

A semismooth Newton method for obstacle-type quasivariational inequalities

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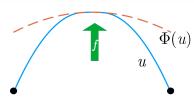


Consider the constraint set: $K(u) := \{v \in H_0^1(\Omega) : v \leq \Phi(u) \text{ a.e.}\}$

$$\min_{u \in K(u)} \int_{\Omega} \frac{1}{2} |\nabla u|^2 - f \cdot u \, \mathrm{d}x$$

First-order optimality condition is an obstacle-type QVI

Find $u \in H^1_0(\Omega)$: $(\nabla u, \nabla (v - u))_{L^2(\Omega)} \ge (f, v - u)_{L^2(\Omega)}$ for all $v \in K(u)$



Sandpiles, thermoforming, elastic bilayers, image processing, option pricing, fluid flow with pressure constraints... Why doesn't everyone model with QVIs? ...they are very hard to solve!





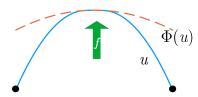


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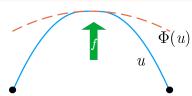


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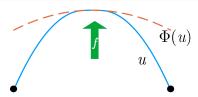


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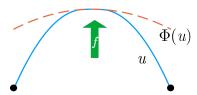


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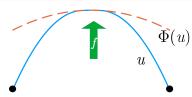


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Rewrite the QVI as the fixed point problem $u = S(\Phi(u))$.

Obstacle map $S: H_0^1(\Omega) \to H_0^1(\Omega), S: \phi \mapsto u_0$

$$u_{\phi} = S(\phi)$$
 maps from the obstacle $ightarrow$ solution of the obstacle VI, i.e.

$$(\nabla u_{\phi}, \nabla (v - u_{\phi}))_{L^2(\Omega)} \ge (f, v - u_{\phi})_{L^2(\Omega)} \text{ for all } v \in H^1_0(\Omega), \ v \le \phi.$$

 \triangle Evaluating $\Phi(u)$ might require a nonlinear PDE solve.

 \triangle Evaluating $S(\phi)$ requires a VI solve.

SSN step for the QVI

Let $R(u) = u - S(\Phi(u))$. The SSN iteration is $u_{i+1} = u_i + \delta$ where



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Chain rule

$$G_R(u_i) = \mathrm{Id} - G_S(\Phi(u_i))G_{\Phi}(u_i)$$

Theorem

The obstacle map $S: \phi \mapsto u_{\phi}$ is *semismooth* with a Newton derivative G_S where $||G_S|| \le 1$. Moreover,

$$G_{\mathcal{S}}(\phi)\zeta = \zeta + Z_{\mathcal{O}}$$

where $z_{\zeta} \in H_0^1(\mathcal{I}(\phi))$ satisfies

$$(\nabla z_{\zeta} - \nabla \zeta, \nabla v) = 0 \text{ for all } v \in H_0^1(\mathcal{I}(\phi))$$

and $\mathcal{I}(\phi) = \{x \in \Omega : \mathcal{S}(\phi)(x) < \phi(x) \text{ a.e.}\} \subseteq \Omega$



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SSN System

SSN update δ satisfies

$$[\operatorname{Id} - G_{\mathcal{S}}(\Phi(u_i))G_{\Phi}(u_i)]\delta = -R(u_i).$$

Introduce auxiliary variables $\eta = G_{\Phi}(u_i)\delta$ and $\mu = G_{S}(\Phi(u_i))\eta - \eta$. Reformulate SSN system as

$$\begin{pmatrix} \operatorname{Id} & -\operatorname{Id} & -\operatorname{Id}|_{\mathcal{I}(u_i)} \\ G_{\Phi}(u_i) & -\operatorname{Id} & 0 \\ 0 & (G_{S}(\Phi(u_i)) - \operatorname{Id})|_{\mathcal{I}(u_i)} & -\operatorname{Id}|_{\mathcal{I}(u_i)} \end{pmatrix} \begin{pmatrix} \delta \\ \eta \\ \mu \end{pmatrix} = -\begin{pmatrix} R(u_i) \\ 0 \\ 0 \end{pmatrix}.$$

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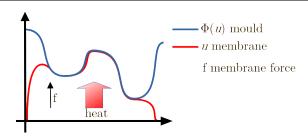
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Thermoforming: an obstacle-type QVI



Mode

Find $u \in H_0^1(\Omega)$ satisfying $u \leq \Phi(u) := \Phi_0 + \psi T$ and

$$(\nabla u, \nabla (v-u))_{L^2(\Omega)} - (f, v-u)_{L^2(\Omega)} \ge 0$$
 for all $v \in H^1_0(\Omega), v \le \Phi(u)$

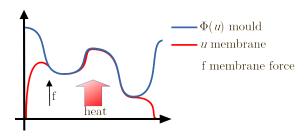
with T as the solution of

$$kT - \Delta T = g(\Phi_0 + \psi T - u) \text{ in } \Omega, \qquad \partial_{\nu} T = 0 \text{ on } \partial \Omega,$$





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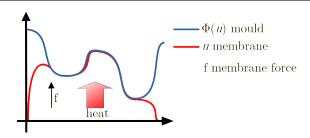
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Example: setup

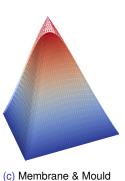
$$\Omega = (0,1)^2, \qquad \Phi_0(x_1, x_2) = 1 - 2 \max(|x_1 - 0.5|, |x_2 - 0.5|),$$

$$f(x_1, x_2) = 25, \qquad \psi(x_1, x_2) = \sin(\pi x_1) \sin(\pi x_2), \qquad k = 1,$$

$$g(s) = \begin{cases} 1/5 & \text{if } s \le 0, \\ (1 - s)/5 & \text{if } 0 < s < 1, \\ 0 & \text{otherwise.} \end{cases}$$



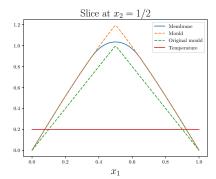




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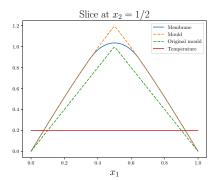


- CG₁ FEM discretization for u and T
- Active set in SSN step implemented via one step of vinewtonrsls.
- VI solver for evaluating $S(\phi)$: path-following Moreau-Yosida regularization (PFMY) + feasibility restoration with vinewtonrs1s.
- Fixed point method: $u_{i+1} = S(\Phi(u_i))$ [Converges linearly].





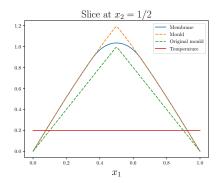
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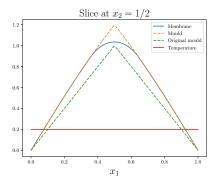
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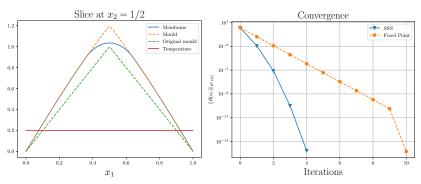
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Example: mesh independence

	Outer loop	Evaluate Φ Evalua		Evaluate <i>S</i>
h	SSN	Newton	PFMY	+vinewtonrsls
0.04	4	8	84	11
0.02	4	8	79	10
0.01	4	8	79	15
0.00667	4	8	79	19
0.005	4	9	79	20
0.004	4	8	79	16
0.00333	3	9	64	17

Table: Mesh independence of the SSN.





- A semismooth Newton method for solving obstacle-type QVIs;
- An active-set strategy implemented in Firedrake ♥;
- Theory relies on recent semismooth results for the obstacle map S.

A globalized inexact semismooth Newton method for nonsmooth fixed point equations involving variational inequalities

A. Alphonse, C. Christof, M. Hintermüller, I. P. A. Papadopoulos, to appear, 2024.

semismoothQVIs 👺 🗘

https://github.com/ioannisPApapadopoulos/semismoothQVIs.





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Depending on your platform, PETSc may take an hour or more to build!







Thank you for listening!

 \bowtie papadopoulos@wias-berlin.de

