

Nonlocal Inpainting of Manifold-valued Data on Finite Weighted Graphs

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University of Kaiserslautern

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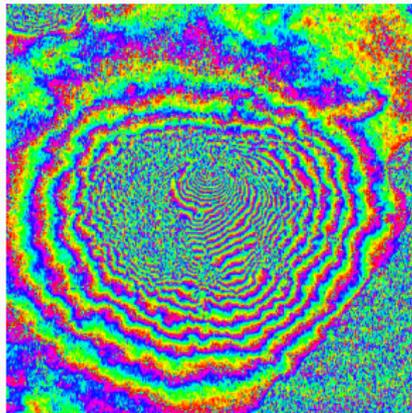
^ajoint work with D. Tenbrinck (WWU Münster)

Manifold-valued image processing

Manifold-valued images and data

New data acquisition modalities \Rightarrow non-Euclidean range of data

- Interferometric synthetic aperture radar (InSAR)
- Surface normals
- Diffusion tensors in magnetic resonance imaging (DT-MRI)
- Electron backscattered diffraction (EBSD)
- Directional data: wind, flow, GPS,...



InSAR data of Mt. Vesuvius

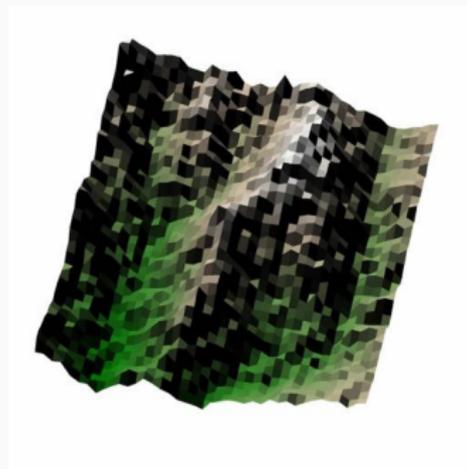
[Rocca, Prati, Guarnieri 1997]

phase valued data, \mathbb{S}^1

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National elevation dataset

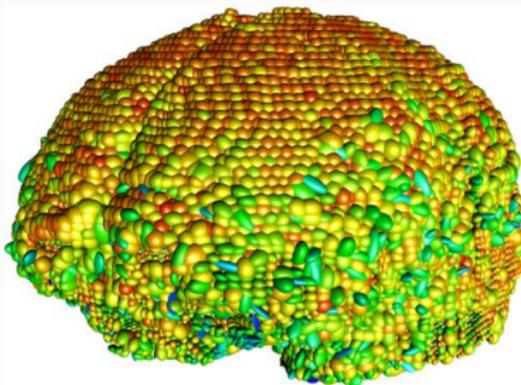
[Gesch, Evans, Mauck, 2009]

directional data, \mathbb{S}^2

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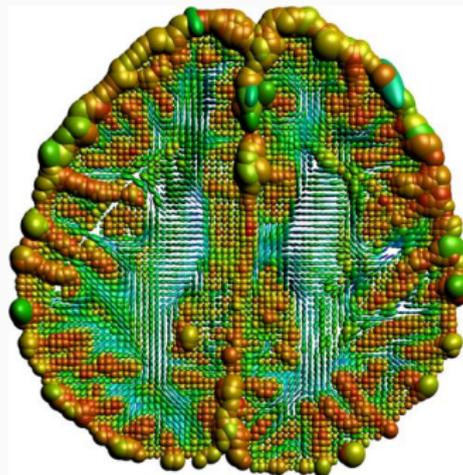
the Camino data set
<http://cmic.cs.ucl.ac.uk/camino>

sym. pos. def. Matrices, $\mathcal{P}(3)$

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Slice # 28 from the Camino data set
<http://cmic.cs.ucl.ac.uk/camino>

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EBSD example from the MTEX toolbox
[Bachmann, Hielscher, since 2005]

rotations (mod. symmetry), $SO(3)/S$.

Manifold-valued images and data

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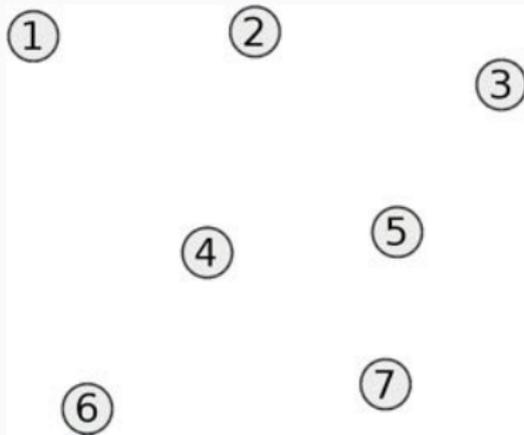
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Common properties

- The values lie on a Riemannian manifold
- tasks from “classical” image processing
- e.g. inpainting

Finite weighted graphs for data processing

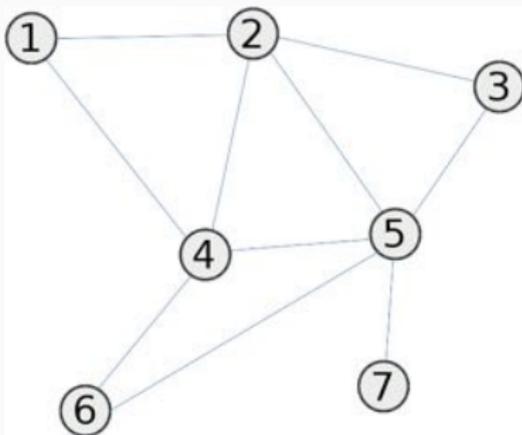
Finite weighted graphs



A finite weighted graph $G = (V, E, w)$ consists of

- a finite set of nodes V

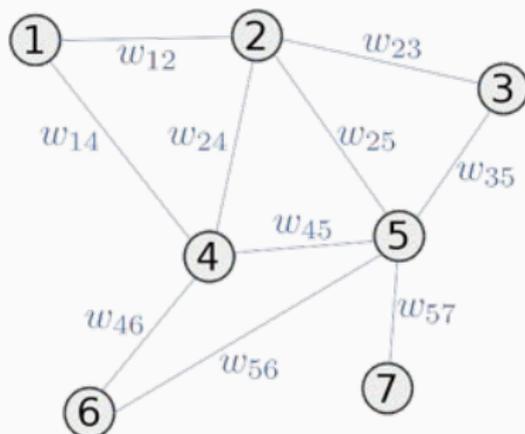
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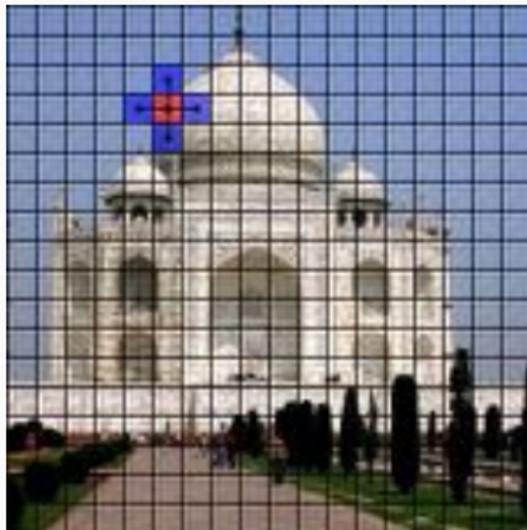


A finite weighted graph $G = (V, E, w)$ consists of

- a finite set of nodes V
- a finite set of **directed** edges $E \subset V \times V$
- a (symmetric) weight function $w : V \times V \rightarrow \mathbb{R}^+$,
 $w(u, v) = 0$ for $v \neq u$.

Finite weighted graphs for modeling discrete data

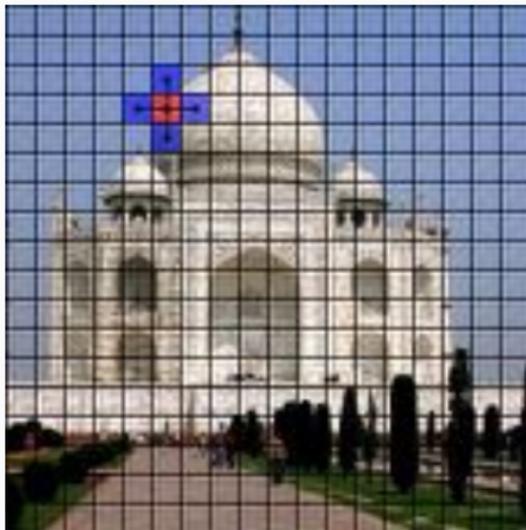
How can we apply graphs for **image processing**?



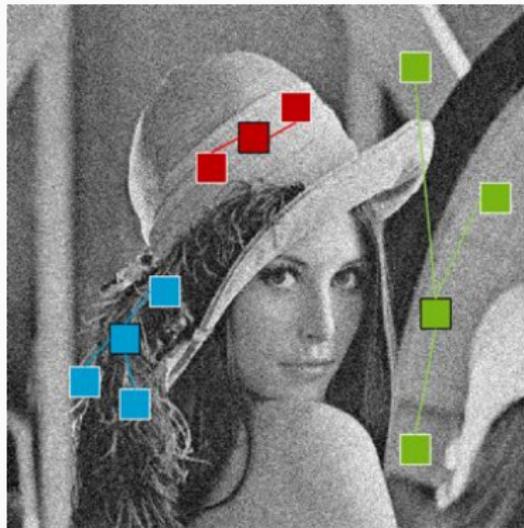
Local neighborhood
of a pixel

Finite weighted graphs for modeling discrete data

How can we apply graphs for image processing?



Local neighborhood
of a pixel



Nonlocal neighborhood
of a pixel

Finite weighted graphs for modeling discrete data

How can we apply graphs for [polygon mesh processing](#)?

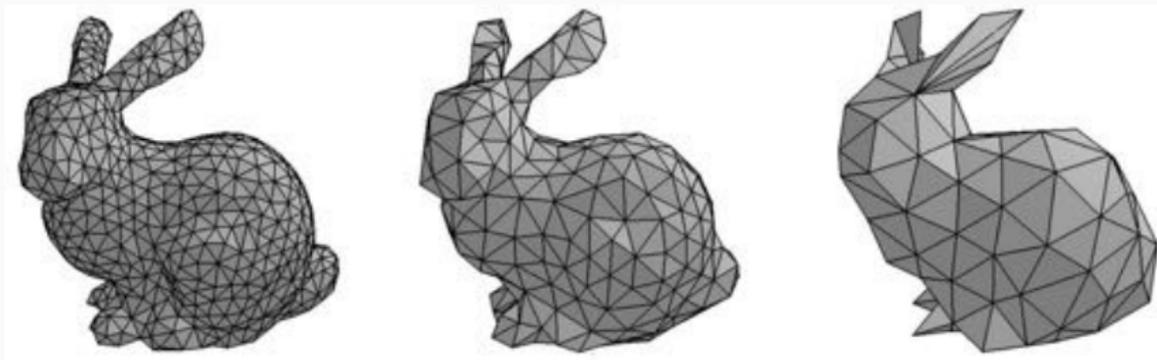


Image courtesy: Gabriel Peyré

Polygon mesh approximation of a 3D surface.

Finite weighted graphs for modeling discrete data

How can we apply graphs for [point cloud processing](#)?

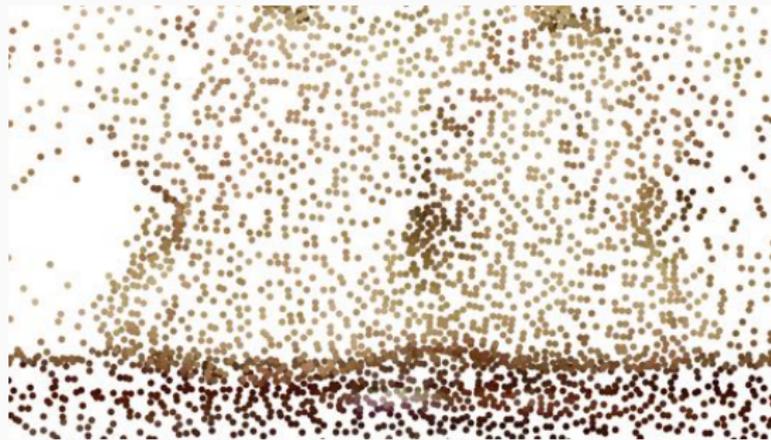


Image courtesy: François Lozes

Colored 3D point cloud data of a scanned chair.

Finite weighted graphs for modeling discrete data

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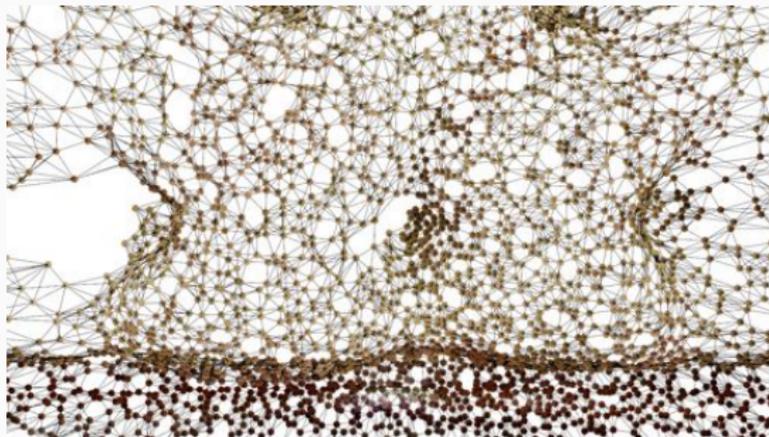
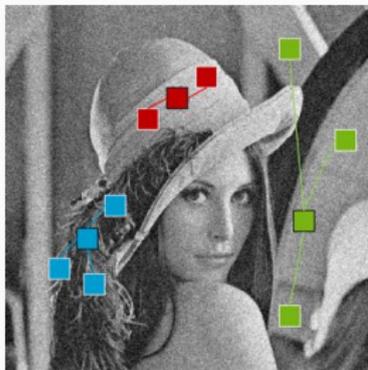


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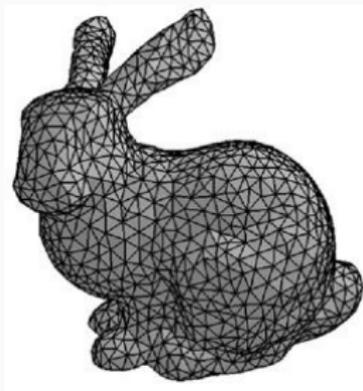
Graph construction on a 3D point cloud

Euclidean graph framework

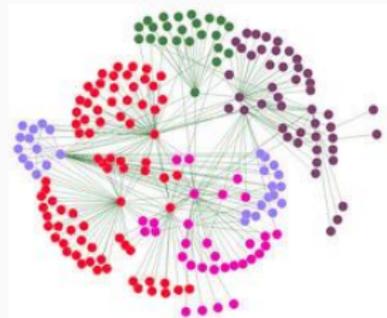
Application data on



a nonlocal
neighborhood



a surface



Source: Wikipedia

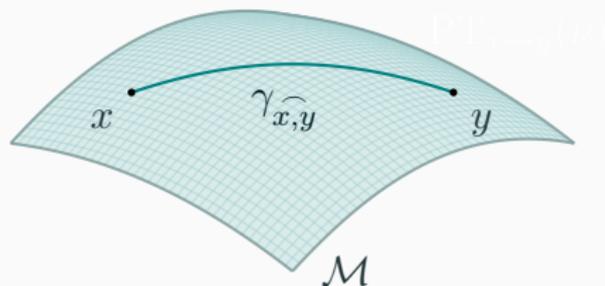
a social
network graph

is represented by a **vertex function** $f: V \rightarrow \mathbb{R}^m$

“Anything can be modeled as a graph”

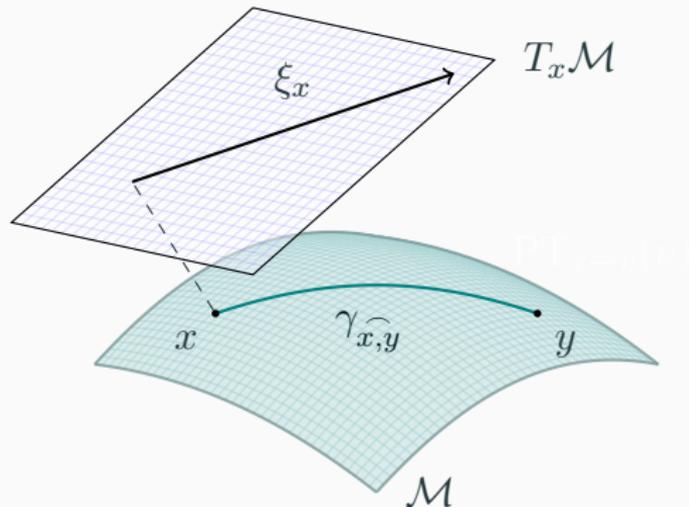
A manifold-valued graph framework & The ∞ -graph Laplace

Notations on a Riemannian manifold \mathcal{M}



geodesic $\gamma_{\widehat{x,y}}$ shortest path (on \mathcal{M}) connecting $x, y \in \mathcal{M}$.

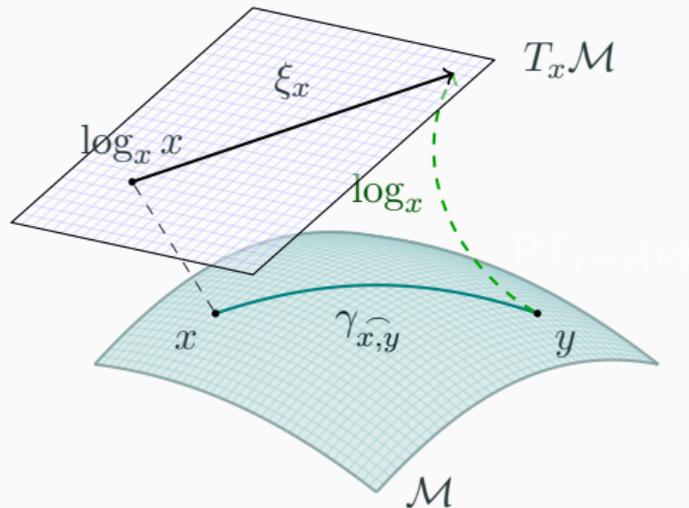
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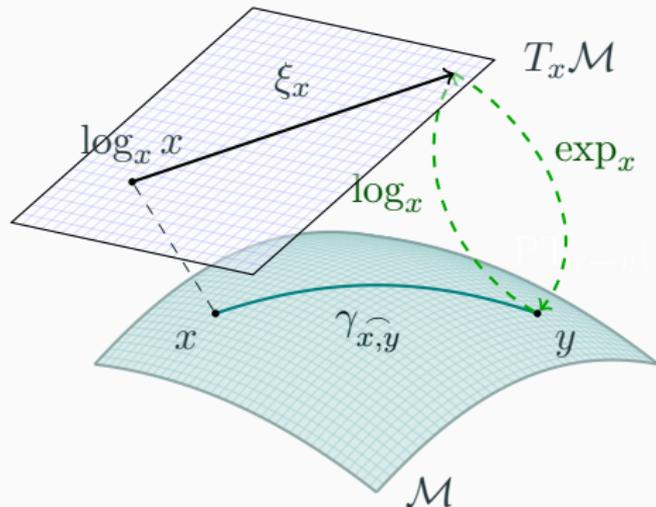


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logarithmic map $\log_x y = \dot{\gamma}_{x,y}(0)$, “velocity towards y ”

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logarithmic map $\log_x y = \dot{\gamma}_{x,y}(0)$, “velocity towards y ”

exponential map $\exp_x \xi_x = \gamma(1)$, where $\gamma(0) = x, \dot{\gamma}(0) = \xi_x$

The real-valued ∞ -Laplacian

Let $\Omega \subset \mathbb{R}^d$ be a bounded, open set and $f: \Omega \rightarrow \mathbb{R}$ smooth.

The **infinity Laplacian** $\Delta_\infty f$ in $x \in \Omega$ is defined as

[Crandall, Evans, Gariepy '01]

$$\Delta_\infty f(x) = \sum_{j=1}^d \sum_{k=1}^d \frac{\partial f}{\partial x_j} \frac{\partial f}{\partial x_k} \frac{\partial^2 f}{\partial x_j \partial x_k}(x).$$

Applications in image **interpolation** and (structure) **inpainting**.

[Caselles, Morel, Sbert '98]

A min-max discretization

Based on a simple approximation by **min-** and **max-values** in a neighborhood [Obermann, '04]

$$\Delta_{\infty}f(x) = \frac{1}{r^2} \left(\min_{y \in B_r(x)} f(y) + \max_{y \in B_r(x)} f(y) - 2f(x) \right) + \mathcal{O}(r^2).$$

a **real-valued** graph-based variant reads [Elmoataz, Desquenes, Lakhdari '14]

$$\begin{aligned} \Delta_{\infty}f(u) &= \|\nabla^+ f(u)\|_{\infty} - \|\nabla^- f(u)\|_{\infty} \\ &= \max_{v \sim u} |\min(\sqrt{w(u,v)}(f(v) - f(u)), 0)| \\ &\quad - \max_{v \sim u} |\max(\sqrt{w(u,v)}(f(v) - f(u)), 0)| \end{aligned}$$

Connection to AML extensions

Observation

[Aronsson '67; Jensen '93]

Any (unique) viscosity solution f^* of the Dirichlet problem

$$\begin{cases} -\Delta_\infty f(x) = 0, & \text{for } x \in \Omega, \\ f(x) = \varphi(x), & \text{for } x \in \partial\Omega, \end{cases}$$

is an absolutely minimizing Lipschitz extension (AML) of φ , i.e.,

$$f^*(x) = g(x) \text{ for } x \in \partial\Sigma \Rightarrow \|Df^*\|_{L^\infty(\Sigma)} \leq \|Dg\|_{L^\infty(\Sigma)},$$

for every open, bounded subset $\Sigma \subset \Omega$ and every $g \in C(\bar{\Sigma})$

\Rightarrow minimize locally the discrete Lipschitz constant [Obermann, '04]

$$\min_{f(x_0)} L(f(x_0)) \quad \text{with} \quad L(f(x_0)) = \max_{x_j \sim x_0} \frac{|f(x_0) - f(x_j)|}{|x_0 - x_j|}$$

\Rightarrow consistent scheme for solving $-\Delta_\infty f = 0$.

Constructing discrete Lipschitz extensions

On \mathbb{R}^m the infinity Laplace operator can be approximated by

$$\Delta_{\infty} f(x_0) = \frac{1}{|x_0 - x_j^*| + |x_0 - x_i^*|} \left(\frac{f(x_0) - f(x_j^*)}{|x_0 - x_j^*|} + \frac{f(x_0) - f(x_i^*)}{|x_0 - x_i^*|} \right)$$

where the neighbors (x_i^*, x_j^*) are determined by [Obermann, '04]

$$(x_i^*, x_j^*) = \operatorname{argmax}_{x_i, x_j \sim x_0} \frac{|f(x_i) - f(x_j)|}{|x_0 - x_i| + |x_0 - x_j|}$$

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$$(x_i^*, x_j^*) = \operatorname{argmax}_{x_i, x_j \sim x_0} \frac{|(f(x_i) - f(x_0)) - (f(x_j) - f(x_0))|}{|x_0 - x_i| + |x_0 - x_j|}$$

Graph ∞ -Laplacian for manifold-valued data

We define the graph- ∞ -Laplace operator for manifold valued data $\Delta_\infty f$ in a vertex $u \in V$ as

$$\Delta_\infty f(u) := \frac{\sqrt{w(u, v_1^*)} \log_{f(u)} f(v_1^*) + \sqrt{w(u, v_2^*)} \log_{f(u)} f(v_2^*)}{\sqrt{w(u, v_1^*)} + \sqrt{w(u, v_2^*)}},$$

where $v_1^*, v_2^* \in \mathcal{N}(u)$ maximize the discrete Lipschitz constant in the local tangent space $T_{f(u)}\mathcal{M}$ among all neighbors, i.e.,

$$\begin{aligned} & (v_1^*, v_2^*) \\ &= \operatorname{argmax}_{(v_1, v_2) \in \mathcal{N}^2(u)} \left\| \sqrt{w(u, v_1)} \log_{f(u)} f(v_1) - \sqrt{w(u, v_2)} \log_{f(u)} f(v_2) \right\|_{f(u)} \end{aligned}$$

Numerical iteration scheme

to solve

$$\begin{cases} \Delta_{\infty} f(u) = 0 & \text{for all } u \in U, \\ f(u) = g(u) & \text{for all } u \in V/U. \end{cases}$$

we introduce an artificial time dimension t , i.e.

$$\begin{cases} \frac{\partial f}{\partial t}(u, t) = \Delta_{\infty} f(u, t) & \text{for all } u \in U, t \in (0, \infty), \\ f(u, 0) = f_0(u) & \text{for all } u \in U, \\ f(u, t) = g(u, t) & \text{for all } u \in V/U, t \in [0, \infty). \end{cases}$$

and propose an **explicit Euler scheme** with step size $\tau > 0$ using $f_k(u) := f(u, k\tau)$ we obtain

$$f_{k+1}(u) = \exp_{f_k(u)}(\tau \Delta_{\infty} f_k(u)), \text{ for all } u \in V$$

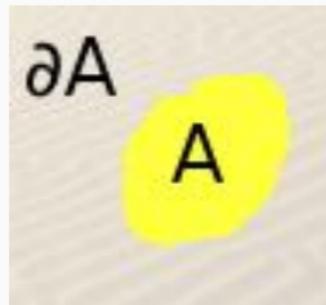
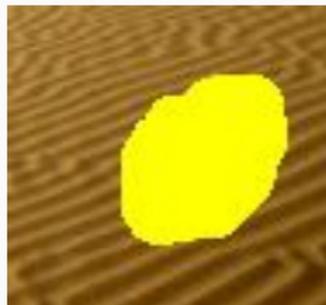
Numerical examples

Interpolation of structure

Goal

Inpaint $A \subset V$ using information in $\partial A = V/A$.

[Elmoataz, Toutain, Tenbrinck '16]



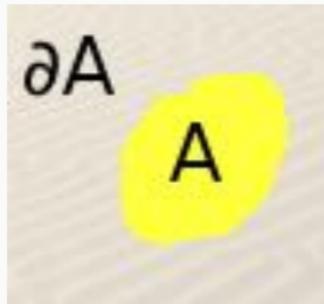
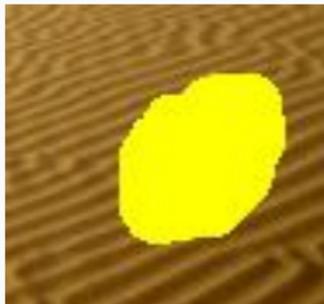
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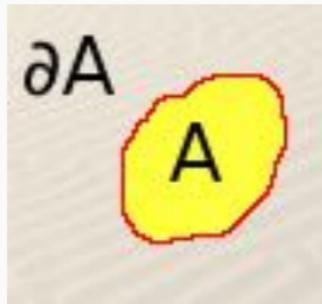
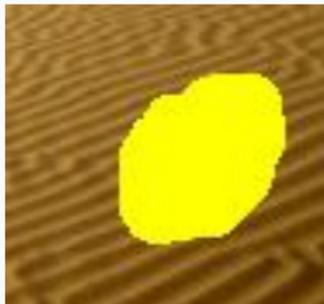
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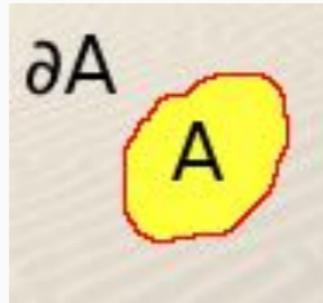
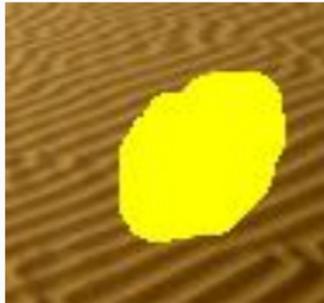
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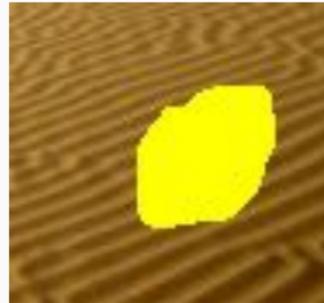
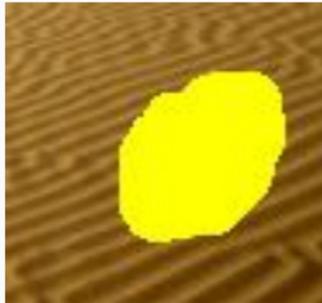
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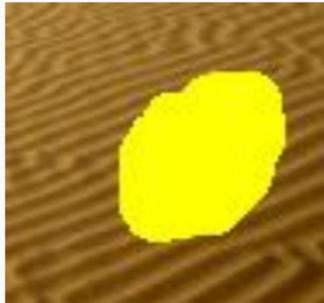
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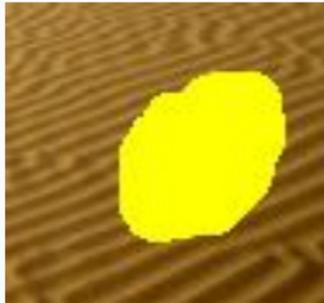
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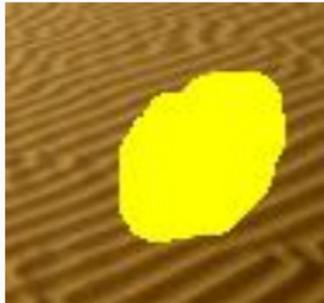
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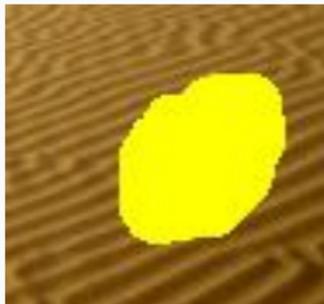
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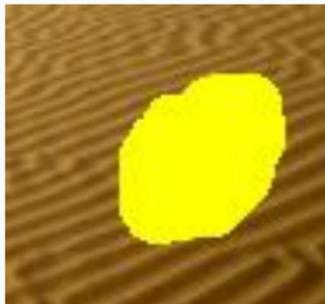
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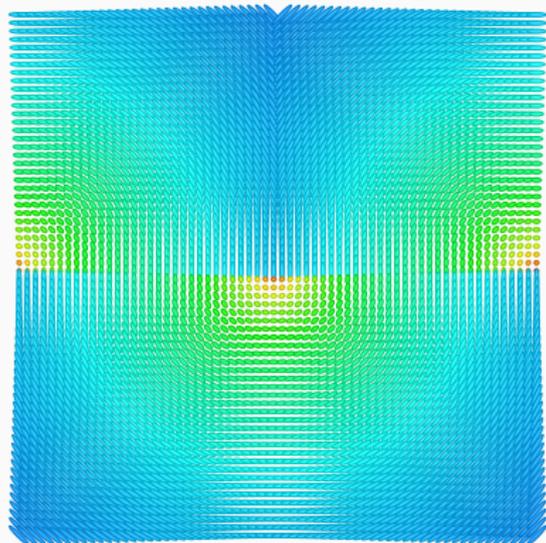
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Inpainting of symmetric positive definite matrices

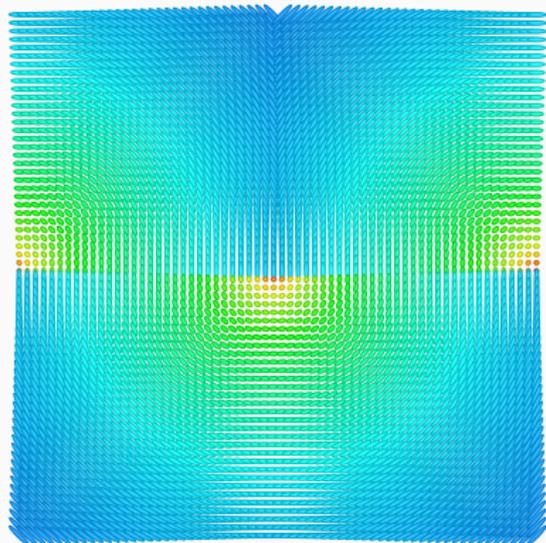
manifold $\mathcal{M} = \mathcal{P}(2)$, graph construction from previous slide



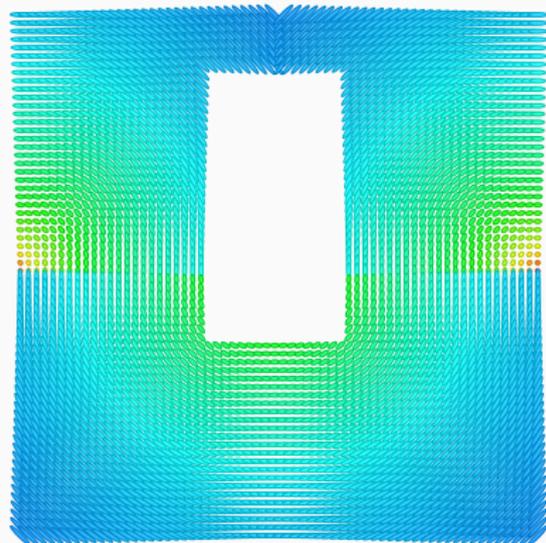
Original data

Inpainting of symmetric positive definite matrices

manifold $\mathcal{M} = \mathcal{P}(2)$, graph construction from previous slide



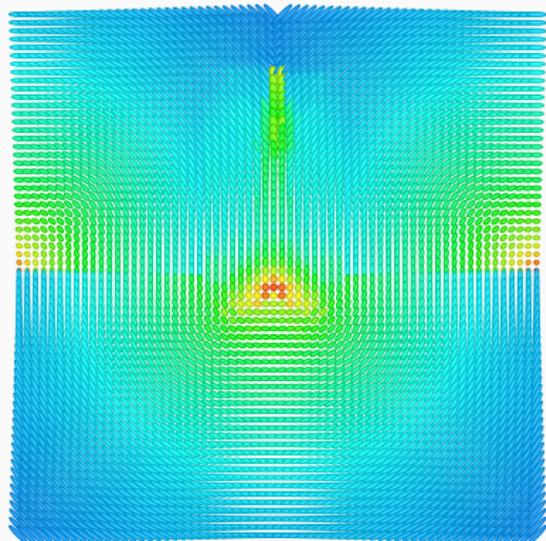
Original data



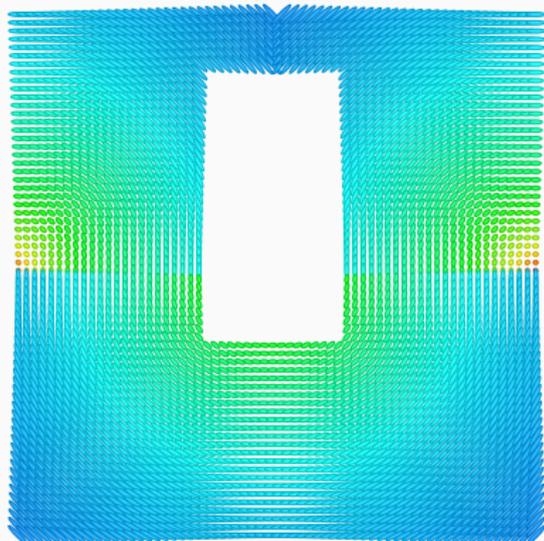
Given (lossy) data

Inpainting of symmetric positive definite matrices

manifold $\mathcal{M} = \mathcal{P}(2)$, graph construction from previous slide



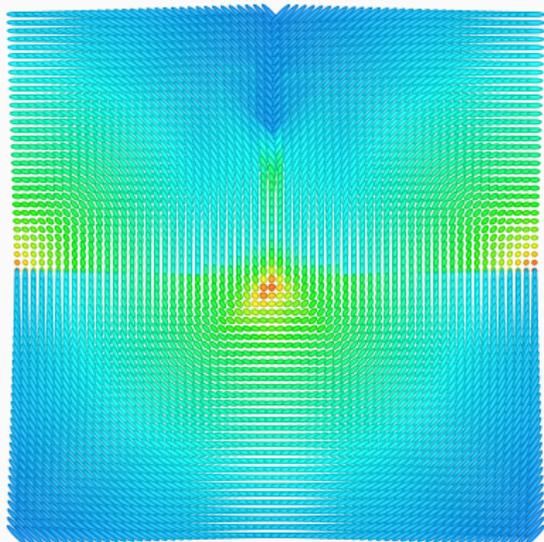
Inpainting with
25 neighbors, patch size 6



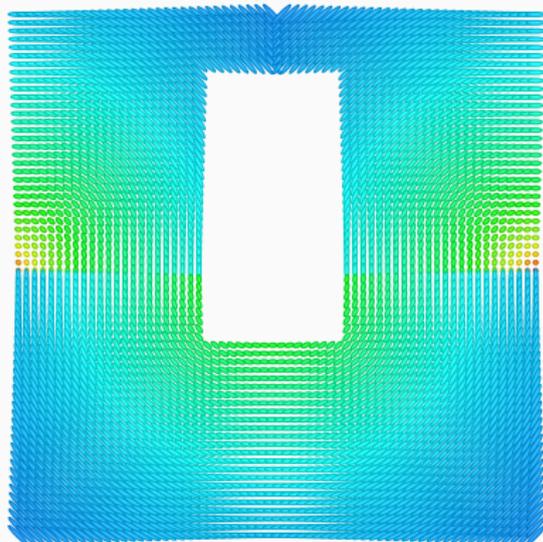
Given (lossy) data

Inpainting of symmetric positive definite matrices

manifold $\mathcal{M} = \mathcal{P}(2)$, graph construction from previous slide



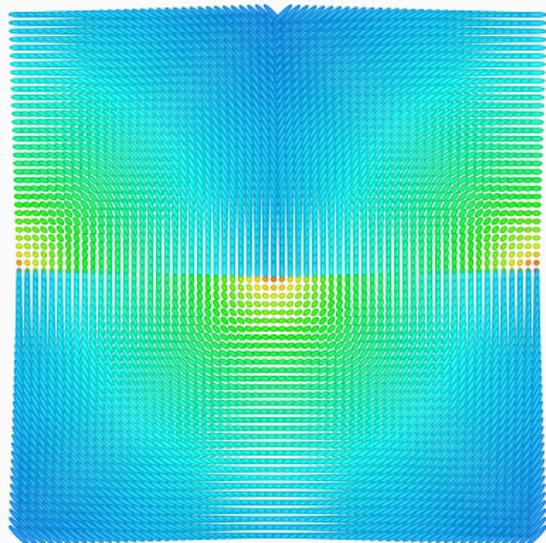
Inpainting with
5 neighbors, patch size 6



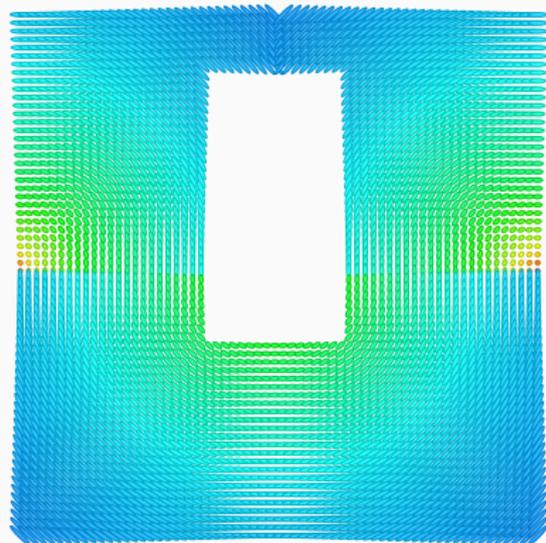
Given (lossy) data

Inpainting of symmetric positive definite matrices

manifold $\mathcal{M} = \mathcal{P}(2)$, graph construction from previous slide



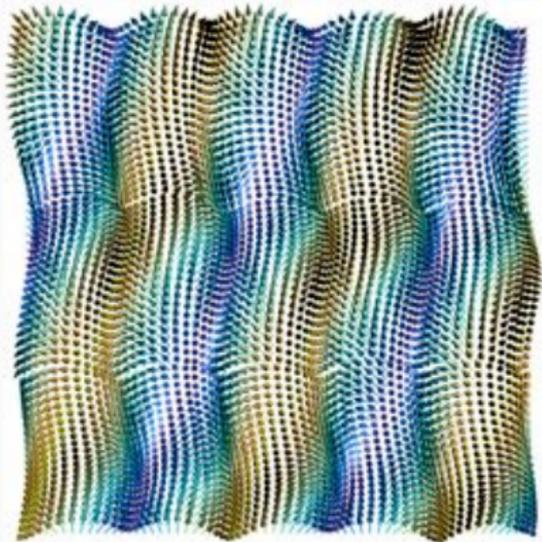
Original data



Given (lossy) data

Inpainting of directional data

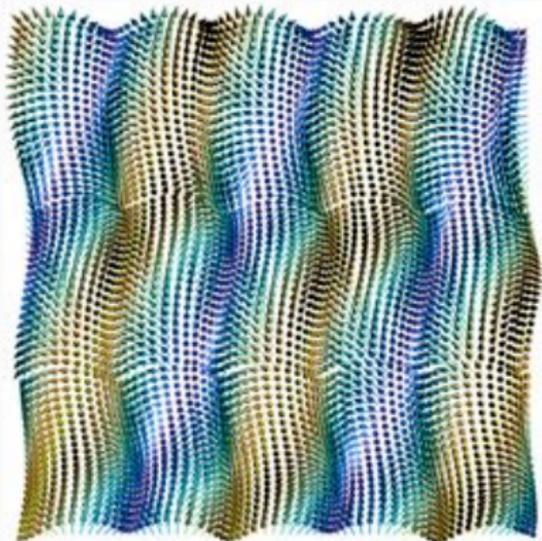
manifold $\mathcal{M} = \mathbb{S}^2$, graph construction from previous slide.



Original data

Inpainting of directional data

manifold $\mathcal{M} = \mathbb{S}^2$, graph construction from previous slide.



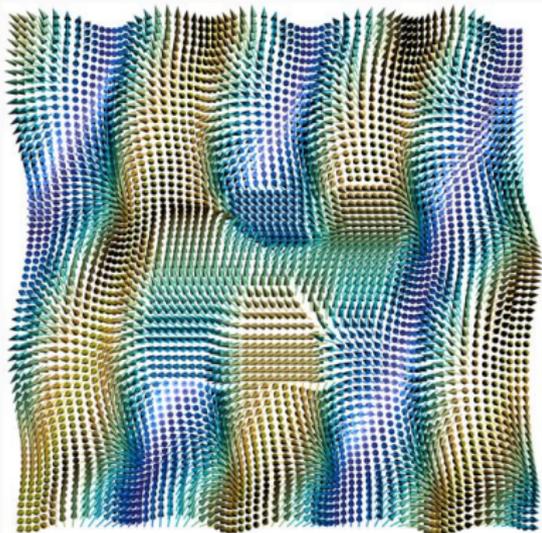
Original data



Given (lossy) data

Inpainting of directional data

manifold $\mathcal{M} = \mathbb{S}^2$, graph construction from previous slide.



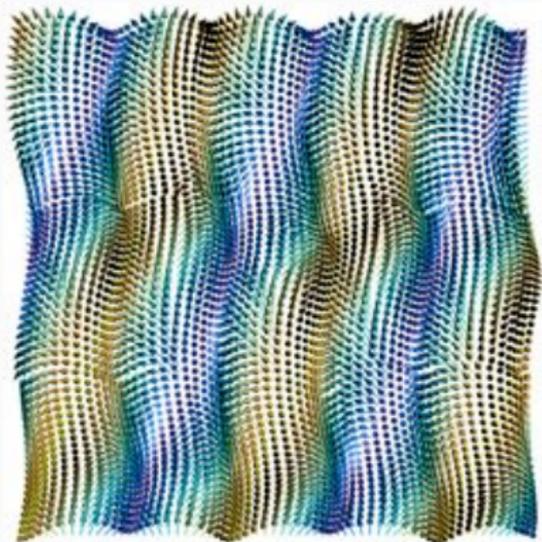
Inpainting with
first and second order TV



Given (lossy) data

Inpainting of directional data

manifold $\mathcal{M} = \mathbb{S}^2$, graph construction from previous slide.



Inpainted with
graph ∞ -Laplace



Given (lossy) data

Inpainting of directional data

manifold $\mathcal{M} = \mathbb{S}^2$, graph construction from previous slide.



Original data



Given (lossy) data

Conclusion

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- manifold-valued graph ∞ -Laplacian for inpainting
- model local and nonlocal features
- inpaint structure on manifold-valued data

Conclusion

- manifold-valued graph ∞ -Laplacian for inpainting
- model local and nonlocal features
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Future work

- consistency
- other graph based PDEs
- other image processing tasks (segmentation)
- other numerical schemes

-  RB and D. Tenbrinck. “A Graph Framework for manifold-valued Data”. In: SIAM J. Imaging Sci. (2017). accepted. arXiv: 1702.05293.
-  RB and D. Tenbrinck. Nonlocal Inpainting of Manifold-valued Data on Finite Weighted Graphs. GSI'17. 2017. arXiv: 1702.05293.
-  A. Elmoataz, M. Toutain, and D. Tenbrinck. “On the p -Laplacian and ∞ -Laplacian on Graphs with Applications in Image and Data Processing”. In: SIAM J. Imag. Sci. 8.4 (2015), pp. 2412–2451.
-  Adam M. Oberman. “A convergent difference Scheme for the Infinity Laplacian: Construction of absolutely minimizing Lipschitz extensions”. In: Math. Comp. 74.251 (2004), pp. 1217–1230.

Open source Matlab software MVIRT:

www.mathematik.uni-kl.de/imagepro/members/bergmann/mvirt/