

Discrete and inter-sample analysis of systems with aperiodic sampling

presented by Laurentiu Hetel
(CNRS - LAGIS - EC Lille)

laurentiu.hetel@ec-lille.fr

French-Israeli Workshop on Delays and Robustness
April 2011

Cooperation

- ▶ **CNRS - CRAN :**
J. Daafouz, C. lung, M. Jungers
- ▶ **TU-E :**
M. Heemels, N.v.d.Wouw, M. Cloosterman, T. Donkers, M. Steinbuch, H. Nijmeijer
- ▶ **CNRS - LAGIS (EC - Lille) :**
A. Kruszewski, W. Perruquetti, J.P. Richard
- ▶ **CNRS - LAAS :**
C. Prieur, S. Tarbouriech
- ▶ **U. Kyoto :**
H. Fujioka

Outline

Introduction and Problem Formulation

Polytopic embeddings

Lyapunov functions

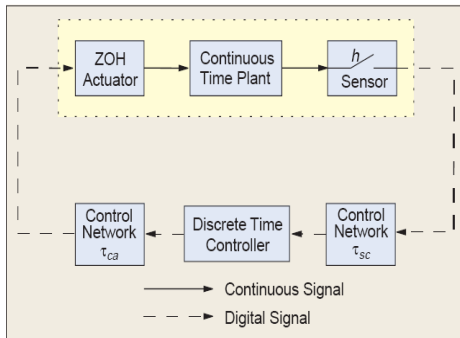
Extensions

Numerical example

Conclusion

Motivating problem

Classical NCS

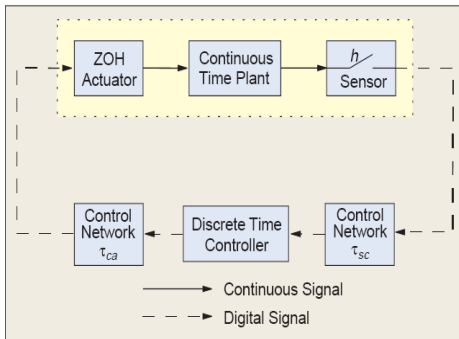


Ideal Hypothesis :

- ▶ Sampling and actuation are periodic and synchronous

Motivating problem

Classical NCS

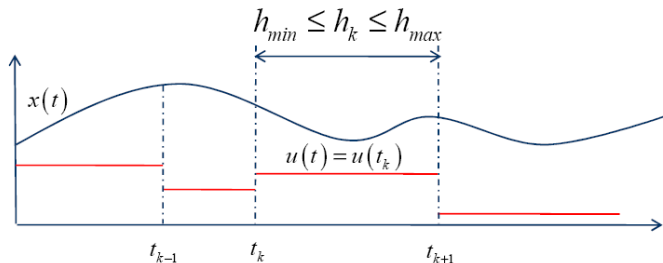


Real-time problem : the system is affected by **timing problems**

- ▶ sampling jitter (sensor, multitasking processors, packet dropouts in communication channels)
- ▶ unknown time varying delays

(Wittenmark, Nilsson, Torngren, 1995)

Simplified Problem Formulation



Consider the system

$$\dot{x}(t) = Ax(t) + Bu(t), \quad \forall t \in \mathbb{R}^+$$

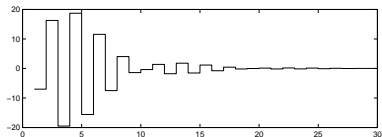
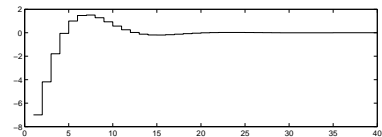
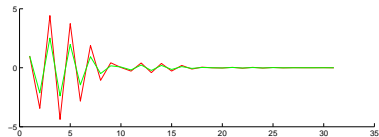
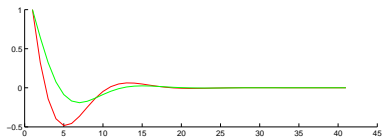
with a sampled-data control :

$$u(t) = Kx(t_k), \quad \forall t \in [t_k, t_{k+1})$$

Problem : Is the system stable under sampling variations ?

Sampling jitter example (Zhang,2001)

$$\dot{x} = Ax + Bu_k, \quad u_k = Kx_k, \quad h_k \in \{T_1, T_2\}$$



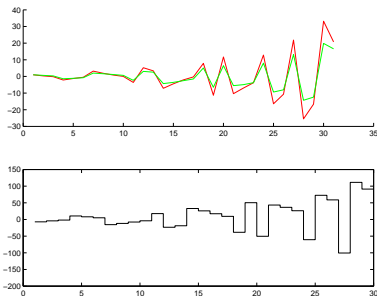
$h = 0.18s$

$h = 0.58s$

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 0.6 \end{bmatrix}; \quad K = -[1 \quad 6]$$

Sampling jitter example (Zhang,2001) \Rightarrow instability

$$\dot{x} = Ax + Bu_k, \quad u_k = Kx_k, \quad h_k \in \{T_1, T_2\}$$



$$A = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 1 \\ 0.6 \end{bmatrix}; \quad K = -[1 \quad 6]$$

Open problem : provide tools for robust stability analysis!

Existing work

Continuous-time

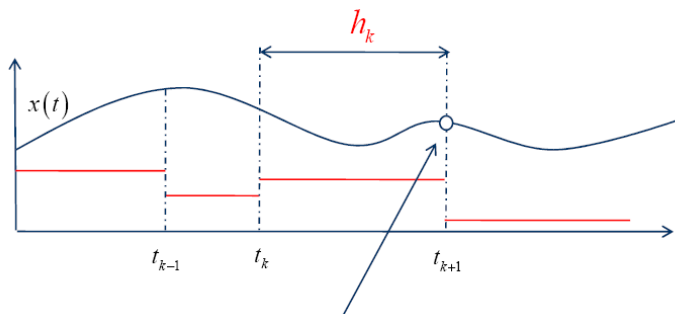
- ▶ E. Fridman et al, Automatica 2004 ; 2010 (input delay approach)
- ▶ L. Mirkin, TAC 2007 (robust control)
- ▶ J. Hespanha, SCL 2008 (impulsive delay diff. eq.)

Discrete-time

- ▶ Sala, Automatica 2004 ; Boyd, TAC 2008 (gridding approach)
- ▶ Hetel, TAC 2006, 2009 (convex embedding)
- ▶ Fujioka, TAC 2009 (gridding + robust control)

Discrete-time model

$$\dot{x} = Ax + Bu_k, \quad u_k = Kx_k, \quad h_k \in [h_{min}, h_{max}]$$



$$x(t_{k+1}) = e^{(t_{k+1}-t_k)A} x(t_k) + \int_0^{(t_{k+1}-t_k)} e^{sA} ds Bu(t_{k+1})$$

$$\Rightarrow x_{k+1} = \Lambda(h_k) x(t_k)$$

Discrete-time model : difference inclusion

Continuous-time model

$$\dot{x} = Ax + Bu_k, \quad u_k = Kx_k, \quad h_k \in [h_{min}, h_{max}]$$

Equivalent discrete-time model

$$x^+ \in \mathcal{H}(x), \quad \mathcal{H}(x) = \{y : y = \Lambda(h)x, \quad h \in [h_{min}, h_{max}]\},$$

with

$$\Lambda(h) = e^{hA} + \int_0^h e^{sA} ds BK$$

(Continuous-time system stable iff Difference inclusion is stable)

Problems for stability analysis :

- ▶ how to deal with the uncertain matrices with exponential form ?

$$\int_0^h e^{sA} ds$$

- ▶ which class of Lyapunov functions should we chose ?

Approach

Address NCS from the point of view of polytopic difference
inclusions
(Daafouz, Benoussou, SCL 2001)

Exponential uncertainty

- ▶ Integration operator

$$\Lambda(h) = e^{hA} + \int_0^h e^{sA} dsBK, \quad h \in [h_{min}, h_{max}]$$

- ▶ For the case of quadratic Lyapunov functions $V(x) = x^T Px$:

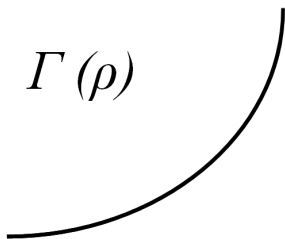
$$P > 0, \quad \Lambda^T(h)P\Lambda(h) - P < 0, \quad h \in [h_{min}, h_{max}]$$

Problem : **infinite number of stability conditions**

Exponential uncertainty

$$\Lambda(\rho) = e^{\rho A} + \int_0^\rho e^{sA} ds BK = I + \int_0^\rho e^{sA} ds (A + BK)$$

$$\Gamma(\rho) = \int_0^\rho e^{As} ds, \quad h_{\min} < \rho < h_{\max}$$



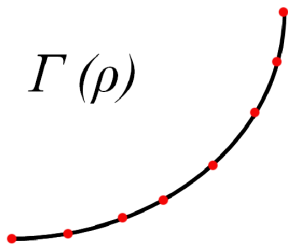
curve in the space of $\mathbb{R}^{n \times n}$ matrices

Exponential uncertainty - Gridding

(Sala, Automatica, 2004)

Consider a grid on the space of parameters ρ

$$\forall \rho \in \{\rho_1, \rho_2, \dots, \rho_N\} \subset [h_{min}, h_{max}].$$



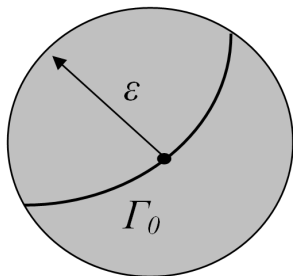
- ▶ Finite number of conditions :

$$P > 0, \quad \Lambda^T(\rho_i)P\Lambda(\rho_i) - P < 0,$$

$$i = 1, \dots, N$$

- ▶ Simple for illustration
- ▶ Not a sufficient condition for stability

Exponential uncertainty - Ellipsoidal embedding

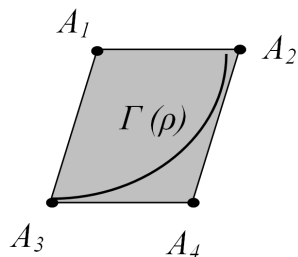


$$\Gamma(\rho) = \Gamma_0 + \Delta\Gamma$$

$$\Delta\Gamma^T \Delta\Gamma < \epsilon I$$

- ▶ LMI solution can be obtained (Gahinet, IEEE TAC, 1994), (Fujioka, IEEE TAC, 2009)
- ▶ Conservatism due to over-approximation.

Exponential uncertainty - Polytopic Embedding



$$\exists \mu_i > 0, \forall i = 1, \dots, N, \sum_{i=1}^N \mu_i = 1$$

Taylor series :

- ▶ (Hetel, Daafouz, lung, TAC 2006)

Jordan Forms :

- ▶ (Cloosterman, et. al, TAC 2009),
- ▶ (Olaru, Niculescu, IFAC World Congress 2007),

Cayley-Hamilton :

- ▶ (Gielen, et al. Automatica, 2010)

Taylor series (Hetel, Daafouz, lung, TAC 2006)

Polynomial approximation :

$$\Gamma(\rho) = \int_0^\rho e^{As} ds \approx \Gamma^P(\rho) = \rho \mathbf{I} + \frac{\rho^2}{2!} A + \dots + \frac{\rho^p}{p!} A^{p-1}$$

$$\rho \in [0, \bar{\rho}]$$

Polytopic Embedding

$$\Gamma^P(\rho) \in \text{co} \{A_1, A_2, \dots, A_{p+1}\}$$

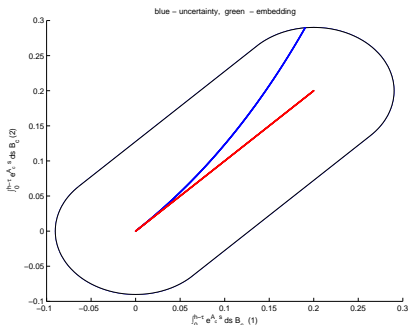
1st order approximation

Polynomial approximation :

$$\Gamma(\rho) = \int_0^\rho e^{As} ds \approx \Gamma^1(\rho) = \rho \mathbf{I}$$

Polytopic Embedding

$$\Gamma^1(\rho) \in \text{co} \{A_1, A_2\}, \quad A_1 = \mathbf{0}, \quad A_2 = \bar{\rho} \mathbf{I},$$



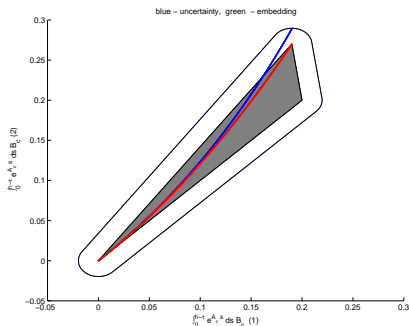
2nd order approximation

Polynomial approximation :

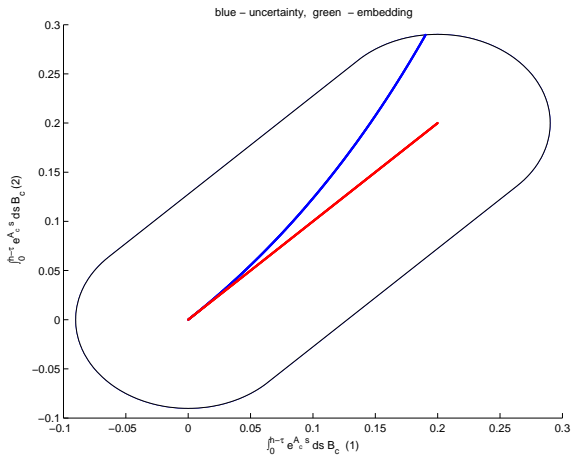
$$\Gamma(\rho) = \int_0^\rho e^{As} ds \approx \Gamma^2(\rho) = \rho \mathbf{I} + \frac{\rho^2}{2!} A$$

Polytopic Embedding

$$\Gamma^1(\rho) \in \text{co} \{A_1, A_2, A_3\}, \quad A_1 = \mathbf{0}, \quad A_2 = \bar{\rho} \mathbf{I}, \quad A_3 = \bar{\rho}^2 \frac{1}{2!} A + \bar{\rho} \mathbf{I}$$

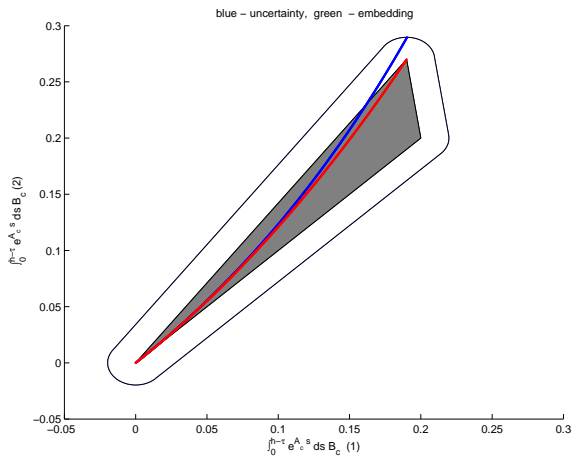


Taylor series approximation



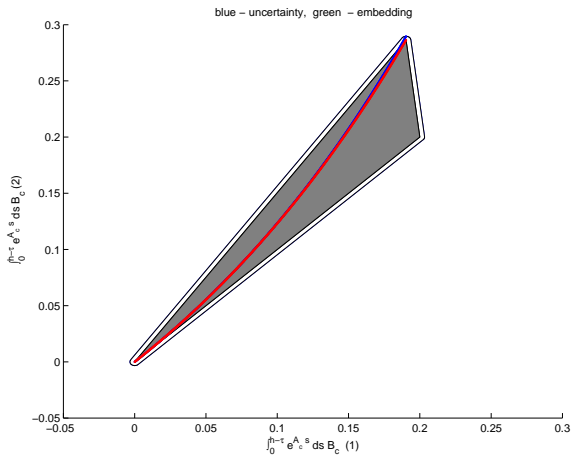
1st order approximation

Taylor series approximation



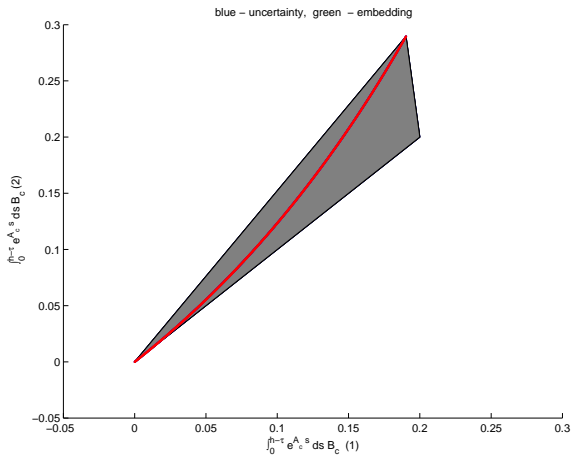
2nd order approximation

Taylor series approximation



4th order approximation

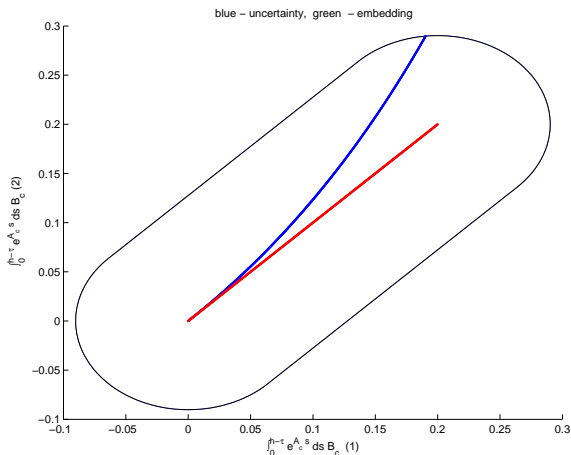
Taylor series approximation



5th order approximation

Scaling + Taylor series approximation

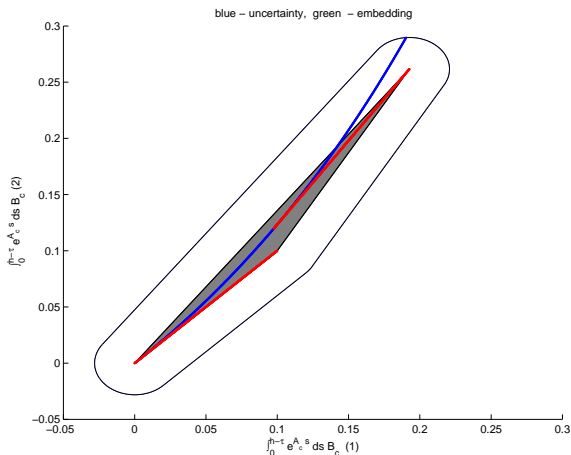
Divide the interval of analysis $[0, \bar{\rho}]$ into segments $[\rho_i, \rho_{i+1}]$



Scaling (1 segment) + 1st order approximation

Scaling + Taylor series approximation

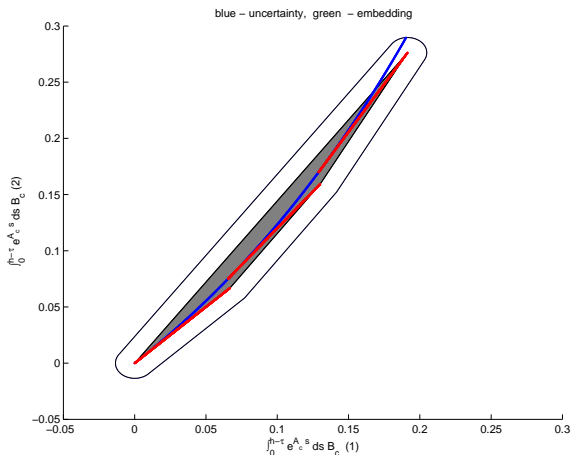
Divide the interval of analysis $[0, \bar{\rho}]$ into segments $[\rho_i, \rho_{i+1}]$



Scaling (2 segments) + 1st order approximation

Scaling + Taylor series approximation

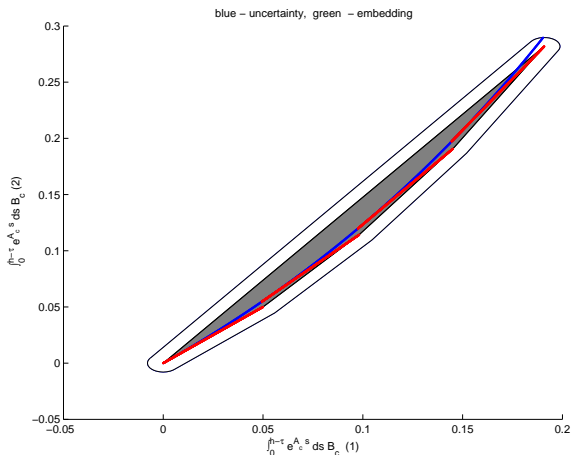
Divide the interval of analysis $[0, \bar{\rho}]$ into segments $[\rho_i, \rho_{i+1}]$



Scaling (3 segments) + 1st order approximation

Scaling + Taylor series approximation

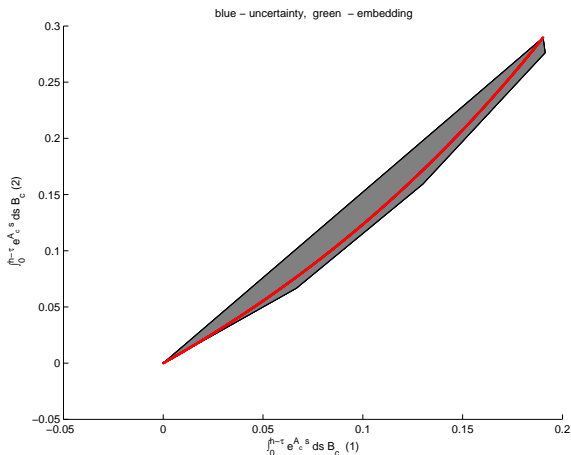
Divide the interval of analysis $[0, \bar{\rho}]$ into segments $[\rho_i, \rho_{i+1}]$



Scaling (4 segments) + 1st order approximation

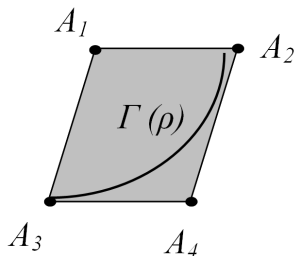
Scaling + Taylor series approximation

Divide the interval of analysis $[0, \bar{\rho}]$ into segments $[\rho_i, \rho_{i+1}]$



Scaling (3 segments) + 5th order approximation

Tractable LMI conditions



$$\Lambda^T(\rho)P\Lambda(\rho) - P < 0$$

$$\Lambda(\rho) = I + \Gamma(\rho)(A + BK)$$

- ▶ $\Lambda(\rho) \in \text{co}\{I + A_j(A + BK)\}_{j=1}^N$

$$P = P^T > 0$$

$$(I + A_j(A + BK))^T P (I + A_j(A + BK)) - P < 0, \forall j = 1, \dots, N$$

- ▶ Finite number of LMI stability conditions !

Remarks about polytopic embeddings

- ▶ The conservatism due to the use of an embedding may be tuned according to the desired numerical complexity
(scaling factor + order of Taylor approximation)
- ▶ Polytopic + NB approach (remainder of Taylor approx.)

$$\Gamma(\rho) = \sum \mu_i \Gamma_i + \Delta\Gamma, \quad \Delta\Gamma' \Delta\Gamma < \epsilon \mathbf{I}$$

(Hetel, Daafouz, lung, TAC 2006)

- ▶ Allow to use more efficient Lyapunov functions (Poly-quadratic, Quasi-quadratic).

Lyapunov functions

Equivalent Difference inclusion

$$x^+ \in \mathcal{H}(x), \quad \mathcal{H}(x) = \{y : y = \Lambda(h)x, h \in \mathcal{T} = [h_{min}, h_{max}]\},$$

with

$$\Lambda(h) = e^{hA} + \int_0^h e^{sA} ds BK$$

General Remarks on Linear Difference Inclusions (LDI) :

- ▶ Quadratic Lyapunov Functions (QLF) $V(x) = x^T P x$ are sufficient only for stability (not necessary)
- ▶ There are cases of LDI which are stable for which no QLF exists

(Dayawansa, Martin, IEEE TAC, 1999)

Lyapunov functions

Equivalent Difference inclusion

$$x^+ \in \mathcal{H}(x), \quad \mathcal{H}(x) = \{y : y = \Lambda(h)x, h \in \mathcal{T} = [h_{min}, h_{max}]\},$$

Poly-quadratic Lyapunov functions (Daafouz, Bernoussou, SCL 2001)

$$V(x, h) = x^T P(h)x$$

Sufficient stability condition

$$\Lambda^T(h_1)P(h_2)\Lambda(h_1) - P(h_1) \prec 0, \forall h_1, h_2 \in \mathcal{T} = [h_{min}, h_{max}]$$

Lyapunov functions

With the polytopic embedding

$$\Lambda(h) \in \text{co}\mathcal{Z}, \quad \mathcal{Z} = \{Z_1, Z_2, \dots, Z_N\},$$

$$\Lambda(h) = \sum_i \mu_i(h) Z_i, \quad \sum_i \mu_i(h) = 1, \quad \mu_i(h) > 0$$

Poly-quadratic Lyapunov functions

$$V(x, h) = x^T \sum_i \mu_i(h) P_i x$$

Sufficient stability condition

$$Z_j^T P_j Z_i - P_i \prec 0, \quad \forall i, j = 1, \dots, N$$

may be used for control design (Hetel, Daafouz, lung, IJC 2007)

Lyapunov functions

Equivalent Difference inclusion

$$x^+ \in \mathcal{H}(x), \quad \mathcal{H}(x) = \{y : y = \Lambda(h)x, h \in \mathcal{T} = [h_{min}, h_{max}]\},$$

General Remarks on Linear Difference Inclusions (LDI) :

- ▶ Necessary and Sufficient stability conditions : the existence of *Quasi-Quadratic* Lyapunov functions

$$V(x) = x^T \mathcal{L}_{[x]} x,$$

$$\mathcal{L}_{[x]} = \mathcal{L}_{[x]}^T = \mathcal{L}_{[ax]}, \quad \forall x \neq 0, a \in \mathbb{R}, a \neq 0$$

(Molchanov and Pyatniskii, SCL 1989)

(Hetel, et al. TAC 2011)

- ▶ stability test in the literature = BMI problem

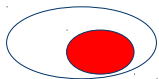
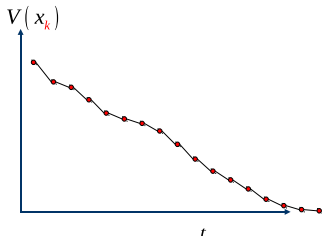
(Hu, Blanchini, Automatica, 2010)

Stability based on non-monotonous functions

(Megretzki, IEEE CDC 1994) ; (Krusezwski, Guerra, IEEE TAC 2008)

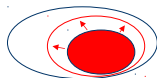
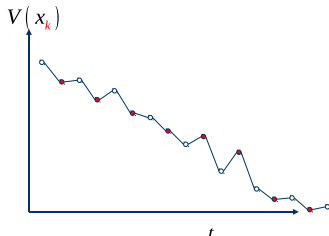
Classical approach

$$\forall x_k, V(x_{k+1}) - V(x_k) < 0$$



New approach

$$\forall x_k, V(x_{k+\alpha}) - V(x_k) < 0$$



Stability based on non-monotonous functions

Properties :

- ▶ $\alpha = 1$ - case of classical Lyapunov functions
- ▶ A LDI is stable iff there exist a finite $\alpha \in \mathbb{N}$ such as

$$V(x_{k+\alpha}) < V(x_k)$$

Stability based on non-monotonous functions

$$x^+ \in \mathcal{H}(x), \quad \mathcal{H}(x) = \{y : y = \Lambda(h)x, h \in \mathcal{T} = [h_{\min}, h_{\max}]\},$$

Denote

- ▶ $\sigma = \{h^i\}_{i=0}^{\alpha-1}$ sequence of α sampling times and
- ▶ $\Phi_\sigma(\alpha)$ transition matrix associated to σ :

$$\Phi_\sigma(\alpha) = \begin{cases} \Lambda(h^{\alpha-1}) \dots \Lambda(h^1) \Lambda(h^0), & \alpha > 0 \\ \mathbf{I}, & \alpha = 0. \end{cases}$$

with the function $V(x) = x^T P x$.

Proposition : *The equilibrium point $x = 0$ is asymptotically stable iff there exists a finite $\alpha \in \mathbb{N}^+$ s.t.*

$$\Phi_\sigma^T(\alpha) P \Phi_\sigma(\alpha) - P < 0$$

for all α length sequences with values in \mathcal{T} .

Stability based on non-monotonous functions

With the polytopic embedding

$$\Lambda(h) \in \text{co}\mathcal{Z}, \quad \mathcal{Z} = \{Z_1, Z_2, \dots, Z_N\}$$

Products of α vertices

$$\mathcal{Y}_\alpha(\mathcal{Z}) = \{Y : Y = \prod_{i=0}^{\alpha-1} Z_{\mu_i}, Z_{\mu_i} \in \mathcal{Z}\}.$$

Stability test : Given α exists $P = P^T \succ 0$ s.t.

$$P \succ Y^T P Y, \quad \forall Y \in \mathcal{Y}_\alpha(\mathcal{Z}),$$

- ▶ finite number of LMI (complexity to be tuned according to number of vertex N and the horizon of analysis α)

Non-monotonous functions / Quasi-Quadratic functions

Proposition. *If there exist a positive integer α and a matrix $P = P^T \succ 0$ that satisfy*

$$P \succ Y^T P Y, \forall Y \in \mathcal{Y}_\alpha(\mathcal{Z}),$$

then there exists a composite quadratic Lyapunov function,

$$V_c(x) = x^T \mathcal{L}_{[x]} x = \max_{i=1, \dots, M} x^T L_i x, \quad M = N^\alpha$$

(Hetel, et al. TAC 2011)

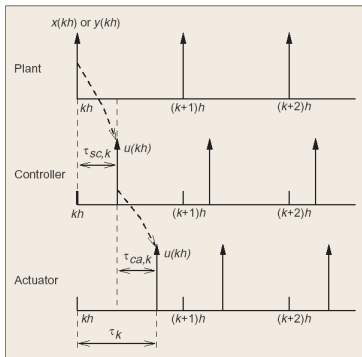
level set = intersection of ellipsoids

L_i - explicit functions of Z_i, P

Extension

- ▶ Systems with delay
- ▶ Reset systems
- ▶ Continuous-time analysis

Extension : systems with delay ($\tau_k < T$)



(Zhang,2001)

$$x_{k+1} = A_d x_k + \int_0^{h-\tau_k} e^{As} ds B u_k$$

$$+ \left(B_d - \int_0^{h-\tau_k} e^{As} ds B \right) u_{k-1}$$

$$u_k = K x_k$$

Augmented state vector :

$$z_k = [x_k^T \ u_{k-1}^T]^T$$

$$z_{k+1} = \underbrace{\begin{bmatrix} A_d + \Gamma(h-\tau_k)BK & B_d - \Gamma(h-\tau_k)B \\ K & 0 \end{bmatrix}}_{\Lambda(\tau_k)} z_k, \tau_k \in [\tau_{min}, \tau_{max}]$$

LDI - similar to the case with sampling jitter

Extensions :

- ▶ Generalization for systems with large delay

$$z_k = [x_k^T \ u_{k-1}^T \ u_{k-2}^T \ \dots \ u_{k-d}^T]^T$$

(Cloosterman, Hetel, v.d.Wouw, Heemels, Daafouz, Nijmeijer, Automatica, 2010)

- ▶ Lyapunov functions $z_k^T P(\tau_k) z_k$ for LDI \Rightarrow generalization of Lyapunov Krasovskii Functions

$$V(x_k, x_{k-1}, x_{k-2}, \dots, x_{k-d}) = \sum_{i=1}^d \sum_{j=1}^d x_{k-i}^T Q^{i,j}(\tau_k) x_{k-j}$$

(Hetel, Daafouz, lung, Nonlin. Anal. Hybr. Syst., 2007 ; Hetel. et al. CDC 2009)

Extension : delay dependent controller

- ▶ Original system

$$x_{k+1} = A_d x_k + \int_0^{h-\tau_k} e^{As} ds B u_k + \left(B_d - \int_0^{h-\tau_k} e^{As} ds B \right) u_{k-1}.$$

- ▶ Equivalent open-loop system

$$z_{k+1} = \bar{A}(\tau_k) z_k + \bar{B}(\tau_k) u_k, \quad z_k = [x_k^T \quad u_{k-1}^T]^T$$

- ▶ Improved controller (adapting to delay value)

$$u(k+1) = K^x(\hat{\tau}_k) x_k + K_1^u(\hat{\tau}_k) u_k + K_2^u(\hat{\tau}_k) u_{k-1}$$

(Hetel, et al. SCL 2011)

Extension : reset systems

Sampled-data systems are particular case of reset systems :

$$\begin{aligned}\dot{z}(t) &= A_c z(t), \forall t \neq t_k \\ z(t_k^+) &= A_r z(t_k) \\ t_{k+1} - t_k &\in [h_{min}, h_{max}]\end{aligned}$$

Sampled-data case

$$\begin{aligned}\begin{pmatrix} \dot{x} \\ \dot{u} \end{pmatrix} &= \begin{pmatrix} A & B \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix}, \forall t \neq t_k \\ \begin{pmatrix} x \\ u \end{pmatrix}^+ &= \begin{pmatrix} \mathbf{I} & 0 \\ \mathbf{K} & \mathbf{0} \end{pmatrix} \begin{pmatrix} x \\ u \end{pmatrix},\end{aligned}$$

Extension : reset systems

Sampled-data systems are particular case of reset systems :

$$\begin{aligned}\dot{z}(t) &= A_c z(t), \forall t \neq t_k \\ z(t_k^+) &= A_r z(t_k) \\ h_k = t_{k+1} - t_k &\in [h_{min}, h_{max}]\end{aligned}$$

LDI model at reset times

$$x(t_{k+1}^+) \in \mathcal{H}(x(t_k^+)), \mathcal{H}(x) = \{y : y = \Lambda(h)x, h \in [h_{min}, h_{max}]\},$$

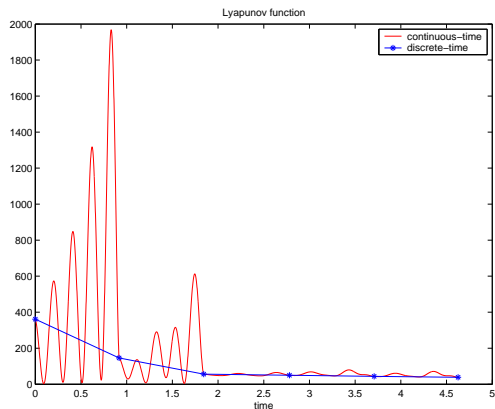
with

$$\Lambda(h_k) = A_r e^{A_c h_k}$$

(Hetel, Daafouz, Tarbouriech, Prieur, IFAC 2011)

Extension : continuous-time analysis

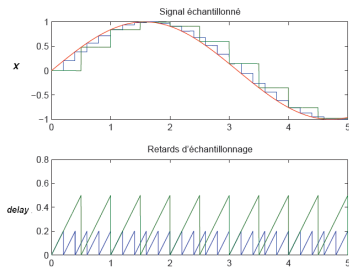
Discrete-time problem



Evolution of Lyapunov function

Extension : continuous-time analysis

Time delay model for systems with jitter



Sawtooth delay

$$\begin{aligned}\dot{x}(t) &= Ax(t) + BKx(t - \tau(t)), \\ \dot{\tau} &= 1, \quad \forall t \in [t_k, t_{k+1}) \\ \tau(t_k^+) &= 0\end{aligned}$$

(Fridman, et al., Automatica, 2004)

$$x(t) = \Lambda(\tau(t))x(t - \tau(t))$$

Extension : continuous-time analysis with $V(x) = x^T P x$

$$\frac{dV(x)}{dt} = 2x^T(t)P(Ax(t) + BKx(t - \tau)) < -\alpha V(x(t)).$$

$$\begin{pmatrix} x(t) \\ x(t - \tau) \end{pmatrix}^T \begin{pmatrix} A^T P + PA + \alpha P & PBK \\ K^T B^T P & \mathbf{0} \end{pmatrix} \begin{pmatrix} x(t) \\ x(t - \tau) \end{pmatrix} < \mathbf{0},$$

and

$$x(t) = \Lambda(\tau) x(t - \tau), \quad \forall \tau \in [0, h_{max}]$$

⇒ LMI problem using Finsler's Lemma

Extension : continuous-time analysis with $V(x) = x^T P x$

LMI problem :

$$\exists P = P^T \succ 0, G_1, G_2 \text{ s.t.}$$

$$\begin{pmatrix} A^T P + PA + G_1 + G_1^T + \alpha P & PBK - G_1 \Lambda(\tau) + G_2^T \\ K^T B^T P - \Lambda^T(\tau) G_1^T + G_2 & -G_2 \Lambda(\tau) - \Lambda^T(\tau) G_2^T \end{pmatrix} \prec \mathbf{0},$$

$$\forall \tau \in [0, h_{max}]$$

(Hetel et. al , TAC, 2011)

- ▶ finite number of LMI using convex polytopes
- ▶ implies that $\Lambda(\tau)$ is non-singular

Non-singularity and Quasi-Quadratic Lyapunov functions

Remark : Existence of functions of the class $V_c(x) = x^T P_{[x]} x$ is necessary when Λ is non-singular

$$\frac{dx(t)}{dt} = Ax(t) + BKx(t_k), \forall t \in [t_k, t_{k+1}),$$

$$x(t_k) = \Lambda^{-1}(\tau)x(t)$$

$$\frac{dx}{dt} \in \mathcal{H}_c(x), \mathcal{H}_c(x) = \{(A + BK\Lambda^{-1}(\tau))x, \tau \in [0, h_{max}]\},$$

based on (Molchanov, Pyatniski, 1989), (Hu, Blanchini, Automatica 2010)

Extension : Quasi-Quadratic Lyapunov functions

For $V_c(x) = \max_{i=1,\dots,M} x^T L_i x$ we obtain the following set of conditions

$$\begin{pmatrix} A^T L_i + L_i A + \lambda L_i - \sum_{i \neq j} \beta_{ij} (L_j - L_i) + G_1 + G_1^T & L_i B K - G_1 \Lambda(\tau) + G_2^T \\ K^T B^T L_i - \Lambda^T(\tau) G_1^T + G_2 & -G_2 \Lambda(\tau) - \Lambda^T(\tau) G_2^T \end{pmatrix} \prec \mathbf{0},$$

$i, j = 1, \dots, M, \forall \tau \in [0, h_{max}]$.

- ▶ BMI conditions if L_i, β_{ij} decision variables
- ▶ LMI if L_i may be computed using discrete-time approach

Extension : Lyapunov - Razumikhin functions

- ▶ Consider the quadratic function $V(x) = x^T P x$, $P = P^T \succ 0$.
- ▶ Asymptotic stability conditions : $\dot{V}(x(t)) < 0$ whenever $V(x(t_k)) < \alpha V(x(t))$, with $\alpha > 1$
- ▶ Matrix Inequalities conditions : $P = P^T \succ 0$, a scalar $\epsilon > 0$, and matrices $G_1, G_2 \in \mathbb{R}^{n \times n}$ s.t.

$$\begin{pmatrix} A^T P + PA + \epsilon \alpha P + G_1 + G_1^T & PBK - G_1 \Lambda(\theta) + G_2^T \\ K^T B^T P - \Lambda^T(\theta) G_1^T + G_2 & -G_2 \Lambda(\theta) - \Lambda^T(\theta) G_2^T - \epsilon P \end{pmatrix} \prec 0.$$

$$\forall \theta \in [0, \theta_{max}]$$

Numerical examples

$$A_c = \begin{pmatrix} -0.5 & 0 \\ 0 & 3.5 \end{pmatrix}, \quad B_c = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \text{and} \quad K = (1.02 \quad -5.62).$$

- ▶ $\Lambda(h)$ is Schur for any sampling interval $h \in [0, 0.46]$.
- ▶ $\Phi = (\Lambda(0.1))^6 \Lambda(0.43)$ is not Schur (exists a periodic unstable sequence).
- ▶ $h_k \in \{0.1, h_{max}\}$
- ▶ Exists a QLF for $h_{max} = 0.36$.
- ▶ Poly-quadratic test $h_{max} = 0.38$
- ▶ Quasi-quadratic LF with $\alpha = 7$, $h_{max} = 0.41$.

Numerical example

Consider a continuous-time system described by :

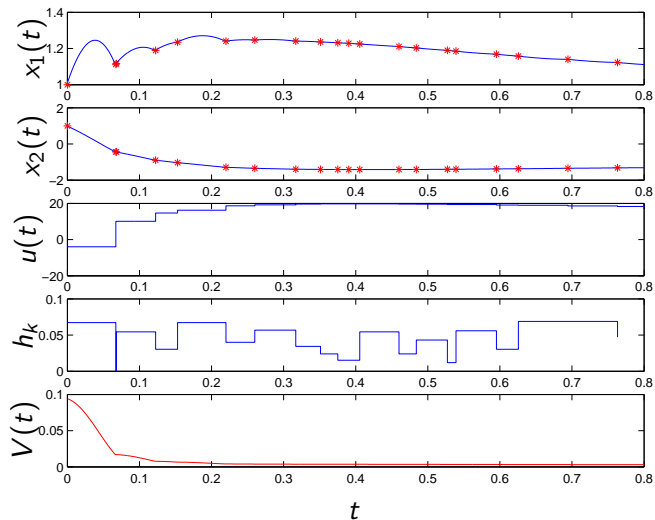
$$A = \begin{pmatrix} 1 & 15 \\ -15 & 1 \end{pmatrix} \text{ and } B = \begin{pmatrix} 1 \\ 1 \end{pmatrix}.$$

- ▶ $\lambda(A) = 1 \pm 15i$
- ▶ K - obtained by pole placement : $\lambda(A + BK) = -1 \pm i$

Stability analysis comparison :

- ▶ (Naghshtabrizi, Hespanha, Teel, SCL 2008) : $h \in [0, 0.033]$
- ▶ (Fujioka, Automatica 2009) : $h \in [0, 0.07]$
- ▶ (Fridman, Automatica 2010) : $h \in [0, 0.012]$
- ▶ continuous-time + polytopic embedding : $h \in [0, 0.09]$
(singularity for 0.092)
- ▶ Lyapunov-Razumikhin + polytopic embedding : $h \in [0, 0.14]$
- ▶ discrete-time approach : $h \in [0.01, 0.15]$

Numerical example



Conclusion

- ▶ Applications of polytopic embedding methods for NCS
- ▶ Provide LMI methods for robust stability under time-varying sampling

Composite quadratic Lyapunov functions

Proposition. *If there exist a positive integer α and a matrix $P = P^T \succ 0$ that satisfy*

$$P \succ Y^T P Y, \forall Y \in \mathcal{Y}_\alpha(\mathcal{Z}),$$

then there exists a composite quadratic Lyapunov function for the LDI,

$$V_c(x) = \max_{i=1, \dots, M} x^T L_i x \text{ s.t. } V_c(x) > \max_{\theta \in \mathcal{T}} V_c(\Lambda(\theta)x)$$

where $L_i, i = 1, \dots, M = N^{\alpha-1}$ are an enumeration of the elements in the set

$$\Omega = \left\{ Q_\sigma^Z(\alpha) = \sum_{j=1}^{\alpha-1} \left(\prod_{r=1}^j Z_{\mu_r} \right)^T P \left(\prod_{r=1}^j Z_{\mu_r} \right) + P, \sigma = \{\mu_r\}_{r=1}^{N-1} \in \{1, \dots, N\}^\alpha \right\}.$$

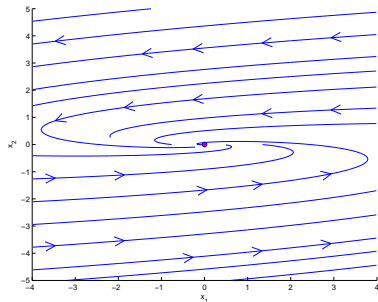
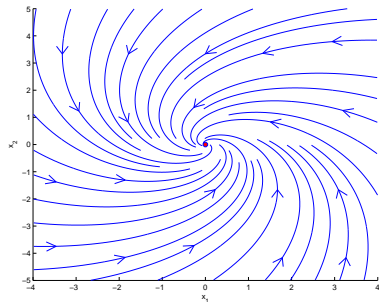
Numerical examples (Dayawansa, Martin, 1999)

Sampled-data version of

$$\dot{x} = A_{\sigma}x, \quad \sigma \in \{1, 2\}$$

$$A_1 = \begin{pmatrix} -1 & -1 \\ 1 & -1 \end{pmatrix}, \quad A_2 = \begin{pmatrix} -1 & -8 \\ 1/8 & -1 \end{pmatrix}$$

No QLP can be found



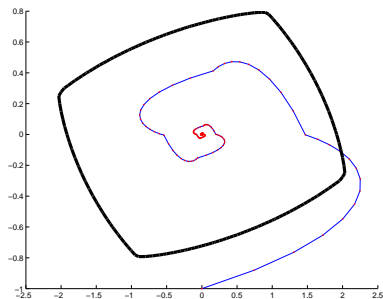
Numerical examples (Dayawansa, Martin, 1999)

Sampled-data version of

$$\dot{x} = A_{\sigma}x, \sigma \in \{1, 2\}$$

$$A_1 = \begin{pmatrix} -1 & -1 \\ 1 & -1 \end{pmatrix}, \quad A_2 = \begin{pmatrix} -1 & -8 \\ 1/8 & -1 \end{pmatrix}$$

No QLP can be found



Delay Compensation

- ▶ Discrete-time model (integration over a sampling period)

$$x_{k+1} = A_d x_k + \Omega(T - \tau_k) B u_k + (B_d - \Omega(T - \tau_k) B) u_{k-1}$$

$$A_d = e^{AT}, \quad B_d = \int_0^T e^{As} ds B, \quad \Omega(\tau) := \int_0^\tau e^{As} ds.$$

- ▶ Control law

$$u_{k+1} = K_x(\hat{\tau}_k) x_k + K_u^0(\hat{\tau}_k) u_k + K_u^1(\hat{\tau}_k) u_{k-1}$$

with

$$\hat{\tau}_k = \tau_k + \delta\tau_k, \quad \delta\tau_{min} \leq \delta\tau_k \leq \delta\tau_{max}$$

Augmented state model

Consider $\eta_k = [x'_k \ u'_{k-1} \ u'_k]'$.

$$\eta_{k+1} = \bar{A}(\tau_k)\eta_k + \bar{B}v_k$$

Delay-free LPV model

$$\bar{A}(\tau_k) = \begin{bmatrix} A_d & B_d - \Omega(T - \tau_k)B & \Omega(T - \tau_k)B \\ \mathbf{0} & \mathbf{0} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{I} \end{bmatrix}$$

with

$$v_k = \mathcal{K}(\hat{\tau}_k)\eta_k$$

and

$$\mathcal{K}(\hat{\tau}_k) = [K_x(\hat{\tau}_k) \ K_u^1(\hat{\tau}_k) \ K_u^0(\hat{\tau}_k)]$$

Closed-loop model

$$\eta_{k+1} = (\bar{A}(\tau_k) + \bar{B}\mathcal{K}(\hat{\tau}_k)) \eta_k$$

(depends both on τ_k , and $\hat{\tau}_k = \tau_k + \delta\tau_k$)

$$\eta_{k+1} = (\bar{A}(\hat{\tau}_k) + \bar{B}\mathcal{K}(\hat{\tau}_k)) \eta_k + E\Omega(\delta\tau_k) \mathcal{F}(\hat{\tau}_k) \eta_k$$

where

$$E\Omega(\delta\tau_k) \mathcal{F}(\hat{\tau}_k) = \bar{A}(\tau_k) - \bar{A}(\hat{\tau}_k)$$

and

$$\Omega(\delta\tau) := \int_0^{\delta\tau} e^{As} ds.$$

Property : $\exists \gamma > 0$ s.t. $\| \Omega(\delta\tau_k) \| \leq \gamma^2, \forall \delta\tau_k \in [\delta\tau_{min}, \delta\tau_{max}]$

Parametric set of LMI

Theorem

The system is stabilizable if there exist a positive scalar λ , symmetric positive definite matrices $\mathcal{S}(\cdot)$ and matrices $\mathcal{R}(\cdot), \mathcal{G}(\cdot)$, s.t. the following set of LMI is feasible :

$$\begin{bmatrix} \mathcal{G}(\theta) + \mathcal{G}'(\theta) - \mathcal{S}(\theta) & \mathcal{G}'(\theta)\bar{A}'(\theta) + \mathcal{R}'(\theta)\bar{B}' & \mathcal{G}'(\theta)\mathcal{F}'(\theta) \\ * & \mathcal{S}(\theta_+) - \lambda EE'\gamma^2 & \mathbf{0} \\ * & * & \lambda \mathbf{I} \end{bmatrix} > 0$$

for all scalars $(\theta, \theta_+) \in [0, T]^2$. The control law is given with $\mathcal{K}(\hat{\tau}_k) = \mathcal{R}(\hat{\tau}_k) (\mathcal{G}(\hat{\tau}_k))^{-1}$.

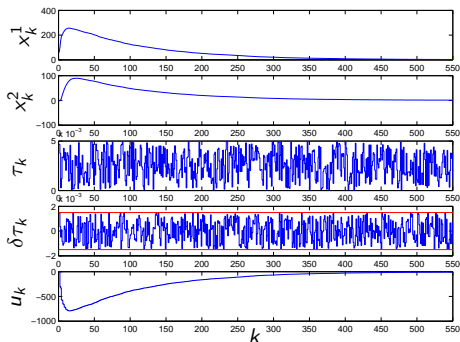
$$V(\eta_k, \hat{\tau}_k) = \eta_k' (\mathcal{S}(\hat{\tau}_k))^{-1} \eta_k$$

(Lyapunov function)

Example of control design for the Polytopic Approach

Motivating Example (unstable under uncertainty and delay variation)

$$A = \begin{bmatrix} 103.5 & 0 \\ 0 & -43.5 \end{bmatrix}, \quad B = \begin{bmatrix} 33.6 \\ -5.1 \end{bmatrix}, \quad T = 0.005s,$$
$$\delta\tau_k \in [-0.0015, 0.0015].$$



Polytopic feedback with 50 vertex.

Example of control design for the Quantization Approach

- ▶ System

$$A = \begin{pmatrix} a & -b \\ b & a \end{pmatrix} \text{ and } B = \begin{pmatrix} 1 \\ 1 \end{pmatrix},$$

with $a = 1$ and $b = -15$

- ▶ $[0, T]$ is divided in 3 subintervals
- ▶ $\hat{\tau}_k \in \{0.015, 0.045, 0.075\}$, $\delta\tau_{min} = -0.015$, $\delta\tau_{max} = 0.015$
- ▶ Gains

$$\mathcal{K}_1 = [9.90 \ 9.03 \ 0.27 \ 0.68],$$

$$\mathcal{K}_2 = [9.93 \ 9.03 \ 0.76 \ 0.19],$$

$$\mathcal{K}_3 = [9.95 \ 9 \ 1.07 \ -0.12]$$

Example of control design for the Quantization Approach

► System

$$A = \begin{pmatrix} a & -b \\ b & a \end{pmatrix} \text{ and } B = \begin{pmatrix} 1 \\ 1 \end{pmatrix},$$

with $a = 1$ and $b = -15$

