



# Numerical Solution of Elliptic Optimal Control Problems

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# **Recent Books on Optimal Control of PDEs**

R. Glowinski, J.L. Lions, and J. He; Exact and Approximate Controllability for Distributed Parameter Systems: A Numerical Approach. Cambridge University Press, Cambridge, 2008.

M. Hinze, R. Pinnau, and M. Ulbrich; Optimization with PDE Constraints. Springer, Berlin-Heidelberg-New York, 2008.

F. Tröltzsch; Optimal Control of Partial Differential Equations. Theory, Methods, and Applications. American Mathematical Society, Providence, 2010.





# Numerical Solution of Elliptic Optimal Control Problems

- Unconstrained Elliptic Optimal Control Problems
- Control Constrained Elliptic Optimal Control Problems
- State Constrained Elliptic Optimal Control Problems





Elliptic Optimal Control Problems Unconstrained Case





### Elliptic Optimal Control Problems: Unconstrained Case

Consider the unconstrained distributed elliptic optimal control problem

$$\begin{array}{ll} \inf_{\mathbf{y},\mathbf{u}} \ \mathbf{J}(\mathbf{y},\mathbf{u}) \ \coloneqq \ \frac{1}{2} \int\limits_{\Omega} |\mathbf{y}\!-\!\mathbf{y}^{\mathrm{d}}|^2 \ \mathrm{d}\mathbf{x} + \frac{\alpha}{2} \ \int\limits_{\Omega} |\mathbf{u}|^2 \ \mathrm{d}\mathbf{x}, \\ (\mathrm{EUC})_1 & -\Delta \mathbf{y} \ = \ \mathbf{u} \quad \mbox{in } \Omega, \\ (\mathrm{EUC})_2 & \mathbf{y} \ = \ \mathbf{0} \quad \mbox{on } \Gamma, \end{array}$$

where  $\mathbf{u} \in \mathbf{L}^2(\Omega)$ .



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### **Existence and Uniqueness of a Solution**

We introduce the control-to-state map

$$G: L^2(\Omega) \to H^1_0(\Omega) \quad, \quad y = Gu \quad solves \quad -\Delta y = u \ .$$

Substituting y = Gu allows to consider the reduced control problem

$$\inf_{\mathbf{u}} \mathbf{J}_{\mathbf{red}}(\mathbf{u}) := \frac{1}{2} \|\mathbf{G}\mathbf{u} - \mathbf{y}^d\|_{\mathbf{L}^2(\Omega)}^2 + \frac{\alpha}{2} \|\mathbf{u}\|_{\mathbf{L}^2(\Omega)}^2$$

Theorem (Existence and uniqueness) The unconstrained elliptic control problem admits a unique solution  $y \in H_0^1(\Omega)$ .

**Proof.** Direct method of the calculus of variations (minimizing sequence).





# **Optimality Conditions for the Distributed Control Problem**

There exists an adjoint state  $p\in H^1_0(\Omega)$  such that the triple (y,p,u) satisfies

$$\begin{split} \mathbf{a}(\mathbf{y},\mathbf{v}) \ &= \ (\mathbf{u},\mathbf{v})_{\mathbf{L}^2(\Omega)} \quad, \quad \mathbf{v} \in \mathbf{H}_0^1(\Omega) \ , \\ \mathbf{a}(\mathbf{p},\mathbf{v}) \ &= \ - \ (\mathbf{y}-\mathbf{y}^d,\mathbf{v})_{\mathbf{L}^2(\Omega)} \quad, \quad \mathbf{v} \in \mathbf{H}_0^1(\Omega) \\ \mathbf{p}-\alpha \mathbf{u} \ &= \ \mathbf{0} \ , \end{split}$$

where  $\mathbf{a}(\cdot,\cdot)$  stands for the bilinear form

$$\mathbf{a}(\mathbf{w},\mathbf{z}) \;=\; \int\limits_{\mathbf{\Omega}} \mathbf{
abla} \mathbf{w} \cdot \mathbf{
abla} \mathbf{z} \;\; \mathbf{d} \mathbf{x} \quad, \quad \mathbf{w},\mathbf{z} \in \mathbf{H}_{\mathbf{0}}^{1}(\mathbf{\Omega})$$





## **Optimality Conditions for the FE Discretized Control Problem**

There exists an adjoint state  $\mathbf{p}_h \in \mathbf{V}_h$  such that the triple  $(\mathbf{y}_h, \mathbf{p}_h, \mathbf{u}_h)$  satisfies

$$\begin{array}{ll} {\bf a}({\bf y}_h,{\bf v}_h) \ = \ ({\bf u}_h,{\bf v}_h)_{L^2(\Omega)} &, \quad {\bf v}_h \in {\bf V}_h \ , \\ {\bf a}({\bf p}_h,{\bf v}_h) \ = \ - \ ({\bf y}_h-{\bf y}^d,{\bf v}_h)_{L^2(\Omega)} &, \quad {\bf v}_h \in {\bf V}_h \ , \\ {\bf p}_h-\alpha {\bf u}_h \ = \ 0 \ . \end{array}$$





## Finite Element Approximation of the Distributed Control Problem

Let  $\mathcal{T}_h(\Omega)$  be a shape regular, simplicial triangulation of  $\Omega$  and let

$$\mathbf{V_h} \ := \ \left\{ \ \mathbf{v_h} \in \mathbf{C}(\Omega) \ | \ \mathbf{v_h}|_{\mathbf{T}} \in \mathbf{P_1}(\mathbf{T}) \ , \ \mathbf{T} \in \mathcal{T}_h(\Omega) \ , \ \mathbf{v_h}|_{\partial \Omega} = \mathbf{0} \ \right\}$$

be the FE space of continuous, piecewise linear finite elements.

Consider the following  $\ensuremath{\text{FE}}$  Approximation of the distributed control problem

$$\begin{array}{lll} \mbox{Minimize} & J(y_h,u_h) \ := \ \frac{1}{2} \ \|y_h-y^d\|_{L^2(\Omega)}^2 \ + \ \frac{\alpha}{2} \ \|u_h\|_{L^2(\Omega)}^2 \\ \mbox{over} & (y_h,u_h) \in V_h \times V_h \ , \\ \mbox{subject to} & a(y_h,v_h) \ = \ (u_h,v_h)_{L^2(\Omega)} \ , \ v_h \in V_h \ . \end{array}$$





Algebraic Formulation of the Discrete Optimality System Let  $V_{\ell} := \operatorname{span}\{\varphi_{\ell}^{(1)}, \dots, \varphi_{\ell}^{(N_{\ell})}\}$ , where  $\varphi_{\ell}^{(i)}, 1 \le i \le N_{\ell}$ , are the nodal basis functions. We refer to  $M_{\ell} \in \mathbb{R}^{N_{\ell} \times N_{\ell}}$  and  $A_{\ell} \in \mathbb{R}^{N_{\ell} \times N_{\ell}}$  as the associated mass matrix and stiffness matrix:

 $(\mathbf{M}_{\boldsymbol{\ell}})_{\mathbf{i}\mathbf{j}} := (\boldsymbol{\varphi}_{\boldsymbol{\ell}}^{(\mathbf{i})}, \boldsymbol{\varphi}_{\boldsymbol{\ell}}^{(\mathbf{j})})_{\mathbf{L}^2(\Omega)} \quad , \quad (\mathbf{A}_{\boldsymbol{\ell}})_{\mathbf{i}\mathbf{j}} := \mathbf{a}(\boldsymbol{\varphi}_{\boldsymbol{\ell}}^{(\mathbf{i})}, \boldsymbol{\varphi}_{\boldsymbol{\ell}}^{(\mathbf{j})}) \ , \ \mathbf{1} \leq \mathbf{i}, \mathbf{j} \leq \mathbf{N}_{\boldsymbol{\ell}}.$ 

The solution of the discrete optimality system requires the computation of  $(\mathbf{y}_{\boldsymbol{\ell}}, \mathbf{p}_{\boldsymbol{\ell}}) \in \mathbb{R}^{N} \boldsymbol{\ell} \times \mathbb{R}^{N} \boldsymbol{\ell}$  as the solution of

 $\begin{pmatrix} \mathbf{A}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \\ \mathbf{M}_{\boldsymbol{\ell}} & \mathbf{A}_{\boldsymbol{\ell}} \end{pmatrix} \begin{pmatrix} \mathbf{y}_{\boldsymbol{\ell}} \\ \mathbf{p}_{\boldsymbol{\ell}} \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{M}_{\boldsymbol{\ell}}\mathbf{y}_{\boldsymbol{\ell}}^{\mathrm{d}} \end{pmatrix}.$ 



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### Left and Right Transforming Iterations

For given  $K \in \mathbb{R}^{N \times N}$ ,  $d \in \mathbb{R}^N$ , we want to solve the linear algebraic system (\*) Kx = d.

Let  $K_L, K_R \in \mathbb{R}^{N \times N}$  be regular. Then, (\*) can be equivalently written as

$$** \big) \qquad \mathbf{K_L}\mathbf{K}\mathbf{K_R}\mathbf{K_R}^{-1}\mathbf{x} = \mathbf{K_L}\mathbf{d}.$$

Assuming  $\tilde{K}$  to be a suitable preconditioner for  $K_L K K_R$ , we consider the transforming iteration

$$\mathbf{K}_{\mathbf{R}}^{-1}\mathbf{x}^{(\boldsymbol{\nu}+1)} = \mathbf{K}_{\mathbf{R}}^{-1}\mathbf{x}^{(\boldsymbol{\nu})} + \mathbf{\tilde{K}}^{-1}(\mathbf{K}_{\mathbf{L}}\mathbf{d} - \mathbf{K}_{\mathbf{L}}\mathbf{K}\mathbf{x}^{(\boldsymbol{\nu})}).$$

Backtransformation yields

$$\mathbf{x}^{(\boldsymbol{\nu}+1)} = \mathbf{x}^{(\boldsymbol{\nu})} + \underbrace{\mathbf{K}_{R}\tilde{\mathbf{K}}^{-1}\mathbf{K}_{L}}_{= (\mathbf{K}_{L}^{-1}\tilde{\mathbf{K}}\mathbf{K}_{R}^{-1})^{-1}} (\mathbf{d} - \mathbf{K}\mathbf{x}^{(\boldsymbol{\nu})}),$$

so that  $\hat{K} := K_L^{-1} \tilde{K} K_R^{-1}$  is an appropriate preconditioner for the original system.





### Left and Right Transforming Iterations II

We apply the idea of left/right transformations to

$$\mathbf{K} = \begin{pmatrix} \mathbf{A}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \\ \mathbf{M}_{\boldsymbol{\ell}} & \mathbf{A}_{\boldsymbol{\ell}} \end{pmatrix} \quad , \quad \mathbf{d} = \begin{pmatrix} \mathbf{0} \\ \mathbf{M}_{\boldsymbol{\ell}}\mathbf{y}_{\boldsymbol{\ell}}^{\mathrm{d}} \end{pmatrix}.$$

We choose the left and right transformations according to

$$\mathbf{K}_{\mathbf{L}} = \begin{pmatrix} \boldsymbol{\alpha}^{1/2} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} \end{pmatrix} \quad , \quad \mathbf{K}_{\mathbf{R}} = \begin{pmatrix} \boldsymbol{\alpha}^{-1/2} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$

This leads to the transformed matrix

$$\mathbf{K}_{\mathbf{L}}\mathbf{K}\mathbf{K}_{\mathbf{R}} = \begin{pmatrix} \mathbf{A}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} \\ -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} & -\mathbf{A}_{\boldsymbol{\ell}} \end{pmatrix}.$$





### Left and Right Transforming Iterations III

Denoting by  $S_{\ell}$  the Schur complement  $S_{\ell} = A_{\ell} + \alpha^{-1}M_{\ell}A_{\ell}^{-1}M_{\ell}$ , we have

$$\begin{pmatrix} \mathbf{A}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} \\ -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} & -\mathbf{A}_{\boldsymbol{\ell}} \end{pmatrix} = \begin{pmatrix} \mathbf{A}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} \\ -\boldsymbol{\alpha}^{-1/2}\mathbf{M}_{\boldsymbol{\ell}} & -\mathbf{S}_{\boldsymbol{\ell}} + \boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}}\mathbf{A}_{\boldsymbol{\ell}}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \end{pmatrix}.$$

Choosing  $\hat{A}_{\ell}$  as a preconditioner for  $A_{\ell}$  and  $\hat{S}_{\ell} := \tau_{\ell}^{-1} \operatorname{diag}(A_{\ell} + \alpha^{-1}M_{\ell}\hat{A}_{\ell}^{-1}M_{\ell})$ , we obtain the symmetric Uzawa preconditioner

$$\tilde{\mathbf{K}}_{\boldsymbol{\ell}} = \begin{pmatrix} \hat{\mathbf{A}}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1/2} \mathbf{M}_{\boldsymbol{\ell}} \\ -\boldsymbol{\alpha}^{-1/2} \mathbf{M}_{\boldsymbol{\ell}} & -\hat{\mathbf{S}}_{\boldsymbol{\ell}} + \boldsymbol{\alpha}^{-1} \mathbf{M}_{\boldsymbol{\ell}} \hat{\mathbf{A}}_{\boldsymbol{\ell}}^{-1} \mathbf{M}_{\boldsymbol{\ell}} \end{pmatrix}$$

Backtransformation results in the following preconditioner

$$\hat{\mathbf{K}}_{\boldsymbol{\ell}} = \mathbf{K}_{\mathbf{L}}^{-1} \tilde{\mathbf{K}}_{\boldsymbol{\ell}} \mathbf{K}_{\mathbf{R}}^{-1} = \begin{pmatrix} \hat{\mathbf{A}}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1} \mathbf{M}_{\boldsymbol{\ell}} \\ \mathbf{M}_{\boldsymbol{\ell}} & \hat{\mathbf{S}}_{\boldsymbol{\ell}} - \boldsymbol{\alpha}^{-1} \mathbf{M}_{\boldsymbol{\ell}} \hat{\mathbf{A}}_{\boldsymbol{\ell}}^{-1} \mathbf{M}_{\boldsymbol{\ell}} \end{pmatrix}$$





## Multigrid Solvers for Elliptic Optimal Control Problems

A. Borzi, K. Kunisch, and D. Y. Kwak; Accuracy and convergence properties of the finite difference multigrid solution of an optimal control optimality system.

SIAM J. Control Optimization 41, 1477-1497, 2003.

A. Borzi and V. Schulz; Multigrid methods for PDE optimization. SIAM Rev. 51, 361-395, 2009.

J. Schöberl, R. Simon, and W. Zulehner; A robust multigrid method for elliptic optimal control problems. Preprint, Inst. of Comput. Math., University of Linz, 2010.





### **Preconditioned Richardson Iteration I**

Step 1: Given iterates  $\mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})}, \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \in \mathbb{R}^{N}\boldsymbol{\ell}$ , compute the residuals

 $\begin{pmatrix} \mathbf{Res}_{\boldsymbol{\ell}}^{(1)} \\ \mathbf{Res}_{\boldsymbol{\ell}}^{(2)} \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{M}_{\boldsymbol{\ell}} \mathbf{y}_{\boldsymbol{\ell}}^{\mathbf{d}} \end{pmatrix} - \mathbf{K}_{\boldsymbol{\ell}} \begin{pmatrix} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \\ \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \end{pmatrix}.$ 

**Step 2:** Solve the linear system

$$\begin{pmatrix} \hat{\mathbf{A}}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \\ \mathbf{M}_{\boldsymbol{\ell}} & \hat{\mathbf{S}}_{\boldsymbol{\ell}} - \boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}}\hat{\mathbf{A}}_{\boldsymbol{\ell}}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \end{pmatrix} \begin{pmatrix} \boldsymbol{\Delta}\mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \\ \boldsymbol{\Delta}\mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \end{pmatrix} = \begin{pmatrix} \operatorname{Res}_{\boldsymbol{\ell}}^{(1)} \\ \operatorname{Res}_{\boldsymbol{\ell}}^{(2)} \end{pmatrix}$$

**Step 3:** Compute the new iterates

$$\begin{pmatrix} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu}+1)} \\ \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu}+1)} \end{pmatrix} = \begin{pmatrix} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \\ \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\Delta} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \\ \boldsymbol{\Delta} \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \end{pmatrix}.$$





### **Preconditioned Richardson Iteration II**

Consider the linear system

$$(*) \qquad \begin{pmatrix} \hat{\mathbf{A}}_{\boldsymbol{\ell}} & -\boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \\ \mathbf{M}_{\boldsymbol{\ell}} & \hat{\mathbf{S}}_{\boldsymbol{\ell}} - \boldsymbol{\alpha}^{-1}\mathbf{M}_{\boldsymbol{\ell}}\hat{\mathbf{A}}_{\boldsymbol{\ell}}^{-1}\mathbf{M}_{\boldsymbol{\ell}} \end{pmatrix} \begin{pmatrix} \boldsymbol{\Delta}\mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \\ \boldsymbol{\Delta}\mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} \end{pmatrix} = \begin{pmatrix} \mathbf{Res}_{\boldsymbol{\ell}}^{(1)} \\ \mathbf{Res}_{\boldsymbol{\ell}}^{(2)} \end{pmatrix}$$

Elimination of  $\Delta y_{\ell}^{(\nu)}$  results in the Schur complement system  $\hat{S}_{\ell} \Delta p_{\ell}^{(\nu)} = \operatorname{Res}_{\ell}^{(2)} - M_{\ell} \hat{A}_{\ell}^{-1} \operatorname{Res}_{\ell}^{(1)}.$ 

Hence, the solution of  $(\ast)$  can be reduced to the successive solution of the three linear systems

$$\begin{split} \hat{A}_{\boldsymbol{\ell}} \tilde{\Delta} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} &= \mathbf{Res}_{\boldsymbol{\ell}}^{(1)}, \\ \hat{S}_{\boldsymbol{\ell}} \Delta \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} &= \mathbf{Res}_{\boldsymbol{\ell}}^{(2)} - \mathbf{M}_{\boldsymbol{\ell}} \tilde{\Delta} \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})}, \\ \hat{A}_{\boldsymbol{\ell}} \Delta \mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})} &= \mathbf{Res}_{\boldsymbol{\ell}}^{(1)} + \alpha^{-1} \mathbf{M}_{\boldsymbol{\ell}} \Delta \mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})}. \end{split}$$





### **Preconditioned Richardson Iteration III**

Theorem [Schöberl/Simon/Zulehner] If the preconditioners  $\hat{A}_{\ell}$  and  $\hat{S}_{\ell}$  are chosen according to

$$\begin{split} \hat{\mathbf{A}}_{\boldsymbol{\ell}} &= \boldsymbol{\sigma}_{\boldsymbol{\ell}}^{-1} \operatorname{diag}(\mathbf{A}_{\boldsymbol{\ell}}) \quad, \quad \hat{\mathbf{S}}_{\boldsymbol{\ell}} = \boldsymbol{\tau}_{\boldsymbol{\ell}}^{-1} \operatorname{diag}(\mathbf{S}_{\boldsymbol{\ell}}), \\ \boldsymbol{\sigma}_{\boldsymbol{\ell}} &\leq \boldsymbol{\lambda}_{\max}((\operatorname{diag}(\mathbf{A}_{\boldsymbol{\ell}}))^{-1} \mathbf{A}_{\boldsymbol{\ell}})^{-1} \quad, \quad \boldsymbol{\tau}_{\boldsymbol{\ell}} \leq \boldsymbol{\lambda}_{\max}((\operatorname{diag}(\mathbf{S}_{\boldsymbol{\ell}}))^{-1} \mathbf{S}_{\boldsymbol{\ell}})^{-1}, \end{split}$$

then there holds

$$\|(\mathbf{y}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})},\mathbf{p}_{\boldsymbol{\ell}}^{(\boldsymbol{\nu})}) - (\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\| \leq C \ (1 + \alpha^{-1/2} \ \mathbf{h}_{\boldsymbol{\ell}}^2) \ \boldsymbol{\eta}(\boldsymbol{\nu}) \ \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - (\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\nu})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - (\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\mu})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\mu})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\mu})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\mu})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta}) + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta}) + \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta}) + \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta})} + \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{\boldsymbol{\eta}(\boldsymbol{\eta}) + \|(\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|_{$$

where

$$\eta(oldsymbol{
u}) \leq \left\{ egin{array}{c} \sqrt{rac{2}{\pi(oldsymbol{
u}-1)}} \ , \ {
m if} \ oldsymbol{
u} \ {
m is \ odd} \end{array} 
ight., \ {
m if} \ oldsymbol{
u} \ {
m is \ odd} \end{array},$$

and C is a positive constant independent of  $h_{\ell}$  and  $\alpha$ .





# Multigrid Solution of the Optimality System

The previous theorem suggests to use the preconditioned iterative solver as a smoother within a multigrid solution of the optimality system.

Theorem. In case of two nested grids  $\mathcal{T}_{\ell-1}(\Omega)$  and  $\mathcal{T}_{\ell}(\Omega)$  let  $(\mathbf{y}_{\ell}^{(0)}, \mathbf{p}_{\ell}^{(0)})$  be a level  $\ell$  startiterate and let  $(\mathbf{y}_{\ell}^{(1)}, \mathbf{p}_{\ell}^{(1)})$  be the result of a two-grid cycle with  $\nu > 0$  smoothing steps. Then there holds

$$\|(\mathbf{y}_{\boldsymbol{\ell}}^{(1)},\mathbf{p}_{\boldsymbol{\ell}}^{(1)}) - (\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\| \leq C \ \frac{1 + \alpha^{-1/2}\mathbf{h}_{\boldsymbol{\ell}}^2}{\sqrt{\nu}} \ \|(\mathbf{y}_{\boldsymbol{\ell}}^{(0)},\mathbf{p}_{\boldsymbol{\ell}}^{(0)}) - (\mathbf{y}_{\boldsymbol{\ell}},\mathbf{p}_{\boldsymbol{\ell}})\|,$$

where C>0 is a constant independent of  $h_{\mbox{\sc l}}$  and  $\alpha.$ 





Elliptic Optimal Control Problems Control Constraints





### **Elliptic Optimal Control Problems: Control Constraints**

Consider the control constrained distributed elliptic optimal control problem

$$\begin{array}{ll} \inf_{y,u} \ J(y,u) \ := \ \displaystyle \frac{1}{2} \int\limits_{\Omega} |y - y^d|^2 \ dx + \displaystyle \frac{\alpha}{2} \ \int\limits_{\Omega} |u|^2 \ dx, \\ (ECC)_1 \ (ECC)_2 \ u = 0 \ on \ \Gamma, \end{array}$$

and

$$\mathbf{u} \in \mathbf{K}_{\mathbf{C}} := \{ \mathbf{v} \in \mathbf{L}^2(\Omega) \ | \ \mathbf{v}(\mathbf{x}) \le \boldsymbol{\psi}(\mathbf{x}) \ \mathbf{f.a.a.} \ \mathbf{x} \in \Omega \},$$

where  $\mathbf{u} \in \mathbf{L}^2(\Omega)$ .





**Control Constraints: Necessary Optimality Conditions** 

Theorem. If  $(y,u)\in H^1_0(\Omega)\times K_C$  is the optimal solution of the optimal control problem, then there exists

 $(\mathbf{p}, \boldsymbol{\lambda}) \in \mathbf{H}_{0}^{1}(\Omega)) \times \mathbf{L}^{2}(\Omega)$ 

such that **p** satisfies the adjoint state equation

$$\begin{split} -\Delta \mathbf{p} \ &= \ -(\mathbf{y}-\mathbf{y}^d) \quad \mbox{in } \Omega, \\ \mathbf{p} \ &= \ \mathbf{0} \qquad \qquad \mbox{on } \Gamma, \end{split}$$

and there holds

$$\mathbf{p} - oldsymbol{\lambda} \ = \ oldsymbol{lpha} \mathbf{u} \quad ext{in } \Omega, \ oldsymbol{\lambda} \ \in \ oldsymbol{\partial} \mathbf{I}_{\mathbf{K}_{\mathbf{c}}}(\mathbf{u}).$$





Elliptic Optimal Control Problems Primal-Dual Active Set Strategy





### Moreau-Yosida Approximation of Multivalued Maps I

Weighted Duality Mapping: Assume that V is a Banach space with dual V<sup>\*</sup> and let  $h : \mathbb{R}_+ \to \mathbb{R}_+$  be a continuous and non-decreasing function such that h(0) = 0 and  $h(t) \to \infty$  as  $t \to \infty$ . Then the mapping  $J_h : V \to 2^{V^*}$ 

$$\mathbf{J}_{\mathbf{h}}(\mathbf{u}) \coloneqq \{\mathbf{u}^* \in \mathbf{V}^* ~|~ \langle \mathbf{u}^*, \mathbf{u} \rangle = \|\mathbf{u}\| \|\mathbf{u}^*\|~,~ \|\mathbf{u}^*\| = \mathbf{h}(\|\mathbf{u}\|)\}$$

is called the duality mapping with weight h.

 $\begin{array}{l} \mbox{Example: For } V = L^p(\Omega), V^* = L^q(\Omega), 1 < p,q < \infty, 1/p + 1/q = 1, \mbox{ and } h(t) = t^{p-1} \mbox{ we have } \\ \\ J_h(u)(x) = \left\{ \begin{array}{l} |u(x)|^{p-1} \mbox{ sgn}(u(x)) \ , \ u(x) \neq 0 \\ 0 \ , \ u(x) = 0 \end{array} \right. \end{array}$ 





### Moreau-Yosida Approximation of Multivalued Maps II

Moreau-Yosida proximal map: Let  $f: V \to \overline{\mathbb{R}}$  be a lower semi-continuous proper convex function with subdifferential  $\partial f$ . For c > 0, the Moreau-Yosida proximal map  $P_c^{\partial f}: V \to 2^V$  is defined such that  $P_c^{\partial f}(w)$ ,  $w \in V$ , is the set of minimizers of

$$\inf_{\mathbf{v}\in\mathbf{V}}\mathbf{f}(\mathbf{v})+c\mathbf{j}_{h}(\frac{\mathbf{v}-\mathbf{w}}{c}),$$

where  $\partial \mathbf{j}_{h} = \mathbf{J}_{h}$ .

Moreau-Yosida approximation: If  $J_h$  is single-valued, then for c>0 the Moreau-Yosida approximation  $(\partial f)_c$  of  $\partial f$  is given by

 $(\partial \mathbf{f})_{\mathbf{c}}(\mathbf{w}) := \mathbf{J}_{\mathbf{h}}(\mathbf{c}^{-1}\mathbf{w} - \mathbf{c}^{-1}\mathbf{P}_{\mathbf{c}}^{\partial \mathbf{f}}(\mathbf{w})).$ 





## Moreau-Yosida Approximation of $\partial I_{K_C}$

Idea: Approximate  $\partial I_{K_C}$  by its Moreau-Yosida approximation  $(\partial I_{K_C})_c$ . Theorem. For any c > 0, we have

 $\boldsymbol{\lambda} \in (\boldsymbol{\partial} \mathbf{I}_{\mathbf{K}_{\mathbf{C}}})_{\mathbf{c}},$ 

if and only if there holds

$$\boldsymbol{\lambda} = \mathbf{c} \Big( \mathbf{u} + \mathbf{c}^{-1} \boldsymbol{\lambda} - \boldsymbol{\Pi}_{\mathbf{K}_{\mathbf{C}}} (\mathbf{u} + \mathbf{c}^{-1} \boldsymbol{\lambda}) \Big) = \mathbf{c} \ \max(\mathbf{0}, \mathbf{u} + \mathbf{c}^{-1} \boldsymbol{\lambda} - \boldsymbol{\psi}),$$

and this is equivalent to

$$\mathbf{u} = \boldsymbol{\Pi}_{\mathbf{K}_{\mathbf{C}}}(\mathbf{u} + \mathbf{c}^{-1}\boldsymbol{\lambda}),$$

where  $\Pi_{K_C}$  denotes the L<sup>2</sup>-projection onto  $K_C$ .





### Primal-Dual Active Set Strategy I

Step 1 (Initialization):

Choose c > 0, start-iterates  $y_h^{(0)}, u_h^{(0)}, \lambda_h^{(0)}$  and set n = 1.

Step 2 (Specification of active/inactive sets):

Compute the active/inactive sets  $\mathcal{A}_n$  and  $\mathcal{I}_n$  according to

 $\mathcal{A}_n := \{ \mathbf{1} \leq \mathbf{i} \leq \mathbf{N} \ | \ (\mathbf{u}_h^{(n-1)} + \mathbf{c}^{-1} \boldsymbol{\lambda}_h^{(n-1)})_\mathbf{i} > (\boldsymbol{\psi}_h)_\mathbf{i} \} \quad, \quad \mathcal{I}_n := \{ \mathbf{1}, \cdots, \mathbf{N} \} \setminus \mathcal{A}_n.$ 

Step 3 (Termination criterion):

If  $n\geq 2$  and  $\mathcal{A}_n=\mathcal{A}_{n-1},$  stop the algorithm. Otherwise, go to Step 4.





### **Primal-Dual Active Set Strategy II**

Step 4 (Update of the state, adjoint state, and control):

Compute  $\mathbf{y}_h^{(n)}, \mathbf{p}_h^{(n)}$  as the solution of

$$(\mathbf{A}_h \mathbf{y}_h^{(n)})_i = \left\{ \begin{array}{ll} (\boldsymbol{\psi}_h)_i \ , \ \text{if} \ i \in \mathcal{A}_n \\ \boldsymbol{\alpha}^{-1} (\mathbf{M}_h^{-1} \mathbf{p}_h)_i \ , \ \ \text{if} \ i \in \mathcal{I}_n \end{array} \right. , \quad \mathbf{A}_h \mathbf{p}_h^{(n)} = -\mathbf{M}_h (\mathbf{y}_h - \mathbf{y}_h^d),$$

and set

$$(\mathbf{u}_h^{(n)})_i := \left\{ \begin{array}{l} (\boldsymbol{\psi}_h)_i \ , \ \text{if} \ i \in \mathcal{A}_n \\ \boldsymbol{\alpha}^{-1}(\mathbf{M}_h^{-1}\mathbf{p}_h^{(n)})_i \ , \ \ \text{if} \ i \in \mathcal{I}_n \end{array} \right. .$$

Step 5 (Update of the multiplier):

$$\mathbf{Set} \ \boldsymbol{\lambda}_{\mathbf{h}}^{(\mathbf{n})} \coloneqq \mathbf{p}_{\mathbf{h}}^{(\mathbf{n})} - \boldsymbol{\alpha} \mathbf{M}_{\mathbf{h}} \mathbf{u}_{\mathbf{h}}^{(\mathbf{n})} \ , \ \mathbf{n} \coloneqq \mathbf{n} + \mathbf{1}, \ \mathbf{and} \ \mathbf{go} \ \mathbf{to} \ \mathbf{Step} \ \mathbf{2}.$$





### PDAS As A Semi-Smooth Newton Method I

Newton differentiability: A function  $f : S \subset X \to Y$  (X, Y Banach spaces) is called Newton differentiable at  $x \in S$ , if there exist a neighborhood  $\mathcal{U}(x) \subset S$  and a family of mappings  $g : \mathcal{U}(x) \to \mathcal{L}(X, Y)$  such that

 $\|\mathbf{f}(\mathbf{x}+\mathbf{h})-\mathbf{f}(\mathbf{x})-\mathbf{g}(\mathbf{x}+\mathbf{h})(\mathbf{h})\|_{\mathbf{Y}}=\mathbf{o}(\|\mathbf{h}\|_{\mathbf{X}})\quad(\mathbf{as}~\|\mathbf{h}\|_{\mathbf{X}}\rightarrow\infty).$ 

 $\mathbf{g}(\mathbf{x})$  is said to be the generalized derivative of f at  $\mathbf{x}.$ 

**Example:** The max-function max :  $L^p(\Omega) \to L^q(\Omega)$  is Newton differentiable for  $1 \leq q . If <math display="inline">f: L^r(\Omega) \to L^p(\Omega)$  is Fréchet-differentiable for some  $1 < r \leq \infty$ , then the function

$$\mathbf{x} \longmapsto \boldsymbol{\chi}_{\mathbf{A}}(\mathbf{x}) \mathbf{f}(\mathbf{u}(\mathbf{x}))$$

is the generalized derivative of  $\max(0, f(\cdot))$ . Here,  $\chi_A$  denotes the characteristic function of the set A where  $f(u(\cdot))$  is nonnegative.





### PDAS As A Semi-Smooth Newton Method II

Setting  $z_h := (y_h, u_h, \lambda_h),$  the discrete optimality conditions require the solution of the nonlinear system

$$\mathbf{F}_{\mathbf{h}}(\mathbf{z}_{\mathbf{h}}) := \begin{pmatrix} \mathbf{A}_{\mathbf{h}}\mathbf{y}_{\mathbf{h}} - \mathbf{M}_{\mathbf{h}}\mathbf{u}_{\mathbf{h}} \\ \boldsymbol{\alpha}\mathbf{A}_{\mathbf{h}}\mathbf{u}_{\mathbf{h}} + \mathbf{M}_{\mathbf{h}}\mathbf{y}_{\mathbf{h}} - \mathbf{y}_{\mathbf{h}}^{d} + \boldsymbol{\lambda}_{\mathbf{h}} \\ -\boldsymbol{\lambda}_{\mathbf{h}} + \mathbf{c} \; \max(\mathbf{0}, \mathbf{u}_{\mathbf{h}} + \mathbf{c}^{-1}\boldsymbol{\lambda}_{\mathbf{h}} - \boldsymbol{\psi}_{\mathbf{h}}) \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}.$$

The primal-dual active set strategy (PDAS) is equivalent to the semi-smooth Newton method

$$\begin{array}{rl} F_{h}'(z_{h}^{(n)})\Delta z_{h}^{(n)} \ = \ -F_{h}(z_{h}^{(n)}), \\ z_{h}^{(n+1)} \ = \ z_{h}^{(n)} + \Delta z_{h}^{(n)}, \end{array}$$

where  $F_h^\prime(z_h^{(n)})$  is the generalized derivative of  $F_h$  at  $z_h^{(n)}.$ 





Elliptic Optimal Control Problems Interior Point Methods





# Interior-Point Methods (General) Gonzaga [1992] , Wright [1992] , Zhang/Tapia/Dennis [1992] Conn/Gould/Toint [1996] , Heinkenschloss [2001] Forsgren/Gill/Wright [2002] , M. Ulbrich [2002] , S. Ulbrich [2003] Interior-Point Methods (PDE Constrained Optimization) Ulbrich/Ulbrich/Heinkenschloss [1999] , Ulbrich/Ulbrich [2000] H./Petrova/Schulz [2002] , H./Petrova [2004] , Weiser [2005] Ulbrich/Ulbrich [2007] , Antil/H./Linsenmann [2007]





### Interior Point Method I

<u>Idea:</u> Coupling of control constraints  $u_h \leq \psi_h$  by, e.g., logarithmic barrier functions with barrier parameter  $\beta > 0$ :

$$\inf_{\mathbf{y}_h,\mathbf{u}_h} \mathbf{B}_h^{(\boldsymbol{\beta})}(\mathbf{y}_h,\mathbf{u}_h) := \mathbf{J}_h(\mathbf{y}_h,\mathbf{u}_h) + \boldsymbol{\beta} \sum_{i=1}^N ln((\boldsymbol{\psi}_h-\mathbf{u}_h)_i),$$

which represents a parameter-dependent family of minimization subproblems.

Coupling of the discrete state equation by a Lagrange multiplier:

$$\inf_{\mathbf{y}_{h},\mathbf{u}_{h}} \sup_{\mathbf{p}_{h}} \mathcal{L}_{h}^{(\boldsymbol{\beta})}(\mathbf{y}_{h},\mathbf{u}_{h},\mathbf{p}_{h}) := \mathbf{B}_{h}^{(\boldsymbol{\beta})}(\mathbf{y}_{h},\mathbf{u}_{h}) + \langle \mathbf{p}_{h},\mathbf{A}_{h}\mathbf{y}_{h} - \mathbf{M}_{h}\mathbf{u}_{h} \rangle.$$





### Interior Point Method II

The barrier path  $\beta \mapsto x_h(\beta) := (y_h(\beta), u_h(\beta), p_h(\beta))$  is the solution of the parameterdependent nonlinear system:

$$F_h(\mathbf{x}_h(\boldsymbol{\beta}),\boldsymbol{\beta}) = \begin{pmatrix} \mathbf{A}_h \mathbf{p}_h + \mathbf{M}_h \mathbf{y}_h - \mathbf{y}_h^d \\ \mathbf{A}_h \mathbf{y}_h - \mathbf{M}_h \mathbf{u}_h \\ \boldsymbol{\alpha}(\mathbf{M}_h \mathbf{u}_h)_1 + \frac{\boldsymbol{\beta}}{(\boldsymbol{\psi}_h - \mathbf{u}_h)_1} \\ \cdots \\ \boldsymbol{\alpha}(\mathbf{M}_h \mathbf{u}_h)_N + \frac{\boldsymbol{\beta}}{(\boldsymbol{\psi}_h - \mathbf{u}_h)_N} \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \\ \cdot \\ \mathbf{0} \end{pmatrix}.$$

Solution by path-following predictor-corrector continuation methods in the barrier parameter.





**Continuation Strategies in Interior-Point Methods** (i) Static Strategies Fiacco/McCormick [1990], Byrd/Hribar/Nocedal [1999] Wächter/Biegler [2005] (ii) Dynamic Update Strategies El-Bakry/Tapia/Tsuchiya/Zhang [1996] , Gay/Overton/Wright [1998] Vanderbei/Shanno [1999] , H./Petrova/Schulz [2002] Tits/Wächter/Bakhtiari/Urban/Lawrence [2003] , H./Petrova [2004] Ulbrich/Ulbrich/Vicente [2004], H./Linsenmann/Petrova [2006] Nocedal/Wächter/Waltz [2006] , Armand/Benoist/Orban [2007]























### Numerical Results: Distributed Control Problem with Control Constraints I











# Numerical Results: Distributed Control Problem with Control Constraints I

Grid after 6 (left) and 10 (right) refinement steps





Numerical Results: Distributed Control Problem with Control Constraints II  $\mathbf{J}(\mathbf{y},\mathbf{u}) \; := \; rac{1}{2} \; \|\mathbf{y}-\mathbf{y}^{\mathbf{d}}\|_{0,\Omega}^2 \; + \; rac{lpha}{2} \; \|\mathbf{u}-\mathbf{u}^{\mathbf{d}}\|_{0,\Omega}^2$ Minimize  $(\mathbf{y},\mathbf{u})\in\mathbf{H}_{0}^{1}(\Omega) imes\mathbf{L}^{2}(\Omega)$ over subject to  $-\Delta y = f + u \text{ in } \Omega$ ,  $\mathbf{u} \in \mathbf{K} := \{ \mathbf{v} \in \mathbf{L}^2(\Omega) \mid \mathbf{v} \leq \boldsymbol{\psi} \text{ a.e. in } \Omega \}$  $\Omega \ := \ (0,1)^2 \quad , \quad y^d \ := \ 0 \quad , \quad u^d \ := \ \hat{u} \ + \ lpha^{-1} ( \hat{\sigma} - \Delta^{-2} \hat{u} ) \ ,$ Data:  $\psi := \left\{ egin{array}{cccc} ({f x}_1 - 0.5)^8 &, & ({f x}_1, {f x}_2) \in \Omega_1, \ ({f x}_1 - 0.5)^2 &, & {
m otherwise} \end{array} 
ight., \quad egin{array}{ccccc} lpha & := & 0.1 \ lpha & := & 0.1 \end{array} 
ight., \quad {f f} := & 0 \end{array} 
ight.$  $\Omega_1 \ := \ \left\{ (x_1, x_2) \in \Omega \ \mid \ \left( (x_1 - 0.5)^2 + (x_2 - 0.5)^2 \right)^{1/2} \le 0.15 \right\} \quad, \quad \Omega_2 \ := \ \left\{ (x_1, x_2) \in \Omega \ \mid \ x_1 \ge 0.75 \right\} \,.$ 











# Numerical Results: Distributed Control Problem with Control Constraints II

Grid after 6 (left) and 10 (right) refinement steps





Elliptic Optimal Control Problems State Constraints





### Literature on State-Constrained Optimal Control Problems

M. Bergounioux, K. Ito, and K. Kunisch (1999) M. Bergounioux, M. Haddou, M. Hintermüller, and K. Kunisch (2000) M. Bergounioux and K. Kunisch (2002) E. Casas (1986) J.-P. Raymond and F. Tröltzsch (2000) K. Deckelnick and M. Hinze (2006) M. Hintermüller and K. Kunisch (2007) K. Kunisch and A. Rösch (2002) C. Meyer and F. Tröltzsch (2006) C. Meyer, U. Prüfert, and F. Tröltzsch (2005) U. Prüfert, F. Tröltzsch, and M. Weiser (2004) H./M. Kieweg (2007) A. Günther, M. Hinze (2007) O. Benedix, B. Vexler (2008) M. Hintermüller/H. (2008) W. Liu, W. Gong and N. Yan (2008)





### **Elliptic Optimal Control Problems: State Constraints**

Consider the state constrained distributed elliptic optimal control problem

$$\begin{array}{ll} \inf_{y,u} \ J(y,u) \ \coloneqq \ \displaystyle \frac{1}{2} \int\limits_{\Omega} |y-y^d|^2 \ dx + \displaystyle \frac{\alpha}{2} \ \displaystyle \int\limits_{\Omega} |u|^2 \ dx, \\ (ESC)_1 & -\Delta y \ = \ u \quad \mbox{in } \Omega, \\ (ESC)_2 & y \ = \ 0 \quad \mbox{on } \Gamma, \end{array}$$

and

$$\mathbf{y} \in \mathbf{K}_{\mathbf{S}} := \{\mathbf{y} \in \mathbf{H}_{\mathbf{0}}^{\mathbf{1}}(\Omega) \ | \ \mathbf{y}(\mathbf{x}) \leq \boldsymbol{\psi}(\mathbf{x}) \ \mathbf{f.a.a.} \ \mathbf{x} \in \Omega\},$$

where  $\mathbf{u} \in \mathbf{L}^2(\Omega)$ .





### State Constraints: Necessary Optimality Conditions

Theorem. The state constrained optimal control problem admits a unique solution  $(\mathbf{y}, \mathbf{u})$  with  $\mathbf{y} \in \mathbf{W}_0^{1, r}(\Omega), r > 2$ , and  $\mathbf{u} \in \mathbf{L}^2(\Omega)$ .

Theorem. Let us assume that there exists  $u_0 \in L^2(\Omega)$  such that the associated solution  $y_0 \in W_0^{1,r}(\Omega)$  of the state equation satisfies  $y_0 \in int(K_S)$  (Slater condition). If (y, u) is the unique solution of the state constrained optimal control problem, there exist  $p \in W_0^{1,s}(\Omega), 1/r + 1/s = 1$ , and  $\lambda \in \mathcal{M}_+(\Omega)$  such that

$$\begin{split} (\boldsymbol{\nabla}\mathbf{p},\boldsymbol{\nabla}\mathbf{v})_{\mathbf{L}^{2}(\Omega)} \ &= \ -(\mathbf{y}-\mathbf{y}^{\mathbf{d}},\mathbf{v})_{\mathbf{L}^{2}(\Omega)} + \langle \boldsymbol{\lambda},\mathbf{v} \rangle \quad , \quad \mathbf{v} \in \mathbf{W}_{\mathbf{0}}^{1,\mathbf{r}}(\Omega), \\ \mathbf{p} \ &= \ \boldsymbol{\alpha}\mathbf{u}, \\ \langle \boldsymbol{\lambda},\mathbf{y}-\boldsymbol{\psi} \rangle \ &= \ \mathbf{0}. \end{split}$$





### **Finite Element Approximation**

Let  $\mathcal{T}_h(\Omega)$  be a simplicial triangulation of  $\Omega$  and let

$$\mathbf{V}_h \ := \ \{ \ \mathbf{v}_h \in \mathbf{C}(\overline{\Omega}) \ | \ \mathbf{v}_h|_T \in \mathbf{P}_1(T) \ , \ T \in \mathcal{T}_h(\Omega) \ , \ \mathbf{v}_h|_{\Gamma} = \mathbf{0} \ \}$$

be the FE space of continuous, piecewise linear functions. Let  $\psi_{\rm h}$  be the V<sub>h</sub>-interpoland of  $\psi$ . Consider the following FE Approximation of the state constrained control problem

Since the constraints are point constraints associated with the nodal points, the discrete multipliers are chosen from

$$\mathcal{M}_{\mathbf{h}} \; := \; \left\{ \boldsymbol{\lambda}_{\mathbf{h}} \in \mathcal{M}(\Omega) \; \mid \; \boldsymbol{\lambda}_{\mathbf{h}} = \mathop{\textstyle\sum}_{\mathbf{a} \in \mathcal{N}_{\mathbf{h}}(\Omega)} \kappa_{\mathbf{a}} \boldsymbol{\delta}_{\mathbf{a}} \; , \; \, \boldsymbol{\kappa}_{\mathbf{a}} \in \mathbb{R} \right\} \; .$$





### Primal-Dual Active Set Strategy I

Step 1 (Initialization):

Choose c > 0, start-iterates  $y_h^{(0)}, u_h^{(0)}, \lambda_h^{(0)}$  and set n = 1.

Step 2 (Specification of active/inactive sets):

Compute the active/inactive sets  $\mathcal{A}_n$  and  $\mathcal{I}_n$  according to

 $\mathcal{A}_n \coloneqq \{1 \leq i \leq N \ | \ (y_h^{(n-1)} + c^{-1} \lambda_h^{(n-1)})_i > (\psi_h)_i \} \quad, \quad \mathcal{I}_n \coloneqq \{1, \cdots, N\} \setminus \mathcal{A}_n.$ 

Step 3 (Termination criterion):

If  $n\geq 2$  and  $\mathcal{A}_n=\mathcal{A}_{n-1},$  stop the algorithm. Otherwise, go to Step 4.





### **Primal-Dual Active Set Strategy II**

Step 4 (Update of the state, adjoint state, control, and multiplier):

Compute  $(y_h^{(n)}, u_h^{(n)}, p_h^{(n)}, \lambda_h^{(n)})$  as the solution of

$$\begin{split} \mathbf{A_h y_h^{(n)} - M_h u_h^{(n)}} &= \mathbf{0}, \\ \mathbf{A_h p_h^{(n)} - (M_h y_h^{(n)} - y_h^d) - \lambda_h^{(n)}} &= \mathbf{0}, \\ \mathbf{p_h^{(n)} - \alpha M_h u_h^{(n)}} &= \mathbf{0}, \\ & (\mathbf{y_h^{(n)}})_i = (\boldsymbol{\psi}_h)_i \quad \text{for } i \in \mathcal{A}_n, \\ & (\boldsymbol{\lambda_h^{(n)}})_i = \mathbf{0} \quad \text{for } i \in \mathcal{A}_n. \end{split}$$

Set n := n + 1 and go to Step 2.



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### Lavrentiev Regularization: Mixed Control-State Constraints

Introduce a regularization parameter  $\varepsilon > 0$  and consider the mixed controlstate constrained optimal control problem

Theorem (Optimality conditions). The optimal solution  $(\mathbf{y}^{\boldsymbol{\varepsilon}}, \mathbf{u}^{\boldsymbol{\varepsilon}}) \in \mathbf{V} \times \mathbf{L}^2(\Omega)$  is characterized by the existence of an adjoint state  $\mathbf{p}^{\varepsilon} \in \mathbf{V}$  and a multiplier  $\lambda^{\boldsymbol{\varepsilon}} \in \mathbf{L}^2_+(\Omega)$  such that

$$\begin{array}{rcl} (\boldsymbol{\nabla} \mathbf{y}^{\boldsymbol{\varepsilon}}, \boldsymbol{\nabla} \mathbf{v})_{\mathbf{L}^{2}(\Omega)} &= (\mathbf{u}^{\boldsymbol{\varepsilon}}, \mathbf{v})_{\mathbf{L}^{2}(\Omega)} &, \quad \mathbf{v} \in \mathbf{V} \ , \\ (\boldsymbol{\nabla} \mathbf{p}^{\boldsymbol{\varepsilon}}, \boldsymbol{\nabla} \mathbf{v})_{\mathbf{L}^{2}(\Omega)} &= -(\mathbf{y}^{\boldsymbol{\varepsilon}} - \mathbf{y}^{d}, \mathbf{v})_{\mathbf{L}^{2}(\Omega)} &+ (\boldsymbol{\lambda}^{\boldsymbol{\varepsilon}}, \mathbf{v})_{\mathbf{L}^{2}(\Omega)} &, \quad \mathbf{v} \in \mathbf{V} \ , \\ \mathbf{p}^{\boldsymbol{\varepsilon}} &- \boldsymbol{\alpha} \ \mathbf{u}^{\boldsymbol{\varepsilon}} &+ \boldsymbol{\varepsilon} \boldsymbol{\lambda}^{\boldsymbol{\varepsilon}} &= \mathbf{0} &, & (\boldsymbol{\lambda}^{\boldsymbol{\varepsilon}}, \boldsymbol{\varepsilon} \mathbf{u}^{\boldsymbol{\varepsilon}} + \mathbf{y}^{\boldsymbol{\varepsilon}} - \boldsymbol{\psi})_{\mathbf{L}^{2}(\Omega)} &= \mathbf{0} \ . \end{array}$$





Numerical Results: Distributed Control Problem with State Constraints I Minimize subject to  $-\Delta y = u$  in  $\Omega$ ,  $y \in K := \{v \in H^1_0(\Omega) \mid v \leq \psi \text{ a.e. in } \Omega\}$  $\Omega \ := \ (-2,+2)^2 \quad , \quad \mathbf{y}^{\mathbf{d}}(\mathbf{r}) \ := \ \mathbf{y}(\mathbf{r}) + \mathbf{\Delta p}(\mathbf{r}) \ + \boldsymbol{\sigma}(\mathbf{r}) \quad , \quad \mathbf{u}^{\mathbf{d}}(\mathbf{r}) \ := \ \mathbf{u}(\mathbf{r}) + \boldsymbol{\alpha}^{-1}\mathbf{p}(\mathbf{r}) \ ,$ Data:  $\psi$  := 0 , lpha := 0.1 , where  $\mathbf{y}(\mathbf{r}), \mathbf{u}(\mathbf{r}), \mathbf{p}(\mathbf{r}), \boldsymbol{\sigma}(\mathbf{r})$  is the solution of the problem:  $\mathbf{y}(\mathbf{r}) \; := \; -\mathbf{r}^{4/3} + \boldsymbol{\gamma}_1(\mathbf{r}) \;, \; \mathbf{u}(\mathbf{r}) = -\Delta \mathbf{y}(\mathbf{r}) \;, \; \mathbf{p}(\mathbf{r}) = \boldsymbol{\gamma}_2(\mathbf{r}) + \mathbf{r}^4 - rac{3}{2}\mathbf{r}^3 + rac{9}{16}\mathbf{r}^2 \;, \; \boldsymbol{\sigma}(\mathbf{r}) := \left\{ egin{array}{c} 0.0 & , & \mathbf{r} < 0.75 \ 0.1 & , & \mathrm{otherwise} \end{array} 
ight.$  $\gamma_1 \ := \ \left\{ \begin{array}{ccc} 1 & , & r < 0.25 \\ -192(r-0.25)^5 + 240(r-0.25)^4 - 80(r-0.25)^3 + 1 & , & 0.25 < r < 0.75 \\ 0 & , & \text{otherwise} \end{array} \right.,$  $\gamma_2 \; := \; \left\{ egin{array}{cccc} 1 & , & {
m r} < 0.75 \ 0 & , & {
m otherwise} \end{array} 
ight. \; .$ 











Numerical Results: Distributed Control Problem with State Constraints II

The solution  $y(r), u(r), p(r), \sigma(r)$  of the problem is given by

$${f y}({f r}) ~\equiv~ 4 ~~,~~ {f u}({f r}) ~\equiv~ 4 ~~,~~ {f p}({f r}) ~=~ rac{1}{4\pi}{f r}^2 - rac{1}{2\pi}{f ln}({f r}) ~~,~~ {m \sigma}({f r}) ~=~ {m \delta}_0 ~.$$











