MEDICAL IMAGE COMPUTING (CAP 5937)

LECTURE 9: Medical Image Segmentation (III) (Fuzzy Connected Image Segmentation)

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Outline

- Fuzzy Connectivity (FC)
  - Affinity functions
- Absolute FC
- Relative FC (and Iterative Relative FC)
- Successful example applications of FC in medical imaging
- Segmentation of Airway and Airway Walls using RFC based method

Motivation

- Connectivity: a popularly used tool for region growing
- Applications: image segmentation, object tracking, object separation
- A fuzzy model for connectivity analysis is essential to capture the global extent of an object using local hanging togetherness and path connectivity

CE-MRA Image data

Segmented vasculature

Separated arteries/veins

Separation of arteries and veins in a contrast-enhanced magnetic resonance angiographic (CE-MRA) image data using iterative relative fuzzy connectivity

Slide credit: P. Saha

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FC segmentation is a methodology for finding M objects in a digital image based on **user-specified seed points** and **user-specified functions**, called (fuzzy) affinities, which map each pair of image points to a value in the real interval [0, 1].

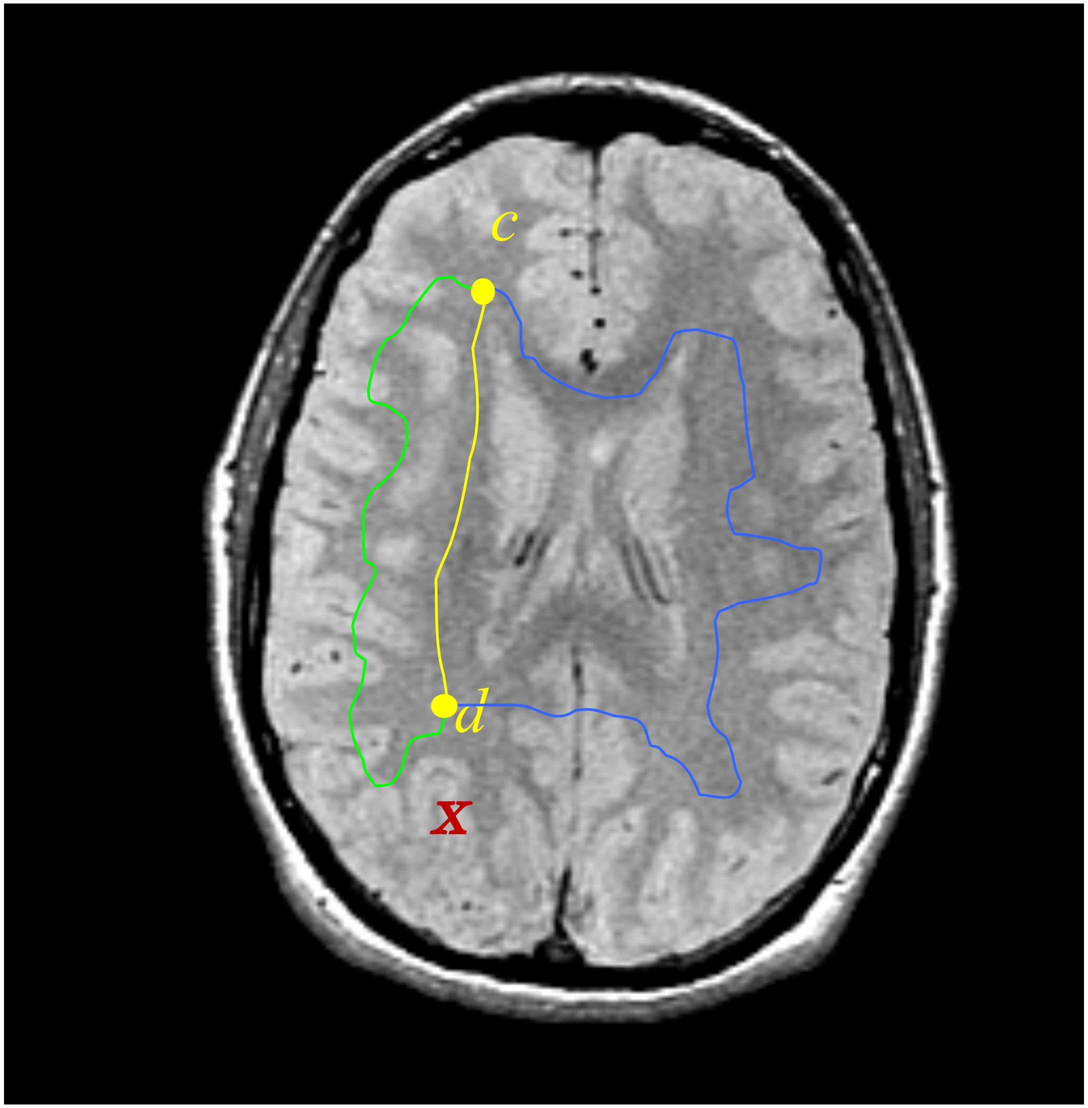
FC Family

- Absolute *FC*
- Scale-based *FC* (*b*-, *t*-, *g*-scale based)
- Relative *FC*
- Iterative Relative *FC*
- Vectorial *FC*
- Hierarchical *FC*
- Model-based *FC*

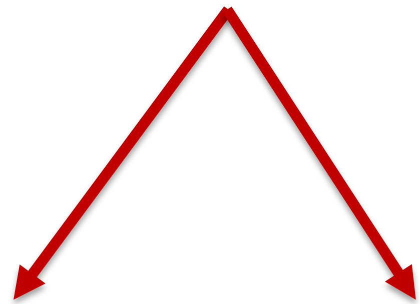
FC Medical Image Segmentation Examples

- MR
  - brain tissue, tumor, MS lesion segmentation
- MRA
  - vessel segmentation and artery-vein separation
- CT bone segmentation
  - kinematics studies
  - measuring bone density
  - stress-and-strain modeling
- CT soft tissue segmentation
  - cancer, cyst, polyp detection and quantification
  - stenosis and aneurism detection and quantification
- Digitized mammography
  - detecting microcalcifications
- Craniofacial 3D imaging
  - visualization and surgical planning

Object Characteristics in the Images



local hanging togetherness
(affinity)



Spatial location

intensity value
(-derived)

FC is a global relation!

- Effectiveness of the FC algorithm is dependent on the choice of **<u>the affinity function</u>**, and the general setup can be divided into three components (for any voxels p and q):

Adjacency Homogeneity Object Feature

<u>FC is a global fuzzy relation between voxels!</u>

All voxels are assessed via defined affinity functions for labelling.

Affinity

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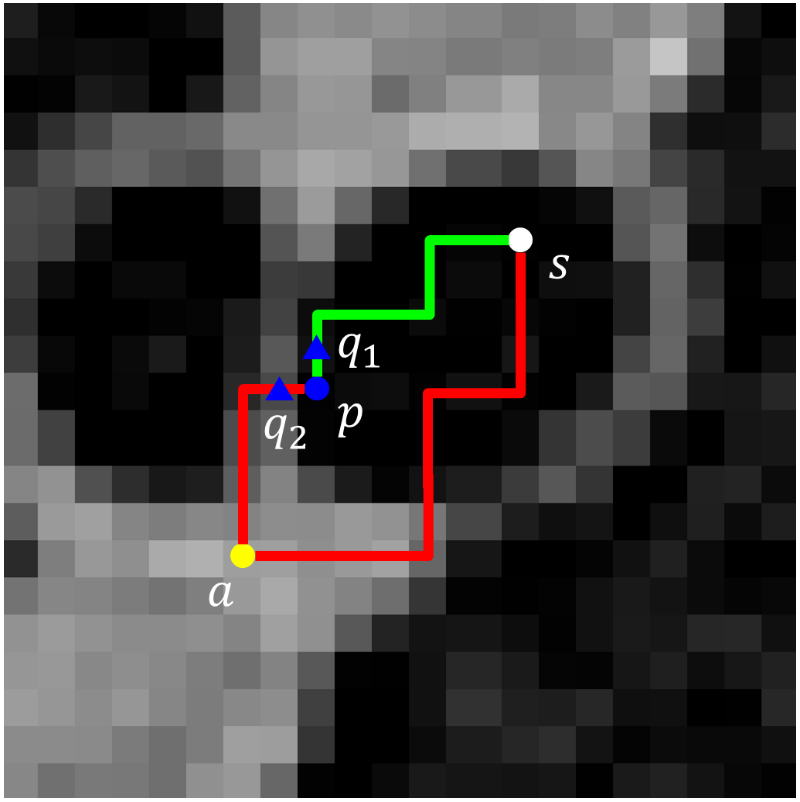
  - If ***u*** and ***v*** are close, affinity should be large



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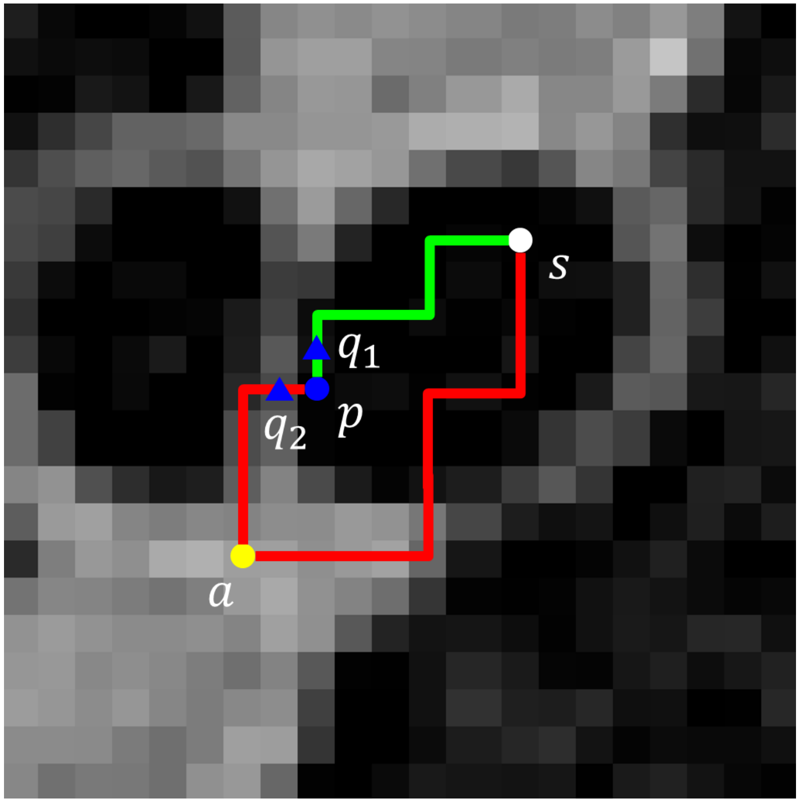

p and q1 hang-together (than p and q2)

Green path is stronger than red path.

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- Its strength $\alpha(a, b)$:

$$\alpha(a, b) = \begin{cases} 1, \text{ if } a = b \\ g(\|a - b\|), \text{ if } \|a - b\| \le D_1 \\ 0, \text{ if } \|a - b\| > D_1 \end{cases}$$

$\mathbf{D_1}$ is a distance (known)
g is a function mapping between [0,1]

Homogeneity and Object Feature Affinities

$$\mu_\psi(p,q) = e^{-\frac{|f(p)-f(q)|^2}{2\sigma_\psi^2}},$$

$$\mu_\phi(p,q) = \min\left(e^{-\frac{|f(p)-m|^2}{2\sigma_\phi^2}}, e^{-\frac{|f(q)-m|^2}{2\sigma_\phi^2}}\right).$$

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$$\kappa(a, b) = h\left[\alpha(a, b),\ \psi(a, b),\ \phi(a, b)\right]$$

Different Affinity Functions can be devised!

$$\Psi(a,b) = e^{-|f(a)-f(b)|}$$

$$\Phi(a,b) = e^{-[\mu \frac{f(a)+f(b)}{2}]^2},$$

f(a) and f(b): intensity values at voxel location a, b.

μ: expected object intensity

Fuzzy Affinity and Path Strength

Fuzzy Affinity (κ): local hanging-togetherness between two spels

- $\kappa(p,q) \in [0,1]$
- $\kappa(p,q)$ is zero if p, q are non-adjacent
- $\kappa(p,p) = 1$, i.e., reflexive
- $\kappa(p,q) = \kappa(q,p)$, i.e. symmetric

Strength (Π) of a path ($\pi = \langle p_1, p_2, \cdots p_l \rangle$)

- $\Pi(\pi)$ = the affinity of the weakest link on the path, i.e.,

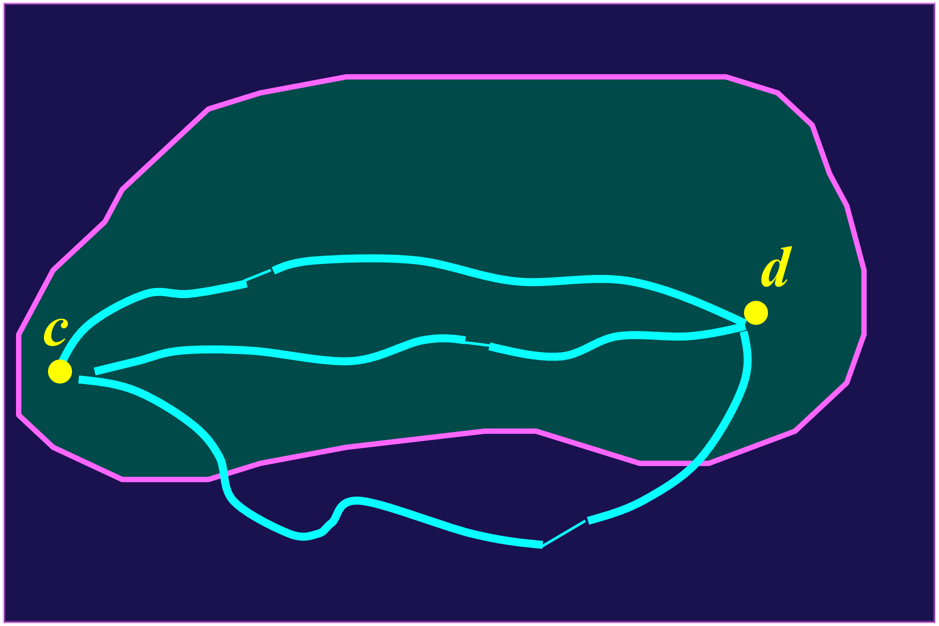
$$\Pi(\pi) = \min_{1 \le i < l} \kappa\left(p_i, p_{i+1}\right)$$

Fuzzy Connectivity

- Fuzzy connectedness is a **global fuzzy relation** K among voxels. Its strength $K(c, d)$ for any c, d is defined as:

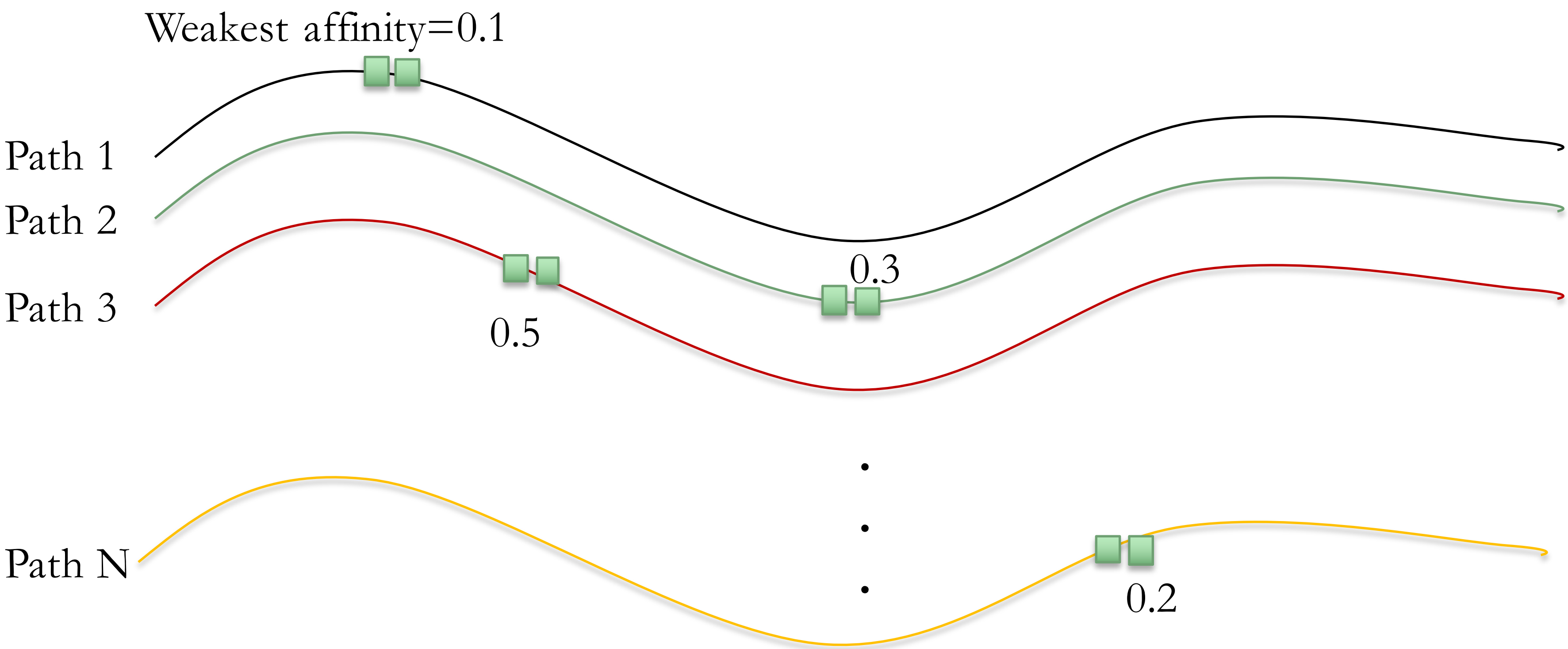
(1) Every path π between c and d has a strength which is the smallest affinity along π.

(2) $K(c, d)$ is the strength of the strongest path.



$$K(c, d) = \max_{\pi} \left\{ \min_{i} \left[\kappa(c_i, c_{i+1}) \right] \right\}$$

Numerical Example



(assuming there are N paths between voxels ***c*** and ***d)***

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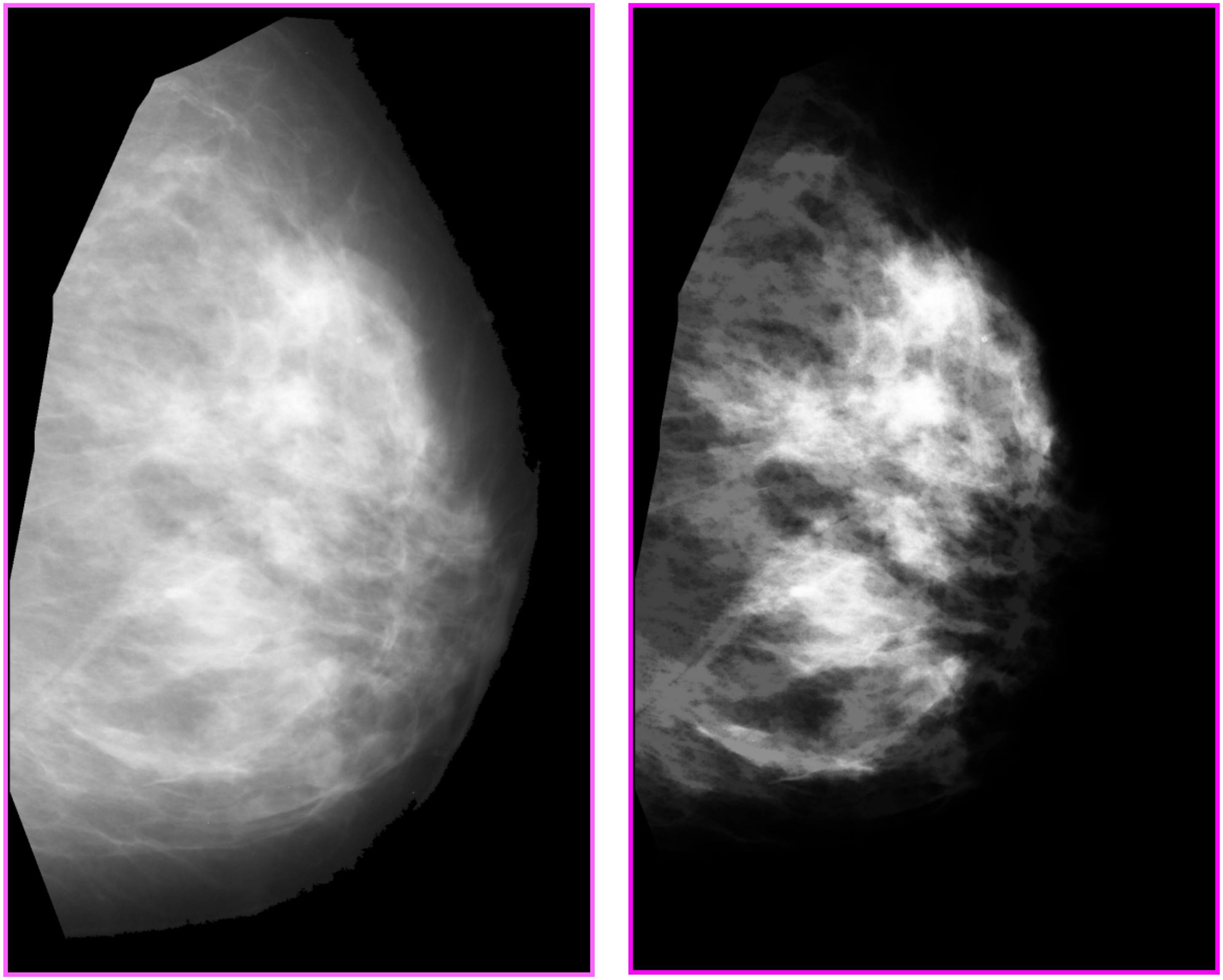
7. Threshold connected map to obtain object containing $\boldsymbol{c}$

(a) (b) (c)

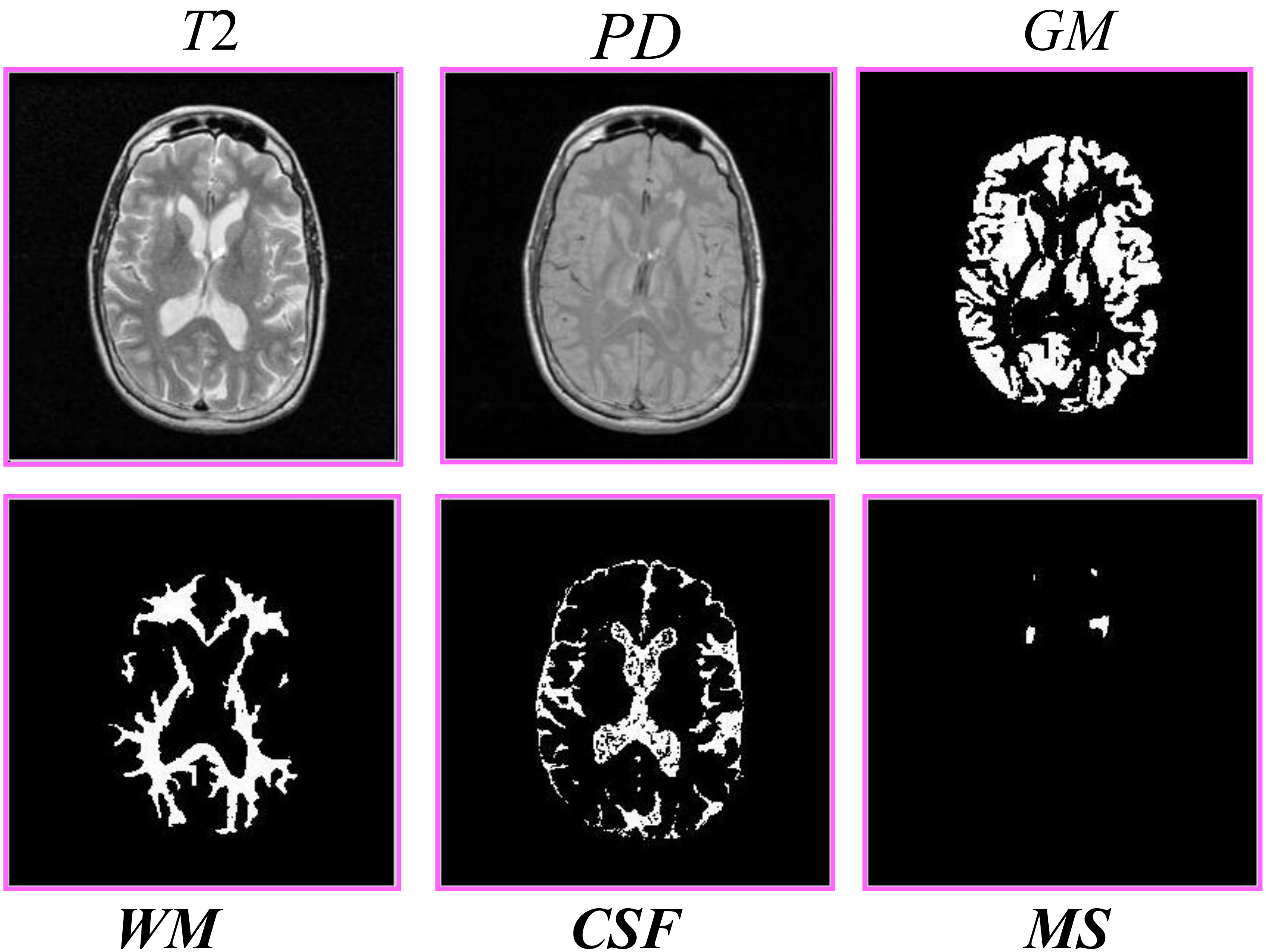
(d) (e)

Illustration of equivalent affinities. (a) A 2D scene — a CT slice of a human knee. (b), (c) Connectivity scenes corresponding to affinities ψ_σ with $\sigma = 1$ and $\sigma = 10.8$, respectively, and the same seed spel (indicated by + in (a)) specified in a soft tissue region of the scene in (a). (d), (e) Identical AFC objects obtained from the scenes in (b) and (c), respectively.

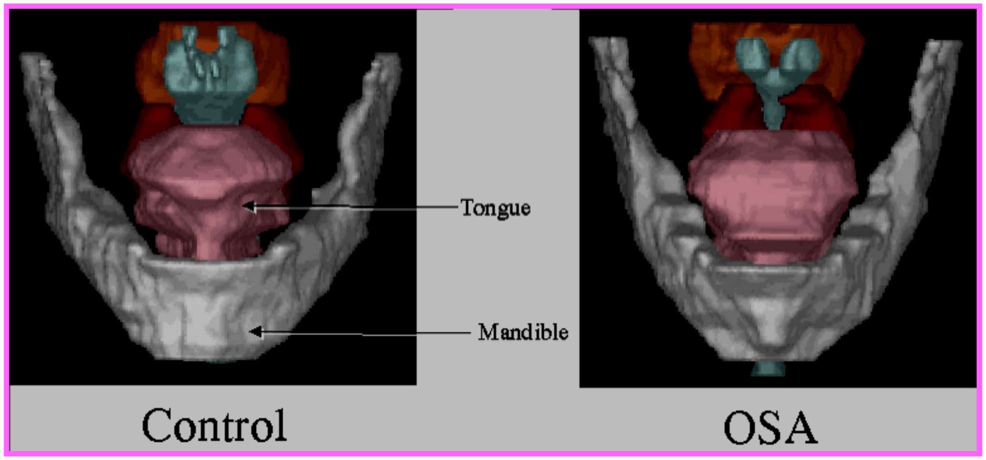
Quantifying Breast Density

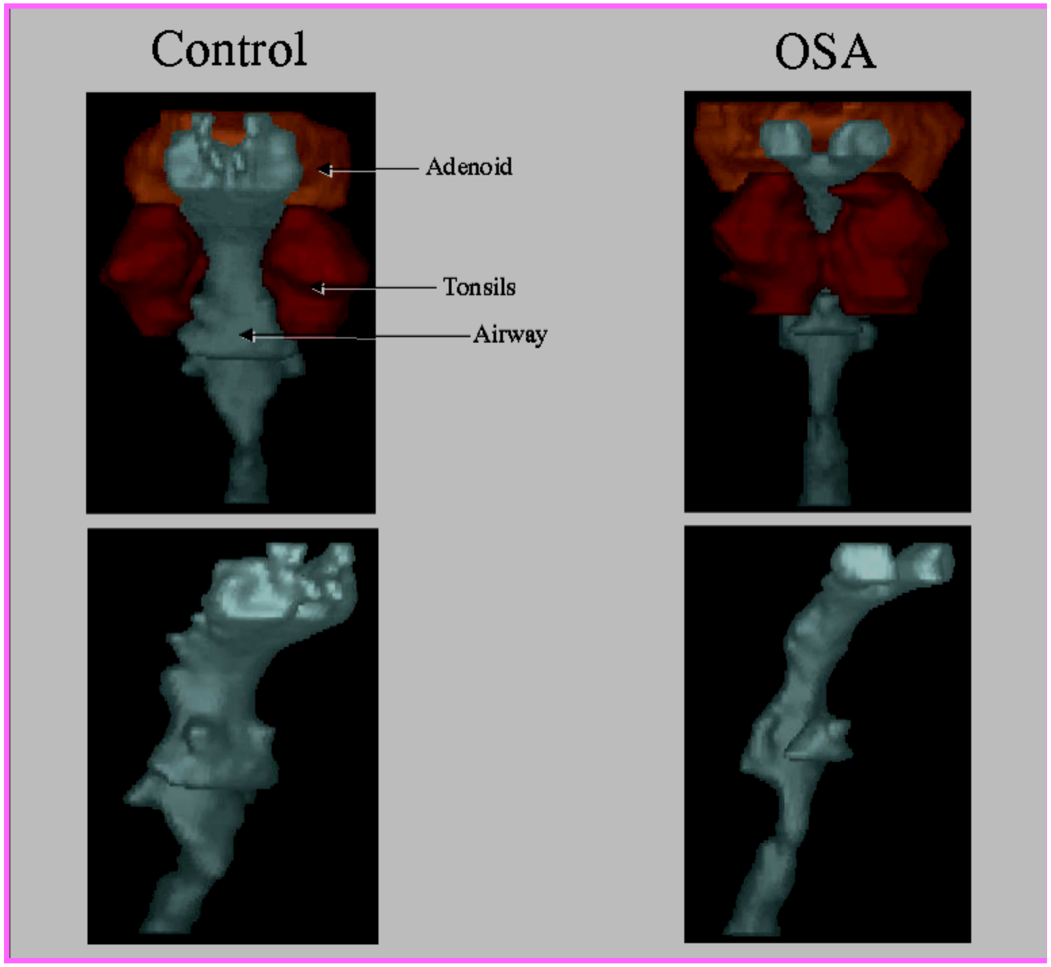


Brain MS Lesion Quantification

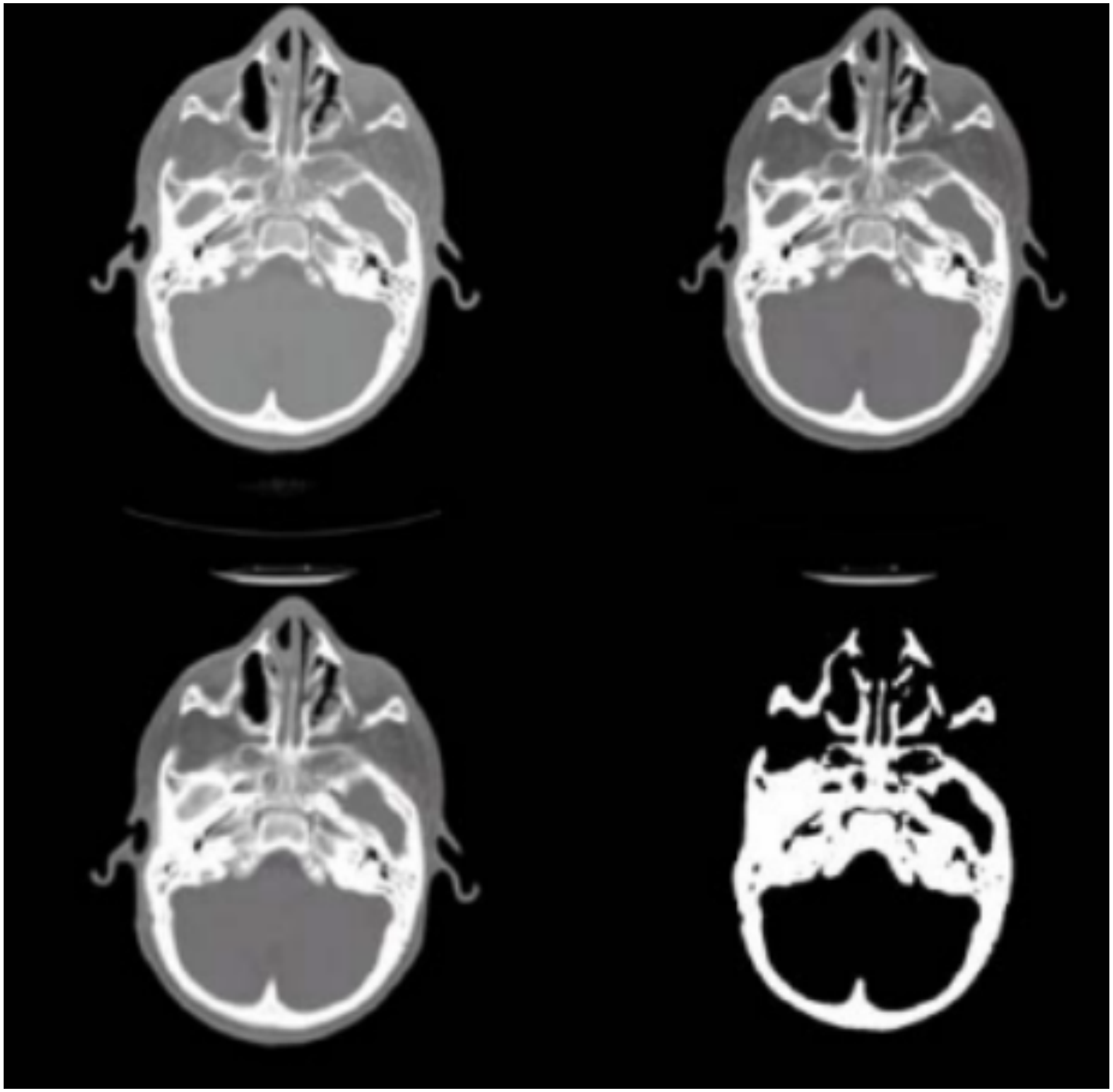


Upper Airway Study in Children with Obstructive Sleep Apnea

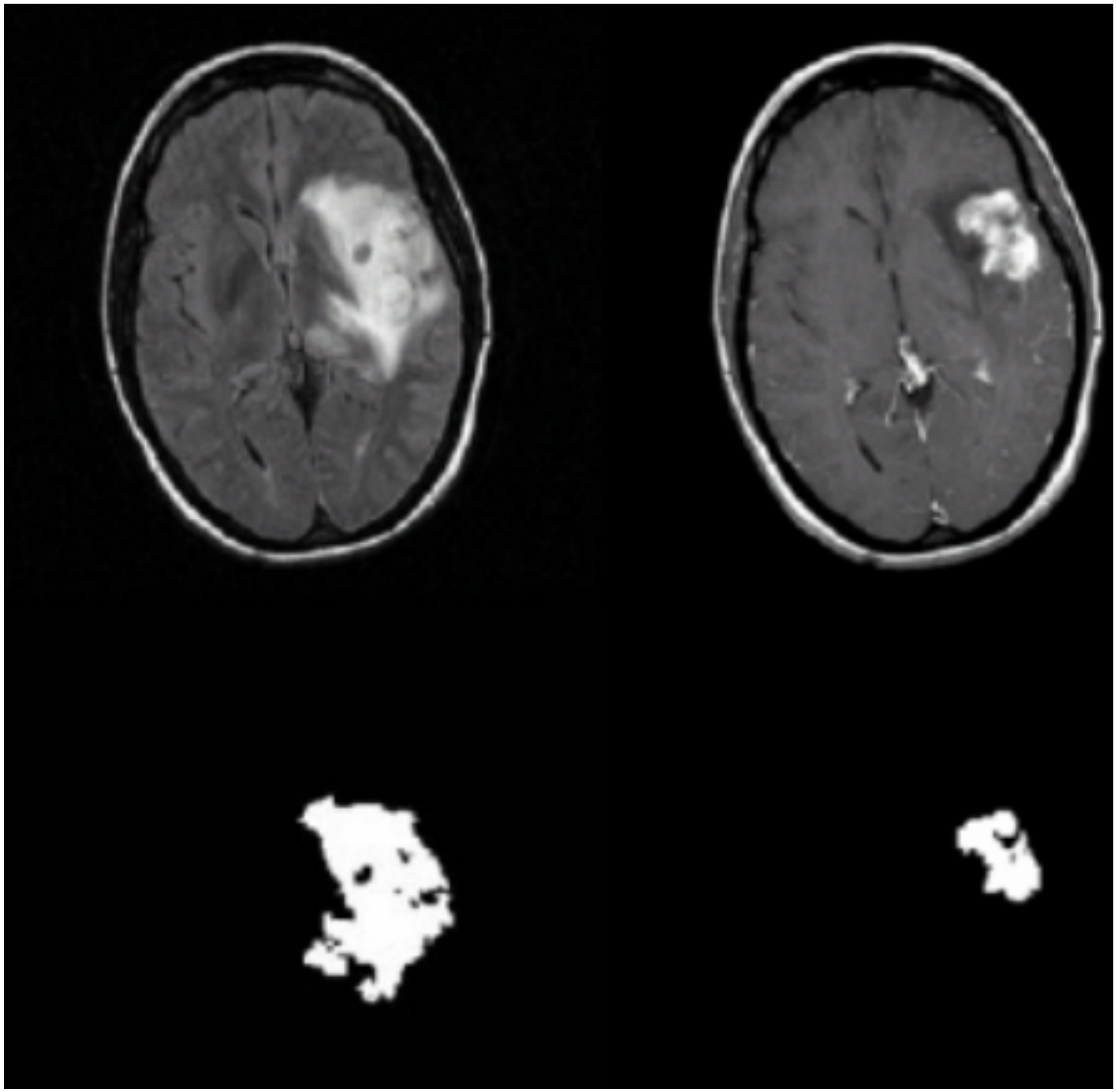




CT Skull Extraction



Brain Tumor Quantification - MRI



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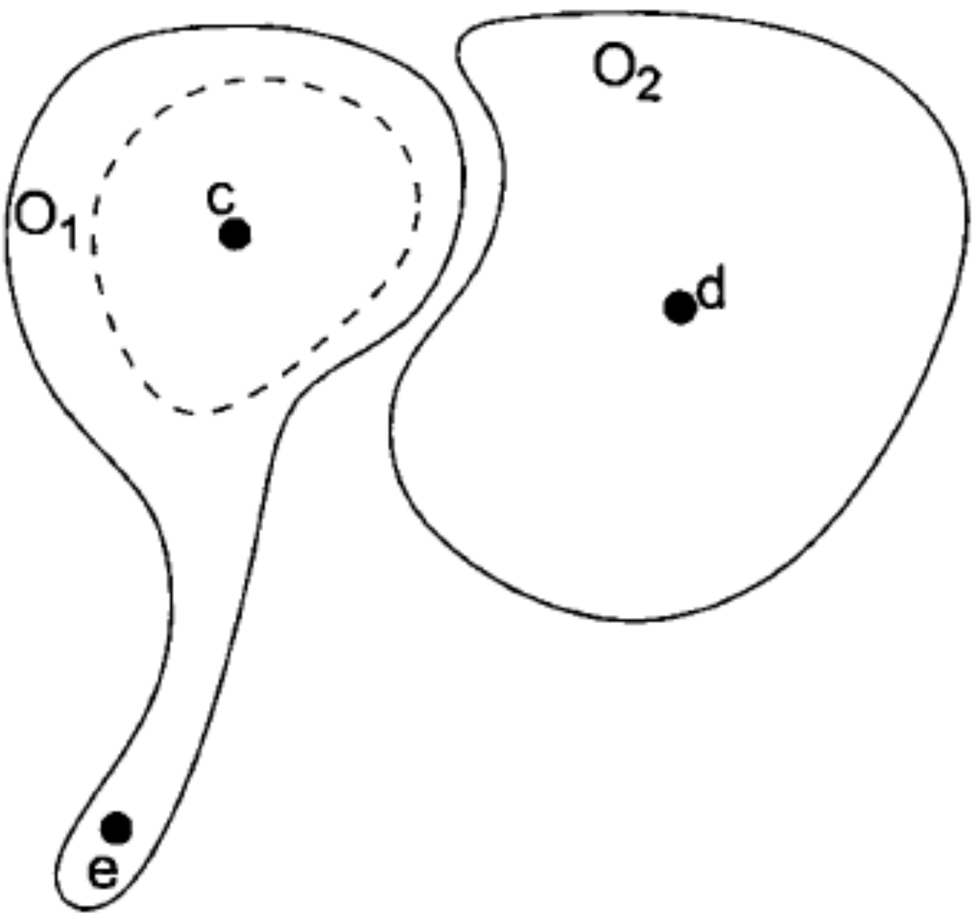
- These 2-object RFC was extended into multiple-object RFC by the same authors

Motivation for RFC (and IRFC)



FC may fail to identify objects in this situation.

-Objects O1 and O2 are located very close to each other.

Due to limited resolution, border
Between O1 and O2 may be weak,
Causing homogeneity between d and e, and
Homogeneity between c and e be similar!

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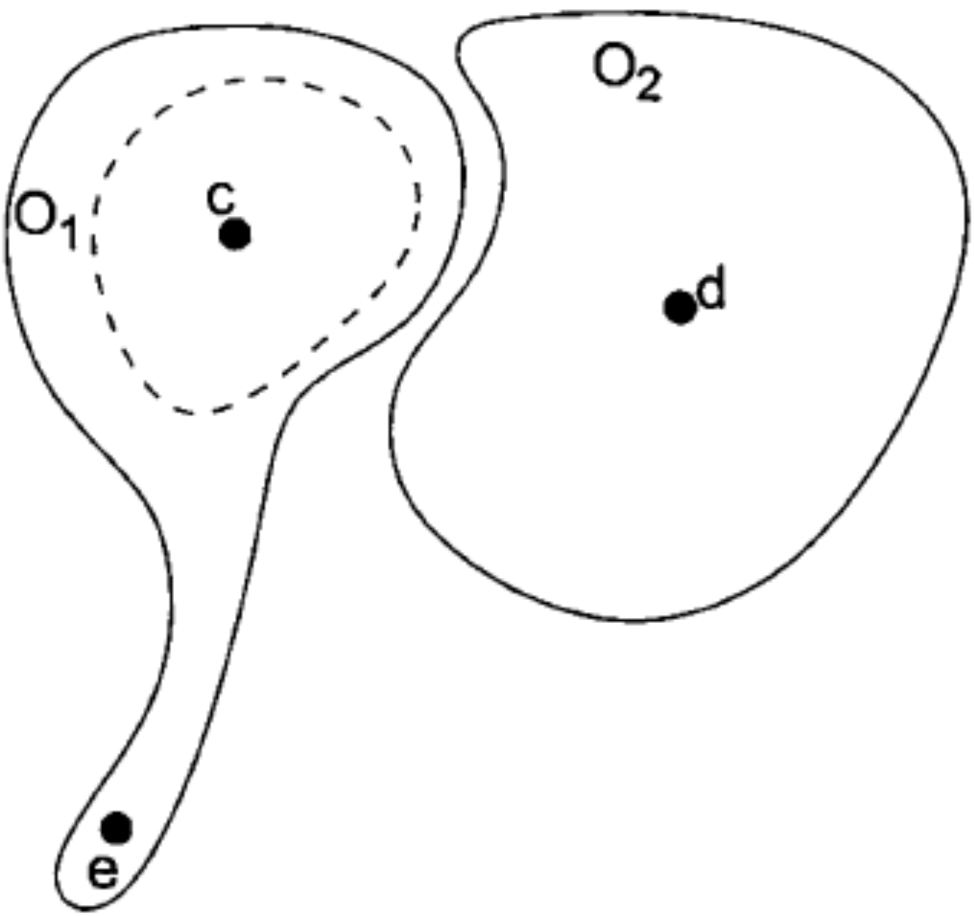

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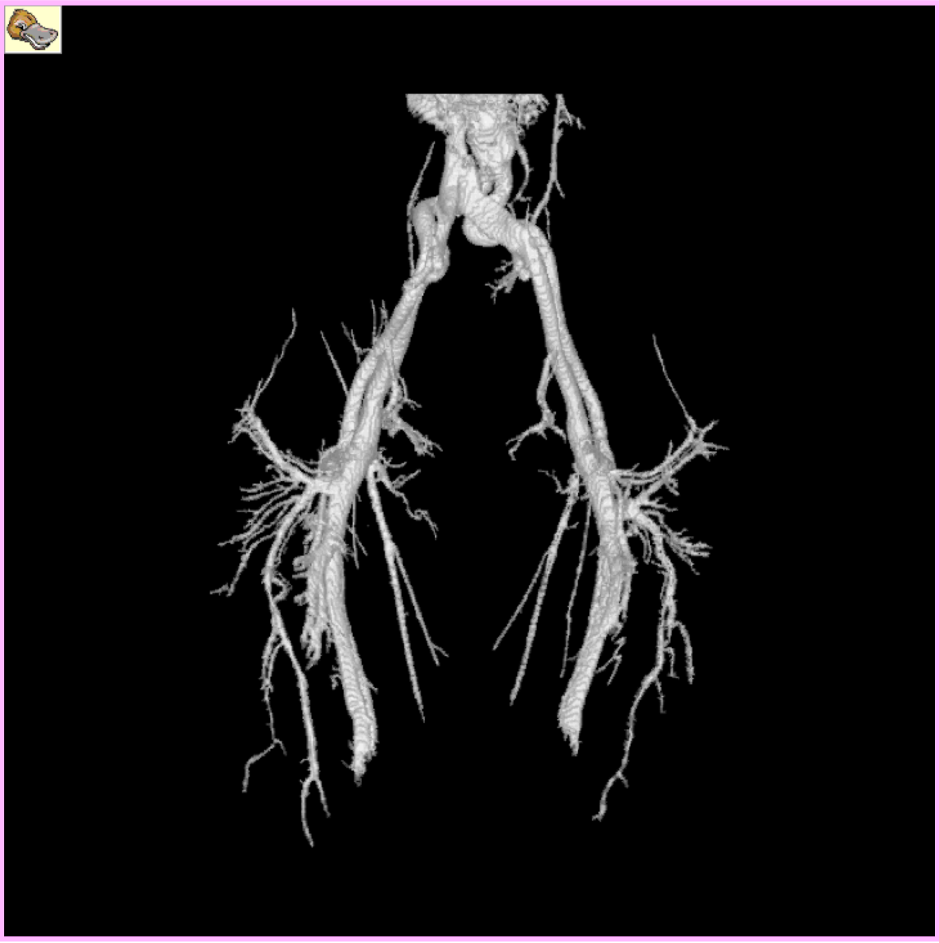
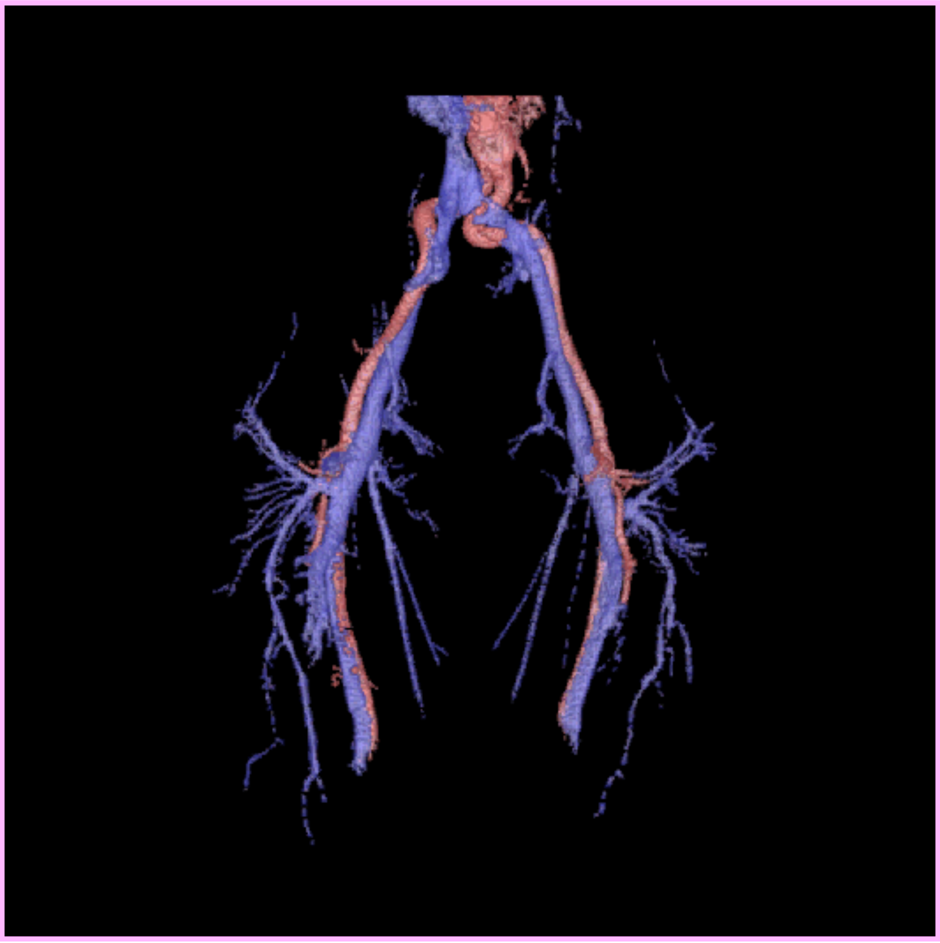
Solution:
If O1 is segmented first, paths between e and d are omitted!
It will be iterative process, IRFC.

Motivation for IRFC

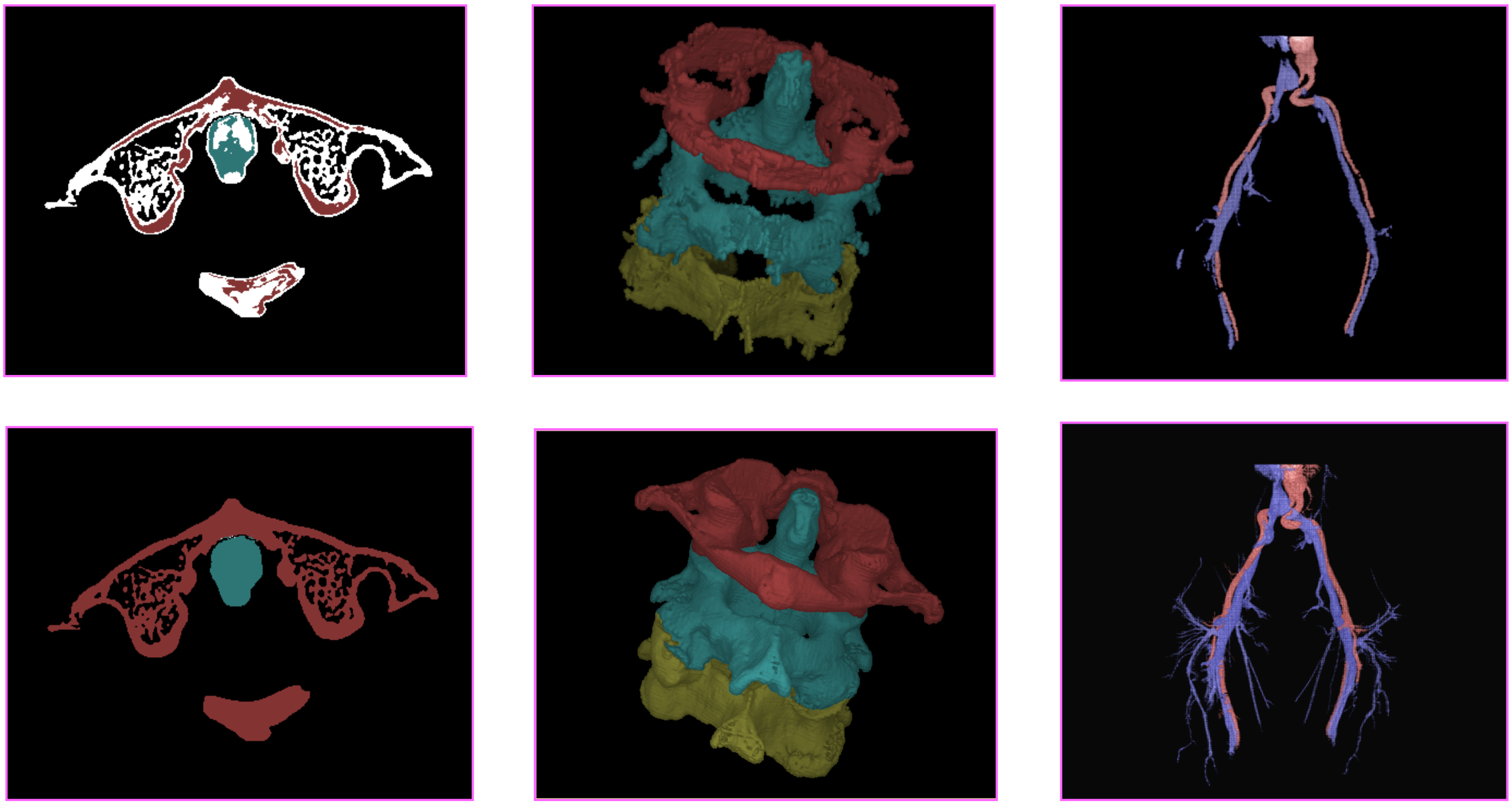
- Artery-vein separation MRA





RFC and IRFC

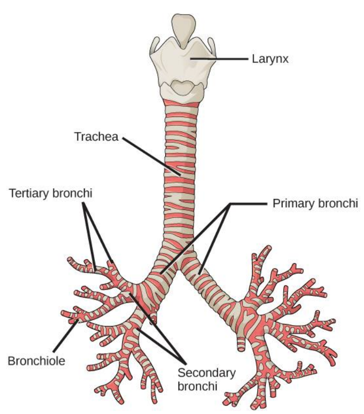
RFC

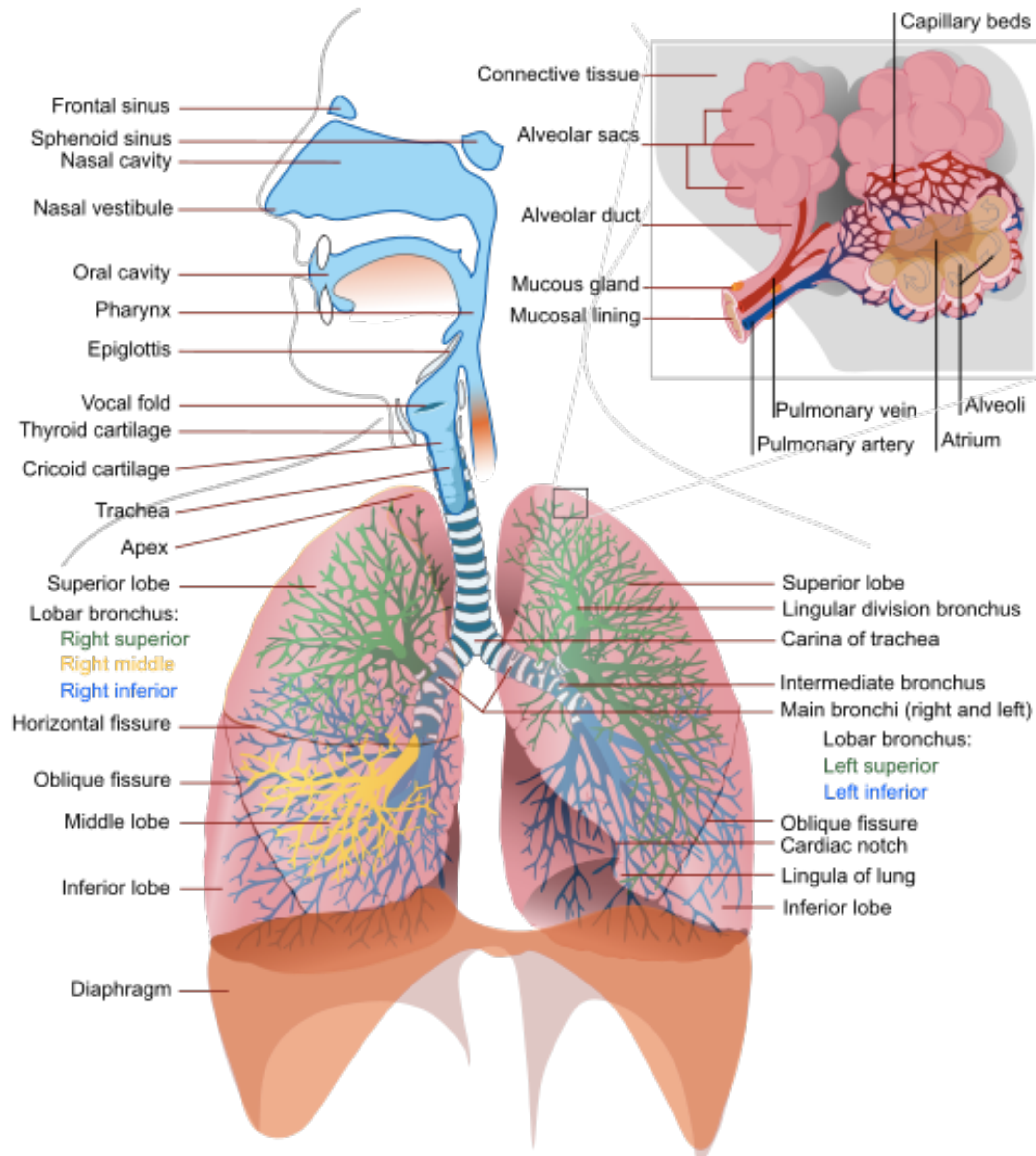


IRFC

Airway and Airway Wall Segmentation with RFC

- Airways are the air-conducting structures (bronchi and bronchioles) bringing air into and out of the lungs from sites of gas exchange (alveoli).

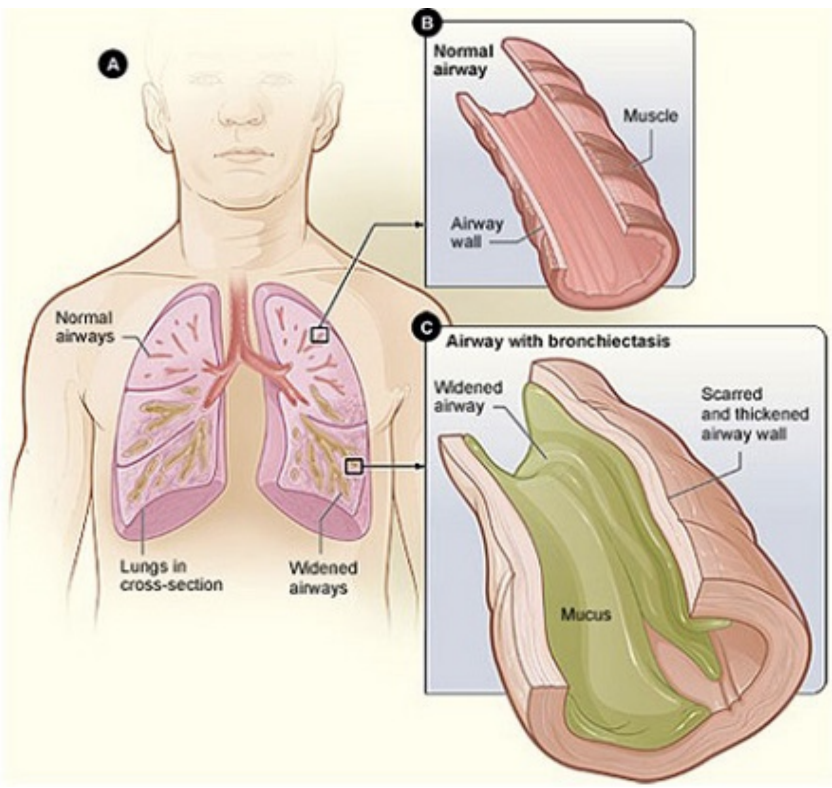




- *Credit: healthhype.com*

Airway and Airway Wall Segmentation with RFC

- Airways are pathologically involved in various lung diseases. As examples, bronchiectasis is the dilation of airways (enlarged lumen), often resulting from chronic infection (Bagci et al., CMIG 2012), obstruction, and inflammation.



Credit: Corehealthclub

Airway and Airway Wall Segmentation with RFC

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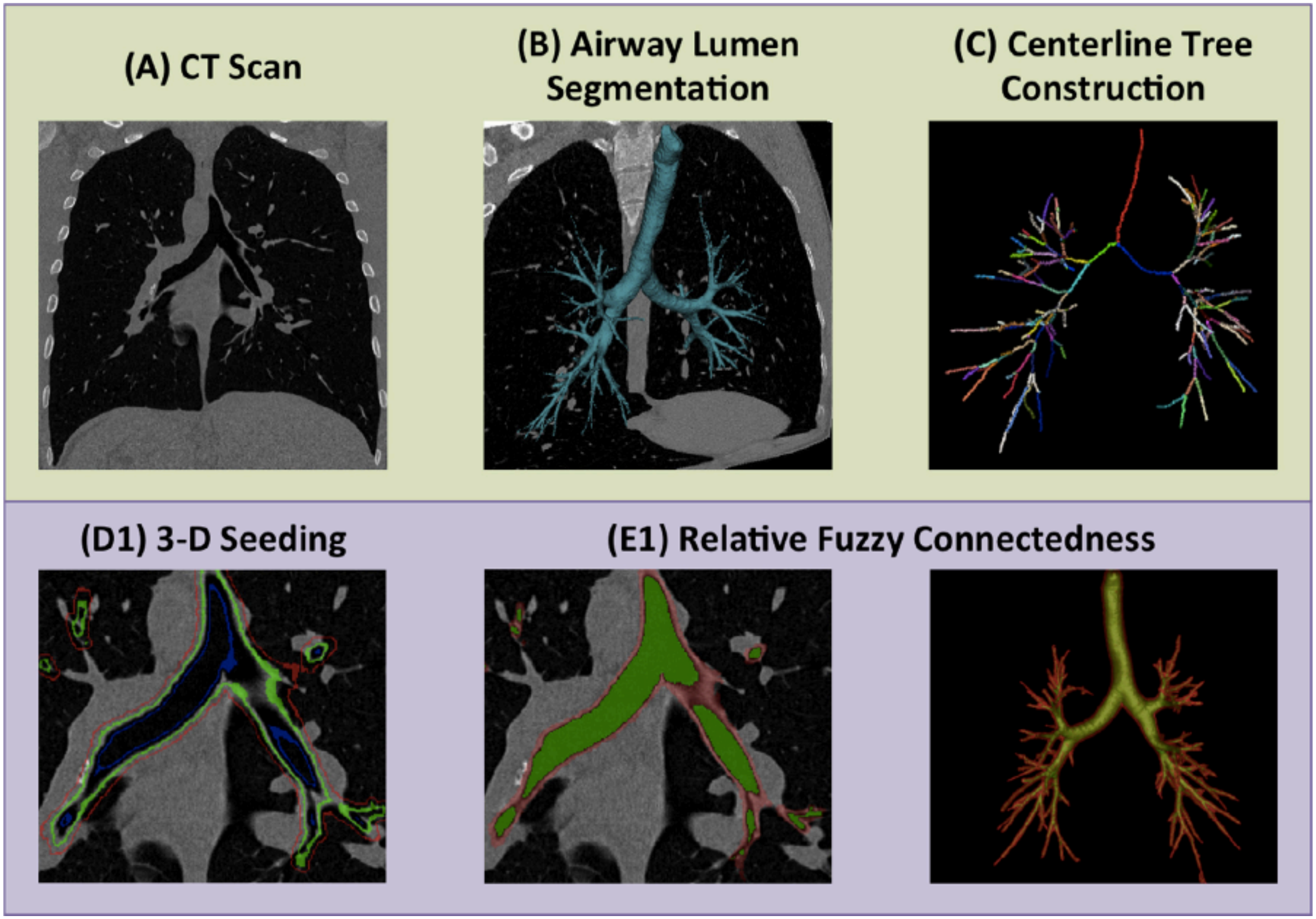
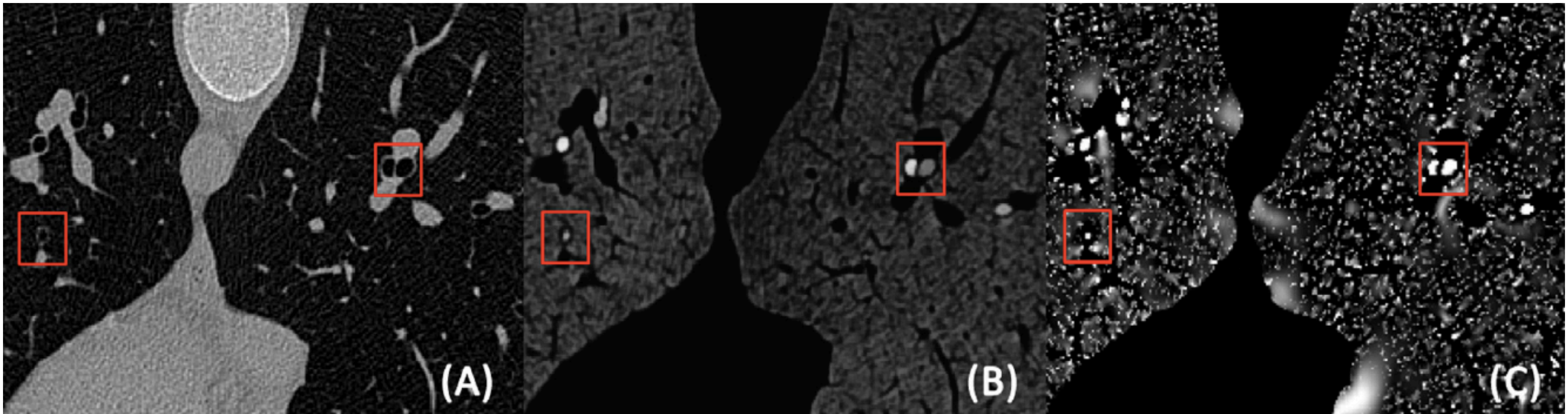
- Airway wall thickening can be associated with airway narrowing, such as asthma and bronchitis. Tumors on airway walls can also form obstructions
- CT imaging provides in-vivo anatomical information of lung structures in a non-invasive manner, which enables a quantitative investigation of airway pathologies
- Due to the inherent complexity of airway structures and the resolution limitations of CT, manually tracing and analyzing airways is an extremely challenging task, taking more than 7 h of intensive work per image
- A precise method for segmentation of airways and its walls may facilitate better quantification of airway pathologies (and understanding of disease progression)

Airway and Airway Wall Segmentation with RFC



(Credit: Xu, Bagci, et al. Medical Image Analysis 2015. The state of the art method)

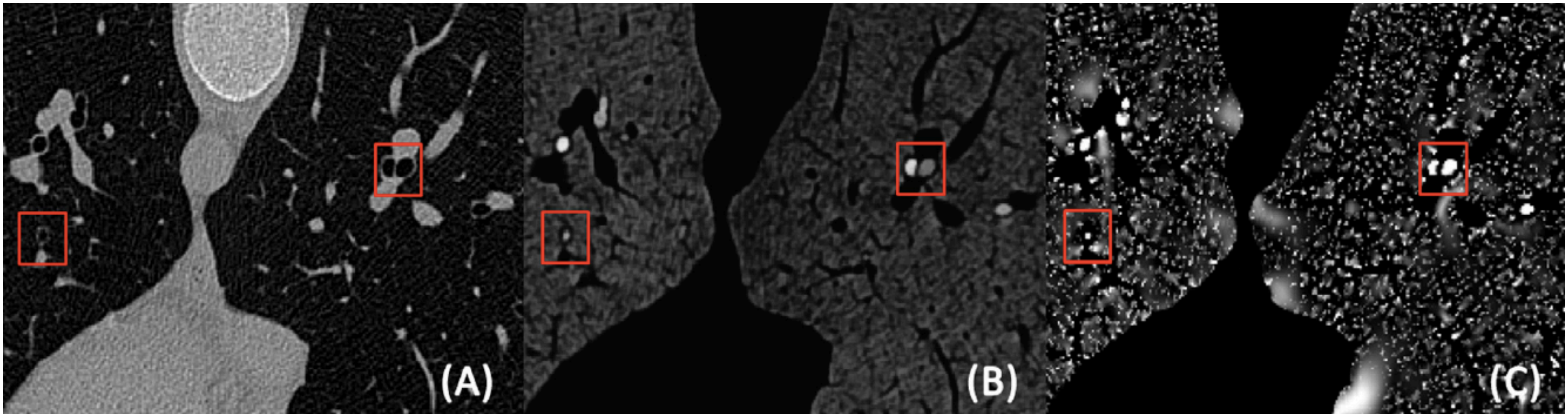
Airway Segmentation



Morphological operations

Vesselness

Airway Segmentation



Morphological operations

Good for large airways,
Small airways can be detected to some extent, but limited.
computationally expensive

Vesselness

Good for small airways,
But numerous false positives

FC can combine these two methods within a single framework!

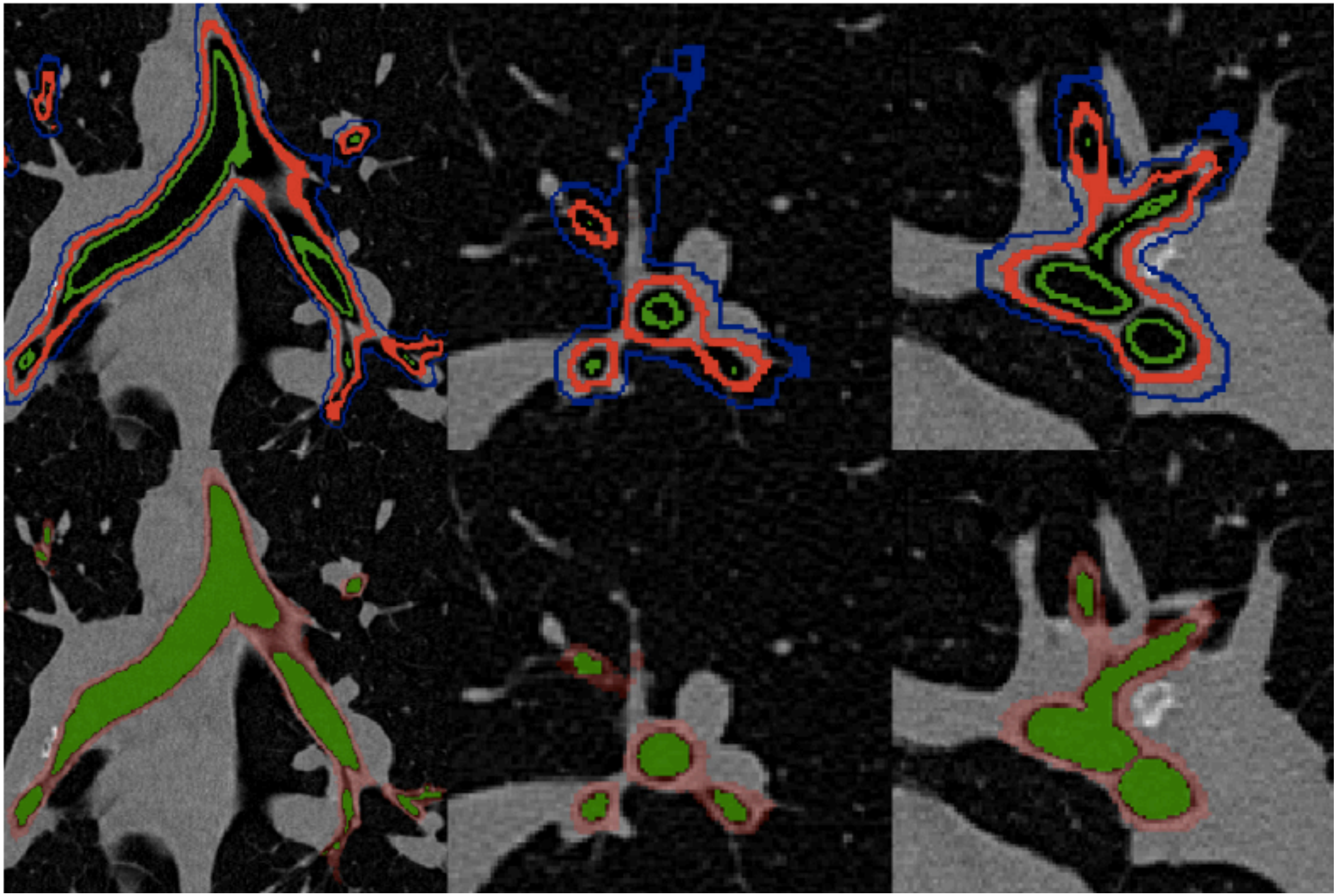
Large airways

$$\mu^{FC}_{\psi/\phi} = \begin{cases} \mu^{I}_{\psi/\phi}, & \text{if } ls > ls^{\max}; \\ k\mu^{I}_{\psi/\phi} + (1-k)\sqrt{\mu^{D}_{\psi/\phi}\mu^{V}_{\psi/\phi}}, & \text{otherwise,} \end{cases}$$

small airways

Where **ls** denotes local scale, k is a weight parameter, and D shows morphologically processed Image, V indicates vesselness image.

Airway and Airway Wall Segmentation with RFC



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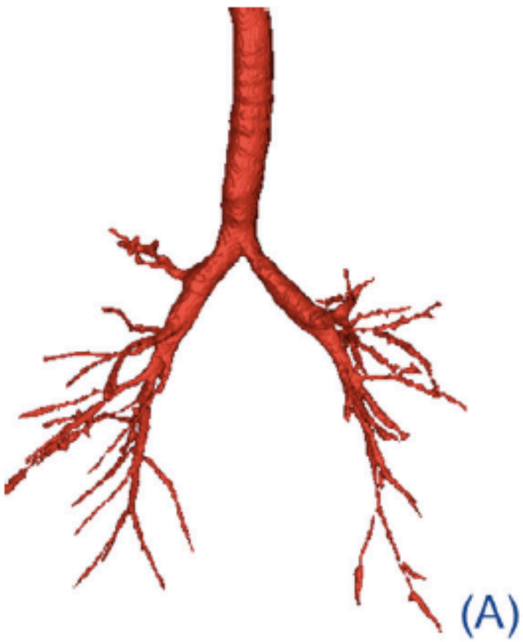
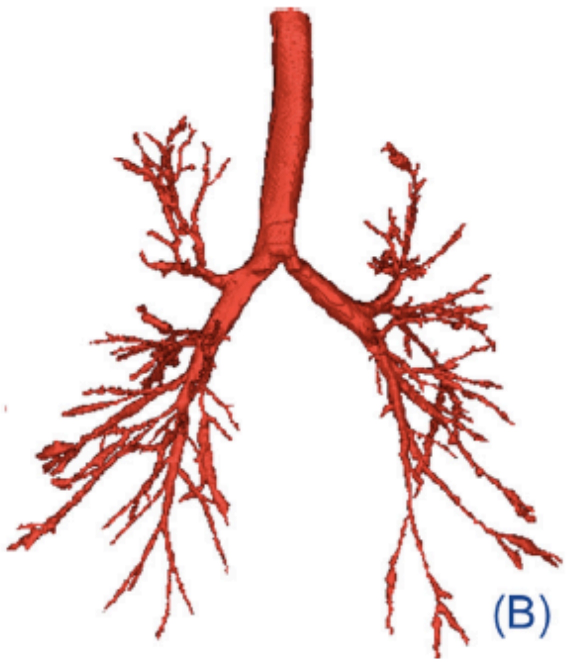
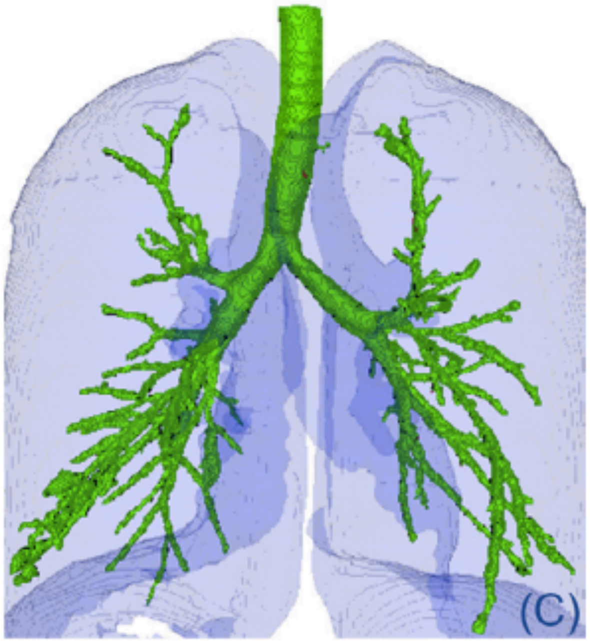


Segmentation results
Without fine tuning of
parameters



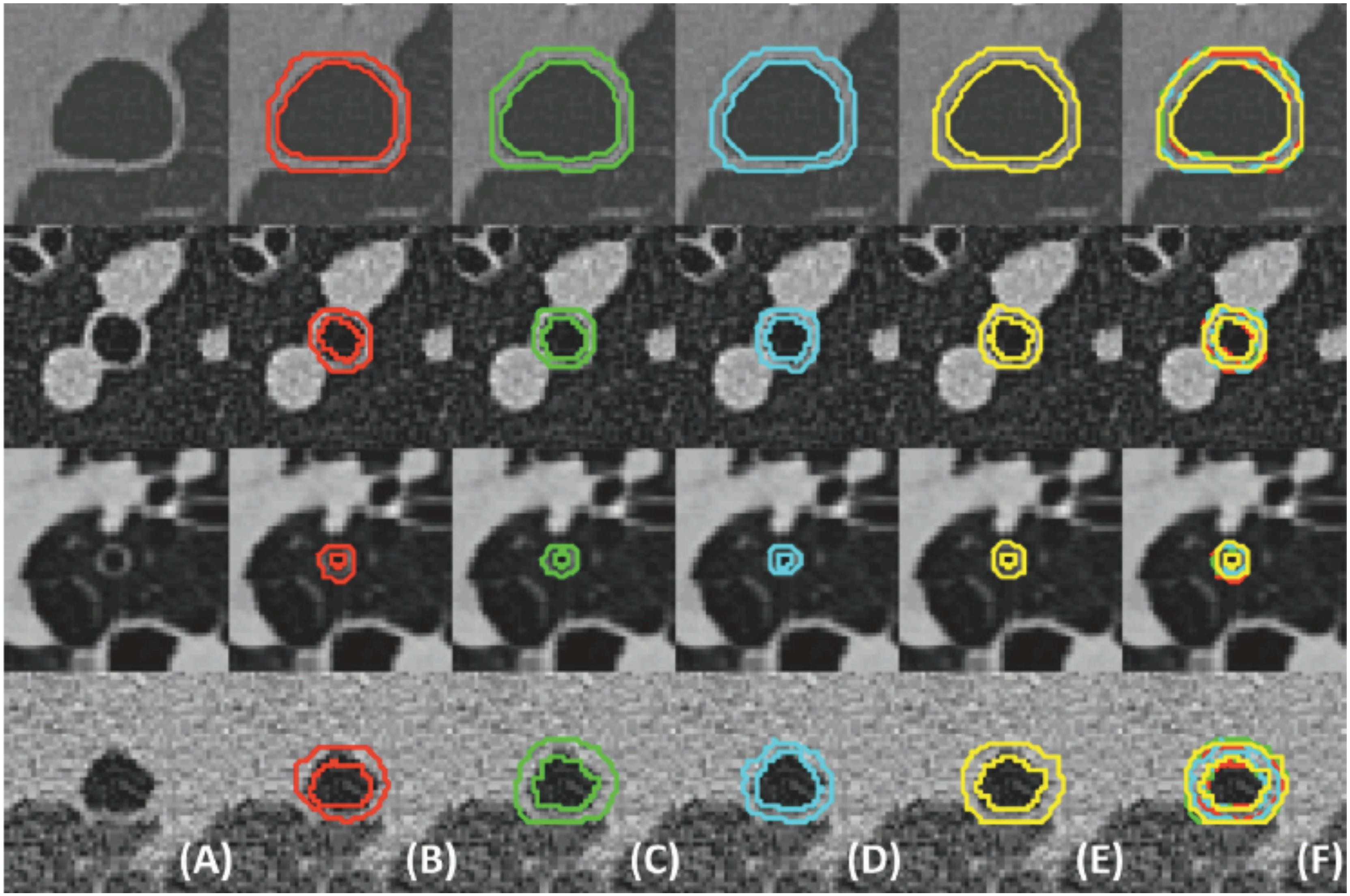
Segmentation results
With fine tuning



Reference segmentation
results

EXACT 09 Segmentation Challenge, CASE36

Airway and Airway Wall Segmentation with RFC



Manual 1 Manual 2 Random Walk RFC Fused

Summary

- FC is a strong segmentation tool fit for many biomedical image segmentation problems
- Affinity functions are the key stones for FC
- FC family has different version of FC, suitable for challenging tasks
- RFC and IRFC are quite successful in segmenting complex shaped objects

Slide Credits and References

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