Segmentation of the pulmonary vascular trees in 3D CT images using variational region-growing

IMA 204

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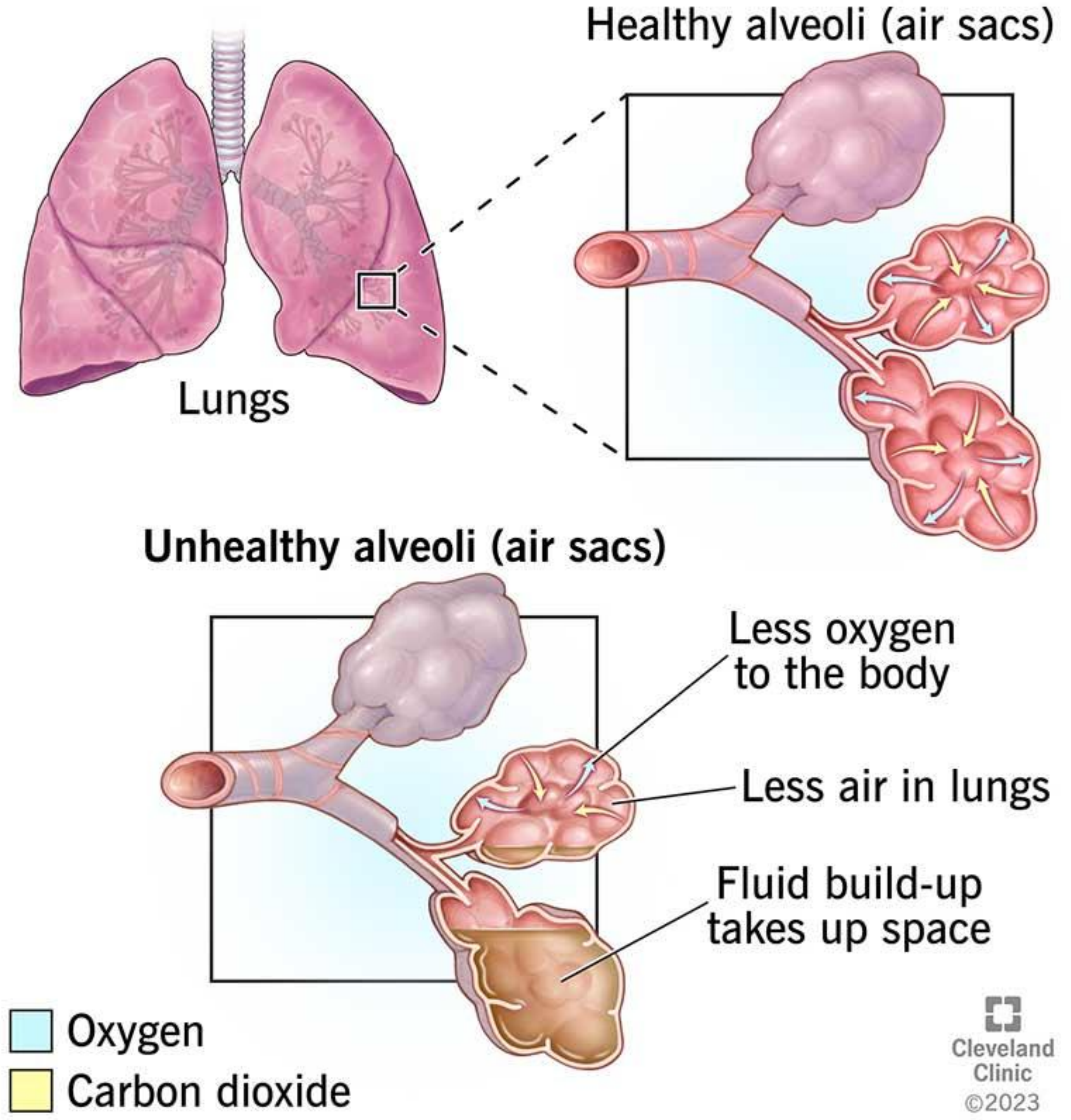
Acute Respiratory Distress Syndrome (ARDS)



Intense pulmonary inflammation and hyperpermeability caused by different aggressions affecting the functional tissues of the lungs.

How to automatically quantify lung aeration in ARDS CT images ?

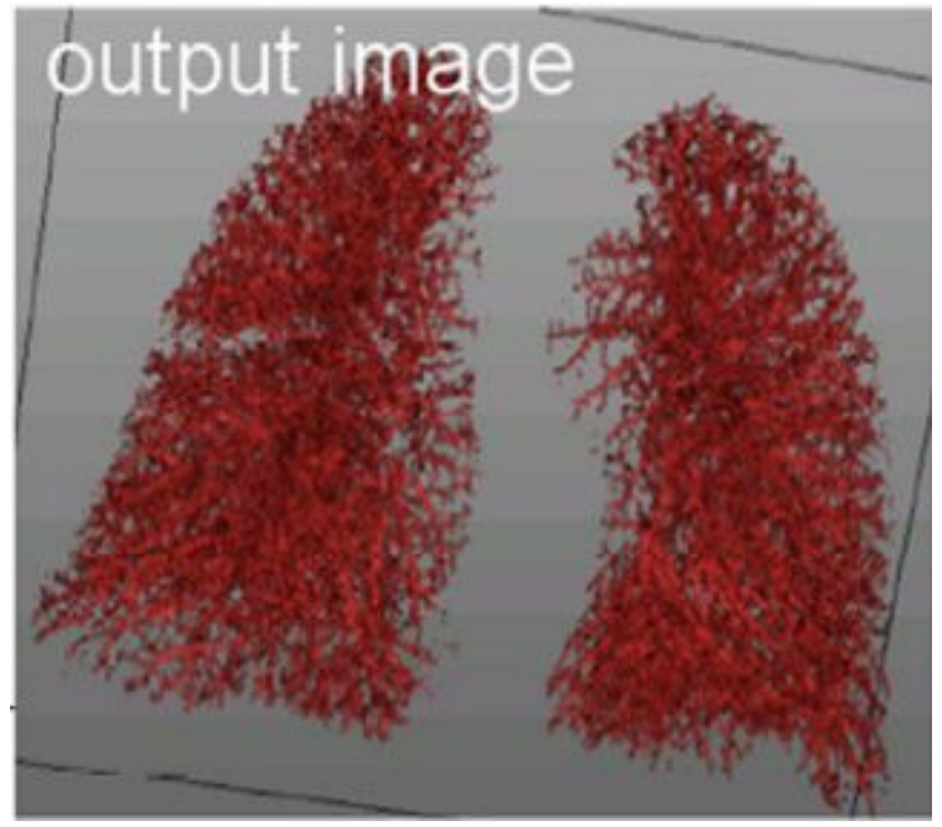
Objective of the article

Quantification of lung aeration in 3D CT scans requires :

- Lung delineation
- Separation of airways and blood-vessels

Goal :
Present a method to segment pulmonary vascular trees and evaluate it

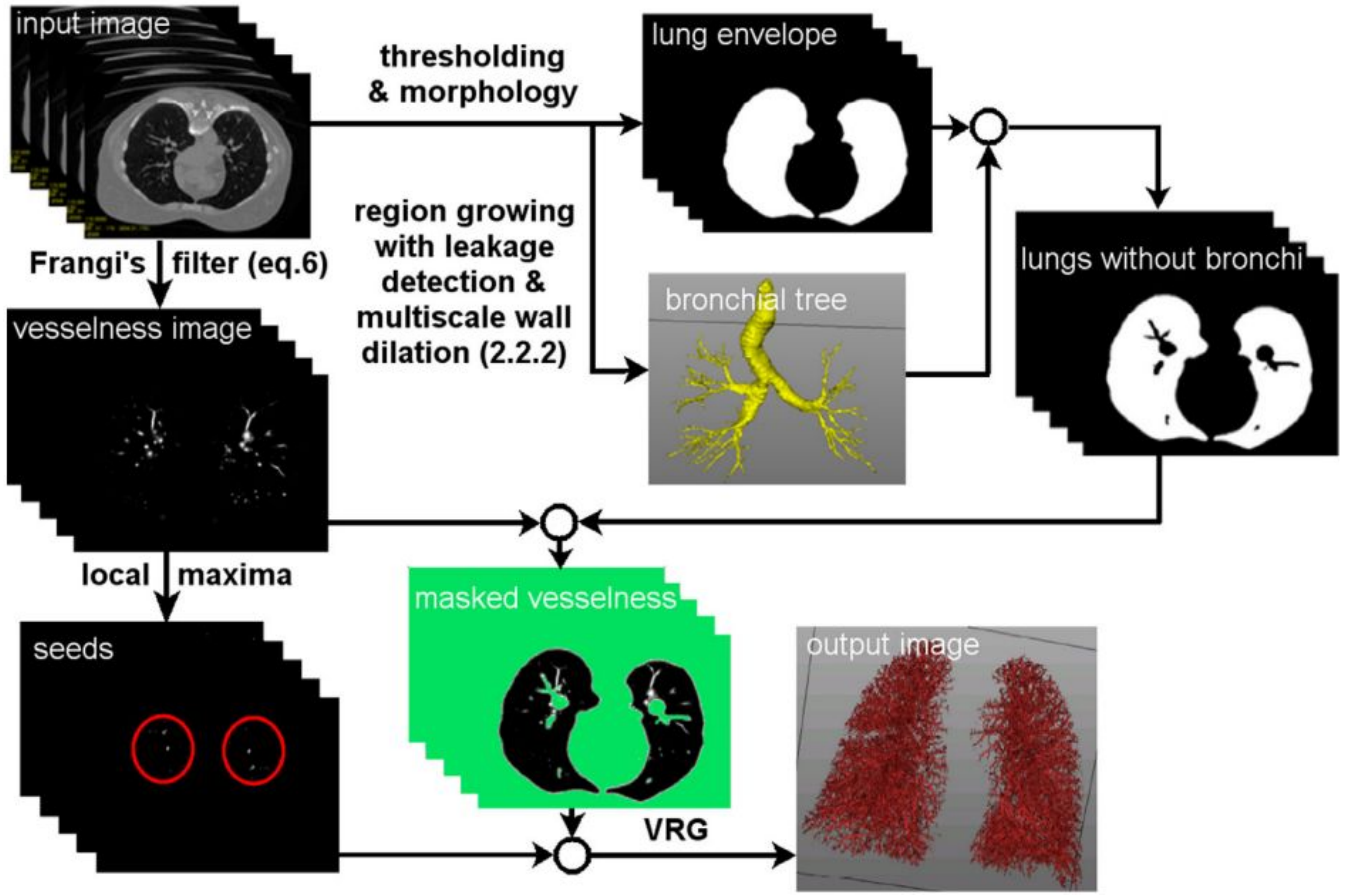
lung 3D CT image



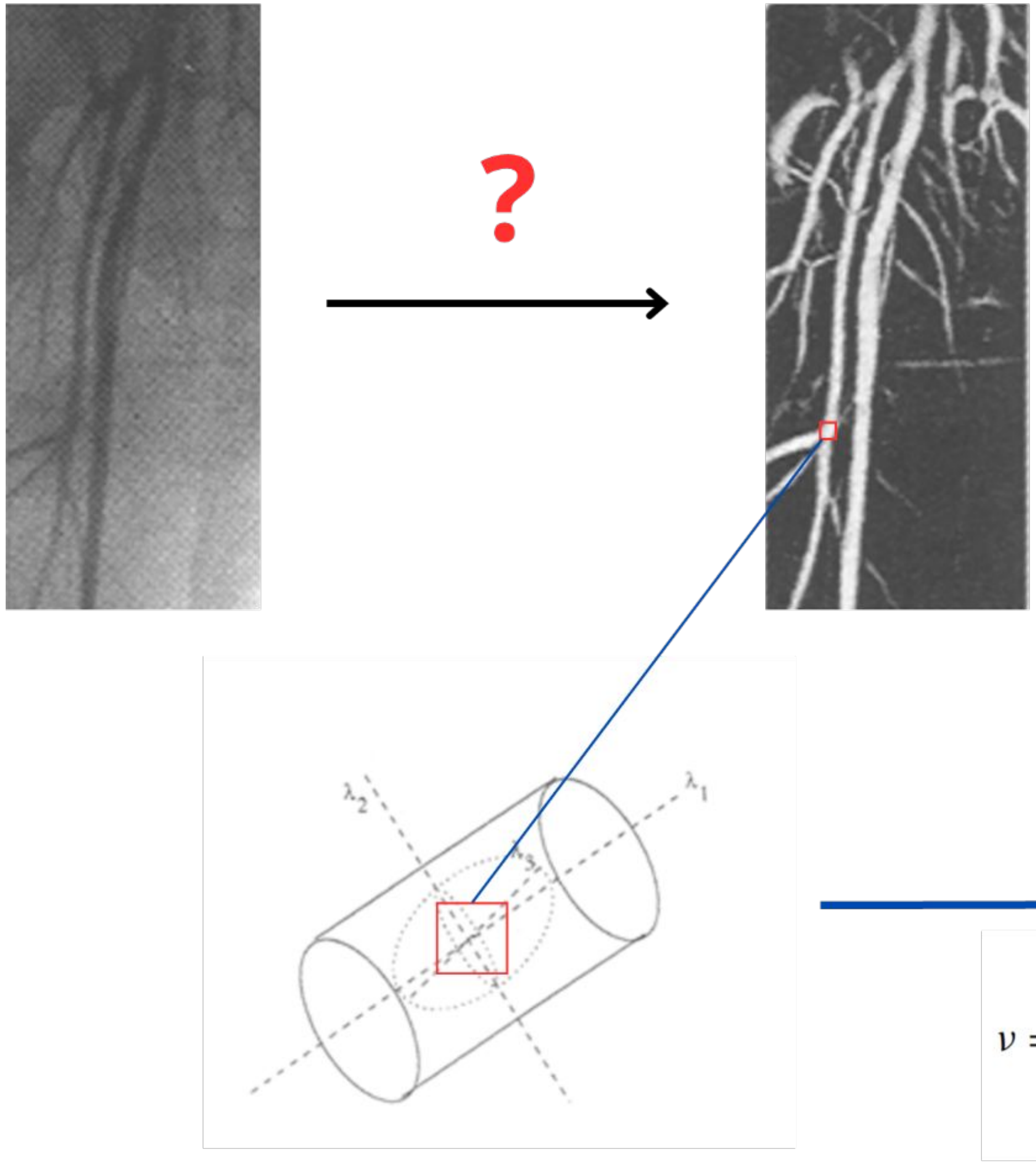
segmented vascular trees

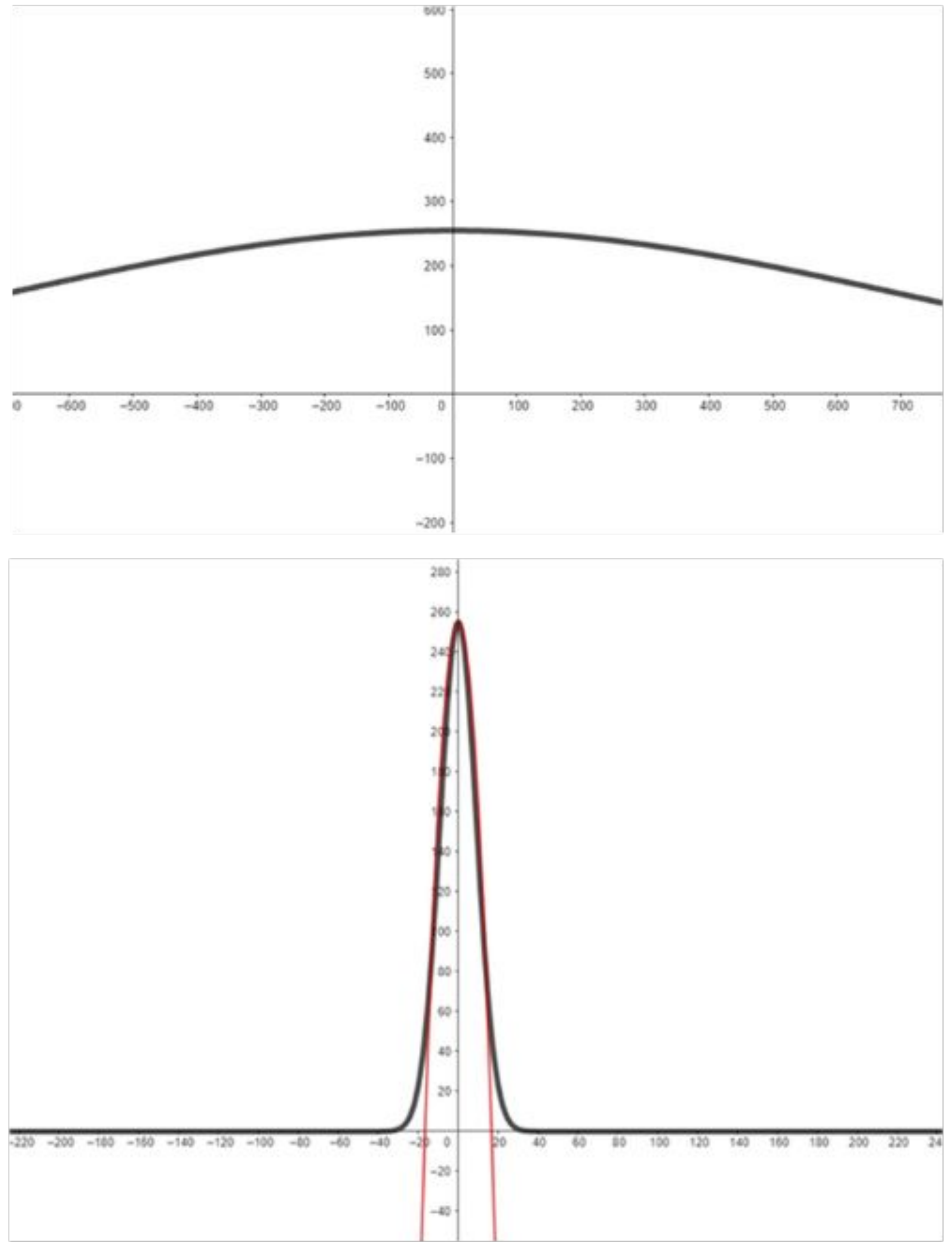
Main steps of the method

- Segmentation of the lung envelope and extraction of the bronchial-tree
- Computation of the “vesselness image” and detection of the seed-points
- Final segmentation of the vascular trees starting from the seeds using VRG



Methodology





The red pixel is located at the center of a vessel.

$$\Longleftrightarrow$$

$$\lambda_3 \approx \lambda_2 \ll \lambda_1 \approx 0$$

$$R_A = |\lambda_2/\lambda_3|$$

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

$$S = \|\mathrm{H}\|_F = \sqrt{{\lambda_1}^2 + {\lambda_2}^2 + {\lambda_3}^2}$$

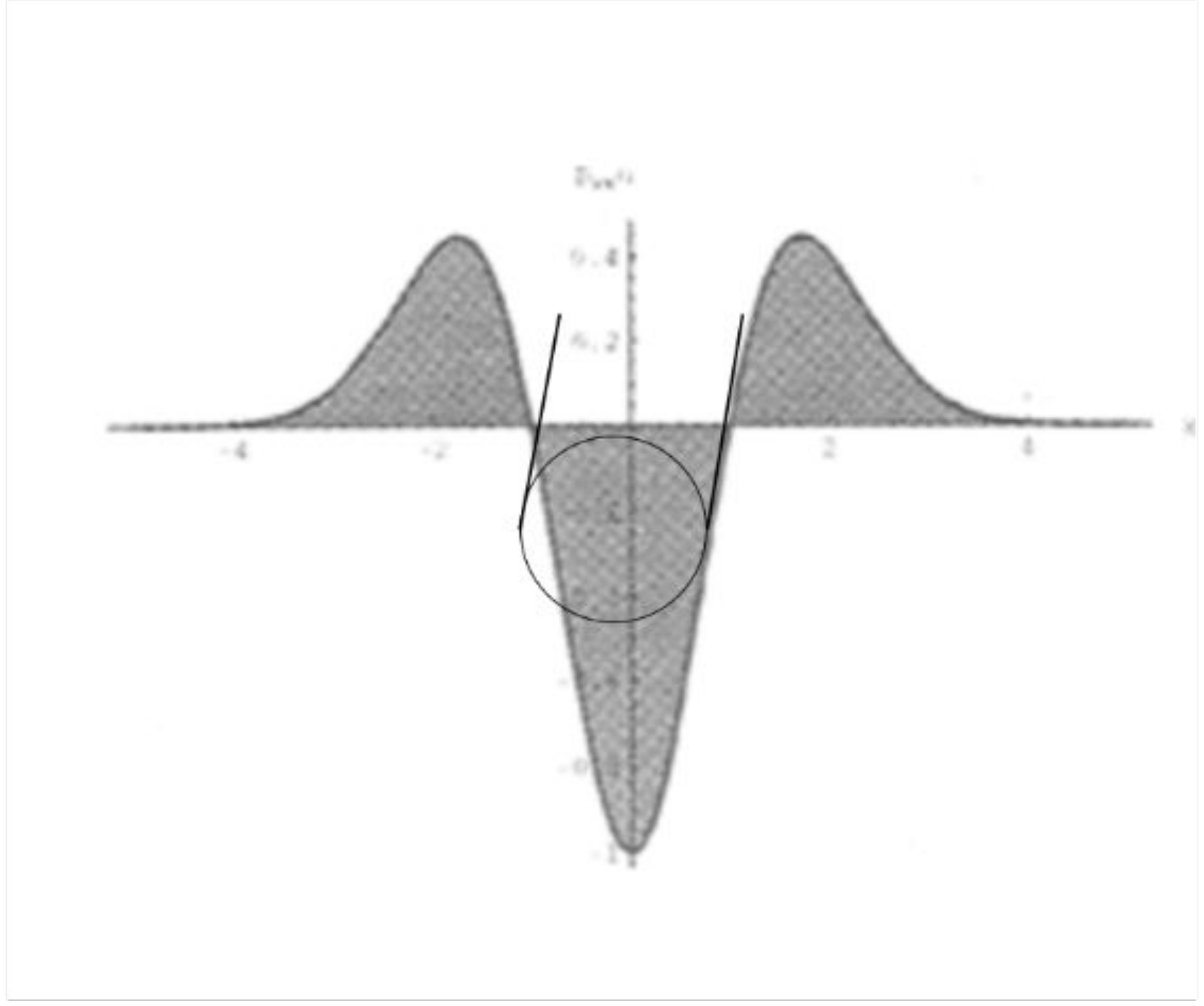
$$\nu = \begin{cases} 0, \text{ if } \quad \lambda_2 > 0 \text{ or } \quad \lambda_3 > 0 \\ \left(1 - \exp\left(-\frac{{R_A}^2}{2\alpha^2}\right)\right) \exp\left(-\frac{{R_B}^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right), \text{ otherwise,} \end{cases}$$

Methodology

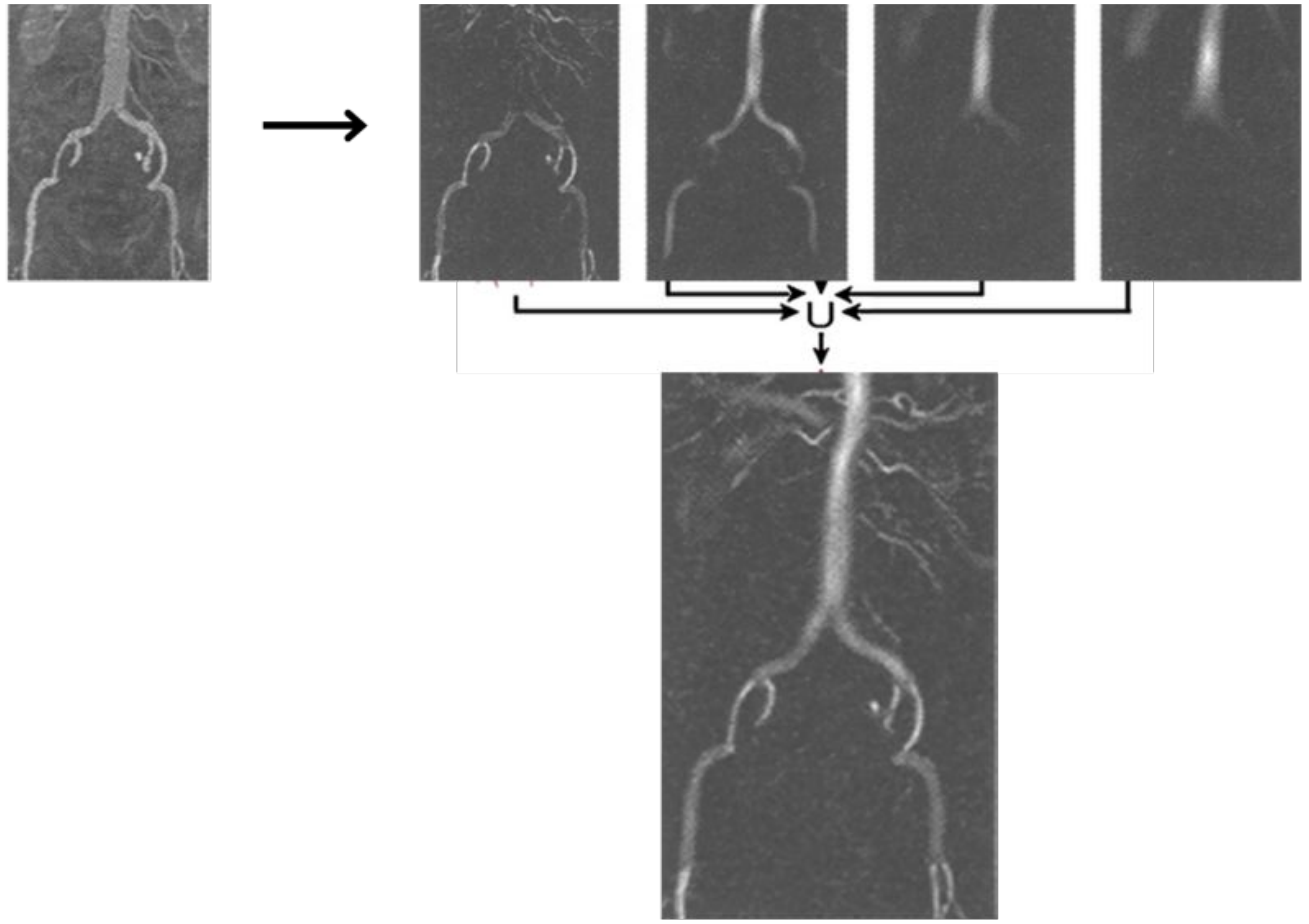
Implementation:

$$H_{ij}(\mathbf{x}, s) = s^2\, I(\mathbf{x}) * \frac{\partial^2}{\partial x_i \partial x_j} G(\mathbf{x}, s) \;\; \text{for } i, j = 1, \ldots, D,$$

$$G(\mathbf{x}, s) = (2\pi s^2)^{-D/2} \exp(-\mathbf{x}^{\mathrm{T}}\mathbf{x}/2s^2)$$



- Enables a multi-scale analysis by adjusting the parameter σ of the Gaussian kernel to match the local radii of the vessels.
- Retains the most significant response across different scales.

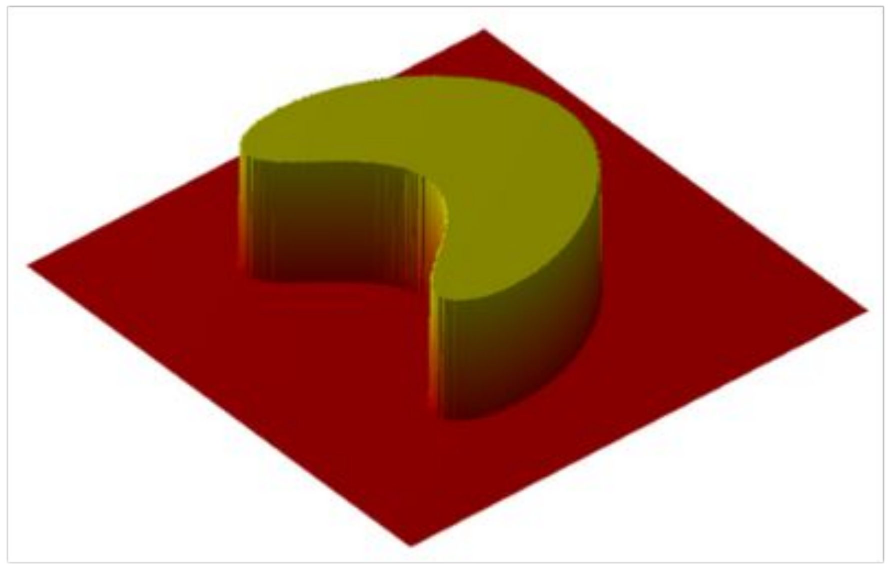


Optimisation :

The diagonalization process is computationally expensive, so we first analyze the Hessian matrix calculated in the canonical basis using matrix invariants:

$$\det(\mathrm{H}(x)) = \lambda_1.\lambda_2.\lambda_3 \qquad \mathrm{tr}(\mathrm{H}(x)) = \lambda_1 + \lambda_2 + \lambda_3$$

Methodology



$$\phi(\mathbf{x}) = \begin{cases} 1, & \text{if } \mathbf{x} \in \Omega_{\text{in}} \\ 0, & \text{if } \mathbf{x} \in \Omega_{\text{out}} \end{cases}$$

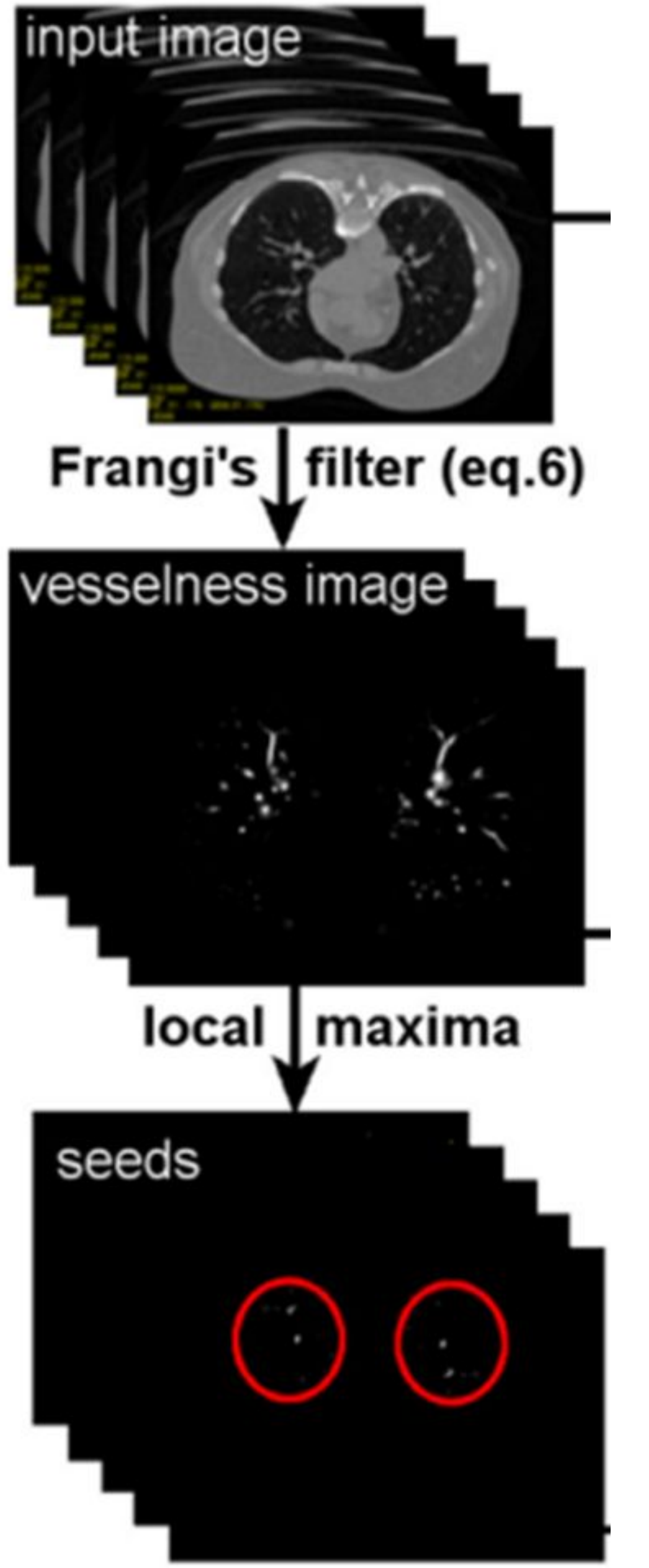
- Formulate segmentation as an optimization problem: minimizing an energy
- Grow the initial inner Ω_{in} by adding Ω_{out} out Voxels at each iteration until reaching the minimum of the energy J.

$$J(\phi^n) = \sum_{\mathbf{x} \in \Omega} k(\mathbf{x})\, \phi^n(\mathbf{x})$$

$$J\left(\phi^{n+1}\right) = J\left(\phi^n\right) + \Delta J\left(\phi^{n+1}\right)$$

$$\phi^{n+1}(\mathbf{x}) = \frac{1}{2}\left(1 - \operatorname{sign}\left(\Delta J\left(\phi^{n+1}\right)\right)\right)$$

$$\Delta J\left(\phi^{n+1}(\mathbf{x})\right) = \left(1 - 2\phi^n(\mathbf{x})\right) k(\mathbf{x})$$



Methodology

Region descriptor for pulmonary vascular trees

VRG incorporates a shape prior (tubular in this case) via the function k defined as follows :

$$k(\mathbf{x}) = \frac{\nu(\mathbf{x})}{M_\nu}\left(\left|\nu(\mathbf{x}) - \mu_{\nu_{\text{in}}}\right|^2 - \left|\nu(\mathbf{x}) - \mu_{\nu_{\text{out}}}\right|^2\right) + \frac{f(\mathbf{x})}{M_f}\left(\left|f(\mathbf{x}) - \mu_{f_{\text{in}}}\right|^2 - \left|f(\mathbf{x}) - \mu_{f_{\text{out}}}\right|^2\right)$$

where :

$\nu(\mathbf{x})$: the value of "vesselness" ν at a voxel $\mathbf{x}$

$\mu_{\nu_{\text{in}}}$ $\mu_{\nu_{\text{out}}}$: the mean value of ν calculated within the vessels segmented thus far (Ω_{in}) and within the background (Ω_{out}) respectively

$f(\mathbf{x})$: the value of the image intensity at a voxel $\mathbf{x}$

$\mu_{f_{\text{in}}}$ $\mu_{f_{\text{out}}}$: the mean value of f in Ω_{in} and Ω_{out} respectively

Methodology

Elimination of bronchial wall

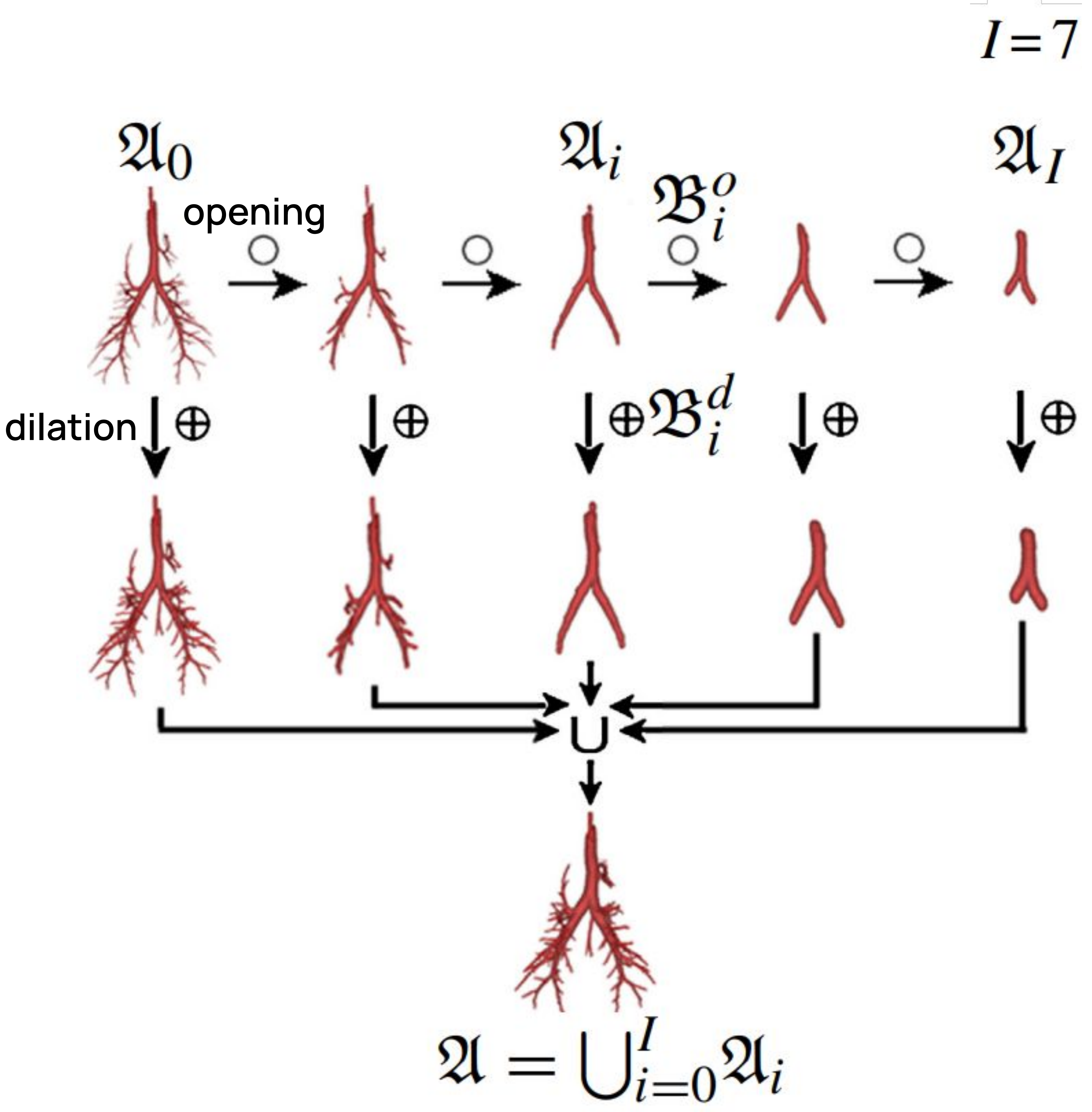
- First step : a series of morphological opening with ball-shaped structuring elements of increasing radius :

$$r_i^o = 2\,(i + 1)$$

- Second step : morphological dilation of each tree using ball-shaped structuring elements also with increasing radius :

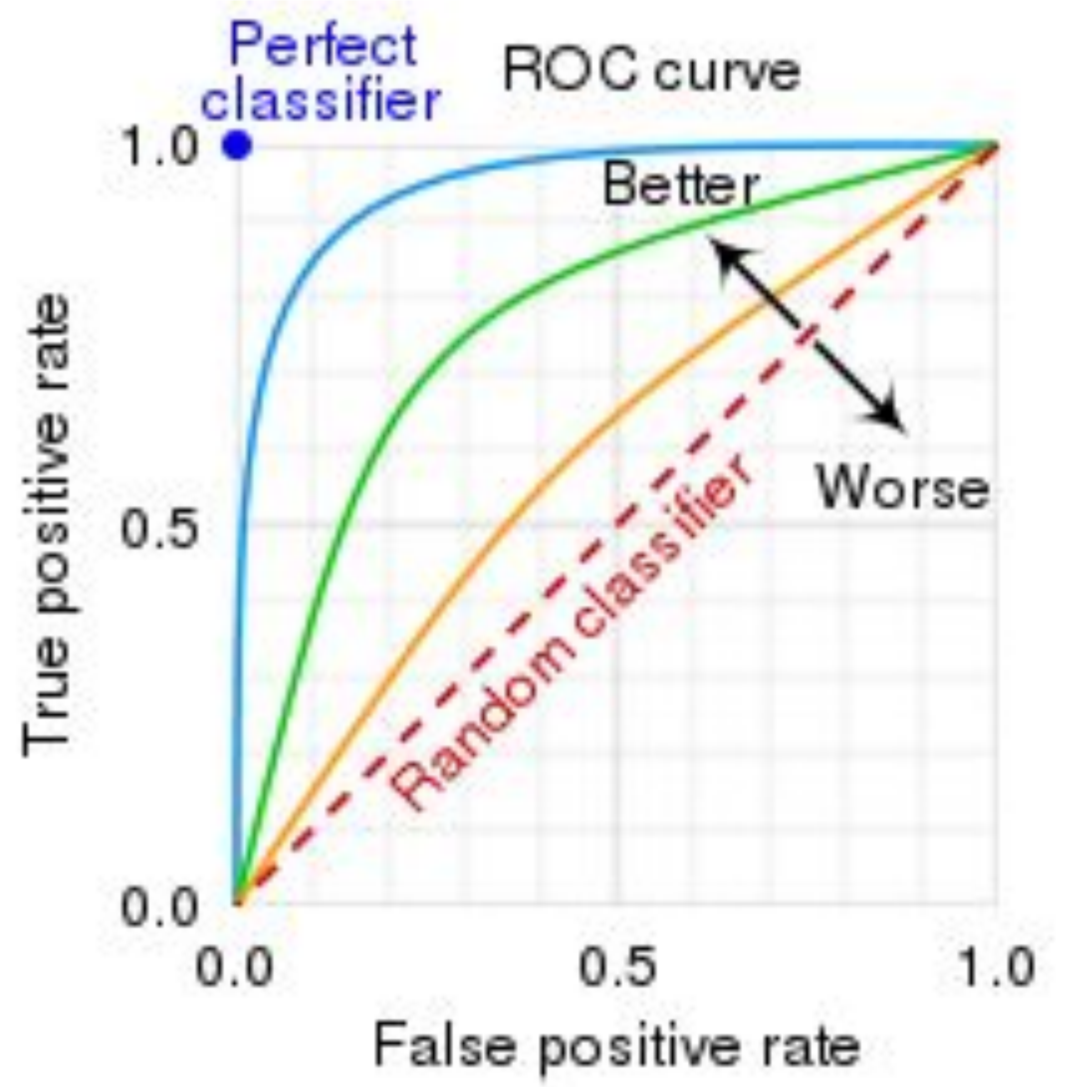
$$r_i^d = i + 1$$

- Final tree : the union of all individually dilated trees. It covers the airway lumen and walls.



Data and evaluation criteria

- 20 chest CT scans for evaluation and 3 additional scans for training.
- Diversity in sources, imaging protocols, and diseases (presence of emphysema, nodules, and pulmonary embolisms in about half of the datasets).
- About half of the datasets were acquired after contrast agent injection.
- The image resolution is nearly isotropic with voxel sizes ranging from 0.6 to 1.0 mm.
- The images were annotated by three observers for the purpose of evaluation.

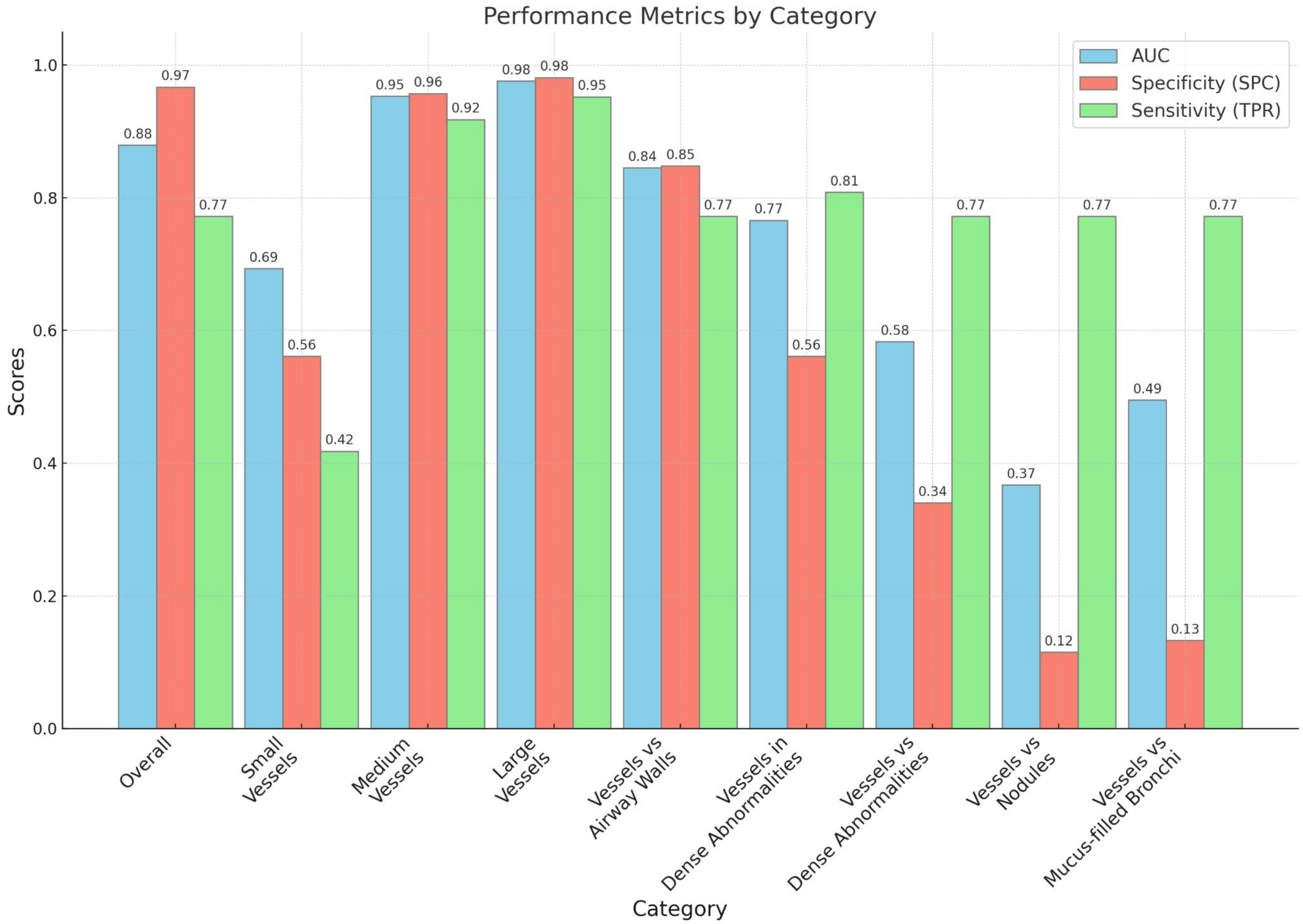


$$TPR = TP/(TP + FN)$$

$$SPC = TN/(FP + TN)$$

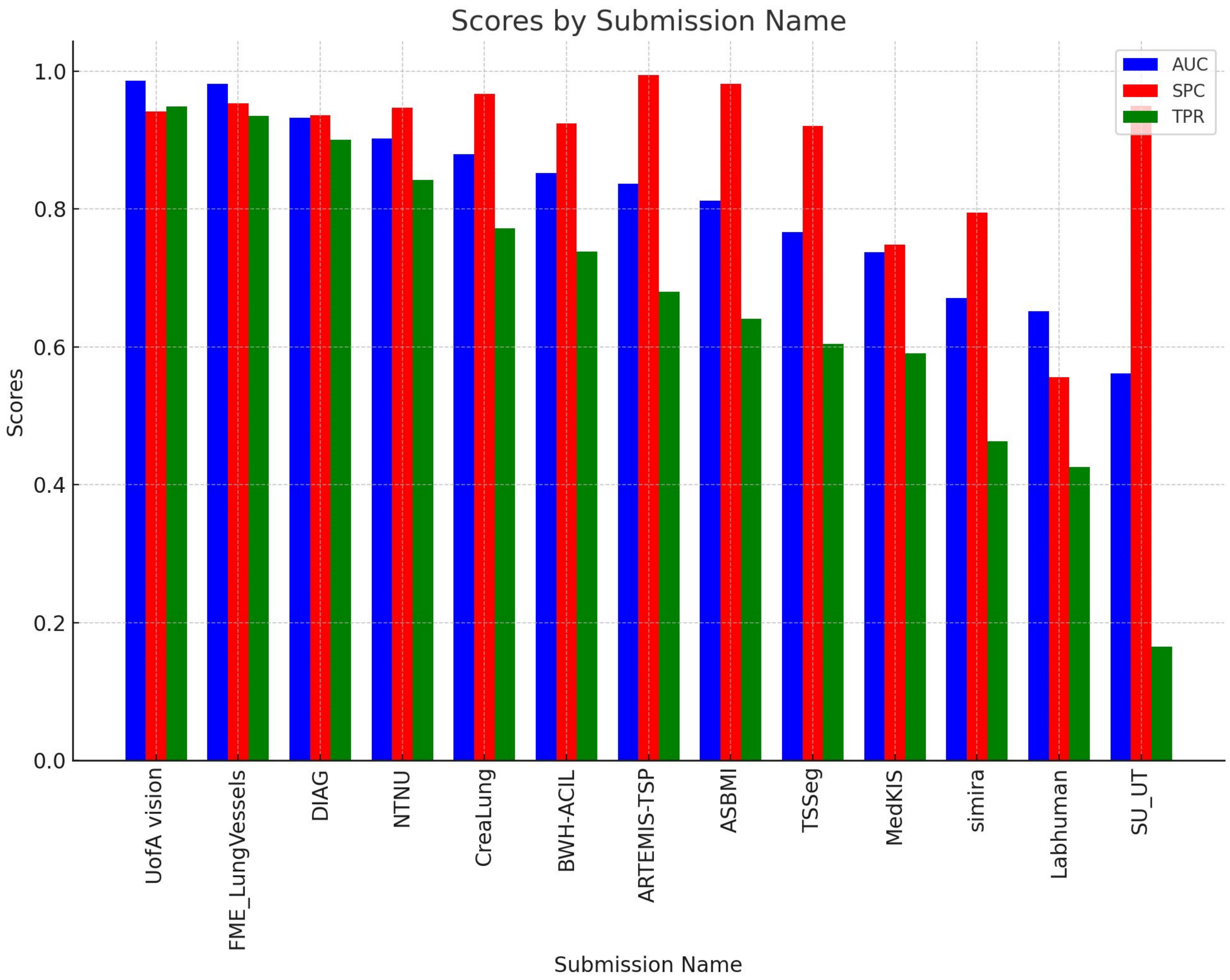
area under the curve (AUC)

Results

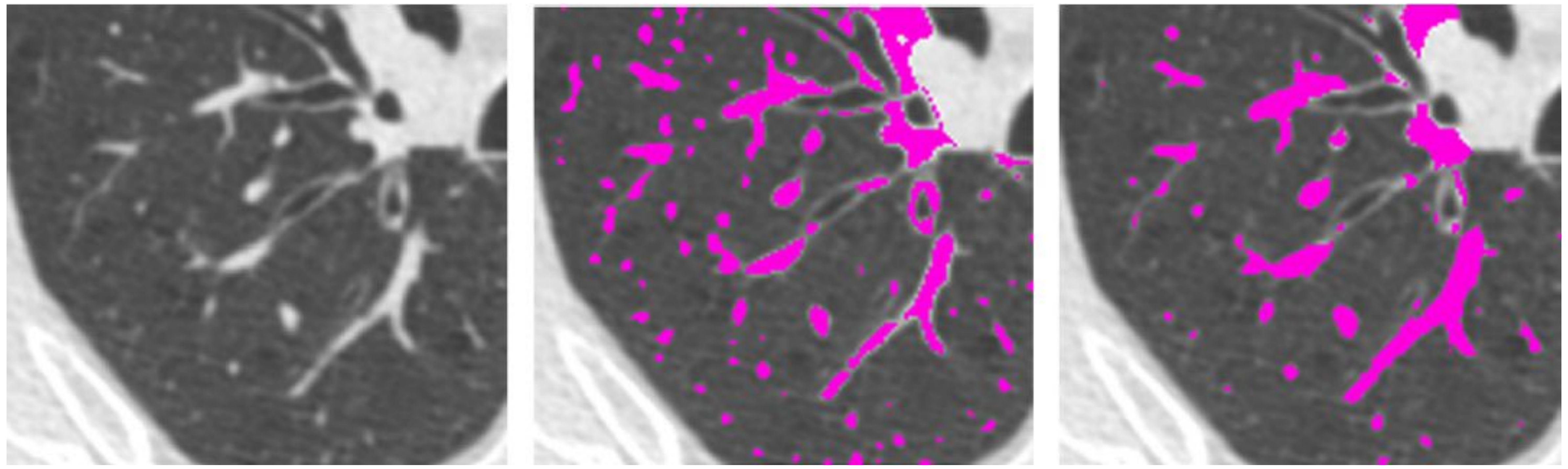


Performance Metrics by Category
AUC
Specificity (SPC)
Sensitivity (TPR)
Scores
1.0
0.8
0.6
0.4
0.2
0.0
0.88 0.97 0.77
0.69 0.56 0.42
0.95 0.96 0.92
0.98 0.98 0.95
0.84 0.85 0.77
0.77 0.56 0.81
0.58 0.34 0.77
0.37 0.12 0.77
0.49 0.13 0.77
Overall
Small Vessels
Medium Vessels
Large Vessels
Vessels vs Airway Walls
Vessels in Dense Abnormalities
Vessels vs Dense Abnormalities
Vessels vs Nodules
Vessels vs Mucus-filled Bronchi
Category

Results

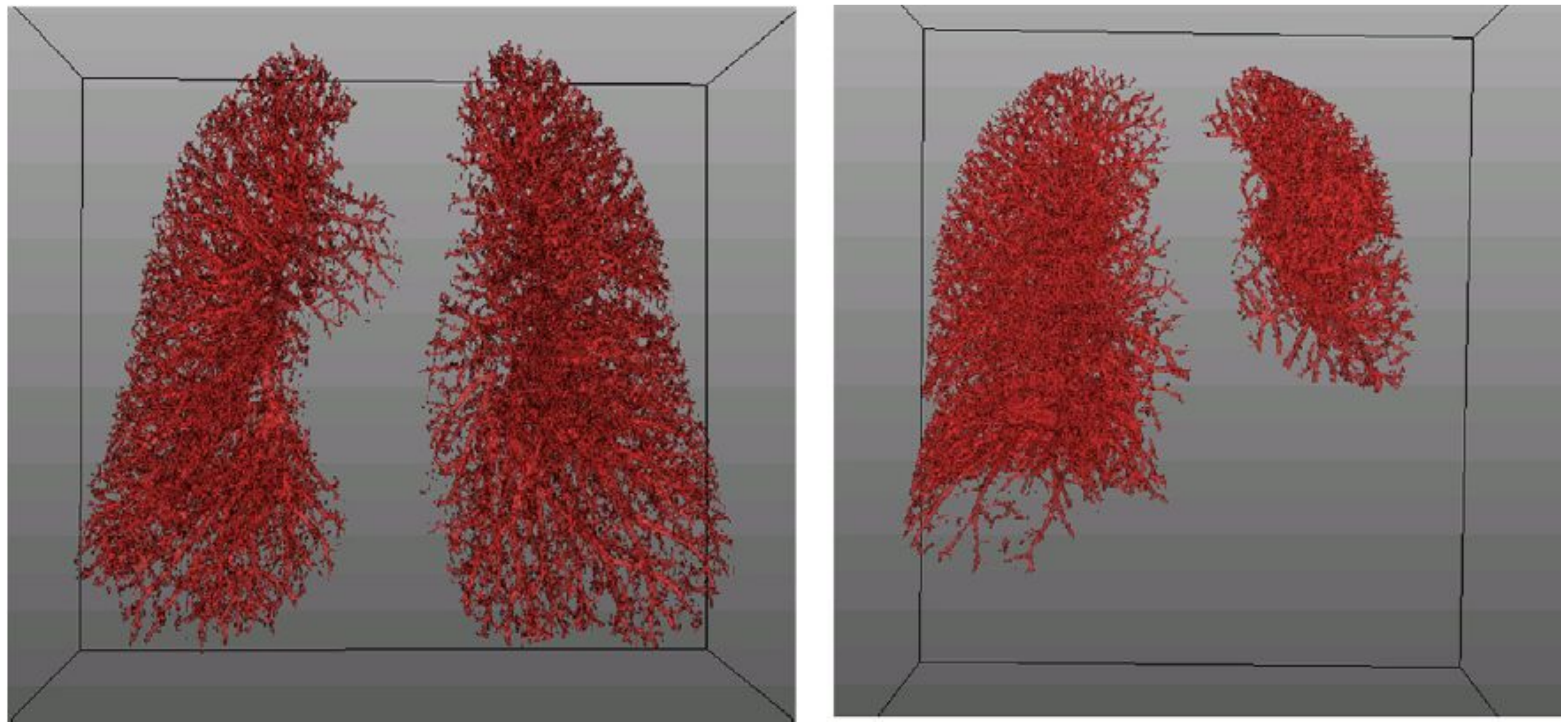

Scores by Submission Name
AUC
SPC
TPR
Scores
1.0
0.8
0.6
0.4
0.2
0.0
UofA vision
FME_LungVessels
DIAG
NTNU
CreaLung
BWH-ACIL
ARTEMIS-TSP
ASBMI
TSSeg
MedKIS
simira
Labhuman
SU_UT
Submission Name

Results



Small-vessel detection.

Airway wall elimination.



Vascular trees segmented by our method

Conclusion

- Key features of this method include the use of a region descriptor for pulmonary vascular trees and a novel approach for eliminating the bronchial wall
- The method shows good specificity but lower sensitivity in detecting small vessels
- It also successfully differentiates vessels from airway walls and detects vessels in dense abnormalities, especially with contrast agent use
- We are optimistic about proceeding with its implementation.
- Improving this method could involve enhancing its sensitivity to small vessels
- Applying this method to other data or applications seems promising

Thank you !

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