

Kernel Embedding for Particle Gibbs-Based Optimal Control

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Intermediate Report Master's Thesis

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Motivation



[Xiloyannis, Chiaradia, Frisoli and Masia 2019]

Challenges:

- Unknown Dynamic
- Latent States
- Safety

Problem Statement - System

Given: Dataset $\mathbb{D} = \{\mathbf{u}_t, \mathbf{y}_t\}_{t=-T:-1}$ from unknown system

$$\begin{aligned}\mathbf{x}_{t+1} &= \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{v}_t, & \mathbf{v}_t &\sim \mathcal{V}, \\ \mathbf{y}_t &= \mathbf{g}(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{w}_t, & \mathbf{w}_t &\sim \mathcal{W}\end{aligned}$$

Assumptions

- Known system structure

$$\begin{aligned}\mathbf{x}_{t+1} &= \mathbf{f}_\theta(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{v}_t, & \mathbf{v}_t &\sim \mathcal{V}_\theta, \\ \mathbf{y}_t &= \mathbf{g}_\theta(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{w}_t, & \mathbf{w}_t &\sim \mathcal{W}_\theta.\end{aligned}$$

- Known priors $p(\theta)$ and $p(\mathbf{x}_{-T})$

Problem Statement - Optimal Control Problem

Goal: Solve optimal control problem (OCP)

Stochastic OCP

$$\min_{\mathbf{u}_{0:H}} J_H(\mathbf{u}_{0:H})$$

subject to:

$$P[h_i(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}, \mathbf{y}_{0:H}) \leq 0] \geq 1 - \alpha, \forall i = 1, \dots, n_c$$

Problem: Underlying data distribution P is unknown

Related Works

Particle Gibbs Based Optimal Control [Lefringhausen, Srithasan, Lederer and Hirche 2024]

⇒ Risk factor α has to be calculated retroactively and cannot be controlled directly

Alternative Approaches:

- Wasserstein Ambiguity [Hota, Cherukuri and Lygeros 2019]

⇒ Constraints limited to affine functions

- Kernel Embeddings [Nemmour, Kremer, Schoelkopf and Zhu 2022]

[Thorpe, Lew, Oishi and Zhu 2022]

Particle Gibbs Scenarios

Particle Gibbs gives us the scenarios $\delta^{[1:N]} = \{\boldsymbol{\theta}, \mathbf{x}_0, \mathbf{v}_{0:H}, \mathbf{w}_{0:H}\}^{[1:N]}$ that characterize the system

Goal: Reformulate chance-constraint problem with scenarios $\delta^{[1:N]}$

Chance Constraints

$$P[h_i(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}, \mathbf{y}_{0:H}) \leq 0] \geq 1 - \alpha, \forall i = 1, \dots, n_c$$



Scenario Approach (used in [Lefringhausen+ 2024])

$$h(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}^{[n]}, \mathbf{y}_{0:H}^{[n]}) \leq 0, \forall n = 1, \dots, N$$

\Rightarrow Risk factor α not considered in optimization

Maximum Mean Discrepancy (MMD) ambiguity sets

Goal: Reformulate chance-constraint problem with scenarios $\delta^{[1:N]}$

Idea: Replace distribution P with the ambiguity set \mathcal{P}

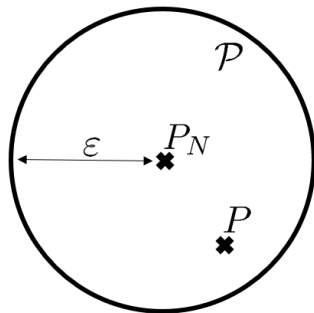
MMD ambiguity set

$$\mathcal{P} = \left\{ \tilde{P} : \text{MMD}(\tilde{P}, P_N) \leq \varepsilon \right\}.$$



Expanded Chance-Constraints

$$\inf_{\tilde{P} \in \mathcal{P}} \tilde{P} [h_i(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}, \mathbf{y}_{0:H}) \leq 0] \geq 1 - \alpha.$$



Constraint Reformulation

Goal: Reformulate chance-constraint problem with scenarios $\delta^{[1:N]}$

Feasible Region of chance constraint

$$Z_i := \left\{ \mathbf{u}_{0:H} \in \mathcal{U}^{H+1} : \inf_{\tilde{P} \in \mathcal{P}} \tilde{P} \left[\tilde{h}_i(\mathbf{u}_{0:H}, \boldsymbol{\delta}) \leq 0 \right] \geq 1 - \alpha \right\}$$

\Downarrow

Reformulated Feasible Region [Nemmour+ 2022]

$$Z_i := \left\{ \mathbf{u}_{0:H} \in \mathcal{U}^{H+1} : \begin{array}{l} g_0 + \frac{1}{N} \sum_{n=1}^N (\mathbf{K}\boldsymbol{\gamma})_n + \varepsilon \sqrt{\boldsymbol{\gamma}^\top \mathbf{K} \boldsymbol{\gamma}} \leq t\alpha \\ [\tilde{h}_i(\mathbf{u}_{0:H}, \boldsymbol{\delta}^{[n]}) + t]_+ \leq g_0 + (\mathbf{K}\boldsymbol{\gamma})_n, \quad n = 0, \dots, N \\ g_0 \in \mathbb{R}, \boldsymbol{\gamma} \in \mathbb{R}^N, t \in \mathbb{R} \end{array} \right\}$$

Problem Formulation

Goal: Reformulate chance-constraint problem with scenarios $\delta^{[1:N]}$

$$\begin{aligned} & \min_{\mathbf{u}_{0:H}, \{g_0, \gamma, t'\}^{[1:n_c]}} J_H(\mathbf{u}_{0:H}) \\ & \text{subject to: } \forall n \in \mathbb{N}_{\leq N}, \forall t \in \mathbb{N}_{\leq H}^0, \forall i \in \mathbb{N}_{\leq n_c} \\ & \left. \begin{aligned} \mathbf{x}_{t+1}^{[n]} &= \mathbf{f}_{\boldsymbol{\theta}^{[n]}}(\mathbf{x}_t^{[n]}, \mathbf{u}_t) + \mathbf{v}_t^{[n]} \\ \mathbf{y}_t^{[n]} &= \mathbf{g}_{\boldsymbol{\theta}^{[n]}}(\mathbf{x}_t^{[n]}, \mathbf{u}_t) + \mathbf{w}_t^{[n]} \end{aligned} \right\} \text{Dynamic Constraints} \\ & \left. \mathbf{u}_{0:H} \in Z_i(g_0^{[i]}, \gamma^{[i]}, t'^{[i]}) \right\} \text{Reformulated Chance Constraints} \end{aligned}$$

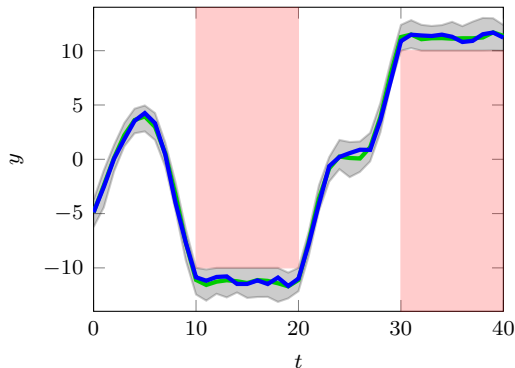
Simulation Setup

- Unknown system:
$$\mathbf{f}(\mathbf{x}, u) = \begin{bmatrix} 0.8x_1 - 0.5x_2 \\ 0.4x_1 + 0.5x_2 + u \end{bmatrix}$$
$$\mathbf{v}_t \sim \mathcal{N}\left(\mathbf{0}, \mathbf{Q} = \begin{bmatrix} 0.03 & -0.004 \\ -0.004 & 0.01 \end{bmatrix}\right).$$
- Known system structure: $\mathbf{f}(\mathbf{x}, u) = \mathbf{A} [x_1, x_2, u]^\top + \mathbf{v}_t, \mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$
- Priors:
$$\mathbf{Q} \sim \mathcal{IW}(100\mathbf{I}_2, 10)$$
$$\mathbf{A} \sim \mathcal{MN}(\mathbf{0}, \mathbf{Q}, 10\mathbf{I}_2) \quad [\text{Andrieu+ 2017}]$$
$$\mathbf{x}_{-T} \sim \mathcal{N}([2, 2]^\top, \mathbf{I}_2)$$
- Known measurement model $g(\mathbf{x}, u) = x_1, w_t \sim \mathcal{N}(0, 0.1)$
- Cost function $J_H = \sum_{t=0}^H u_t^2$
- Input constraints $|u| \leq 10$
- Gaussian kernels with bandwidth σ set via the median heuristic [Garreau+ 2018]
- Ambiguity set radius ε set via bootstrap construction [Nemmour+ 2022].

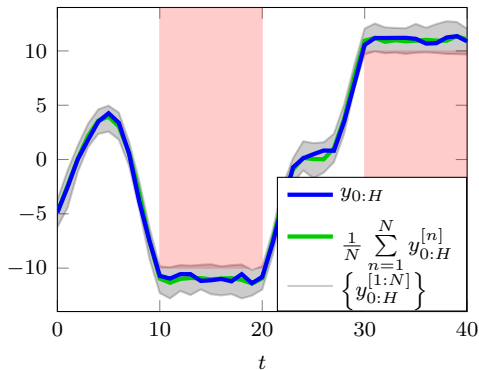
Optimal Control with Constrained Outputs

Number of scenarios used for optimization: $N = 200$

Scenario Approach



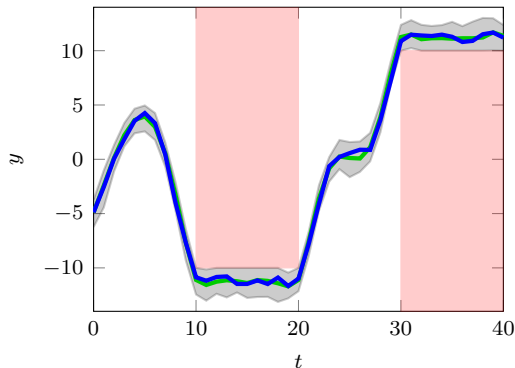
Kernel Approach ($\alpha = 0.1$)



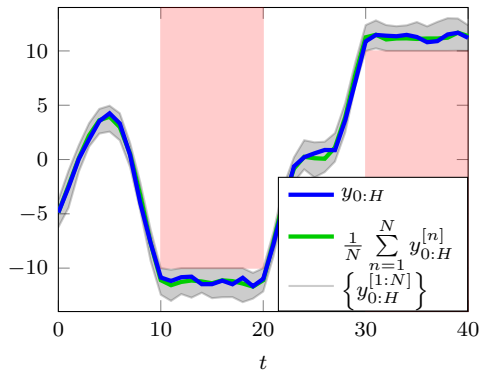
Optimal Control with Constrained Outputs

Number of scenarios used for optimization: $N = 200$

Scenario Approach



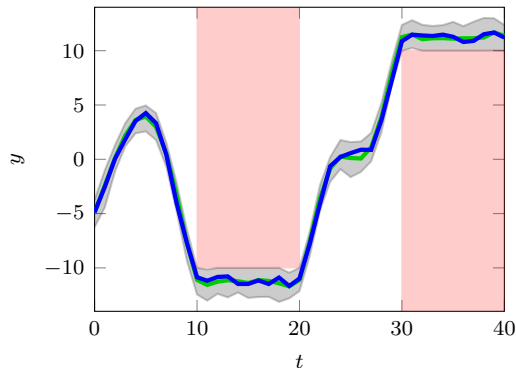
Kernel Approach ($\alpha = 0.01$)



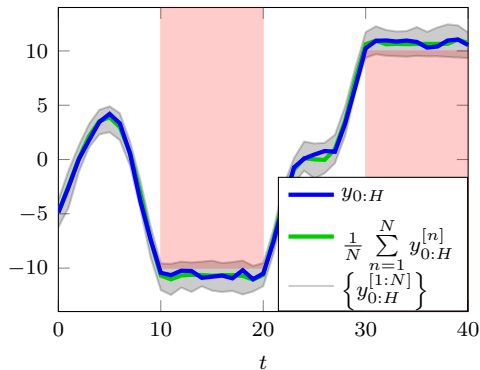
Optimal Control with Constrained Outputs

Number of scenarios used for optimization: $N = 200$

Scenario Approach

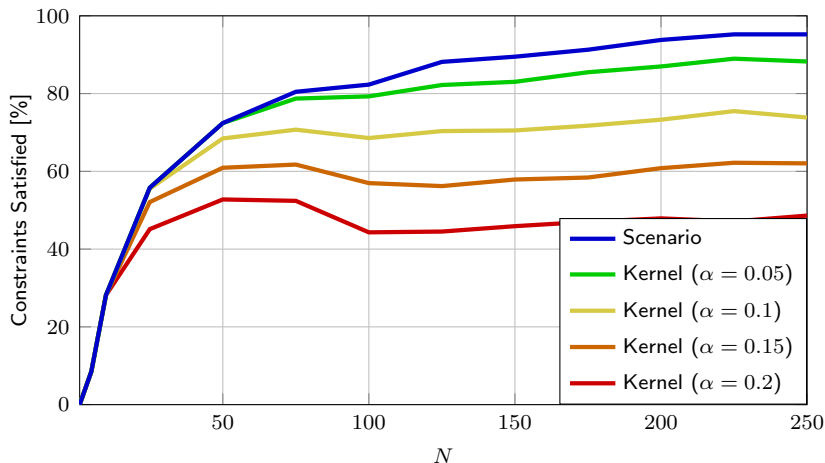


Kernel Approach ($\alpha = 0.3$)



Successrate of Solution

$N = 2000$: Number of Scenarios used to test $u_{0:H}$



Conclusion

Summary: Kernel Embeddings allow for ...

- Solving of chance-constrained OCPs
- Controlling of risk factor α

Future Plans:

- Use Kernel Embeddings on non-linear systems
- Parameter tuning of σ
- Alternative approach of reformulating chance constraints

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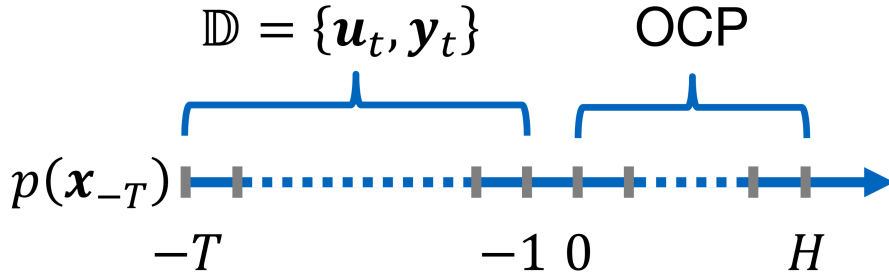


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Timeline



Scenario Generation

Goal: Generate scenarios $\delta^{[1:N]}$ using the observations \mathbb{D}

Algorithm: Scenario Generation

For $n = 1, \dots, N$:

1. Sample $\{\boldsymbol{\theta}, \mathbf{x}_{-T:-1}\}^{[n]}$ from $p(\boldsymbol{\theta}, \mathbf{x}_{-T:-1} \mid \mathbb{D})$ using PMCMC [Lefringhausen+ 2024].
2. Sample $\mathbf{v}_t^{[n]}$ from $\mathcal{V}_{\boldsymbol{\theta}^{[n]}}$ and $\mathbf{w}_t^{[n]}$ from $\mathcal{W}_{\boldsymbol{\theta}^{[n]}}$ for $t = -1, \dots, H$
3. Set $\mathbf{x}_0^{[n]} = \mathbf{f}_{\boldsymbol{\theta}^{[n]}}(\mathbf{x}_{-1}^{[n]}, \mathbf{u}_{-1}) + \mathbf{v}_{-1}^{[n]}$

Output: Scenarios $\delta^{[1:N]} = \{\boldsymbol{\theta}, \mathbf{x}_0, \mathbf{v}_{0:H}, \mathbf{w}_{0:H}\}^{[1:N]}$

Bootstrap Construction

Algorithm: Bootstrap MMD ambiguity set

1. $\mathbf{K} \leftarrow \text{kernel}(\delta, \delta)$
2. **For** $m = 1, \dots, B$
3. $I \leftarrow N$ numbers from $\{1, \dots, N\}$ with replacement
4. $K_x \leftarrow \sum_{i,j=1}^N K_{ij}$, $K_y \leftarrow \sum_{i,j \in I} K_{ij}$, $K_{xy} \leftarrow \sum_{j \in I} \sum_{i=1}^N K_{ij}$
5. $\text{MMD}[m] \leftarrow \frac{1}{N^2} (K_x + K_y - 2K_{xy})$
6. **End For**
7. $\text{MMD} \leftarrow \text{sort}(\text{MMD})$
8. $\varepsilon \leftarrow \text{MMD}[\text{ceil}(B\beta)]$

Output: Gram matrix \mathbf{K} , Radius of MMD ambiguity set ε

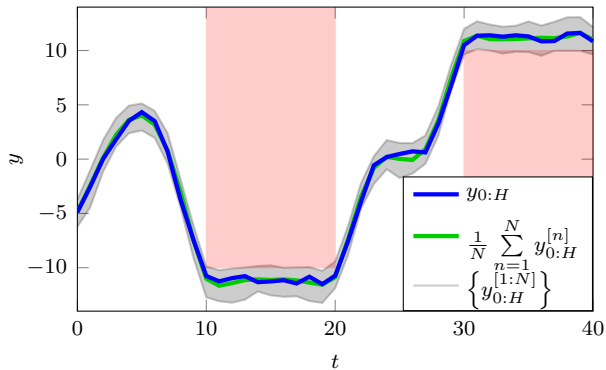
$$B = 1000, \beta = 0.95$$

Max Constraint

Chance Constraint

$$P[\max(\mathbf{h}(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}, \mathbf{y}_{0:H})) \leq 0] \geq 1 - \alpha$$

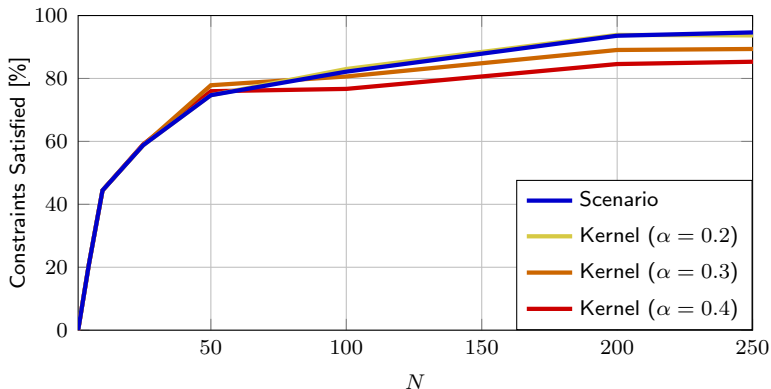
Constrained Output ($\alpha = 0.5$)



Max Constraint

Chance Constraint

$$P[\max(\mathbf{h}(\mathbf{u}_{0:H}, \mathbf{x}_{0:H}, \mathbf{y}_{0:H})) \leq 0] \geq 1 - \alpha$$



Maximum Mean Discrepancy (MMD)

Maximum Mean Discrepancy

$$\begin{aligned}\text{MMD}(\tilde{P}, P_N) &= \|\mu_{\tilde{P}} - \mu_{P_N}\|_{\mathcal{H}} \\ &= \mathbb{E}_{x, x' \sim \tilde{P}}[k(x, x')] + \mathbb{E}_{y, y' \sim P_N}[k(y, y')] - 2\mathbb{E}_{x \sim \tilde{P}, y \sim P_N}[k(x, y)]\end{aligned}$$

(Biased) MMD estimator

$$\widehat{\text{MMD}}(\tilde{P}, P_N) = \frac{1}{N^2} \sum_{i, j=1}^N k(\boldsymbol{\delta}^{[i]}, \boldsymbol{\delta}^{[j]}) + k(\tilde{\boldsymbol{\delta}}^{[i]}, \tilde{\boldsymbol{\delta}}^{[j]}) - 2k(\boldsymbol{\delta}^{[i]}, \tilde{\boldsymbol{\delta}}^{[j]})$$