Scalable and Robust Computation of Medial Axes and Surfaces in 2D and 3D State of the art



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Some often-heard statements:

- Medial objects are in general
 - hard to compute
 - sensitive to noise
 - computable only for binary shapes
 - mainly useful for navigation, shape matching/analysis
- 3D medial surfaces are
 - very slow to compute
 - impractical for real-world applications



Some statements:

- Medial objects are in general
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Definition

$S(\Omega) = \{x \in \Omega | \exists y \neq z \in \partial \Omega, ||x - y|| = ||x - z|| = DT_{\partial \Omega}(x)\}$

2D skeleton:

- 1D structure
- centers of maximally inscribed discs

3D surface skeleton:

- 2D structure
- centers of maximally inscribed balls

3D curve skeleton

- 1D structure
- no agreed formal definition





Global 2D detectors

Collapsed boundary metric

[Ogniewicz & Kubler '95] [Falcao *et al.* '02] [Telea & Van Wijk '02]





- monotonic and continuous on whole shape Ω
- leads to a robust, multiscale skeleton

Implementation

Augmented Fast Marching Method (AFMM)

• O(N log N^{1/2}), 2 fps @ 1024² pixels

CUDA Banding Algorithm

- O(N), 500 fps @ 1024² pixels
- The fastest, simplest, most robust 2D skeletonization method out there





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[Telea & Van Wijk'03]

[Hurter et al., TVCG'11]

Generalized Skeletons

[Strzodka & Telea '04]



Change the distance metric!



Generalized Skeletons



Change the distance metric!



Saliency Skeletons

Saliency metric: $\sigma(p) = \rho(p) / DT(p)$







Saliency Skeletons

More complex examples...





0)







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r)



s)

p)

t)

Saliency Skeletons

Most challenging example

- very noisy CT segmentation
- saliency-based smoothing:
 - connect specks
 - reconstruct perceived sharp corners







Dense Skeletons

Generalize skeletons

- for a whole color/grayscale image
- not just a binary shape



• this generates a 2-dimensional image scale-space



Applications

Image segmentation

- select a few most relevant layers
- simplify each layer (using salience metric)



input image

dense skeletons (60% layers)

mean shift segmentation [Comaniciu & Meer '02]

• skeletons: we get less jaggies and we keep sharp corners!



Applications

Image compression

• same procedure as before







d) reconstruction (MSSIM=0.55, 61 layers removed)

Applications

Artistic image manipulation

• keep few, highly simplified, skeletons



input images

Papari et al., TPAMI'07

our method



3D Skeletons

Generalize the 2D collapse metric to 3D!

Define vector field ${\it F}$ and mass ρ on Ω so that

$$F|_{\partial\Omega} = n, \rho |_{\partial\Omega} = 1$$

F = $\nabla(DT) |_{\Omega \setminus S}$
div $\rho F = 0$ on entire Ω (also on *S*!)

Intuition: Mass...

- flows straight from $\partial \Omega$ to surface skeleton S (2D)
- flows on S to curve skeleton C (1D)
- flows on C to a global root-sink R (0D)

Collapse $\rho(x)$: mass passing through *x* en route to *R*

3D Surface and Curve Skeletons

[Reniers et al., TVCG'08]

• Directly compute collapse:

- no advection
- Curve skeleton formal definition:
 - $x \in S$ that have two shortest paths between their two feature points

Collapse:

- $x \in C$: smaller area of the two $\partial \Omega$ components due to the two shortest paths
- $x \in S$: length of single shortest-path





3D Surface and Curve Skeletons









[TVCG'08, DGCI'06, DGCI'08]























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Curve Skeletons: Part Segmentation





[CGF'08, TVC'08, SMI'07, SMI'08]

Curve Skeletons: Patch Segmentation



Surface Skeletons: Shape Classification

Robust surface classification

Cortex structure





Scalability



[Jalba et al., TPAMI'12]

GPU implementation

- point clouds & meshes
- 1M points/second (GTX 280)
- 3D surface skeletons are finally practical

Real-time Reconstruction

Surface skeleton

(technique: mesh projection)

(technique: depth splatting)





Shape thickness

Find thin shape parts

- important in 3D metrology (e.g. 3D printing)
- how to define/compute shape thickness? ۲
- solution:

Thickness($p \in \partial \Omega$) = min $_{q \in FT^{-1}(p)} DT(q)$

easy to implement, real-time to compute





roningen

On to our unified framework...

Challenge 1: Definition

- what is a curve skeleton?
- many algorithms, few formal definitions (except Dey & Sun '06, Reniers et al.' 08)



Which is the 'correct' curve skeleton?

Challenge 2: Unification

- can we define and compute the C-skeleton from the S-skeleton...
- ...in the **same** way we compute the S-skeleton from the input shape?









Unified framework: Yes we can 3

Use exactly the same definition for S-skeleton and C-skeleton (!)

 $S(\Omega) = \{\mathbf{x} \in \Omega \mid \exists \mathbf{y}, \mathbf{z} \in \partial \Omega, \mathbf{y} \neq \mathbf{z}, \|\mathbf{x} - \mathbf{y}\| = \|\mathbf{x} - \mathbf{z}\| = DT_{\partial \Omega}(\mathbf{x})\}$

2D skeleton

3D S-skeleton

3D C-skeleton



Ω: input shape (2D) $\|\cdot\|$: Euclidean dist. (Ω)





Ω: input shape (3D) $\|\cdot\|$: Euclidean dist. (Ω) Ω : S-skeleton $\|\cdot\|$: geodesic distance (S)

[Jalba and Telea, EGUK'12 Best paper]

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- advect S in $\nabla DT_{\partial S}$
- compute $\nabla DT_{\partial S}$ analytically using observation in [Reniers *et al.*, TVCG'08]



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Advect S-skeleton into C-skeleton:

$$\mathbf{s}^{i+1} = P_{T(\mathbf{s}^{i})} \left(\mathbf{s}^{i} + \frac{\nabla DT_{\partial S}(\mathbf{\tilde{s}}^{i})}{\|\nabla DT_{\partial S}(\mathbf{\tilde{s}}^{i})\|} \delta \right)$$

keep advection in S-
skeleton (triangle-fan at \mathbf{s}^{i}) normalize $\nabla \mathsf{DT}_{\partial \mathsf{S}}$ to
control advection speed nearest-neighbor of \mathbf{s}^{i}
on S-skeleton

Stop advecting points when $T(s^i) < \varepsilon$







Advection



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Applications: Graph visualization

Edge bundling

- how to capture & draw the essence of a large graph (>100K edges)
- probably the hottest area in large graph visualization (10..20 top papers/year)



[Holten, InfoVis'06]



Skeleton-based edge bundles (SBEB)

[Ersoy *et al.*, TVCG'11] [Hurter *et al.*, TVCG'11]

Simple idea

iterate the following steps:



implementation: fully image-based (CUDA)



Pseudo-shading







US Migrations graph: 1715 nodes, 9780 edges, 6 clusters, 3 sec.





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France airlines graph: 34550 nodes, 17272 edges, 207 clusters, 27 sec.





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Kernel density edge bundling (KDEEB)

[Hurter et al., CGF'12]

If bundling sharpens the edge density, then sharpening the edge density should bundle



This is nothing but mean shift [Comaniciu & Meer '02] on the edge-space!





Bundling dynamic graphs

Time-dependent graphs

- streaming data (millions of edges, arriving in real time)
- solution: time-dependent mean shift **real-time** bundling on the GPU!



[Hurter et al. PacificVis'13]



Ongoing work

NPR sculpting

- reduce 3D shape to smooth surfaces bounded by **pixel-sharp feature edges**
- solution: process surface normal using 3D surface skeleton

- simple (~20 lines C++)
- fast (real-time)
- intriguing...

Ongoing work

Large graph visualization

- reduce huge graphs to shapes
- encode data in shading/color



amazon graph (~1M edges): image generated in real-time (GTX 680)



Conclusions

Revisited a few 'myths': Skeletons are

- fundamentally **stable** and **robust** shape descriptors
- computable accurately in real-time for large shapes
- admitting a single unified definition in nD
- useful for much more than shape matching





www.cs.rug.nl/svcg/Shapes

- examples, applications
- code
- papers

