# Angiographic image processing to detect and quantify arterial lesions


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# Outline

- **Angiographic imaging**
- **Filtering/denoising**
  - Local orientation estimation
  - Medialness measures
- **Model-based segmentation/quantification**
  - Centerline extraction
  - Boundary extraction
- **Lesion detection**
- **Vascular tree extraction**

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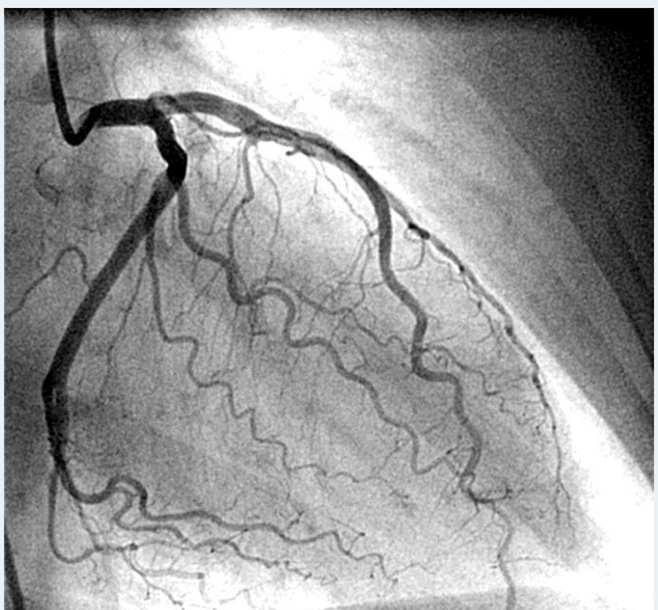
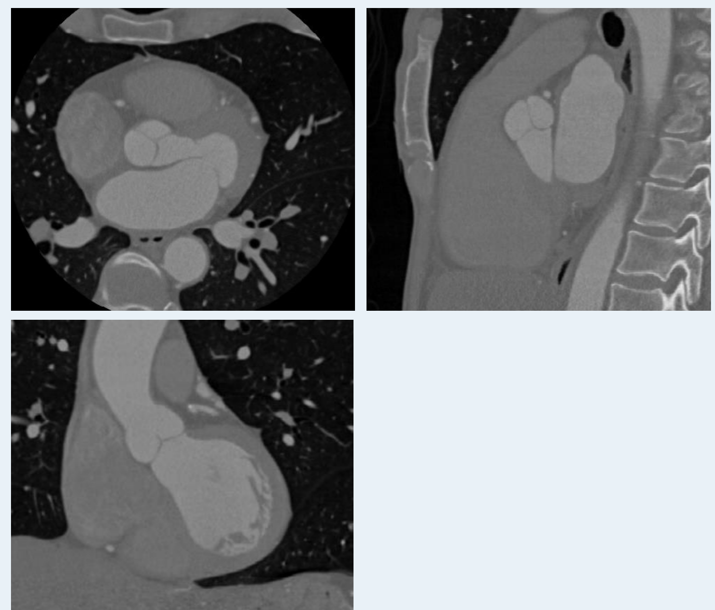
# Angiographic imaging

- **Definition**
  - ἀνγεῖον *angeion* (vessel) and γράφειν *graphein* (to write)
  - traditionally: procedure performed to view blood vessels after **injecting** them with a **radiopaque dye** that outlines them on **X-ray** (www.medicinenet.com)



2D coronary angiogram



3D coronary CT angiogram

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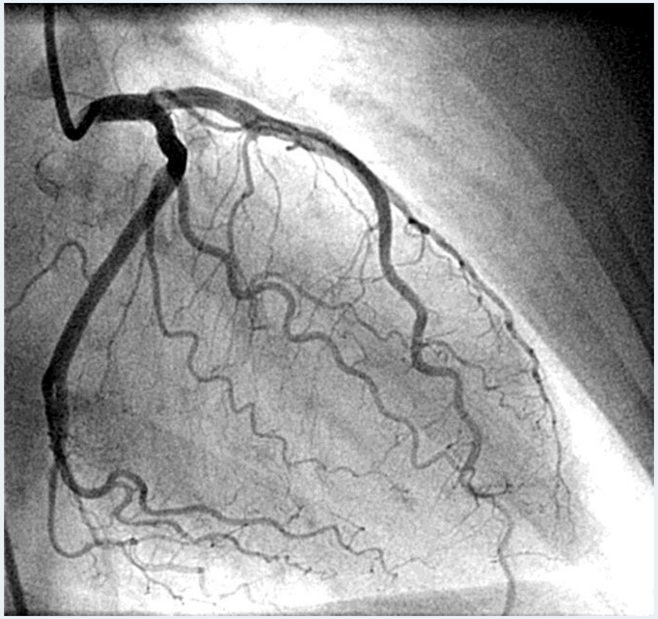

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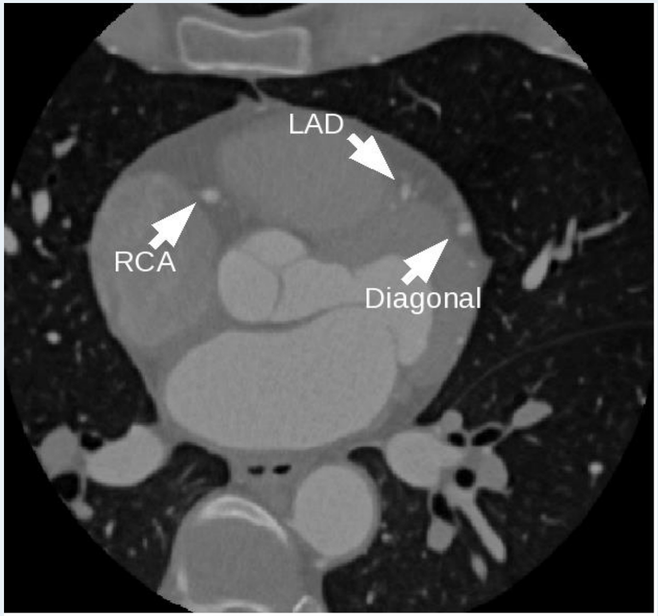
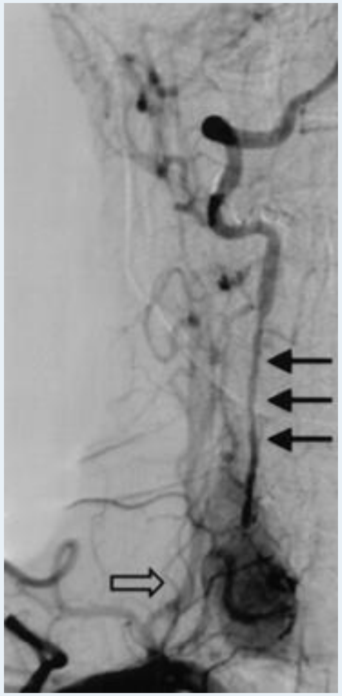
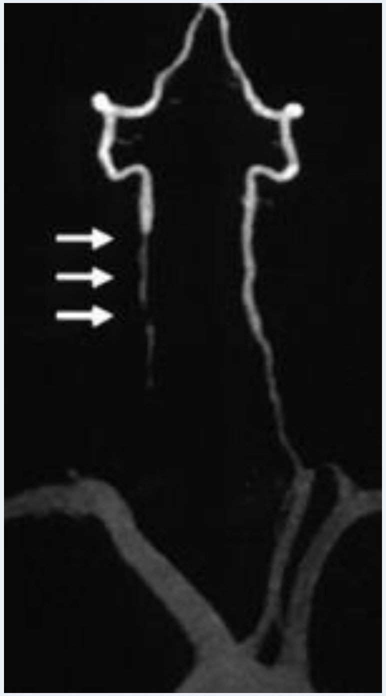
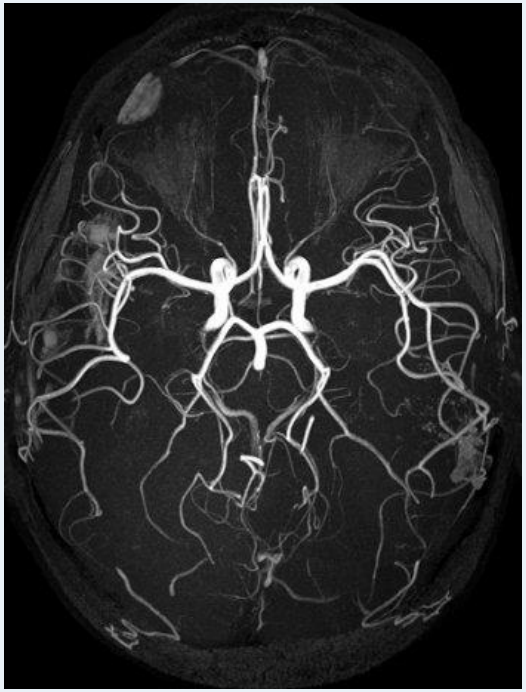



3D coronary CT angiogram

- **Definition**
  - ἀγγεῖον *angeion* (vessel) and γράφειν *graphein* (to write)
  - traditionally: procedure performed to view blood vessels after **injecting** them with a **radiopaque dye** that outlines them on **X-ray** (www.medicinenet.com)
  - more generally: vascular **lumen** imaging using a **contrast agent** or some **physical property** (e.g., motion) to enhance the circulating blood

# Angiographic imaging



- examples:
  - magnetic resonance angiography (CE MRA – gado, TOF MRA…)
  - ultrasound (CEUS – microbubbles, Doppler…)
  - …
- angiograms = arteriograms ∪ venograms

# Angiographic imaging

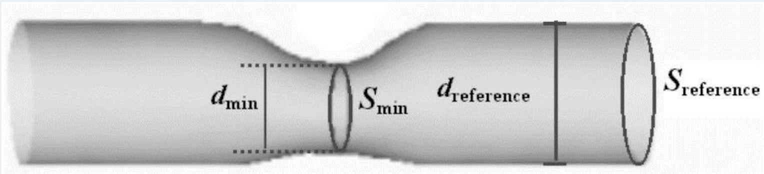
- **Challenges**
  - reducing radiation dose
  - reducing acquisition time

  noise, low contrast, resolution

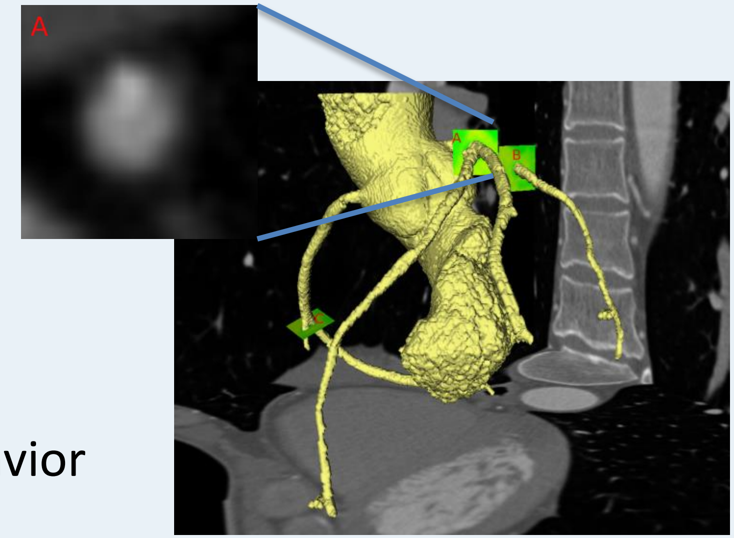
  - image-intensity range overlapping with other tissues
  - anatomical differences (diameters, tortuosity, neighbors)
  - other acquisition-specific problems
    - motion artifacts – heart beat, breathing
    - inhomogeneity of the contrast-agent dilution
      - synchronization
    - motion orientation with respect to imaging geometry (TOF MRA…)
    - crossings, loss of depth information (2D images)
    - reconstruction artifacts (e.g., in CTA: streaking, blooming…)
- No general-purpose solution

# Angiographic imaging

- **Applications**
  - stenosis quantification
    - accurate lumen delineation
    - single vascular segment




  - per-operative guidance
    - accurate centerline/bifurcation extraction
    - real-time 2D/3D registration
    - vascular trees
  - computer-aided diagnosis
    - automated localization of lesions
      - calcified/soft plaques
      - aneurysms
      - wall dissection
    - assessment of biomechanical behavior




- No general-purpose solution

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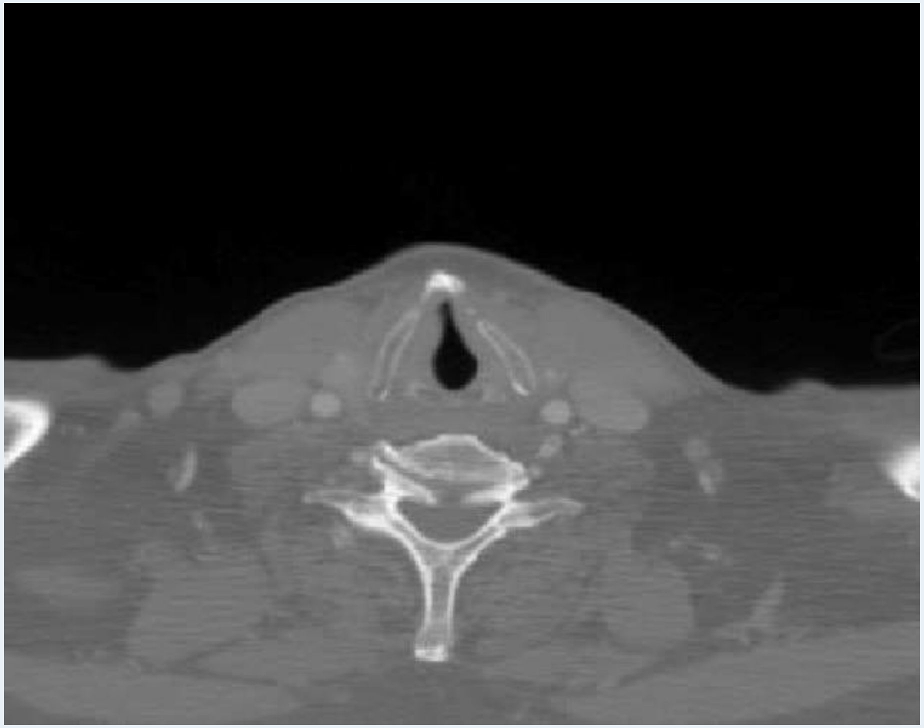
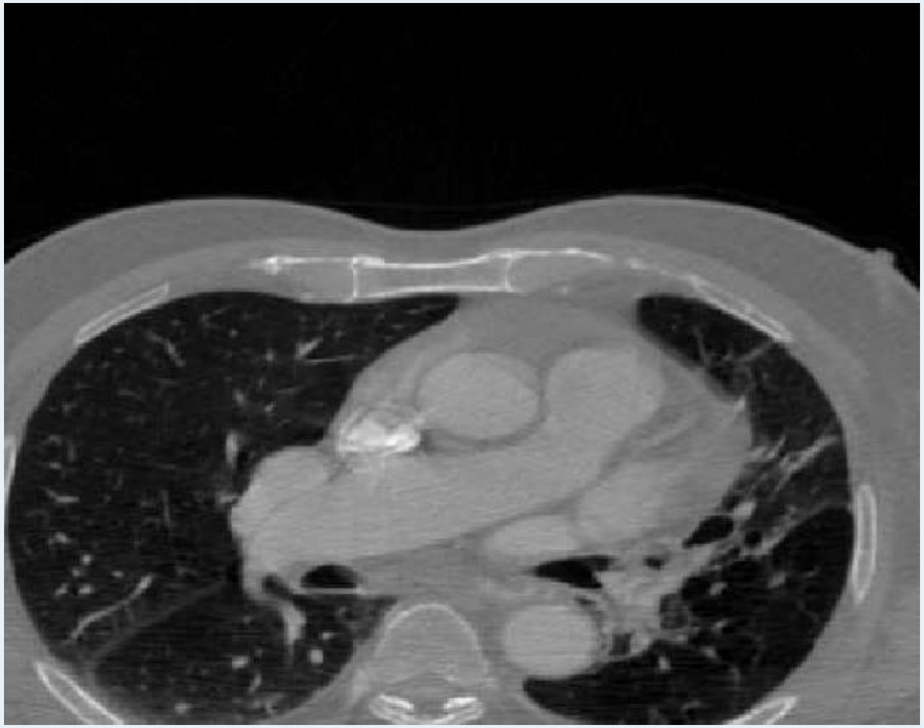
# Filtering/denoising

- **Purposes**
  - noise reduction in low-dose/fast acquisitions
  - attenuate artifacts
    - example: Dual Tree Complex Wavelet Transform

[Zuluaga et al. MICCAI 2009]





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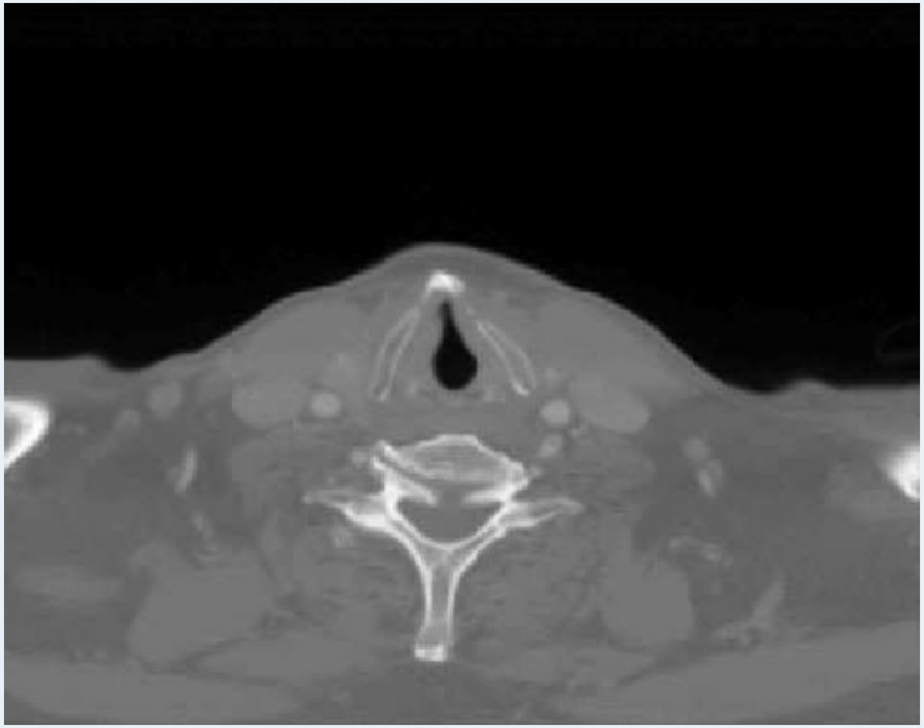

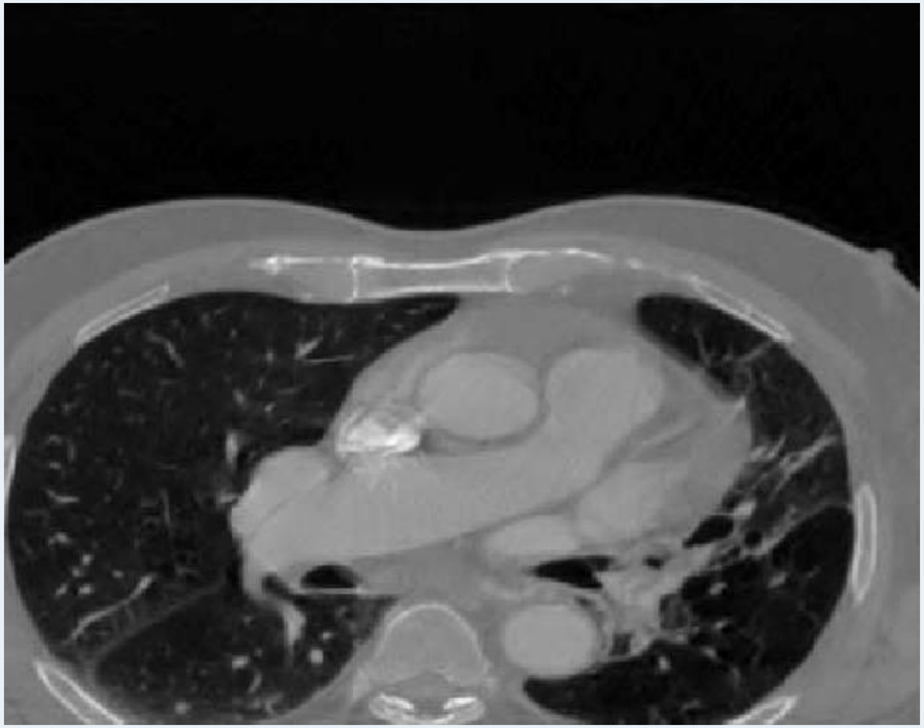

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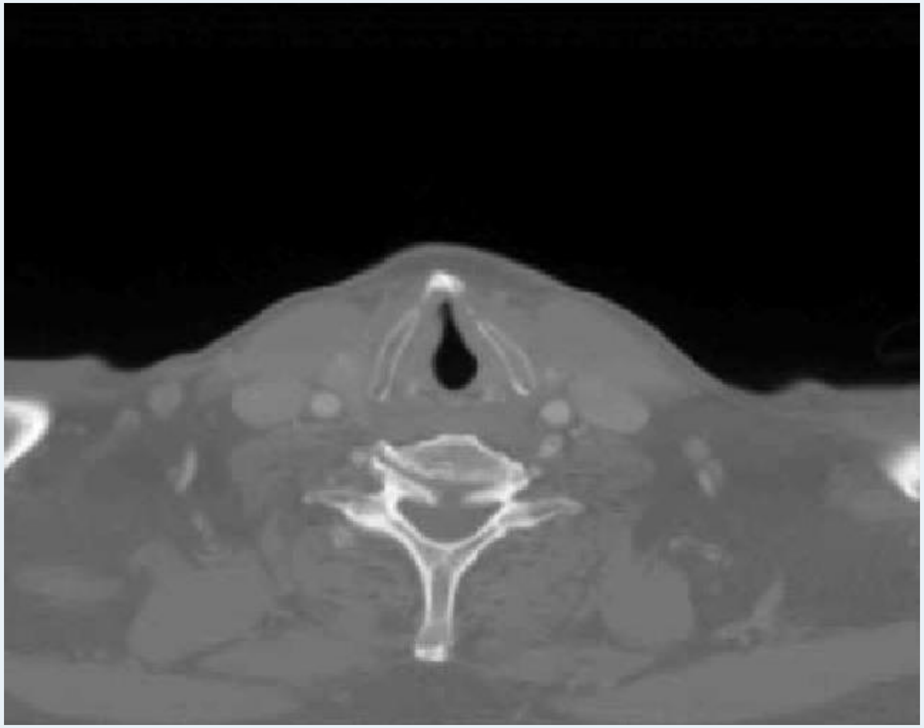
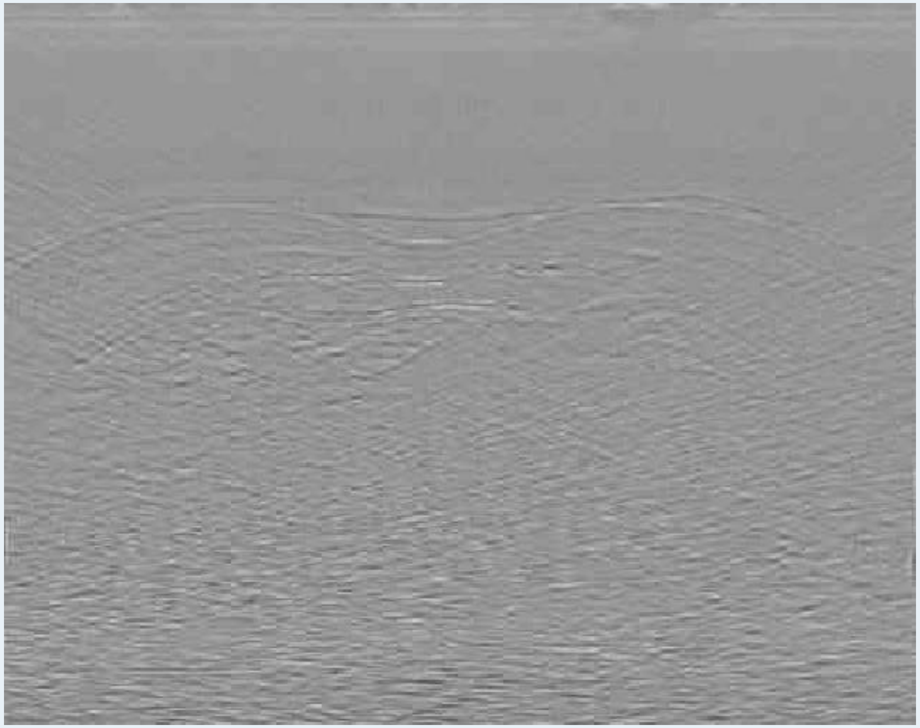
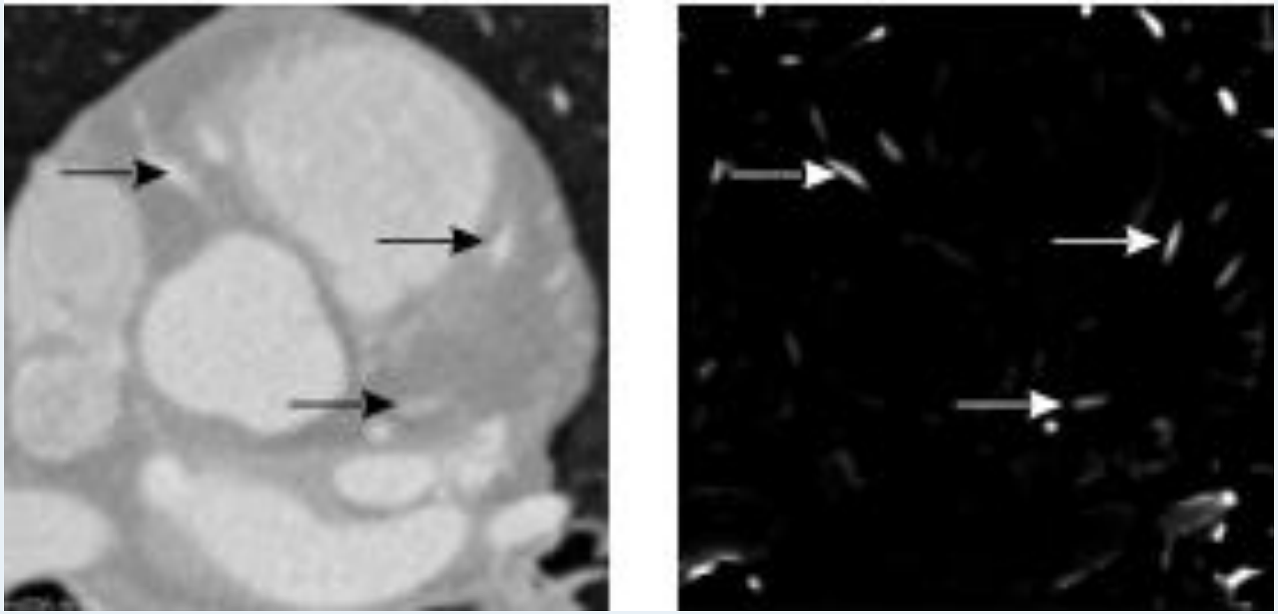




# Filtering/denoising

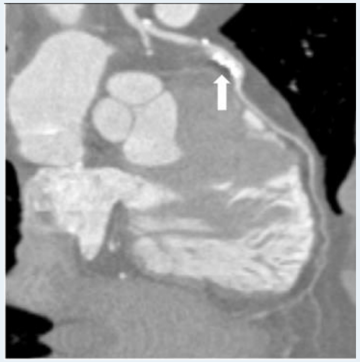
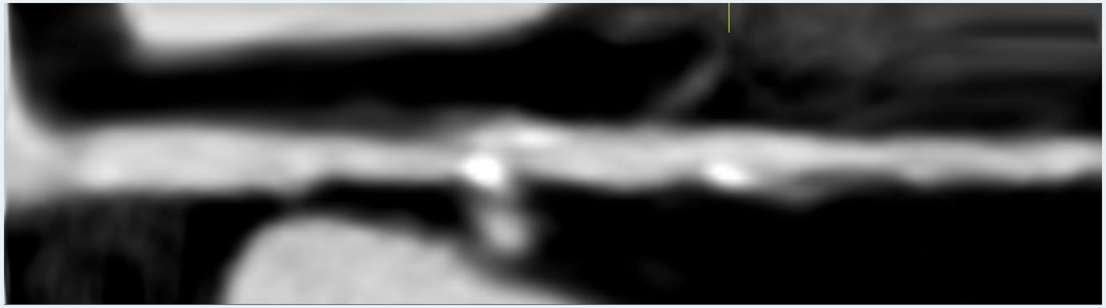
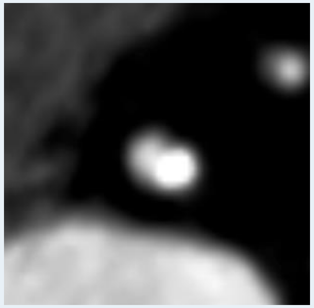
- **Purposes**
  - noise reduction in low-dose/fast acquisitions
  - attenuate artifacts
  - enhance structures of interest
    - example: Hessian eigenvalue-based filters

[Orlowski & Orkisz, IRBM 2009]

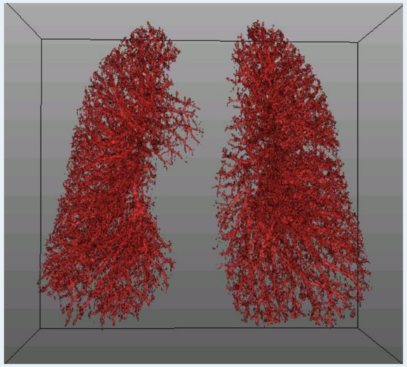


# Filtering/denoising

- **Specificities**
  - pixel/voxel-size details to be preserved
  - application-dependent (e.g., preserve small calcifications?)

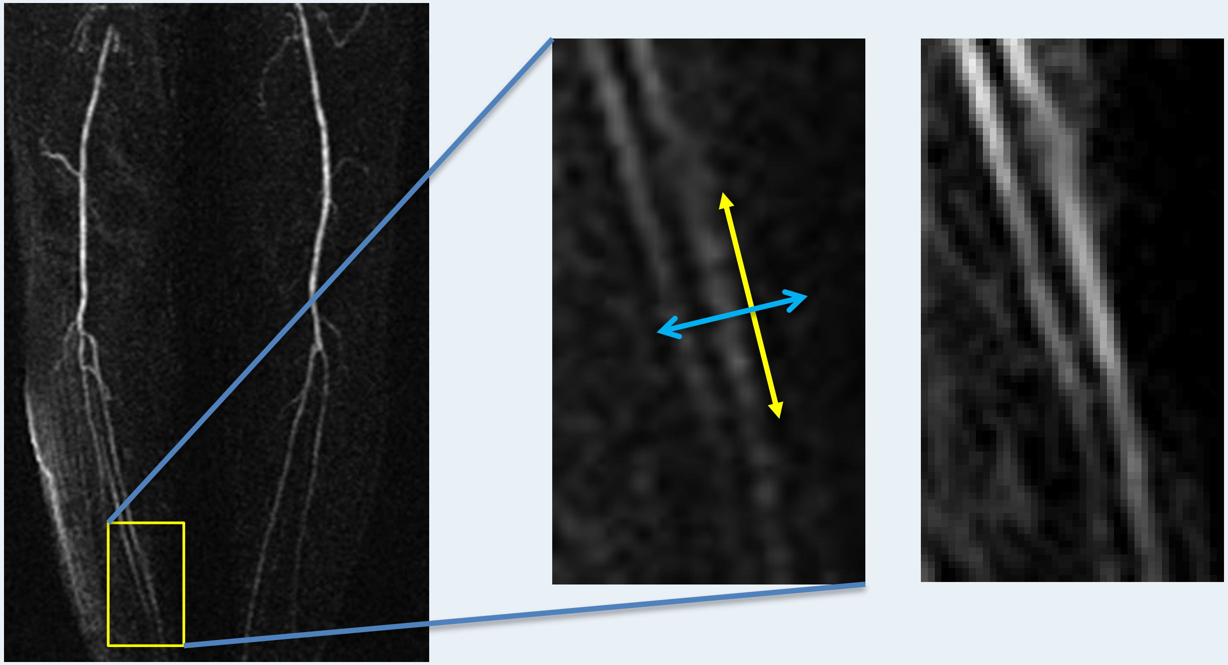




  - strongly **elongated/oriented/curved** objects of interest
  - circular cross-sections (if healthy)
  - branching structures



- **Appearance models**
  - implicitly/explicitly cylindrical (ellipsoidal) and homogeneous

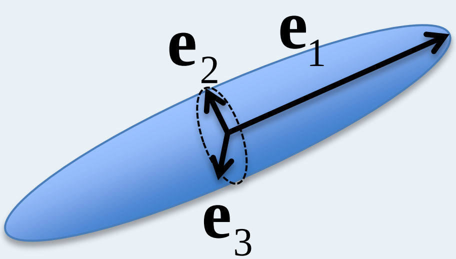
- **Examples of approaches**
  - with explicit estimation of the local orientation
    - **find local orientation**
    - measure cross-sectional circularity and longitudinal homogeneity
    - **enhance cross-sectional contrast**
    - and/or **smooth intensities longitudinally**

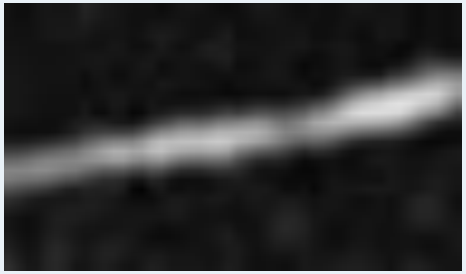


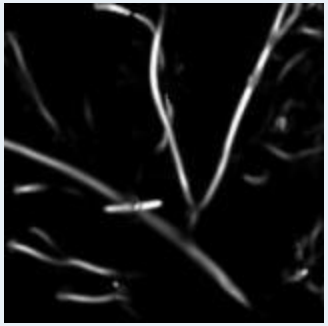
# Filtering/denoising

- **Examples of approaches**
  - with explicit estimation of the local orientation
    - **find local orientation**
    - measure cross-sectional circularity and longitudinal homogeneity
    - **enhance cross-sectional contrast**
    - and/or **smooth intensities longitudinally**
  - without explicit estimation of the local orientation
    - calculate derivatives or moments in the **global reference frame**
    - **diagonalize the appropriate matrix** at each location
    - **combine eigenvalues** to measure elongation/circularity
    - possibly use eigenvectors to explicitly estimate orientation and switch to the previous approach
  - …

- **Eigenvalue-based approach**
  - Hessian (Frangi, Krissian, Sato, Li, etc.)
    - convolution with 2nd derivatives of a Gaussian kernel
    - $\|\lambda_1\| \leq \|\lambda_2\| \leq \|\lambda_3\|$ and $\lambda_1 \cong 0, \lambda_2 \cong \lambda_3 \ll 0$ if $\sigma \cong r$
    - combine eigenvalues, e.g.:
      elongation $\lambda_1^{\,2} / \lambda_2\lambda_3 \to 0$, circularity $\lambda_2 / \lambda_3 \to 1$
    - multiscale - find $\sigma$ with strongest response

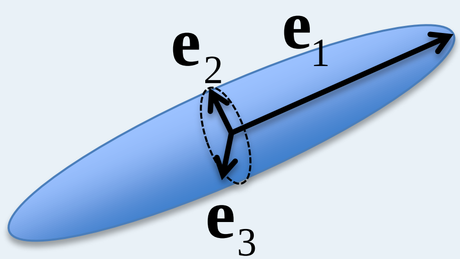


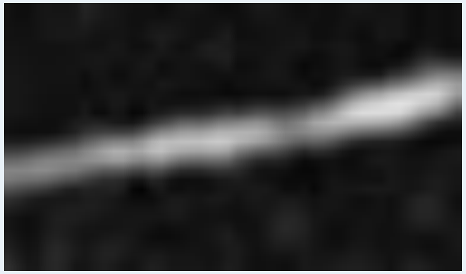



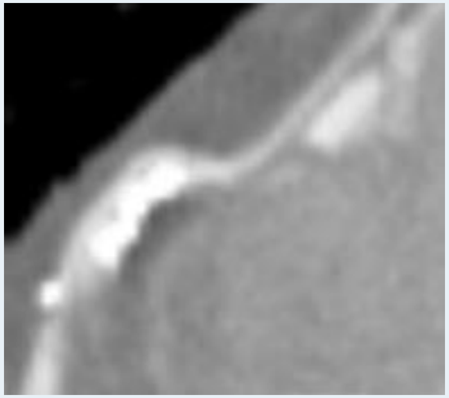


    - sensitive to noise, bifurcations, time-consuming

- **Eigenvalue-based approach**
  - Inertia (Toumoulin, **Hernández Hoyos**)
    - mechanical analogy: voxel gray level = elementary mass
    - inertia moments in a (spherical) neighborhood
    - $0 < \lambda_1 \ll \lambda_2 \cong \lambda_3$
    - sensitive to neighboring bright structures (e.g., calcifications)



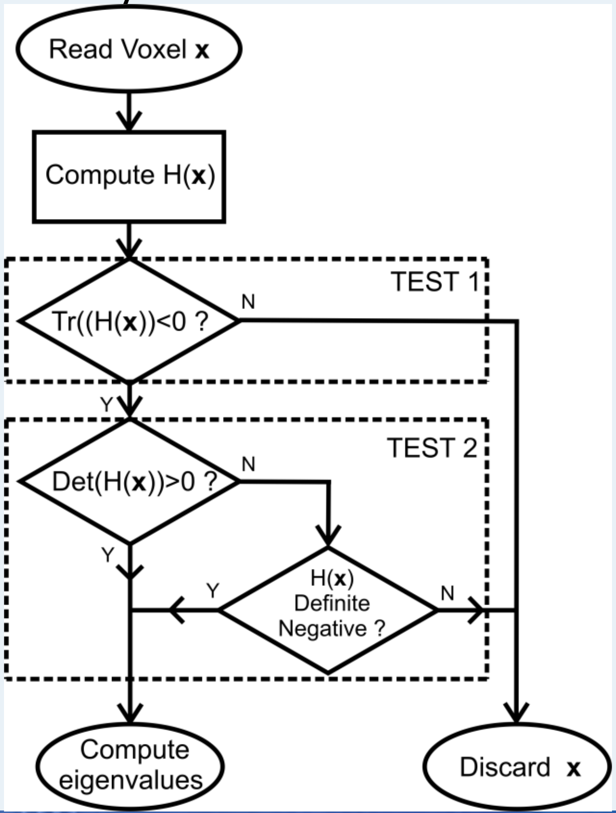


  - Optimally oriented flux (Law, Benmansour, etc.)
    - $1^{st}$ derivatives

- **Eigenvalue-based approach**
  - speeding-up computation [Orlowski & Orkisz, IRBM 2009]
    - avoid useless diagonalization
      - slow if accurate
      - fast but prone to numerical instability if analytic
    - analyze matrix invariants
    - set to zero voxels unlikely to meet

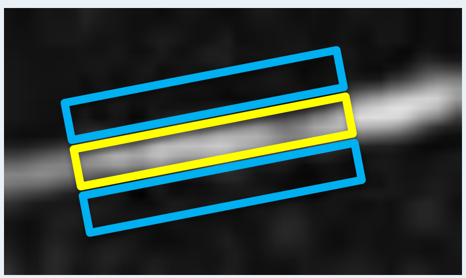
$$\lambda_1 \cong 0, \lambda_2 \cong \lambda_3 \ll 0$$

    - 70% discarded voxels in coronary CTA



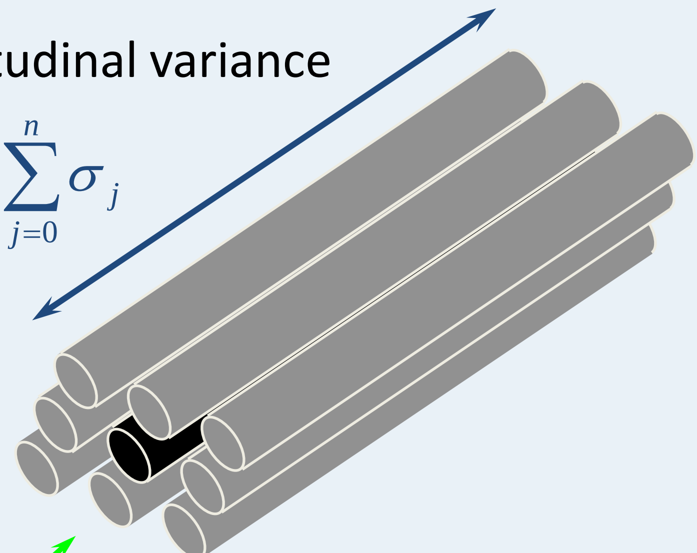
# Filtering/denoising

- **Explicitly estimating local orientation**
  - HD filter [Orkisz *et al*. MRM 1997]
    - set of parallel “sticks” $j$ = 1,… , $n$+1
    - selected orientation $\vartheta = \arg\max_i \left( \bar{g}_i - \alpha \bar{\sigma}_i \right), \alpha \in R_+$

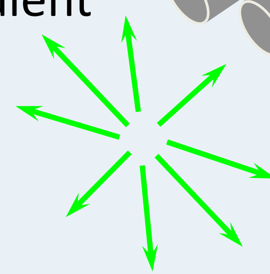


- small average longitudinal variance

$$\bar{\sigma}_i = \frac{1}{n+1} \sum_{j=0}^{n} \sigma_j$$



- large average transversal gradient



$$\bar{g}_i = \frac{1}{n} \sum_{j=1}^{n} \left| \overline{\nabla I}_j \right|$$

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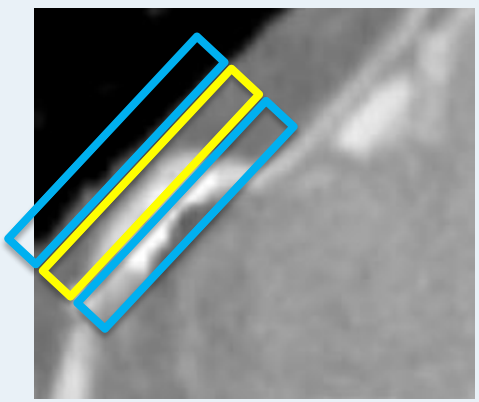
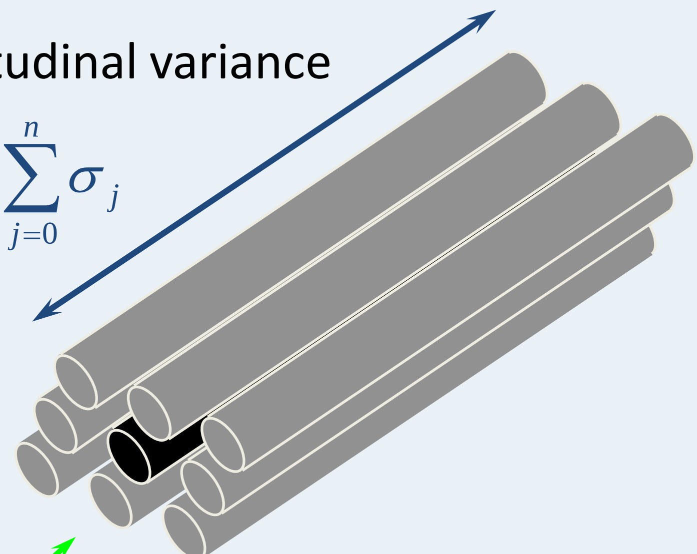


- small average longitudinal variance

$$\overline{\sigma}_i = \frac{1}{n+1}\sum_{j=0}^{n}\sigma_j$$



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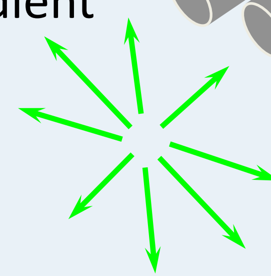


$$\overline{g}_i = \frac{1}{n}\sum_{j=1}^{n}\left|\overline{\nabla I}_j\right|$$

☺ Can detect branching points

- **Oriented operator** [Orkisz *et al.* MGV 2000]
  - directional smoothing: truncated mean within each "stick" for the orientation $\vartheta$

$$m_\vartheta^j = \frac{1}{2W+1}\sum_{k=k_0-W}^{k_0+W} I_k,\ k_0 = (L+1)/2$$

  - enhancement: Laplacian in the plane $\perp$ to $\vartheta$

$$f = m_\vartheta^{\,0} + n\cdot m_\vartheta^{\,0} - (m_\vartheta^{\,1} + \ldots + m_\vartheta^{\,n})$$

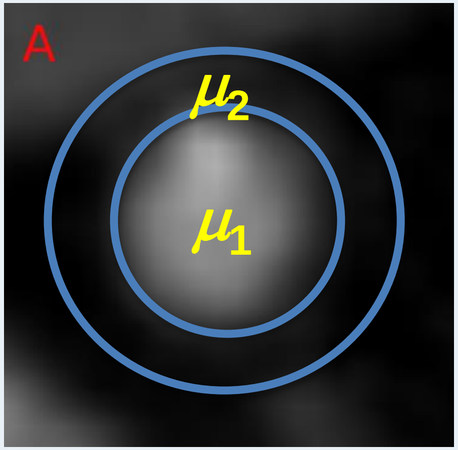
$$\boxed{f = (1-\gamma)\cdot m_\vartheta^{\,0} - \gamma\cdot(m_\vartheta^{\,1} + \ldots + m_\vartheta^{\,n}),\ \gamma \in [0, 1/2]}$$

☺ **Good results**

😐 **Never tested in multiscale**

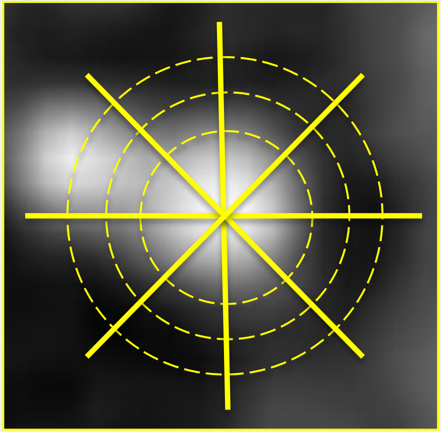
☹ **Time-consuming in 3D** **but easy to parallelize (GPU)**

- **Other oriented (2D) operators**
  - Ribbon [Florin *et al.* MICCAI 2005]




$$v = \mu_1 - \mu_2$$

  - Cores [Fridman *et al.* MICCAI 2003]
  - [Krissian *et al.* 2000], [Gülsün & Tek, MICCAI 2008]
  - Flux and MFlux [Lesage *et al.* MedIA 2009]
    - sum of directional gradients



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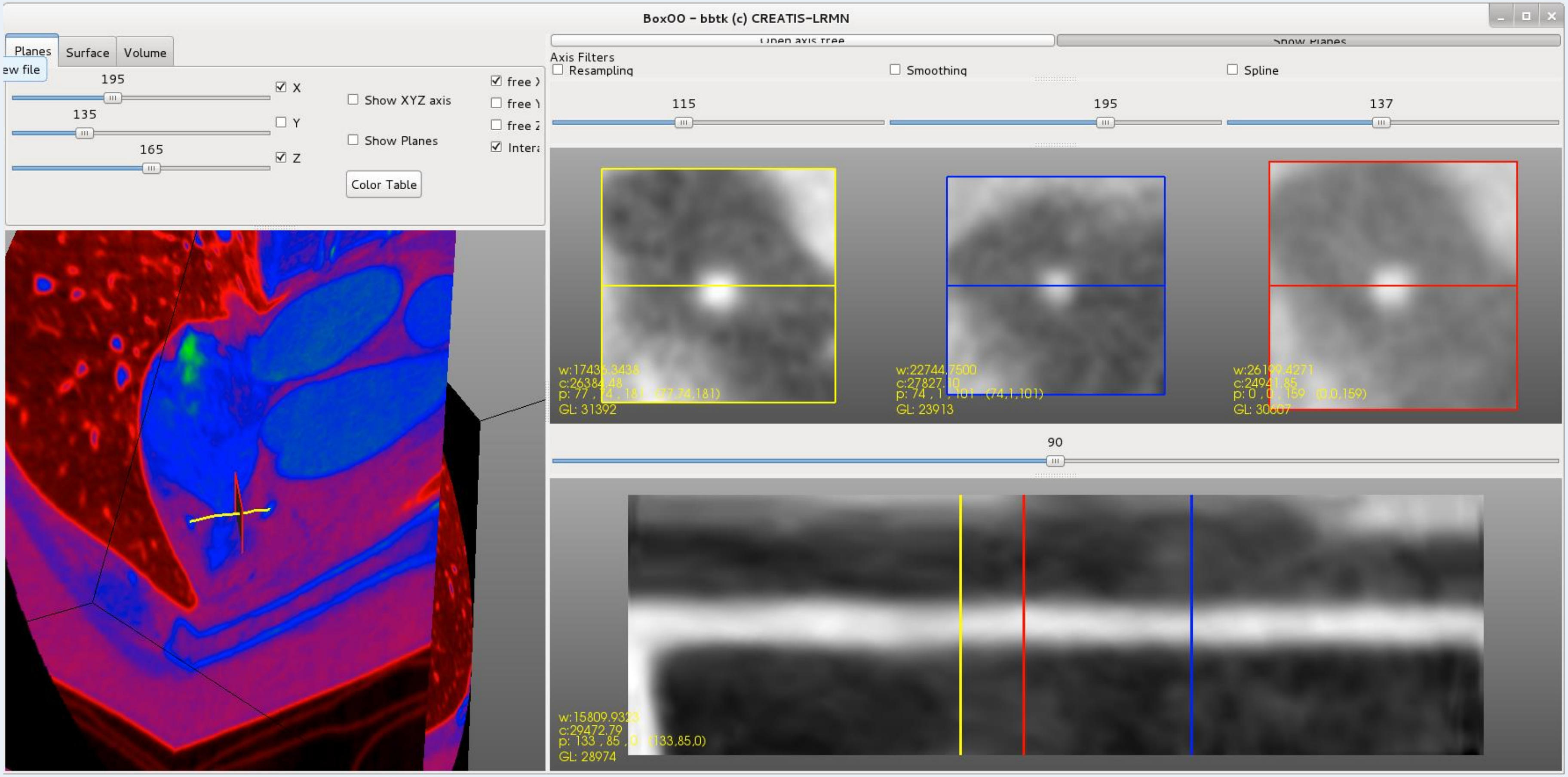
# Segmentation: centerline

- **Centerline - what for?**
  - visualization
  - measurement (length, diameters, …)



# Segmentation: centerline

- **Centerline - what for?**
  - visualization
  - measurement (length, diameters, …)
  - initialization of contour/surface segmentation

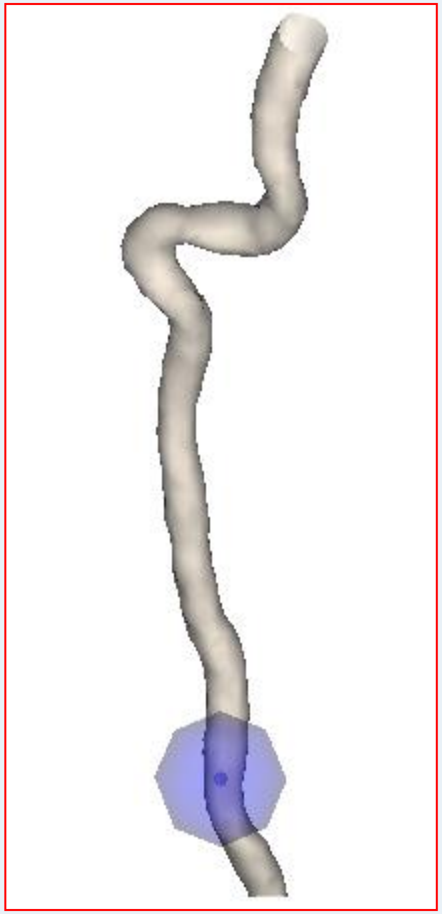
    → automated quantification
- **Main approaches for centerline extraction**
  - skeletonization (if presegmentation available)
  - tracking in a prediction/estimation scheme
    - deterministic
    - stochastic
  - minimum-cost paths

# Segmentation: centerline

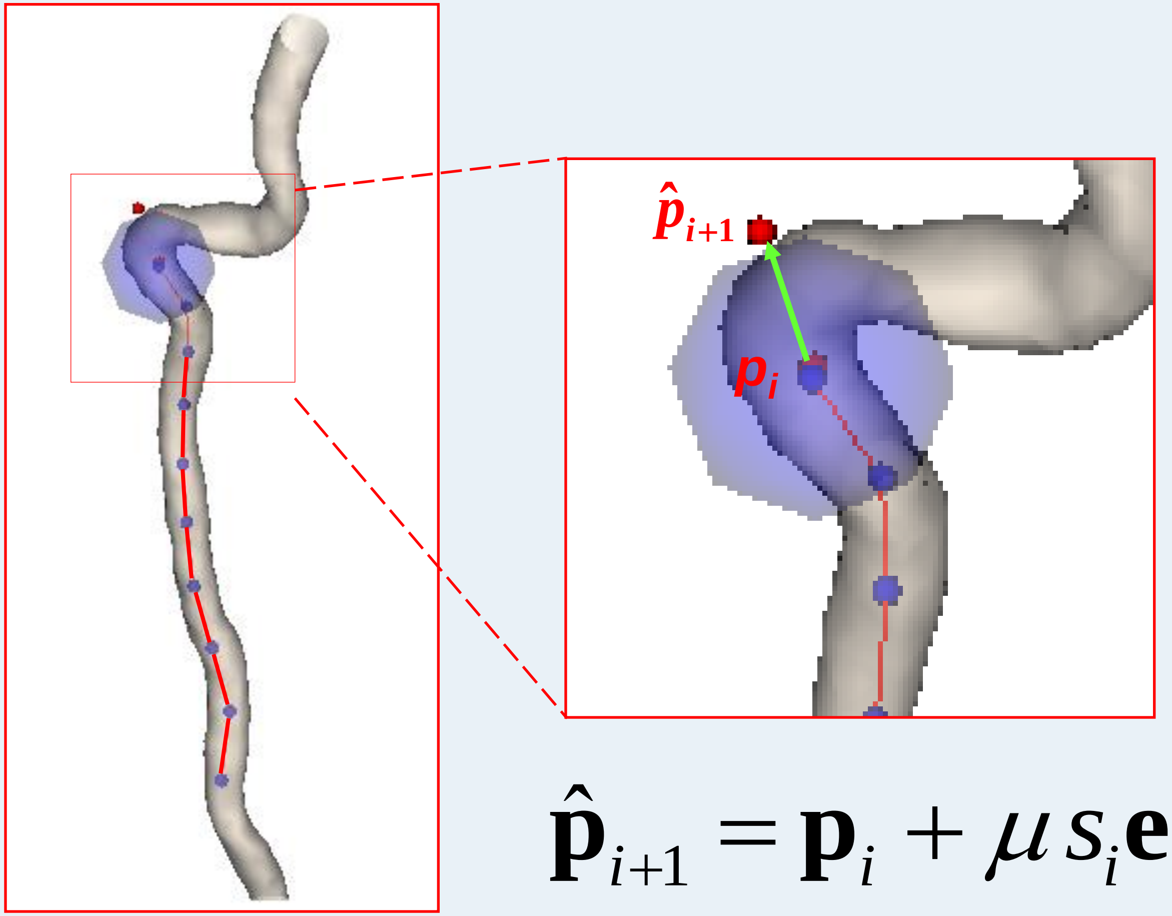
- **Centerline tracking with extensible-skeleton model**

  [Hernández Hoyos et al. MGV 2005, IJCARS 2006]

  - multi-scale eigen-analysis of the inertia matrix



- **Prediction**
  - displacement along the current orientation $\mathbf{e}_i$




$\mu$ : amplitude

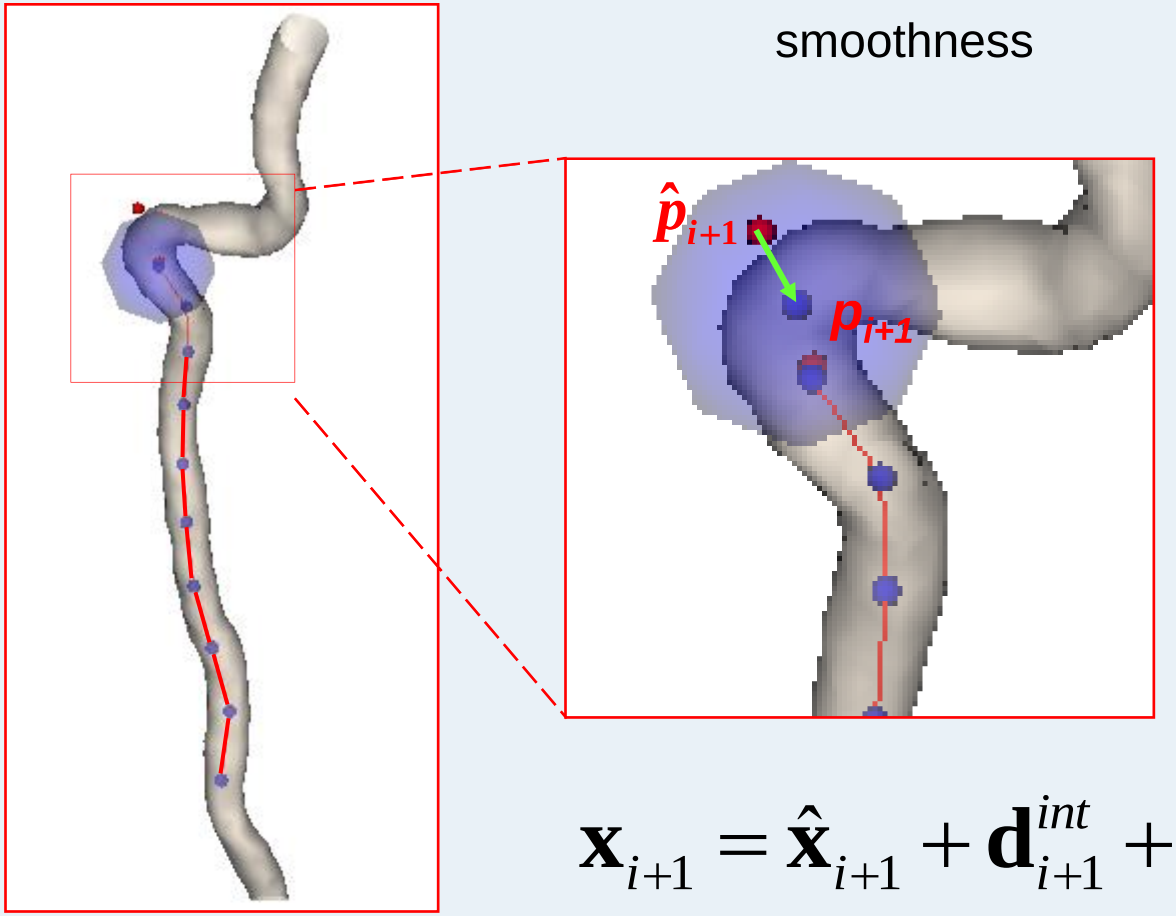
$s_i$ : sign

$$\hat{\mathbf{p}}_{i+1} = \mathbf{p}_i + \mu s_i \mathbf{e}_i$$

# Segmentation: centerline

- **Estimation**
  - correction: influence of internal and external forces

continuity centroid
smoothness



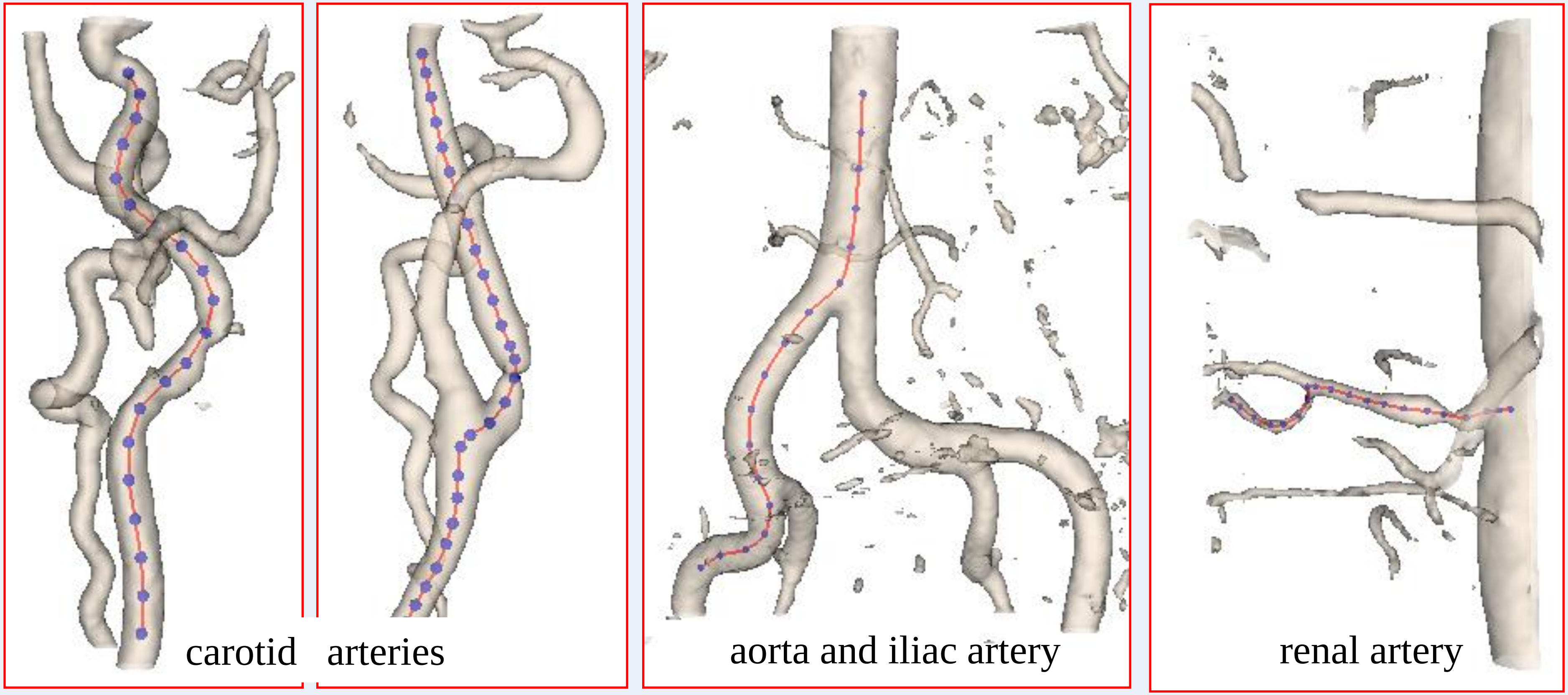

$\mathbf{d}_{i+1}^{int}$ : displacement owing to internal forces

$\mathbf{d}_{i+1}^{ext}$ : displacement owing to external forces

$$\mathbf{x}_{i+1} = \hat{\mathbf{x}}_{i+1} + \mathbf{d}_{i+1}^{int} + \mathbf{d}_{i+1}^{ext}$$

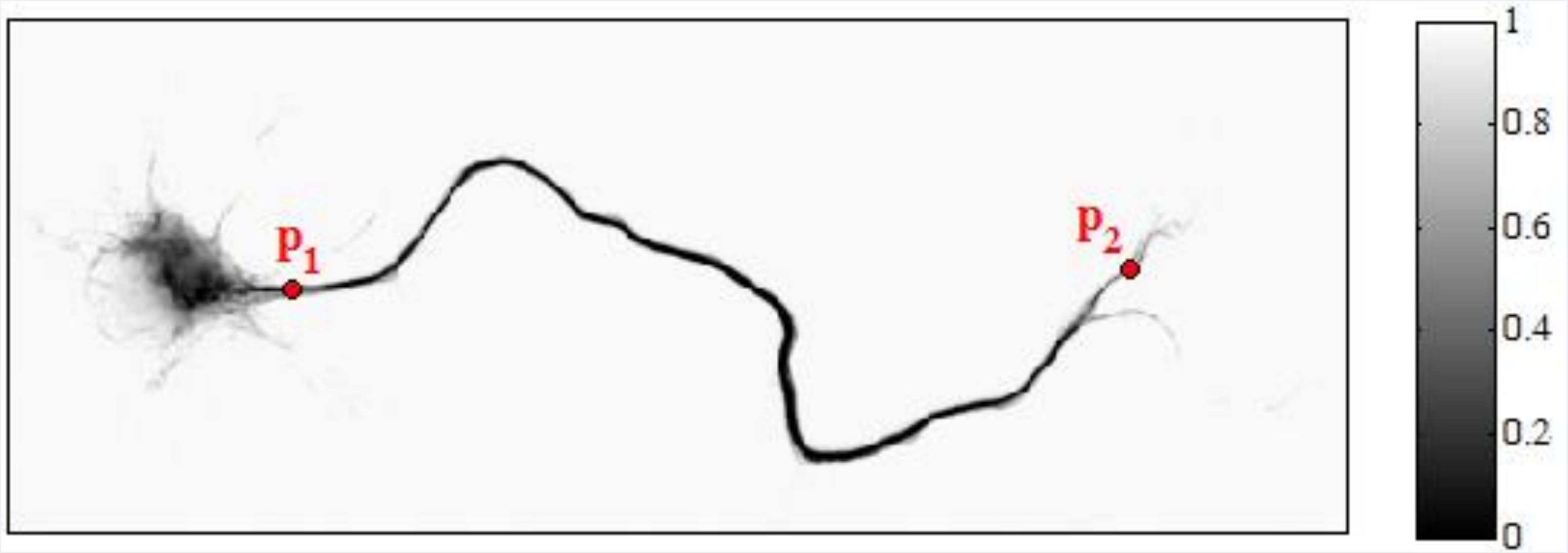
# Segmentation: centerline

- **1 point initialization**
- **Stopping criterion = volume boundary**




- **Possible difficulties: long stenoses**

- **Minimum cost paths**
  - two or more initialization points
  - front propagation
    - Dijkstra [Flórez Valencia *et al.* MICCAI 2012]
    - Fast Marching [Benmansour *et al*. ISRACAS 2009]
      - energy minimization $E(C) = \int_0^L P(C(s))ds$



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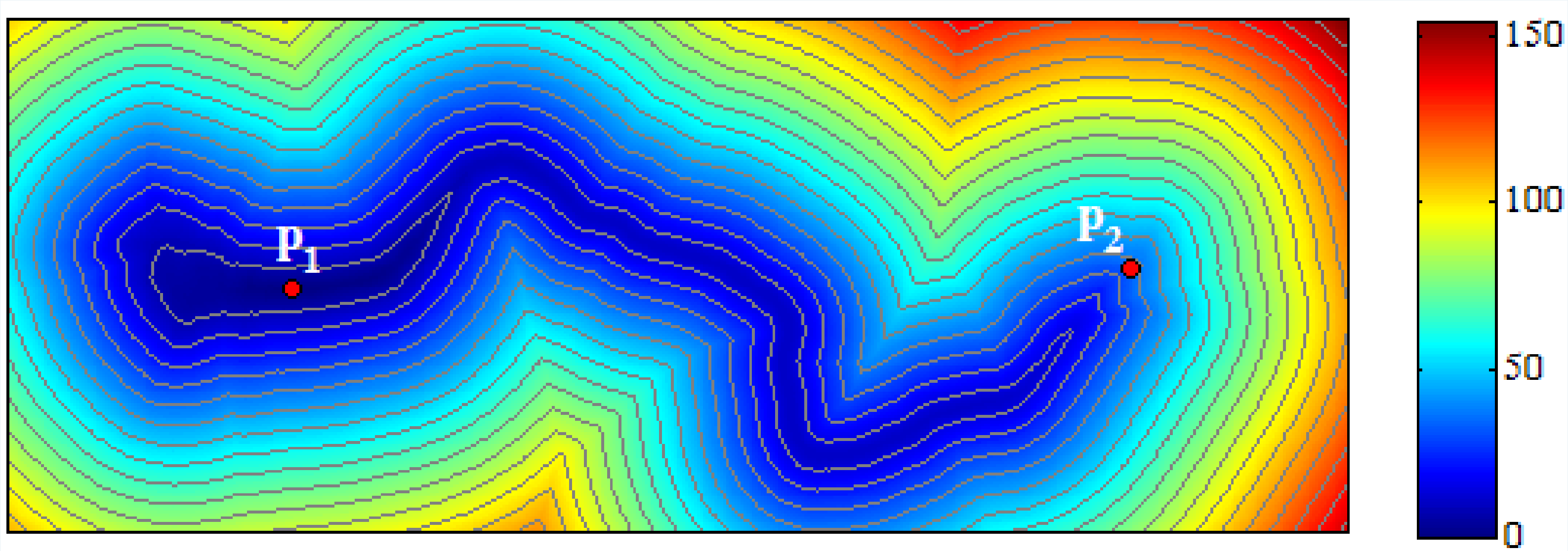
$$U_{p1}(p) = \inf_{C(0)=p1;\, C(L)=p} \big(E(C)\big) = \inf_{C(0)=p1;\, C(L)=p} \left(\int_0^L P(C(s))ds\right)$$



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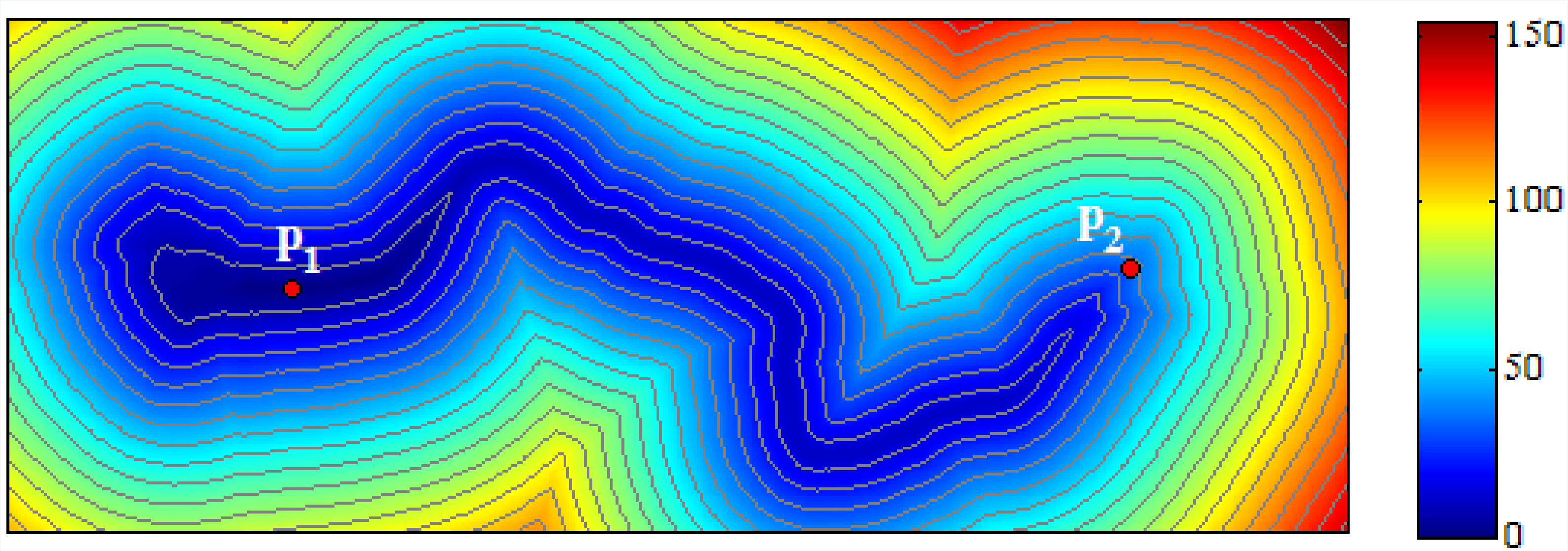
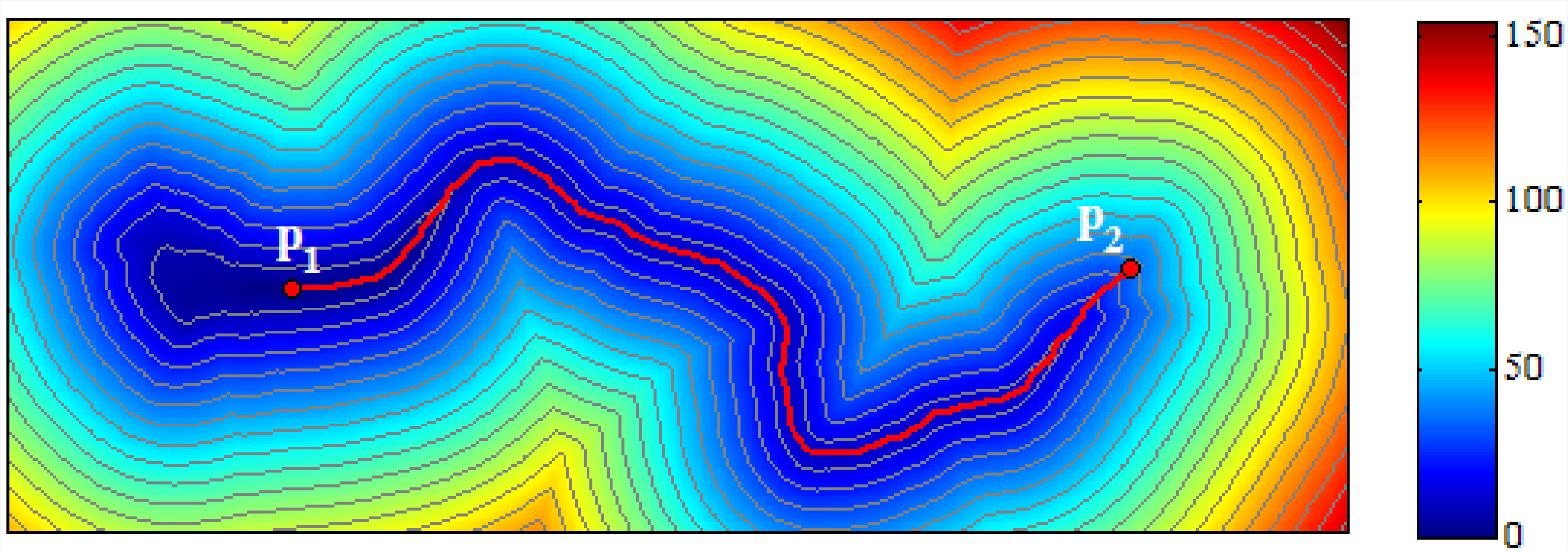
  - front propagation
    - Dijkstra [Flórez Valencia *et al.* MICCAI 2012]
    - Fast Marching [Benmansour *et al*. ISRACAS 2009]
      - Eikonal equation $\left\|\nabla U_{p1}(x)\right\| = P(x)$ and $U_{p1}(p1) = 0$



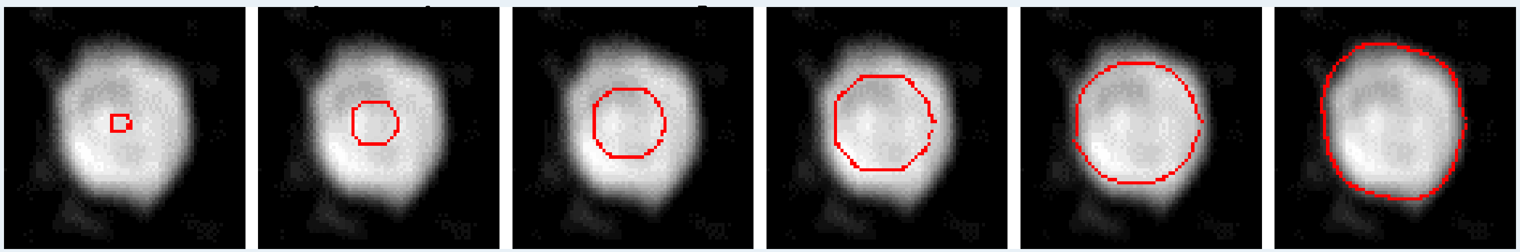
# Segmentation: centerline

- **Minimum cost paths**
  - 2 or more initialization points
  - front propagation
    - Dijkstra [Flórez Valencia *et al.* MICCAI 2012]
    - Fast Marching [Benmansour *et al*. ISRACAS 2009]
      - – backtracking

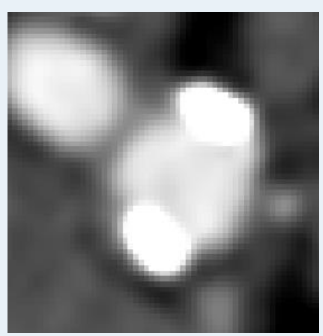


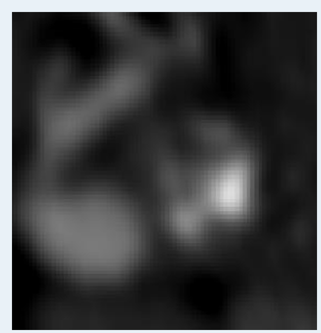
# Segmentation: boundaries

- **Contour extraction in cross-sectional planes**
  - adaptive isocontours [Hernández Hoyos *et al*. MGV 2005, IJCARS 2006] – thresholding
  - deformable contours
    - explicit [Hernández Hoyos *et al*. Radiographics 2002, Desbleds



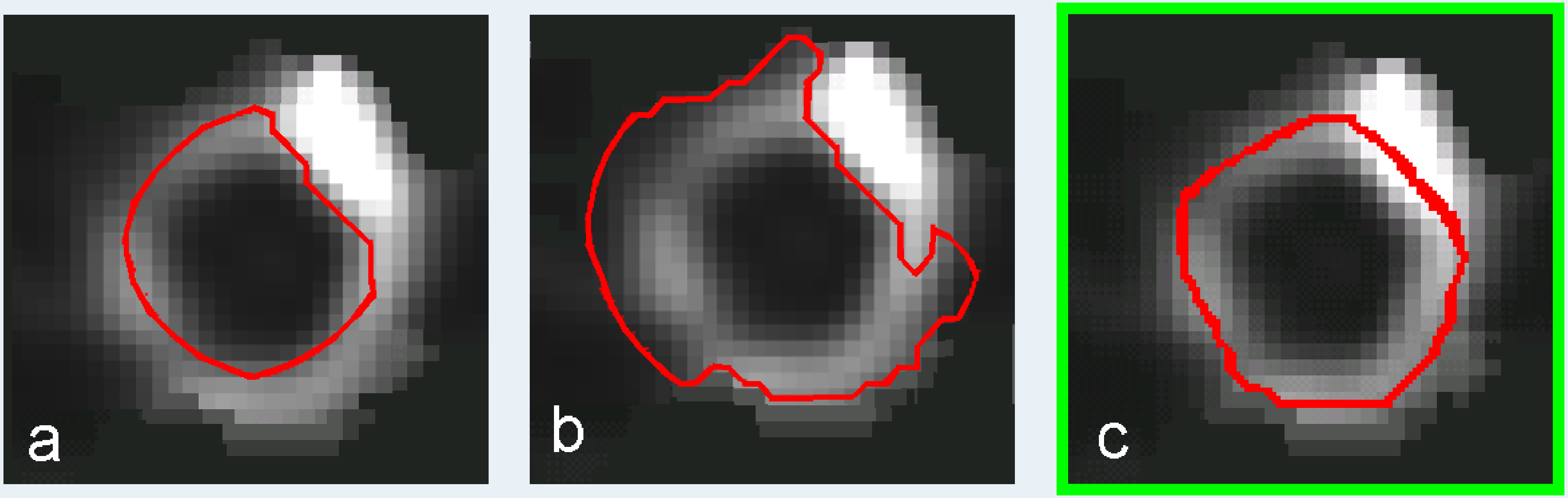
    - implicit [Baltaxe *et al*. IEEE EMBC] – Fast Marching





# Segmentation: boundaries

- **Contour extraction in cross-sectional planes**
  - Fast Marching [Baltaxe *et al*. IEEE EMBC 2007]

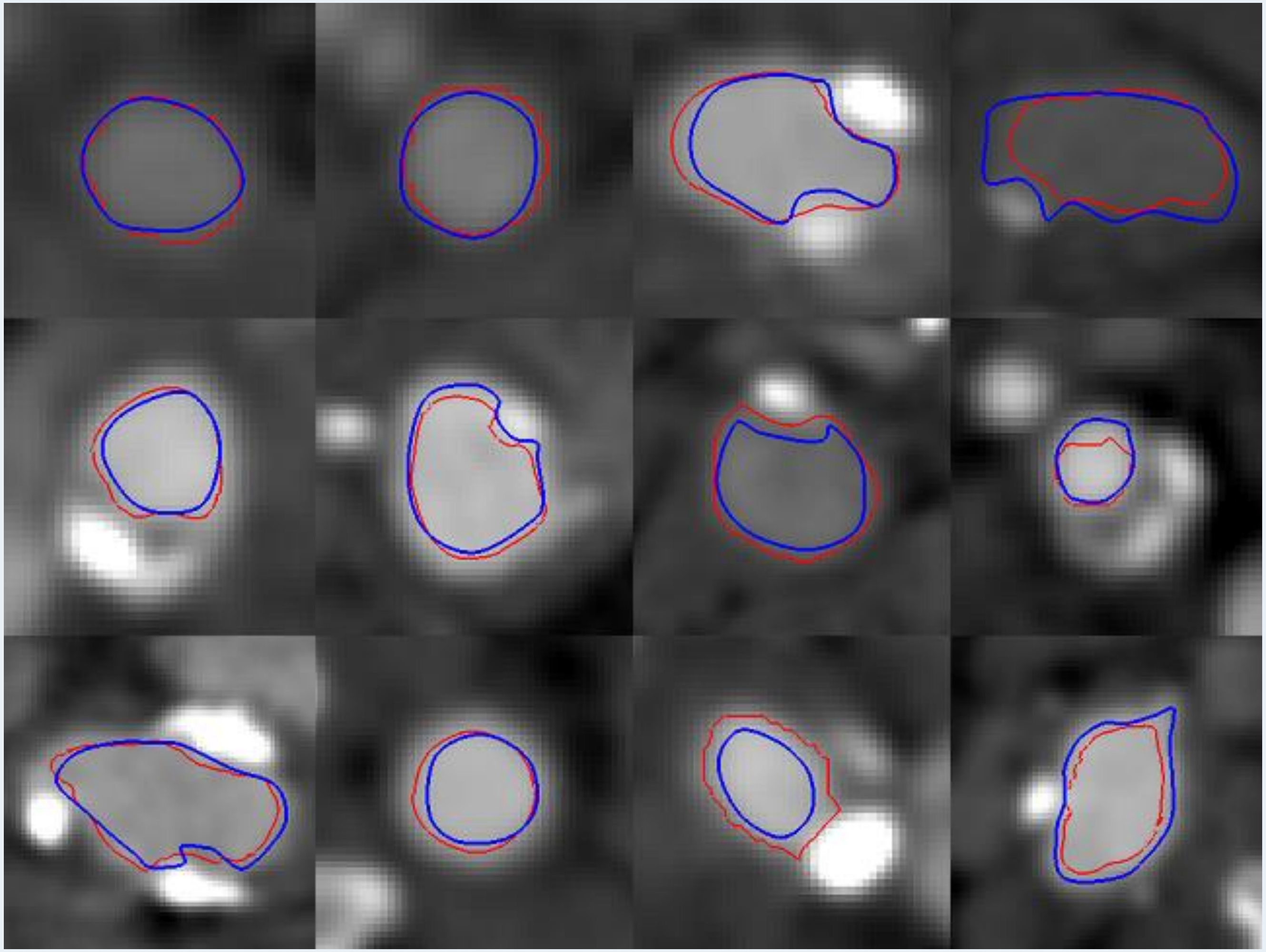



standard speed function proposed function

a. high-contrast boundary is not reached

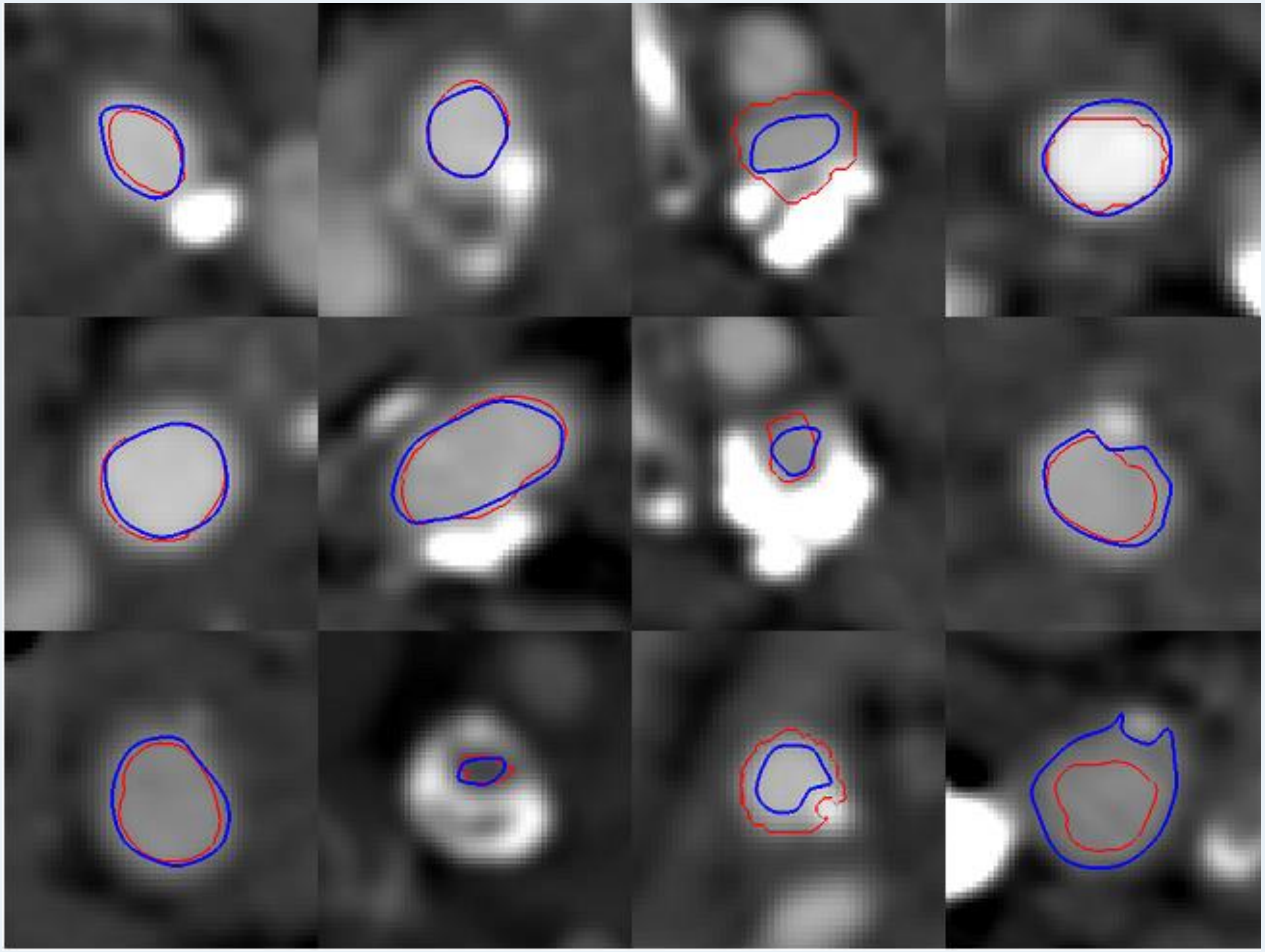
b. leakage through low-contrast breaches

# Segmentation: boundaries



blue = reference red = method

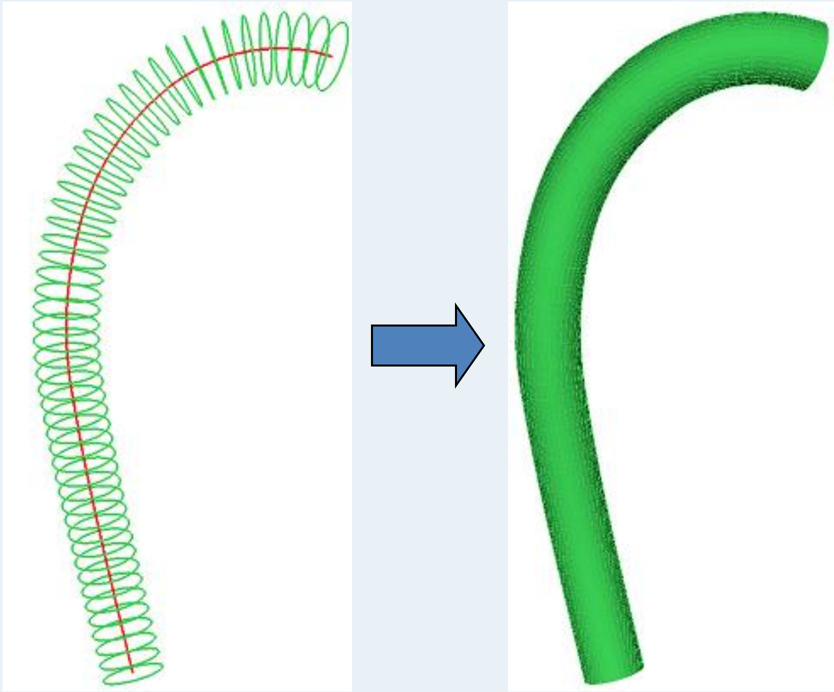
# Segmentation: boundaries



**blue** = reference **red** = method

# Segmentation: boundaries

- **Continuous surface from discrete contours**
  - RGC model [Azencot & Orkisz, Graph Mod 2003, Flórez-Valencia *et al*. ICIP 2006, MICCAI 2009]
  - piece-wise constant parameters
    - curvature and torsion of the axis – helix
    - derivatives of the Fourier coefficients of the contours
  - parameter identification
    - Kalman filter
    - direct access to measures
      - diameters
      - areas
    - **quantification**



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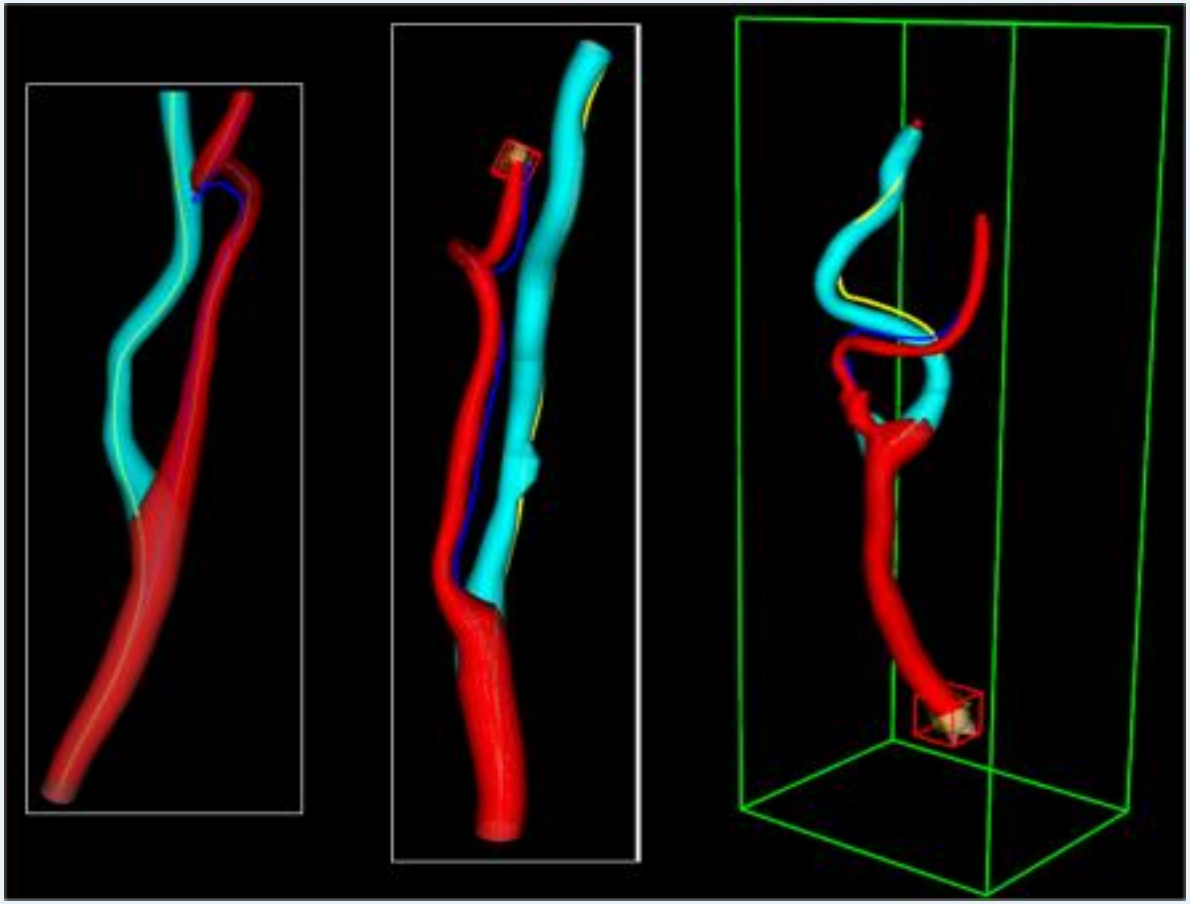
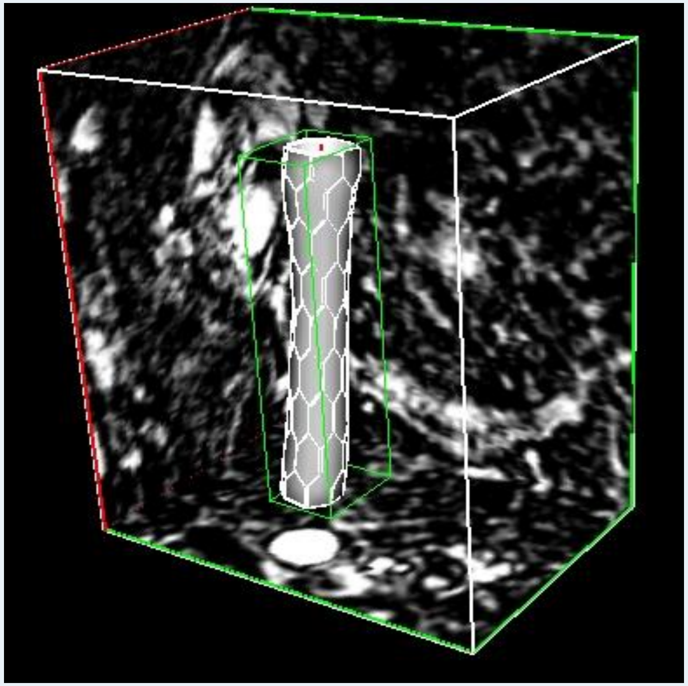


- **Deformable surface initialized by the centerline**
  - simplex model (mesh)

$$E_{simplex} = \int_{\Omega} E_{\text{int}}(t) + E_{\text{ext}}(t)dt$$



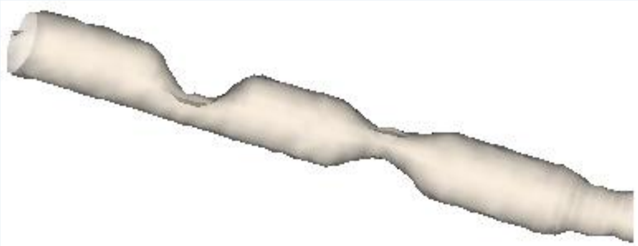
- the internal force preserves continuity and smoothness
- the external forces attract the model to the boundaries in the image
- **specific cylindrical forces preserve overall shape**

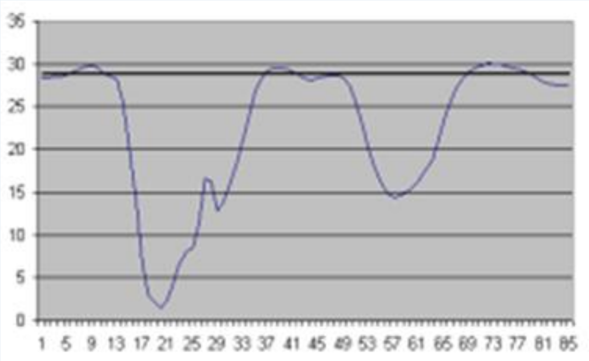
$$\mathbf{v}_i^{t+1} = \mathbf{v}_i^t + \gamma(\mathbf{v}_i^t - \mathbf{v}_i^{t-1}) + \lambda\left(\mathbf{f}_i^{\text{int}} + \beta \mathbf{f}_i^{\text{ext}}\right)$$
$$+ (1-\lambda)\left(\mathbf{f}^{\text{axial}}(\mathbf{v}_i^t) + \mathbf{f}^{\text{radial}}(\mathbf{v}_i^t)\right)$$

# Outline

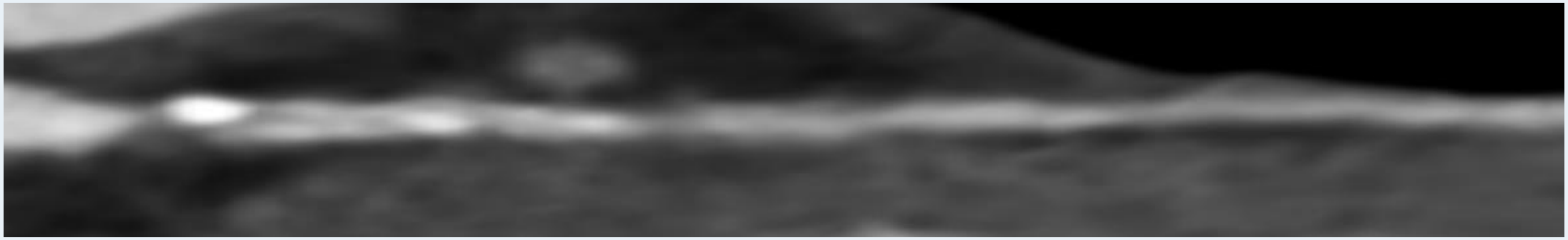
- **Angiographic imaging**
- **Filtering/denoising**
  - Local orientation estimation
  - Medialness measures
- **Model-based segmentation/quantification**
  - Centerline extraction
  - Boundary extraction
- **Lesion detection**
- **Vascular tree extraction**

- **Stenosis quantification**





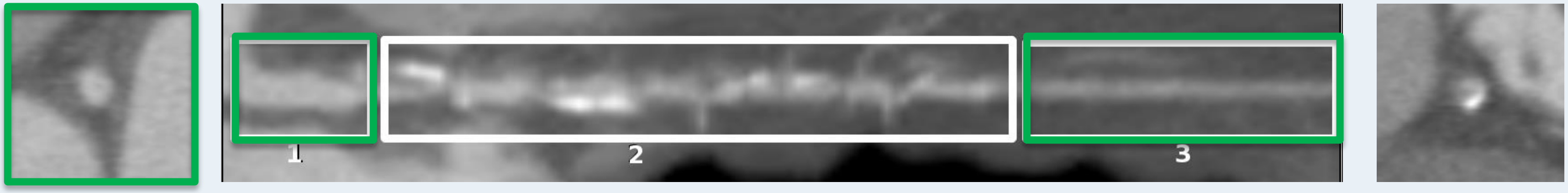

- **Stenosis degree is not the only risk factor**
  - risk depends on plaque composition



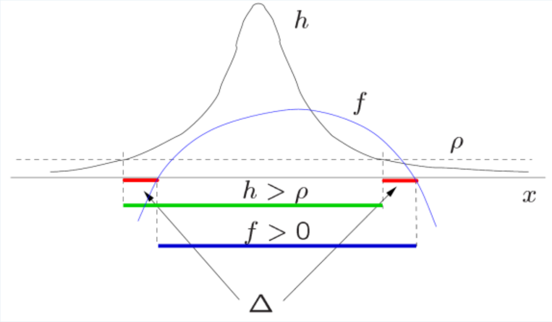
  - need to detect all lesions regardless their nature
    - attract user's attention
    - display together with stenosis degree

# Lesion detection

- **No deterministic model of the lesions**
  - variable shape and locations, overlapping intensity range
  - modality-dependent appearance
- **Machine learning**
  - supervised – requires many representative labels
    - all types of lesions
    - normality
  - unsupervised – no labels needed
  - semi-supervised – labels only for normality
    - based on cross-sections [Zuluaga *et al*. IJCARS 2011, MICCAI 2011, IRBM 2014]

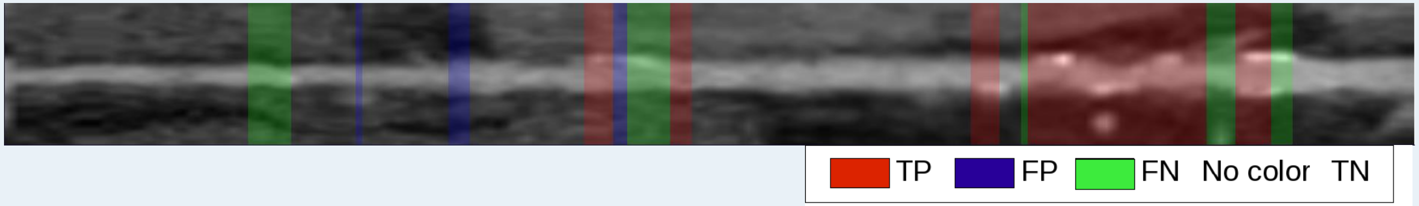


- **Density-level detection**
  - content density of probability distribution in feature space
    - high = normality : $h > \rho$
    - outliers = abnormalities : $h \leq \rho$
    - $\rho$ is unknown !
  - seek normality and deduce abnormalities from the complement
    - find a function $f$ such that $f > 0$ best approximates $h > \rho$
      - use an empirical risk function
      - solve the problem using Support Vector Machine
  - Unsupervised version (DLD-SVM)
    - TPR = 0.86 , underestimates lesions
    - TNR = 0.82, detects bifurcations as abnormalities

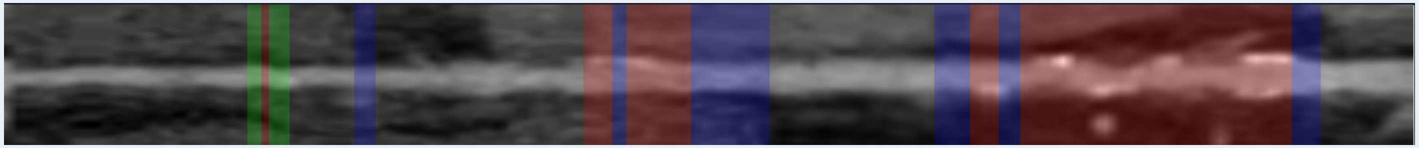


## Lesion detection

**DLD-SVM**



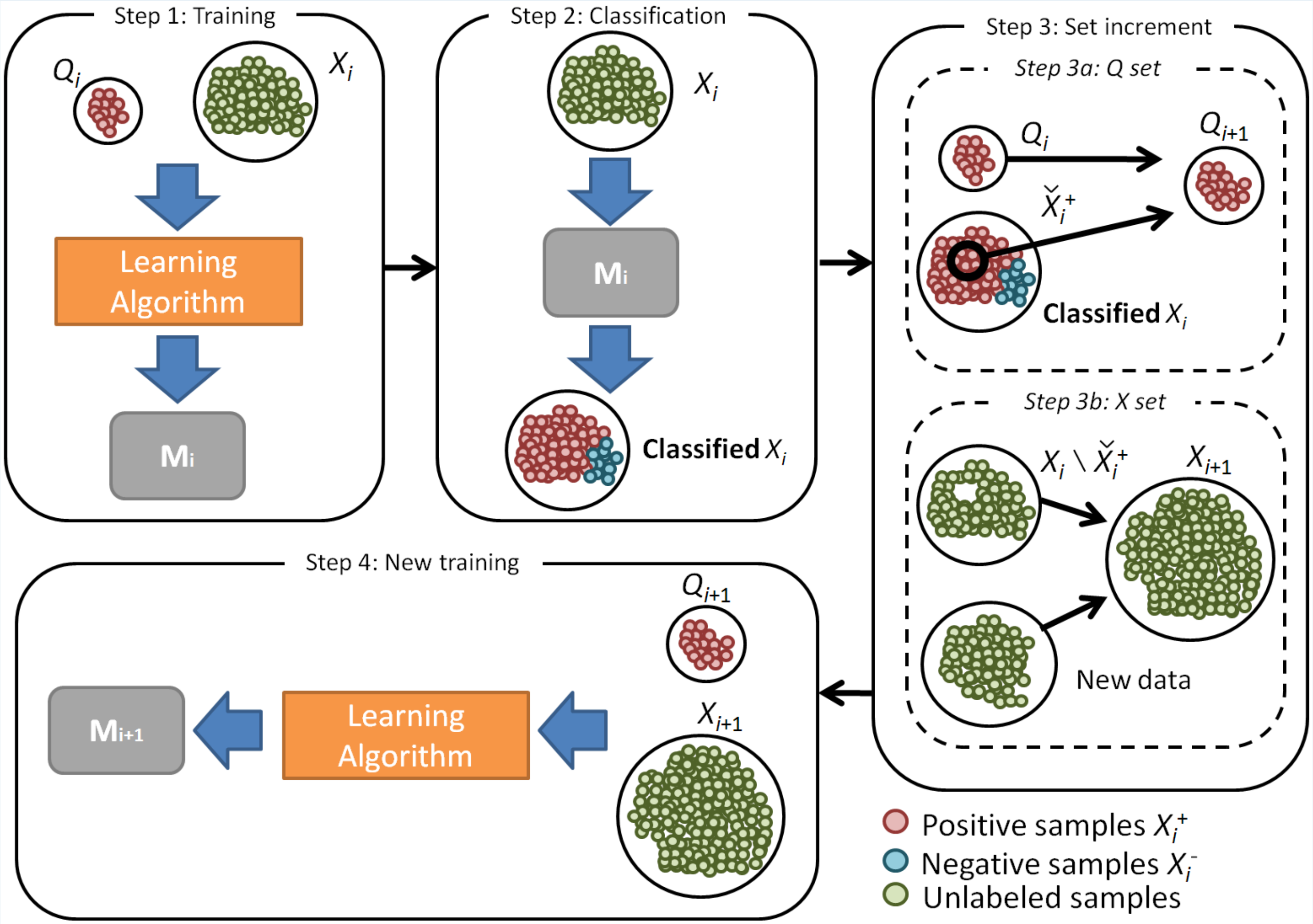

- **Semi-supervised version**
  - LPU = learning from positive and unlabeled samples



  - reasonable accuracy with a small number of labeled samples
  - tends to overestimate abnormalities (unseen normal samples)
  - can iteratively include new knowledge

# Lesion detection

- **Semi-supervised version**
  - LPU = learning from positive and unlabeled samples



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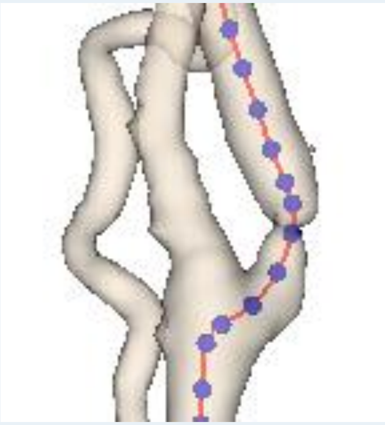
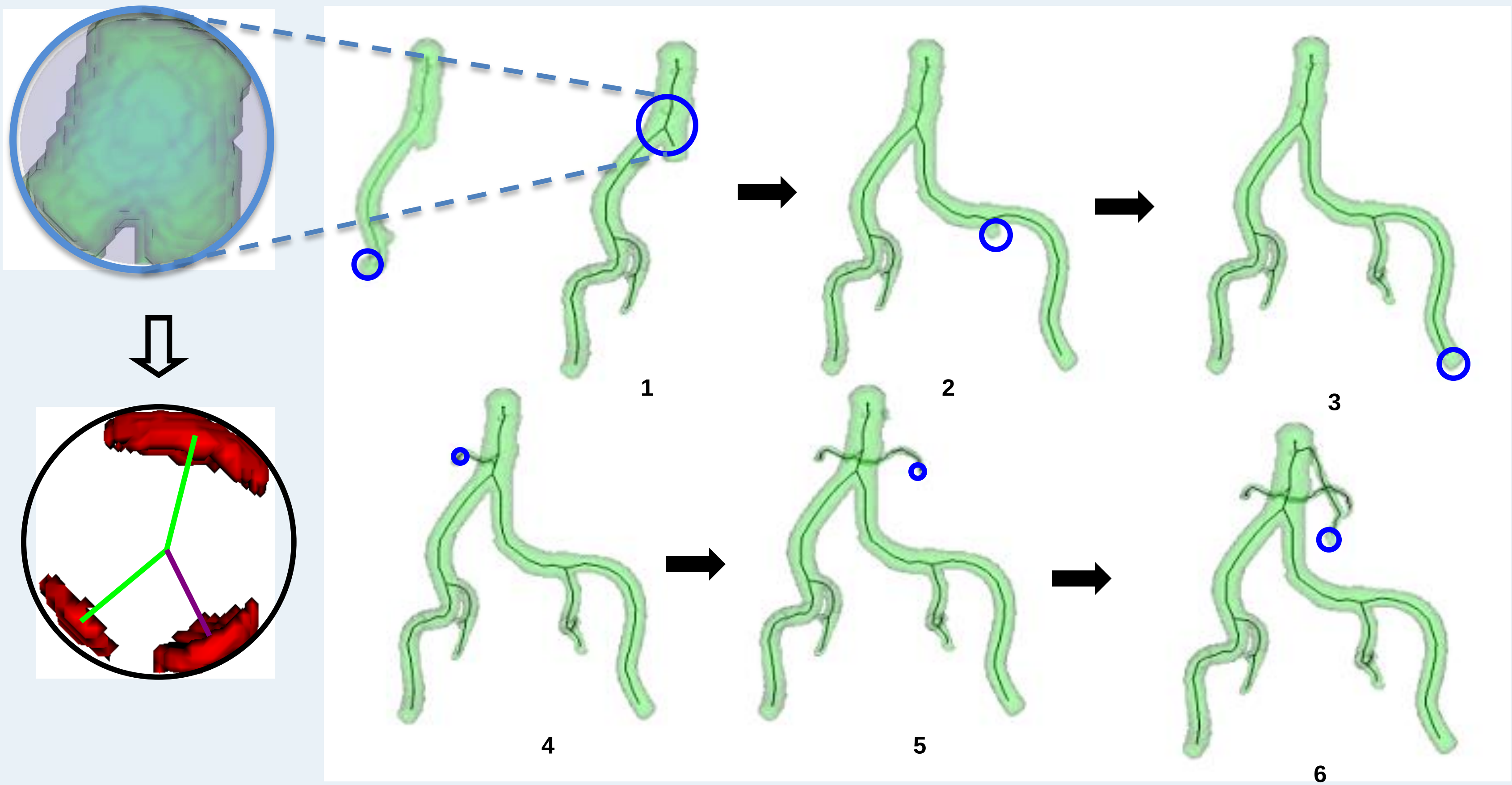
# Tree extraction



- **What about branching points?**
  - ignored may disturb
    - centerline location and orientation
    - boundary detection – quantification
    - lesion detection
  - whole tree is needed to fully automate a CAD system
- **Examples of approaches**
  - recursive tracking
    - extract mother branch in its full extent
    - detect branching points and extract each daughter branch, etc.
  - minimum-cost paths
    - find end-points
    - connect them to the root

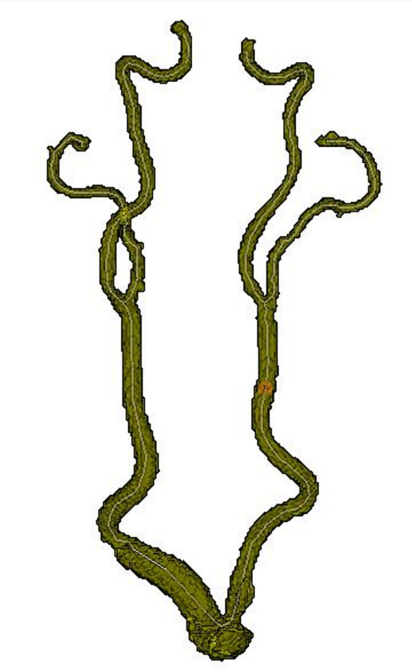
# Tree extraction : recursive tracking

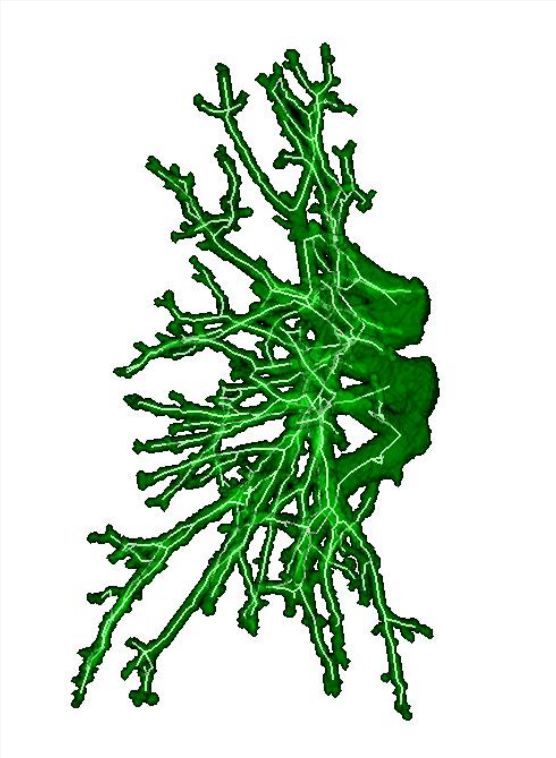
- **Connected components analysis [Carrillo *et al*. IJCARS 2006]**
  - surface of an adaptive spherical cell

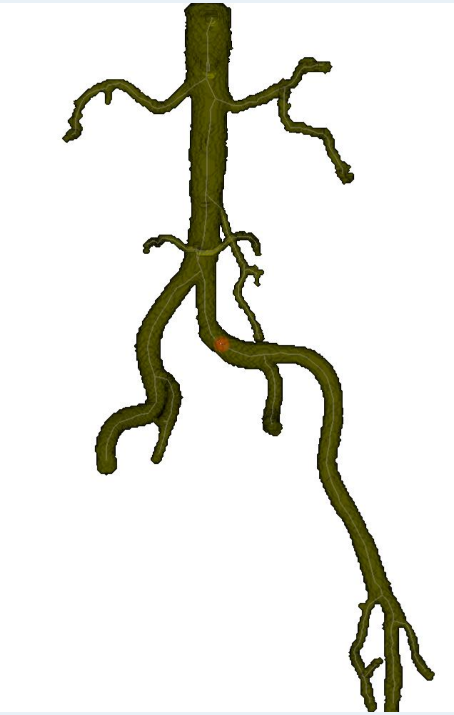


# Tree extraction : recursive tracking

- **Limitations**
  - tends to stop on stenoses
  - trade-off between detecting bifurcations and tracking


Carotid MRA

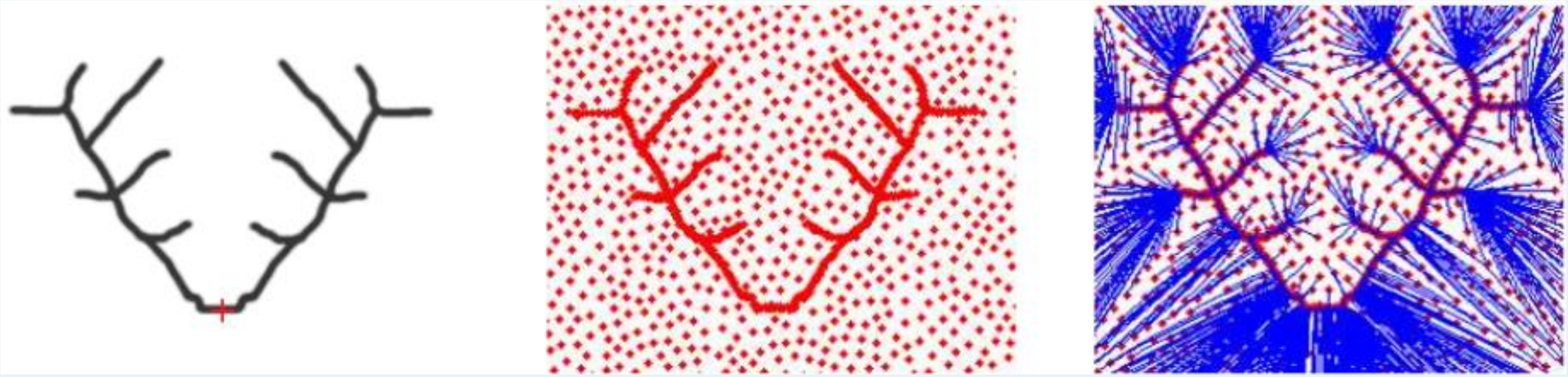

Pulmonary CTA


Aorto-iliac MRA


Coronary CTA

# Tree extraction : minimum-cost paths

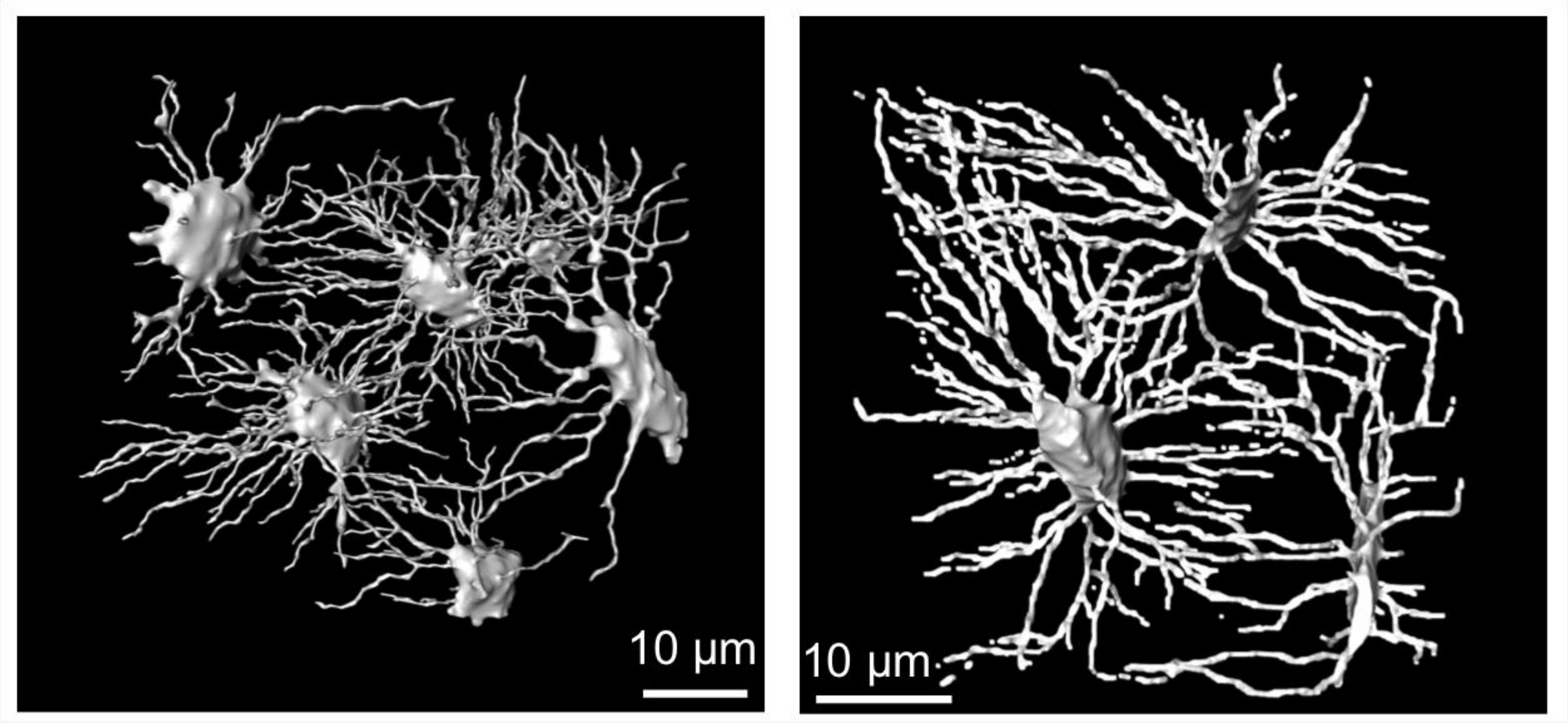
- **Geodesic voting [Rouchdy&Cohen, ICPR 2008]**
  - one starting point / multiple end-points
  - paths converge towards vessels
  - counting paths that pass through each pixel



  - continuity is guaranteed
  - how to scatter the end-points?
  - how to reduce computational time?

# Tree extraction : minimum-cost paths

- **Geodesic voting [Zuluaga *et al*. PMB 2014]**
  - 3D images of bone lacuno-canalicular networks
  - Voronoi tesselation from lacunae centroids
    - starting point at the centroid
    - end-points on the dilated Voronoi-cell sufrace



# Conclusions

- **Use simple algorithms where applicable and keep sophisticated ones for difficult regions**
  - evaluate existing solutions
  - detect difficult cases
- **Semi-automatic methods**
  - smart interaction (and visualization)
- **Performance comparison**
  - challenges
  - open data and metadata
  - open source