

# Lyapunov methods in robustness—Part E

Franco Blanchini<sup>1</sup>

<sup>1</sup>Dipartimento di Matematica e Informatica  
Università degli Studi di Udine

May 11, 2016

# Robotic manipulators 1

A preliminary result. Consider the system

$$\dot{x}(t) = f(x(t), w(t)) + B(I + \Delta_B)u$$

where  $\Delta_B(x(t), w(t))$  represents a matched uncertainty.

## Proposition

*Assume that  $\Psi(x)$  is a control Lyapunov function with associated with*

$$u = -\gamma B^T \nabla \Psi(x)^T$$

*for the system with  $\Delta_B = 0$ . Then it is also a CLF for the uncertain system provided that*

$$\Delta_B^T \Delta_B < \lambda^2 I, \quad \text{with } \lambda < 1.$$

$$\begin{aligned}\dot{\Psi}(x) &= \nabla\Psi(x)f(x(t), w(t)) - \gamma\nabla\Psi(x)BB^T\nabla\Psi(x)^T \\ &\quad - \gamma\nabla\Psi(x)B\Delta_B B^T\nabla\Psi(x)^T = \\ &= \nabla\Psi(x)f(x(t), w(t)) - (1-\lambda)\gamma\nabla\Psi(x)BB^T\nabla\Psi(x)^T \\ &\quad \underbrace{- \gamma\nabla\Psi(x)B(\lambda I - \Delta_B)B^T\nabla\Psi(x)^T}_{\leq 0} \\ &\leq \nabla\Psi(x)f(x(t), w(t)) - \hat{\gamma}\nabla\Psi(x)BB^T\nabla\Psi(x)^T \leq -\phi(\|x\|)\end{aligned}$$

where  $\hat{\gamma} = (1-\lambda)\gamma$ .

The prize to contrast  $\Delta_B$  is to increase  $\gamma$  as  $\gamma = \hat{\gamma}/(1-\lambda)$ .

# Robotic manipulators 3

A typical robotic manipulator has equation

$$M(q(t))\ddot{q}(t) + H(q(t), \dot{q}(t))\dot{q}(t) + G(q(t)) = \tau(t)$$

$M(q)$  nonsingular for all  $q$ .

# Robotic manipulators 3

A typical robotic manipulator has equation

$$M(q(t))\ddot{q}(t) + H(q(t), \dot{q}(t))\dot{q}(t) + G(q(t)) = \tau(t)$$

$M(q)$  nonsingular for all  $q$ .

## Procedure

- *Consider the control*

$$\tau(t) = M(q)u(t) + H(q, \dot{q})\dot{q} + G(q)$$

*the resulting system is  $M(q(t))[\ddot{q}(t) - u(t)] = 0$*

- *Since  $M(q)$  is invertible we get  $m$  decoupled equations*

$$\ddot{q}_i(t) = u_i(t).$$

Problem: the model is uncertain, so we must consider an estimated model.

$$\tau = \tilde{M}(q)u(t) + \tilde{H}(q, \dot{q})\dot{q} + \tilde{G}(q)$$

$$\begin{aligned}\ddot{q}(t) = & u + \underbrace{M(q)^{-1}[\tilde{M}(q) - M(q)]}_{-I + \Delta_B} u(t) + \\ & + \underbrace{M(q)^{-1}[\tilde{H}(q, \dot{q}) - H(q, \dot{q})]\dot{q} + M(q)^{-1}[\tilde{G}(q) - G(q)]}_{\Delta_f}\end{aligned}$$

$$\ddot{q}(t) = [I + \Delta_B]u(t) + \Delta_f$$

If  $\tilde{M}(q)$  is a sufficiently accurate estimate of  $M(q)$  we can assume that

$$\Delta_B = M^{-1}(\tilde{M} - M)$$

satisfies

$$\Delta_B^T \Delta_B < \lambda^2 I, \quad \text{with } \lambda < 1.$$

along with

$$\|\Delta_f(q, \dot{q})\| \leq \alpha + \beta \|x\|.$$

## Procedure



## Procedure

- 1 Apply the feedback  $\tau = \tilde{M}(q)u(t) + \tilde{H}(q, \dot{q})\dot{q} + \tilde{G}(q)$

## Procedure

- 1 Apply the feedback  $\tau = \tilde{M}(q)u(t) + \tilde{H}(q, \dot{q})\dot{q} + \tilde{G}(q)$
- 2 Consider the nominal system  $\ddot{q} = u$  (assume  $\Delta_B = 0$ ,  $\Delta_f = 0$ )

$$A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ I \end{bmatrix}$$

## Procedure

- 1 Apply the feedback  $\tau = \tilde{M}(q)u(t) + \tilde{H}(q, \dot{q})\dot{q} + \tilde{G}(q)$
- 2 Consider the nominal system  $\ddot{q} = u$  (assume  $\Delta_B = 0$ ,  $\Delta_f = 0$ )

$$A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ I \end{bmatrix}$$

- 3 Find a control  $u(t) = -\gamma B^T P x(t)$  and the CLF  $x^T P x$ ,

$$QA^T + AQ + R^T B^T + BR = -S < 0, \quad P = Q^{-1}$$

## Procedure

- 1 Apply the feedback  $\tau = \tilde{M}(q)u(t) + \tilde{H}(q, \dot{q})\dot{q} + \tilde{G}(q)$
- 2 Consider the nominal system  $\ddot{q} = u$  (assume  $\Delta_B = 0$ ,  $\Delta_f = 0$ )

$$A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ I \end{bmatrix}$$

- 3 Find a control  $u(t) = -\gamma B^T P x(t)$  and the CLF  $x^T P x$ ,

$$QA^T + AQ + R^T B^T + BR = -S < 0, \quad P = Q^{-1}$$

- 4 Practically stabilize the actual system by taking  $\gamma$  large.

# Robotic manipulators 7

First assume  $\Delta_B = 0$ . It can be shown that

$$\alpha \|B^T Sx\| - \gamma \|B^T Sx\|^2 \leq \frac{\alpha}{2\gamma}.$$

Fix  $\varepsilon > 0$   $\gamma_\varepsilon$  such that, for  $x^T P x > \varepsilon$ ,  $x^T Sx/2 \geq \alpha/2\gamma_\varepsilon$ . Let  $\sigma_{\min}(S) > 0$  the smallest eigenvalue of  $S$

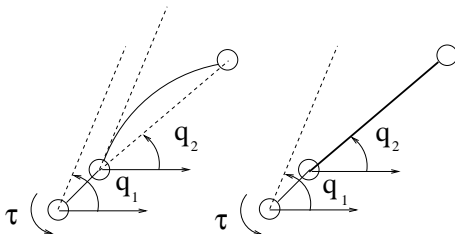
$$\begin{aligned}\dot{\Psi}(x) &= -x^T Sx + x^T SB\Delta_f - \hat{\gamma} x^T SBB^T Sx \\ &\leq -x^T Sx + \alpha \|B^T Sx\| + \beta \|B^T Sx\| \|x\| - \hat{\gamma} \|B^T Sx\|^2 = \\ &= -x^T Sx/2 + \beta \|B^T Sx\| \|x\| - (\gamma - \gamma_\varepsilon) \|B^T Sx\|^2 \\ &\quad + \underbrace{-x^T Sx/2 + \alpha \|B^T Sx\| - \hat{\gamma}_\varepsilon \|B^T Sx\|^2}_{\leq 0} \\ &\leq -\sigma_{\min}(S) \|x\|^2/2 + \beta \|B^T Sx\| \|x\| - (\hat{\gamma} - \gamma_\varepsilon) \|B^T Sx\|^2 < 0\end{aligned}$$

For  $\hat{\gamma}$  large enough. Finally accommodate  $\Delta_B$  by taking  $\gamma = \hat{\gamma}/(1 - \lambda)$ .

# Robotic manipulators 8

The case with elastic joint Spong (1998) can be modeled as follows.

$$\begin{aligned}M(q_2)\ddot{q}_2 + C(\dot{q}_2, q_2)\dot{q}_2 + g(q_2) + K(q_1 - q_2) &= 0 \\ J\ddot{q}_1 + K(q_2 - q_1) &= \tau\end{aligned}$$



Strict feedback form: backstepping applies.

# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

- $q(t)$  is an uncontrolled (exogenously determined) unknown to the controller;



# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

- $q(t)$  is an uncontrolled (exogenously determined) unknown to the controller;
- $q(t)$  is an uncontrolled (exogenously determined) but known to the controller;

# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

- $q(t)$  is an uncontrolled (exogenously determined) unknown to the controller;
- $q(t)$  is an uncontrolled (exogenously determined) but known to the controller;
- $q(t)$  is a controlled switching signal

# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

- $q(t)$  is an uncontrolled (exogenously determined) unknown to the controller;
- $q(t)$  is an uncontrolled (exogenously determined) but known to the controller;
- $q(t)$  is a controlled switching signal
- We say **switching systems** if  $q(t)$  is uncontrolled;

# Switching and switched systems 1

A switching system is a system of the form

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

with  $q(t) \in \mathcal{Q}$ , a finite set. Important cases:

- $q(t)$  is an uncontrolled (exogenously determined) unknown to the controller;
- $q(t)$  is an uncontrolled (exogenously determined) but known to the controller;
- $q(t)$  is a controlled switching signal
- We say **switching systems** if  $q(t)$  is uncontrolled;
- We say **switched systems** if  $q(t)$  is controlled.

# Switching and switched systems 2

Uncontrolled switch – stability.

$$\dot{x}(t) = f(x(t), p(t))$$

We have to cope with the condition

$$\dot{\Psi}(x, p) = \nabla \Psi(x) f(x, p) \leq -\phi(\|x\|). \quad \forall p \in \mathcal{P}$$

$\mathcal{P} = \{1, 2, \dots, N_P\}$ . The previous condition is equivalent to

$$\dot{\Psi}(x, \alpha) = \sum_{p=1}^{N_p} \alpha_p \nabla \Psi(x) f(x, p) \leq -\phi(\|x\|)$$

In the linear case the stability of

$$\dot{x}(t) = A_p x(t), \quad \text{and of} \quad \dot{x}(t) = \left[ \sum_{p=1}^{N_p} \alpha_p A_p \right] x(t)$$

are equivalent and they can be analyzed as previously described.

# Switching and switched systems 3

Switched systems – stabilizability.

$$\dot{x}(t) = f(x(t), p(t)), \text{ (} p \text{ is the control).}$$

# Switching and switched systems 3

Switched systems – stabilizability.

$$\dot{x}(t) = f(x(t), p(t)), \text{ (} p \text{ is the control).}$$

## Proposition

*Assume that there exist a system  $\dot{x}(t) = \bar{f}(x)$  which is stable with Lyapunov function*

$$\nabla \Psi(x) \bar{f}(x) \leq -\phi(\|x\|)$$

*and such that  $\bar{f}(x) \in \text{conv}\{f(x, p), p = 1, 2, \dots, N_p\}$ , then there exists a stabilizing strategy of the form*

$$p = \Phi(x) = \arg \min_p \nabla \Psi(x) f(x, p)$$

# Switching and switched systems 3

Switched systems – stabilizability.

$$\dot{x}(t) = f(x(t), p(t)), \quad (p \text{ is the control}).$$

## Proposition

*Assume that there exist a system  $\dot{x}(t) = \bar{f}(x)$  which is stable with Lyapunov function*

$$\nabla \Psi(x) \bar{f}(x) \leq -\phi(\|x\|)$$

*and such that  $\bar{f}(x) \in \text{conv}\{f(x, p), p = 1, 2, \dots, N_p\}$ , then there exists a stabilizing strategy of the form*

$$p = \Phi(x) = \arg \min_p \nabla \Psi(x) f(x, p)$$

It is immediately seen that

$$\min_p \nabla \Psi(x) f(x, p) \leq \nabla \Psi(x) \bar{f}(x) \leq -\phi(\|x\|)$$



# Switching and switched systems 4

In the case of a switched linear plant

$$\dot{x}(t) = A_i x(t), \quad i = 1, 2, \dots, r$$

the problem is easily solved if there exists

$$\tilde{A} \in \text{conv}\{A_i\}$$

which is stable. Take positive definite matrix  $P$  such that

$$\tilde{A}^T P + P \tilde{A} \leq -x^T Q x, \quad Q > 0$$

Then the control law

$$\Phi(x) = \arg \min_i \dot{\Psi}(x) = \arg \min_i x^T P A_i x,$$

assures the condition

$$\dot{\Psi}(x) \leq -x^T Q x$$

## Example

The existence of such a stable  $\tilde{A}$  is not necessary.

$$A(w) = \begin{bmatrix} 0 & 1 \\ -1+w & -a \end{bmatrix}$$

where  $a < 0$  is not stable for any value of  $a$ . If  $w \in \{-\bar{w}, \bar{w}\} < 1$  is a switched parameter and  $a$  is small enough, then there exists a stabilizing strategy.

## Example

There exists linear switched systems which can be stabilized by a control law of the form  $i = i(x)$  but do not admit [convex](#) control–Lyapunov functions. For instance

$$A_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} A_2 = \begin{bmatrix} \gamma & -1 \\ 1 & \gamma \end{bmatrix}$$

is an example (Blanchini and Savorgnan 2008).

## Example

There exists linear switched systems which can be stabilized by a control law of the form  $i = i(x)$  but do not admit **convex** control–Lyapunov functions. For instance

$$A_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad A_2 = \begin{bmatrix} \gamma & -1 \\ 1 & \gamma \end{bmatrix}$$

is an example (Blanchini and Savorgnan 2008).

## Claim

*The same problem holds if we replace **convex** by **smooth**.*

# Switching and switched systems 6

## Example

There exists linear switched systems which can be stabilized by a control law of the form  $i = i(x)$  but do not admit **convex** control–Lyapunov functions. For instance

$$A_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad A_2 = \begin{bmatrix} \gamma & -1 \\ 1 & \gamma \end{bmatrix}$$

is an example (Blanchini and Savorgnan 2008).

## Claim

*The same problem holds if we replace **convex** by **smooth**.*

## Claim

*The problem is more difficult than the switching stability case!*

# Switching and switched systems 7

Stabilization problem

$$\dot{x}(t) = A_i x(t) + B_i u(t)$$

If in the convex hull there exists a stabilizable systems

$$[\tilde{A}, \tilde{B}] = [\sum_{i=1}^s w_i A_i, \sum_{i=1}^s w_i B_i], \quad \sum_{i=1}^s w_i = 1, \quad w_i \geq 0.$$

We can consider a stabilizing feedback  $u = \tilde{K}x$ , so that

$$\tilde{A} + \tilde{B}\tilde{K} = \sum_{i=1}^s w_i [A_i + \tilde{K}B_i] = \sum_{i=1}^s w_i [\hat{A}_i]$$

and we can subsequently apply the strategy to the switched system.

# Switched fluid system 1



## Example

Convergence speed-up.

$$\begin{aligned}\dot{h}_1(t) &= -\alpha \sqrt{x_1(t) + \bar{h}_1 - x_2(t) - \bar{h}_2} + u(t) + \bar{q} \\ \dot{h}_2(t) &= \alpha \sqrt{x_1(t) + \bar{h}_1 - x_2(t) - \bar{h}_2} - \beta \sqrt{x_2(t) + \bar{h}_2}\end{aligned}$$

The steady state conditions

$$\bar{h}_1 = \left(\frac{\bar{q}}{\alpha}\right)^2 + \left(\frac{\bar{q}}{\beta}\right)^2, \quad \bar{h}_2 = \left(\frac{\bar{q}}{\beta}\right)^2.$$

The system is stable. The problem is to improve convergence.



# Switched fluid system 3

Candidate Lyapunov function

$$\Psi(x) = \frac{1}{2} (x_1^2 + x_2^2)$$

The derivative is

$$\begin{aligned} \dot{\Psi}(x, u) &= \\ &= \underbrace{\alpha(x_1 - x_2) \left( \sqrt{x_1(t) + \bar{h}_1} - x_2(t) - \bar{h}_2 - \bar{q} \right) + x_2 \left( \beta \sqrt{x_2(t) + \bar{h}_2} - \bar{q} \right)}_{\doteq \dot{\Psi}_N(x)} \\ &+ x_1 u \leq \underbrace{\dot{\Psi}_N(x)}_{\leq -\phi_N(\|x\|)} + x_1 u \end{aligned}$$

Note that  $\dot{\Psi}_N(x) \leq -\phi_N(x_1, x_2)$ , the “natural derivative”, is negative definite: the system is stable.

# Switched fluid system 4

Control input admits three values

$$u(t) \in \{-\bar{q}; 0, \bar{q}\}$$

We can take the switching law that minimizes the derivative

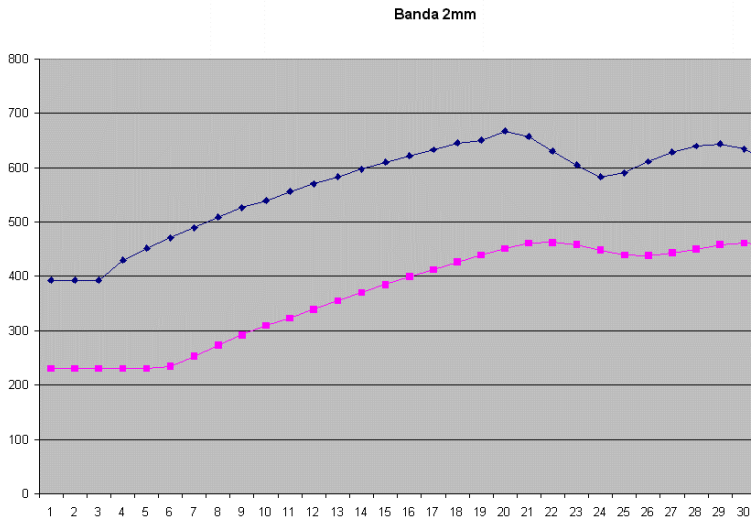
$$\dot{\Psi}(x, u) = \dot{\Phi}_N(x_1, x_2) + x_1 u$$

$$u = -\bar{q} \operatorname{sgn}(x_1)$$

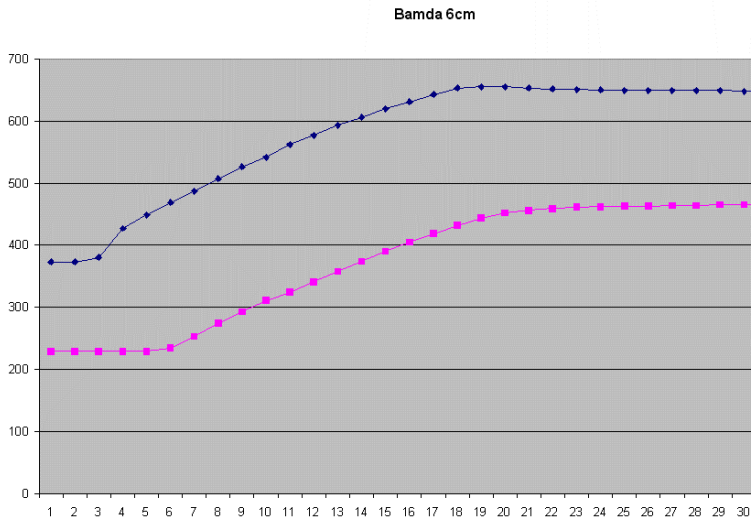
From a practical point of view, the controller has to be implemented with a threshold.

$$u = \begin{cases} -\bar{q} \operatorname{sgn}(x_1) & \text{if } |x_1| > \varepsilon \\ 0 & \text{if } |x_1| \leq \varepsilon \end{cases}$$

# Switched fluid system 5



# Switched fluid system 6



# Limitations of Lyapunov approach to robustness 1

# Limitations of Lyapunov approach to robustness 1

- It is not always clear how to choose a candidate Lyapunov function.

# Limitations of Lyapunov approach to robustness 1

- It is not always clear how to choose a candidate Lyapunov function.
- The theory basically works for state-feedback types of controls, the output feedback is still a very hard problem to be faced by means of these tools.

# Limitations of Lyapunov approach to robustness 1

- It is not always clear how to choose a candidate Lyapunov function.
- The theory basically works for state-feedback types of controls, the output feedback is still a very hard problem to be faced by means of these tools.
- The theory is conservative when we deal with constant uncertain parameter or slowly time-varying parameters.



# Advantages of Lyapunov approach to robustness 1

# Advantages of Lyapunov approach to robustness 1

- This theory provides necessary and sufficient conditions when dealing with uncertain systems with time-varying parameters.

# Advantages of Lyapunov approach to robustness 1

- This theory provides necessary and sufficient conditions when dealing with uncertain systems with time-varying parameters.
- The theory proposes techniques that are effective and insightful.

# Advantages of Lyapunov approach to robustness 1

- This theory provides necessary and sufficient conditions when dealing with uncertain systems with time-varying parameters.
- The theory proposes techniques that are effective and insightful.
- For important classes of problems and special classes of functions the theory is supported by efficient numerical tools such as those based on LMIs.

# Advantages of Lyapunov approach to robustness 1

- This theory provides necessary and sufficient conditions when dealing with uncertain systems with time-varying parameters.
- The theory proposes techniques that are effective and insightful.
- For important classes of problems and special classes of functions the theory is supported by efficient numerical tools such as those based on LMIs.
- There is no valid alternative to Lyapunov theory for nonlinear uncertain systems.

*Merci!*