

Lecture 2 2025-08-28

Recap: guidance-navigation-controls vs.
sense-plan-act

Today: propagating differential equations

$x \in \mathbb{R}^{n_x}$: state vector of dimension n_x

$u \in \mathbb{R}^{n_u}$: control vector of dimension n_u

Linear Systems

continuous & time-varying:

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

continuous & time-invariant:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

discrete & time-varying:

$$x_{k+1} = A_k x_k + B_k u_k$$

discrete & time-invariant:

$$x_{k+1} = Ax_k + Bu_k$$

How to convert continuous LTI system to discrete?

$$\dot{x} = Ax + Bu \rightarrow \text{integrate over duration } \Delta t$$

$$\text{last time: } \dot{x} \approx \frac{x_{k+1} - x_k}{\Delta t} = Ax_k + Bu_k$$

where we want Δt to be "small" relative to the time constant of the dynamics

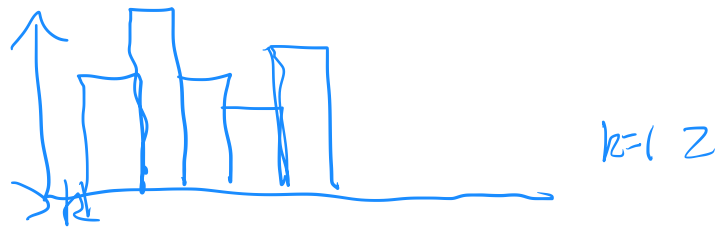
$$\rightarrow x_{k+1} - x_k = (\Delta t A)x_k + (\Delta t B)u_k$$

$$\rightarrow x_{k+1} = (I + \Delta t A)x_k + (\Delta t B)u_k$$

$$\text{where } I = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix} \text{ is } n_x \times n_x \text{ identity}$$

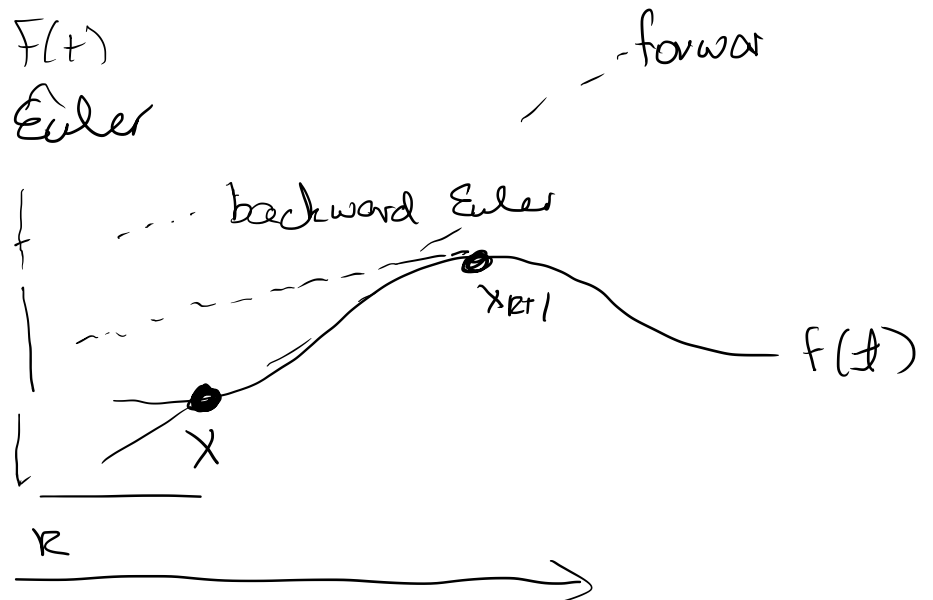
zero-order hold

u



Can we do better for LTI systems?

$$x_{k+1} = (I + \Delta t A) x_k + \Delta t B u_k \quad \begin{array}{l} \text{Forward} \\ \text{Euler} \end{array}$$



alternatively, evaluate at $k+1$:

$$\dot{x} \approx \frac{x_{k+1} - x_k}{\Delta t} = A x_{k+1} + B u_{k+1}$$

$$\rightarrow (I - \Delta t A) x_{k+1} = x_k + \Delta t B u_{k+1} \quad \begin{array}{l} \text{Backward} \\ \text{Euler's} \end{array}$$

Are there better integration schemes?

→ Trapezoidal integration

→ Hermite-Simpson

→ Runge-Kutta (e.g., RK4, RK8)

→ higher-order methods to model $x(t)$ and $u(t)$

e. g., pseudospectral methods

Analytical solutions via exponential matrix:

$$\dot{x} = Ax + Bu \quad \xrightarrow{\text{solve scalar form}} \quad \dot{x} = ax + bu$$

$$x \in \mathbb{R}^{n_x}, u \in \mathbb{R}^{n_u} \quad \quad \quad x \in \mathbb{R}, u \in \mathbb{R}$$

$$\dot{x} = ax \quad \leftarrow \text{how to solve this?}$$

solve with characteristic equation:

$$\dot{x} = ax \rightarrow s - a = 0 \rightarrow x(t) = x(t_0) e^{a(t-t_0)}$$

now add back in $bu(t)$:

$$\dot{x}(t) = ax(t) + bu(t) \rightarrow \dot{x} - ax = bu$$

multiply by integrating factor e^{-at} :

$$e^{-at} [\dot{x} - ax] = e^{-at} bu$$

$$\frac{d}{dt} [ab] = \dot{a}b + a\dot{b} \rightarrow \frac{d}{dt} [e^{-at} \overset{\uparrow}{\dot{x}} - a e^{-at} x] = e^{-at} \dot{x} - a e^{-at} x$$

→ integrate both sides from T_0 to T_f :

$$\int_{T_0}^{T_f} \frac{d}{dt} [e^{-at} \dot{x}(t)] dt = \int_{T_0}^{T_f} e^{-at} b u(t) dt$$

$$\rightarrow e^{-at} \dot{x}(t) \Big|_{t=T_0}^{t=T_f} = \int_{T_0}^{T_f} e^{-at} b u(t) dt$$

$$\rightarrow e^{-aT_f} \dot{x}(T_f) - e^{-aT_0} \dot{x}(T_0) = \int_{T_0}^{T_f} e^{-at} b u(t) dt$$

shuffle around terms & multiply by e^{aT_f} :

$$\rightarrow e^{-aT_f} \dot{x}(T_f) = e^{-aT_0} \dot{x}(T_0) + \int_{T_0}^{T_f} e^{-at} b u(t) dt$$

$$\rightarrow x(T_f) = e^{-a(T_f - T_0)} x(T_0) + \int_{T_0}^{T_f} e^{-at} b u(t) dt$$

Can we apply this approach to state space eqn?

$$\dot{x}(t) = Ax(t) + Bu(t)$$

where $x \in \mathbb{R}^{n_x}$, $u \in \mathbb{R}^{n_u}$, $A \in \mathbb{R}^{n_x \times n_x}$, $B \in \mathbb{R}^{n_x \times n_u}$

recall our approach with scalar version was:

1. assume solution takes exponential form
2. multiply by integrating factor e^{-at}

Exponential matrix: given $A \in \mathbb{R}^{n \times n}$

$$\begin{aligned} e^{At} &= \sum_{k=0}^{\infty} \frac{(At)^k}{k!} \\ &= \frac{(At)^0}{0!} + \frac{(At)^1}{1!} + \frac{(At)^2}{2!} + \frac{(At)^3}{3!} + \dots \end{aligned}$$

$$= I + At + \frac{A^2 t^2}{2!} + \frac{A^3 t^3}{3!} + \dots$$

$$\frac{d}{dt} [e^{At}] = \frac{d}{dt} \left[I + tA + \frac{t^2 A^2}{2!} + \frac{t^3 A^3}{3!} + \dots \right]$$

$$= A + tA^2 + \frac{t^2 A^3}{2!} + \dots$$

$$= A \left[I + tA + \frac{t^2 A^2}{2!} + \dots \right]$$

e^{tA}

$$= A e^{tA}$$

$$\rightarrow \frac{d}{dt} [e^{A^+ t}] = A e^{A^+ t} = e^{A^+ t} A$$

Comparisons between e^{at} vs. $e^{A^+ t}$:

$$1. e^{A(t_1+t_2)} = e^{At_1} e^{At_2}$$

$$2. e^{A0} = I$$

$$3. e^A e^B \neq e^{A+B} \quad (\text{only in certain cases})$$

Now let's apply e^{tA} to the LTI system:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$\rightarrow \dot{x} - Ax = Bu \quad \text{left multiply by } e^{-At}$$

$$\begin{aligned} \rightarrow e^{-At} [\dot{x} - Ax] &= e^{-At} Bu \\ &= e^{-At} \dot{x} - e^{-At} Ax \\ &= \frac{d}{dt} [e^{-At} x(t)] \end{aligned}$$

Integrate both sides between T_0 to T_f

$$\rightarrow \int_{T_0}^{T_f} \frac{d}{dt} [e^{-At} x(t)] dt = \int_{T_0}^{T_f} e^{-At} B u(t) dt$$

$$= e^{-At} x(t) \Big|_{t=T_0}^{t=T_f}$$

$$= e^{-AT_f} x(T_f) - e^{-AT_0} x(T_0)$$

$$\rightarrow e^{-AT_f} x(T_f) = e^{-AT_0} x(T_0) + \int_{T_0}^{T_f} e^{-At} B u dt$$

$$\rightarrow x(T_f) = e^{A(T_f - T_0)} x(T_0) + \int_{T_0}^{T_f} e^{A(T_f - t)} B u dt$$

Let's change the variables around to get this into a nicer form:

integrate over $d\tau$, let $T_0 = 0$ and $T_f = t$

$$\rightarrow x(t) = \underbrace{e^{At}}_{\substack{\uparrow \\ \Phi(t,0)}} x(0) + \int_0^t \underbrace{e^{A(t-\tau)}}_{\substack{\uparrow \\ \Phi(t,\tau)}} B u(\tau) d\tau$$

$\Phi(t,0)$ & $\Phi(t,\tau)$ are called state transition matrices

example: a common LTI system is the double integrator:

$$\dot{x} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} 0 \\ 1 \end{pmatrix} u$$

say we have a robot arm with n_q joints and $q \in \mathbb{R}^{n_q}$ is the vector of joint angles

& $\dot{q} \in \mathbb{R}^{n_q}$ is the vector of joint velocities

modeling the joints as a double integrator would look like:

$$\begin{pmatrix} \ddot{q} \\ \dot{q} \\ q \end{pmatrix} = \begin{pmatrix} 0^{n_q \times n_q} & I^{n_q} & 0^{n_q \times n_u} \\ 0^{n_q \times n_q} & 0^n & 1^{n_q \times n_u} \end{pmatrix} \begin{pmatrix} \ddot{q} \\ \dot{q} \\ q \end{pmatrix} + \begin{pmatrix} 0^{n_q} \\ 0^n \\ I^n \end{pmatrix} u$$

where $u \in \mathbb{R}^{n_u}$ is the force applied to each joint,
i. e. $n_u = n_q \rightarrow u \in \mathbb{R}^{n_q}$

How can e^{tA} be computed if it's an infinite expansion?

Cayley-Hamilton Thm: every square matrix
 $A \in \mathbb{R}^{n \times n}$

satisfies its own characteristic equation

where the characteristic equation is

$$p_A(\lambda) = \det |\lambda I - A| = 0$$

$$e. A = \begin{pmatrix} 3 & 4 \\ 5 & 8 \end{pmatrix} \rightarrow \det \begin{bmatrix} \lambda - 3 & -4 \\ -5 & \lambda - 8 \end{bmatrix} =$$

$$\begin{aligned} \rightarrow (\lambda - 3)(\lambda - 8) - (-4)(-5) &= \lambda^2 - 11\lambda + 24 - 20 \\ &= \lambda^2 - 11\lambda + 4 = 0 \end{aligned}$$

$$\text{CH says } \rightarrow A^2 - 11A + 4 = 0 \rightarrow A^2 = 11A - 4$$

$$\begin{aligned} \rightarrow A^3 &= A^2 A = (11A - 4)A = 11A^2 - 4A \\ &= 121A - 44 - 4A = 117A - 44 \end{aligned}$$

$A^4 = A^3 A$ & the procedure continues.

→ takeaway: can compute e^{tA} only with A^k !

Linearity

A function $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is linear if:

1. $f(x+y) = f(x) + f(y) \forall x, y \in \mathbb{R}^n$

2. $f(ax) = a f(x) \forall x \in \mathbb{R}^n, a \in \mathbb{R}$

e.g., $y = Ax$ where $A \in \mathbb{R}^{m \times n}$

pf: 1. $A(x_1 + x_2) = Ax_1 + Ax_2 = y_1 + y_2$ ✓

2. $A(ax_1) = aAx_1 = ay_1$ ✓

e. g., $y = Ax + b$ where $A \in \mathbb{R}^{m \times n}$ & $b \in \mathbb{R}^m$

change of variables $\rightarrow \underbrace{\begin{bmatrix} y \\ 1 \end{bmatrix}}_{:= \bar{y}} = \underbrace{\begin{bmatrix} A & b \\ 0 & 1 \end{bmatrix}}_{:= \bar{A}} \underbrace{\begin{bmatrix} x \\ 1 \end{bmatrix}}_{:= \bar{x}}$

$$\rightarrow \bar{y} = \bar{A} \bar{x}$$

pf:

$$1. \quad \bar{A}(\bar{x}_1 + \bar{x}_2) = \begin{pmatrix} A & b \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_1 + x_2 \\ 1 + 1 \end{pmatrix}$$

$$= \begin{pmatrix} Ax_1 + b \\ 1 + 1 \end{pmatrix} = \begin{bmatrix} Ax_1 + b \\ 1 \end{bmatrix} + \begin{bmatrix} Ax_2 + b \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} A & b \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ 1 \end{bmatrix} + \begin{bmatrix} A & b \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_2 \\ 1 \end{bmatrix}$$

$$= \bar{A} \bar{y}_1 + \bar{A} \bar{y}_2 \quad \checkmark$$

$$2. \bar{A} \begin{pmatrix} a \bar{x}_1 \\ + ab \end{pmatrix} = \begin{bmatrix} A & b \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a x_1 \\ a \end{bmatrix} = \begin{bmatrix} a A x_1 \\ a \end{bmatrix}$$

a

$$= a \begin{bmatrix} A x_1 + b \\ 1 \end{bmatrix} = a \bar{y}_1 \quad \checkmark$$

$\checkmark$

Quick comment on complexity:

If $A \in \mathbb{R}^{m \times n}$, what is the complexity of Ax ?

pseudo-code:

for $i = 1, \dots, m$: # iterate over m rows

$$y_i = 0$$

for $j = 1, \dots, n$ # iterate over n columns

$$y_i += a_{ij} \cdot x_j$$

→ matrix-vector multiplication is complexity $\mathcal{O}(m \cdot n)$