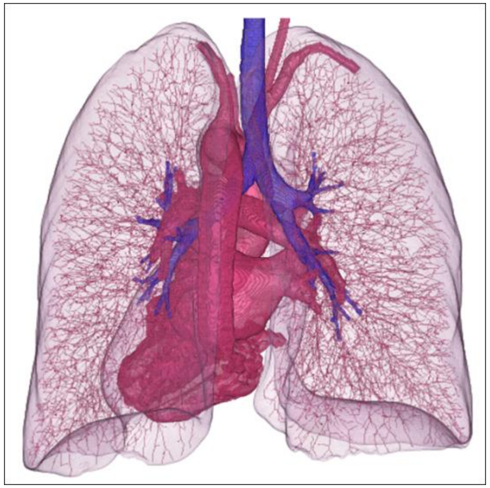
Medical Image Analysis
Lecture 11

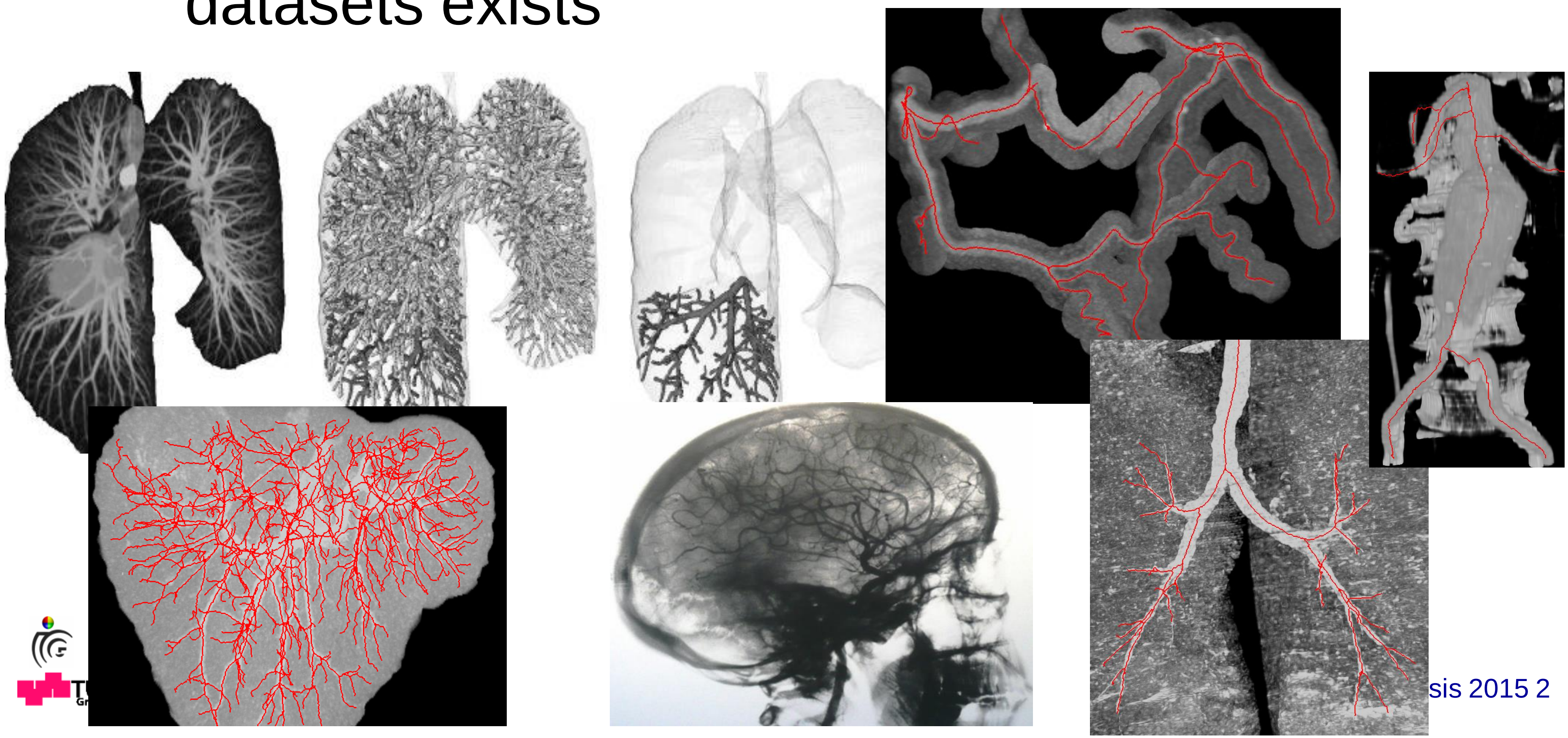


Vascular Structures

Martin Urschler

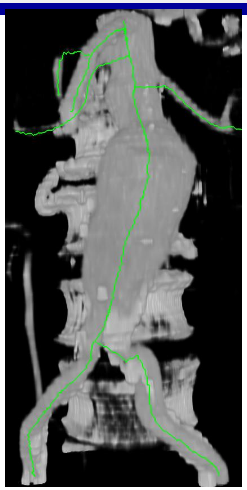
Vascular Structures

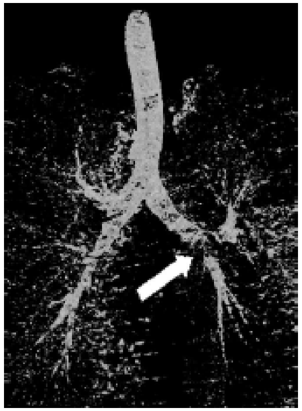
- Variety of 3D tubular structures in medical datasets exists

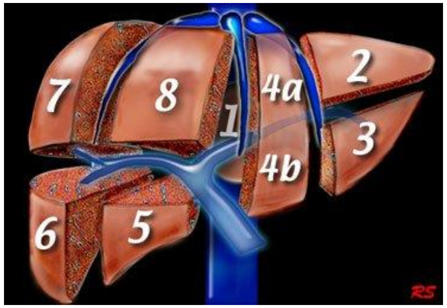


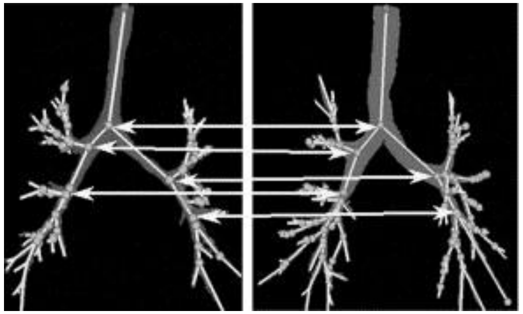
Vascular Structures

- Clinical Motivation
  - Visualization & Detection of Stenoses (calcification) / Aneurisms / Tumors
  - Segmentation of sub-parts
    - Liver segments, lung lobes
  - Registration according to corresponding structures
  - Virtual Broncho-/Colonoscopy



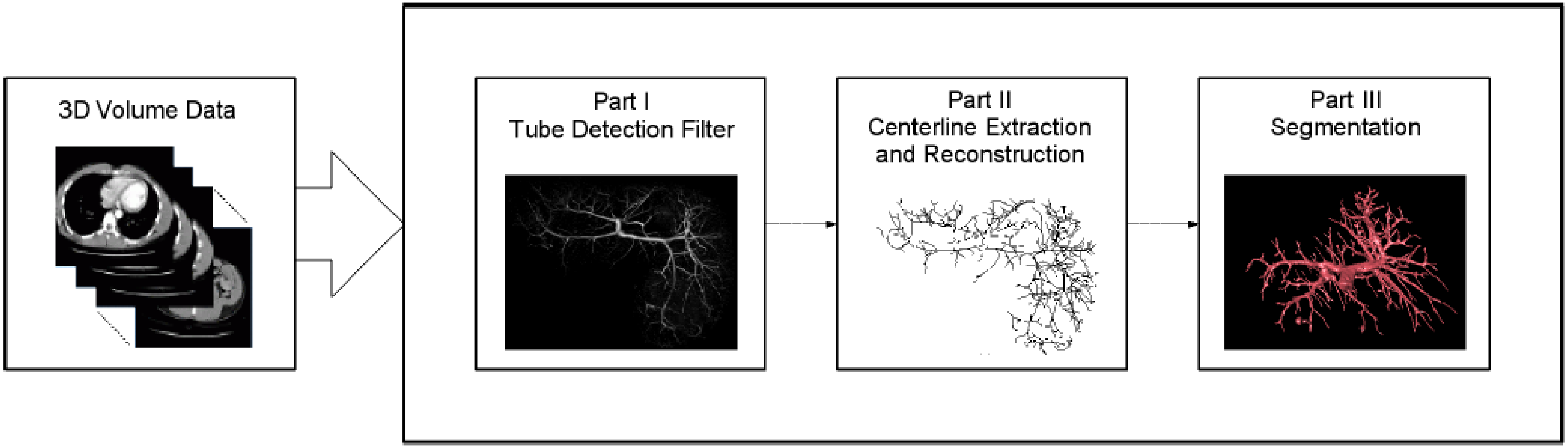






Vascular Structures

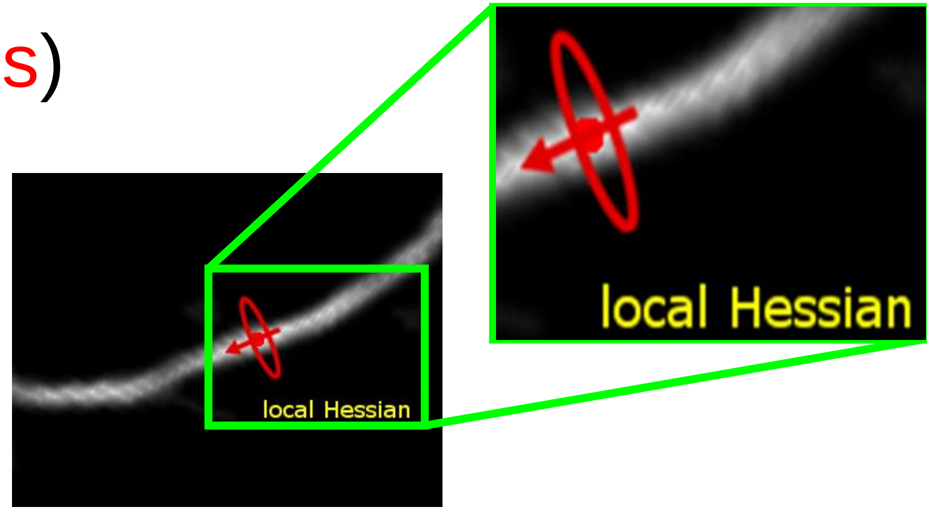
- Overview



Credits belong to Christian Bauer

Vascular Structures

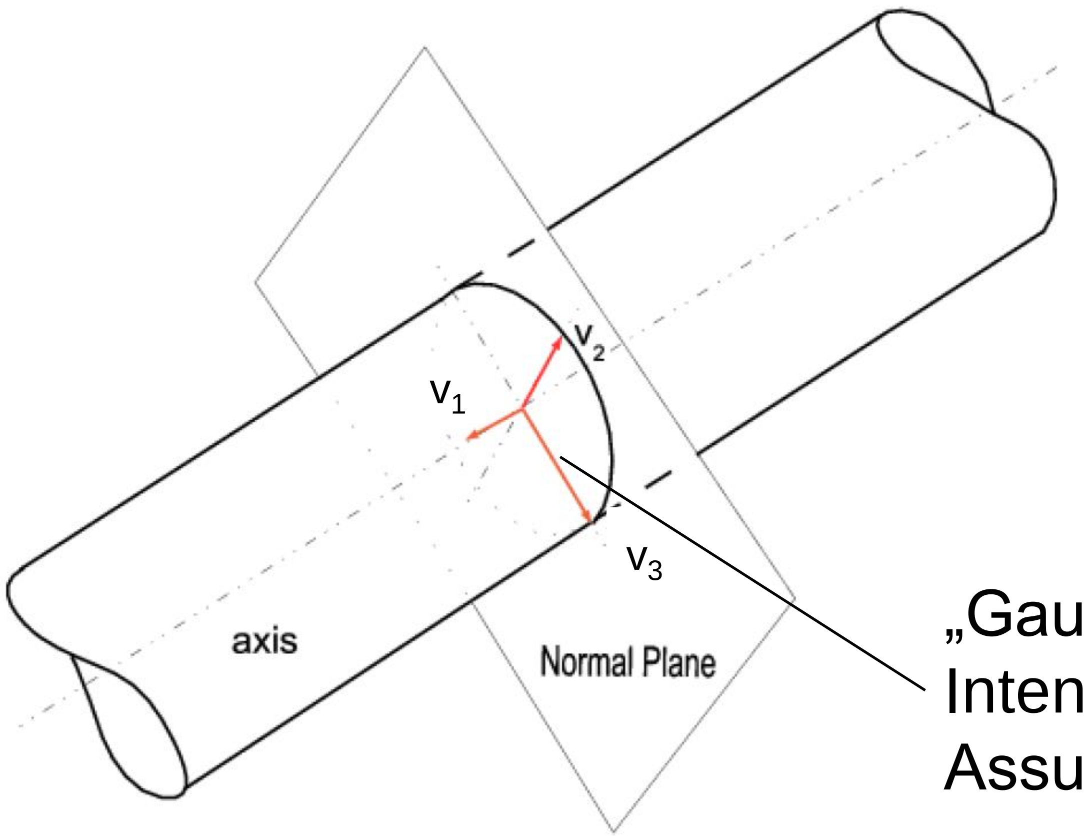
- Mathematically, they have local similarity to a circle in common (tubularity assumption!)
- Analyze using point-wise 2nd derivatives of greyvalues (Hessian eigenvalues)
- A measure for curvilinear structures



Vascular Structures

- Image intensity function I(x,y,z)
- Local 2nd order Taylor approximation -> curvature
- Hessian at x,y,z
- Analysis of eigenvalues & eigenvectors of Hessian matrix!

Vascular Structures



„Gaussian Intensity Profile Assumption“

Vascular Structures

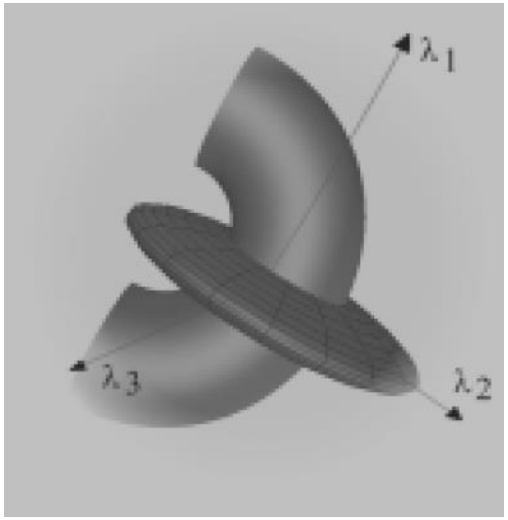
- Algorithm 1:
  - For all pixel (x,y,z):
    - Compute Hessian matrix at (x,y,z)
    - Compute its Eigenvalues
    - Investigate magnitude of eigenvalues to define a (central) medialness response function R(x,y,z)

Vascular Structures

- Algorithm 1 according to Frangi et al.

$$\mathrm{R} = \begin{cases} 0 & \text{if} \quad \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ \left(1 - e^{-\frac{\mathcal{R}_\mathcal{A}^2}{2\alpha^2}}\right)\left(e^{-\frac{\mathcal{R}_\mathcal{B}^2}{2\beta^2}}\right)\left(1 - e^{-\frac{\mathcal{S}^2}{2c^2}}\right) & \text{else} \end{cases}$$

with $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$.

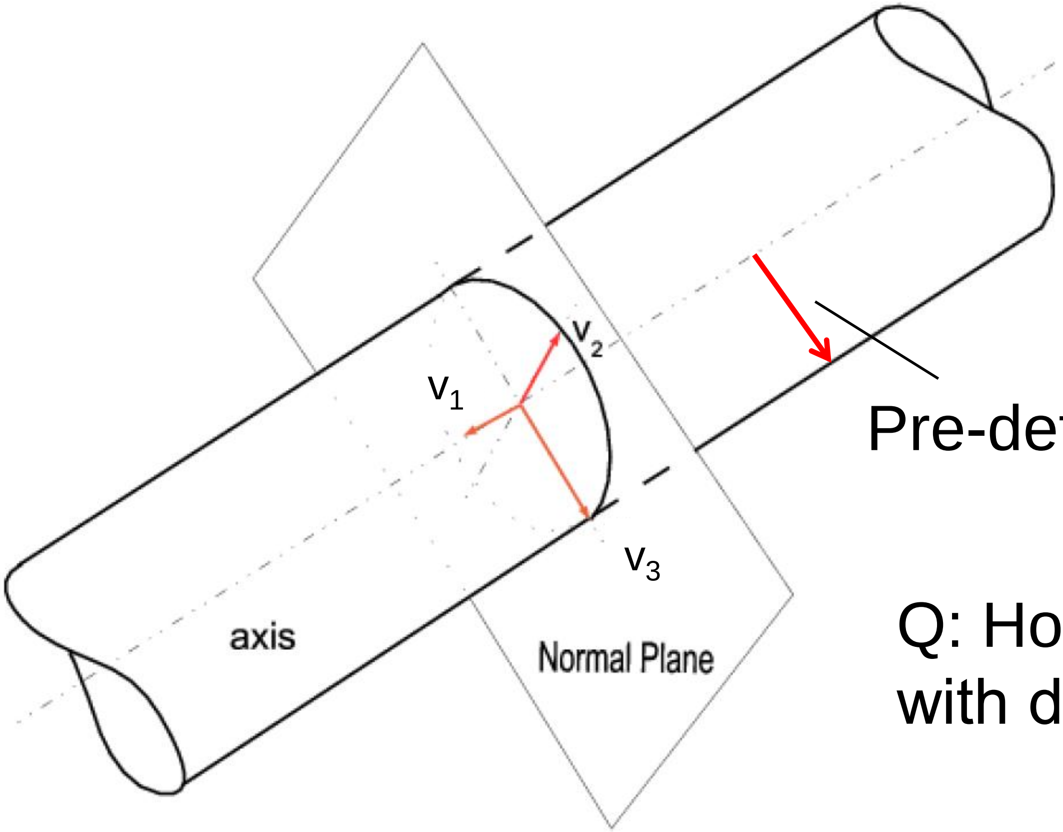


$$\mathcal{R}_\mathcal{B} = \frac{\text{Volume}/(4\pi/3)}{(\text{Largest Cross-Section Area}/\pi)^{3/2}} = \frac{|\lambda_1|}{\sqrt{|\lambda_2\lambda_3|}}$$

$$\mathcal{R}_\mathcal{A} = \frac{(\text{Largest Cross-Section Area})/\pi}{(\text{Largest Axis Semi-length})^2} = \frac{|\lambda_2|}{|\lambda_3|}$$

$$\mathcal{S} = ||\mathcal{H}_\sigma||_F = \sqrt{\sum_j \lambda_j^2} \qquad j = 1, 2, 3$$

Vascular Structures

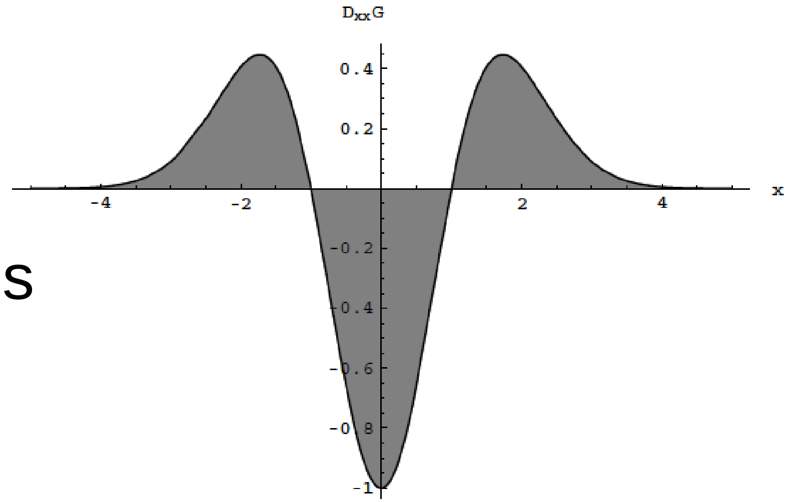


Pre-defined radius r

Q: How do we deal with different r‘s?

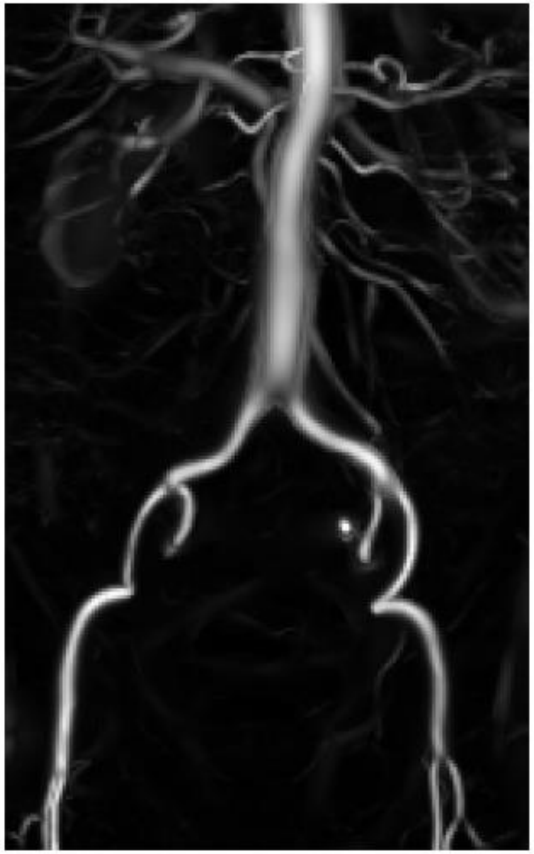
Vascular Structures

- Multi-Scale Analysis
  - Construct a scale-space by convolving the initial image I(x,y,z) with Gaussian derivative kernels of increasing std.dev
  - Perform the medialness filter at each scale
  - Choose the maximum response of the medialness across the scale



Results of Frangi Method

a)



b)

Maximum Intensity Projection (MIP) of
a) initial MRA data set
b) data after vessel enhancement

Vascular Structures

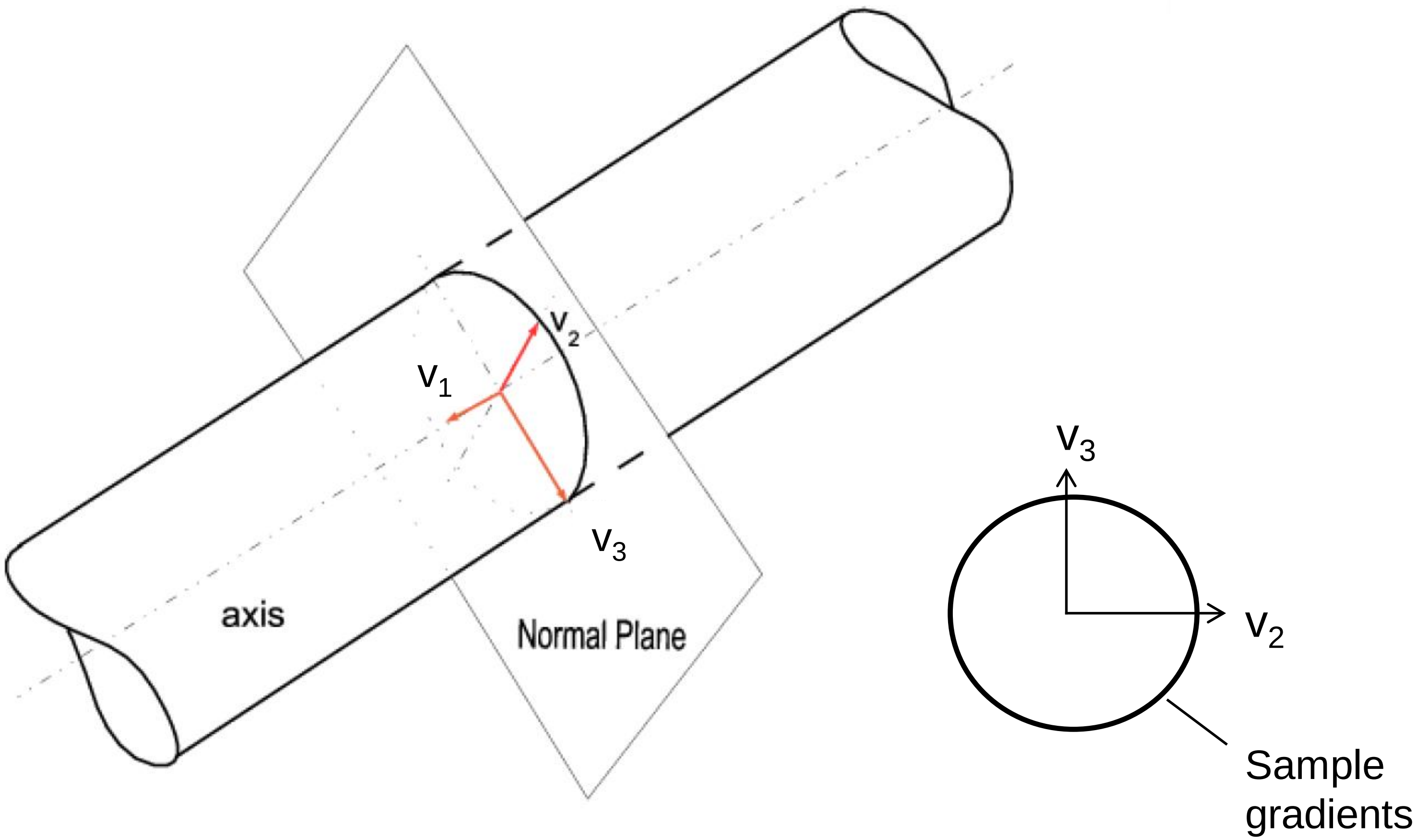
- Disadvantages of Frangi [1] method:
  - Choice of parameters
  - Limited use of directional information (restricted to eigenvalues)
  - Problems when deviation from ideal gaussian intensity profile exists

[1] A. Frangi. Three-Dimensional Model-Based Analysis of Vascular and Cardiac Images. PhD thesis, University Medical Center Utrecht, Netherlands, 2001.

Vascular Structures

- Offset medialness functions take eigenvectors of Hessian stronger into account
- Investigate gradients at the border of the tube
- Medialness response now incorporates the symmetry of the tubular structure at the border!

Vascular Structures



Vascular Structures

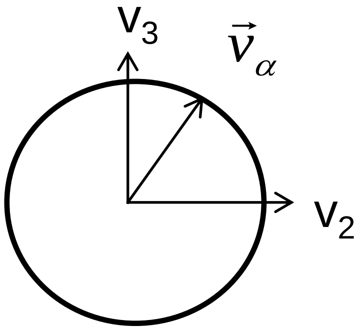
- Algorithm 2:
  - For all pixel (x,y,z)
    - Compute Hessian matrix at (x,y,z)
    - Compute its Eigenvalues & Eigenvectors
    - Investigate eigenvector direction according to smallest eigenvalue -> tube direction
    - Other two eigenvectors form normal plane
    - Sample the (pre-computed) gradient directions at distance r in the normal plane -> compute offset medialness response R(x,y,z)

Vascular Structures

- Algorithm 2 according to Krissian et al.[2]

$$R(\vec{x},\sigma,\theta) = \frac{1}{2\Pi}\int_{\alpha=0}^{2\Pi} -\sigma^{\gamma}\nabla I^{(\sigma)}\left(\vec{x}+\theta\sigma\,\vec{v}_{\alpha}\right)\cdot\vec{v}_{\alpha}\,d\alpha$$

$$\vec{v}_{\alpha} = \cos(\alpha)\,\vec{v}_2 + \sin(\alpha)\,\vec{v}_3$$



[2] K. Krissian et al. Model-based detection of tubular structures in 3D images. *Computer Vision and Image Understanding*, 80(2):130-171, 2000.

Vascular Structures

- Further improving the offset medialness algorithm:
  1. Compute mean gradients along border and weight by circularity measure (dot product of gradient direction g and v)

$$c_i = \begin{cases} -\vec{g}\left(\vec{x} + r\vec{v}_{\alpha_i}\right) \cdot \vec{v}_{\alpha_i} & if \; -\vec{g}\left(\vec{x} + r\vec{v}_{\alpha_i}\right) \cdot \vec{v}_{\alpha_i} > 0 \\ 0 & \text{otherwise} \end{cases}$$

This gives us a weighted mean gradient as initial medialness R_i

Vascular Structures

- Further improving the offset medialness algorithm:
  2. Calculate symmetry criterion by looking at the variance s^2 of the gradients w.r.t. the initial medialness. Symmetric structures have small variance!

$$S(\vec{x},r)=1-\frac{s^2(\vec{x},r)}{R_i^2(\vec{x},r)}$$

Then, S measures the homogeneity of the boundary between 0 and 1, and the symmetry based medialness R_s

$$R_s(\vec{x},r)=R_i(\vec{x},r)S(\vec{x},r)$$

Vascular Structures

- Further improving the offset medialness algorithm:
  3. Define an adaptive threshold to define minimum medialness responses for robustness to noise.

     Medialness must be larger than the magnitude of the gradient on the tube centerline R_c.

$$R_c(\vec{x}, r) = \sigma^\gamma \left|\nabla I^{(\sigma)}\right|$$

- The final medialness is

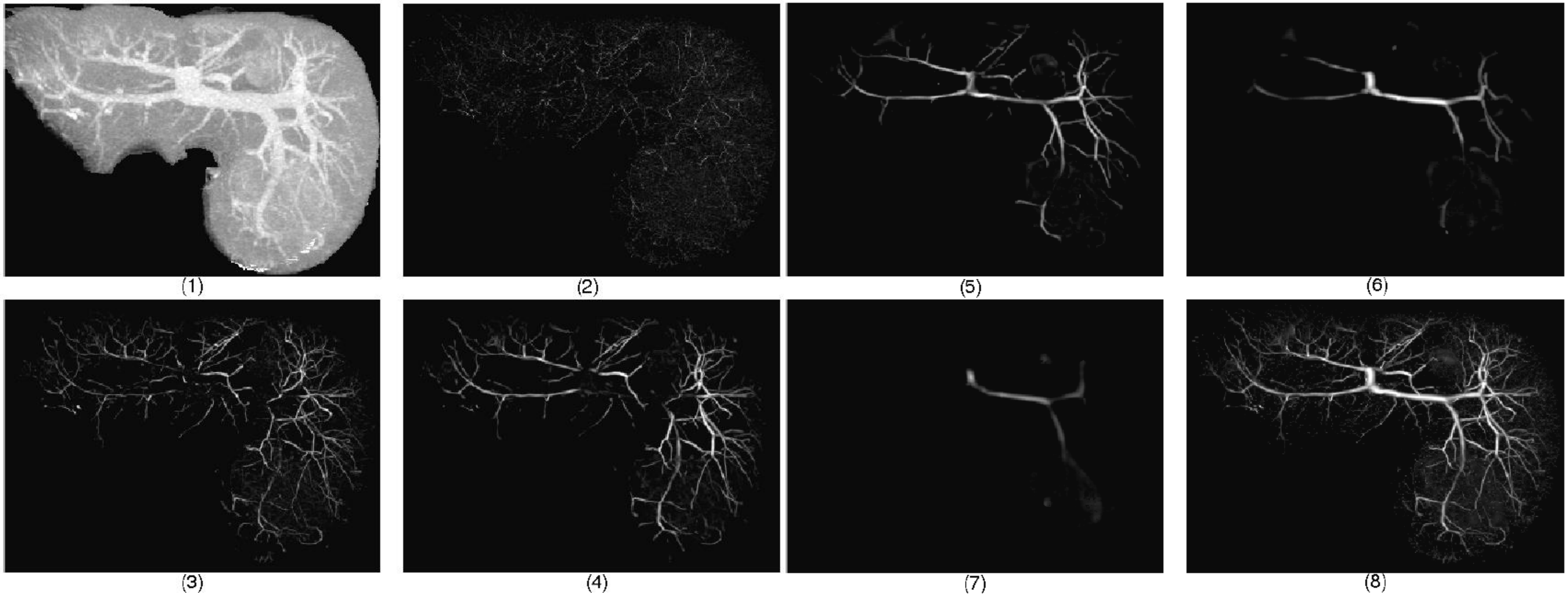
$$R(\vec{x}, r) = \begin{cases} R_s(\vec{x}, r) - R_c(\vec{x}, r) & if\ R_s > R_c \\ 0 & otherwise \end{cases}$$

Vascular Structures

- A very sophisticated vessel enhancement scheme is Algorithm 3:
- Repeat
  - For all pixel (x,y,z)
    - Pre-compute gradients & Hessian matrix at (x,y,z)
  - For all pixel (x,y,z)
    - Compute its Hessian Eigenvalues & Eigenvectors
    - Compute initial & symmetry based medialness
    - Using gradient at (x,y,z): compute final medialness

For all scales

Results of Algorithm 3



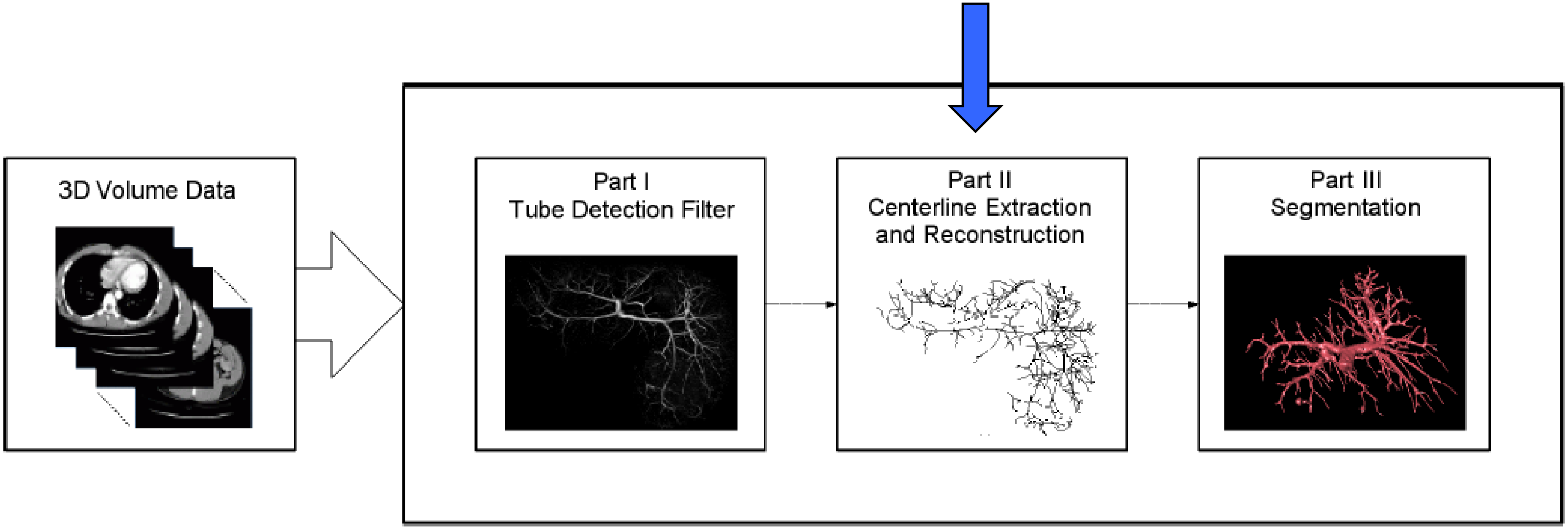
Liver CT data set, responses at different scales,
(8) shows combined multiscale medialness response

Results of Algorithm 3

- LungVessels movie (VLC)

Vascular Structures

- Overview



Vascular Structures

- Centerline Extraction with hysteresis thresholding
  - First, local medialness maxima selection (=non-max suppression)
  - Second, queue-based reconnection

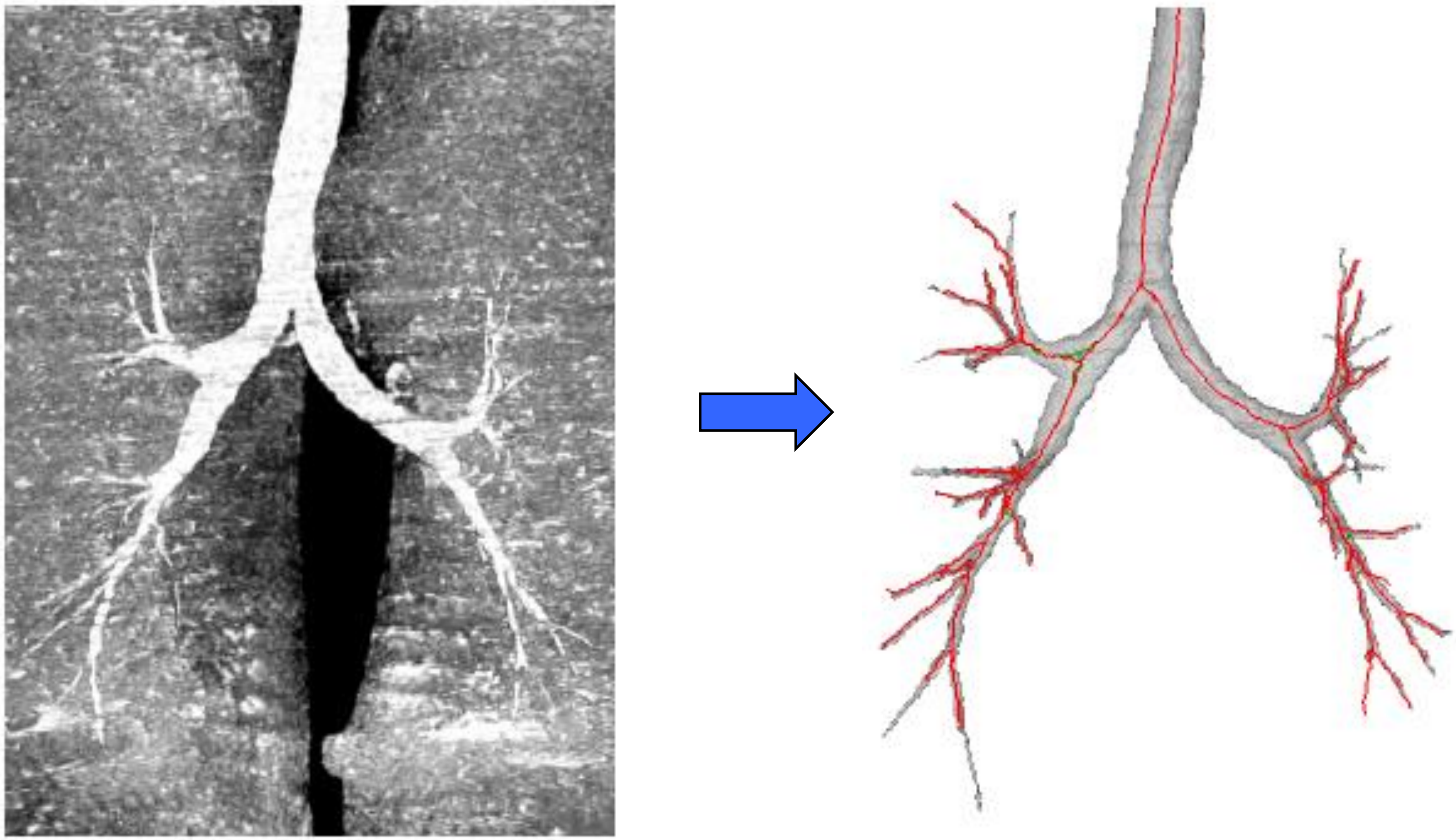
Vascular Structures

- Local medialness maxima
  - For all pixel (x,y,z) we can look at the medialness response of 8 neighboring points interpolated in the plane orthogonal to the tube direction
  - We keep the medialness response for the local maxima image only if the pixel is a local maximum in this plane, and larger than a conservative noise threshold t_{low}

Vascular Structures

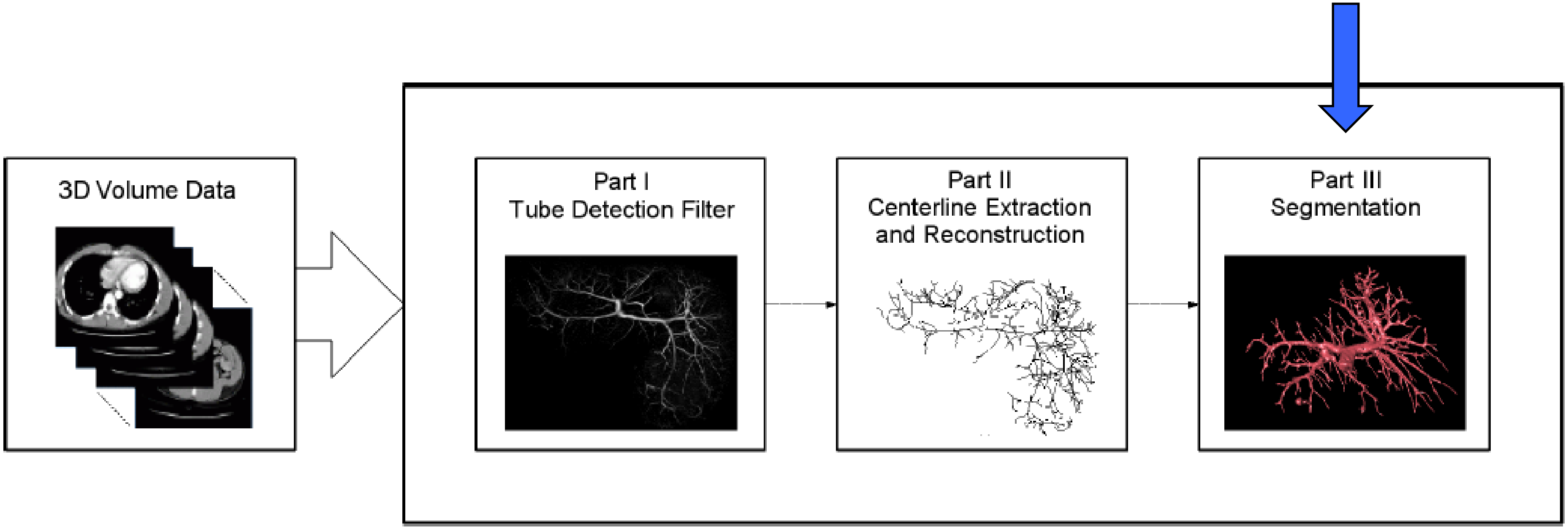
- Queue-based reconnection
  - We put all local maxima into a queue if larger than t_{high}
  - While the queue is filled, we follow the pos. & neg. tangent directions of the extracted queue entry as long as the medialness maximum is larger than t_{low}
    - Pixel are added to centerline as long as this tracing continues
    - We can also incorporate vessel direction (eigenvectors!) as a constraint, and try to bridge small gaps (branching points)

Centerline Example



Vascular Structures

- Overview



Use e.g. Geodesic Active Contour based on weighted TV

END

Thank you for your attention,

this concludes MIA 2015!