

*A semismooth Newton method
for a class of semilinear optimal control problems
with box and volume constraints*

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General formulation

- ▶ (\mathcal{P}) : $\min_{(u,y) \in U_{ad} \times Y} J(u, y)$ subject to $E(u, y) = 0$,

$$U := \{u \in L^2(D), 0 \leq u \leq 1 \text{ a.e. in } D\},$$

$$U_{ad} := \{u \in U, \int_D u = m\}, \quad 0 < m < |D|,$$

- ▶ D is a bounded domain of \mathbb{R}^N , $N \in \{2, 3\}$.
 - ▶ $J : L^2(D) \times Y \rightarrow \mathbb{R}$ and $E : U \times Y \rightarrow Z$.
 - ▶ Y, Z are Banach spaces.
 - ▶ E denotes a class of semilinear equations.
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- ▶ Ito & Kunisch (2004): L^2 -control cost, primal-dual active set method for nonlinear problems and bilateral constraints.
 - ▶ Stadler (2009), Wachsmuth (2011): L^1 -control cost, linear case.

Shape/topology optimization

Shape optimization: the control is a set $\Omega \subset \mathbb{R}^N$, or its indicator function χ_Ω which takes values in $\{0, 1\}$.

Topology optimization: if the topology is unknown.

- ▶ **Allaire, Bendsøe...**: Relaxed formulation.
- ▶ **Delfour-Zolésio, Murat-Simon...**: Smooth boundary perturbations.
- ▶ **Masmoudi, Sokolowski...**: Topological derivative.

Optimal control approach

- ▶ With an L^1 -control cost and a linear elliptic state equation, the control u eventually takes 0 – 1 values.
- ▶ Nonsmooth Newton methods available.
- ▶ L^1 -control cost $\|u\|_{L^1}$ corresponds to a volume constraint.
- ▶ Total Variation $\|Du\|_{L^1}$ corresponds to a perimeter constraint.

Nonsmooth Newton Method

Main idea

- ▶ Reformulation of the optimality conditions for (\mathcal{P}) :

$$\Phi(u, y, p, \lambda) = 0$$

where (p, λ) are Lagrange multipliers.

- ▶ Φ is a **nonsmooth, nonlinear** vector function.
- ▶ Generalized differentiability of Φ : **Newton derivative**.
- ▶ Use a **semismooth Newton Method** (Hintermüller, Ito, Kunisch ...)

Binary and sparse solutions

- ▶ In certain cases we show that the solution is binary.
- ▶ Numerical solutions exhibits in general a piecewise constant nature for the semilinear problem.
- ▶ The volume constraint allows to exactly control the level of **sparsity** of u .

Problem statement and optimality conditions

Definition

For every $u \in U_{ad}$ we define the cone $K(u) \subset L^2(D)$ by

$$\forall v \in L^2(D), \quad v \in K(u) \iff \begin{cases} v = 0 \text{ a.e. in } [0 < u < 1], \\ v \geq 0 \text{ a.e. in } [u = 0], \\ v \leq 0 \text{ a.e. in } [u = 1]. \end{cases}$$

Theorem (optimality conditions)

Let (\bar{u}, \bar{y}) be an optimal solution of (P) . With appropriate minimal assumptions on E, J , there exists $(\bar{\lambda}, \bar{p}) \in \mathbb{R} \times Z'$ such that

$$\begin{aligned} L_u(\bar{u}, \bar{y}, \bar{p}) + \bar{\lambda} &\in K(\bar{u}), \\ L_y(\bar{u}, \bar{y}, \bar{p}) &= 0, \\ L_p(\bar{u}, \bar{y}, \bar{p}) &= 0, \\ \int_D \bar{u} &= m. \end{aligned}$$

Problem statement and optimality conditions

For all $(u, y, p, \lambda, g) \in L^2(D) \times Y \times Z' \times \mathbb{R} \times L^2(D)$ we set

$$T(u, g) := u \max(0, g) + (1 - u) \min(0, g),$$

and

$$\Phi(u, y, p, \lambda) := \begin{pmatrix} T(u, L_u(u, y, p) + \lambda) \\ L_y(u, y, p) \\ L_p(u, y, p) \\ \int_D u - m \end{pmatrix}.$$

Theorem

Let $(\bar{u}, \bar{y}, \bar{p}, \bar{\lambda}) \in L^2(D) \times Y \times Z' \times \mathbb{R}$. The optimality conditions are equivalent to

$$\Phi(\bar{u}, \bar{y}, \bar{p}, \bar{\lambda}) = 0.$$

Semismooth Newton method

Newton derivative

Let \mathcal{X}, \mathcal{Y} be Banach spaces and $\mathcal{U} \subset \mathcal{X}$ open. If there exists $G : \mathcal{U} \rightarrow \mathcal{L}(\mathcal{X}, \mathcal{Y})$ such that for all $u \in \mathcal{U}$

$$\lim_{h \rightarrow 0} \frac{1}{\|h\|_{\mathcal{X}}} \|F(u+h) - F(u) - G(u+h)h\|_{\mathcal{Y}} = 0$$

then $F : \mathcal{U} \rightarrow \mathcal{Y}$ is **Newton differentiable**, G is the **Newton derivative**.

Semismooth Newton method

Suppose $F(u^*) = 0$ and $F : \mathcal{X} \rightarrow \mathcal{Y}$ is Newton differentiable in \mathcal{U} containing u^* , with Newton derivative G . If $G(u)$ is nonsingular for all $u \in \mathcal{U}$ and $\{\|G(u)^{-1}\|_{\mathcal{L}(\mathcal{Y}, \mathcal{X})}, u \in \mathcal{U}\}$ is bounded, then

$$u_{n+1} = u_n - G(u_n)^{-1} F(u_n)$$

converges superlinearly to u^* , if $\|u_0 - u^*\|_{\mathcal{X}}$ is sufficiently small.

Regularization

- ▶ **Problem:** the generalized Jacobian of Φ is not invertible.
- ▶ **Remedy:** regularization of Φ by means of

$$\Phi^\varepsilon(u, y, p, \lambda) := \begin{pmatrix} T^\varepsilon(u, L_u(u, y, p) + \lambda) \\ L_y(u, y, p) \\ L_p(u, y, p) \\ \langle \mathbf{1}, u \rangle - m \end{pmatrix}.$$

- ▶ Examples of regularization:

$$T^\varepsilon(u, g) = u \max(0, g + \varepsilon) + (1 - u) \min(0, g - \varepsilon),$$

$$T^\varepsilon(u, g) = \sqrt{\varepsilon^2 + g^2} + \min(0, g).$$

- ▶ $D\Phi^\varepsilon(u, y, p, \lambda)$ is invertible and $\|D\Phi^\varepsilon(u, y, p, \lambda)^{-1}\|$ is uniformly bounded for (u, y, p, λ) close to the solution.

Semilinear problem

- ▶ (\mathcal{P}) : $\min_{(u,y) \in U_{ad} \times Y} J(u,y)$ subject to $E(u,y) = 0$,

$$J(u,y) = \frac{1}{2} \int_D (y - y^\dagger)^2,$$

$$E(u,y) = Ay + \psi(y) - u,$$

where $y^\dagger \in L^2(D)$, $Y = H_0^1(D)$, $Z = H^{-1}(D)$, $A = -\Delta$, and $\psi \in \mathcal{C}^3(\mathbb{R})$, non-decreasing, and such that

$$\|\psi^{(k)}\|_{L^\infty} \leq M_\psi^k, \quad k = 1, 2, 3,$$

for some positive constants M_ψ^k .

- ▶ D is of class \mathcal{C}^2 or convex.
- ▶ For all $u \in L^2(D)$, there exists a unique solution $y(u) \in H^2(D) \cap H_0^1(D)$ to the equation $E(u, y(u)) = 0$.

Existence of Regularized solutions

(A): Assumption on ρ

$\exists \gamma > 0$ such that, for all $(u, y, p) \in U \times H_0^1(D) \times H_0^1(D)$ satisfying

$$\begin{aligned} Ay + \psi(y) &= u, \\ [A + \psi'(y)]p &= -(y - y^\dagger), \end{aligned}$$

there holds

$$1 + \psi''(y)p \geq \gamma.$$

This assumption is fulfilled if M_ψ^2 is small enough.

Theorem (Existence of solutions)

Let Assumption (A) hold. For each $\varepsilon > 0$ there exists

$$(u_\varepsilon, y_\varepsilon, p_\varepsilon, \lambda_\varepsilon) \in L^2(D, [0, 1]) \times (H^2 \cap H_0^1)(D) \times (H^2 \cap H_0^1)(D) \times \mathbb{R}$$

such that $\Phi^\varepsilon(u_\varepsilon, y_\varepsilon, p_\varepsilon, \lambda_\varepsilon) = 0$.

Convergence of the Newton algorithm

Theorem

Assume Assumption (A) holds and $\Phi^\varepsilon(\zeta^\varepsilon) = 0$ with $\zeta^\varepsilon = (u_\varepsilon, y_\varepsilon, p_\varepsilon, \lambda_\varepsilon)$. Then

$$\zeta_{n+1} = \zeta_n - D\Phi^\varepsilon(\zeta_n)^{-1}\Phi^\varepsilon(\zeta_n)$$

is well-defined and converges superlinearly to ζ^ε as long as $\|\zeta_0 - \zeta^\varepsilon\|$ is sufficiently small.

Proof

The main tasks are:

- ▶ the invertibility of the generalized gradient $D\Phi^\varepsilon(\zeta)$,
- ▶ a uniform bound on $\|D\Phi^\varepsilon(\zeta)^{-1}\|$ in an appropriate norm.

Convergence of the regularized solution

Theorem

Let $\{\varepsilon_k\}_{k \in \mathbb{N}}$, ε_k positive, $\varepsilon_k \rightarrow 0$ and $\Phi^{\varepsilon_k}(\zeta^{\varepsilon_k}) = 0$.

- ▶ For any $s < 2$ there exists a subsequence $\{\varepsilon_{k_l}\}_{l \in \mathbb{N}}$ and $(u^*, \lambda^*) \in L^2(D, [0, 1]) \times \mathbb{R}$ such that

$$\begin{aligned} u^{\varepsilon_{k_l}} &\rightharpoonup u^* \text{ weakly in } L^2(D), & y^{\varepsilon_{k_l}} &\rightarrow y^* \text{ strongly in } H^s(D), \\ p^{\varepsilon_{k_l}} &\rightarrow p^* \text{ strongly in } H^s(D), & \lambda^{\varepsilon_{k_l}} &\rightarrow \lambda^* \text{ in } \mathbb{R}, \end{aligned}$$

where y^*, p^* are given by

$$\begin{aligned} Ay^* + \psi(y^*) &= u^*, \\ B(y^*)p^* &= -(y^* - y^\dagger). \end{aligned}$$

- ▶ Every cluster point ζ^* (for $s < 2$ large enough) satisfies

$$\Phi(\zeta^*) = 0.$$

- ▶ Ensure a constant rate of convergence of the merit function

$$R(\varepsilon) = \frac{1}{2} \|\Phi(\zeta^\varepsilon)\|^2.$$

- ▶ Look for a sequence $\{\varepsilon_k\}$ such that

$$\frac{R(\varepsilon_{k+1})}{R(\varepsilon_k)} \approx \tau \quad \text{with } 0 < \tau < 1.$$

- ▶ Define $\Psi(\varepsilon, \zeta) = \Phi^\varepsilon(\zeta)$. Update

$$\varepsilon_{k+1} = \varepsilon_k \tau^{\beta_k},$$

$$\beta_k = \frac{-R(\varepsilon_k)}{\varepsilon_k \langle D\Phi(\zeta^{\varepsilon_k}) D\Phi^{\varepsilon_k}(\zeta^{\varepsilon_k})^{-1} D_\varepsilon \Psi(\varepsilon_k, \zeta^{\varepsilon_k}), \Phi(\zeta^{\varepsilon_k}) \rangle}.$$

- ▶ Define $\rho(\ln \varepsilon) = \ln R(\varepsilon)$. Stopping criterions

$$\frac{\|\zeta_k - \zeta_{k-1}\|}{\|\zeta_{k-1}\|} < \kappa_N \quad \text{and} \quad \rho'(\ln \varepsilon) < \kappa_E.$$

Numerical experiments: linear case

- ▶ domain $D =]0, 1[^2$, volume constraint $m = 0.5$, $n = 39601$ nodes,
- ▶ convergence rate for $R(\varepsilon)$: $\tau = 0.1$
- ▶ stopping criterions: $\kappa_N = 10^{-8}$, $\kappa_E = 10^{-3}$
- ▶ $y_1^\dagger \equiv 0.01$ and $y_2^\dagger(x_1, x_2) = \sin(2\pi x_1) \sin(2\pi x_2)$
- ▶ CPU time: 5 minutes (Matlab-Desktop PC)

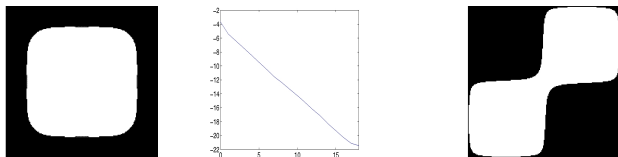


Figure: optimal control for $y^\dagger = y_1^\dagger$ (left), convergence history of $\log_{10} R(\varepsilon)$ for $y^\dagger = y_1^\dagger$ (middle), and optimal control for $y^\dagger = y_2^\dagger$ (right).

Numerical experiments: nonlinear case

- ▶ Fix $y^\dagger = 0.01$, and consider two functions ψ :

$$\begin{aligned}\psi_1(t) &= e^{at} - 1, & a &= 10^3, \\ \psi_2(t) &= \arctan(at), & a &= 10^2.\end{aligned}$$

- ▶ ψ_2 satisfies our assumptions, but not ψ_1 .
- ▶ appearance of intermediate regions.

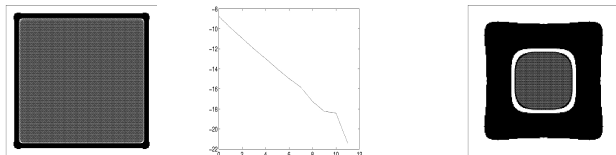


Figure: optimal control for $\psi = \psi_1$ (left), convergence history of $\log_{10} R(\epsilon)$ for $\psi = \psi_1$ (middle), and optimal control for $\psi = \psi_2$ (right).

Thanks for your attention!