

SCE 594: Special Topics in Intelligent Automation & Robotics

Lecture 19: Lyapunov's direct method II



Outline

- Recap last lectures
- More on Positive Definiteness
- Geometric interpretation of $\dot{V}(x)$
- Application of Lyapunov's direct method



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Recap: State Space Model

- A nonlinear dynamic system can be represented by a set of nonlinear differential equations in the form

$$\begin{aligned}\dot{x} &= f(x) + g(x) u \\ y &= h(x)\end{aligned}$$

which is called the **state space model** of the dynamic system.

- We are focusing on analyzing the stability of the **equilibrium points** x_* systems of the form

$$\dot{x} = f(x)$$

Special case: Linear
time-invariant systems

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx\end{aligned}$$



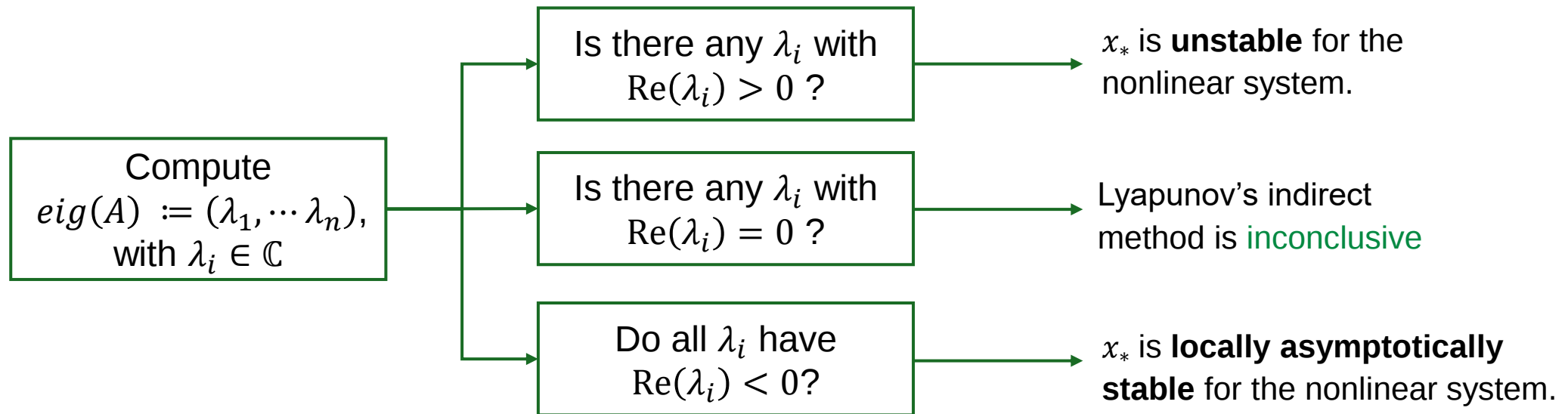
Recap: Lyapunov's indirect method

- The linearization of $\dot{x} = f(x)$ around the equilibrium point x_* is given by:

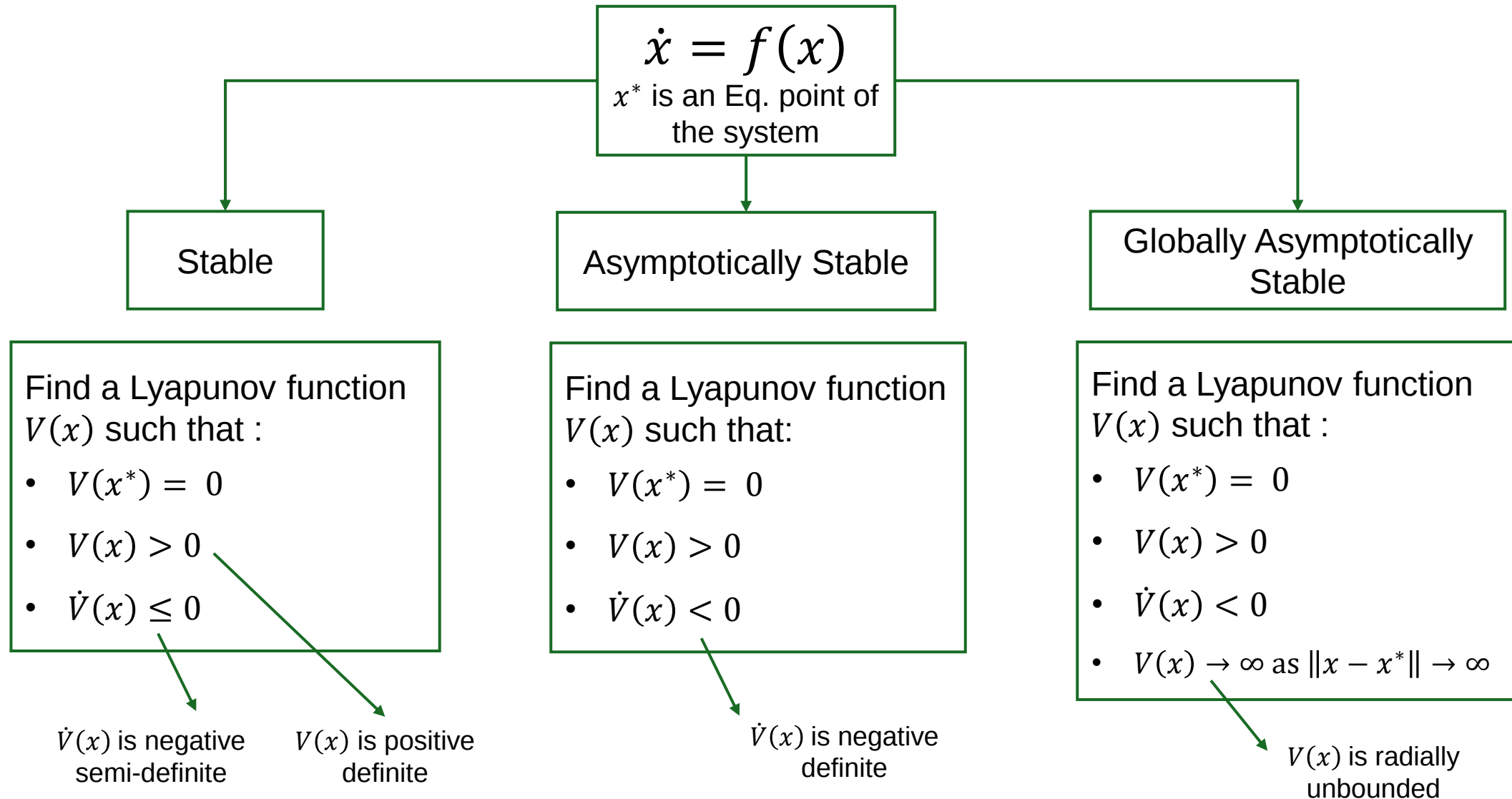
$$\dot{z} = A z$$

where $z := x - x_* \in \mathbb{R}^n$ and $A := J_f(x_*)$ is the Jacobian of $f(x)$ evaluated at the equilibrium points.

- Stability Conditions:**



Recap: Lyapunov's Direct Method



Recap: Pendulum Case study

- State space model:

- $\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} x_2 \\ -c_2 x_2 - c_1 \sin x_1 \end{pmatrix}, \quad c_1, c_2 > 0$

Equilibrium Points:

$$x_{*,1} := (0,0), \quad x_{*,2} := (\pi, 0)$$



Recap: Pendulum Case study

- State space model:

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- Lyapunov's indirect method:

- $A_1 := J_f(x_{*,1}) = \begin{pmatrix} 0 & 1 \\ -c_1 & -c_2 \end{pmatrix}$

For A_1 , $\text{Re}(\lambda_i) < 0, \forall c_1, c_2 > 0$

$\therefore x_{*,1} := (0,0)$ is locally asymptotically stable.

- $A_2 := J_f(x_{*,2}) = \begin{pmatrix} 0 & 1 \\ c_1 & -c_2 \end{pmatrix}$

For A_2 , $\text{Re}(\lambda_2) > 0, \forall c_1, c_2 > 0$

$\therefore x_{*,2} := (\pi, 0)$ is unstable.

Equilibrium Points:

$$x_{*,1} := (0,0), \quad x_{*,2} := (\pi, 0)$$



Recap: Pendulum Case study

- State space model:

- $\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} x_2 & \\ -c_2 x_2 & -c_1 \sin x_1 \end{pmatrix}, \quad c_1, c_2 > 0$

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$\therefore x_{*,2} := (\pi, 0)$ is unstable.

- Lyapunov's direct method:

- $V(x) = \frac{1}{2}x_2^2 + c_1(1 - \cos x_1)$

$$V(x_{*,1}) = 0, \quad V(x) > 0 \quad \forall x \in \mathcal{X} / \{x_{*,1}\}$$

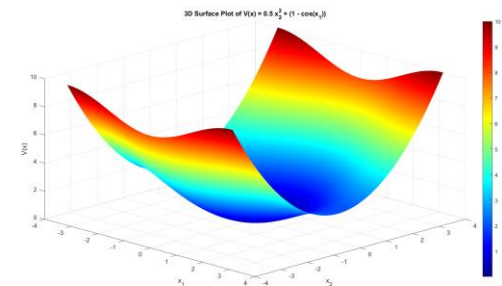
- $\dot{V}(x) = -c_2 x_2^2 \leq 0$

$\dot{V}(x)$ is negative semi-definite

$\therefore x_{*,1} := (0,0)$ is stable.

Equilibrium Points:

$$x_{*,1} := (0,0), \quad x_{*,2} := (\pi, 0)$$



Recap: Satellite Case study

- State space model:

- $\dot{\omega} = -J^{-1}(\omega \wedge J\omega)$

- $\begin{pmatrix} \dot{\omega}_1 \\ \dot{\omega}_2 \\ \dot{\omega}_3 \end{pmatrix} = \begin{pmatrix} c_1 \omega_2 \omega_3 \\ c_2 \omega_3 \omega_1 \\ c_3 \omega_1 \omega_2 \end{pmatrix}, \quad c_1, c_3 > 0, \text{ and } c_2 < 0$

- **Equilibrium Points:**

- $\omega_{*,a} = (0,0,0)$

- $\omega_{*,b} = (\Omega, 0, 0)$

- $\omega_{*,c} = (0, \Omega, 0)$

- $\omega_{*,d} = (0, 0, \Omega)$



Recap: Satellite Case study

- State space model:

- $\dot{\omega} = -J^{-1}(\omega \wedge J\omega)$

- $\begin{pmatrix} \dot{\omega}_1 \\ \dot{\omega}_2 \\ \dot{\omega}_3 \end{pmatrix} = \begin{pmatrix} c_1 \omega_2 \omega_3 \\ c_2 \omega_3 \omega_1 \\ c_3 \omega_1 \omega_2 \end{pmatrix}, \quad c_1, c_3 > 0, \text{ and } c_2 < 0$

- Equilibrium Points:

- $\omega_{*,a} = (0,0,0)$
- $\omega_{*,b} = (\Omega, 0, 0)$
- $\omega_{*,c} = (0, \Omega, 0)$
- $\omega_{*,d} = (0, 0, \Omega)$

- Lyapunov's indirect method:

$$A_a = J_f(\omega_{*,a}) = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$A_c = J_f(\omega_{*,c}) = \begin{pmatrix} 0 & 0 & c_1 \Omega \\ 0 & 0 & 0 \\ c_3 \Omega & 0 & 0 \end{pmatrix}$$

$$A_b = J_f(\omega_{*,b}) = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & c_2 \Omega \\ 0 & c_3 \Omega & 0 \end{pmatrix}$$

$$\begin{aligned} \lambda_1 &= 0 \\ \lambda_2 &= \Omega \sqrt{c_1 c_3} > 0 \\ \lambda_3 &= -\Omega \sqrt{c_1 c_3} < 0 \end{aligned}$$

$$A_d = J_f(\omega_{*,d}) = \begin{pmatrix} 0 & c_1 \Omega & 0 \\ c_2 \Omega & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$\therefore \omega_{*,b} = (\Omega, 0, 0)$ is unstable.



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- **More on Positive Definiteness**
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Positive definite functions

- A function $\psi: \mathcal{X} \rightarrow \mathbb{R}$ is **locally positive definite** about $x_* \in \mathcal{X}$ if:
 - $\psi(x_*) = 0$
 - There exists a neighborhood $\mathcal{U} \subset \mathcal{X}$ that includes x_* (i.e., $x_* \in \mathcal{U}$) such that $\psi(x) > 0 \forall x \in \mathcal{U} \setminus \{x_*\}$.
- $\psi: \mathcal{X} \rightarrow \mathbb{R}$ is locally positive **semi-definite** if $\psi(x) \geq 0 \forall x \in \mathcal{U} \setminus \{x_*\}$.
- $\psi: \mathcal{X} \rightarrow \mathbb{R}$ is **globally** positive definite if $\psi(x) > 0 \forall x \in \mathcal{X} \setminus \{x_*\}$.
- $\psi: \mathcal{X} \rightarrow \mathbb{R}$ is locally **negative** (semi-)definite if $-\psi(x)$ is locally positive (semi-)definite.



Positive definite functions

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 - $\psi(x_*) = 0$
 - There exists a neighborhood $\mathcal{U} \subset \mathcal{X}$ that includes x_* (i.e., $x_* \in \mathcal{U}$) such that $\psi(x) > 0 \forall x \in \mathcal{U} \setminus \{x_*\}$.
- In other words, x_* is a **strict local minimum** of $\psi(x)$, and the function increases in every direction away from x_* within $\mathcal{U}$.
- Recall the classic result of calculus:
 - If ψ is differentiable, and x_* is a local minimum, then the gradient must vanish there i.e., $J_\psi(x_*) = 0$.
- We call points $x_* \in \mathcal{X}$ a **critical zero** for the smooth function $\psi: \mathcal{X} \rightarrow \mathbb{R}$ if $\psi(x_*) = 0$ and $J_\psi(x_*) = 0$.



Positive Definite Matrices

- A real symmetric matrix $A \in \mathbb{R}^{n \times n}$ is called a **positive definite matrix** if we have that

$$x^T A x > 0, \quad \forall x \in \mathbb{R}^n \setminus \{0\}.$$

- $A \in \mathbb{R}^{n \times n}$ is called a positive **semi-definite** matrix if $x^T A x \geq 0$.
- $A \in \mathbb{R}^{n \times n}$ is called a **negative** definite matrix if $x^T A x < 0$.
- $A \in \mathbb{R}^{n \times n}$ is called a negative **semi-definite** matrix if $x^T A x \leq 0$.
- Key property:
 - $A \succ 0$ is positive definite if and only if all its **eigenvalues** are positive.
 - $A \succcurlyeq 0$ is positive semi-definite if and only if all its **eigenvalues** are non-negative.
 - $A \prec 0$ is negative definite if and only if all its **eigenvalues** are negative.
 - $A \preccurlyeq 0$ is negative definite if and only if all its **eigenvalues** are non-positive.



Using Taylor Expansion for Positive Definiteness

- Suppose you have a smooth scalar function $V: \mathbb{R}^n \rightarrow \mathbb{R}$, and you want to check whether it's positive definite around $x_* \in \mathbb{R}^n$.
- You can expand $V(x)$ as a Taylor series of order 2:

$$V(x) = V(x_*) + J_V(x_*) (x - x_*) + \frac{1}{2} (x - x_*)^\top H_V(x_*) (x - x_*) + \dots$$

where $H_V(x_*) \in \mathbb{R}^{n \times n}$ is called the **Hessian** matrix with the entry of the i th row and the j th column is $(H_V)_{ij} := \frac{\partial^2 V}{\partial x_i \partial x_j} : \mathbb{R}^n \rightarrow \mathbb{R}$.



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- However, since x_* is a **critical zero** of V , the function is locally approximated by

$$V(x) \approx \frac{1}{2} (x - x_*)^\top H_V(x_*) (x - x_*)$$



Using Taylor Expansion for Positive Definiteness

$$V(x) \approx \frac{1}{2} (x - x_*)^\top H_V(x_*) (x - x_*)$$

- Therefore, we have that $V(x)$ is a locally positive definite function if and only if the Hessian $H_V(x_*)$ is a positive definite matrix, which can be assessed from its eigenvalues.
- This result is a basic result from what is known as **Morse theory**.



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