ME 433 – STATE SPACE CONTROL

Lecture 10

Continuous Dynamic Optimization

1. Distinctions between continuous and discrete systems

1- Continuous control laws are simpler
2- We must distinguish between *differentials* and *variations* in a quantity

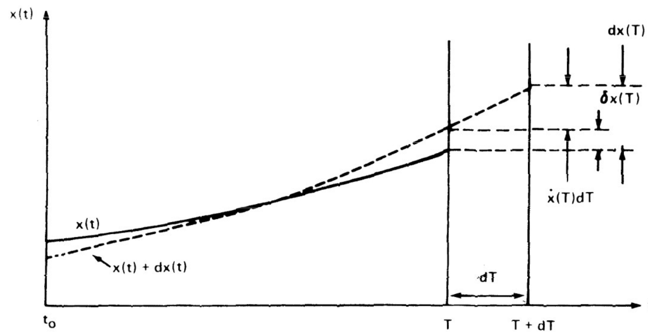
2. The calculus of variations

If $x(t)$ is a continuous function of time t, then the differentials $dx(t)$ and dt are not independent. We can however define a small change in $x(t)$ that is independent of dt. We define the *variation* $\delta x(t)$, as the incremental change in $x(t)$ when time t is held fixed.

What is the relationship between $dx(t)$, dt, and $\delta x(t)$?

Continuous Dynamic Optimization

Final time variation: $dx(T) = \delta x(T) + \dot{x}(T)dT$



Leibniz's rule: $J(x) = \int_{t_0}^{T} h(x(t),t)dt$

$$dJ = h(x(T),T)dT - h(x(t_0),t_0)dt_0 + \int_{t_0}^{T} \left[h_x^T(x(t),t)\delta x\right]dt$$

Continuous Dynamic Optimization

3. Continuous Dynamic Optimization

The plant is described by the general nonlinear continuous-time time-varying dynamical equation

$$\dot{x} = f(t,x,u), \qquad t_0 < t < T$$

with initial condition x_0 given. The vector x has n components and the vector u has m components.

The problem is to find the sequence $u^*(t)$ on the time interval $[t_0,T]$ that drives the plant along a trajectory $x^*(t)$, minimizes the performance index

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

and such that

$$\psi(T,x(T)) = 0$$

Continuous Dynamic Optimization

We adjoin the constraints (system equations and terminal constraint) to the performance index J with a multiplier function $\lambda(t) \in R^n$ and a multiplier constant $\nu \in R^p$.

$$\bar{J}(t_0) = \phi(T,x(T)) + \nu^T\psi(T,x(T)) + \int_{t_0}^{T}\left[L(t,x(t),u(t)) + \lambda^T(t)\left(f(t,x,u) - \dot{x}\right)\right]dt$$

For convenience, we define the *Hamiltonian* function

$$H(t,x,u) = L(t,x,u) + \lambda^T(t)f(t,x,u)$$

Thus,

$$\bar{J}(t_0) = \phi(T,x(T)) + \nu^T\psi(T,x(T)) + \int_{t_0}^{T}\left[H(t,x(t),u(t),\lambda(t)) - \lambda^T(t)\dot{x}\right]dt$$

Continuous Dynamic Optimization

We want to examine now the increment in $\bar{J}$ due to increments in all the variables x, λ, ν, u and t. Using Leibniz's rule, we compute

$$d\bar{J}(t_0) = \left(\phi_x + \psi_x^T\nu\right)^T dx\big|_T + \left(\phi_t + \psi_t^T\nu\right)dt\big|_T + \psi^T\big|_T d\nu$$
$$+\left(H - \lambda^T\dot{x}\right)dt\big|_T - \left(H - \lambda^T\dot{x}\right)dt\big|_{t_0}$$
$$+\int_{t_0}^{T}\left[H_x^T\delta x + H_u^T\delta u - \lambda^T\delta\dot{x} + \left(H_\lambda - \dot{x}\right)^T\delta\lambda\right]dt$$

We integrate by parts, $\int_{t_0}^{T}\lambda^T\delta\dot{x}dt = \lambda^T\delta x\big|_T - \lambda^T\delta x\big|_{t_0} - \int_{t_0}^{T}\dot{\lambda}^T\delta x dt$, to obtain

$$d\bar{J}(t_0) = \left(\phi_x + \psi_x^T\nu - \lambda^T\right)^T dx\big|_T + \left(\phi_t + \psi_t^T\nu + H - \lambda^T\dot{x} + \lambda^T\dot{x}\right)dt\big|_T$$
$$+\psi^T\big|_T d\nu - \left(H - \lambda^T\dot{x} + \lambda^T\dot{x}\right)dt\big|_{t_0} + \lambda^T dx\big|_{t_0}$$
$$+\int_{t_0}^{T}\left[\left(H_x + \dot{\lambda}\right)^T\delta x + H_u^T\delta u + \left(H_\lambda - \dot{x}\right)^T\delta\lambda\right]dt$$

$$\boxed{dx(t) = \delta x(t) + \dot{x}(t)dt}$$

Continuous Dynamic Optimization

We assume that t_0 and $x(t_0)$ are both fixed and given, then dt_0 and $dx(t_0)$ are both zero. According to the Lagrange theory the constrained minimum of J is attained at the unconstrained minimum of $\bar{J}$. This is achieved when $d\bar{J} = 0$ for all independent increments in its arguments. Then, the necessary conditions for a minimum are:

$$\psi|_T = 0$$

$$\left.\begin{aligned} H_\lambda - \dot{x} = 0 \Rightarrow \dot{x} = H_\lambda = f \\ H_x + \dot{\lambda} = 0 \Rightarrow -\dot{\lambda} = H_x = L_x + \lambda^T f_x \end{aligned}\right\} \text{Two-point Boundary-value Problem}$$

$$H_u = L_u + \lambda^T f_u = 0$$

$$\left(\phi_x + \psi_x^T \nu - \lambda^T\right)^T dx|_T + \left(\phi_t + \psi_t^T \nu + H\right)^T dt|_T = 0$$

The initial condition for the Two-point Boundary-value Problem is the known value for x_0. For a fixed T, the final condition is either a desired value of $x(T)$ or the value of $\lambda\ (T)$ given by the last equation. This equation allows for possible variations in the final time $T \rightarrow$ minimum time problems.

Continuous Dynamic Optimization

System Properties | SUMMARY | Controller Properties

System Properties

System Model

$$x(t) = f(t, x, u)$$

Performance Index

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

Final-state Constraint

$$\psi(T, x(T)) = 0$$

Hamiltonian

$$H(t, x, u, \lambda) = L(t, x, u) + \lambda(t) f(t, x, u)$$

Controller Properties

State Equation

$$\dot{x} = \frac{\partial H}{\partial \lambda} = f(t, x, u), \quad t \geq t_0$$

Costate Equation

$$-\dot{\lambda} = \frac{\partial H}{\partial x} = \frac{\partial L}{\partial x} + \lambda^T \frac{\partial f}{\partial x}, \quad t \leq T$$

Stationary Condition

$$\frac{\partial H}{\partial u} = \frac{\partial L}{\partial u} + \lambda^T \frac{\partial f}{\partial u} = 0$$

Boundary Condition

$$x(t_0) \text{ given}$$

$$\left(\phi_x + \psi_x^T \nu - \lambda^T\right)^T dx|_T + \left(\phi_t + \psi_t^T \nu + H\right)^T dt|_T = 0$$

Continuous Dynamic Optimization

The time derivative of the Hamiltonian is

$$\dot{H} = H_t + H_x^T \dot{x} + H_u^T \dot{u} + \dot{\lambda}^T f$$
$$= H_t + H_u^T \dot{u} + \left(H_x + \dot{\lambda}\right)^T f$$

If $u(t)$ is an optimal control, then

$$\dot{H} = H_t$$

In the time-invariant case, f and L, and therefore H, are not explicit functions of time.

$$\dot{H} = 0$$

Hence, for time-invariant systems and cost functions, the Hamiltonian is a constant on the optimal trajectory.

Continuous Dynamic Optimization

4. Hamilton's Principle in Classical Dynamics

For a conservative system in classical mechanics, "*of all possible paths along which a dynamical system may move from one point to another within a specified time interval (consistent with any constraints), the actual path followed is that which minimizes the time integral of the difference between the kinetic and potential energies*"

A- Lagrange's Equation of Motion:

q	generalized coordinate vector (state)
$u = \dot{q}$	generalized velocities (dynamics)
$U(q)$	potential energy
$T(q,u)$	kinetic energy
$L(q,u) = T(q,u) - U(q)$	Lagrangian of the system

Continuous Dynamic Optimization

Plant: $\dot{q} = u \equiv f(q,u)$

Performance index: $J(0) = \int_0^T L(q,u)dt$

Hamiltonian: $H = L + \lambda^T u$

Costate Equation: $-\dot{\lambda} = \frac{\partial H}{\partial q} = \frac{\partial L}{\partial q}$

Stationary Condition: $\frac{\partial H}{\partial u} = \frac{\partial L}{\partial u} + \lambda = 0$

$$\frac{\partial L}{\partial q} - \frac{\partial}{\partial t}\frac{\partial L}{\partial \dot{q}} = 0$$

Lagrange Equation (Mechanics)

Euler's Equation (Variational Problems)

In this case, the condition $\dot{H} = 0$ is a statement of conservation of energy

Continuous Dynamic Optimization

B- Hamilton's Equation of Motion:

Generalized momentum: $\lambda = -\frac{\partial L}{\partial \dot{q}}$ (Stationary Condition)

Then, the equations of motion can be written in Hamilton's form:

$$\dot{q} = \frac{\partial H}{\partial \lambda}$$ (State Equation)

$$-\dot{\lambda} = \frac{\partial H}{\partial q}$$ (Costate Equation)

Hence, in the optimal control problem, the state and costate equations are a generalized formulation of Hamilton's equations of motion

Continuous Dynamic Optimization

Examples:

Continuous Dynamic Optimization

5. Linear Quadratic Regulator (LQR) Problem

The plant is described by the linear continuous-time dynamical equation

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

with initial condition x_0 given. We assume that the final time T is fixed and given, and that no function of the final state ψ is specified. We want to find the sequence $u^*(t)$ that minimizes the performance index:

$$J(t_0) = \frac{1}{2}x^T(T)S(T)x(T) + \frac{1}{2}\int_{t_0}^{T}\left(x^T Q(t)x + u^T R(t)u\right)dt$$

Linear because of the system dynamics

Quadratic because of the performance index

Regulator because of the absence of a tracking objective---we are interested in regulation around the zero state.

Continuous Dynamic Optimization

We adjoin the system equations (constraints) to the performance index J with a multiplier sequence $\lambda(t) \in R^n$.

$$\bar{J}(t_0) = \frac{1}{2}x^T(T)S(T)x(T) + \frac{1}{2}\int_{t_0}^{T}\left[x^T Q(t)x + u^T R(t)u\dot{x} + \lambda^T\left(A(t)x + B(t)u - \dot{x}\right)\right]dt$$

We define the Hamiltonian

$$H(t) = x^T Q(t)x + u^T R(t)u\dot{x} + \lambda^T\left(A(t)x + B(t)u\right)$$

Thus, the necessary conditions for a stationary point are:

$$\dot{x} = \frac{\partial H}{\partial \lambda} = A(t)x + B(t)u \qquad \textit{State Equation}$$

$$-\dot{\lambda} = \frac{\partial H}{\partial x} = Qx + A^T(t)\lambda \qquad \textit{Costate Equation}$$

$$\frac{\partial H}{\partial u} = Ru + B^T\lambda = 0 \Rightarrow \boxed{u(t) = -R^{-1}B^T\lambda(t)} \qquad \textit{Stationary Condition}$$

Continuous Dynamic Optimization

We must solve the Two-point Boundary-value Problem

$$\dot{x} = \frac{\partial H}{\partial \lambda} = A(t)x - B(t)R^{-1}B^T(t)\lambda(t)$$

$$-\dot{\lambda} = \frac{\partial H}{\partial x} = Qx + A^T(t)\lambda$$

for $t_0 \le t \le T$, with boundary conditions

$$x(t_0) = x_0$$

We will solve this system for two special cases:

1- Fixed final state → Open loop control

2- Free final state → Closed loop control

Continuous Dynamic Optimization

5.1 Fixed-Final State and Open-Loop Control

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

$$J(t_0) = \frac{1}{2}\int_{t_0}^{T} u^T R(t) u\, dt$$

If $Q \neq 0$, the problem is intractable analytically. The Two-point Boundary-value Problem is now simplified:

$$\dot{x} = \frac{\partial H}{\partial \lambda} = Ax - BR^{-1}B^T\lambda \qquad\qquad \dot{x} = \frac{\partial H}{\partial \lambda} = Ax - BR^{-1}B^T\lambda$$

$$-\dot{\lambda} = \frac{\partial H}{\partial x} = Qx + A^T\lambda \quad \Rightarrow \quad \dot{\lambda} = \frac{\partial H}{\partial x} = -A^T\lambda$$

Continuous Dynamic Optimization

The costate equation is decoupled from the state equation, and it has an easy solution:

$$\dot{\lambda} = -A^T\lambda \Rightarrow \boxed{\lambda(t) = e^{A^T(T-t)}\lambda(T)}$$

We replace λ in the state equation and solve:

$$\dot{x} = Ax - BR^{-1}B^T e^{A^T(T-t)}\lambda(T) \Rightarrow \boxed{x(t) = e^{A(t-t_0)}x_0 - \int_{t_0}^{t} e^{A(T-\tau)}BR^{-1}B^T e^{A^T(T-\tau)}\lambda(T)\, d\tau}$$

We solve now for $\lambda(T)$:

$$x(T) = e^{A(T-t_0)}x_0 - \int_{t_0}^{T} e^{A(T-\tau)}BR^{-1}B^T e^{A^T(T-\tau)}d\tau\,\lambda(T) = r_T$$

$$\lambda(T) = -G_C^{-1}(t_0,T)\left(r_T - e^{A(T-t_0)}x_0\right) \qquad G_C(t_0,T) = \int_{t_0}^{T} e^{A(T-\tau)}BR^{-1}B^T e^{A^T(T-\tau)}d\tau$$

Weighted Controllability Gramian of $[A,B]$

Continuous Dynamic Optimization

Summary:

$$G_C(t_0,T) = \int_{t_0}^{T} e^{A(T-\tau)} B R^{-1} B^T e^{A^T(T-\tau)} d\tau$$

The inverse of the gramian $G_C(t_0,T)$ exits if and only if the system is controllable.

$$\lambda(T) = -G_C^{-1}(t_0,T)\left(r_T - e^{A(T-t_0)}x_0\right)$$

$$x(t) = e^{A(t-t_0)}x_0 - \int_{t_0}^{t} e^{A(T-\tau)} B R^{-1} B^T e^{A^T(T-\tau)} \lambda(T) d\tau$$

$$u^*(t) = R^{-1}B^T e^{A^T(T-t)} G_C^{-1}(t_0,T)\left(r_T - e^{A(T-t_0)}x_0\right)$$

Continuous Dynamic Optimization

5.2 Free-Final-State and Closed-Loop Control

$$\dot{x} = A(t)x + B(t)u, J(t_0) = \frac{1}{2}x^T(T)S(T)x(T) + \frac{1}{2}\int_{t_0}^{T}\left(x^T Q(t) x + u^T R(t) u\right)dt$$

The Two-point Boundary-value Problem is:

$$\dot{x} = \frac{\partial H}{\partial \lambda} = Ax - BR^{-1}B^T\lambda$$

$$-\dot{\lambda} = \frac{\partial H}{\partial x} = Qx + A^T\lambda$$

We need $\left[\left.\frac{\partial \phi}{\partial x}\right|_T - \lambda^T(T)\right]^T \left.dx\right|_T = 0 \Rightarrow \lambda^T(T) = \left.\frac{\partial \phi}{\partial x}\right|_T = x^T(T)S(T)$

Let us assume that this relationship holds for all $t_0 \le t \le T$ (Sweep Method)

$$\lambda(t) = S(t)x(t)$$

Continuous Dynamic Optimization

We differentiate the costate and use the state equation,

$$\dot{\lambda} = \dot{S}x + S\dot{x} = \dot{S}x + S\left(Ax - BR^{-1}B^T Sx\right)$$

We use now the costate equation,

$$-\left(Qx + A^T Sx\right) = \dot{S}x + S\left(Ax - BR^{-1}B^T Sx\right)$$

$$-\dot{S}x = \left(A^T S + SA - SBR^{-1}B^T S + Q\right)x$$

Since this must hold for any trajectory x,

$$-\dot{S} = A^T S + SA - SBR^{-1}B^T S + Q$$ Ricatti Equation (RE)

The optimal control is given by,

$$u(t) = -R^{-1}B^T Sx(t) = -K(t)x(t)$$ Feedback Control!!!

$$K(t) = R^{-1}B^T S(t)$$ Kalman Gain

Continuous Dynamic Optimization

This expresses u as a time-varying, linear, state-variable, feedback control. The feedback gain K is computed ahead of time via S, which is obtained by solving the Riccati equation backward in time with terminal condition S_T.

Similarly to the discrete-time case, it is possible to rewrite the cost function as

$$J(t_0) = \frac{1}{2}x^T(t_0)S(t_0)x(t_0) + \frac{1}{2}\int_{t_0}^{T}\left\|R^{-1}B^T Sx + u\right\|_R^2 dt$$

If we select the optimal control, the value of the cost function for $t_0 \le t \le T$ is just

$$J(t_0) = \frac{1}{2}x^T(t_0)S(t_0)x(t_0)$$

Continuous Dynamic Optimization

Examples:

Steady-State Feedback

6. Steady-State Feedback for discrete-time systems

The solution of the LQR optimal control problem for discrete-time systems is a state feedback of the form

$$u_k = -K_k x_k$$

where

$$K_k = \left(R + B^T S_{k+1} B\right)^{-1} B^T S_{k+1} A$$

$$S_k = A^T S_{k+1} A - A^T S_{k+1} B \left(B^T S_{k+1} B + R\right)^{-1} B^T S_{k+1} A + Q$$

The closed-loop system is time-varying!!!

$$x_{k+1} = \left(A - BK_k\right) x_k$$

What about a suboptimal constant feedback gain?

$$u_k = -K x_k = -K_\infty x_k$$

Steady-State Feedback

6.1 The Algebraic Riccati Equation (ARE)

$$S_k = A^T S_{k+1} A - A^T S_{k+1} B \left(B^T S_{k+1} B + R \right)^{-1} B^T S_{k+1} A + Q \qquad \text{RDE}$$

Let us assume that when $k \rightarrow -\infty$, the sequence S_k converges to a steady-state matrix S_∞. If S_k does converge, then $S_k = S_{k+1} = S$. Thus, in the limit

$$S = A^T \left[S - SB \left(B^T S B + R \right)^{-1} B^T S \right] A + Q \qquad \text{ARE}$$

The limiting solution S_∞ is clearly a solution of the ARE. Under some circumstances we may be able to use the following time-invariant feedback control instead of the optimal control,

$$u_k = -K_\infty x_k$$

$$K_\infty = \left(R + B^T S_\infty B \right)^{-1} B^T S_\infty A$$

Steady-State Feedback

1- When does there exist a bounded limiting solution S_∞ to the Ricatti equation for all choices of S_N?

2- In general, the limiting solution S_∞ depends on the boundary condition S_N. When is S_∞ the same for all choices of S_N?

3- When is the closed-loop system ($u_k = -K_\infty x_k$) asymptotically stable?

Theorem: Let (A, B) be stabilizable. Then, for every choice of S_N there is a bounded solution S_∞ to the RDE. Furthermore, S_∞ is a positive semidefinite solution to the ARE.

Theorem: Let C be a square root of the intermediate-state weighting matrix, so that $Q = C^T C \geq 0$, and suppose $R > 0$. Suppose (A, C) is observable. Then, (A, B) is stabilizable if and only if:

a- There is a unique positive definite limiting solution S_∞ to the RDE. Furthermore, S_∞ is the unique positive definite solution to the ARE.

b- The closed-loop plant

$$x_{k+1} = \left(A - BK_\infty \right) x_k$$

is asymptotically stable, where K_∞ is given by $K_\infty = \left(R + B^T S_\infty B \right)^{-1} B^T S_\infty A$

Steady-State Feedback

7. Steady-State Feedback for continuous-time systems

The solution of the LQR optimal control problem for continuous-time systems is a state feedback of the form

$$u(t) = -K(t)x(t)$$

where

$$K(t) = R^{-1}B^T S(t)$$

$$-\dot{S} = A^T S + SA - SBR^{-1}B^T S + Q$$

The closed-loop system is time-varying!!!

$$\dot{x}(t) = \left(A - BK(t)\right)x(t)$$

What about a suboptimal constant feedback gain?

$$u(t) = -K(t)x(t) = -K_\infty x(t)$$

Steady-State Feedback

7.1 The Algebraic Riccati Equation (ARE)

$$-\dot{S} = A^T S + SA - SBR^{-1}B^T S + Q \qquad \text{RDE}$$

Let us assume that when $t \to -\infty$, the sequence $S(t)$ converges to a steady-state matrix S_∞. If $S(t)$ does converge, then $dS/dt = 0$. Thus, in the limit

$$0 = A^T S + SA - SBR^{-1}B^T S + Q \qquad \text{ARE}$$

The limiting solution S_∞ is clearly a solution of the ARE. Under some circumstances we may be able to use the following time-invariant feedback control instead of the optimal control,

$$u = -K_\infty x$$

$$K_\infty = R^{-1}B^T S_\infty$$

Steady-State Feedback

1- When does there exist a bounded limiting solution S_∞ to the Ricatti equation for all choices of $S(T)$?

2- In general, the limiting solution S_∞ depends on the boundary condition $S(T)$. When is S_∞ the same for all choices of $S(T)$?

3- When is the closed-loop system (u=-$K_\infty x$) asymptotically stable?

Theorem: Let (A, B) be stabilizable. Then, for every choice of $S(T)$ there is a bounded solution S_∞ to the RDE. Furthermore, S_∞ is a positive semidefinite solution to the ARE.

Theorem: Let C be a square root of the intermediate-state weighting matrix Q, so that $Q{=}C^TC{\geq}0$, and suppose $R{>}0$. Suppose (A, C) is observable. Then, (A, B) is stabilizable if and only if:

a- There is a unique positive definite limiting solution S_∞ to the RDE. Furthermore, S_∞ is the unique positive definite solution to the ARE.

b- The closed-loop plant

$$\dot{x} = \left(A - BK_\infty\right)x$$

is asymptotically stable, where K_∞ is given by $K_\infty = R^{-1}B^TS_\infty$

Steady-State Feedback

Examples:

Receding Horizon LQ Control

8. Receding Horizon LQ Control

So far we have seen two kinds of LQ control problems:

Finite Horizon: Finite duration, time-varying solution (even for time invariant systems), solution via RDE, no stability properties necessary.

Discrete time: $$J = \frac{1}{2} x_N^T S_N x_N + \frac{1}{2} \sum_{k=0}^{N-1} \left(x_k^T Q_k x_k + u_k^T R_k u_k \right)$$

$$S_k = A_k^T S_{k+1} A_k - A_k^T S_{k+1} B_k \left(B_k^T S_{k+1} B_k + R_k \right)^{-1} B_k^T S_{k+1} A_k + Q_k$$

$$u_k = -\left(R_k + B_k^T S_{k+1} B_k \right)^{-1} B_k^T S_{k+1} A_k x_k$$

Continuous time: $$J(t_0) = \frac{1}{2} x^T(T) S(T) x(T) + \frac{1}{2} \int_{t_0}^{T} \left(x^T Q(t) x + u^T R(t) u \right) dt$$

$$-\dot{S} = A^T S + SA - SBR^{-1} B^T S + Q$$

$$u(t) = -R(t)^{-1} B(t)^T S(t) x(t)$$

Receding Horizon LQ Control

Infinite Horizon: Infinite duration, time invariant solution (for LTI systems + QTI cost), solution via ARE, stability via detectability.

Discrete time: $$J = \frac{1}{2} \sum_{k=0}^{\infty} \left(x_k^T Q x_k + u_k^T R u_k \right)$$

$$S_\infty = A^T \left[S_\infty - S_\infty B \left(B^T S_\infty B + R \right)^{-1} B^T S_\infty \right] A + Q$$

$$u_k = -\left(R + B^T S_\infty B \right)^{-1} B^T S_\infty A x_k$$

Continuous time: $$J = \frac{1}{2} \int_0^{\infty} \left(x^T Q(t) x + u^T R(t) u \right) dt$$

$$0 = A^T S_\infty + S_\infty A - S_\infty B R^{-1} B^T S_\infty + Q$$

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

Receding Horizon LQ Control

Receding Horizon: At each time i (discrete) or t (continuous) we solve a finite horizon problem

Discrete time:

$$J = \frac{1}{2} x_{i+N}^T S_N x_{i+N} + \frac{1}{2} \sum_{k=0}^{N-1} \left(x_{i+k}^T Q_k x_{i+k} + u_{i+k}^T R_k u_{i+k} \right)$$

$$S_k = A_k^T S_{k+1} A_k - A_k^T S_{k+1} B_k \left(B_k^T S_{k+1} B_k + R_k \right)^{-1} B_k^T S_{k+1} A_k + Q_k \qquad 0 \le k \le N-1$$

$$u_i = -\left(R_i + B_i^T S_0 B_i \right)^{-1} B_i^T S_0 A_i x_i$$

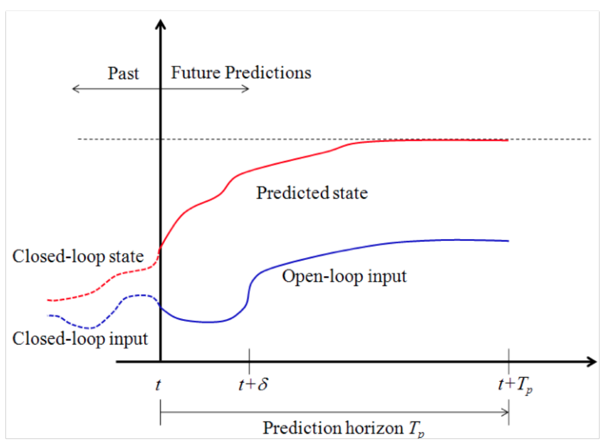
Continuous time:

$$J(t) = \frac{1}{2} x^T(t+T) S(T) x(t+T) + \frac{1}{2} \int_0^T \left(x(t+\tau)^T Q(\tau) x(t+\tau) + u(t+\tau)^T R(\tau) u(t+\tau) \right) d\tau$$

$$-\dot{S} = A^T S + SA - SBR^{-1} B^T S + Q \qquad 0 \le t \le T$$

$$u(t) = -R(t)^{-1} B(t)^T S(0) x(t)$$

Receding Horizon LQ Control



Receding Horizon LQ Control

Receding Horizon: At each time i (discrete) or t (continuous) we solve a finite horizon problem

- An infinite-horizon strategy → we need to understand its stabilization properties
- Time-invariant for LTI problems
- Capable of working in the nonlinear, constrained context, using explicit optimization

Receding Horizon LQ Control

We define now the Fake Algebraic Riccati Equation (FARE)

Discrete time:

$$u_i = -\left(R_i + B_i^T S_0 B_i\right)^{-1} B_i^T S_0 A_i x_i$$

$$S_k = A_k^T S_{k+1} A_k - A_k^T S_{k+1} B_k \left(B_k^T S_{k+1} B_k + R_k\right)^{-1} B_k^T S_{k+1} A_k + Q_k \quad 0 \le k \le N-1$$

⇓

$$S_{k+1} = A_k^T S_{k+1} A_k - A_k^T S_{k+1} B_k \left(B_k^T S_{k+1} B_k + R_k\right)^{-1} B_k^T S_{k+1} A_k + \overline{Q}_k$$

$$\overline{Q}_k = Q_k + S_{k+1} - S_k$$

We can study the stability properties of the Receding Horizon control as an Infinite Horizon control with a new Q (detectability + monotonicity).