
EE 16B
Spring 2022
Lecture 11
2/22/2022



LECTURE 11

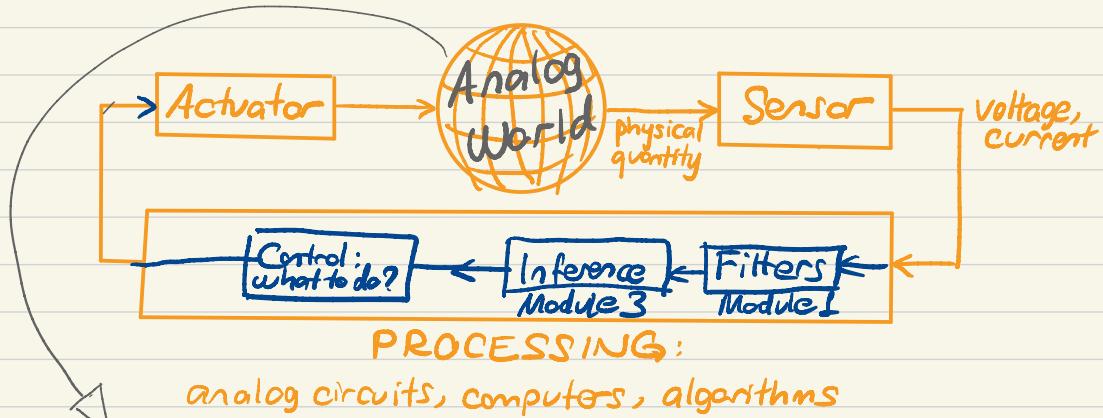
New module: Control and Robotics

- Today:
- Introduction to Control
 - Continuous- to discrete-time
 - System identification

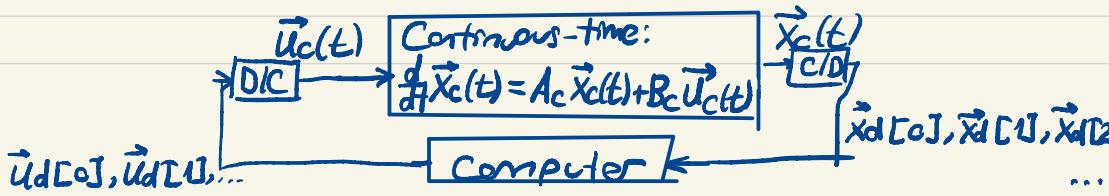
New prof
(Murat)



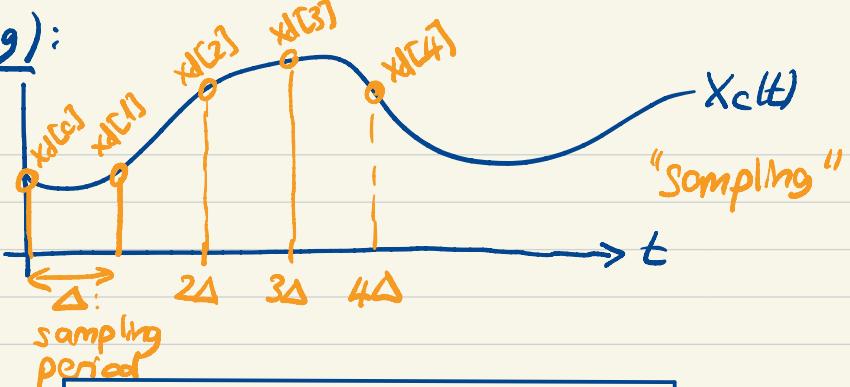
EECS view of the World from Lecture 1:



Control & inference blocks are algorithms executed digitally in a computer, in discrete time. Rest of the system evolves in continuous time. How do we connect the two worlds?

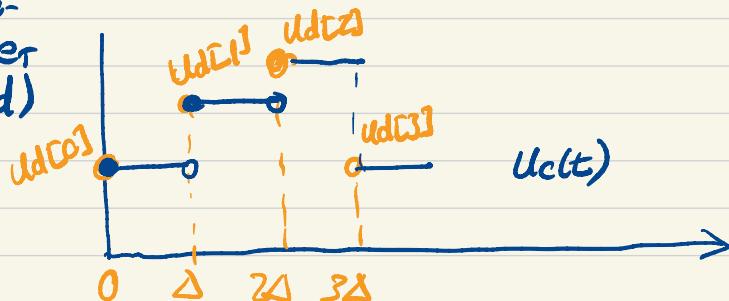


C/D (Sampling):



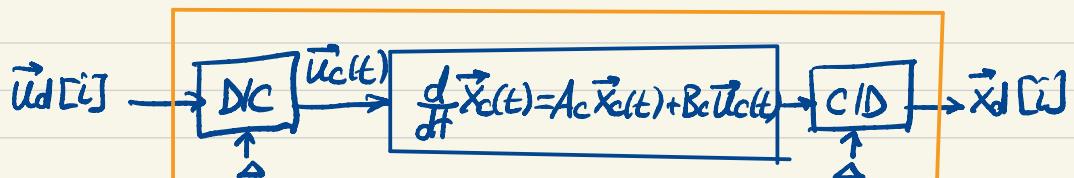
$$\vec{x}_d[i] = \vec{x}_c(i\Delta) \quad i=0, 1, 2, \dots \quad \text{Sampling}$$

D/C (Zero-order Hold)



$$\vec{u}_c(t) = \vec{u}_d[i] \quad t \in [i\Delta, (i+1)\Delta]$$

Discretization



$$\vec{x}_d[i+1] = A_d \vec{x}_d[i] + B_d \vec{u}_d[i]$$

- recurrence relation that describes how the system evolves from sample to sample

How to find A_d and B_d given A_c, B_c, Δ .

i.e.

given $\vec{x}_d[i]$ and $\vec{u}_d[i]$ what is $\vec{x}_d[i+1]$?

$\vec{x}_d[i] = \vec{x}_c(i\Delta)$ $\vec{x}_d[i+1] = \vec{x}_c((i+1)\Delta)$ from Sampling
eq'n above

$\vec{x}_d[i+1]$ is the sol'n of diff.eq'n

$$\frac{d}{dt} \vec{x}_c(t) = A_c \vec{x}_c(t) + B_c \vec{u}_c(t) = \vec{u}_d[t]$$

at time $(i+1)\Delta$ from initial condition $\vec{x}_c(i\Delta) = \vec{x}_d[i]$
at $t_0 = i\Delta$.

First, scalar case:

$$\frac{d}{dt} x_c(t) = \lambda x_c(t) + b u_d[i] \quad x_c(t_0) = x_d[i]$$

Discussion

$$2A/6A: \quad x_c(t) = e^{\lambda(t-t_0)} x_c(t_0) + \left(\int_{t_0}^t e^{\lambda(t-\tau)} d\tau \right) b u_d[i]$$

Substitute $t_0 = i\Delta$, $t = (i+1)\Delta$: $\underbrace{\qquad}_{\downarrow \text{see discussion}}$

$$x_c((i+1)\Delta) = e^{2\Delta} x_c(i\Delta) + \underbrace{\left(\frac{e^{2\Delta} - 1}{\lambda} \right) b u_d[i]}_{x_d[i+1] \quad Ad \quad x_d[i]}$$

when $\lambda \neq 0$,
replace with Δ
when $\lambda = 0$

$$Bd = \begin{cases} \frac{e^{2\Delta} - 1}{\lambda} b & \text{if } \lambda \neq 0 \\ \Delta b & \text{if } \lambda = 0 \end{cases}$$

Summary (scalar case):

$$Ad = e^{2\Delta}, \quad Bd = \quad "$$

Vector Case:

$$\frac{d}{dt} \vec{x}_c(t) = A_c \vec{x}_c(t) + B_c \vec{u}_d[i]$$

$$t_0 = i\Delta$$

$$t = (i+1)\Delta$$

Recall Lecture 6: diagonalization

$$\vec{y}_c = V^{-1} \vec{x}_c \Rightarrow \vec{x}_c = V \vec{y}_c$$

$$\frac{d}{dt} \vec{y}_c(t) = V^{-1} \frac{d}{dt} \vec{x}_c(t) = V^{-1} \underbrace{A_c \vec{x}_c(t)}_{V \vec{y}_c(t)} + V^{-1} B_c \vec{u}_d[i]$$

$$\frac{d}{dt} \vec{y}_c(t) = \underbrace{V^{-1} A_c V}_{\begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}} \vec{y}_c(t) + (V^{-1} B_c \vec{u}_d[i])$$

$$\frac{d}{dt} y_{c,k}(t) = \lambda_k y_{c,k}(t) + (V^{-1} B_c \vec{u}_d[i])_k$$

kth entry of vector \vec{y}_c

kth entry of vector $V^{-1} B_c \vec{u}_d[i]$

From scalar case above:

$$y_{d,k}[i+1] = e^{2\pi k\Delta} y_{d,k}[i] + \underbrace{\frac{e^{2\pi k\Delta} - 1}{2\pi}}_{\text{if } 2\pi k \neq 0; \text{ otherwise replace w/ } \Delta} (V^{-1} B_c \vec{u}_d[i])_k$$

stack up from $k=1$ to $k=n$

$$\vec{y}_d[i+1] = \left[e^{2\pi \Delta} \quad \dots \quad e^{2\pi n\Delta} \right] \vec{y}_d[i] + \left[\frac{e^{2\pi \Delta} - 1}{2\pi} \quad \dots \quad \frac{e^{2\pi n\Delta} - 1}{2\pi} \right] V^{-1} B_c \vec{u}_d$$

$$\vec{x}_d = V \vec{y}_d$$

multiply both sides by V

$$\vec{y}_d = V^{-1} \vec{x}_d$$

$$\vec{x}_d[i+1] = V \left[\begin{array}{c} e^{2\Delta} \\ - \\ e^{-2\Delta} \end{array} \right] V^+ \vec{x}_d[i] + V \left[\begin{array}{c} \frac{e^{2\Delta}-1}{2\Delta} \\ - \\ \frac{e^{-2\Delta}-1}{2\Delta} \end{array} \right] V^+ \vec{u}_d[i]$$

Ad
Bd

System Identification:

$$\vec{x}_d[i+1] = Ad \vec{x}_d[i] + Bd \vec{u}_d[i]$$

Can we learn the entries of Ad and Bd by observing the input sequence $\vec{u}_d[0], \vec{u}_d[1], \dots$ and resulting state sequence $\vec{x}_d[1], \vec{x}_d[2], \dots$?

Yes, under appropriate conditions. Will use Least Squares.

Least Squares Review:

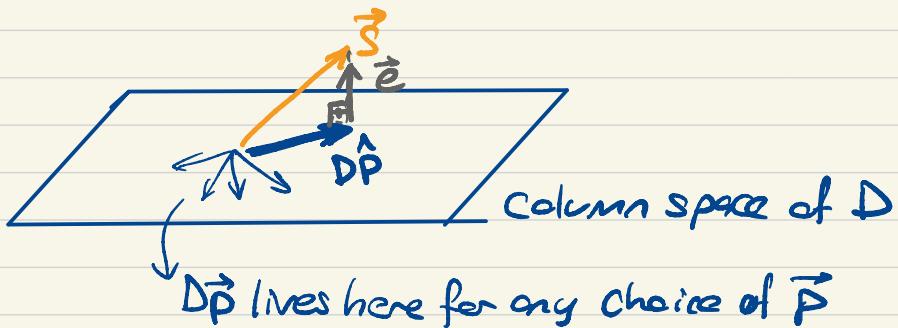
$$\vec{s} = D \vec{p} + \vec{e}$$

$\vec{s} \in R^l$: vector of measurements

$\vec{p} \in R^q$: unknown parameters (typically $q < l$)

$D \in R^{l \times q}$: known matrix

Find \hat{p} s.t. $D\hat{p}$ is as close to \vec{s} as possible
in the sense that
 $\|\vec{e}\| = \|\vec{s} - D\hat{p}\|$ is minimized when $\vec{p} = \hat{p}$.



$\|\vec{e}\|^2$ is minimized when $\vec{e} \perp \text{column space of } D$

$$\vec{d}_1^T \vec{e} = 0 \quad \text{where } D = [\vec{d}_1 \dots \vec{d}_q]$$

$$\underbrace{\vec{d}_q^T \vec{e} = 0}_{D^T \vec{e} = 0}$$

$$D^T \vec{e} = \begin{bmatrix} \vec{d}_1^T \\ \vdots \\ \vec{d}_q^T \end{bmatrix}$$

$$\vec{e} = \vec{s} - D\vec{p} \rightarrow D^T(\vec{s} - D\vec{p}) = 0$$

$$D^T D \vec{p} = D^T \vec{s}$$

If $D^T D$ invertible LS solution is

$$\hat{p} = (D^T D)^{-1} D^T \vec{s}$$

I incorrectly wrote "if D invertible" in Lecture. Corrected after class.