Medial Scaffolds for 3D data modelling: status and challenges



Frederic Fol Leymarie



Outline

Background

Method and some algorithmic details

Applications

Shape representation: From the Medial Axis to the Medial Scaffold

Wave propagation Blum, Voronoi, Turing, *et al.*





Maximal disks Blum, Wolter, Leyton, Kimia, Giblin, *et al.*





Study 3D shape with minimal assumptions



Context: 1st reconstruct a surface mesh from *unorganized* points, with a "minimal" set of assumptions: the samples are nearby a "possible" surface (thick volumetric traces not considered here). Benefit: reconstruction across many types of surfaces.

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Study shape with minimal assumptions

To find a *general* approach, applicable to various topologies, without assuming strong *input constraints*, *e.g.:*

- No surface normal information.
- Unknown topology (with boundary, for a solid, with holes, non-orientable).
- No a priori surface smoothness assumptions.
- Practical sampling condition: non-uniformity, with varying degrees of noise.
- Practical large input size (> millions of points).



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How: Overview of Our Approach (2D)

Not many clues from the assumed loose input constraints.

• Work on the shape itself to recover the sampling process.



Key ideas:

- Relate the sampled shape with the underlying (unknown) surface by a sequence of shape deformations (growing from samples).
- Represent (2D) shapes by their medial "shock graphs". [Kimia et al.]
- Handle shock transitions across different shock topologies to recover gaps.

How: Sampling / Meshing as Deformations

Schematic view of sampling: infinitesimal holes grows, remaining are the samples.



We consider the removing of a patch from the surface as a Gap Transform.



How: Sampling / Meshing as Deformations

Special case where input consists only of points (in 3D), then the Medial Scaffold consists of only:

 A_1^2 Sheets, A_1^3 Curves, A_1^4 Vertices.



How: Sampling / Meshing as Deformations



CVIU 2009, Chang, Fol Leymarie, Kimia.

Classify shock points into 5 general types,

and organized into a hyper-graph form

[Giblin&Kimia PAMI'04, Leymarie&Kimia PAMI'07]:

- Shock Sheet: A_1^2
- Shock Curves: A³₁ (Axial), A₃ (Rib)
- Shock Vertices: A₁⁴, A₁A₃

A_kⁿ: contact (max. ball) at n distinct points, each with k+1 degree of contact.









Figure 1.3: Types of flows along \mathcal{MA} structures. (a) For \mathcal{MA} sheets, the flow is generally initiated at a single point, and the sheet is grown outward and radially from that point. (b) At the top are shown the typical flows along \mathcal{MA} curves, *i.e.*, regular, initial and final. At the bottom are shown the typical sets of inward and outward flows (along \mathcal{MA} curves) at \mathcal{MA} vertices where the number of inward flows is indicated.





Figure 3.14: Example of a 2D Voronoi diagram (a), medial axis (b), and shock scaffold (c) for a set of eleven point generators (large grey disks) in the plane. Voronoi or shock vertices are indicated as smaller green disks, Voronoi edges or shock curves are drawn as straight lines, Voronoi regions are hashed in red. In (c), A_1^2 -2 shock sources are indicated as blue squares. In (b) we see that the VD minus the interior of its Voronoi regions coincides with the MA.



Study the topological events of the graph structure under **perturbations** and **shape deformations**.

Singularity theory (Arnold et al., since the 1990's):

In 3D, 26 topologically different perestroikas of linear shock waves.



"Perestroikas of shocks and singularities of minimum functions" I. Bogaevsky, 2002.

Study the topological events of the graph structure under **perturbations** and **shape deformations**.

Transitions of the MA (Giblin, Kimia, Pollit, PAMI 2009): Under a 1-parameter family of deformations, only **seven transitions** are relevant.

Transition	Collision of Types
A_1^4	$A_1^3 - A_1^3$
A_1^5	A_1^4 - A_1^4 , A_1^4 - A_1^3
A_5	$A_1A_3 - A_1A_3, A_3 - A_3$
$A_1A_3 - I$	$A_1A_3 - A_1A_3$
$A_1A_3 - II$	$A_1A_3 - A_1A_3, A_1^3 - A_3$
10.24 24	$A_1^4 - A_1 A_3$
$A_1^2 A_3 - II$	A_1^3 - A_1A_3

Study the topological events of the graph structure under **perturbations** and **shape deformations**.

Transitions of the MA:

Under a 1-parameter family of deformations, only seven transitions are relevant.



 A_1A_3 -I (protrusion-like, Leymarie, PhD, 2002)

Study the topological events of the graph structure under **perturbations** and **shape deformations**.



Total of 11 cases for regularization across transitions (M.C. Chang et al.)

Study the topological events of the graph structure under **perturbations** and **shape deformations**.



Towards surface regularisations via transitions (Leymarie, Giblin, Kimia, 2004)

Study the topological events of the graph structure under **perturbations** and **shape deformations**.



Capture transitions via geodesy on MA (Chang, Kimia, Leymarie, on-going)



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How: Organise/Order Deformations (2D)





Deformation in shape space

NB: A & B share **object** symmetries. Symmetries due to the **sampling** need to be identified.

How: Organise/Order Deformations (3D)

- Recover a mesh (connectivity) structure by using Medial Axis transitions modelled via the Medial Scaffold (MS).
 - Meshing as shape deformations in the 'shape space'.
- The Medial Scaffold of a point cloud includes both the symmetries due to sampling and the original object symmetries.
 - Rank order Medial Scaffold *edits* (gap transforms) to "segregate" and to simulate the recovery of sampling.



Shock Segregation [Leymarie, PhD'03], Surface reconstruction [CVIU'09]

Algorithmic Method

- Consider Gap Transforms on all A₁³ shock curves in a ranked-order fashion:
 - best-first (greedy) with error recovery.
- Cost reflects:
 - Likelihood that a shock curve (triangle) represents a surface patch.
 - Consistency in the local context (neighboring triangles).
 - Allowable (local surface patch) topology.

3 Types of A_1^3 shock curves (dual Delaunay triangles): Represented in the MS by "singular shock points" (A_1^3 -2)





Three A₁² shock sheets

(unlikely to be correct candidate)

Algorithmic Method

How we order gap transforms:

- Favor small "compact" triangles.
- Favor recovery in "nice" (simple) areas, *e.g.*, away from ridges, corners, necks.
- Favor simple local continuity (similar orientation).
- Favor simple local topologies (2D manifold).
- BUT: allow for error recovery!

Ranking Isolated Shock Curves (Triangles)

Triangle geometry:

 $D = \max(d_1, d_2, d_3)$ $P = d_1 + d_2 + d_3$ $m = (d_1 + d_2 - d_3)(d_3 + d_1 - d_2)(d_2 + d_3 - d_1)$ $A = \sqrt{(P \cdot m)/16} \quad (\text{Heron's formula})$ $C = 4\sqrt{3} \cdot A/(d_1^2 + d_2^2 + d_3^2), \text{ (Compactness, Gueziec's formula, 0<C<1)}$

Cost: favors *small compact* triangles with large shock radius *R*.



The side of smaller shock radius is more salient.

$$\rho_1 = \begin{cases} \frac{P}{R} \cdot \frac{1}{C^2} \,, & \text{if } D < d_{\max} \\ \infty \,, & \text{if } D \ge d_{\max} \end{cases}$$

R: minimum shock radius

 d_{max} : maximum expected triangle, estimated from d_{med}



Surface meshed from confident regions toward the sharp ridge region.

Cost Reflecting Local Context & Topology

Cost to reflect smooth continuity of edge-adjacent triangles:

$$\rho_2 = \frac{d}{R} \cdot \frac{1}{C^2} \cdot f(\theta) ,$$

$$f(\theta) = [\exp^{\theta} - 1]^2 - 1 \begin{cases} \theta = 0, f(\theta) = -1 \\ \theta = 40^\circ, f(\theta) \simeq 0 \\ \theta = 80^\circ, f(\theta) \simeq 8.24 \end{cases}$$

Typology of triangles sharing an edge:





Point data courtesy of Ohtake et al.

Strategy in the Greedy Meshing Process

Problem: Local ambiguous decisions \rightarrow errors.

Solutions:

Multi-pass greedy iterations

First construct confident surface triangles without ambiguities.

- Postpone ambiguous decisions
 - Delay related candidate Gap Transforms close in rank, until additional supportive triangles (built in vicinity) are available.
 - Delay potential topology violations.
- Error recovery
 - For each Gap Transform, re-evaluate cost of both related neighboring (already built) & candidate triangles.
 - If cost of any existing triangle exceeds top candidate, undo its Gap Transform.



Queue of ordered triangles



vertex-face incidence



Dealing with sampling quality

Input of non-uniform and low-density sampling:





Response to additive noise:



100%



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From Fine to Coarse Scales



Bone shape study



3D Tubular & Branching Shapes



3D Tubular & Branching Shapes



3D Tubular & Branching Shapes



3D Convoluted Shapes: Brains



3D Shape Matching/Registration



3D Shape in Molecular biochemistry





FoldSynth project: Docking www.foldsynth.com



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Next: 3D Shape Deformation

• [Kimia *et al.*] represent shape as a member of an equivalent class ('shape cell'), each defined as the set of shapes sharing a common shock graph (in 3D, Medial Scaffold) topology.



- Link this to **Information Models**: incorporation of human expert knowledge; e.g. in building taxonomies.
- Statistical analysis; definition of classes; distribution of features.
- Combine **exterior** with interior scaffolds.



Figure 1.1: (a) Adapted from [34, Fig. 29. p. 252]: An example of an anthropomorphic figure and a sketch of its (2D) medial axis (\mathcal{MA}) representation. Flows indicating directions of increasing radii values are indicated by arrows. Initial flows pointing in two opposite directions are indicated by a diamond shape; these map to necks of the shape. Note how tips of branches relate to convex extrema of the boundary, for the interior part of the \mathcal{MA} , and concave extrema, for the exterior part. (b) and (c) A preview of the *shock scaffold*, a structure organizing the \mathcal{MA} in a useful manner, for the 3D shape of a human male body scanned with a Cyberware Inc. system resulting in 21500 3D points (shown as white dots). This preview of the shock scaffold is shown in terms of medial surfaces and a network of axial curves (in pink) where these intersect. Flow along the medial surfaces, *i.e.*, how the radius function varies is indicated by color variations. (b) is the *interior* part of the computed shock scaffold, while (c) is the *exterior* (with respect to the scanned surface of the body; a recovered surface interpolant is shown in Figure 1.6.(c)).

Other open issues:

 Combine or study relations with other existing main shape representations based on propagations: Voronoi, Morse/Reeb, flow complex, 3D Curve skeletons

- Interactions between 2D and 3D inputs : visual inputs/snapshots (2D) versus 3D percepts : no trivial correspondence between 2D and 3D medial representations (including Voronoi)

Other open issues:



- Medial representations directly from intensity fields : images, video, 3D medical volumetric data : e.g. work of Kovacs et al. on robust symmetries.



- related: using a probabilistic framework or robust measures to deal with noisy inputs or sampling obtained in sausages (neighborhoods) rather than precisely on an outline/surface

- Complexity, proofs of convergences for realistic data (not too smooth).