Optimizing Particle Systems for Image Feature Sampling

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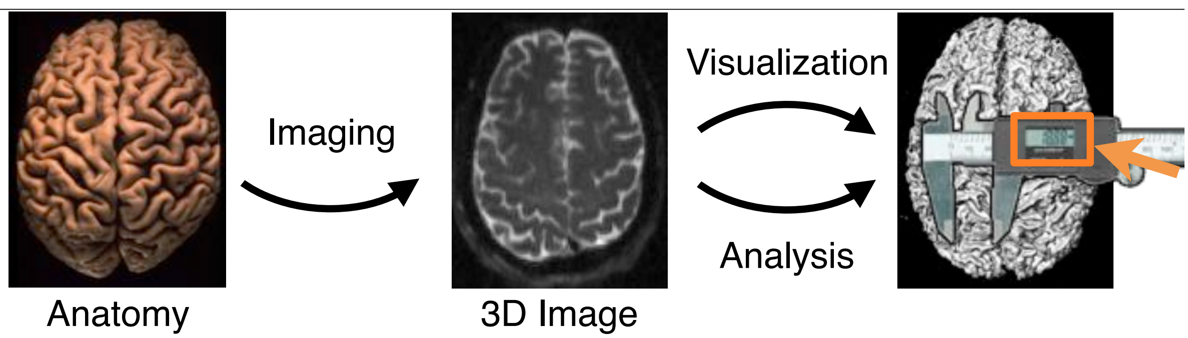
COMPUTER SCIENCE

Computation Institute

Imaging as starting point for Computational Science



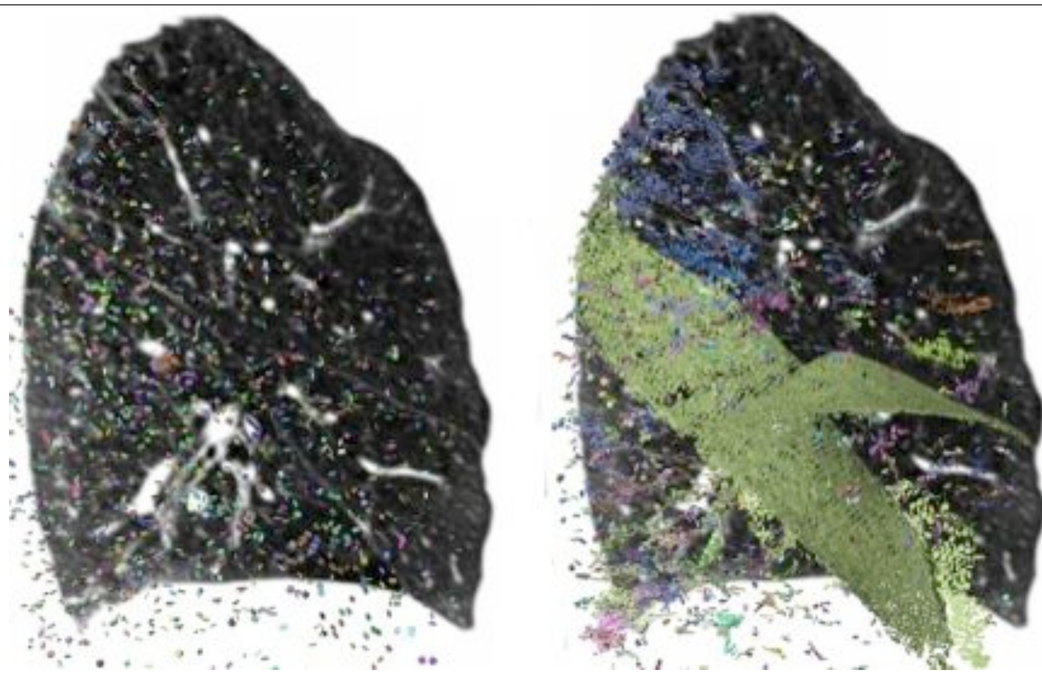
- Imaging measures whole 3D objects
- Examples: CT, MRI (functional, diffusion, etc)
- Imaging is a powerful way to detect & quantify biology
- Visualization → **pictures**, for seeing qualitative whole
  - e.g. Volume rendering
- Analysis → geometric **models**, for quantitative measurements
  - e.g. Segmentation, Classification, Feature Extraction
  - **This talk: Particle Systems for Feature Extraction**

Outline

Please interrupt!

- Applications
  - Clinical Lung Studies (chest CT, Emphysema)
  - Brain Structure (diffusion MRI, white matter)
  - Zebrafish phenotyping (micro CT, eyes, etc)
- Method: Particle Systems for Features
  - Feature definition & extraction
  - Decomposition into Particles
  - System Optimization
- Particle System Economization
  - Decomposition of Costs
  - Parameter tuning, algorithmic tuning?

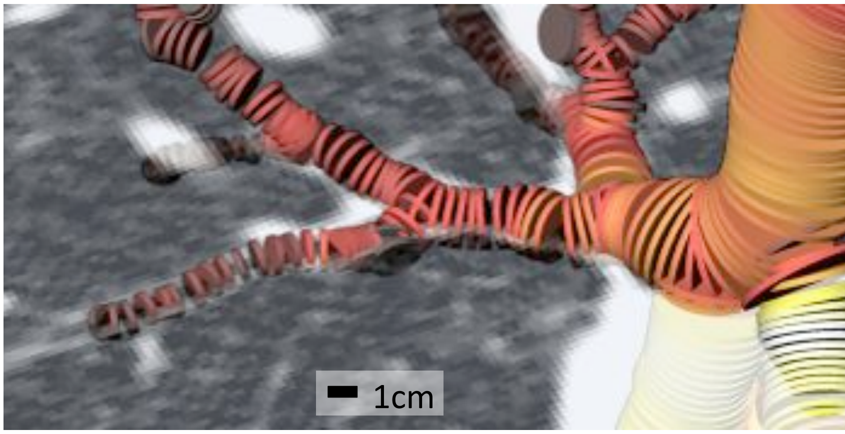
Lung lobes from clinical CT



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

 (Applications)

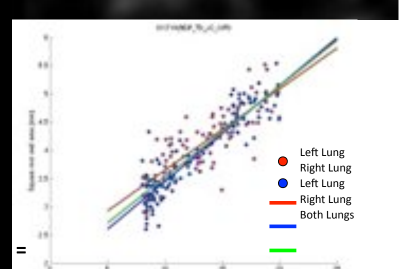
Lung airways from clinical CT



•Reliably finding and measuring lobes and airways in lung CT, especially with clinical data, is an open problem

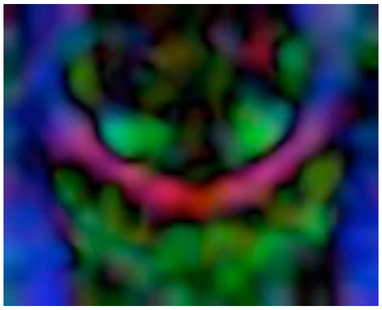
• Pixels are **expensive**: working at scale of individual pixels → **continuous** domain

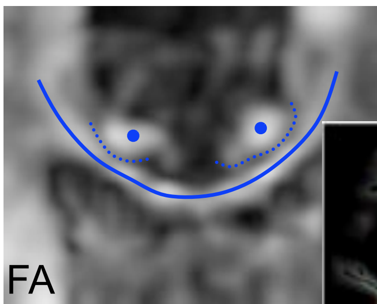
Lung airways from clinical CT



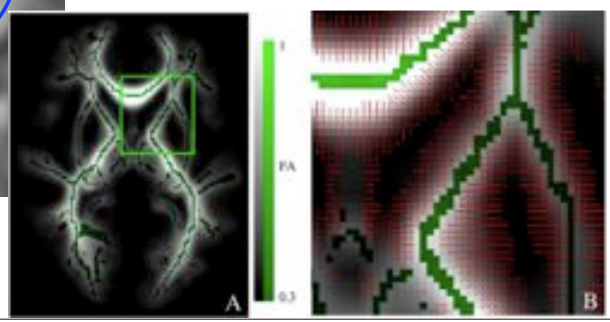
Collaboration with Brigham & Women's Hospital, Harvard Medical School: Raúl San José Estépar, Ph.D., James C. Ross, M.S. Alejandro A. Diaz, M.D., Edwin K. Silverman, M.D., Ph.D., George R Washko[2], M.D. and the COPDGene Investigators

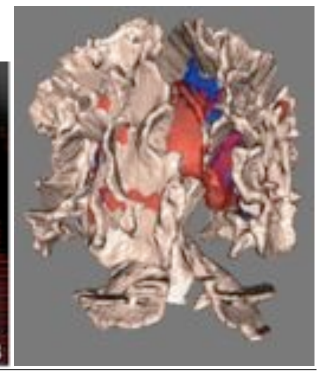
Brain white matter from diffusion MRI





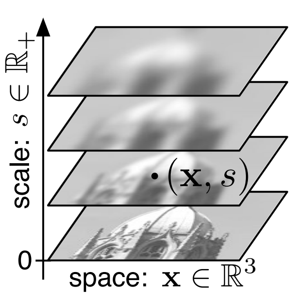
- Goal: automatically delineate large-scale white matter structures
- “Sulci for white matter”
- **Shape**, not connectivity
- Smith et. al. “Tract-Based Spatial Statistics” NeuroImage ’06

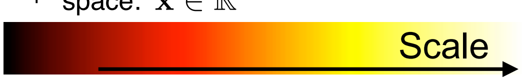


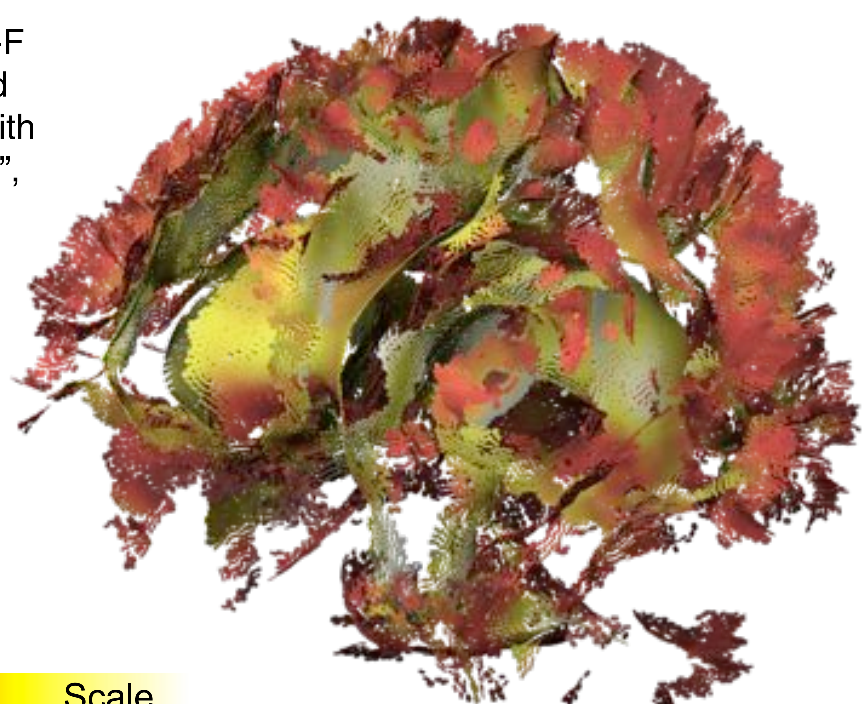


Brain white matter from diffusion MRI

G Kindlmann, RSJ Estepar, SM Smith, C-F Westin, “Sampling and Visualizing Creases with Scale-Space Particles”, IEEE Trans. on Visualization and Computer Graphics, 2009, 15:1415-1424







Genetics Model Organisms w/ MicroCT

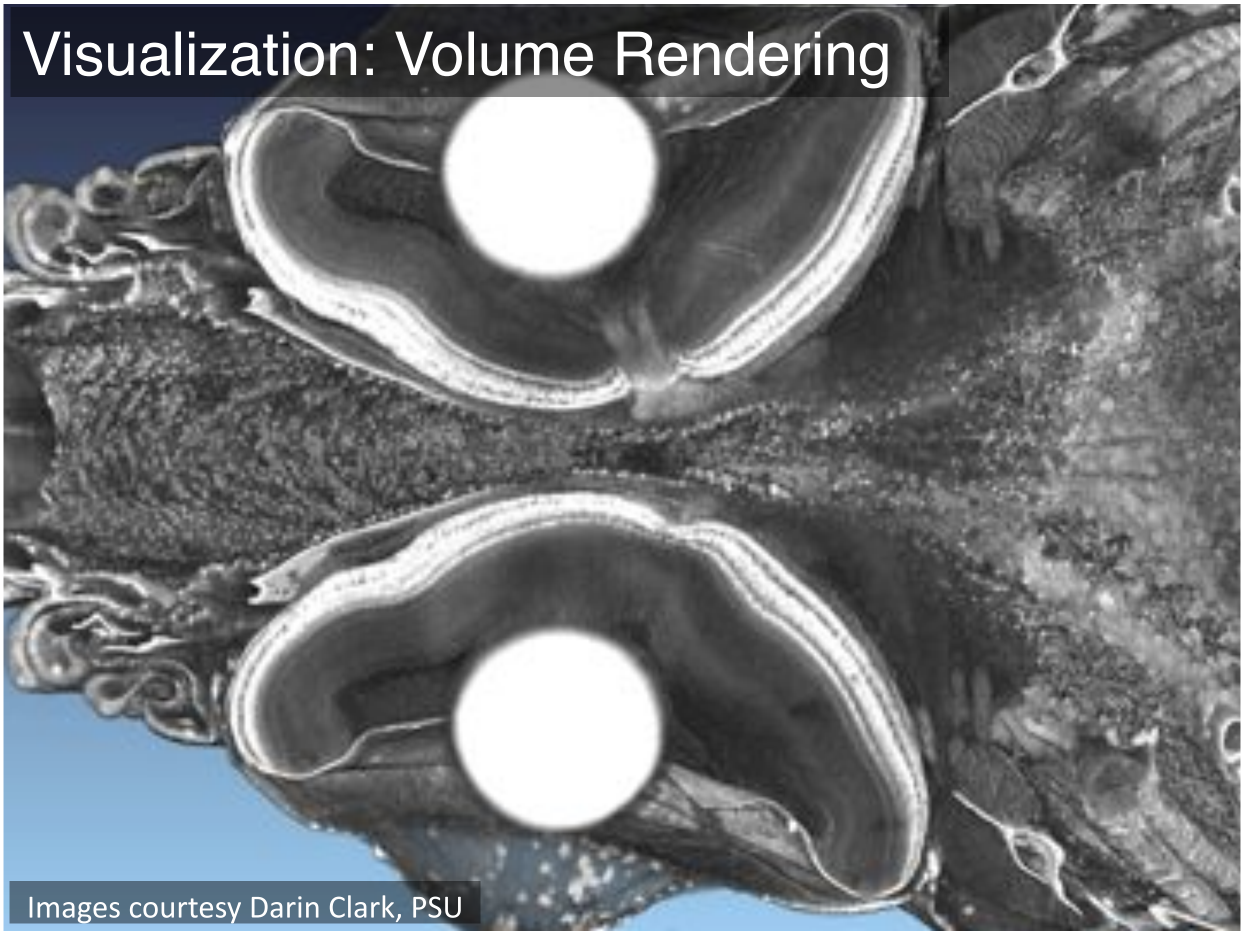
- Argonne National Lab; Advanced Photon Source
- Multiple beamlines, one for microscopic CT

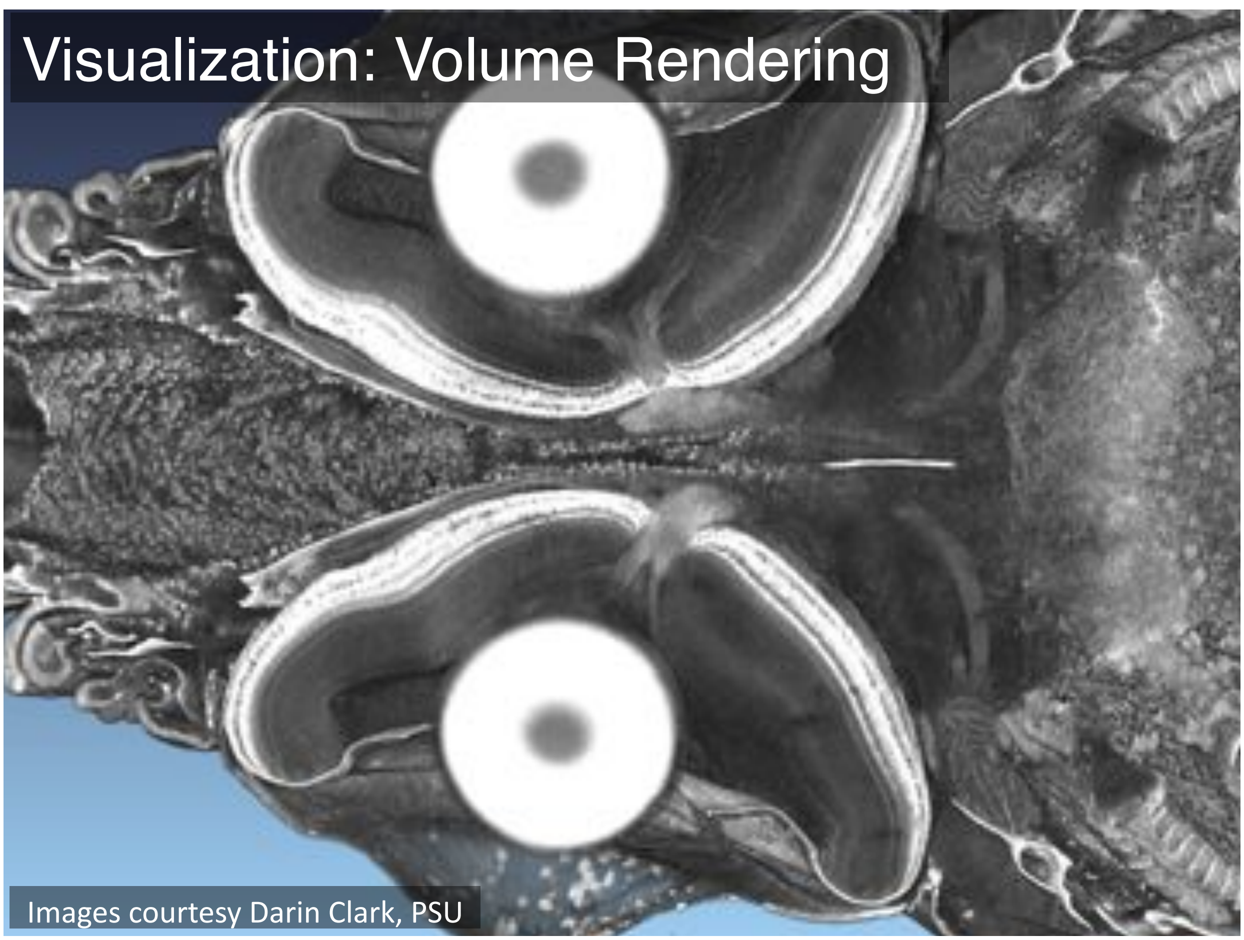
- ~5 micron resolution; output volumes 2000 x 2000 x 4000 (versus clinical CT ≈ 256 x 256 x 256)
- Working on building infrastructure for data movement between Argonne and UChicago

Genetics Model Organisms w/ MicroCT

- Zebrafish is a model organism for genetics
  - Visual system model for human vision
  - Dr. Keith Cheng, Penn State University
- Some phenotypes are manifest only in adult zebrafish
- Opaque ⇒ No Confocal ⇒ MicroCT
- Have 1000s of mutants

- Need high-throughput tools for:
  - inspecting acquisition & analysis pipeline
  - feature quantification for phenotyping


Visualization: Volume Rendering
Images courtesy Darin Clark, PSU


Visualization: Volume Rendering
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Visualization: Volume Rendering
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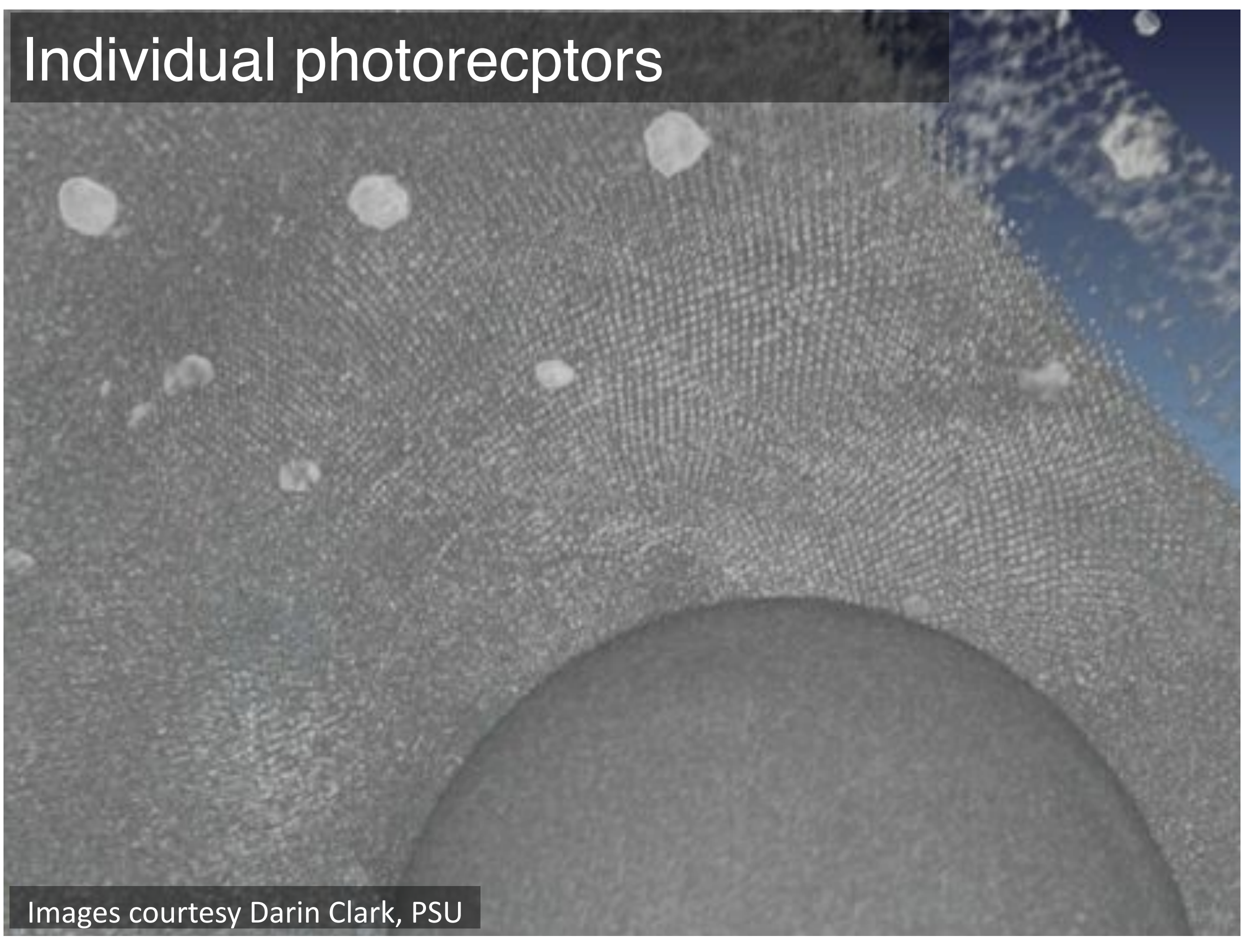
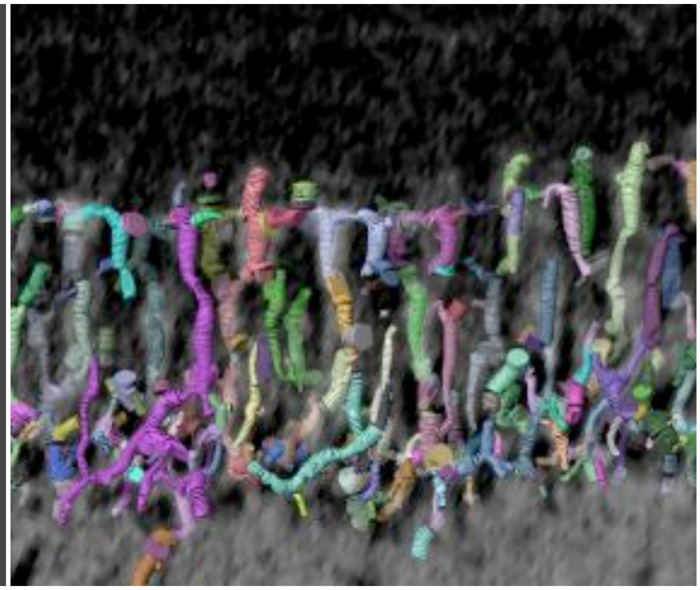

Individual photorecptors
Images courtesy Darin Clark, PSU

Particle systems for micro-anatomy

- First extraction of individual photoreceptors from microCT
- Wealth of anatomical features at larger scales

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  - Feature definition & extraction
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  - System Optimization

Tell me how I can be doing this better!

- Particle System Economization
  - Decomposition of Costs
  - Parameter tuning, algorithmic tuning?

Feature Definition

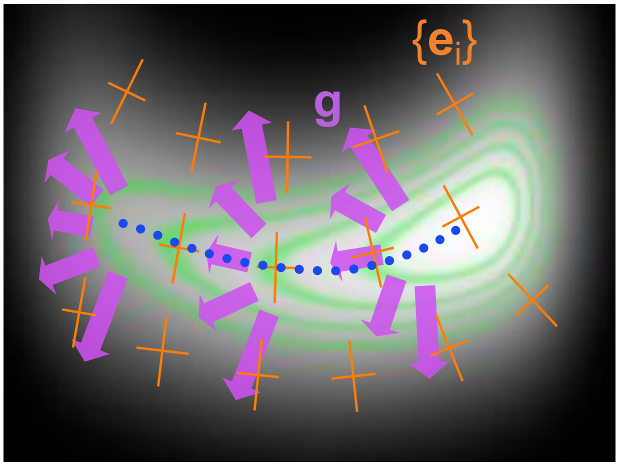
- Assume: continuous, differentiable image f(**x**)
- **Feature**: set of positions **x** in image domain satisfying a defining formula p(f, **x**) = true
  - Relies on local measurements, especially derivatives
  - Intent: Properties of the feature should correspond to properties of underlying object of scientific study
- **Feature strength**: measure of validity or reliability of feature s(f, **x**) $\in \mathbb{R}$
  - Intent: Avoid extracting feature at locations where it is not meaningful or informative

Feature Definition Examples

- Isosurface at v_0
  - f(**x**) = v_0
  - s(f,**x**) = ?
  - One parameter

- Laplacian 0-crossing
  - ∇^2 f(**x**) = 0
  - s(f,**x**) = |∇ f(**x**)|
  - Zero parameters

Ridges/Valleys = Creases



"Ridges in Image and Data Analysis" Eberly '96

Constrained extremum

Gradient **g**

Hessian eigensystem $\mathbf{e}_i, \lambda_i$

Crease: **g** orthogonal to one or more $\mathbf{e}_i$

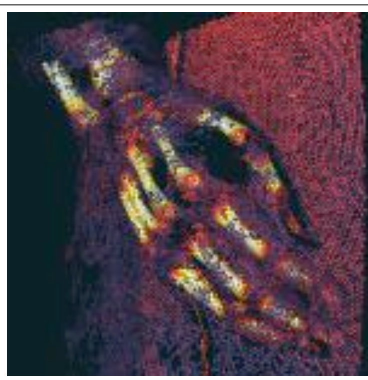
Eigenvalues determine strength s

$$\text{Ridge surface: } \mathbf{g} \cdot \mathbf{e}_3 = 0; \qquad s = -\lambda_3$$

$$\text{Ridge line: } \mathbf{g} \cdot \mathbf{e}_3 = \mathbf{g} \cdot \mathbf{e}_2 = 0; \qquad s = -\lambda_2$$

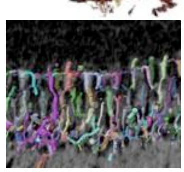
$$\text{Valley surface: } \mathbf{g} \cdot \mathbf{e}_1 = 0; \qquad s = \lambda_1$$

Feature Definition Examples



Isosurface

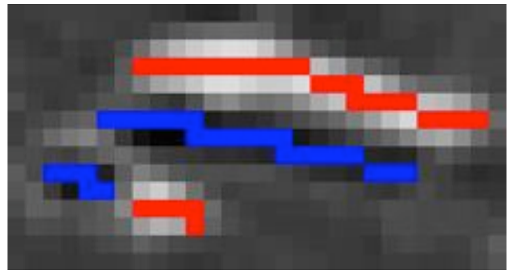
Creases ...



Laplacian zero-crossing

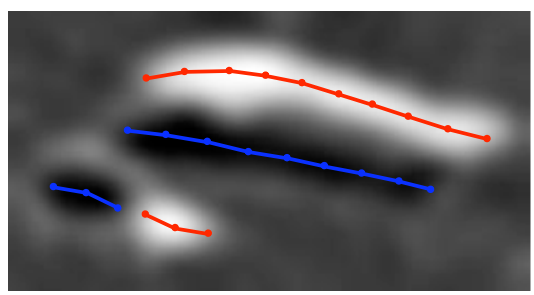
Feature Extraction Options

- Representation: **Raster** or **Polygonal**
- **Raster**: Binary mask (traditional classification) computes pixels of g[**x**] ∈ {0,1}; p(f, **x**) ⇔ g(**x**)=1

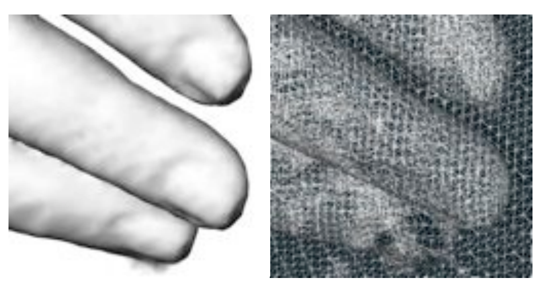


  - Loose sub-pixel accuracy
  - Often seeking structure at limits of resolution (pixels are expensive)
- Level-Sets (Sethian&Osher) compute pixels in new raster image of g(**x**) ∈ $\mathbb{R}$; p(f, **x**) ⇔ g(**x**)=0
  - Assumes that features are co-dimension 1; not the case with crease lines (co-dimension 2)

Feature Extraction

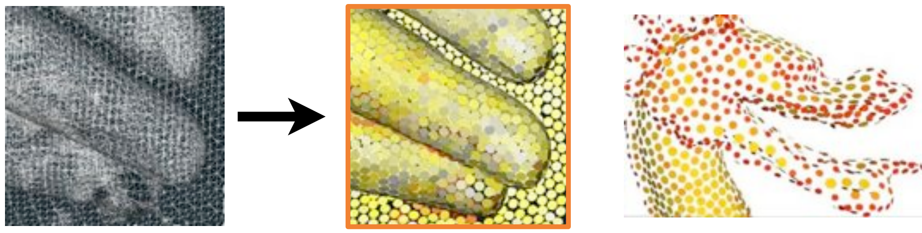


- **Polygonal** representation
  - sub-pixel accuracy
  - co-dimension 1 or 2
- To extract feature:
  - Compute vertex locations and connectivity
- Marching Cubes does both at same time



  - Image grid determines both vertex location and connectivity
  - Location could be optimized separately ...

Particles for Image Features



Miriah Meyer's work 2005-2008

- Compute vertex location separately from computing vertex connectivity
- vertex location: local image feature detection
  - entirely determined by feature definition
  - implement one particle, and you're done
- vertex connectivity: computational geometry
  - many apps don't actually need connectivity
- Handles different co-dimensions equally well

Driving equation for particle system

$$\underset{\mathbf{x}_i, N}{\operatorname{argmin}}\ \mathcal{E} = \underset{\mathbf{x}_i, N}{\operatorname{argmin}}\ (1-\alpha) \underbrace{\sum_{i=1}^{N} E_i}_{} + \frac{\alpha}{2} \underbrace{\sum_{i,j=1}^{N} E_{ij}}_{}$$

Particle positions

Number of Particles

Particle-image energy (for feature detection in scale-space)

Inter-particle energy: induces uniform sampling

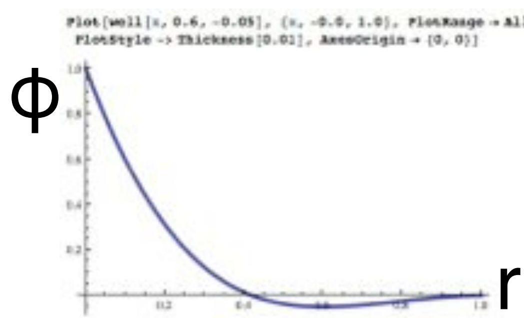
without scale-space: $\boxed{\underset{\mathbf{x}_i, N}{\operatorname{argmin}}\ \mathcal{E} = \underset{\mathbf{x}_i, N}{\operatorname{argmin}} \sum_{i,j=1}^{N} E_{ij}}$

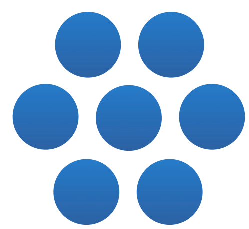
- **Particle system goal: minimize inter-particle energy in the presence of (energy-free) feature constraints**
  - Minimizing energy: Moving, adding, removing particles
  - Constraints: isosurface ($f(\mathbf{x})-v_0=0$): Newton's method
  - Ridges and Valleys ($\nabla f(\mathbf{x}) \cdot \mathbf{e}_3 = 0$): Newton optimization

Inter-particle energy E_{ij}

- Determines system behavior and converged configuration
- Currently:
  - no orientation wrt feature
  - uniform scale σ_r
  - small zone of attraction
- Attractive zone allows population control to be folded into energy minimzation

$$E_{ij} = \Phi\left(\frac{|\mathbf{x}_i - \mathbf{x}_j|}{\sigma_r}\right)$$





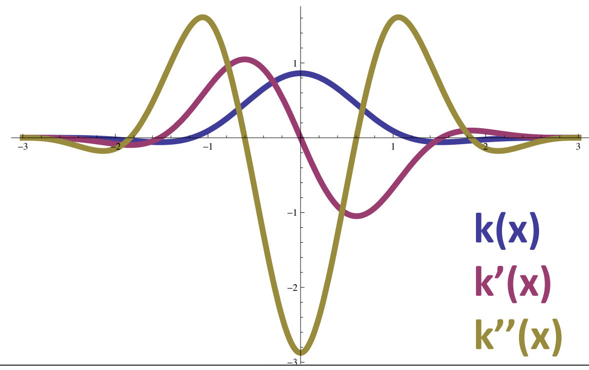
Current Energy minimization

- No particle mass; Asynchronous updates
- For each particle i (at position $\boldsymbol{x}_i$, with step size h_i)
  - Learn neighbors j and compute
    - energy $e_i = \Sigma_j\, \phi(\boldsymbol{x}_j - \boldsymbol{x}_i)$ & force $\boldsymbol{f}_i = -\Sigma_j\, \nabla\phi(\boldsymbol{x}_j - \boldsymbol{x}_i)$
  - do {
    - $\boldsymbol{x}_{test} = \boxed{\text{ConstraintSatisfy}}(\boldsymbol{x}_i + h_i{*}\boldsymbol{f}_i)$
    - $e_{test} = \Sigma_j\, \phi(\boldsymbol{x}_j - \boldsymbol{x}_{test})$
    - $badstep = e_{test} > e_i + e_{perm}$
    - if $badstep$: $h_i = h_i * backoff$
  - } while $badstep$
  - $\boldsymbol{x}_i = \boldsymbol{x}_{test}$
  - $h_i = h_i * creepup$
- parms: $backoff$=0.1, $creepup$=1.1, e_{perm}=0.001

Bottleneck!

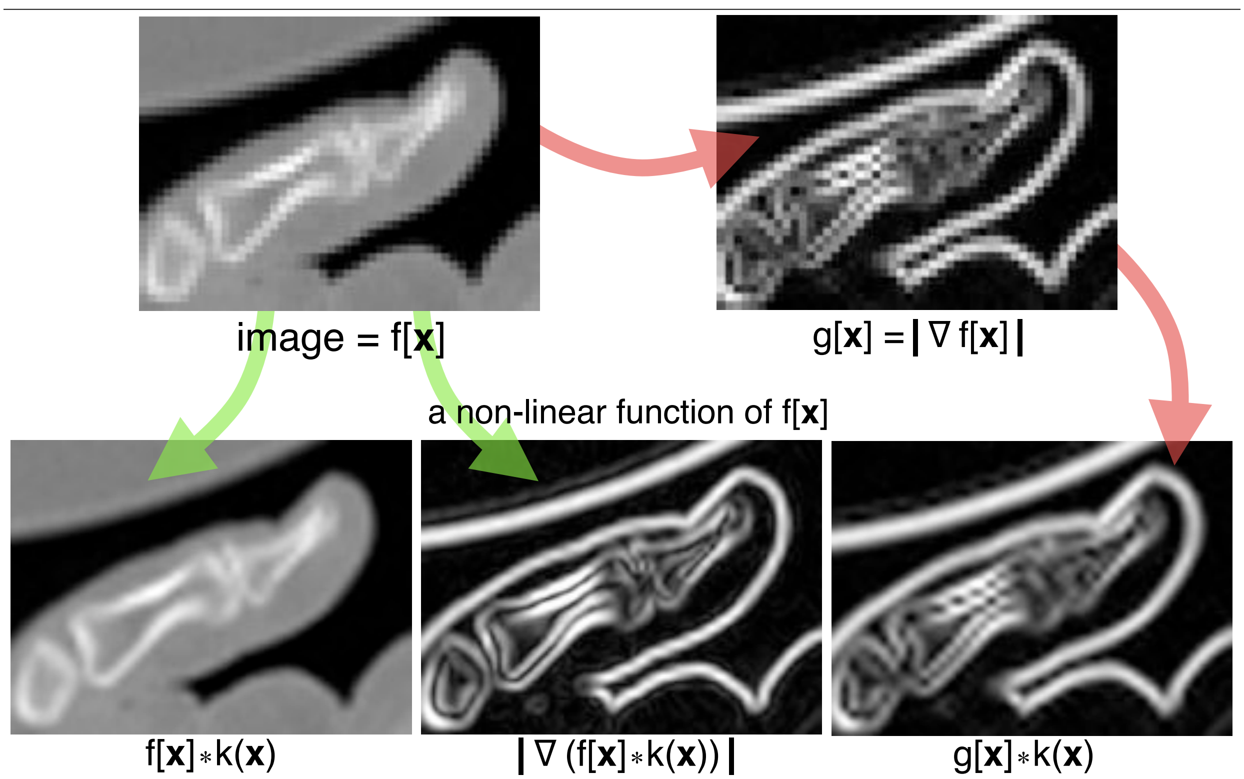
Value & Derivative measurement

- Need smooth field from discrete image data
- **Convolution** (Separable → 3D kernels)
- Differentiability required for gradients, Hessians used in constraint satisfaction
- Accuracy (in the Taylor sense) avoids sample-frequency ripple in image features



6-sample support Piece-wise 6th-order polynomial
C^4 continuity 4th-order error
"Evaluation and Design of Filters Using a Taylor Series Expansion," Möller et al. IEEE TVCG '97

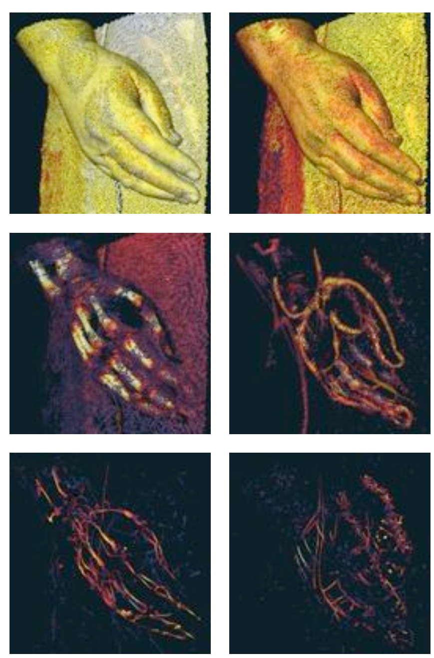
Derivative measurement: Can't skimp



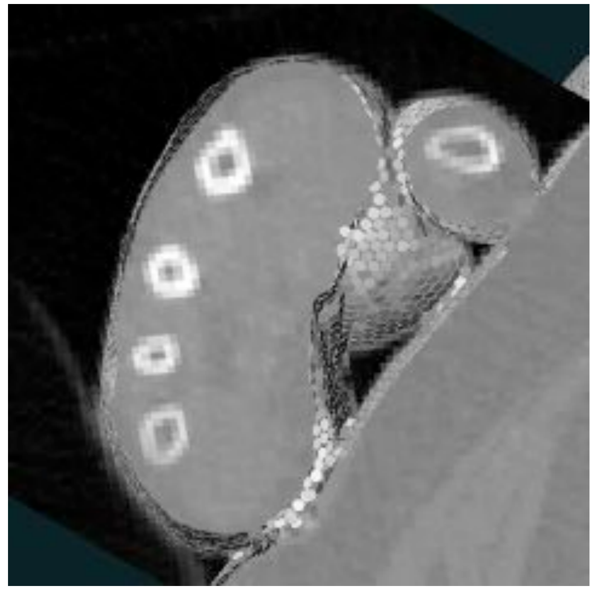
Demo on synthetic dataset ...

Gallery of particles for different features

- Illustrated with hand from Visible Human, Female CT
- Feature types
  - Isosurface
  - Laplacian zero-crossing
  - Ridges & Valleys ("creases")
    - surfaces or lines
- **Particle system samples features**
  - each little glyph = one particle
  - show local feature ingredients



Isosurface

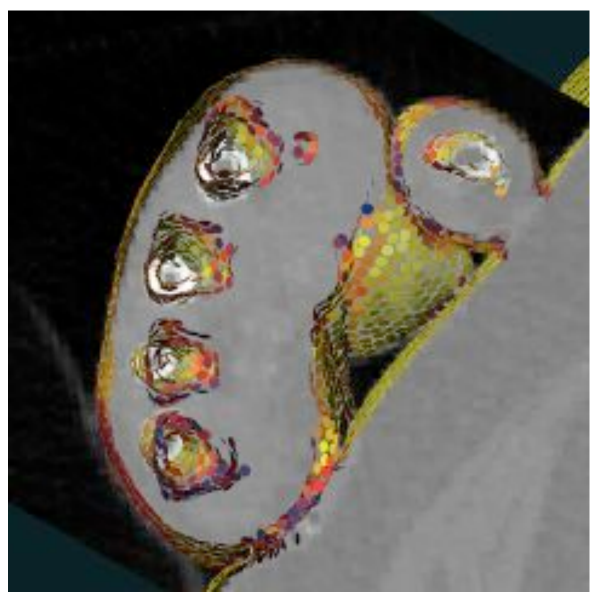


Outside 3D view

Different, Cropped 3D view w/ 2D plane

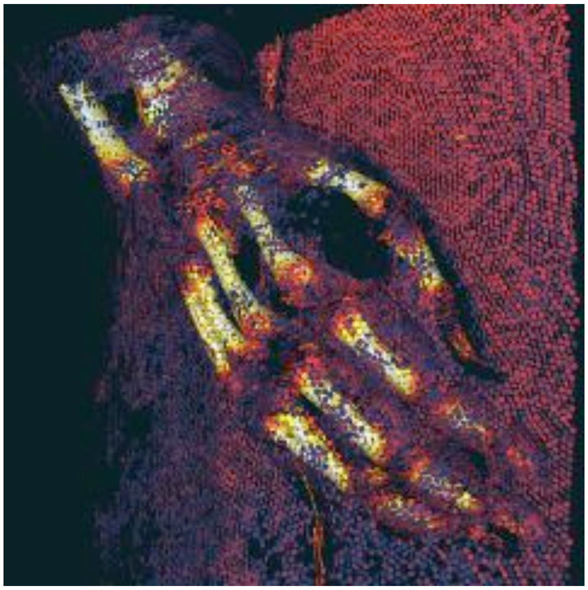
- AKA isophote, isocontour, level set
- $f(\mathbf{x}) = v_0$

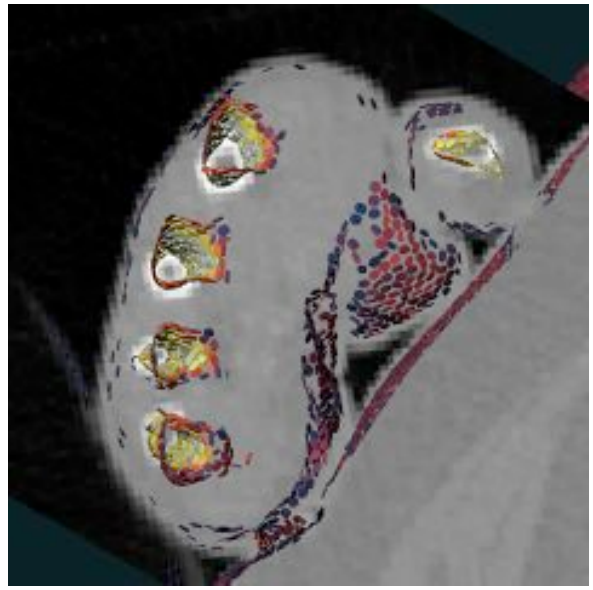
Laplacian 0-crossing



- Classical definition of edge
- $\nabla^2 f(\mathbf{x}) = 0$; strength = $|\nabla f(\mathbf{x})|$

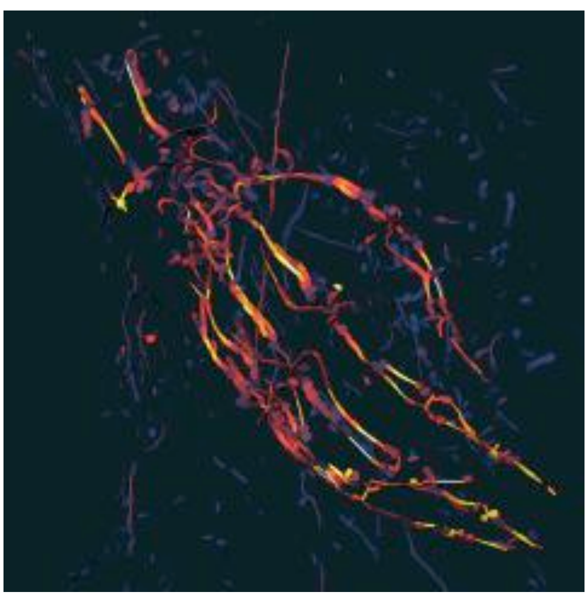
Ridge Surface

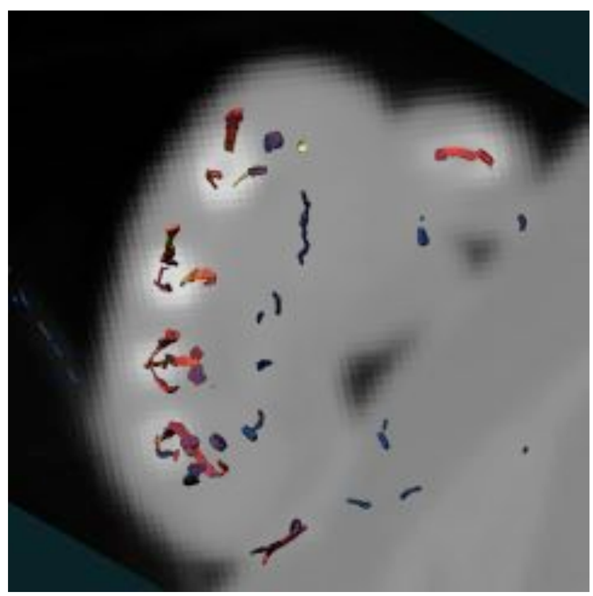




- Maximal surface wrt Hessian minor eigenvector $\mathbf{e}_3$
- $\nabla f(\mathbf{x}) \cdot \mathbf{e}_3(\mathbf{x}) = 0$; strength = $-\lambda_3$

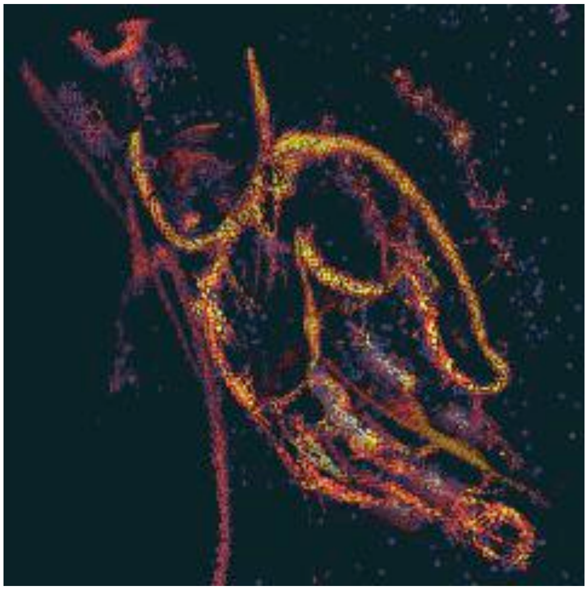
Ridge Line

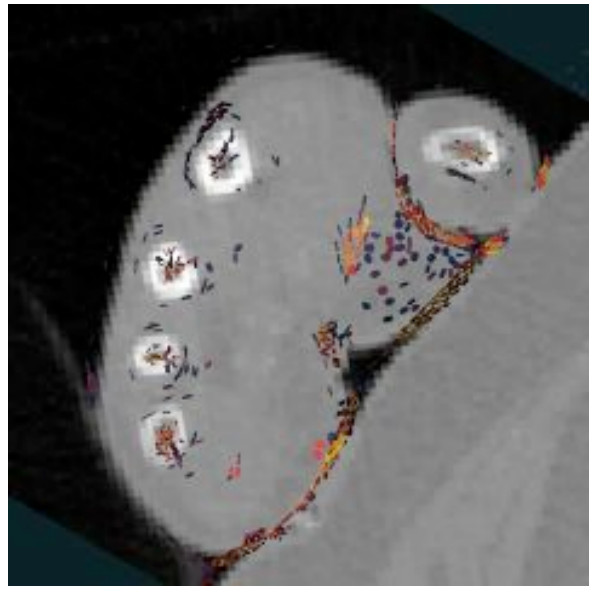




- Maximal curve wrt Hessian minor,medium eigenvectors
- $\nabla f(\mathbf{x}) \cdot \mathbf{e}_3(\mathbf{x}) = 0$, $\nabla f(\mathbf{x}) \cdot \mathbf{e}_2(\mathbf{x}) = 0$; strength = $-\lambda_2$

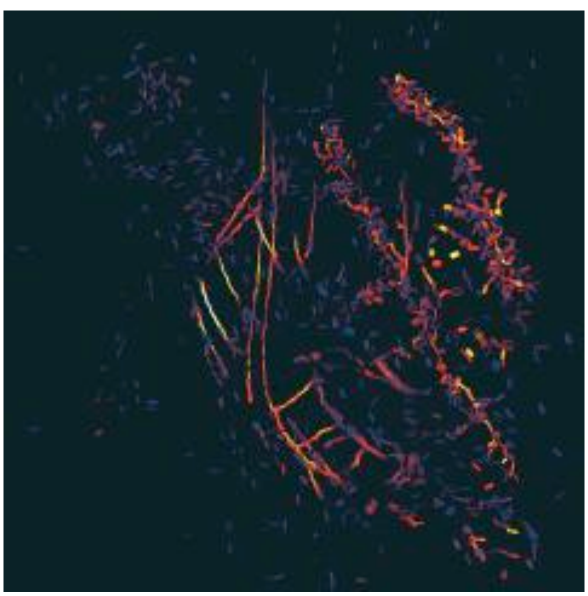
Valley Surface

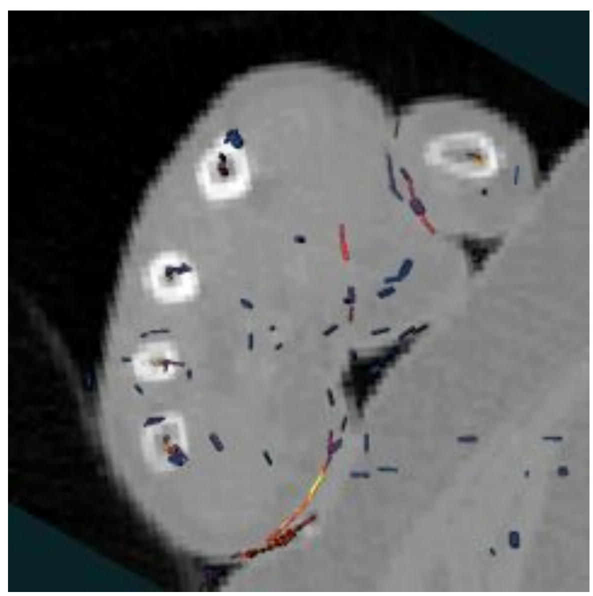




- Minimal surface wrt Hessian major eigenvector $\mathbf{e}_1$
- $\nabla f(\mathbf{x}) \cdot \mathbf{e}_1(\mathbf{x}) = 0$; strength = λ_1

Valley Line





- Minimal curve wrt Hessian major,medium eigenvectors
- $\nabla f(\mathbf{x}) \cdot \mathbf{e}_1(\mathbf{x}) = 0$, $\nabla f(\mathbf{x}) \cdot \mathbf{e}_2(\mathbf{x}) = 0$; strength = λ_2

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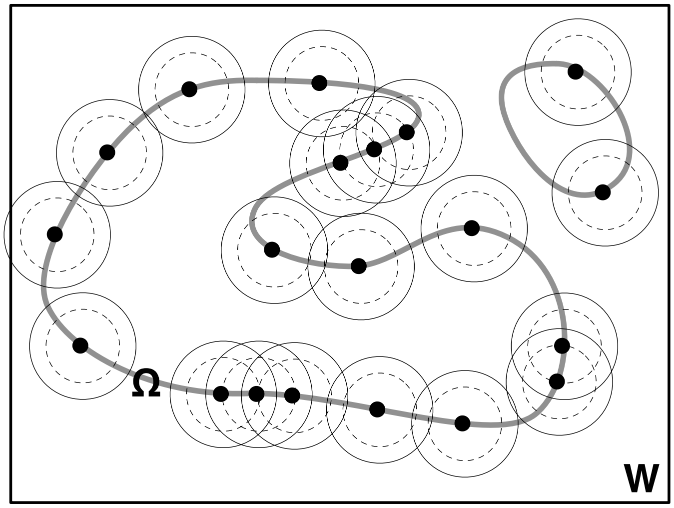
  - Clinical Lung Studies (chest CT, Emphysema)
  - Brain Structure (diffusion MRI, white matter)
  - Zebrafish phenotyping (micro CT, eyes, etc)
- Method: Particle Systems for Features
  - Feature definition & extraction
  - Decomposition into Particles
  - Results
- Particle System Economization
  - Decomposition of Costs
  - Parameter tuning, algorithmic tuning?

Want new ideas & connections & terminology!

Parameters in current approach

- Want to minimize computation to find convergence
- Algorithm for energy minimization
  - currently opportunistic gradient descent
- Method of population control
  - when/how to check if add/nix → decrease energy
- Shape of inter-particle potential function ϕ
  - some shapes may lead faster to nice distribution
- Initialization (seeding system with particles)
  - currently brute-force search through ~all voxels
- **What is the conceptual framework for optimizing (in the sense of computational economization) all these choices & parameters?**

Conceptual view: governing eq.s



$$P = \{\mathbf{x}_i\}_{i=1}^{N}; \mathbf{x}_i \in \Omega$$

Set of particles on feature

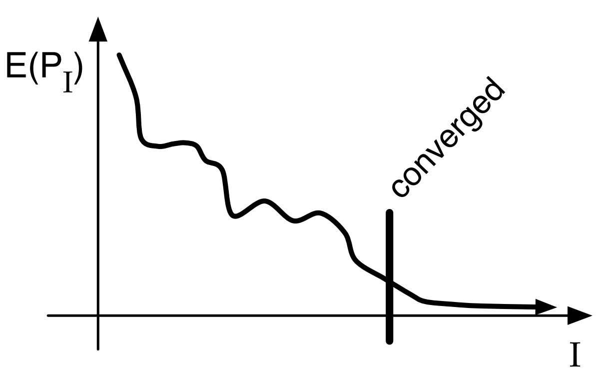
$$E(P) = \frac{1}{2} \sum_{i,j=1}^{N} \phi\left(\frac{|\mathbf{x}_i - \mathbf{x}_j|}{\sigma}\right)$$

Energy of particle set

$$\text{argmin}\; E(P) = \underset{\{\mathbf{x}_i\},N}{\text{argmin}}\; \frac{1}{2} \sum_{i,j=1}^{N} \phi\left(\frac{|\mathbf{x}_i - \mathbf{x}_j|}{\sigma}\right)$$

System adds/nixes/moves particles to minimize energy

Conceptual view: iteration/convergence



- Computation of system should be towards convergence: condition where add/kill/move particles won't make a dramatic difference

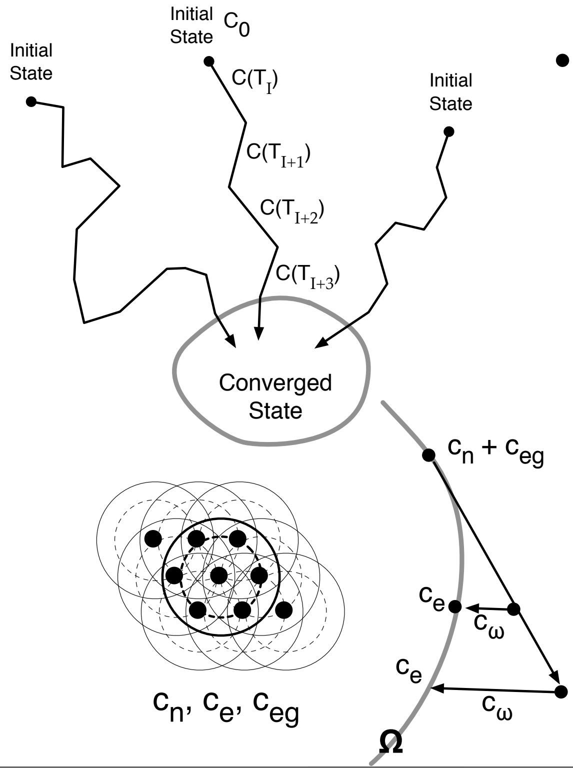
$$P_I \xrightarrow{T_I} P_{I+1} \xrightarrow{T_{I+1}} P_{I+2} \xrightarrow{T_{I+2}}$$

$$P_{I+1} = T(P_I) = T(\{\mathbf{x}_i\}_{i=1}^{N_I}) = \bigcup_{i=1}^{N_I} t(\mathbf{x}_i)$$

$$t(\mathbf{x}_i) = \begin{cases} \{\} & \mathbf{x}_i \text{ is killed} \\ \{\mathbf{x}_i'\} & \mathbf{x}_i \text{ is moved} \\ \{\mathbf{x}_i', \mathbf{y}_i'\} & \mathbf{x}_i \text{ created new particle} \end{cases}$$

- Transition function T computes next iteration

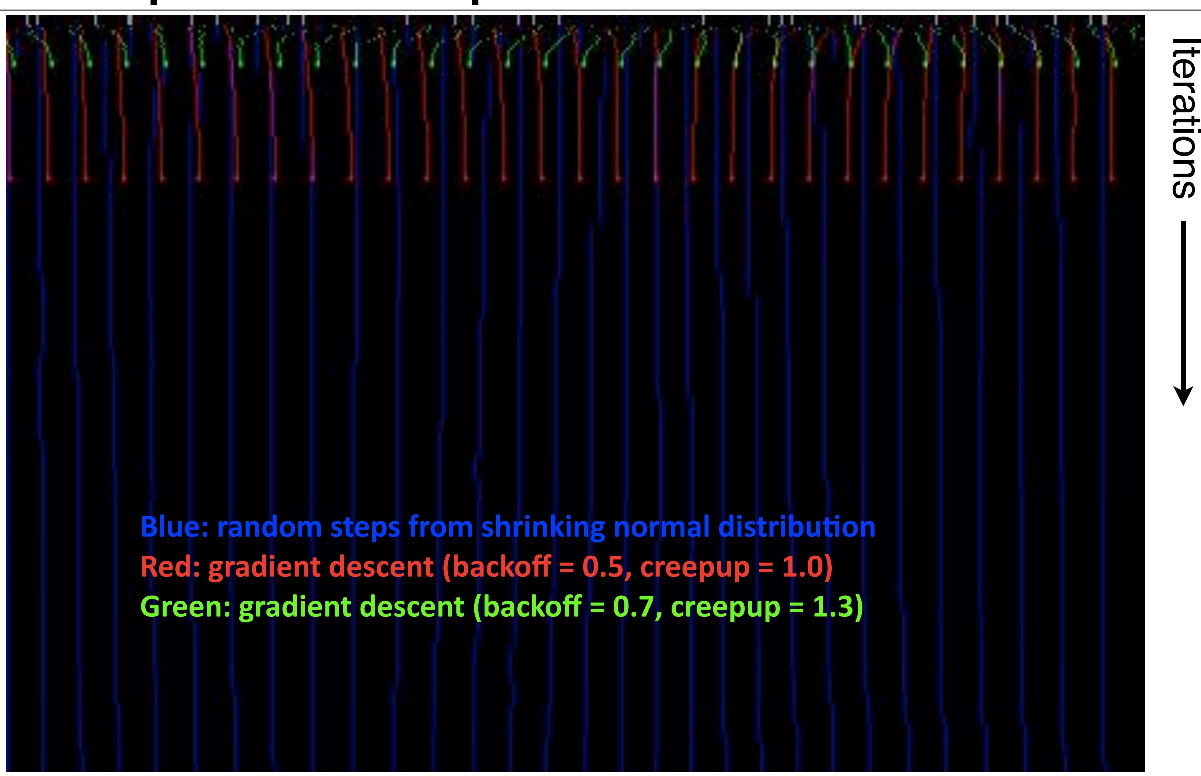
Conceptual view: Economization



- Every transition has a cost C(T), and we want to **find a path into convergence that minimizes** $C_0 + \sum_I C(T_I)$

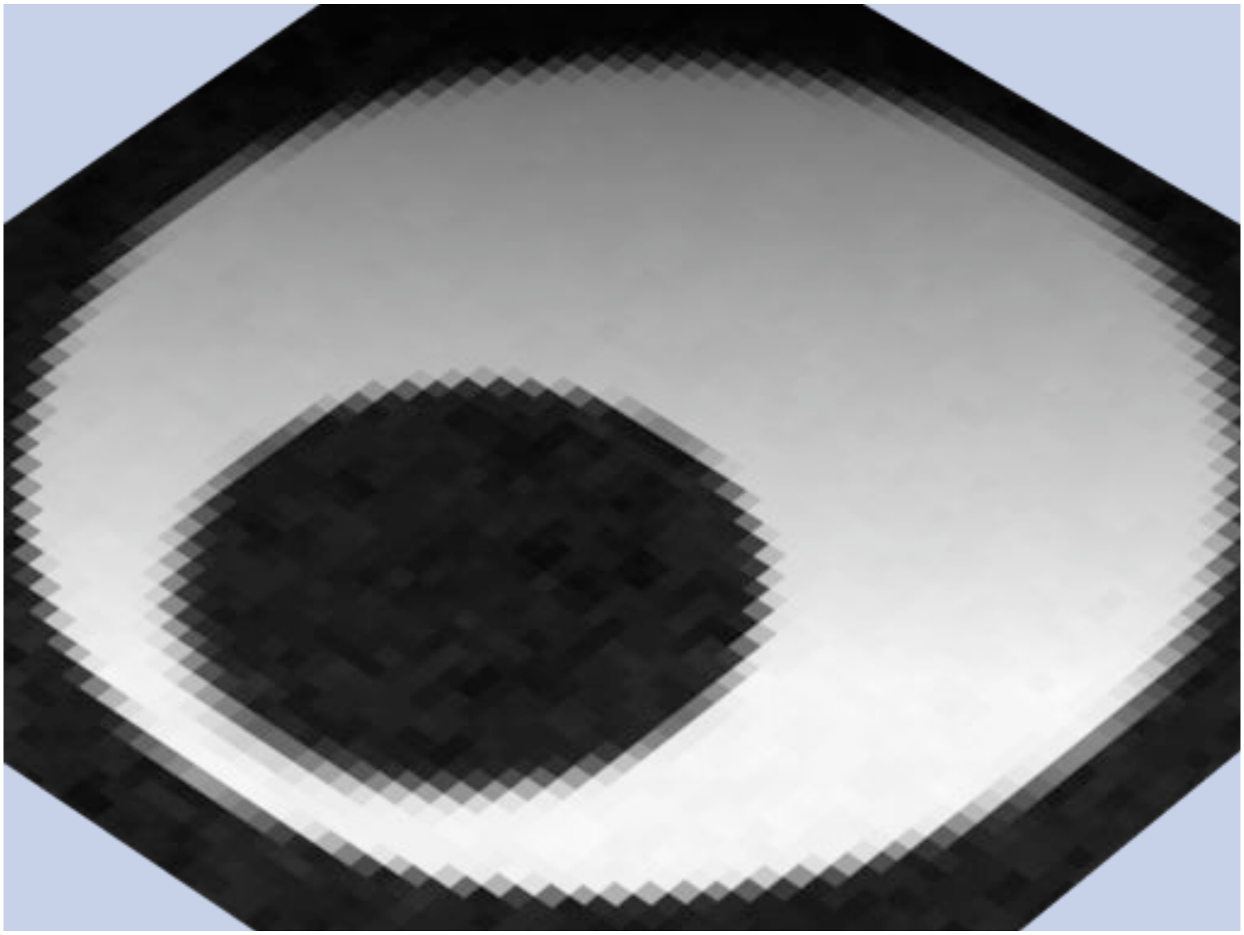
- c_n: cost of learning neighb in support of Φ(r)
- c_e: cost of computing energy due to neighbors
- c_{eg}: cost of computing energy and gradient
- c_ω: cost of re-asserting the constraint

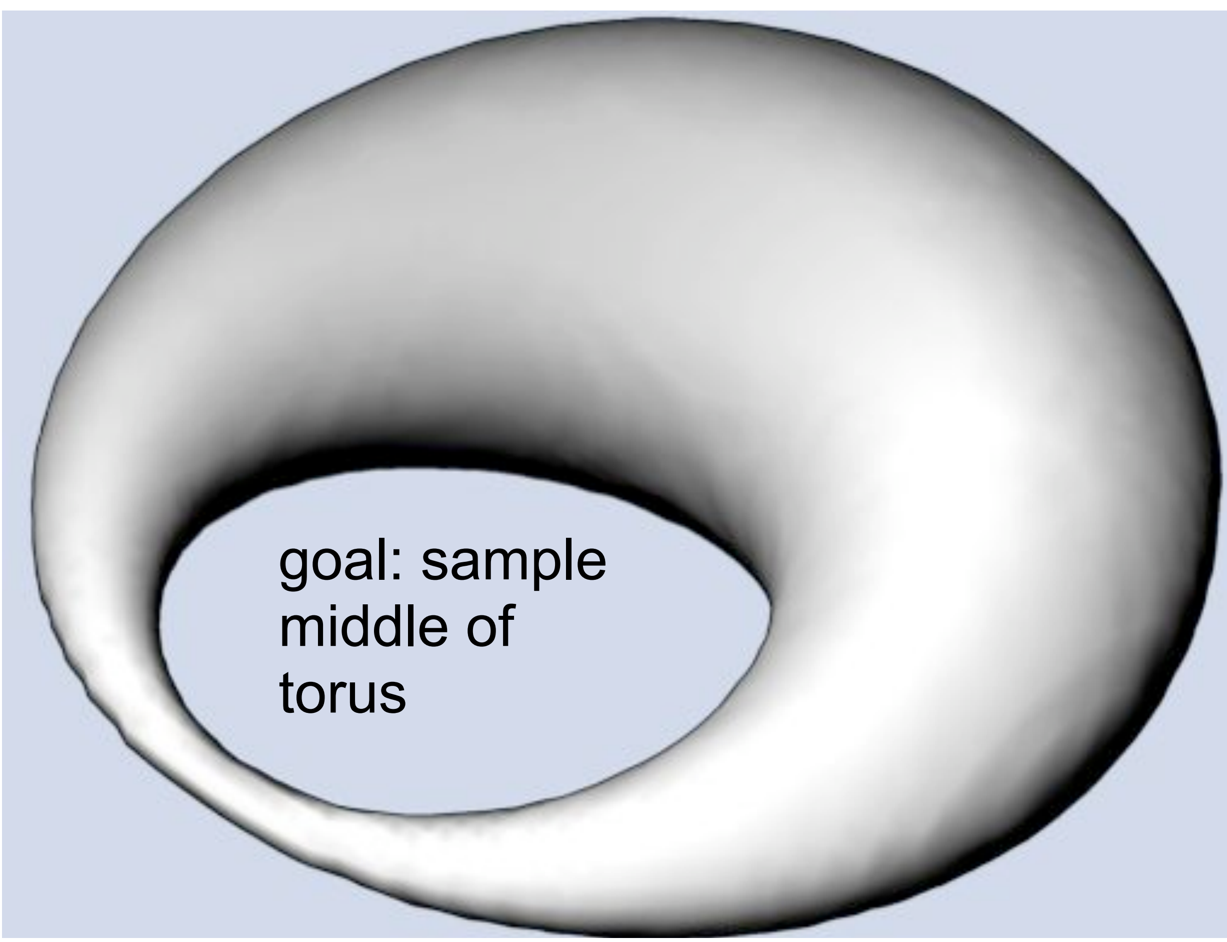
Simple case: particles on a circle

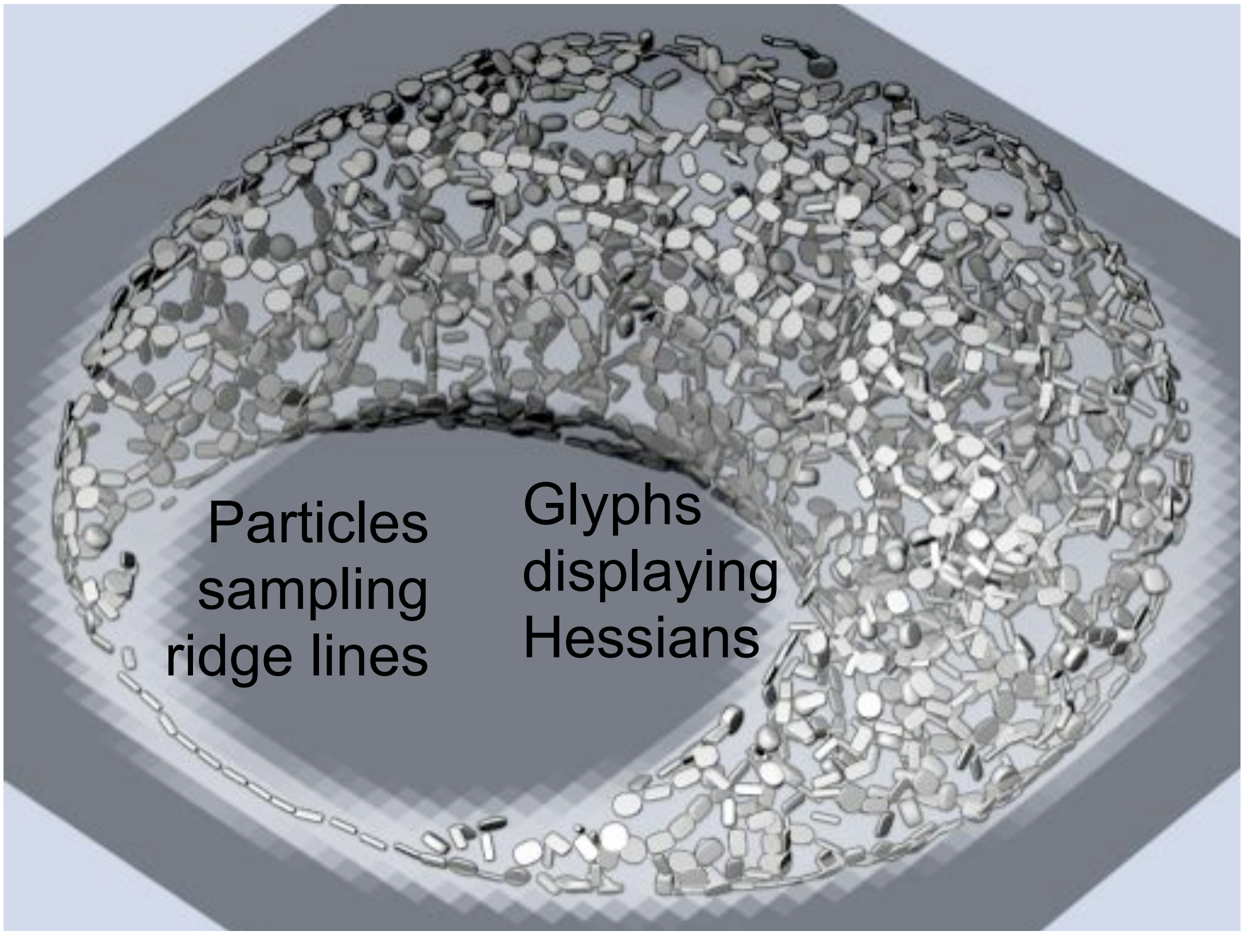


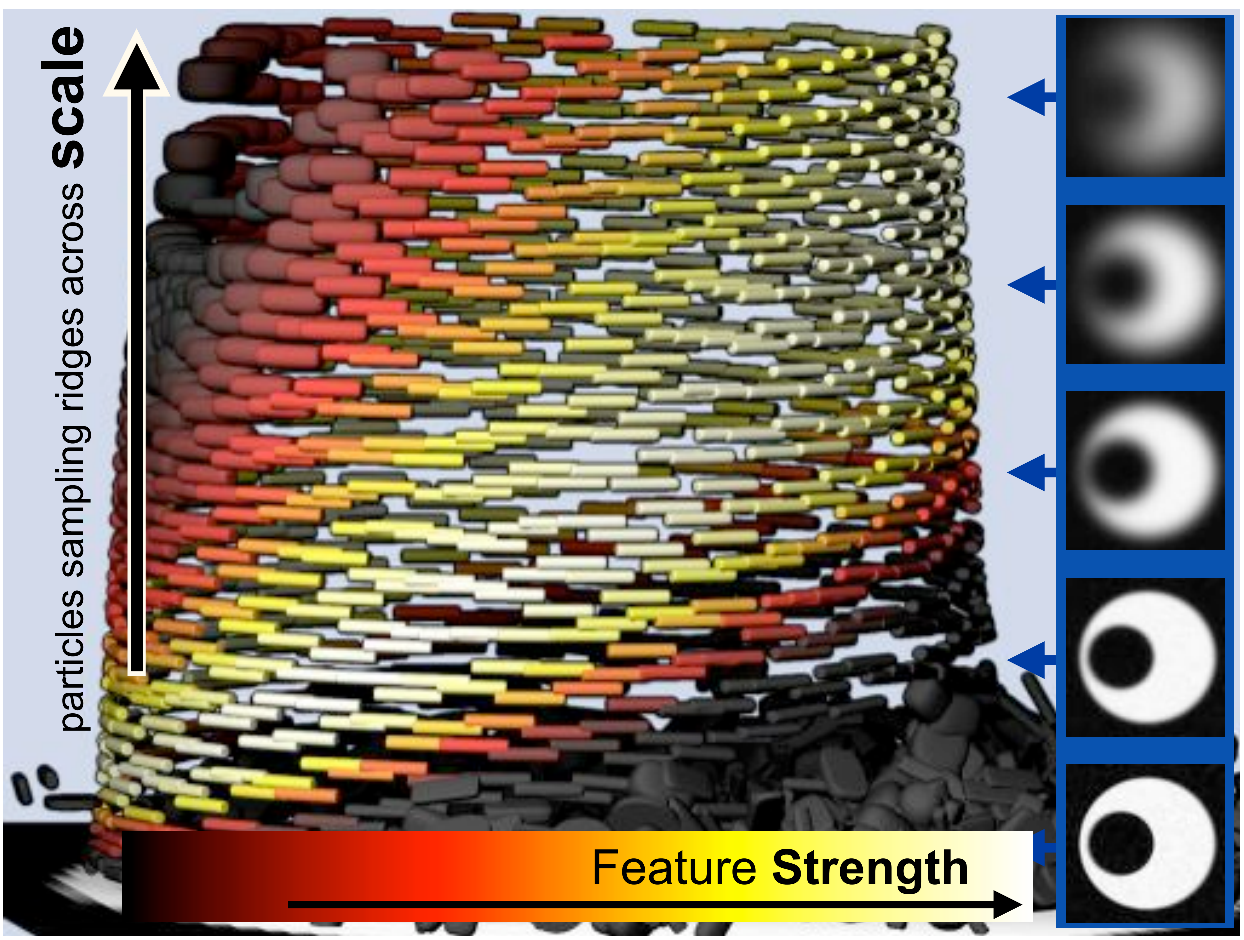
Conclusions/Discussion

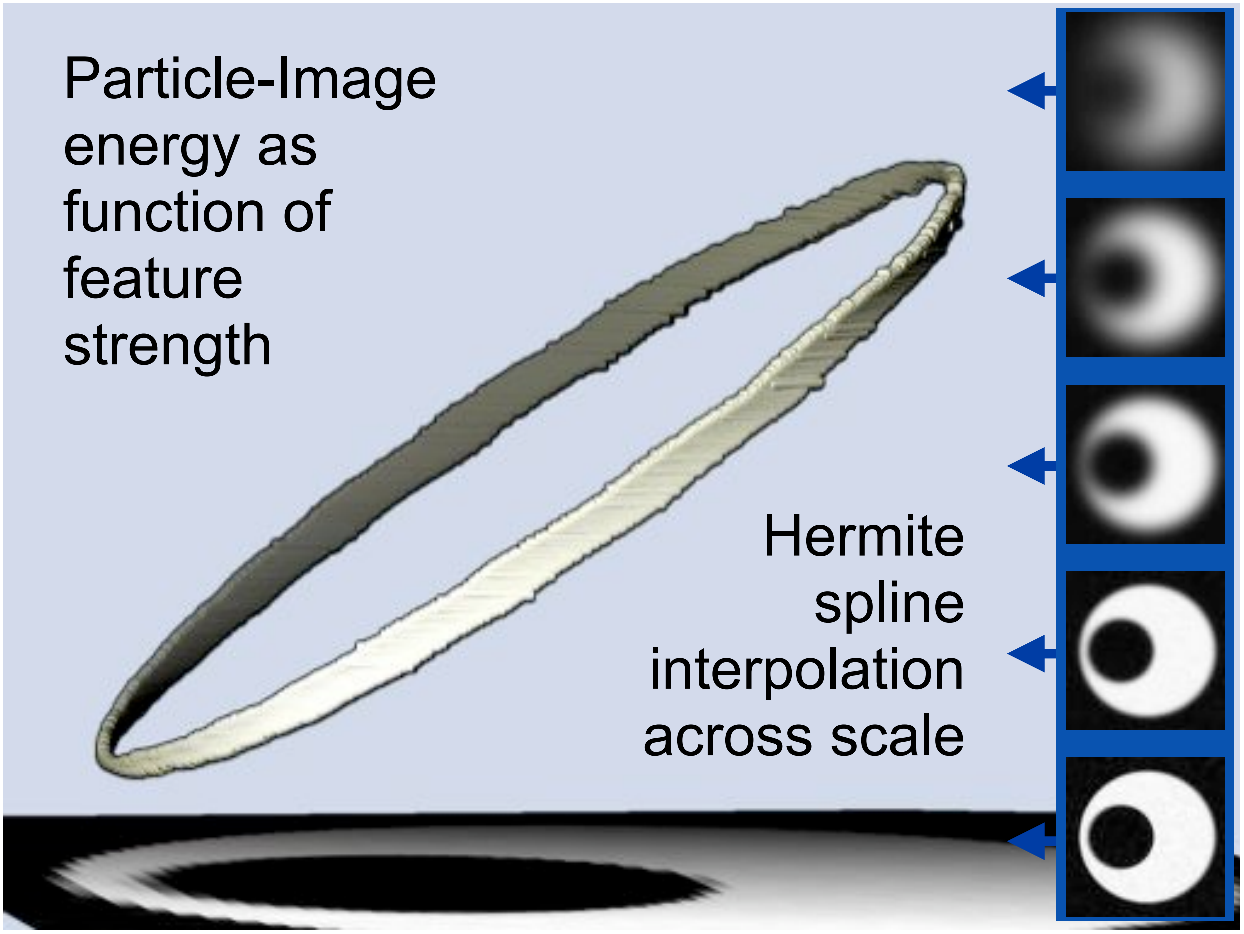
- Particles powerful tool for feature sampling
  - many biomedical applications
  - likely non-biomedical applications!
- Particles separate feature sampling from connectivity
- Practical need: better user interface, more testing
- Theoretical research
  - Economization (right word?) of system optimization
  - Fast rejection of non-feature areas
  - Interested in hearing your ideas
- **Thanks for your attention!**
  - glk@uchicago.edu

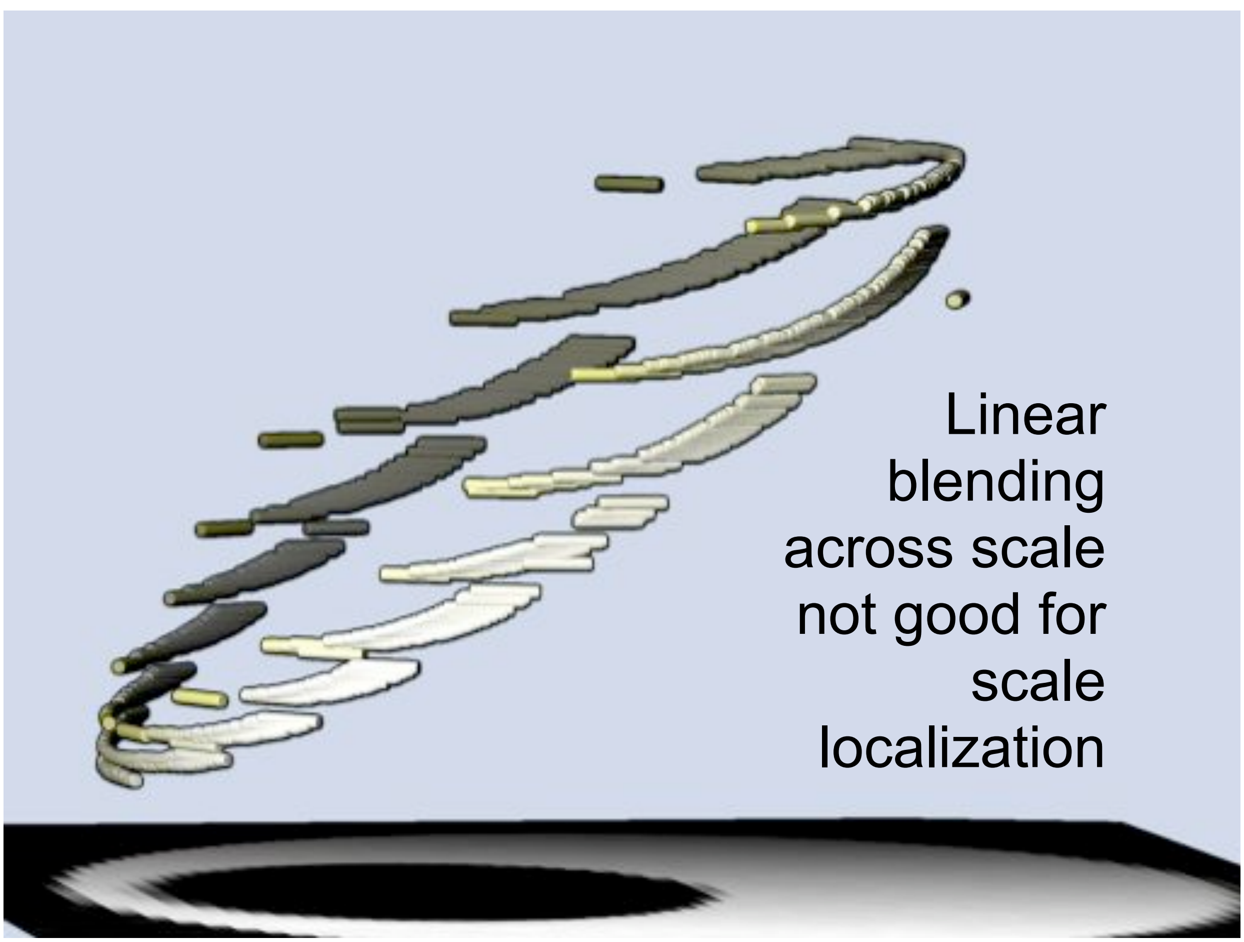


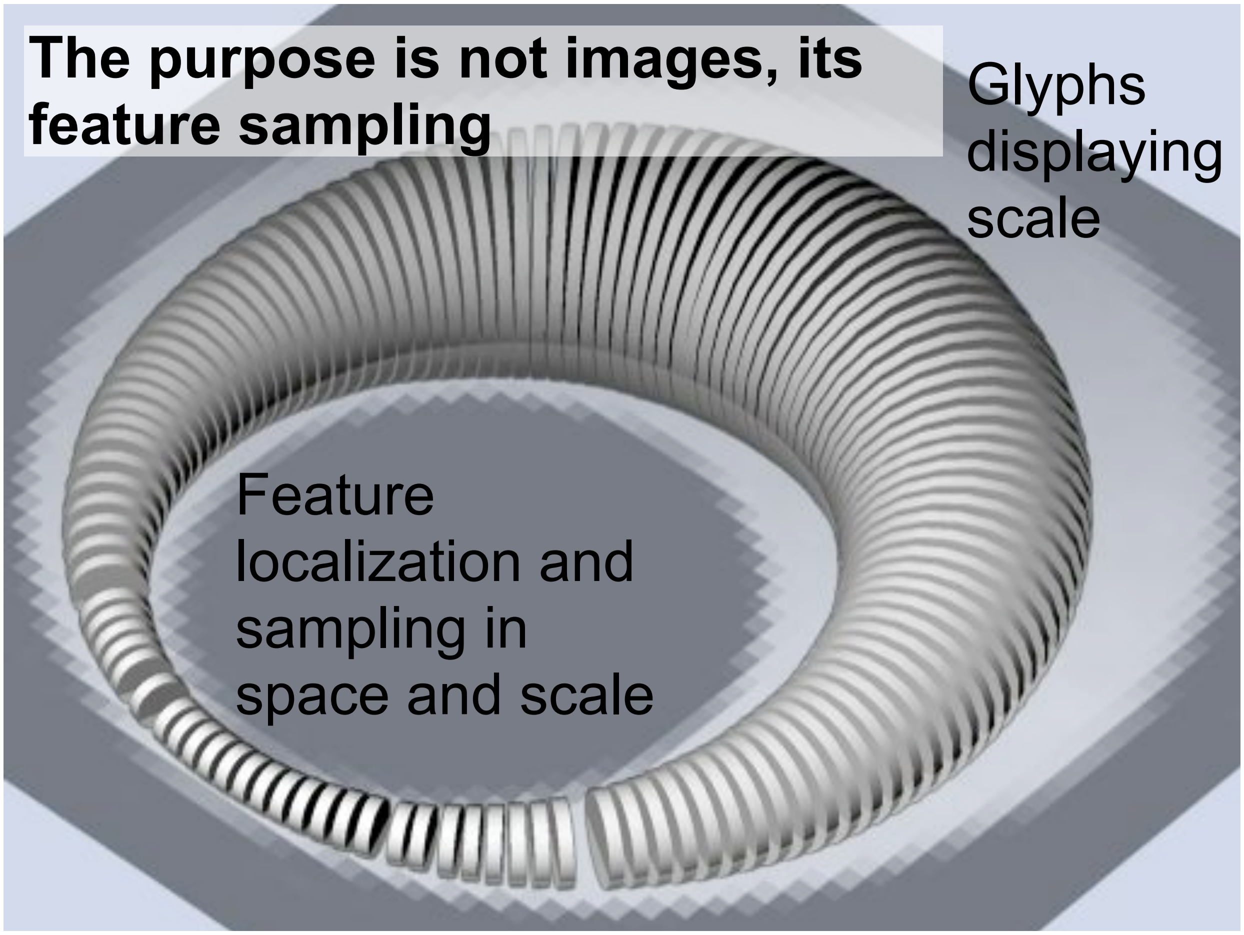

goal: sample
middle of
torus


Particles
sampling
ridge lines
Glyphs
displaying
Hessians


particles sampling ridges across scale
Feature Strength


Particle-Image energy as function of feature strength
Hermite spline interpolation across scale


Linear blending across scale not good for scale localization


The purpose is not images, its feature sampling
Glyphs displaying scale
Feature localization and sampling in space and scale