

# Sampled-Data Control Design A Differential LMI Approach

**José C. Geromel**

School of Electrical and Computer Engineering  
UNICAMP, Brazil

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# Outline

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# Notation

- ▶ Real ( $\mathbb{R}$ ), nonnegative real ( $\mathbb{R}_+$ ) and natural numbers ( $\mathbb{N}$ )
- ▶ The **trace** function is  $\mathbf{tr}(\cdot)$
- ▶ Positive definite symmetric real matrix  $X > 0$
- ▶ Maximum eigenvalue  $\sigma_{max}(\cdot)$
- ▶ Norm bounded signals - continuous  $\mathcal{L}_2$  and discrete-time  $\ell_2$
- ▶  $\psi(t^-) = \lim_{\varepsilon \rightarrow 0^-} \psi(t + \varepsilon)$
- ▶  $f(t_k) = f(t)|_{t=t_k}$  for  $k \in \mathbb{N}$  is denoted  $f[k]$

# Motivation

► **Stability:** Matrix  $A \in \mathbb{R}^{n \times n}$  is

- Hurwitz stable  $\operatorname{Re}\{\lambda_i(A)\} < 0, \forall i = 1, \dots, n$
- Schur stable  $|\lambda_i(A)| < 1, \forall i = 1, \dots, n$

↓

**Simple and useful relationship:** For any  $h > 0$

$A$  Hurwitz stable  $\iff e^{Ah}$  Schur stable

# Motivation

- ▶ Consider  $h > 0$  and a polytopic convex set  $\mathcal{A}_c \subset \mathbb{R}^{n \times n}$

$$\underbrace{\mathcal{A}_d}_{\text{generic!}} = \left\{ e^{Ah} : A \in \underbrace{\mathcal{A}_c}_{\text{polytopic}} \right\}$$

- ▶ **Robust stability (analysis):**

$$\underbrace{\forall A \in \mathcal{A}_c}_{\text{Hurwitz}} \iff \underbrace{\forall e^{Ah} \in \mathcal{A}_d}_{\text{Schur}}$$

# Motivation

- ▶ **Robust stability (synthesis):**

- ▶ Find a matrix  $L$  of appropriate dimensions

$$\underbrace{e^{Ah} + \left( \int_0^h e^{A\tau} B d\tau \right) L}_{\text{Schur}} \Leftarrow \forall (A, B) \in \mathcal{A}_c \times \mathcal{B}_c$$

- ▶ Nonlinear and nonconvex parameter dependence
- ▶ **Hard to solve**
- ▶ Robust performance similar difficulty!

# Motivation

## ► Quadratic stability:

- Continuous-time polytopic system

$$A'S + SA < 0, S > 0, \forall A \in \mathcal{A}_c$$

$$\Downarrow \forall h > 0$$

- Sampled-data polytopic system

$$\begin{cases} \dot{P}(t) + A'P(t) + P(t)A < 0 \\ P(0) = P(h) = S > 0 \end{cases} \quad t \in [0, h), \forall A \in \mathcal{A}_c$$



$$e^{A'h} S e^{Ah} - S < 0, S > 0, \forall A \in \mathcal{A}_c$$

# Motivation

- ▶ **Differential Linear Matrix Inequality (DLMI):** General form arising in  $\mathcal{H}_\infty$  control design

$$\begin{bmatrix} \dot{P}(t) + F'P(t) + P(t)F & P(t)J & G' \\ \bullet & -\gamma^2 I & 0 \\ \bullet & \bullet & -I \end{bmatrix} < 0, \quad t \in [0, h)$$

$$P(0), P(h) \iff LMI$$

- ▶ **Linearity** with respect to the parameters
- ▶ Feasible solution  $P(t)$  of specific form:

piecewise linear (Allerhand & Shaked, 2013) and (Briat, 2013)  
polynomial, *sinc*( $\cdot$ ) functions, ...



# Motivation

- ▶ **Sampled-data control:** Zero order hold

$$u \in \mathcal{U} \iff u(t) = \underbrace{u[k]}_{u(t_k)}, \quad \forall t \in [t_k, t_{k+1}), \quad \forall k \in \mathbb{N}$$

- ▶ Sampling times  $t_0 = 0$ ,  $t_{k+1} - t_k = h > 0$ ,  $\forall k \in \mathbb{N}$
- ▶  $\mathcal{H}_2$  and  $\mathcal{H}_\infty$  optimization subject to  $u \in \mathcal{U}$
- ▶ Three seminal books:

J. R. Ragazzini & G. F. Franklin, 1958

T. Chen & B. A. Francis, 1995

A. Ichicawa & H. Katayama, 2001

# Sampled-data control

▶ LTI plant

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t) + E_c w_c(t), \quad x(0) = x_0 \\ z(t) &= C_c x(t) + D_c u(t)\end{aligned}$$

- ▶  $x(\cdot) \in \mathbb{R}^{n_x}$  is the state
- ▶  $w_c(\cdot) \in \mathbb{R}^{r_c}$  is the exogenous continuous-time input
- ▶  $z(\cdot) \in \mathbb{R}^{n_z}$  is the controlled output
- ▶  $u(\cdot) \in \mathbb{R}^{n_u}$  is the control input

$$u \in \mathcal{U} \iff u(t) = u[k], \quad t \in [t_k, t_{k+1}), \quad \forall k \in \mathbb{N}$$

## Sampled-data control

- ▶ State feedback with control noise

$$u[k] = \hat{C}x[k] + E_d \underbrace{w_d[k-1]}_{\in \mathbb{R}^{r_d}}$$

- ▶ Dynamic output feedback with measurement noise

$$\underbrace{y[k]}_{\in \mathbb{R}^{n_y}} = C_d x[k] + E_d w_d[k-1]$$

$$\begin{aligned}\hat{x}[k] &= \hat{A}\hat{x}[k-1] + \hat{B}y[k] \\ u[k] &= \hat{C}\hat{x}[k-1] + \hat{D}y[k]\end{aligned}$$

- ▶ Initial condition  $\hat{x}[-1] = 0$
- ▶ Full order controller  $\hat{x}[\cdot] \in \mathbb{R}^{n_c}$  with  $n_c = n_u + n_x!$

# Sampled-data control

- ▶ **Sampled-data control design in a general framework**



Hybrid Systems



# Sampled-data control

- ▶ **Sampled-data control design in a general framework**



Hybrid Systems



Bellman's Principle of Optimality

# Hybrid systems

- ▶ The closed-loop sampled-data system can be rewritten as a

$$\dot{\psi}(t) = F\psi(t) + J_c w_c(t)$$

$$z(t) = G\psi(t)$$

$$\psi(t_k) = H\psi(t_k^-) + J_d w_d[k-1]$$

valid in the time interval  $t \in [t_k, t_{k+1})$  for all  $k \in \mathbb{N}$

- ▶ **Necessary and sufficient condition** for asymptotic stability

$$\psi(t_k) \rightarrow \psi(t_{k+1}^-) \rightarrow \psi(t_{k+1}), \quad \forall k \in \mathbb{N}$$

- ▶ Performance index calculation

# Hybrid systems

- ▶ State space matrices

$$\underbrace{F, J_c, G}_{\text{open-loop system data}}$$

and

$$\underbrace{H, J_d}_{\text{controller state space matrices}}$$

- ▶ The process starts at  $t_0 = 0$  with

$$\psi(0) = H \underbrace{\psi(0^-)}_{\psi_0} + J_d w_d[-1]$$

# Hybrid systems

- ▶ Given  $\gamma \in \mathbb{R}_+$ , consider the function

$$\rho_\gamma(\psi(0)) = \sup_{w_c \in \mathcal{L}_2, w_d \in \ell_2} \|z\|_2^2 - \gamma^2 \underbrace{\left( \|w_c\|_2^2 + \|w_d\|_2^2 \right)}_{\text{disturbance}}$$

- ▶  $\mathcal{H}_\infty$  sampled-data control:

$$J_\infty = \inf \{ \gamma^2 : \rho_\gamma(0) \leq 0 \}$$

- ▶  $\mathcal{H}_2$  sampled-data control:

$$J_2 = \sum_{\ell=1}^{r_c+r_d} \rho_\infty(\psi_\ell(0))$$



## $\mathcal{H}_2$ performance

- **Proposition:** Let  $h \in \mathbb{R}_+$  be given. The hybrid linear system is **asymptotically stable** and the  $\mathcal{H}_2$  performance index **equals** the optimal solution to the convex programming problem

$$J_2 = \inf_{P(\cdot)} \left\{ \text{tr}(J'_c P(h) J_c) + \underbrace{\text{tr}(J'_d P(0) J_d)}_{\text{controller}} \right\}$$

subject to the **DLMI**

$$\dot{P}(t) + F'P(t) + P(t)F + G'G < 0$$

satisfying the boundary condition

$$\underbrace{\begin{bmatrix} P(h) & H' \\ \bullet & P(0)^{-1} \end{bmatrix}}_{\text{controller}} > 0$$

## $\mathcal{H}_2$ performance

- ▶ Matrix  $S = P(0) > 0$  satisfies the **strict Lyapunov inequality**

$$e^{F'h} H' S H e^{Fh} < S - \underbrace{\int_0^h e^{F't} G' G e^{Ft} dt}_{\geq 0}$$

which admits a solution if and only if  $He^{Fh}$  is **Schur stable**

- ▶ The optimal sampled-data  $\mathcal{H}_2$  control follows from

$$\inf_{\text{controller}, P(\cdot)} \left\{ \text{tr}(J'_c P(h) J_c) + \text{tr}(\underbrace{J'_d P(0) J_d}_{\text{controller}}) \right\} \rightarrow \text{CONVEX}$$

## $\mathcal{H}_\infty$ performance

- **Proposition:** Let  $h \in \mathbb{R}_+$  be given. The hybrid linear system is **asymptotically stable** and the  $\mathcal{H}_\infty$  performance index **equals** the optimal solution to the convex programming problem

$$J_\infty = \inf_{P(\cdot), \gamma} \gamma^2$$

subject to the **DLMI**

$$\dot{P}(t) + F'P(t) + P(t)F + \gamma^{-2}P(t)J_c J_c' P(t) + G'G < 0$$

satisfying the boundary condition

$$\underbrace{\begin{bmatrix} P(h) & H' & 0 \\ \bullet & P(0)^{-1} & J_d \\ \bullet & \bullet & \gamma^2 I \end{bmatrix}}_{\text{controller}} > 0$$

## $\mathcal{H}_\infty$ performance

- ▶ A solution exists provided that  $\gamma > 0$  is large enough
- ▶ The optimal sampled-data  $\mathcal{H}_\infty$  control follows from

$$J_\infty = \inf_{\text{controller}, P(\cdot), \gamma} \left\{ \gamma^2 : \underbrace{\begin{bmatrix} P(h) & H' & 0 \\ \bullet & P(0)^{-1} & J_d \\ \bullet & \bullet & \gamma^2 I_{r_d} \end{bmatrix}}_{\text{controller}} > 0 \right\}$$



CONVEX

# Boundary conditions

## ▶ Aperiodic sampling

$$\underbrace{\begin{bmatrix} P(h) & H' & 0 \\ \bullet & P(0)^{-1} & J_d \\ \bullet & \bullet & \gamma^2 I \end{bmatrix}}_{\text{controller}} > 0, \quad h \in [h_{min}, h_{max}]$$

guaranteed performance (upper bound) optimization!

## ▶ LTI systems

$$H = I, \quad J_d = 0 \implies \underbrace{P(0) = P(h) = P(t)}_{\text{stationary solution}} > 0, \quad \forall t \in [0, h]$$

# Linearization

- ▶ Four square blocks partitioning, (Scherer, 1995)

$$P(t) = \begin{bmatrix} X(t) & V(t) \\ \bullet & \hat{X}(t) \end{bmatrix}, \quad P(t)^{-1} = \begin{bmatrix} Y(t) & U(t) \\ \bullet & \hat{Y}(t) \end{bmatrix}$$

leads to:

- ▶ **Differential LMIs** and boundary **LMI** constraints
- ▶ One-to-one change of variables yields the optimal controller
- ▶ Full order controller  $n_c = n_x$  due to pole / zero cancelation!
- ▶ Generalization to **Markov jump linear systems**

# Numerical issue

## ► Class of convex problems to be solved

$$f^* = \inf_{(P_0, P_h) \in \Omega} \left\{ f(P_0, P_h) : \mathcal{L}(\dot{P}(t), P(t)) < 0, t \in [0, h] \right\}$$

- $f(\cdot, \cdot)$  is linear
- $\mathcal{L}(\cdot, \cdot)$  is linear
- $(P(0), P(h)) = (P_0, P_h) \in \Omega$  is expressed by LMIs

↑

$$P(t) = \sum_{i=0}^{n_\phi-1} X_i \phi_i(t)$$

## Numerical issue

- ▶ **Piecewise linear:** For  $\eta = h/n_\phi$  and  $\phi_i(t) = \phi(t - i\eta)$

$$\phi(t) = \begin{cases} 1 - \frac{|t|}{\eta} & , \quad |t| \leq \eta \\ 0 & , \quad \text{otherwise} \end{cases}$$

- ▶  $P(t)$  is continuous and is feasible if and only if

$$\begin{aligned} \mathcal{L} \left( \frac{X_{i+1} - X_i}{\eta}, X_i \right) &< 0 \\ \mathcal{L} \left( \frac{X_{i+1} - X_i}{\eta}, X_{i+1} \right) &< 0 \\ (X_0, X_{n_\phi}) &\in \Omega \end{aligned}$$

Optimal solution in only one shot  $\Leftrightarrow 2n_\phi + 1$  LMIs!



# Numerical issue

- ▶ **Polynomial:**

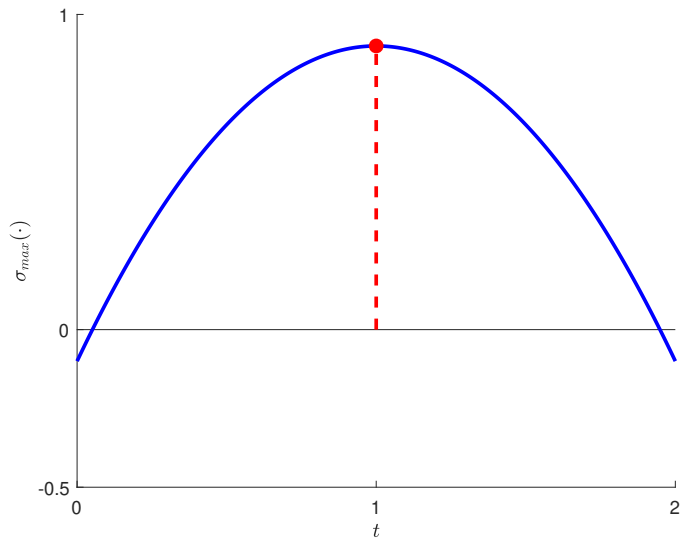
$$\phi_i(t) = \left(\frac{t}{h}\right)^i$$

- ▶ Iterative solution by **outer linearization**

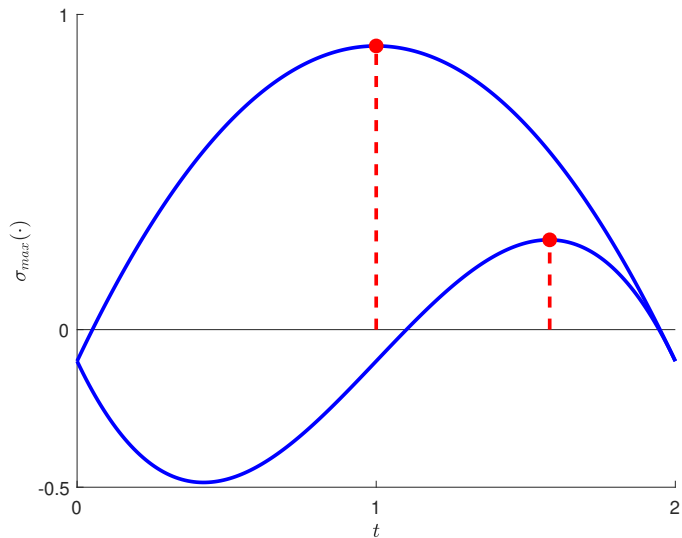
- ▶ Simple to solve convex (LMI) subproblem
- ▶ Global convergence
- ▶ Optimality test

$$\max_{t \in [0, h]} \sigma_{\max} \left( \mathcal{L} \left( \dot{P}(t), P(t) \right) \right) < 0$$

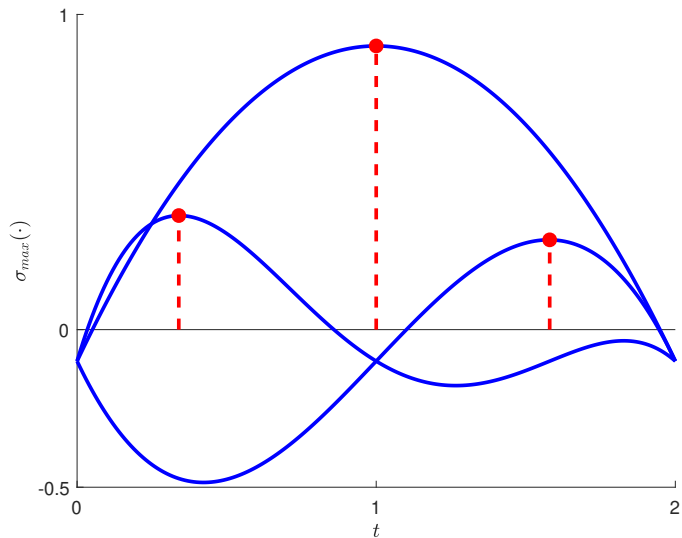
# Outer linearization



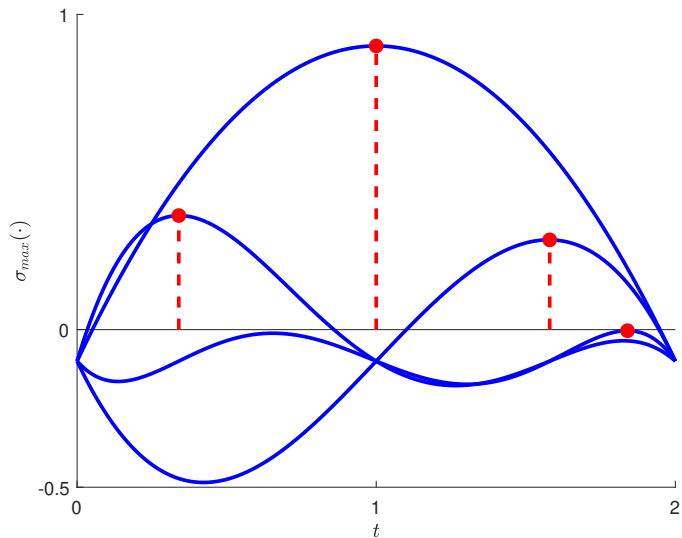
# Outer linearization



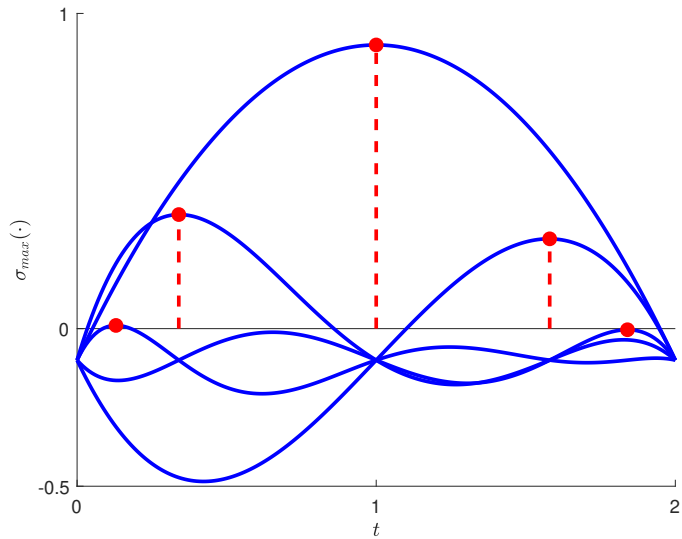
# Outer linearization



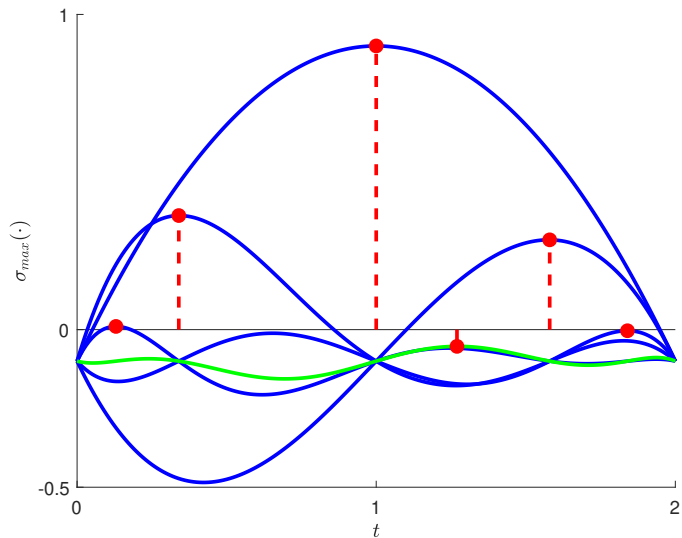
# Outer linearization



# Outer linearization



# Outer linearization



## Example

- ▶ Example borrowed from (**Ichicawa & Katayama, 2001**)

$$A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \quad B = E_c = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C'_d = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$C_c = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad D_c = \begin{bmatrix} 0 \\ d \end{bmatrix}, \quad E_d = d, \quad h = 1.0$$

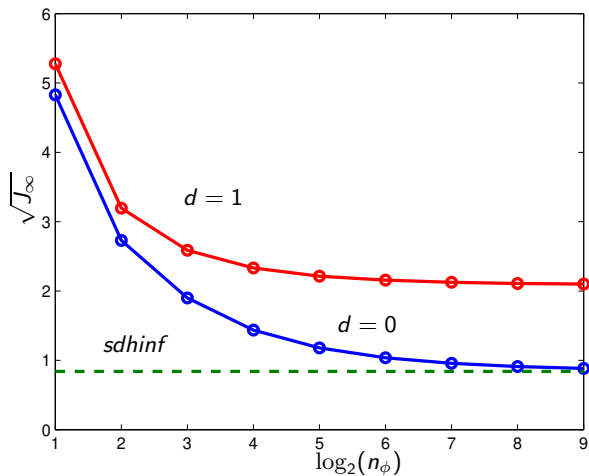
For  $d = 1$ , the optimal  $\mathcal{H}_\infty$  sampled-data controller

$$c^*(\zeta) = \frac{-0.3225\zeta^3 + 0.8686\zeta^2 - 8.012 \cdot 10^{-10}\zeta}{\zeta^3 + 0.2865\zeta^2 + 0.01608\zeta + 1.697 \cdot 10^{-12}}$$

imposes the performance cost  $\gamma_* = 2.16$ .



## Example - Piecewise linear



# Comparison

- ▶ **Piecewise linear**

- ▶ Non iterative method
- ▶  $n_\phi \approx 2^6$  time segments

- ▶ **Outer linearization**

- ▶ Iterative method
- ▶ Polynomial function of degree  $n_\phi \approx 2 \times 6$

# Conclusion

- ▶ **Open problems:**
  - ▶ **Dynamic output feedback control:** in the context of Markov Jump Linear Systems.
  - ▶ **Nonuniform sampling:** optimality

# Conclusion

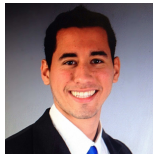
- ▶ This research has been developed in collaboration with



Gabriela Werner Gabriel



Rafael Fernandes Cunha



Tiago Rocha Gonçalves

## Conclusion

Thank you for your attention!!!