Explicit Model Predictive Control

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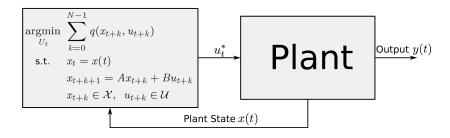
Fall Semester 2015

- 1. Explicit Model Predictive Control
- 1.1 Introduction
- 1.2 mpQP
- 1.3 mpLP
- 1.4 Constrained Finite Time Optimal Control
- 1.5 Online Evaluation: Point Location Problem
- 1.6 MPT Example
- 1.7 Summary

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Introduction



Requires at each time step on-line solution of an optimization problem

Introduction

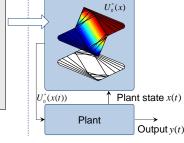
OFFLINE

$$U_0^*(x(t)) = \operatorname{argmin} \ x_N^T P x_N + \sum_{k=0}^{N-1} x_k' Q x_k + u_k' R u_k$$
 subj. to $x_0 = x(t)$
$$x_{k+1} = A x_k + B u_k, \ k = 0, \dots, N-1$$

$$x_k \in \mathcal{X}, \ u_k \in \mathcal{U}, \ k = 0, \dots, N-1$$

$$x_N \in \mathcal{X}_f$$

ONLINE



- Optimization problem is parameterized by state
- Pre-compute control law as function of state x
- Control law is piecewise affine for linear system/constraints

Result: Online computation dramatically reduced and *real-time* Tool: *Parametric programming*

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mpQP - Problem formulation

$$J^*(x) = \min_{z} \qquad \frac{1}{2}z'Hz,$$
 subj. to $Gz \le w + Sx$

where H > 0, $z \in \mathbb{R}^s$, $x \in \mathbb{R}^n$ and $G \in \mathbb{R}^{m \times s}$.

Given a closed and bounded polyhedral set $\mathcal{K} \subset \mathbb{R}^n$ of parameters denote by $\mathcal{K}^* \subseteq \mathcal{K}$ the region of parameters $x \in \mathcal{K}$ such that the problem is feasible

$$\mathcal{K}^* \triangleq \{x \in K : \exists z, \ Gz \le w + Sx\}$$

Goals:

- 2 find all x for which the problem has a solution
- \blacksquare compute the value function $J^*(x)$

Active Set and Critical Region

Let $I \triangleq \{1, \dots, m\}$ be the set of constraint indices.

Definition: Active Set

We define the active set at x, A(x), and its complement, NA(x), as

$$A(x) \triangleq \{ i \in I : G_i z^*(x) - S_i x = w_i \}$$

$$NA(x) \triangleq \{ i \in I : G_i z^*(x) - S_i x < w_i \}.$$

 G_i , S_i and w_i are the *i*-th row of G, S and w, respectively.

Definition: Critical Region

 CR_A is the set of parameters x for which the same set $A\subseteq I$ of constraints is active at the optimum. For a given $\bar{x}\in\mathcal{K}^*$ let $(A,NA)\triangleq (A(\bar{x}),NA(\bar{x}))$. Then,

$$CR_A \triangleq \{x \in \mathcal{K}^* : A(x) = A\}.$$

mpQP - Global properties of the solution

The following theorem summarizes the properties of the mpQP solution.

Theorem: Solution of mpQP

- i) The feasible set \mathcal{K}^* is a **polyhedron**.
- ii) The optimizer function $z^*(x): \mathcal{K}^* \to \mathbb{R}^m$ is:
 - continuous
 - polyhedral piecewise affine over \mathcal{K}^* . It is affine in each critical region \mathcal{CR}_i , every \mathcal{CR}_i is a polyhedron and $\bigcup \mathcal{CR}_i = \mathcal{K}^*$.
- iii) The value function $J^*(x): \mathcal{K}^* \to \mathbb{R}$ is:
 - continuous
 - convex
 - **polyhedral piecewise quadratic over** \mathcal{K}^* , it is quadratic in each \mathcal{CR}_i

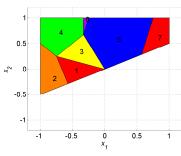
mpQP - Example (1/4)

Consider the example

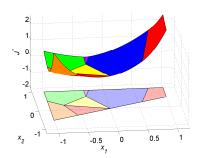
$$\min_{z(x)} \qquad \qquad \frac{1}{2}(z_1^2+z_2^2)$$
 subj. to
$$z_1 \leq 1+x_1+x_2 \\ -z_1 \leq 1-x_1-x_2 \\ z_2 \leq 1+x_1-x_2 \\ -z_2 \leq 1-x_1+x_2 \\ z_1-z_2 \leq x_1+3x_2 \\ -z_1+z_2 \leq -2x_1-x_2 \\ -1 \leq x_1 \leq 1, \ -1 \leq x_2 \leq 1$$

mpQP - Example (2/4)

The explicit solution is defined over $i=1,\ldots,7$ regions $\mathcal{P}_i=\{x\in\mathbb{R}^2\mid A_ix\leq b_i\}$ in the parameter space x_1-x_2 .



Critical regions



Piecewise quadratic objective function $J^*(x)$

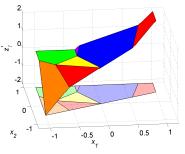
mpQP - Example (3/4)

Primal solution is given as piecewise affine function $z(x) = F_i + g_i x$ if $x \in \mathcal{P}_i$.

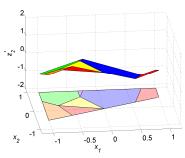
$$z^*(x) = \begin{cases} \begin{pmatrix} 0.5 & 1.5 \\ -0.5 & -1.5 \end{pmatrix} x & \text{if } x \in \mathcal{P}_1 \\ \begin{pmatrix} 2 & 2 \\ 1 & -1 \end{pmatrix} x + \begin{pmatrix} 1 \\ 1 \end{pmatrix} & \text{if } x \in \mathcal{P}_2 \\ \vdots \\ \vdots \end{cases}$$

mpQP - Example (4/4)

Primal solution is given as piecewise affine function $z(x) = F_i + g_i x$ if $x \in \mathcal{P}_i$.



Piecewise affine function $z_1^*(x)$



Piecewise affine function $z_2^*(x)$

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mpLP - Problem formulation

$$J^*(x) = \min_{z} \qquad c'z$$
 subj. to $Gz \le w + Sx$

where $z \in \mathbb{R}^s$, $x \in \mathbb{R}^n$ and $G \in \mathbb{R}^{m \times s}$.

Given a closed and bounded polyhedral set $\mathcal{K} \subset \mathbb{R}^n$ of parameters, denote by $\mathcal{K}^* \subseteq \mathcal{K}$ the region of parameters $x \in \mathcal{K}$ such that the problem is feasible

$$\mathcal{K}^* \triangleq \{ x \in K : \exists z, \ Gz \le w + Sx \}$$

Goals:

- 2 find all x for which the problem has a solution
- ${\bf 3}$ compute the value function $J^*(x)$

mpLP - Global properties of the solution

The following theorem summarizes the properties of the mpLP solution.

Theorem: Solution of mpLP

- i) The feasible set \mathcal{K}^* is a **polyhedron**.
- ii) If the optimal solution z^* is unique $\forall x \in \mathcal{K}^*$, the optimizer function $z^*(x): \mathcal{K}^* \to \mathbb{R}^m$ is:
 - continuous
 - **polyhedral piecewise affine over** \mathcal{K}^* . It is affine in each critical region \mathcal{CR}_i , every \mathcal{CR}_i is a polyhedron and $\bigcup \mathcal{CR}_i = \mathcal{K}^*$.

Otherwise, it is always possible to choose such a continuous and PPWA optimizer function $z^*(x)$.

- iii) The value function $J^*(x): \mathcal{K}^* \to \mathbb{R}$ is:
 - continuous
 - convex
 - **polyhedral piecewise affine over** \mathcal{K}^* , it is affine in each \mathcal{CR}_i .

mpLP - Example (1/4)

Consider the example

$$\min_{z(x)} \qquad -3z_1 - 8z_2$$
 subj. to
$$z_1 + z_2 \leq 13 + x_1$$

$$5z_1 - 4z_2 \leq 20$$

$$-8z_1 + 22z_2 \leq 121 + x_2$$

$$-4z_1 - z_2 \leq -8$$

$$-z_1 \leq 0$$

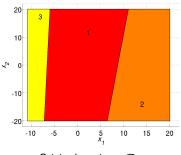
$$-z_2 \leq 0$$

$$-1 \leq x_1 \leq 1$$

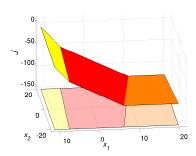
$$-1 \leq x_2 \leq 1$$

mpLP - Example (2/4)

The explicit solution is defined over $i=1,\ldots,3$ regions $\mathcal{P}_i=\{x\in\mathbb{R}^2\mid A_ix\leq b_i\}$ in the parameter space x_1-x_2 .



Critical regions \mathcal{P}_i



Piecewise affine objective function $J^*(x)$

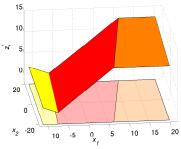
mpLP - Example (3/4)

Primal solution is given as piecewise affine function $z^*(x) = F_i x + g_i$ if $x \in \mathcal{P}_i$.

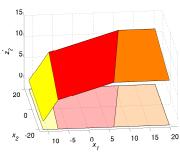
$$z^*(x) = \begin{cases} \begin{pmatrix} 0.733 & -0.033 \\ 0.267 & 0.033 \end{pmatrix} x + \begin{pmatrix} 5.5 \\ 7.5 \end{pmatrix} & \text{if } x \in \mathcal{P}_1 \\ \begin{pmatrix} 0 & 0.051 \\ 0 & 0.064 \end{pmatrix} x + \begin{pmatrix} 11.846 \\ 9.808 \end{pmatrix} & \text{if } x \in \mathcal{P}_2 \\ \begin{pmatrix} -0.333 & 0 \\ 1.333 & 0 \end{pmatrix} x + \begin{pmatrix} -1.667 \\ 14.667 \end{pmatrix} & \text{if } x \in \mathcal{P}_3 \end{cases}$$

mpLP - Example (4/4)

Primal solution is given as piecewise affine function $z^*(x) = F_i x + g_i$ if $x \in \mathcal{P}_i$.



Piecewise affine function $z_1^*(x)$



Piecewise affine function $z_2^*(x)$

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Problem Formulation - Quadratic Cost

Quadratic cost function

$$J_0(x(0), U_0) = x_N' P x_N + \sum_{k=0}^{N-1} x_k' Q x_k + u_k' R u_k$$
 (1)

with $P \succeq 0$, $Q \succeq 0$, $R \succ 0$.

Constrained Finite Time Optimal Control problem (CFTOC).

$$J_0^*(x(0)) = \min_{U_0} \quad J_0(x(0), U_0)$$
subj. to $x_{k+1} = Ax_k + Bu_k, \ k = 0, \dots, N-1$

$$x_k \in \mathcal{X}, \ u_k \in \mathcal{U}, \ k = 0, \dots, N-1$$

$$x_N \in \mathcal{X}_f$$

$$x_0 = x(0)$$
(2)

N is the time horizon and \mathcal{X} , \mathcal{U} , \mathcal{X}_f are polyhedral regions.

Construction of the QP with substitution

■ **Step 1**: Rewrite the cost as (see lectures on Day 1 & 2)

$$J_0(x(0), U_0) = U'_0 H U_0 + 2x(0)' F U_0 + x(0)' Y x(0)$$

= $[U'_0 x(0)'] \begin{bmatrix} H F' \\ F Y \end{bmatrix} [U'_0 x(0)']'$

Note: $\begin{bmatrix} H & F' \\ F & Y \end{bmatrix} \succeq 0$ since $J_0(x(0), U_0) \geq 0$ by assumption.

■ **Step 2**: Rewrite the constraints compactly as (details provided on the next slide)

$$G_0 U_0 \le w_0 + E_0 x(0)$$

■ **Step 3**: Rewrite the optimal control problem as

$$J_0^*(x(0)) = \min_{U_0} \quad [U_0' \ x(0)'] \begin{bmatrix} H \ F' \\ Y \end{bmatrix} [U_0' \ x(0)']'$$
 subj. to
$$G_0 U_0 \le w_0 + E_0 x(0)$$

Solution

$$J_0^*(x(0)) = \min_{U_0} \quad [U_0' \ x(0)'] \begin{bmatrix} H \ F' \end{bmatrix} [U_0' \ x(0)']'$$

subj. to $G_0 U_0 \le w_0 + E_0 x(0)$

For a given x(0) U_0^* can be found via a QP solver.

Construction of QP constraints with substitution

If \mathcal{X} , \mathcal{U} and \mathcal{X}_f are given by:

$$\mathcal{X} = \{x \mid A_x x \le b_x\} \qquad \mathcal{U} = \{u \mid A_u u \le b_u\} \qquad \mathcal{X}_f = \{x \mid A_f x \le b_f\}$$

Then G_0 , E_0 and w_0 are defined as follows

$$G_{0} = \begin{bmatrix} A_{u} & 0 & \dots & 0 \\ 0 & A_{u} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & A_{u} \\ 0 & 0 & \dots & A_{u} \\ 0 & 0 & \dots & 0 \\ A_{x}B & 0 & \dots & 0 \\ A_{x}AB & A_{x}B & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{f}A^{N-1}B & A_{f}A^{N-2}B & \dots & A_{f}B \end{bmatrix}, E_{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ -A_{x} \\ -A_{x}A \\ -A_{x}A^{2} \\ \vdots \\ -A_{f}A^{N} \end{bmatrix}, w_{0} = \begin{bmatrix} b_{u} \\ b_{u} \\ \vdots \\ b_{u} \\ b_{x} \\ b_{x} \\ \vdots \\ b_{f} \end{bmatrix}$$

2-Norm State Feedback Solution

Start from QP with substitution.

■ Step 1: Define $z \triangleq U_0 + H^{-1}F'x(0)$ and transform the problem into

$$\hat{J}^*(x(0)) = \min_{z \text{ subj. to }} z'Hz$$
subj. to $G_0z \le w_0 + S_0x(0)$,

where
$$S_0 \triangleq E_0 + G_0 H^{-1} F'$$
, and $\hat{J}^*(x(0)) = J_0^*(x(0)) - x(0)' (Y - F H^{-1} F') x(0)$.

The CFTOC problem is now a multiparametric quadratic program (mp-QP).

- **Step 2**: Solve the mp-QP to get explicit solution $z^*(x(0))$
- **Step 3**: Obtain $U_0^*(x(0))$ from $z^*(x(0))$

2-Norm State Feedback Solution

Main Results

- I The Open loop optimal control function can be obtained by solving the mp-QP problem and calculating $U_0^*(x(0))$, $\forall x(0) \in \mathcal{X}_0$ as $U_0^* = z^*(x(0)) H^{-1}F'x(0)$.
- The first component of the multiparametric solution has the form

$$u^*(0) = f_0(x(0)), \quad \forall x(0) \in \mathcal{X}_0,$$

 $f_0:\mathbb{R}^n \to \mathbb{R}^m$, is continuous and piecewise affine on polyhedra

$$f_0(x) = F_0^i x + g_0^i$$
 if $x \in CR_0^i$, $i = 1, ..., N_0^r$

- The polyhedral sets $CR_0^i=\{x\in\mathbb{R}^n|H_0^ix\leq K_0^i\},\ i=1,\ldots,N_0^r$ are a partition of the feasible polyhedron \mathcal{X}_0 .
- **4** The value function $J_0^*(x(0))$ is convex and piecewise quadratic on polyhedra.

Example

Consider the double integrator

$$\begin{cases} x(t+1) &= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t) \\ y(t) &= \begin{bmatrix} 1 & 0 \end{bmatrix} x(t) \end{cases}$$

subject to constraints

$$-1 \le u(k) \le 1, \ k = 0, \dots, 5$$
$$\begin{bmatrix} -10 \\ -10 \end{bmatrix} \le x(k) \le \begin{bmatrix} 10 \\ 10 \end{bmatrix}, \ k = 0, \dots, 5$$

Compute the **state feedback** optimal controller $u^*(0)(x(0))$ solving the CFTOC

problem with N=6, $Q=\left[\begin{smallmatrix}1&0\\0&1\end{smallmatrix}\right]$, R=0.1, P the solution of the ARE, $\mathcal{X}_f=\mathbb{R}^2.$

Example

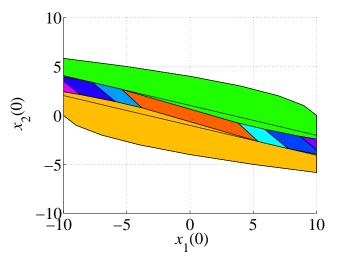


Figure: Partition of the state space for the piecewise affine control law $u^{st}(0)$ ($N_0^r=13$)

Problem Formulation - Piecewise Linear Cost

Piecewise linear cost function

$$J_0(x(0), U_0) := \|Px_N\|_p + \sum_{k=0}^{N-1} \|Qx_k\|_p + \|Ru_k\|_p$$
 (3)

with p=1 or $p=\infty$, P, Q, R full column rank matrices

Constrained Finite Time Optimal Control Problem (CFTOC)

$$J_{0}^{*}(x(0)) = \min_{U_{0}} \quad J_{0}(x(0), U_{0})$$
subj. to $x_{k+1} = Ax_{k} + Bu_{k}, \ k = 0, \dots, N-1$

$$x_{k} \in \mathcal{X}, \ u_{k} \in \mathcal{U}, \ k = 0, \dots, N-1$$

$$x_{N} \in \mathcal{X}_{f}$$

$$x_{0} = x(0)$$
(4)

N is the time horizon and \mathcal{X} , \mathcal{U} , \mathcal{X}_f are polyhedral regions.

Construction of the LP with substitution

Recall that the $\infty-$ norm problem can be equivalently formulated as

$$\min_{z_0} \qquad \varepsilon_0^x + \ldots + \varepsilon_N^x + \varepsilon_0^u + \ldots + \varepsilon_{N-1}^u$$
subj. to
$$-\mathbf{1}_n \varepsilon_k^x \le \pm Q \left[A^k x_0 + \sum_{j=0}^{k-1} A^j B u_{k-1-j} \right],$$

$$-\mathbf{1}_r \varepsilon_N^x \le \pm P \left[A^N x_0 + \sum_{j=0}^{N-1} A^j B u_{N-1-j} \right],$$

$$-\mathbf{1}_m \varepsilon_k^u \le \pm R u_k,$$

$$A^k x_0 + \sum_{j=0}^{k-1} A^j B u_{k-1-j} \in \mathcal{X}, \ u_k \in \mathcal{U},$$

$$A^N x_0 + \sum_{j=0}^{N-1} A^j B u_{N-1-j} \in \mathcal{X}_f,$$

$$k = 0, \ldots, N-1$$

$$x_0 = x(0)$$

Construction of the LP with substitution

The problem yields the following standard LP

$$\min_{z_0} c_0' z_0$$

subj. to $\bar{G}_0 z_0 \le \bar{w}_0 + \bar{S}_0 x(0)$

where
$$z_0:=\{\varepsilon_0^x,\ldots,\varepsilon_N^x,\varepsilon_0^u,\ldots,\varepsilon_{N-1}^u,u_0',\ldots,u_{N-1}'\}\in\mathbb{R}^s$$
, $s\triangleq (m+1)N+N+1$ and

$$\bar{G}_0 = \left[\begin{array}{cc} G_{\varepsilon} & 0 \\ 0 & G_0 \end{array} \right], \ \bar{S}_0 = \left[\begin{array}{c} S_{\varepsilon} \\ S_0 \end{array} \right], \ \bar{w}_0 = \left[\begin{array}{c} w_{\varepsilon} \\ w_0 \end{array} \right]$$

For a given x(0) U_0^{*} can be obtained via an LP solver (the 1-norm case is similar).

1- $/\infty$ -Norm State Feedback Solution

Main Results

- II The Open loop optimal control function can be obtained by solving the mp-LP problem and calculating $z_0^*(x(0))$
- 2 The component $u_0^*=[0\ \dots 0\ I_m\ 0\ \dots\ 0]z_0^*(x(0))$ of the multiparametric solution has the form

$$u^*(0) = f_0(x(0)), \quad \forall x(0) \in \mathcal{X}_0,$$

 $f_0:\mathbb{R}^n o\mathbb{R}^m$, is continuous and piecewise affine on polyhedra

$$f_0(x) = F_0^i x + g_0^i$$
 if $x \in CR_0^i$, $i = 1, \dots, N_0^r$

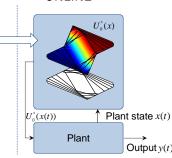
- The polyhedral sets $CR_0^i = \{x \in \mathbb{R}^n | H_0^i x \leq K_0^i\}, i = 1, \dots, N_0^r \text{ are a partition of the feasible polyhedron } \mathcal{X}_0.$
- 4 In case of multiple optimizers a piecewise affine control law exists.
- **5** The value function $J_0^*(x(0))$ is convex and piecewise affine on polyhedra.

Explicit MPC

OFFLINE

$$\begin{split} U_0^*(x(t)) &= \text{argmin} \quad x_N^T P x_N + \sum_{k=0}^{N-1} x_k' Q x_k + u_k' R u_k \\ \text{subj. to} \quad x_0 &= x(t) \\ x_{k+1} &= A x_k + B u_k, \ k = 0, \dots, N-1 \\ x_k &\in \mathcal{X}, \ u_k \in \mathcal{U}, \ k = 0, \dots, N-1 \\ x_N &\in \mathcal{X}_f \end{split}$$

ONLINE



- Optimization problem is parameterized by state
- $lue{}$ Pre-compute control law as function of state x
- Control law is piecewise affine for linear system/constraints

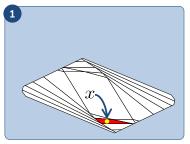
Result: Online computation dramatically reduced and *real-time* Tool: *Parametric programming*

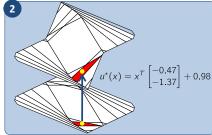
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Online evaluation: Point location

Calculation of piecewise affine function:

- Point location
- 2 Evaluation of affine function





Sequential search

$$CR(B_1) = \{x \mid A_1x + b_1 \le 0\}$$

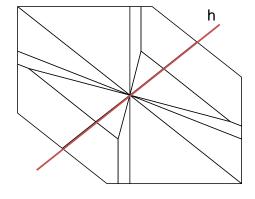
$$CR(B_2) = \{x \mid A_2x + b_2 \le 0\}$$

$$CR(B_3) = \{x \mid A_3x + b_3 \le 0\}$$

Sequential search for each i if $A_i x + b_i \leq 0$ then x is in region i

- Very simple
- Linear in number of regions

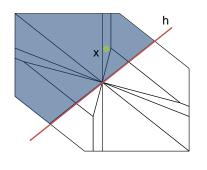
Logarithmic search (1/6)

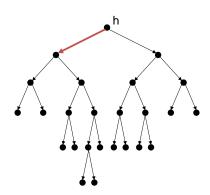


Offline construction of search tree

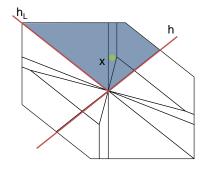
- Find hyperplane that separates regions into two equal sized sets
- Repeat for left and right sets

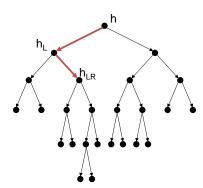
Logarithmic search (2/6)



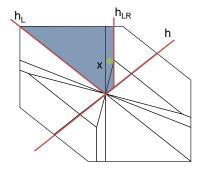


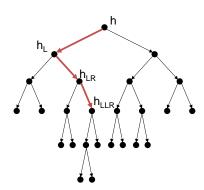
Logarithmic search (3/6)



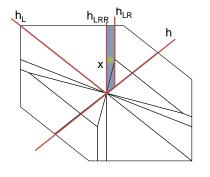


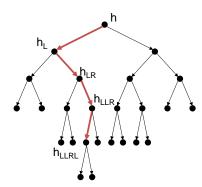
Logarithmic search (4/6)



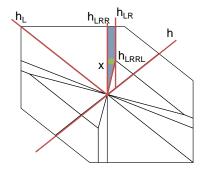


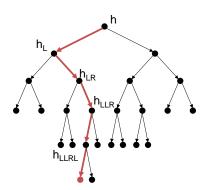
Logarithmic search (5/6)





Logarithmic search (6/6)





Point Location - Summary

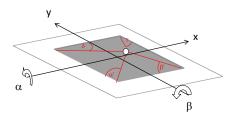
- Sequential search
 - Very simple
 - Works for all problems
- Search tree
 - Potentially logarithmic
 - lacksquare Significant offline processing (reasonable for <1'000 regions)
- Many other options for special cases

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1. Explicit Model Predictive Control

- 1.1 Introduction
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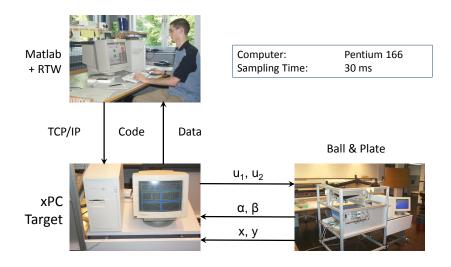
Ball and Plate



- Linearized model: four states for each axis: plate angle, ball position, plate angular speed, ball speed.
- Constraints on inputs and states
 - Plate angle
 - Ball position
 - Acceleration
- MPC objective: path tracking



Ball and Plate - System



Ball and Plate - MPC Problem

- 4 states + 1 tracking variable = 5 parameters
- Move-blocking reduces complexity
 - Horizon of 10
 - Inputs 2-10 must be equal

$$\min \sum_{i=0}^{9} 100 \|y_i - y_t\|_2^2 + 0.1 \|u_i\|_2^2$$

$$s.t. \ x_0 = x$$

$$x_{i+1} = Ax_i + Bu_i$$

$$y_i = Cx_i$$

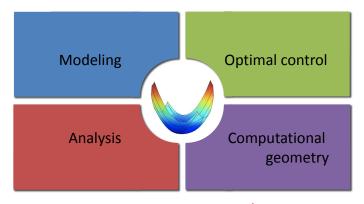
$$u_{\min} \le u_i \le u_{\max}$$

$$y_{\min} \le y_i \le y_{\max}$$

$$x_{\min} \le x_i \le x_{\max}$$

$$u_{i+1} = u_i, i = \{1, \dots, 9\}$$

Multi-Parametric Toolbox



control.ee.ethz.ch/~mpt

M P T % Linear discrete-time prediction model model=LTISystem('A', A, 'B', B, 'C', C);

- % Input constraints model.u.min = -10; model.u.max = 10;
 - % Output constraints model.y.min = -30; model.y.max = 30;
 - % State constraints model.x.min = [-30; -15; -15*pi/180; -1]; model.x.max = [30; 15; 15*pi/180; 1];
 - % Penalties in the cost function model.y.penalty = QuadFunction(100); model.u.penalty = QuadFunction(0.1);
 - % Adjustment via input blocking model.u.with('block'); model.u.from = 1; model.u.to = 9;
 - % Time varying reference signal model.y.with('reference'); model.y.reference = 'free';

```
% Online MPC object online ctrl = MPCController( model, 9 )
```

$$\min \sum_{i=0}^{9} 100 \|y_i - y_t\|_2^2 + 0.1 \|u_i\|_2^2$$
s.t. $x_0 = x$

$$x_{i+1} = Ax_i + Bu_i$$

$$y_i = Cx_i$$

$$u_{\min} \le u_i \le u_{\max}$$

$$y_{\min} \le y_i \le y_{\max}$$

$$x_{\min} \le x_i \le x_{\max}$$

$$u_{i+1} = u_i, \quad i = \{1, \ldots, 9\}$$

M P T

```
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```

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- % State constraints model.x.min = [-30; -15; -15*pi/180; -1]; model.x.max = [30: 15: 15*pi/180; 11:
- % Penalties in the cost function model.y.penalty = QuadFunction(100); model.u.penalty = QuadFunction(0.1);
- % Adjustment via input blocking model.u.with('block'); model.u.from = 1; model.u.to = 9;
- % Time varying reference signal model.y.with('reference'); model.y.reference = 'free';

% Online MPC object online ctrl = MPCController(model, 9)

$$\min \sum_{i=0}^{9} 100 \|y_i - y_t\|_2^2 + 0.1 \|u_i\|_2^2$$
s.t. $x_0 = x$

$$\sim x_{i+1} = Ax_i + Bu_i$$

$$y_i = Cx_i$$

$$u_{\mathsf{min}} \leq u_i \leq u_{\mathsf{max}}$$

$$y_{\min} \le y_i \le y_{\max}$$

$$x_{\min} \le x_i \le x_{\max}$$

$$u_{i+1} = u_i, \quad i = \{1, \dots, 9\}$$

Multi-Parametric Toolbox 3.0 Formulation

% Linear discrete-time prediction model model=LTISvstem('A', A, 'B', B, 'C', C); $\min \sum 100||y_i - y_t||_2^2 + 0.1||u_i||_2^2$ М % Input constraints model.u.min = -10; model.u.max = 10; s.t. $x_0 = x$ % Output constraints $x_{i+1} = Ax_i + Bu_i$ model.y.min = -30; model.y.max = 30; $v_i = Cx_i$ % State constraints $u_{\min} < u_i < u_{\max}$ model.x.min = [-30; -15; -15*pi/180; -1];model.x.max = [30; 15; 15*pi/180; 1]; $\sim V_{\min} < V_i < V_{\max}$ % Penalties in the cost function • $X_{\min} < X_i < X_{\max}$ model.v.penalty = QuadFunction(100): model.u.penalty = QuadFunction(0.1): $u_{i+1} = u_i, \quad i = \{1, \dots$ 9} % Adjustment via input blocking model.u.with('block'); model.u.from = 1; model.u.to = 9; % Time varying reference signal model.y.with('reference'); model.y.reference = 'free'; % Online MPC object online ctrl = MPCController(model, 9)

M P T % Linear discrete-time prediction model model=LTISvstem('A', A, 'B', B, 'C', C);

- % Input constraints model.u.min = -10; model.u.max = 10;
 - % Output constraints model.y.min = -30; model.y.max = 30;
 - % State constraints model.x.min = [-30; -15; -15*pi/180; -1]; model.x.max = [30; 15; 15*pi/180; 1];
 - % Penalties in the cost function model.y.penalty = QuadFunction(100); model.u.penalty = QuadFunction(0.1);
 - % Adjustment via input blocking model.u.with('block'); model.u.from = 1; model.u.to = 9; *
 - % Time varying reference signal model.y.with('reference'); model.y.reference = 'free';
- % Online MPC object online ctrl = MPCController(model, 9)

$$\min \sum_{i=0}^{9} 100 \|y_i - y_t\|_2^2 + 0.1 \|u_i\|_2^2$$

s.t.
$$x_0 = x$$

 $x_{i+1} = Ax_i + Bu_i$

$$y_i = Cx_i$$

$$u_{\mathsf{min}} \leq u_i \leq u_{\mathsf{max}}$$

$$y_{\min} \le y_i \le y_{\max}$$

$$x_{\min} \le x_i \le x_{\max}$$

M P T % Linear discrete-time prediction model model=LTISvstem('A', A, 'B', B, 'C', C);

- % Input constraints model.u.min = -10; model.u.max = 10;
 - % Output constraints model.y.min = -30; model.y.max = 30;
 - % State constraints model.x.min = [-30; -15; -15*pi/180; -1]; model.x.max = [30: 15: 15*pi/180; 11:
 - % Penalties in the cost function model.y.penalty = QuadFunction(100); model.u.penalty = QuadFunction(0.1);
 - % Adjustment via input blocking model.u.with('block'); model.u.from = 1; model.u.to = 9;
 - % Time varying reference signal model.y.with('reference'); model.y.reference = 'free';

% Online MPC object
online ctrl = MPCController(model, 9)

min
$$\sum_{i=0}^{9} 100 \|y_i - y_t\|_2^2 + 0.1 \|u_i\|_2^2$$

s.t. $x_0 = x$
 $x_{i+1} = Ax_i + Bu_i$
 $y_i = Cx_i$
 $u_{\min} \le u_i \le u_{\max}$
 $y_{\min} \le y_i \le y_{\max}$
 $x_{\min} \le x_i \le x_{\max}$
 $u_{i+1} = u_i, \quad i = \{1, \dots, 9\}$

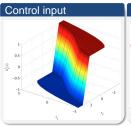
Explicit Solution

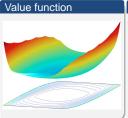
M % Compute explicit solution explicit_ctrl = online_ctrl.toExplicit()

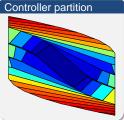
% Plot control law (primal solution) explicit_ctrl.optimizer.fplot('primal')

% plot the objective function explicit ctrl.optimizer.fplot('obi')

% Plot controller partition explicit_ctrl.optimizer.plot







Exporting Explicit Solutions

Search tree and export to flat c-file

Export to flat c-file, sequential search



% export control law to C explicit_ctrl.optimizer.toC('primal')

```
6.347758e-01, -7.726964e-01, 2.699058e+00,
                                                            1.300000e+01
                                                                          static long mpt searchTree (const real T *X, real T *U)
-2.528581e-01. -9.675034e-01. -4.781395e-01. -5.000000e+00.
                                                                          static long mpt searchTree(const float *X, float *U)
-6.811331e-01. 7.321596e-01. 4.632449e+00. 1.600000e+01.
                                                            1.900000e+01
6.811331e-01. -7.321596e-01. 4.632449e+00. 2.000000e+01.
6.669647e-01, -7.450893e-01, 3.576296e+00, 2.200000e+01,
                                                            2.300000e+01
5.225216e-01, -8.526260e-01, 2.007907e+00, 2.400000e+01, 2.500000e+01
                                                                             for (iu=0; iu<MPT NU; iu++) (
2.990218e-01,
              9.542463e-01, 1.489549e+00, -4.000000e+00, -1.400000e+0
                                                                             while (node > 0) (
                                                                                 hx = 0:
                                                                                 row = (node-1)*(NPT NX+3);
                                                                                 for (ix=0; ix<MPT NX; ix++) (
                                                                                    hx = hx + MPT ST[row+ix]*X[ix];
                                                                                 k = MPT ST[row+MPT NX];
```

Ball and Plate - Explicit Controller

- 4 states + 1 tracking variable = 5 parameters
- Move-blocking reduces complexity
 - Horizon of 10
 - Inputs 2-10 must be equal

$$J^{*}(x, y_{t}) = \min \sum_{i=0}^{9} 100 \|y_{i} - y_{t}\|_{2}^{2} + 0.1 \|u_{i}\|_{2}^{2}$$
s.t. $x_{0} = x$

$$x_{i+1} = Ax_{i} + Bu_{i}$$

$$y_{i} = Cx_{i}$$

$$u_{\min} \le u_{i} \le u_{\max}$$

$$y_{\min} \le y_{i} \le y_{\max}$$

$$u_{i+1} = u_{i}, \quad i = \{1, \dots, 9\}$$

Explicit solution (per dimension)

Regions: 529

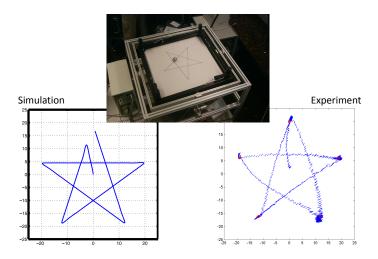
Storage: 48'000 numbers

(192 kB)

Computation: 89'000 FLOPS

(~1ms)

Ball and Plate - Pentagram



Real-time MPC Software Toolbox

Formal specification

- YALMIP
- HYSDEL
- · Linear + Hybrid models

Verified controller



Control law

- Explicit MPC
- Fixed-complexity solutions

Software synthesis

- · Real-time workshop
- Bounded-time solvers
- · Verifiable code generation

Multi-Parametric Toolbox (MPT)

- Computational geometry
- Multi-parametric programming
- Control of linear and hybrid systems







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Summary

- Linear MPC + Quadratic or linear-norm cost ⇒ Controller is PWA function
- We can pre-compute this function offline efficiently
- Online evaluation of a PWA function is very fast (ns μ s)
- We can only do this for very small systems! (3-6 states)