

Constrained control of uncertain discrete-time systems. An interpolation based approach

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Project and collaborations

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- Project: A practical approach for constrained control of uncertain or time-varying discrete-time systems subject to bounded disturbances.
- Collaboration
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Outline

- 1 Abstract
- 2 Constrained control
- 3 Interpolation based control
- 4 Case study - Ball and plate
- 5 Conclusion

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Abstract

Goal: Regulate to the origin

$$x(k+1) = A(k)x(k) + B(k)u(k) + D(k)w(k)$$

Constraints:

$$x(k) \in X, X = \{x : F_x x \leq g_x\}$$

$$u(k) \in U, U = \{u : F_u u \leq g_u\}$$

$$w(k) \in W, W = \{w : F_w w \leq g_w\}$$

Approach:

- Interpolation
- Minimizing an appropriate objective function
 - 1 Recursive feasibility
 - 2 Robustly asymptotically stable closed-loop behavior

Outline

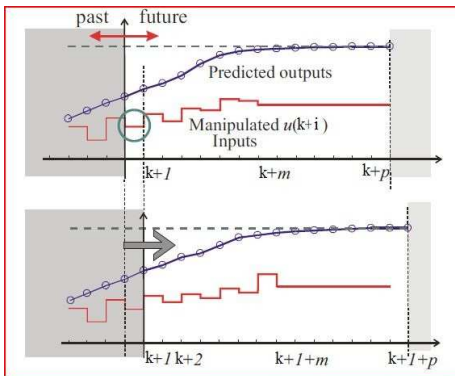
- 1 Abstract
- 2 Constrained control
 - Constrained control - an overview
 - Model predictive control
 - Vertex control law
- 3 Interpolation based control
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Constrained control - an overview

Many solutions, among them:

- ① Optimal control
 - Almost open loop
- ② Model predictive control
 - Implicit: optimal control problem solved at each sampling interval over a finite receding horizon,
 - Explicit: piecewise affine state feedback control laws computed off-line,
 - Extends with complexity to the uncertain plant case.
- ③ Vertex control law
 - Low cost alternative (from the complexity point of view)
 - Include the uncertain plant case
 - No optimality

Model predictive control - Implicit solution



- 1 Determine state $x(k)$.
- 2 Determine *on-line* optimal sequence of inputs over horizon.
- 3 Implement first input $u(k)$.
- 4 Wait for next sampling time $k = k + 1$.

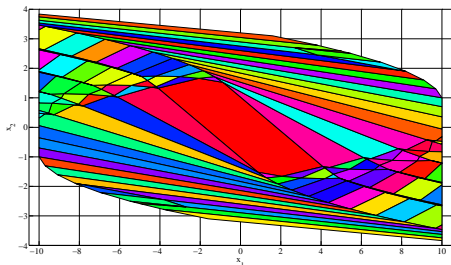
Model predictive control - Explicit solution

Feasible polyhedron C_N of initial states computed *off-line* by multi-parametric programming, where the parameterization is taken with respect to the initial state $x(0)$.

$$J = \sum_{i=1}^{14} (\|Qx(k+i)\|_2 + \|Ru(k+i-1)\|_2)$$

$$x(k+1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x(k) + \begin{bmatrix} 1 \\ 0.3 \end{bmatrix} u(k)$$

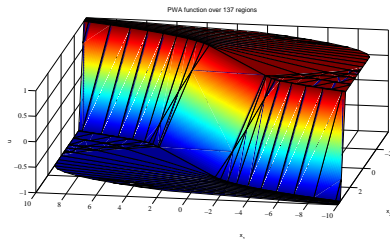
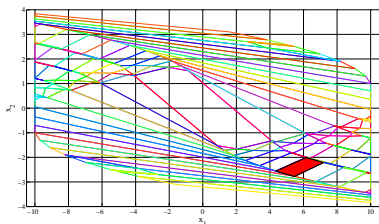
Constraints $-1 \leq u \leq 1$, $-10 \leq x_1 \leq 10$, $-5 \leq x_2 \leq 5$.



Model predictive control - Explicit solution, cont.

- C_N is divided in sub-polyhedra, an affine control law is found, **off-line**, for each sub-polyhedra, $u = K_j x + c_j$.
- The control is implemented **on-line** by finding to which sub-polyhedra the measured state belongs.

$$\begin{bmatrix} -0.19 & -0.98 \\ 0.19 & 0.98 \\ 0.31 & -0.95 \\ -0.29 & 0.96 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 1.68 \\ -0.80 \\ 4.33 \\ -3.72 \end{bmatrix} \quad u = -0.43x_1 - 2.23x_2 - 2.83$$



Model predictive control - Explicit solution, cont.

1) Advantages

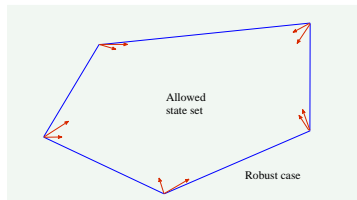
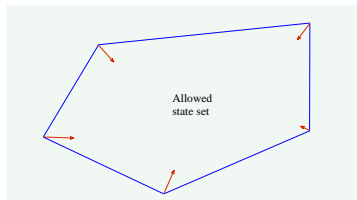
- Easy to implement
- Fast on-line evaluation

2) Challenges

- Number of controller regions can become large (for the double integrator example - the number of regions is 137)
- Although off-line, computation time may become prohibitive

Vertex control

- The necessary and sufficient condition for constrained stabilization: at each vertex of the feasible set C_N exists a feasible control signal $u \in U$ that brings the state to $\text{int}(C_N)$ in finite time.
- See details in Gutman and Cwikel (1986).
- The extension to the uncertain plant case - Blanchini (1994).

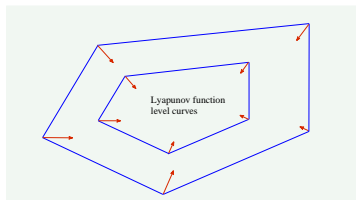
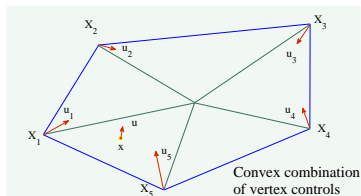


Vertex control - cont.

- The stabilizing controller is obtained by the convex combination of vertex controls in each sector
- Lyapunov level-functions are the scaling of the frontier of C_N .

$$x = \alpha x_1 + \beta x_5$$

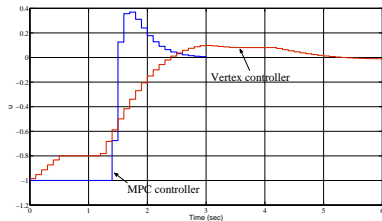
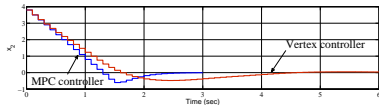
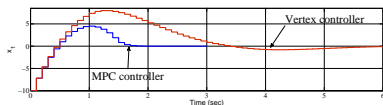
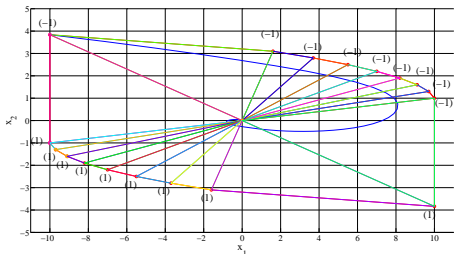
$$u = \alpha u_1 + \beta u_5$$



Vertex control - cont.

$$x(k+1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x(k) + \begin{bmatrix} 1 \\ 0.3 \end{bmatrix} u(k)$$

$$\begin{aligned} -1 &\leq u \leq 1, \\ -10 &\leq x_1 \leq 10, \quad -5 \leq x_2 \leq 5 \\ x(0) &= [-10 \quad 3.84]^T \end{aligned}$$

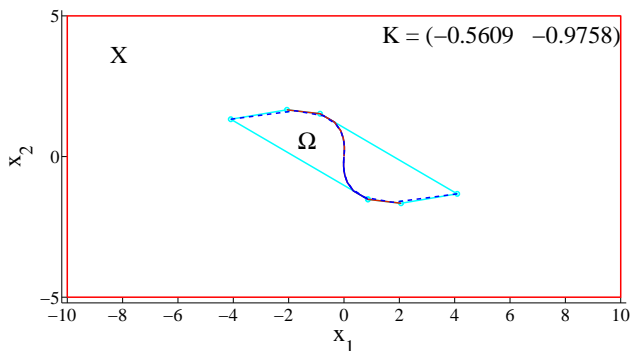


Outline

- 1 Abstract
- 2 Constrained control
- 3 Interpolation based control**
 - Set invariance
 - Interpolation based control via LP
 - Interpolation based control via QP
 - Interpolation via QP for uncertain systems with disturbances
- 4 Case study - Ball and plate
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Maximal admissible set (MAS)

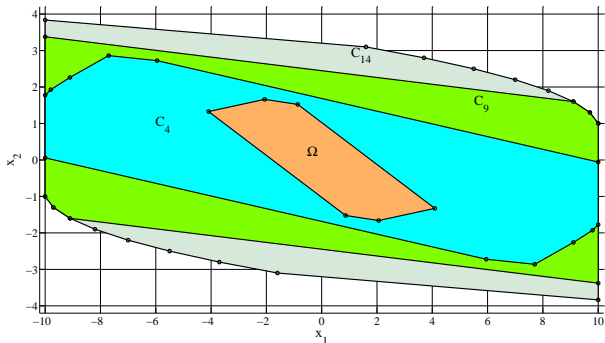
- For a given local feedback control $u = Kx$ there exists a polyhedral set $\Omega = \{x : F_0x \leq g_0\}$ such that for all $x(k) \in \Omega$, it follows $Kx(k) \in U$ and $x(k+1) = (A(k) + B(k)K)x(k) + D(k)w(k) \in \Omega$.
- See nominal LTI details in - Gilbert and Tan (1991) - Maximal admissible set (MAS)



Controlled invariant set

Using the one step pre-image set of the set $C_0 = \{x : F_0x \leq g_0\}$ one can obtain the collection of states that can be brought in one step into C_0 by a feasible constrained control action.

C_N is the set of states, that can be steered to the MAS Ω in no more than N step.

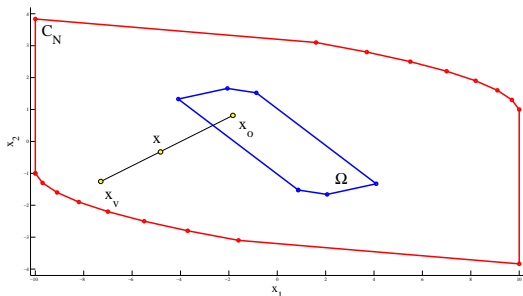


Interpolation based control - Implicit solution

$x \in C_N$ is decomposed as $x = cx_v + (1 - c)x_o$ with $x_v \in C_N$, $x_o \in \Omega$

u_v : vertex control

u_o : local control



Theorem: The control law $u = cu_v + (1 - c)u_o$ is feasible for all $x \in C_N$ and the closed loop system is robustly asymptotically stable.

Interpolation based control - Feasibility proof

Prove that $u(k) \in U$

$$\begin{aligned}
 F_u u(k) &= F_u (cu_v(k) + (1 - c)u_o(k)) \\
 &= cF_u u_v(k) + (1 - c)F_u u_o(k) \\
 &\leq cg_u + (1 - c)g_u = g_u
 \end{aligned}$$

And $x(k + 1) \in C_N$

$$\begin{aligned}
 x(k + 1) &= A(k)x(k) + B(k)u(k) \\
 &= A(k) \{cx_v(k) + (1 - c)x_o(k)\} + B(k) \{cu_v(k) + (1 - c)u_o(k)\} \\
 &= c \{A(k)x_v(k) + B(k)u_v(k)\} + (1 - c) \{Ax_o(k) + Bu_o(k)\} \\
 &\in C_N
 \end{aligned}$$

Interpolation based control - Stability proof

$\min c = c^*$ by finding *best* x_v, x_o .

Theorem: c^* is a positive and non-increasing Lyapunov function.

$$\begin{aligned}x(k) &= c^*(k)x_v(k) + (1 - c^*(k))x_o(k) \\u(k) &= c^*(k)u_v(k) + (1 - c^*(k))u_o(k)\end{aligned}$$

and

$$\begin{aligned}x(k+1) &= A(k)x(k) + B(k)u(k) + D(k)w(k) \\&= c^*(k)x_v(k+1) + (1 - c^*(k))x_o(k+1)\end{aligned}$$

Hence $c^*(k)$ is a feasible decomposition at time instant $k+1$.

By interpolation

$$x(k+1) = c^*(k+1)x_v^+(k+1) + (1 - c^*(k+1))x_o^+(k+1)$$

Hence $c^*(k+1) \leq c^*(k)$.

Nonlinear v.s. Linear Optimization

$$c^*(x) = \min_{c, x_o, x_v} c \text{ s.t. } \begin{cases} F_N x_v \leq g_N \\ F_o x_o \leq g_o \\ c x_v + (1 - c) x_o = x \\ 0 \leq c \leq 1 \end{cases}$$

Changing variables: $r_v = c x_v$, $r_o = (1 - c) x_o$.

$$c^*(x) = \min_{c, r_v, r_o} c \text{ s.t. } \begin{cases} F_N r_v \leq c g_N \\ F_o r_o \leq (1 - c) g_o \\ r_v + r_o = x \\ 0 \leq c \leq 1 \end{cases}$$

Interpolation based control via LP - Implicit solution

Computational scheme:

- 1 Measure state $x(k)$
- 2 Determine the optimal c^*
- 3 $u(k) = c^*(k)u_v(k) + (1 - c^*(k))u_o(k)$
- 4 Wait for next sampling time $k := k + 1$

At each time instant, only one LP with dimension $n_x + 1$ is solved.

System:

$$x(k+1) = A(k)x(k) + B(k)u(k)$$

$$A(k) = \alpha(k)A_1 + (1 - \alpha(k))A_2$$

$$B(k) = \alpha(k)B_1 + (1 - \alpha(k))B_2$$

$$A_1 = \begin{bmatrix} 1 & 0.1 \\ 0 & 1 \end{bmatrix} \quad B_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 1 & 0.2 \\ 0 & 1 \end{bmatrix} \quad B_2 = \begin{bmatrix} 0 \\ 1.5 \end{bmatrix}$$

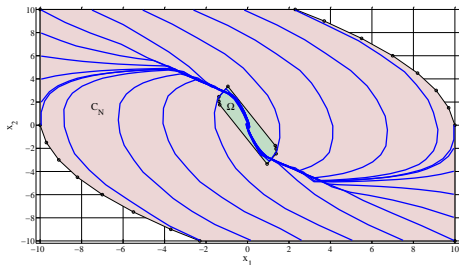
Interpolation based control via LP - Implicit solution, cont.

Constraints:

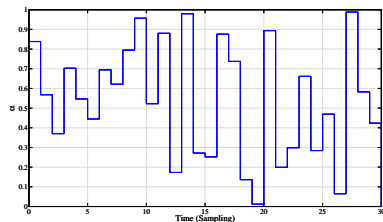
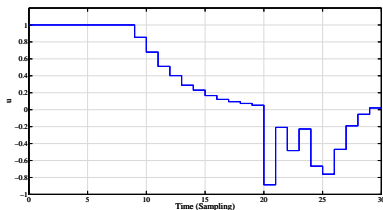
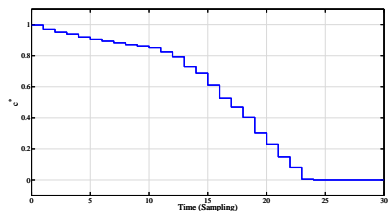
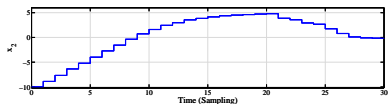
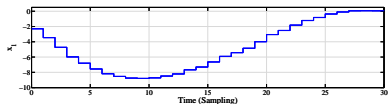
$$\begin{aligned} -10 \leq x_1 \leq 10, \quad -10 \leq x_2 \leq 10, \\ -1 \leq u \leq 1 \end{aligned}$$

Local feedback controller:

$$K = [-1.8112 \quad -0.8092]$$



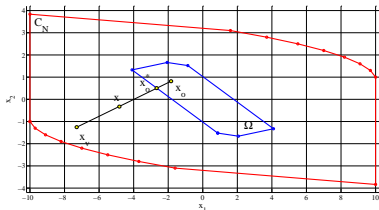
Interpolation based control via LP - Implicit solution, cont.



Geometric properties

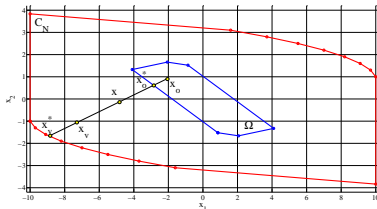
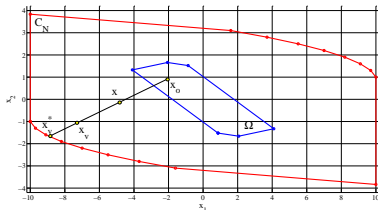
$$\begin{aligned}x &= cx_v + (1 - c)x_o \\ &= c^*x_v + (1 - c^*)x_o^*\end{aligned}$$

c is optimal iff $x_o \in \text{Fr}(\Omega)$.



$$\begin{aligned}x &= cx_v + (1 - c)x_o \\ &= c^*x_v^* + (1 - c^*)x_o\end{aligned}$$

c is optimal iff $x_v \in \text{Fr}(C_N)$



Geometric properties, cont.

- It is obvious that $c = 0$ for all $x \in \Omega$.
- For all $x \in C_N \setminus \Omega$, the smallest value c is reached if and only if $x_v \in \text{Fr}(C_N)$ and $x_o \in \text{Fr}(\Omega)$.

Fact: If $x \in C_N \setminus \Omega$ the smallest value c will be reached when the region $C_N \setminus \Omega$ is decomposed into polytopes. These polytopes can be further decomposed into simplices, each formed by s vertices of C_N and one vertex of Ω or one vertex of C_N and $n + 1 - s$ vertices of Ω with $1 \leq s \leq n$.

Geometric properties, cont.

Suppose x belongs to a simplex with $n + 1$ vertices of $C_N \setminus \Omega$

$$x = \alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_{n+1} x_{n+1}$$

with $\alpha_j \geq 0$ and $\sum_{i=1}^{n+1} \alpha_i = 1$. Hence

$$\alpha = \begin{bmatrix} x_1 & x_2 & \dots & x_{n+1} \\ 1 & 1 & \dots & 1 \end{bmatrix}^{-1} \begin{bmatrix} x \\ 1 \end{bmatrix}$$

The corresponding control value

$$\begin{aligned} u &= \alpha_1 u_1 + \alpha_2 u_2 + \dots + \alpha_{n+1} u_{n+1} \\ &= \begin{bmatrix} u_1 & u_2 & \dots & u_{n+1} \end{bmatrix} \begin{bmatrix} x_1 & x_2 & \dots & x_{n+1} \\ 1 & 1 & \dots & 1 \end{bmatrix}^{-1} \begin{bmatrix} x \\ 1 \end{bmatrix} \end{aligned}$$

The controller is an affine feedback state law whose gains are obtained simply by linear interpolation of the control values at the vertices of the simplex.

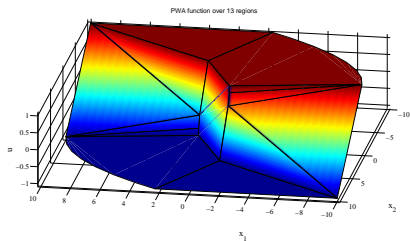
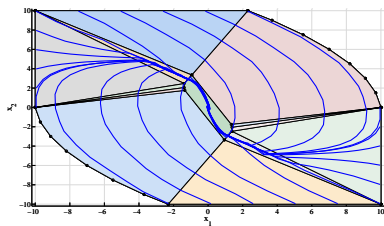
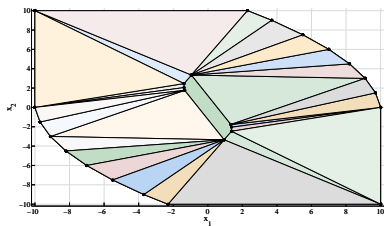
Explicit solution

Algorithm

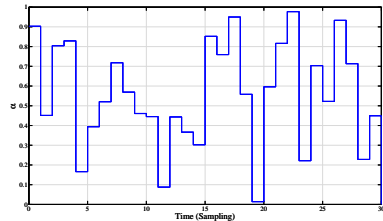
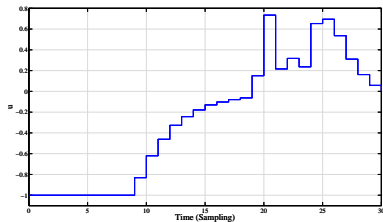
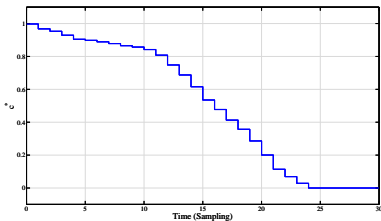
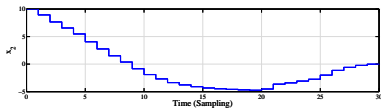
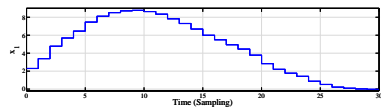
- 1 One gets the state space partition of $C_N \setminus \Omega$ by using explicit multi-parametric programming, where the parameter is x .
- 2 Decompose each partition of $C_N \setminus \Omega$ in a sequence of simplices.
- 3 In the MAS Ω the control law is $u = Kx$
- 4 In each simplex $C_k \subset C_N \setminus \Omega$ the control law is $u(x) = L_k x + v_k$ where

$$(L_k \quad v_k) = [u_1 \quad \dots \quad u_{n+1}] \begin{bmatrix} x_1^k & \dots & x_{n+1}^k \\ 1 & \dots & 1 \end{bmatrix}^{-1}$$

Explicit solution, cont.



Explicit solution, cont.



Problem formulation

For the system

$$x(k+1) = A(k)x(k) + B(k)u(k)$$

Given r invariant polyhedral sets with the feedback $u = K_i x$,
 $i = 1, 2, \dots, r$.

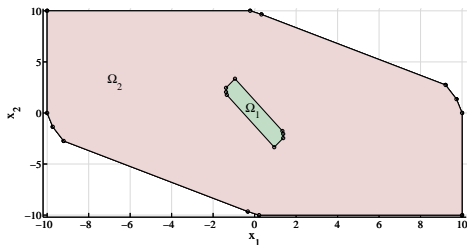
The first polytope is used for the performance. The last $r - 1$ polytopes are used for enlarging the domain of attraction.

Question

- Is convex hull of the set of polytopes invariant?
- How to construct a control law for this region?

Interpolation via QP

$\Omega_i = \{x : F_o^{(i)}x \leq g_o^{(i)}\}$: robust positively invariant set for $u = K_ix$.



$$\Omega = \text{Convex hull}(\Omega_i)$$

$$x(k) = \lambda_1 \hat{x}_1(k) + \lambda_2 \hat{x}_2(k) + \dots + \lambda_r \hat{x}_r(k)$$

$$\hat{x}_i \in \Omega_i, \quad \sum_{i=1}^r \lambda_i = 1.$$

$$u(k) = \lambda_1 K_1 \hat{x}_1(k) + \lambda_2 K_2 \hat{x}_2(k) + \dots + \lambda_r K_r \hat{x}_r(k)$$

Interpolation via QP, cont.

Denote $x_i(k) = \lambda_i \hat{x}_i(k)$. It follows that

$$F_o^{(i)} x_i \leq \lambda_i g_o^{(i)}$$

and

$$u(k) = K_1 x_1(k) + K_2 x_2(k) + \dots + K_r x_r(k)$$

$$\begin{aligned} x(k+1) &= A(k)x(k) + B(k)u(k) = A(k) \sum_{i=1}^r x_i(k) + B(k) \sum_{i=1}^r K_i x_i(k) \\ &= \sum_{i=1}^r x_i(k+1) \end{aligned}$$

with

$$x_i(k+1) = (A(k) + B(k)K_i)x_i(k)$$

Cost function determination

Q_i, R_i are weighting matrices

$$V_i(x_i) = x_i^T P_i x_i, i = 2, 3, \dots, r$$

where P_i is chosen to satisfy

$$V_i(x_i(k+1)) - V_i(x_i(k)) \leq -x_i(k)^T Q_i x_i(k) - u_i(k)^T R_i u_i(k)$$

LMI condition

$$\begin{bmatrix} P_i - Q_i - K_i^T R_i K_i & (A + BK_i)^T P_i \\ P_i(A + BK_i) & P_i \end{bmatrix} \succeq 0$$

Interpolation via QP

Objective function

$$V = \sum_{i=2}^r x_i^T P_i x_i + \sum_{i=2}^r \lambda_i^2$$

Algorithm: at each time instant

$$\min\{V\}$$

subject to

$$\left\{ \begin{array}{l} F_o^{(i)} x_i \leq \lambda_i g_o^{(i)} \\ \sum_{i=1}^r x_i = x \\ \sum_{i=1}^r \lambda_i = 1, \lambda_i \geq 0 \end{array} \right.$$

and apply as input the control action $u = \sum_{i=1}^r K_i x_i$.

Theorem: The interpolation based controller guarantees recursive feasibility and robust asymptotic stability for all initial states $x(0) \in \Omega$.

Feasibility and stability proof

Feasibility proof:

- Linearity of the system.
- Convexity of the feasible set.

Stability proof:

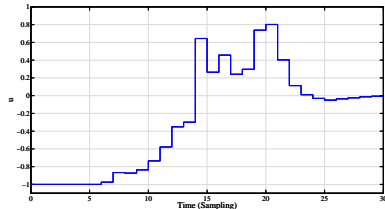
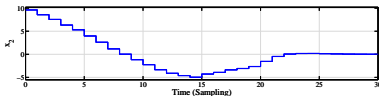
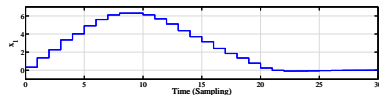
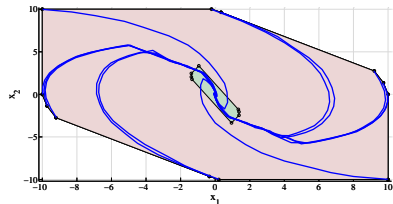
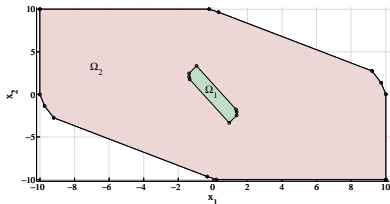
- If $x_i^o(k)$ and $\lambda_i^o(k)$: optimal solution at time instant k . Then $x_i^o(k)$ and $\lambda_i^o(k)$: feasible solution at time instant $k + 1$.
- $V(x)$ is a Lyapunov function

$$V(x(k+1)) - V(x(k)) \leq - \sum_{i=2}^r (x_i^T Q_i x_i + u_i^T R_i u_i)$$

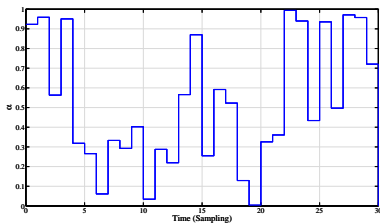
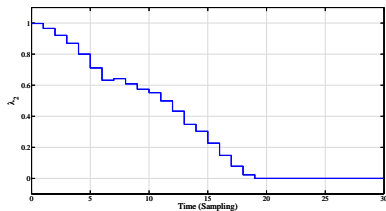
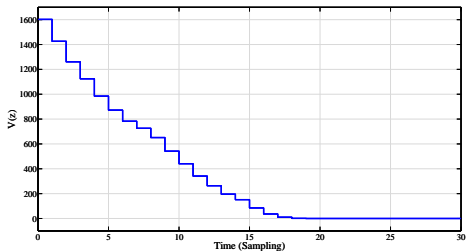
Interpolation via QP - Example

$$K_1 = [-1.8112 \quad -0.8092],$$

$$K_2 = [-0.0786 \quad -0.1010]$$



Interpolation via QP - Example, cont.



Interpolation via QP for uncertain systems with disturbances

System

$$x(k+1) = A(k)x(k) + B(k)u(k) + D(k)w(k)$$

Main ingredient

- A set of robust asymptotically stabilizing feedback controllers $u = K_i x$, $i = 1, 2, \dots, r$.
- A set of robust invariant polytopes Ω_i , $\Omega = \text{Convex hull}(\Omega_i)$

$$x(k) = \lambda_1 \hat{x}_1 + \lambda_2 \hat{x}_2 + \dots + \lambda_r \hat{x}_r$$

$$\hat{x}_i \in \Omega_i, \sum_{i=1}^r \lambda_i = 1.$$

$$u(k) = \lambda_1 K_1 \hat{x}_1 + \lambda_2 K_2 \hat{x}_2 + \dots + \lambda_r K_r \hat{x}_r$$

Preliminary definitions: Input to state stability

System

$$x(k+1) = A_c(k)x(k) + D(k)w(k)$$

ISS Stability: System is ISS iff

$$\|x(k)\| \leq \beta(\|x(0)\|, k) + \phi\left(\sup_{0 \leq i \leq k-1} \|w(i)\|\right)$$

ISS Lyapunov function: Function $V : \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ is an ISS Lyapunov function iff

$$\begin{cases} \gamma_1(\|x\|) \leq V(x) \leq \gamma_2(\|x\|) \\ V(x(k+1)) - V(x(k)) \leq -\gamma_3(\|x(k)\|) + \theta(\|w(k)\|) \end{cases}$$

Theorem: System is input to state stable if it admits an ISS Lyapunov function.

Interpolation via QP for uncertain system with disturbances

$x_i(k) = \lambda_i \hat{x}_i$. As in the previous slides

$$x(k) = \sum_{i=1}^r x_i(k+1)$$

where $z(k) = [x_1(k)^T \quad x_2(k)^T \quad \dots \quad x_r(k)^T]^T$ satisfies

$$z(k+1) = \Phi(k)z(k) + S(k)\eta(k)$$

$$\Phi(k) = \begin{bmatrix} A_c^{(1)} & 0 & \dots & 0 \\ 0 & A_c^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & A_c^{(r)} \end{bmatrix}, S(k) = \begin{bmatrix} D & 0 & \dots & 0 \\ 0 & D & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & D \end{bmatrix}$$

$$A_c^{(i)} = A(k) + B(k)K_i$$

Interpolation via QP for uncertain system with disturbances

Q , R are weighting matrices.

$$V(z) = z^T P z$$

where

$$V(z(k+1)) - V(z(k)) \leq -x(k)^T Q x(k) - u(k)^T R u(k) + \tau \eta(k)^T \eta(k)$$

LMI condition

$$\begin{bmatrix} P - Q_1 - R_1 & 0 & \Phi^T P \\ 0 & \tau I & S^T P \\ P \Phi & P S & P \end{bmatrix} \succeq 0$$

$$\min \tau$$

Interpolation via QP for uncertain system with disturbances

At each time instant

$$\min\{V(z)\}$$

subject to

$$\left\{ \begin{array}{l} F_o^{(i)} x_i \leq \lambda_i g_o^{(i)} \\ \sum_{i=1}^r x_i = x \\ \sum_{i=1}^r \lambda_i = 1, \lambda_i \geq 0 \end{array} \right.$$

and apply as input the control action $u = \sum_{i=1}^r K_i x_i$.

Theorem: The interpolation based controller guarantees recursive feasibility and the closed loop system is ISS for all initial states $x(0) \in \Omega$.

Example

System

$$x(k+1) = A(k)x(k) + Bu(k) + w(k)$$

$$A(k) = \alpha(k)A_1 + (1 - \alpha(k))A_2$$

$$A_1 = \begin{bmatrix} 1.1 & 1 \\ 0 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 0.6 & 1 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

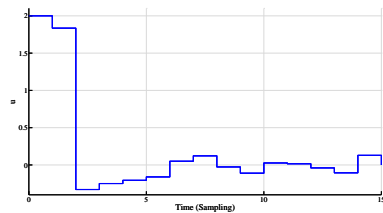
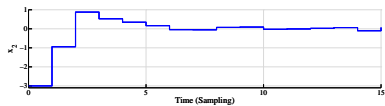
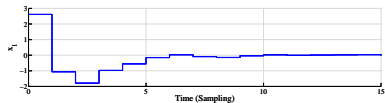
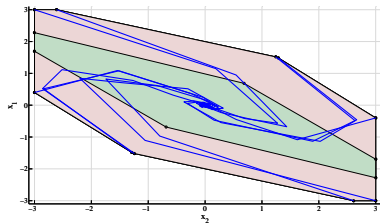
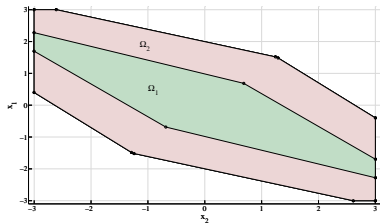
Constraints

$$\begin{aligned} -3 \leq x_1 \leq 3, \quad -3 \leq x_2 \leq 3 \\ -2 \leq u \leq 2 \\ -0.1 \leq w_1 \leq 0.1, \quad -0.1 \leq w_2 \leq 0.1 \end{aligned}$$

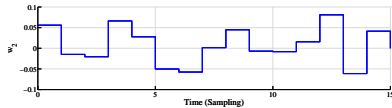
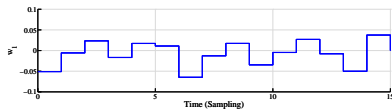
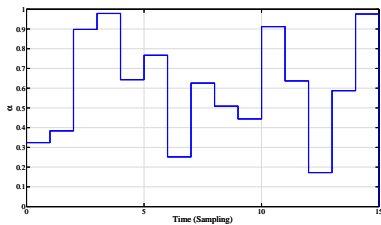
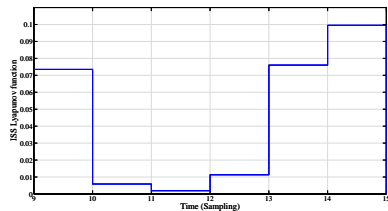
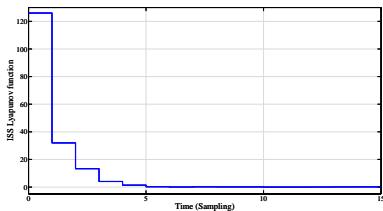
Controllers

$$\begin{aligned} K_1 &= [-0.8802 \quad -2.0355] \\ K_2 &= [-0.3856 \quad -1.0024] \end{aligned}$$

Example, cont.



Example, cont.



Outline

- 1 Abstract
- 2 Constrained control
- 3 Interpolation based control
- 4 Case study - Ball and plate**
- 5 Conclusion

System description

System description

- An mechanical plate.
- Two actuation mechanisms for tilting the plate around two orthogonal axes.
- A ball position sensor (touch screen)



System modeling

Only the model along the x -axis is considered here.

$$\begin{aligned} x(k+1) - 1.6736x(k) + 0.3632x(k-1) + 0.2959x(k-2) &= \\ &= 0.0157u_x(k-1) + 0.0701u_x(k-2) \end{aligned}$$

Constraints

$$-1 \leq x \leq 1, \quad -1 \leq u_x \leq 1$$

State variables

$$\begin{cases} x_1(k) = x(k) \\ x_2(k) = x(k-1) \\ x_3(k) = x(k-2) \\ x_4(k) = u(k-1) \\ x_5(k) = u(k-2) \end{cases}$$

System modeling, cont.

State space model

$$x_n(k+1) = Ax_n(k) + Bu_x(k)$$

with

$$x_n = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5]^T$$

and

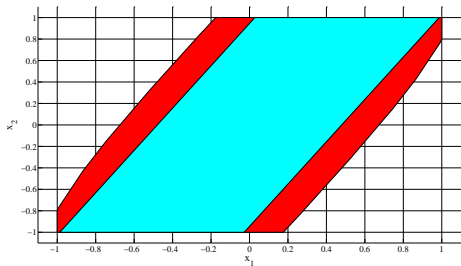
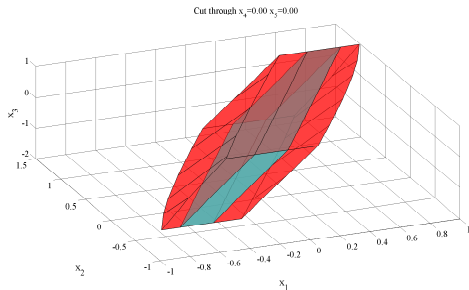
$$A = \begin{bmatrix} 1.6736 & -0.3632 & -0.2959 & 0.0157 & 0.0701 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$B = [0 \quad 0 \quad 0 \quad 1 \quad 0]^T$$

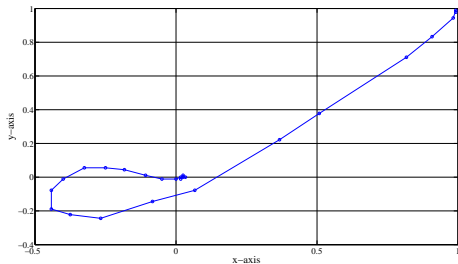
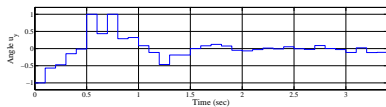
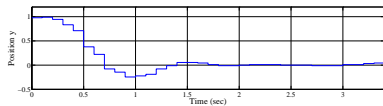
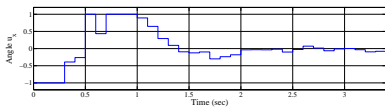
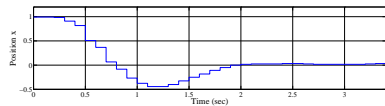
Local controller

$$K = [-9.0103 \quad 4.5692 \quad 2.2384 \quad -0.5503 \quad -0.5303]$$

Ball and plate, cont.



Ball and plate, cont.



Outline

- 1 Abstract
- 2 Constrained control
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Conclusion

- Several novel interpolation schemes are introduced.
- A robust control law with guaranteed of constrained stability is obtained.
- The resulting control law is affine over a polyhedral partition of the state space.
- The proposed control law is considerably simpler with fewer polyhedral subsets in the explicit case, and with extremely simple and fast LP(or QP)-computations in the implicit case, and hence with less on-line computations than the MPC one.

Thank you for your attention!