# Medical Image Analysis and Processing

## Medical Image Segmentation
## Introduction

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Distance/online Course: Session 17

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# Contents

# Definition

› Definition(s):

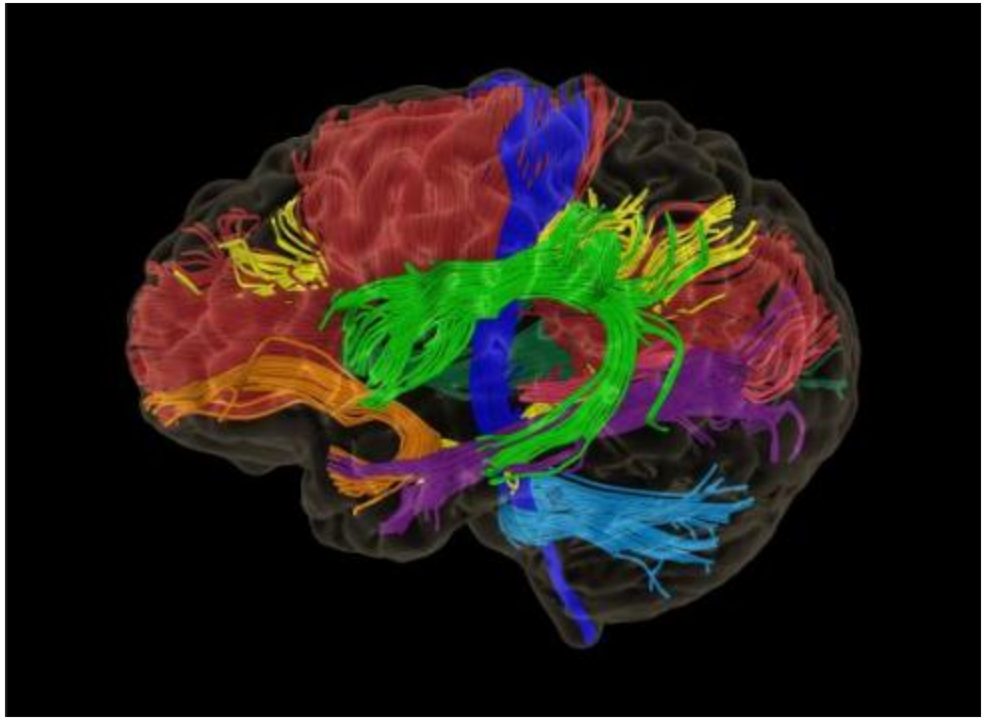
1. Classically, image segmentation is defined as the *partitioning* of an image into *non-overlapping*, constituent regions which are *homogeneous* with respect to some *characteristic* or *feature* such as *intensity, texture* or *shape*.
2. The process of *assigning* a *label* with *biological meaning* to each pixel or voxel in such a way that the pixels or voxels with the *same label share* certain *characteristics* or belong to the *same* anatomical region.
3. Segmentation: *Separation* of structures of *interest* from the *background* and from *each other*.

# Examples

› CT Bone Segmentation:

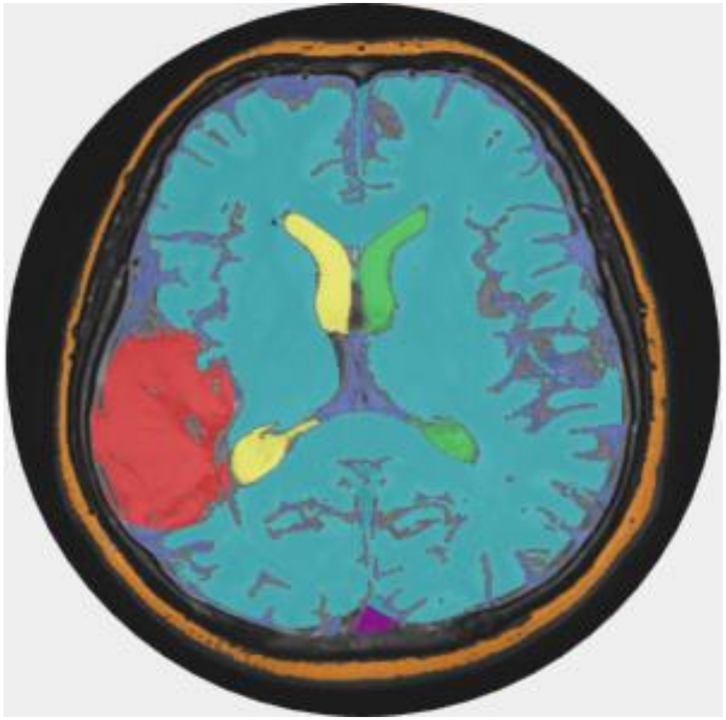
# Examples

› Tractography:



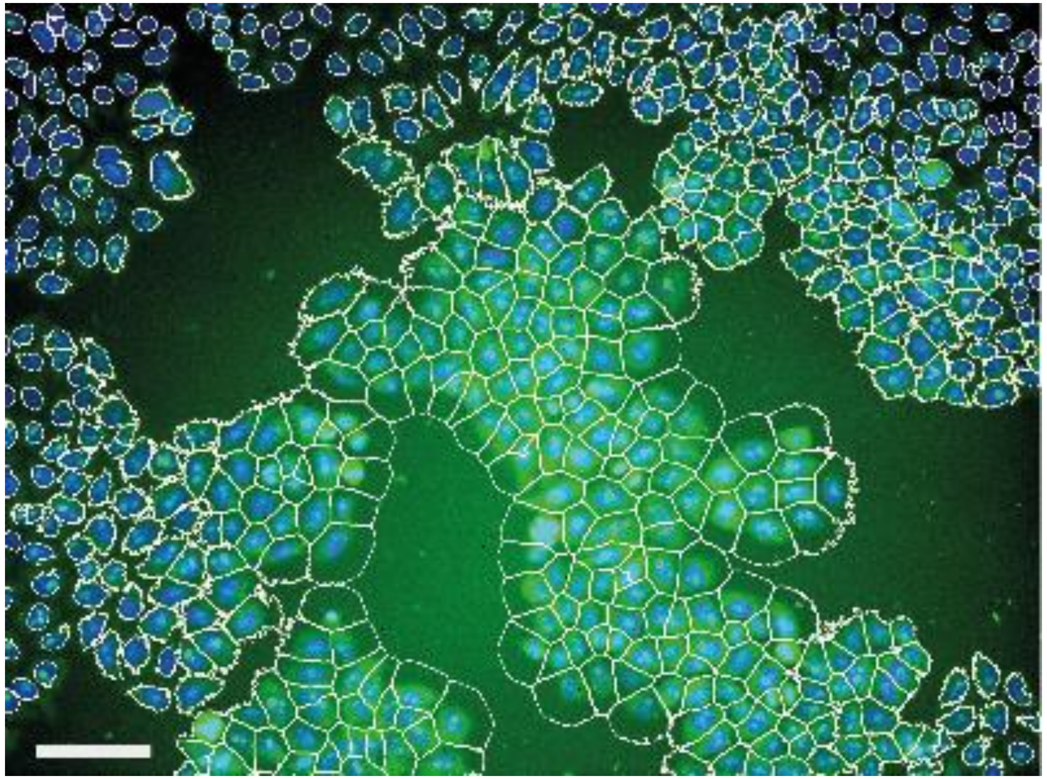
# Examples

- Structural MRI:



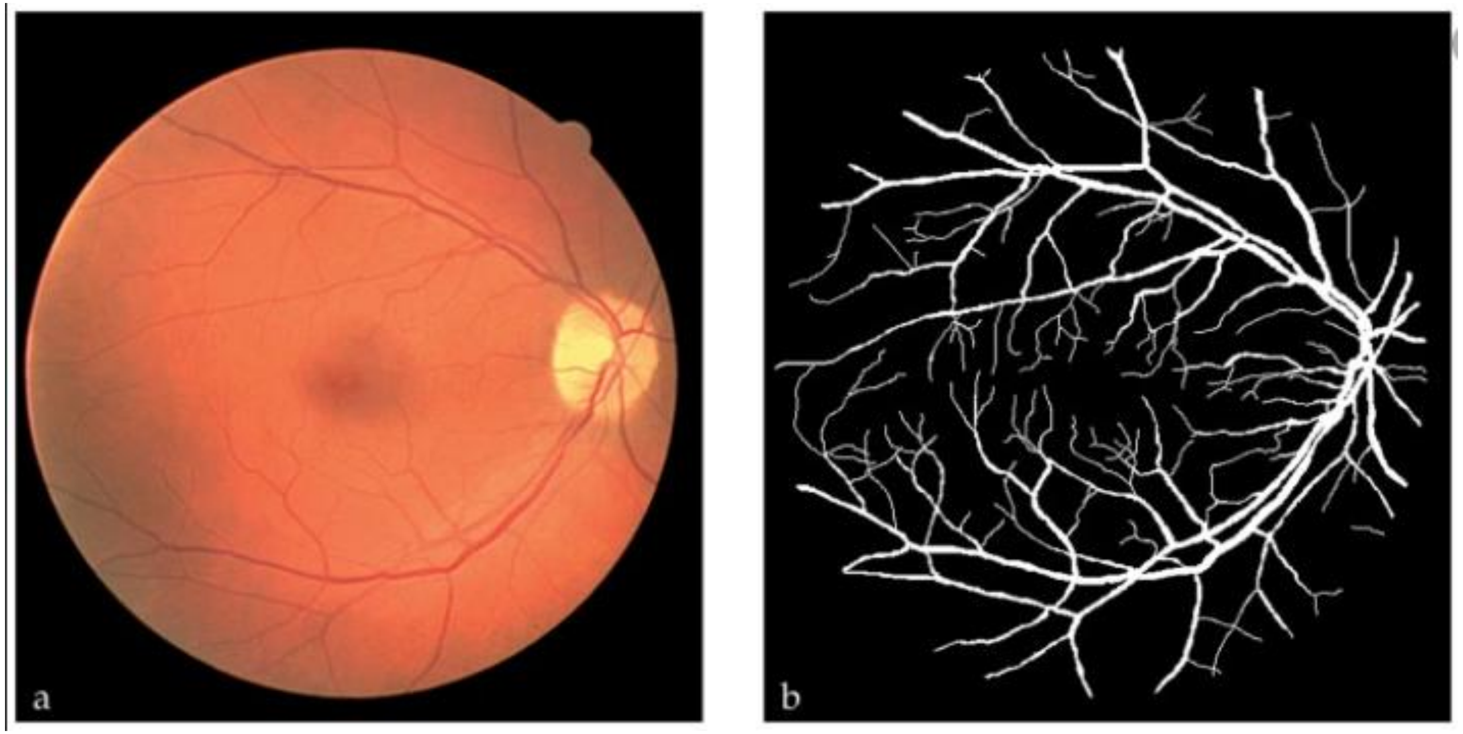
# Examples

› Cell Segmentation:



# Examples

› Retina Vessel Segmentation:



# Importance:

- The first and most important pre(or main) processing in medical image processing:
- Since *qualitative* evaluation of brain morphological characteristics is very subjective and therefore *quantified* techniques are needed.

# Application:

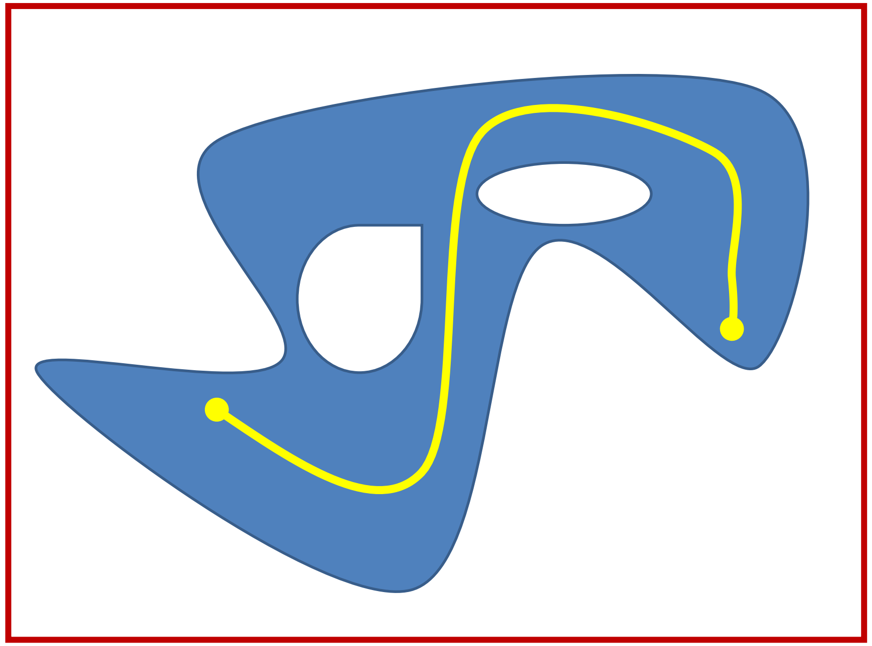
- Feature extraction,
- Image measurements,
- Image display.
- Tissue classification,
- Localization of tumors,
- Tumor volume estimation,
- Delineation of blood cells,
- Surgical planning,
- Atlas matching,
- Image registration.
- …

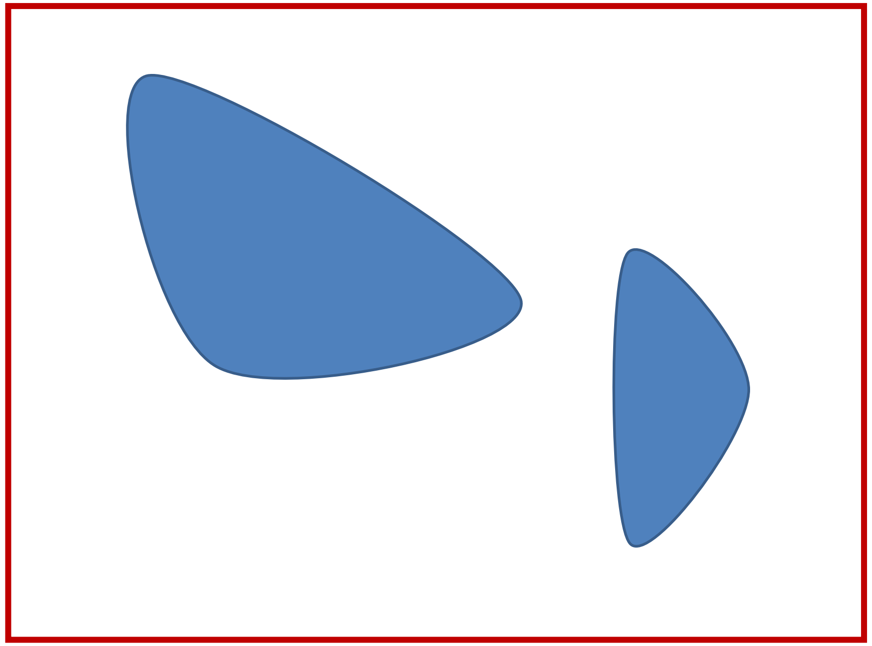
# Mathematical Definition

- Segmentation of Image ($I$) to C partitions, $\{S_k\}_{k=1}^{C}$:
  - $I = \bigcup_{i=1}^{C} S_k$
  - $S_k \subset I$
  - $S_k \cap S_j = \emptyset, \forall j \neq k$
  - All $S_k$'s are *connected* regions
  - $Property(S_k) = True$
  - $Property\left(S_k \cup S_j\right) = False, \forall j \neq k$
- If we relax connectivity condition, segmentation is *pixel classification* task

# Mathematical Definition

› Connected (left) vs disconnected (right) Regions:





# Mathematical Definition

› Pixel Classification:

# Mathematical Definition

- *Labelling*: Process of assigning a meaningful designation to each region or class and can be performed separately from segmentation.
- It maps the numerical index $k$ of segment $S_k$, to an anatomical designation (gray matter, white matter, CSF, …)

# Challenges

- Medical Image Segmentation is a challenging task suffering from the limitations and artifacts in the images, including:
  - Soft tissue (weak boundaries),
  - Sensor noise and artifact,
  - Patient difference and motion,
  - Pathology, surgery, and contrast agents,
  - Partial scan and field of view
  - Similar intensities in the different regions,
  - *Intensity inhomogeneity!*
  - *Partial Volume Effect (PVE)!*

# Challenges

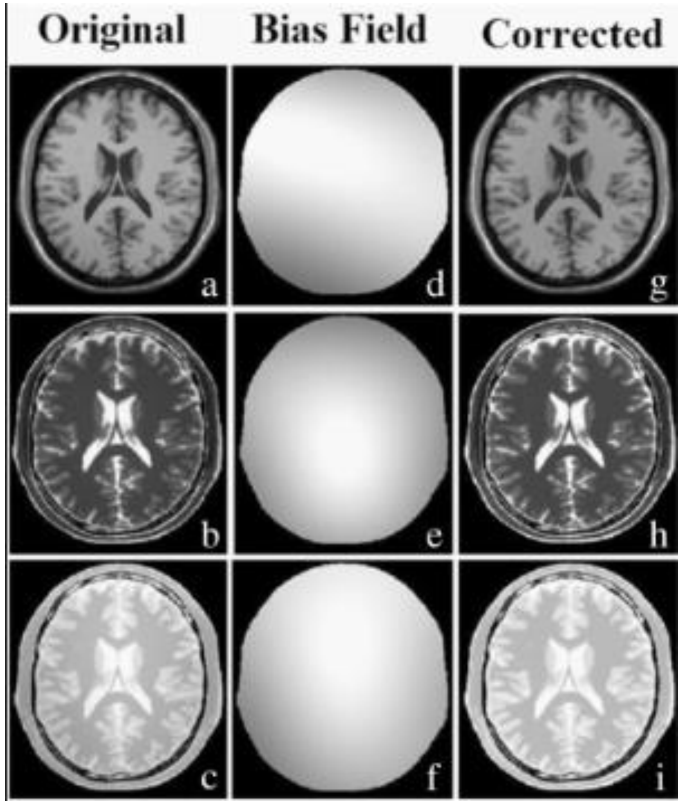
- Intensity inhomogeneity (Bias Field):
- Mostly appear in MRI due to magnetic field inhomogeneity:
- Simple Model:

$$I_{Record}(x,y,z) = B_0(x,y,z) \odot I_{Correct}(x,y,z)$$

- Ideally: $B_0(x,y,z) = B_0$

# Challenges

› Intensity inhomogeneity (Bias Field):

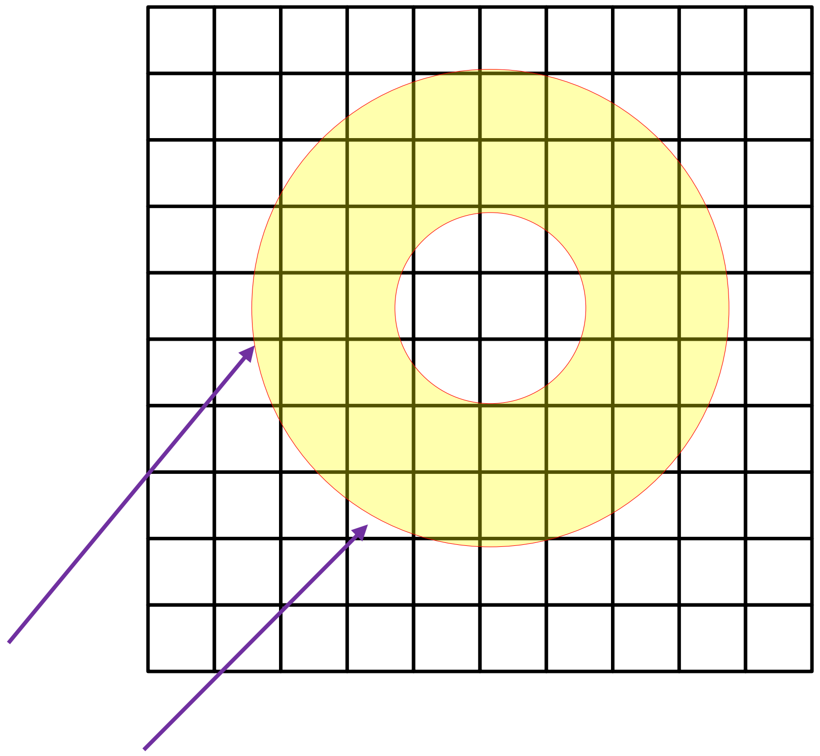


# Challenges

- Partial Volume Effect (PVE):
- Mixing of *different* tissue types in a *single voxel*, and therefore possessing a signal average of both tissues.
- PVE caused by the finite spatial resolution of the images (Non-ideal PSF)
- PVE blurs the edges

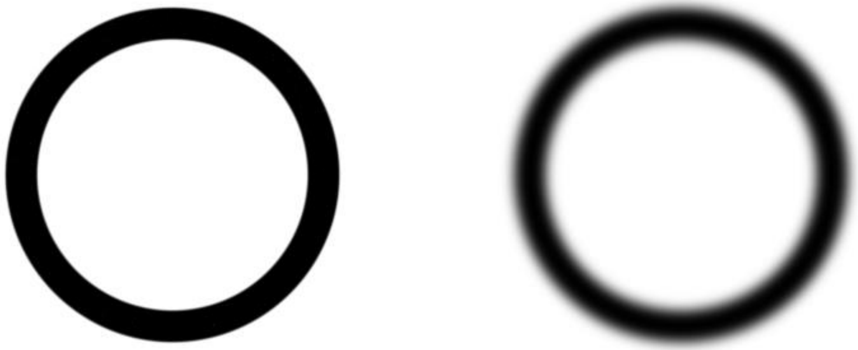
# Challenges

› Partial Volume Effect (PVE):



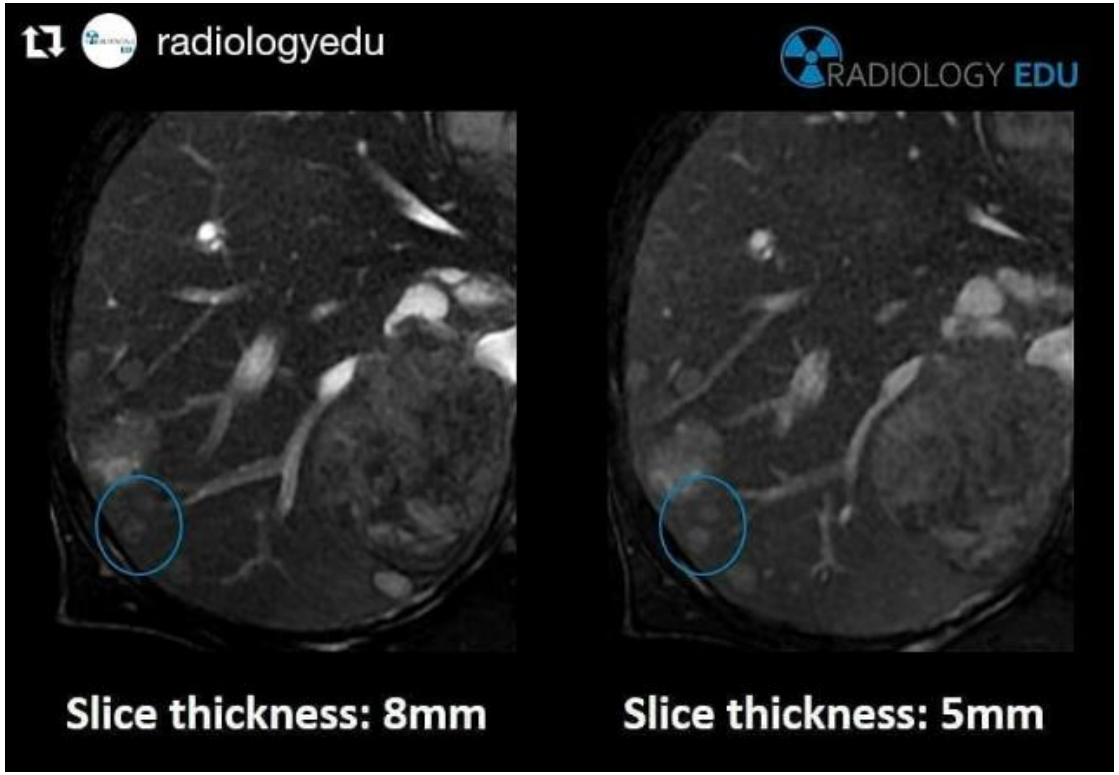
# Challenges

› Partial Volume Effect (PVE):



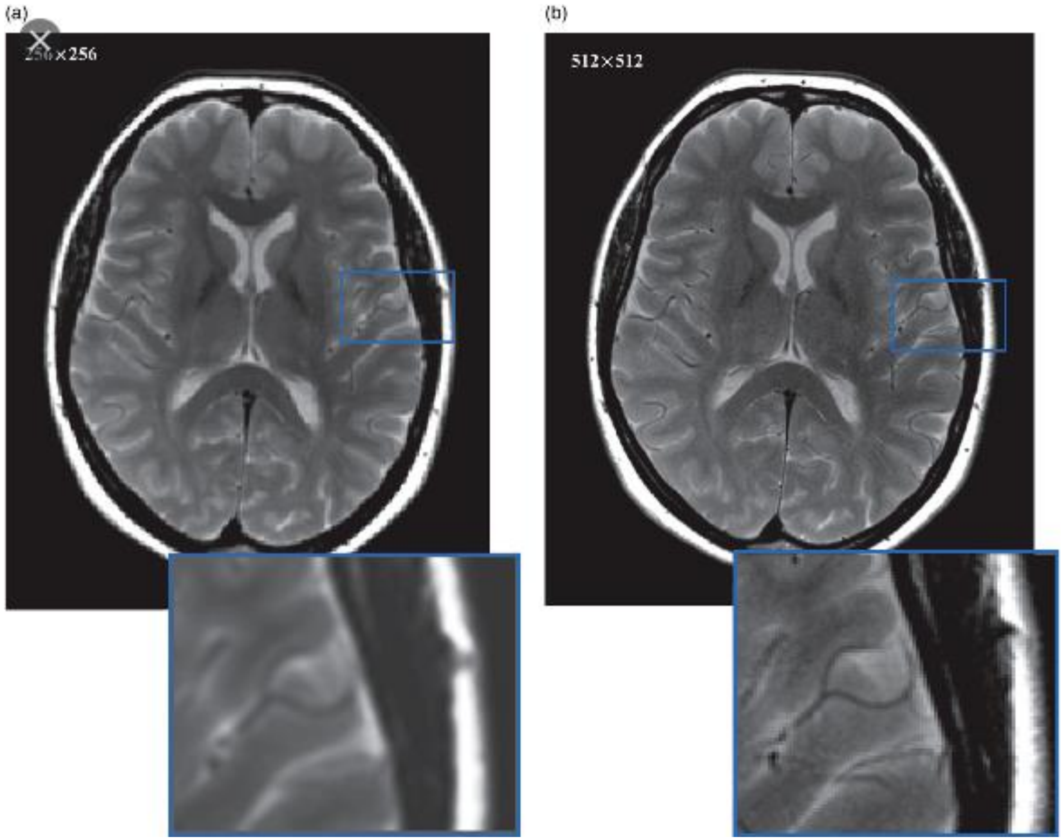
# Challenges

› Partial Volume Effect (PVE):



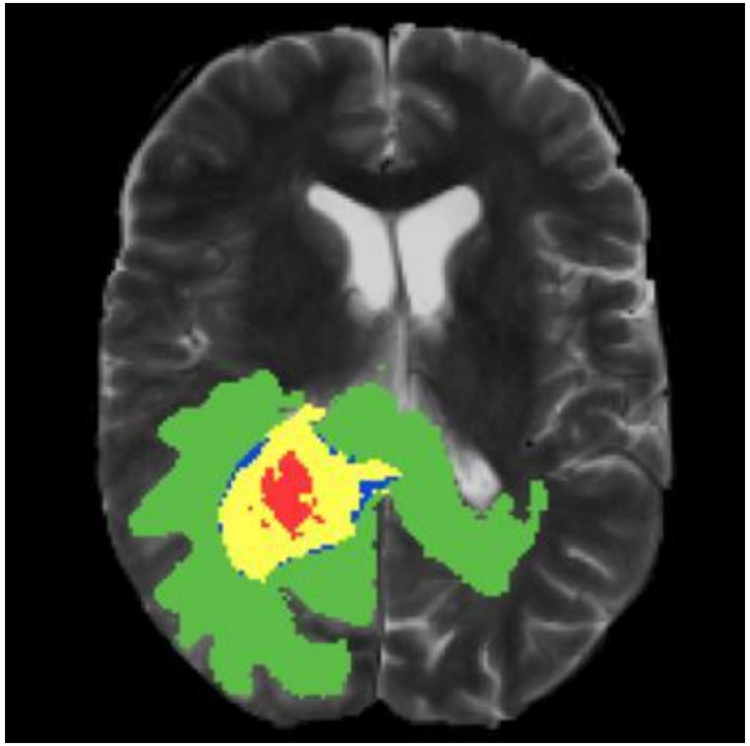
# Challenges

› Partial Volume Effect (PVE):



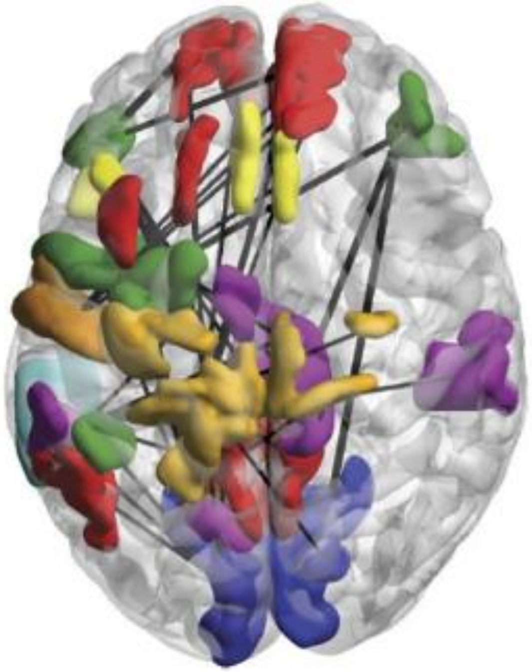
# Categorization - Dimensionality

› 2D: Segment 2D images



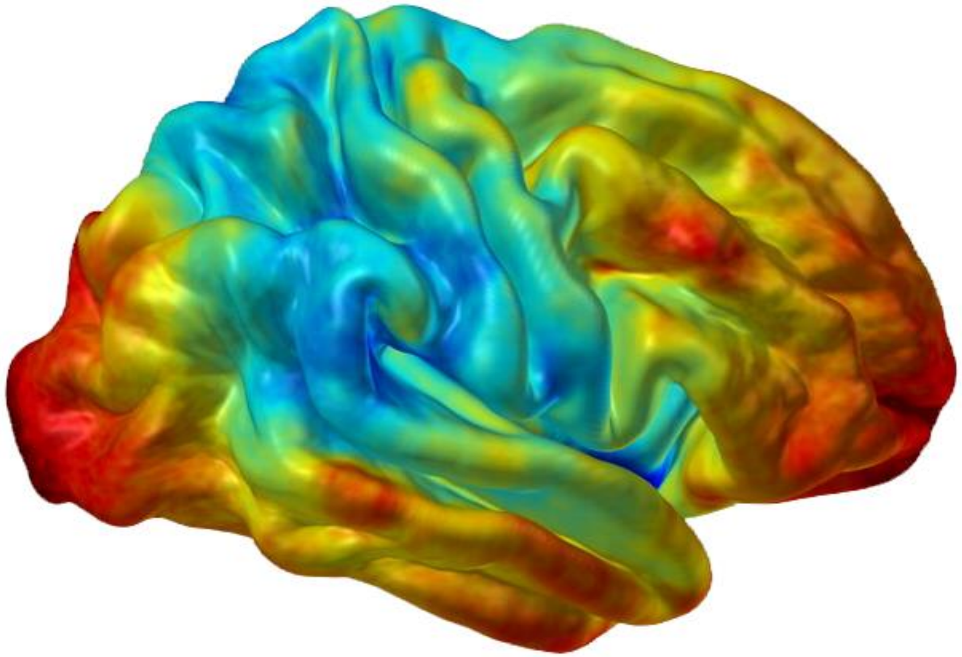
# Categorization- Dimensionality

- 3D (may be performed by applying 2D algorithm, sequentially, to the slices of a 3-D image)



# Categorization - Dimensionality

- Non-Euclidean: Segmentation performed on surfaces (manifold)



# Categorization – Soft versus Hard

- Hard Segmentation:

  *A pixel is inside or outside the segment*

- Mathematical definition using characteristic/membership function:
- For a pixel $i$ and segment $k$ we define:

$$m_k(x_i) = \begin{cases} 1, & x_i \in S_k \\ 0, & x_i \notin S_k \end{cases}, \; m_k(\cdot): \mathbb{R}^3 \to \{0,1\}$$

- It cannot model partial volume effects (PVE)

# Categorization – Soft versus Hard

› Soft Segmentation:

*A pixel is completely (or partially) inside one (or more) segments*

› Mathematical definition using characteristic/membership function:

› For a pixel $i$ and segment $k$ we define:

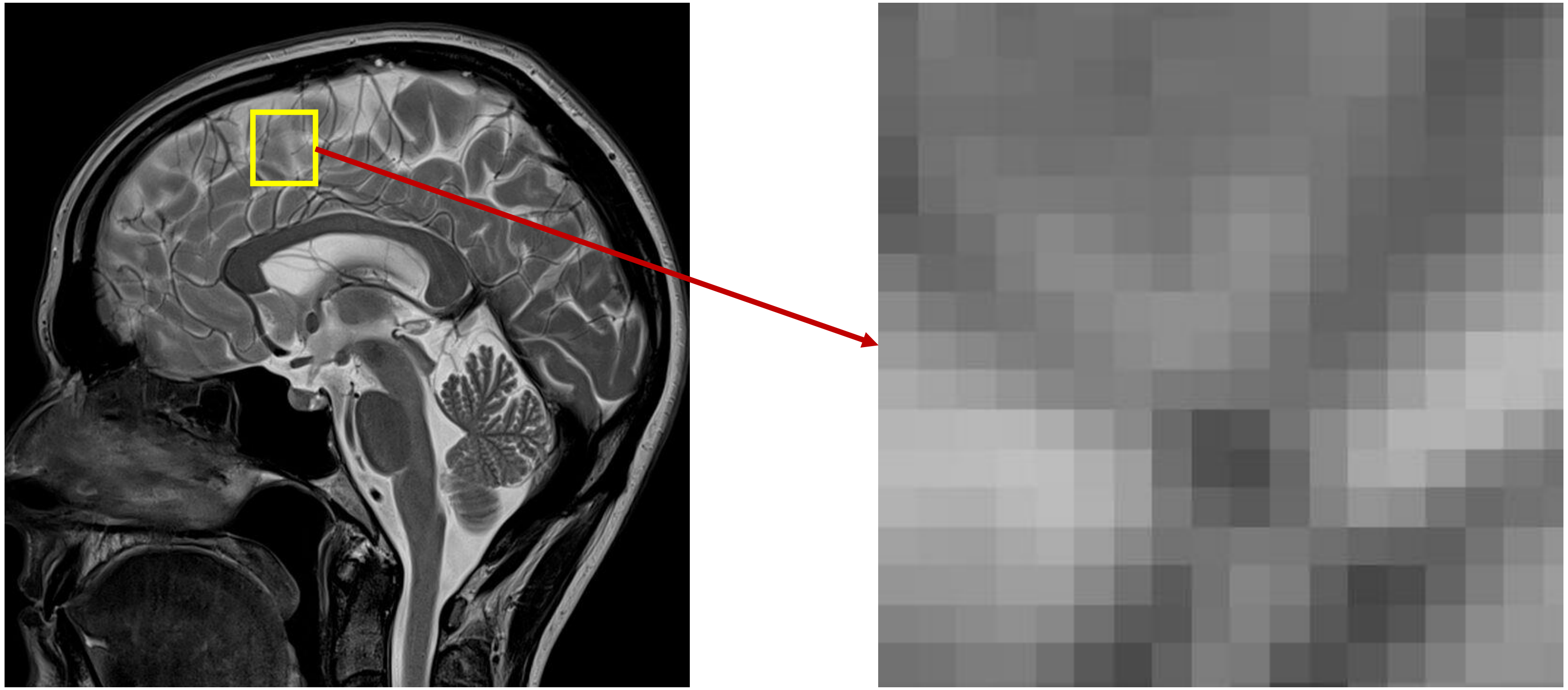
$$\begin{cases} 0 \leq m_k(x_i) \leq 1 \\ \sum_{k=1}^{C} m_k(x_i) = 1 \end{cases}, m_k(\cdot): \mathbb{R}^3 \to [0,1]$$

› Partial volume is supported!

π

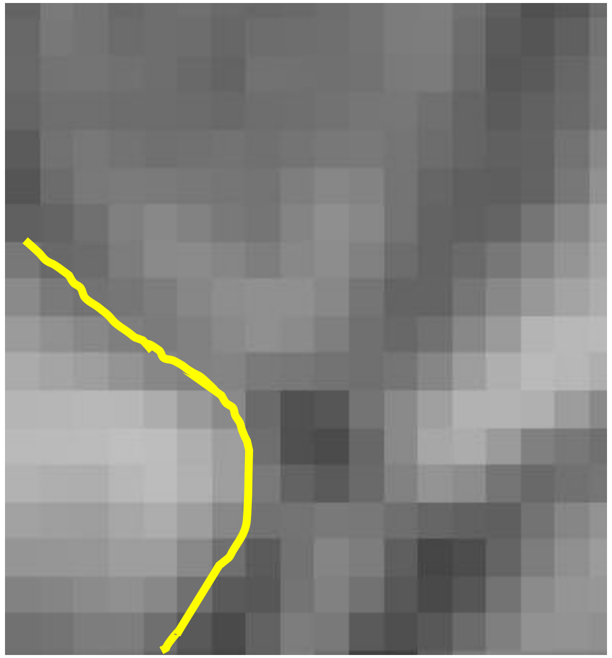
# Categorization – Continuous vs Discrete

- Discrete Segmentation: Operate on the same discrete grid as the image.



# Categorization – Continuous vs Discrete

- Continuous Segmentation: Operating in the continuous spatial domain, thereby providing the potential for *subpixel accuracy* in delineating structures!



# Categorization – User Interaction

- User Interaction:
  - Completely Manual:
    - Expert segment the whole image
  - Semi-Automated:
    - Expert provide initial condition
  - Fully Automated
    - No interaction with expert

# Validation

- Validation

  Compare quantitively with ground truth (gold standard)

- Ground truth:
  - Expert Segmentation
  - Physical Phantom
  - Mathematical Phantom

# Validation

- Expert Segmentation:
- Highly acceptable
- Expensive
- Time Consuming
- Expert Performance Variability
- Limited availability (mostly brain MRI)

# Validation

- Physical Phantom:
  - Medical imaging phantoms are objects used as stand-ins for human tissues to ensure that *systems* and *methods* for imaging the human body are operating correctly.
  - Provide an accurate depiction of the image acquisition process
  - Do not present a realistic representation of anatomy (3D printers!)


# Validation

- Mathematical Phantom:
  - Medical imaging system simulators (Codes that simulate imaging procedure)
  - Simulate the image acquisition process using only simplified models
  - More realistic representation of digital anatomy (input: 3D matrix)
    - BrainWeb: Simulated Brain Database
    - MRiLab - A numerical MRI simulator
    - CTSim - The Open Source Computed Tomography Simulator
    - Field II - Ultrasound Simulation Program
    - …

# Databases

- Data Sets for Medical Image Segmentation:
  - Medical segmentation decathlon (MSD),
  - Segmentation in Chest Radiographs (SCR),
  - Brain tumor segmentation (BRATS),
  - Digital database for screening mammography (DDSM),
  - Ischemic stroke lesion segmentation (ISLES),
  - Liver tumor segmentation (LiTS),
  - Prostate MR image segmentation (PROMISE12),
  - Lung image database consortium image collection (LIDC-IDRI),
  - Open Access Series of Imaging Studies (OASIS),
  - Digital retinal images for vessel extraction (DRIVE),
  - Mammographic Image Analysis Society (MIAS),
  - The Internet Brain Segmentation Repository (IBSR18)
  - LONI Probabilistic Brain Atlas3 (LPBA40)

# Performance Measure

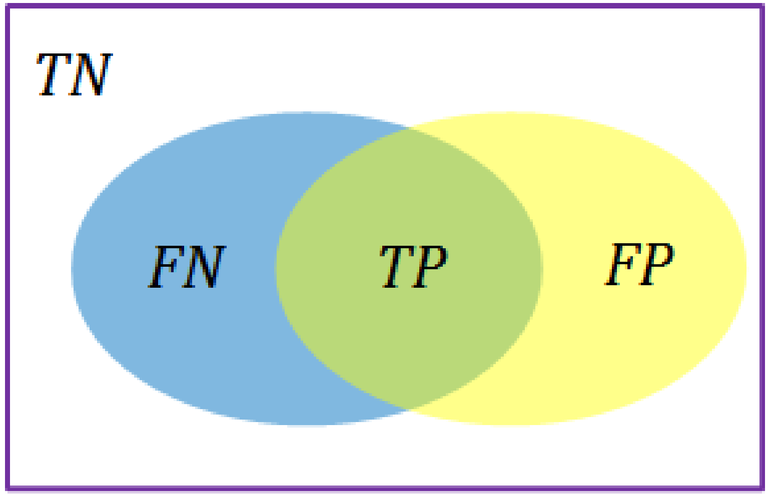
- Performance measure is based on confusion matrix, for two classes (segments) problem:

| # of pixels | Predicted Segment #1 | Predicted Segment #2 |
|---|---|---|
| Actual Segment #1 | TP | FN |
| Actual Segment #2 | FP | TN |

- **T**rue **P**ositive: Pixel Classified Correctly as #1 (inside)
- **F**alse **P**ositive: Pixel Classified Incorrectly as #1 (inside)
- **F**alse **N**egative: Pixel Classified Incorrectly as #2(outside)
- **T**rue **N**egative: Pixel Classified Correctly as #2 (outside)

# Performance Measure

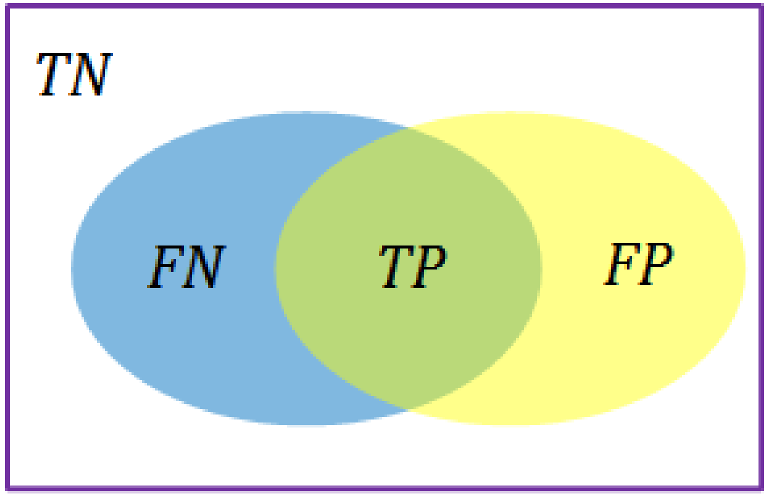
› Venn Diagram (**G**round Truth: Blue, **A**lgorithm: Yellow)




| # of pixels | Predicted Segment #1 | Predicted Segment #2 |
|---|---|---|
| **Actual Segment #1** | TP | FN |
| **Actual Segment #2** | FP | TN |

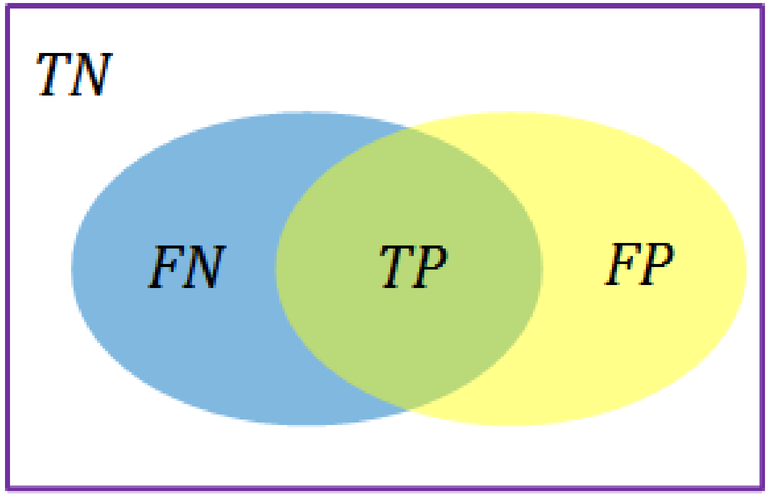
# Performance Measure

- Performance Quantification:
- $Accuracy = \frac{TN+TP}{TP + FP + TN + FN}$
- $Specificity = \frac{TN}{TN + FP}$
- $Sensitivity\ (Recall) = \frac{TP}{TP + FN}$
- $Precision = \frac{TP}{TP + FP}$
- $False\ Positive\ Rate(FPR) = \frac{FP}{FP + TN}$



# Performance Measure

- Performance Quantification:
- Jaccard Index (IoU*): $J = \frac{|G \cap A|}{|G \cup A|} = \frac{TP}{TP + FP + FN}$
- Dice Similarity Coefficient $Dice = \frac{2|G \cap A|}{|G|+|A|} = \frac{2TP}{2TP + FP + FN}$




- IoU: Intersection over Union

# Performance Measure

- Performance Quantification:
- Hausdorff Distance:

$$HD(G,A) = max\big(hd(G,A), hd(A,G)\big)$$

- where:
- $hd(G,A) = \max_{\boldsymbol{g}\in G} \min_{\boldsymbol{a}\in A} \|\boldsymbol{g} - \boldsymbol{a}\|_2$
- $hd(A,G) = \max_{\boldsymbol{a}\in A} \min_{\boldsymbol{g}\in G} \|\boldsymbol{g} - \boldsymbol{a}\|_2$

# Performance Measure

- Hausdorff distance:
- $HD(G,A) = max\big(hd(G,A), hd(A,G)\big)$
- $hd(G,A) = \max_{\boldsymbol{g}\in G} \min_{\boldsymbol{a}\in A} \|\boldsymbol{g} - \boldsymbol{a}\|_2$
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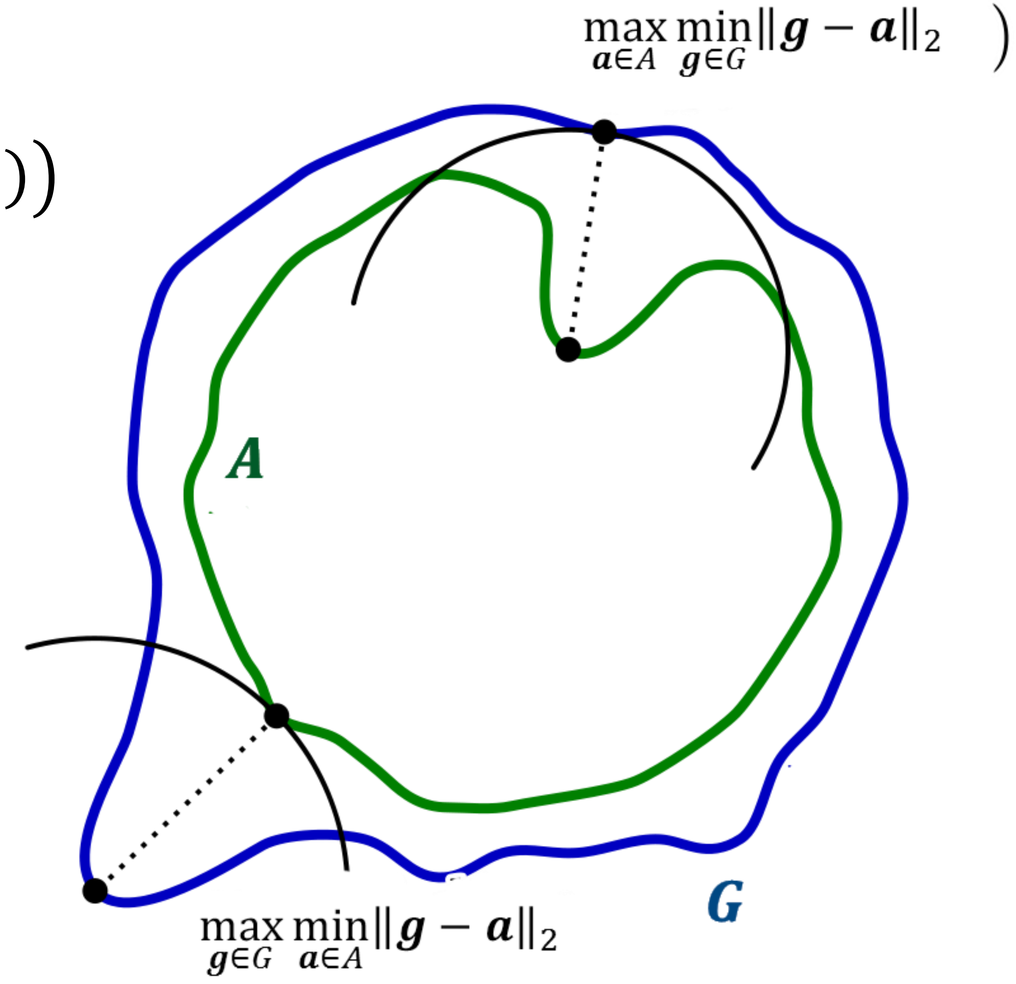



MEDICAL IMAGE ANALYSIS AND PROCESSING, E.FATEMIZADEH (2020)

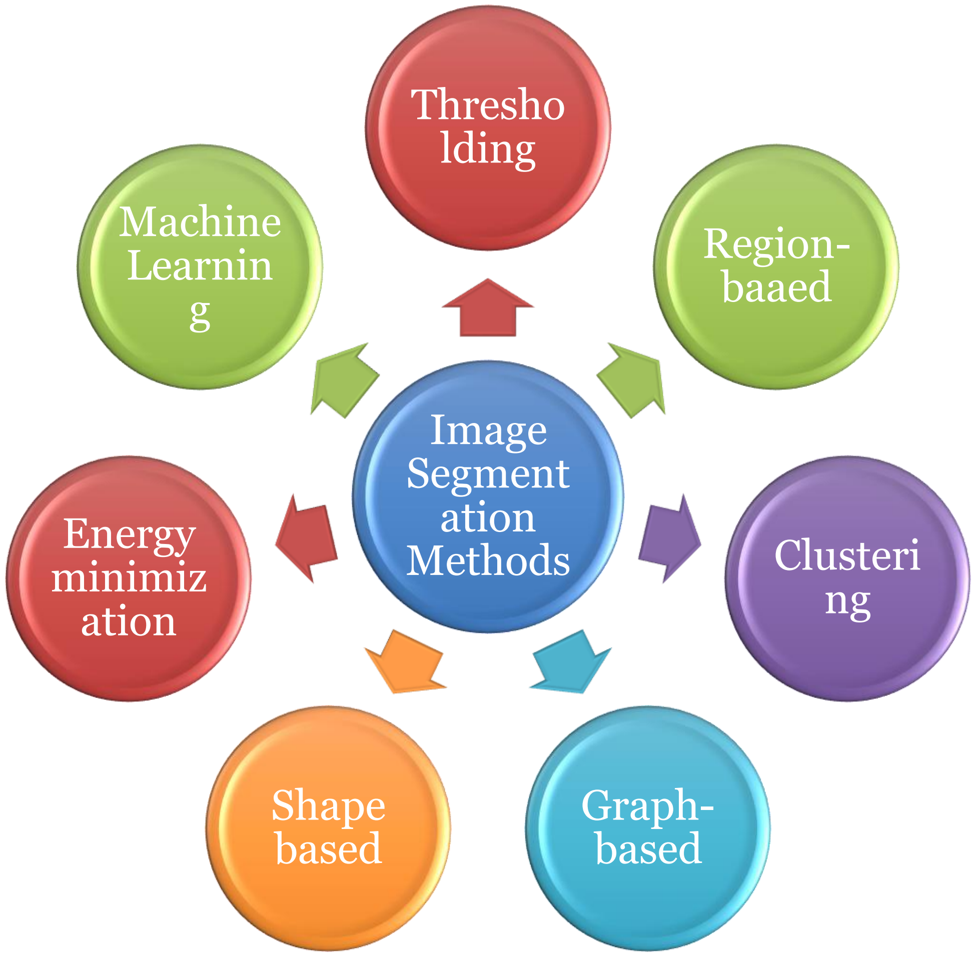
# Performance Measure (Multi-Segment)

- Performance Quantification (K: # of segments):
- Pixel Accuracy (PA): $PA = \frac{\sum_{i=0}^{K} P_{ii}}{\sum_{i=0}^{K} \sum_{j=0}^{K} P_{ij}}$
- $P_{ij}$: Number of pixels of segment *i* predicted as belonging to segment *j*
- Mean Pixel Accuracy (MPA): $MPA = \frac{1}{K+1} \sum_{i=0}^{K} \frac{P_{ii}}{\sum_{j=0}^{K} P_{ij}}$
- Mean-IoU/Jaccard (MIoU): Average IoU over all segments

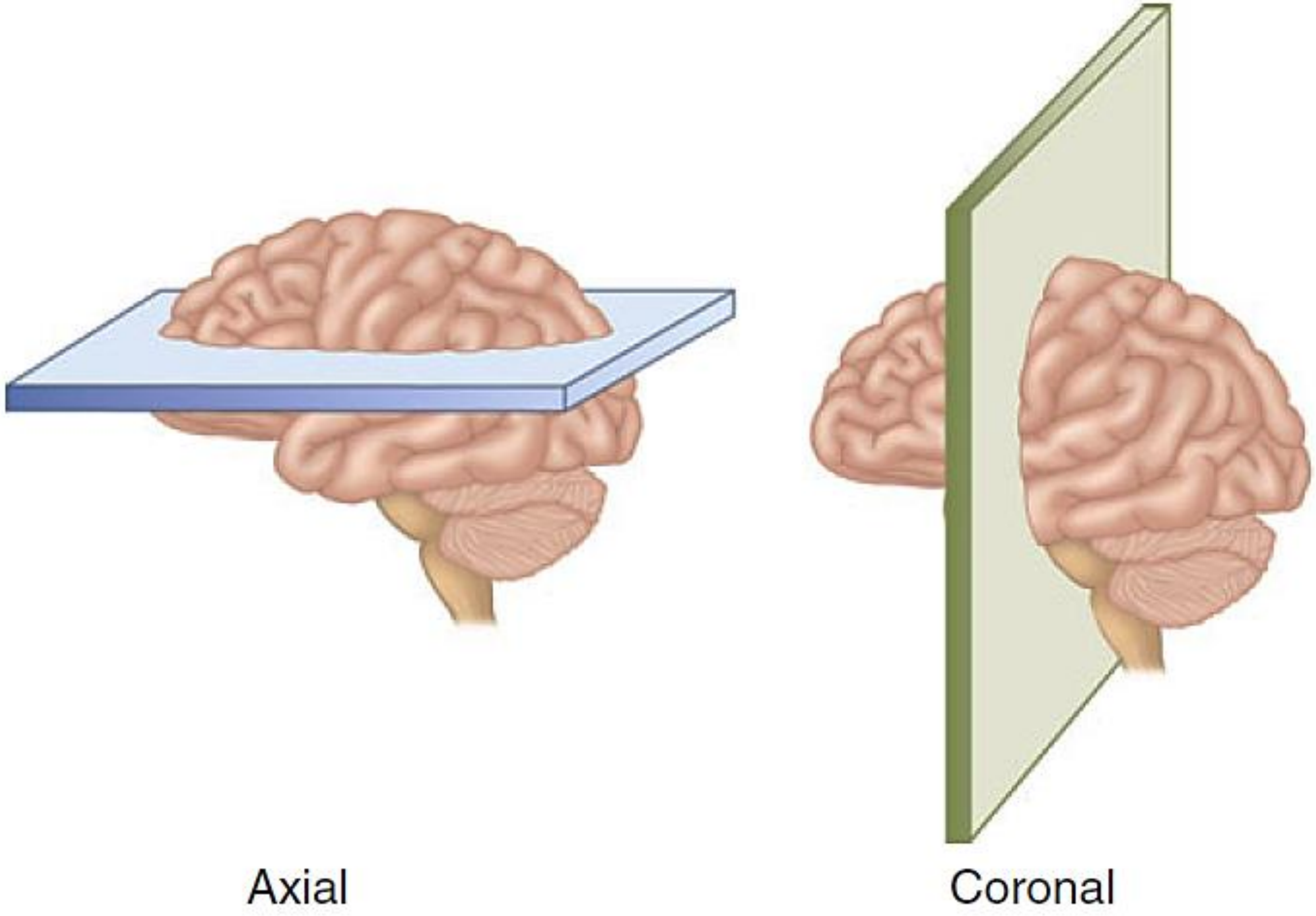
# Segmentation Strategy

- Intensity Based
- Edge Based
- Region/Texture Based

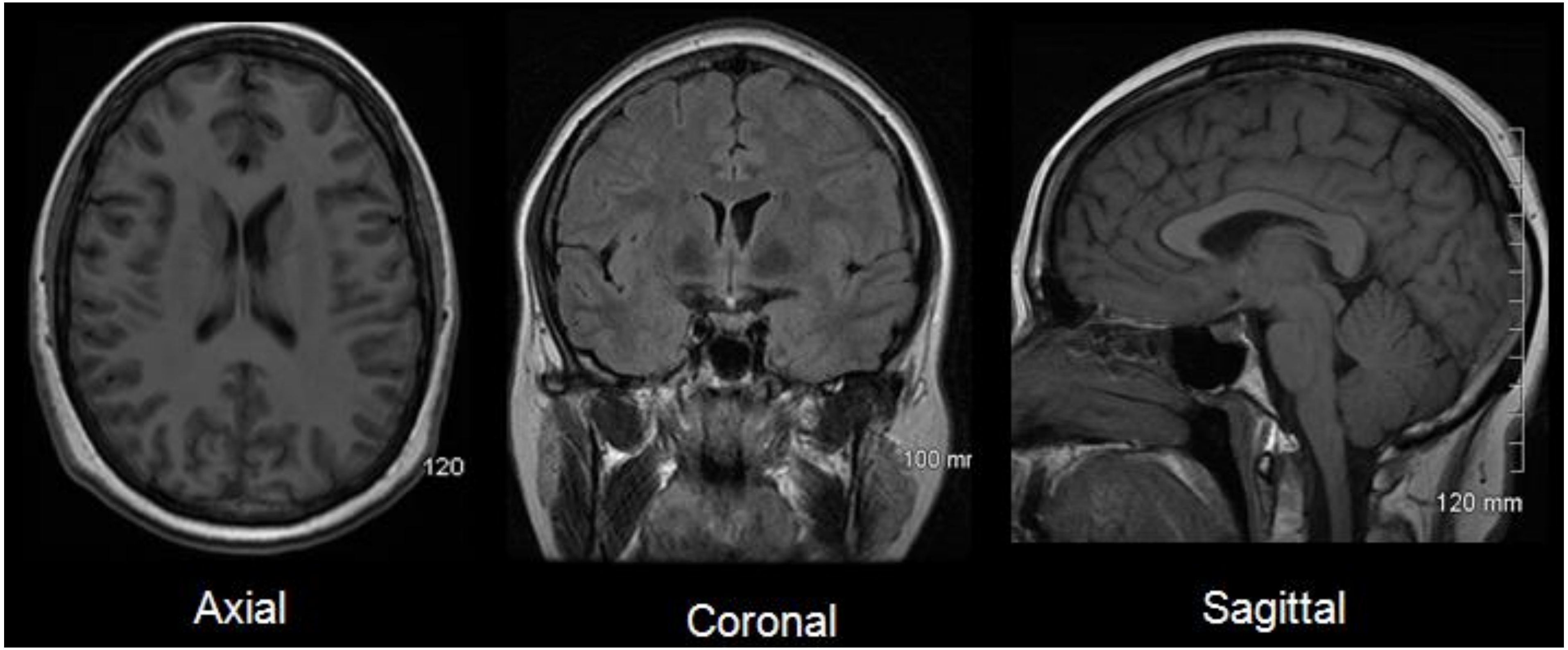
# Segmentation Strategy



# Image Orientation

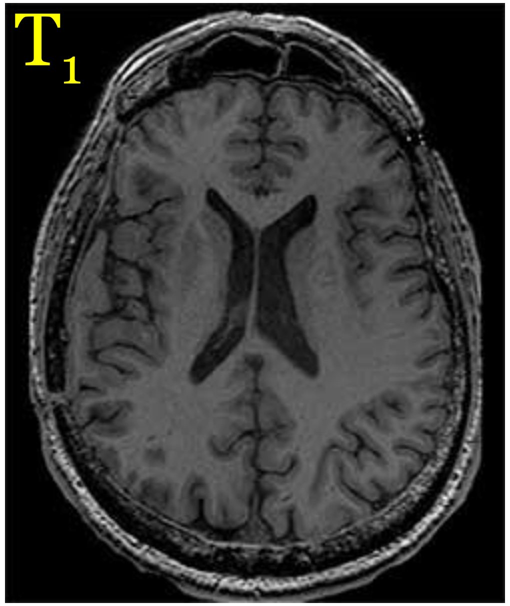


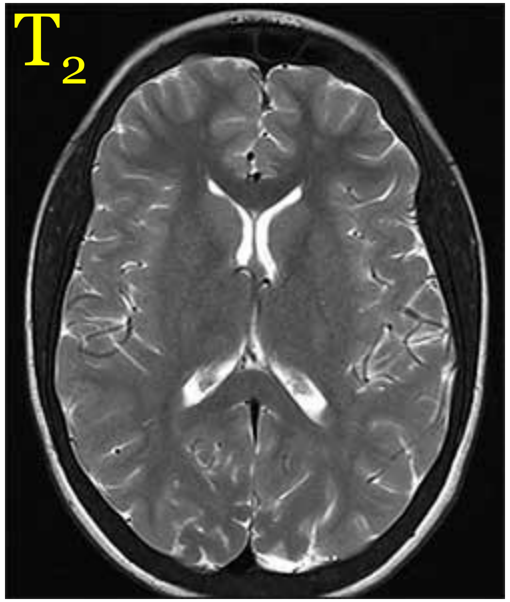
# Image Orientation

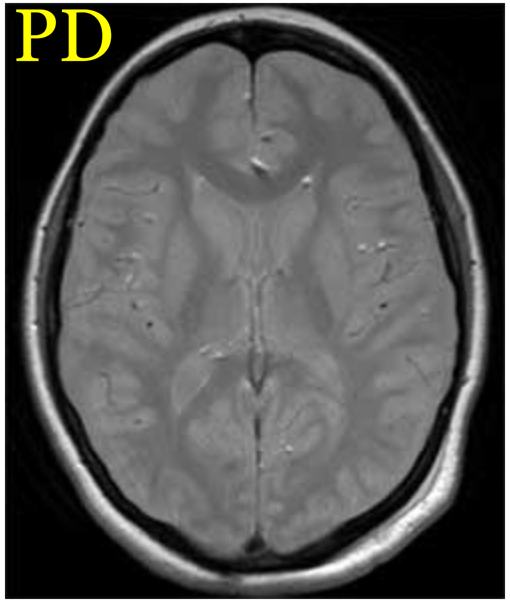


# Imaging Modalities

- MRI is parametric (pulse sequences) imaging system, using different pulse sequences, different images capture!
- Main MRI modalities are $T_1$-$T_2$-PD images:

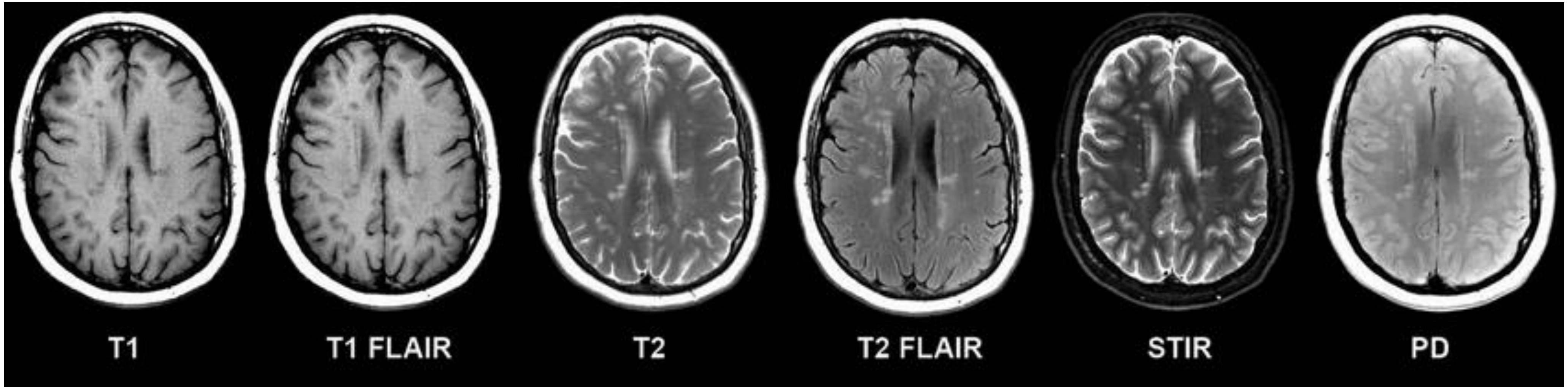


# Imaging Modalities

› More modalities are possible:



# The End

- AnY QuEsTiOn?