

Variational curvatures and total variation regularization

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Introduction

We consider an ill-posed (e.g. A compact) linear operator equation

$$Au = f + w$$

where $u: \Omega \to \mathbb{R}$ for $\Omega \subset \mathbb{R}^d$, $d \ge 2$, and w noise (deterministic).

Assumption: the true data u^{\dagger} to be recovered consists of distinct objects; smooth areas separated by sharp, discontinuous edges.



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Total variation regularization: Assuming $A:L^q(\Omega)\to Y$ bounded with Y a Banach space and fixing $\sigma>1$, the regularized solutions

$$u_{\alpha,w} \in \underset{u \in L^q(\Omega)}{\operatorname{arg \, min}} \frac{1}{\sigma} \|Au - (f+w)\|_Y^{\sigma} + \alpha \text{TV}(u)$$

balance a priori information about u encoded in having a low variation, and fidelity to the measurements available f+w.

Spaces/exponents: Typically q = d/(d-1), Y generic, will usually write $\sigma = 2$ (which does not always fit the assumptions) for simplicity.

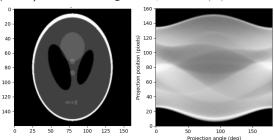


TV is more than denoising

Radon transform in the plane: Integrate over lines determined by $(\theta,t)\in S^1\times\mathbb{R}$,

$$\mathcal{R}u(\theta,t) = \int_{\{x \cdot \theta = t\}} u(x) \, \mathrm{d}\mathcal{H}^1(x).$$

 $\|\mathcal{R}u\|_{H^{s+\frac{1}{2}}} \leqslant C\|u\|_{H^s}$ for compactly supported u, so inversion is ill-posed (noise is amplified). In our setting $s=0,\,Y=L^4(\Omega)$ or $Y=L^2(\Omega)$.



Also higher dimensions: A reasonable starting model for computed tomography is the 3D analogue (X-Ray transform). Here $q \neq 2$.



Definitions

Definition: We call total variation the norm of the distributional gradient as a vector-valued Radon measure.

$$TV(u) := \sup \left\{ \int_{\Omega} u \operatorname{div} z \, dx \, \middle| \, z \in C_0^{\infty}(\Omega; \mathbb{R}^d), \|z\|_{L^{\infty}(\Omega)} \leqslant 1 \right\}.$$

If finite for $u \in L^1(\Omega)$, then u has bounded variation: $u \in BV(\Omega)$.

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If u smooth, $TV(u) = \int_{\Omega} |\nabla u| dx$.

For 1_E the indicatrix of a set E, define the perimeter $Per(E) := TV(1_E)$.



For a ball B(x,r) we have $\mathrm{TV}(1_{B(x,r)})=2\pi r$ and the optimal z is aligned with the normal to the circle $\partial B(x,r)$.

We have in particular

$$Per(A \cup B) + Per(A \cap B) \leq Per(A) + Per(B)$$

generalizing 'length of the boundary' to irregular sets.



Convergence of solutions

First theoretical question: Analyze the low-noise regime in which the noise intensity and the a priori chosen parameter α tend to zero.

¹R. Acar, C. R. Vogel. Inverse Prob. 10(6), 1994.



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Basic convergence result¹: If $f \in \text{Ran}(A)$ and $\alpha_n, w_n \to 0$ with $\|w_n\|_Y^2/\alpha_n \leqslant C$, for

$$u_n := u_{\alpha_n, w_n} \in \operatorname*{arg\,min}_{u \in L^q(\Omega)} \frac{1}{2} \left\| Au - (f+w) \right\|_Y^2 + \alpha \mathrm{TV}(u)$$

we have (up to a subsequence) $u_n \rightharpoonup u^{\dagger}$ weakly in $L^{d/(d-1)}(\Omega)$ where u^{\dagger} is a minimal TV solution of Au = f.

Moreover, also $u_n \to u^\dagger$ strong in $L^{\bar q}_{\rm loc}(\Omega)$ for $\bar q < d/(d-1)$, and in $L^{\bar q}(\Omega)$ if Ω is bounded.

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Moreover, also $u_n \to u^{\dagger}$ strong in $L_{loc}^{\bar{q}}(\Omega)$ for $\bar{q} < d/(d-1)$, and in $L^{\bar{q}}(\Omega)$ if Ω is bounded.

Convergence rates: Linear rates in Bregman distance², under the source condition $A^*p_0 \in \partial TV(u^{\dagger})$ and linear parameter choice $||w_n||/\alpha_n \leqslant C$.

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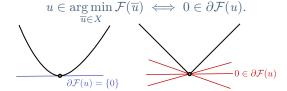
²M. Burger, S. Osher. Inverse Prob. 20(5), 2004.



Subgradients and Bregman distances

If $\mathcal{F}: X \to \mathbb{R} \cup \{+\infty\}$, define the (set-valued) subgradient in X^* by $v \in \partial \mathcal{F}(u) \subset X^* \iff \mathcal{F}(\overline{u}) \geqslant \mathcal{F}(u) + \langle v, \overline{u} - u \rangle_{(X^*, X)}$.

Fermat theorem for convex unconstrained minimization:

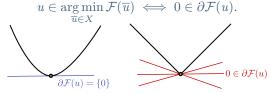




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Bregman distance: Denoting $v_0 := A^* p_0 \in \partial TV(u^{\dagger})$,

$$D_{v_0}(u_n, u^{\dagger}) := \mathrm{TV}(u_n) - \mathrm{TV}(u^{\dagger}) - \langle v_0, u_n - u^{\dagger} \rangle_{(L^2, L^2)}$$

involves $\mathrm{TV}(u_n)$, no translation to $\|u_n - u^{\dagger}\|_{L^2}$ without strong convexity.

However: Convergence rates in norm are possible³ under an assumption of the type " $A^*A \ge \epsilon \operatorname{Id}$ on $\Sigma \supset \operatorname{supp} Du^{\dagger}$ with Lipschitz boundary".

³T. Valkonen. Regularisation, optimisation, subregularity. arXiv:2011.07575



Optimality condition I

Formal Euler-Lagrange equation: (with $Y = L^2$)

$$-\frac{A^*(Au_{\alpha,w}-f-w)}{\alpha} = \operatorname{div}\left(\frac{\nabla u_{\alpha,w}}{|\nabla u_{\alpha,w}|}\right).$$

With $u_{\alpha,w} \in C^2$ and at x with $\nabla u_{\alpha,w}(x) \neq 0$, the right hand side $\operatorname{div}(\nabla u_{\alpha,w}(x)/|\nabla u_{\alpha,w}(x)|)$ is the mean curvature of $\partial \{u_{\alpha,w} > u_{\alpha,w}(x)\}$.



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But these assumptions are very far from the typical use cases:



Ideal $u_0 \in \{0,1\}$, blurry and noisy $f = Au_0 + w$, solution $u_{\alpha,w}$, $\partial \{u_{\alpha,w} > 0.5\}$ in red.



Optimality condition II

Rigorous optimality condition: (with j duality mapping of Y)

$$v_{\alpha,w}:=-rac{1}{lpha}A^*j(Au_{\alpha,w}-f-w)\in\partial\mathrm{TV}(u_{\alpha,w}),$$
 or

$$\mathrm{TV}(u_{\alpha,w}) - \int_{\Omega} v_{\alpha,w} u_{\alpha,w} \leqslant \mathrm{TV}(\overline{u}) - \int_{\Omega} v_{\alpha,w} \overline{u}, \text{ for all } \overline{u} \in L^q(\Omega).$$

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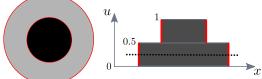
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Level sets? Slice with the coarea and layer-cake formulas

$$\mathrm{TV}(u) = \int_{-\infty}^{\infty} \mathrm{Per}(\{u > t\}) \, \mathrm{d}t, \quad \int_{\Omega} \overline{u} \, \mathrm{d}x = \int_{0}^{\infty} |\{\overline{u} > t\}| \, \mathrm{d}t \text{ if } \ \overline{u} \geqslant 0$$





Variational curvatures of level sets

We can write optimality directly in terms of the level sets:

$$\{u_{\alpha,w} > t\} \in \underset{F}{\operatorname{arg\,min}} \operatorname{Per}(F) - \int_{F} v_{\alpha,w} \quad (\text{for } t > 0)$$

which is the definition⁴ of having variational mean curvature $v_{\alpha,w}$. If everything was smooth, it would mean $v_{\alpha,w}\big|_{\partial\{u_{\alpha,w}>t\}}$ is the mean curvature of $\partial\{u_{\alpha,w}>t\}$ (as before).

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Variational curvatures are not unique and nonlocal, since they are defined with Lebesgue/volume integrals!

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Variational curvatures are not unique and nonlocal, since they are defined with Lebesgue/volume integrals!

Integrability properties of $v_{\alpha,w}$ imply regularity of $\partial\{u_{\alpha,w}\}$. For the energy to not encourage small structures need to control $v_{\alpha,w}$ in L^d_{loc} , scaling:

$$\int_{B(x,r)} |v_{\alpha,w}| \leqslant r^{d-1} \|v_{\alpha,w}\|_{L^d(B(x,r))}, \text{ and } \operatorname{Per}\left(B(x,r)\right) = C r^{d-1}.$$

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A better mode of convergence

Convergence in L^p norm $||u_n - u^{\dagger}||_{L^p} \to 0$, not really adequate for measuring shapes of objects $U, V \subset \mathbb{R}^d$ with boundaries $\partial U, \partial V$:

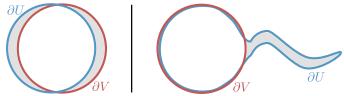


Situations with comparable $|U\Delta V| = ||1_U - 1_V||_{L^p}^p$.



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Situations with comparable $|U\Delta V| = \|1_U - 1_V\|_{L^p}^p$, but very different $d_H(\partial U, \partial V)$.

Better mode: Convergence of boundaries in Hausdorff distance

$$d_{H}(\partial U, \partial V) := \max \left\{ \sup_{x \in \partial U} \inf_{y \in \partial V} |x - y|, \sup_{y \in \partial V} \inf_{x \in \partial U} |x - y| \right\}$$

can be seen as a geometric version of uniform convergence. Desirable to have it for the level set boundaries $\partial \{u_{\alpha,w} > t\}$ to $\partial \{u_0 > t\}$.



How to get Hausdorff convergence?

If the u_n have a common compact support, L^1_{loc} convergence $u_n \to u$ implies $|\{u_n>t\}\Delta\{u^\dagger>t\}|\to 0$ for a.e. t.



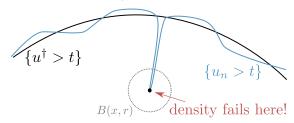
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To improve to Hausdorff, it is sufficient to prove that there are $r_0>0$ and C>0 such that for all $r\leqslant r_0$ and $x\in\partial\{u_n>t\}$

$$\frac{|\{u_n>t\}\cap B(x,r)|}{|B(x,r)|}\geqslant C \text{ and } \frac{|B(x,r)\setminus\{u_n>t\}|}{|B(x,r)|}\geqslant C,$$

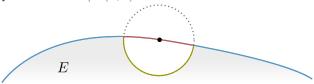
density estimates, uniform in n, x and t.





Density estimates I

Let $E = \{u_{\alpha,w} > t\}$. To get⁵ the estimate for $|E \cap B(x,r)|$, test optimality of E with $E \setminus B(x,r)$:



Using minimality and basic properties of the perimeter:

Lemma

$$\operatorname{Per}(E \cap B(x,r)) - \int_{E \cap B(x,r)} v_{\alpha,w} \leqslant 2 \operatorname{Per}(B(x,r); E^{(1)})$$
$$= 2 \frac{d}{dr} |E \cap B(x,r)| \text{ for a.e. } r.$$

⁵E. Gonzalez, U. Massari, I. Tamanini. Atti Accad. Naz. Lincei Cl. Sci. Fis. Mat. Nat. Rend. Lincei, 4(3), 1993.



Density estimates II

With Hölder inequality:

$$\left| \int_{E \cap B(x,r)} v_{\alpha,w} \right| \leq |E \cap B(x,r)|^{\frac{d-1}{d}} ||v_{\alpha,w}||_{L^{d}(E \cap B(x,r))}$$

$$\leq |E \cap B(x,r)|^{\frac{d-1}{d}} \left(||v_{\alpha,0}||_{L^{d}(E \cap B(x,r))} + ||v_{\alpha,w} - v_{\alpha,0}||_{L^{d}(\mathbb{R}^{d})} \right).$$



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If we can (choosing r small enough and α large in terms of ||w||) get

$$\|v_{\alpha,0}\|_{L^d(E\cap B(x,r))}<\varepsilon$$
 and $\|v_{\alpha,w}-v_{\alpha,0}\|_{L^d(\mathbb{R}^d)}<\eta$,

the isoperimetric inequality $\operatorname{Per}(E \cap B(x,r)) \geqslant C_d |E \cap B(x,r)|^{\frac{d-1}{d}}$ and the lemma provide

$$|E \cap B(x,r)|^{\frac{d-1}{d}}(C_d - \varepsilon - \eta) \leq 2\frac{\mathrm{d}}{\mathrm{d}r}|E \cap B(x,r)|$$
 for a.e. r ,

a differential inequality giving $|E \cap B(x,r)| \geqslant Cr^d = C'|B(x,r)|$.



Strategy

This Hausdorff convergence was proved proved first⁶ for $A = \mathrm{Id}$ (denoising) and $\Omega = \mathbb{R}^2$ under the conditions $\partial \mathrm{TV}(u^\dagger) \neq \emptyset$ and $\|w_n\|_{L^2(\Omega)}/\alpha_n \leqslant C$.

Our goal has been to extend this result to linear inverse problems, higher dimensions, bounded domains, and possibly without source condition.

⁶A. Chambolle, V. Duval, G. Peyré, and C. Poon. Inverse Prob. 33(1), 2017.



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General proof scheme:

- Fenchel dual problem lives in in $(L^q)^* = L^{q/(q-1)}$ and involves $v_{\alpha,w}$ that should belong to L^d .
- Strong L^d convergence of noiseless dual variables $v_{\alpha,0}$.
- Stability estimates for $v_{\alpha,w}$ with respect to w.
- Both of these together imply uniform density estimates of $\{u_{\alpha,w} > t\}$ to improve the mode of convergence.

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The dual problem

Using the characterization for one-homogeneous functionals

$$v \in \partial TV(u) \iff v \in \partial TV(0) \text{ and } \int_{\Omega} vu = TV(u),$$

the Fenchel dual of our problem is to maximize among $p \in Y^*$ such that $A^*p \in \partial TV(0)$, the quantity

$$\mathcal{D}_{\alpha,w}(p) := \langle p, f + w \rangle_{(Y^*,Y)} - \frac{\alpha}{2} \|p\|_{Y^*}^2.$$



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$$\mathcal{D}_{\alpha,w}(p) := \langle p, f + w \rangle_{(Y^*,Y)} - \frac{\alpha}{2} \|p\|_{Y^*}^2.$$

A is continuous and the fidelity term as well, so strong duality holds:

$$\inf_{u \in L^q(\Omega)} \mathcal{F}_{\alpha,w}(u) = \sup_{A^* p \in \partial \text{TV}(0)} \mathcal{D}_{\alpha,w}(p),$$

the maximizer $p_{\alpha,w}$ is unique and we have the (already familiar) optimality condition

$$v_{\alpha,w} := A^* p_{\alpha,w} \in \partial TV(u_{\alpha,w}).$$



Stability of the dual wrt noise

$$p_{\alpha,w} = \underset{\substack{p \in Y^* \\ A^*p \in \partial \text{TV}(0)}}{\arg \min} \|\alpha^{-1}(f+w)\|_Y^2 - \frac{2}{\alpha} \left(\langle p, f+w \rangle_{(Y^*,Y)} - \frac{\alpha}{2} \|p\|_{Y^*}^2 \right).$$



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This parallels the formula for projections onto a convex set in a Hilbert space (which are nonexpansive, so they give a linear stability estimate)

$$\inf_{\substack{p \in H \\ A^* p \in \partial \mathrm{TV}(0)}} \left\| \frac{f+w}{\alpha} \right\|_H^2 - 2 \left\langle p, \, \frac{f+w}{\alpha} \right\rangle_H + \|p\|_H^2 = \inf_{\substack{p \in H \\ A^* p \in \partial \mathrm{TV}(0)}} \left\| p - \frac{f+w}{\alpha} \right\|_H^2.$$



Stability of the dual wrt noise

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Our dual can be interpreted as a generalized (not metric!) projection⁷ which is also stable assuming uniform convexity of Y^* :

$$||p_{\alpha,w} - p_{\alpha,0}||_{Y^*} \le \rho_{Y,2} \left(\frac{||w||_Y}{2\alpha}\right),$$

applying A^* we can pick α with $\|v_{\alpha,w}-v_{\alpha,0}\|_{L^{q'}(\Omega)}\leqslant \eta$ for any $\eta>0$.

⁷Alber, Notik. Comm. Appl. Nonlinear Anal., 1995.



Strong convergence of noiseless duals

The formal limits of the primal and dual problems when $\alpha, w \to 0$ write

$$\inf\{\mathrm{TV}(u)\ |\ u\in L^q(\Omega),\, Au=f\} \text{ attained by } u^\dagger\text{, and}$$

$$\sup_{A^*p\in\partial\mathrm{TV}(0)} \langle p\,,\,f\rangle_{(Y^*,\,Y)} = \sup_{A^*p\in\partial\mathrm{TV}(0)} \int_\Omega (A^*p) u^\dagger.$$



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The fidelity term became a constraint (discontinuous), so no strong duality. Attainment in the dual for u^{\dagger}, p_0 with **source condition**

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In consequence the sequence $(v_{\alpha_n,0})=(A^*p_{\alpha_n,0})$ is L^d -equiintegrable: for each $\varepsilon>0$ there is r_0 for which

$$\int_{B(x,r_0)} |v_{\alpha_n,0}|^d \leqslant \varepsilon^d \text{ for all } x \text{ and } n.$$



Geometric convergence under source condition

We assumed that the $\{u_{\alpha,w}\}$ have a common compact support, but for q=d/(d-1) this can be proved again with stability and equiintegrability at infinity

$$\int_{\Omega \backslash B(0,R)} |v_{\alpha,0}|^d \leqslant \varepsilon^d \text{ for } R > R_0.$$



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Theorem (I., Mercier, Scherzer '18 (d=2), I., Mercier '20 (d>2))

Let q=d/(d-1), $\sigma\leqslant d/(d-1)$, Ω either \mathbb{R}^d or a bounded domain with Neumann or Dirichlet (geometric restrictions!) boundary, $\alpha_n,w_n \xrightarrow[n \to \infty]{} 0$ related by

$$\alpha_n^{\frac{1}{\sigma-1}} \geqslant C(d, \Omega, Y, \sigma) \|w_n\|_Y$$

and assume the source condition $\operatorname{Ran}(A^*) \cap \partial \operatorname{TV}(u^{\dagger}) \neq \emptyset$.

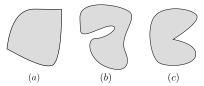
Then for u_n a subsequence of minimizers such that $u_n \to u^\dagger$ in L^1_{loc} and almost every t>0, the level set boundaries $\partial\{u_n>t\}$ converge to $\partial\{u^\dagger>t\}$ in the sense of Hausdorff convergence.



Density estimates with boundary conditions

Dirichlet: Prescribe zero values outside Ω which has a variational curvature κ_{Ω} with $\kappa_{\Omega}|_{\mathbb{R}^d\setminus\Omega}\in L^d(\mathbb{R}^d\setminus\Omega)$,

 $\kappa_{\alpha,w} = v_{\alpha,w} 1_{\Omega} + \kappa_{\Omega} 1_{\mathbb{R}^d \setminus \Omega}$ also a curvature for $\{u_{\alpha,w} > t\}$.



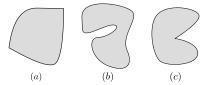
(a) and (b) are allowed, (c) is not.



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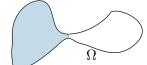
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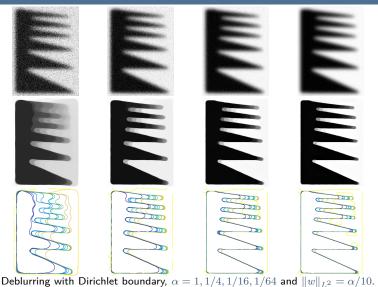
(a) and (b) are allowed, (c) is not.

Neumann: Variation in Ω , isoperimetric inequality fails but we have the BV Poincaré-Sobolev inequality (η depends on embedding constant).





A numerical example





Boundedness under source condition

Theorem (Bredies, I., Mercier, soon)

Under the same conditions (minus the geometric restriction on Ω), and for the full sequence,

$$\|u_n\|_{L^{\infty}(\Omega)} \leqslant C\left(u^{\dagger}, \sup_{n} \alpha_n^{-\frac{1}{\sigma-1}} \|w_n\|_Y\right) < +\infty,$$

and in consequence, if Ω is bounded and $u_n o u^\dagger$ in L^1 , also

$$u_n \to u^{\dagger}$$
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Under the same conditions (minus the geometric restriction on Ω), and for the full sequence,

$$||u_n||_{L^{\infty}(\Omega)} \leqslant C\left(u^{\dagger}, \sup_{n} \alpha_n^{-\frac{1}{\sigma-1}} ||w_n||_Y\right) < +\infty,$$

and in consequence, if Ω is bounded and $u_n \to u^{\dagger}$ in L^1 , also

$$u_n \to u^{\dagger}$$
 strongly in L^p for all $p \in (1, \infty)$.

Remarks:

The measurements f+w could be unbounded. And even if they were bounded, there is A to deal with.

Analogously if $\partial TV(u^{\dagger}) \neq \emptyset$, then u^{\dagger} itself is bounded.

The bound is not explicit, since we use equiintegrability of $v_{\alpha,0}$.



Source condition and L^d curvatures

The source condition is not harmless: for the indicatrix of $S=(0,1)^2\subset\mathbb{R}^2$, we have no curvature in L^2 and $\partial_{L^2}\mathrm{TV}(1_S)=\emptyset$.

This is because 'cutting' a corner K_{δ} of side length δ reduces perimeter by a fixed factor, which would contradict $v_S \in L^2$:

$$C\delta \leqslant \operatorname{Per}(S) - \operatorname{Per}(S \setminus K_{\delta}) \leqslant \int_{K_{\delta}} v_{S} \leqslant \delta ||v_{S}||_{L^{2}(K_{\delta})}^{2},$$







'Denoised' ($A=\mathrm{Id}$), large lpha

But the square satisfies density estimates. And without noise, one can find a solution explicitly and the Hausdorff convergence still holds.



Spaces for curvatures and regularity

So far: To prove density estimates one uses (local) bounds in L^d , which in turn prevent mild singularities which we want to still handle.

Strong regularity: For p>d and d<8, a set E having a variational curvature in L^p implies⁸ that $\partial E\in C^{1,\alpha}$.

Regularity with L^d **curvature?** bi-Hölder local parametrizations of the boundary⁹, bi-Lipschitz¹⁰ for d=2. There are examples¹¹ of planar sets with singular points but with variational mean curvatures in L^2 .

What is the optimal space? A more general (critical) setting for variational curvatures is the Morrey space $L^{1,d-1}$, but there are counterexamples¹² with no density estimates.

⁸U. Massari. Rend. Sem. Mat. Univ. Padova, 53, 1975.

⁹E. Paolini. Manuscripta Math., 97(1), 1998.

¹⁰L. Ambrosio, E. Paolini. Ricerche Mat. 48(suppl.), 1999.

¹¹E. Gonzalez, U. Massari, I. Tamanini. Atti Accad. Naz. Lincei Cl. Sci. Fis. Mat. Nat. Rend. Lincei, 4(3), 1993.

¹²Q. Li, M. Torres. Adv. Calc. Var. 12(2), 2019.



Denoising by comparison I

For denoising we can work on $v_{\alpha,w} = \alpha^{-1}(f + w - u_{\alpha,w})$ pointwise.

Lemma

Assume that the finite perimeter sets E_1 and E_2 admit variational mean curvatures κ_1 and κ_2 respectively, and such that $\kappa_1 < \kappa_2$ in $E_1 \setminus E_2$. Then $|E_1 \setminus E_2| = 0$, that is $E_1 \subseteq E_2$ up to Lebesgue measure zero.

Write

$$\Pr(E_1) - \int_{E_1} \kappa_1 \leqslant \Pr(E_1 \cap E_2) - \int_{E_1 \cap E_2} \kappa_1,$$

 $\Pr(E_2) - \int_{E_2} \kappa_2 \leqslant \Pr(E_1 \cup E_2) - \int_{E_1 \cup E_2} \kappa_2.$

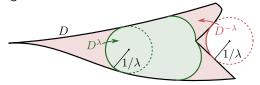
Summing and using $Per(E_1) + Per(E_2) \leq Per(E_1 \cap E_2) + Per(E_1 \cup E_2)$,

$$\int_{E_1 \setminus E_2} \kappa_2 \leqslant \int_{E_1 \setminus E_2} \kappa_1.$$



Denoising by comparison II

Let D be a bounded set of finite perimeter. Then D has 13 at least one variational mean curvature in $\kappa_D \in L^1(\mathbb{R}^d)$, minimal in $L^p(D)$ norm for all p>1 among such curvatures.



With $g \in L^1(\mathbb{R}^d)$ with g > 0 consider

$$D^{\lambda} \in \operatorname*{arg\,min}_{E \subset D} \operatorname{Per}(E) - \lambda \int_{E} g, \text{ and } \mathbb{R}^{d} \backslash D^{-\lambda} \in \operatorname*{arg\,min}_{F \subset \mathbb{R}^{d} \backslash D} \operatorname{Per}(F) - \lambda \int_{F} g.$$

For $\lambda \to \infty$ the D^{λ} exhaust D, so for $x \in D$ we can define

$$\kappa_D(x) := \inf \left\{ \lambda g(x) \mid \lambda > 0 \text{ and } x \in E^{\lambda} \right\}.$$

¹³E. Barozzi, E. Gonzalez, and I. Tamanini. Proc. Amer. Math. Soc., 99(2), 1987.



Denoising by comparison III

Theorem (I., Mercier '21)

Let
$$q=\sigma=d/(d-1)$$
, $\Omega=\mathbb{R}^d$, $A=\mathrm{Id}$, α_n,w_n related by $\alpha_n^{\frac{1}{\sigma-1}}\geqslant C(d)\|w_n\|$, and $f=1_D$ for D bounded of finite perimeter.

Then for u_n a subsequence of minimizers and almost every t>0, the level set boundaries $\partial\{u_n>t\}$ converge to ∂D in the sense of Hausdorff convergence.

Compare with $\kappa_D \in L^1(\mathbb{R}^d)$, which acts as replacement of $p_0 \in \partial \mathrm{TV}(f)$. Denoising reduces curvature pointwise:

$$|v_{\alpha,0}| \leq |\kappa_D|$$
 and $\operatorname{sign}(v_{\alpha,0}) = \operatorname{sign}(\kappa_D)$.

Since D is arbitrary, the density estimates are not uniform anymore. But using the additional bound obtained by comparing with balls

$$|\kappa_D| \leq \operatorname{dist}(\cdot, \partial D)$$

the Hausdorff convergence still holds.



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- J. A. Iglesias, G. Mercier. Influence of dimension on the convergence of level-sets in total variation regularization. ESAIM. Control, Optimisation and Calculus of Variations, 26:52, 2020. arXiv:1811.12243
- J. A. Iglesias, G. Mercier. Convergence of level sets in total variation denoising through variational curvatures in unbounded domains. SIAM Journal on Mathematical Analysis, 53(2):1509-1545, 2021. arXiv:2005.13910