

March 12, 99 (8)

5.5 Dynamic Optimization

5.5.2 Continuous-time

Goal to minimize an integral performance criterion

$$J(x(t_0), t_0) = \int_{t_0}^{t_f} L(x(t), u(t)) dt + g(x(t_f))$$

along trajectories of a dynamic system

$$\dot{x}(t) = f(x(t), u(t)), \quad x(t_0) = x_0$$

f = continuous and continuously differentiable function

u = piecewise continuous function

$x(t)$ = n -dimensional state vector

$u(t)$ = m -dimensional control vector

$g(x(t_f))$ = terminal condition (at t_f certain condition must be satisfied - aircraft on a runway)

$u = u(t)$ = open-loop (or programming) control

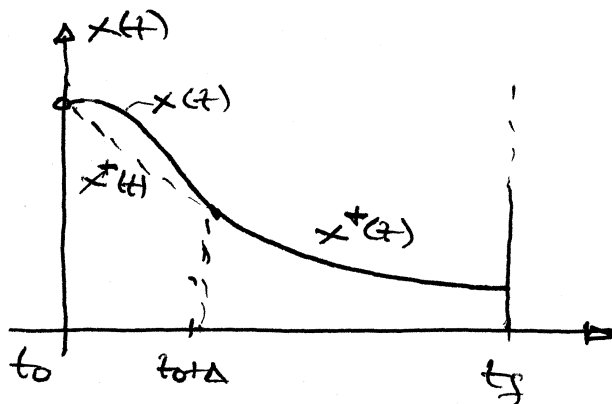
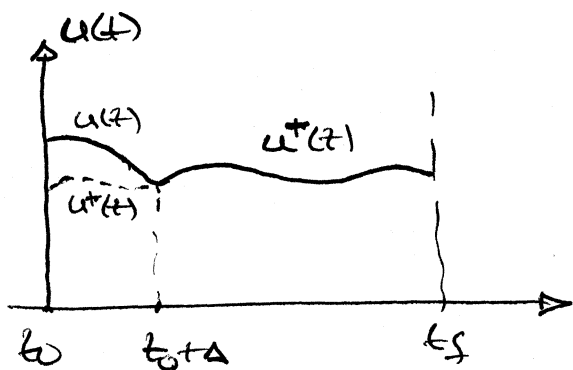
$u = u(x(t))$ = feedback control is desirable since the strategy depends on the state of the system (game)

Assume that an optimal u^* that minimizes J exists. Then

$$J^*(x(t_0), t_0) = \int_{t_0}^{t_f} L(x^*(t), u^*(t)) dt + g(x^*(t_f))$$

$$\dot{x}^*(t) = f(x^*(t), u^*(t)), \quad x^*(t_0) = x_0$$

If the optimal control is not applied for every $t \in [t_0, t_f]$ we have



$$J^*(x(t_0), t_0) \leq \int_{t_0}^{t_0+\Delta} L(x, u) dt + \underbrace{\int_{t_0+\Delta}^{t_f} L(x^*, u^*) dt + g(x(t_f))}_{\triangleq J^*(x^*(t_0+\Delta), t_0+\Delta)}$$

$$J^*(x(t_0), t_0) - J^*(x^*(t_0+\Delta), t_0+\Delta) \leq \int_{t_0}^{t_0+\Delta} L(x, u) dt$$

$$\lim_{\Delta \rightarrow 0} \left\{ \frac{J^*(x^*(t_0+\Delta), t_0+\Delta) - J^*(x(t_0), t_0)}{\Delta} \right\} \leq \lim_{\Delta \rightarrow 0} \frac{1}{\Delta} \int_{t_0}^{t_0+\Delta} L(x, u) dt$$

$$- \frac{\partial J^*}{\partial t_0} (x^*(t_0), t_0) \leq L(x(t_0), u(t_0))$$

Since t_0 can be taken arbitrary, say $t_0 = t$ we have

$$- \frac{\partial J^*}{\partial t} (x^*(t), t) \leq L(x(t), u(t))$$

If the optimal control is used along the entire trajectory we have the equality, that is

$$\boxed{- \frac{\partial J^*}{\partial t} (x^*(t), t) = L(x^*(t), u^*(t))}$$

Note that

$$-\frac{dJ}{dt}(x(t), t) = -\frac{\partial J}{\partial t} - \frac{\partial J}{\partial x} \cdot \frac{dx}{dt} = -\frac{\partial J}{\partial t} - \frac{\partial J}{\partial x} \cdot f(x, u)$$

Hence, we have

$$-\frac{\partial J^*}{\partial t} - \frac{\partial J^*}{\partial x} f(x^*, u^*) = L(x^*, u^*)$$

This partial differential equation is known as the Hamilton-Jacobi-Bellman equation.

Note that from the original definition of J we have

$$J(x(t_f), t_f) = 0 + g(x(t_f))$$

The above H-J-B equation can be written as

$$-\frac{\partial J^*}{\partial t} = L(x^*, u^*) + \frac{\partial J^*}{\partial x} f(x^*, u^*)$$

$$\Rightarrow \underbrace{-\frac{\partial J^*}{\partial t} + \frac{\partial J^*}{\partial x} f(x^*, u^*)}_{\triangleq H(x^*, u^*)} = \text{called Hamiltonian}$$

$$-\frac{\partial J^*}{\partial t} = H(x^*, u^*) = \min_u \left\{ H(x, u) \right\} \quad (5.25) \quad \text{text}$$

In the case of time invariant systems with $t_f \rightarrow \infty$, and J not explicitly depending on t H-J-B equation has the form

$$0 = H(x^*, u^*) \quad \Leftrightarrow \quad \text{on the optimal trajectory (under the optimal control) the Hamiltonian is equal to zero}$$

How to solve the H-B-J equations? (4)

$$-\frac{\partial J^*}{\partial t} = \min_u H(x, u, \frac{\partial J}{\partial x}) = \min_u \{ L(x^*, u^*) + \frac{\partial J^*}{\partial x} f(x^*, u^*) \}$$

$$\frac{\partial H}{\partial u} = 0 \implies \text{hopefully } u^* = \varphi(x^*, \frac{\partial J^*}{\partial x})$$

going back to H-B-J equations

$$-\frac{\partial J^*}{\partial t} = L(x^*, \varphi(x^*, \frac{\partial J^*}{\partial x})) + \frac{\partial J^*}{\partial x} f(x^*, \varphi(x^*, \frac{\partial J^*}{\partial x}))$$

Partial differential equations (in general very very difficult for solving) whose solutions are

$$\frac{\partial J^*}{\partial t} \text{ and } \frac{\partial J^*}{\partial x} \implies u^* = \varphi(x^*, \frac{\partial J^*}{\partial x})$$

Using the definition of the Hamiltonian

$$H(x^*, u^*, \frac{\partial J^*}{\partial x}) = L(x^*, u^*) + \frac{\partial J^*}{\partial x} f(x^*, u^*)$$

we have

$$\begin{aligned} (1) \quad \dot{x}^* &= \frac{\partial H^*}{\partial p} > x^*(t_0) = x_0 & p &= \frac{\partial J}{\partial x} \\ (2) \quad \dot{p}^* &= -\frac{\partial H^*}{\partial x} > p^*(t_1) = \frac{\partial J^*(t_1)}{\partial x} = \frac{\partial g(t_1)}{\partial x} \\ (3) \quad \frac{\partial H^*}{\partial u} &= 0 \implies u^* = \varphi(x^*, p^*) \end{aligned}$$

These three equations constitute necessary conditions for the optimum.

5

Note that in the case of constraints, for example $|u(t)| < \text{const}$, $|x(t)| < \text{const}$, we can not use the unconstrained optimization $\frac{\partial H}{\partial u} = 0$ to find

$$\min_u \{ H(x, u, \frac{\partial J}{\partial x}) \}$$

In that case we have the solution given by the so-called MINIMUM PRINCIPLE OF PONTRYAGIN, which says

$$H(x^*, u^*, \frac{\partial J^*}{\partial x}) \leq H(x^*, u, \frac{\partial J^*}{\partial x}) \quad (3a)$$

(EXAMPLE) Linear-quadratic optimization

$$\begin{cases} J = \frac{1}{2} \int_0^t (x^T Q x + u^T R u) dt + \frac{1}{2} x^T(t_f) F x(t_f), R=R^T > 0 \\ \dot{x} = Ax + Bu, \quad x(t_0) = x_0, \quad Q=Q^T \geq 0, F=F^T \geq 0 \end{cases}$$

Hamiltonian:

$$H = \frac{1}{2} (x^T Q x + u^T R u) + p^T (Ax + Bu) \quad p^T = \frac{\partial J}{\partial x}$$

Necessary conditions:

$$(1) \dot{x} = \frac{\partial H}{\partial p} = Ax + Bu$$

$$(2) \dot{p} = -\frac{\partial H}{\partial x} = -Qx - A^T p$$

$$(3) \frac{\partial H}{\partial u} = Ru + B^T p = 0 \Rightarrow u^* = -R^{-1} B^T p$$

Note $\frac{\partial}{\partial x} (x^T M x) = 2Mx$ assuming $M=M^T$

$\frac{\partial}{\partial x} (p^T A x) = A^T p$ A-any compatible matrix

(3) on (1)-(2) \Rightarrow

$$(1) \quad \dot{x} = Ax - B\bar{D}^{-1}B^T p, \quad x(t_0) = x_0$$

$$(2) \quad \dot{p} = -Qx - A^T p, \quad p(t_f) = Fx(t_f) = \frac{\partial g}{\partial x}(t_f)$$

use $B\bar{D}^{-1}B^T = S$

$$(1) \quad \dot{x} = Ax - Sp, \quad x(t_0) = x_0 = \text{given}$$

$$(2) \quad \dot{p} = -Qx - A^T p, \quad p(t_f) = Fx(t_f)$$

\uparrow
unknown

This is a two-point boundary value problem (note split terminal and initial conditions)

We solve the problem by looking for its solution in the form $p(t) = P(t)x(t)$

$$\Rightarrow \dot{p} = \dot{P}x + Px\dot{x}$$

$$-Qx - A^T p = \dot{P}x + PAx - PSPx$$

$$-\dot{P}x = Qx + A^T Px + PAx - PSPx$$

since this has to hold for every $x(t)$ we get

$$\boxed{-\dot{P} = A^T P + PA + Q - PSP}$$

$$p(t_f) = P(t_f)x(t_f) = Fx(t_f) \Rightarrow \boxed{P(t_f) = F}$$

This is the famous differential Riccati equation. At steady state ($t_f \rightarrow \infty$ and constant matrices) we have

$$\boxed{0 = A^T P + PA + Q - PSP}$$

Algebraic Riccati equations.

There are close to one thousand journal papers written about the Riccati equation (most of them are algebraic one)