

2. LINEAR QUADRATIC DETERMINISTIC PROBLEM

Notations:

- For a vector Z , $\|Z\| = \sqrt{\langle Z, Z \rangle}$ is the Euclidean norm (here $\langle Z, Z \rangle = \sum_i Z_i^2$ is the inner product);
- For a vector Z and nonnegative definite matrix Q , $\|Z\|_Q = \sqrt{\langle Z, QZ \rangle}$ is \mathbb{L}^2 -norm with the Kernel Q :

$$\langle Z, QZ \rangle = \sum_{i,j} Z_i Q_{ij} Z_j.$$

- * is transposition symbol;
- “grad” is symbol of gradient;

A controlled process X_t is defined by a linear vector differential equation with control action $U(t)$:

$$\dot{X}_t = a(t)X_t + c(t)U(t) \tag{2.1}$$

subject to the fixed initial condition $X_0 = x$.

Here X_t and $U(t)$ are vectors of sizes k and r , and $a(t)_{|k \times k}$, $c(t)_{|k \times r}$ are matrix valued functions of the argument t .

The control $U(t)$ has to be chosen such that to track a smooth vector valued function $\phi(t)$, of the size k , in a sense of the minimization of cost functional

$$J(x, \phi; U) = \|X_T - \phi(T)\|_h^2 + \int_0^T \left(\|X_t - \phi(t)\|_{H(t)}^2 + \|U(t)\|_{R(t)}^2 \right) dt, \tag{2.2}$$

where $h_{|k \times k}$, $H(t)_{|k \times k}$ and $R(t)_{|r \times r}$ are nonnegative definite matrices ($R(t)$ is uniformly in t nonsingular).

2.1. Preliminaries. Set $Y_t = X_t - \phi(t)$. Since $\phi(t)$ is assumed to be differentiable, by (2.1) we find the differential equation for Y_t

$$\dot{Y}_t = a(t)Y(t) + [a(t)\phi(t) - \dot{\phi}(t)] + c(t)U(t) \tag{2.3}$$

subject to $Y_0 = X_0 - \phi(0) := y$.

Notice also that the cost functional $J(x, \phi : U)$ is transformed to

$$J(y, \phi; U) = \|Y_T\|_h^2 + \int_0^T \left(\|Y_t\|_{H(t)}^2 + \|U(t)\|_{R(t)}^2 \right) dt. \tag{2.4}$$

As in Lecture 1, we introduce the Bellman function

$$V(t, y) = \min_{U(s): s \leq t \leq T} \|Y_T\|_h^2 + \int_t^T \left(\|Y_s\|_{H(s)}^2 + \|U(s)\|_{R(s)}^2 \right) ds$$

and apply Bellman's principle of optimality:

$$V(t, y) = \min_{U(s): t \leq s \leq t+\delta} \left(\int_t^{t+\delta} \left(\|Y_s\|_{H(s)}^2 + \|U(s)\|_{R(s)}^2 \right) ds + V(t + \delta, Y_{t+\delta}) \right), \quad (2.5)$$

where $Y_t = y$ and for $s > t$

$$\dot{Y}_s = a(s)Y_s + [a(s)\phi(s) - \dot{\phi}(s)] + c(s)U(s).$$

With a help of (2.5) we derive heuristically the Bellman equation

$$\begin{aligned} -\frac{\partial V(t, y)}{\partial t} = \min_U \left(\|y\|_{H(t)}^2 + \|U\|_{R(t)}^2 \right. \\ \left. + \text{grad}_y V(t, y) \left[a(t)y + [a(t)\phi(t) - \dot{\phi}(t)] + c(t)U \right] \right) \end{aligned} \quad (2.6)$$

subject to boundary condition $V(T, y) = \|y\|_h^2$.

2.2. The optimal control. We find now

$$U^\circ(t, y) = \underset{U}{\text{argmin}} \left(\|y\|_{H(t)}^2 + \|U\|_{R(t)}^2 + \text{grad}_y V(t, y) \left[a(t)y + [a(t)\phi(y) - \dot{\phi}(t)] + c(t)U \right] \right)$$

Obviously, this procedure is reduced to a minimization in U of the quadratic form

$$Q(U) := \|U\|_{R(t)}^2 + \text{grad}_y V(t, y)c(t)U.$$

Since $Q(U)$ is the quadratic form U° solves the equation

$$\text{grad}_U Q(U) = 0.$$

Notice that $\text{grad}_U \|U\|_{R(t)}^2 = 2U^*R(t)$, so that

$$\text{grad}_U Q(U) = 2U^*R(t) + \text{grad}_y V(t, y)c(t).$$

Hence,

$$U^\circ(t, y) = -\frac{1}{2}R^{-1}(t)c^*(t) \left(\text{grad}_y V(t, y) \right)^*. \quad (2.7)$$

Then, the Bellman equation is transformed to

$$\begin{aligned} -\frac{\partial V(t, y)}{\partial t} = \left(\|y\|_{H(t)}^2 + \frac{1}{4} \left\| \text{grad}_y V(t, y)c(t)R^{-1} \right\|_{R(t)}^2 \right. \\ \left. + \text{grad}_y V(t, y) \left\{ a(t)y + [a(t)\phi(y) - \dot{\phi}(t)] \right\} \right. \\ \left. - \frac{1}{2} \text{grad}_y V(t, y)c(t)R^{-1}(y)c^*(t) \left(\text{grad}_y V(t, y) \right)^* \right). \end{aligned}$$

Owing to

$$\text{grad}_y V(t, y) c(t) R^{-1}(t) c^*(t) \left(\text{grad}_y V(t, y) \right)^* = \frac{1}{4} \left\| \text{grad}_y V(t, y) c(t) R^{-1}(t) \right\|_{R(t)}^2$$

we find that

$$\begin{aligned} -\frac{\partial V(t, y)}{\partial t} = & \left(\|y\|_{H(t)}^2 - \frac{1}{4} \left\| \text{grad}_y V(t, y) c(t) R^{-1}(t) \right\|_{R(t)}^2 \right. \\ & \left. + \text{grad}_y V(t, y) \left\{ a(t)y + [a(t)\phi(t) - \dot{\phi}(t)] \right\} \right). \end{aligned} \quad (2.8)$$

As in Lecture 1, we shall find a solution of (2.8) as quadratic form in y with nonnegative definite matrix $\Gamma(t)$:

$$V(t, y) = y^* \Gamma(t) y + y^* B(t) + Q(t);$$

in particular, then $\text{grad}_y V(t, y) = 2y^* \Gamma(t) + B^*(t)$. Substituting that $V(t, y)$ and $\text{grad}_y V(t, y)$ in (2.8) we arrive at the identity

$$\begin{aligned} & -y^* \dot{\Gamma}(t) y + y^* \dot{B}(t) + \dot{Q}(t) \\ & \equiv \|y\|_{H(t)}^2 \\ & - \frac{1}{4} \left(2y^* \Gamma(t) + B^*(t) \right) c(t) R^{-1}(t) c^*(t) \left(2y^* \Gamma(t) + B^*(t) \right)^* \\ & + \left(2y^* \Gamma(t) + B^*(t) \right) \left(a(t)y + [a(t)\phi(t) - \dot{\phi}(t)] \right) \end{aligned}$$

which provide, with $2y^* \Gamma(t) a(t) y \equiv y^* \Gamma(t) a(t) y + y^* a^*(t) \Gamma(t) y$, the differential equations

$$\begin{aligned} -\dot{\Gamma}(t) &= H(t) - \Gamma(t) c(t) R^{-1} c^*(t) \Gamma(t) + \Gamma(t) a(t) + a^*(t) \Gamma(t) \\ -\dot{B}(t) &= \left(a^*(t) - \Gamma(t) c(t) R^{-1} c^*(t) \right) B(t) + 2\Gamma(t) [a(t)\phi(t) - \dot{\phi}(t)] \\ -\dot{Q}(t) &= -\frac{1}{4} B^*(t) c(t) R^{-1}(t) c^*(t) B(t) \end{aligned} \quad (2.9)$$

subject to the boundary conditions $\Gamma(T) = h$, $Q(T) = 0$ and $Q(T) = 0$.

Hence, by (2.7),

$$U^\circ(t, y) = -R^{-1}(t) c^*(t) \left(\Gamma(t) y + B(t) \right). \quad (2.10)$$

Thus, the optimal control for the original problem is defined as follows

$$U^\circ(t, X_t^\circ) = -R^{-1}(t) c^*(t) \left(\Gamma(t) \{X_t^\circ - \phi(t)\} + B(t) \right)$$

where

$$\dot{X}_t^\circ = a(t) X_t^\circ + c(t) U^\circ(t, X_t^\circ).$$

Remark. If $\dot{\phi}(t) \equiv a(t)\phi(t)$, then $B(t) \equiv 0$ and $Q(t) \equiv 0$.

2.3. Infinite horizon. From application point of view, it makes sense to analyze a case of very large time T , that is $T = \infty$.

To simplify an analysis, we assume that all matrices are time-independent, i.e.

$$\dot{X}_t = aX_t + cU(t), \quad (2.11)$$

$\phi(t) \equiv 0$, and

$$J(x, U) = \int_0^\infty \left(\|X_t\|_H^2 + \|U(t)\|_R^2 \right) dt. \quad (2.12)$$

The main problem for this setting is a requirement that there exists a control action $U(t)$ for which $J(x, U) < \infty$. We give conditions, guaranteeing the latter, expressed in terms of matrices a , c and H . Recall that matrix R is nonsingular.

With $T_k \nearrow \infty$, we consider a family of cost functionals $(J_{T_k}(x, U))_{k \geq 1}$. For every k , we have

$$J_{T_k}(x, U) = \int_0^{T_k} \left(\|X_t\|_H^2 + \|U(t)\|_R^2 \right) dt.$$

For fixed k , denote the optimal control by $U^k(t)$. From the obtained above result we know that (by Remark $B(t) \equiv 0, Q(t) \equiv 0$) $U^k(t) = -R^{-1}c^*\Gamma^k(t)$, where $\Gamma^k(t)$ solves the Riccati equation

$$-\dot{\Gamma}^k(t) = a^*\Gamma^k(t) + \Gamma^k a + H - \Gamma^k(t)cR^{-1}c^*\Gamma^k$$

subject to the boundary condition $\Gamma^k(T) = 0$. Moreover,

$$\min_{U(s): 0 \leq s \leq T_k} J_{T_k}(x, U) = \|x\|_{\Gamma^k(0)}^2.$$

We show that $(\|x\|_{\Gamma^k(0)}^2)_{k \geq 1}$ is an increasing sequence.

Denote by X_t^k the controlled process associated with optimal control $U^k(t)$ on $[0, T_k]$. Then

$$\|x\|_{\Gamma^k(0)}^2 = \int_0^{T_k} \left(\|X_t^k\|_H^2 + \|U^k(t)\|_R^2 \right) dt$$

and so

$$\begin{aligned} \|x\|_{\Gamma^{k+1}(0)}^2 &= \int_0^{T_{k+1}} \left(\|X_t^{k+1}\|_H^2 + \|U^{k+1}(t)\|_R^2 \right) dt \\ &\geq \int_0^{T_k} \left(\|X_t^{k+1}\|_H^2 + \|U^{k+1}(t)\|_R^2 \right) dt \quad (\text{since } T^{k+1} > T^k) \\ &\geq \int_0^{T_k} \left(\|X_t^k\|_H^2 + \|U^k(t)\|_R^2 \right) dt \quad (\text{since } U^k \text{ is optimal}) \\ &= \|x\|_{\Gamma^k(0)}^2. \end{aligned}$$

Consequently, $\lim_{k \rightarrow \infty} \|x\|_{\Gamma^k(0)}^2$ exists but we can not be sure that this limit is finite. To prove

$$\lim_{k \rightarrow \infty} \|x\|_{\Gamma^k(0)}^2 < \infty,$$

notice that it suffices to choose some control action $\tilde{U}(t)$ such that $J(x, \tilde{U}) < \infty$. Then, whereas $\|x\|_{\Gamma^k(0)}^2 \leq J_{T_k}(x, \tilde{U}) \leq J(x, \tilde{U})$, for any k , we get the desired property.

Assuming the matrix

$$A = \left(\int_0^1 e^{-as} cc^* e^{-a^*s} ds \right)^{-1}$$

is nonsingular. Then, taking

$$\tilde{U}(t) = \begin{cases} -c^* e^{a^*t} \left(\int_0^1 e^{-as} cc^* e^{-a^*s} ds \right)^{-1} x & 0 \leq t \leq 1 \\ 0, & t > 1, \end{cases} \quad (2.13)$$

where $x = \tilde{X}_0$ and $\dot{\tilde{X}}_t = a\tilde{X}_t + c\tilde{U}(t)$, we find

$$\begin{aligned} \tilde{X}_1 &= e^a \left(x + \int_0^1 e^{-at} c \tilde{U}(t) dt \right) \\ &= e^a \left[I - \int_0^1 e^{-at} cc^* e^{-a^*t} dt \left(\int_0^1 e^{-at} cc^* e^{-a^*t} dt \right)^{-1} \right] x \\ &= 0. \end{aligned}$$

The latter allows us to conclude that $\tilde{X}_t \equiv 0$, $t \geq 1$, and at the same time

$$J(x, \tilde{U}) = J_1(x, \tilde{U}) < \infty.$$

So, it remains to prove that A is nonsingular matrix.

Theorem. *The matrix A is nonsingular, if the block-matrix (of size $k \times kr$)*

$$G(a, c) = \begin{pmatrix} c & ac & \dots & a^{k-1}c \end{pmatrix}. \quad (2.14)$$

is of the full rank k .

Proof. Assume A is singular. Since A is nonnegative definite, there is vector Z so that

$$0 = Z^* \int_0^1 e^{-at} cc^* e^{-a^*t} ds Z = \int_0^1 Z^* e^{-at} cc^* e^{-a^*t} Z dt.$$

On the other hand, $Z^* e^{-at} cc^* e^{-a^*t} Z$, being nonnegative and continuous in t , is equal zero for all $t \in [0, 1]$. Hence, $Z^* e^{-at} c \equiv 0$. Differentiating this identity in t and letting

$t = 0$, we get

$$\begin{aligned} \left(z^* e^{-at} c \right) \Big|_{t=0} &= z^* c = 0 \\ - \left(\frac{d}{dt} (z^* e^{-at} c) \right) \Big|_{t=0} &= z^* a c = 0 \\ \dots\dots\dots &\dots\dots\dots \\ - \left(\frac{d^j}{dt^j} (z^* e^{-at} c) \right) \Big|_{t=0} &= z^* a^j c = 0 \\ \dots\dots\dots &\dots\dots\dots \end{aligned}$$

Consequently, $Z^* G(a, c) G^*(a, c) Z = \sum_{j=0}^{k-1} Z^* c a^j (a^j)^* c^* Z = 0$, so that the matrix $G(a, c) G^*(a, c)$ is singular.

The contradiction obtained, finishing the proof. □

Definition. *The pair of matrices (a, c) is said to be controllable, if the matrix $G(a, c)$ is of rank k .*

Thus, if (a, c) is controllable, $\lim_{k \rightarrow \infty} \|x\|_{\Gamma^k(0)}^2$ exists for any x and is finite. Then, obviously, $\lim_{k \rightarrow \infty} \Gamma^k(0)$ exists as well and denote this limit by Γ . Since

$$-\dot{\Gamma}^k(t) = a^* \Gamma^k(t) + \Gamma^k(t) a + H - \Gamma^k(t) c R^{-1} c^* \Gamma^k(t)$$

subject to $\Gamma^k(T) = 0$, the limit Γ solves the algebraic Riccati equation

$$a^* \Gamma + \Gamma a + H - \Gamma c R^{-1} c^* \Gamma = 0. \tag{2.15}$$

The next fact we use (without proof) is that (2.15) possesses the unique positive definite solution provided that the matrix

$$g(H, c) = \begin{pmatrix} H \\ Hc \\ \vdots \\ Hc^{k-1} \end{pmatrix}$$

is of the full rank k . In particular, it holds if H is nonsingular.

Definition. *The pair of matrices (H, c) is said to be observable, if the matrix $g(H, c)$ is of rank k .*

2.3.1. The optimal control for infinite horizon. Since $\|x \Gamma^k(0)\|^2 \leq J_{T_k}(x, U) \leq J(x, U)$ for any k , and $\lim_{k \rightarrow \infty} \|x\|_{\Gamma^k(0)}^2 = \|x \Gamma\|^2$, we find the lower bound

$$J(x, U) \geq \|x \Gamma\|^2. \tag{2.16}$$

The optimal control regarding to $[0, T_k]$ is

$$U^\circ(t, X_t^\circ) = -R^{-1}(t) c^*(t) \Gamma^k(t) X_t^\circ.$$

Hence a control $U^\circ(t, X_t^\circ) = -R^{-1}(t)c^*(t)\Gamma X_t^\circ$. is a candidate to be the optimal control for the infinite horizon. The check that supposition, let us consider a quadratic form $\|X_t^\circ\|_\Gamma^2$. Write

$$\begin{aligned}
\frac{d}{dt}\|X_t^\circ\|_\Gamma^2 &= \dot{X}_t^\circ\Gamma X_t^\circ + X_t^\circ\Gamma\dot{X}_t^\circ \\
&= \left(X_t^\circ a^* + U^\circ(X_t) c^*\right)\Gamma X_t^\circ + X_t^\circ\Gamma\left(aX_t^\circ + cU^\circ(X_t^\circ)\right) \\
&= \left(X_t^\circ\left[a^* - \Gamma cR^{-1}c^*\right]\right)\Gamma X_t^\circ + X_t^\circ\Gamma\left(\left[a - cR^{-1}c^\circ\Gamma\right]X_t^\circ\right) \\
&= X_t^\circ\left(a^\circ\Gamma + \Gamma a - 2PcR^{-1}c^*\Gamma\right)X_t^\circ \\
&= -X_t^\circ\left(H + \Gamma cR^{-1}c^\circ\Gamma\right)X_t^\circ \\
&= -X_t^\circ H X_t^\circ - X_t^\circ\Gamma cR^{-1}R R^{-1}c^\circ\Gamma X_t^\circ \\
&= -X_t^\circ H X_t^\circ - U^\circ(X_t^\circ)R U^\circ(X_t^\circ).
\end{aligned}$$

Hence, we find that for any $T > 0$

$$J_T(x, U^\circ) = \|x\|_\Gamma^2 - \|X_T^\circ\|_\Gamma^2 \leq \|x\|_\Gamma^2.$$

Thereby, $J(x, U^\circ) = \lim_{T \rightarrow \infty} J_T(x, U^\circ) \leq \|x\|_\Gamma^2$. So, by (2.16) we have

$$J(x, U^\circ) = \|x\|_\Gamma^2,$$

that is $U^\circ(X_{\circ t})$ is the optimal control.

1. Home work: Vector case. Feedback control. Bellman equation

Let $X_t, t = 0, 1, \dots, N$ be the controlled vector sequence sequence defined by linear vector-matrix recursion

$$X_{t+1} = aX_t + cU(t),$$

where U_t is the control. X_t and U_t are vectors of sizes k and r respectively. $a = a_{k \times k}$ and $c = c_{k \times r}$ are known matrices. $X_0 = x$ and x is known.

It is required to choose the optimal control $U^\circ(t)$ minimizing the cost functional ($h_{k \times k}, H_{k \times k}$ are nonnegative definite matrices, $R_{r \times r}$ is positive definite matrix)

$$J(x, U) = \|X_T\|_h^2 + \sum_{t=1}^{T-1} \|X_t\|_H^2 + \|U(t)\|_R^2. \quad (2.17)$$

1. Derive Bellman's equation for the Bellman function

$$V(x, t) = \min_{U_s: t \leq s \leq T} \left[\|X_T\|_h^2 + \sum_{s=t}^{T-1} \|X_s\|_H^2 + \|U(s)\|_R^2 \right]$$

2. Find the optimal control.