

Properties of Laplace Transform

- $\mathcal{L}[Af(t)] = A\mathcal{L}[f(t)]$ where A is a constant.
- $\mathcal{L}[A_1 f_1(t) + A_2 f_2(t)] = A_1 \mathcal{L}[f_1(t)] + A_2 \mathcal{L}[f_2(t)]$
- The transfer function of a linear time-invariant differential equation is defined as
$$G(s) = \frac{\mathcal{L}[\text{output}]}{\mathcal{L}[\text{input}]} = \frac{C(s)}{R(s)} = \frac{b_m s^m + b_{m-1} s^{m-1} + \dots + b_0}{a_0 s^n + a_1 s^{n-1} + \dots + a_n}$$
- In deriving a transfer function, all initial conditions are assumed zero.
- Proper Transfer Function: The transfer function $G(s)$ is called proper if $n \geq m$ (i.e., $G(s)|_{s=\infty} = \text{constant}$).
- Strictly proper transfer function: The transfer function $G(s)$ is called strictly proper if $n > m$ (i.e., $G(s)|_{s=\infty} = 0$).
- Order of a system: The highest power of "s" in the denominator of $G(s)$ is called the order of the system.
- Poles of $G(s)$: The roots of the denominator polynomial of $G(s)$.
- Zeros of $G(s)$: The roots of the numerator polynomial of $G(s)$.
- Definition: A system is called a linear system if for every t_0 and any two triplets $(x_1(t_0), u_1(t))$ for $t \geq t_0$, $y_1(t)$ for $t \geq t_0$, $(x_2(t_0), u_2(t))$ for $t \geq t_0$, $y_2(t)$ for $t \geq t_0$, we have for any real α the following two triplets:

$$(x_1(t_0) + x_2(t_0), u_1(t) + u_2(t)) \text{ for } t \geq t_0, y_1(t) + y_2(t) \text{ for } t \geq t_0 \quad (\text{additivity})$$

and $(\alpha x_1(t_0), \alpha u_1(t))$ for $t \geq t_0$, $\alpha y_1(t)$ for $t \geq t_0$ (homogeneity)

The above two properties can be combined into one

$$\{\alpha_1 x_1(t_0) + \alpha_2 x_2(t_0), \alpha_1 u_1(t) + \alpha_2 u_2(t)\} \text{ for } t \geq t_0, \alpha_1 y_1(t) + \alpha_2 y_2(t) \text{ for } t \geq t_0$$

for any real constants α_1 and α_2 .

The above property is known as superposition.

A nonlinear system is one where the superposition property does not hold.

Norms of matrices also has the following properties

- $\|Ax\| \leq \|A\| \|x\|$
- $\|A+B\| \leq \|A\| + \|B\|$
- $\|AB\| \leq \|A\| \|B\|$

Orthonormal set of vectors

- A vector is said to be normalized if $\|x\|_2 = 1$
- Two vectors $x, y \in \mathbb{R}^n$ are orthogonal if $x^T y = 0$.
- A set of vectors, x_1, x_2, \dots, x_m is said to be orthonormal if

$$x_i^T x_j = \begin{cases} 0, & \text{if } i \neq j; \\ 1, & \text{if } i = j. \end{cases}$$

Null Space and Nullity of a Matrix

- The null space of matrix A is

$$N(A) = \{x \in \mathbb{R}^n : \text{such that } Ax = 0\}$$

- Nullity of A is the number of linearly independent vectors of $N(A)$ and is denoted by $\nu(A)$.
- Null space of A consists of all its null vectors.

Remark: If $\nu(A) = 0$, it means that 0 is the only element in $N(A)$.

Properties of rank:

- Let $A \in \mathbb{R}^{m \times n}$. Then
$$\rho(AC) = \rho(A) \text{ and } \rho(DA) = \rho(D)$$
- for any $n \times n$ and $m \times m$ non-singular matrices C and D .
- Given $A \in \mathbb{R}^{n \times n}$ and $B \in \mathbb{R}^{m \times n}$ and $y = Ax$. There exists a vector $x \in \mathbb{R}^n$ satisfying the above equation if and only if $y \in R(A)$ or equivalently,

$$\rho(A) = \rho(A - y)$$

- Given $A \in \mathbb{R}^{m \times n}$. For every $y \in \mathbb{R}^m$, there exists a vector $x \in \mathbb{R}^n$ such that $y = Ax$ if and only if $\rho(A) = m$.

Properties of Inverse and Determinant:

- If any two rows or columns of A are linearly dependent, then $\det(A) = 0$.
- $\det(A) = \det(A^T)$.
- $\det(AB) = \det(A)\det(B)$ if A and B are both square matrices.
- $\det(A) = \lambda_1 \cdot \lambda_2 \cdots \lambda_n$ where λ_i s are the eigenvalues of A .
- If $A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{m \times n}, C \in \mathbb{R}^{n \times m}$, and $D \in \mathbb{R}^{m \times m}$, then

$$\det \begin{pmatrix} A & B \\ 0 & D \end{pmatrix} = \det \begin{pmatrix} A & 0 \\ 0 & D \end{pmatrix} = \det(A)\det(D)$$

Theorem 2.1: Suppose $f(\lambda)$ is given and $A \in \mathbb{R}^{n \times n}$ matrix with char. polynomial

$$\det(\lambda I - A) = \prod_{i=1}^n (\lambda - \lambda_i)^{n_i}$$

where $n = \sum_{i=1}^m n_i$. Define another $(n-1)$ degree polynomial

$$h(\lambda) = \beta_0 + \beta_1 \lambda^1 + \beta_2 \lambda^2 + \dots + \beta_{n-1} \lambda^{n-1}$$

with n unknown coefficients β_i . These unknowns can be obtained by solving the following set of n equations:

$$\frac{d^k f(\lambda)}{d\lambda^k}|_{\lambda=\lambda_i} = \frac{d^k h(\lambda)}{d\lambda^k}|_{\lambda=\lambda_i} \quad \text{for } k = 0, 1, \dots, (n-1) \text{ and } i = 1, 2, \dots, m$$

Then we have

$$f(A) = h(A)$$

and we say that $f(A)$ equals to $h(\lambda)$ on the spectrum of A .

Example: Suppose $f(\lambda) = e^\lambda$ and $A = \begin{pmatrix} 0 & 1 \\ -1 & 2 \end{pmatrix}$. Choose $h(\lambda) = \beta_0 + \beta_1 \lambda$.

Using Theorem 2.1 with $\lambda_1 = -1, \lambda_2 = 2$ means

$$\epsilon^{-1} = \beta_0 - \beta_1$$

$$\epsilon^{-2} = \beta_0 - 2\beta_1$$

Solving $\beta_0 = 2e^{-1} - e^{-2}$ and $\beta_1 = e^{-1} - e^{-2}$. Then

$$f(A) = h(A) = \beta_0 I + \beta_1 A = \begin{pmatrix} \beta_0 - \beta_1 & \beta_1 \\ 0 & \beta_0 - 2\beta_1 \end{pmatrix}$$

• A square matrix A is symmetric if $A = A^T$.

• The scalar function $x^T Ax$ where $x \in \mathbb{R}^n$, $A = A^T \in \mathbb{R}^{n \times n}$ is called a quadratic form.

• A real symmetric matrix A is said to be positive definite if for all $x \in \mathbb{R}^n$, $x \neq 0$, $x^T Ax > 0$.

• Similarly, a real symmetric matrix A is said to be positive semi-definite if for all $x \in \mathbb{R}^n$, $x \neq 0$, $x^T Ax \geq 0$.

• A symmetric matrix A is positive definite if all its leading minors are positive i.e.,

$$a_{11} > 0, \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} > 0, \begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} > 0 \dots$$

• A symmetric matrix A is positive definite if and only if its eigenvalues are positive.

• If $D \in \mathbb{R}^{n \times n}$ then $D^T D = A$ is positive definite if and only if D has full rank n .

因果性 causal/non-anticipatory $\Rightarrow p \geq q$ in $G(s)$

Lumped system 集中型 带阻抗. Distributed 空间型

$$\dot{x}_1 = A_1 x_1 + B_1 u_1 \quad Y_1(s) = G_1(s) U_1(s)$$

$$Y_1(s) = C_1 x_1 + D_1 u_1 \quad y_1(s) = \int_{t_0}^s y_1(t) dt + \int_{t_0}^s C_1 x_1(t) dt$$

线性时变 LTI 线性时变

$X \in \mathbb{R}^{n \times n}, A \in \mathbb{R}^{n \times n}$.

特征根: $\det(\lambda I - A) = 0$, A non-singular.

Example: find $\det(\lambda I - A) = \lambda^2 - 4\lambda + 3$

$$\det(A - \lambda I) = \begin{vmatrix} 1-\lambda & 2 \\ 1 & 4-\lambda \end{vmatrix} = (\lambda-1)(\lambda-3)$$

$$\lambda_1 = 1, \lambda_2 = 3$$

$$A_1 = \begin{pmatrix} 1 & 2 \\ 1 & 4 \end{pmatrix}$$

$$A_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$B_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$B_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$C_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$C_2 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

$$D_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$D_2 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

Not all distinct λ are eigenvalues: Jordan Form

when $\lambda_1 \neq \lambda_2$, $\lambda_1 \neq \lambda_2$:

$$J = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}$$

when $\lambda_1 = \lambda_2$, $\lambda_1 = \lambda_2$:

$$J = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{pmatrix}$$

Homogeneous LTI System

$$\dot{x} = Ax$$

$$\dot{x} = Adx$$

$$\dot{x} = \int_0^t Adt$$

$$\dot{x} = \int_0^t Adt = A(t-t_0)x(t_0)$$

$$\dot{x}(t) = e^{At}x(t_0)$$

$$\dot{x}(t) = e^{At}x(t_0)$$

$$\text{Properties: } e^{At} = \frac{1}{k!} A^k t^k$$

$$de^{At} = A^k t^{k-1}$$

$$At = \frac{1}{k+1} (A^k A t^k)$$

$$\begin{aligned} H(s) &= \frac{1}{s^2 + 2\zeta_1 s + \omega_n^2} = \frac{1}{s^2 + 2\zeta_1 s + 1} = \frac{1}{(s+1)^2} \\ M(s) &= \frac{1}{s^2 + 2\zeta_2 s + \omega_n^2} = \frac{1}{s^2 + 2\zeta_2 s + 4} = \frac{1}{(s+2)^2} \end{aligned}$$

From the transient performance specifications, you can design the positions of the desired poles.

$$g_1(s) = \prod_{i=1}^n (s - \lambda_i) = s^n + \gamma_{n-1}s^{n-1} + \dots + \gamma_1s + \gamma_0$$

This is the desired closed-loop characteristic polynomial.

Pole Placement

Given a plant $\dot{x} = Ax + Bu$, $y = Cx$.

Build a state feedback controller:

$$u = -Kx + Fr$$

The closed loop: $\dot{x} = Ax + Bu - Kx + Fr = (A - BK)x + BFr$

Design K such that the characteristic polynomial of the closed loop

$$\det(sI - (A - BK)) = s^n + \gamma_{n-1}s^{n-1} + \dots + \gamma_0$$

SISO system: The open loop pole: $\lambda = A$, $u = r - Kx$.

The state feedback gain: $u = r - Kx$.

$$y = Cx = Kx + Fr$$

What is the condition on the system to be controllable? (desired)

If the system is controllable, the poles can be placed anywhere.

We used the controllable canonical form to derive the Ackermann's formula

$$k^T = [0, \dots, 0, 1]^\top \phi_k(A),$$

$$\phi_k(A) = \phi_k[\begin{bmatrix} A & B \\ 0 & I \end{bmatrix}] = A^k + \gamma_{k-1}A^{k-1} + \dots + \gamma_0I$$

What if you forgot Ackermann's formula?

The easiest way is directly comparing the coefficients of the two polynomials:

$$\det(sI - (A - BK)) = s^n + \gamma_{n-1}s^{n-1} + \dots + \gamma_0$$

Then you will find that the number of design parameters in K is greater than the number of poles. So, there may be some poles you can't infinite number of choices.

Pole Placement for MIMO systems

One simple rule is to make the FIMO to SISO

$$u = gx \Rightarrow u = Ax - Bu$$

$$= Ax - \underbrace{Bv}_{\text{desired}}$$

Step 1. Choose the weight vector q such that the pair (A, Bq) is controllable.

Step 2. Use any single-input pole placement algorithm for the pair (A, Bq) to determine K such that

$$A - BK^T$$

has the desired eigenvalues (closed-loop poles).

Overall, the required state feedback matrix is $K = qk^T$.

Algorithm For Full rank pole placement

Given controllable $\{A, B\}$ and the desired $\Phi(s)$,

(i) Obtain the controllable canonical form in the state x via

$$\dot{x} = Tx,$$

such that

$$\dot{\bar{x}} = T\bar{x} + \bar{B}u$$

is in the controllable canonical form.

The most time-consuming part is computing T .

Once T is obtained, then we can get the controllable canonical form:

$$\dot{\bar{x}} = T\bar{x} + \bar{B}u$$

First compute the controllability matrix

$$W_p = (B \quad AB \quad A^2B \quad \dots \quad A^{n-1}B)$$

Check whether it is full or not. If it is not, then move on to the next step.

For single input system, the controllability matrix is a square matrix, all of the vectors are independent.

For MIMO system, we need to select the independent vectors from the controllability matrix in the order after B .

In this way, we assure that all the inputs will play a part in the placement.

After the vectors are selected, it is important to regroup them in a square matrix C in the following form

$$C = [\bar{x}_1 \quad \dots \quad \bar{x}_n \quad A\bar{x}_1 \quad \dots \quad A^{n-1}\bar{x}_1]$$

Where the indices i imply the number of vectors in C related to the i -th input, u .

The controllable canonical form can then be computed from this matrix C .

$$\text{Compute the inverse of } C, C^{-1}$$

For multi-input case, we need to take out n rows from C^{-1} corresponding to the m inputs, and form T :

$$\begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \\ \bar{x}_1' \\ \vdots \\ \bar{x}_m' \end{bmatrix} \Rightarrow \bar{B} = TB =$$

where \bar{x}_i' given by $\bar{x}_i' = C^{-1}(A^{i-1})^T B$

$$= \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} (A^{i-1})^T \begin{bmatrix} B \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$T = \begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \\ \bar{x}_1' \\ \vdots \\ \bar{x}_m' \end{bmatrix} \Rightarrow \bar{B} = TB =$

$$= \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} (A^{i-1})^T \begin{bmatrix} B \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

\bar{B} corresponds to the relative degree of the transfer function for each row.

We need to very clear on how to compute this indicator, which is the key design parameter for decoupling.

The key to decoupling problem is to express $G(s)$ in the form of

$$G(s) = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} + \begin{bmatrix} B & 0 & \dots & 0 \\ 0 & B & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & B \end{bmatrix} s$$

where B' and C' are defined as

$$B' = \begin{bmatrix} c_1' & c_2' & \dots & c_m' \\ c_1' & c_2' & \dots & c_m' \\ \vdots & \vdots & \ddots & \vdots \\ c_1' & c_2' & \dots & c_m' \end{bmatrix}$$

$$C' = \begin{bmatrix} c_1' & c_2' & \dots & c_m' \\ c_1' & c_2' & \dots & c_m' \\ \vdots & \vdots & \ddots & \vdots \\ c_1' & c_2' & \dots & c_m' \end{bmatrix}$$

C' corresponds to the relative degree of the transfer function for each row.

B' correspond to the leading coefficients of the zero polynomials.

The key to prove is to express $G(s) = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} + \begin{bmatrix} B & 0 & \dots & 0 \\ 0 & B & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & B \end{bmatrix} s$ as infinite series:

$$(sI - A)^{-1} = \begin{bmatrix} 0 & 1 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} + \begin{bmatrix} B & 0 & \dots & 0 \\ 0 & B & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & B \end{bmatrix}$$

Design the state feedback controller: $u = -Kx + Fr$.

$$F = B^{-1}, \quad K = B^{-1}C^*$$

Then, the closed-loop transfer function matrix is given by

$$H(s) = \text{diag}\left(s^{\alpha_1}, s^{\alpha_2}, \dots, s^{\alpha_m}\right)$$

which is called an integrator-decoupled system.

For this case,

$$\begin{aligned} C &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ C^* &= \begin{bmatrix} 1 & 3 & -1 \\ 0 & 2 & -1 \\ 0 & 1 & 0 \end{bmatrix} \end{aligned}$$

How many vectors in C are associated with us?

Which rows should we take out to form T ?

The first (d₁) and third (d₃ d₁ + d₃) rows!

The second (d₂) row is not associated with us.

Define $T = \begin{bmatrix} 1 & 3 & -1 \\ 0 & 2 & -1 \\ 0 & 1 & 0 \end{bmatrix}$

$T^{-1} = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

$\bar{B} = TB = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

There are two rows, so there are two non-trivial rows since the inputs only affect the non-trivial rows.

Design the feedback gain matrix for the controllable canonical form

Form the closed-loop matrix:

$$A - BK = \begin{bmatrix} -1 & 3 & -1 \\ 0 & -2 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

What is the key to form the transformation matrix T ? The rest is simple.

$\bar{A} = TAT^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

$\bar{B} = TB = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

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Design the feedback controller: $u = -Kx + Fr$.

Define $K = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

Form the state feedback controller: $u = -Kx + Fr$.

can make the resultant feedback system have the desired stable transfer function.

Design procedure: The decoupling problem with stability by output feedback can be solved by designing $K(s)$ in two stages, i.e., $K = K_1, K_2, \dots, K_m$ to make $G(s)$ diagonal and non-singular with no unstable pole cancellations. In this step, $K_1(s)$ is not required to be proper.

Step 1: Whenever such a $K_1(s)$ is found in step 1, it always possible to design a diagonal controller $K_1(s)$ to stabilize the resultant $G(s)$ with SISO methods or pole placement techniques loop so that decoupling is not affected, and to ensure that there are no unstable pole cancellation between $G(s)$ and $K_1(s)$, and to make $K(s)$ proper.

Design for decoupler $K_1(s)$ when $G(s)$ is non-singular. Write

$$G(s) = \text{diag}\left(\frac{1}{s - \alpha_1}, \frac{1}{s - \alpha_2}, \dots, \frac{1}{s - \alpha_m}\right)$$

where d_i is the least common denominator of i -th row of $G(s)$ so that

$$\bullet G(s)K_1(s) = \frac{N(s)}{d_1} \text{ and } \det(G(s)) = \det(N(s))$$

One problem with this simple method is that the order of the system is large.

Refinement: One way to reduce the order of the decoupler is to elaborate the above method as follows. Express $G(s)$ as

$$G(s) = \text{diag}\left(\frac{1}{s - \alpha_1}, \frac{1}{s - \alpha_2}, \dots, \frac{1}{s - \alpha_m}\right)$$

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One problem with this simple method is that the order of the decoupler is large.

One way to reduce the order of the decoupler is to elaborate the above method as follows. Express $G(s)$ as

$$G(s) = \text{diag}\left(\frac{1}{s - \alpha_1}, \frac{1}{s - \alpha_2}, \dots, \frac{1}{s - \alpha_m}\right)$$

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