Systems Dynamics

Course ID: 267MI - Fall 2018

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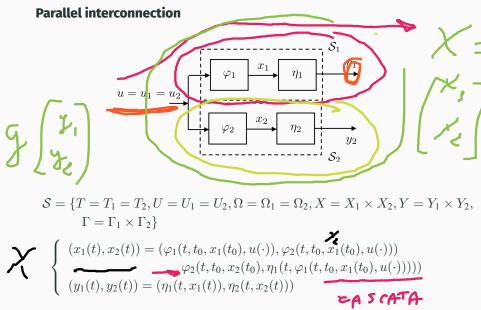
University of Trieste Department of Engineering and Architecture



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Lecture 1 Generalities: systems and models

Interconnection of Dynamic Systems

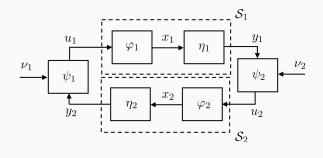


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TP GF - L1-p14

Feedback interconnection

General scheme:

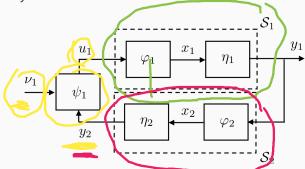


 $u_1(t) = \psi_1(y_2(t), \nu_1(t), t)$ $u_2(t) = \psi_2(y_1(t), \nu_2(t), t)$

Interconnection of Dynamic Systems

Feedback interconnection

Commonly used scheme:

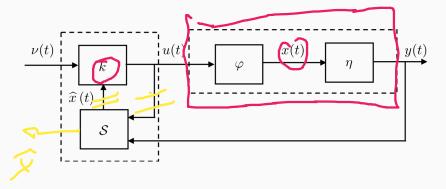


$$S = \{T = T_1 = T_2, U = V_1, \Omega = \Omega_{\nu_1}, X = X_1 \times X_2, Y = Y_1, \Gamma = \Gamma_1\}$$

$$\begin{cases} (x_1(t), x_2(t)) = (\varphi_1(t, t_0, x_1(t_0), \psi_1(\nu_1(\cdot), y_2(\cdot)), \varphi_2(t, t_0, x_2(t_0), y_1(\cdot)))) \\ y(t) = y_1(t) = \eta_1(t, x_1(t)) \end{cases}$$

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A notable example of feedback interconnection is the **state control law + state observer** scheme (will be dealt with in the *Control Theory* course)



Finite-dimensional Regular Systems

A dynamic systems is **regular** if:

- U, Ω, X, Y, Γ are normed vector spaces
- + $\varphi(\cdot,\cdot,\cdot,\cdot)$ is a continuous function with respect its arguments d
- $\frac{\mathrm{d}}{\mathrm{d}t}\varphi(t,t_0,x_0,u(\cdot))$ does exist and it is continuous for all values of the arguments where $u(\cdot)$ is continuous

The state movement $\varphi(t, t_0, x_0, u(\cdot))$ of a regular finite-dimensional dynamic system is the **unique solution** of a suitable vector differential equation

and

Finite-dimensional Discrete-time Dynamic Systems

Discrete-time dynamic systems obtain by sampling a continuous-time regular system

- U, X, Y finite-dimensional normed vector spaces
 Ω = {u(·) : piecewise constant u_i(·), i = 1,...,m}
- Sampling time ΔT :

$$u(k) = u(t), \ t_0 + k\Delta T \le t < t_0 + (k+1)\Delta T, \ k = 0, 1, \dots$$

$$y(k) = y(t_0 + k\Delta T), \ k = 0, 1, \dots$$

Then:

$$\begin{aligned} \widetilde{x(k+1)} &= f_d(x(k), u(k), k) \\ y(k) &= g_d(x(k), u(k), k) \end{aligned}$$

where (from composition property of φ):

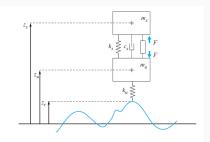
$$f_d(x(k), u(k), k) = \varphi(t_0 + (k+1)\Delta T, t_0 + k\Delta T, x(k), u(k))$$

$$g_d(x(k), u(k), k) = \eta(x(k), u(k), t_0 + k\Delta T)$$

An example: continuous-time model of a car suspension



From a real vehicle ...

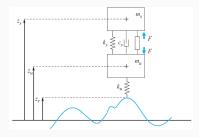


to a simplified quarter-car model

quarter-car model hypotheses

- vehicle as assembly of four decoupled parts
- each part consists of
 - the sprung mass: a quarter of the vehicle mass, supported by a suspension actuator, placed between the vehicle and the tyre
 - the unsprung mass: the wheel/tyre sub-assembly
- the model allows only for vertical motion: the vehicle is moving forward with an almost constant speed

Continuous-time model of a car suspension (cont.)



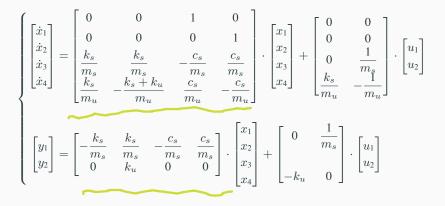
- state variables:
 - vertical positions of sprung and unsprung masses vs. the corresponding steady-state values
 - vertical speeds of masses

$$\begin{array}{rcl} x_1(t) &=& z_s(t) - \bar{z}_s \\ x_2(t) &=& z_u(t) - \bar{z}_u \\ x_3(t) &=& \dot{x}_1(t) \\ x_4(t) &=& \dot{x}_2(t) \\ \\ u_1(t) &=& z_r(t) - \bar{z}_r \\ u_2(t) &=& F(t) \\ \\ y_1(t) &=& \ddot{x}_1 \\ y_2(t) &=& k_u \left(x_2(t) - u_1(t) \right) \end{array}$$

- inputs:
 - ground vertical position vs. the steady-state
 - active actuator force
- outputs:
 - sprung mass vertical acceleration
 - contact force between tyre and ground

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Continuous-time model of a car suspension (cont.)



Assuming

$$\begin{split} m_s &= 400.0 \ \text{kg} & m_u = 50.0 \ \text{kg} & c_s = 2.0 \ 10^3 \ \text{N} \, \text{s} \, \text{m}^{-1} \\ k_s &= 2.0 \ 10^4 \ \text{N} \, \text{m}^{-1} & k_u = 2.5 \ 10^5 \ \text{N} \, \text{m}^{-1} \end{split}$$

the car suspension model becomes

$$\begin{cases} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1.0 \\ -50.0 & 50.0 & -5.0 & 5.0 \\ 400.0 & -5400.0 & 40.0 & -40.0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 2.510^{-3} \\ 5.010^3 & -2.010^{-2} \end{bmatrix} \cdot \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$
$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} -50.0 & 50.0 & -5.0 & 5.0 \\ 0 & 2.510^5 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 & 2.510^{-3} \\ -2.510^5 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

Let's get a **sampled-time** description of the same dynamic system:

- How does the sampled-time description correlate with the continuous-time model?
- What happens if we increase or decrease the sampling rate?
 Does the sampled-time model change with the sampling time?
- Does the sampled-time model describe the behaviour of the continuous-time dynamic system for **any possible choice** of the sampling time value?

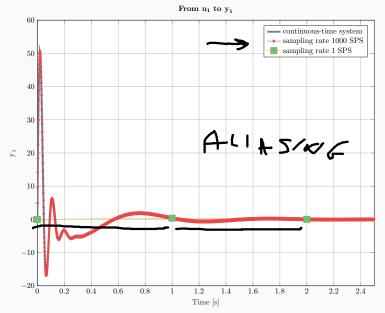
Using 1000 samples per second as sampling rate

$$\begin{cases} \begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \\ x_4(k+1) \end{bmatrix} = \begin{bmatrix} 9.98 \ 10^{-1} & 2.05 \cdot 10^{-5} & 9.98 \cdot 10^{-4} & 2.47 \cdot 10^{-6} \\ 1.97 \cdot 10^{-4} & 0.99 & 1.98 \cdot 10^{-5} & 9.80 \cdot 10^{-4} \\ -4.89 \cdot 10^{-2} & 3.65 \cdot 10^{-3}8 & 9.95 \cdot 10^{-1} & 4.91 \cdot 10^{-3} \\ 3.91 \cdot 10^{-1} & -5.29 & 3.93 \cdot 10^{-2} & 0.96 \end{bmatrix} \cdot \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} \\ + \begin{bmatrix} 4.13 \cdot 10^{-6} & 1.23 \cdot 10^{-9} \\ 2.47 \cdot 10^{-3} & -9.85 \cdot 10^{-9} \\ 1.24 \cdot 10^{-2} & 2.44 \cdot 10^{-6} \\ 4.90 & -1.95 \cdot 10^{-5} \end{bmatrix} \cdot \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix} \\ \begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} -50.0 & 50.0 & -5.0 & 5.0 \\ 0 & 2.5 \cdot 10^5 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} \\ + \begin{bmatrix} 0 & 2.5 \cdot 10^{-3} \\ -2.5 \cdot 10^5 & 0 \end{bmatrix} \cdot \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix}$$

Instead, using 1 sample per second as sampling rate

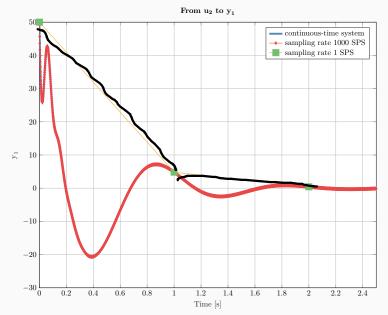
$$\begin{cases} \begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \\ x_4(k+1) \end{bmatrix} = \begin{bmatrix} 1.17 \cdot 10^{-1} & -1.76 \cdot 10^{-2} & 4.65 \cdot 10^{-3} & 1.34 \cdot 10^{-4} \\ 7.75 \cdot 10^{-3} & -4.87 \cdot 10^{-3} & 1.07 \cdot 10^{-3} & 1.29 \cdot 10^{-5} \\ -1.79 \cdot 10^{-1} & -4.90 \cdot 10^{-1} & 9.94 \cdot 10^{-2} & 3.64 \cdot 10^{-4} \\ -4.84 \cdot 10^{-2} & -1.62 \cdot 10^{-2} & 2.91 \cdot 10^{-3} & -2.95 \cdot 10^{-5} \end{bmatrix} \cdot \begin{bmatrix} x_1(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} \\ + \begin{bmatrix} 9.00 \cdot 10^{-1} & 4.41 \cdot 10^{-5} \\ 9.97 \cdot 10^{-1} & -3.88 \cdot 10^{-7} \\ 6.70 \cdot 10^{-1} & 8.96 \cdot 10^{-6} \\ 6.46 \cdot 10^{-2} & 2.42 \cdot 10^{-6} \end{bmatrix} \cdot \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix} \\ \begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} -50.0 & 50.0 & -5.0 & 5.0 \\ 0 & 2.5 \cdot 10^5 & 0 & 0 \\ 0 & 2.5 \cdot 10^5 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \end{bmatrix} \\ + \begin{bmatrix} 0 & 2.5 \cdot 10^{-3} \\ -2.5 \cdot 10^5 & 0 \end{bmatrix} \cdot \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix}$$

Step responses comparison



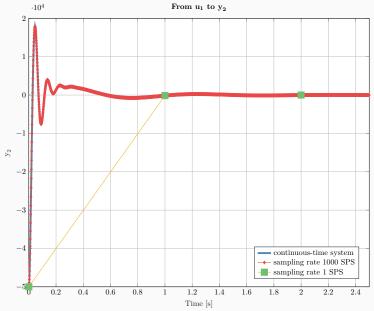
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Step responses comparison (cont.)



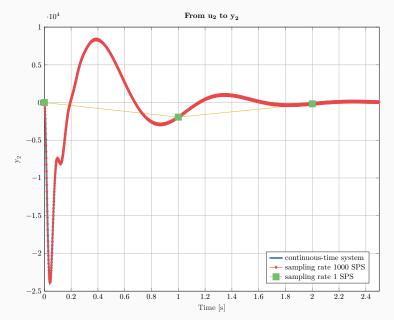
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Step responses comparison (cont.)



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Step responses comparison (cont.)



Remarks

- by selecting different sampling rate we obtained different representations of the same continuous-time dynamic system
- **sampling** may **heavily distort the information**, giving a completely wrong discrete-time representation of the original continuous-time system: indeed the model obtained using *one* sample per second as the sampling rate is wrong!

Continuous-time State Equations

$$\begin{array}{l} \forall t \in \mathbb{R} \\ u_1(t), \dots, u_m(t) \in \mathbb{R} \\ \textbf{is } \\ \textbf{is } \\ \textbf{is } \\ \textbf{(dynamic)} \end{array} \qquad \left\{ \begin{array}{l} \dot{x}_1(t) = f_1(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t), t) \\ \vdots \\ \dot{x}_n(t) = f_n(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t), t) \\ \vdots \\ \textbf{(algebraic)} \end{array} \right. \\ \left\{ \begin{array}{l} y_1(t) = g_1(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t), t) \\ \vdots \\ y_p(t) = g_p(x_1(t), \dots, x_n(t), u_1(t), \dots, u_m(t), t) \end{array} \right. \end{array} \right.$$

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Continuous-time State Equations (cont.)

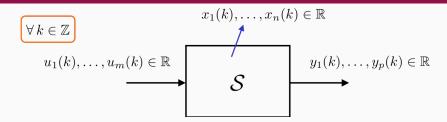
$$u(t) = \begin{bmatrix} u_{1}(t) \\ \vdots \\ u_{m}(t) \end{bmatrix} \in \mathbb{R}^{m}, \ y(t) = \begin{bmatrix} y_{1}(t) \\ \vdots \\ y_{p}(t) \end{bmatrix} \in \mathbb{R}^{p}$$

$$x(t) = \begin{bmatrix} x_{1}(t) \\ \vdots \\ x_{n}(t) \end{bmatrix} \in \mathbb{R}^{n} \quad f(x, u, t) = \begin{bmatrix} f_{1}(x, u, t) \\ \vdots \\ f_{n}(x, u, t) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, t) = \begin{bmatrix} f_{1}(x, u, t) \\ \vdots \\ f_{n}(x, u, t) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, t) = \begin{bmatrix} f_{1}(x, u, t) \\ \vdots \\ f_{n}(x, u, t) \end{bmatrix} \in \mathbb{R}^{n}$$

Discrete-time State Equations



State equations (dynamic)

Output equations (algebraic)

$$\begin{cases} x_1(k+1) = f_1(x_1(k), \dots, x_n(k), u_1(k), \dots, u_m(k), k) \\ \vdots \\ x_n(k+1) = f_n(x_1(k), \dots, x_n(k), u_1(k), \dots, u_m(k), k) \end{cases}$$

$$\begin{array}{c} \begin{array}{c} \begin{array}{c} y_1(k) = g_1(x_1(k), \dots, x_n(k), u_1(k), \dots, u_m(k), k) \\ \\ \vdots \\ \\ \end{array} \\ \begin{array}{c} y_p(k) = g_p(x_1(k), \dots, x_n(k), u_1(k), \dots, u_m(k), k) \end{array} \end{array}$$

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Discrete-time State Equations (cont.)

$$u(k) = \begin{bmatrix} u_{1}(k) \\ \vdots \\ u_{m}(k) \end{bmatrix} \in \mathbb{R}^{m}, \ y(k) = \begin{bmatrix} y_{1}(k) \\ \vdots \\ y_{p}(k) \end{bmatrix} \in \mathbb{R}^{p}$$

$$x(k) = \begin{bmatrix} x_{1}(k) \\ \vdots \\ x_{n}(k) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, k) = \begin{bmatrix} f_{1}(x, u, k) \\ \vdots \\ f_{n}(x, u, k) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, k) = \begin{bmatrix} f_{1}(x, u, k) \\ \vdots \\ f_{n}(x, u, k) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, k) = \begin{bmatrix} f_{1}(x, u, k) \\ \vdots \\ f_{n}(x, u, k) \end{bmatrix} \in \mathbb{R}^{n}$$

$$f(x, u, k) = \begin{bmatrix} f_{1}(x, u, k) \\ \vdots \\ f_{n}(x, u, k) \end{bmatrix} \in \mathbb{R}^{n}$$

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More Definitions and Properties

• Time-invariant Dynamic Systems

$$\begin{cases} \dot{x}(t) = f(x(t), u(t), \bigstar) \\ y(t) = g(x(t), u(t), \bigstar) \\ x(k+1) = f(x(k), u(k), \bigstar) \\ y(k) = g(x(k), u(k), \bigstar) \end{cases} \implies \begin{cases} \dot{x}(t) = f(x(t), u(t)) \\ y(t) = g(x(t), u(t)) \\ y(k) = g(x(k), u(k), \bigstar) \\ y(k) = g(x(k), u(k), \bigstar) \end{cases}$$

Strictly Proper Dynamic Systems

$$\begin{cases} \dot{x}(t) = f(x(t), u(t), \mathbf{x}) \\ y(t) = g(x(t), u(t), \mathbf{x}) \\ x(k+1) = f(x(k), u(k), \mathbf{x}) \\ y(k) = g(x(k), u(k), \mathbf{x}) \\ y(k) = g(x(k), u(k), \mathbf{x}) \end{cases} \implies \begin{cases} \dot{x}(t) = f(x(t), u(t), t) \\ y(t) = g(x(t), t) \\ x(k+1) = f(x(k), u(k), \mathbf{x}) \\ y(k) = g(x(k), u(k), \mathbf{x}) \\ y(k) = g(x(k), k) \\ y(k) = g(x(k), k) \end{cases}$$

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More Definitions and Properties (cont.)

Forced and Free Dynamic Systems

$$\begin{cases}
\dot{x}(t) = f(x(t), u(t), t) \\
y(t) = g(x(t), u(t), t)
\end{cases} \implies \begin{cases}
\dot{x}(t) = f(x(t), t) \\
y(t) = g(x(t), t)
\end{cases}$$

$$\begin{cases}
\dot{x}(t) = f(x(t), t) \\
y(t) = g(x(t), t)
\end{cases}$$

$$\begin{cases}
\dot{x}(k+1) = f(x(k), u(k), k) \\
y(k) = g(x(k), u(k), k)
\end{cases} \implies \begin{cases}
x(k+1) = f(x(k), k) \\
y(k) = g(x(k), k)
\end{cases}$$

It is worth noting that in case the input function u(t), $\forall t$ or input sequence u(k), $\forall k$ are **known beforehand**, the dynamic system can be re-written as a free one:

$$\begin{cases} \dot{x}(t) = f(x(t), u(t), t) = \tilde{f}(x(t), t) \\ y(t) = g(x(t), u(t), t) = \tilde{g}(x(t), t) \\ x(k+1) = f(x(k), u(k), k) = \tilde{f}(x(k), k) \\ y(k) = g(x(k), u(k), k) = \tilde{g}(x(k), k) \end{cases}$$