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Adaption of the Eikonal Equation over Weighted Graphs

(1) Introduction

The static eikonal equation is

$$\begin{cases} \|\nabla f(x)\| - P(x) = 0 & x \in \Omega \subset \mathbb{R}^m \\ f(x) = \phi(x) & x \in \Gamma \subset \Omega \end{cases},$$
(1)

where ϕ (boundary condition) is a positive speed function defined on Ω , f(x) is the traveling time or distance from source Γ and *P* a potential function. Solution of (1) represents the shortest distance from x to the zero distance curve given by Γ (where $\phi(x)=0$) and describes the evolution of a front *V* is the set of vertices of the graph, V_0 is the initial set driven by *P*.

tion (1) have been proposed: iterative schemes [1], fast sweeping methods [2] and fast marching meth- Advantages: ods [3,4].

Another approach is to consider a time dependent version:

$$\begin{cases} \partial f(x,t) / \partial t = - \|\nabla f(x)\| + P(x) & x \in \Omega \subset \mathbb{R}^{m} \\ f(x,t) = \phi(x) & x \in \Gamma \subset \mathbb{R}^{m} \\ f(x,0) = \phi_{0}(x) & x \in \Omega \end{cases}$$
(2)

Contributions: We propose an adaption of (2) over weighted graph of arbitrary structure based on partial difference equations (PdEs).

The analogue of (2) on a weighted graph G =(V, E, w) is

$$\begin{cases} \partial f(u,t)/\partial t = -\|\nabla_w^- f(u)\|_p + P(u) & u \in V \\ f(u,t) = \phi(u) & u \in V_0 \subset V , \\ f(u,0) = \phi_0(u) & u \in V \end{cases}$$
(3)

of seed vertices, ∇_w^- is a weighted internal morpho-Solutions and numerical schemes for static equalogical gradient on graph and $\|.\|_p$ is the \mathcal{L}_p -norm.

- Any domains (high dimensional and irregular) that can be represented by a graph can be considered.
- No spatial discretization or triangulation step.
- For images: local and nonlocal configurations are enabled in a same formulation.
- The formulation recovers well known schemes.

(2) Graphs and Weights

Weighted graph: A weighted graph G = (V, E, w) Graphs weights: Function w reflects similariis composed of a set *V* of *vertices*, a set $E \subset V \times V$ of **ties between data**. One can use weighted *edges* and a *weight function* $w: V \times V \rightarrow \mathbb{R}^+$. An *edge uv* of *E* connects two adjacent vertices *u* and $g_0(uv) = 1$ (constant weight case), v. The Hilbert space of functions defined on V is $g_1(uv) = (\rho(F(f^0, u), F(f^0, v)) + \epsilon)^{-1}$ or noted $\mathcal{H}(V)$.

Neighborhood graphs: Any discrete domain can be represented by a weighted graph where functions of $\mathcal{H}(V)$ represent the data to process. We focus on two neighborhood graphs:

- the *k* nearest neighbors graphs (*k*-NNG).
- The τ -neighborhood graph (G_{τ}).

2D images $(f^0: V \subset \mathbb{Z}^2 \to \mathbb{R}^m)$ can be represented by one is $F(f^0, .) = f^0$. For images, another choice is G_{τ} graphs. For instance: the 4-adjacency grid graph provided by image patches: $F(f^0, u) = F_{\tau}(f^0, u) =$ (G₀) with the city block distance. Another use- $\{f^0(v) : v \in V \text{ with } \rho(u, v) \leq \tau\}$ (τ a threshold paful graph for image is the region adjacency graph rameter). This feature vector has been proposed in (RAG) where vertices correspond to image regions the context of texture synthesis [5], and further used and edges regions adjacency relationships.

 $g_2(uv) = \exp(-\rho(F(f^0, u), F(f^0, v))^2 / \sigma^2)$

 $\sigma > 0$ controls the similarity, ϵ is defined as $\epsilon > 0$, $\epsilon \rightarrow 0$, ρ is usually the Euclidean distance.

 $F(f^0, u) \in \mathbb{R}^m$ is the features vector of $u \in V$ where $f^0 \in \mathcal{H}(V)$ is an initial function.

Several choices of *F* can be used. The simplest in the context of image and data processing [6–8].

(3) A Family of Gradients on Weighted Graphs

From [8] that defines for a function $f \in \mathcal{H}(V)$

• the weighted difference operator on graphs for $uv \in E$

 $\partial_v f(u) = \sqrt{w_{uv}}(f(v) - f(u))$

• the weighted gradient operator for $u \in V$

 $(\nabla_w f)(u) = (\partial_v f(u))_{uv \in E}$

We define in [9]

• two new weighted directional difference deriva- **Properties:** tives for an edge $uv \in E$ with Df(u) = f(v) - f(u)

external: $\partial_v^+ f(u) = \sqrt{w_{uv}} \max(0, Df(u))$ **internal:** $\partial_v^- f(u) = \sqrt{w_{uv}} \min(0, Df(u))$

• two new weighted morphological gradients

external: $(\nabla_w^+ f)(u) = (\partial_v^+ f(u))_{uv \in E}$ internal: $(\nabla_w^- f)(u) = (\partial_v^- f(u))_{uv \in E}$

The corresponding \mathcal{L}_p (0<p< ∞) and \mathcal{L}_∞ ($p = \infty$) norms are, respectively

$$\| (\nabla_{w}^{\pm} f)(u) \|_{p} = \left[\sum_{v \sim u} w_{uv}^{p/2} | (0, Df(u))^{\pm} |^{p} \right]^{1/p}$$

$$\| (\nabla_{w}^{\pm} f)(u) \|_{\infty} = \max_{v \sim u} (\sqrt{w_{uv}} | (0, Df(u))^{\pm} |)$$

$$(4)$$

where $v \sim u$ means that v is neighbor of u. These gradients norms have the following properties

$$\| (\nabla_w f)(u) \|_p^p = \| (\nabla_w^+ f)(u) \|_p^p + \| (\nabla_w^- f)(u) \|_p^p \| (\nabla_w f)(u) \|_{\infty} = \max(\| (\nabla_w^+ f)(u) \|_{\infty}, \| (\nabla_w^- f)(u) \|_{\infty})$$

- These general definitions are defined on graphs of arbitrary topology.
- They can be used to process any discrete regular or irregular data sets that can be represented by a weighted graph.
- Local and nonlocal settings are directly handled in these definitions and both are expressed by the graph topology in terms of neighborhood connectivity [10].

(4) Numerical Schemes for Morphological Processes

Time dependent eikonal equation (2) **is linked** graph G=(V, E, w), a function $f \in \mathcal{H}(V)$ with mathematical morphology processes and can **be viewed as morphological evolution equations.** $\partial_t \delta(f(u)) = \partial_t f(u) = + \|(\nabla_w^+ f)(u)\|_p$

Dilation and Erosion: The two fundamental operations in mathematical morphology are **dila**tions $\delta: \mathbb{R}^m \to \mathbb{R}^m$ and **erosions** $\varepsilon: \mathbb{R}^m \to \mathbb{R}^m$. Classically, these operations are performed by considering lattices and their implementations are **algebraic** (discrete).

Continuous morphology [11] defines **flat** dilation and erosion of a function $f: \mathbb{R}^m \to \mathbb{R}$ with the following partial differential equations (PDEs):

$$\partial_t \delta(f) = \partial_t f = + \|\nabla f\|_p$$
 and $\partial_t \varepsilon(f) = \partial_t f = - \|\nabla f\|_p$

Analogues on Weighted Graphs: In [9] we have proposed analogues over graphs of the continuous morphological equations by using morphological gradients and their numerical schemes (4). For a

 $\partial_t \varepsilon(f(u)) = \partial_t f(u) = -\|(\nabla_w^- f)(u)\|_p$ (5) These equations constitute a morphological framework [9] based on PdEs that extends algebraic and

(5)

continuous morphological operators for images and high dimensional data processing.

Relations with Algebraic Formulations: For the particular case where $w = g_0 = 1$ and with the \mathcal{L}_{∞} -norm, our definitions recover the definitions of algebraic:

- classical internal and external differences and gradients definitions.
- morphological gradient operator $\|(\nabla_w^+ f)(u)\|_{\infty} + \|(\nabla_w^- f)(u)\|_{\infty}.$
- morphological Laplace operator $\|(\nabla_w^+ f)(u)\|_{\infty} \|(\nabla_w^- f)(u)\|_{\infty}.$
- dilation and erosion on graphs.

(5) Eikonal Equation over Weighted Graphs

regarding the minus sign and a constant potential ∞) norms, we have function *P*. The adaption of the eikonal equation on graphs can be directly obtained with the erosion process defined in (5) and by replacing operator ∇f by the internal gradient $\nabla_w^- f$. The analogue of (2) over graphs (2) (parameterized by p and w) is

$$\begin{cases} \partial f(u,t) / \partial t = - \| (\nabla_w^- f)(u) \|_p + P(u) & u \in V \\ f(u,t) = \phi(u) & u \in V_0 \subset V \\ f(u,0) = \phi_0(u) & u \in V \end{cases}$$

tices.

Numerical Schemes and Algorithms: With our definitions of morphological gradients, we can directly obtain the numerical schemes to solve (6) without any spatial discretization thanks to the discrete form of our operators on graphs. With $f^n(u) \approx f(u, n\Delta t)$, we have

$$\frac{f^{n+1}(u) - f^n(u)}{\Delta t} = -\|(\nabla_w^- f^n)(u)\|_p + P(u).$$
 (7)

System (2) can be viewed as an erosion process. With the corresponding \mathcal{L}_p (0<p< ∞) and \mathcal{L}_{∞} (p =

$$\frac{f^{n+1}(u) - f^{n}(u)}{\Delta t} = -\left[\sum_{v \sim u} w_{uv}^{p/2} |\min(0, Df^{n}(u))|^{p}\right]^{\frac{1}{p}} + P(u) \quad (8)$$
$$\frac{f^{n+1}(u) - f^{n}(u)}{\Delta t} = -\max_{v \sim u} (\sqrt{w_{uv}} |\min(0, Df^{n}(u))|) + P(u) \quad (9)$$

These numerical schemes work on any graph of arbitrary topology. This implies that our formulation (6) constitutes a simple and unified method to solve the where V_0 corresponds to the initial set of seed ver- eikonal equation for any data defined on regular or irregular domains that can be modeled by a graph in any dimensions.

> Relations with other Schemes: With specific parameters and graphs, the proposed formulation recovers the Osher-Sethian discretization scheme for a *m*-dimensional grid (with (8) when *p* = 2) and a **Dijkstra like algorithm** (with (9) when $p = \infty$) for any graphs methods.

(6a) Experiments — Distance Computation **Images**



Adaptive Framework for Generalized Weighted Distance Computation with different *p* values (distance maps with isolevels superimposed).

Potential P = 1 and graph configurations are:

- first row (local): G_0 , $w=g_0$, $F=f^0$
- second row (nonlocal): G_2 , $w=g_2$, $F=F_5(f^0,.)$

(6b) Experiments — Distance Computation Delaunay Graphs and Meshes



(6c) Experiments — Distance Computation **Unorganized High Dimensional Data: Data Ranking (1)**



(6c) Experiments — Distance Computation **Unorganized High Dimensional Data: Data Ranking (2)**



(6d) Experiments — Nonlocal Segmentation: Images



Image segmentation with class membership computation. Potential *P* is original image gradient.

Graphs configurations: local case: G_0 , $w = g_0$, $F = f^0$, nonlocal case:

- First and second rows: G_3 , $w = g_2$, $F = F_2(f^0, .)$.
- Third: $G_0 \cup 4$ -NNG, $w = g_1$, $F = F_3(f^0, .)$.

(6e) Experiments — Nonlocal Segmentation **Region Based Graphs (1)**



Segmentation by distance map thresholding. Advantages of regions based

graph:

- Nonlocal object segmentation.
- Minimal number of seeds.
- Fast computation: original image, |V| = 65536 pixels; image partition, |V| = 1324 regions 98% of reduction in terms of vertices.

Graph configurations:

- local case: RAG, $w = g_2$
- nonlocal case: RAG \cup 5 NNG, $w = g_2$

(6e) Experiments — Nonlocal Segmentation **Region Based Graphs (2)**



Graphs configuration: RAG \cup 4-NNG, $w = g_2$.

(6f) Experiments — Nonlocal Segmentation: Unorganized High Dimensional Data Clustering and Classification

Original set



Original set

Seeds and Classification Results







Seeds and Classification Results



Graphs configuration: first row 20-NNG, second row: 5-NNG, for both $w = g_1$ and $f^0 : V \to \mathbb{R}^{16}$ Classification rates: 93.1% and 100%

References

- [1] E. Rouy and A. Tourin, "A viscosity solutions approach to shape-from-shading," SIAM Journal on Numerical Analysis, vol. 3, pp. 867–884, 1992.
- [2] H. Zhao, "Fast sweeping method for eikonal equations," Mathematics of Computation, vol. 74, pp. 603–627, 2005.
- [3] J. N. Tsitsiklis, "Efficient algorithms for globally optimal trajectories," IEEE Transactions on Automatic Control, vol. 40, no. 9, pp. 1528–1538, 1995.
- [4] J. A. Sethian, Level Set Methods and Fast Marching Methods: Evolving Interfaces in Computational Geometry, Fluid Mechanics, Computer Vision and Materials Science. Cambridge University Press, 1999.
- [5] A. A. Efros and T. K. Leung, "Texture synthesis by nonparametric sampling," in Proceedings of ICCV, vol. 2, 1999, pp. 1033-1038.
- movie denoising," International Journal of Computer Vision, vol. 76, no. 2, pp. 123–139, 2008.

- [7] G. Gilboa and S. Osher, "Nonlocal linear image regularization and supervised segmentation," SIAM Multiscale Modeling and Simulation, vol. 6, no. 2, pp. 595–630, 2007.
- [8] A. Elmoataz, O. Lézoray, and S. Bougleux, "Nonlocal discrete regularization on weighted graphs: A framework for image and manifold processing," IEEE Transactions on Image Processing, vol. 17, no. 7, pp. 1047–1060, jul 2008.
- [9] V.-T. Ta, A. Elmoataz, and O. Lézoray, "Partial difference equations over graphs: Morphological processing of arbitrary discrete data," in Proceedings of 10th ECCV, ser. LNCS 5304. Springer, oct 2008, pp. 668–680.
- [10] A. Elmoataz, O. Lézoray, S. Bougleux, and V.-T. Ta, "Unifying local and nonlocal processing with partial difference operators on weighted graphs," in Proceedings of LNLA, aug 2008, pp. 11-26.
- [6] A. Buades, B. Coll, and J.-M. Morel, "Nonlocal image and [11] R. W. Brockett and P. Maragos, "Evolution equations for continuous-scale morphology," in Proceedings of ICASSP, vol. 3, 1992, pp. 125–128.

Acknowledgment This work was partially supported under a research grant of the ANR Foundation (ANR-06-MDCA-008-01/FOGRIMMI) and a doctoral grant of the Conseil Régional de Basse-Normandie and of the Cœur et Cancer association in collaboration with the Department of Anatomical and Cytological Pathology from Cotentin Hospital Center.

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