Advanced Model Predictive Control

Recitation 1 Introduction to LMIs and Optimization Toolboxes

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Linear Matrix Inequalities [1]

Linear Matrix Inequalities (LMIs) are convex constraints with respect to symmetric matrices.

• General form (strict, but the following slides also hold for non-strict):

$$F(x) = F_0 + \sum_{i=1}^{m} x_i F_i > 0$$
 (1)

where $x \in \mathbb{R}^m$, $F_i \in \mathbb{R}^{n \times n}$.

- $F(x) \succ 0$ implies that F(x) is positive definite, $F(x) \prec 0$ implies that it is negative definite and $F(x) \succ G(x) \Leftrightarrow F(x) G(x) \succ 0$.
- (1) implies that $z^T F(x)z > 0, \forall z \neq 0, z \in \mathbb{R}^n$.
- (1) can be rewritten as n polynomial constraints (all n principle minors positive)

Homework (PS1): Show that the set of positive definite matrices is convex.

[1] VanAntwerp and Braatz. A tutorial on linear and bilinear matrix inequalities. Journal of Process Control, 2000.

Linear Matrix Inequalities [1]

LMIs are not unique ⇒ Congruence transformation:

$$A \succ 0 \Leftrightarrow z^T A z > 0, \forall z \neq 0$$

 $\Leftrightarrow y^T M^T A M y > 0, \forall y \neq 0, M \text{ nonsingular}$
 $\Leftrightarrow M^T A M \succ 0$

Multiple LMIs can be expressed as a single LMI

$$F^{1}(x) \succ 0, F^{2}(x) \succ 0, \dots, F^{q}(x) \succ 0$$

 $F(x) = F_{0} + \sum_{i=1}^{m} x_{i}F_{i} = \text{diag}\{F^{1}(x), F^{2}(x), \dots, F^{q}(x)\} \succ 0$

where
$$F_i = \text{diag}\{F_i^1, F_i^2, ..., F_i^q\}, \ \forall i = 0, ..., m.$$

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Linear Matrix Inequalities [1]

Schur complement allows rewriting a class of convex nonlinear inequalities as LMIs

$$R(x) \succ 0, \ Q(x) - S(x)R(x)^{-1}S(x)^T \succ 0$$

$$\Leftrightarrow \begin{bmatrix} Q(x) & S(x) \\ S(x)^T & R(x) \end{bmatrix} \succ 0$$

Exercise. Use Schur's complement to rewrite an ellipsoidal inequality as an LMI.

$$E = \{x \mid (x - x_c)^T P(x - x_c) \leq 1\} P > 0$$

$$1 - (y - x_c)^T P(x - x_c) \approx 0$$

$$2 - (x - x_c)^T P(x - x_c) \approx 0$$

$$3 - (x - x_c)^T P(x - x_c) \approx 0$$

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Optimization Toolboxes

A large amount of toolboxes exist that help you solve mathematical optimization problems.

- YALMIP: high level interface to (mostly) convex optimization solvers (SeduMi, quadprog, MOSEK, . . .).
 - ⇒ Used for very easy problem formulation (directly implement constraints as (in)equalities).
- CasADi: high level interface to nonlinear optimization solvers (IPOPT, ...) and automatic differentiation
 - ⇒ Used to manipulate nonlinear functions and to directly implement nonlinear constraints.
- MPT3: toolbox for parametric optimization and computational geometry.
 - \Rightarrow Used for easy polytope manipulation.

Quadratic Programming using YALMIP

Example:

QP:
$$\min_{x,u} \sum_{i=0}^{4} ||x_i||_Q^2 + ||u_i||_R^2$$

s.t. $\forall i = 0, ..., 4$
 $x_0 = x(k)$
 $x_i \in \mathbb{X} = \{x \in \mathbb{R}^n | A_x x \le b_x\}$
 $x_{i+1} = Ax_i + Bu_i$
 $x_5 = 0$

Quadratic Programming using YALMIP

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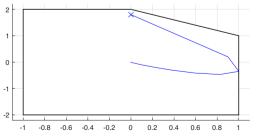
```
% Define optimization variables
   x = sdpvar(2, 6, 'full'); u = sdpvar(1, 5, 'full');
   x_k = sdpvar(2, 1, 'full');
   % Define objective
   objective = 0;
   for i=1.5
        objective = objective ...
             +x(:,i)'*Q*x(:,i)+u(:,i)'*R*u(:,i);
    end
10
   % Define constraints
   constraints = [x(:,1) == x_k]:
   for i = 1:5
14
        constraints = [constraints, ...
                       \bar{x}(:,i+1) == A*x(:,i) + B*u(:,i);
        constraints = \lceil \text{constraints}, A_x * x(:,i) \le b_x \rceil;
16
    end
   constraints = [constraints, x(:,6) == zeros(2,1)];
   % Define YALMIP Optimizer
   opt_MPC = optimizer (constraints, objective, [], {x_k}
         \{u(:,1)\});
   % Simulate for 30 time steps
   x_k = [0: 1.8]:
   for k = 1:30
        u_k = opt_MPC(x_k(:,k));
        x_k(:,k+1) = A*x_k(:,k) + B*u_k;
   end
```

Quadratic Programming using YALMIP

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```

Exercise: Compute the largest ellipsoid $\mathcal{E} = \{x \in \mathbb{R}^n \mid x^T P x \leq 1\}$ subset of a polytope $\mathbb{X} = \{x \in \mathbb{R}^n | A_x x \leq b_x\}$ with $A_x \in \mathbb{R}^{n_x \times n}$, $b_x \in \mathbb{R}^{n_x}$. Hint: Volume of $\mathcal{E} \propto \text{logdet}(P^{-1})$, which is concave. An ellipsoid is contained within a halfspace $a^T x \leq b$ if $a^T P^{-1} a \leq b^2$.

Exercise: Compute the largest ellipsoid $\mathcal{E} = \{x \in \mathbb{R}^n \mid x^T P^x \leq 1\}$ subset of a polytope $\mathbb{X} = \{x \in \mathbb{R}^n | A_x x \leq b_x\}$ with $A_x \in \mathbb{R}^{n_x \times n}$, $b_x \in \mathbb{R}^{n_x}$. Hint: Volume of $\mathcal{E} \propto \text{logdet}(P^{-1})$, which is concave. An ellipsoid is contained within a halfspace $a^T x \leq b$ if $a^T P^{-1} a \leq b^2$. SDP: $a_x = b^2$. SDP: $a_x = b^2$. St. $a_x = b^2$. St. $a_x = b^2$. St. $a_x = b^2$. The proof of $a_x = b^2$ is $a_x = b^2$.

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where $P = F^{-1}$.

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```
SDP: \min_{E} - \text{logdet } E

s.t. \forall i = 0, ..., n_{X}

E \succeq 0

[A_{X}]_{i} E[A_{X}]_{i}^{T} \leq [b_{X}]_{i}^{2}
```

where $P = E^{-1}$.

```
% Define A_x, b_x and symmetric variable E
2 A<sub>x</sub> = [1,0; -1,0; 0,1; 0,-1; 1,1];

3 b<sub>x</sub> = [1; 1; 2; 2; 2];

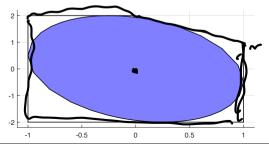
4 E = sdpvar(2, 2);
6 % Define objective
   objective = -logdet(E);
  % Define constraints
   % The operator >= denotes matrix inequality
   constraints = [E >= 0];
12 for i=1:size(A_x,1)
        constraints = [constraints, ...
            A_x(i,:)*E*A_x(i,:)' \le b_x(i)^21
   end
   % Solve the YALMIP Problem
   optimize (constraints, objective)
   % Display the result
   disp(inv(value(E)))
```

Exercise: Compute the largest ellipsoid $\mathcal{E} = \{x \in \mathbb{R}^n \mid x^T P x \leq 1\}$ subset of a polytope $\mathbb{X} = \{x \in \mathbb{R}^n | A_x x \leq b_x\}$ with $A_x \in \mathbb{R}^{n_x \times n}$, $b_x \in \mathbb{R}^{n_x}$. Hint: Volume of \mathcal{E} which is concave. An ellipsoid is contained within a halfspace $a^T x < b$ if $a^T P^{-1} a < b^2$.

SDP:
$$\min_{E} - \text{logdet } E$$

s.t. $\forall i = 0, ..., n_x$
 $E \succeq 0$
 $[A_x]_i E[A_x]_i^T \leq [b_x]_i^2$

where $P = E^{-1}$.



```
% Define A_x, b_x and symmetric variable E
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4 E = sdpvar(2, 2);
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   objective = -logdet(E);
  % Define constraints
  % The operator >= denotes matrix inequality
  constraints = [E >= 0];
  for i=1:size(A_x,1)
       constraints = [constraints, ...
            A_x(i,:)*E*A_x(i,:)' \le b_x(i)^2:
   end
  % Solve the YALMIP Problem
  optimize(constraints, objective)
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  disp(inv(value(E)))
```