}Ge^{\Lambda_s(T-t)}) (U_{11} + U_{12}e^{-\Lambda_u(T-t)}Ge^{\Lambda_s(T-t)})^{-1}.
$$

Leture 4 : Linear Quadratic Optimal Control II

Example

Consider a system $\dot{x} = u$ with a cost function $V(x(0), u(\cdot), 0) = \int_0^T (x^2 + u^2) dt$. We have the Hamilton matrix

$$
H = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}.
$$

The eigenvalues are $\lambda_s = -1$ and $\lambda_u = 1$, and the transformation matrix is

$$
U=\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}.
$$

With $S = 0$, we have $G = 1$ and

$$
P(t) = \frac{1 - e^{-2(T - t)}}{1 + e^{-2(T - t)}}.
$$

Note that the time-varying state feedback gain is

$$
K = -R^{-1}B^T P(t) \qquad \text{if } N = 0.
$$

Example

Consider the speed control problem, with a plant equation

$$
\dot{\omega}(t) = -a\omega(t) + bu(t) \qquad \text{and cost function}
$$

$$
\int_0^T (\omega^2(t) + \rho u^2(t))dt + s\omega^2(T).
$$

The numerical values are $a=0.5$ sec $^{-1}$, $b=150$ rad/(V sec 2), $\rho=10^4$ and $s=0.$ Consider solutions of the Riccati equation $P(t)$ with different time horizons T , ranging from $T = 1$ to $T = 10$. The we have the Hamiltonian matrix as

$$
H = \begin{bmatrix} 0.5 & -22.5 \\ -1 & -0.5 \end{bmatrix} \qquad \text{and} \qquad U = \begin{bmatrix} 0.9737 & 0.9825 \\ 0.2280 & -0.1864 \end{bmatrix}
$$

The solution or the Riccati equation is

$$
P(t) = \frac{0.2280 - 0.2280e^{-9.5394(T-t)}}{0.9739 + 1.2017e^{-9.5394(T-t)}}.
$$

It is clear that *P*(*t*) is constant during most of the time interval and changes only when approaching the final time. If we select $T = \infty$, it will be no different between $P(t)$ and a constant *P*.

Existence of the Solution

Consider the system

$$
\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t), \qquad \begin{bmatrix} x_{10} \\ x_{20} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}
$$

and the performance index

$$
V = \int_0^\infty (x_1^2 + x_2^2 + u^2) dt.
$$

- **F** from $\dot{x}_1 = x_1$, we have $x_1 = e^t$, which is independent of the control input. The cost function will contain the term e^{2t} no matter what control is chosen, and the performance index will be infinite.
- \triangleright Why there exists no solution in this example?
- Firstly the unstable mode x_1 is uncontrollable.
- \blacktriangleright Secondly the unstable and uncontrollable mode is reflected in the performance index.
- \triangleright We have two problems that must be addresses: a) does a solution to the problem exist, and b) is the solution stable.

Existence of the Solution

Existence

A solution *P* is the algebraic Riccati equation for the infinite time regulator problem exists if the system (A, B) is controllable. (It means $P < \infty$.)

I the controllability implies the existence of a state feedback gain *F* such that (*A − BF*) is stable. Then the control input $u(t) = -Fx(t)$, which is not necessarily optimal, stabilizes the system, and the resulting performance index $V(x_0, u, t_0)$ will be finite. But it is clear that

$$
V^*(x_0) \le V(x_0, u) < \infty.
$$

Since $V^*(x_0) = x_0^T P x_0$ (proof is in the references), we conclude that $x_0^T P x_0 < \infty$; and because this holds for any x_0 , it is follows that P is bounded.

Stability

Controllability ensures the existence of bounded solution *P* to the algebraic Riccati equation and of a state feedback gain that minimizes the performance index. However it does not imply closed-loop stability. Consider a system

$$
\dot{x}=x+u
$$

and the performance index

$$
V = \int_0^\infty u^2 dt.
$$

The system is controllable, and the optimal control is $u^*(t) \equiv 0$, resulting in $V=0$ and an unstable closed-loop system.

 \blacktriangleright The instability is due to the fact that the unstable mode is not reflected in the performance index. A bounded solution *P* guarantees stability if all modes are reflected in the performance index.

Stability

The stability of the closed-loop system is guaranteed if (*A, C*) is observable.

Stability

Proof

- \blacktriangleright The system $\dot{x} = \bar{A}x$ is stable if there exists a Lyapunov function $V = x^T P x$ such that *P* > 0 and $\dot{V} \le 0$, and where $\dot{V} \equiv 0$ implies $x(t) \equiv 0$.
- \blacktriangleright Let \bar{A} denote the optimal closed-loop state matrix

$$
\bar{A} = A + BF^* = A - BR^{-1}B^T P.
$$

First show that (A, C) observable implies $P > 0$ by showing that $P \ge 0$ leads to a contradiction. Assume $P \geq 0$, then there exists a nonzero initial state $x_0 \neq 0$ such that

$$
V = x_0^T P x_0 = \int_0^\infty \left(x^T C^T C x + u^T R u \right) dt = 0.
$$

But this can only be true if $Cx(t) = Ce^{At}x_0 \equiv 0$ for $0 \le t < \infty$, and (A, C) observable then implies that $x_0 = 0$, which contradicts the assumption $x_0 \neq 0$.

 \blacktriangleright Next we prove that

$$
\dot{V} = \frac{d}{dt} \left(x^T P x \right) \le 0
$$

and that $\dot{V} \equiv 0$ implies $x(t) \equiv 0$.

Stability

Proof

 \blacktriangleright Observe that form the algebraic Riccati equation and from the definition of \bar{A} we have

$$
\bar{A}^T P + P\bar{A} = -P B R^{-1} B^T P - C^T C.
$$

Substituting the right hand side in

$$
\dot{V} = \dot{x}^T P x + x^T P \dot{x} = x^T \left(\bar{A}^T P + P \bar{A} \right) x
$$

gives

$$
\dot{V} = -x^T P B R^{-1} B^T P x - x^T C^T C x,
$$

so clearly $\dot{V} \le 0$, and $\dot{V} \equiv 0$ can only be true if $Cx(t) \equiv 0$, which by observability implies $x_0 = 0$ and thus $x(t) \equiv 0$. Invoking the Lyaponov stability result quoted above, this proves that observability of (*A, C*) guarantees stability of the optimal closed-loop system.

Closed-loop Eigenvalues

Using the algebraic Riccati equation, one can show that the optimal closed-loop eigenvalues are the stable eigenvalues of the Hamiltonian matrix: apply the similarity transformation

$$
T^{-1}HT = \tilde{H}, \qquad T = \begin{bmatrix} I & 0 \\ P & I \end{bmatrix}
$$

to the Hamiltonian matrix. The result is

$$
\tilde{H} = \begin{bmatrix} \bar{A} & -BR^{-1}B^T \\ 0 & -\bar{A}^T \end{bmatrix},
$$

so the eigenvalues of *H* are the eigenvalues of \bar{A} together with those of $-\bar{A}$.

The derivation of *G*

From $X(T) = I$ and $Y(T) = S$, we have

$$
I = U_{11}\tilde{X}(T) + U_{12}\tilde{Y}(T)
$$

\n
$$
S = U_{21}\tilde{X}(T) + U_{22}\tilde{Y}(T)
$$
\n(1)
\n(2)

By multiplying (1) with *S* from the left we have

$$
S = SU_{11}\tilde{X}(T) + SU_{12}\tilde{Y}(T)
$$

$$
S = U_{21}\tilde{X}(T) + U_{22}\tilde{Y}(T).
$$

Then equal both equation we obtain

$$
\tilde{Y}(T) = -(U_{22} - SU_{12})^{-1}(U_{21} - SU_{11})\tilde{X}(T) = G\tilde{X}(T),
$$

where
$$
G = -(U_{22} - SU_{12})^{-1}(U_{21} - SU_{11}).
$$

Reference

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