

Lecture 21

Linear Systems

11/29/12

Last time:

- Reachability of DT LTI systems
- Kalman rank test

Today:

- Reachability Gramian
- Minimum energy control
- Standard form for unreachable systems

Recall: $x(0)=0$ $\oplus$ $x(k+1) = Ax(k) + Bu(k)$

$$x(k) = \begin{bmatrix} A^{k-1}B & \dots & B \end{bmatrix} \begin{bmatrix} u(0) \\ \vdots \\ u(k-1) \end{bmatrix} = R_k u_k$$

$$x(k+1) = Ax(k) + Bu(k) \quad (*)$$

↳ Reachability ✓

[i.e. we can reach any $x_f \in \mathbb{R}^n$ in n (or fewer) time steps]

$$\Leftrightarrow \text{rank } R_n = n$$

$$R_n = \begin{bmatrix} A^{n-1}B & A^{n-2}B & \dots & AB & B \end{bmatrix}$$

on-off test

Reachability Gramian: $P_k = R_k R_k^T = \sum_{i=0}^{k-1} A^i B B^T (A^i)^T$

Lyapunov Eq:

$$A P_k A^T - P_{k+1} = -B B^T \quad \text{for stable systems } (|\lambda_i(A)| < 1)$$

$$A P_\infty A^T - P_\infty = -B B^T$$

$$P_\infty = \lim_{k \rightarrow \infty} P_k$$

$$\text{CT: } \text{lyap}(A, B) = P_\infty$$

$$\text{DT: } \text{dlyap}(A, B) = P_\infty \quad \text{check}$$

$$P_k \geq 0 \quad (\text{positive semi definite})$$

$$x^T P_k x = x^T \underbrace{R_k R_k^T}_Z x = z^T z = \sum z_i^2 \geq 0$$

$$P_l - P_k \geq 0, \quad l \geq k$$

$$P_l = \sum_{i=0}^{l-1} A^i B B^T (A^i)^T = P_k + \underbrace{\sum_{i=k}^{l-1} A^i B B^T (A^i)^T}_{(*)}$$

$$x^T P_l x = x^T P_k x + (*) \geq 0$$

Assume:

- Reachability of $\textcircled{*}$
- Let $K > n$

$$x_f = R_K \underline{u}_K$$

$$\begin{bmatrix} x_f \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}_n = \underbrace{\begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}}_{\substack{\text{fat matrix} \\ n \times m \cdot K}} \begin{bmatrix} \underline{u}_K \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}_{K \cdot m}$$

$\xrightarrow{\text{# of controls}}$
 $\xrightarrow{\text{# of time steps}}$

There are many control inputs that can bring us to $x(K) = x_f$

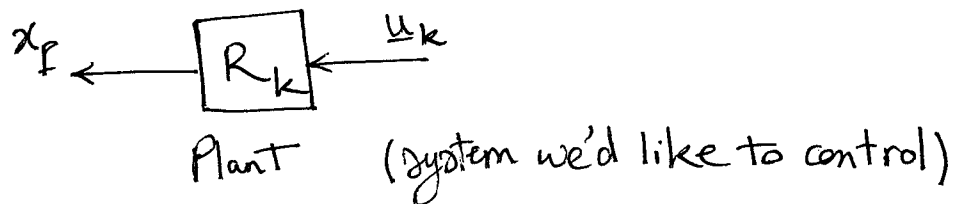
Choose one with the minimum ~~min~~ energy

Minimum energy state transfer (from $x(0) = 0$
to $x(k) = x_f$)

$$\begin{cases} \text{minimize} & \underline{u}_k^T \underline{u}_k \\ \text{subject to} & x_f - R_k \underline{u}_k = 0 \end{cases}$$

Problem data : x_f, R_k

Optimization variable : $\underline{u}_k = \begin{bmatrix} u(0) \\ \vdots \\ u(k-1) \end{bmatrix}$
(unknown)

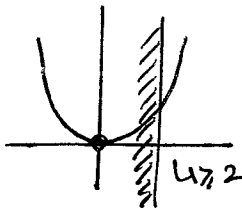


For the minimization above : in the absence of
problem constraints the optimal value is zero
which is achieved by $\underline{u}_k = 0$.

$$\underline{u}_k^T \underline{u}_k = \sum_{i=0}^{k-1} \underbrace{u^T(i) u(i)}_{\text{quadratic} \geq 0} \geq 0$$

If minimize u^2

$$(u^2)' = 2u = 0$$



form lagrangian :

$$\mathbf{L}(\underline{u}_k, \lambda) = \underline{u}_k^T \underline{u}_k + \lambda^T (\mathbf{x}_f - \mathbf{R}_k \underline{u}_k)$$

↓
Lagrange
multiplier

(Price for violating constraints)

$$\frac{\partial \mathbf{L}}{\partial \underline{u}_k} = 2 \underline{u}_k^T - \lambda^T \mathbf{R}_k = \mathbf{0}$$

$$\frac{\partial \mathbf{L}}{\partial \lambda} = \mathbf{x}_f - \mathbf{R}_k \underline{u}_k = \mathbf{0}$$

$$\underline{u}_k = \frac{1}{2} \mathbf{R}_k^T \lambda$$

$$\Rightarrow \underbrace{\mathbf{x}_f}_{\text{known}} = \frac{1}{2} \underbrace{\mathbf{R}_k \mathbf{R}_k^T}_{\text{known}} \underbrace{\lambda}_{\text{unknown}}$$

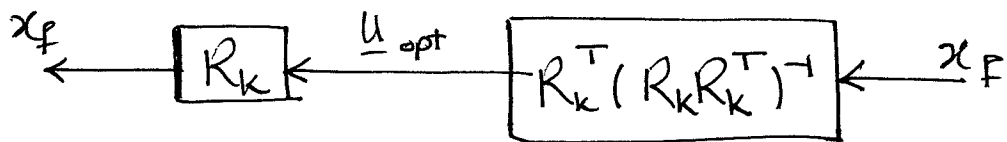
Aside

$\mathbf{R}_k$ full rank matrix
↓
 $\mathbf{R}_k \mathbf{R}_k^T$ invertible

$$\Rightarrow \lambda = 2(\mathbf{R}_k \mathbf{R}_k^T)^{-1} \mathbf{x}_f$$

$$\underline{u}_{\text{opt}} = \mathbf{R}_k^T (\mathbf{R}_k \mathbf{R}_k^T)^{-1} \mathbf{x}_f$$

pseudo-inverse $\rightarrow \text{Pinv}(\mathbf{R}_k)$



$$\underline{u}_{opt} = R_k^T P_k^{-1} x_f$$

Note! If the system is not reachable we can add

$(x_f - R_k \underline{u}_k)^T (x_f - R_k \underline{u}_k)$ to the objective function

which is a least squares problem.

$$\boxed{\underline{u}_{opt}^T \underline{u}_{opt}} = x_f^T P_k^{-1} \underbrace{R_k R_k^T}_{P_k} P_k^{-1} x_f = \boxed{x_f^T P_k^{-1} x_f}$$

$$P_l \geq P_k, \quad l \geq k$$

$$\Rightarrow P_k^{-1} \geq P_l^{-1}, \quad l \geq k$$

Summary! The longer we wait, the less energy we spend.

$$x_f = R_k \underline{u}_k \stackrel{\text{SVD}}{=} U \Sigma V^* \underline{u}_k \\ = \sum \sigma_i u_i v_i^* \underline{u}_k$$

If we choose input $\underline{u}_k = u_j \Rightarrow x_f = \sigma_j u_j$

(from SVD) $U = [u_1 \dots u_n]$

$$P_k = R_k R_k^T = U \Sigma \underbrace{V^* V}_{I} \Sigma^* U^*$$

$$P_k U = U \Sigma \Sigma^*$$

$$P_k u_i = \sigma_i^2 u_i \rightarrow \text{e-value decomposition of } P_k$$

$$P_k^{-1} u_i = \frac{1}{\sigma_i^2} u_i$$

Q. If we want to have $x_f = u_i$, what is $\underline{u}_{\text{opt}}^T \underline{u}_{\text{opt}}$?

$$\boxed{\underline{u}_{\text{opt}}^T \underline{u}_{\text{opt}}} = x_f^T P_k^{-1} x_f = u_i^T P_k^{-1} u_i = u_i^T \left(\frac{1}{\sigma_i^2} \right) u_i \quad (u_i \text{'s orthogonal}) \\ = \boxed{\frac{1}{\sigma_i^2}}$$

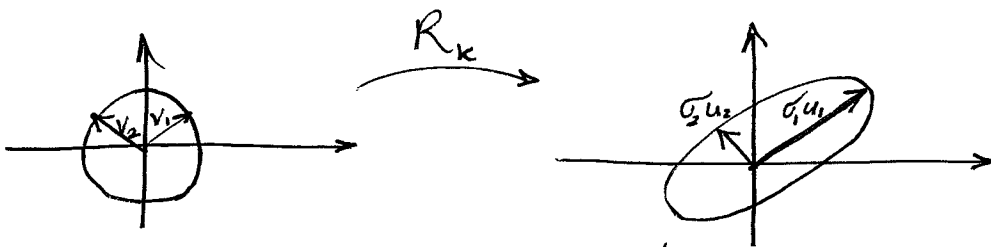
By using $x_f = u_i \Rightarrow$ energy is proportional to the inverse of the corresponding e-value of the reachability Gramian

Summary! evalue decomposition of the Reachability Gramian provides insight into how easy it is to achieve some final state.

[e-values small $\Rightarrow$ direction difficult]

[e-values large $\Rightarrow$ easy]

Space of control:



reachability ellipsoide which grows with time, but will not grow beyond certain level.
with unit energy ^{input} all points inside this ellipsoid can be reached



Reachability ellipsoid tells us what we can reach w/unit energy input.