

# Optimal Control

## Lecture 9

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Suggested reading: Section 3.10 and Section 4.1 of Ref[1] (see class website or the class syllabus for the list of references)

# Discrete LQR (Derivation through DP app<sub>o</sub>)

- For most cases, dynamic programming must be solved numerically - often quite challenging.
- A few cases can be solved analytically - discrete LQR is one of them
- Goal: select control inputs to minimize

$$J = \frac{1}{2} x_N^T H x_N + \frac{1}{2} \sum_{k=0}^{N-1} (x_k^T Q_k x_k + u_k^T R_k u_k)$$

$$\Rightarrow J_d(x_k, u_k) = \frac{1}{2} x_k^T Q_k x_k + u_k^T R_k u_k$$

s.t.

$$x_{k+1} = A_k x_k + B_k u_k$$

- Assume  $H = H^T \geq 0$ ,  $Q = Q^T \geq 0$ ,  $R = R^T > 0$

- Including any other constraints greatly complicates the problem.

- Clearly  $J_N^*(x_N) = \frac{1}{2} x_N^T H x_N \Rightarrow$  now need to find  $J_{N-1}^*(x_{N-1})$

$$J_{N-1}^*(x_{N-1}) = \min \left\{ J_d(x_{N-1}, u_{N-1}) + J_N^*(x_N) \right\}$$

$$= \min_{u_{N-1}} \frac{1}{2} \left\{ x_{N-1}^T Q_{N-1} x_{N-1} + u_{N-1}^T R_{N-1} u_{N-1} + x_N^T H x_N \right\}$$

- Note that  $x_N = A_{N-1} x_{N-1} + B_{N-1} u_{N-1}$  so that

$$J_{N-1}^*(x_{N-1}) = \min_{u_{N-1}} \frac{1}{2} \left[ u_{N-1}^T Q_{N-1} x_{N-1} + u_{N-1}^T R_{N-1} u_{N-1} + (A_{N-1} x_{N-1} + B_{N-1} u_{N-1})^T H (A_{N-1} x_{N-1} + B_{N-1} u_{N-1}) \right]$$

- Take derivative w.r. to the control inputs

$$\frac{\partial J_{N-1}^*(u_{N-1})}{\partial u_{N-1}} = R_{N-1} u_{N-1} + B_{N-1}^T H (A_{N-1} x_{N-1} + B_{N-1} u_{N-1})$$

Now set this derivative equal to zero

- Recall that both equations are solved backward from  $k+1$  to  $k$

• Now consider time  $k-1$  with

$$J_{k-1}^+(x_{k-1}) = \min_{u_{k-1}} \left\{ \frac{1}{2} x_{k-1}^T Q_{k-1} x_{k-1} + u_{k-1}^T R_{k-1} u_{k-1} + J_k^+(x_k) \right\}$$

• Taking derivative with respect to  $u_{k-1}$  gives

$$\frac{\partial J_{k-1}^+(x_{k-1})}{\partial u_{k-1}} = u_{k-1}^T R_{k-1} + (A_{k-1} x_{k-1} + B_{k-1} u_{k-1})^T P_k B_{k-1}$$

so that the best control input is

$$u_{k-1}^* = - (R_{k-1} + B_{k-1}^T P_k B_{k-1})^{-1} B_{k-1}^T P_k A_{k-1} x_{k-1}$$

$$= - F_{k-1} x_{k-1}$$

• substitute this control into the expression for  $J_{k-1}^+(x_{k-1})$

to show that

$$J_{k-1}^+(x_{k-1}) = \frac{1}{2} x_{k-1}^T P_{k-1} x_{k-1}$$

and

$$P_{k-1} = Q_{k-1} + F_{k-1}^T R_{k-1} F_{k-1} + (A_{k-1} - B_{k-1} F_{k-1})^T P_k$$

$$(A_{k-1} - B_{k-1} F_{k-1})$$

• Thus the same properties hold at time  $k-1$  and  $k$  and  $N$  and  $N-1$  in particular, so they will always be true.

$$(R_{N-1} + B_{N-1}^T H B_{N-1}) u_{N-1} + B_{N-1}^T H A_{N-1} x_{N-1} = 0$$

which suggests a couple of key things.

- The best control action at time  $N-1$  is a linear state feedback on the state at time  $N-1$

$$u_{N-1}^* = - (R_{N-1} + B_{N-1}^T H B_{N-1})^{-1} B_{N-1}^T H A_{N-1} x_{N-1}$$

$$\equiv - F_{N-1} x_{N-1}$$

- Furthermore, can show that

$$\frac{\delta^2 J_{N-1}^*(x_{N-1})}{\delta u_{N-1}^2} = R_{N-1} + B_{N-1}^T H B_{N-1} > 0$$

satisfied  
because  
 $R_{N-1} > 0$   
 $H \geq 0$

So that the stationary point is minimum.

• with this control decision, take another look at

$$J_{N-1}^*(x_{N-1}) = \frac{1}{2} x_{N-1}^T (Q_{N-1} + F_{N-1}^T R_{N-1} F_{N-1} + (A_{N-1} - B_{N-1} F_{N-1})^T H (A_{N-1} - B_{N-1} F_{N-1})) x_{N-1} \equiv \frac{1}{2} x_{N-1}^T P_{N-1} x_{N-1}$$

- Note that  $P_N = H$  which suggests a convenient form for

gain  $F$

$$F_{N-1} = [R_{N-1} + B_{N-1}^T P_N B_{N-1}]^{-1} B_{N-1}^T P_N A_{N-1}$$

• Now can continue using induction - assume that at time  $k$  the control will be of the form  $u_k^* = -F_k x_k$  where

$$F_k = [R_k + B_k^T P_{k+1} B_k]^{-1} B_k^T P_{k+1} A_k$$

and  $J_k^*(x_k) = \frac{1}{2} x_k^T P_k x_k$  where

$$P_k = Q_k + F_k^T R_k F_k + (A_k - B_k F_k)^T P_{k+1} (A_k - B_k F_k)$$

# Algorithm.

Can summarize the above in the algorithm.

- (i)  $P_N = H$
  - (ii)  $F_k = (R_k + B_k^T P_{k+1} B_k)^{-1} B_k^T P_{k+1} A_k$
  - (iii)  $P_k = Q_k + F_k^T R_k F_k + (A_k - B_k F_k)^T P_{k+1} (A_k - B_k F_k)$
- cycle through steps ii and iii from  $N-1 \rightarrow 0$

Note

- the result is a state feedback control <sup>with</sup> time varying <sup>gain</sup>, even if  $A, B, Q, R$  are constant.

- clear that  $P_k$  and  $F_k$  are independent of the state and can be computed ahead of time, off-line. (see your earlier notes on LQR)

- possible to eliminate the  $F_k$  part of the cycle and just cycle through  $P_k$

$$P_k = Q_k + A_k^T (P_{k+1} - P_{k+1} B_k (R_k + B_k^T P_{k+1} B_k)^{-1} B_k^T P_{k+1}) A_k$$

Initial assumption  $R_k > 0$  or  $k$  can be relaxed, but we must ensure that

$$(R_{k+1} + B_k^T P_{k+1} B_k) > 0$$

In the expression

$$J^*(x_k^i, t_k) = \min_{u_k^j} [g(x_k^i, u_k^j, t_k) + J^*(x_{k+1}^i, t_{k+1})]$$

The term  $J^*(x_{k+1}^i, t_{k+1})$  plays the role of a "cost to go" which is very common in DP - a rather control problem

# Calculus of variation and its connection to optimal control

We are going to focus on solving

$$\mathbf{u}^*(t) \Big|_{t \in [t_0, t_f]} = \underset{\mathbf{u}(t) \in \mathcal{U}}{\operatorname{argmin}} (J = h(\mathbf{x}(t_f), t_f) + \int_{t_0}^{t_f} g(\mathbf{x}(t), \mathbf{u}(t), t)), \text{ s.t.}$$

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t),$$

$$\mathbf{x}(t_0), t_0 \text{ is given,}$$

$$\mathbf{m}(\mathbf{x}(t_f), t_f) = 0 \leftarrow \text{when final state is constrained,}$$

$$\mathbf{x}(t) : \mathbb{R} \rightarrow \mathbb{R}^n, \quad \mathbf{u}(t) : \mathbb{R} \rightarrow \mathbb{R}^m, \quad \mathbf{f} : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R} \rightarrow \mathbb{R}^n.$$

## Observations:

- $J$  is a function of  $\mathbf{x}(t)$ ,  $\mathbf{u}(t)$  both functions over  $t \in [t_0, t_f]$
- $J$  is a functional (function of a function)

## Static parameter optimization:

- objective: determine a point that minimizes a specific function (the performance measure)

## Optimization in continuous-time:

- objective: determine a function that minimizes a specific functional (the performance measure)

## Function vs. functional

**Def (function):** A function  $f$  is a rule of correspondence that assigns to each element  $q$  in a certain set  $\mathcal{D}$  (domain of the function) a unique element in a set  $\mathcal{R}$  (range or image of the function)

**Def (functional):** A functional  $J$  is a rule of correspondence that assigns to each function  $x$  in a certain class  $\Omega$  (domain of the functional) a unique real number. The set of real numbers associated with the functions  $\Omega$  is called the range of the functional.

- functional: function of function
- domain is a class of functions

**Example:**  $x$ : continuous function of  $t$  defined in the interval  $[t_0, t_f]$  and

$$J(x) = \int_{t_0}^{t_f} x(t) dt.$$

is a functional. Its range is the area under  $x(t)$  curves.

