Introduction to Model Predictive Control Lectures 5-6: Optimization

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Summarizing...

Need

- A discrete-time model of the system (Matlab, Simulink)
- A state observer
- Set up an Optimization Problem (Matlab, MPT toolbox/Yalmip)
- Solve an optimization problem (Matlab/Optimization Toolbox, NPSOL)
- Verify that the closed-loop system performs as desired (avoid infeasibility/stability)
- Make sure it runs in real-time and code/download for the embedded platform

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Fundamental Concepts

Abstract Optimization Problems

- Optimization problems are abundant in economical daily life
- General abstract features of problem formulation:
 - ▶ Decision set Z
 - ▶ **Constraints** on decision and subset $S \subseteq Z$ of **feasible** decisions.
 - ▶ Assign to each decision a **cost** $f(x) \in \mathbb{R}$.
 - ► Goal is to **minimize** the cost by choosing a suitable decision.
- Concrete features of problem formulation:
 - ▶ Z is real vector space: Continuous problem.
 - ▶ Z is discrete set: Discrete or combinatorial problem.
 - if dim(Z) is finite: Finite Dimensional problem.
 - if dim(Z) is infinite: Infinite Dimensional problem.

Concrete Optimization Problems

Generally formulated as

$$\inf_{z} \qquad f(z)$$
 such that $z \in S \subseteq Z$ (1)

- The **vector** z collects the decision variables
- Z is the **domain** of the decision variables,
- $S \subseteq Z$ is the set of feasible or admissible decisions.
- The function $f:Z\to\mathbb{R}$ assigns to each decision z a cost $f(z)\in\mathbb{R}$.

Shorter form of problem (1)

$$\inf_{z \in S \subseteq Z} f(z) \tag{2}$$

Problem (2) is a called nonlinear mathematical program or simply nonlinear program.

Concrete Optimization Problems

Solving problem (2) means

• Compute the least possible cost J^* (called the **optimal value**)

$$J^* \triangleq \inf_{z \in S} f(z) \tag{3}$$

 J^* is the greatest lower bound of f(z) over the set S:

$$f(z) \ge J^*, \ \forall z \in S$$

AND

1

$$\exists \bar{z} \in S : f(\bar{z}) = J^*$$

OR

2

$$\forall \varepsilon > 0 \ \exists z \in S | \ f(z) \le J^* + \varepsilon$$

• Compute the **optimizer**, $z^* \in S$ with $f(z^*) = J^*$. If z^* exists, then rewrite (3) as

$$J^* = \min_{z \in S} f(z) \tag{4}$$

Concrete Optimization Problems

Consider the Nonlinear Program (NLP)

$$J^* = \min_{z \in S} f(z)$$

Notation:

- If $J^* = -\infty$ the problem is unbounded below.
- If the set S is empty then the problem is said to be infeasible (we set $J^* = +\infty$).
- If S = Z the problem is said to be unconstrained.
- The set of all optimal solutions is denoted by

$$\operatorname{argmin}_{z \in S} f(z) \triangleq \{ z \in S : f(z) = J^* \}$$

Continuous Problems

- ullet The domain Z is a subset of \mathbb{R}^s (the finite-dimensional Euclidian vector-space)
- The subset of admissible vectors defined through a list of real valued functions:

$$\inf_{z} \qquad f(z)$$
 such that
$$g_{i}(z) \leq 0 \quad \text{ for } i = 1, \dots, m$$

$$h_{i}(z) = 0 \quad \text{ for } i = 1, \dots, p$$

$$z \in Z$$

$$(5)$$

- The inequalities $g_i(z) \le 0$ are called inequality constraints and the equations $h_i(z) = 0$ are called equality constraints.
- A point $\bar{z} \in \mathbb{R}^s$ is feasible for problem (5) if it satisfies all inequality and equality constraints
- The set of feasible vectors is

$$S = \{ z \in \mathbb{R}^s : g_i(z) \le 0, \ i = 1, \dots, m, h_i(z) = 0, \ i = 1, \dots, p \}.$$

Local and Global Optimizer

- Let J^* be the optimal value of problem (5). A **global optimizer**, if it exists, is a feasible vector z^* with $f(z^*) = J^*$.
- A feasible point \bar{z} is a **local optimizer** for problem (5) if there exists an R>0 such that

$$f(\bar{z}) = \inf_{z} \qquad f(z)$$
 such that
$$g_{i}(z) \leq 0 \quad \text{for } i = 1, \dots, m$$

$$h_{i}(z) = 0 \quad \text{for } i = 1, \dots, p$$

$$\|z - \bar{z}\| \leq R$$

$$z \in Z$$
 (6)

Active, Inactive and Redundant Constraints

Consider

$$\begin{array}{ll} \inf_z & f(z) \\ \text{such that} & g_i(z) \leq 0 & \text{ for } i=1,\ldots,m \\ & h_i(z) = 0 & \text{ for } i=1,\ldots,p \\ & z \in Z \end{array}$$

- The *i*-th inequality constraint $g_i(z) \leq 0$ is active at \bar{z} if $g_i(\bar{z}) = 0$.
- If $g_i(\bar{z}) < 0$ we say that the constraint $g_i(z) \le 0$ is inactive at \bar{z} .
- Equality constraints are always active for all feasible points.
- We say that a constraint is redundant if removing it from the list of constraints does not change the feasible set S. This implies that removing a redundant constraint from the optimization problem does not change its solution.

Problem Description

- The functions f, g_i and h_i can be available in **analytical form** or can be described through an **oracle model** (also called "black box" or "subroutine" model).
- In an oracle model $f,\ g_i$ and h_i are not known explicitly but can be evaluated by querying the oracle. Often the oracle consists of subroutines which, called with the augment z, return f(z), $g_i(z)$ and $h_i(z)$ and their gradients $\nabla f(z)$, $\nabla g_i(z)$, $\nabla h_i(z)$.

Integer and Mixed-Integer Problems

- If the decision set Z in the optimization problem is finite, then the optimization problem is called combinatorial or discrete.
- If $Z \subseteq \{0,1\}^s$, then the problem is said to be integer.
- If Z is a subset of the Cartesian product of an integer set and a real Euclidian space, i.e., $Z\subseteq\{[z_c,z_b]:z_c\in\mathbb{R}^{s_c},z_b\in\{0,1\}^{s_b}\}$, then the problem is said to be mixed-integer.

The standard formulation of a mixed-integer non-linear program is

$$\inf_{[z_c, z_b]} \qquad f(z_c, z_b) \\ \text{such that} \qquad g_i(z_c, z_b) \le 0 \quad \text{ for } i = 1, \dots, m \\ \qquad h_i(z_c, z_b) = 0 \quad \text{ for } i = 1, \dots, p \\ \qquad z_c \in \mathbb{R}^{s_c}, \ z_b \in \{0, 1\}^{s_b}$$
 (7)

Convexity

A set $S \in \mathbb{R}^s$ is convex if

$$\lambda z_1 + (1 - \lambda)z_2 \in S \text{ for all } z_1, z_2 \in S, \lambda \in [0, 1].$$

A function $f:S\to\mathbb{R}$ is convex if S is convex and

$$f(\lambda z_1 + (1 - \lambda)z_2) \le \lambda f(z_1) + (1 - \lambda)f(z_2)$$

for all $z_1, z_2 \in S, \lambda \in [0, 1]$.

A function $f:S \to \mathbb{R}$ is strictly convex if S is convex and

$$f(\lambda z_1 + (1 - \lambda)z_2) < \lambda f(z_1) + (1 - \lambda)f(z_2)$$

for all $z_1, z_2 \in S, \lambda \in (0, 1)$.

A function $f: S \to \mathbb{R}$ is concave if S is convex and -f is convex.

Operations preserving convexity

- The intersection of an arbitrary number of convex sets is a convex set: if S_1, S_2, \ldots, S_k are convex, then $S_1 \cap S_2 \cap \ldots \cap S_k$ is convex.
- ② The sub-level sets of a convex function f on S are convex: if f(z) is convex then $S_{\alpha} \triangleq \{z \in S : f(z) \leq \alpha\}$ is convex $\forall \alpha$.
- § If f_1, \ldots, f_N are convex functions, then $\sum_{i=1}^N \alpha_i f_i$ is a convex function for all $\alpha_i \geq 0$, $i = 1, \ldots, N$.
- The composition of a convex function f(z) with an affine map z = Ax + b generates a convex function f(Ax + b) of x.

Operations preserving convexity

 The pointwise maximum of a set of convex functions is a convex function:

$$f_1(z), \ldots, f_k(z)$$
 convex functions \Rightarrow $f(z) = \max\{f_1(z), \ldots, f_k(z)\}$ is a convex function.

- A linear function f(z) = c'z + d is both convex and concave.
- A quadratic function f(z)=z'Qz+2s'z+r is convex if and only if $Q\in\mathbb{R}^{s\times s}$ is positive semidefinite.
- A quadratic function f(z)=z'Qz+2s'z+r is strictly convex if and only if $Q\in\mathbb{R}^{s\times s}$ is positive definite.

Convex optimization problems

- The optimization problem (5) is said to be convex if the cost function f is convex on Z and S is a convex set.
- A fundamental property of convex optimization problems is that local optimizers are also global optimizers. It suffices to compute a local minimum to problem (5) to determine its global minimum.
- Convexity also plays a major role in most non-convex optimization problems: solved by iterating between the solutions of convex sub-problems.
- Difficult to determine whether the feasible set S is convex or not except in special cases. For example, if the functions g_1,\ldots,g_m are convex and all the $h_i(z)$ (if any) are affine in z, then the feasible region S is an intersection of convex sets and therefore convex.
- Moreover there are non-convex problems which can be transformed into convex problems through a change of variables and manipulations on cost and constraints.

Polyhedra, Polytopes and Simplices

General Set Definitions and Operations

- An n-dimensional ball $B(x_0,\rho)$ is the set $B(x_0,\rho)=\{x\in\mathbb{R}^n|\ \sqrt{\|x-x_0\|_2}\leq\rho\}$. The vector x_0 is the center of the ball and ρ is the radius.
- Affine sets are sets described by the solutions of a system of linear equations:

$$F = \{x \in \mathbb{R}^n : Ax = b, \text{ with } A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m\}.$$

- The affine combination of a finite set of points x_1, \ldots, x_k belonging to \mathbb{R}^n is defined as the point $\lambda_1 x_1 + \ldots + \lambda_k x_k$ where $\sum_{i=1}^k \lambda_i = 1$.
- The affine hull of $K \subseteq \mathbb{R}^n$ is the set of all affine combinations of points in K and it is the smallest affine set that contains K.
- The dimension of an affine set is the dimension of the largest ball of radius $\rho > 0$ included in the set.

General Set Definitions and Operations

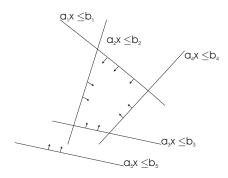
- The convex combination of a finite set of points x_1, \ldots, x_k is defined as the point $\lambda_1 x_1 + \ldots + \lambda_k x_k$ where $\sum_{i=1}^k \lambda_i = 1$ and $\lambda_i \geq 0$, $i = 1, \ldots, k$.
- The convex hull of a set $K \subseteq \mathbb{R}^n$ is the set of all convex combinations of points in K and it is denoted as $\operatorname{conv}(K)$:

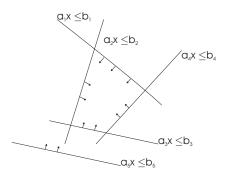
$$\operatorname{conv}(K) \triangleq \{\lambda_1 x_1 + \ldots + \lambda_k x_k \mid x_i \in K, \ \lambda_i \ge 0, \ \sum_{i=1}^k \lambda_i = 1\}.$$

An \mathcal{H} -polyhedron \mathcal{P} in \mathbb{R}^n denotes an intersection of a finite set of closed halfspaces in \mathbb{R}^n :

$$\mathcal{P} = \{ x \in \mathbb{R}^n : \ Ax \le b \}$$

where $Ax \leq b$ is $a_i x \leq b_i$, i = 1, ..., m, where $a_1, ..., a_m$ are the rows of A, and $b_1, ..., b_m$ are the components of b.





- Inequalities which can be removed without changing the polyhedron are called redundant.
- The representation of an \mathcal{H} -polyhedron is minimal if it does not contain redundant inequalities.

- **1** An \mathcal{H} -polytope is a bounded \mathcal{H} -polyhedron.
- ② A \mathcal{V} -polytope is the convex hull of a finite set of points $V = \{V_1, \dots, V_k\}$

$$\mathcal{P} = \operatorname{conv}(V)$$

- **3** Any \mathcal{H} -polytope is a \mathcal{V} -polytope.
- A polytope P ⊂ Rⁿ, is full-dimensional if it is possible to fit a non-empty n-dimensional ball in P

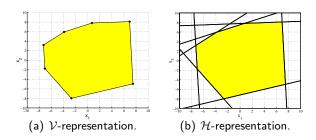
 Otherwise, we say that polytope P is lower-dimensional.
- $\textbf{ If } \|P_i^x\|_2 = 1, \text{ where } P_i^x \text{ denotes the } i\text{-th row of a matrix } P^x, \text{ we say that the polytope } \mathcal{P} \text{ is normalized}.$

lacktriangledown A face of $\mathcal P$ is any nonempty set of the form

$$\mathcal{F} = \mathcal{P} \cap \{ z \in \mathbb{R}^s | cz = c_0 \}$$

where $cz \leq c_0$ is satisfied for all points in \mathcal{P} .

- ② The faces of dimension 0,1, and dim(P)-1 are called vertices, edges and facets, respectively.
- **3** A d-simplex is a polytope of \mathbb{R}^d with d+1 vertices.



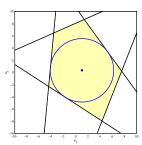
Basic Operations on Polytopes

• Convex Hull of a set of points $V = \{V_i\}_{i=1}^{N_V}$, $\mathcal{P} = \operatorname{conv}(V)$ is used to switch from a \mathcal{V} -representation of a polytope to an \mathcal{H} -representation.

ullet Vertex Enumeration of a polytope ${\cal P}$ given in ${\cal H}$ -representation. (dual of the convex hull operation)

Basic Operations on Polytopes

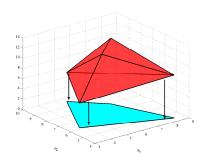
- Polytope reduction is the computation of the minimal representation of a polytope.
- The Chebychev Ball of a polytope \mathcal{P} corresponds to the largest radius ball $\mathcal{B}(x_c,R)$ with center x_c , such that $\mathcal{B}(x_c,R) \subset \mathcal{P}$.



Basic Operations on Polytopes

• Projection Given a polytope $\mathcal{P} = \{[x'y']' \in \mathbb{R}^{n+m} \ : \ P^x x + P^y y \leq P^c\} \subset \mathbb{R}^{n+m} \ \text{the projection}$ onto the x-space \mathbb{R}^n is defined as

$$\operatorname{Proj}_{x}(\mathcal{P}) := \{ x \in \mathbb{R}^{n} \mid \exists y \in \mathbb{R}^{m} : P^{x}x + P^{y}y \leq P^{c} \}.$$



Affine Mappings and Polyhedra

Consider a polyhedron $\mathcal{P}=\{x\in\mathbb{R}^n\mid P^xx\leq P^c\},$ and an affine mapping f(z)

$$f: z \in \mathbb{R}^n \mapsto Az + b, A \in \mathbb{R}^{n \times n}, b \in \mathbb{R}^n$$

Define the composition of ${\mathcal P}$ and f as

$$\mathcal{P} \circ f \triangleq \{ z \in \mathbb{R}^n \mid Az + b \in \mathcal{P} \}$$

It can be obtained by computing the following polyhedron

$$\mathcal{P} \circ f = \{ z \in \mathbb{R}^n \mid P^x f(z) \le P^c \} = \{ z \in \mathbb{R}^n \mid P^x Az \le P^c - P^x b \}$$

Affine Mappings and Polyhedra

Define the composition of f and $\mathcal P$ as the following polyhedron

$$f \circ \mathcal{P} \triangleq \{ y \in \mathbb{R}^n \mid y = Az + b \ \forall z \in \mathcal{P} \}$$

The polyhedron $f \circ \mathcal{P}$ in (29) can be computed as follows.

- Write \mathcal{P} in \mathcal{V} -representation $\mathcal{P} = \operatorname{conv}(V)$
- 2 Map the vertices $V = \{V_1, \dots, V_k\}$ through the transformation f.
- § Because the transformation is affine, the set $f \circ \mathcal{P}$ is the convex hull of the transformed vertices

$$f \circ \mathcal{P} = \operatorname{conv}(F), \ F = \{AV_1 + b, \dots, AV_k + b\}.$$

Note: If f is invertible $z = A^{-1}y - A^{-1}b$ and therefore

$$f \circ \mathcal{P} = \{ y \in \mathbb{R}^n \mid P^x A^{-1} y \le P^c + P^x A^{-1} b \}$$

Homework

Homework

- 1 Installation the Multiparametrix Toolbox (http://control.ee.ethz.ch/ mpt/)
- 2 run 'mpt_demo1' in Matlab to study the demo of MPT package, skip operation not shown during lecture. Also run 'help mpt/polytope' to learn the list of commands for working with polytopes
- 8 What is the V-representation of the following polyhedron?

$$H = \begin{bmatrix} 0 & 1 \\ -1 & 0 \\ -1 & -1 \\ 1 & 1 \end{bmatrix}, \quad K = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Ompute the projection on the (x_1,x_2) space of the following polyhedron where $x=(x_1,x_2,x_3)$. Plot the projected 2 dimensional polyhedron.

$$P:=\left[\begin{array}{cccc} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & -1 & 0 \\ -1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -1 \end{array}\right] x \leq \left[\begin{array}{c} 2 \\ 2 \\ 2 \\ 2 \\ 1 \\ 2 \\ 2 \end{array}\right]$$

$$\mathcal{X}_0 := \left[\begin{array}{ccc} 0 & 1 \\ 1 & 0 \\ 0 & -1 \\ -1 & 0 \end{array} \right] x \le \left[\begin{array}{c} 2 \\ 2 \\ 2 \\ 2 \end{array} \right]$$

Read the help of linprog and quadprog commands (Type "help linprog" and "help quadprog" in Matlab)