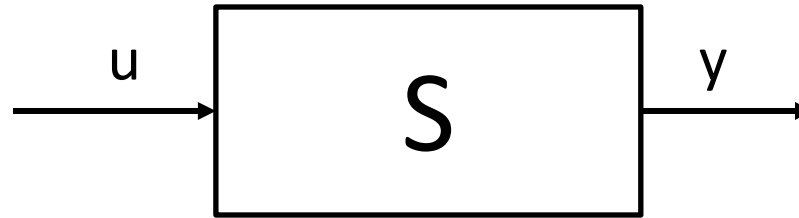


Lecture #0.1

Math tools for Control Engineering

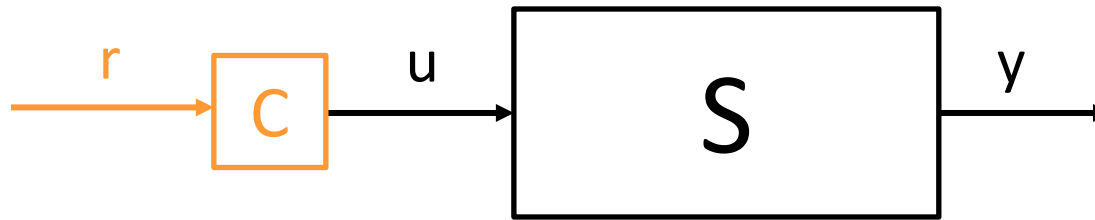
- Introduction to dynamical systems
- LTI systems
- Time domain response and Lagrange formula
- Laplace transform and transfer function
- Equilibria and stability
- Example: state feedback
- Harmonic response function
- Discrete-time systems (hints)

Introduction



- We want to assign a desired behaviour to the **system S**
- the **output $y(t)$** should be close to some **reference signal $r(t)$**
- To do so, we look for a suitable **input $u(t)$**

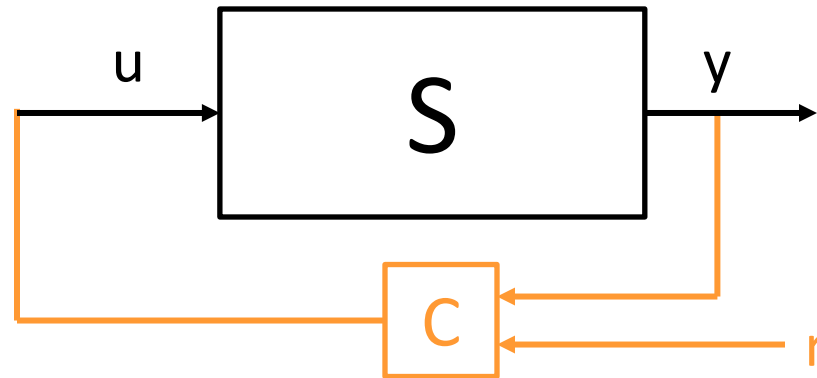
Introduction



- Two possible strategies

1. **Open-loop**: find u that allows to reach the desired y *a priori* (usually based on an **inverse model** of the system)
(*feedforward* control)

Introduction



- Two possible strategies
2. **Closed-loop**: calculate u *online* based on a measurement of the output y (*feedback control*)

Open-loop control

Example:

$$c\dot{T} = -k(T - T_e) + P_{in}$$

- T oven temperature [$^{\circ}\text{C}$]
- T_e external temperature [$^{\circ}\text{C}$]
- c thermal capacity [$\text{J}/^{\circ}\text{C}$]
- k thermal conductivity [$\text{W}/^{\circ}\text{C}$]
- P_{in} input power [W]



Open-loop control

Example: $c\dot{T} = -k(T - T_e) + P_{in}$

- Desired steady-state temperature of 150° , assuming

$$T_e = 20$$

$$k = 10$$

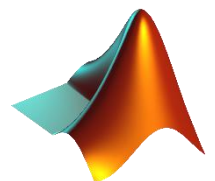
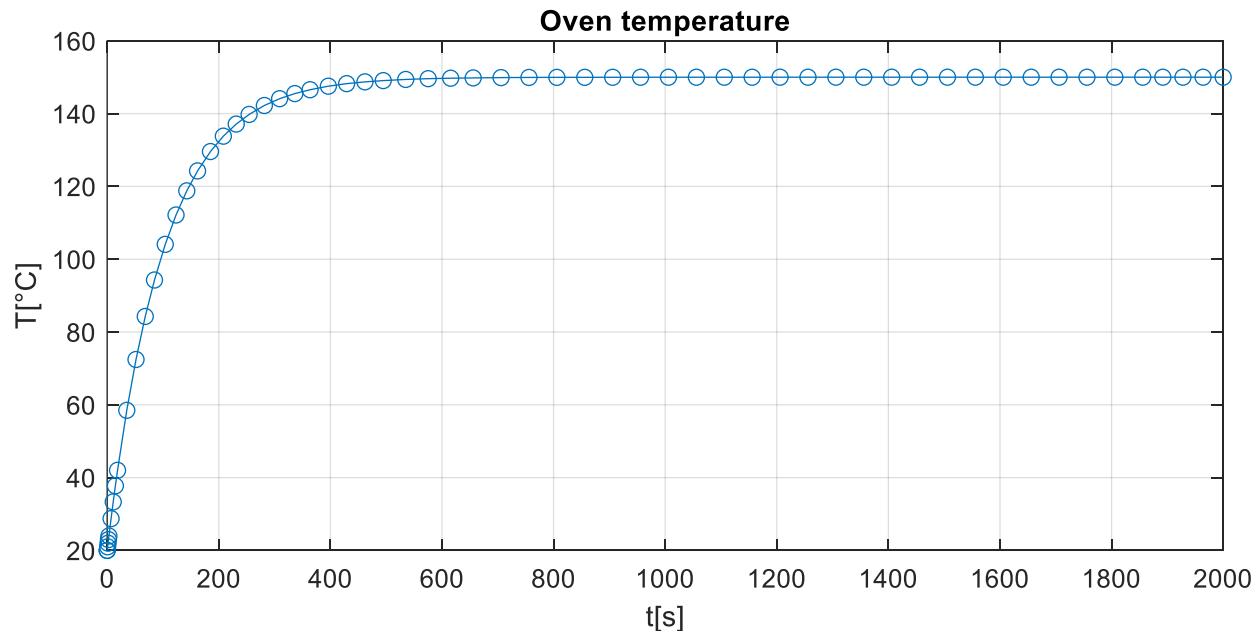
$$c = 1000$$

→ feedforward strategy:

$$P_{in} = k(150^\circ - T_e) = 1300 \text{ W}$$

Open-loop control

```
>> T_e = 20;  
>> c = 1000;  
>> k = 10;  
>> ode45(@(t,T) -k/c*(T-T_e)+P_in/c, [0 2000], T_e)
```



Open loop control

- What could go wrong?
 - uncertainty on model coefficients
 - uncertainty on environment temperature
 - not all power levels may be available
 - relay/bang-bang control
 - may be *slow*...
 - improve dynamical performance
- Moreover, feedforward is not viable for **unstable systems!**

Why feedback control?

Why design a **feedback** controller?

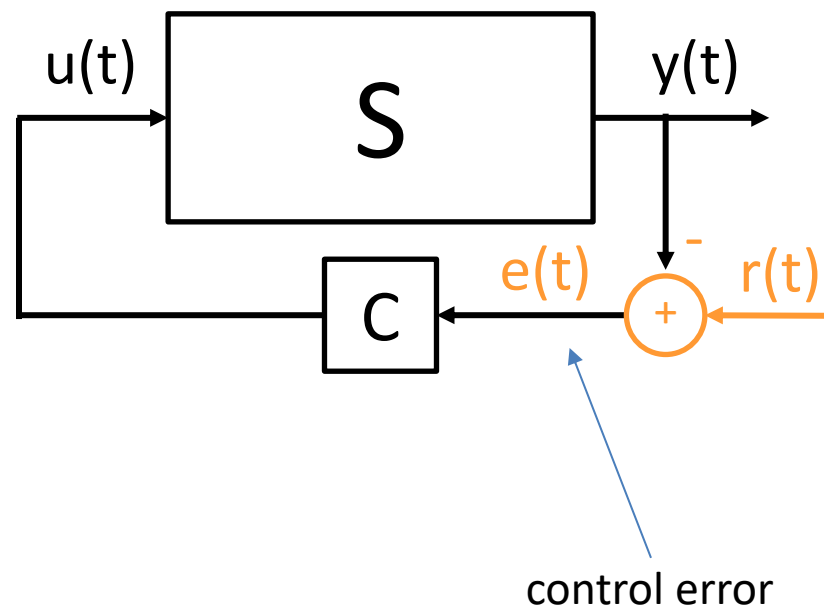
1. **Uncertainties:**
the model may not be accurate
2. **External disturbances:**
unforeseen and uncontrollable inputs may act on the system
3. **Efficiency:**
optimize the time/amount of energy needed
4. **Flexibility:**
we may not know the reference in advance

Why feedback control?

- But above all:
 - open-loop control changes the **output** of the system
 - closed-loop control **changes system dynamics:**
 - we can **stabilize an unstable system!**

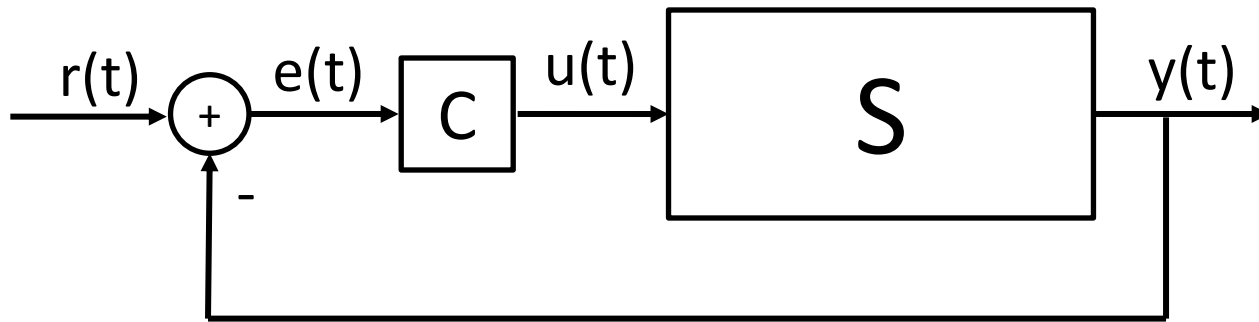
Closed-loop control

- The reference is usually compared with the measured output to generate a control error signal



Closed-loop control

Classic closed-loop control scheme



- $r(t)$: reference
- $e(t)$: control error
- $u(t)$: control action
- $y(t)$: controlled output

Dynamical systems

- **Dynamical system**: mathematical model that represents how a given process (**system**) with a certain number of degrees of freedom evolves over time
- Behavior typically depends on **previous history**, which is compactly captured by a set of **state variables**
(e.g. position and speed of a material point)
- Typically, evolution is described by a set of **differential equations**

Dynamical systems

- General equations of a dynamical system

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t); t), & \mathbf{x}(t_0) &= \mathbf{x}_0 \\ \underbrace{\mathbf{y}(t)}_{\text{outputs}} &= \underbrace{\mathbf{g}(\mathbf{x}(t))}_{\text{state}}, \underbrace{\mathbf{u}(t)}_{\text{inputs (controllable or not)}}; t\end{aligned}$$

- This representation is called **Input-State-Output** (or **ISO**)
- In general, a system can be non-linear, time-varying, MIMO, complex, multi-agent...

LTI dynamical systems

- Special case: Linear Time-Invariant (SISO) systems

$$\begin{aligned}\dot{\mathbf{x}}(t) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t), & \mathbf{x}(t_0) &= \mathbf{x}_0 \\ y(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{D}u(t)\end{aligned}$$

- linear systems \rightarrow superposition principle!

Free evolution

- We take advantage of the superposition principle to decompose the system as (#1)

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}\mathbf{x}, & \mathbf{x}(t_0) &= \mathbf{x}_0 \\ \mathbf{u} &= \mathbf{0}\end{aligned}$$

NOTE: a system whose state **does not depend on external inputs** is said to be **autonomous** (but the same terminology is also used for nonlinear systems that do not depend explicitly on time)

Free evolution

$$\dot{\mathbf{x}} = A\mathbf{x}$$

- This system evolves according to

$$\mathbf{x}(t) = e^{A(t-t_0)} \mathbf{x}_0$$

Matrix exponential

$$\frac{d}{dt} e^{At} = A e^{At}$$

→ free evolution/natural response ($u = 0, \mathbf{x}(t_0) \neq 0$)

NOTE: the dependency on $t - t_0$ and not on t and t_0 separately comes from the time-invariance hypothesis

Forced response

- We take advantage of the superposition principle to decompose the system as (#2)

$$\dot{x} = Ax + Bu, \quad x(t_0) = 0$$



$$x(t) = \int_{t_0}^t e^{A(t-\tau)} Bu(\tau) d\tau$$

→ **forced response** ($u \neq 0, \quad x(t_0) = 0$)

Lagrange formula

- Adding up the two contributions

$$\begin{aligned}\dot{x} &= Ax + Bu, & x(t_0) &= x_0 \\ y &= Cx + Du\end{aligned}$$


$$\begin{aligned}x(t) &= e^{A(t-t_0)}x_0 + \int_{t_0}^t e^{A(t-\tau)}Bu(\tau)d\tau \\ y(t) &= Cx(t) + Du(t)\end{aligned}$$

Convolution integral
also written as
 $e^{At} \star u(t)$

Lagrange's formula

Lagrange formula

- Assume for simplicity $D = 0^*$ (**strictly proper** system)
*If not, the system could be separated into a dynamical and a purely algebraic part (D)

$$\begin{aligned}\dot{x} &= Ax + Bu, & x(t_0) &= x_0 \\ y &= Cx + \cancel{Du}\end{aligned}$$



$$y(t) = Ce^{A(t-t_0)}x_0 + C \int_{t_0}^t e^{A(t-\tau)}Bu(\tau)d\tau$$

NOTE: from here on we will assume (wlog) $t_0 = 0$

Natural modes

- We defined the **matrix exponential function** through the property

$$\frac{d}{dt} e^{At} = A e^{At}$$

- But we can also express it through its **Taylor series**

$$e^{At} = I + \sum_k \frac{A^k}{k!} t^k$$

Natural modes

- In the case of a **diagonal matrix**

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix} \Rightarrow e^{\Lambda} = I + \sum_k \frac{\Lambda^k}{k!} = \begin{bmatrix} e^{\lambda_1} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & e^{\lambda_n} \end{bmatrix}$$

- More in general, if the dynamical matrix is diagonalizable^{*}:

$$\begin{aligned} \Lambda &= T^{-1}AT \\ \dot{\mathbf{x}} &= T\Lambda T^{-1}\mathbf{x} \\ (T^{-1}\dot{\mathbf{x}}) &= \Lambda(T^{-1}\mathbf{x}) \end{aligned}$$

^{*} For simplicity we only consider the case of eigenvalues with multiplicity one

Natural modes

Defining

$$\xi = T^{-1}x$$

we get

$$\begin{aligned}\xi(t) &= e^{\Lambda t} \xi_0 = \\ &= \xi_{0,1} e^{\lambda_1 t} + \xi_{0,2} e^{\lambda_2 t} + \dots + \xi_{0,n} e^{\lambda_n t}\end{aligned}$$

$$x(t) = T\xi(t) = \underbrace{Te^{\Lambda t}T^{-1}}_{= e^{At}} x_0$$

The evolution of the system is associated with exponential modes related to **the eigenvalues of the A matrix**

Natural modes

These modes can be:

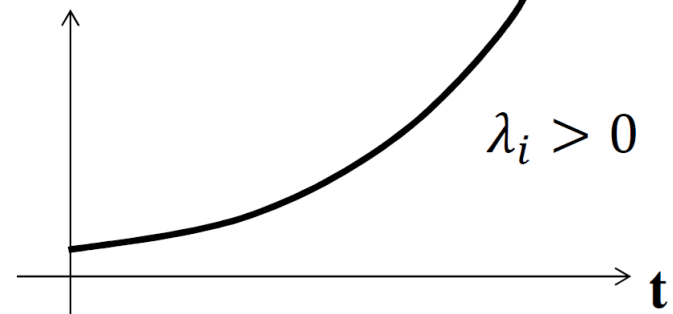
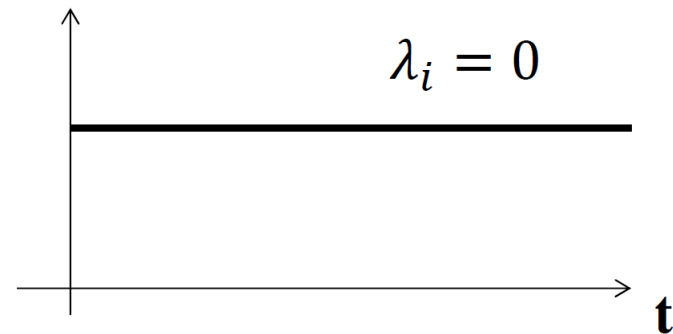
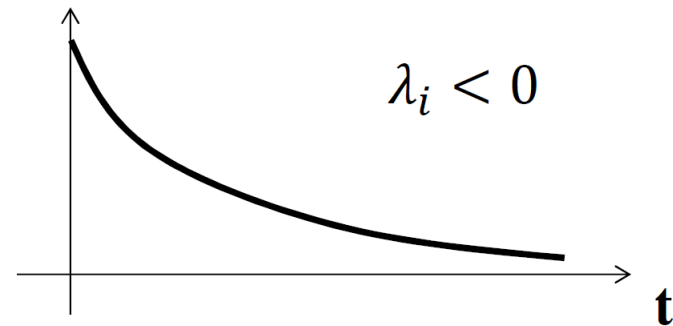
- **Aperiodic** → real eigenvalues
 $c_i e^{\lambda_i t}$
- **Pseudoperiodic** → complex eigenvalues
 $c_i e^{\alpha_i t} e^{i\omega_i t}$

NOTE: in the case of complex eigenvalues, a pseudoperiodic mode will correspond to a **pair** of conjugated eigenvalues. More details [here](#)

Natural modes

Aperiodic modes

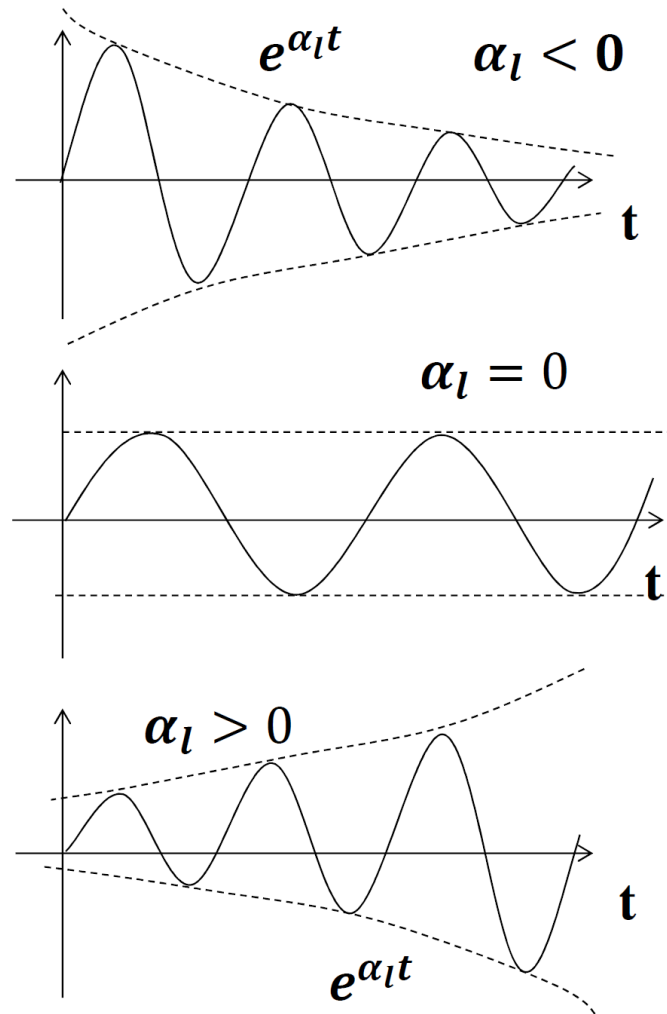
- Convergent
- Constant
- Divergent



Natural modes

Pseudo-periodic modes

- Convergent
- Constant
- Divergent



Hurwitz theorem

- A is said to be a **Hurwitz** (or **stable**) matrix if all of its eigenvalues have **negative real part**
- Dynamical systems with a Hurwitz A matrix are **stable**

Laplace Transform

- We can apply the [Laplace Transform](#) to the equations of our system

$$L[f(t)] = F(s) := \int_0^{\infty} f(t)e^{-st} dt$$

- We consider the **monolateral** transform: we want to preserve **causality**
- Mono and bi-lateral transforms coincide if $f(t) = f(t) \cdot \mathbb{1}(t)$

Laplace Transform

Laplace transform has the following properties

- Linearity
- Translation in the Laplace domain

$$L[e^{\alpha t} f(t)] = F(s - \alpha)$$

- Translation in time

$$L[f(t - T)] = F(s)e^{-sT}$$

Laplace Transform

Laplace transform has the following properties

- **Derivative** in time

$$L \left[\frac{df}{dt} \right] = sF(s) - f(0)$$

- **Integral** in time

$$L \left[\int_0^t f(\tau) d\tau \right] = \frac{1}{s} F(s)$$

Laplace Transform

Laplace transform has the following properties

- **Convolution**

$$L[f * g] = F(s)G(s)$$

→ thanks to this property, we can turn the convolution integral seen before into a **product** of Laplace transforms (see later)

Laplace Transform

The following theorems also apply

- Initial value

$$f(0) = \lim_{s \rightarrow \infty} sF(s)$$

- Final value

$$\lim_{t \rightarrow \infty} f(t) = \lim_{s \rightarrow 0} sF(s)$$

List of transforms

- Dirac's delta fcn

$$L[\delta(t)] = 1$$

- Step fcn

$$L[1(t)] = 1/s$$

- Ramp

$$L[R(t)] = 1/s^2$$

- Exponential

$$L[e^{\alpha t}] = \frac{1}{s - \alpha}$$

- Sine

$$L[\sin(\omega t)] = \frac{\omega}{s^2 + \omega^2}$$

- Cosine

$$L[\cos(\omega t)] = \frac{s}{s^2 + \omega^2}$$

Transfer function

- We can apply the [Laplace Transform](#) to the equations of our system

$$\begin{aligned} sX(s) - x_0 &= AX(s) + BU(s) \\ Y(s) &= CX(s) + DU(s) \end{aligned}$$



$$Y(s) = C(sI - A)^{-1}x_0 + \underbrace{(C(sI - A)^{-1}B + D)}_{\text{transfer function}}U(s)$$

transfer function

Transfer function

The expression

$$H(s) := \frac{Y(s)}{U(s)} = C(sI - A)^{-1}B$$

is also called **transfer function** of the system

→ The tf is an **Input-Output (IO)** representation of the system

Transfer function

In particular, since $L[\delta(t)] = 1$

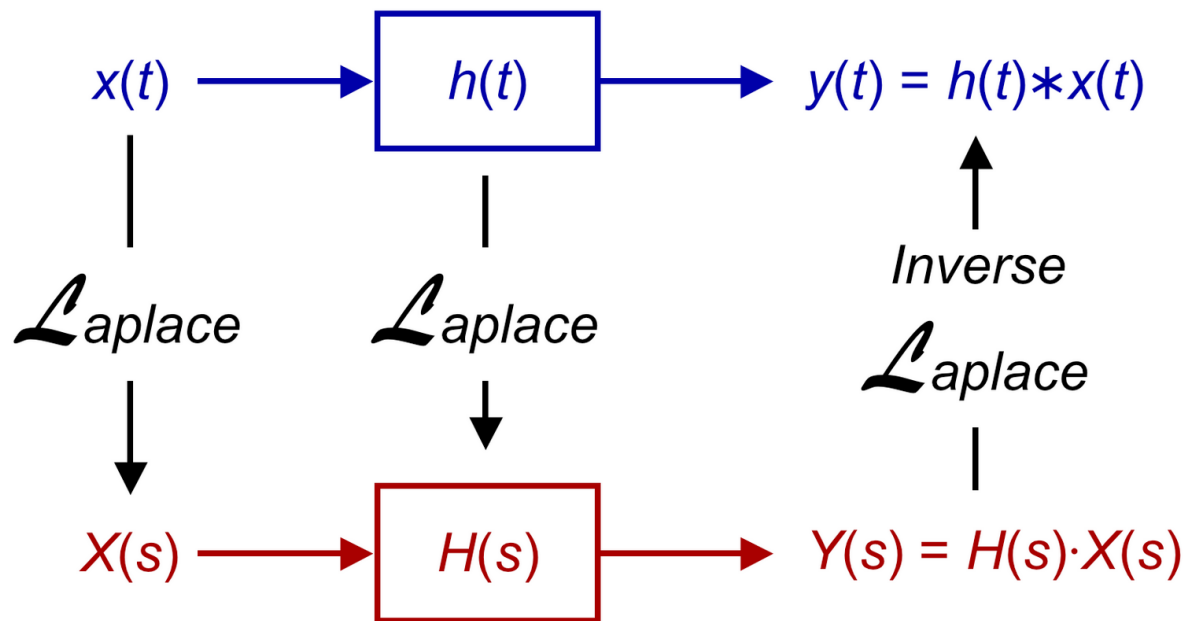
$$u(t) = \delta(t) \Rightarrow Y(s) = H(s)U(s) = H(s)$$

→ The transfer function of a linear system is the Laplace transform of the **impulse response**

Transfer function

Real differential equation \rightarrow Complex algebraic equation

Time domain



Frequency domain

Transfer function

For LTI systems, the tf will be a **ratio of polynomials**

$$H(s) = \frac{\text{num}(s)}{\text{den}(s)} = \frac{a_m s^m + a_{m-1} s^{m-1} + \dots + a_1 s + a_0}{b_n s^n + b_{n-1} s^{n-1} + \dots + b_1 s + b_0}$$

- The roots of $\text{num}(s)$ are called **zeros**
- The roots of $\text{den}(s)$ are called **poles**
- $\text{den}(s) = \det(sI - A) \rightarrow$ characteristic polynomial of A !

The poles coincide with the eigenvalues of the system

Transfer function

The tf can be broken down to terms of the form

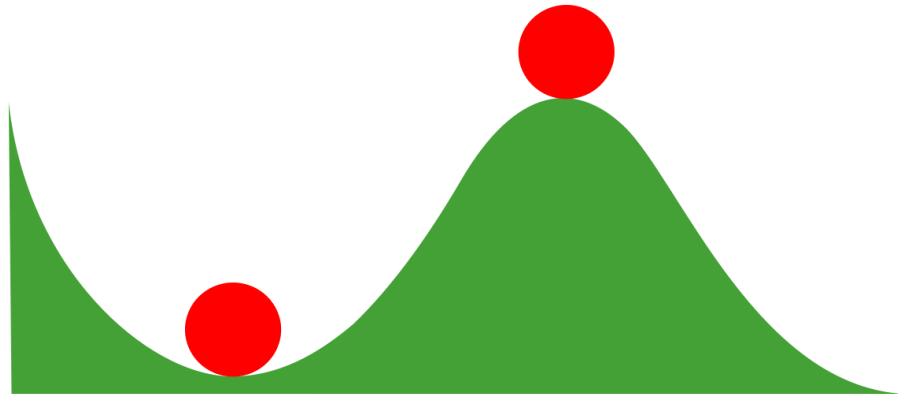
- $\frac{1}{s-\lambda} \xrightarrow{L^{-1}} e^{\lambda t} \cdot \mathbb{1}(t)$
- $\frac{\omega}{(s-\alpha)^2 + \omega^2} \xrightarrow{L^{-1}} e^{\alpha t} \sin(\omega t) \cdot \mathbb{1}(t)$
- $\frac{s}{(s-\alpha)^2 + \omega^2} \xrightarrow{L^{-1}} e^{\alpha t} \cos(\omega t) \cdot \mathbb{1}(t)$

→ Again the [natural evolution modes](#) seen before!

Equilibria and stability

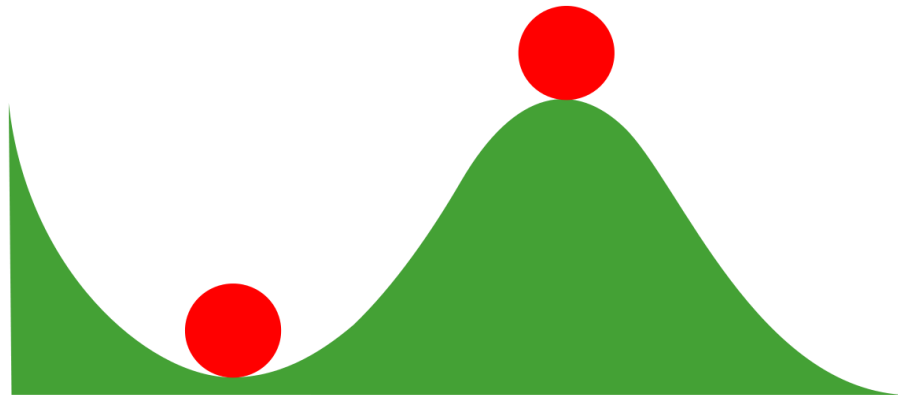
- **Equilibrium points** are defined by the equation

$$\dot{x} = f(x, u) = 0$$



Equilibria and stability

- Without external forcing, a system that is at an equilibrium point will stay there
- However, equilibria can be **stable** or **unstable**



Equilibria and stability

- For linear systems, the only equilibrium point is

$$Ax = 0$$

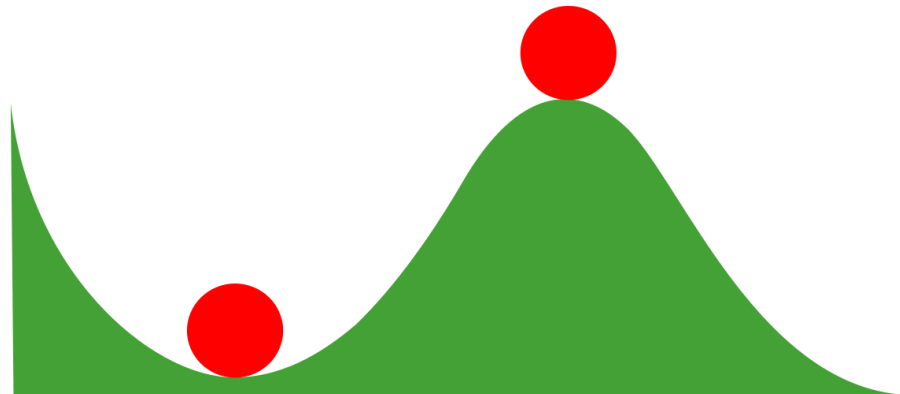
- This equilibrium is **stable** if A is Hurwitz

Equilibria and stability

The system is **unstable** if the matrix A

1. has eigenvalues in the **right-half Gauss plane**
2. has eigenvalues with **0 real-part** and multiplicity > 1

(if eigenvalues with 0 real part are present with multiplicity one, the system is said to be **marginally stable**)



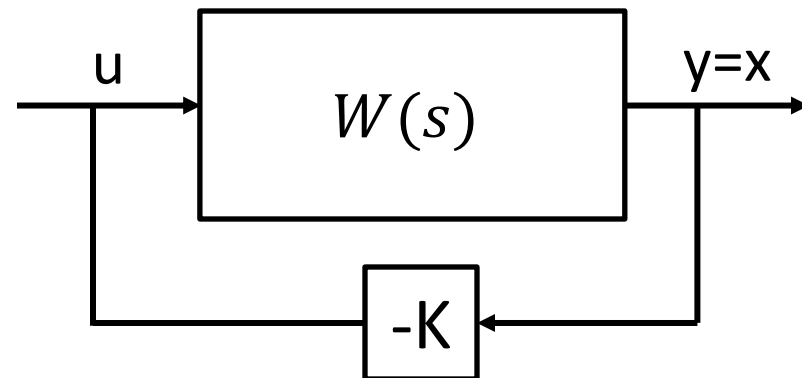
Example: state feedback

- A simple example of feedback control is as follows (**state feedback**)

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t), \quad \mathbf{x}(t_0) = \mathbf{x}_0$$

$$\mathbf{y} = \mathbf{x}(t)$$

$$\mathbf{u} = -\mathbf{K}\mathbf{x}$$



Example: state feedback

- Substituting the expression of $u(t)$:

$$\dot{\mathbf{x}} = (\mathbf{A} - \mathbf{BK})\mathbf{x}(t)$$

- With this choice, the original system is recast into an autonomous system with dynamical matrix $\mathbf{A} - \mathbf{BK}$
- The system will evolve with the modes associated to $\mathbf{A} - \mathbf{BK}$: if these can be chosen arbitrarily (i.e. the state is *measurable* and the system is *controllable*...), we are free to assign a desired dynamic behaviour to the system!

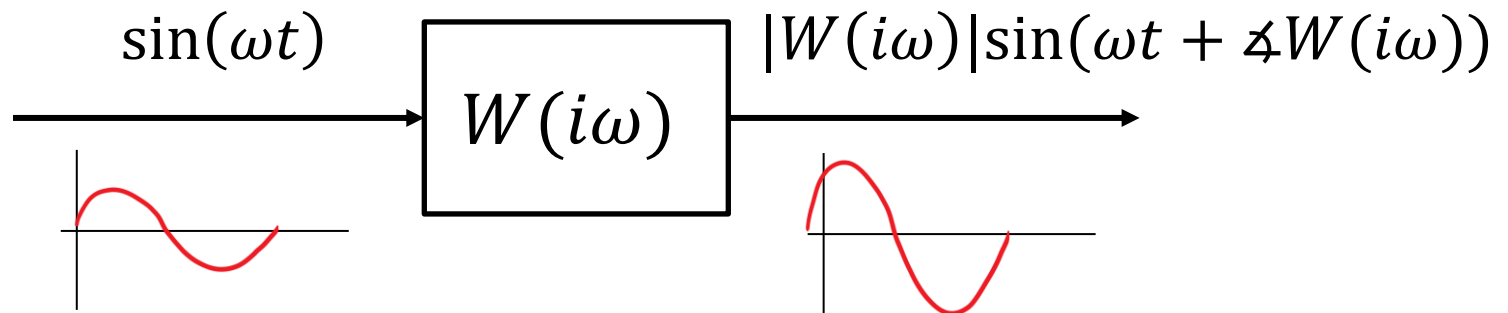
Frequency response

- **Frequency domain analysis** is a tool widely used in the analysis and control of dynamical systems
- The **harmonic response function** can be obtained by applying the **Fourier transform** to the system
- For stable* LTI systems this is equivalent to evaluate the tf along the imaginary axis $s = i\omega$

* Stable systems have convergence abscissa < 0

Frequency response

- A LTI system under a sinusoidal input will produce a **sinusoidal output**
- **Module and phase** of the output sinusoid are related to the **harmonic response function**



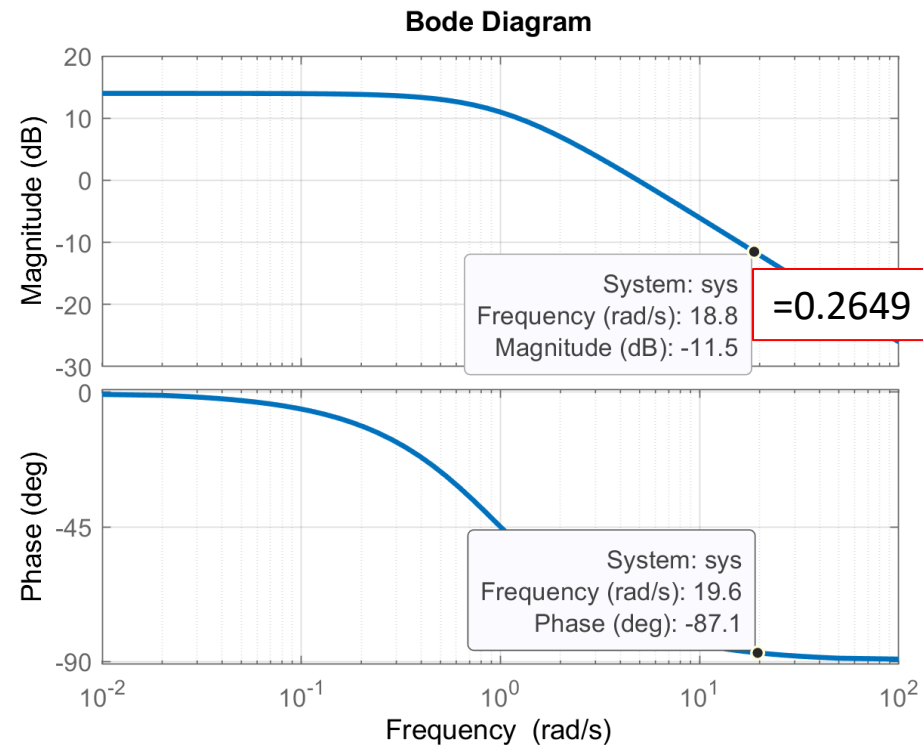
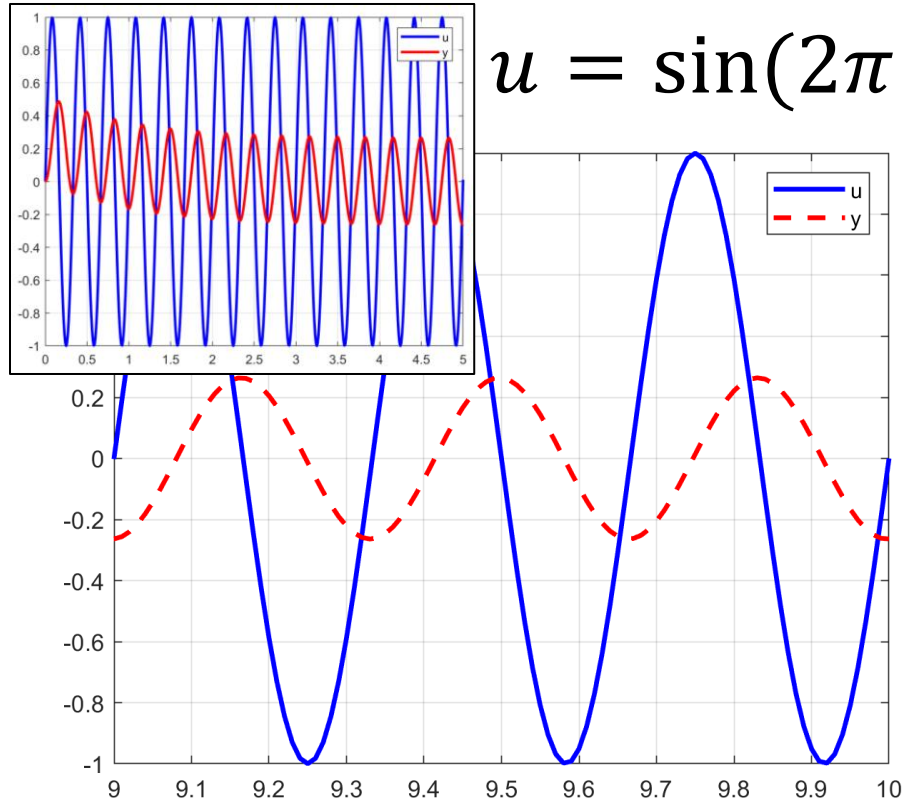
Frequency response

- It can be shown that feeding a sinusoid $u(t) = \sin(\omega_0 t)$ to a LTI system, it reaches **sinusoidal regime**, where:
 - the output is **shifted by $\angle P(\omega_0)$**
 - it is **scaled by $|P(\omega_0)|$**
- NOTE: $P(i\omega) = -P^*(i\omega) \rightarrow$ phase is odd, module is even
(...of course - can you see why?)

Frequency response

- example:

$$\dot{x} = -x + 5u, \quad y = x$$
$$u = \sin(2\pi \cdot 3t)$$

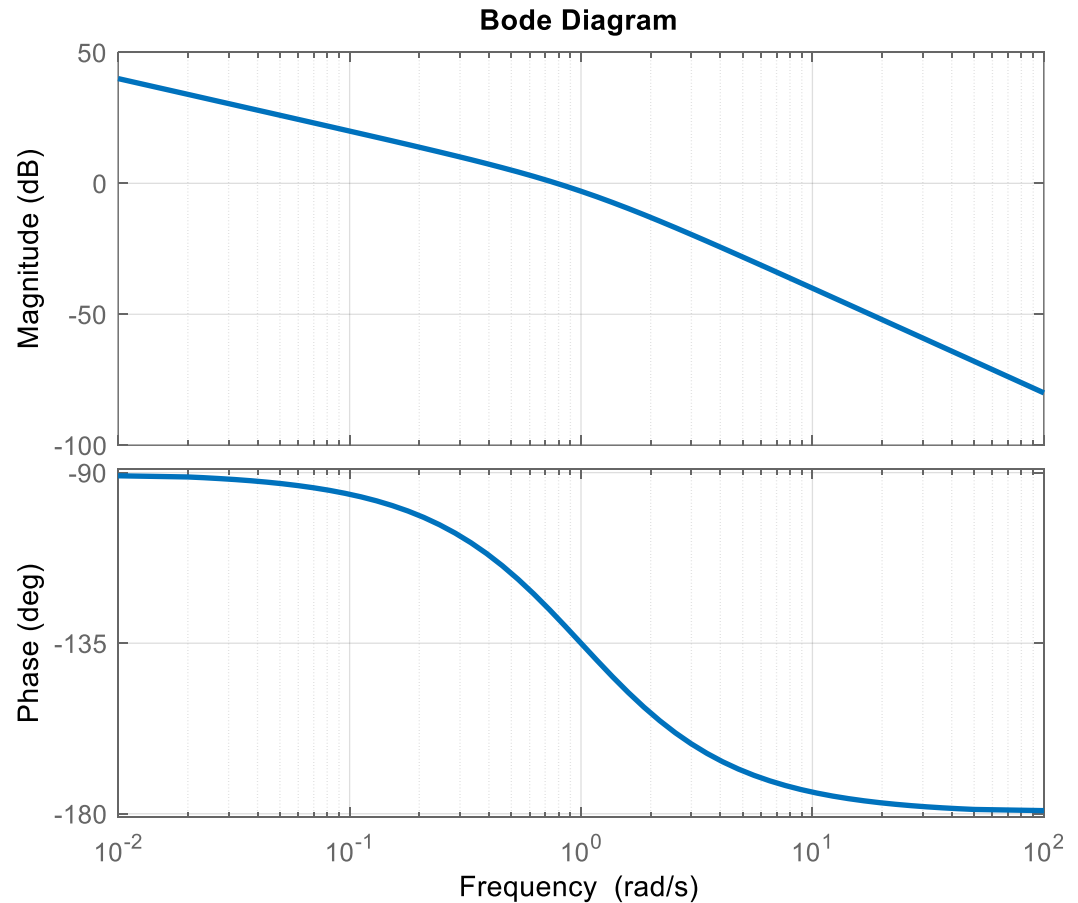


Graphical representation

- Some **graphical representations** are widely used in control engineering
- They focus on different aspects of the harmonic response

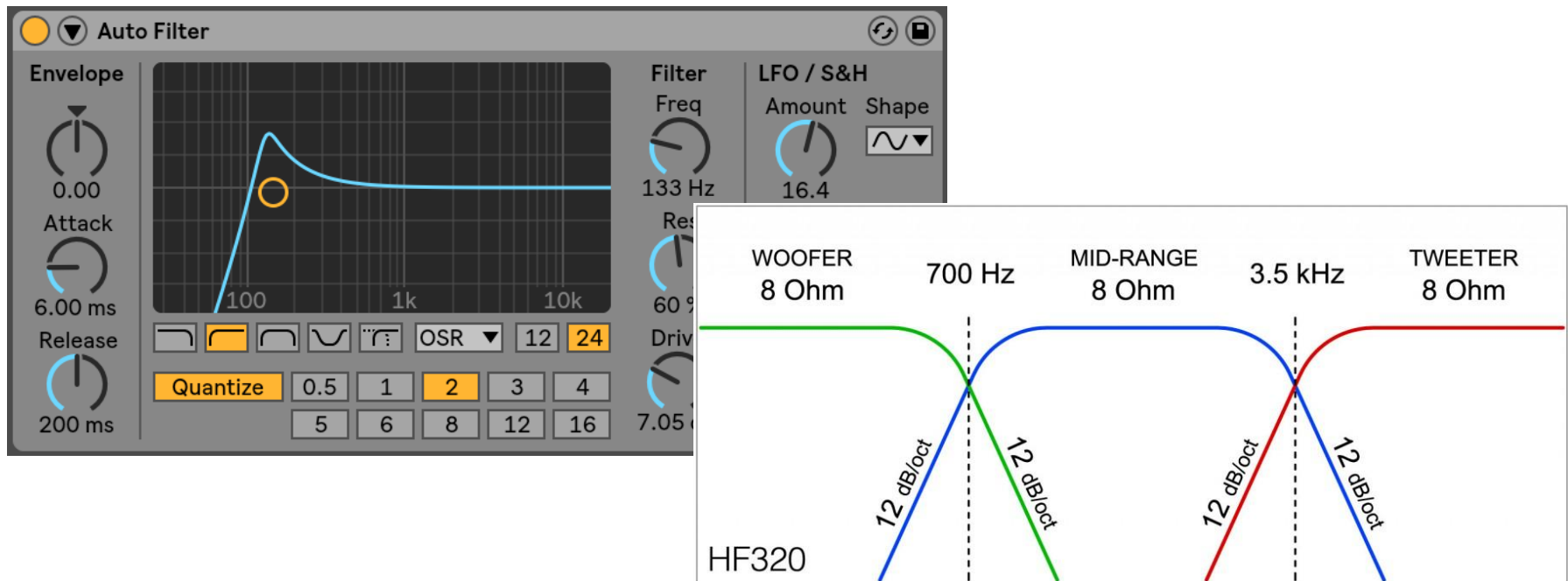
Bode diagram

- **Magnitude** and **phase** of $G(i\omega)$ separately
- wide frequency ranges
→ usually x axis in **logarithmic scale**
- Example:
$$P(i\omega) = \frac{1}{s(s+1)}$$



Bode diagram

- Bode diagrams (magnitude in particular) are quite common also in other fields



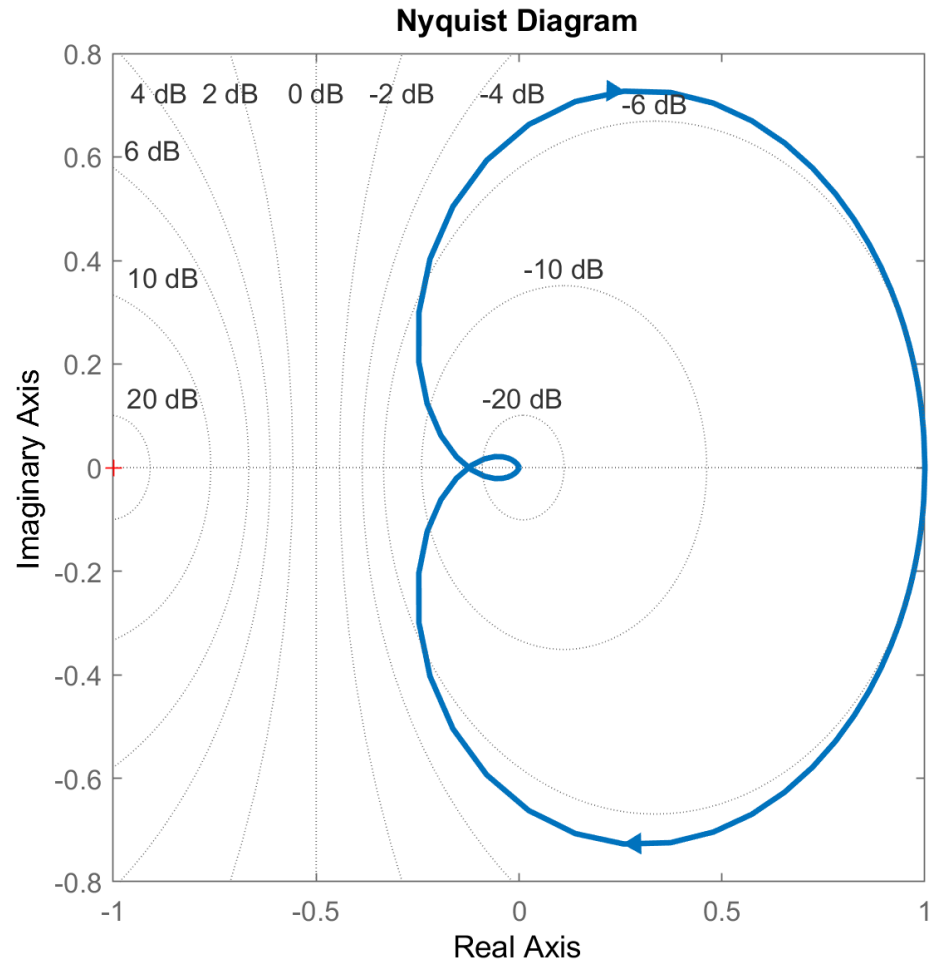
Nyquist diagram

- Real and imaginary parts of $G(i\omega)$ on the same graph

- Very useful to study stability

- Example:

$$G(i\omega) = \frac{1}{(s + 1)^3}$$



Discrete-time systems

- In many cases, it may be necessary to **discretize** the dynamics of the system
- Typical example: **digital control systems**

$$\dot{x} = Ax(t) + Bu(t) \rightarrow x(k+1) = \tilde{A}x(k) + \tilde{B}u(k)$$

Z-transform

- In this case the **Z-transform** can be used

$$F(s) = \int_0^{+\infty} e^{-st} f(t) dt$$

- represent sampled signal as

$$t = kT_s \Rightarrow f(kT_s) \approx \sum_0^{\infty} f(t) \delta(t - kT_s)$$

Z-transform

- apply Laplace transform

$$\begin{aligned} F(s) &= \int_0^{+\infty} e^{-st} \sum_0^{\infty} f(t) \delta(t - kT_s) dt \\ &= \sum_0^{\infty} f(kT_s) e^{-skT_s} \end{aligned}$$

- so it is natural to define

$$z = e^{sT_s} \Rightarrow F(z) = \sum_0^{\infty} f(kT_s) z^{-k}$$

Z-transform

The Z-transform inherits many properties

- Linearity

- Translation in time

$$Z[f(k - 1)] = F(z)z^{-1}$$

- sometimes written as

$$f(k - 1) = z^{-1}f(k)$$

- Final value

$$\lim_{t \rightarrow \infty} f(t) = \lim_{z \rightarrow 1} (z - 1)F(z)$$

Transfer function (discrete case)

- Similar to the Laplace transform

$$\begin{aligned} zX(z) - x_0 &= AX(z) + BU(z) \\ Y(z) &= CX(z) + DU(z) \end{aligned}$$



$$Y(z) = C(zI - A)^{-1}x_0 + \underbrace{(C(zI - A)^{-1}B + D)}_{\text{again a rational function}}U(z)$$

Hurwitz theorem (discrete case)

- For continuous systems

$$\dot{x} = \lambda x \rightarrow x(t) = e^{\lambda(t-t_0)} x_0$$

– stability $\Leftrightarrow \operatorname{Re}(\lambda) < 0$

- For discrete systems

$$x_{k+1} = \lambda x_k \rightarrow x_k = \lambda^k x_0$$

– stability $\Leftrightarrow |\lambda| < 1$

Continuous to discrete

- To approximate a continuous system with a discrete one, we could just apply the substitution

$$z = e^{sT_s} \Rightarrow s = \frac{1}{t} \ln z$$

in the Laplace transform

- Unfortunately, this is **not linear!**

Continuous to discrete

- Different approximations are possible

$$sX(s) \leftrightarrow ? X(z)$$

- Forward/Explicit Euler (FE)

$$sX(s) \rightarrow \frac{x(k+1) - x(k)}{T_s} \rightarrow \frac{z - 1}{T_s} X(z)$$

- Backward/implicit Euler (BE)

$$sX(s) \rightarrow \frac{x(k) - x(k-1)}{T_s} \rightarrow \frac{1 - z^{-1}}{T_s} X(z)$$

Continuous to discrete

- Trapezoids (or Crank-Nicholson, or Tustin)

$$y(t) = \int_0^{t_k} x(\tau) d\tau = y(k-1) + \int_{t_{k-1}}^{t_k} x(\tau) d\tau$$
$$\approx y(k-1) + \frac{x(k) + x(k-1)}{2} T_s$$

$$\rightarrow Y(z) = z^{-1}Y(z) + X(z)\left(1 + z^{-1}\right)\frac{T_s}{2}$$

$$\frac{X(s)}{s} \rightarrow \frac{1 - z^{-1}}{1 + z^{-1}} \frac{2}{T_s} X(z)$$