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Probabilistic Design of Robust Dual-Mode MPC without Set Invariance



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Tatsuya Miyano

Tokyo Institute of Technology Fujita Laboratory

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1. Introduction
2. Feasibility Region
3. Dual-Mode MPC Algorithm
4. Numerical Simulations
5. Conclusions and Future Works

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Previous Works

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- MPC has been utilized in slow systems (e.g. chemical processes).
- There are some attempts to apply MPC to fast systems.
 - Multi-parametric (MP) techniques: e.g. Bemporad et.al (2000)

These techniques enable us to trade off on-line complexity with off-line computation.

 These techniques require to solve NP-hard MP program !

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These techniques enable us to trade off on-line complexity with off-line computation.

 These techniques require to solve NP-hard MP program !

• Robust dual mode MPC based on ellipsoids: e.g. Imsland et.al (2006)

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Problem Formulation

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$$x(t+1) = A(\Delta)x(t) + B(\Delta)u(t)$$

State and input $x(t) \in \mathcal{X}, u(t) \in U, \forall t \in \mathcal{Z}_+$

QAs D is a random parameter on the probability space $(D, \mathcal{D}, \text{Prob}_{\Delta})$.

We will design the ‘predicted’ input sequence via a dual-mode MPC strategy.

Problem Formulation

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We will design the ‘predicted’ input sequence via a dual-mode MPC strategy.

$$\begin{aligned} u(t+k | t) &= -Kx(t+k | t) + c(k) && \text{Mode 1} \\ &\quad \text{if } k \in \{0, \dots, n_c - 1\} \\ u(t+k | t) &= -Kx(t+k | t) && \text{Mode 2} \\ &\quad \text{if } k \geq n_c \end{aligned}$$

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K minimizes the infinite horizon LQ cost, J_{LQ} , with weights $Q > 0, R > 0$ in the absence of system constraints.

Feasibility Region

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Prediction Model

$$\begin{aligned} x(t+k+1 | t) &= \Phi(\Delta)x(t+k | t) + B(\Delta)c(k) \\ u(t+k | t) &= -Kx(t+k | t) + c(k) \\ c(k) &= 0 \quad \forall k \geq n_c \quad \Phi(\Delta) := A(\Delta) - B(\Delta)K \end{aligned}$$

The following augmented model is equivalent to the above prediction model.

$$\begin{aligned} \xi(k+1) &= \tilde{A}(\Delta)\xi(k) \quad \xi(k) := [x^T(t+k | t) \quad \tilde{c}^T(k)]^T \\ u(k) &= \tilde{C}\xi(k) \quad \tilde{c}(k) := [c^T(k) \quad c^T(k+1) \quad \dots \quad c^T(k+n_c-1)]^T \\ \tilde{A}(\Delta) &:= \begin{bmatrix} A(\Delta) - B(\Delta)K & B(\Delta)E \\ 0 & I_L \end{bmatrix} \quad \tilde{C} := [-K \quad E] \quad E := [I \quad 0 \quad \dots \quad 0] \\ I_L & : \text{nilpotent matrix} \end{aligned}$$

Augmented Model

Feasibility Region

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Definition: Feasibility Region (FR)

A set \mathcal{F} is said to be an FR if its any element $\xi(0) \in \mathcal{F}$ satisfies $\xi(k) \in \mathcal{X} \times U \quad \forall \Delta \in D, k \in \mathcal{Z}_+$.

We employ an ellipsoidal feasibility region (EFR) to reduce on-line complexity. Then we obtain EFR $\Omega(Q_p)$.

Feasibility Region

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$$\Omega(Q_p) := \{\xi \mid \xi^T Q_p^{-1} \xi \leq 1\}$$

State and input constraints:

$$\forall \Delta \in D \quad M_0(\Delta) := \begin{bmatrix} M_0(\Delta) & M_0(\Delta)(i,:)Q_pM_0^T(\Delta)(i,:) \leq 1 \\ [M_x \quad 0]\tilde{A}^k(\Delta) & \text{State constraints} \\ M_y \tilde{C}\tilde{A}^k(\Delta) & \text{Input constraints} \end{bmatrix}$$

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Optimization Problem

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We define a cost $J(\xi) := \xi^T P \xi$. Then an optimization problem is as follows.

Off-line

$$\min_{Q_p, P} \ln \det(T Q_p T^T)^{-1} + \text{tr}(P)$$

$$M_0(\Delta)(i,:) Q_p M_0^T(\Delta)(i,:) \leq 1 \quad P - \tilde{A}^T(\Delta) P \tilde{A}(\Delta) > \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix} + \tilde{C}^T R \tilde{C}$$

$$\forall \Delta \in D$$

On-line

$$\min_{\tilde{c}} J(x(t), \tilde{c}(t)) \quad \text{subject to } [x^T(t) \quad \tilde{c}^T(t)]^T \in \Omega(Q_p)$$

$$\tilde{c}(t) = \begin{cases} c_0 & \text{if } [x^T(t) \quad c_0^T]^T \in \Omega(Q_p) \\ c_a & \text{otherwise} \end{cases}$$

c_0 is an analytical solution in the absence of system constraints.
 c_a is an analytical solution with system constraints.

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Optimization Problem

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In case

- i) $[x^T(t+1) \quad \tilde{c}^T(t+1)]^T \notin \Omega(Q_p)$ Infeasible Asymptotic stability is not proved
- ii) $J(\xi(t+1)) > J(x(t+1), [c^T(t+1) \quad c^T(t+2) \quad \dots \quad c^T(t+n_c-1) \quad 0]^T)$

→ $\tilde{c}(t+1) = [c^T(t+1) \quad c^T(t+2) \quad \dots \quad c^T(t+n_c-1) \quad 0]^T$

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Scenario Approach

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Off-line

$$\min_{Q_p, P} \ln \det(T Q_p T^T)^{-1} + \text{tr}(P)$$

$$M_0(\Delta)(i,:) Q_p M_0^T(\Delta)(i,:) \leq 1 \quad P - \tilde{A}^T(\Delta) P \tilde{A}(\Delta) > \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix} + \tilde{C}^T R \tilde{C}$$

$$\forall \Delta \in D$$

The off-line computation requires the solution of an **NP-hard robust convex program**.

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The probability that P and Q_p do not satisfy constraints with probability greater than $1 - \varepsilon$ is less than δ .

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Numerical Simulations

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We apply a dual-mode MPC strategy to SICE-DD ARM.

The model is as follows. It has uncertain physical parameters.

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{B}{M+2R} \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ \frac{1}{M+2R} \end{bmatrix} u(t) \quad x(t) = \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix} \quad u(t) = \tau_i$$

$$M := I_1 + I_2 + m_1 r_1^2 + m_2 (l_1^2 + r_2^2)$$

$$R := m_2 l_1 r_2$$

B : viscosity resistance of link1
 m_i : mass of linki
 I_i : moment of inertia of linki
 l_i : length of linki
 r_i : length to center of gravity of linki
 θ_i : angle of linki τ_i : torque of linki
 $\dot{\theta}_i$: angular velocity of linki

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Numerical Simulations

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We tried to demonstrate the effectiveness of our method through the numerical simulations. But in fail.

Projection to \mathcal{X} -space

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Conclusions and Future Works

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- Conclusions
- We tried to demonstrate the effectiveness of our method through the numerical simulations. But in fail.
- Future works
- More meaningful numerical simulations
- Extension to exact-linearized or linearized model

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