

# THRESHOLD-BASED GRAPH RECONSTRUCTION USING DISCRETE MORSE THEORY

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FWCG, 2018

## PROBLEM STATEMENT

Given a (noisy) sample  $S$  taken around a (hidden) embedded graph  $G$ , how one can “reconstruct” the topology and geometry of  $G$  from  $S$ .

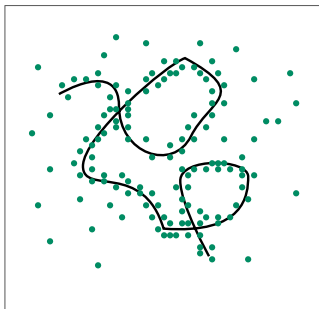
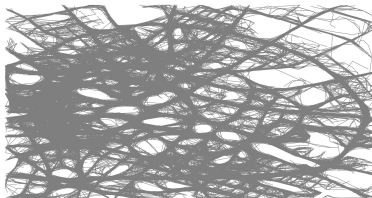


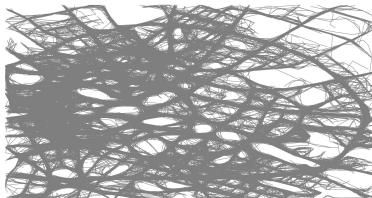
FIGURE: Sample around an embedded graph

# APPLICATION: MAP RECONSTRUCTION FROM GPS TRACES



**FIGURE:** GPS traces of Berlin ([mapconstruction.org](http://mapconstruction.org))

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**FIGURE:** A reconstruction

## NOISE MODELS

- 1 Hausdorff noise
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## WHAT TO RECONSTRUCT?

- 1 Topology (same homotopy type)
- 2 Geometry (small Hausdorff-distance)

## GENERIC DENSITY-BASED ALGORITHM

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- 1 Compute density  $f$  of  $S$  over  $\tilde{D}$ .

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- Histogram Computation
- Kernel Density Estimate

$$K(x, y; b) := \exp\left(\frac{-\|x - y\|^2}{2b^2}\right)$$

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③ heuristic pruning methods are applied this super-level set to approximate  $G$ .

## RECENT WORKS

- 1 Choosing thresholds systematically using [Persistent Homology](#). (AFGW15)

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## LIMITATIONS

- ① Thresholds are chosen heuristically.
- ② Theoretical guarantees on the topological/geometric correctness is not proved.
- ③ The output is often a thick region around the hidden graph.

## $(\omega, \beta_1, \beta_2, \nu)$ -APPROXIMATION OF $G$

Let  $\omega > 0$  such that  $G^\omega$  has a deformation retract onto  $G$ .

$$f(x) \in \begin{cases} [\beta_1, \beta_1 + \nu], & x \in V^\omega \\ [\beta_2, \beta_2 + \nu], & x \in G - V^\omega \\ [0, \nu], & \text{otherwise} \end{cases}$$

$V$  denotes the set of vertices of  $G$ .

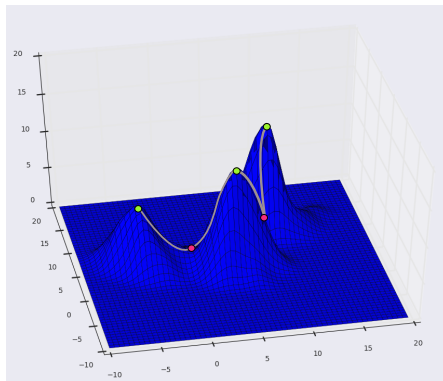


FIGURE: KDE

If the samples are concentrated around a graph, then the mountain ridges on the graph of the density function are expected to capture it.

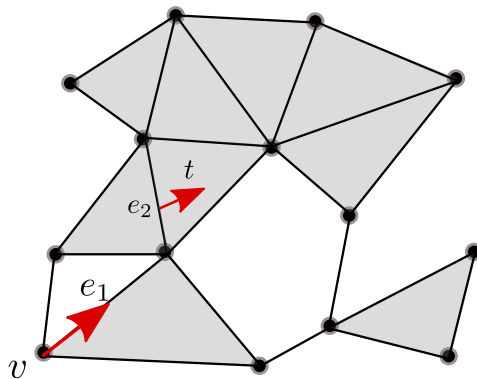


FIGURE: Simplicial Complex  $K$  and discrete vector

## DISCRETE VECTOR

$(\sigma, \tau)$  is a **discrete vector** in  $K$  if  $\sigma < \tau$  i.e.  $\sigma$  is a boundary of  $\tau$ .

$(v, e_1)$  and  $(e_2, t)$  are two discrete vectors on  $K$ .



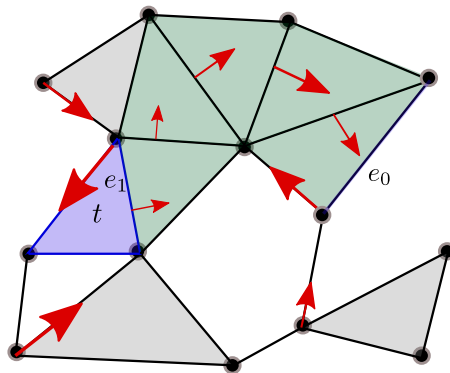


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## DISCRETE VECTOR FIELD

A discrete vector field  $V$  is a collection of discrete vectors such that every simplex of  $K$  is head/tail of at most one vector.

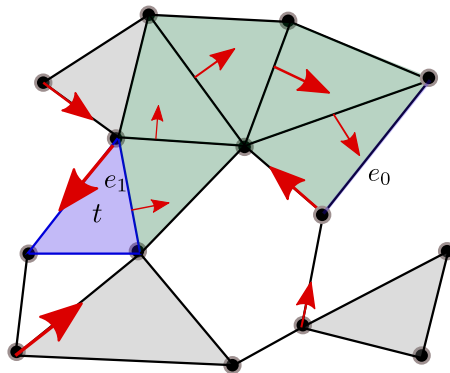


FIGURE: V-path

## V-PATH

$$\sigma_0, \tau_0, \sigma_1, \tau_1, \dots, \sigma_{l+1}$$

where  $(\sigma_i, \tau_i)$  is a vector and  $\tau_i < \sigma_{i+1}$ .

# BACKGROUND: MORSE CANCELLATION

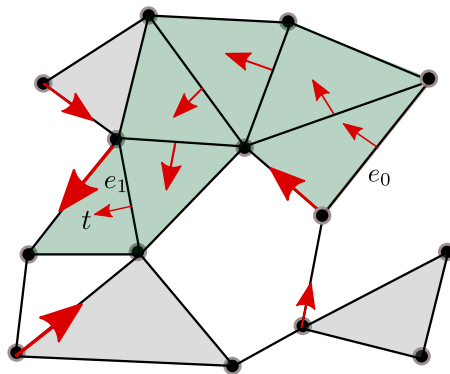


FIGURE: Morse Cancellation

Morse cancellation cancels critical points.

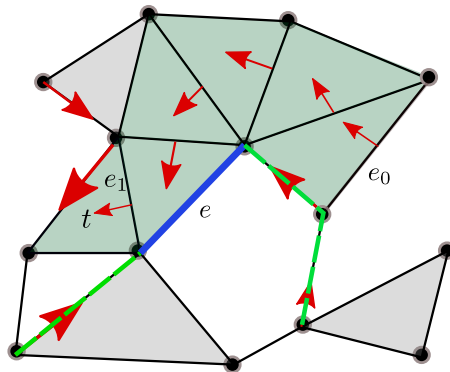


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## STABLE MANIFOLD

For a critical edge  $e$ , its **stable manifold** is the set of all V-paths ending at the boundary of  $e$ .

Input: The discretized domain  $K$ , the density function  $f$ , the threshold  $\delta$

Output: The reconstructed graph  $\hat{G}$

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Try to perform a Morse cancellation for the pair and update  $V$ .



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- 4 For each  $(v, e) \in P(K)$  and  $(e, t) \in P(K)$  with  $Pers(v) \geq \delta$ ,  $\hat{G} = \hat{G} \cup \{\text{stable manifold of } e\}$ .

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- 5 output  $\hat{G}$

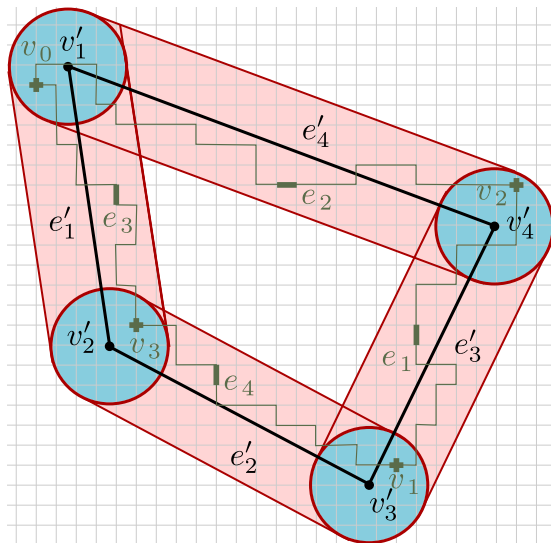


FIGURE: Algorithm in Picture

## THEOREM

*If  $G$  is a connected, embedded planar graph in a cubical complex  $K$  and  $f$  is an  $(\omega, \beta_1, \beta_2, \nu)$ -approximation then the output  $\hat{G}$  has the same homotopy type as  $G$ . Moreover,  $d_H(G, \hat{G}) < \omega$ .*

- 1 Extend the result to higher dimensions.
- 2 What condition on the density function gives up a small Fréchet distance between the edges of the output and the edges of the graph.
- 3 How to circumvent the heavy persistence computation for all nodes.

Thanks  
and  
Questions?



Mahmuda Ahmed, Brittany Terese Fasy, Matt Gibson, and Carola Wenk, *Choosing thresholds for density-based map construction algorithms*, Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems (New York, NY, USA), SIGSPATIAL '15, ACM, 2015, pp. 24:1–24:10.



Tamal K. Dey, Jiayuan Wang, and Yusu Wang, *Graph reconstruction by discrete Morse theory*, 34th International Symposium on Computational Geometry, 2018, pp. 31:1–31:15.