# Particle systems for visualizing the connection between math and anatomy

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### Context



Anatomy

3D Image Data

- Goal: geometric models of anatomic features for quantitative analysis of large image datasets
- Strategy: generality WRT feature co-dimension
- Method: particle systems for feature sampling
- Question: how do I know if a given mathematical feature is plausible as an anatomic feature?

## Outline

- Features
- Particles
- Scale-space
- Stability with respect to scale
- Results
- Discussion

## What I mean by mathematical "feature"

- In a continuous & differentiable field f(x) created by convolution:
- Feature = positions **x** satisfying feature equation
  - Isocontours:  $f(\mathbf{x}) = f_0$
  - Laplacian zero-crossing edges:  $\nabla^2 f = 0$
- (No models, priors, blend of data & smoothing terms ...)
- $(\mathbf{g} = \nabla f; \mathbf{H} = \nabla \otimes \nabla f; \mathbf{H} = \sum_{i} \lambda_{i} \mathbf{e}_{i} \otimes \mathbf{e}_{i}; \lambda_{1} \ge \lambda_{2} \ge \lambda_{3})$
- Combinations of maxima and minima WRT  $\boldsymbol{e}_i$ 
  - Ridge Surface (Eberly '96):  $\mathbf{g} \cdot \mathbf{e}_3 = 0$ ;  $\lambda_3 < 0$
  - Ridge Line:  $\mathbf{g} \cdot \mathbf{e}_3 = \mathbf{g} \cdot \mathbf{e}_2 = 0; \ \lambda_3 < 0; \lambda_2 < 0$
  - Various valleys and connectors possible (Damon '98)
  - Iterative update scheme (Newton optimization) to move closer to feature if near it: we can sample features

## **Dynamic Particle Systems**

- G. L. Kindlmann, R. San Jose Estepar, S. M. Smith, C.-F. Westin, Sampling and Visualizing Creases with Scale-Space Particles. IEEE Trans. Vis. Comp. Graph, 15(6):1415-1424 (2009)
- Set of points subject to (particle-image) feature constraint and (interparticle) energy minimization

$$\underset{\mathbf{x}_{i},N}{\operatorname{argmin}} \mathcal{E} = \underset{\mathbf{x}_{i},N}{\operatorname{argmin}} \sum_{i,j=1}^{N} E_{ij}$$

Hard constraint of particles to feature; no energy



## Scale Space

- Image & continuous family of blurrings
- Practical requirements
  - Probe at arbitrary points in scale space
  - Efficiently handle real-world 3D datasets (minimize memory usage and resulting cache misses)

scale

0

 $\cdot(\mathbf{X}, s)$ 

space:  $\mathbf{x} \in$ 

 Scale interpolation based on Lindeberg's "Gaussian" (soln. to heat eq. in discrete domain)





![](_page_7_Picture_1.jpeg)

![](_page_8_Picture_1.jpeg)

![](_page_9_Figure_1.jpeg)

## Stability with respect to scale

- One possible measure of feature significance: feature doesn't move with small additional blur
  - e.g. SIFT for image stitching
- Recover scale stability at p<sub>i</sub> from covariance tensor Σ of vectors p<sub>j</sub> - p<sub>i</sub> to interacting particles
  - stability  $\approx \sum_{ss} * (1 + codim) / trace(\Sigma)$
- Look at joint histogram of stability and scale

![](_page_10_Figure_6.jpeg)

#### Results for codim-2 features in hand

![](_page_11_Picture_1.jpeg)

#### Results for codim-2 features in hand

	<b>e</b> <sub>1</sub>	<b>e</b> <sub>2</sub>	<b>e</b> <sub>3</sub>	A	B	C
Α		min	min			
В	min		min		50 E	
С	min	min				
D		min	MAX			
Ε	min		MAX			
F	min	MAX				
G		MAX	MAX	G		
Н	MAX		MAX			
I	MAX	MAX		Salata and a	and the Office	

### Lung lobes from clinical CT

![](_page_13_Picture_1.jpeg)

J Ross, RSJ Estepar, G Kindlmann, A Diaz, C-F Westin, E Silverman, G Washko, "Automatic Lung Lobe Segmentation Using Particles, Thin Plate Splines, and Maximum a Posteriori Estimation", Proceedings MICCAI 2010, pp 163-171

## Discussion

- New imaging modalities, contrast mechanisms, and their combination => proliferation of possibly useful features; this may help show the way
- "Finding" features in 2 senses: where, and which
- From image samples to feature samples
- Future work & possible collaborations:
  - Points into polyline trees, polygonal meshes
  - Shape modeling and statistics
- Why not more work on **applied** 3D scale-space?
- Thanks for your attention; questions?