#### Surface and Medial Axis Topology through Distance Flows Induced by Discrete Samples

- PhD Final Examination -

Bardia Sadri University of Illinois at Urbana-Champaign

## **Geometric Modeling of Objects**



Engineering: simulation, visualization, CAD, ... Entertainment: animation, games, virtual reality, ... Sciences: medicine, biology, ...

#### **The Surface Reconstruction Problem**







Given a point cloud sampled from a surface  $\Sigma$ , we want to compute a surface  $\hat{\Sigma}$  that has the same topology as  $\Sigma$  and closely approximates it geometrically.



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#### There are many surface reconstruction methods!

- ♦ As a 0-set of an approximate signed distance function:
- [Hoppe et al. '92, Curless et al.'96, ...]
- ♦ As other iso-surfaces:
- NN Interpolation [Boissonnat-Cazals '02]
- MLS [Levin'98, Alexa et al. '01, Amenta-Kil '04, Bremer-Hart '05,
- Kolluri '05, Dey et al. '05, ...]
- SVM [Schölkopf et al. '04, ...]

#### ♦ Delaunay Methods:

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♦ Using distance functions:

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The medial axis of a surface  $\Sigma$  is the union of medial axes of all components of  $\mathbb{R}^n \setminus \Sigma$ .

### **Problem of Medial Axis Approximation**

Given a sample of the smooth surface enclosing a shape, we want to approxiamate the MA of shape geometrically and capture its topology.



Applications: shape analysis, motion planning, mesh partitioning, medical imaging, ....

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### Medial Axis and Embedding of Surface

The outer shapes of torus and knotted torus have different homotopy types.



**Theorem.** [Lieutier'04] Any bounded open subset of  $\mathbb{R}^n$  has the same homotopy type as its medial axis.

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#### Some History on Medial Axis Approximation

- ♦ Exact Methods: for limited classes of shapes
- [Manocha et al. '04] for polytopes
- [Zerroug et al. '94] for Generalized Cylinders
- ♦ Voronoi Filtering:
- [Amenta & Bern '99] 2d
- [Amenta & Choi & Kolluri '01] Power-Crust
- [Boissonnat & Cazals '02]
- [Dey & Zhao '04]
- [Lieutier & Chazal '05]  $\lambda$ -medial axis
- $\diamond$  Other:
- Thinning Methods
- Grid Methods
- PDA Methods

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#### Samples of Surfaces

We use the  $\varepsilon$ -sampling framework of [Amenta-Ben'99].

For a point  $x \in \Sigma$ , the local feature size of x is

 $\mathsf{lfs}(x) := d(x, M).$ 



#### $P \subset \Sigma$ is an $\varepsilon$ -sample if every $x \in \Sigma$ has a sample within distance $\varepsilon$ lfs(x).

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#### Our Approach: A Lot is Encoded in Distance Functions

The distance function induced by  $\Sigma$  in S is

 $s: S \to \mathbb{R}, \qquad x \mapsto \min_{y \in \Sigma} \|x - y\|$ 



 $\diamond M(S) = \{ \text{points in } S \text{ where } s \text{ is not differentiable} \}.$ 

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## Acknowledgments and Agenda

#### Contributions

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- [2] J. Giesen, E. A. Ramos, B. Sadri, Medial axis approximation and unstable flow complex. SoCG, 2006. (Invited to IJCGA special issue)
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#### The rest of this talk

- 1. Introduction of the tools.
- 2. Medial Axis Approximation.
- 3. Shape Reconstruction.
- 4. Analysis of WRAP.

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#### Covered in Prelim

# 1 The Machinery

## (Squared) Distance to Discrete Point Sets

P is a discrete set of points The squared distance function induced by P is

$$h(x) = \min_{p \in P} ||x - p||^2$$

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**Observation.** h is smooth at points with a unique closest point in P.



![](_page_35_Figure_0.jpeg)

[Giesen-John'03] J. Giesen, M. John, Flow complex: A data structure for geometric modeling. SODA, 2003.








V(x): lowest-dimensional Voronoi face containing x.



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# **Continuity of the Induced Flow**

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$$\Sigma_{\delta} = \{ x \in \mathbb{R}^n \setminus M : ||x - \hat{x}|| < \delta f(\hat{x}) \}$$
  
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**Theorem [DGRS'05]** If h is induced by an  $\varepsilon$ -sample of  $\Sigma$  with  $\varepsilon < 1/\sqrt{3}$ , the all critical points of h are contained in either  $\Sigma_{\varepsilon^2}$  or  $M_{2\varepsilon^2}$ .

### **Stable Manifold of a Critical Point**

Stable manifold of a critical point c is everything that flows into c.

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**Proposition.** Let X and  $Y \subseteq X$  be arbitrary sets and

 $H:[0,1]\times X\to X$ 

be a continuous function (on both variables) satisfying

1. 
$$\forall x \in X : H(0, x) = x$$

2. 
$$\forall y \in Y, \forall t \in [0, 1] : H(t, y) \in Y$$

3. 
$$\forall x \in X : H(1, x) \in Y$$

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Then X and Y have the same homotopy type.

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**Proposition.** Let X and  $Y \subseteq X$  be arbitrary sets and

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Then X and Y have the same homotopy type.

This is the idea Lieutier used in [Lieuteir'04] to show  $M(S) \simeq S$ .

**Key Theorem.** If  $Y \subset X$  are bounded and

- 1.  $\phi(X) = X$  and  $\phi(Y) = Y$ , and
- 2.  $||v(x)|| \ge c > 0$  for  $x \in X \setminus Y$ ,

then X and Y are homotopy equivalent.



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**Proof.** If  $\phi(t, x) \notin Y$ , then

h

$$(\phi(t,x)) = h(x) + \int_0^t ||v(\phi(\tau,x))||^2 d\tau$$
  

$$\geq h(x) + \int_0^t c^2 d\tau$$
  

$$= h(x) + tc^2$$
  

$$< d_H(X,P)^2.$$



# A Handy Lower Bound for Speed

If  $V(x) \cap D(x) = \emptyset$  then

$$\begin{aligned} \|v(x)\| &= 2 \cdot \|x - d(x)\| \\ &\geq 2 \cdot \mathsf{dist}(V(x), D(x)). \end{aligned}$$

 $\dot{x}$ 

d

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If  $V(x) \cap D(x) = \{c\}$  then  $x \in Um(c)$ .

 $\dot{x}$ 

#### A Handy Lower Bound for Speed

If  $V(x) \cap D(x) = \emptyset$  then  $||v(x)|| = 2 \cdot ||x - d(x)||$  $\dot{x}$  $\geq 2 \cdot \operatorname{dist}(V(x), D(x)).$ If  $V(x) \cap D(x) = \{c\}$  then  $x \in Um(c)$ .  $\dot{x}$  $\mathcal{C}$ So, if  $Um(c) \subset Y$  we are fine!



# Medial Axis Approximation



## The Inner CORE

**Definition.** Let N be the set of all inner medial axis critical points of h.

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#### Geometric Quality and Flow Closure

Can we diverge too far away from MA when taking flow closure?

**Theorem.** If  $\rho(x) = \sqrt{h(x)} = 1$  and x has a medial axis point within distance  $O(\sqrt{\varepsilon})$ , then for any  $t \ge 0$ ,  $y = \phi(t, x)$  has a medial axis point within distance

 $O(\sqrt{\varepsilon})\rho(y)^{1+O(\sqrt{\varepsilon})}.$ 



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**Theorem.** If  $\rho(x) = \sqrt{h(x)} = 1$  and x has a medial axis point within distance  $O(\sqrt{\varepsilon})$ , then for any  $t \ge 0$ ,  $y = \phi(t, x)$  has a medial axis point within distance

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# Surface (Shape) Reconstruction

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# WRAP: Reconstruction Revisited

[Edelsbrunner'04] H. Edelsbrunner, Surface reconstruction by wrapping finite point-sets in space. Discrete & Computational Geometry, 2004.

# Flow Induced by Weighted Points





Squared distance to p with weight  $w_p$  is  $||x - p||^2 - w_p$ . The squared distance to a set P of weighted points is  $h(x) = \min_{p \in P} ||x - p||^2 - w_p$ .

# Polarity

For every set  ${\cal P}$  of weighted points there is a set Q of weighted points such that

Vor P = Del Q and Del P = Vor Q



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### Voronoi Vertices as Weighted Points



For unweighted P, Q is the Voronoi vertices of P and for  $q \in Q$ :

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A simplex  $\tau \in \text{Del } P$  that contains a critical point is called a critical simplex. We treat  $\mathbb{R}^n \setminus \text{conv } P$  as an abstract critical simplex  $\omega$ .



 $\tau \prec \sigma$ : some flow line of  $\phi^*$  visits relative interiors of  $\sigma$  and  $\tau$  consecutively.



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# The WRAP Algorithm

#### The WRAP Algorithm [Edelsbrunner'04]

- 1. For every  $\tau \in \text{Del } P$ , if the only critical simplex that precedes  $\tau$  is the abstract critical simplex  $\omega$ , then remove  $\tau$ .
- 2. Return what is left as WRAP.



#### The WRAP Algorithm

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**Theorem.** WRAP and closure of shape are homotopy equivalent. (in 3D) Lemma.  $\phi^*(\Sigma_{\delta}) = \Sigma_{\delta}$ .



#### Summary of Results

Using the distance flow maps induced by samples,

- We showed that the critical points of the distance function induced by an ε-sample of a surface are concentrated close to the surface or to the medial axis and these two types can be distinguished algorithmically.
- We gave an algorithm that reconstructs the shape homotopically (and its boundary homeomorphically in 3D) and approximates these closely in geometric terms.
- We introduced the notion of the CORE for medial axis approximation and established its homotopy equivalence with the medial axis. We also showed how the core can be extended by any other MA-approximation algorithm. We also bounded the rate of degradation of geometric approximation of MA in taking flow closures.
- We modified Edelsbrunner's WRAP reconstruction algorithm and proved that this modified version captures the topology of the sampled shape (for ε-samples in 3D and for uniform samples in any dimension).

#### Some Open Questions

- In RECONSTRUCTION, is the union of stable manifolds of surface critical points also homotopy equivalent to surface?
- The "primal" analog of WRAP corresponds to an approximation of CORE by a subcomplex of Vor *P*. A geometric analysis showing this approximation is close to MA is enough to prove the same topological guarantee for the approximation.
- Can these ideas (especially WRAP) be generalized for reconstruction of shapes with non-smooth surfaces? How should the sampling condition be defined? (some work done in [Lieutier-Chazal'06])
- In general when (and in what sense) can stable and unstable manifolds of critical points be approximated by sub-complexes of Vor P or Del P.
- Can the proof of existence of a continuous flow map be generalized to non-discrete sets of weighted points (generalization of Lieutier's result)?

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# Thank You!