

**Proximal gradient methods applied to
optimization problems with L^p -cost,
 $p \in [0, 1)$**

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Outline

1. Introduction
2. Optimality conditions
3. Proximal gradient method
4. Convergence analysis
5. Numerical results

The sparse control problem

Optimal control problem = minimization problem

$$\min f(u)$$

with controls

$$u : \Omega \rightarrow \mathbb{R}, \quad u \in L^2(\Omega)$$

on bounded set $\Omega \in \mathbb{R}^d$.

Sparse controls: Penalize measure of support of controls

$$\|u\|_0 := \text{meas}\{x \in \Omega : u(x) \neq 0\}$$

or some p -'norm' $\|u\|_p$ with $p \in (0, 1)$

$$\|u\|_p := \int_{\Omega} |u(x)|^p dx.$$

Optimization problem

Let $p \in [0, 1)$.

Minimize

$$J(u) := f(u) + \frac{\alpha}{2} \|u\|_{L^2(\Omega)}^2 + \beta \|u\|_p$$

over all $u \in L^2(\Omega)$ satisfying

$$u \in \mathcal{U}_{\text{ad}} := \{v \in L^2(\Omega) : |v| \leq b \text{ a.e. on } \Omega\}.$$

Reference: [Ito-Kunisch '14][DW '19]

Example

$f(u) = \frac{1}{2} \|y(u) - y_d\|_{L^2(\Omega)}^2$ with $y(u)$ being the solution of a pde to control u .

Lower semicontinuity

- $x \mapsto |x|_p$ is lower semicontinuous on \mathbb{R} ,
- $u \mapsto \|u\|_p$ is lower semicontinuous on $L^q(\Omega)$,
- $u \mapsto \|u\|_p$ is seq. weakly lower semicontinuous on ℓ^q ,
- $u \mapsto \|u\|_p$ is *NOT* seq. weakly lower semicontinuous on $L^q(\Omega)$.

Example

Define $\Omega = (0, 1)$ and

$$f_n(x) := 1 + \text{sign} \sin(2n\pi x).$$

Then $f_n \rightharpoonup 1 =: f$ in $L^q(\Omega)$, $1 \leq q < \infty$, but

$$\|f_n\|_p = 2^{p-1} < 1, \quad \|f\|_p = 1.$$

Existence of solutions cannot be proven. No regularizing effect.

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Finite-dimensional case

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be continuously differentiable. Consider

$$\min f(x) + \|x\|_p$$

with $\|x\|_p := \sum_i |x_i|_p$.

- (1) The point $x = 0$ is always a local minimum.
- (2) If \bar{x} is locally optimal, then

$$\nabla f(\bar{x})_i + p \operatorname{sign}(\bar{x}_i) |\bar{x}_i|^{p-1} = 0 \quad \forall i : \bar{x}_i \neq 0.$$

No information on $\nabla f(\bar{x})_i$ if $\bar{x}_i = 0$.

- (3) Analogous results hold for optimization in sequence spaces.

Pontryagin maximum principle

Theorem

Let \bar{u} be a local solution of the L^p -problem. Then it holds

$$\bar{u}(x) = \arg \min_{|u| \leq b} \nabla f(\bar{u})(x) \cdot u + \frac{\alpha}{2} |u|^2 + \beta |u|_p$$

for almost all $x \in \Omega$.

- Stronger optimality condition than in the finite-dimensional case.
- No derivative of $u \mapsto |u|_p$ appears.

Proof uses needle perturbations

$$d_n(x) = \chi_{B_{r_n}(x_0)}(x) \cdot (v - \bar{u}(x)) : \quad r_n \rightarrow 0, \quad |v| \leq b$$

and Lebesgue's differentiation theorem.

[Casas '94][Ito, Kunisch '14]

Optimality conditions - ideas of proof

Convex differentiable optimization:

Fix direction $u - \bar{u}$, compute

$$\lim_{t \searrow 0} \frac{f(\bar{u} + t(u - \bar{u})) - f(\bar{u})}{t}.$$

Pontryagin maximum principle:

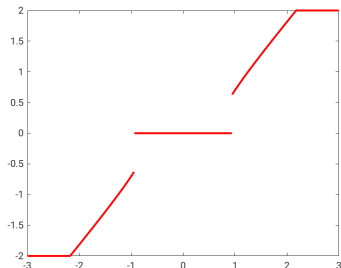
Fix amplitude $v \in \mathbb{R}$, compute

$$\lim_{r \searrow 0} \frac{f(\bar{u} + \chi_{B_r(x)}(v - \bar{u})) - f(\bar{u})}{|B_r(x)|}.$$

Pontryagin maximum principle

The control \bar{u} satisfies PMP if and only if

$$(-\nabla f(\bar{u})(x), \bar{u}(x)) \in P \quad \text{for a.a. } x$$



$P : \mathbb{R} \rightrightarrows \mathbb{R}$ is monotone with closed graph, but not maximal monotone.

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Motivation - steepest descent

Consider

$$\min f(x).$$

Gradient descent step

$$x_{k+1} = x_k - t_k \nabla f(x_k)$$

is a solution of

$$\min f(x_k) + \nabla f(x_k)(x - x_k) + \frac{1}{2t_k} \|x - x_k\|^2.$$

Motivation - proximal gradient

Consider

$$\min f(x) + g(x).$$

Compute x_{k+1} as one solution of

$$\min f(x_k) + \nabla f(x_k)(x - x_k) + \frac{1}{2t_k} \|x - x_k\|^2 + g(x).$$

or equivalently as

$$x_{k+1} \in \text{prox}_{t_k g}(x_k - t_k \nabla f(x_k))$$

Still involves the non-smooth function g .

Example

For $g = \|\cdot\|_1$ the resulting method is soft-thresholding applied to a gradient step.

Proximal gradient step - pointwise

Set $L := \frac{1}{t}$.

Determine u_{k+1} as a solution of

$$\begin{aligned} \min f(u_k) + \nabla f(u_k)(u - u_k) + \frac{L}{2} \|u - u_k\|_{L^2(\Omega)}^2 \\ + \frac{\alpha}{2} \|u\|_{L^2(\Omega)}^2 + \beta \|u\|_p + h_{\mathcal{U}_{\text{ad}}}(u). \end{aligned}$$

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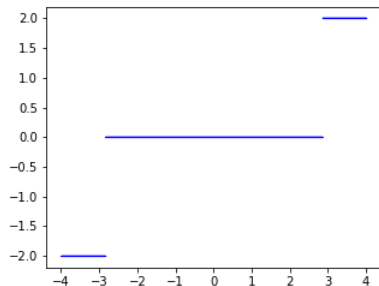
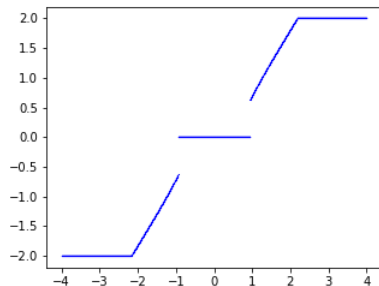
Pointwise minimization:

$$u_{k+1}(x) \in \text{prox}_{L^{-1}g} \left(u_k(x) - L^{-1} \nabla f(u_k)(x) \right) \quad \text{for a.a. } x \in \Omega$$

where

$$g(u) := \frac{\alpha}{2} |u|^2 + \beta |u|_p + I_{[-b,b]}(u).$$

Proximal operator of g



Important property for $u \in \text{prox}_{L^{-1}g}(v)$:

$$\text{Either } u = 0 \text{ or } |u| \geq u_0$$

with $u_0 > 0$ depending on L .

Iteration methods based on PMP

PMP is equivalent to minimizing some Hamiltonian:

$$\bar{u}(x) = \arg \min_{|u| \leq b} H(\bar{y}(x), u, \bar{p}(x)).$$

Fixed-point method

[Krylov, Černous'ko '62]

$$u_{k+1} := \arg \min_{|u| \leq b} H(y_k(x), u, p_k(x))$$

.. and with prox-term

$$u_{k+1} := \arg \min_{|u| \leq b} H(y_k(x), u, p_k(x)) + \frac{L_k}{2} (u - u_k(x))^2$$

[Sakawa, Shindo '80, Bonnans '86, Breitenbach, Borzi '19]

If control appears linearly in the state equation, this method is equivalent to the proximal gradient method.

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Setting

(A1) $g(u) := \frac{\alpha}{2}|u|^2 + \beta|u|_p + I_{[-b,b]}(u)$

(A2) $f : L^2(\Omega) \rightarrow \mathbb{R}$ is weakly lower semicontinuous and bounded from below,

(A3) $f : L^2(\Omega) \rightarrow \mathbb{R}$ is Fréchet differentiable,

(A4) ∇f is Lipschitz continuous from $L^2(\Omega)$ to $L^2(\Omega)$ with modulus L_f :

$$\|\nabla f(u_1) - \nabla f(u_2)\|_{L^2(\Omega)} \leq L_f \|u_1 - u_2\|_{L^2(\Omega)}$$

for all $u_1, u_2 \in L^2(\Omega)$.

Convergence analysis

Theorem

Suppose $L > L_f$.

- (1) The sequence $(f(u_k) + g(u_k))$ is monotonically decreasing and converging.
- (2) $\sum_{k=1}^{\infty} \|u_{k+1} - u_k\|_{L^2(\Omega)}^2 \rightarrow 0$.
- (3) The sequences (u_k) and $(\nabla f(u_k))$ are bounded in $L^2(\Omega)$ if $\alpha > 0$ or $b < +\infty$.

Characteristic functions (χ_k) converge: no oscillation.

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Define

$$\chi_k(x) := |u_k(x)|_0.$$

- (4) $\sum_{k=1}^{\infty} \|\chi_k - \chi_{k+1}\|_{L^1(\Omega)} < +\infty$.
- (5) $\chi_k \rightarrow \chi$ in $L^1(\Omega)$ for some characteristic function χ .

Characteristic functions (χ_k) converge: no oscillation.

Weak limit points for L^0 -problems

Theorem

Let g be induced by $\|\cdot\|_0$.

Let $u^* \in U_{ad}$ be a weak sequential limit point of the iterates (u_k) in $L^2(\Omega)$. Then it holds

$$f(u^*) + g(u^*) \leq \liminf_{k \rightarrow \infty} (f(u_k) + g(u_k))$$

and

$$(1 - \chi)u^* = 0$$

with χ as above.

Lower semicontinuity along the iterates for L^0 -problems.

[DW '19]

Strong convergence for integer-valued problems

Theorem

Suppose $g = \delta_{\mathbb{Z}}$.

Then $u_k \rightarrow u^*$ in $L^1(\Omega)$.

Proof: $\|u_{k+1} - u_k\|_{L^2(\Omega)}^2 \geq \|u_{k+1} - u_k\|_{L^1(\Omega)}$

$$\sum_{k=0}^{\infty} \|u_{k+1} - u_k\|_{L^1(\Omega)} \leq \sum_{k=0}^{\infty} \|u_{k+1} - u_k\|_{L^2(\Omega)}^2 < +\infty$$

Passing to the limit in PMP

Two problems:

(1) $\frac{L}{2}(u - u_k)^2$ is there to stay: u_{k+1} satisfies

$$\begin{aligned} \nabla f(u_k)(u_{k+1} - u_k) + \frac{L}{2}(u_{k+1} - u_k)^2 + g(u_{k+1}) \\ \leq \\ \nabla f(u_k)(u - u_k) + \frac{L}{2}(u - u_k)^2 + g(u) \end{aligned}$$

for all $u \in \mathbb{R}$ for a.a. x .

(2) weak convergence of (u_k) in $L^2(\Omega)$, no pointwise convergence.

Stationarity of limit points

Goal: Rewrite the inclusion

$$u_{k+1} \in \text{prox}_{L^{-1}g} \left(u_k - L^{-1} \nabla f(u_k) \right)$$

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Suppose $\nabla f : L^2(\Omega) \rightarrow L^2(\Omega)$ is completely continuous, e.g.,

$$v_k \rightarrow v \Rightarrow \nabla f(v_k) \rightarrow \nabla f(v).$$

Then $u_{k_n} \rightarrow u^*$ in $L^2(\Omega)$ implies

$$\nabla f(u_{k_n}) + L(u_{k_{n+1}} - u_{k_n}) \rightarrow \nabla f(u^*).$$

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Define G (depending on L) by

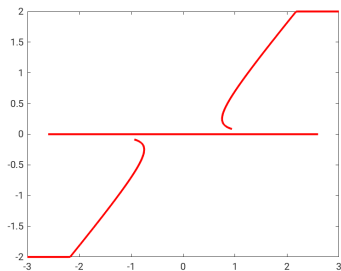
$$u_{k+1} \in G \left(- (\nabla f(u_k) + L(u_{k+1} - u_k)) \right).$$

(Fixed points of $G \circ (-\nabla f)$ are L -stationary [Beck, Eldar '13])

Stationarity of limit points

Given

$$u_{k+1}(x) \in G\left(-(\nabla f(u_k) + L(u_{k+1} - u_k))(x)\right)$$



$G, \tilde{G} : \mathbb{R} \rightrightarrows \mathbb{R}$ have closed graphs, are not single-valued, not monotone, $G \supset \tilde{G} \supset P$.

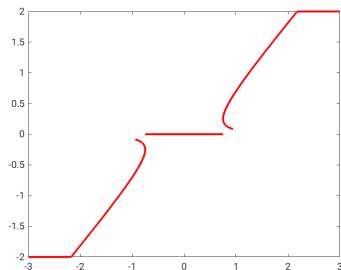
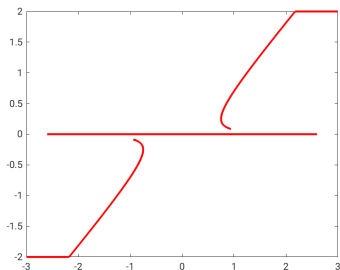
Stationarity of limit points

Given

$$u_{k+1}(x) \in G\left(-(\nabla f(u_k) + L(u_{k+1} - u_k))(x)\right)$$

construct \tilde{u}_{k+1} such that $\chi_{k+1}\tilde{u}_{k+1} = \chi_{k+1}u_{k+1}$ and

$$\tilde{u}_{k+1}(x) \in \chi_{k+1}(x)\tilde{G}\left(-(\nabla f(u_k) + L(u_{k+1} - u_k))(x)\right).$$



$G, \tilde{G} : \mathbb{R} \rightrightarrows \mathbb{R}$ have closed graphs, are not single-valued, not monotone, $G \supset \tilde{G} \supset P$.

Stationarity of limit points

Theorem

Suppose $\nabla f : L^2(\Omega) \rightarrow L^2(\Omega)$ is completely continuous.
Let u^* be a weak limit point of (u_k) . Then it holds

$$u^*(x) \in \left[G \cup \overline{\text{conv}} \tilde{G} \right] \left(-\nabla f(u^*)(x) \right)$$

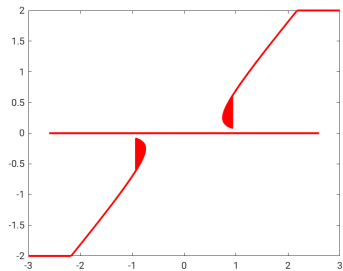
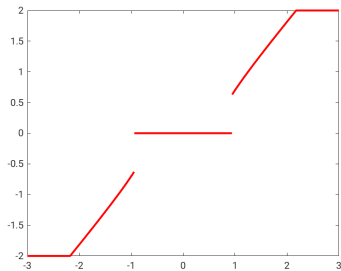
and

$$(1 - \chi)u^* = 0.$$

- Weaker than PMP (even without taking $\overline{\text{conv}}$). Maps G, \tilde{G} depend monotonically on L . For $L = 0$, PMP is recovered.
- For convex g , weak sequential limit points would be stationary.
- If $(\nabla f(u_k))$ converges pointwise a.e., then result holds without $\overline{\text{conv}}$.

PMP versus stationarity of limit points

Comparison of P and $G \cup \overline{\text{conv}}\tilde{G}$:



Strong convergence

$$\Omega_{k,\text{bad}} := \left\{ x : u_k(x) \neq 0 \text{ and } u_k(x) \text{ is on bad branch of } G(\cdot) \right\}$$

Theorem

Suppose $\nabla f : L^2(\Omega) \rightarrow L^2(\Omega)$ is completely continuous. Let g be induced by $\|\cdot\|_p$, $p \in (0, 1)$. Let $\alpha > 0$.

Assume

$$\text{meas}(\Omega_{k,\text{bad}}) \rightarrow 0.$$

Suppose $u_{k_n} \rightharpoonup u^*$. Then $u_{k_n} \rightarrow u^*$ and

$$\chi u^*(x) \in \chi G\left(-\nabla f(u^*)(x)\right).$$

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Example

Define $f(u)$ by

$$f(u) := \frac{1}{2} \|y_u - y_d\|_{L^2(\Omega)}^2,$$

where y_u denotes the weak solution of the elliptic partial differential equation

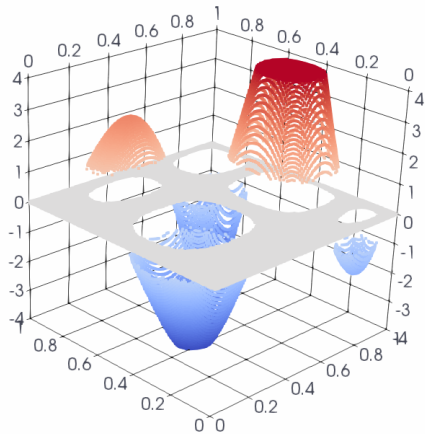
$$-\Delta y = u \quad \text{in } \Omega, \quad y = 0 \quad \text{on } \partial\Omega.$$

Here, we chose $\Omega = (0, 1)^2$, [Ito, Kunisch '14]

$$y_d(x_1, x_2) = 10x_1 \sin(5x_1) \cos(7x_2), \quad \alpha = 0.01, \quad \beta = 0.01, \quad b = 4$$

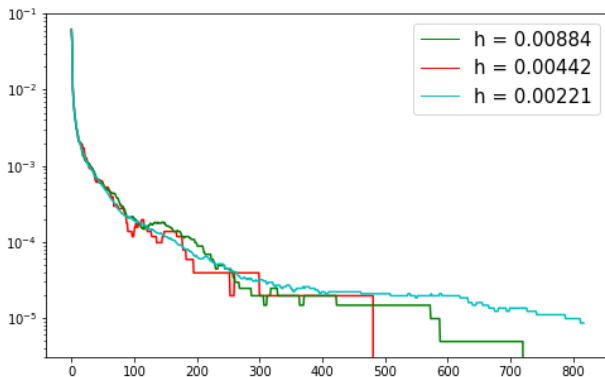
Solution

Optimal control u for $p = 0.8$



The bad set

Measure of $\Omega_{k,\text{bad}}$ for three different discretizations



Outlook

- results extend to sparsity-promoting g
- L^0 -constraints $\|u\|_0 \leq \tau$,
- group sparsity: L^0 in space, L^2 in time,
- second-order optimality conditions in cooperation with Eduardo Casas [SICON'20] and with Gerd Wachsmuth,
- H^1 -regularization (existence of solutions, but no maximum principle),
- H^s -regularization.