

### 1. Minimum Energy Control & Spectral Theorem

In controllability/reachability analysis, we try to solve the linear system:

$$C_{i^*} \begin{bmatrix} \vec{u}[0] \\ \vdots \\ \vec{u}[i^* - 1] \end{bmatrix} = \vec{x}^* - A^{i^*} \vec{x}_0 \quad (1)$$

for the vector quantities  $\vec{u}[0], \dots, \vec{u}[i^* - 1]$ . Cleaning up notation, let us fix  $i^*$ , let  $C := C_{i^*}$ , let  $\vec{z} := \vec{x}^* - A^{i^*} \vec{x}_0$ , and let  $\vec{u} := \begin{bmatrix} \vec{u}[0] \\ \vdots \\ \vec{u}[i^* - 1] \end{bmatrix}$ . Then this linear system becomes

$$C\vec{u} = \vec{z} \quad (2)$$

In the real world, we would like to use this framework to control mechanical systems, often expending the **minimum energy** possible.

But what do we mean by the "energy" of the control? In this context, we will use the squared norm of the input vector  $\|u\|^2 = u_1^2 + \dots + u_n^2$  as the model for the cost to applying a set of controls to our system.

Why do we use this definition? This formula for the cost model is closely connected to many physical scenarios relating to energy. Consider a few examples below:

- $E_{\text{capacitor}} = \frac{1}{2}CV^2$
- $E_{\text{spring}} = \frac{1}{2}kx^2$
- $E_{\text{kinetic}} = \frac{1}{2}mv^2$

And so we find that the definition we use is a natural one.

Optional EECS16A Refresher: Recall the following vector spaces:

The range (or column space) of a matrix  $A$  refers to the following vector space  $\text{Col}(A) = \{A\vec{x} : \vec{x} \in \mathbb{R}^n\}$ . It is the vector space consisting of all possible linear combinations of the columns of  $A$ .

Then, there is the null space of  $A$ , which refers to the following vector space  $\text{Null}(A) = \{\vec{x} : A\vec{x} = 0\}$ .

$$\min_{x \in \mathbb{R}} x^2 + 1 = 1 \quad \text{argmin}_{x \in \mathbb{R}} (x^2 + 1) = 0$$


- (a) Suppose we would like to solve for the minimum energy (or minimum norm) solution of the linear system  $C\vec{u} = \vec{z}$ . This problem can be expressed as the following optimization problem:

$$\operatorname{argmin}_{\vec{u}} \|\vec{u}\|^2 = \operatorname{argmin}_{u[i]} \sum_{i=0}^{\ell-1} u[i]^2 \quad \text{"find the min energy s.t."} \quad (3)$$

$$\text{s.t. } C\vec{u} = \vec{z} \quad \leftarrow \text{constraint} \quad (4)$$

Symmetric matrices can make calculations and reasoning about the properties of a matrix much easier. Suppose  $C$  is a *real, symmetric matrix*. **Rewrite  $C$  in terms of its spectral decomposition** (take  $Q$  to be the orthonormal basis of eigenvectors of  $C$  and  $\Lambda$  to be the diagonal matrix of the eigenvalues).

$$\text{if } C = C^T, \text{ then } C = Q\Lambda Q^T$$

- (b) One way to look at minimum energy control is through lens of our vector spaces. How might we do this?

Well, Spectral Theorem tells us that  $Q$  is an orthonormal basis of  $\mathbb{R}^n$ . If  $\operatorname{Rank}(C) = r$ , then  $Q$  can be written as the block matrix  $\begin{bmatrix} Q_r & Q_{n-r} \end{bmatrix}$  where  $Q_r$  forms an orthonormal basis for  $\operatorname{Col}(C)$  and  $Q_{n-r}$  similarly forms one for  $\operatorname{Null}(C)$ .

Let's perform an orthonormal basis change:

$$\vec{u} = Q\tilde{\vec{u}} \quad (5)$$

**Using our new basis, rewrite  $\vec{u}$  in terms of  $Q_r$  and  $Q_{n-r}$ .**

(HINT: Consider breaking up  $Q$  and  $\vec{u}$  into a block matrix and partitioned vector respectively.)

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Let's perform an orthonormal basis change:

$$\tilde{u} = Q\tilde{u} \quad (5)$$

**Using our new basis, rewrite  $\tilde{u}$  in terms of  $Q_r$  and  $Q_{n-r}$ .**

(HINT: Consider breaking up  $Q$  and  $\tilde{u}$  into a block matrix and partitioned vector respectively.)

$$C \in \mathbb{R}^{n \times n}$$

$$\text{rank}(C) = r$$

$$Q \in \mathbb{R}^{n \times n}$$

$$Q = \left[ \begin{array}{c|c} \overbrace{\left[ \begin{array}{ccc|c} | & | & | & \dots \\ \hline \end{array} \right]}^r & \left[ \begin{array}{c|c} \dots & | & | & | \\ \hline \end{array} \right] \\ \underbrace{\phantom{\left[ \begin{array}{ccc|c} | & | & | & \dots \\ \hline \end{array} \right]}}_{Q_r} & \underbrace{\phantom{\left[ \begin{array}{c|c} \dots & | & | & | \\ \hline \end{array} \right]}}_{Q_{n-r}} \end{array} \right]$$

$$\text{Col}(Q_r) = \text{Col}(C)$$

~~$\text{Null}(Q_{n-r}) = \text{Null}(C)$~~  OR  $\text{Col}(Q_{n-r}) = \text{Null}(C)$

$$u = Q \tilde{u}$$

$$u = \begin{bmatrix} Q_r & Q_{n-r} \end{bmatrix} \tilde{u}$$

$$u = \begin{bmatrix} Q_r & Q_{n-r} \end{bmatrix} \begin{bmatrix} \tilde{u}_{\text{Col}(C)} \\ \tilde{u}_{\text{Null}(C)} \end{bmatrix} = Q_r \tilde{u}_{\text{Col}(C)} + Q_{n-r} \tilde{u}_{\text{Null}(C)}$$

is  $Q_r \tilde{u}_{\text{Col}(C)} \in \text{Col}(C)$  or  ~~$\tilde{u}_{\text{Col}(C)} \in \text{Col}(C)$~~

is  $Q_{n-r} \tilde{u}_{\text{Null}(C)} \in \text{Null}(C)$  or  ~~$\tilde{u}_{\text{Null}(C)} \in \text{Null}(C)$~~

$$\text{Col}(C) \subseteq \mathbb{R}^n$$

$$\dim \text{Col}(C) = r \leq n$$

- (c) Ultimately, the objective we are trying to minimize is still  $\|\vec{u}\|^2$ . **Use your findings from part (b) to show that**  $\|\vec{u}\|^2 = \|\vec{u}_{\text{Col}(C)}\|^2 + \|\vec{u}_{\text{Null}(C)}\|^2$ .

(HINT: Given some arbitrary orthonormal matrix  $U$  and arbitrary vector  $\vec{p}$ , how are  $\|\vec{p}\|$  and  $\|U\vec{p}\|$  related?)

given  $\|u\|^2$  how do we introduce variable  $\vec{q}$ ?

$$u = Q\vec{q}$$

$$\|u\|^2 = \|Q\vec{q}\|^2 = \|\vec{q}\|^2$$

↑  
orthonormal matrix

$$\|x\|^2 = x^T x$$

$$(Q\vec{q})^T (Q\vec{q}) = \vec{q}^T \overbrace{Q^T Q}^I \vec{q} = \vec{q}^T \vec{q}$$

$$\|\vec{u}\|^2 \longrightarrow \|\vec{u}_{\text{Col}(C)}\|^2 + \|\vec{u}_{\text{Null}(C)}\|^2$$

$$\vec{u} = \begin{bmatrix} \vec{u}_{\text{Col}(C)} \\ \vec{u}_{\text{Null}(C)} \end{bmatrix}$$

- (d) Putting everything from the last two parts together, let us now solve for the solution to the minimum energy problem (written once more for convenience):

$$\underset{\vec{u}}{\operatorname{argmin}} \|\vec{u}\|^2 = \underset{u[i]}{\operatorname{argmin}} \sum_{i=0}^{\ell-1} u[i]^2 \quad (6)$$

$$\text{s.t. } C\vec{u} = \vec{z} \quad (7)$$

**Solve for the optimal minimum energy input  $\vec{u}^*$  in its simplest form in terms of  $\vec{u}_{\text{Col}(C)}$  and/or  $\vec{u}_{\text{Null}(C)}$ . Explain what your result means intuitively.**

(HINT: Which of  $\vec{u}_{\text{Col}(C)}$  or  $\vec{u}_{\text{Null}(C)}$  doesn't effect  $C\vec{u}$  (try to think about your vector space definitions)? What should we do to that value if we want to minimize the squared norm of the input?)

$$\textcircled{1} \quad u = Q_r \tilde{u}_{\text{col}(C)} + Q_{n-r} \tilde{u}_{\text{Null}(C)}$$

$$\text{col}(Q_r) = \text{col}(C)$$

$$\text{col}(Q_{n-r}) = \text{Null}(C)$$

$$\textcircled{2} \quad \|u\|^2 = \|\tilde{u}_{\text{col}(C)}\|^2 + \|\tilde{u}_{\text{Null}(C)}\|^2$$

how does  $u = Q\tilde{u}$  affect  $Cu = z$ ?

$$u = Q_r \tilde{u}_{\text{col}(C)} + Q_{n-r} \tilde{u}_{\text{Null}(C)}$$

$$\begin{aligned} Cu &= C(Q_r \tilde{u}_{\text{col}(C)} + Q_{n-r} \tilde{u}_{\text{Null}(C)}) \\ &= C Q_r \tilde{u}_{\text{col}(C)} + \underbrace{C Q_{n-r} \tilde{u}_{\text{Null}(C)}}_{\vec{0}} \end{aligned}$$

$$Q_{n-r} \tilde{u}_{\text{Null}(C)} \in \text{Null}(C)$$

$$Cu = C Q_r \tilde{u}_{\text{col}(C)} = z$$

does  $C Q_r \tilde{u}_{\text{col}(C)}$  depend on  $\tilde{u}_{\text{Null}(C)}$ ?

$$\tilde{u} = \begin{bmatrix} \tilde{u}_{\text{col}(C)} \\ \tilde{u}_{\text{Null}(C)} \end{bmatrix}$$

$$\operatorname{argmin}_u \|u\|^2$$

$$\text{s.t. } Cu = z$$

$\tilde{u}$  coordinates

$$\operatorname{argmin}_{\tilde{u}} \|\tilde{u}_{\text{col}(C)}\|^2 + \|\tilde{u}_{\text{null}(C)}\|^2$$

$$C \text{ or } \tilde{u}_{\text{col}(C)} = z$$

$$\text{need to set } \tilde{u}_{\text{null}(C)} = 0$$

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$x_{top}$  (pointing to  $x_1$ )

$x_{bottom}$  (pointing to the bottom part of the vector)

$$\|X\|^2 = \underbrace{(x_1)^2}_{\|x_{top}\|^2} + \underbrace{(x_2^2 + x_3^2 + x_4^2)}_{\|x_{bottom}\|^2}$$



(e) Now, let's do a numerical example. Consider the following linear discrete time system

$$\bar{x}[i+1] = \underbrace{\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}}_A \bar{x}[i] + \underbrace{\begin{bmatrix} -1 \\ 1 \end{bmatrix}}_b u[i] \quad (8)$$

Find the controllability matrix  $C$  for this system.

$$C = \begin{bmatrix} Ab & b \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

(f) Now, suppose we want to achieve desired state of  $\bar{x}[2] = \begin{bmatrix} 4 \\ -4 \end{bmatrix}$  at timestep  $i = 2$ . Assume your initial condition is  $\bar{x}[0] = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ .

Write your linear system to solve for the input vector  $\bar{u} = \begin{bmatrix} \bar{u}[0] \\ \bar{u}[1] \end{bmatrix}$  in the form  $C\bar{u} = \bar{z}$ . Then, solve for one  $\bar{u}$  that achieves the desired system state. Remember, there will be many solutions as the system is underdetermined.

(HINT: Make use of the linear system formulation that comes as a result of controllability analysis shown on page 1.)

$$x[1] = Ax[0] + bu[0]$$

$$x[2] = Ax[1] + bu[1]$$

$$x[2] = \cancel{Ax[0]} + \overset{\vec{0}}{Abu[0]} + bu[1]$$

$$x[2] = Abu[0] + bu[1]$$

$$x[2] = \begin{bmatrix} Ab & b \\ 1 & 1 \end{bmatrix} \begin{bmatrix} u[0] \\ u[1] \end{bmatrix}$$

$$\bar{z} = x[2] = C\bar{u}$$

$$\begin{bmatrix} 4 \\ -4 \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} u[0] \\ u[1] \end{bmatrix} \quad u_1 = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$$

$$u_2 = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$$

(g) Finally, notice that  $\text{Col}(C) = \text{span} \left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$  and  $\text{Null}(C) = \text{span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\}$ .  $C = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$

The minimum norm solution is  $\vec{u}_{\min} = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$ . We will compare this to another arbitrary solution

$$\begin{bmatrix} 3 \\ -1 \end{bmatrix}.$$

i Write both  $\vec{u}_{\min}$  and  $\begin{bmatrix} 3 \\ -1 \end{bmatrix}$  as a linear combination of the column and null space span vectors. Compare the coefficients of the null space span vector.

$$\begin{bmatrix} 2 \\ -2 \end{bmatrix} = 2 \begin{bmatrix} 1 \\ -1 \end{bmatrix} + 0 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

ii Compare the norms of the two solutions. Verify that  $\|\vec{u}_{\min}\|$  is smaller.

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