

Discrete calculus model of Ambrosio-Tortorelli's functional

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Workshop Phase-field models of fracture
Banff International Research Station

Collaborators



Marion Foare



David Coeurjolly



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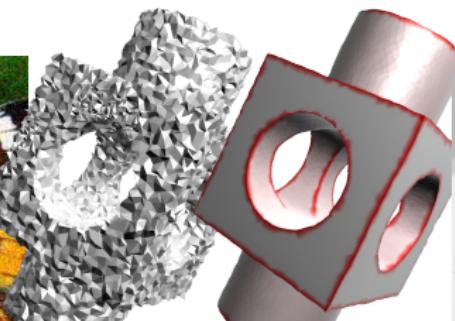


Nicolas Bonneel

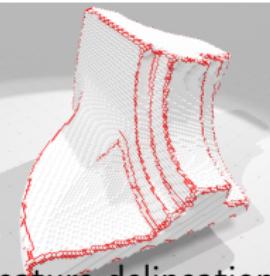
A versatile tool for piecewise smooth image and geometry processing



Image restoration



Mesh denoising



Feature delineation

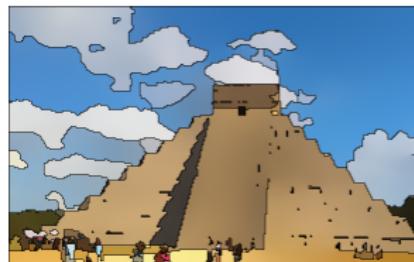
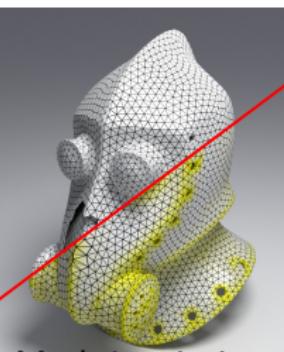
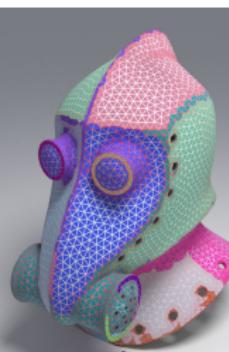


Image segmentation



Mesh segmentation



Mesh inpainting

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Ambrosio-Tortorelli's functional

A brief introduction to discrete calculus

A discrete calculus model of AT

Applications

Mumford-Shah functional

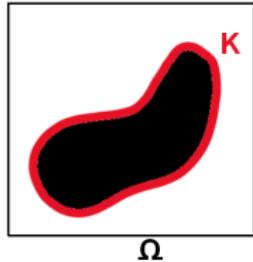
[Mumford and Shah, 1989]

Mumford-Shah functional for image restoration

We minimize

$$\mathcal{MS}(K, \mathbf{u}) = \underbrace{\alpha \int_{\Omega \setminus K} |\mathbf{u} - g|^2 \, dx}_{\text{fidelity term}} + \underbrace{\int_{\Omega \setminus K} |\nabla \mathbf{u}|^2 \, dx}_{\text{smoothness term}} + \lambda \underbrace{\mathcal{H}^1(K \cap \Omega)}_{\text{discontinuities length}}$$

- Ω the image domain
- g the input image
- \mathbf{u} a piecewise smooth approximation of g
- K the set of discontinuities
- \mathcal{H}^1 the Hausdorff measure



Mumford-Shah functional

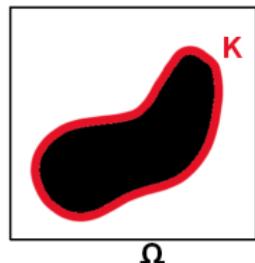
[Mumford and Shah, 1989]

Mumford-Shah functional for image restoration

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Mumford-Shah functional

[Mumford and Shah, 1989]

Notably difficult to minimize

Many relaxations and convexifications have been proposed.

- Total Variation [Rudin et al., 1992] and its variants
- Multi-phase level sets [Vese and Chan, 2002] and follow-ups
- Discrete graph approaches
[Boykov et al., 2001, Boykov and Funka-Lea, 2006]
- Calibration method [Alberti et al., 2003] and associated algorithms
[Pock et al., 2009, Chambolle and Pock, 2011]
- Ambrosio-Tortorelli functional [Ambrosio and Tortorelli, 1992]
- convex relaxations of AT [Kee and Kim, 2014]

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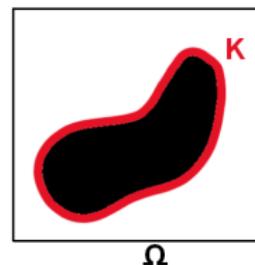
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Ambrosio-Tortorelli functional

[Ambrosio and Tortorelli, 1992]

$$AT_\varepsilon(\textcolor{brown}{u}, \textcolor{green}{v}) = \alpha \int_{\Omega} |\textcolor{brown}{u} - g|^2 \, dx + \int_{\Omega} \textcolor{green}{v}^2 |\nabla \textcolor{brown}{u}|^2 \, dx + \lambda \int_{\Omega} \varepsilon |\nabla \textcolor{green}{v}|^2 + \frac{1}{\varepsilon} \frac{(1 - \textcolor{green}{v})^2}{4} \, dx$$

- Ω the image domain
- g the input image
- $\textcolor{brown}{u}$ a piecewise smooth approximation of g
- $\textcolor{green}{v}$ a smooth approximation of $1 - \chi_K$
- ✓ whole domain integration
- ✓ no Hausdorff measure

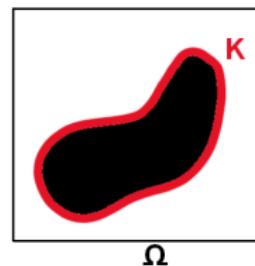


Ambrosio-Tortorelli functional

[Ambrosio and Tortorelli, 1992]

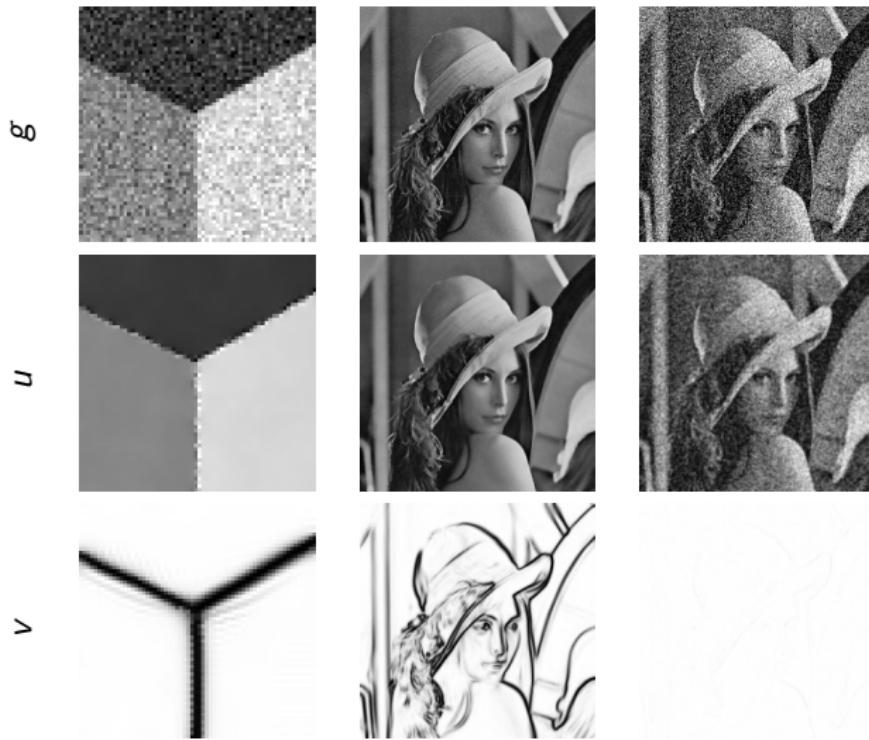
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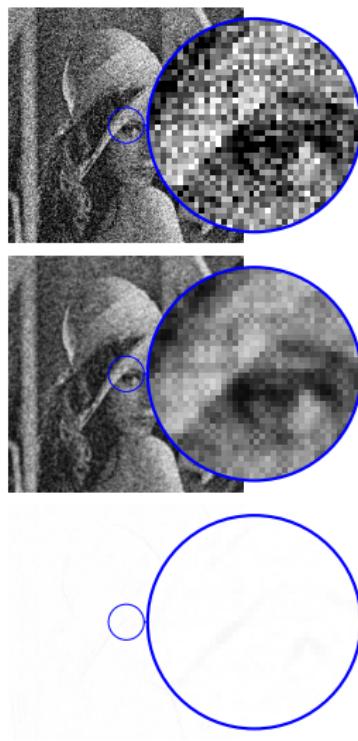
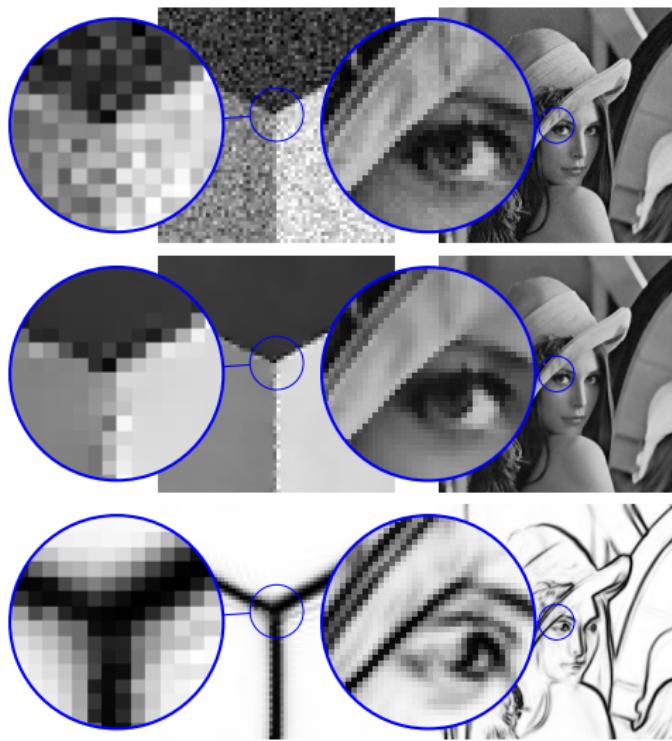


$$\Gamma\text{-convergence: } AT_\varepsilon \xrightarrow[\varepsilon \rightarrow 0]{} \mathcal{MS}$$

Finite differences implementation

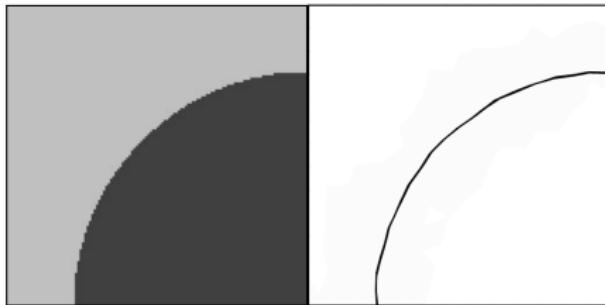


Finite differences implementation



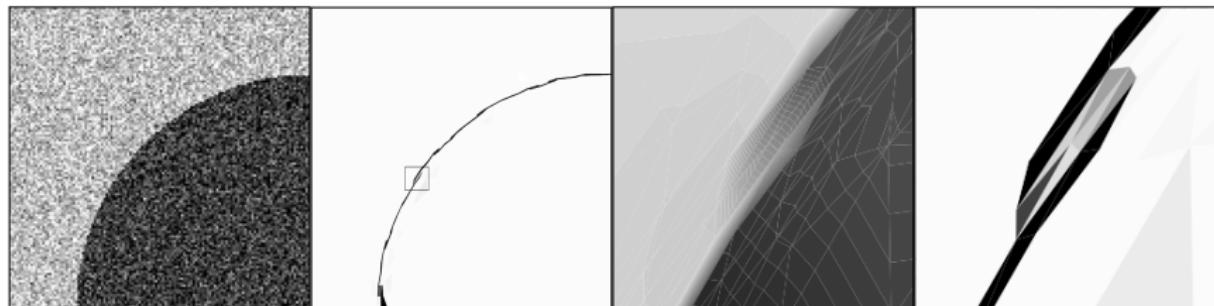
Finite elements implementation

- ▷ Proposed in [Bourdin and Chambolle, 2000]



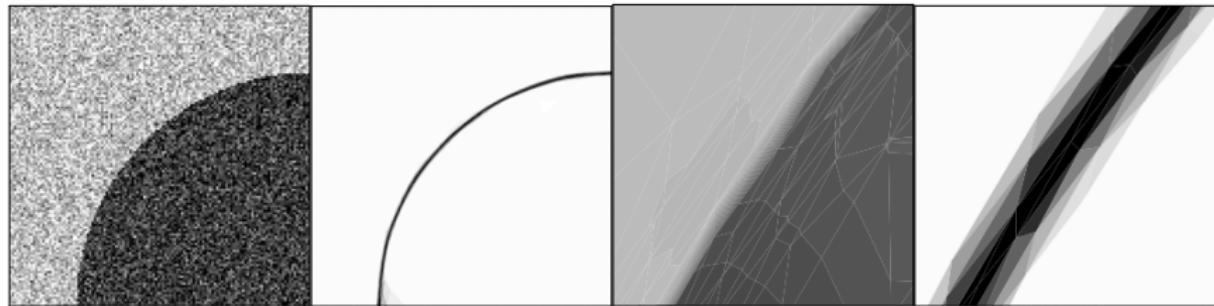
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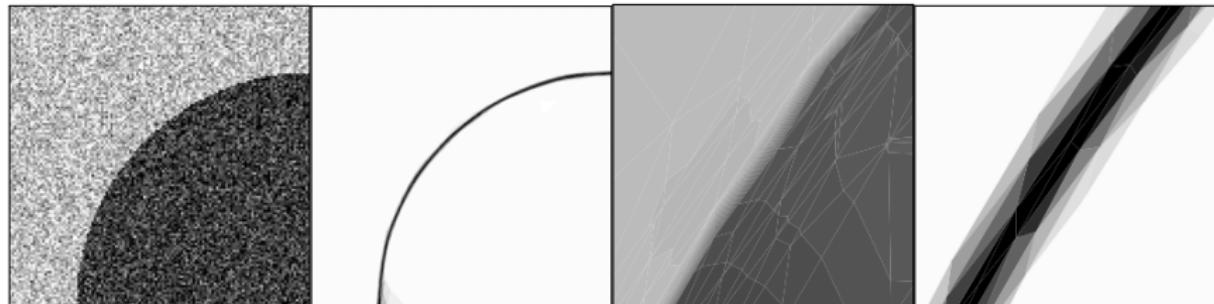
Finite elements implementation

- ▷ Proposed in [Bourdin and Chambolle, 2000]
- ▷ Finite elements with mesh **refinement** and **realignment**



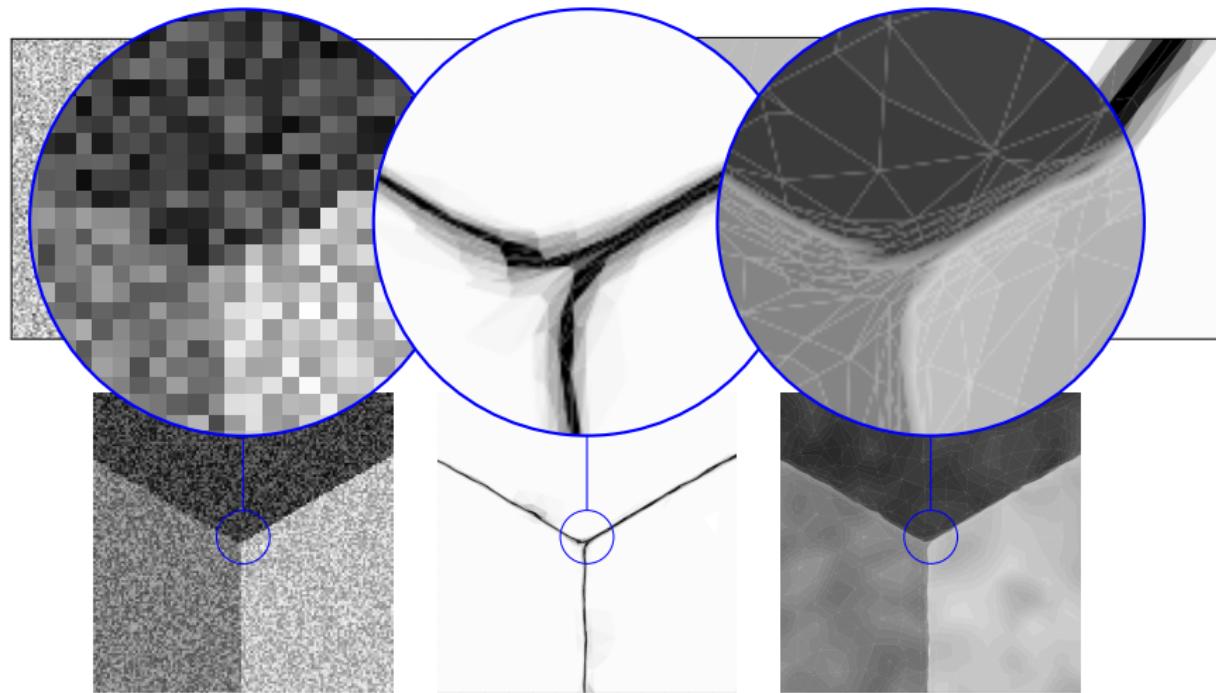
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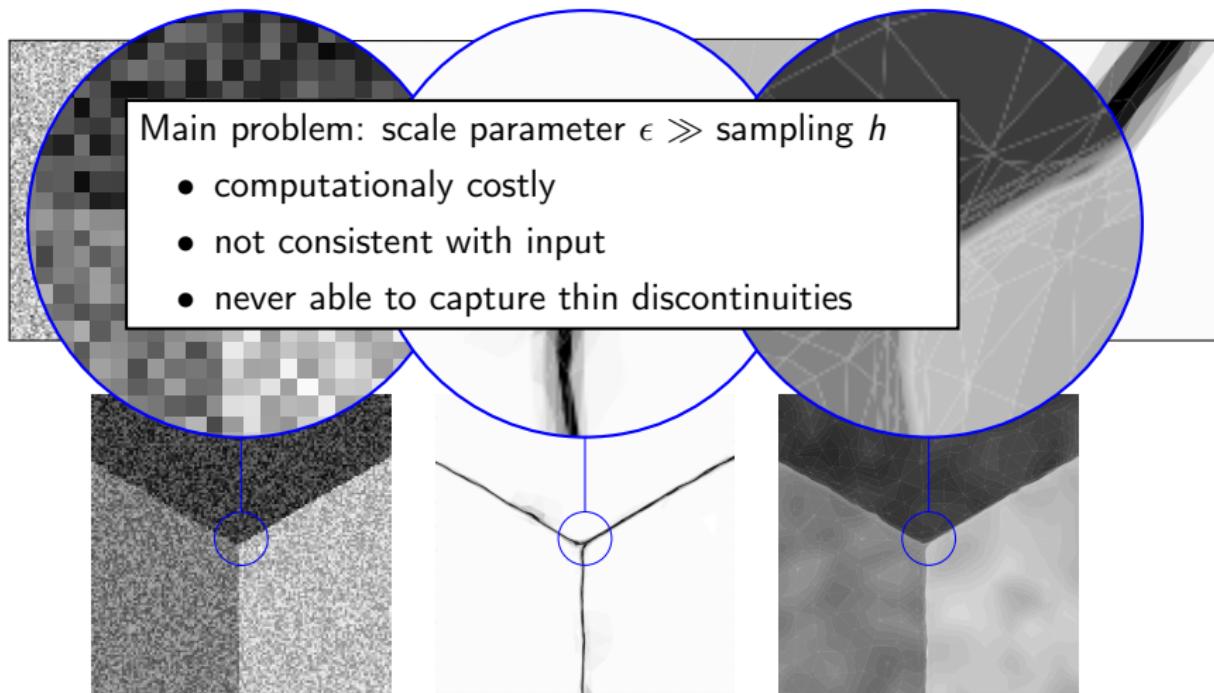
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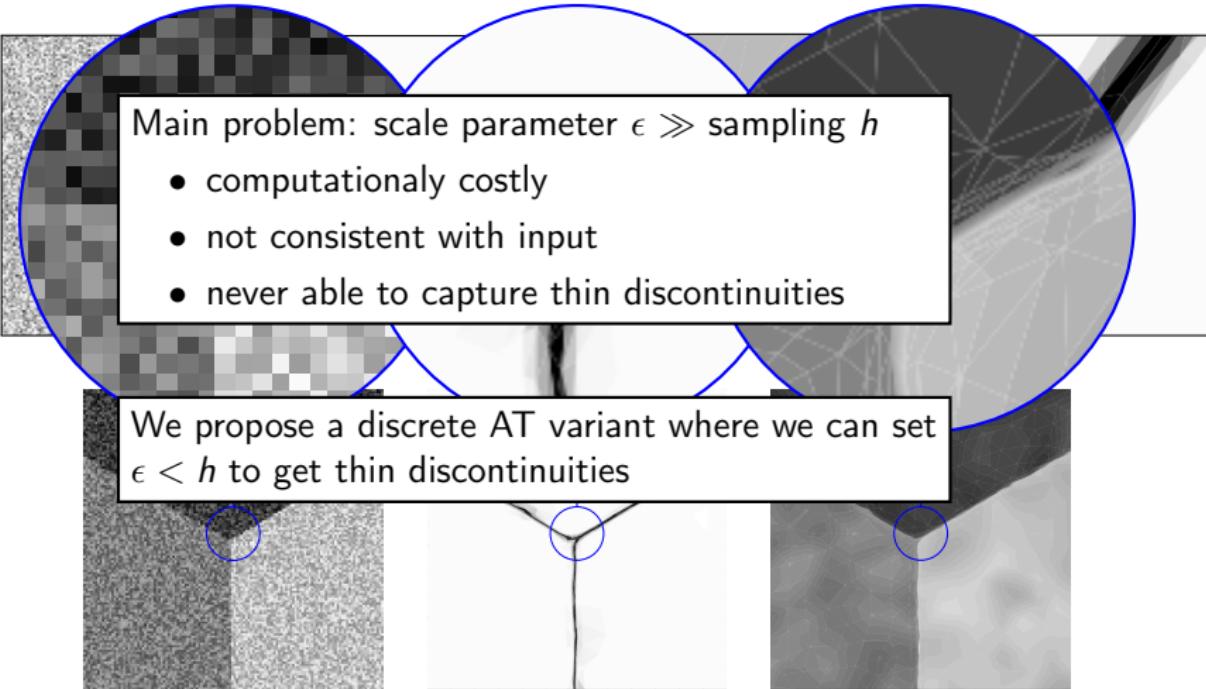
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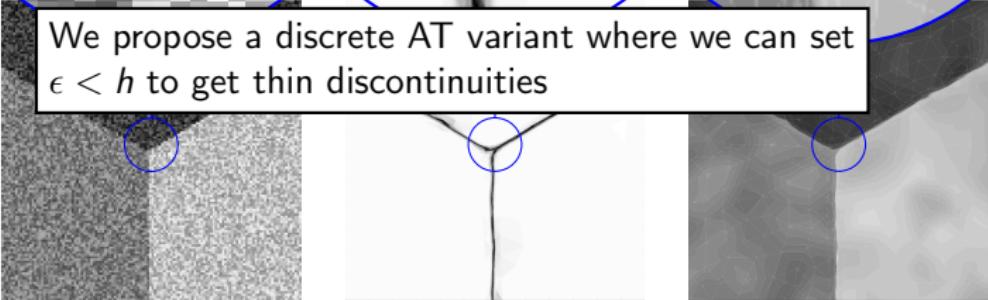
Finite elements implementation

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Main problem: scale parameter $\epsilon \gg$ sampling h

- computationally costly
- not consistent with input
- never able to capture thin discontinuities



We propose a discrete AT variant where we can set $\epsilon < h$ to get thin discontinuities

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Applications

Discrete Calculus

Computer graphics, geometry processing, shape optimization



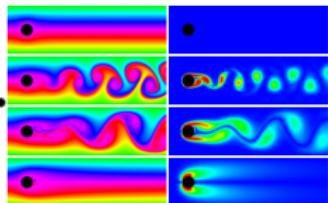
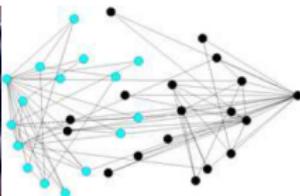
(Images: Knöppel et al. 2015, Crane et al. 2013, Springborn et al. 2010)

Discrete exterior calculus [Desbrun, Hirani, Leok, ...]

Discrete differential calculus [Polthier, Pinkall, Bobenko, ...]

Discrete calculus [Grady, Polimeni, ...]

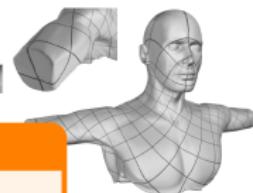
Graph and network analysis, image processing, fluid simul.



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Discrete Calculus

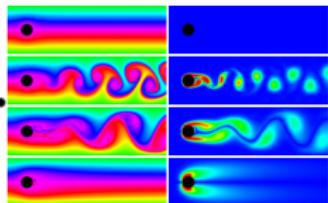
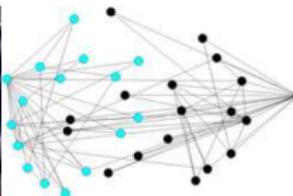
Computer graphics, geometry processing, shape optimization



Discrete exterior calculus (DEC)

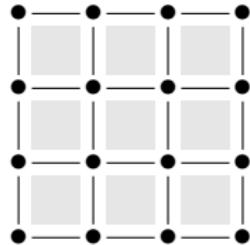
- no discretization, discrete by nature
- keep algebraic properties of calculus, exact Stokes' theorem
- reduces to matrix/vectors
- works without embedding, just metric
- “any” cell complex, arbitrary dimension

Graph and network analysis, image processing, fluid simul.



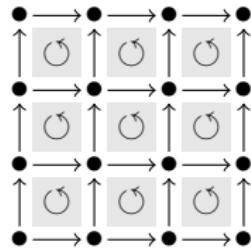
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Cell complex, chains, boundary, forms



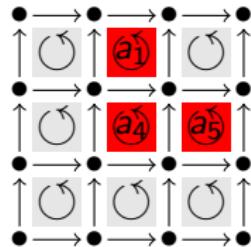
- *cell complex K :* vertices, edges, faces (pixels)

Cell complex, chains, boundary, forms



- *cell complex K :* vertices, edges, faces (pixels) with orientation

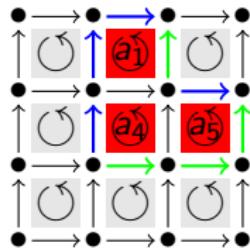
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$$\sigma := a_1 + a_4 + a_5 \in C_2(K)$$

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- *k-chains*: $C_k(K)$ are integral formal sums of oriented cells

Cell complex, chains, boundary, forms



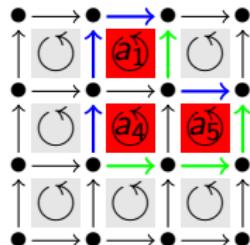
$$\sigma := a_1 + a_4 + a_5 \in C_2(K)$$

$$\eta := \sum e_i - \sum e_j \in C_1(K)$$

$$\eta = \partial_2 \sigma$$

- *cell complex* K : vertices, edges, faces (pixels) with orientation
- *k-chains*: $C_k(K)$ are integral formal sums of oriented cells
- *boundary operators*: $\cdots C_2(K) \xrightarrow{\partial_2} C_1(K) \xrightarrow{\partial_1} C_0(K) \xrightarrow{\partial_0} 0$

Cell complex, chains, boundary, forms



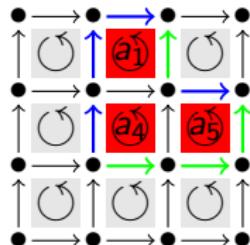
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- *discrete k -forms*: elements of $C^k(K) := \text{Hom}(C_k(K), \mathbb{R})$
 - ▷ 0-forms: functions, i.e. a value per vertex
 - ▷ 1-forms: differential forms/vector field, i.e. a value per edge
 - ▷ 2-forms: area forms, i.e. a value per face

Cell complex, chains, boundary, forms



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- *Integral* $\int_{\sigma} \alpha$ = pairing k -form α with k -chain σ

$$\int_{\sigma} \alpha := \alpha(\sigma) = \sum_i a_i \alpha(c_i) \quad \text{if } \sigma = \sum_i a_i c_i$$

Exterior derivative, Stokes theorem

- exterior derivative defined by duality: $\mathbf{d}_k : C^k(K) \rightarrow C^{k+1}(K)$

$$(\mathbf{d}_k \alpha^k)(\sigma_{k+1}) := \alpha^k(\partial_{k+1} \sigma_{k+1})$$

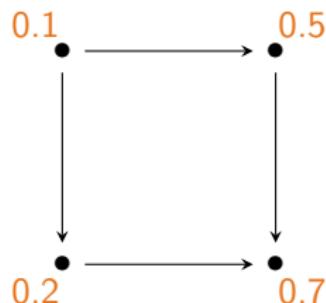
thus incidence relations define derivative by duality

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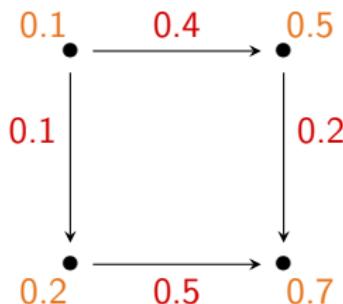
- Function or discrete 0-form : $\alpha = (0.2, 0.7, 0.1, 0.5)$

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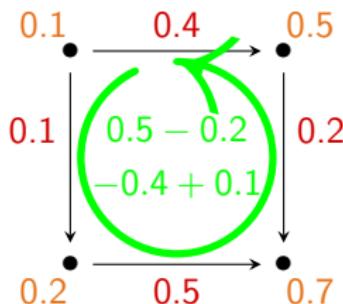
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- 1-form $\mathbf{d}_0(\alpha) = \beta = (0.5, 0.1, 0.2, 0.4)$

Exterior derivative, Stokes theorem

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- 1-form $\mathbf{d}_0(\alpha) = \beta = (0.5, 0.1, 0.2, 0.4)$
- 2-form $\mathbf{d}_1(\beta) = 0$, since $\mathbf{d}_1 \mathbf{d}_0 = 0$

Exterior derivative, Stokes theorem

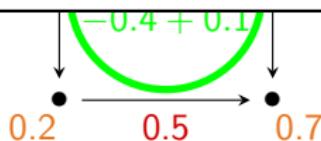
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$$(\mathbf{d}_k \alpha^k)(\sigma_{k+1}) := \alpha^k(\partial_{k+1} \sigma_{k+1})$$

thus (discrete) Stokes theorem is trivial by definition

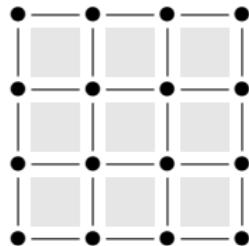
$$\int_{\sigma} \mathbf{d}\alpha = \int_{\partial\sigma} \alpha$$

for σ any k -chain and α any $k - 1$ -form

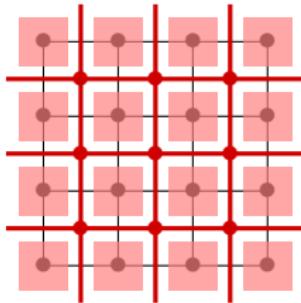


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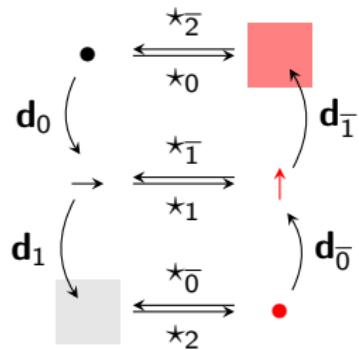
Dual cell complex, Hodge star, calculus



complex K



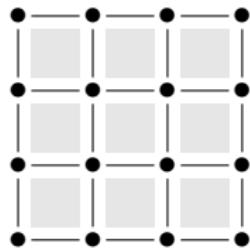
dual complex \bar{K}



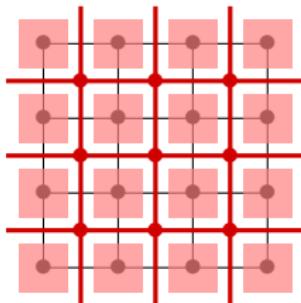
primal dual

- Hodge duality created with dual/orthogonal structure

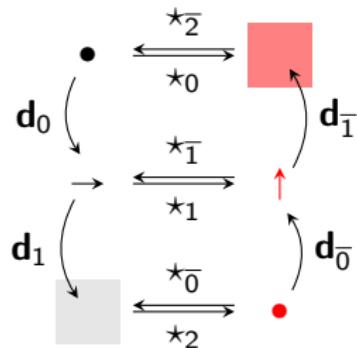
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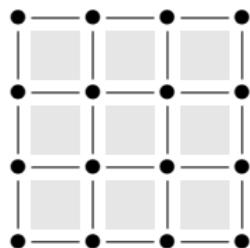
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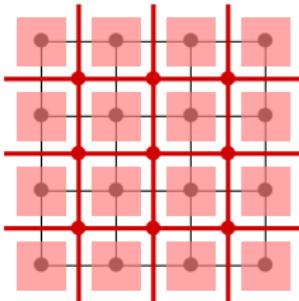
primal dual

- Hodge duality created with dual/orthogonal structure
- anti-derivatives d_k^- are derivatives in dual complex
 - ▷ in matrix form $d_k^{-T} := d_{n-1-k}$

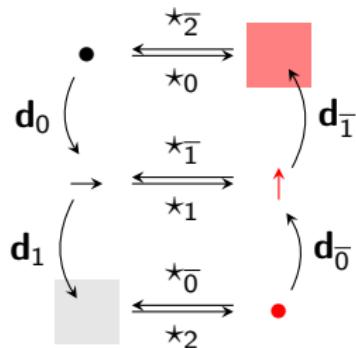
Dual cell complex, Hodge star, calculus



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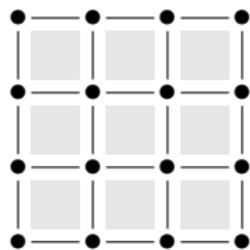
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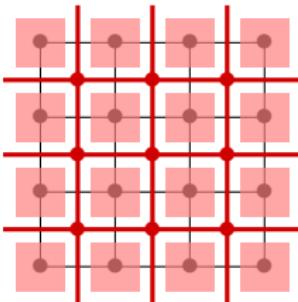
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- anti-derivatives \mathbf{d}_k^- are derivatives in dual complex
 - ▷ in matrix form $\mathbf{d}_k^{-T} := \mathbf{d}_{n-1-k}$
- Hodge stars \star_k transport k -forms to dual $2 - k$ -forms
 - ▷ diagonal matrices incorporating metric information
 - ▷ e.g. $\star_k \mathbf{1} = \alpha$ is the area 2-form dA

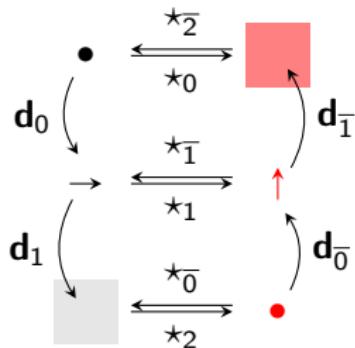
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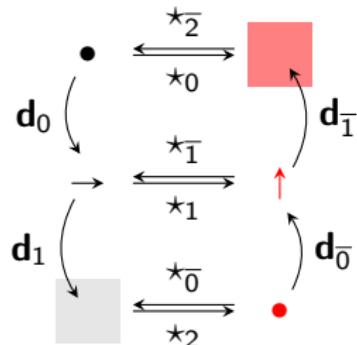
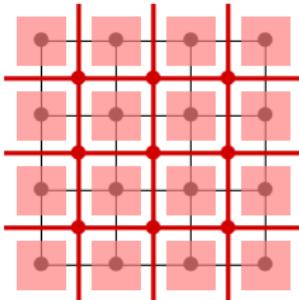
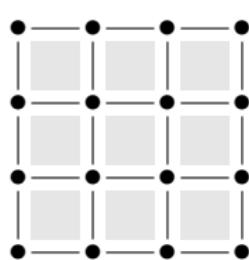
dual complex \bar{K}



primal dual

- Hodge duality created with dual/orthogonal structure
- anti-derivatives \mathbf{d}_k^- are derivatives in dual complex
 - ▷ in matrix form $\mathbf{d}_k^{-T} := \mathbf{d}_{n-1-k}$
- Hodge stars $*_k$ transport k -forms to dual $2 - k$ -forms
 - ▷ diagonal matrices incorporating metric information
 - ▷ e.g. $*_k \mathbf{1} = \alpha$ is the area 2-form dA
- wedge products satisfy algebraic properties (Leibniz rules . . .)
 - ▷ $\alpha \wedge \beta := \text{diag}(\alpha)\beta$, for $\alpha \in C^k(K), \beta \in C^{2-k}(\bar{K})$,
 - ▷ $f \wedge \gamma := \text{diag}(\mathbf{M}_{01}f)\gamma$, for $f \in C^0(K), \gamma \in C^1(K)$. . .

Dual cell complex, Hodge star, calculus



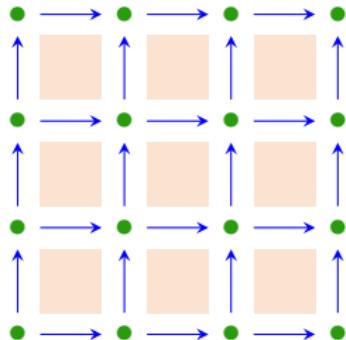
Almost all the calculus is built from the previous operators

- codifferentials $\delta_1 := -\star_2 \mathbf{d}_1 \star_1$, $\delta_2 := -\star_1 \mathbf{d}_0 \star_2$,
 - Laplacian $\Delta := \delta_1 \mathbf{d}_0$
 - Edge Laplacian $\Delta_1 := \mathbf{d}_0 \delta_1 + \delta_2 \mathbf{d}_1$,
 - musical ops : Vector field $\xrightarrow{\flat}$ 1-form $\xrightarrow{\sharp}$ Vector field
 - gradient $\nabla f := (\mathbf{d}_0 f)^\sharp$
 - divergence $\text{div } \mathbf{V} := \delta_1 \mathbf{V}^\flat$
 - L^2 inner-product $(\alpha, \beta)_{\Omega, k} := \int_{\Omega} \alpha \wedge \star_k \beta$, for α, β k -forms
- $f \wedge \gamma := \text{diag}(\mathbf{M}_{01} f) \gamma$, for $f \in C^0(K)$, $\gamma \in C^1(K)$...

Discrete formulation of AT

On faces and vertices

$$AT_{\varepsilon}(u, v) = \alpha \int_{\Omega} |u - g|^2 \, dx + \int_{\Omega} v^2 |\nabla u|^2 \, dx + \lambda \int_{\Omega} \varepsilon |\nabla v|^2 + \frac{1}{4\varepsilon} (1 - v)^2 \, dx$$



We choose :

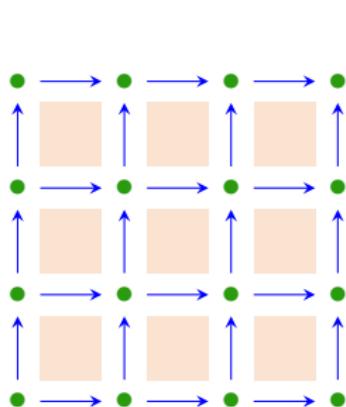
- functions u, g to live on faces
 - ▷ u, g are **2-forms**
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- function v to live on vertices
 - ▷ v is a **0-form**



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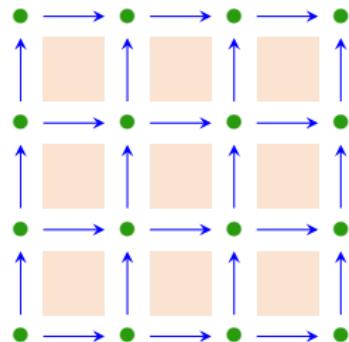


$$AT_{\varepsilon}^{2,0}(u, v) = \alpha (u - g, u - g)_{\Omega, 2}$$

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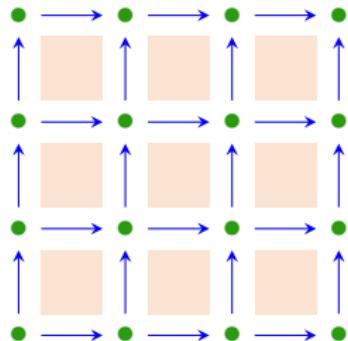


$$\begin{aligned} AT_{\varepsilon}^{2,0}(u, v) &= \alpha (u - g, u - g)_{\Omega, 2} \\ &+ \lambda \varepsilon (\mathbf{d}_0 v, \mathbf{d}_0 v)_{\Omega, 1} \end{aligned}$$

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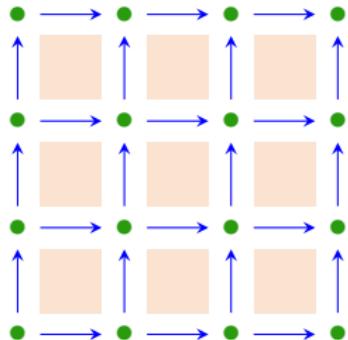
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Discrete formulation of AT

Cross term mixing u and v

$$\int_{\Omega} v^2 |\nabla u|^2 \, dx = (\mathbf{v} \delta_2 \mathbf{u}, \mathbf{v} \delta_2 \mathbf{u})_{\Omega,1}$$

- $\mathbf{v} \delta_2 \mathbf{u} = \mathbf{v} \wedge \delta_2 \mathbf{u} = \text{diag}(\mathbf{M}_{01} \mathbf{v}) \delta_2 \mathbf{u}$

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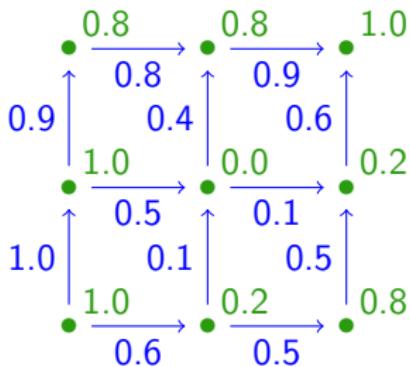
- 0-form \mathbf{v}

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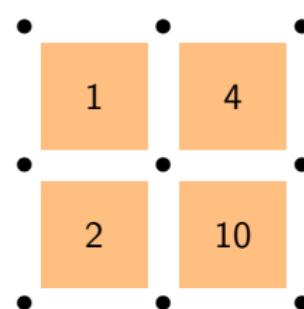
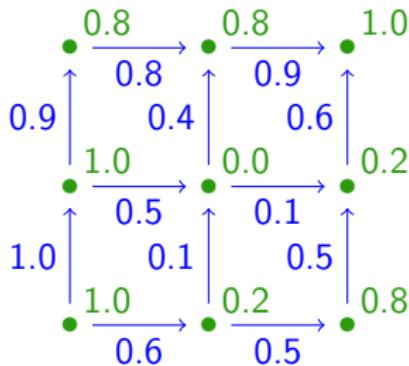
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- 0-form v
- 1-form $\mathbf{M}_{01} \mathbf{v}$

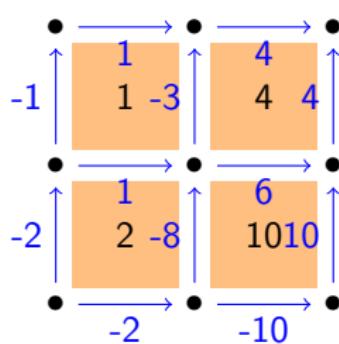
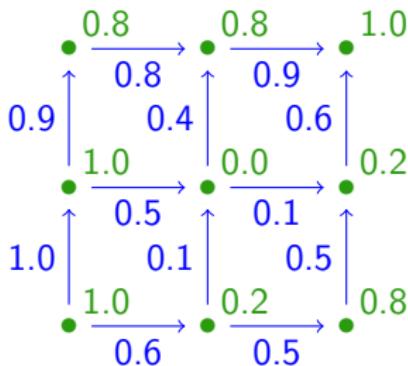
- 2-form u

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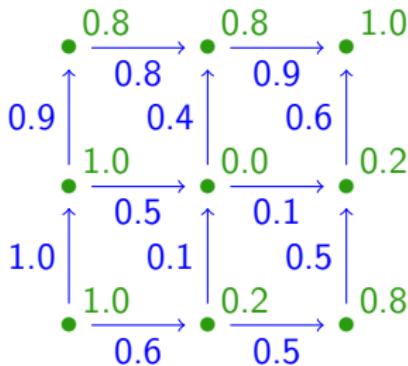
- 0-form v
- 1-form $\mathbf{M}_{01} v$
- 2-form u
- 1-form $\delta_2 u$

Discrete formulation of AT

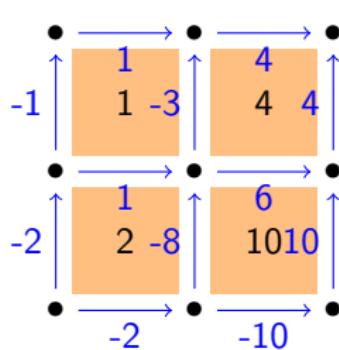
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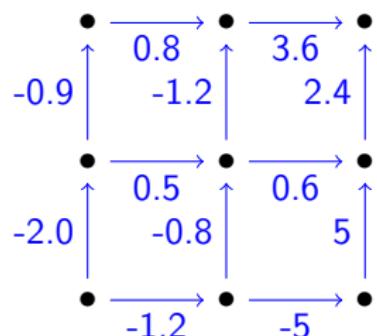
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- 1-form $\delta_2 \mathbf{u}$



- 1-form
 $\text{diag}(\mathbf{M}_{01} \mathbf{v}) \delta_2 \mathbf{u}$

Discrete calculus model of Ambrosio-Tortorelli's functionnal

Ambrosio-Tortorelli's functional

A brief introduction to discrete calculus

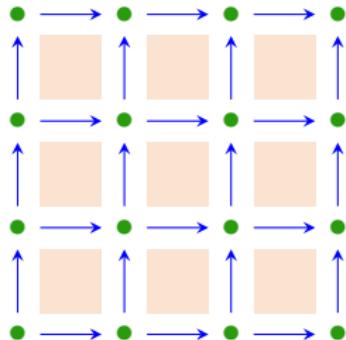
A discrete calculus model of AT

Applications

Discrete formulation of AT

On faces and vertices

$$AT_{\varepsilon}(u, v) = \alpha \int_{\Omega} |u - g|^2 \, dx + \int_{\Omega} v^2 |\nabla u|^2 \, dx + \lambda \int_{\Omega} \varepsilon |\nabla v|^2 + \frac{1}{4\varepsilon} (1 - v)^2 \, dx$$



We choose :

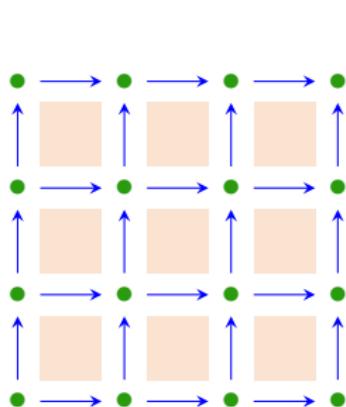
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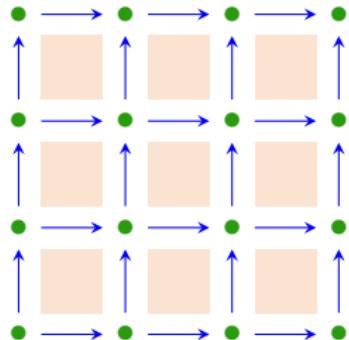


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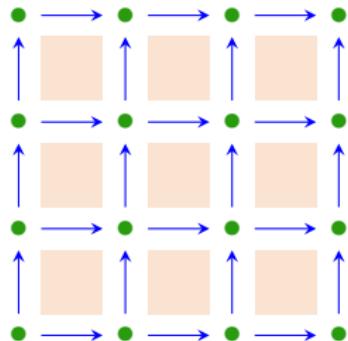


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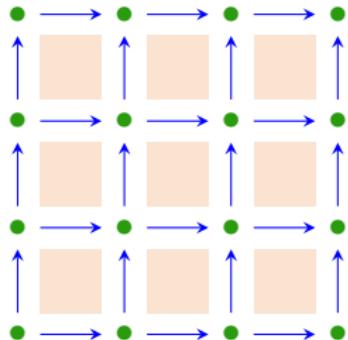
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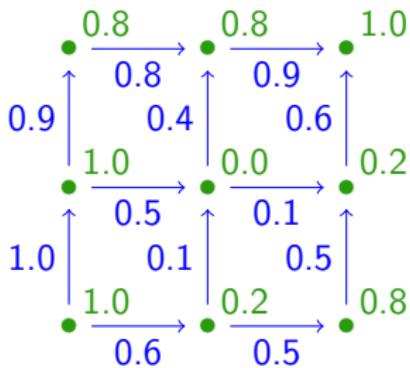
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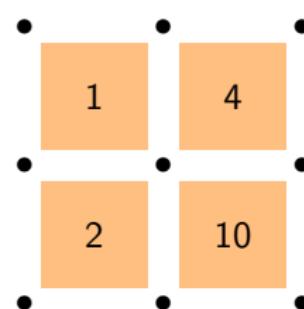
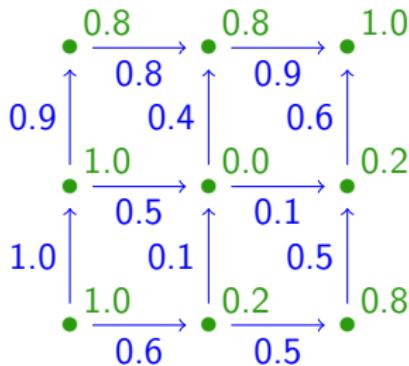
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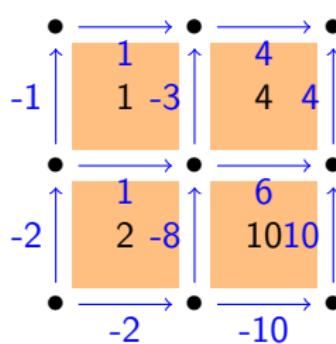
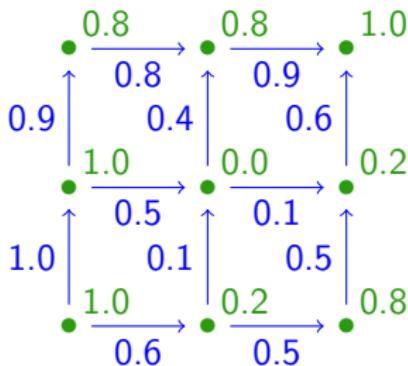
- 2-form u

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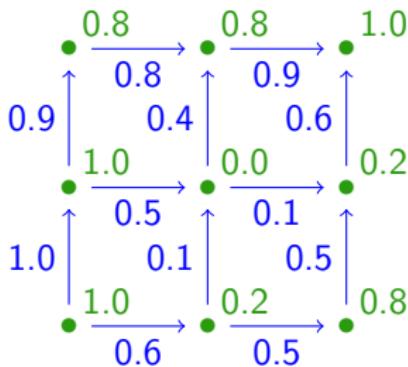
- 0-form v
- 1-form $\mathbf{M}_{01} \mathbf{v}$
- 2-form u
- 1-form $\delta_2 u$

Discrete formulation of AT

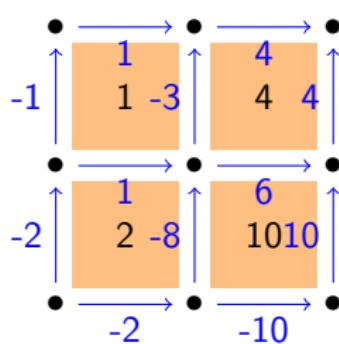
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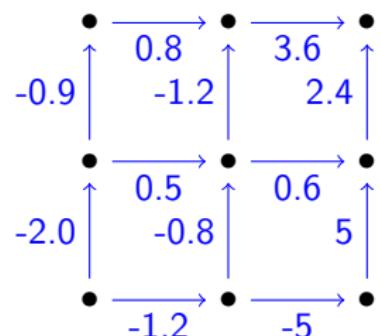
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- 2-form \mathbf{u}
- 1-form $\delta_2 \mathbf{u}$



- 1-form
 $\text{diag}(\mathbf{M}_{01} \mathbf{v}) \delta_2 \mathbf{u}$

Discrete formulation of AT

$$\begin{aligned} \text{AT}_{\varepsilon}^{2,0}(\textcolor{brown}{u}, \textcolor{green}{v}) &= \alpha (\textcolor{brown}{u} - \textcolor{brown}{g}, \textcolor{brown}{u} - \textcolor{brown}{g})_{\Omega,2} + (\text{diag}(\mathbf{M}_{01}\textcolor{green}{v})\delta_2\textcolor{brown}{u}, \text{diag}(\mathbf{M}_{01}\textcolor{green}{v})\delta_2\textcolor{brown}{u})_{\Omega,1} \\ &\quad + \lambda \varepsilon (\mathbf{d}_0\textcolor{green}{v}, \mathbf{d}_0\textcolor{green}{v})_{\Omega,1} + \frac{\lambda}{4\varepsilon} (\textcolor{green}{1} - \textcolor{green}{v}, \textcolor{green}{1} - \textcolor{green}{v})_{\Omega,0} \end{aligned}$$

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- with matrices $\mathbf{A} := \mathbf{d}_0$, $\mathbf{B}' := \delta_2$, $\mathbf{G}_k := \star_k$.

$$\begin{aligned} \text{AT}_{\varepsilon}^{2,0}(\mathbf{u}, \mathbf{v}) &= \alpha(\mathbf{u} - \mathbf{g})^T \mathbf{G}_2(\mathbf{u} - \mathbf{g}) + \mathbf{u}^T \mathbf{B}'^T \text{diag}(\mathbf{M}_{01}\mathbf{v})^2 \mathbf{G}_1 \mathbf{B}' \mathbf{u} \\ &\quad + \lambda \varepsilon \mathbf{v}^T \mathbf{A}^T \mathbf{G}_1 \mathbf{A} \mathbf{v} + \frac{\lambda}{4\varepsilon} (\mathbf{1} - \mathbf{v})^T \mathbf{G}_0 (\mathbf{1} - \mathbf{v}) \end{aligned}$$

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- Euler-Lagrange: $\min_{\mathbf{u}, \mathbf{v}} \text{AT}_{\varepsilon}^{2,0} \Rightarrow \frac{d\text{AT}_{\varepsilon}^{2,0}}{d\mathbf{u}} = 0$ and $\frac{d\text{AT}_{\varepsilon}^{2,0}}{d\mathbf{v}} = 0$
- $\text{AT}_{\varepsilon}^{2,0}$ is **quadratic** in \mathbf{u} and in \mathbf{v}

Discrete formulation of AT

$$\begin{aligned} \text{AT}_{\varepsilon}^{2,0}(\mathbf{u}, \mathbf{v}) &= \alpha (\mathbf{u} - \mathbf{g}, \mathbf{u} - \mathbf{g})_{\Omega,2} + (\text{diag}(\mathbf{M}_{01}\mathbf{v})\delta_2\mathbf{u}, \text{diag}(\mathbf{M}_{01}\mathbf{v})\delta_2\mathbf{u})_{\Omega,1} \\ &\quad + \lambda\varepsilon (\mathbf{d}_0\mathbf{v}, \mathbf{d}_0\mathbf{v})_{\Omega,1} + \frac{\lambda}{4\varepsilon} (\mathbf{1} - \mathbf{v}, \mathbf{1} - \mathbf{v})_{\Omega,0} \end{aligned}$$

- with matrices $\mathbf{A} := \mathbf{d}_0$, $\mathbf{B}' := \delta_2$, $\mathbf{G}_k := \star_k$.

$$\begin{aligned} \text{AT}_{\varepsilon}^{2,0}(\mathbf{u}, \mathbf{v}) &= \alpha(\mathbf{u} - \mathbf{g})^T \mathbf{G}_2(\mathbf{u} - \mathbf{g}) + \mathbf{u}^T \mathbf{B}'^T \text{diag}(\mathbf{M}_{01}\mathbf{v})^2 \mathbf{G}_1 \mathbf{B}' \mathbf{u} \\ &\quad + \lambda\varepsilon \mathbf{v}^T \mathbf{A}^T \mathbf{G}_1 \mathbf{A} \mathbf{v} + \frac{\lambda}{4\varepsilon} (\mathbf{1} - \mathbf{v})^T \mathbf{G}_0 (\mathbf{1} - \mathbf{v}) \end{aligned}$$

- Euler-Lagrange: $\min_{\mathbf{u}, \mathbf{v}} \text{AT}_{\varepsilon}^{2,0} \Rightarrow \frac{d\text{AT}_{\varepsilon}^{2,0}}{d\mathbf{u}} = 0$ and $\frac{d\text{AT}_{\varepsilon}^{2,0}}{d\mathbf{v}} = 0$
- $\text{AT}_{\varepsilon}^{2,0}$ is quadratic in \mathbf{u} and in \mathbf{v}
- We solve alternatively for \mathbf{u} and \mathbf{v} the sparse linear systems:

$$\left\{ \begin{array}{l} \left[\alpha \mathbf{G}_2 - \mathbf{B}'^T \text{diag}(\mathbf{M}_{01}\mathbf{v})^2 \mathbf{G}_1 \mathbf{B}' \right] \mathbf{u} = \alpha \mathbf{G}_2 \mathbf{g}, \\ \left[\frac{\lambda}{4\varepsilon} \mathbf{G}_0 + \lambda\varepsilon \mathbf{A}^T \mathbf{G}_1 \mathbf{A} + \mathbf{M}_{01}^T \text{diag}(\mathbf{B}' \mathbf{u})^2 \mathbf{G}_1 \mathbf{M}_{01} \right] \mathbf{v} = \frac{\lambda}{4\varepsilon} \mathbf{G}_0 \mathbf{1}. \end{array} \right.$$

Discrete formulation of AT: vectorial data

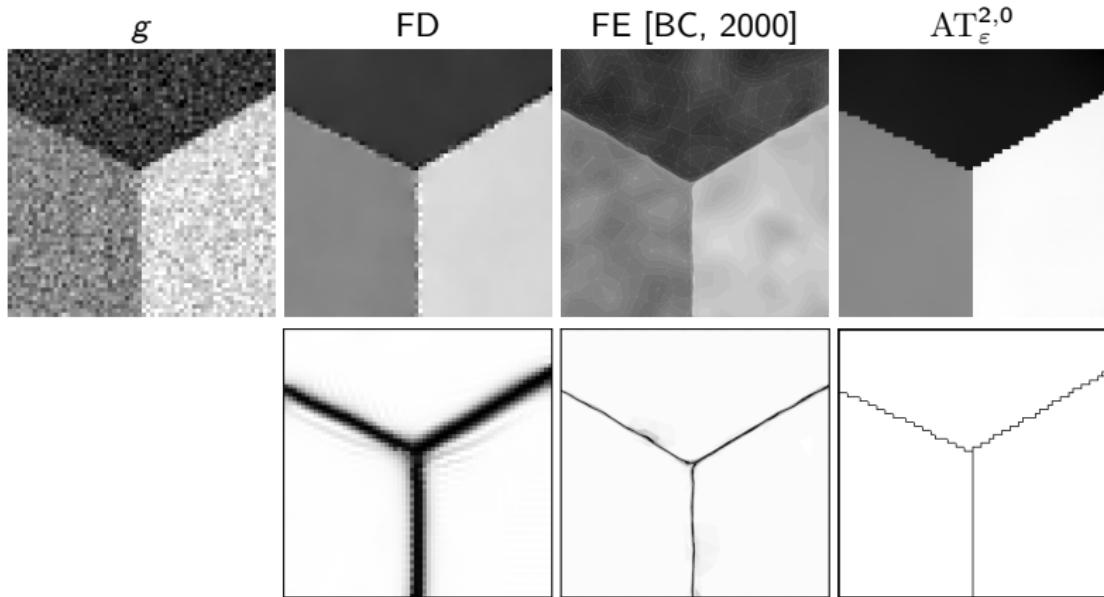
$$\begin{aligned} \text{AT}_\varepsilon^{2,0}(\mathbf{u}_1, \dots, \mathbf{u}_n, \mathbf{v}) = & \alpha \sum_i (\mathbf{u}_i - \mathbf{g}_i, \mathbf{u}_i - \mathbf{g}_i)_{\Omega,2} \\ & + \sum_i (\text{diag}(\mathbf{M}_{01}\mathbf{v})\delta_2 \mathbf{u}_i, \text{diag}(\mathbf{M}_{01}\mathbf{v})\delta_2 \mathbf{u}_i)_{\Omega,1} \\ & + \lambda \varepsilon (\mathbf{d}_0 \mathbf{v}, \mathbf{d}_0 \mathbf{v})_{\Omega,1} + \frac{\lambda}{4\varepsilon} (\mathbf{1} - \mathbf{v}, \mathbf{1} - \mathbf{v})_{\Omega,0} \end{aligned}$$

- We solve alternatively for the \mathbf{u}_i and \mathbf{v} the sparse linear systems:

$$\left\{ \begin{array}{l} \forall i \in \{1, \dots, n\}, \left[\alpha \mathbf{G}_2 - \mathbf{B}'^\top \text{diag}(\mathbf{M}_{01}\mathbf{v})^2 \mathbf{G}_1 \mathbf{B}' \right] \mathbf{u}_i = \alpha \mathbf{G}_2 \mathbf{g}_i, \\ \left[\frac{\lambda}{4\varepsilon} \mathbf{G}_0 + \lambda \varepsilon \mathbf{A}^\top \mathbf{G}_1 \mathbf{A} + \mathbf{M}_{01}^\top (\sum_i \text{diag}(\mathbf{B}' \mathbf{u}_i)^2) \mathbf{G}_1 \mathbf{M}_{01} \right] \mathbf{v} = \frac{\lambda}{4\varepsilon} \mathbf{G}_0 \mathbf{1}. \end{array} \right.$$

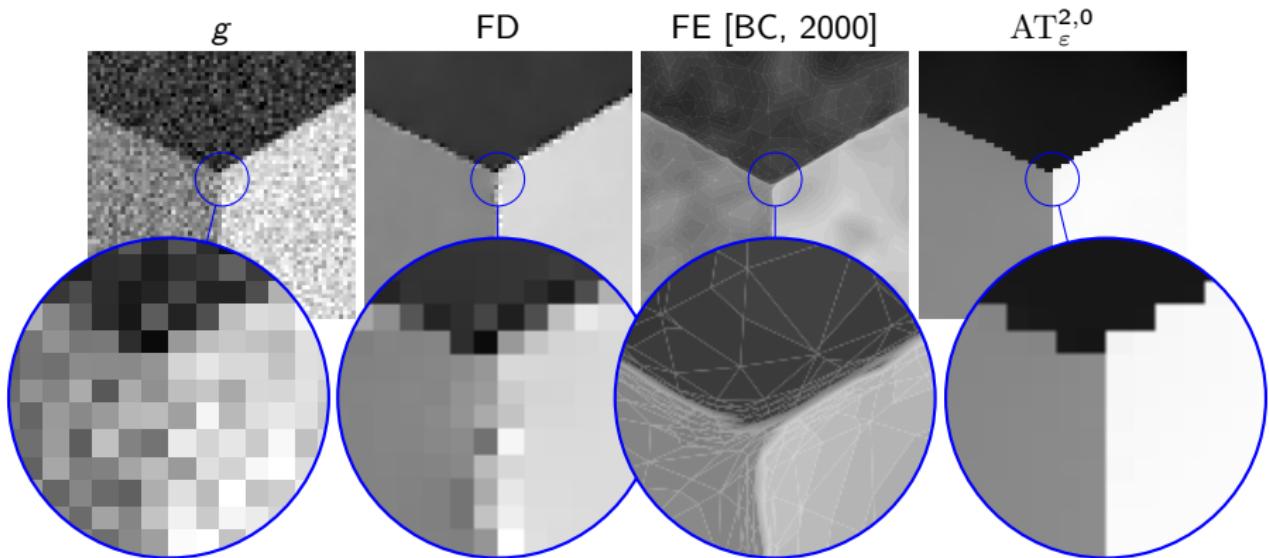
- Our algorithm progressively decreases ε to get a better chance of capturing the optimum
 - $\triangleright \varepsilon$ follows typically sequence 2, 1, 0.5, 0.25 (for $h = 1$ sampling)
 - \triangleright results on \mathbf{u} and \mathbf{v} are starting point for next ε

Image restoration on toy examples



- systems are solved using Cholesky decomposition (Eigen)
- ϵ takes the successive values 2, 1, 0.5, 0.25, for sampling step $h = 1$.

Image restoration on toy examples



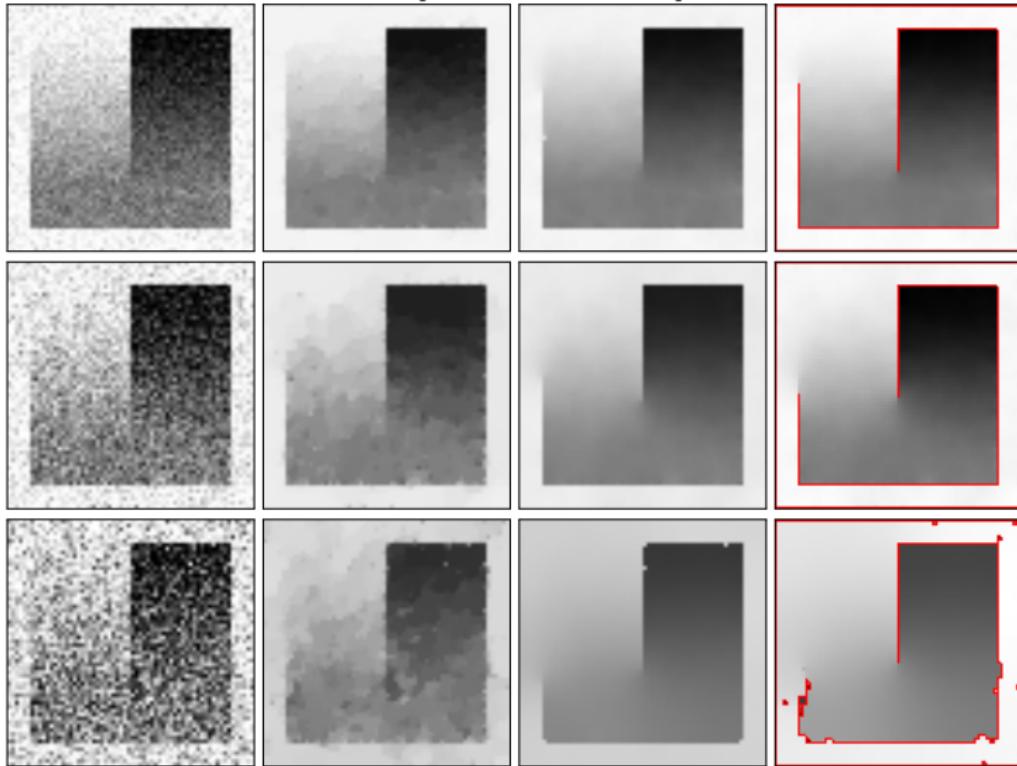
- systems are solved using Cholesky decomposition (Eigen)
- ϵ takes the successive values 2, 1, 0.5, 0.25, for sampling step $h = 1$.

g

TV [Duran et al.
2013]

[Strek. et al.
2014]

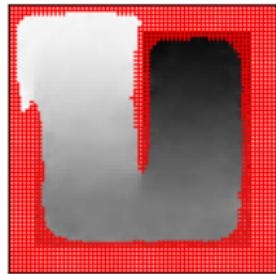
$AT_{\varepsilon}^{2,0}$



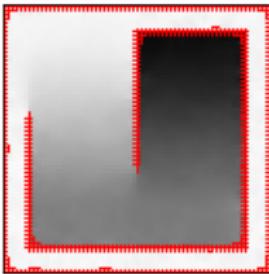
Influence of parameter ε

$$AT_\varepsilon(u, v) = \alpha \int_{\Omega} |u - g|^2 \, dx + \int_{\Omega} v^2 |\nabla u|^2 \, dx + \lambda \int_{\Omega} \varepsilon |\nabla v|^2 + \frac{1}{\varepsilon} \frac{(1-v)^2}{4} \, dx$$

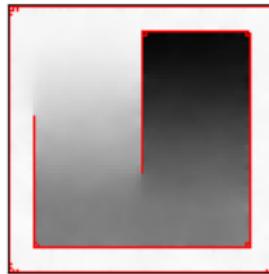
- Γ -convergence parameter
- Controls the thickness of the contours
 - ▷ large ε convexifies AT and helps to detect the discontinuities;
 - ▷ as ε goes to 0, the discontinuities become thinner and thinner.



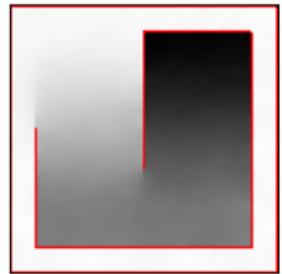
$\varepsilon = 2 \searrow 2$



$\varepsilon = 2 \searrow 1$



$\varepsilon = 2 \searrow 0.5$



$\varepsilon = 2 \searrow 0.25$

Discrete calculus model of Ambrosio-Tortorelli's functionnal

Ambrosio-Tortorelli's functional

A brief introduction to discrete calculus

A discrete calculus model of AT

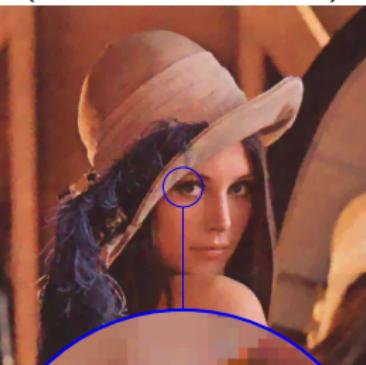
Applications

Image restoration / denoising

g
(PSNR = 20.23 dB)



TV
(PSNR = 29.36 dB)



$\text{AT}_\varepsilon^{2,0}$
(PSNR = 29.03 dB)

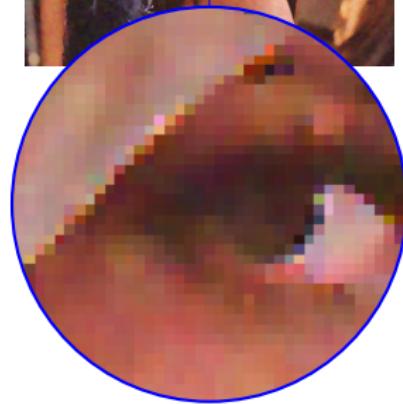
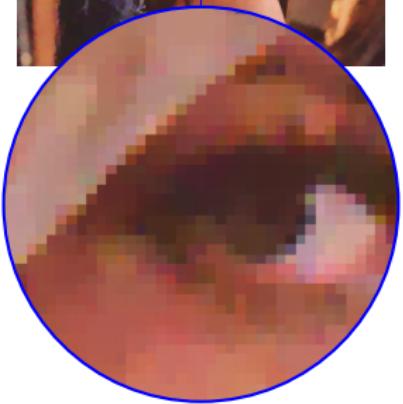
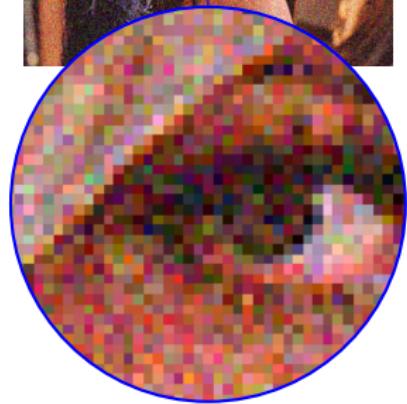
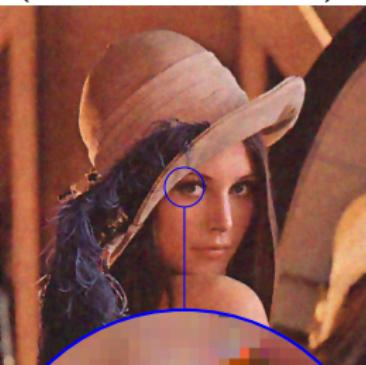
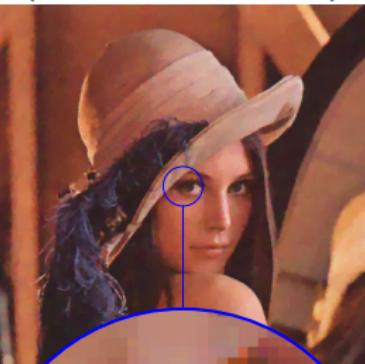


Image restoration / denoising

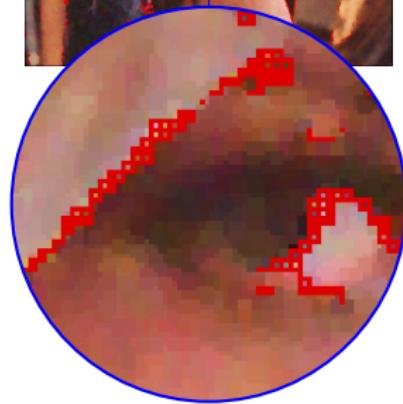
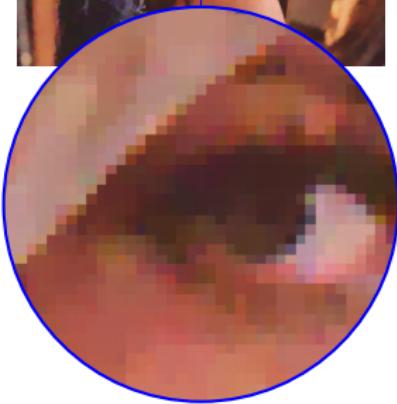
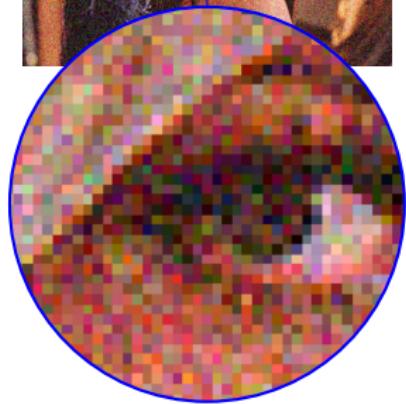
g
(PSNR = 20.23 dB)



TV
(PSNR = 29.36 dB)



$\text{AT}_{\varepsilon}^{2,0}$
(PSNR = 29.03 dB)



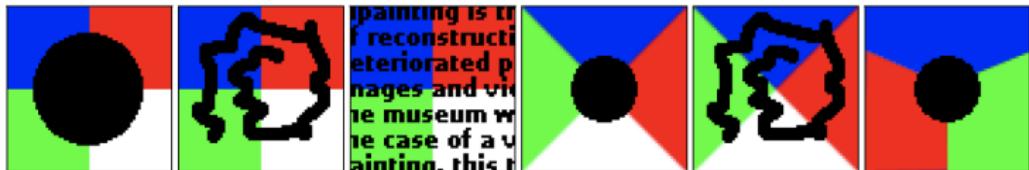
Scale-space given by α and λ and image segmentation



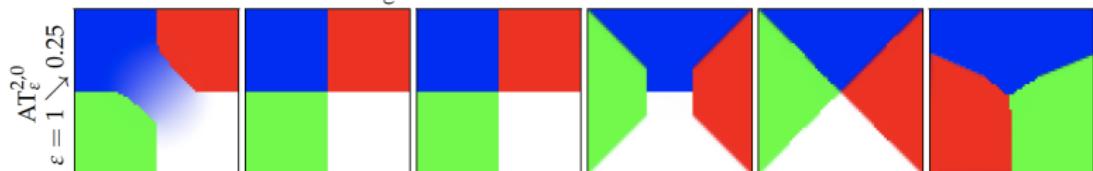
for decreasing λ

Image inpainting (on toy example)

- mask (in black) : domain M where data g (in color) is unknown
- $\alpha(x) := \{\alpha \in \Omega \setminus M, 0 \text{ elsewhere}\}$
- initialization: u random in M , $= g$ in $\Omega \setminus M$



$AT_{\epsilon}^{2,0}$ with ϵ from 1 to 0.25



$AT_{\epsilon}^{2,0}$ with ϵ from 4 to 0.25

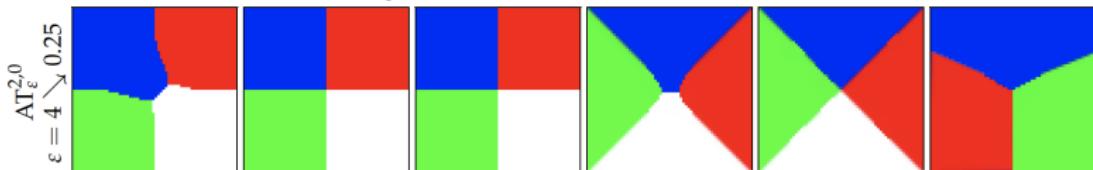
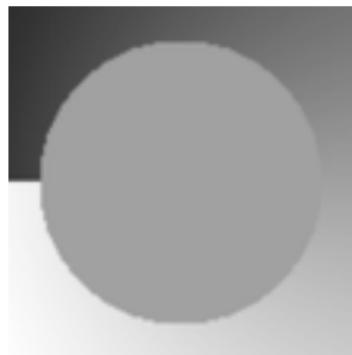


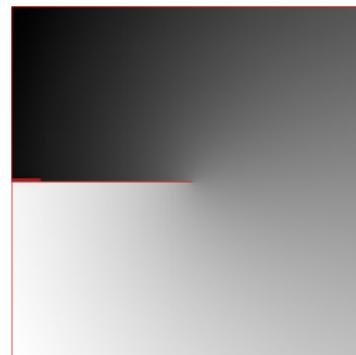
Image inpainting (on classical crack-tip example)



g



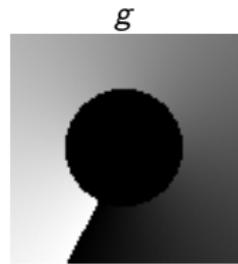
mask M



$\text{AT}_\epsilon^{2,0}, \alpha = 1, \lambda = 0.0024$

- Decreasing sequence of λ (irreversibility !?)
- same result as [Pock, Bishof, Cremers, Pock 2009], based on MS relaxation of [Alberti, Bouchitté, Dal Maso 2003]
- result independent of initialization as long as first ϵ is big enough (ϵ from 4 to 0.25 here, for image of size 110×110).

Image inpainting (crack-tip + decreasing λ)



mask M

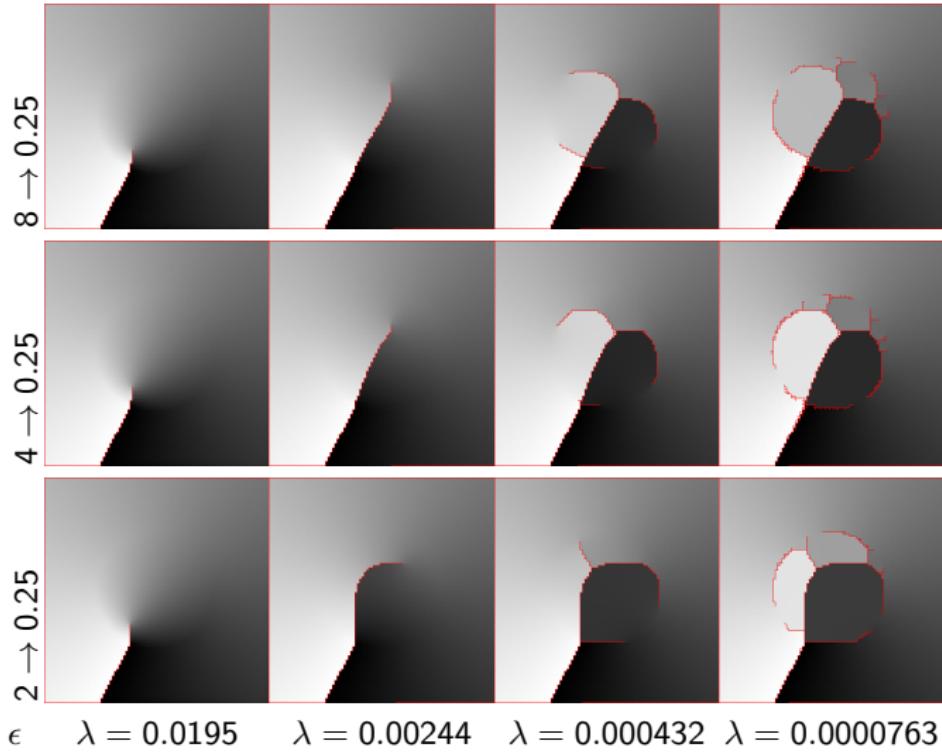
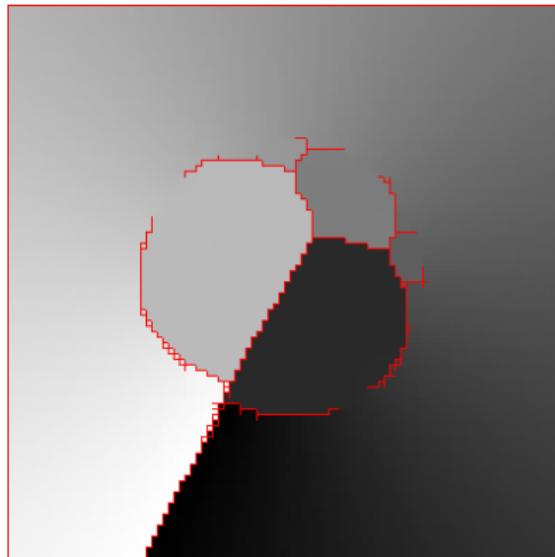


Image inpainting (crack-tip + changing resolution)

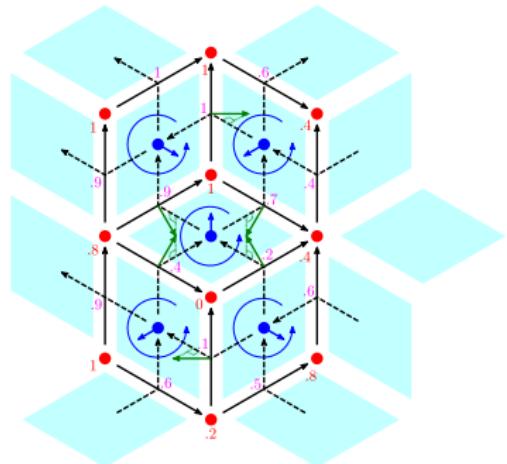


100×100
 $\lambda = 0.0000763$
 $\alpha = 1$

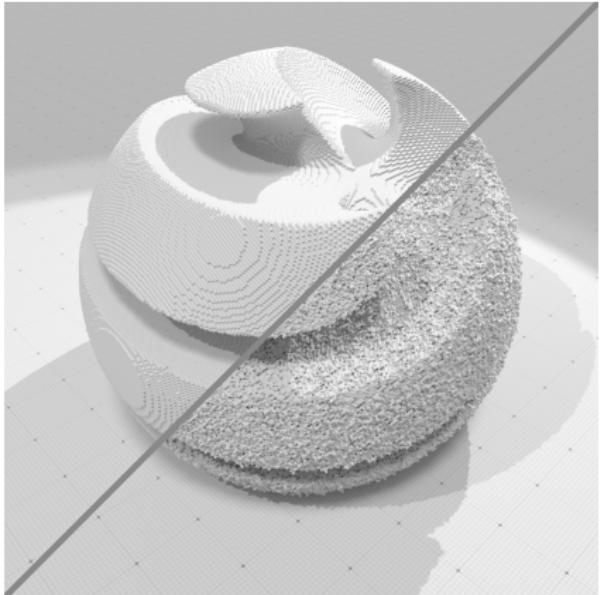
200×200
 $\lambda = 0.0000381$
 $\alpha = 1$

Feature delineation on digital surfaces

digital surface = boundary of set of voxels



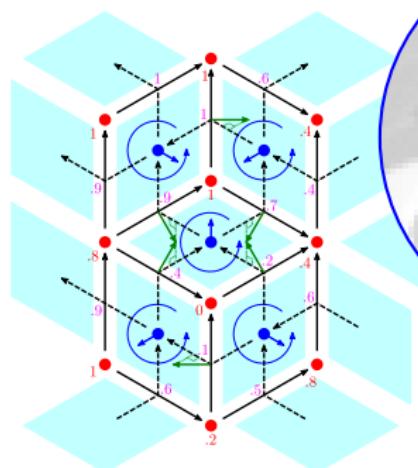
same discrete calculus
same $AT_{\varepsilon}^{2,0}$



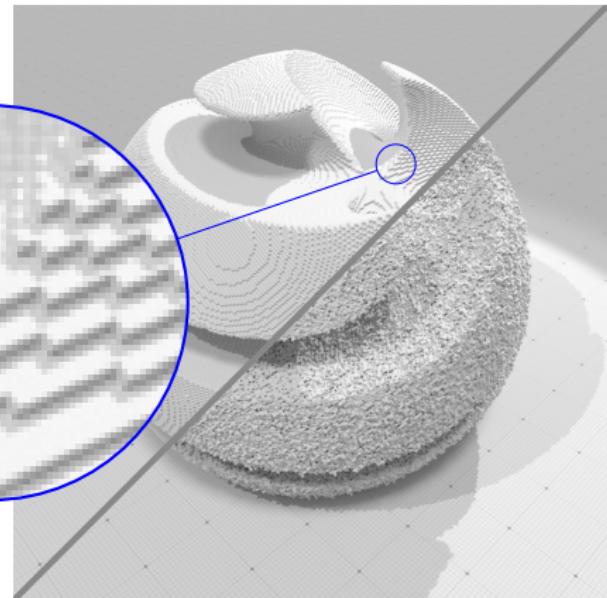
Input: normal vector field g estimated by Integral Invariant digital normal estimator.

Feature delineation on digital surfaces

digital surface = boundary of set of voxels



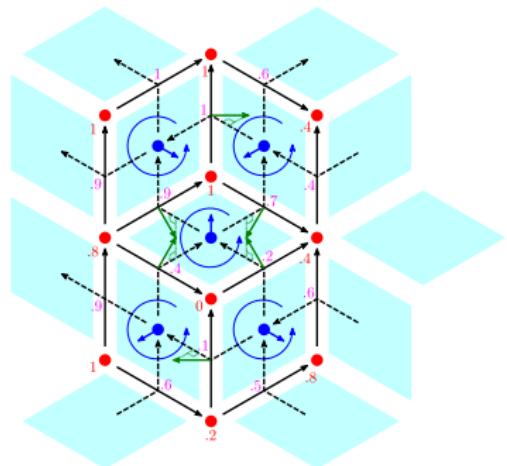
same discrete calculus
same $AT_{\varepsilon}^{2,0}$



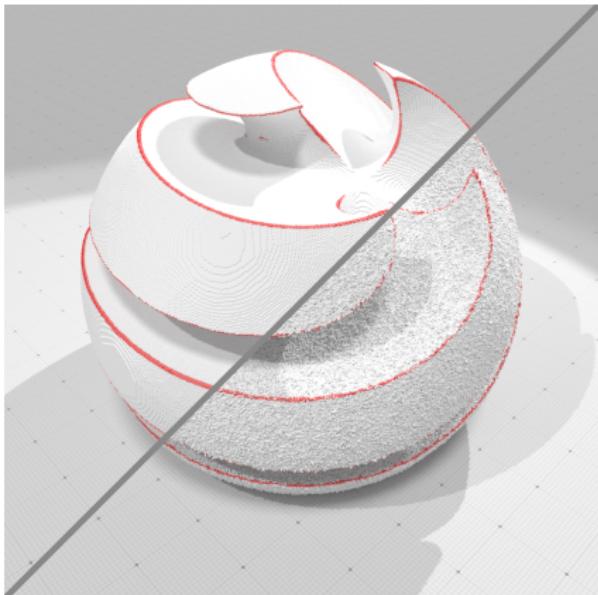
Input: normal vector field \mathbf{g} estimated by Integral Invariant digital normal estimator.

Feature delineation on digital surfaces

digital surface = boundary of set of voxels



same discrete calculus
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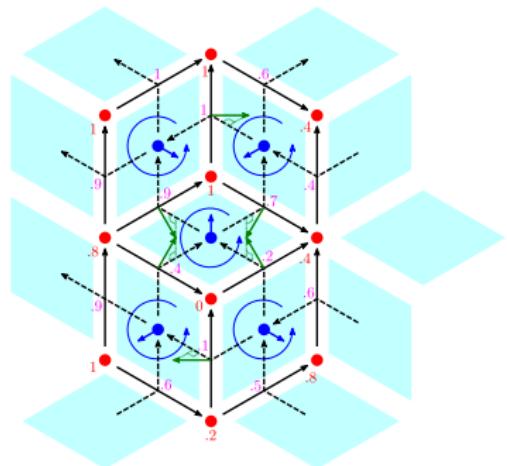


Input: normal vector field \mathbf{g} estimated by Integral Invariant digital normal estimator.

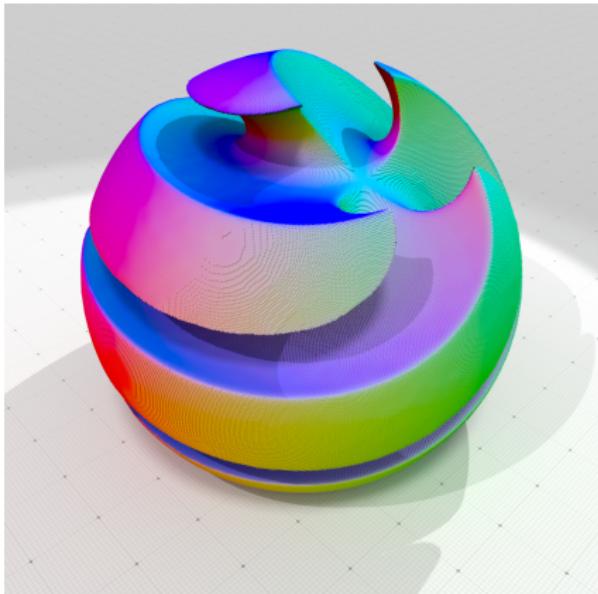
Output: piecewise smooth normals $(\mathbf{u}_i)_{i=1,2,3}$ and features \mathbf{v}

Feature delineation on digital surfaces

digital surface = boundary of set of voxels



same discrete calculus
same $AT_{\varepsilon}^{2,0}$

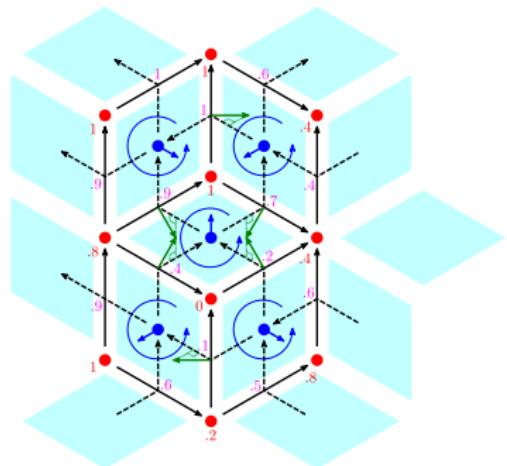


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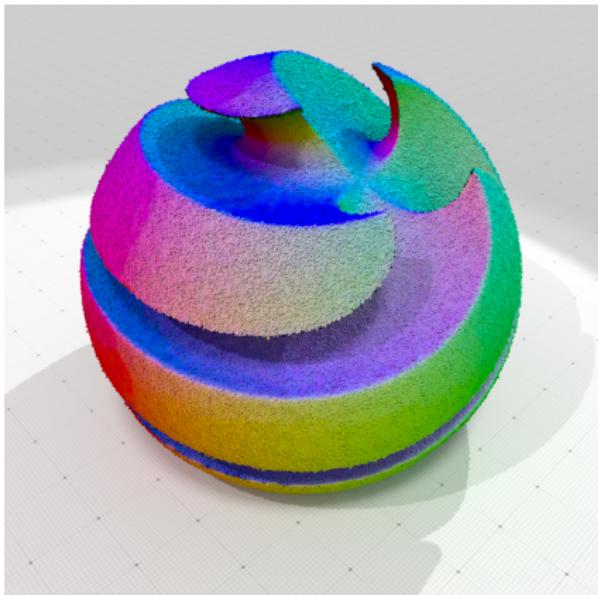
Output: piecewise smooth normals $(\mathbf{u}_i)_{i=1,2,3}$ and features \mathbf{v}

Feature delineation on digital surfaces

digital surface = boundary of set of voxels



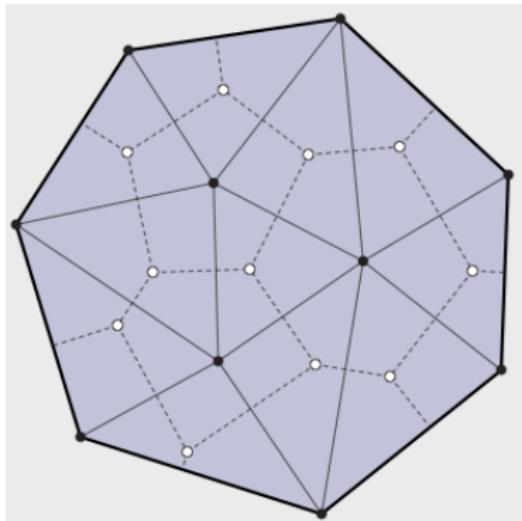
same discrete calculus
same $AT_{\varepsilon}^{2,0}$



Input: normal vector field \mathbf{g} estimated by Integral Invariant digital normal estimator.

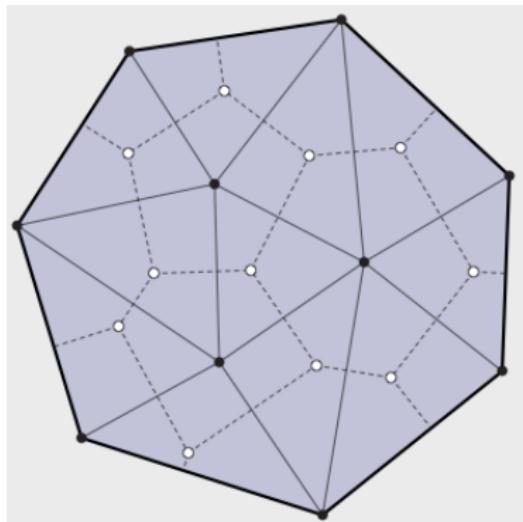
Output: piecewise smooth normals $(\mathbf{u}_i)_{i=1,2,3}$ and features \mathbf{v}

Discrete calculus on triangulated mesh



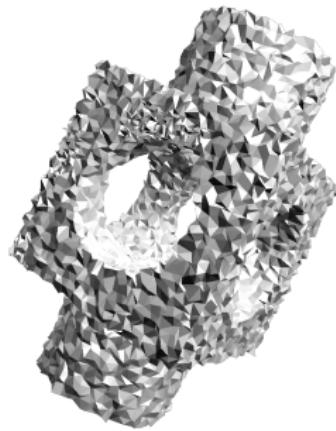
- dual mesh \perp primal mesh
- dual vertex = center of triangle circumcircle
- Hodge stars are no more trivial but still diagonal matrices
- $\star_0(v) := \text{Area}(\text{dual}(v))$
- $\star_1(e) := \text{length}(\text{dual}(e))/\text{length}(e)$
- $\star_2(t) := 1/\text{Area}(t)$
- otherwise same discrete calculus

Discrete calculus on triangulated mesh



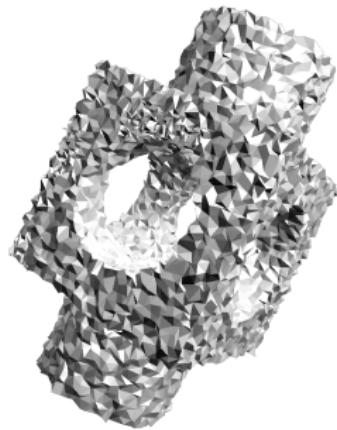
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- $\star_1(e) := \text{length}(\text{dual}(e))/\text{length}(e)$
- $\star_2(t) := 1/\text{Area}(t)$
- otherwise same discrete calculus
- $\mathbf{AT}_\epsilon^{2,0}$ is then the same !

Mesh denoising



0. Bad mesh with positions \mathbf{x}^0 , $k \leftarrow 0$

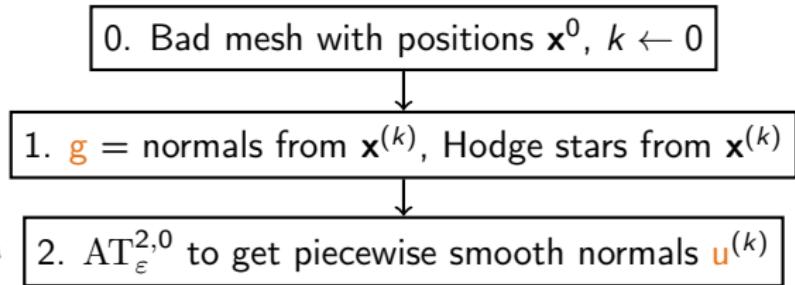
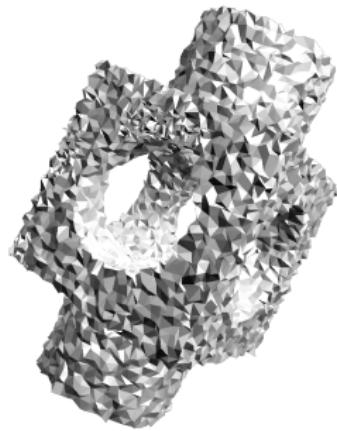
Mesh denoising



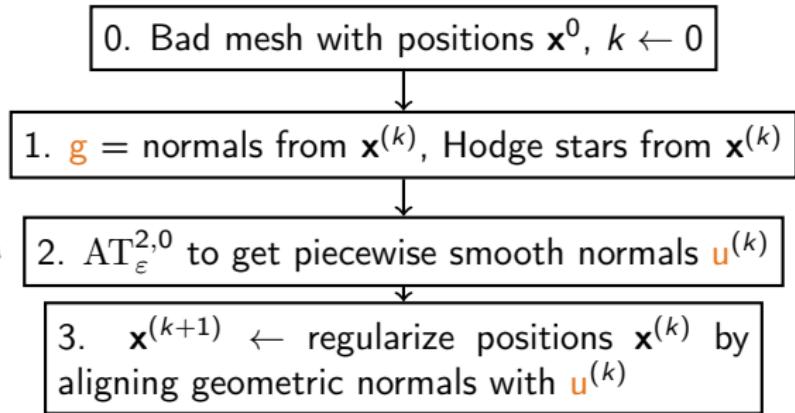
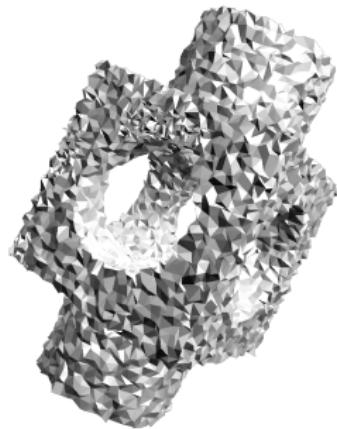
0. Bad mesh with positions \mathbf{x}^0 , $k \leftarrow 0$

1. \mathbf{g} = normals from $\mathbf{x}^{(k)}$, Hodge stars from $\mathbf{x}^{(k)}$

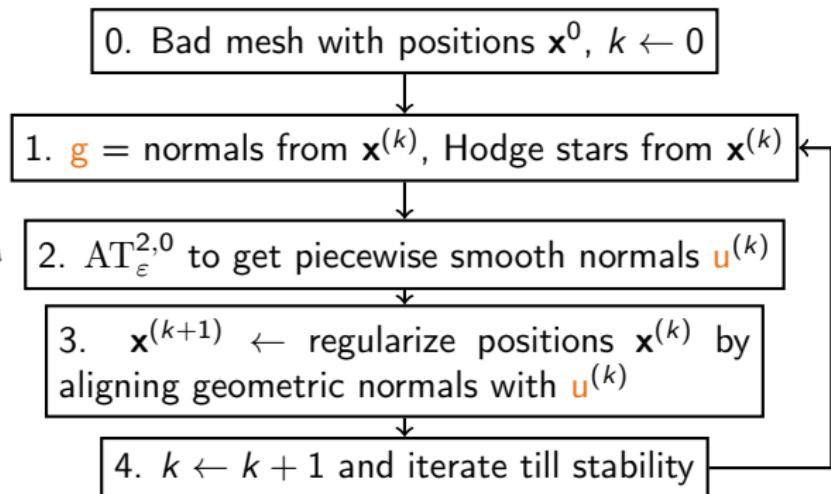
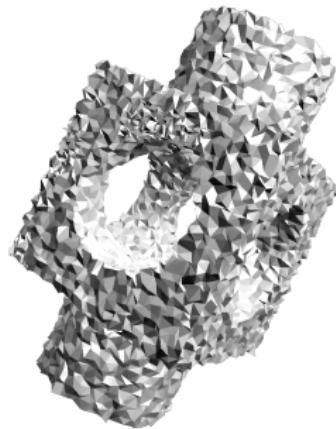
Mesh denoising



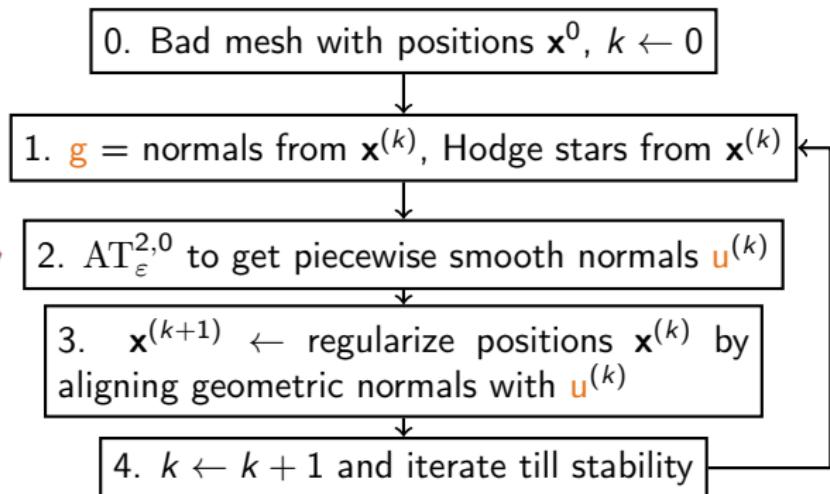
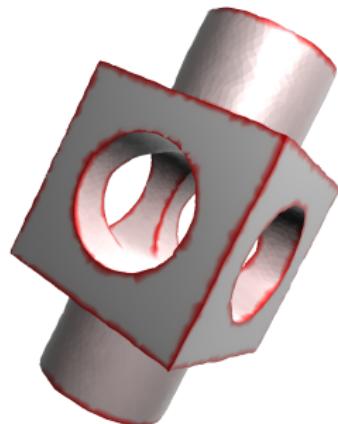
Mesh denoising



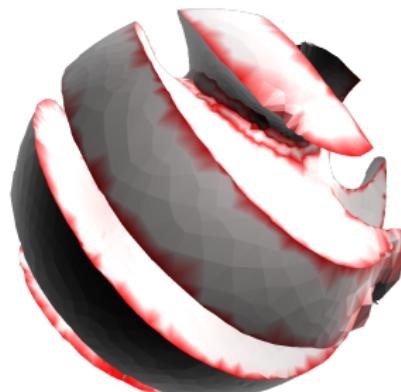
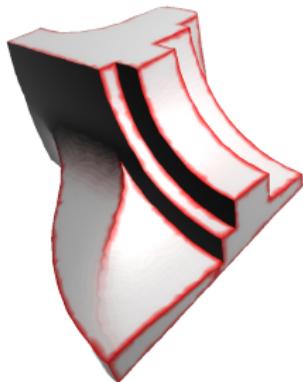
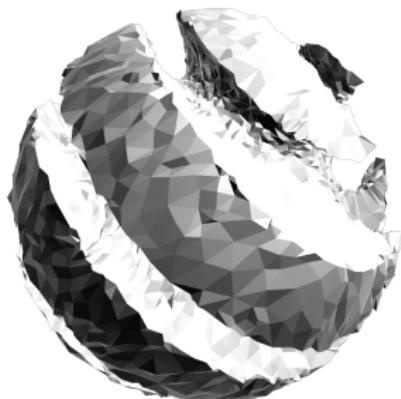
Mesh denoising



Mesh denoising



Mesh denoising (a few results)

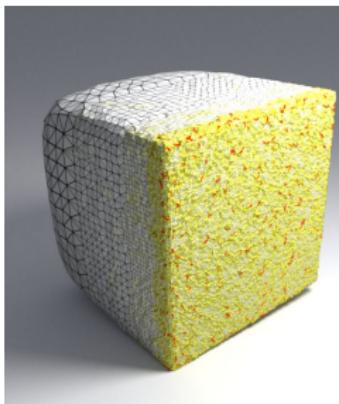


Mesh denoising (Comparison with FEM)

noise free



with noise

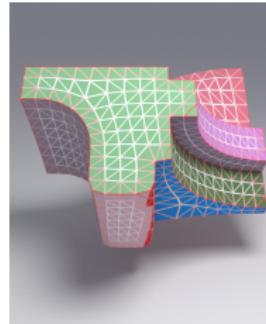
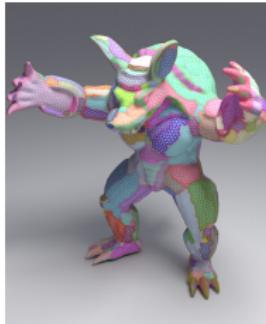


FEM [Tong and Tai 2016]



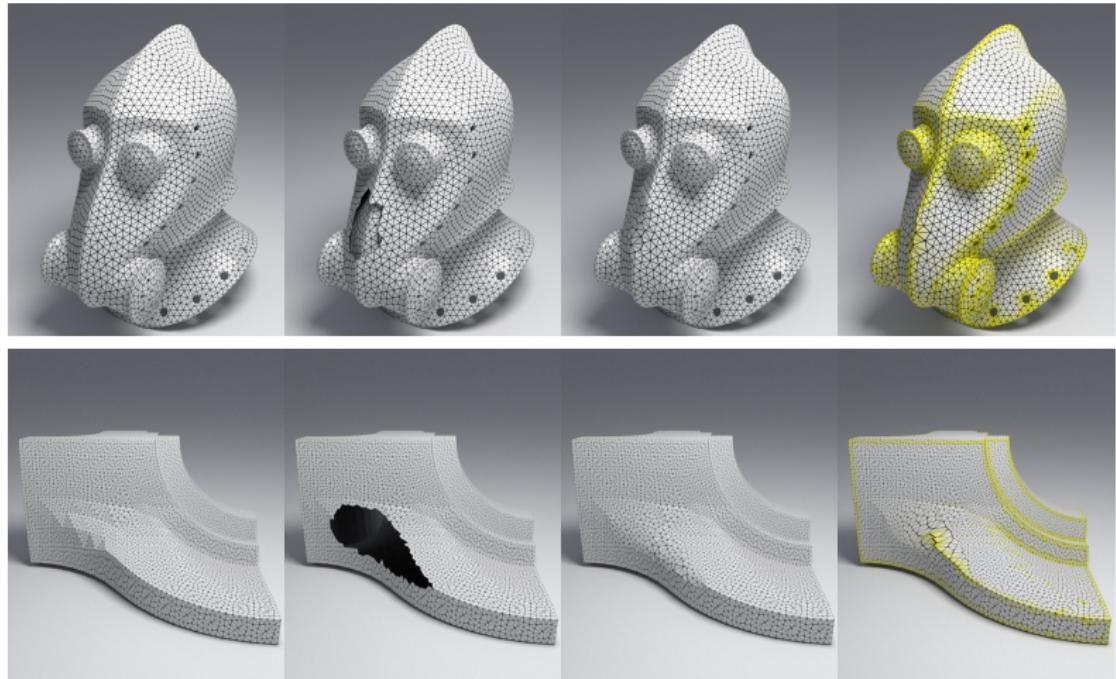
our approach

Mesh segmentation



- \checkmark is used as a probability of edge merge in a graph connected component algorithm

Mesh inpainting



Original

Missing area

CGAL filling

Our inpainting

Conclusion

- Discrete calculus model of AT recovers discontinuities
 - ▷ usual “phase-field” ones —→ **thin** discontinuities
- very generic formulation: 2D images, digital surfaces, triangulated meshes, graph structures, 3D hexahedral, tetrahedral or mixed meshes, ...
- opens a wide range of applications
 - ▷ image processing
 - ▷ 3D geometry processing
- open-source C++ code available, mostly on dgtal.org, otherwise on github.com
- reasonable computation times: from seconds to a few minutes

Open questions. Debatable statements.

- What about Γ -convergence of $AT_{\varepsilon}^{2,0}$ to MS ?

Open questions. Debatable statements.

- What about Γ -convergence of $\text{AT}_\varepsilon^{2,0}$ to MS ?
 - ▷ If $\epsilon < h$ or $\epsilon \approx h$, terms $\lambda\varepsilon (\mathbf{d}_0 \mathbf{v}, \mathbf{d}_0 \mathbf{v})_{\Omega,1} + \frac{\lambda}{4\varepsilon} (1 - \mathbf{v}, 1 - \mathbf{v})_{\Omega,0}$ do **not** converge to $\lambda \mathcal{H}^{N-1}(J_u)$

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 - ▷ Agreed, but it is also the case for FDM or FEM !

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- What about Γ -convergence of $\text{AT}_\varepsilon^{2,0}$ to MS ?
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 - ▷ Agreed, but it is also the case for FDM or FEM !
- Probably $\epsilon \gg h$, $\text{AT}_\varepsilon^{2,0}$ Γ -converges to MS (same as FDM or FEM)
 - ▷ what is the speed of convergence, error , etc ...

Open questions. Debatable statements.

- What about Γ -convergence of $\text{AT}_\varepsilon^{2,0}$ to MS ?
 - ▷ If $\epsilon < h$ or $\epsilon \approx h$, terms $\lambda\varepsilon(\mathbf{d}_0\mathbf{v}, \mathbf{d}_0\mathbf{v})_{\Omega,1} + \frac{\lambda}{4\varepsilon}(1-\mathbf{v}, 1-\mathbf{v})_{\Omega,0}$ do **not** converge to $\lambda\mathcal{H}^{N-1}(J_u)$
 - ▷ Agreed, but it is also the case for FDM or FEM !
- Probably $\epsilon \gg h$, $\text{AT}_\varepsilon^{2,0}$ Γ -converges to MS (same as FDM or FEM)
 - ▷ what is the speed of convergence, error , etc ...
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 - ▷ Grid approach: differential and derivatives aligned with edges
 - ▷ both cases: tensors located both on primal and dual vertices !

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 - ▷ Agreed, but it is also the case for FDM or FEM !
- Probabilistic $\text{AT}^{2,0}$ Γ -converges to MS (same as FDM or FEM)
 - ▷ wh Thank you for your attention !.
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