University of Stuttgart
Germany

Controller Design via Experimental Exploration with Robustness Guarantees

Tobias Holicki

Introductory Comments

- This talk is highly inspired by the work [1].
- Related works are, e.g., [2], [3], [4], [5].
- The aim is to extend some of the aspects of [1] while focusing on a deterministic setup.

[1] Marco et al. "On the design of LQR kernels for efficient controller learning". 2017
[2] Ferizbegovic et al. "Learning Robust LQ-Controllers Using Application Oriented Exploration". 2020
[3] Boczar, Matni, and Recht. "Finite-Data Performance Guarantees for the Output-Feedback Control of an Unknown System". 2018
[4] Kober, Bagnell, and Peters. "Reinforcement learning in robotics: A survey". 2013
[5] Berkenkamp and Schoellig. "Safe and robust learning control with Gaussian processes". 2015

Contents

Contents

Setting and Goal

Let us consider the feedback interconnection

$$\begin{pmatrix} \dot{x}(t) \\ \hline z(t) \\ e(t) \\ y(t) \end{pmatrix} = \left(\begin{array}{c|ccc} A & B_1 & B_2 & B_3 \\ \hline C_1 & D_{11} & D_{12} & D_{13} \\ C_2 & D_{21} & D_{22} & D_{23} \\ I & 0 & 0 & 0 \end{array}\right) \begin{pmatrix} x(t) \\ \hline w(t) \\ d(t) \\ u(t) \end{pmatrix}, \quad w(t) = \Delta_0 z(t)$$

for some uncertain parameter Δ_0 contained in a known compact set $\mathbf{\Delta}$.

Setting and Goal

Let us consider the feedback interconnection

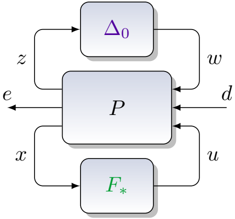
$$\begin{pmatrix} \dot{x}(t) \\ \hline z(t) \\ e(t) \\ y(t) \end{pmatrix} = \left(\begin{array}{c|ccc} A & B_1 & B_2 & B_3 \\ \hline C_1 & D_{11} & D_{12} & D_{13} \\ C_2 & D_{21} & D_{22} & D_{23} \\ I & 0 & 0 & 0 \end{array}\right) \begin{pmatrix} x(t) \\ \hline w(t) \\ d(t) \\ u(t) \end{pmatrix}, \quad w(t) = \Delta_0 z(t)$$

for some uncertain parameter Δ_0 contained in a known compact set $\mathbf{\Delta}$.

Goal: We wish to find a state-feedback controller

$$u(t) = F_* x(t)$$

which stabilizes $\Delta_0 \star P$ and turns the closed-loop H_∞ norm is as small as possible.



I.e., we search for a minimizer of the function

$$J : F \mapsto \|\Delta_0 \star P \star F\|_\infty .$$

that stabilizes $\Delta_0 \star P$.

Setting and Goal

Let us consider the feedback interconnection

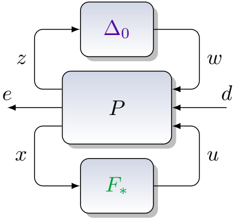
$$\begin{pmatrix} \dot{x}(t) \\ \hline z(t) \\ e(t) \\ y(t) \end{pmatrix} = \left(\begin{array}{c|ccc} A & B_1 & B_2 & B_3 \\ \hline C_1 & D_{11} & D_{12} & D_{13} \\ C_2 & D_{21} & D_{22} & D_{23} \\ I & 0 & 0 & 0 \end{array}\right) \begin{pmatrix} x(t) \\ \hline w(t) \\ d(t) \\ u(t) \end{pmatrix}, \quad w(t) = \Delta_0 z(t)$$

for some uncertain parameter Δ_0 contained in a known compact set $\mathbf{\Delta}$.

Goal: We wish to find a state-feedback controller

$$u(t) = F_* x(t)$$

which stabilizes $\Delta_0 \star P$ and turns the closed-loop H_∞ norm is as small as possible.



I.e., we search for a minimizer of the function

$$J : F \mapsto \|\Delta_0 \star P \star F\|_\infty.$$

that stabilizes $\Delta_0 \star P$.

Issue: Finding an (close-to-)optimal controller is difficult as Δ_0 is unknown.

Standard Design Approaches

Via standard H_∞ design, we can compute for any fixed $\Delta \in \mathbf{\Delta}$:

$$\gamma_{\mathrm{nom}}(\Delta) := \inf_{F \text{ stabilizes } \Delta \star P} \|\Delta \star P \star F\|_\infty.$$

Goal: We wish to determine $\gamma_{\mathrm{nom}}(\Delta_0)$ and design a corresponding controller.

Standard Design Approaches

Via standard H_∞ design, we can compute for any fixed $\Delta \in \mathbf{\Delta}$:

$$\gamma_{\rm nom}(\Delta) := \inf_{F \text{ stabilizes } \Delta\star P} \|\Delta \star P \star F\|_\infty.$$

Goal: We wish to determine $\gamma_{\rm nom}(\Delta_0)$ and design a corresponding controller.

Via standard robust design (by exploiting knowledge of $\mathbf{\Delta}$), we can compute upper bounds $\gamma_{\rm sep}$ on the worst-case closed-loop H_∞ norm:

$$\inf_{F\in\mathbb{F}} \sup_{\Delta\in\mathbf{\Delta}} \|\Delta \star P \star F\|_\infty \leq \gamma_{\rm sep}.$$

Here, we abbreviate the set of robustly stabilizing controllers as

$$\mathbb{F} := \{F \ : \ F \text{ stabilizies } \Delta \star P \text{ for all } \Delta \in \mathbf{\Delta}\}.$$

Standard Design Approaches

Via standard H_∞ design, we can compute for any fixed $\Delta \in \mathbf{\Delta}$:

$$\gamma_{\mathrm{nom}}(\Delta) := \inf_{F \text{ stabilizes } \Delta \star P} \|\Delta \star P \star F\|_\infty.$$

Goal: We wish to determine $\gamma_{\mathrm{nom}}(\Delta_0)$ and design a corresponding controller.

Via standard robust design (by exploiting knowledge of $\mathbf{\Delta}$), we can compute upper bounds γ_{sep} on the worst-case closed-loop H_∞ norm:

$$\inf_{F \in \mathbb{F}} \sup_{\Delta \in \mathbf{\Delta}} \|\Delta \star P \star F\|_\infty \leq \gamma_{\mathrm{sep}}.$$

Here, we abbreviate the set of robustly stabilizing controllers as

$$\mathbb{F} := \{F \ : \ F \text{ stabilizies } \Delta \star P \text{ for all } \Delta \in \mathbf{\Delta}\}.$$

Clearly, we have

$$\gamma_{\mathrm{nom}}(\Delta_0) \leq \gamma_{\mathrm{sep}}$$

and there might be a very large gap between both values.

Setting and Goal (Continued)

Additional Assumption: E.g. by running and measuring multiple closed-loop experiments, the function

$J : F \mapsto \|\Delta_0 \star P \star F\|_\infty$ can be evaluated for finitely many controllers $F_1, \ldots, F_N$.

New Goal: Based on this additional information, find a controller F such that $J(F) = \|\Delta_0 \star P \star F\|_\infty$ is much closer to $\gamma_{\mathrm{nom}}(\Delta_0)$ than γ_{sep}.

Setting and Goal (Continued)

Additional Assumption: E.g. by running and measuring multiple closed-loop experiments, the function

$J : F \mapsto \|\Delta_0 \star P \star F\|_\infty$ can be evaluated for finitely many controllers $F_1, \ldots, F_N$.

New Goal: Based on this additional information, find a controller F such that $J(F) = \|\Delta_0 \star P \star F\|_\infty$ is much closer to $\gamma_{\mathrm{nom}}(\Delta_0)$ than γ_{sep}.

The above assumption suggests to perform a numerical minimization of a function that interpolates the data points

$$(F_1, J(F_1)), \ldots, (F_N, J(F_N)).$$

This gives rise to the following essential questions.

- How can suitable test controllers $F_1, \ldots, F_N$ be selected systematically?
- How can the resulting data points be interpolated?

Contents

Robust Stability

Issue: Stability is a critical property as interconnecting a controller to the given system that is not stabilizing can lead to catastrophic results.

Remedy: Following [1], we only search for robustly stabilizing controllers in $\mathbb{F}$.

[1] Marco et al. "On the design of LQR kernels for efficient controller learning". 2017

Robust Stability

Issue: Stability is a critical property as interconnecting a controller to the given system that is not stabilizing can lead to catastrophic results.

Remedy: Following [1], we only search for robustly stabilizing controllers in $\mathbb{F}$.

It is not possible to include this safety requirement for free as we usually have

$$\gamma_{\mathrm{nom}}(\Delta_0) = \inf_{F \text{ stabilizes } \Delta_0 \star P} J(F) < \inf_{F \in \mathbb{F}} J(F).$$

- We show later on how to get closer to $\gamma_{\mathrm{nom}}(\Delta_0)$ by increasing the set of admissible controllers while still being able to guarantee safe operation.

[1] Marco et al. "On the design of LQR kernels for efficient controller learning". 2017

Sampling and Gridding

Issue: It can be difficult to find controllers in $\mathbb{F} \subset \mathbb{R}^{n_u \times n_y}$ based on gridding or sampling especially if

- the dimension of $\mathbb{R}^{n_u \times n_y}$ is large,
- $\mathbb{F}$ is an unbounded set or
- $\mathbb{F}$ has measure zero in $\mathbb{R}^{n_u \times n_y}$.

Remedy: In contrast to [1], we propose a systematic approach to find such controllers based on gridding or sampling in the compact set $\boldsymbol{\Delta}$.

Motivation

As motivation, let us define the function (assuming it is well-defined)

$$\mathcal{F} : \boldsymbol{\Delta} \to \mathbb{F}, \ \Delta \mapsto F \in \operatorname*{arg\,min}_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty .$$

Then $\mathcal{F}(\Delta)$ is a robustly stabilizing controller that yields the smallest H_∞ norm of $\Delta \star P \star F$ among all robustly stabilizing controllers.

Motivation

As motivation, let us define the function (assuming it is well-defined)

$$\mathcal{F} : \boldsymbol{\Delta} \to \mathbb{F}, \ \Delta \mapsto F \in \operatorname*{arg\,min}_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty .$$

Then $\mathcal{F}(\Delta)$ is a robustly stabilizing controller that yields the smallest H_∞ norm of $\Delta \star P \star F$ among all robustly stabilizing controllers.

By its definition we have

$$\|\Delta \star P \star \mathcal{F}(\Delta)\|_\infty \leq \|\Delta \star P \star F\|_\infty \quad \text{for all} \quad F \in \mathbb{F} \quad \text{and all} \quad \Delta \in \boldsymbol{\Delta}.$$

Motivation

As motivation, let us define the function (assuming it is well-defined)

$$\mathcal{F} : \boldsymbol{\Delta} \to \mathbb{F}, \ \Delta \mapsto F \in \operatorname*{arg\,min}_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty .$$

Then $\mathcal{F}(\Delta)$ is a robustly stabilizing controller that yields the smallest H_∞ norm of $\Delta \star P \star F$ among all robustly stabilizing controllers.

By its definition we have

$$\|\Delta \star P \star \mathcal{F}(\Delta)\|_\infty \le \|\Delta \star P \star F\|_\infty \quad \text{for all} \quad F \in \mathbb{F} \quad \text{and all} \quad \Delta \in \boldsymbol{\Delta}.$$

For $L := J \circ \mathcal{F} : \Delta \mapsto \|\Delta_0 \star P \star \mathcal{F}(\Delta)\|_\infty$ this implies

$$\inf_{F \in \mathbb{F}} J(F) = \inf_{F \in \mathbb{F}} \|\Delta_0 \star P \star F\|_\infty = L(\Delta_0) \le L(\Delta) \quad \text{for all} \quad \Delta \in \boldsymbol{\Delta}.$$

Motivation

As motivation, let us define the function (assuming it is well-defined)

$$\mathcal{F} : \boldsymbol{\Delta} \to \mathbb{F},\ \Delta \mapsto F \in \operatorname*{arg\,min}_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty .$$

Then $\mathcal{F}(\Delta)$ is a robustly stabilizing controller that yields the smallest H_∞ norm of $\Delta \star P \star F$ among all robustly stabilizing controllers.

By its definition we have

$$\|\Delta \star P \star \mathcal{F}(\Delta)\|_\infty \leq \|\Delta \star P \star F\|_\infty \quad \text{for all} \quad F \in \mathbb{F} \quad \text{and all} \quad \Delta \in \boldsymbol{\Delta}.$$

For $L := J \circ \mathcal{F} : \Delta \mapsto \|\Delta_0 \star P \star \mathcal{F}(\Delta)\|_\infty$ this implies

$$\inf_{F \in \mathbb{F}} J(F) = \inf_{F \in \mathbb{F}} \|\Delta_0 \star P \star F\|_\infty = L(\Delta_0) \leq L(\Delta) \quad \text{for all} \quad \Delta \in \boldsymbol{\Delta}.$$

Why useful? We can minimize $L : \boldsymbol{\Delta} \to \mathbb{R}$ instead of $J : \mathbb{F} \to \mathbb{R}$ based on I/O samples.

Observations

Observation: A successful minimization of L would even allow to identify the uncertain parameter Δ_0 if the minimizer is unique.

Observations

Observation: A successful minimization of L would even allow to identify the uncertain parameter Δ_0 if the minimizer is unique.

Issue: It is not easily possible to compute $\mathcal{F}(\Delta)$ or $\inf_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty$ for any fixed $\Delta \in \mathbf{\Delta}$ as we are facing a robust multi-objective problem.

- The underlying problem is nonconvex and also nonsmooth in general.

Observations

Observation: A successful minimization of L would even allow to identify the uncertain parameter Δ_0 if the minimizer is unique.

Issue: It is not easily possible to compute $\mathcal{F}(\Delta)$ or $\inf_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty$ for any fixed $\Delta \in \boldsymbol{\Delta}$ as we are facing a robust multi-objective problem.

- The underlying problem is nonconvex and also nonsmooth in general.

However, as for robust controller design we can compute upper bounds on the optimal value and synthesize corresponding controllers!

Robust Multi-Objective Design

Lemma 1. Let $\Delta \in \boldsymbol{\Delta}$ be fixed. Then there is a controller $F \in \mathbb{F}$ satisfying $\|\Delta \star P \star F\|_\infty < \gamma$ if there exist a matrix M and symmetric Y, P satisfying

$$Y \succ 0,$$

$$P \in \mathbb{P}(\boldsymbol{\Delta}), \quad (\bullet)^T \left(\begin{array}{cc|c} 0 & I & \\ I & 0 & \\ \hline & & P \end{array}\right) \left(\begin{array}{cc} I & 0 \\ -(AY + B_3 M)^T & -(C_1 Y + D_{13} M)^T \\ \hline 0 & I \\ -B_1^T & -D_{11}^T \end{array}\right) \succ 0, \quad \text{(RS)}$$

$$(\bullet)^T \left(\begin{array}{cc|c} 0 & I & \\ I & 0 & \\ \hline & & P_\gamma^{-1} \end{array}\right) \left(\begin{array}{cc} I & 0 \\ -(A^\Delta Y + B_3^\Delta M)^T & -(C_2^\Delta Y + D_{23}^\Delta M)^T \\ \hline 0 & I \\ -(B_2^\Delta)^T & -(D_{22}^\Delta)^T \end{array}\right) \succ 0. \quad (\text{NP}\Delta)$$

If the above LMIs are feasible, a suitable controller is $F := MY^{-1}$. Moreover,

$$\inf_{F \in \mathbb{F}} \|\Delta \star P \star F\|_\infty \leq \gamma_{\mathrm{mo}}(\Delta)$$

for $\gamma_{\mathrm{mo}}(\Delta)$ being the infimal γ such that the above LMIs are feasible.

Consequences and Remarks

Instead of using $\mathcal{F}$ and for $\varepsilon > 0$, Lemma 1 suggests to employ the function

$$\mathcal{F}_{\mathrm{mo}} : \Delta \mapsto \text{ a corresp. close-to-optimal controller } (\gamma = (1+\varepsilon)\gamma_{\mathrm{mo}}(\Delta))$$

- $\mathcal{F}_{\mathrm{mo}}(\Delta)$ is easily determined by solving a convex semi-definite program.
- Optimal controllers might be bad conditioned or do not even exist.

Consequences and Remarks

Instead of using $\mathcal{F}$ and for $\varepsilon > 0$, Lemma 1 suggests to employ the function

$$\mathcal{F}_{\rm mo} : \Delta \mapsto \text{ a corresp. close-to-optimal controller } (\gamma = (1+\varepsilon)\gamma_{\rm mo}(\Delta))$$

- $\mathcal{F}_{\rm mo}(\Delta)$ is easily determined by solving a convex semi-definite program.
- Optimal controllers might be bad conditioned or do not even exist.

Finally, we obtain suitable test controllers by choosing

$$F_1 := \mathcal{F}_{\rm mo}(\Delta_1), \ldots, F_N := \mathcal{F}_{\rm mo}(\Delta_N) \text{ for samples } \Delta_1, \ldots, \Delta_N \in \boldsymbol{\Delta}.$$

Consequences and Remarks

Instead of using $\mathcal{F}$ and for $\varepsilon > 0$, Lemma 1 suggests to employ the function

$$\mathcal{F}_{\mathrm{mo}} : \Delta \mapsto \text{ a corresp. close-to-optimal controller } (\gamma = (1+\varepsilon)\gamma_{\mathrm{mo}}(\Delta))$$

- $\mathcal{F}_{\mathrm{mo}}(\Delta)$ is easily determined by solving a convex semi-definite program.
- Optimal controllers might be bad conditioned or do not even exist.

Finally, we obtain suitable test controllers by choosing

$$F_1 := \mathcal{F}_{\mathrm{mo}}(\Delta_1), \ldots, F_N := \mathcal{F}_{\mathrm{mo}}(\Delta_N) \text{ for samples } \Delta_1, \ldots, \Delta_N \in \mathbf{\Delta}.$$

- For $L_{\mathrm{mo}} := J \circ \mathcal{F}_{\mathrm{mo}},\ \Delta \mapsto \|\Delta_0 \star P \star \mathcal{F}_{\mathrm{mo}}(\Delta)\|_\infty$ we have

$$\gamma_{\mathrm{nom}}(\Delta_0) \leq L(\Delta_0) \leq L_{\mathrm{mo}}(\Delta_0) \leq (1+\varepsilon)\gamma_{\mathrm{mo}}(\Delta_0)$$

Consequences and Remarks

Instead of using $\mathcal{F}$ and for $\varepsilon > 0$, Lemma 1 suggests to employ the function

$$\mathcal{F}_{\rm mo} : \Delta \mapsto \text{ a corresp. close-to-optimal controller } (\gamma = (1+\varepsilon)\gamma_{\rm mo}(\Delta))$$

- $\mathcal{F}_{\rm mo}(\Delta)$ is easily determined by solving a convex semi-definite program.
- Optimal controllers might be bad conditioned or do not even exist.

Finally, we obtain suitable test controllers by choosing

$$F_1 := \mathcal{F}_{\rm mo}(\Delta_1), \ldots, F_N := \mathcal{F}_{\rm mo}(\Delta_N) \text{ for samples } \Delta_1, \ldots, \Delta_N \in \mathbf{\Delta}.$$

- For $L_{\rm mo} := J \circ \mathcal{F}_{\rm mo},\ \Delta \mapsto \|\Delta_0 \star P \star \mathcal{F}_{\rm mo}(\Delta)\|_\infty$ we have

$$\gamma_{\rm nom}(\Delta_0) \leq L(\Delta_0) \leq L_{\rm mo}(\Delta_0) \leq (1+\varepsilon)\gamma_{\rm mo}(\Delta_0)$$

- A minimizer of L is not necessarily a minimizer of $L_{\rm mo}$ and, conversely, a minimizer of $L_{\rm mo}$ is not necessarily a minimizer of L.
  - This is due to the conservatism in the convex design.

Example

Let us consider a slight variation of an example from COMPl$_e$ib [6] with

$$\boldsymbol{\Delta} := \boldsymbol{\delta} I, \quad \boldsymbol{\delta} := [-1, 1], \quad \Delta_0 := \delta_0 I, \quad \delta_0 = 0.7.$$

We obtain

$$\gamma_{\mathrm{nom}}(\delta_0) = 1.20, \quad \min_{\delta \in \boldsymbol{\delta}} L_{\mathrm{mo}}(\delta) = L_{\mathrm{mo}}(0.66) = 1.39 \quad \text{and} \quad \gamma_{\mathrm{sep}} = 2.02.$$

[6] Leibfritz. *COMPl$_e$ib: COnstraint Matrix-optimization Problem library - a collection of test examples for nonlinear semidefinite programs, control system design and related problems*. 2004

Example

Let us consider a slight variation of an example from COMPl$_e$ib [6] with

$$\mathbf{\Delta} := \boldsymbol{\delta} I, \quad \boldsymbol{\delta} := [-1, 1], \quad \Delta_0 := \delta_0 I, \quad \delta_0 = 0.7.$$

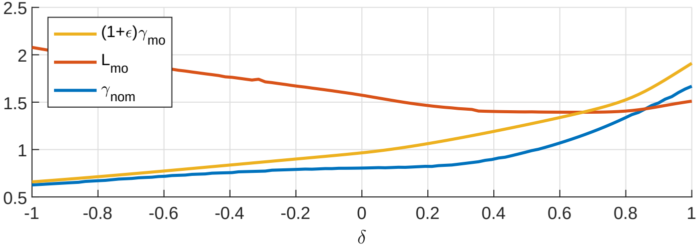
We obtain

$$\gamma_{\mathrm{nom}}(\delta_0) = 1.20, \quad \min_{\delta \in \boldsymbol{\delta}} L_{\mathrm{mo}}(\delta) = L_{\mathrm{mo}}(0.66) = 1.39 \quad \text{and} \quad \gamma_{\mathrm{sep}} = 2.02.$$

- Minimizing L_{mo} leads as desired to better closed-loop H_∞ performance if compared to robust design.
- Safe operation is assured as robustly stabilizing controllers are designed.
- Here $\mathbb{F}$ is a subset of $\mathbb{R}^{4\times 8}$ which has dimension 36 and turns sampling or gridding very tedious.
- The minimizer of L_{mo} is not necessarily equal to δ_0.

[6] Leibfritz. *COMPl$_e$ib: COnstraint Matrix-optimization Problem library - a collection of test examples for nonlinear semidefinite programs, control system design and related problems*. 2004

Observations

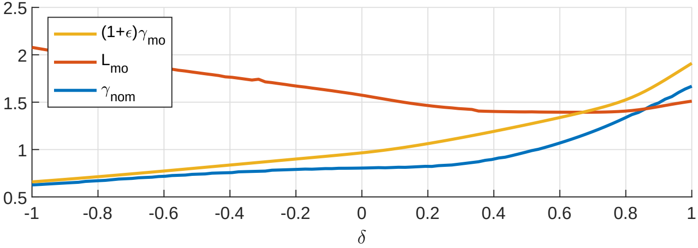


Interesting Bonus Feature:

- We can assure that δ_0 is contained in $[0.65, 0.9]$ as we have inequality

$$\gamma_{\mathrm{nom}}(\delta_0) \leq L_{\mathrm{mo}}(\delta_0) \leq (1+\varepsilon)\gamma_{\mathrm{mo}}(\delta_0).$$

Observations



Interesting Bonus Feature:

- We can assure that δ_0 is contained in $[0.65, 0.9]$ as we have inequality

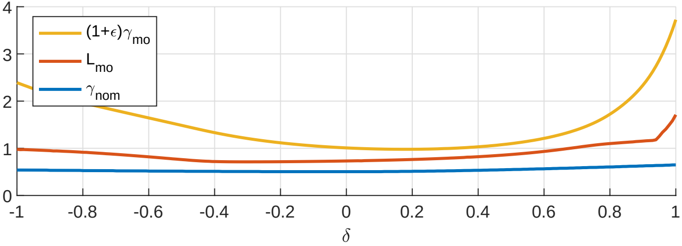
$$\gamma_{\mathrm{nom}}(\delta_0) \leq L_{\mathrm{mo}}(\delta_0) \leq (1+\varepsilon)\gamma_{\mathrm{mo}}(\delta_0).$$

- This allows to repeat the procedure for $\boldsymbol{\Delta}$ replaced by $\tilde{\boldsymbol{\Delta}} := [0.65, 0.9]I$.

- This yields even better controllers as easier robust problems are involved:

$$\gamma_{\mathrm{nom}}(\delta_0) = 1.20, \quad \min_{\delta\in[0.65,0.9]} L_{\mathrm{mo}}(\delta) = 1.31 \;\text{ and }\; \gamma_{\mathrm{sep}} = 1.66.$$

“Negative” Example



- Shrinking $\boldsymbol{\Delta}$ by a large amount is not always possible as the curves do not have to intersect at all.
- But it can as well be possible to iteratively apply the shrinking.

Interpolation/Approximation

Goal: Interpolate/Approximate L_{mo} with as few evaluations as possible.

- Evaluating L_{mo} requires (expensive?) closed-loop experiments.

Interpolation/Approximation

Goal: Interpolate/Approximate L_{mo} with as few evaluations as possible.

- Evaluating L_{mo} requires (expensive?) closed-loop experiments.
- In principle any interpolation / approximation scheme can be used.

Interpolation/Approximation

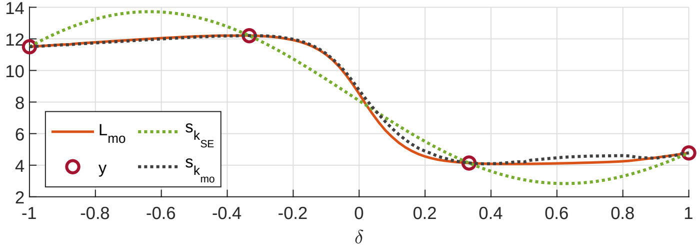
Goal: Interpolate/Approximate L_{mo} with as few evaluations as possible.

- Evaluating L_{mo} requires (expensive?) closed-loop experiments.
- In principle any interpolation / approximation scheme can be used.
- As in [1], we propose a kernel based approach with customized kernels.
- Allows for an extension to the stochastic setting with Gaussian processes.

Interpolation/Approximation

Goal: Interpolate/Approximate L_{mo} with as few evaluations as possible.

- Evaluating L_{mo} requires (expensive?) closed-loop experiments.
- In principle any interpolation / approximation scheme can be used.
- As in [1], we propose a kernel based approach with customized kernels.
- Allows for an extension to the stochastic setting with Gaussian processes.



Contents

Conclusions and Outlook

Conclusions:

- Evaluations of closed-loop experiments allow to design safe controllers with superior performance if compared to a standard robust design.
- Systematic selection of suitable test controllers.

Conclusions and Outlook

Conclusions:

- Evaluations of closed-loop experiments allow to design safe controllers with superior performance if compared to a standard robust design.
- Systematic selection of suitable test controllers.

Outlooks:

- (Output-feedback) synthesis based on superior analysis results.
- How to handle time-varying uncertainties?
- Systematic approaches for higher dimensions.

University of Stuttgart
Germany

Thank you!

Tobias Holicki

tobias.holicki@imng.uni-stuttgart.de

University of Stuttgart
Department of Mathematics
Mathematical Systems Theory