1 Systems Theory

1.1 Linearization

1.2 Discretization

Exact

Forward-Euler

Backward-Euler

1.3 Lyapunov Function

$$V(0) = 0, x \neq 0 \implies V(x) > 0, V(g(x(k+1))) - V(x(k+1)) \leq -\alpha(x(k))$$

System asymptotically stable if V(x) exists. Globally stable iff $||x|| \to \infty \implies V(x) \to \infty$.

Check Eig. values of (APA - P) neg., $V(x) = x^T Px$?

2 Unconstrained Control

DARE Initialize $P_N = P$, sometimes $F_k = K$.

$$P_k = A^T P_{k+1} A + Q - A^T P_{k+1} B (B^T P_{k+1} B + R)^{-1} B^T P_{k+1} A$$

 $F_k - (B^T P_{k+1} B + R)^{-1} B^T P_{k+1} A$

Infinite Horizon unconstrained, LQR gives P_{∞} satisfying equations above. If (A, B) stabilizable and (A, G) detectable, P_{∞} unique, where $GG^T = Q$.

3 (Convex) Optimization

General Problem $\min_{x \in \text{dom}(f)} f(x)$ s. t. $g_i(x) \leq 0$ and $h_j(x) = 0$.

RHC

QP with substitution

QP with out substitution

3.1 Duality

Lagrangian Dual Function

$$L(x, \lambda, \nu) = f(x) + \sum_{i=1}^{m} \lambda_i g_i(x) + \sum_{i=1}^{p} \nu_i h_i(x)$$
$$d(\lambda, \nu) = \inf_{x \in \mathcal{X}} L(x, \lambda, \nu) \quad \text{i.e. } \nabla_x L(x, \lambda, \nu) = 0$$

Dual Problem (always convex) $\max_{\lambda,\nu} d(\lambda,\nu)$ s. t. $\lambda \geq 0$. Optimal value is lower bound for primal: $d^* < p^*$.

If primal convex, Slater condition (strict feasibility) implies strong duality:

$$\{x \mid Ax = b, f_i(x) < 0, \} \neq \emptyset \Rightarrow d^* = p^*$$

Karush-Kuhn-Tucker (KKT) Conditions are necessary for optimality (and sufficient if primal convex).

Primal Feasibility:

$$f_i(x^*) \le 0$$
 $i = 1, ..., m$
 $h_i(x^*) = 0$ $i = 1, ..., p$

- Dual Feasibility: $\lambda^* \geq 0$
- Complementary Slackness:

$$\lambda_i^* \cdot f_i(x^*) = 0$$
 $i = 1, \ldots, m$

Stationarity:

$$\nabla_x L(x^*, \lambda^*, \nu^*) = 0$$

3.2 Constrained Finite Time Optimal Control (CFTOC)

- 3.3 Invariance
- 3.4 Feasability, Stability
- 3.5 Practical MPC
- 3.6 Robust MPC

Tube-MPC

- 3.7 Explicit MPC
- 3.8 Hybrid MPC

4 Numerical Optimization

Gradient, Newton, Interior Point

5 Observer Based Control

5.1 LTI Observer

LTI System:

$$x(k) = Ax(k-1) + Bu(k-1) + v(k-1)$$

$$z(k) = Hx(k) + w(k)$$

Linear Static Gain Observer (Luenberger Observer):

$$\hat{x}(k) = A\hat{x}(k-1) + Bu(k-1) + K(z(k) - \hat{z}(k))$$

$$\hat{z}(k) = H(A\hat{x}(k-1) + Bu(k-1))$$

$$e(k) = (I - KH) A e(k-1)$$

 $e(k) \to 0$ for $k \to \infty$ if and only if (I - KH)A is stable.

Steady State:

$$\hat{x}(k) = (I - K_{\infty}H) A \hat{x}(k-1) + (I - K_{\infty})B u(k-1) + K_{\infty}z(k)$$

The steady-state KF is one way to design the observer gain K (optimal in minimizing the Steady State mean squared error).

(A, H) detectable $\Rightarrow K$ exists such that (I - KH)A is stable.

5.2 Static State Feedback Control

Design of a controller without paying attention to the state estimation:

$$x(k) = Ax(k-1) + Bu(k-1)$$
 (Process without noise)
 $z(k) = x(k)$ (Perfect State information)
 $u(k) = F \cdot z(k) = F \cdot x(k)$ (Control Law)

Closed loop dynamics: x(k) = (A + BF). Hence system is stable if (A + BF) is stable. Such an F exists only if (A, B) is stabilizable. If (A, B) is stabilizable and (A, G) detectable, then F is given by

$$F = -(B^T P B + \bar{R})^{-1} \cdot B^T P A; \qquad P \ge 0$$

P from DARE: $P = A^T P A + \bar{Q} - A^T P B (B^T P B + \bar{R})^{-1} \cdot B^T P A$

5.3 Separation Principle (Linear Systems only)

Combining Luenberger Observer and Static State Feedback control yields:

$$\begin{bmatrix} x(k) \\ e(k) \end{bmatrix} = \begin{bmatrix} A+BF & -BF \\ 0 & (I-KH)A \end{bmatrix} \cdot \begin{bmatrix} x(k-1) \\ e(k-1) \end{bmatrix}$$

Eigenvalues of closed loop are given bei Eigenvalues of (I - KH)A and (A + BF). System is stable as long as there exists no $|\lambda| \ge 1$.

5.4 Separation Theorem

- 1. Design steady-state KF which does not depend on $\bar{Q}, \bar{R}. \Rightarrow \hat{x}(k)$
- 2. Design state-feedback u(k) = Fx(k) and put both together.