

Lecture 12

03/08/2021

Last time: Constructing Lyapunov functions

LaSalle's invariance principle

Lyapunov theory for linear systems

Today: Finish discussion on Lyapunov's indirect method for linear systems

Lyapunov direct method

Theorem $\dot{x} = Ax$ is stable ($\bar{x}=0$ is GAS)

i.e., A is Hurwitz ($\lambda_i(A) \in LHP$)



$\forall Q = Q^T > 0$, there is $P = P^T > 0$ s.t.

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



If this holds, then $P = \int_0^\infty e^{AT} Q e^{At} dt$ is the

Unique Soln to the Lyapunov equation and

$V(x) = x^T P x$ is the Lyapunov function

for $\dot{x} = Ax$.

Aside

$$\begin{cases} \dot{x} = Ax \\ y = Cx \end{cases}$$

$$A^T P + PA = -C^T C$$

P: observability Gramian

} useful
in the
context of
stability

$$\dot{x} = Ax + Bu : AX + XA^T = -BB^T$$

X: controllability Gramian

Ex.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ -a & -b \end{bmatrix}}_A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\det(sI - A) = \det \begin{pmatrix} s & -1 \\ a & s+b \end{pmatrix} = s^2 + bs + a$$

$a, b > 0 \Leftrightarrow A$ Hurwitz

Question: Can $Q = Q^T \succcurlyeq 0$ work here?

$$V(x) = \int_0^{x_1} g(\xi) d\xi + \frac{1}{2} x_2^2 = \frac{1}{2} a x_1^2 + \frac{1}{2} x_2^2$$

$$g\xi$$

$$\bar{x}^T P \bar{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}^T P \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$P = \frac{1}{2} \begin{bmatrix} a & 0 \\ 0 & 1 \end{bmatrix}$$

Q

From the Pendulum example

$$\begin{aligned} \dot{V}(x) &= Qx_1^2 - bx_2^2 \\ &= -(x_1, x_2) \begin{bmatrix} 0 & 0 \\ 0 & b \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \end{aligned}$$

Note $Q = \underbrace{\begin{bmatrix} 0 \\ \sqrt{b} \end{bmatrix}}_{C^T} \underbrace{\begin{bmatrix} 0 & \sqrt{b} \end{bmatrix}}_C$

* Thus, P is an observability Gramian for an LTI system $\begin{cases} \dot{x} = Ax \\ y = Cx \end{cases}$

$$A = \begin{bmatrix} 0 & 1 \\ -a & -b \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & \sqrt{b} \end{bmatrix}$$

$$\dot{V} = -bx_2^2 = -y^2(t) = 0$$

$$y = Cx = \begin{bmatrix} 0 & \sqrt{b} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

study these problematic cases for LaSalle ...

Given the observability of the system, the output
can only be zero if the initial condition is zero.

$$x_2(t) = e^{\text{At}} \underline{x_2(0)}$$
$$x_2 = 0 \iff x_2(0) = 0$$

Fact
LaSalle's Invariance Principle for LTI systems

with $A^T P + PA = -C^T C \leq 0$



$\bar{x} = 0$ is GAS if pair (A, C) is observable.

let's check the observability matrix for the example above.

Observability matrix

$$\begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 0 & \sqrt{b} \\ -a\sqrt{b} & -b\sqrt{b} \end{bmatrix} = \sqrt{b} \begin{bmatrix} 0 & 1 \\ -a & -b \end{bmatrix}$$

if $\det \begin{bmatrix} C \\ CA \end{bmatrix} = ab \neq 0$ then we have

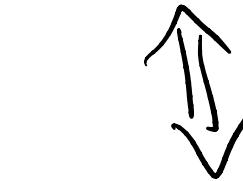
observability.

$b=0 \rightarrow$ conservative system & this analysis
doesn't even apply.

\Rightarrow thus $a \neq 0$

Recap: $P := \frac{1}{2} \begin{bmatrix} a & 0 \\ 0 & 1 \end{bmatrix} \Rightarrow Q \succ 0$

for the example
presented
here



$$P^T = P \succ 0$$

$$\dot{V} = -x^T Q x ; Q = \begin{bmatrix} 0 & 0 \\ 0 & b \end{bmatrix} \Rightarrow b \succ 0$$



$$Q = Q^T \succ 0$$

Thus, theorem can be relaxed to :

$$\dot{x} = Ax \text{ stable}$$



$$\forall Q = Q^T \succcurlyeq 0 \quad \textcircled{+} \quad \text{pair } (A, Q^{1/2}) \text{ observable}$$

there exists $P = P^T \succcurlyeq 0$ st.

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

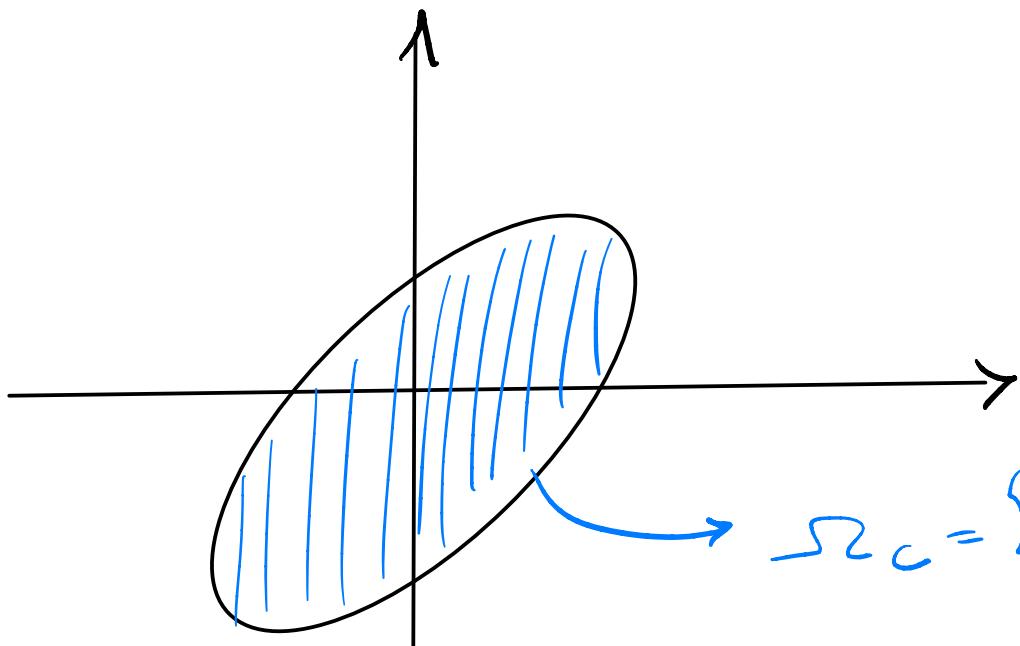
Moral

The "Big" Lyapunov theorem we learned about in linear systems theory was direct application of Lyapunov's indirect method with quadratic Lyap. function $V = \mathbf{x}^T P \mathbf{x}$.

LaSalle's invariance principle allows us to relax the second part of Lyapunov's theorem and account for $Q = Q^T > 0$ when we have observability of $(A, Q^{1/2})$.

Region of Attraction :

Set of points st. $\{x_0, \underbrace{\phi(t, x_0)}_{x(t) \text{ st. } x(0)=x_0} \rightarrow 0\}$



$$\Sigma_c = \{x; V(x) \leq c\}$$

$$\dot{V}(x) < 0 \text{ in } \Sigma_c$$

Q. How to estimate the region of attraction?

A possible approach: use Lyapunov based analysis
(caveat: maybe conservative!)

for example: use of $V(x) = x^T P x$ where P is $P^T P > 0$
as $\underline{\cong}$ Lyapunov function for the
corresponding linearization.

use of sum-of-squares (SOS) techniques

Can reduce conservatism

(mainly based on work
of P. Parrilo
@ MIT)

(caveat: computationally expensive)

Lyapunov direct method (linearization)

LDM

stability via linear approximation of nonlinear system.

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

$f(0) = 0 \Rightarrow \bar{x} = 0$ is an equilibrium point

linearization around $\bar{x} = 0$;

replace $x(t) = \bar{x} + \tilde{x}(t)$ and substitute
into the dynamics

$$\dot{x} = f(x) = \cancel{\dot{\bar{x}}} + \dot{\tilde{x}} = f(\bar{x} + \tilde{x})$$

O

$$= \dot{\tilde{x}} = f(\bar{x} + \tilde{x})$$

nonlinear equation for \tilde{x}

$$\dot{\tilde{x}} = A\tilde{x} + g(\tilde{x}) \quad (\text{I})$$

Taylor series expansion : $A = \cancel{\frac{\partial f}{\partial x}} \Big|_{x=\bar{x}}$

$$g(\tilde{x}) = f(\bar{x}) - A\tilde{x}$$

higher
order
term
in Taylor series

$$f(\tilde{x}) \approx f(\bar{x}) + \left. \frac{\partial f}{\partial x} \right|_{x=\bar{x}} \tilde{x} + \underbrace{\text{H.O.T.}}_{g(\tilde{x})}$$

Key assumption

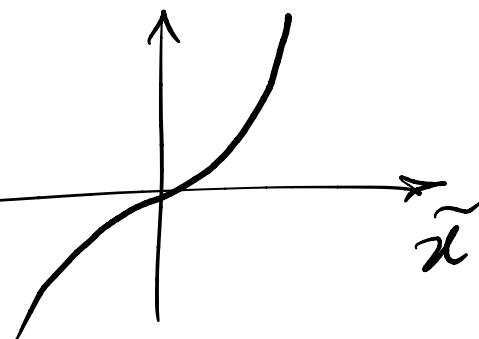
$$\frac{\|g(\tilde{x})\|}{\|\tilde{x}\|} \xrightarrow{\| \tilde{x} \| \rightarrow 0} 0$$

i.e.,

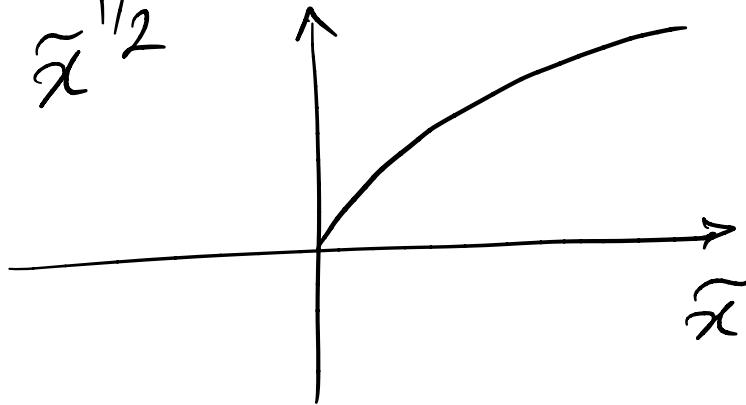
$$\lim_{\|x\| \rightarrow 0} \frac{\|g(x)\|}{\|x\|} = 0$$

Examples

$$g(\tilde{x}) = \tilde{x}^3$$



however, $g(\tilde{x}) = \tilde{x}^{1/2}$



bad!

doesn't meet assumption

Let $\dot{\tilde{x}} = A\tilde{x}$ be stable (A Hurwitz $\text{Re}\{\lambda_i(A)\} < 0$)
LTI \nearrow GAS at e.p. $\tilde{x}=0$

We know that $P = P^T > 0$ s.t. $V(\tilde{x}) = \tilde{x}^T P \tilde{x}$
is a Lyapunov function for LTI system

We are going to use the Lyapunov function to assess stability of the nonlinear system.

for nonlinear system (\mathcal{I}), $V(\tilde{x})$ works as Lyapunov function

$$\bar{A}^T P + P \bar{A} = -Q$$

$$Q = Q^T > 0$$

Now, study $\frac{dV}{dt}$ along solns of (I)

$$V = \tilde{x}^T P \tilde{x}$$

$$\dot{V} = \dot{\tilde{x}}^T P \tilde{x} + \tilde{x}^T P \dot{\tilde{x}}$$

$$= (A\tilde{x} + g(\tilde{x}))^T P \tilde{x} + \tilde{x}^T P (A\tilde{x} + g(\tilde{x}))$$

$$= \tilde{x}^T (\underbrace{A^T P + P A}_{-Q}) \tilde{x} + 2\tilde{x}^T P g(\tilde{x})$$

? $\not\propto 0$



sign-indefinite

We want to minimize damage by figuring out what the worst values of $2\tilde{x}^T Pg(\tilde{x})$ could be.

↓ let's upper bound \hat{V} :

$$\hat{V} = -\tilde{x}^T Q \tilde{x} + 2\tilde{x}^T Pg(\tilde{x})$$

$$\leftarrow -\lambda_{\min}(Q) \|\tilde{x}\|_2^2 + 2\|\tilde{x}\|_2 \|P\|_{2i} \cdot \|g(\tilde{x})\|_2$$

aside Note that

$$\lambda_{\min}(Q) \|x\|_2^2 \leq x^T Q x \leq \lambda_{\max}(Q) \|x\|_2^2$$

$$\Rightarrow -x^T Q x \geq -\lambda_{\min}(Q) \|x\|_2^2$$

$$x^T y \leq \|x\|_2 \|y\|_2$$

proof

$$x^T y = \|x\|_2 \|y\|_2 \cos(\theta)$$

Here, we consider $y = Pz \Rightarrow \|P\|_2 := \sup \frac{\|Pz\|_2}{\|z\|_2}$

$$\frac{\|Pz\|_2}{\|z\|_2} \leq \|P\|_{2i} \Rightarrow \|Pz\|_2 \leq \|P\|_{2i} \|z\|_2$$

Going back:

$$\check{V} \leq -\|\tilde{x}\|_2 \left(\lambda_{\min}(Q) \|\tilde{x}\|_2 - 2\|P\|_{2i} \|g(\tilde{x})\|_2 \right)$$

need to be positive

we can find a region around the origin where
this is true

$$\Rightarrow \|\tilde{x}\|_2 > \frac{2\|P\|_{2:}}{\lambda_{\min}(Q)} \|g(\tilde{x})\|$$

if $\frac{\|g(\tilde{x})\|_2}{\|\tilde{x}\|_2} \xrightarrow{\|\tilde{x}\|_2 \rightarrow 0} 0$

the quantity inside the parentheses on the right
will be positive and we can conclude
LAS of $\tilde{x}=0$ with ROA.
region of attraction.