

C21 Nonlinear Systems

Mark Cannon

4 lectures

Michaelmas Term 2017



Lecture 1

Introduction and Concepts of Stability

1. Types of stability
2. Linearization
3. Lyapunov's direct method
4. Regions of attraction
5. Linear systems and passive systems

- J.-J. Slotine & W. Li *Applied Nonlinear Control*, Prentice-Hall 1991.
 - ★ Stability
 - ★ Interconnected systems and passive systems
- H.K. Khalil *Nonlinear Systems*, Prentice-Hall 1996.
 - ★ Stability
 - ★ Passive systems
- M. Vidyasagar *Nonlinear Systems Analysis*, Prentice-Hall 1993.
 - ★ Stability & passivity (more technical detail)

Why use nonlinear control?

- Real systems are nonlinear
 - ★ friction, non-ideal components
 - ★ actuator saturation
 - ★ sensor nonlinearity
- Analysis via linearization
 - ★ accuracy of approximation?
 - ★ conservative?
- Account for nonlinearities in high performance applications
 - ★ Robotics, Aerospace, Petrochemical industries, Process control, Power generation ...
- Account for nonlinearities if linear models inadequate
 - ★ large operating region
 - ★ model properties change at linearization point

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Linear vs nonlinear system properties

Free response

Linear system

$$\dot{x} = Ax$$

- Unique equilibrium point:
 $Ax = 0 \iff x = 0$
- Stability independent of initial conditions

Nonlinear system

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

- Multiple equilibrium points
 $f(x) = 0$
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Linear vs nonlinear system properties

Forced response

Linear system

$$\dot{x} = Ax + Bu$$

- $\|u\|$ finite $\Rightarrow \|x\|$ finite if open-loop stable
- Frequency response:
 $u = U \sin \omega t \Rightarrow x = X \sin(\omega t + \phi)$
- Superposition:
 $u = u_1 + u_2 \Rightarrow x = x_1 + x_2$

Nonlinear system

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

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- No frequency response
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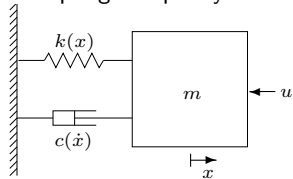
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Example: step response

Mass-spring-damper system

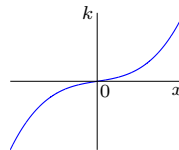


Equation of motion:

$$\ddot{x} + c(\dot{x}) + k(x) = u$$

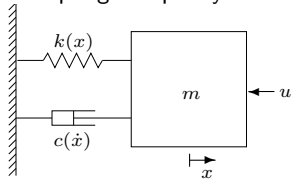
$$c(\dot{x}) = \dot{x}$$

$k(x)$ nonlinear:



Example: step response

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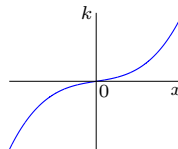


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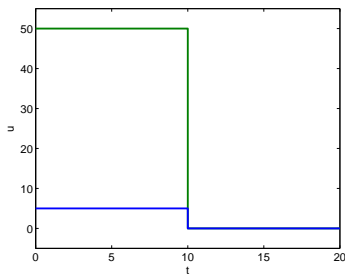
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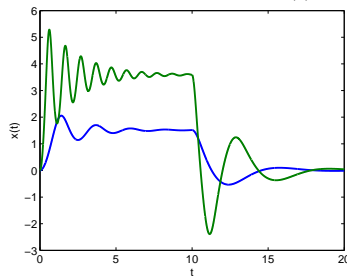
$k(x)$ nonlinear:



Input $u(t)$



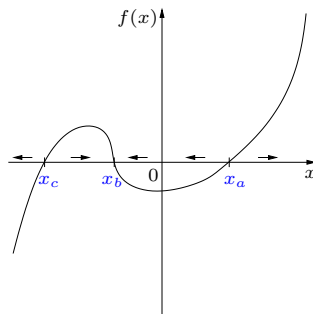
Response $x(t)$



apparent **damping ratio** depends on size of input step

Example: multiple equilibria

First order system: $\dot{x} = f(x)$

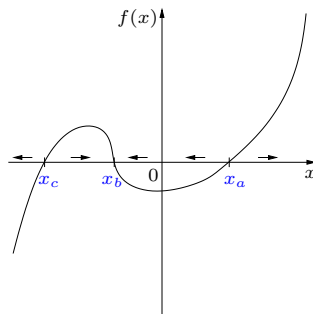


$x > x_a$	\implies	$f(x) > 0$	\implies	$x(t)$ increases
$x_b < x < x_a$	\implies	$f(x) < 0$	\implies	$x(t)$ decreases
$x_c < x < x_b$	\implies	$f(x) > 0$	\implies	$x(t)$ increases
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- x_a , x_c are **unstable** equilibrium points
- x_b is a **stable** equilibrium point

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Example: limit cycle

Van der Pol oscillator:

$$\ddot{x} + (x^2 - 1)\dot{x} + x = 0$$

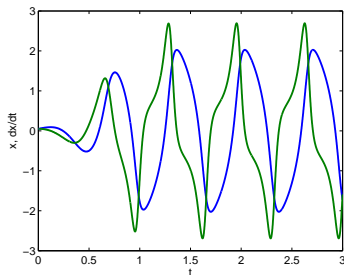
- Response $x(t)$ tends to a **limit cycle** (= trajectory forming a closed curve)
- Amplitude independent of initial conditions

Example: limit cycle

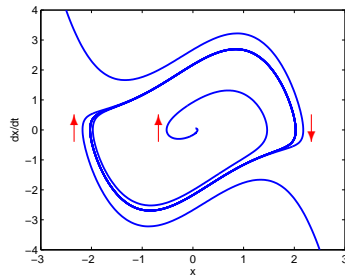
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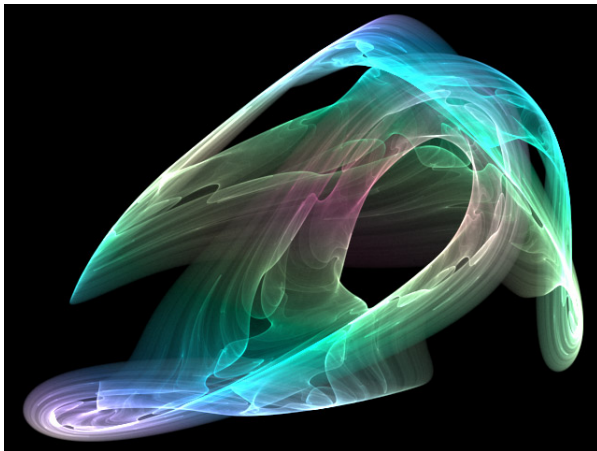
Response with $x(0) = 0.05$, $\dot{x}(0) = 0.05$



State trajectories $(x(t), \dot{x}(t))$

Example: chaotic behaviour

Strange attractor



Example: chaotic behaviour

Lorenz attractor

- Simplified model of atmospheric convection:

$$\dot{x} = \sigma(y - x)$$

$$\dot{y} = x(\rho - z) - y$$

$$\dot{z} = xy - \beta z$$

- State variables

$x(t)$: fluid velocity

$y(t)$: difference in temperature of ascending and descending fluid

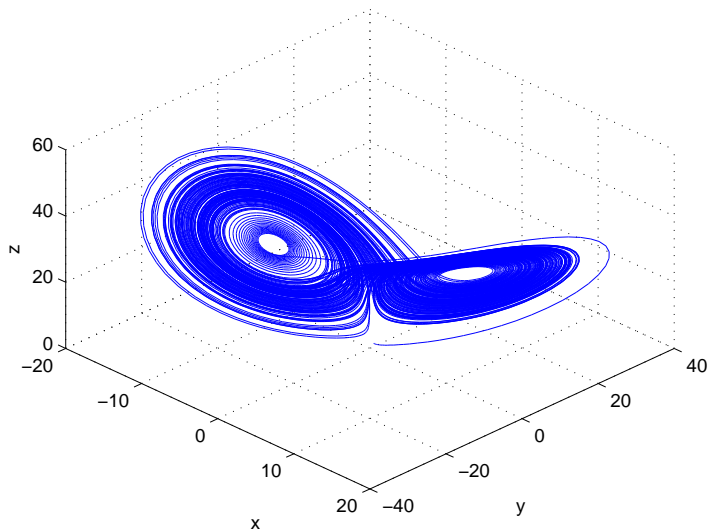
$z(t)$: characterizes distortion of vertical temperature profile

- Parameters $\sigma = 10$, $\beta = 8/3$, $\rho = \text{variable}$

Example: chaotic behaviour

Lorenz attractor

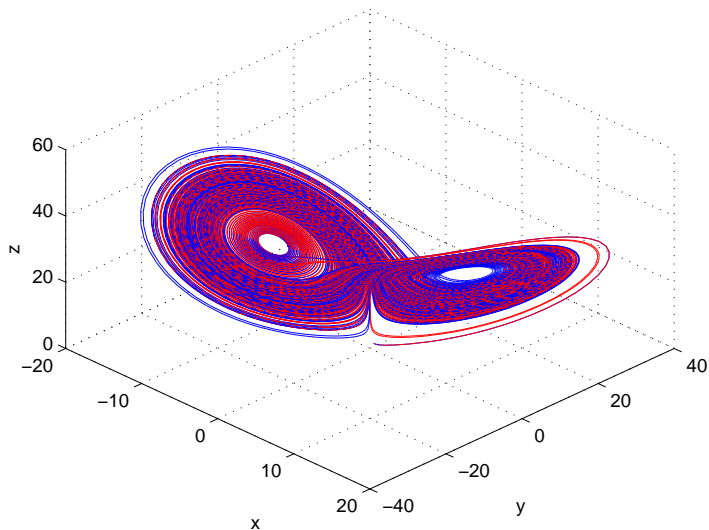
$\rho = 28 \Rightarrow$ "strange attractor":



Example: chaotic behaviour

Lorenz attractor

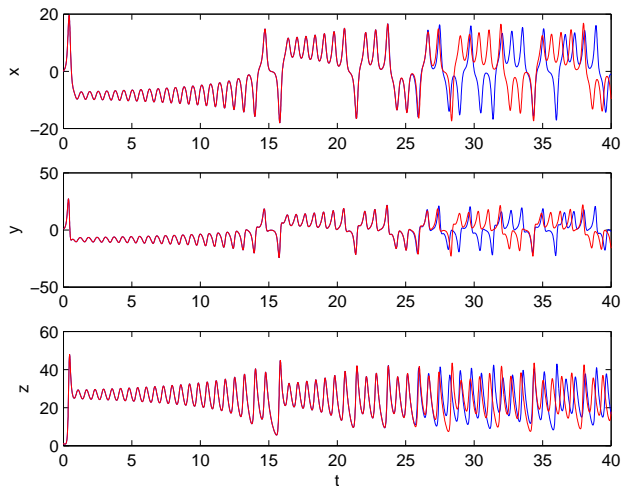
sensitivity to initial conditions



Example: chaotic behaviour

Lorenz attractor

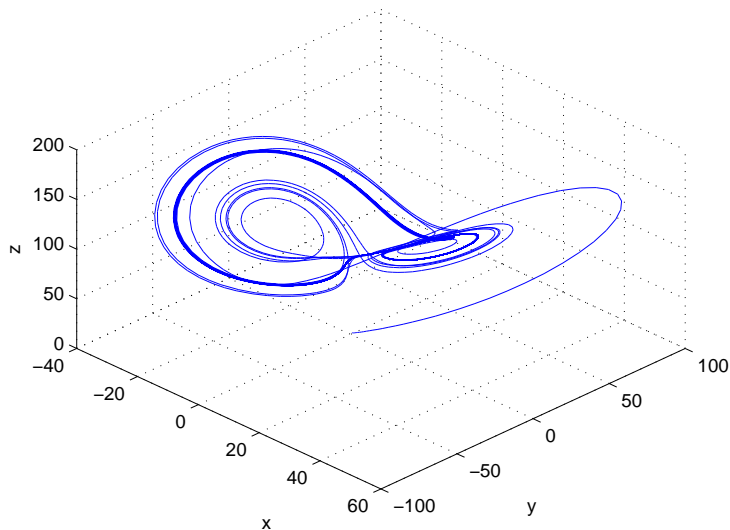
sensitivity to initial conditions **blue:** $(x, y, z) = (0, 1, 1.05)$
 red: $(x, y, z) = (0, 1, 1.050001)$



Example: chaotic behaviour

Lorenz attractor

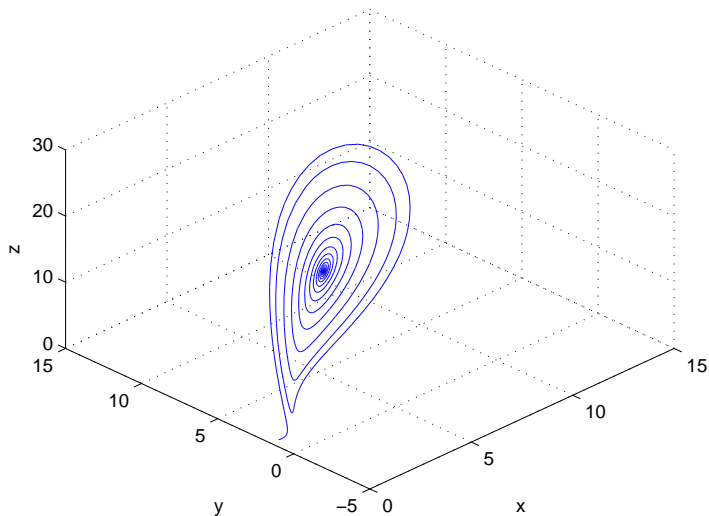
$\rho = 99.96 \Rightarrow$ limit cycle:



Example: chaotic behaviour

Lorenz attractor

$\rho = 14 \implies$ convergence to a stable equilibrium:



State space equations

$$\dot{x} = f(x, u, t) \quad \begin{array}{l} x : \text{state} \\ u : \text{input} \end{array}$$

e.g. n th order differential equation:

$$\frac{d^n y}{dt^n} = h\left(y, \dots, \frac{d^{n-1}y}{dt^{n-1}}, u, t\right)$$

has state vector (one possible choice)

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} y \\ \dot{y} \\ \vdots \\ d^{n-1}y/dt^{n-1} \end{bmatrix}$$

and state space dynamics:

$$\dot{x} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} x_2 \\ x_3 \\ \vdots \\ h(x_1, x_2, \dots, x_n, u, t) \end{bmatrix} = f(x, u, t)$$

Equilibrium points

x^* is an **equilibrium point** of system $\dot{x} = f(x)$ iff:

$$x(0) = x^* \quad \text{implies} \quad x(t) = x^* \quad \forall t > 0$$

$$\text{i.e. } f(x^*) = 0$$

Examples:

(a) $\ddot{y} + \alpha \dot{y}^2 + \beta \sin y = 0$ (damped pendulum)

$$x = \begin{bmatrix} y \\ \dot{y} \end{bmatrix}, \quad x^* = \begin{bmatrix} n\pi \\ 0 \end{bmatrix}, \quad n = 0, \pm 1$$

(b) $\ddot{y} + (y-1)^2 \dot{y} + y - \sin(\pi y/2) = 0$

$$x = \begin{bmatrix} y \\ \dot{y} \end{bmatrix}, \quad x^* = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \quad \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

- ★ Consider **local** stability of individual equilibrium points
- ★ Convention: define f so that $x = 0$ is equilibrium point of interest
- ★ **Autonomous** system: $\dot{x} = f(x) \implies x^* = \text{constant}$

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Stability definition

An equilibrium point $x = 0$ is **stable** iff:

$\max_t \|x(t)\|$ can be made arbitrarily small
by making $\|x(0)\|$ small enough

- Is $x = 0$ a stable equilibrium for the Van der Pol oscillator example?
- No guarantee of convergence to the equilibrium point

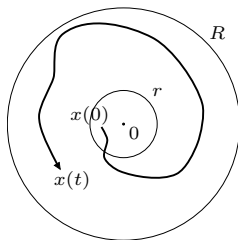
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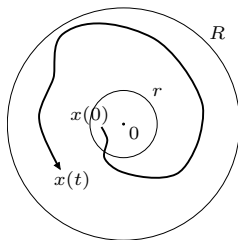
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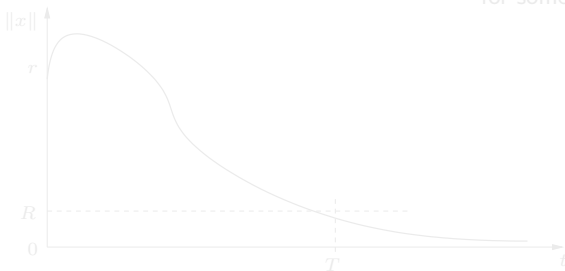
- (i). $x = 0$ is stable
- (ii). $\|x(0)\| < r \implies \|x(t)\| \rightarrow 0 \text{ as } t \rightarrow \infty$

(ii) is equivalent to:

for any $R > 0$,

$$\|x(0)\| < r \implies \|x(t)\| < R \quad \forall t > T$$

for some r, T



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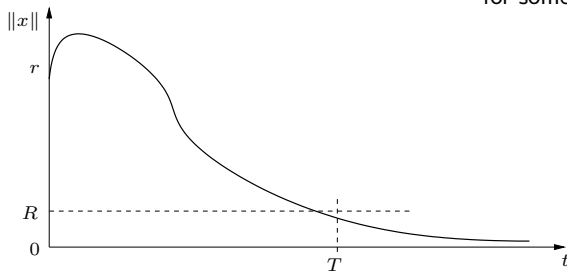
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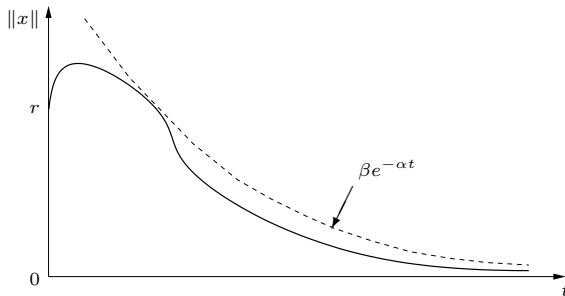


Exponential stability definition

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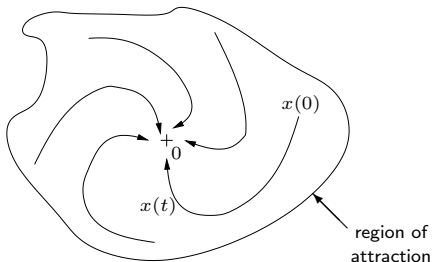
$$\|x(0)\| < r \implies \|x(t)\| \leq \beta e^{-\alpha t} \quad \forall t > 0$$

exponential stability is a special case of asymptotic stability



Region of attraction

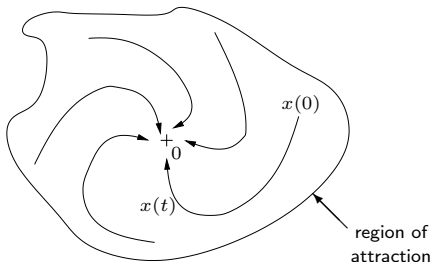
The region of **attraction** of $x = 0$ is the set of all initial conditions $x(0)$ for which $x(t) \rightarrow 0$ as $t \rightarrow \infty$



- Every asymptotically stable equilibrium point has a region of attraction
- $r = \infty \implies$ entire state space is a region of attraction
 $\implies x = 0$ is **globally** asymptotically stable
- Are stable linear systems asymptotically stable?

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- Nonlinear **state space** equations: $\dot{x} = f(x, u)$
 x = state vector, u = control input
- **Equilibrium points**: x^* is an equilibrium point
of $\dot{x} = f(x)$ if $f(x^*) = 0$
- **Stable** equilibrium point: x^* is stable if state trajectories starting close to x^* remain near x^* at all times
- **Asymptotically stable** equilibrium point: x^* must be stable and state trajectories starting near x^* must tend to x^* asymptotically
- **Region of attraction**: the set of initial conditions from which state trajectories converge asymptotically to equilibrium x^*

Lecture 2

Linearization and Lyapunov's direct method

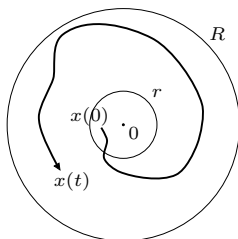
Linearization and Lyapunov's direct method

- Review of stability definitions
- Linearization method
- Direct method for stability
- Direct method for asymptotic stability
- Linearization method revisited

Review of stability definitions

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

- ★ unforced system (i.e. closed-loop)
- ★ consider stability of individual equilibrium points



0 is a **stable** equilibrium if:

$$\|x(0)\| \leq r \implies \|x(t)\| \leq R \quad \text{for any } R > 0$$

Stability

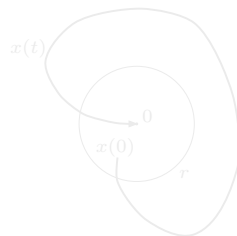
Asymptotic stability



local property



global if $r = \infty$ allowed



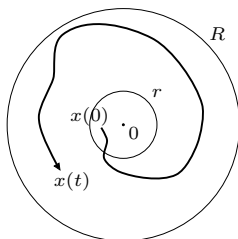
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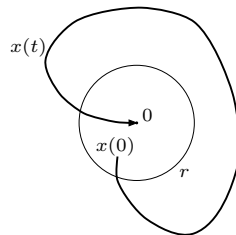
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$$\|x(0)\| \leq r \implies \|x(t)\| \leq R \quad \text{for any } R > 0$$



0 is **asymptotically** stable if:

$$\|x(0)\| \leq r \implies \|x(t)\| \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

Stability



local property

Asymptotic stability

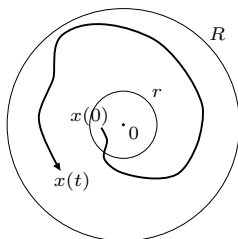


global if $r = \infty$ allowed

Review of stability definitions

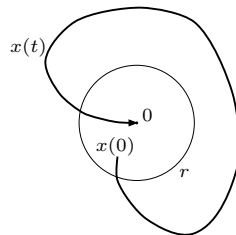
System: $\dot{x} = f(x)$

- ★ unforced system (i.e. closed-loop)
- ★ consider stability of individual equilibrium points



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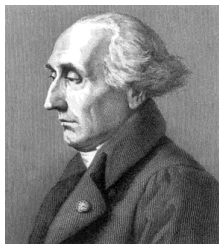
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Historical development of Stability Theory

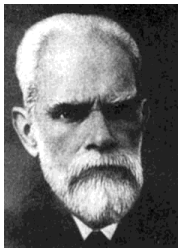
- Potential energy in conservative mechanics (Lagrange 1788):

An equilibrium point of a conservative system is stable if it corresponds to a minimum of the potential energy stored in the system

- Energy storage analogy for general ODEs (Lyapunov 1892)
- Invariant sets (Lefschetz, La Salle 1960s)



J-L. Lagrange 1736-1813



A. M. Lyapunov 1857-1918



S. Lefschetz 1884-1972

Lyapunov's linearization method

- Determine stability of equilibrium at $x = 0$ by analyzing the stability of the linearized system at $x = 0$.
- Jacobian linearization:

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

original nonlinear dynamics

$$= f(0) + \left. \frac{\partial f}{\partial x} \right|_{x=0} x + R_1$$

Taylor's series expansion, $R_1 = O(\|x\|^2)$

$$\approx Ax$$

since $f(0) = 0$

where

$$A = \left. \frac{\partial f}{\partial x} \right|_{x=0} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix}, \quad \frac{\partial f}{\partial x} \text{ assumed continuous at } x = 0$$

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Lyapunov's linearization method

Conditions on A for stability of original nonlinear system at $x = 0$:

stability of linearization	stability of nonlinear system at $x = 0$
$\operatorname{Re}(\lambda(A)) < 0$	asymptotically stable (locally)
$\max \operatorname{Re}(\lambda(A)) = 0$	stable or unstable
$\max \operatorname{Re}(\lambda(A)) > 0$	unstable

Lyapunov's linearization method

- Some examples

(stable)	$\dot{x} = -x^3$	$\xrightarrow{\text{linearize}}$	$\dot{x} = 0$	(indeterminate)
(unstable)	$\dot{x} = x^3$	$\xrightarrow{\text{linearize}}$	$\dot{x} = 0$	(indeterminate)
			\uparrow	
			higher order terms determine stability	

- Why does linear control work?

1. Linearize the model:

$$\begin{aligned}\dot{x} &= f(x, u) \\ &\approx Ax + Bu, \quad A = \frac{\partial f}{\partial x}(0, 0), \quad B = \frac{\partial f}{\partial u}(0, 0)\end{aligned}$$

2. Design a linear feedback controller using the linearized model:

$$u = -Kx, \quad \max \operatorname{Re}(\lambda(A - BK)) < 0$$

closed-loop linear model strictly stable

nonlinear system $\dot{x} = f(x, -Kx)$ is **locally** asymptotically stable at $x = 0$

Lyapunov's linearization method

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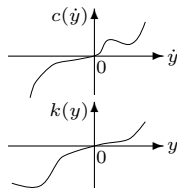
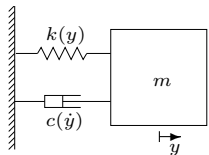
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Lyapunov's direct method: mass-spring-damper example



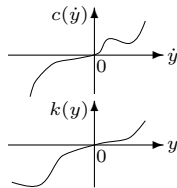
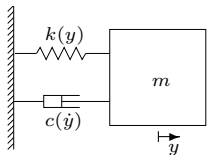
Equation of motion: $m\ddot{y} + c(\dot{y}) + k(y) = 0$

Stored energy: $V = \text{K.E.} + \text{P.E.} \quad \left\{ \begin{array}{l} \text{K.E.} = \frac{1}{2}m\dot{y}^2 \\ \text{P.E.} = \int_0^y k(y) dy \end{array} \right.$

Rate of energy dissipation $\dot{V} = \frac{1}{2}m\ddot{y} \frac{d}{d\dot{y}} \dot{y}^2 + \dot{y} \frac{d}{dy} \left[\int_0^y k(y) dy \right]$
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 $\leq 0 \quad \leftarrow \text{since } \text{sign}(c(\dot{y})) = \text{sign}(\dot{y})$

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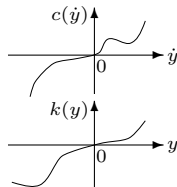
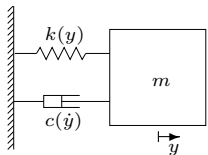
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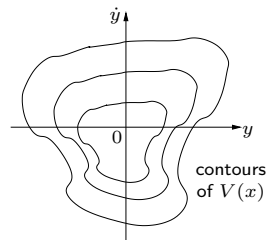
Mass-spring-damper example contd.

- System state: e.g. $x = [y \ \dot{y}]^T$
- $\dot{V}(x) \leq 0$ implies that $x = 0$ is stable



$V(x(t))$ must decrease over time
but

$V(x)$ increases with increasing $\|x\|$



- Formal argument:

for any given $R > 0$:

$$\begin{aligned} \|x\| < R & \quad \text{whenever} \quad V(x) < \bar{V} \text{ for some } \bar{V} \\ \text{and } V(x) < \bar{V} & \quad \text{whenever} \quad \|x\| < r \text{ for some } r \end{aligned}$$

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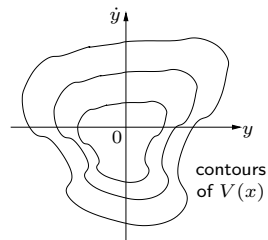
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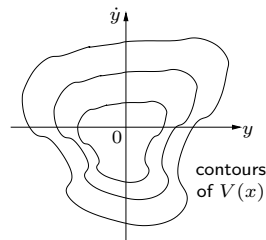
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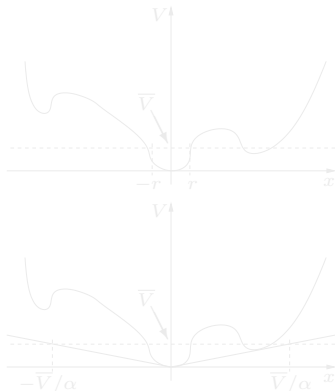
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Positive definite functions

- What if $V(x)$ is not monotonically increasing in $\|x\|$?
- Same arguments apply if $V(x)$ is continuous and **positive definite**, i.e.

- (i). $V(0) = 0$
- (ii). $V(x) > 0$ for all $x \neq 0$



for any given $\bar{V} > 0$,
can always find r so that

$$V(x) < \bar{V} \quad \text{whenever} \quad \|x\| < r$$

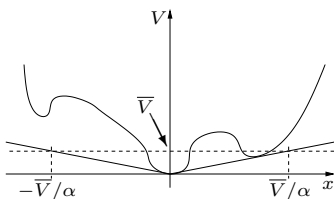
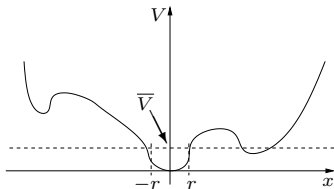
$V(x) \geq \alpha \|x\|^n$
for some constants α, n , so

$$\|x\| < (\bar{V}/\alpha)^{1/n} \quad \text{whenever} \quad V(x) < \bar{V}$$

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If there exists a continuous function $V(x)$ such that

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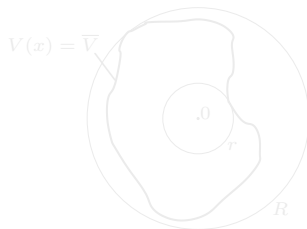
then $x = 0$ is **stable**.

To show that this implies $\|x(t)\| < R$ for all $t > 0$ whenever $\|x(0)\| < r$

for any R and some r :

1. choose \bar{V} as the minimum of $V(x)$ for $\|x\| = R$
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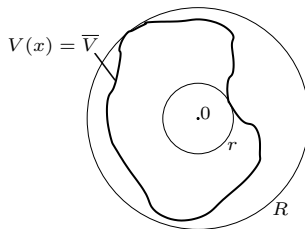
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- Lyapunov's direct method also applies if $V(x)$ is locally positive definite, i.e. if

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- Apply the theorem without determining R, r
 - only need to find p.d. $V(x)$ satisfying $\dot{V}(x) \leq 0$.

- Examples

$$\text{(i). } \dot{x} = -a(t)x, \quad a(t) > 0$$

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Lyapunov stability theorem

- More examples

(iii). $\dot{x} = -a(x), \quad \int_0^x a(x) dx > 0$

$$\begin{aligned} V = \int_0^x a(x) dx \quad \implies \quad \dot{V} &= a(x)\dot{x} \\ &= -a^2(x) \leq 0 \end{aligned}$$

(iv). $\ddot{\theta} + \sin \theta = 0$

$$\begin{aligned} V = \frac{1}{2}\dot{\theta}^2 + \int_0^\theta \sin \theta d\theta \quad \implies \quad \dot{V} &= \ddot{\theta}\dot{\theta} + \dot{\theta} \sin \theta \\ &= 0 \end{aligned}$$

Asymptotic stability theorem

If there exists a continuous function $V(x)$ such that

$$\begin{array}{ll} V(x) & \text{is positive definite} \\ \dot{V}(x) & \text{is negative definite} \end{array}$$

then $x = 0$ is **locally asymptotically stable**.

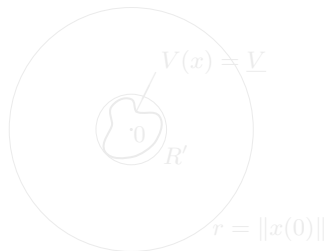
$$(\dot{V} \text{ negative definite} \iff -\dot{V} \text{ positive definite})$$

Asymptotic convergence $x(t) \rightarrow 0$ as $t \rightarrow \infty$ can be shown by contradiction:

if $\|x(t)\| > R'$ for all $t \geq 0$, then

$$\left. \begin{array}{l} \dot{V}(x) < -W \\ V(x) \geq \underline{V} \end{array} \right\} \text{ for all } t \geq 0$$

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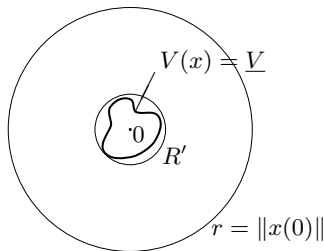
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Linearization method and asymptotic stability

- Asymptotic stability result also applies if $\dot{V}(x)$ is only **locally** negative definite.

- Why does the linearization method work?

★ consider 1st order system: $\dot{x} = f(x)$

linearize about $x = 0$: $\dot{x} = -ax + R$ $R = O(x^2)$

★ assume $a > 0$ and try Lyapunov function V :

$$V(x) = \frac{1}{2}x^2$$

$$\begin{aligned}\dot{V}(x) &= x\dot{x} = -ax^2 + Rx = -x^2(a - R/x) \\ &\leq -x^2(a - |R/x|)\end{aligned}$$

★ but $R = O(x^2)$ implies $|R| \leq \beta x^2$ for some constant β , so

$$\begin{aligned}\dot{V} &\leq -x^2(a - \beta|x|) \\ &\leq -\gamma x^2 \quad \text{if } |x| \leq (a - \gamma)/\beta\end{aligned}$$

$\Rightarrow \dot{V}$ negative definite for $|x|$ small enough

$\Rightarrow x = 0$ locally asymptotically stable

Generalization to n th order systems is straightforward

Linearization method and asymptotic stability

- Asymptotic stability result also applies if $\dot{V}(x)$ is only **locally** negative definite.
- Why does the linearization method work?

★ consider 1st order system: $\dot{x} = f(x)$
linearize about $x = 0$: $\dot{x} = -ax + R$ $R = O(x^2)$

★ assume $a > 0$ and try Lyapunov function V :

$$\begin{aligned} V(x) &= \frac{1}{2}x^2 \\ \dot{V}(x) &= x\dot{x} = -ax^2 + Rx = -x^2(a - R/x) \\ &\leq -x^2(a - |R/x|) \end{aligned}$$

★ but $R = O(x^2)$ implies $|R| \leq \beta x^2$ for some constant β , so

$$\begin{aligned} \dot{V} &\leq -x^2(a - \beta|x|) \\ &\leq -\gamma x^2 \quad \text{if } |x| \leq (a - \gamma)/\beta \end{aligned}$$

$\Rightarrow \dot{V}$ negative definite for $|x|$ small enough

$\Rightarrow x = 0$ locally asymptotically stable

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Generalization to n th order systems is straightforward

Global asymptotic stability theorem

If there exists a continuous function $V(x)$ such that

$$\left. \begin{array}{l} V(x) \text{ is positive definite} \\ \dot{V}(x) \text{ is negative definite} \\ V(x) \rightarrow \infty \text{ as } \|x\| \rightarrow \infty \end{array} \right\} \text{ for all } x$$

then $x = 0$ is **globally asymptotically stable**

- If $V(x) \rightarrow \infty$ as $\|x\| \rightarrow \infty$, then $V(x)$ is **radially unbounded**
- Test whether $V(x)$ is radially unbounded by checking if $V(x) \rightarrow \infty$ as each individual element of x tends to infinity (necessary).

Global asymptotic stability theorem

- Global asymptotic stability requires:

$$\|x(t)\| \text{ finite } \left\{ \begin{array}{l} \text{for all } t > 0 \\ \text{for all } x(0) \end{array} \right.$$

↑

not guaranteed by \dot{V} negative definite

in addition to asymptotic stability of $x = 0$

- Hence add extra condition: $V(x) \rightarrow \infty$ as $\|x\| \rightarrow \infty$

↕ equiv. to

level sets $\{x : V(x) \leq \bar{V}\}$ are finite

↕ equiv. to

$\|x\|$ is finite whenever $V(x)$ is finite

↑

prevents $x(t)$ drifting away from 0 despite $\dot{V} < 0$

Asymptotic stability example

System: $\dot{x}_1 = (x_2 - 1)x_1^3$
 $\dot{x}_2 = -\frac{x_1^4}{(1+x_1^2)^2} - \frac{x_2}{1+x_2^2}$

- Trial Lyapunov function $V(x) = x_1^2 + x_2^2$:

$$\begin{aligned}\dot{V}(x) &= 2x_1\dot{x}_1 + 2x_2\dot{x}_2 \\ &= -2x_1^4 + 2x_2x_1^4 - 2\frac{x_2x_1^4}{(1+x_1^2)^2} - 2\frac{x_2^2}{1+x_2^2} \not\leq 0\end{aligned}$$

change V to make
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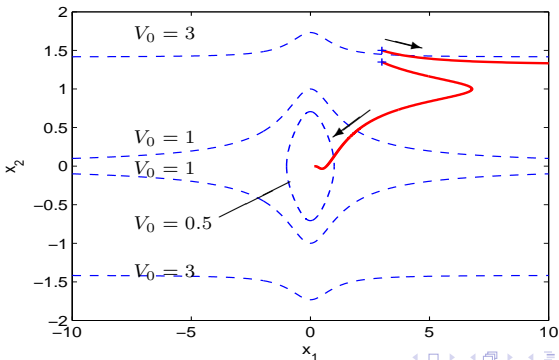
- New trial Lyapunov function $V(x) = \frac{x_1^2}{1+x_1^2} + x_2^2$:

$$\begin{aligned}\dot{V}(x) &= 2\left[\frac{x_1}{1+x_1^2} - \frac{x_1^3}{(1+x_1^2)^2}\right]\dot{x}_1 + 2x_2\dot{x}_2 \\ &= -2\frac{x_1^4}{(1+x_1^2)^2} - 2\frac{x_2^2}{1+x_2^2} \leq 0\end{aligned}$$

$V(x)$ positive definite, $\dot{V}(x)$ negative definite $\implies x = 0$ a.s.

But $V(x)$ not radially unbounded, so cannot conclude global asymptotic stability

State trajectories:



- Positive definite functions
- Derivative of $V(x)$ along trajectories of $\dot{x} = f(x)$
- Lyapunov's direct method for: stability
asymptotic stability
global stability
- Lyapunov's linearization method

Lecture 3

Convergence and invariant sets

Convergence and invariant sets

- Review of Lyapunov's direct method
- Convergence analysis using Barbalat's Lemma
- Invariant sets
- Global and local invariant set theorem
- Example

Review of Lyapunov's direct method

Positive definite functions

- If

$$V(0) = 0$$

$$V(x) > 0 \quad \text{for all } x \neq 0$$

then $V(x)$ is **positive definite**

- If \mathcal{S} is a set containing $x = 0$ and

$$V(0) = 0$$

$$V(x) > 0 \quad \text{for all } x \neq 0, x \in \mathcal{S}$$

then $V(x)$ is **locally positive definite** (within \mathcal{S})

- e.g.

$$V(x) = x^T x$$

← positive definite

$$V(x) = x^T x (1 - x^T x)$$

← locally positive definite
within $\mathcal{S} = \{x : x^T x < 1\}$

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Review of Lyapunov's direct method

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

Storage function: $V(x)$

Time-derivative of V : $\dot{V}(x) = \frac{\partial V}{\partial x} \frac{dx}{dt} = \nabla V(x)^T \dot{x} = \nabla V(x)^T f(x)$

- If

$$\left. \begin{array}{l} \text{(i). } V(x) \text{ is positive definite} \\ \text{(ii). } \dot{V}(x) \leq 0 \end{array} \right\} \text{ for all } x \in \mathcal{S}$$

then the equilibrium $x = 0$ is **stable**

- If

$$\text{(iii). } \dot{V}(x) \text{ is negative definite} \quad \text{for all } x \in \mathcal{S}$$

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- If

$$\begin{array}{l} \text{(iv). } \mathcal{S} = \text{entire state space} \\ \text{(v). } V(x) \rightarrow \infty \text{ as } \|x\| \rightarrow \infty \end{array}$$

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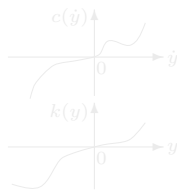
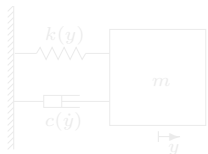
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Convergence analysis

- What can be said about convergence of $x(t)$ to 0 if $\dot{V}(x) \leq 0$ but $\dot{V}(x)$ is not negative definite?

- Revisit m-s-d example:

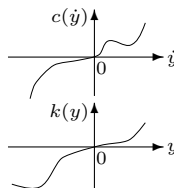
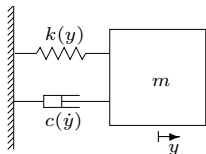


Equation of motion: $m\ddot{y} + c(\dot{y}) + k(y) = 0$

Storage function: $V = \text{K.E.} + \text{P.E.} = \frac{1}{2}m\dot{y}^2 + \int_0^y k(y) dy$
 $\dot{V} = -c(\dot{y})\dot{y}$

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Convergence analysis

- V is p.d. and $\dot{V} \leq 0$ so: $(y, \dot{y}) = (0, 0)$ is stable
and $V(y, \dot{y})$ tends to a finite limit as $t \rightarrow \infty$
- but does (y, \dot{y}) converge to $(0, 0)$?

\Updownarrow equivalent to

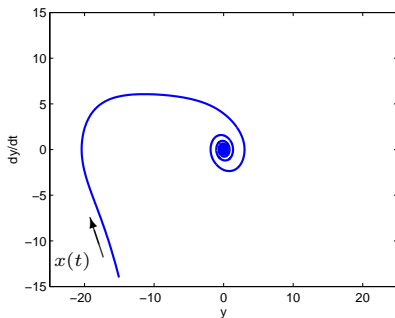
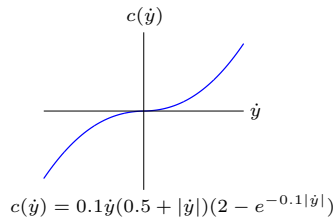
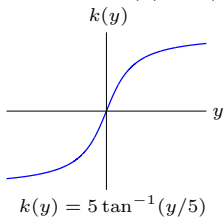
can $V(y, \dot{y})$ “get stuck” at $V = V_0 \neq 0$ as $t \rightarrow \infty$?

\downarrow

need to consider motion at points (y, \dot{y}) for which $\dot{V} = 0$

Example

Equation of motion: $m\ddot{y} + c(\dot{y}) + k(y) = 0$



Storage function:

$$V = \frac{1}{2}\dot{y}^2 + \int_0^y 5 \tan^{-1}(y/5) dy$$

$$\dot{V} = -c(\dot{y})\dot{y} \leq 0$$

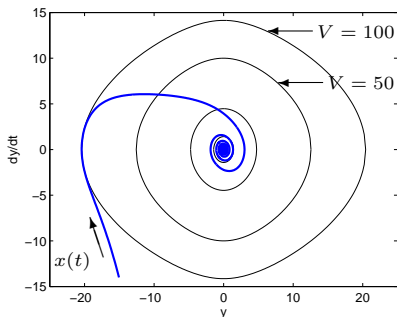
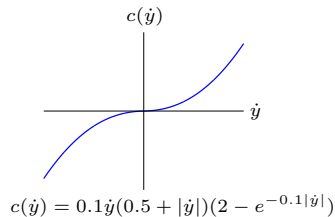
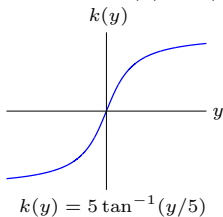
↓
 $\dot{V} = 0$ when $\dot{y} = 0$

but $k(y) \neq 0 \implies \ddot{y} \neq 0 \implies \ddot{V} \neq 0$

⇓
 V continues to decrease until $y = \dot{y} = 0$

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2. determine the set \mathcal{R} of points x for which $\dot{V}(x) = 0$
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then $x(t)$ has to converge to \mathcal{M} as $t \rightarrow \infty$

This approach is the basis of the [invariant set theorems](#)

Barbalat's Lemma

Barbalat's lemma: For any function $\phi(t)$, if

- (i). $\int_0^t \phi(\tau) d\tau$ converges to a finite limit as $t \rightarrow \infty$
- (ii). $\dot{\phi}(t)$ is finite for all t

then $\lim_{t \rightarrow \infty} \phi(t) = 0$

- Obvious for the case that $\phi(t) \geq 0$ for all t
- Condition (ii) is needed to ensure that $\phi(t)$ remains continuous for all t



Can construct discontinuous $\phi(t)$ for which $\int_0^t \phi(\tau) d\tau$ converges
but $\phi(t) \not\rightarrow 0$ as $t \rightarrow \infty$

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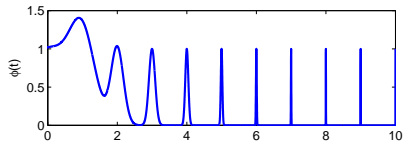
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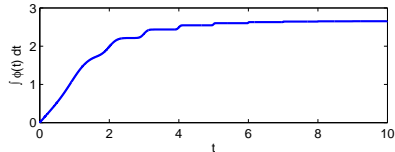
Barbalat's Lemma

Example: pulse train $\phi(t) = \sum_{k=0}^{\infty} e^{-4^k(t-k)^2}$:

$\phi(t)$:



$\int_0^t \phi(\tau) d\tau$:



From the plots it is clear that

$\int_0^t \phi(s) ds$ tends to a finite limit

but $\phi(t) \not\rightarrow 0$ as $t \rightarrow \infty$ because $\dot{\phi}(t) \rightarrow \infty$ as $t \rightarrow \infty$

Barbalat's Lemma contd.

Apply Barbalat's Lemma to $\dot{V}(x(t)) = \phi(t) \leq 0$:

- **Integrate:**

$$\int_0^t \phi(s) ds = V(x(t)) - V(x(0))$$

← finite limit as $t \rightarrow \infty$

- **Differentiate:**

$$\dot{\phi}(t) = \ddot{V}(x(t)) = f^T(x) \frac{\partial^2 V}{\partial x^2}(x) f(x) + \nabla V(x) \frac{\partial f}{\partial x}(x) f(x)$$

= finite for all t if $f(x)$ continuous and $V(x)$ continuously differentiable



$$\dot{V}(x) \rightarrow 0 \text{ as } t \rightarrow \infty$$

The above arguments rely on $\|x(t)\|$ remaining finite for all t , which is implied by:

$V(x)$ positive definite

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Convergence analysis

Summary of method:

1. show that $\dot{V}(x) \rightarrow 0$ as $t \rightarrow \infty$
 \rightarrow true whenever $\dot{V} \leq 0$ & V, f are smooth & $\|x(t)\|$ is bounded
2. determine the set \mathcal{R} of points x for which $\dot{V}(x) = 0$
 \rightarrow algebra!
3. identify the subset \mathcal{M} of \mathcal{R} for which $\dot{V}(x) = 0$ at all future times
 $\rightarrow \mathcal{M}$ must be invariant

[by Barbalat's Lemma]

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Invariant sets

- A set of points \mathcal{M} in state space is **invariant** if

$$x(t_0) \in \mathcal{M} \implies x(t) \in \mathcal{M} \quad \text{for all } t > t_0$$

Examples:

- ★ Equilibrium points
- ★ Limit cycles
- ★ Level sets of $V(x)$ provided $\dot{V}(x) \leq 0$ ← i.e. $\{x : V(x) \leq V_0\}$ for constant V_0

- If $\dot{V}(x) \rightarrow 0$ as $t \rightarrow \infty$, then

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Global invariant set theorem

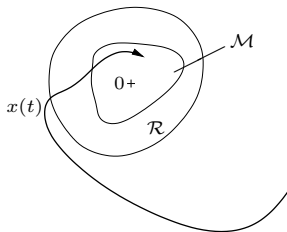
If there exists a continuously differentiable function $V(x)$ such that

$$\begin{aligned} V(x) &\text{ is positive definite} \\ \dot{V}(x) &\leq 0 \\ V(x) &\rightarrow \infty \text{ as } \|x\| \rightarrow \infty \end{aligned}$$

then: (i). $\dot{V}(x) \rightarrow 0$ as $t \rightarrow \infty$

(ii). $x(t) \rightarrow \mathcal{M} = \text{the largest invariant set contained in } \mathcal{R}$

where $\mathcal{R} = \{x : \dot{V}(x) = 0\}$



• $\dot{V}(x)$ negative definite $\implies \mathcal{M} = 0$

• Determine \mathcal{M} by considering system dynamics within \mathcal{R}

(c.f. Lyapunov's direct method)

Global invariant set theorem

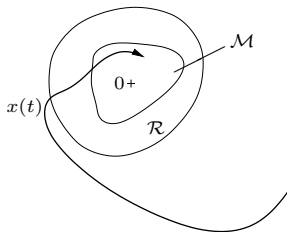
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Revisit m-s-d example (for the last time)

- $V(x)$ is positive definite, $V(x) \rightarrow \infty$ as $\|x\| \rightarrow \infty$, and

$$\dot{V}(y, \dot{y}) = -c(\dot{y})\dot{y} \leq 0$$

- therefore $\dot{V} \rightarrow 0$, implying $\dot{y} \rightarrow 0$ as $t \rightarrow \infty$
i.e. $\mathcal{R} = \{(y, \dot{y}) : \dot{y} = 0\}$
- but $\dot{y} = 0$ implies $\ddot{y} = -k(y)/m$
- therefore $\ddot{y} \neq 0$ unless $y = 0$, so $\dot{y}(t) = 0$ for all t only if $y(t) = 0$
i.e. $\mathcal{M} = \{(y, \dot{y}) : (y, \dot{y}) = (0, 0)\}$



$(y, \dot{y}) = (0, 0)$ is a globally asymptotically stable equilibrium!

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Local invariant set theorem

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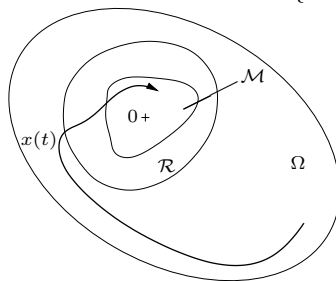
the level set $\Omega = \{x : V(x) \leq V_0\}$ is bounded for some V_0
and $\dot{V}(x) \leq 0$ whenever $x \in \Omega$

then: (i). Ω is an invariant set

(ii). $x(0) \in \Omega \implies \dot{V}(x) \rightarrow 0$ as $t \rightarrow \infty$

(iii). $x(t) \rightarrow \mathcal{M} = \text{largest invariant set contained in } \mathcal{R}$

where $\mathcal{R} = \{x : \dot{V}(x) = 0\}$



Local invariant set theorem

- $V(x)$ doesn't have to be positive definite or radially unbounded

- Result is based on Barbalat's Lemma applied to \dot{V}



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Example: local invariant set theorem

- Second order system: $\dot{x}_1 = x_2$
 $\dot{x}_2 = -(x_1 - 1)^2 x_2^3 - x_1 + \sin(\pi x_1/2)$

- Equilibrium points: $(x_1, x_2) = (0, 0), (1, 0), (-1, 0)$

- Trial storage function:

$$V(x) = \frac{1}{2}x_2^2 + \int_0^{x_1} (y - \sin(\pi y/2)) dy$$

V is not positive definite

but $V(x) \rightarrow \infty$ if $x_1 \rightarrow \infty$ or $x_2 \rightarrow \infty$



level sets of V are finite

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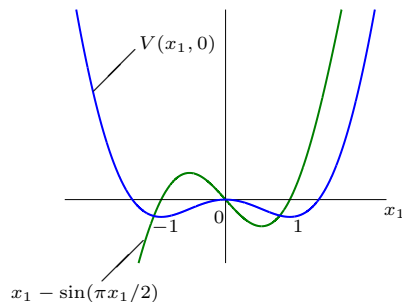
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Example: local invariant set theorem contd.

- Differentiate: $\dot{V}(x) = -(x_1 - 1)^2 x_2^4 \leq 0$

$$\dot{V}(x) = 0 \iff x \in \mathcal{R} = \{x : x_1 = 1 \text{ or } x_2 = 0\}$$

- From the system model, $x \in \mathcal{R}$ implies:

$$x_1 = 1 \implies (\dot{x}_1, \dot{x}_2) = (x_2, 0)$$

and

$$x_2 = 0 \implies (\dot{x}_1, \dot{x}_2) = (0, \sin(\pi x_1/2) - x_1)$$

therefore $\begin{cases} x(t) \text{ remains on line } x_1 = 1 \text{ only if } x_2 = 0 \\ x(t) \text{ remains on line } x_2 = 0 \text{ only if } x_1 = 0, 1 \text{ or } -1 \end{cases}$

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- Apply local invariant set theorem to any level set $\Omega = \{x : V(x) \leq V_0\}$:

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Example: local invariant set theorem contd.

- From any initial condition, $x(t)$ **converges asymptotically** to $(0,0)$, $(1,0)$ or $(-1,0)$
but $x = (0,0)$ is unstable
(linearized system at $(0,0)$ has poles $\pm\sqrt{\frac{\pi}{2}-1}$ so is unstable)
- Contours of $V(x)$:

Use local invariant set theorem on level sets $\Omega = \{x : V(x) \leq V_0\}$ for $V_0 < 0$

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 $x = (1,0), x = (-1,0)$ are **stable** equilibrium points

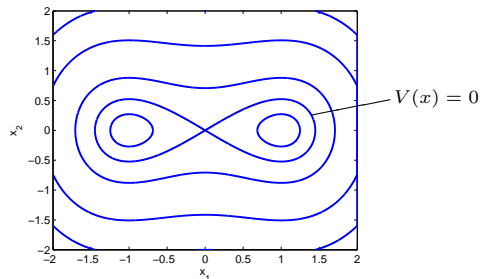
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- Convergence analysis using [Barbalat's lemma](#)
- [Invariant](#) sets
- Invariant set methods for convergence: [local](#) invariant set theorem
[global](#) invariant set theorem

Lecture 4

Linear systems, passivity, and the circle criterion

Linear systems, passivity, and the circle criterion

- Summary of stability methods
- Lyapunov functions for linear systems
- Passive systems
- Passive linear systems
- The circle criterion
- Example

Summary of stability methods

- Linearization method

$$\dot{x} = Ax \text{ is strictly stable, } A = \left. \frac{\partial f}{\partial x} \right|_{x=0}$$



$x = 0$ locally asymptotically stable

- Lyapunov's direct method

$V(x)$ locally p.d.

$$\dot{V}(x) \leq 0 \text{ locally}$$



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$$\left. \begin{array}{l} V(x) \text{ p.d.} \\ \dot{V}(x) \text{ p.d.} \end{array} \right\} \implies x = 0 \text{ unstable}$$

- Lyapunov stability criteria are only **sufficient**, e.g.

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$$x = 0 \text{ stable} \implies V(x) \text{ demonstrating stability exists}$$

(can swap premises and conclusions in Lyapunov's direct method)



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$\dot{x} = Ax$ strictly stable \implies can always find constant matrix P
so that $\dot{V}(x)$ is negative definite

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- How is P computed?

$$\left. \begin{array}{l} \dot{x} = Ax \\ V(x) = x^T P x \end{array} \right\} \implies \begin{array}{l} \dot{V}(x) = x^T P \dot{x} + \dot{x}^T P x \\ = x^T (PA + A^T P) x \end{array}$$

$\therefore x = 0$ is globally asymptotically stable if, for some Q :

$$PA + A^T P = -Q \quad Q = Q^T > 0$$

Lyapunov matrix equation

- Pick $Q > 0$ and solve $PA + A^T P = -Q$ for P , then

$$\operatorname{Re}[\lambda(A)] < 0 \iff \begin{array}{l} \text{unique solution for } P \\ \text{and } P = P^T > 0 \end{array}$$

Proof:

\Leftarrow due to $\dot{V}(x) = -x^T Q x$ negative definite

\Rightarrow follows from integrating \dot{V} w.r.t. t : $P = \int_0^\infty e^{A^T t} Q e^{A t} dt$

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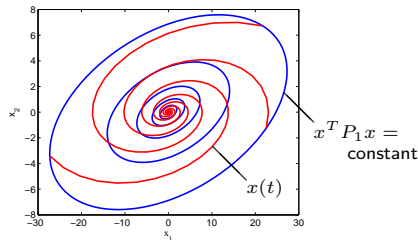
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Example: Lyapunov matrix equation

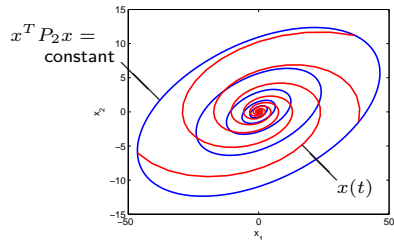
Stable linear system $\dot{x} = Ax$: $\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & -16 \\ 1 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ $\lambda(A) = -1 \pm i\sqrt{15}$

Solve $PA + A^T P = -Q$ for P :

$$Q_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \Rightarrow P_1 = \begin{bmatrix} 0.33 & -0.5 \\ -0.5 & 4.25 \end{bmatrix}$$



$$Q_2 = \begin{bmatrix} 0.41 & -0.19 \\ -0.19 & 0.11 \end{bmatrix} \Rightarrow P_2 = \begin{bmatrix} 0.12 & -0.21 \\ -0.21 & 1.67 \end{bmatrix}$$

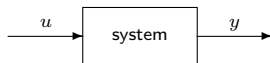


Here:

- ★ **any** choice of $Q > 0$ gives $P > 0$ (since A is strictly stable)
- ★ **but** not every $P > 0$ gives $Q > 0$

Passive systems

- **Systematic method** for constructing storage functions
- Input-output representation of system:



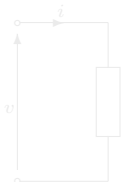
input : u
output : y

The system is **passive** if

$$\dot{V} = yu - g \quad \text{for some } V(t) \geq 0, \quad g(t) \geq 0$$

also the system is **dissipative** if $\int_0^\infty yu \, dt \neq 0 \implies \int_0^\infty g \, dt > 0$

- Motivated by electrical networks with no internal power generation

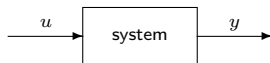


input: i
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stored energy: $V = \int_0^t vi \, dt$
 $\dot{V} = iv$

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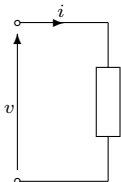
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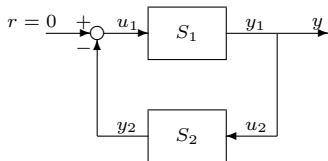


$$\left. \begin{array}{l} \text{input: } i \\ \text{output: } v \end{array} \right\} \quad \text{stored energy: } \begin{array}{l} V = \int_0^t vi \, dt \\ \dot{V} = iv \end{array}$$

Passive systems

Passivity is useful for determining storage functions for feedback systems

- Closed-loop system with passive subsystems S_1, S_2 :



$$S_1 : \quad V_1 \geq 0 \quad \dot{V}_1 = y_1 u_1 - g_1$$

$$S_2 : \quad V_2 \geq 0 \quad \dot{V}_2 = y_2 u_2 - g_2$$

$$V_1 + V_2 \geq 0$$

$$\begin{aligned} \dot{V}_1 + \dot{V}_2 &= y_1 u_1 + y_2 u_2 - g_1 - g_2 \\ &= y_1 (-y_2) + y_2 y_1 - g_1 - g_2 \\ &= -g_1 - g_2 \\ &\leq 0 \end{aligned}$$

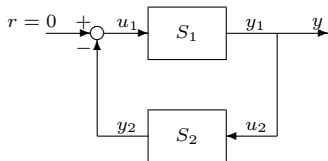
$\Rightarrow V = V_1 + V_2$ is a Lyapunov function for the closed-loop system

if V is a p.d. function of the system state

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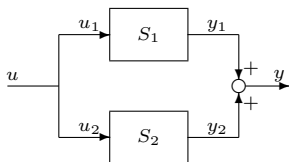
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Interconnected passive systems

- Parallel connection:



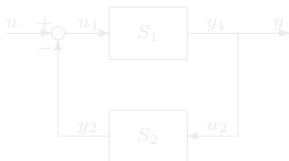
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$$\begin{aligned}\dot{V}_1 + \dot{V}_2 &= y_1 u_1 + y_2 u_2 - g_1 - g_2 \\ &= (y_1 + y_2)u - g_1 - g_2 \\ &= yu - g_1 - g_2\end{aligned}$$



Overall system from u to y is passive

- Feedback connection:



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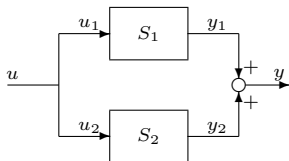
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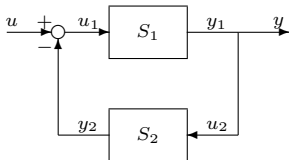
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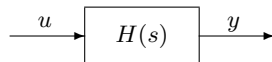
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Passive linear systems

Transfer function : $\frac{Y(s)}{U(s)} = H(s)$



- H is passive if and only if

- (i). $\operatorname{Re}(p_i) \leq 0$, where $\{p_i\}$ are the poles of $H(s)$
- (ii). $\operatorname{Re}[H(j\omega)] \geq 0$ for all $0 \leq \omega \leq \infty$

★ H must be stable, otherwise $V(t) = \int_0^t yu \, dt$ is not defined for all u

★ From Parseval's theorem:

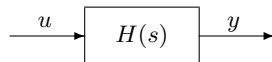
$$\operatorname{Re}[H(j\omega)] \geq 0 \iff \int_0^t yu \, dt \geq 0 \text{ for all } u(t) \text{ and } t$$

↗
frequency domain criterion for passivity

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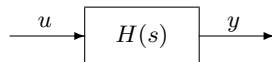
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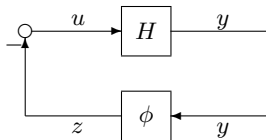
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Linear system + static nonlinearity



$$H \text{ linear: } \frac{Y(s)}{U(s)} = H(s)$$

$$\phi \text{ static nonlinearity: } z = \phi(y)$$

What are the conditions on H and ϕ for closed-loop stability?

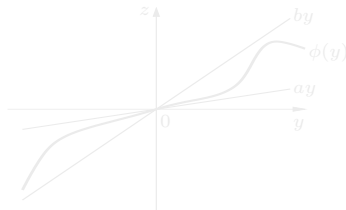
- A common problem in practice, due to e.g.
 - ★ actuator saturation (valves, dc motors, etc.)
 - ★ sensor nonlinearity
- Determine closed-loop stability given:

ϕ belongs to sector $[a, b]$

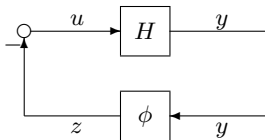


$$a \leq \frac{\phi(y)}{y} \leq b$$

"Absolute stability problem"



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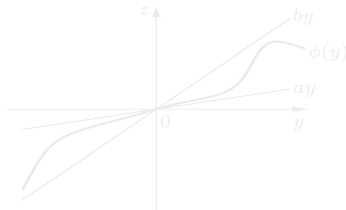
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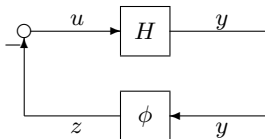


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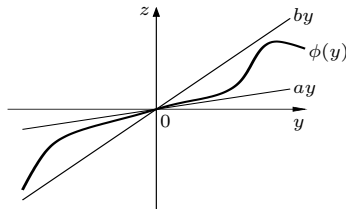
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- Aizerman's conjecture (1949):

Closed-loop system is stable if stable for $\phi(y) = ky$, $a \leq k \leq b$

false (necessary but not sufficient)

- Sufficient conditions for closed-loop stability:

Popov criterion (1960) } based on passivity
Circle criterion }

- The passivity approach:

(1). If H is dissipative (i.e. if $\operatorname{Re}[H(j\omega)] > 0$ and H is stable), then:

$$\left. \begin{aligned} V &= x^T P x \\ \dot{V} &= y u - x^T Q x \\ &= -y \phi(y) - x^T Q x \end{aligned} \right\} \text{ for some } P > 0, Q > 0$$

(2). If ϕ belongs to sector $[0, \infty)$, then:

$$y \phi(y) \geq 0$$

$$(1) \ \& \ (2) \implies \dot{V} \leq -x^T Q x$$

$$\implies x = 0 \text{ is globally asymptotically stable}$$



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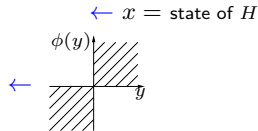
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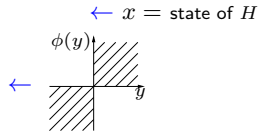
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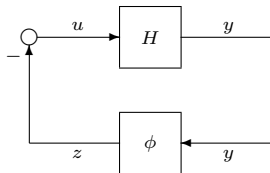
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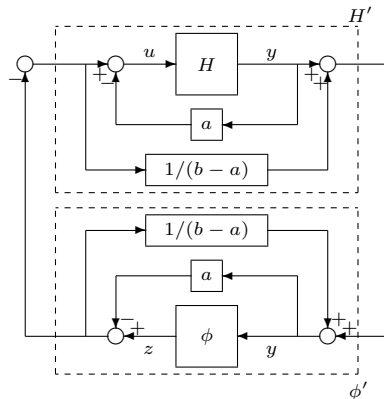


Circle criterion

Use **loop transformations** to generalize the approach for $\begin{cases} H \text{ not passive} \\ \phi \notin [0, \infty) \end{cases}$



\longleftrightarrow
equiv. to



$\phi \in [a, b]$ a, b arbitrary

$$\phi \in [a, b] \implies \phi' \in [0, \infty]$$

$$H'(j\omega) = \frac{H(j\omega)}{1 + aH(j\omega)} + \frac{1}{b - a}$$

Circle criterion

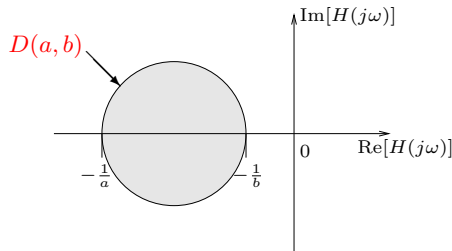
To make $H'(j\omega) = \frac{H(j\omega)}{1 + aH(j\omega)} + \frac{1}{b-a}$ dissipative, need:

$$(i). H' \text{ stable} \iff \frac{H(j\omega)}{1 + aH(j\omega)} \text{ stable}$$
$$\Updownarrow$$

Nyquist plot of $H(j\omega)$ goes through ν anti-clockwise encirclements of $-1/a$ as ω goes from $-\infty$ to ∞

(ν = no. poles of $H(j\omega)$ in RHP)

$$(ii). \operatorname{Re}[H'(j\omega)] > 0 \iff \begin{cases} H(j\omega) \text{ lies outside } D(a,b) & \text{if } ab > 0 \\ H(j\omega) \text{ lies inside } D(a,b) & \text{if } ab < 0 \end{cases}$$



Graphical interpretation of circle criterion

$x = 0$ is globally asymptotically stable if:

★ $0 < a < b$

$H(j\omega)$ lies in shaded region and does ν anti-clockwise encirclements of $D(a, b)$

★ $b > a = 0$

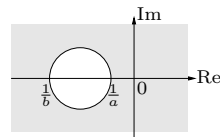
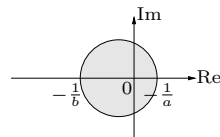
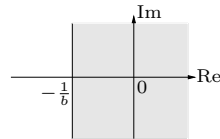
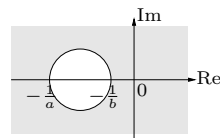
$H(j\omega)$ lies in shaded region and $\nu = 0$
(can't encircle $-1/a$)

★ $a < 0 < b$

$H(j\omega)$ lies in shaded region and $\nu = 0$
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★ $a < b < 0$

$-H(j\omega)$ lies in shaded region and does ν anti-clockwise encirclements of $D(-b, -a)$



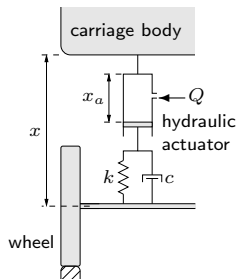
- Circle criterion is **equivalent** to Nyquist criterion for $a = b > 0$

$$\begin{array}{c} \uparrow \\ \text{then } D(a, b) = -\frac{1}{a} \text{ (single point)} \end{array}$$

- Circle criterion is only **sufficient** for closed-loop stability for general a, b
- Results apply to time-varying static nonlinearity: $\phi(y, t)$

Example: Active suspension system

- Active suspension system for high-speed train:



$$Q = \phi(u)$$

$$\dot{x}_a = Q/A$$

u : valve input signal

Q : flow rate

ϕ : valve characteristics, $\phi \in [0.005, 0.1]$

A : actuator working area

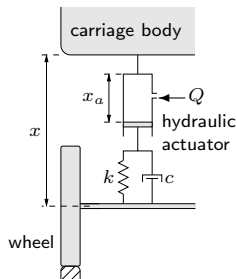
- Force exerted by suspension system on carriage body: F_{susp}

$$\begin{aligned} F_{\text{susp}} &= k(x_a - x) + c(\dot{x}_a - \dot{x}) \\ &= (k \int^t Q dt + cQ)/A - kx - c\dot{x}, \quad Q = \phi(u) \end{aligned}$$

- Design controller to compensate for the effects of (constant) unknown load on displacement x despite uncertain valve characteristics $\phi(u)$.

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Active suspension system contd.

- Dynamics:

$$F_{\text{susp}} - F = m\ddot{x}$$
$$\implies m\ddot{x} + c\dot{x} + kx = (k \int^t Q dt + cQ)/A - F, \quad Q = \phi(u)$$

F : unknown load on suspension unit

m : effective carriage mass

- Transfer function model:

$$X(s) = \frac{cs + k}{ms^2 + cs + k} \cdot \frac{Q(s)}{As} - \frac{F}{ms^2 + cs + k} \quad Q = \phi(u)$$

- Try linear compensator $C(s)$:

$$U(s) = C(s)E(s) \quad e = -x, \quad \text{setpoint: } x = 0$$



Active suspension system contd.

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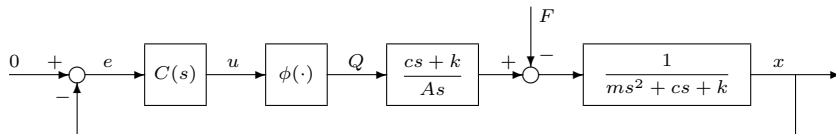
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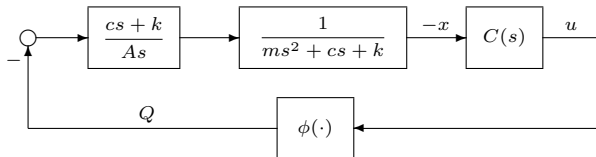
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Active suspension system contd.

- For constant F , we need to stabilize the closed-loop system:



linear system: $H(s) = \frac{cs + k}{As(ms^2 + cs + k)} \cdot C(s)$

static nonlinearity: $\phi \in [0.005, 0.1]$

- P+D compensator (no integral term needed):

$$C(s) = K(1 + \alpha s) \implies H(s) = \frac{K(1 + \alpha s)(cs + k)}{As(ms^2 + cs + k)}$$

H open-loop stable ($\nu = 0$)

- From the circle criterion, closed-loop (global asymptotic) stability is ensured if:

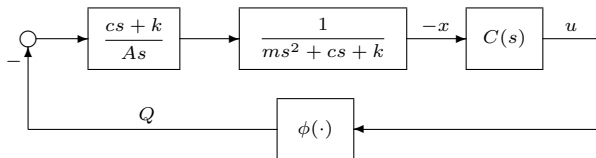
$$H(j\omega) \text{ lies outside } D(0.005, 0.1)$$

↑

sufficient condition: $\text{Re}[H(j\omega)] > -10$

Active suspension system contd.

- For constant F , we need to stabilize the closed-loop system:



linear system: $H(s) = \frac{cs + k}{As(ms^2 + cs + k)} \cdot C(s)$

static nonlinearity: $\phi \in [0.005, 0.1]$

- P+D compensator (no integral term needed):

$$C(s) = K(1 + \alpha s) \implies H(s) = \frac{K(1 + \alpha s)(cs + k)}{As(ms^2 + cs + k)}$$

H open-loop stable ($\nu = 0$)

- From the circle criterion, closed-loop (global asymptotic) stability is ensured if:

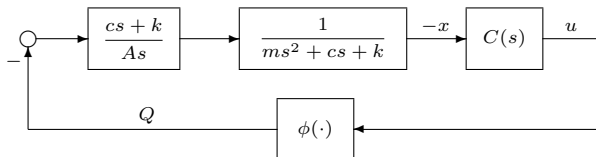
$$H(j\omega) \text{ lies outside } D(0.005, 0.1)$$

↑

sufficient condition: $\text{Re}[H(j\omega)] > -10$

Active suspension system contd.

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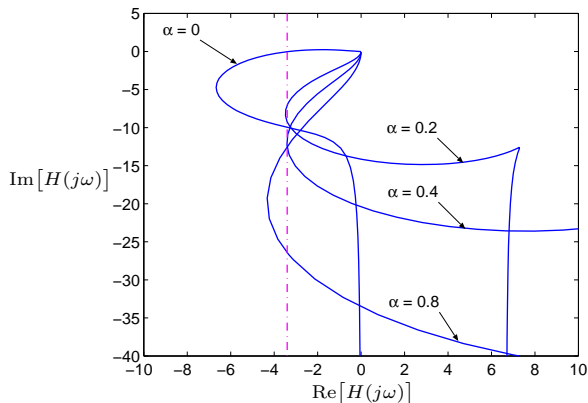
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sufficient condition: $\text{Re}[H(j\omega)] > -10$

Active suspension system contd.

- Nyquist plot of $H(j\omega)$ for $K = 1$ and $\alpha = 0, 0.2, 0.4, 0.8$:



- To maximize gain margin:

choose $\alpha = 0.2$

$$K \leq 10/3.4 = 2.94$$

← allows for largest K

At the end of the course you should be able to do the following:

- Understand the basic Lyapunov stability definitions (lecture 1)
- Analyse stability using the linearization method (lecture 2)
- Analyse stability by Lyapunov's direct method (lecture 2)
- Determine convergence using Barbalat's Lemma (lecture 3)
- Understand how invariant sets can determine regions of attraction (lecture 3)
- Construct Lyapunov functions for linear systems and passive systems (lecture 4)
- Use the circle criterion to design controllers for systems with static nonlinearities (lecture 4)

Addendum – Limit cycle stability analysis

System has state $x = (x_1, x_2)$ and dynamics:

$$\dot{x}_1 = -x_2 - x_1 h(x)$$

$$\dot{x}_2 = x_1 - x_2 h(x)$$

where $h(x) = x_1^2 + x_2^2 - 1$.

Limit cycle

Differentiate $h(x)$ w.r.t. t using system dynamics:

$$\dot{h} = 2x_1\dot{x}_1 + 2x_2\dot{x}_2 = -2(x_1^2 + x_2^2)h(x) = -2(h+1)h$$

hence $h = 0 \implies \dot{h} = 0$, so $\{x : x_1^2 + x_2^2 = 1\}$ must contain a limit cycle.

Addendum – Limit cycle stability analysis

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$$\dot{x}_1 = -x_2 - x_1 h(x)$$

$$\dot{x}_2 = x_1 - x_2 h(x)$$

where $h(x) = x_1^2 + x_2^2 - 1$.

Limit cycle stability

Let $V(x) = h^2(x)$, then $\dot{V} = 2h\dot{h} = -4h^2(h+1)$
 $= -4h^2(x)(x_1^2 + x_2^2) \leq 0$

- $\{x : V(x) \leq c\}$ is an **invariant set** for any constant c
and $\{x : V(x) = 0\} = \{x : x_1^2 + x_2^2 = 1\}$ is **stable**
- $\dot{V} = 0 \implies h = 0$ (or $x_1 = x_2 = 0$)
 $h = 0 \implies \dot{h} = 0$
 \implies the limit cycle $\{x : h = 0\}$ is the largest invariant set
contained in $\{x : V(x) < 1 \text{ and } \dot{V}(x) = 0\}$, so is **asymptotically stable**