

# A semismooth Newton algorithm for semidiscrete Optimal Control Problems with control constraints

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# Overview

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- 2 Newton algorithm and semismoothness
- 3 Implementation
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## Aim:

Algorithm to approximate the solution of an optimal control problem.

- linear-quadratic
- tracking-type cost functional
- box constraints to the control

## The Problem

$$\min_{u, y \in L^2(Q)} \frac{1}{2} \|y - z\|_{L^2(Q)}^2 + \frac{\alpha}{2} \|u\|_{L^2(Q)}^2$$

u.d.N.

$$Su = y$$

$$a \leq u \leq b \quad \text{a.e. in } Q$$

# Approach

- 1 Chose an appropriate discretization of the state equation  $\Rightarrow S_d$ .
- 2 Semi-discretization: replace  $S$  by  $S_d$ ; discretize bounds.
- 3 Apply a Newton algorithm to the first order optimality condition.
- 4 Use an iterative solver for the occuring linear equations (for example a CG alg. for the linear operators involved are self adjoint)

## The semidiscrete Problem

$$\min_{u, y \in L^2(Q)} \frac{1}{2} \|y - z\|_{L^2(Q)}^2 + \frac{\alpha}{2} \|u\|_{L^2(Q)}^2$$

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## Why using the semidiscretization? I

The strength of the semidiscrete approach shows in the following theorem.

### Theorem ( $L^2$ -convergence)

Let  $\bar{u}$  and  $\bar{u}_d$  be the solutions of the continuous and the discrete problem. Then there holds

$$\alpha \|\bar{u}_d - \bar{u}\|_{L^2(Q)} \leq \|S - S_d\| \left( \|(S\bar{u} - z)\|_{L^2(Q)} + \|S_d\| \|\bar{u}\|_{L^2(Q)} \right) \dots \\ + \left( \alpha + \|S_d\|^2 \right) (\|a - a_d\|_{L^2(Q)} + \|b - b_d\|_{L^2(Q)})$$

The numerical results confirm this result.

*Remark:* The assertions may be weakened a lot. Normwise convergence of the operators  $S$  and  $S_d$  which usually requires (at least) a smooth boundary is not necessary.

In the case of a parabolic Discontinuous Galerkin discretization  $S_d$  (piecewise constant in time, piecewise linear and globally continuous in space) one has the following convergence result.

## Why using the semidiscretization? II

**Theorem ( $L^\infty$ -convergence (parabolical case, Dirichlet boundary cond.))**

Assume  $\Omega \subset \mathbb{R}^2$  to be a convex polyhedral domain in  $\mathbb{R}^2$  and let  $\partial_t(S^* S\bar{u}), \partial_t(S^* z) \in L^\infty([0, T], L^\infty(\Omega))$  hold as well as  $S^* S\bar{u}, S^* z \in L^\infty([0, T], H^2(\Omega))$ . Then there holds for the solutions  $\bar{u}_d$  and  $\bar{u}$

$$\begin{aligned} \|\bar{u}_d - \bar{u}\|_\infty &\leq C(|\log k| + 1)^{\frac{1}{2}} \left( k(\|\partial_t(S^* z)\|_\infty + \|\partial_t(S^* S\bar{u})\|_\infty) \dots \right. \\ &\quad \left. + h^2(\|S^* z\|_{L^\infty([0, T], H^2(\Omega))} + \|S^* S\bar{u}\|_{L^\infty([0, T], H^2(\Omega))}) \right) \dots \\ &\quad + C(|\log h| + 1)^{\frac{1}{2}} (h^2 + k) \|\bar{u}\|_{L^2([0, T], L^2(\Omega))} . \end{aligned}$$

## Necessary conditions

The optimum  $\bar{u}_d$  of the semidiscrete problem fulfills the following necessary condition.

$$\langle S_d^* S_d \bar{u}_d - z + \alpha \bar{u}_d, u - \bar{u}_d \rangle_{L^2(Q)} \geq 0, \quad \forall u : a \leq u \leq b.$$

Since the feasible set is convex and the  $L^2$ -projection onto it equals the pointwise projection this is equivalent to

$$\bar{u}_d = P_{[a,b]} (\bar{u}_d - c (\alpha \bar{u}_d + S_d^* (S_d \bar{u}_d - z)))$$

for any  $c > 0$ . The choice  $c = \frac{1}{\alpha}$  yields some insight into the

structure of  $\bar{u}_d$ .

$$\bar{u}_d = P_{[a,b]} \left( -\frac{1}{\alpha} S_d^* (S_d \bar{u}_d - z) \right)$$

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## Solving the optimality system

### Fixed point iteration

For  $\alpha > \|S_d\|$  the solution  $\bar{u}_d$  can be computed by simple fixed point iteration.

### Newton algorithm

Given that

$$G_d(u) = u - P_{[a_d, b_d]} \left( -\frac{1}{\alpha} S_d^*(S_d u - z) \right)$$

is semismooth, a Newton algorithm will converge at least locally superlinearly.

# Semismoothness I

- We assume a finite element space of piecewise linear globally continuous functions over a quasiuniform Triangulation  $T_h$  with maximal diameter  $h$ . (in space)
- In the case of a linear parabolic solution operator  $S$  over a parabolic cylinder  $Q_T = \Omega \times [0, T]$  the Ansatz functions are piecewise constant in time.

## Corollary from a theorem of M.Ulbrich

The operator  $G_d : L^2(Q) \rightarrow L^2(Q)$

$$G_d(u) = u - P_{[a,b]} \left( - \frac{1}{\alpha} S_d^* (S_d u - z) \right)$$

is semismooth of order  $\delta$  für  $0 < \delta < \frac{1}{2}$ , provided that  $S_d^* (S_d u - z)$  maps continuously into  $L^p(Q)$  for  $1 < p < \infty$ .

## Semismoothness II

- An elliptic solution operator  $S : L^2(\Omega) \rightarrow L^2(\Omega)$  will map continuously into  $H^2(\Omega)$ , given smooth enough data. Given a little more smoothness  $S^*(Su - z)$  then maps into  $H^4(\Omega)$ . For  $\Omega \subset \mathbb{R}^n$ ,  $n \leq 3$  the space  $H^2(\Omega)$  is continuously embedded in  $C^0(\Omega)$ .
- An elliptic solution operator  $S_\delta^* : L^2(\Omega) \rightarrow L^2(\Omega)$  will at least map  $L^2$  continuously into  $H^1(\Omega)$ . The embedding  $H^1(\Omega) \hookrightarrow L^p(\Omega)$  holds for  $1 < p < \infty$  if  $n = 2$  and for  $1 < p \leq 6$ . For  $n = 3$  we obtain semismoothness of order  $0 < \delta < \frac{1}{3}$ .
- A parabolic solution operator  $S_\delta^* : L^2(Q_T) \rightarrow L^2(Q_T)$  maps  $L^2(Q_T)$  continuously into  $L^\infty([0, T], H^1(\Omega))$  which for  $n = 2$  lies in any  $L^\infty([0, T], L^p(\Omega))$  for  $1 < p < \infty$ . For  $n = 3$  at least  $L^\infty([0, T], H^1(\Omega)) \hookrightarrow L^\infty([0, T], L^6(\Omega))$  and we obtain semismoothness of order  $0 < \delta < \frac{1}{3}$ .



# Newton algorithm

The Newton step for  $G_d(u) = 0$  reads

## Newton step

$$\left( I + \frac{g_i}{\alpha} S_d^* S_d \right) (s_i) = -u_i + P_{[a,b]} \left( -\frac{1}{\alpha} (S_d^* (S_d u_i - z)) \right)$$

where  $g_i$  is the characteristic function of the inactive set in the  $i$ -th iteration.

- $\left( I + \frac{g_i}{\alpha} S_d^* S_d \right)$  invertible?
- Practicability?
- Solver for the linear equation?

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## Practicability

Dampened Newton Algorithm:  $u_{i+1} = u_i + \beta_i s_i$ .

### Problem

$$\begin{aligned} u_{i+1} &= u_i + \beta_i s_i \\ &= (1 - \beta_i u_i) + \beta_i P_{[a,b]} \left( -\frac{1}{\alpha} (S_d^* (S_d u_i - z)) \right) - \beta_i \frac{g_i}{\alpha} S_d^* S_d (s_i) \end{aligned}$$

$\Rightarrow$  Not implementable for  $\beta \neq 1$ . BUT: The next iterate  $u_{i+1}$  depends only on  $S_d^* S_d u_i$ .

### Way out

Projection of  $u_{i+1}$  to prevent accumulation of jumps. For example by  $L^2$ -projecting  $u_{i+1}$  onto the current FE space that contains  $P_{[a,b]} \left( -\frac{1}{\alpha} (S_d^* (S_d u_{i+1} - z)) \right)$  as well as the base FE space. Or by applying  $S_d^* S_d$  to the above equation.

# Invertability

The undamped Newton step can be written as

## Newton II

$$\left(I + \frac{g_i}{\alpha} S_d^* S_d\right) u_{i+1} = P_{[a,b]} \left( -\frac{1}{\alpha} (S_d^* (S_d u_i - z)) \right) + \frac{g_i}{\alpha} S_d^* S_d u_i$$

- Invertability of  $\left(I + \frac{g_i}{\alpha} S_d^* S_d\right)$  not obvious yet.
- Not self-adjoint.

## Way out

$$\begin{aligned} \left(I + \frac{g_i}{\alpha} S_d^* S_d\right) g_i u_{i+1} = & P_{[a,b]} \left( -\frac{1}{\alpha} (S_d^* (S_d u_i - z)) \right) + \frac{g_i}{\alpha} S_d^* S_d u_i \dots \\ & - \left(I + \frac{g_i}{\alpha} S_d^* S_d\right) (1 - g_i) u_{i+1} \end{aligned}$$

## Self-adjointness

- On the active set  $u_{i+1}$  is already known.
- On the inactive set there holds

Equation to solve.

$$\left(I + \frac{g_i}{\alpha} S_d^* S_d\right) g_i u_{i+1} = \frac{g_i}{\alpha} S_d^* z - \frac{g_i}{\alpha} S_d^* S_d (1 - g_i) u_{i+1}$$

A CG routine can be applied!

We also get an estimate for the inverse

$$\left\| \left(I + \frac{1}{\alpha} g S_d^* S_d\right)^{-1} \right\| \leq 1 + \frac{1}{\alpha} \|S_d\|^2$$

which together with the semismoothness is sufficient for local superlinear convergence.

# Convergence of the Newton algorithm

## Global convergence

For  $\alpha > \frac{4}{3} \|S_d\|^2$  the iteration converges independently of the initial guess  $u_0$ .

So the global convergence properties of the algorithm are (nearly) as good as those of the fixed point iteration.

## Globalization

If inexact Amijo linesearch works for the canonical Merit functional

$$\left\| u - P_{[a,b]} \left( -\frac{1}{\alpha} S_d^* (S_d u - z) \right) \right\|^2$$

it works also for the projection strategies proposed for damping .

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## elliptic, Dirichlet boundary condition

Consider the problem

$$\min_{u, y \in L^2(\Omega)} \|y - y_d\|_{L^2(\Omega)}^2 + \alpha \|u\|_{L^2(\Omega)}^2$$

under the constraints

$$\begin{aligned} -\Delta y &= u - r \quad \text{in } \Omega = [0, 1]^2, & y &= 0 \quad \text{auf } \partial\Omega \\ a &\leq u \leq b & & \text{a.e.} \end{aligned}$$

with  $\alpha = 0.001$  and parameters

$$\begin{aligned} r &= P_{[a,b]}(2 \sin(\pi x) \sin(\pi y)), \\ y_d &= -4\pi^2 \alpha \sin(\pi x) \sin(\pi y) \end{aligned}$$

and bounds  $a = 0.3$ ,  $b = 1$ .

The problem admits a unique solution  $\bar{u} = r$ .



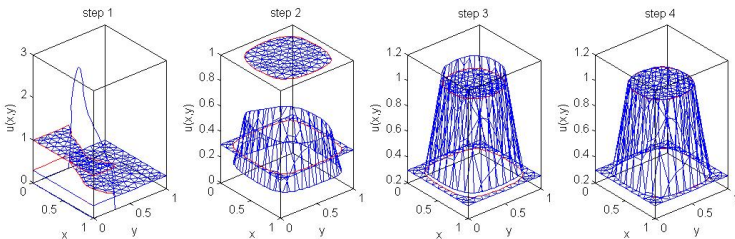


Figure: The first four Newton iterates for a random initial guess scaled by  $10^6$ .

mesh param. $h$	$ERR$	$ERR_\infty$	$EOC$	$EOC_\infty$
0.1	4.0728e-003	1.8773e-002	-	-
0.05	9.2078e-004	2.4076e-003	2.1451	2.9629
0.025	2.2090e-004	8.7739e-004	2.0594	1.4563
0.0125	5.6551e-005	2.7165e-004	1.9658	1.6915
0.00625	1.3913e-005	9.4819e-005	2.0232	1.5185

Table:  $L^2$ - and  $L^\infty$ -errors for different meshes and estimated order of convergence.

## global convergence

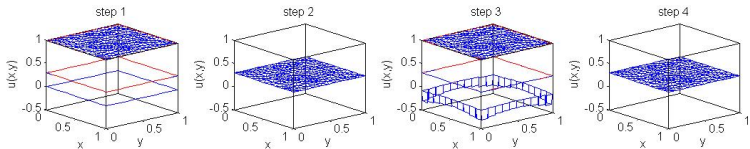
On smooth domains  $\Omega$  the mapping  $u \mapsto y(u) \in L^2(\Omega)$  can be shown to be a continuous (in fact compact) operator with norm  $2\pi^2$ . The fixed point iteration for the equation

$$u = P_{[a,b]} \left( -\frac{1}{\alpha} S_h^* (S_h u - y_d) \right)$$

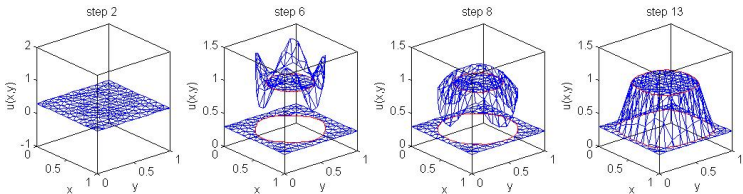
converges for  $\|S_h\|^2/\alpha < 1$ . Yet the operator norm  $\|S_h\|$  converges to  $2\pi^2$ , so the iteration is convergent for  $\alpha \gtrsim (4\pi^4)^{-1} \simeq 390^{-1}$ . For the Newton algorithm a similar estimate holds.

### global convergence

The undampened Newton algorithm converges globally if  $\alpha > \frac{4}{3} \|S_h\|^2$ .



**Figure:** Undamped Newton steps for  $\alpha = 10^{-5}$ . The iterates bounce between upper and lower bound.



**Figure:**  $\alpha = 10^{-5}$ . The inexactly Amijo-damped Newton algorithm terminates after 13 steps, when the jump along the border between active and inactive set is smaller than  $10^{-12}$ .

## better damping strategy

Instead of solving the fixed point equation

$$G_d(u) = u - P_{[a_d, b_d]} \left( -\frac{1}{\alpha} S_d^* (S_d u - z) \right) = 0$$

we may switch to the equivalent problem

$$p - S_d^* S_d P_{[a_d, b_d]} \left( -\frac{1}{\alpha} p \right) + S_d^* z = 0$$

and apply a semismooth Newton algorithm to it. (This is a finite dimensional problem!)

The construction of the algorithm remains nearly the same (Invertability, Selfadjointness...)

mesh param. $h$	$ERR$	$ERR_\infty$	$EOC$	$EOC_\infty$	Iterations
0.1	3.4920e-003	2.3977e-002	-	-	28
0.05	6.8772e-004	3.8290e-003	2.3442	2.6466	18
0.025	1.6901e-004	1.3261e-003	2.0247	1.5298	19
0.0125	4.0953e-005	3.2358e-004	2.0451	2.0350	18
0.00625	1.0065e-005	9.3818e-005	2.0247	1.7862	18

Table: Development of the error and number of Newton iterations for  $\alpha = 10^{-7}$ .

## parabolic example, Neumann boundary condition

Consider the problem

$$\begin{aligned} \min_{u, y \in L^2(Q_T)} \quad & \|y - y_d\|^2 + \alpha \|u\|^2 \\ \partial_t y - \Delta y = u - r \quad & \text{in } Q_T = [0, T] \times \Omega, \\ \partial_\nu y = 0 \quad & \text{on } [0, T] \times \partial\Omega \text{ and } y|_{t=0} = 0 \\ a \leq u \leq b \quad & \text{a.e. in } Q_T \end{aligned}$$

with  $\alpha = 1$  and parameters  $r, y_d \in L^2(Q_T)$  with

$$\begin{aligned} r &= \max \left( -0.5, \min (0.5, \sin(\pi t) \cos(\pi x) \cos(\pi y)) \right), \\ y_d &= \pi \alpha \cos(\pi x) \cos(\pi y) (2\pi \cos(\pi t) - \sin(\pi t)) \end{aligned}$$

and bounds  $a = -0.5, b = 0.5$ .

The choice of parameters leads to a solution  $\bar{u} = r$ .

## parabolic example

1. Newton step

2. Newton step

3. Newton step

mesh param. $(h, k)$	$ERR$	$ERR_\infty$	$EOC$	$EOC_\infty$
$(0.1, 0.01)$	4.0723e-003	2.9171e-002	-	-
$(\frac{0.1}{\sqrt{2}}, \frac{0.1}{2})$	1.9935e-003	1.5093e-002	2.0611	1.9012
$(0.05, \frac{0.1}{4})$	9.9564e-004	7.6957e-003	2.0032	1.9436
$(\frac{0.05}{\sqrt{2}}, \frac{0.1}{8})$	5.1607e-004	3.8858e-003	1.8961	1.9717
$(0.025, \frac{0.1}{16})$	2.5036e-004	1.9531e-003	2.0871	1.9848
$(\frac{0.025}{\sqrt{2}}, \frac{0.1}{32})$	1.2566e-004	9.7917e-004	1.9889	1.9923

# Result

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- Fully implementable algorithm.
- The Newton alg. converges locally superlinearly with exponent 1.5.
- Global convergence for  $\alpha$  sufficiently large.
- Globalization by inexact linesearch for smaller  $\alpha$ .

## Outlook

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- Superconvergence to a post processed fully discretized approach? [1]
- Application to a moving surface problem? [3]
- Application as a post processing step?
- Nonlinear PDEs?

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THANK YOU.

- [1] "Superconvergence Properties of Optimal Control Problems", C. Meyer, A. Rösch, SIAM J. Control Optim., Vol. 43, 2004
- [2] "A mesh-independence result for semismooth Newton methods", Michael Hintermüller, Michael Ulbrich, Math. Program., Ser B 101, 2004
- [3] "Finite elements for evolving surfaces", G. Dziuk, C.M. Elliot, IMA J.numer. Anal., 2006