Lecture 2, Sep 13, 2023

System Modeling (Continuous and Discrete Time)



Figure 1: Example 1: Modeling the wheel motion of a car.



Figure 2: Modeling the example as a simple mechanical system.

- Example 1: modeling the wheel motion of a car when it encounters a bump in the road
 - Assumptions: constant velocity, 2D system model, variable step height $y_s(x)$
 - Begin with a simple mechanical system:
 - * k_w is a spring representing the wheel; *m* is the mass of the wheel axle
 - * The spring-damper system k_b and c model the shock absorber in the car
 - * In addition, we assume $m_b \gg m$, so that the car itself is approximately stationary and only the wheel axle moves; we also assume the suspension is 1D and that the car is at rest in the vertical direction before we hit the bump
 - Now we can use Newton's second law to form a mathematical model:
 - * $m\ddot{y} = \sum f = -c\dot{y} k_b y k_w (y y_s)$
 - * $m\ddot{y} + c\dot{y} + (k_b + k_w)y = m\ddot{y} + c\dot{y} + ky = k_w y(s) = u(t)$
 - This is a second order, linear, nonhomogeneous, time-invariant system
 - The initial conditions are $y(0) = \dot{y}(0) = 0$ and we wish to find y, \dot{y}, \ddot{y} for $t \ge 0$
 - $\ast\,$ Now we need to represent it in a standard form

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$$\begin{bmatrix} \dot{y} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{c}{m} \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix} u$$

- This is now in standard form: $\dot{x} = Ax + bu, x(0) = \begin{vmatrix} y(0) \\ \dot{y}(0) \end{vmatrix}$
- This form corresponds to the following simulation block diagram:



Figure 3: Simulation block diagram of a standard linear system.

- Example 2: modelling how a drone reacts to given motor inputs
 - Assumptions: horizontal motion is stabilized



Figure 4: Simple mechanical system for Example 2.

- Applying Newton's laws:

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$$m\ddot{z} = -mg - c\dot{z} + f$$

* We again have a second order, linear, nonhomogeneous, time-invariant system

- In standard form:
$$\begin{bmatrix} \dot{z} \\ \ddot{z} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{c}{m} \end{bmatrix} \begin{bmatrix} z \\ \dot{z} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ \frac{1}{m} \end{bmatrix} u$$

– But how do we actually perform the simulation?

Summary

In general for any linear system we have: a set of inputs $\boldsymbol{u}(t)$ (which we partially control); a set of outputs $\boldsymbol{y}(t)$ which we can measure; and states $\boldsymbol{x}(t)$ that are internal to the system which we cannot directly manipulate or measure.

To model a linear system in continuous time:

$$egin{aligned} \dot{oldsymbol{x}}(t) &= oldsymbol{A}oldsymbol{x}(t) + oldsymbol{B}oldsymbol{u}(t), oldsymbol{x}(0) = oldsymbol{x}_0 \ oldsymbol{y}(t) &= oldsymbol{C}oldsymbol{x}(t) + oldsymbol{D}oldsymbol{u}(t) \end{aligned}$$

where $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}, \boldsymbol{D}$ are state matrices.

To model a nonlinear system in continuous time:

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t)), \boldsymbol{x}(0) = \boldsymbol{x}_0$$
$$\boldsymbol{y}(t) = \boldsymbol{h}(\boldsymbol{x}(t), \boldsymbol{u}(t))$$

- If we have n states, m inputs and p outputs, then A is $n \times n$, B is $n \times m$, C is $p \times n$ and D is $p \times m$
- In practice, we often need to represent things in discrete time, since the computers running simulations are discrete
- To represent things in discrete time, we replace continuous signals with a sequence of regular samples at $t_k = kh$
 - $-t_k = kh$ is the sampling time

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$$f_s = \frac{1}{1}$$
 is the sampling frequency

- So how do we convert our continuous model to a discrete one?
 - Recall that the solution for $\dot{\boldsymbol{x}}(t) = \boldsymbol{A}\boldsymbol{x}$ is $\boldsymbol{x} = e^{\boldsymbol{A}t}\boldsymbol{x}_0$
 - Over a short time interval $t_k \leq t \leq t_{k+1}$ the solution evolves as:

$$\mathbf{x}(t) = e^{\mathbf{A}(t-t_k)} \mathbf{x}(t_k) + \int_{t_k}^t e^{\mathbf{A}(t-\tau)} \mathbf{B} \mathbf{u}(\tau) \, \mathrm{d}\tau$$
$$= e^{\mathbf{A}(t-t_k)} \mathbf{x}(t_k) + \int_{t_k}^t e^{\mathbf{A}(t-\tau)} \mathbf{B} \, \mathrm{d}\tau \mathbf{u}(t_k)$$
$$= \mathbf{\Phi}(t, t_k) \mathbf{x}(t_k) + \Gamma(t, t_k) \mathbf{u}(t_k)$$

• Note that we have assumed $\boldsymbol{u}(\tau) = \boldsymbol{u}(t_k)$ (i.e. \boldsymbol{u} stays constant over the timestep), which is referred to as a zero-order hold

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$$\boldsymbol{x}(t_{k+1}) = \boldsymbol{\Phi}(t_{k+1}, t_k)\boldsymbol{x}(t_k) + \Gamma(\boldsymbol{t}_{k+1}, t_k)\boldsymbol{u}(t_k) = \boldsymbol{A}_d\boldsymbol{x}(t_k) + \boldsymbol{B}_d\boldsymbol{u}(t_k)$$

• We have discretized the system

• We now have difference equations for the system (*h* is the sampling period):

 $- oldsymbol{x}_{k+1} = oldsymbol{A}_d oldsymbol{x}_k + oldsymbol{B}_d oldsymbol{u}_k$

$$- y_{k} = Cx_{k} + Du_{k}$$

$$- A_{d} = \Phi(t_{k+1}, t_{k}) = e^{Ah}$$

$$- B_{d} = \Gamma(t_{k+1}, t_{k}) = \int_{0}^{h} e^{A\tau'} d\tau' B$$

• To solve for A_{d} and B_{d} :

$$- \text{ Note that } \frac{d}{dt} \Phi(t) = \Phi(t) A \text{ and } \frac{d}{dt} \Gamma(t) = \Phi(t) B$$

$$- \text{ Using this we have: } \frac{d}{dt} \begin{bmatrix} \Phi(t) & \Gamma(t) \\ 0 & I \end{bmatrix} = \begin{bmatrix} \Phi(t) & \Gamma(t) \\ 0 & I \end{bmatrix} \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix}$$

* Now we can use another matrix exponential to solve this

$$- \begin{bmatrix} A_{d} & B_{d} \\ 0 & I \end{bmatrix} = \exp\left(\begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} h\right)$$

Note

The matrix exponential can be calculated with the Matlab function expm() or scipy function scipy.linalg.expm(). We can also manually do a series expansion of the matrix exponential function. Alternatively, c2d() in Matlab or control.matlab.c2d() can be used to do the same conversion (which computes the matrix exponentials internally).

• We can now recursively apply the difference equations to propagate the state:

$$\begin{array}{l} - \boldsymbol{x}_1 = \boldsymbol{A}_d \boldsymbol{x}_0 + \boldsymbol{B}_d \boldsymbol{u}_0 \\ - \boldsymbol{x}_2 = \boldsymbol{A}_d (\boldsymbol{A}_d \boldsymbol{x}_0 + \boldsymbol{B}_d \boldsymbol{u}_0) + \boldsymbol{B}_d \boldsymbol{u}_1 \\ - \boldsymbol{x}_3 = \boldsymbol{A}_d (\boldsymbol{A}_d^2 \boldsymbol{x}_0 + \boldsymbol{A}_d \boldsymbol{B}_d \boldsymbol{u}_0 + \boldsymbol{B}_d \boldsymbol{u}_1) + \boldsymbol{B}_d \boldsymbol{u}_2 \text{ and so on} \\ \end{array}$$

$$- \text{ We can stack all these together:} \begin{bmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \\ \vdots \\ \boldsymbol{x}_N \end{bmatrix} = \boldsymbol{F} \begin{bmatrix} \boldsymbol{u}_0 \\ \boldsymbol{u}_1 \\ \vdots \\ \boldsymbol{u}_{N-1} \end{bmatrix} + \boldsymbol{F}_0 \boldsymbol{x}_0$$

Definition

A system is *reachable* or *controllable* if and only if

$$\operatorname{rank} \begin{bmatrix} \boldsymbol{A}_d^{N-1} \boldsymbol{B}_d & \boldsymbol{A}_d^{N-2} \boldsymbol{B}_d & \cdots & \boldsymbol{B}_d \end{bmatrix} = N$$

where N is the dimension of the state x_k . Physically this means that there is a given sequence of control inputs to reach any state.

Definition

A system is *observable* if and only if

$$\operatorname{rank} \begin{bmatrix} \boldsymbol{C} \\ \boldsymbol{C} \boldsymbol{A}_d \\ \vdots \\ \boldsymbol{C} \boldsymbol{A}_d^{N-1} \end{bmatrix} = N$$

Physically this means that given some sequence of outputs, we can derive the system state.

- Example: consider the system: $\dot{x}(t) = u(t), y(t) = x(t), x(0) = x_0$; find the difference equations assuming a zero-order hold at the input and sampled output, with sampling period h
 - Note that we have $\boldsymbol{A} = 0$ and $\boldsymbol{B} = 1$
 - For $t_k \leq t \leq t_{k+1}$:

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$$x(t) = x(t_k) + \int_{t_k}^t u(\tau) d\tau$$

 $= x(t_k) + \int_{t_k}^t 1 d\tau u(t_k)$
 $= x(t_k) + (t - t_k)u(t_k)$
* Applying this at $t = t_{k+1} = t_k + h$ we get $x_{k+1} = x_k + hu_k$
Example: $\ddot{x} = u$
- State: $z = \begin{bmatrix} x \\ \dot{x} \end{bmatrix}$
- Continuous time: $\dot{z} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} z + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u = Az + Bu$
- $\begin{bmatrix} A_d & B_d \\ 0 & I \end{bmatrix} = \exp\left(\begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} h \right) = \exp\left(\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} h \right) = \exp(Eh)$
- Notice that $E^2 = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$ and $E^3 = \mathbf{0}$ so E is nilpotent
- Using the series expansion: $\exp(Eh) = I + Eh + \frac{1}{2}E^2h^2 = \begin{bmatrix} 1 & h & \frac{1}{2}h^2 \\ 0 & 1 & h \\ 0 & 0 & 1 \end{bmatrix}$
- Therefore $A_d = \begin{bmatrix} 1 & h \\ 0 & 1 \end{bmatrix}, B_d = \begin{bmatrix} \frac{1}{2}h^2 \\ h \end{bmatrix}$
- $z_{k+1} = \begin{bmatrix} 1 & h \\ 0 & 1 \end{bmatrix} z_k + \begin{bmatrix} \frac{1}{2}h^2 \\ h \end{bmatrix} u_k$
* Notice that if we substitute the definition of z , we get the simple kinematic equations $x_{k+1} = x_k + hv_k + \frac{1}{2}h^2u_k v_{k+1} = v_k + hu_k$

* Assuming a zero-order hold, we can see that this is exact

Summary

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Given some linear continuous system given by

$$\begin{split} \dot{\boldsymbol{x}}(t) &= \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}\boldsymbol{u}(t), \boldsymbol{x}(0) = \boldsymbol{x}_{0} \\ \boldsymbol{y}(t) &= \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{D}\boldsymbol{u}(t) \end{split}$$

we can discretize it to find discrete state matrices A_d and B_d so that the system can be equivalently modelled discretely by:

$$oldsymbol{x}_{k+1} = oldsymbol{A}_d oldsymbol{x}_k + oldsymbol{B}_d oldsymbol{u}_k \ oldsymbol{y}_k = oldsymbol{C} oldsymbol{x}_k + oldsymbol{D} oldsymbol{u}_k$$

which is an exact model with the assumption of a zero-order hold on the input. The matrices A_d, B_d can be found by the matrix exponential

$$\begin{bmatrix} \boldsymbol{A}_d & \boldsymbol{B}_d \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} = \exp\left(\begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{0} \end{bmatrix} h \right)$$

where h is the size of each discrete time step.