

# Exercise 1

## Discrete-time systems and Lyapunov Theory

Giancarlo Ferrari Trecate<sup>1</sup>

<sup>1</sup>Automatic Control Laboratory  
École Polytechnique Fédérale de Lausanne (EPFL), Switzerland  
[giancarlo.ferraritrecate@epfl.ch](mailto:giancarlo.ferraritrecate@epfl.ch)

## Outline

- Linear Time Invariant (LTI) system in Discrete Time (DT)
  - ▶ Equilibria
  - ▶ Stability: definitions and test through eigenvalues
  - ▶ Stability test through Lyapunov functions
- DT Linear Time Varying (LTV) systems
  - ▶ Definitions of stability
  - ▶ DT linear switched systems: stability test through Lyapunov functions

# Discrete-time (DT) linear systems

- $k \in \mathbb{N}$  : discrete time

LTV models:

$$x(k+1) = A(k)x(k) + B(k)u(k)$$

$$y(k) = C(k)x(k) + D(k)u(k)$$

LTI models if  $A, B, C$  and  $D$  do not depend on  $k$ .

► alternative notation:

- $x_{k+1} = x(k+1)$

- drop  $k$  and define  $x^+ = x_{k+1}$

$$x(k+1) = x(k) \circ \varphi$$

$$x^+ = Ax + Bu$$

$$x_{k_0} = x_0$$

$$y = Cx + Du$$

- Transition map  $x_k = \phi(k, k_0, x_0, u)$

- For LTV models, the initial time  $k_0$  of the experiment is important

- Superposition principle, Lagrange formula, free and forced states are given in the Appendix (very similar to the CT case)

# Stability of equilibria of LTI systems

$$x^+ = Ax + Bu$$

$$x(0) = x_0$$

- $(\bar{x}, \bar{u}) \in \mathbb{R}^n \times \mathbb{R}^m$  is an equilibrium if  $\bar{x} = A\bar{x} + B\bar{u}$   
 $(I - A)\bar{x} - B\bar{u} = 0$
- $(\bar{x}, \bar{u}) = (0, 0)$  is always an equilibrium.

Definitions  $\forall \varepsilon > 0, \exists \delta > 0 : \|x(0) - \bar{x}\| < \delta \Rightarrow \|x(k) - \bar{x}\| < \varepsilon \forall k \geq 0$

- Stability, AS, instability: same definitions in the CT case replacing  $t$  with  $k$
- $\bar{x}$  is (globally) exponentially stable (ES) if there are  $\alpha > 0, \rho \in [0, 1)$  such that

$$\|x(k) - \bar{x}\| \leq \alpha \rho^k \|x(0) - \bar{x}\|, \forall x(0) \in \mathbb{R}^n,$$

and the constant  $\beta$  such that  $\rho = e^\beta$  is the decay rate.

# Stability - relevant properties

$$x^+ = Ax + Bu$$

$$x(0) = x_0$$

For a linear systems, all equilibria have the same stability properties

- Focus on the stability of  $(\bar{x}, \bar{u}) = (0, 0)$
- The whole system can be termed stable/AS/unstable/ES

Theorem (stability and free states)

The above system is

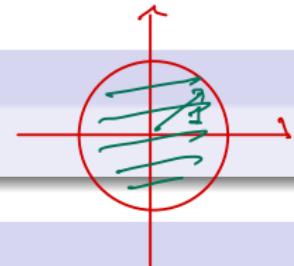
$$\begin{aligned} x(1) &= A\bar{x} & x(2) &= A^2\bar{x} \\ x(k+1) &= Ax(k) & & \\ x(0) &= \bar{x} & & \\ x(k) &= A^k\bar{x} & & \end{aligned}$$

- stable  $\Leftrightarrow$  free states  $x(k) = \phi(k, k_0, x_0, 0)$  are bounded  $\forall x_0 \in \mathbb{R}^n$
- AS  $\Leftrightarrow$  ES  $\Leftrightarrow$  all the free states converge to zero  $\forall x_0 \in \mathbb{R}^n$

# Stability test through the eigenvalues of A

## Definition

A is Schur if all eigenvalues  $\lambda \in \text{Spec}(A)$  verify  $|\lambda| < 1$



## Theorem (stability test)

An LTI system is

- AS  $\Leftrightarrow$  if A is Schur
- unstable if there is  $\lambda \in \text{Spec}(A)$  with  $|\lambda| > 1$
- stable if all  $\lambda \in \text{Spec}(A)$  verify  $|\lambda| \leq 1$  and those verifying  $|\lambda| = 1$  are simple.

## Remark

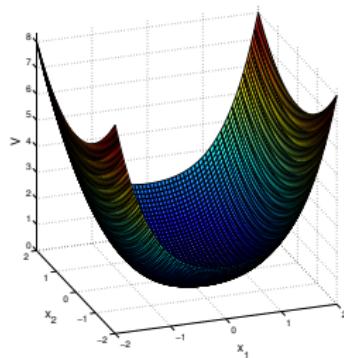
Similar to the continuous time case, multiple eigenvalues with  $|\lambda| = 1$  can lead either to stability or instability.

# Lyapunov stability theory

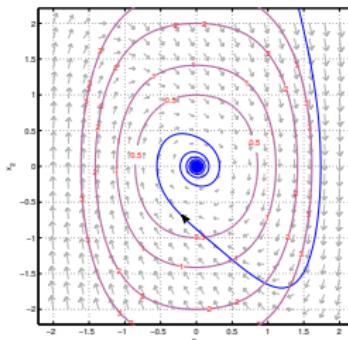
- We focus on **stability of the origin** for the LTI system  $x^+ = Ax$
- Idea: if an energy-like function of the state decreases to zero, the origin is stable.
  - ▶ what is an **energy function**?

# Lyapunov stability theory

Energy  $V(x)$



$(x_1, x_2)$ -plane



- $V(x)$  is a measure of the distance of  $x$  from the origin
  - ▶ If  $V(x)$  can only decrease over time, then  $\bar{x} = 0$  should be stable
- Next: make statements more rigorous!

# Review: positive-definite matrices and quadratic functions

## Definition

A symmetric matrix  $M \in \mathbb{R}^{n \times n}$  is

- (a) positive definite (pd) if  $x \neq 0 \Rightarrow x^T M x > 0$ . Notation:  $M > 0$
- (b) positive semidefinite (psd) if  $x^T M x \geq 0, \forall x \in \mathbb{R}^n$ . Notation:  $M \geq 0$
- (c) negative definite/semidefinite (nd/nsd) if  $-M$  is pd/psd. Notation:  $M < 0/M \leq 0$

## Properties of the quadratic function $x^T M x$

- A symmetric matrix  $M$  has real eigenvalues
- If  $M > 0$ , defining  $\lambda_{\min}(M)$  and  $\lambda_{\max}(M)$  as the minimum and maximum eigenvalue of  $M$ , respectively, one has

$$\lambda_{\min}(M) \|x\|^2 \leq x^T M x \leq \lambda_{\max}(M) \|x\|^2$$

## Energy forward difference

$$x^+ = Ax$$

Consider a quadratic energy-like function:  $V(x) = x^T Px$ , where  $P \in \mathbb{R}^{n \times n}$  is symmetric and positive definite

- Compute  $\Delta V(x) = V(x(k+1)) - V(x(k))$

$$\Delta V(x) = x^T A^T PAx - x^T Px = x^T (A^T PA - P)x$$

- We are sure that  $\Delta V(x) \leq 0$  if

$$A^T PA - P \leq 0$$

# Lyapunov theorems

## Theorem 1: stability

The LTI system  $x^+ = Ax$  is stable, if and only if there is  $P > 0$  such that  $A^T PA - P \leq 0$

## Theorem 2 (AS/ES)

For the LTI system  $x^+ = Ax$ , the following statements are equivalent

- (a) the system is ES
- (b) for an arbitrary symmetric matrix  $Q > 0$ , there is a matrix  $P^T = P > 0$  solving the Lyapunov equation

$$A^T PA - P = -Q$$

- (c) there is  $P = P^T > 0$  verifying  $A^T PA - P < 0$ .

# Lyapunov theorems

## Terminology

- $V(x) = x^T Px$  is a candidate Lyapunov function
- If  $V(x)$  verifies one of the two theorems, it is a Lyapunov function

## Remark

- $A^T PA - P = -Q$  is a system of linear equations in the elements of  $P$ , for a given  $Q$
- $A^T PA - P \leq 0$  is a Linear Matrix inequality (LMI) in the elements of  $P$  - see next lecture!

Proof that (b)  $\Rightarrow$  (a)

$$(b) \quad A^T P A - P = -Q, \quad \lambda_{\min}(Q) \leq x^T Q x$$

The positive definiteness of  $Q$  implies that  $\exists \gamma > 0$  verifying  $-x^T Q x \leq -\gamma \|x\|^2$ . For instance, one can choose  $\gamma \in (0, \lambda_{\min}(Q)]$ . Similarly,  $P > 0$  implies that

$$\lambda_{\min}(P) \|x\|^2 \leq x^T P x \leq \lambda_{\max}(P) \|x\|^2 \quad \hookrightarrow \|x\|^2 \geq \frac{V(x)}{\lambda_{\max}(P)}$$

Step 1: using the forward difference, deduce how much  $V$  decreases.

From  $\Delta V(x) = -x^T Q x$

$$\Delta V(x) \leq -\gamma \|x\|^2 \leq \frac{-\gamma}{\lambda_{\max}(P)} x^T P x \leq \frac{-\gamma}{\lambda_{\max}(P)} V(x) \quad (2)$$

which implies

$$V(x(k+1)) \leq \left(1 - \frac{\gamma}{\lambda_{\max}(P)}\right) V(x(k)) \quad (3)$$

Since  $\gamma$  can be chosen arbitrarily small, select it such that

$$\rho^2 = 1 - \frac{\gamma}{\lambda_{\max}(P)} \text{ verifies } \rho \in [0, 1).$$

## Proof that (b) $\Rightarrow$ (a) (ctd.)

Step 2: iterate backwards to relate  $V(x(k))$  to  $V(x(0))$ .

From

$$V(x(k+1)) \leq \rho^2 V(x(k)) \quad (4)$$

one has

$$V(x(k)) \leq \rho^{2k} V(x(0))$$

Step 3: use bounds on  $V$  to make states appear.

Using (1) and defining  $m^2 = \frac{\lambda_{\max}(P)}{\lambda_{\min}(P)}$ , one obtains

$$\|x(k)\| \leq m\rho^k \|x(0)\|$$

## Proof that (a) $\Rightarrow$ (b) $\ominus$ Home

$\Rightarrow$  For a given  $Q > 0$ , if  $A$  is Schur (which is guaranteed by ES), it can be shown that the Lyapunov equation has a solution  $P = P^T$  given by

$$P = \sum_{k=0}^{\infty} (A^T)^k Q A^k = Q + A^T Q A + \dots$$

Show at home that this  $P$  fulfills the Lyapunov equation !

Since  $Q > 0$  and  $(A^T)^k Q A^k \geq 0$ ,  $k \geq 1$ , one has  $P > 0$ .

1h 5x1  $\downarrow$

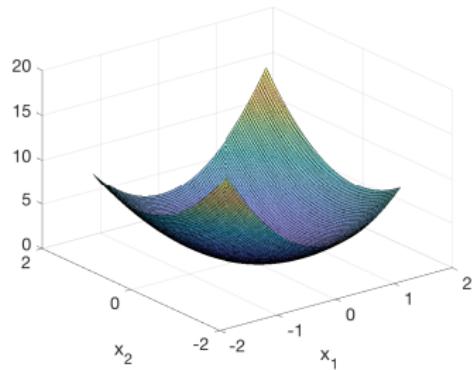
## Example

$$x^+ = \begin{bmatrix} -0.81 & -0.09 \\ -0.45 & 0.63 \end{bmatrix} x \quad \text{Spec}(A) = \{-0.8376, 0.6576\}$$

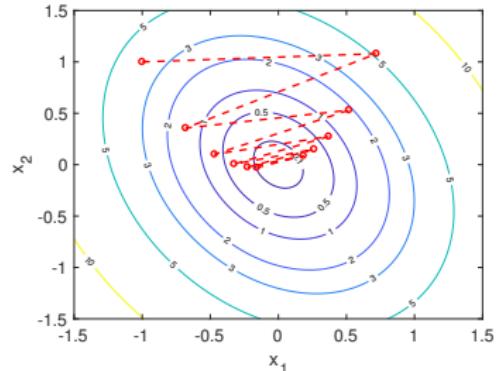
Set  $Q = I$  and solve  $A^T P A - P = -Q$  (`P=dlyap(A, Q)`)

$$P = \begin{bmatrix} 3.2661 & 0.7302 \\ 0.7302 & 2.0683 \end{bmatrix} \quad \text{Spec}(P) = \{1.7728, 3.6116\}$$

Energy  $V(x)$



Level sets



## Why Lyapunov theory?

Much more flexible then the analysis of  $\text{Spec}(A)$ . Generalizes to

- nonlinear systems
- LTV systems - see next!

Moreover, Lyapunov theory allows to cast stability tests into optimization problems (see next lectures on LMIs)

# Stability concepts for LTV systems

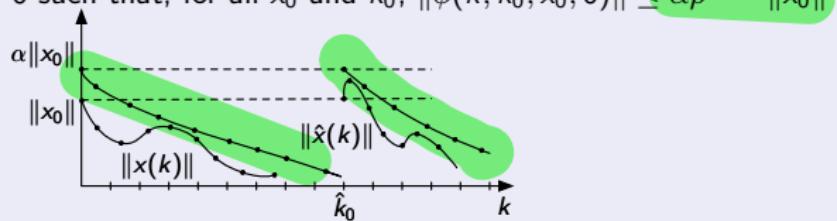
$$x(k+1) = A(k)x(k) + B(k)u(k) \quad x(k_0) = x_0$$

How to define stability? Focus on  $(\bar{x}, \bar{u}) = (0, 0)$

Definition:

The equilibrium  $(\bar{x}, \bar{u}) = (0, 0)$  is

- (1) stable if for all  $x_0$  and  $k_0$ ,  $x(k) = \phi(k, k_0, x_0, 0)$  is bounded for  $k \geq k_0$
- (2) AS if  $\forall x_0$  and  $k_0$ ,  $x(k) \rightarrow 0$  as  $k \rightarrow +\infty$
- (3) ES if  $\exists \rho \in [0, 1)$  and  $\alpha > 0$  such that, for all  $x_0$  and  $k_0$ ,  $\|\phi(k, k_0, x_0, 0)\| \leq \alpha \rho^{k-k_0} \|x_0\|$



Abuse of language: “ $x(k+1) = A(k)x(k)$  is AS”, “ $A(k)$  is AS”, etc..

Remarks

- $\alpha, \rho$  in (3) do not depend on  $k_0$
- In (3), the constant  $\beta \geq 0$  such that  $\rho = e^{-\beta}$  is the decay rate
- AS  $\not\Rightarrow$  ES (different from LTI system)

## Example: for LTV systems AS $\not\Rightarrow$ ES

$$x(k+1) = A(k)x(k) \quad A(k) = \left( \frac{k+1}{k+2} \right)^2$$

$$x(k_0) = x_0$$

**Remark:**  $A(k) \rightarrow 1$  as  $k \rightarrow +\infty$ , implying slower and slower convergence rate

- Computations:

$$x(2) = \left( \frac{2+1}{2+2} \right)^2 x(1) = \frac{(2+1)^2}{(2+2)^2} x(1) = \frac{x_0}{4} \cdot \frac{(3+1)^2}{(4+2)^2} x(2) = \frac{x_0}{4} \cdot \frac{(4+1)^2}{(5+2)^2} x(3) = \dots$$
$$x(k+1) = \left( \frac{k_0+1}{k+2} \right)^2 x_0 \Rightarrow \text{AS since } x(k) \rightarrow 0, \forall x_0 = \frac{(k+1)^2}{(k+2)^2} \frac{(0+1)^2}{(0+2)^2} x(0)$$

- For studying ES, fix  $k_0 = 0$ ,  $x_0 = 1$ . Assume that  $\exists \alpha > 0, \rho \in [0, 1)$  such that

$$\left( \frac{k_0+1}{k+2} \right)^2 x_0 = \left( \frac{1}{k+2} \right)^2 \leq \alpha \rho^k, \forall k \geq 0$$

- This implies

$$\frac{1}{\alpha} \leq (k+2)^2 \rho^k$$

which is a contradiction because  $(k+2)^2 \rho^k \rightarrow 0$  as  $k \rightarrow +\infty$

# Discrete-time Linear Switched system

System with a finite set  $\mathcal{I} = \{1, \dots, M\}$  of modes of operation and a switching signal indicating the active mode at each time instant

$$x_{k+1} = A_{\sigma(k)}x_k \quad x_k \in \mathbb{R}^n \quad \sigma(k) \in \mathcal{I} \quad \begin{matrix} \mathcal{I} = \{1, 2\} \\ A_1 = 0.5 \\ A_2 = 2 \end{matrix} \quad (5)$$

$\sigma(\cdot)$  is an exogenous input

- For any fixed sequence  $\sigma(0), \sigma(1), \dots$ , system (5) is LTV: stability = stability of the zero solution.

$$\begin{matrix} k_0 = 0 & \sigma(0) = 1 & x(1) = A_1 x_0 \\ x_0 = 1 & \sigma(1) = 2 & x(2) = A_2 x_1 \\ & \sigma(2) = 2 & x(3) = A_2 x_2 \end{matrix}$$

## Definition

The switched system (5) is exponentially stable if for any sequence  $\sigma(k)$  the resulting LTV system is ES. Equivalently, for all  $x_0, k_0$  and  $\{\sigma(k)\}_{k=k_0}^{+\infty}$

$$\exists \rho \in [0, 1) \text{ and } \alpha > 0 \text{ such that } \|\phi(k, k_0, x_0, 0)\| \leq \alpha \rho^{k-k_0} \|x_0\|$$

## Remark

- For stability, it is not sufficient that all matrices  $A_i, i \in \mathcal{I}$  are Schur (examples in the exercise sessions!)

# Discrete-time Linear Switched system

System with a finite set  $\mathcal{I} = \{1, \dots, M\}$  of modes of operation and a switching signal indicating the active mode at each time instant

$$x_{k+1} = A_{\sigma(k)} x_k \quad x_k \in \mathbb{R}^n \quad \sigma(k) \in \mathcal{I} \quad (5)$$

## Theorem

If there is  $P \in \mathbb{R}^{n \times n}$ ,  $P = P^T > 0$  such that

$$A_i^T P A_i - P < 0, \quad \forall i \in \mathcal{I},$$

$$\mathcal{I} = \{1, 2\}$$

$$A_1^T P A_1 - P < 0 \quad \text{And}$$

$$A_2^T P A_2 - P < 0$$

then (5) is exponentially stable

- $V(x) = x^T P x$  is a *common* Lyapunov function for all the modes
- The condition is *only sufficient* and implies all modes of operation are exponentially stable
- How to find  $P$ ? By solving a Linear Matrix Inequality (LMI) optimization problem (see next lecture)

# Appendix

# Superposition principle (LTV system)

- The *same* as for CT linear systems
- For  $\alpha, \beta \in \mathbb{R}$ , let
  - ▶  $x_a(k) = \phi(k, k_0, x_{0,a}, u_a)$  and  $y_a(k)$  the corresponding output
  - ▶  $x_b(k) = \phi(k, k_0, x_{0,b}, u_b)$  and  $y_b(k)$  the corresponding output
  - ▶  $x(k) = \phi(k, k_0, \alpha x_{0,a} + \beta x_{0,b}, \alpha u_0 + \beta u_0)$  and  $y(k)$  the corresponding output
- Then,  $\forall k \geq k_0$ 
  - ▶  $x(k) = \alpha x_a(k) + \beta x_b(k)$
  - ▶  $y(k) = \alpha y_a(k) + \beta y_b(k)$

# LTI systems: Lagrange formula

How the transition map looks like for an LTI system?

$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) & x(0) &= x_0 \\y(k) &= Cx(k) + Du(k)\end{aligned}$$

We assume, for simplicity, the experiment starts at time  $k_0 = 0$ . One has

$$x(1) = Ax_0 + Bu_0$$

$$x(2) = Ax(1) + Bu(1) = A^2x(0) + ABu(0) + Bu(1)$$

$$x(3) = Ax(2) + Bu(2) = \dots = A^3x(0) + A^2Bu(0) + ABu(1) + Bu(2)$$

$$x(k) = \phi(k, 0, x_0, u) = \underbrace{A^{(k-k_0)}x_0}_{\phi(k, 0, x_0, \textcolor{red}{0}) = \text{free state}} + \underbrace{\sum_{i=0}^{k-1} A^{(k-i-1)}Bu(i)}_{\phi(k, 0, \textcolor{red}{0}, u) = \text{forced response}}$$

$$y(k) = \phi(k, 0, x_0, u) = \underbrace{CA^kx_0}_{\text{free output}} + C \underbrace{\sum_{i=0}^{k-1} A^{(k-i-1)}Bu(i)}_{\text{forced output}} + Du(k)$$

- Easy to generalize for  $k_0 \neq 0$  and for LTV systems - just more complex