

Nonlinear infinite-horizon control using generalized Lyapunov equations

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Linear quadratic control problems

Consider a linear system

$$\begin{aligned} \dot{y}(t) &= Ay(t) + Bu(t), \quad y(0) = y_0 \in Y, \\ y_{\text{obs}}(t) &= Cy(t) \end{aligned}$$

- Hilbert spaces U, Y, Z ,
- A generator of an analytic C_0 -semigroup e^{At} on Y ,
- control operator $B \in \mathcal{L}(U, Y)$, s.t. (A, B) is stabilizable,
- output operator $C \in \mathcal{L}(Y, Z)$, s.t. (A, C) is detectable.

Let us focus on the infinite-horizon control problem

$$\min_{u \in L^2(0, \infty; U)} \mathcal{J}(y_0, u) = \int_0^\infty \frac{1}{2} \|y_{\text{obs}}\|_Z^2 + \frac{\beta}{2} \|u\|_U^2 dt.$$

Optimal feedback $\bar{u} = -\frac{1}{\beta} B^* \Pi \bar{y}$ by algebraic Riccati equation

$$A^* \Pi + \Pi A - \frac{1}{\beta} \Pi B B^* \Pi + C^* C = 0.$$

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The ARE: feedback, optimal cost

Well-known: $\exists!$ stabilizing $\Pi = \Pi^* \succeq 0 \in \mathcal{L}(Y)$ s.t. $\forall y_1, y_2 \in \mathcal{D}(A)$:

$$\langle Ay_1, \Pi y_2 \rangle_Y + \langle \Pi y_1, Ay_2 \rangle_Y + \langle Cy_1, Cy_2 \rangle_Z - \frac{1}{\beta} \langle B^* \Pi y_1, B^* \Pi y_2 \rangle_U = 0.$$

Minimal value function $\mathcal{V}(y_0) := \min_u \mathcal{J}(y_0, u) = \frac{1}{2} \langle y_0, \Pi y_0 \rangle_Y$.

Note: for $B \in \mathcal{L}(U, [D(A^*)]')$ not obvious that $B^* \Pi \in \mathcal{L}(Y, U)$

Alternative interpretation for $A_\pi := A - \frac{1}{\beta} BB^* \Pi$

$$\mathcal{T}(A_\pi y_1, y_2) + \mathcal{T}(y_1, A_\pi y_2) = \mathcal{R}(y_1, y_2), \quad (1)$$

where

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Outline of this talk

Consider the multidimensional analogue of (1)

$$\sum_{i=1}^k \mathcal{T}_k(y_1, \dots, y_{i-1}, A_{\pi} y_i, y_{i+1}, \dots, y_k) = \mathcal{R}_k(y_1, \dots, y_k)$$

where $(y_1, \dots, y_k) \in \mathcal{D}(A)^k$ and $\mathcal{R}_k \in \mathcal{M}(\mathcal{D}(A)^k, \mathbb{R})$.

Questions:

- Why should we consider these equations?
- Which theoretical results do we have for these equations?
- How should we treat these equations numerically?

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Nonlinear ∞ -horizon control: \mathbb{R}^n

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$$\begin{aligned} \dot{y}(t) &= Ay(t) + f(y(t)) + Bu(t), \quad y(0) = y_0, \\ y_{\text{obs}}(t) &= Cy(t), \end{aligned}$$

- $A \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, $C \in \mathbb{R}^{p \times n}$, $f: \mathbb{R}^n \rightarrow \mathbb{R}^n$, $f(0) = 0$

Associated **minimal value function**

$$\mathcal{V}(y_0) = \inf_{u \in L^2(0, \infty; \mathbb{R}^m)} \frac{1}{2} \int_0^\infty \|y_{\text{obs}}(t)\|^2 dt + \frac{\beta}{2} \int_0^\infty \|u(t)\|^2 dt.$$

If \mathcal{V} sufficiently smooth, the **Hamilton-Jacobi-Bellman** equation

$$(Ay + f(y))^\top \nabla \mathcal{V}(y) + \frac{1}{2} \|Cy\|^2 - \frac{1}{2\beta} \|B^\top \nabla \mathcal{V}(y)\|^2 = 0$$

yields **optimal feedback law** $\bar{u}(\bar{y}) = -\frac{1}{\beta} B^\top \nabla \mathcal{V}(\bar{y})$.

Taylor expansions – basic idea

Idea: **Expand** \mathcal{V} around 0 as follows

$$\mathcal{V}(y) = \mathcal{V}(0) + D\mathcal{V}(0)(y) + \frac{1}{2!}D^2\mathcal{V}(0)(y, y) + \frac{1}{3!}D^3\mathcal{V}(0)(y, y, y) + \dots$$

and **approximate optimal feedback law** via

$$u_d(y) = -\frac{1}{\beta} \sum_{k=2}^d \frac{1}{(k-1)!} B^\top D^k \mathcal{V}(0)(\cdot, y, \dots, y).$$

Finite-dimensional case:

[AGUILAR, AL'BREKHT, CEBUHAR, COSTANZA, GARRARD, KRENER, LUKES, ...]

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Taylor expansions – deriving the equations

Consider again

$$DV(y)(Ay + f(y)) + \frac{1}{2} \|Cy\|^2 - \frac{1}{2\beta} \|B^T DV(y)(\cdot)\|^2 = 0,$$

⇒ **one differentiation** in direction $z_1 \in \mathcal{D}(A)$ yields

$$\begin{aligned} D^2V(y)(Ay + f(y), z_1) + DV(y)(Az_1 + Df(y)(z_1)) \\ + \langle Cy, Cz_1 \rangle - \frac{1}{\beta} \langle B^T D^2V(y)(\cdot, z_1), B^T DV(y)(\cdot) \rangle = 0. \end{aligned}$$

⇒ **two differentiations** in directions $z_1, z_2 \in \mathcal{D}(A)$ yield

$$\begin{aligned} D^3V(y)(Ay + f(y), z_1, z_2) + D^2V(y)(Az_2 + Df(y)(z_2), z_1) \\ + D^2V(y)(Az_1 + Df(y)(z_1), z_2) + DV(y)(D^2f(y)(z_1, z_2)) \\ + \langle Cz_1, Cz_2 \rangle - \frac{1}{\beta} \langle B^T D^3V(y)(\cdot, z_1, z_2), B^T DV(y)(\cdot) \rangle \\ - \frac{1}{\beta} \langle B^T D^2V(y)(\cdot, z_1), B^T D^2V(y)(\cdot, z_2) \rangle = 0. \end{aligned}$$

Taylor expansions – deriving the equations

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$$D\mathcal{V}(y)(Ay + f(y)) + \frac{1}{2}\|C_y\|^2 - \frac{1}{2\beta}\|B^\top D\mathcal{V}(y)(\cdot)\|^2 = 0,$$

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Taylor expansions – deriving the equations

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$$D\mathcal{V}(y)(Ay + f(y)) + \frac{1}{2}\|Cy\|^2 - \frac{1}{2\beta}\|B^\top D\mathcal{V}(y)(\cdot)\|^2 = 0,$$

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⇒ **three differentiations** and evaluation in zero yields

$$\begin{aligned} 0 = & D^3\mathcal{V}(0)(Az_3 + Df(0)(z_3), z_1, z_2) - \frac{1}{\beta}\langle B^\top D^3\mathcal{V}(0)(\cdot, z_1, z_2), B^\top D^2\mathcal{V}(0)(\cdot, z_3) \rangle \\ & + D^3\mathcal{V}(0)(Az_2 + Df(0)(z_2), z_1, z_3) - \frac{1}{\beta}\langle B^\top D^3\mathcal{V}(0)(\cdot, z_1, z_3), B^\top D^2\mathcal{V}(0)(\cdot, z_2) \rangle \\ & + D^3\mathcal{V}(0)(Az_1 + Df(0)(z_1), z_2, z_3) - \frac{1}{\beta}\langle B^\top D^3\mathcal{V}(0)(\cdot, z_2, z_3), B^\top D^2\mathcal{V}(0)(\cdot, z_1) \rangle \\ & + D^2\mathcal{V}(0)(D^2f(0)(z_2, z_3), z_1) + D^2\mathcal{V}(0)(D^2f(0)(z_1, z_3), z_2) \\ & + D^2\mathcal{V}(0)(D^2f(0)(z_1, z_2), z_3) \end{aligned}$$

Recall: $\sum_{i=1}^k \mathcal{T}_k(y_1, \dots, y_{i-1}, A_\pi y_i, y_{i+1}, \dots, y_k) = \mathcal{R}_k(y_1, \dots, y_k)$

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Nonlinear ∞ -horizon control: Navier-Stokes

Given: $\Omega \subset \mathbb{R}^3$ with $C^{1,1}$ boundary Γ , vector valued φ, ψ

Goal: $\tilde{B} \in \mathcal{L}(\mathbb{L}^2(\omega), \mathbb{L}^2(\Omega))$, find **control** u s.t. solution (\mathbf{z}, q) of

$$\begin{aligned} \frac{\partial \mathbf{z}}{\partial t} &= \nu \Delta \mathbf{z} - (\mathbf{z} \cdot \nabla) \mathbf{z} - \nabla q + \varphi + \tilde{B}u && \text{in } \Omega \times (0, T), \\ \operatorname{div} \mathbf{z} &= 0 && \text{in } \Omega \times (0, T), \\ \mathbf{z} &= \psi && \text{on } \Gamma \times (0, T), \\ \mathbf{z}(0) &= \bar{\mathbf{z}} + \mathbf{y}_0 \end{aligned}$$

s.t. $\lim_{t \rightarrow \infty} \mathbf{z}(t) = \bar{\mathbf{z}}$ for *small* \mathbf{y}_0 , where $(\bar{\mathbf{z}}, \bar{q})$ is a **stationary solution** of

$$\begin{aligned} -\nu \Delta \bar{\mathbf{z}} + (\bar{\mathbf{z}} \cdot \nabla) \bar{\mathbf{z}} + \nabla \bar{q} &= \varphi && \text{in } \Omega, \\ \operatorname{div} \bar{\mathbf{z}} &= 0 && \text{in } \Omega, \\ \bar{\mathbf{z}} &= \psi && \text{on } \Gamma. \end{aligned}$$

Navier-Stokes - state space formulation

Consider the spaces [BARBU,BOYER,FABRIE,FOIAS,TEMAM,...]

$$Y := \{ \mathbf{y} \in \mathbb{L}^2(\Omega) \mid \operatorname{div} \mathbf{y} = 0, \mathbf{y} \cdot \vec{n} = 0 \text{ on } \Gamma \},$$

$$V := \{ \mathbf{y} \in \mathbb{H}_0^1(\Omega) \mid \operatorname{div} \mathbf{y} = 0 \}.$$

We have the **orthogonal decomposition**

$$\mathbb{L}^2(\Omega) = Y \oplus \{ \mathbf{z} = \nabla p \mid p \in H^1(\Omega) \}.$$

Rewrite as abstract Cauchy problem

$$\dot{\mathbf{y}}(t) = A\mathbf{y} - F(\mathbf{y}) + \underbrace{P\tilde{B}}_{=B} u, \quad \mathbf{y}(0) = \mathbf{y}_0,$$

where

$P: \mathbb{L}^2(\Omega) \rightarrow Y$ denotes the **Leray projector**,

$$A\mathbf{y} = P(\nu \Delta \mathbf{y} - (\mathbf{y} \cdot \nabla) \bar{\mathbf{z}} - (\bar{\mathbf{z}} \cdot \nabla) \mathbf{y}), \quad \mathcal{D}(A) = \mathbb{H}^2(\Omega) \cap V,$$

$$F: \mathbb{H}^2(\Omega) \cap V \rightarrow Y, \quad F(\mathbf{y}) = P((\mathbf{y} \cdot \nabla) \mathbf{y}).$$

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where

$P: \mathbb{L}^2(\Omega) \rightarrow Y$ denotes the **Leray projector**,

$$A\mathbf{y} = P(\nu \Delta \mathbf{y} - (\mathbf{y} \cdot \nabla) \bar{\mathbf{z}} - (\bar{\mathbf{z}} \cdot \nabla) \mathbf{y}), \quad \mathcal{D}(A) = \mathbb{H}^2(\Omega) \cap V,$$

$$F: \mathbb{H}^2(\Omega) \cap V \rightarrow Y, \quad F(\mathbf{y}) = P((\mathbf{y} \cdot \nabla) \mathbf{y}).$$

Navier-Stokes - the infinite-horizon problem

For $A_\lambda := \lambda I - A$, $\lambda > 0$ sufficiently large, we introduce

$$W_\infty(\mathcal{D}(A_\lambda), Y) := \left\{ \mathbf{y} \in L^2(0, \infty; \mathcal{D}(A_\lambda)) \mid \frac{d}{dt} \mathbf{y} \in L^2(0, \infty; Y) \right\}$$

with

$$\|\mathbf{y}\|_{W_\infty(\mathcal{D}(A_\lambda), Y)} := \left(\|A_\lambda \mathbf{y}\|_{L^2(0, \infty; Y)}^2 + \|\dot{\mathbf{y}}\|_{L^2(0, \infty; Y)}^2 \right)^{\frac{1}{2}}.$$

and consider the **infinite-horizon optimal control** problem

$$\begin{aligned} \inf_{u \in L^2(0, \infty; U)} \mathcal{J}(\mathbf{y}_0, u) &= \frac{1}{2} \int_0^\infty \|\mathbf{y}\|_Y^2 dt + \frac{\alpha}{2} \int_0^\infty \|u(t)\|_U^2 dt, \\ \text{s.t. } \dot{\mathbf{y}} &= A\mathbf{y} - F(\mathbf{y}) + \underbrace{P\tilde{B}}_{=B} u, \quad \mathbf{y}(0) = \mathbf{y}_0 \in V. \end{aligned}$$

Differentiability of \mathcal{V} on V

Smoothness of the value function

There exists $\delta > 0$ s.t. \mathcal{V} is **infinitely differentiable** on $B_{\delta, V}(0)$.

Proof based on

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Optimality conditions

There exists $\delta > 0$ s.t. for all $\mathbf{y}_0 \in B_{\delta, V}(0)$, and for all solutions $(\bar{\mathbf{y}}, \bar{u})$, there exists a unique costate $\mathbf{p} \in W_{\infty}(Y, [\mathcal{D}(A_{\lambda})]')$ satisfying

$$\begin{aligned} -\dot{\mathbf{p}} - A' \mathbf{p} - P((\bar{\mathbf{y}} \cdot \nabla) \mathbf{p} - (\nabla \bar{\mathbf{y}})^T \mathbf{p}) &= \bar{\mathbf{y}} \quad (\text{in } L^2(0, \infty; [\mathcal{D}(A_{\lambda})]')), \\ \beta \bar{u} + B^* \mathbf{p} &= 0. \end{aligned}$$

Remark: The above equation is satisfied in the sense that

$$\langle \mathbf{p}, \dot{\mathbf{z}} \rangle_{L^2(0, \infty; Y)} - \langle \mathbf{p}, A\mathbf{z} - P((\bar{\mathbf{y}} \cdot \nabla) \mathbf{z} + (\mathbf{z} \cdot \nabla) \bar{\mathbf{y}}) \rangle_{L^2(0, \infty; Y)} = \langle \bar{\mathbf{y}}, \mathbf{z} \rangle_{L^2(0, \infty; Y)},$$

for all $\mathbf{z} \in W_{\infty}^0(\mathcal{D}(A_{\lambda}), Y) = \{\mathbf{z} \in W_{\infty}(\mathcal{D}(A_{\lambda}), Y) \mid \mathbf{z}(0) = 0\}$.

Differentiability of \mathcal{V} on V

Smoothness of the value function

There exists $\delta > 0$ s.t. \mathcal{V} is **infinitely differentiable** on $B_{\delta, V}(0)$.

Proof based on

Sensitivity analysis

- $X := V \times L^2(0, \infty; Y) \times L^2(0, \infty; [\mathcal{D}(A_\lambda)]') \times L^2(0, \infty; U)$
- $\Phi: W_\infty(\mathcal{D}(A_\lambda), Y) \times L^2(0, \infty; U) \times W_\infty(Y, [\mathcal{D}(A_\lambda)]') \rightarrow X$
- $\Phi(\mathbf{y}, u, \mathbf{p}) = \begin{pmatrix} \mathbf{y}(0) \\ \dot{\mathbf{y}} - A\mathbf{y} + F(\mathbf{y}) - B\mathbf{u} \\ -\dot{\mathbf{p}} - A'\mathbf{p} - P((\mathbf{y} \cdot \nabla)\mathbf{p} - (\nabla\mathbf{y})^T\mathbf{p}) - \mathbf{y} \\ \beta\mathbf{u} + B^*\mathbf{p} \end{pmatrix}$
- $\Phi(\bar{\mathbf{y}}, \bar{u}, \bar{\mathbf{p}}) = (\mathbf{y}_0, 0, 0, 0)$

A formal HJB equation

Let us formally consider the HJB equation

$$D\mathcal{V}(\mathbf{y})(A\mathbf{y} - F(\mathbf{y})) + \frac{1}{2}\|\mathbf{y}\|_Y^2 - \frac{1}{2\beta}\|B^*D\mathcal{V}(\mathbf{y})\|_U^2 = 0 \text{ for } \mathbf{y} \in \mathcal{D}(A).$$

Problem: not rigorous since we only know $D\mathcal{V}(\mathbf{y}) \in \mathcal{L}(V, \mathbb{R})$.

Remark: in the 2D-case, one can show that $D^k\mathcal{V}(0) \equiv \mathcal{T}_k$ with

$$\sum_{i=1}^k \mathcal{T}_k(\mathbf{z}_1, \dots, \mathbf{z}_{i-1}, A_\pi \mathbf{z}_i, \mathbf{z}_{i+1}, \dots, \mathbf{z}_k) = \mathcal{R}_k(\mathbf{z}_1, \dots, \mathbf{z}_k),$$

where the multilinear form $\mathcal{R}_k: \mathcal{D}(A)^k \rightarrow \mathbb{R}$ is given by

$$\begin{aligned} \mathcal{R}_k(\mathbf{z}_1, \dots, \mathbf{z}_k) &= \frac{1}{2\beta} \sum_{i=2}^{k-2} \binom{k}{i} \text{Sym}_{i, k-i} (C_i \otimes C_{k-i})(\mathbf{z}_1, \dots, \mathbf{z}_k) \\ &\quad + \frac{k(k-1)}{2} \text{Sym}_{k-2, 2} (\mathcal{T}_{k-1} \otimes D^2F(0))(\mathbf{z}_1, \dots, \mathbf{z}_k) \end{aligned}$$

$$C_i(\mathbf{z}_1, \dots, \mathbf{z}_i) = B^* \mathcal{T}_{i+1}(\cdot, \mathbf{z}_1, \dots, \mathbf{z}_i), \quad D^2F(0)(\mathbf{z}_1, \mathbf{z}_2) = (\mathbf{z}_1 \cdot \nabla) \mathbf{z}_2 + (\mathbf{z}_2 \cdot \nabla) \mathbf{z}_1.$$

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Regularity properties of \mathcal{T}_k

Idea: analyze the same equation in 3D for $\mathcal{T}_k \stackrel{?}{\neq} D^k \mathcal{V}(0) \in \mathcal{M}(V^k, \mathbb{R})$

Multilinear Lyapunov operator equations

For $k \geq 3$ and $z_1, \dots, z_k \in V$, let

$$\mathcal{T}_k(z_1, \dots, z_k) = - \int_0^\infty \mathcal{R}_k(e^{A_\pi t} z_1, \dots, e^{A_\pi t} z_k) dt.$$

Then $\mathcal{T}_k \in \mathcal{M}(V^k, \mathbb{R})$ is the unique solution of

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Moreover: $\mathcal{T}_k \in \mathcal{S}_k(V, V') := \bigcap_{\ell=1}^k \mathcal{M}(V^{\ell-1} \times V' \times V^{k-\ell}, \mathbb{R})$.

Proof idea: cp. with $A_\pi^* \Pi + \Pi A_\pi = -BB^* \Rightarrow \Pi = - \int_0^\infty e^{A_\pi^* t} BB^* e^{A_\pi t} dt$

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Error estimates for polynomial system

Based on \mathcal{T}_k , let us define

- $u_d(\mathbf{y}) = -\frac{1}{\beta} \sum_{k=2}^d \frac{1}{(k-1)!} B^* \mathcal{T}_k(\cdot, \mathbf{y}, \dots, \mathbf{y})$
- $\mathcal{V}_d: V \rightarrow \mathbb{R}, \quad \mathcal{V}_d(\mathbf{y}) := \sum_{k=2}^d \frac{1}{k!} \mathcal{T}_k(\mathbf{y}, \dots, \mathbf{y}).$

Consider then the perturbed cost functional

$$\mathcal{J}_d(\mathbf{y}_0, u) := \frac{1}{2} \int_0^{\infty} \|\mathbf{y}\|_Y^2 dt + \frac{\beta}{2} \int_0^{\infty} \|u\|_U^2 dt + \int_0^{\infty} r_d(\mathbf{y}) dt.$$

where $r_d(\mathbf{y})$ is a **polynomial** remainder term.

Observation:

- $u_d(\mathbf{y}_d)$ is optimal for $\mathcal{J}_d(\mathbf{y}_0, u)$
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Structured tensor equations

How to numerically solve

$$\sum_{i=1}^k \mathcal{T}_k(y_1, \dots, y_{i-1}, A_{\Pi} y_i, y_{i+1}, \dots, y_k) = \frac{1}{2\beta} \mathcal{R}_k(z_1, \dots, z_k)$$

Identify \mathcal{T}_k with tensor $T_k \in \mathbb{R}^{n^k}$ of order k

$$\Rightarrow \text{Solve } \underbrace{\left(\sum_{i=1}^k I^{\otimes k-i} \otimes A_{\Pi}^T \otimes I^{\otimes i-1} \right)}_{\mathbf{A}} T_k = \frac{1}{2\beta} R_k(T_2, \dots, T_{k-1}).$$

Since \mathbf{A} is **stable**:

$$\mathbf{A}^{-1} = - \int_0^{\infty} e^{t\mathbf{A}} dt = - \int_0^{\infty} \bigotimes_{i=1}^k e^{tA_{\Pi}^T} dt \approx - \sum_{\ell=-r}^r w_{\ell} \bigotimes_{i=1}^k e^{t_{\ell} A_{\Pi}^T}.$$

Use **quadrature formula** with suitable weights w_{ℓ} and points t_{ℓ} .

[GRASEDYCK, HACKBUSCH, STENGER]

Summary and future challenges

- infinite-horizon control by **HJB approximations**
- **smoothness of the value function** \mathcal{V} around 0
- $D^k\mathcal{V}(0)$ characterized by **Riccati/multilinear Lyapunov equations**
- **polynomial feedback laws** based on Taylor expansion of $D\mathcal{V}$
- boundary control?
- general semilinear PDEs?
- computation of higher order feedback laws?

Summary and future challenges

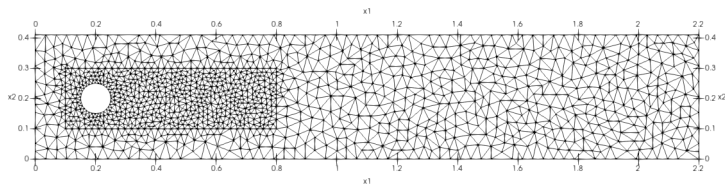
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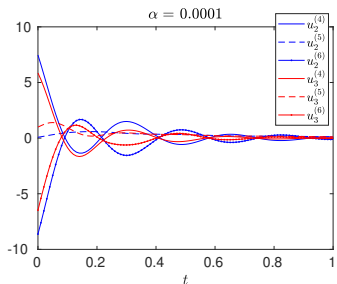
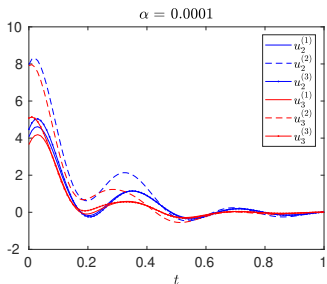
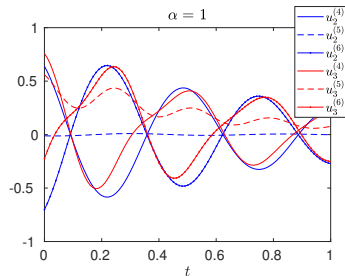
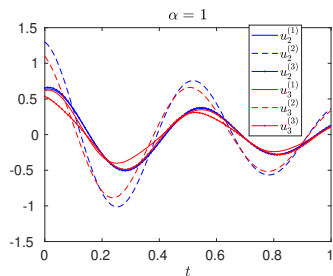
Thank you for your attention!

Setup and discretization

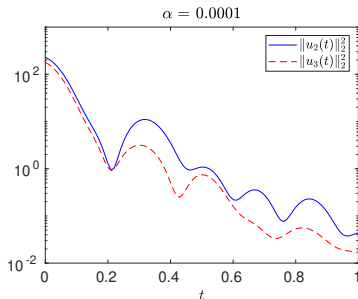
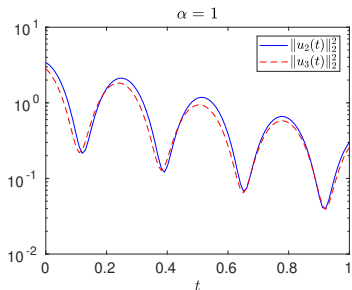
[Behr/Benner/Heiland'18]

- *Taylor-Hood* P_2 - P_1 finite elements
- $Re := \frac{1}{\nu} = 90$, $n_v = 9356$, $n_p = 1289$
- control domain $\Omega_c := [0.27, 0.32] \times [0.15, 0.25]$
- control operator $Bu = \sum_{\ell=1}^3 \begin{bmatrix} 0 \\ w_{\ell}(x_2) \end{bmatrix} u_{\ell}(t) + \begin{bmatrix} w_{\ell}(x_2) \\ 0 \end{bmatrix} u_{\ell+3}(t)$,



Control laws for $\alpha = 1$ and $\alpha = 10^{-4}$ 

Dynamics of $\|u(\cdot)\|^2$ for $\alpha = 1$ and $\alpha = 10^{-4}$



The underlying ODE

[Heinkenschloss/Sorensen/Sun'08]

Consider the **discrete system** given by

$$\begin{aligned} E\dot{y}(t) &= Ay(t) + H(y(t) \otimes y(t)) + Bu(t) + Gp(t), \\ 0 &= G^T y(t), \end{aligned}$$

with $E, A \in \mathbb{R}^{n_v \times n_v}$, $H \in \mathbb{R}^{n_n \times n_v^2}$, $B \in \mathbb{R}^{n_v \times 6}$, $G \in \mathbb{R}^{n_v \times n_p}$.

The second equation implies

$$0 = G^T \dot{y}(t) = G^T E^{-1} (Ay(t) + H(y(t) \otimes y(t)) + Bu(t) + Gp(t)).$$

We can **eliminate the pressure** via

$$p(t) = -(G^T E^{-1} G)^{-1} G^T E^{-1} (Ay(t) + H(y(t) \otimes y(t)) + Bu(t)).$$

Using the **projection** $P = I - G(G^T E^{-1} G)^{-1} G^T E^{-1}$, we obtain

$$E\dot{y}(t) = PAy(t) + PH(y(t) \otimes y(t)) + PBu(t).$$

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with $E, A \in \mathbb{R}^{n_v \times n_v}$, $H \in \mathbb{R}^{n_n \times n_v^2}$, $B \in \mathbb{R}^{n_v \times 6}$, $G \in \mathbb{R}^{n_v \times n_p}$.

The second equation implies

$$0 = G^T \dot{y}(t) = G^T E^{-1} (Ay(t) + H(y(t) \otimes y(t)) + Bu(t) + Gp(t)).$$

We can **eliminate the pressure** via

$$p(t) = -(G^T E^{-1} G)^{-1} G^T E^{-1} (Ay(t) + H(y(t) \otimes y(t)) + Bu(t)).$$

Using the **projection** $P = I - G(G^T E^{-1} G)^{-1} G^T E^{-1}$, we obtain

$$E\dot{y}(t) = PAy(t) + PH(y(t) \otimes y(t)) + PBu(t).$$

The underlying ODE

[Heinkenschloss/Sorensen/Sun'08]

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For the system

$$(PEP^T)\dot{y}(t) = (PAP^T)y(t) + (PHP^T \otimes P^T)(y(t) \otimes y(t)) + (PB)u(t)$$

decompose $P = \Theta_\ell \Theta_r^T$ with $\Theta_\ell^T \Theta_r = I$ and **project** onto $\text{range}(P)$

$$\underbrace{(\Theta_r^T E \Theta_r)}_{\tilde{E}} \dot{\tilde{y}}(t) = \underbrace{(\Theta_r^T A \Theta_r)}_{\tilde{A}} \tilde{y}(t) + \underbrace{(\Theta_r^T H \Theta_r \otimes \Theta_r)}_{\tilde{H}} \tilde{y}(t) \otimes \tilde{y}(t) + \underbrace{(\Theta_r^T B)}_{\tilde{B}} u(t),$$

where $\tilde{y} = \Theta_\ell^T y(t)$.

Consequence: ODE system instead of DAE system.

Note: **avoid explicit computation**, in particular, for \tilde{H} !

Computing the feedback gain

Consider a **third order** feedback of the form

$$u_3(\mathbf{y}) = -\frac{1}{\alpha} B^* \mathcal{T}_2(\cdot, \mathbf{y}) - \frac{1}{2\alpha} B^* \mathcal{T}_3(\cdot, \mathbf{y}, \mathbf{y})$$

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Its corresponding **discretized version** reads

$$u_3(\tilde{\mathbf{y}}) = -\frac{1}{\alpha} (\tilde{\mathbf{y}}^T \tilde{\mathbf{E}}^T \otimes \tilde{\mathbf{B}}^T) \pi - \frac{1}{2\alpha} (\tilde{\mathbf{y}}^T \tilde{\mathbf{E}}^T \otimes \tilde{\mathbf{y}}^T \tilde{\mathbf{E}}^T \otimes \tilde{\mathbf{B}}^T) \sigma.$$

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For obtaining $\pi = \text{vec}(\Pi)$, solve **algebraic Riccati equation**

$$\tilde{A}^T \Pi \tilde{E} + \tilde{E}^T \Pi \tilde{A} - \tilde{E}^T \Pi \tilde{B} \tilde{B}^T \Pi \tilde{E} + \Theta_r^T \Theta_r = 0.$$

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For obtaining σ , solve **linear tensor equation**

$$\underbrace{\left(\tilde{E}^T \otimes \tilde{E}^T \otimes \tilde{A}_\pi^T + \tilde{E}^T \otimes \tilde{A}_\pi^T \otimes \tilde{E}^T + \tilde{A}_\pi^T \otimes \tilde{E}^T \otimes \tilde{E}^T \right)}_{\mathcal{A}^T} \sigma = f,$$

where

$$f = -2 \left(\tilde{H}^T \otimes \tilde{E}^T + \tilde{E}^T \otimes \tilde{H}^T + (I \otimes \mathcal{P}^T)(\tilde{H}^T \otimes \tilde{E}^T) \right) \pi.$$

Computing the feedback gain cont'd

Problem: how to store/compute solution σ of $A^T \sigma = f$?

⇒ requires ≈ 4 TB of memory!

Remedy 1: only compute the feedback gain $\tilde{K} = (\tilde{E}^T \otimes \tilde{E}^T \otimes \tilde{B}^T) \sigma$

⇒ requires ≈ 4 GB of memory

Remedy 2: approximate $\tilde{K} = (\tilde{E}^T \otimes \tilde{E}^T \otimes \tilde{B}^T) A^{-T} f$ via quadrature

$$A^{-1} = - \int_0^{\infty} \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) dt$$

$$\approx - \sum_{j=-r}^r \frac{2w_j}{\lambda} \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right)$$

and utilizing properties of tensor multiplication.

Computing the feedback gain cont'd

Problem: how to store/compute solution σ of $\mathcal{A}^T \sigma = f$?

⇒ requires ≈ 4 TB of memory!

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Remedy 2: approximate $\tilde{K} = (\tilde{E}^T \otimes \tilde{E}^T \otimes \tilde{B}^T) \mathcal{A}^{-T} f$ via **quadrature**

$$\begin{aligned} \mathcal{A}^{-1} &= - \int_0^{\infty} \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{t\tilde{E}^{-1}\tilde{A}_\pi \tilde{E}^{-1}} \right) dt \\ &\approx - \sum_{j=-r}^r \frac{2w_j}{\lambda} \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right) \otimes \left(e^{\frac{t_j}{\lambda} \tilde{E}^{-1} \tilde{A}_\pi \tilde{E}^{-1}} \right) \end{aligned}$$

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Computing the feedback gain cont'd

Problem: how to store/compute solution σ of $\mathcal{A}^T \sigma = f$?

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and utilizing properties of **tensor multiplication**.