



ELEC 441: Control Systems

Lecture 9: Lyapunov Theorem

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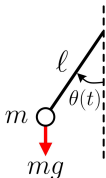
Topics	CT	DT
Modeling	✓	✓
Stability	→ ● ←	→ ● ←
Controllability/Observability		
Realization		
State Feedback/Observers		
LQR/Kalman Filter		

Review and Examples

- **Eigenvalue criteria** for internal stability:

- ▶ **CT system:** asymptotically stable $\iff \text{Re}\{\lambda_i\} < 0, \forall i$
- ▶ **DT system:** asymptotically stable $\iff |\lambda_i| < 1, \forall i$

Example: Pendulum



$$\begin{bmatrix} \dot{\theta}(t) \\ \ddot{\theta}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{g}{\ell} & 0 \end{bmatrix} \begin{bmatrix} \theta(t) \\ \dot{\theta}(t) \end{bmatrix}$$

$$\text{eig}(A) = \pm j\sqrt{\frac{g}{\ell}} \text{ (Marginally Stable)}$$

Example: Inverted Pendulum



$$\begin{bmatrix} \dot{\theta}(t) \\ \ddot{\theta}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{g}{\ell} & 0 \end{bmatrix} \begin{bmatrix} \theta(t) \\ \dot{\theta}(t) \end{bmatrix}$$

$$\text{eig}(A) = \pm\sqrt{\frac{g}{\ell}} \text{ (Unstable)}$$

- Lyapunov theorem is another method for assessing the **internal** stability of state-space models (**equivalent to Eigenvalue criterion**)
- Lyapunov theorem topic outline:
 - ▶ Positive definiteness concept
 - ▶ Lyapunov theorem
 - ▶ Examples
 - ▶ Idea behind Lyapunov theorem

Positive Definiteness

- A square and symmetric matrix P is **positive definite** if

$$x^T P x > 0, \forall x \in \mathbb{R}^n, x \neq 0$$

- Notation: $P > 0$ means P is **positive definite**
- Note that $x^T P x$ yields a **scalar**. Hence, three possibilities:
 - ▶ $x^T P x > 0 \rightarrow P$ is **Positive Definite**
 - ▶ $x^T P x < 0 \rightarrow P$ is **Negative Definite**
 - ▶ $x^T P x > 0$ and $x^T P x < 0$ depending on $x \rightarrow P$ is **Indefinite**

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- Example: $P = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$

$$\implies x^T P x = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 2x_1^2 + x_2^2 > 0, \forall x \neq 0$$

Positive Definite Matrix Properties

- ① **Property 1:** positive definite matrices have **real** & **positive** Eigenvalues

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- ② **Property 2:** Sylvester's criterion (positive leading principal minor)

$$P > 0 \iff \det(P[1:i, 1:i]) > 0, \forall i$$

- Example: $P = \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$

$$\implies \det(P[1, 1]) = 2 > 0$$

$$\implies \det(P[1:2, 1:2]) = \det(P) = 1 > 0$$

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- **Note:** positive entries do NOT mean positive definite

- ③ **Property 3:** positive definite matrices have **positive** diagonal entries

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- Note:** always check diagonal elements first
 - ▶ If there are **negative** diagonal entries, then P is NOT positive definite
 - ▶ If all diagonal entries are **positive**, then P may or may not be positive definite

- All the Eigenvalues of a matrix A lie in the open left half plane (i.e. $\text{Re}\{\lambda_i\} < 0, \forall i$) if and only if the solution P to the following Lyapunov equation

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

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- **Note:** for LTI state-space models, Lyapunov's theorem has no advantage over Eigenvalue criteria

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- We can choose any positive definite matrix Q , usually we choose $Q = I$ (i.e. identity matrix) which is positive definite
- We can use `dlyap.m` in MATLAB to solve the discrete Lyapunov equation
- We study the idea behind Lyapunov's theorem, which is useful for advanced control (nonlinear, time-varying, and robust control)

Examples $A = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix}$

- Using the Eigenvalue criteria, $\lambda_1 = -1$ and $\lambda_2 = -2$. Hence, this would be **asymptotically stable for CT** and **unstable for DT** systems

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$$\implies P = \frac{1}{4} \begin{bmatrix} 5 & 1 \\ 1 & 1 \end{bmatrix} > 0 \implies \text{Asymptotically stable!}$$

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$$\implies P = \begin{bmatrix} 4p_3 + 1 & 2p_3 \\ 2p_3 & p_3 \end{bmatrix} \implies \text{Not unique!}$$

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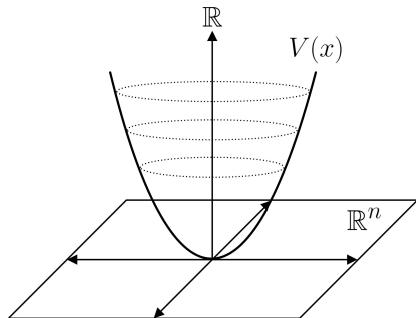
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$$\implies P = \begin{bmatrix} 4p_3 + 1 & 2p_3 \\ 2p_3 & p_3 \end{bmatrix} \implies \text{Not asymptotically stable!}$$

- 1 For a fixed $P > 0$, define a
Lyapunov function

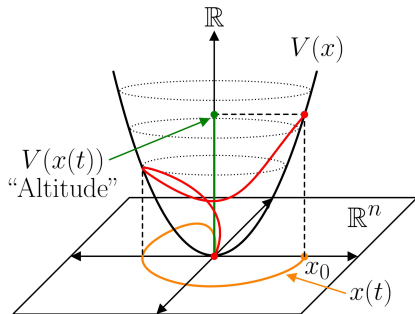
$$V(x) := x^T P x, \quad x \in \mathbb{R}^n$$



- ② Consider the trajectory $V(x(t))$, where the behaviour of $x(t)$ is subject to

$$\dot{x}(t) = Ax(t)$$

We want to look at the **altitude** as $x(t)$ varies over time



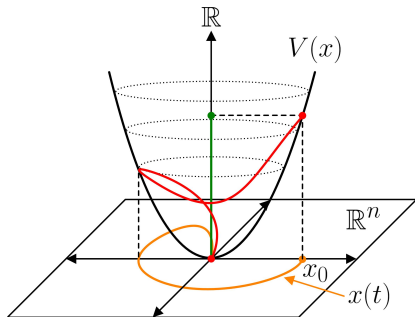
Idea Behind Lyapunov's Theorem

- Take the derivative of $V(x(t))$ w.r.t. t , to get

$$\begin{aligned}\dot{V}(x(t)) &= \frac{d}{dt} (x(t)^T P x(t)) \\ &= \dot{x}(t)^T P x(t) \\ &\quad + x(t)^T P \dot{x}(t)\end{aligned}$$

Recognizing that $\dot{x}(t) = Ax(t)$, we can rewrite the above as

$$\dot{V}(x(t)) = x(t)^T (A^T P + P A) x(t)$$



Note: for DT case, we take $V(x[k+1]) - V(x[k])$

Idea Behind Lyapunov's Theorem

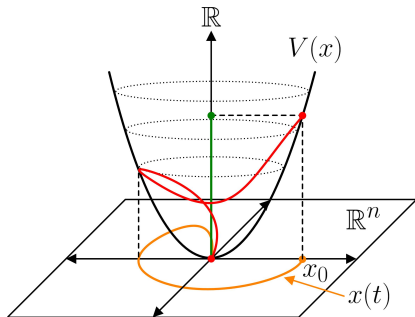


- ④ If $A^T P + P A = -Q < 0$,
then we have that

$$\dot{V}(x(t)) = x(t)^T (-Q) x(t) < 0, \\ \forall x(t) \neq 0$$

Meaning, $V(x(t))$ decreases
as t increases

Therefore,
 $x(t) \rightarrow 0$ as $t \rightarrow \infty$
(i.e. asymptotically stable)



Lyapunov's Theorem Summary



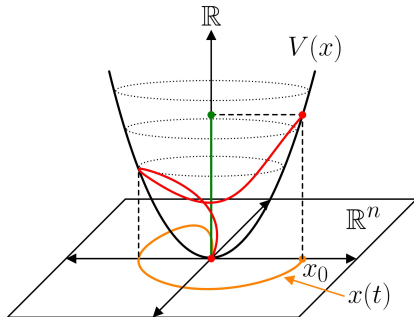
- Solving the Lyapunov equation w.r.t. P

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

is equivalent to finding a
Lyapunov function $V(x)$
such that

$$x(t) \rightarrow 0 \iff V(x(t)) \rightarrow 0$$

- Useful in advanced control!



- Nonlinear systems are **difficult to solve analytically**

$$\dot{x}_1(t) = x_2(t) - x_1(t) (x_1^2(t) + x_2^2(t))$$

$$\dot{x}_2(t) = -x_1(t) - x_2(t) (x_1^2(t) + x_2^2(t))$$

- Lyapunov function:** $V(x(t)) := x_1^2(t) + x_2^2(t) > 0, \forall x \neq 0$
- Derivative of $V(x(t))$ w.r.t t , where $x(t)$ is the trajectory of the nonlinear system is

$$\begin{aligned}\dot{V}(x(t)) &= 2x_1(t)\dot{x}_1(t) + 2x_2(t)\dot{x}_2(t) \\ &= -2(x_1^2(t) + x_2^2(t))^2 < 0, \forall x(t) \neq 0\end{aligned}$$

- Positive definiteness
- Lyapunov theorem
- Idea behind Lyapunov's theorem
- Next, controllability and observability