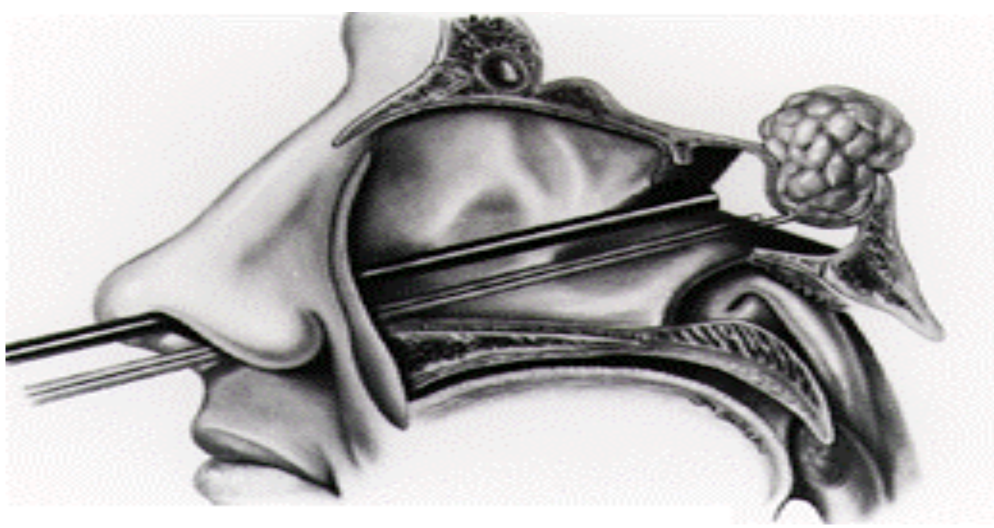
Bone enhancement filtering: application to sinus bone segmentation and simulation of pituitary surgery

M. Descoteaux[1], M. Audette[2], K. Chinzei[2], K. Siddiqi[3]

[1]Odyssée Project Team, INRIA Sophia Antipolis, France
[2]Surgical Assist Group, AIST Tsukuba, Japan
[3]School of Computer Science, McGill University, Montréal, Canada

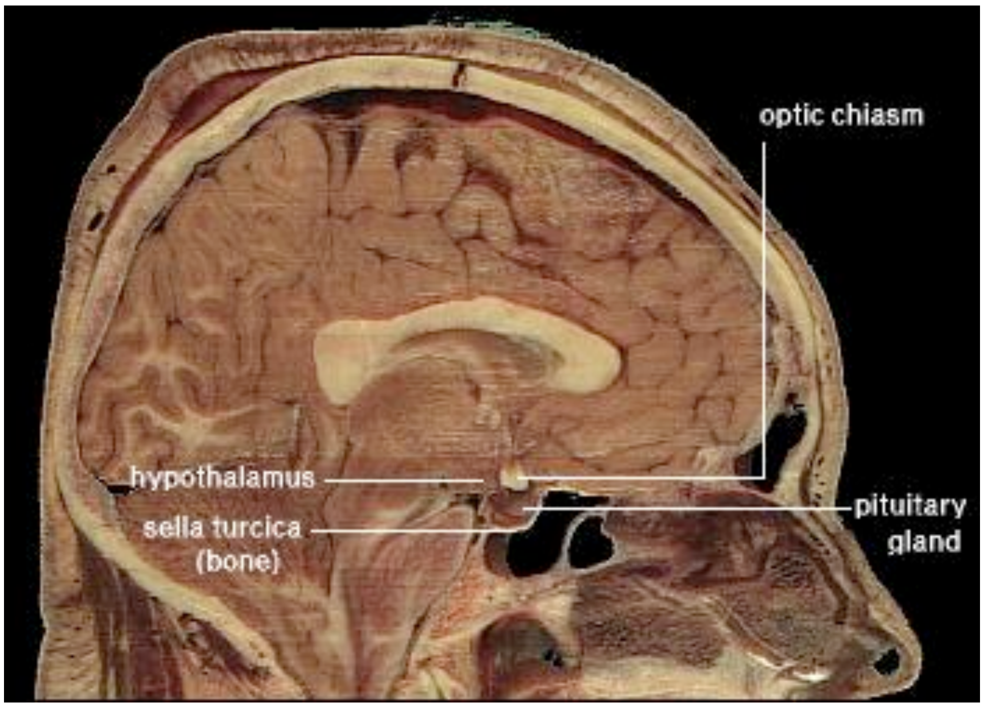
Pituitary surgery

- Surgical simulator for pituitary gland cancer interventions
  - Create a virtual reality environment for students to train
  - Surgeon enters through nasal cavaties and must brake bones and cut soft tissue to reach the gland



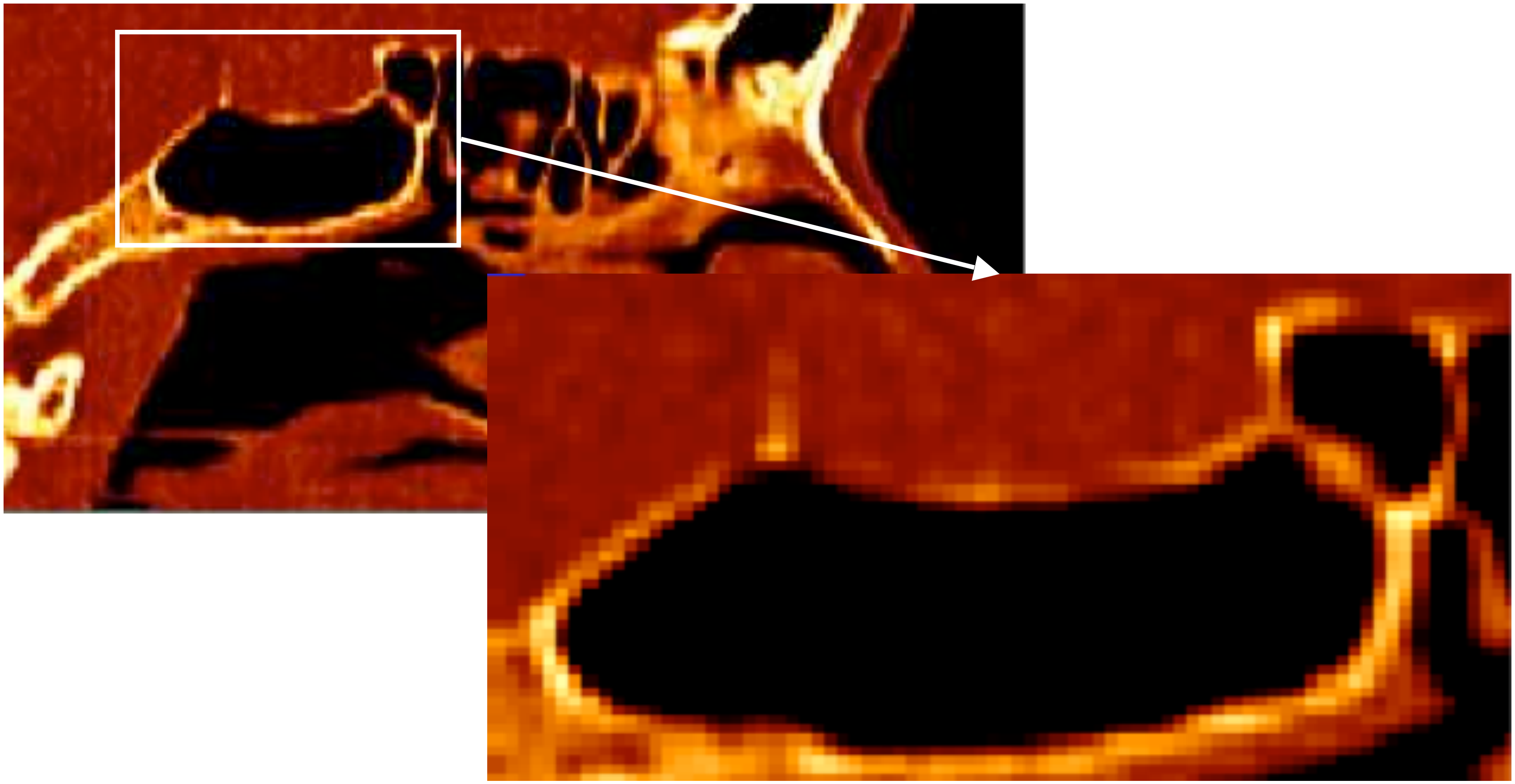
Pituitary gland area

- Need tissue classification of bones, soft tissues and vessels in the pituitary gland area using MRI and CT scans available



Bone segmentation in CT data

cropped CT resampled to 0.468^3 mm resolution



Using the structure tensor

- Structure tensor captures texture information

$$\mathbf{T} = \begin{pmatrix} I_x I_x & I_x I_y & I_x I_z \\ I_y I_x & I_y I_y & I_y I_z \\ I_z I_x & I_z I_y & I_z I_z \end{pmatrix}$$

- Adaptive thresholding based on a local planar measure from eigen values of **T**

$$\textit{thresh\_adaptive}(x) = \textit{thresh\_global} - \beta \cdot \textit{c\_plane}(x)$$

- *c_plane* designed to be 1 for plate structures and 0 otherwise

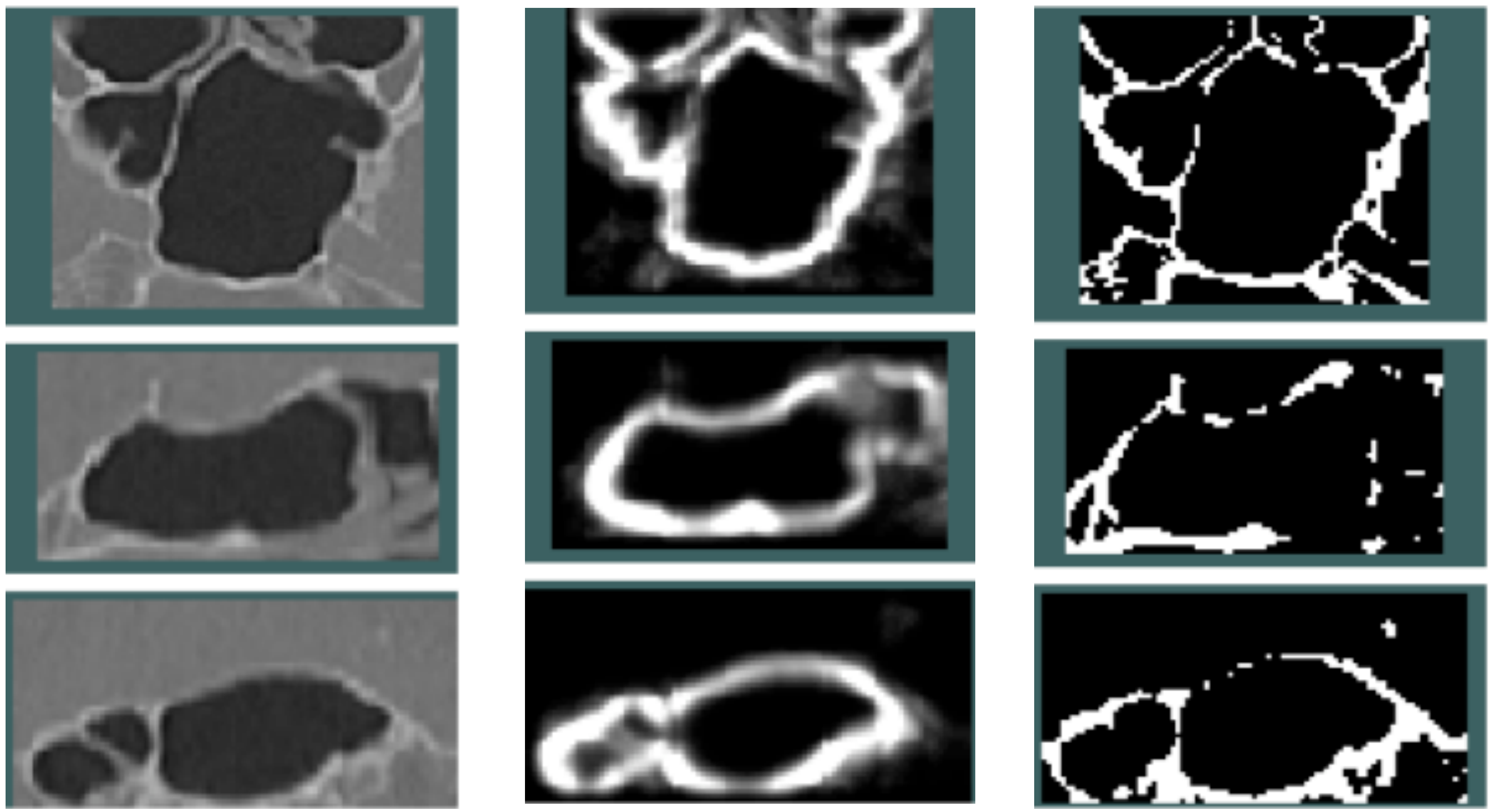
[Westin et al cvpr'97,miccai'98]

Westin et al. segmentation

axial

sagittal

coronal



Orignal CT | Tensor norm | Segmentation

Overview of our algorithm

1. Propose a **new multi-scale sheetness** measure: measure that is maximum on the center sheet and decreasing to the boundaries

2. Use a **geometric flow** to connect the sheetness information together

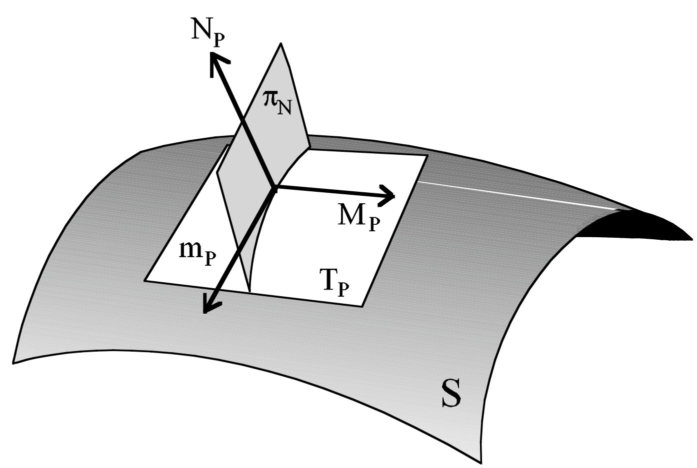
The Hessian operator

- Operator that looks at the underlying shape of the iso-intensity surface

$$H = \begin{bmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{yx} & I_{yy} & I_{yz} \\ I_{zx} & I_{zy} & I_{zz} \end{bmatrix}$$

$\Rightarrow$ **Hessian** matrix, 2nd derivative information -> shape

$\Rightarrow$ Look at how the normal to the surface changes locally



Eigen value properties

- Eigen value decomposition of the Hessian matrix to get λ_1, λ_2, λ_3 and e_1, e_2, e_3 eigen vectors
  - Sheet condition: **$\lambda_1 = \lambda_2 = 0$ and $\lambda_3 >> 0$**
  - Tube condition: **$\lambda_1 = 0$ and $\lambda_2 = \lambda_3 >> 0$**
  - Blob condition: **$\lambda_1 = \lambda_2 = \lambda_3 >> 0$**

- With these properties, we can propose a sheetness measure
  - Inspired by Frangi's vesselness measure

[Frangi miccai'98,]

Constructing sheetness measure

$$R_a = \frac{|\lambda_2|}{|\lambda_3|} = \begin{cases} 0 & \text{for sheets} \\ 1 & \text{for tubes} \\ 1 & \text{for blobs} \\ undefined & \text{for noise} \end{cases}$$

enhance sheets
(set *undefined* = 1)

$$R_c = \frac{|2\lambda_3 - \lambda_2 - \lambda_1|}{|\lambda_3|} = \begin{cases} 2 & \text{for sheets} \\ 1 & \text{for tubes} \\ 0 & \text{for blobs} \\ undefined & \text{for noise} \end{cases}$$

kill blobs and noise
(set *undefined* = 0)

$$S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2} = \begin{cases} \lambda_3 & \text{for sheets} \\ \sqrt{2}\lambda_3 & \text{for tubes} \\ \sqrt{3}\lambda_3 & \text{for blobs} \\ 0 & \text{for noise} \end{cases}$$

kill noise

Multi-scale sheetness measure

$$S(\sigma) = \begin{cases} 0 & \text{if } \lambda_3 > 0 \\ (\exp\left(\frac{-R_a^2}{2\alpha^2}\right))(1 - \exp\left(\frac{-R_c^2}{2\gamma^2}\right))(1 - \exp\left(\frac{-S^2}{2c^2}\right)). \end{cases}$$

- Maximum on the center plane of the structure
- Scale σ corresponds to radius of sheet
- Eigen vector e_3 associated with λ_3 gives normal direction to the plate

(Derivatives computed using Gamma-parametrized Gaussian kernels. [Lindeberg, IJCV 98])

Flow segmentation

- **Flux maximizing geometric flow**

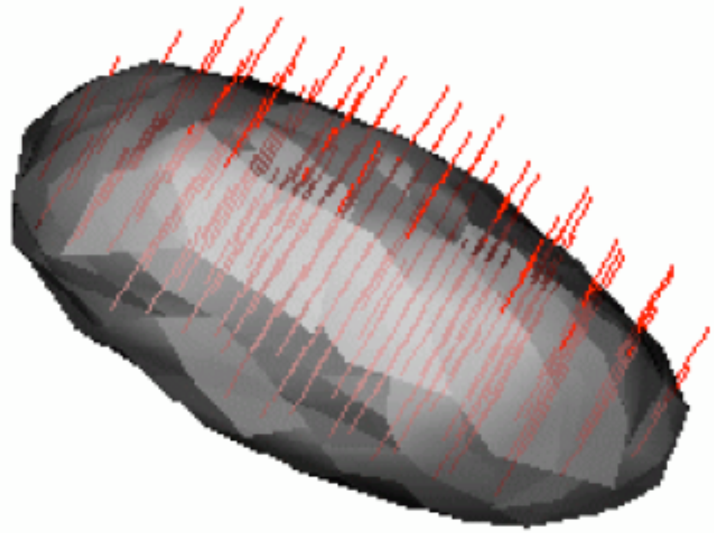
$$\mathcal{S}_t = div(\overrightarrow{\mathcal{V}})\overrightarrow{\mathcal{N}}$$

- Construct new vector field maximum and perpendicular to bone boundaries. Compute its divergence => *speed* term for the flow

$$div(\overrightarrow{V}) = div\left(\phi_{\text{sheet}}\frac{\Delta I}{|\Delta I|}\right)$$

[Vasilevkiy & Siddiqi, PAMI'02]

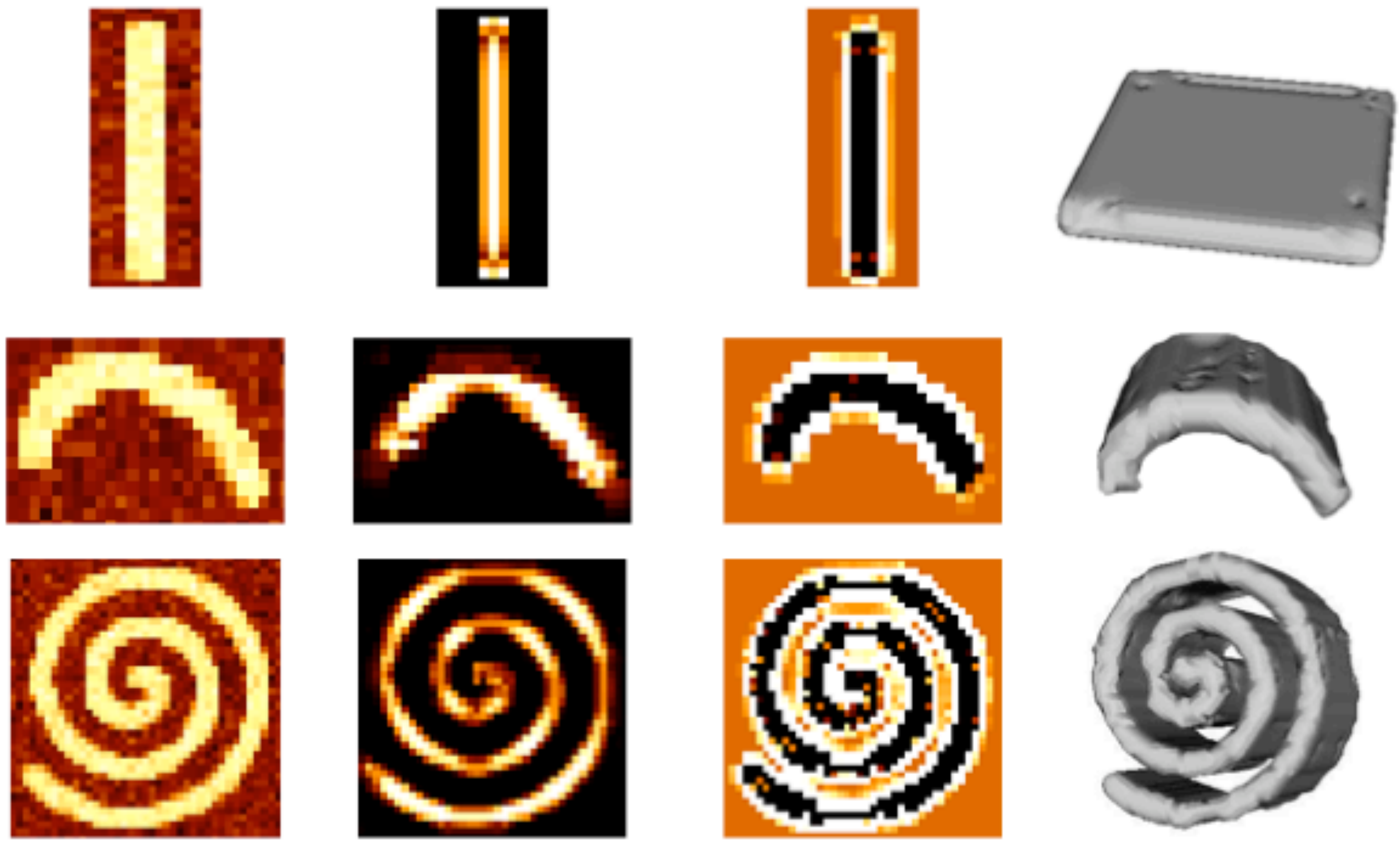
Extending sheetness measure



- Define ϕ_{sheet} by extending the sheetness measure to boundaries
  - Distribute over a flat ellipsoid
  - Radius and orientation based on σ and e_3

[Descoteaux et al, miccai'04]

Synthetic examples



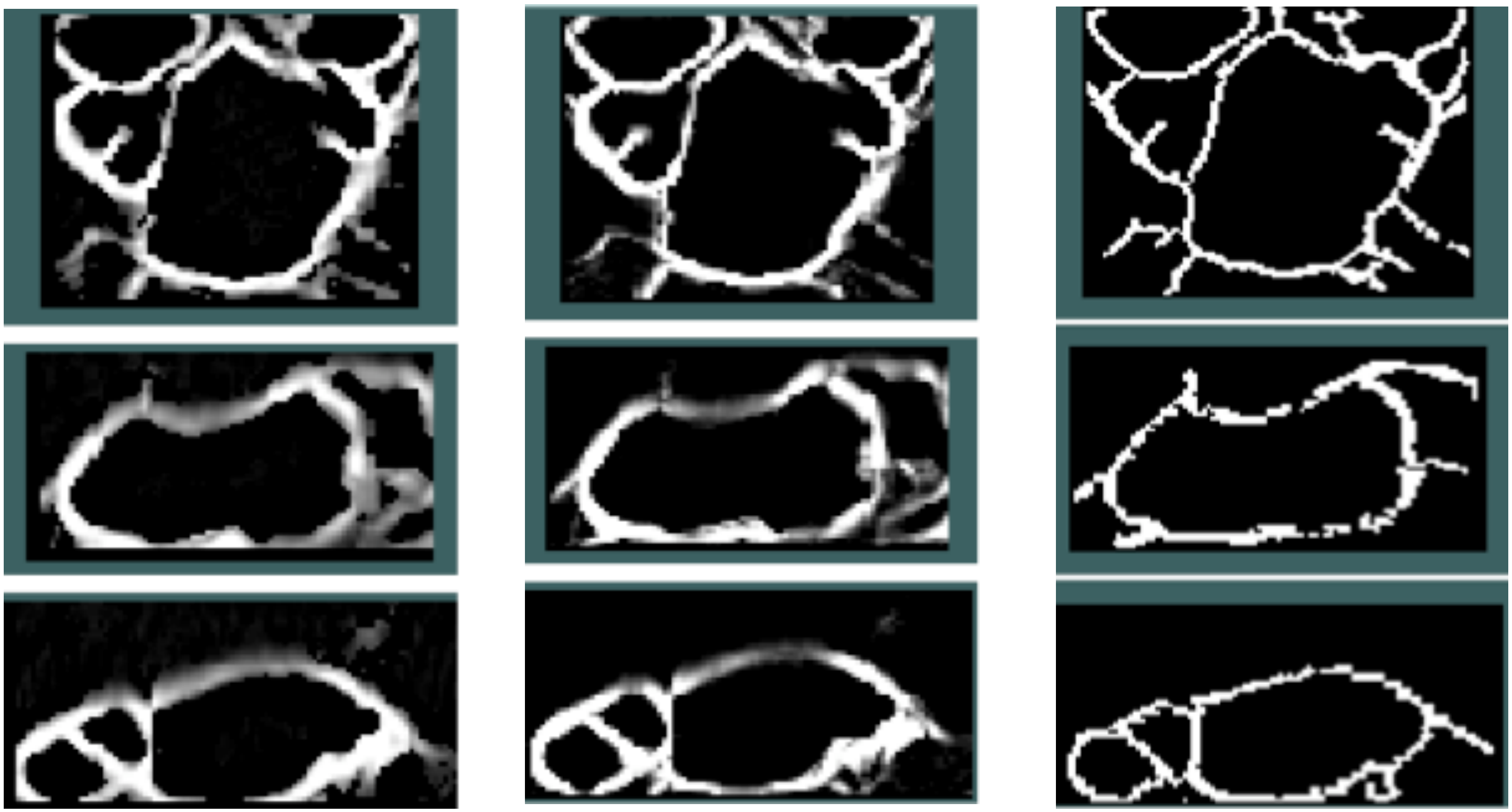
Input Sheetness measure Speed: $div(\overrightarrow{V})$ Segmentation

Quantitative validation

- Validation of the sheetness extension to boundaries
- How do zero-crossings of the speed term agree with the ground truth?
  - Compute Euclidean distance errors between each empirical surface voxel and its closest ground truth point

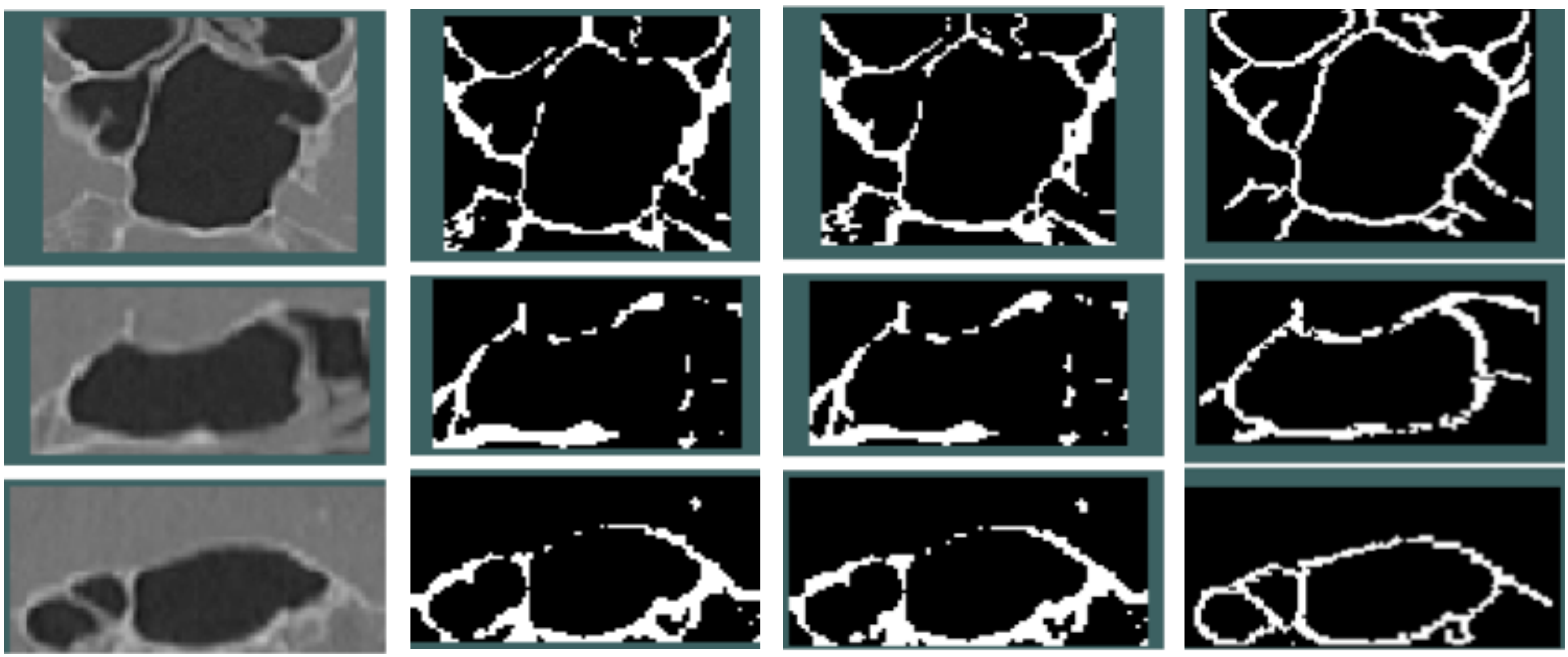
object	average distance error (voxels)	maximum error (voxels)	ratio (%)
plate	0.22	1.00	95
rib	0.25	1.12	95
spiral	0.26	1.22	91

Segmentation result



Hessian norm **Sheetness** **Our segmentation**

Segmentation comparison



Original CT

Simple thresholding

Adaptive thresholding (Westin et al.)

Geometric flow based on a new sheetness measure

Contributions

- New sheetness measure
  - Detect bone structure even in very thin structures and low contrast regions
- Geometric flow segmentation gluing together the multi-scale sheetness information
- Quantitative validation of the sheetness extension on synthetic planar examples
- Qualitative comparison between our Hessian-based approach and an adaptive thresholding method based on the structure tensor

Key References

1) A. Frangi, W. Niessen, K.L. Vincken, M.A. Viergever. **Multi-scale vessel enhancement filtering**. *In MICCAI'1998.*

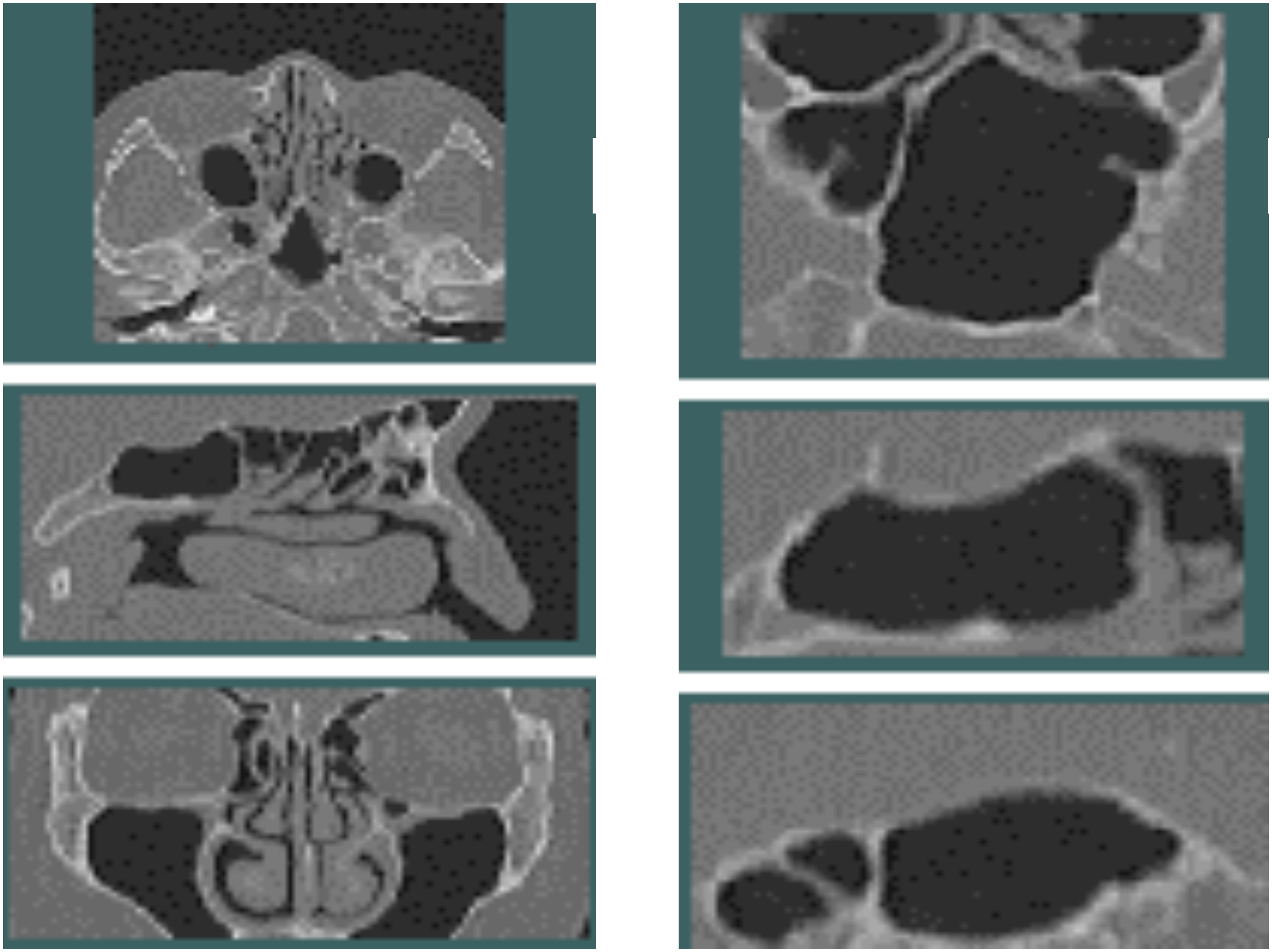
2) A. Vasilevskiy, K. Siddiqi. **Flux maximizing geometric flows**. *In PAMI, vol. 24, 2002.*

3) M. Descoteaux, L. Collins, and K. Siddiqi. **A multi-scale geometric flow for segmenting vasculature in mri.** *In MICCAI'2004.*

4) M. Audette, H. Delinguette, A. Fuchs, K. Chinzei. **A Topologically Faithful, Tissue-guided, Spatially Varying Meshing Strategy for Computing Patient-specific Head Models for Endoscopic Pituitary Surgery Simulation.** *Computer Vision for Biomedical Image Applications, ICCV Workshop.*

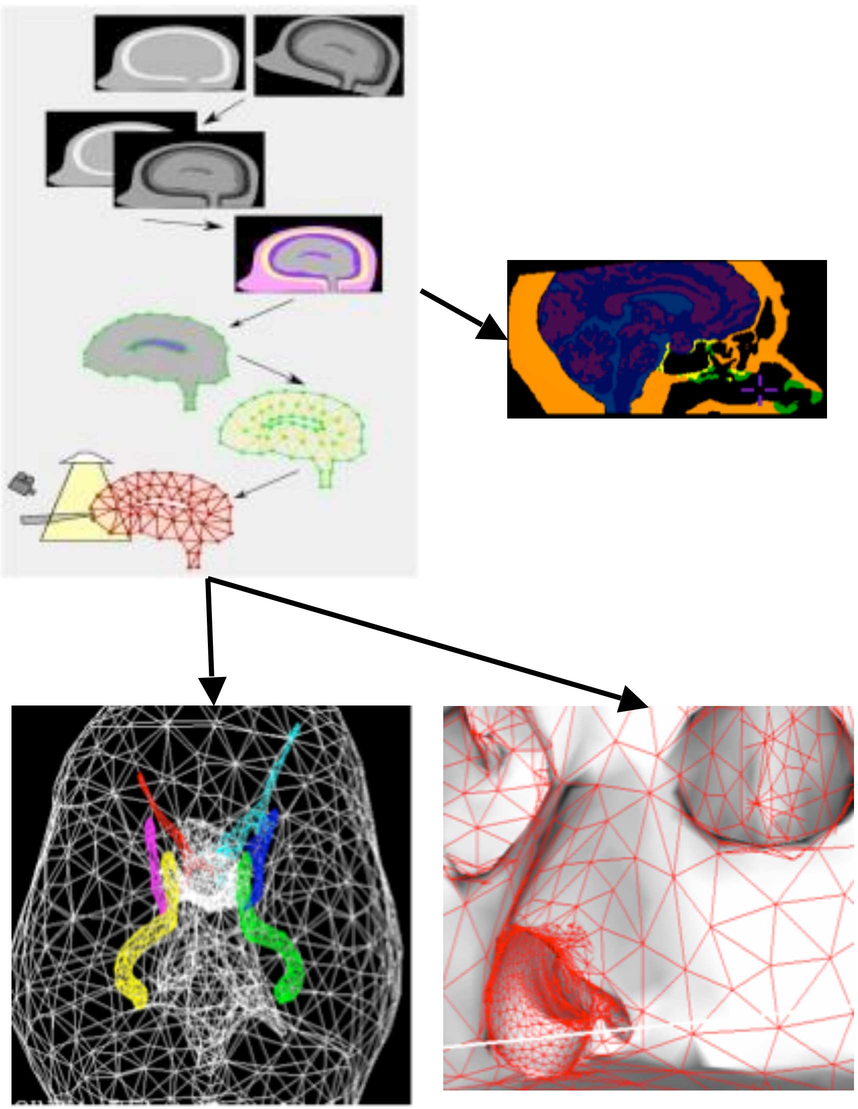
THANK YOU!

Extra slides….



cropped CT resampled to 0.468^3 mm resolution

Proposed framework



1. Registration
2. Identification of tissue classes (arteries, cranial nerves, dura matter & ***sinus bones***)
3. Tissue boundary and interior tessalation, adaptive surface and volume meshing

[Audette et al., Surgical Assist Lab]

Bone segmentation in CT

- Challenging in paranasal sinus area
  - Bones are very thin
  - Low contrast of bone structures and sometimes signal missing

- Previous work:
  - Thresholding
  - Adaptive thresholding based on structure tensor

[Westin et al. CVPR'97, MICCAI'98]

Limitations of existing methods

- Thresholding is too sentitive to noise
- Better result using structure tensor
- Structure tensor has good properties:
  - Robust texture detector that is maximum at boundaries
  - Very good for finding direction of max intensity change

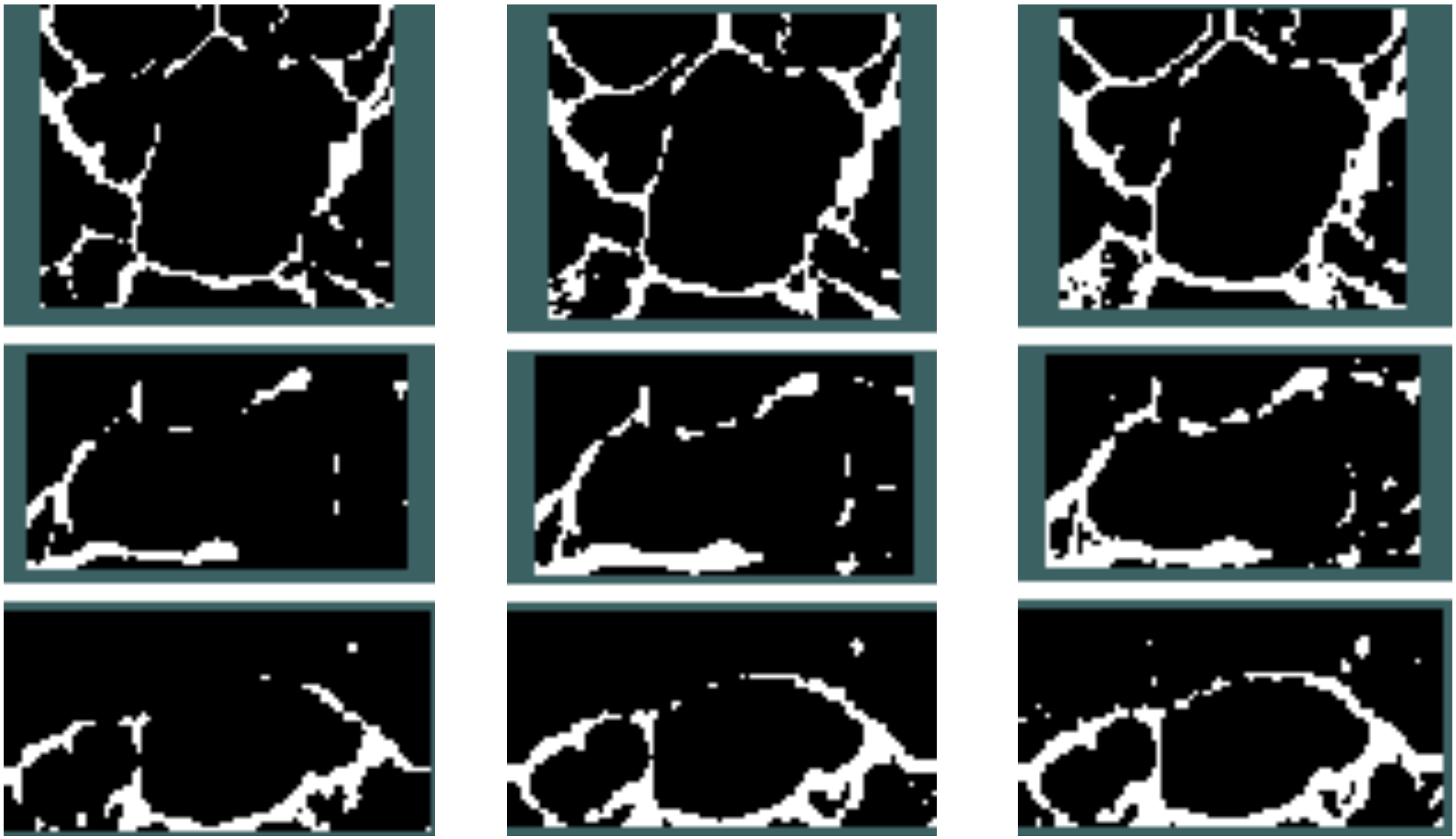
- Structure tensor has disadvantages for our problem:
  - Not well localized (max on boundaries of structure)
  - Positive semi-definite matrix => positive eigen values (Does not make the difference between white/black or black/white contrast)

Thresholding the CT data

axial

sagittal

coronal



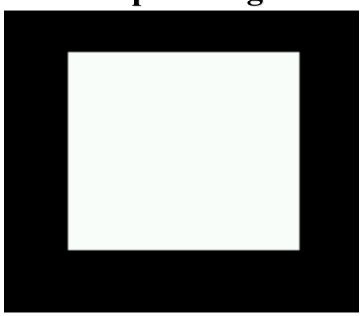
conservative thresh

best thresh

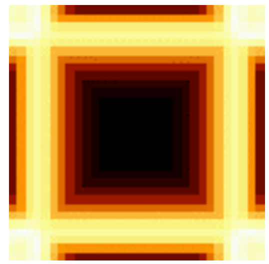
aggressive thresh

Sheetness measure terms

Input image

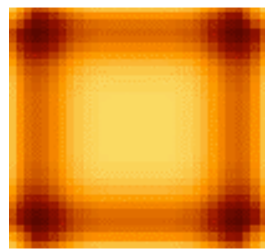


Synthetic plate example



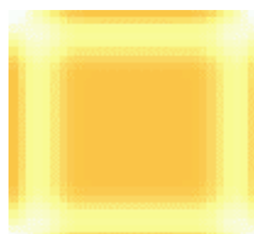
$\mathbf{R_a}$

$$R_a = \frac{|\lambda_2|}{|\lambda_3|} = \begin{cases} 0 & \text{for sheets} \\ 1 & \text{for tubes} \\ 1 & \text{for blobs} \\ undefined & \text{for noise} \end{cases}$$



$\mathbf{R_c}$

$$R_c = \frac{|2\lambda_3 - \lambda_2 - \lambda_1|}{|\lambda_3|} = \begin{cases} 2 & \text{for sheets} \\ 1 & \text{for tubes} \\ 0 & \text{for blobs} \\ undefined & \text{for noise} \end{cases}$$

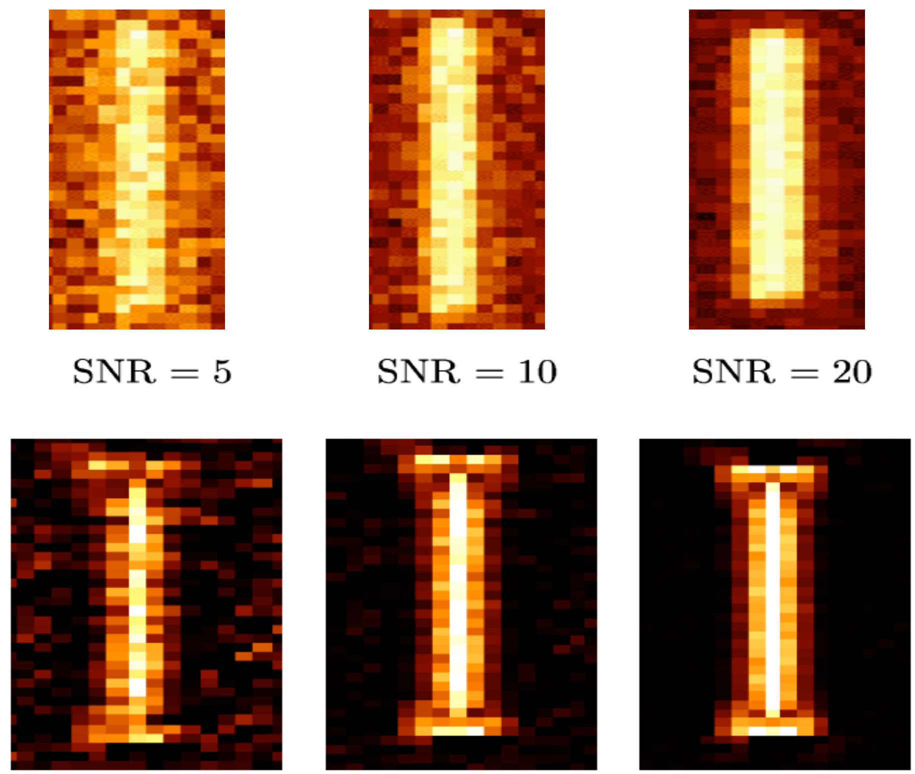


S = Hessian norm

$$S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2} = \begin{cases} \lambda_3 & \text{for sheets} \\ \sqrt{2}\lambda_3 & \text{for tubes} \\ \sqrt{3}\lambda_3 & \text{for blobs} \\ 0 & \text{for noise} \end{cases}$$

Robust to noise

- Sheetness measure and orientation detection very stable and robust under **Gaussian white noise**

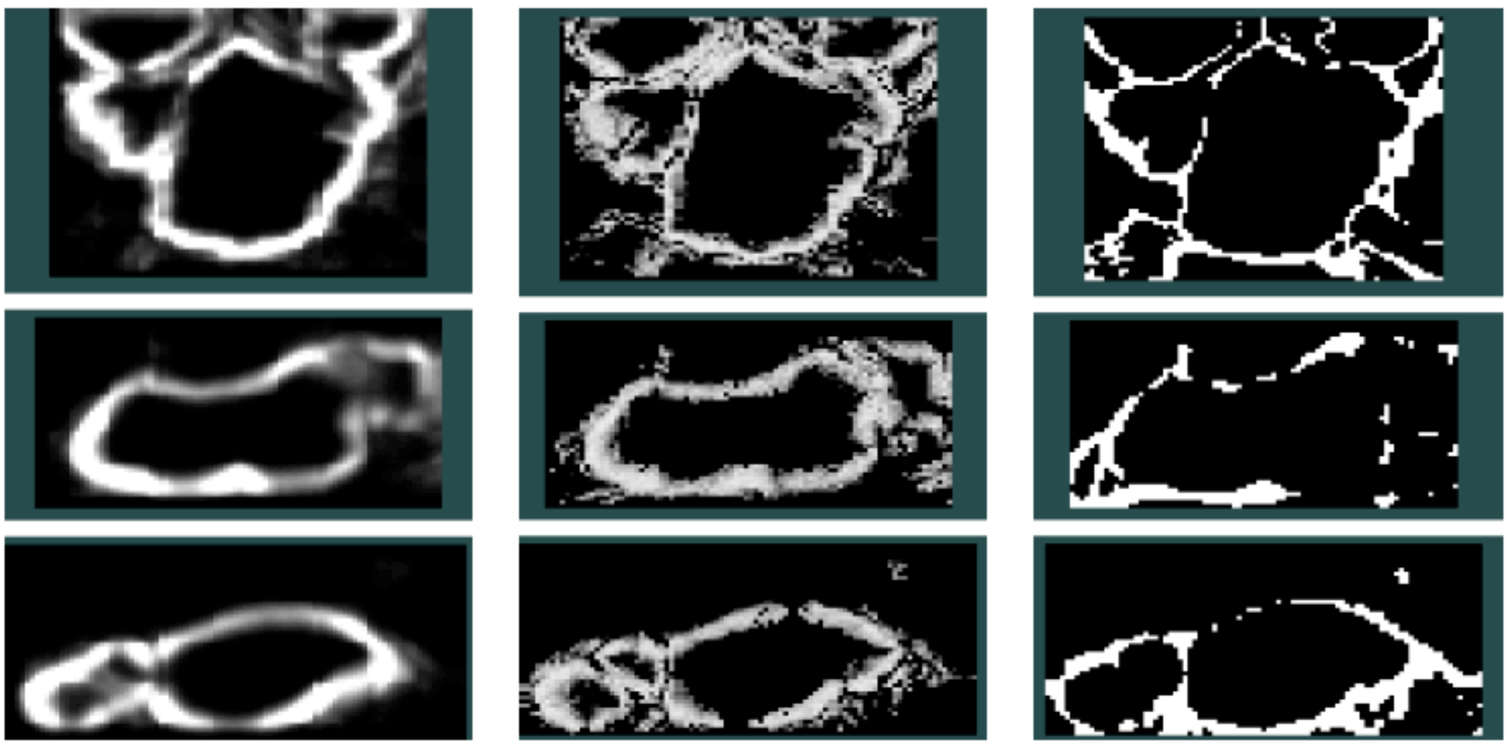


vesselness measure

Westin et al. algorithm

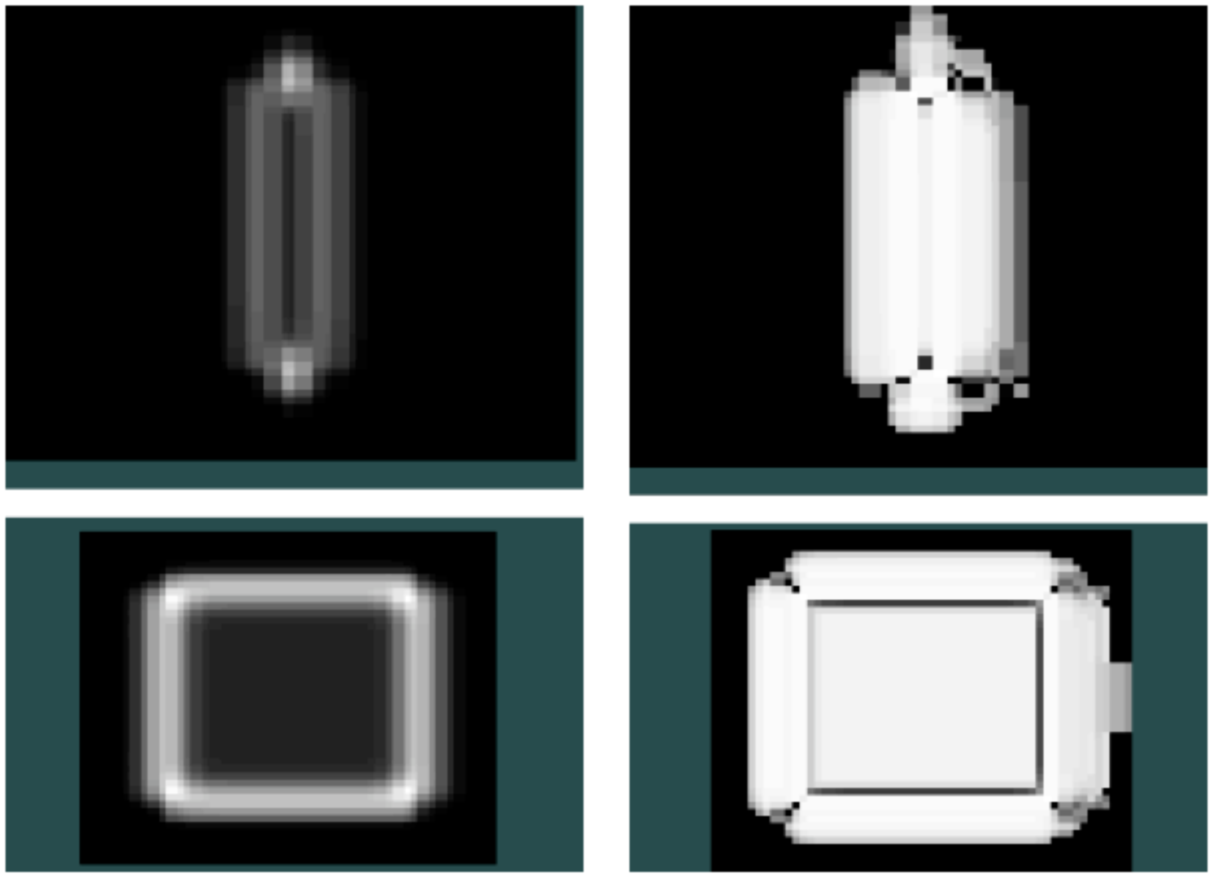
Tensor norm = $\mathrm{sqrt}(\lambda_1^2 + \lambda_2^2 + \lambda_3^2)$ $\qquad$ $c\_plane = (\lambda_3 - \alpha \cdot \lambda_2) / \lambda_3$

$$thresh\_adaptive(\mathrm{x}) = thresh\_global - \beta \cdot c\_plane(\mathrm{x})$$



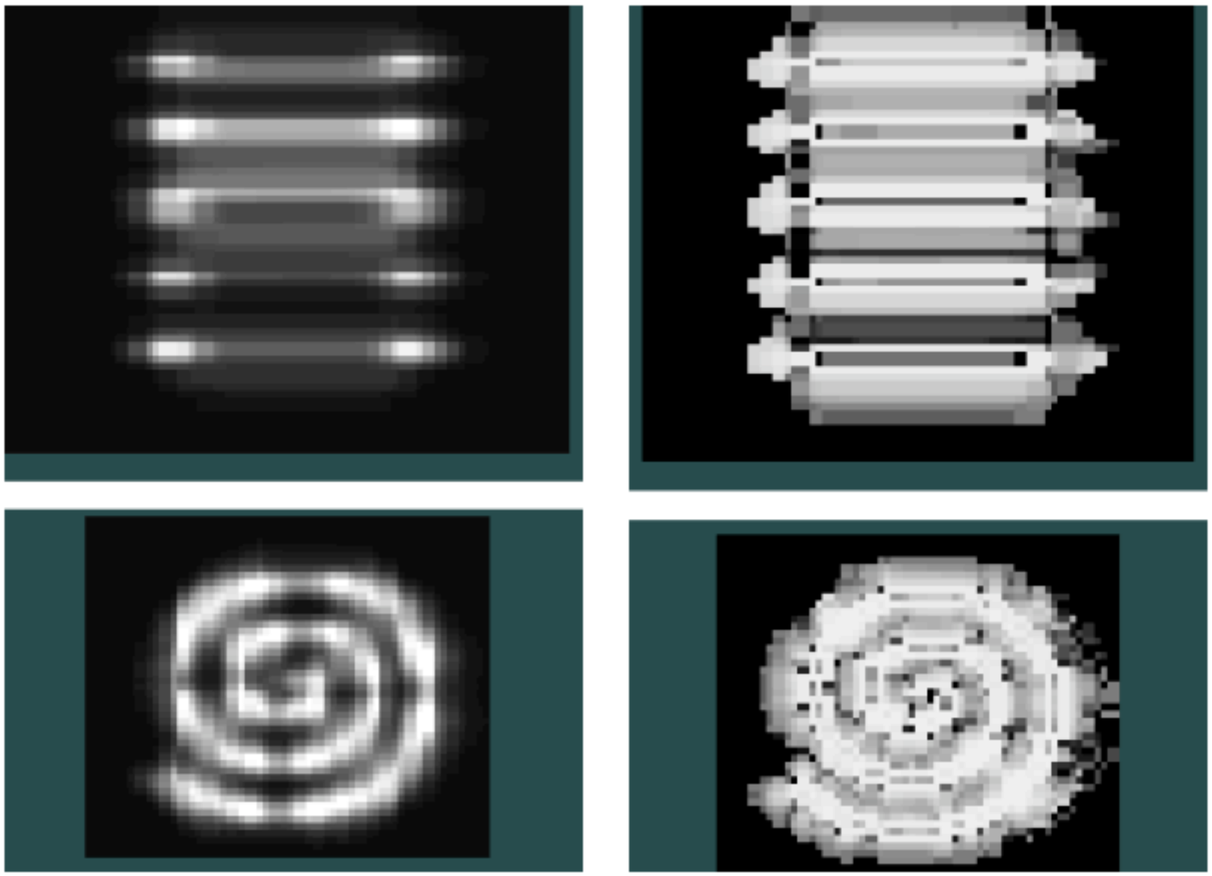
tensor norm $\qquad$ c_plane $\qquad$ tensor segmentation

Synthetic plate example



tensor norm c_plane

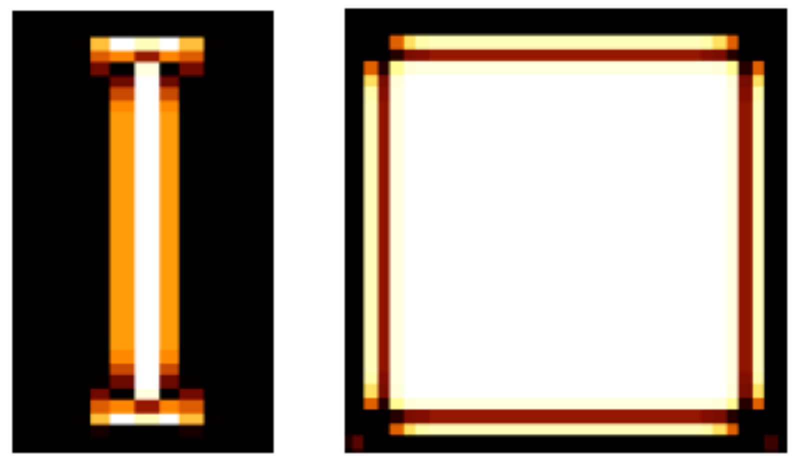
Synthetic spiral example



tensor norm   c_plane

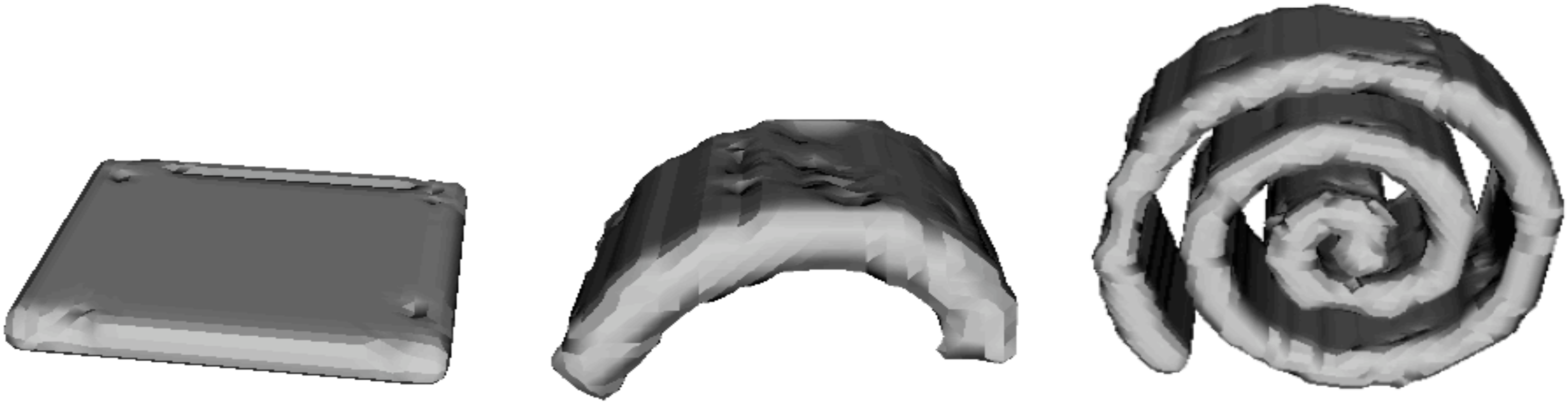
Sheetness measure example

Input binary volume



sheetness measure

Segmentations



Reconstruction of the synthetic binary shapes

Reconstruction of the smoothed synthetic binary shapes

Local structure classification

Eigen value conditions	local structure	examples
$\lambda_1 \approx 0\ ,\ \lambda_2 \approx \lambda_3 >> 0$	tube-like	vessel, bronchus
$\lambda_1 \approx \lambda_2 \approx 0\ ,\ \lambda_3 >> 0$	sheet-like	cortex, skin
$\lambda_1 \approx \lambda_2 \approx \lambda_3 >> 0$	blob-like	nodule
$\lambda_1 \approx \lambda_2 \approx \lambda_3 \approx 0$	noise-like	noise

$$R_B = \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}}$$

blob vs others

$$R_A = \frac{|\lambda_2|}{|\lambda_3|}$$

sheet vs others

$$S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}$$

noise vs others

Vesselness measure

$$V(\sigma) = \begin{cases} 0 & \text{if}\, \lambda_2 < 0 \,\text{or}\, \lambda_3 < 0 \\ \\ (1 - \exp\left(-\frac{R_A^2}{2\alpha^2}\right))\exp\left(-\frac{R_B^2}{2\beta^2}\right)(1 - \exp\left(-\frac{S^2}{2c^2}\right)) & \end{cases}$$

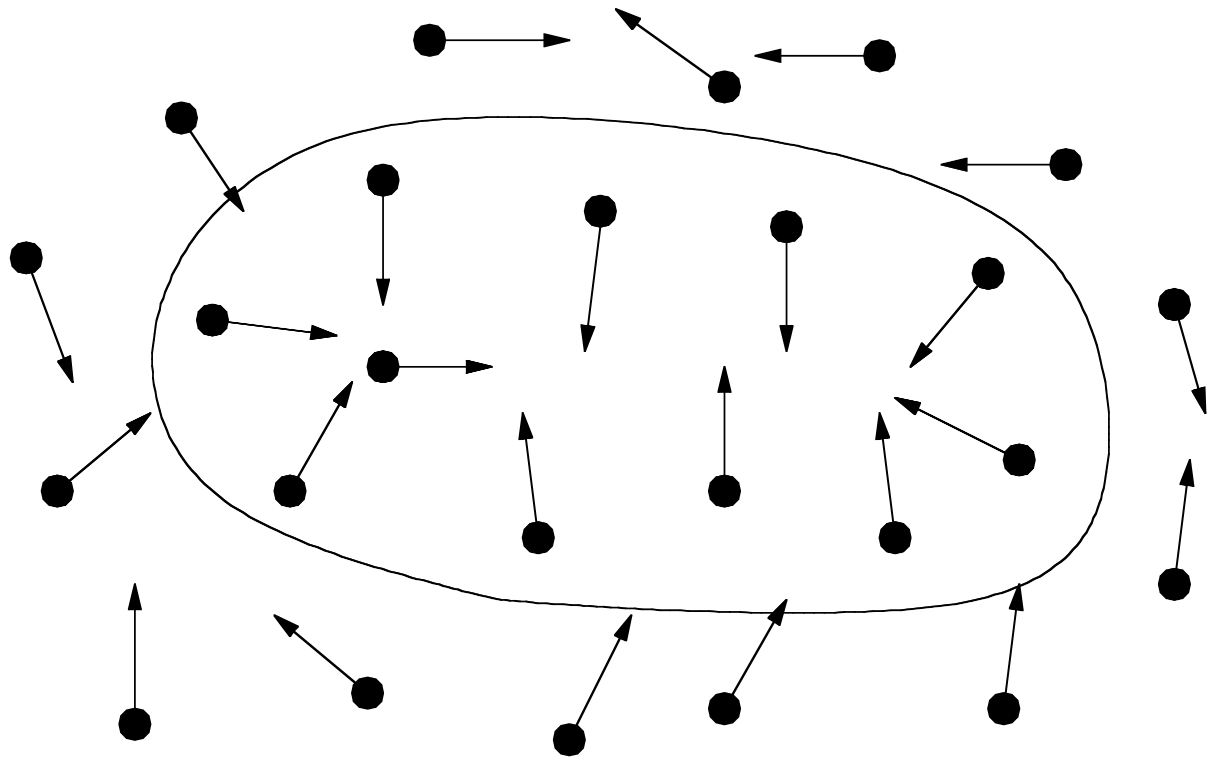
Multi-scale geometric flow

- Consider the vector field $\overrightarrow{\mathcal{V}} = \phi \frac{\nabla \mathcal{I}}{|\nabla \mathcal{I}|}$

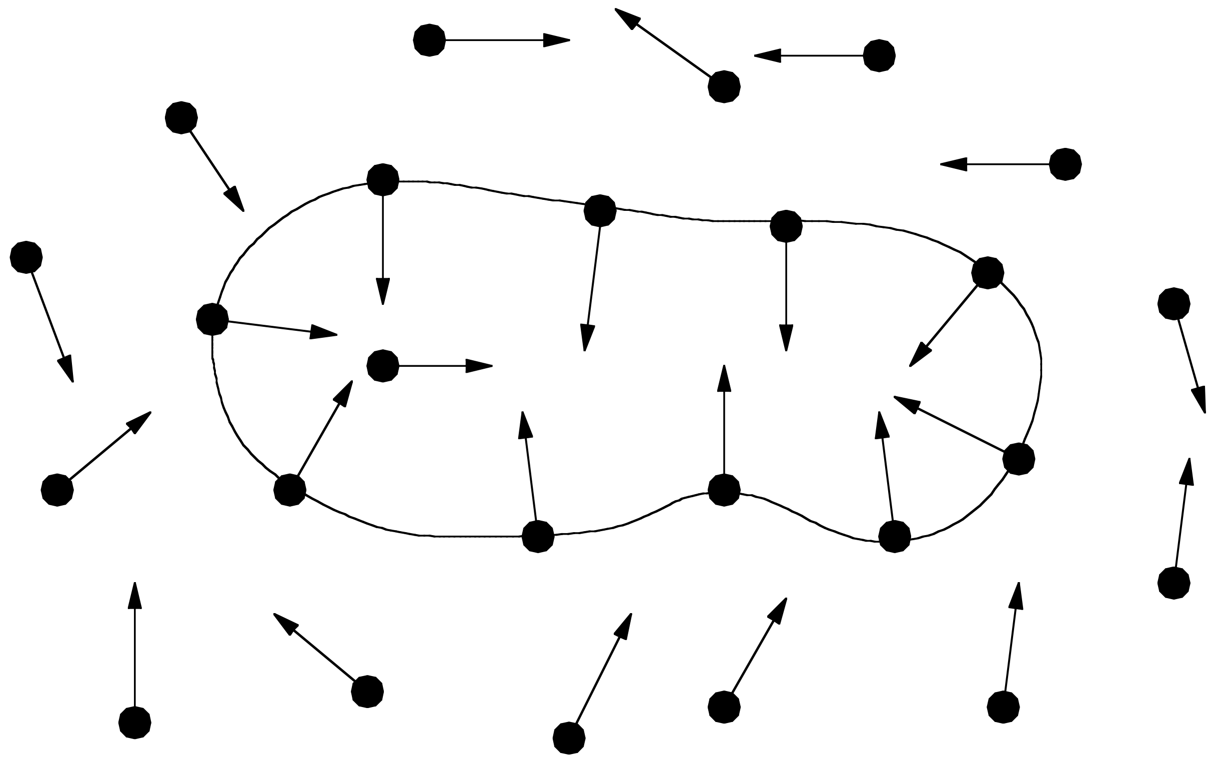
- The associated flux maximizing flow

$$\begin{aligned} S_t &= div(\overrightarrow{\mathcal{V}})\overrightarrow{\mathcal{N}} \\ &= \left[\left\langle \nabla\phi, \frac{\nabla \mathcal{I}}{|\nabla \mathcal{I}|}\right\rangle + \phi div\left(\frac{\nabla \mathcal{I}}{|\nabla \mathcal{I}|}\right)\right]\overrightarrow{\mathcal{N}} \\ &= \left[\left\langle \nabla\phi, \frac{\nabla \mathcal{I}}{|\nabla \mathcal{I}|}\right\rangle + \phi\kappa_{\mathcal{I}}\right]\overrightarrow{\mathcal{N}}. \end{aligned}$$

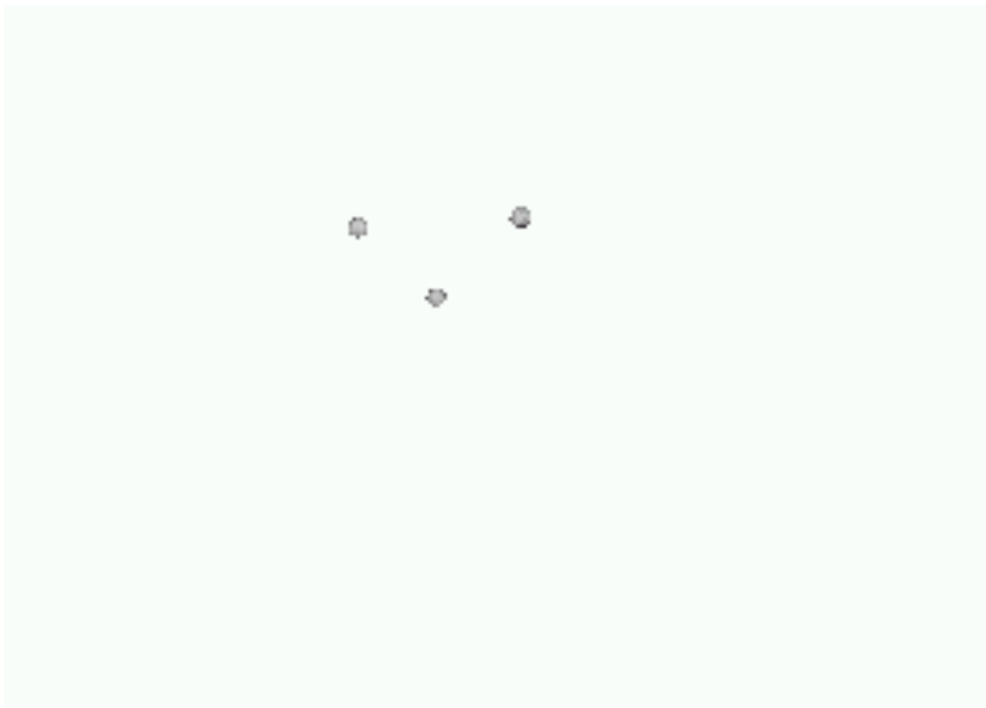
Initial curve



Final curve



Surface evolution



T = 0000