HST.582J / 6.555J / 16.456J Biomedical Signal and Image Processing
Spring 2007

Introduction to Medical Image Segmentation

HST 582

Outline

- Applications
- Terminology
- Probability Review
- Intensity-Based Classification
- Prior models
- Morphological Operators

Applications of Segmentation

- Image Guided Surgery
- Surgical Simulation
- Neuroscience Studies
- Therapy Evaluation

Interactive Segmentation

MRI image sequence removed due to copyright restrictions.

Applications of Segmentation

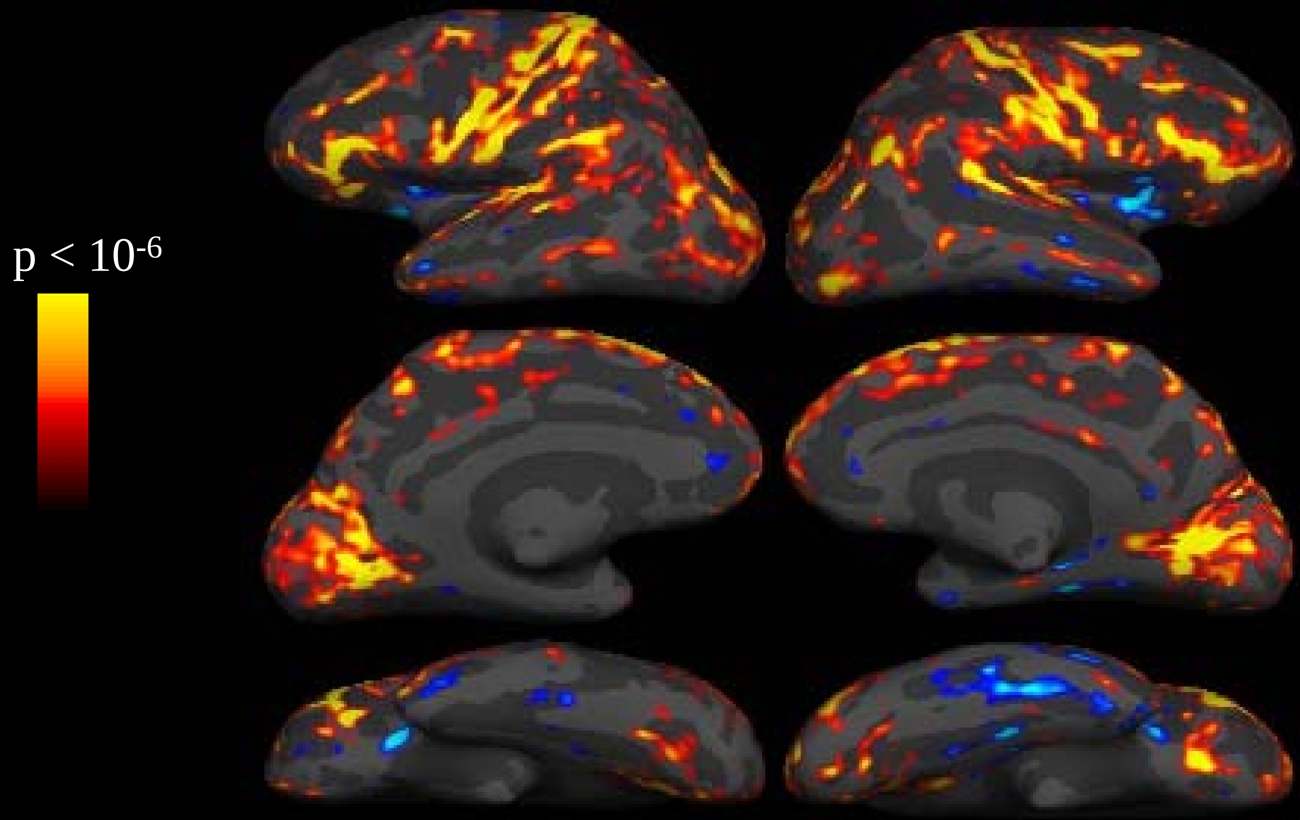
- Image Guided Surgery
- Surgical Simulation

Photo removed due to copyright restrictions.
Two doctors working with a surgical simulation device.

Applications of Segmentation

- Neuroscience Studies

Statistical Map of Cortical Thinning: Aging



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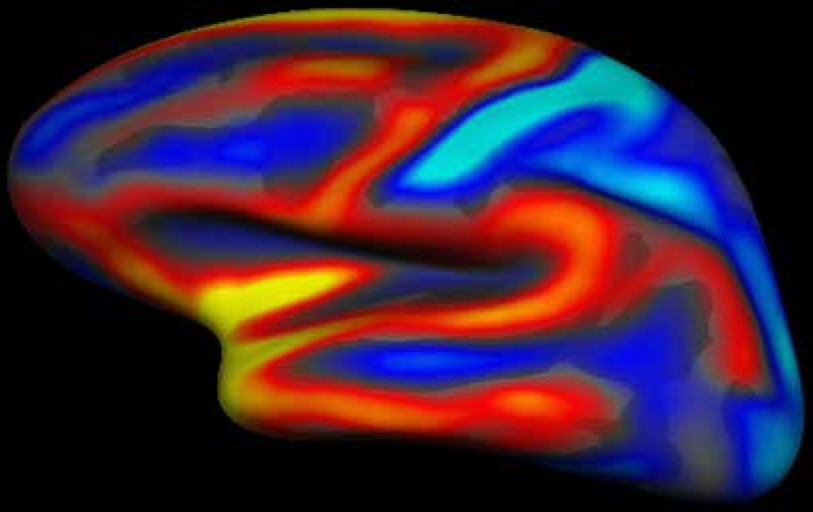
Thanks to Drs. Randy Buckner and David Salat for supplying this slide.

Movie of Cortical Thinning with Aging



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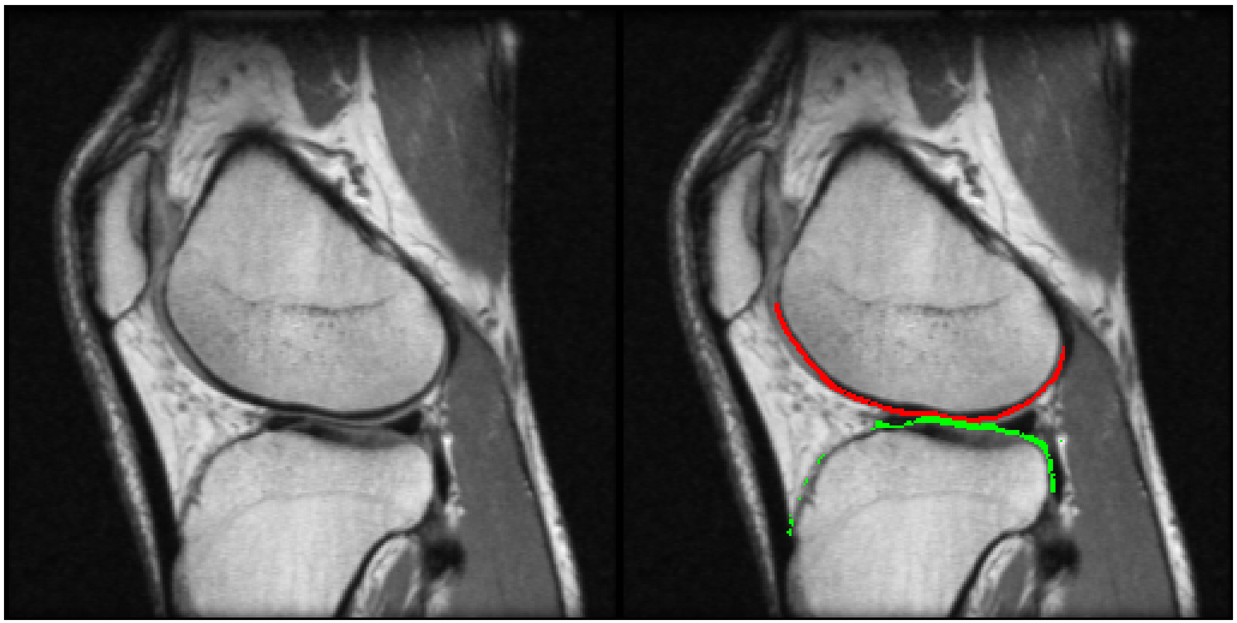
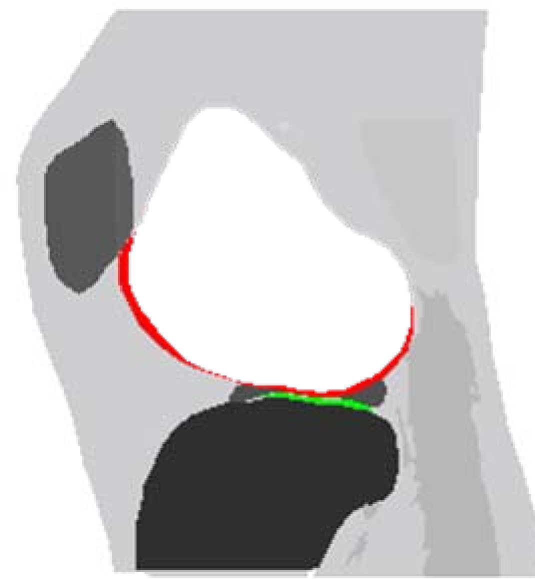
2.0 ← 2.25 ← 2.5 2.5 ← 2.75 ← 3.0

Applications of Segmentation

- Therapy Evaluation
  - Multiple Sclerosis
    - Examples Later in talk
  - Knee Cartilage Repair

Results: Segmentation of Femoral & Tibial Cartilage





MRI Image

Model-Based Segmentation

Manual Segmentation

Source: Kapur, Tina. "Model based three dimensional medical image segmentation." MIT Ph.D. thesis, 1999.

Limitations of Manual Segmentation

- slow (up to 60 hours per scan)
- variable (up to 15% between experts)

[Warfield + 2000]

The Automatic Segmentation Challenge

An automated segmentation method needs to reconcile

- Gray-level appearance of tissue
- Characteristics of imaging modality
- Geometry of anatomy

Terminology: *Segmentation*

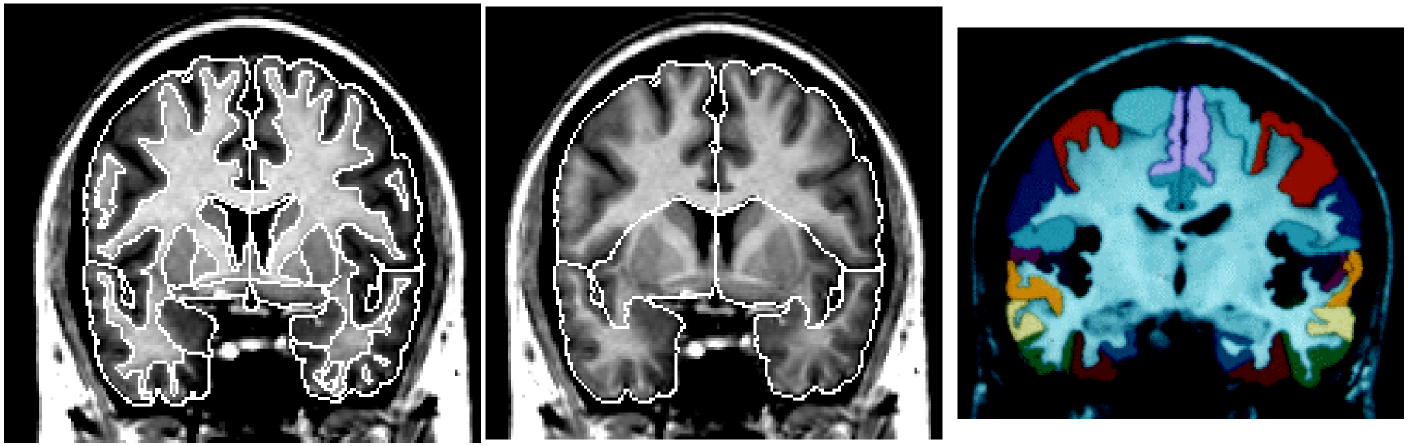
- Graphics Community:
  - Any process that turns images into models
- Another Frequent Usage (HST 582):
  - Labeling images according to tissue type (e.g. White / Gray Matter)
- Another:
  - Dividing imagery into Major Anatomical Subdivisions

Hierarchical Approach (Brain)

David Kennedy, MGH / Martinos Center

- *Segment* into lobes
- *Parcellate* into functional areas

Neuroanatomic Description Hierarchy:



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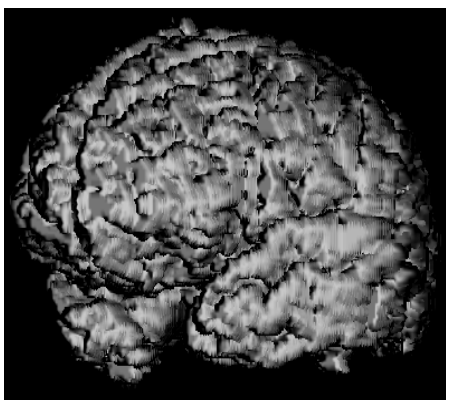

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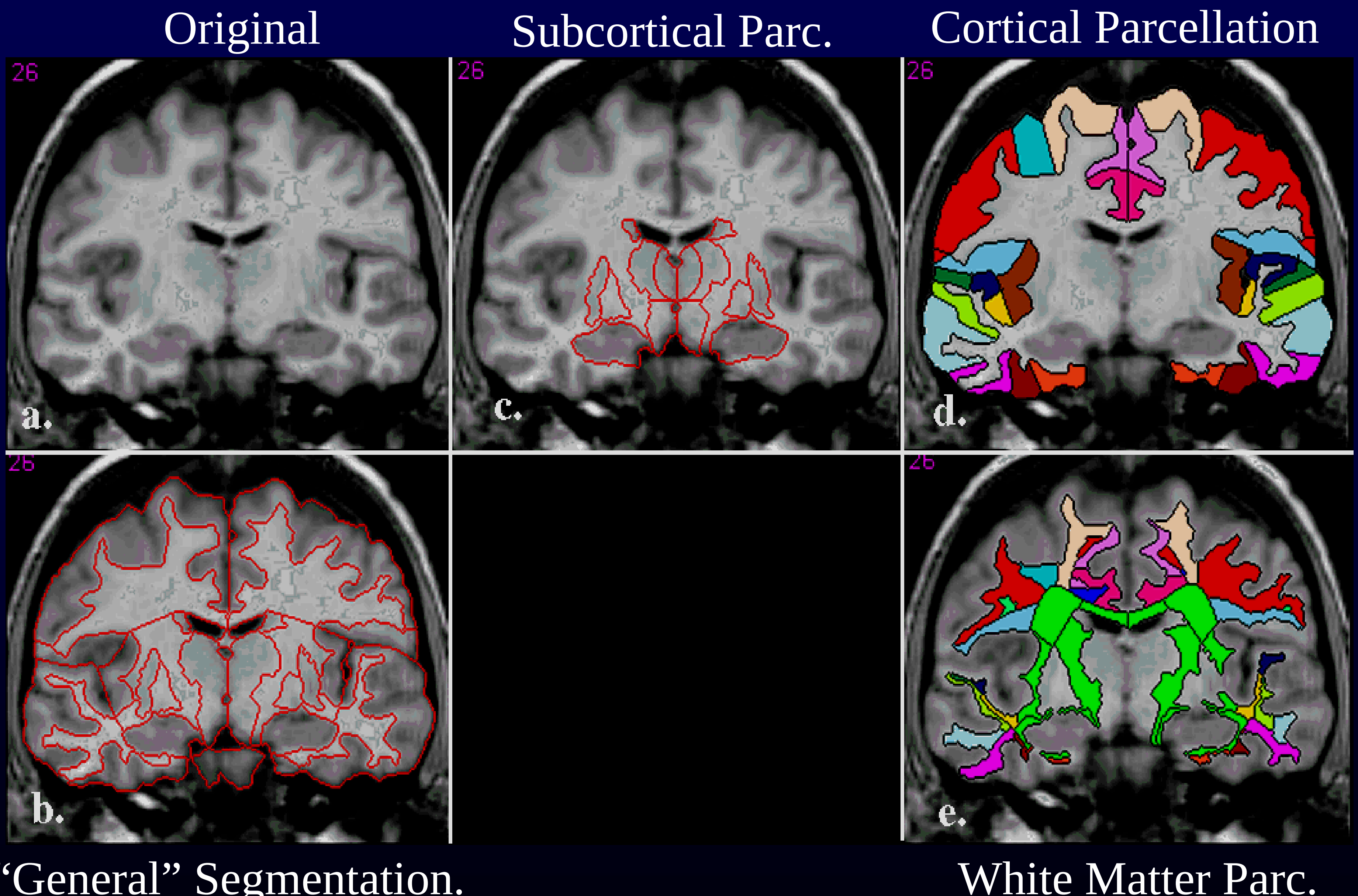
WHOLE BRAIN/STRUCTURE

Stages of Anatomic Analysis



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Probability Review

- Discrete Random Variables (RV)
  - Probability Mass Functions (PMF)
- Continuous Random Variables
  - Cumulative Distribution Functions (CDF)
  - Probability Density Functions (PDF)
- Conditional Probability
- Bayes' Rule

Discrete Random Variable

- Characterized by *Probability Mass Function* (PMF)
  - (sometimes called Distribution)
  - Maps values *x* to their Probabilities *P(x)*

$$0 \leq P(x) \leq 1$$

$$\sum_{x} P(x) = 1$$

Continuous Random Variables

- Define Cumulative Distribution Function (CDF) on RV **x**

$$F_X(x) = P(X \leq x)$$

$$0 \leq F_X(x) \leq 1$$

- Non-Decreasing
- Sometimes called *Distribution Function*

Continuous Random Variables...

- Define *Probability Density Function* (PDF)

$$p(x) = \frac{d}{dx} F_X(x)$$

- Easy to show, using Fundamental

Theorem of Calculus:

$$P(a \leq x \leq b) = \int_a^b p(x)dx$$

More on PDFs : *p(x)*

- Non Negative
- Integrates to One
- (Value can be Greater than One)

Conditional Probability

- Define Conditional Probability:

$$P(X|Y) = \frac{P(X\&Y)}{P(Y)}$$

Bayes' Rule (easy to show)

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- Frequent Situation:
  - A: State of the World
  - B: Measurement
  - *P(B|A)* : Measurement Model
  - *P(A)* : A-Priori Model

Intensity-Based Segmentation

- Statistical Classification
  - ML
  - MAP, a-priori models
  - KNN

Segmentation

- Easy Segmentation
  - Tissue/Air (except bone in MR)
  - Bone in CT
- Feasible Segmentation
  - White Matter/Gray Matter
  - M.S. Lesions

Statistical Classification

- Probabilistic model of intensity as a function of (tissue) class
- Intensity data
- Prior model

Classification of voxels

[Duda, Hart 78]

Measurement Model

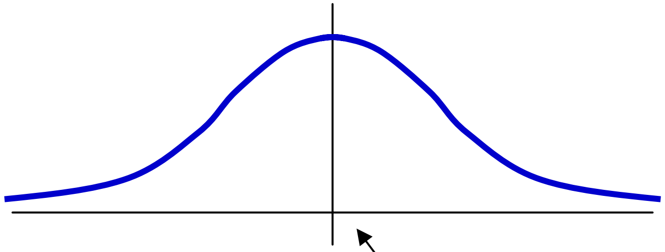
- Characterize sensor

$$p(x|\text{tissue class } J)$$

probability density

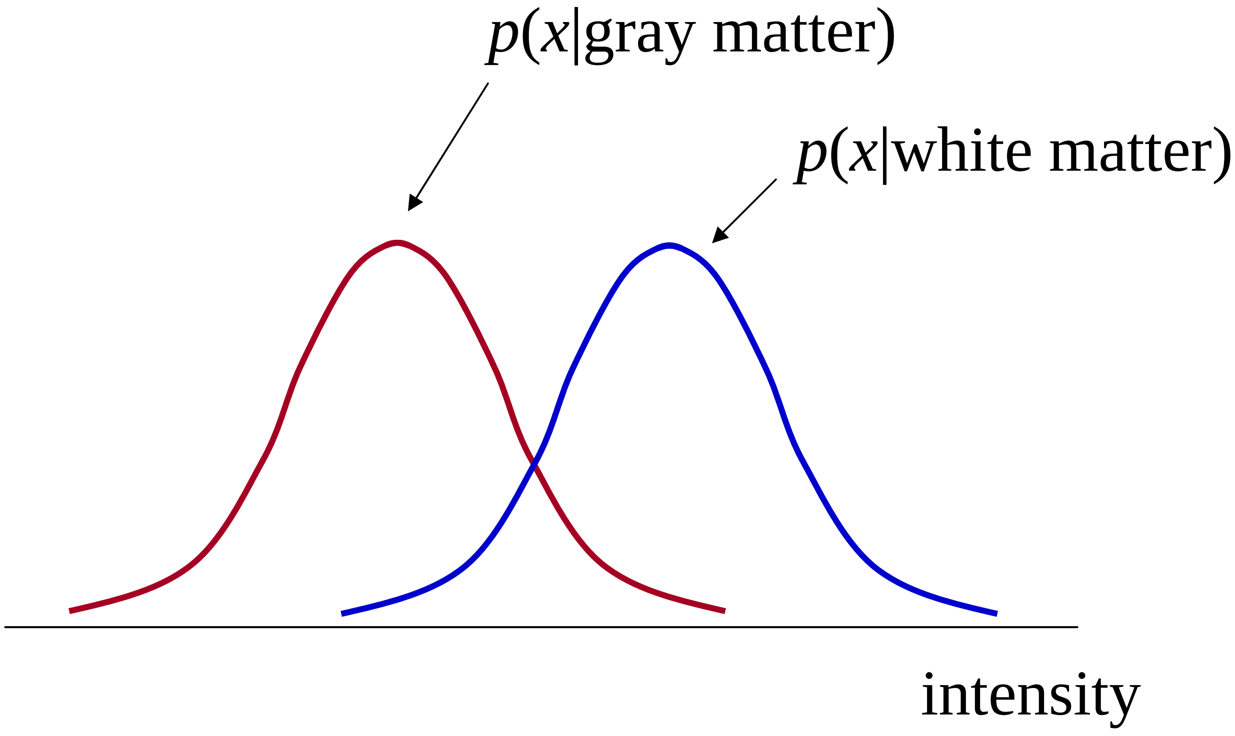
intensity

Tissue class conditional model of signal intensity



mean for tissue J

Example



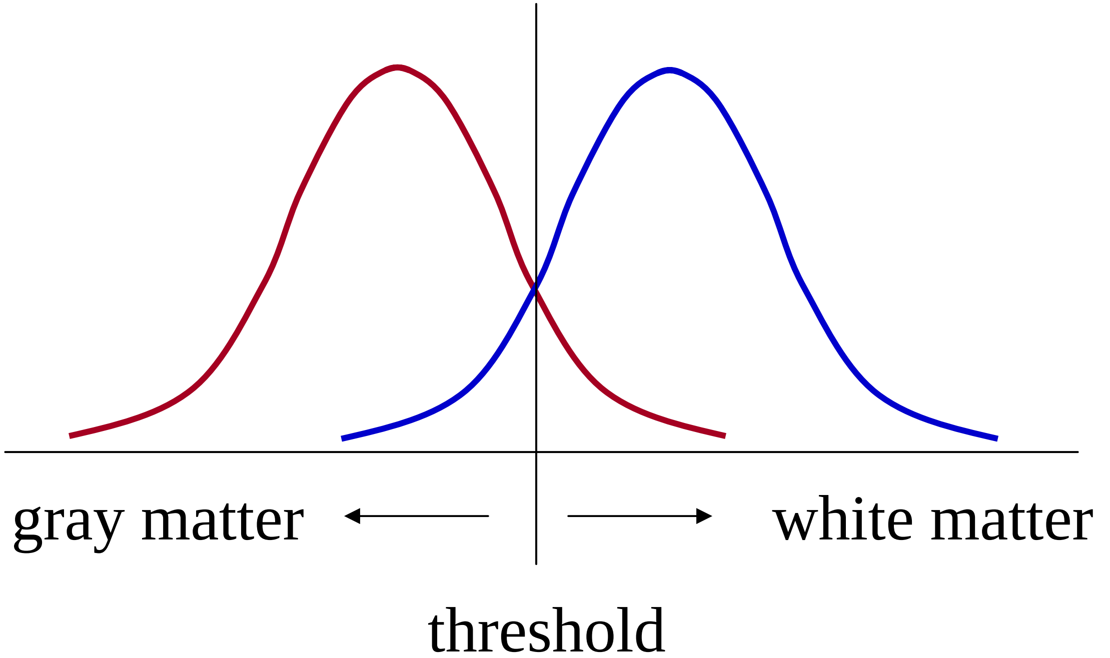
Maximum Likelihood Classification

- Measure intensity, x_o, and we want to know the tissue class

$$\boxed{L(TC_j) = p(x_o \mid TC_j)}$$

- Pick tissue class that maximizes L
- L is not a probability
  - Called: Likelihood

Example - revisited



Anatomical Knowledge

- *A priori* model
  - Before the measurement is considered

$$\boxed{P(TC_j)}$$

MAP Classifier

- Choose TC to Maximize the *A Posteriori* probability

measurement model

prior

$$\boxed{P(TC \mid x_o) = \frac{p(x_o \mid TC)P(TC)}{p(x_0)}}$$

posterior probability

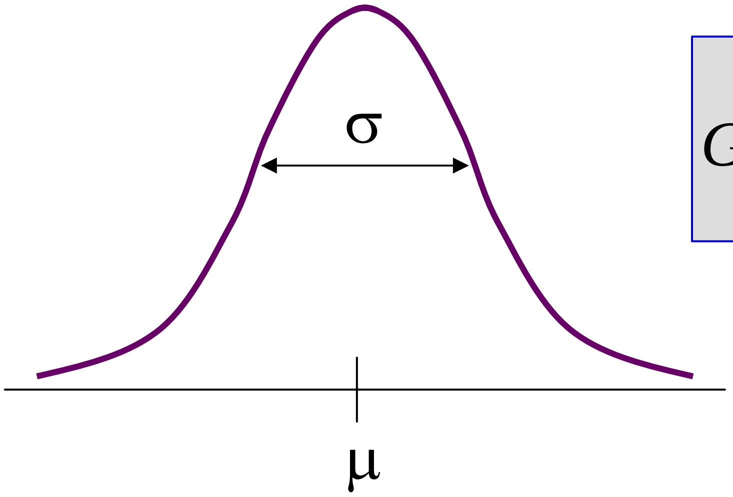
not important

Measurement Model

- Training data
  - Get an expert to label some of the voxels
- Optional: Use a parametric model
  - Assume functional form
    - Popular choice: Gaussian

Gaussian Density – 1D

- Why?
  - Central Limit Theorem
  - Makes math easy (when doing parameter estimation)



$$G(\mu,\sigma,x)=\frac{1}{\sqrt{2\pi}\sigma}e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Choosing σ and μ

- Use training data: $\{Y_1, Y_2, \ldots, Y_N\}$
- ML parameter estimation

$$\mu = \frac{1}{N}\sum_i Y_i \qquad \sigma^2 = \frac{1}{N}\sum_i (Y_i - \mu)^2$$

- MAP tissue classifier with Gaussian measurement model: choose tissue class to maximize:

$$P(TC_j \mid x_o) = \frac{G(\mu_j, \sigma_j, x_o) P(TC_j)}{\ldots}$$

Gaussian Density – 2d Data

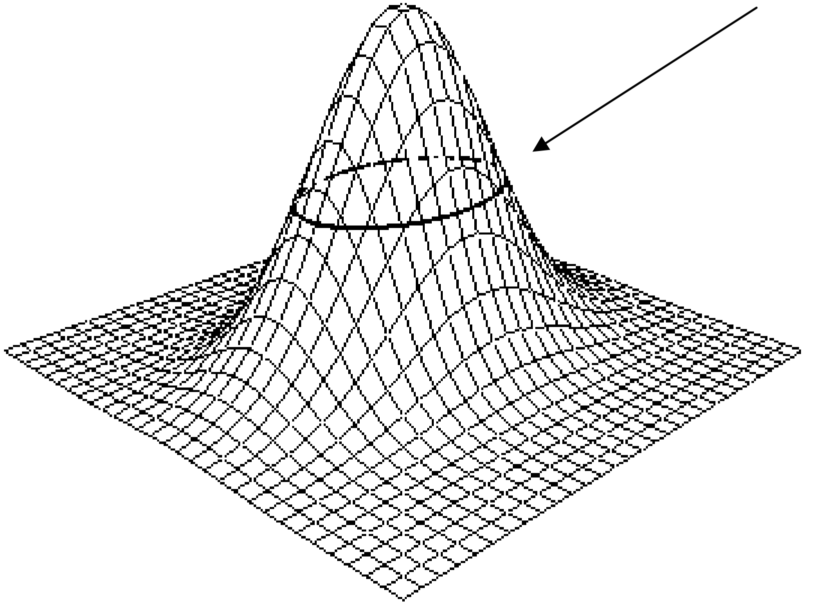
- Example

$$X = \begin{pmatrix} \text{proton density intensity} \\ \text{T2 weighted intensity} \end{pmatrix}$$

Vector Gaussian

$$\boxed{G(M,\Sigma,X) = \frac{1}{(2\pi)^{\frac{N}{2}}\,|\Sigma|^{\frac{1}{2}}} e^{-(X-M)^T\Sigma^{-1}(X-M)}}$$

2D Gaussian: Example

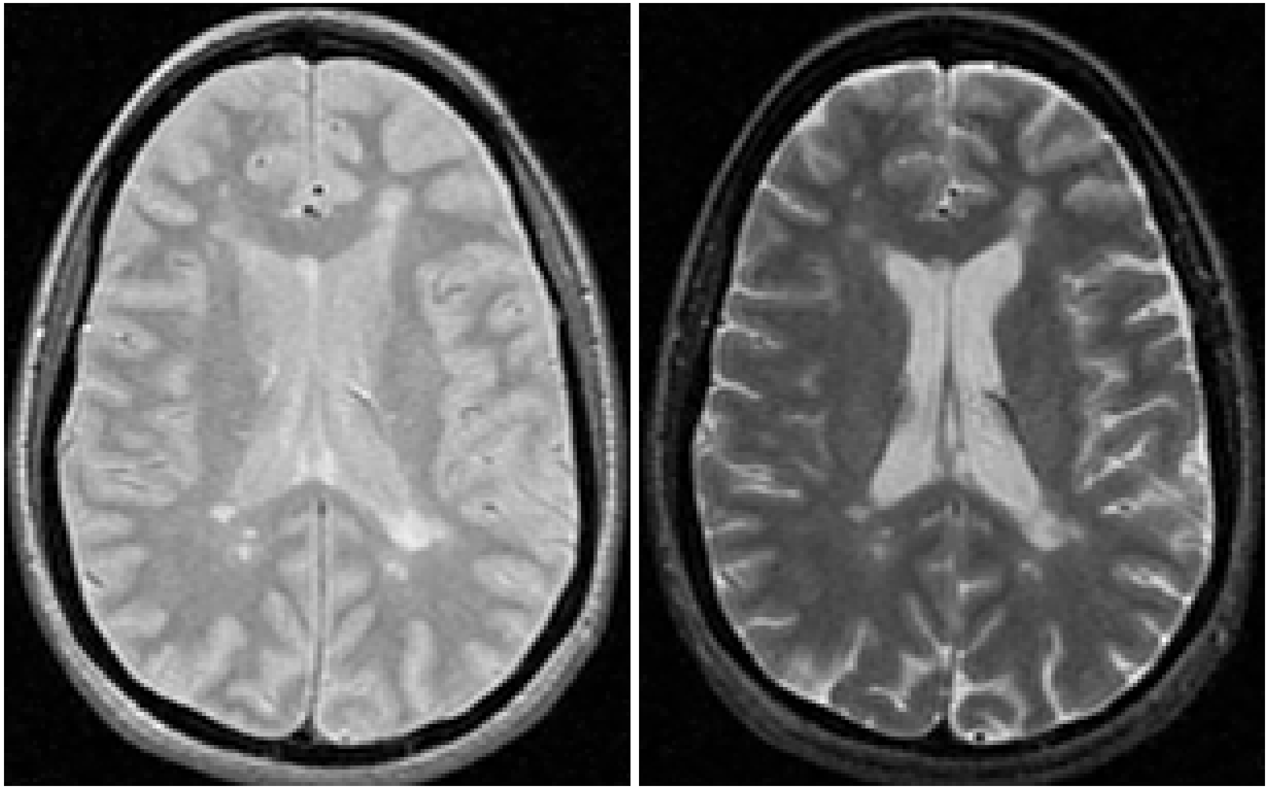


iso probability
contour is
ellipse

Multiple Sclerosis Example

- Dual echo MRI
  - 1 x 1 x 3 mm
  - Registered slice pairs
- Proton density image
  - Good: white/gray
  - Bad: gray/csf
- T2-weighted image
  - Good: CSF/
  - Not so good: white/gray
  - Good: MS lesions

Multiple Sclerosis



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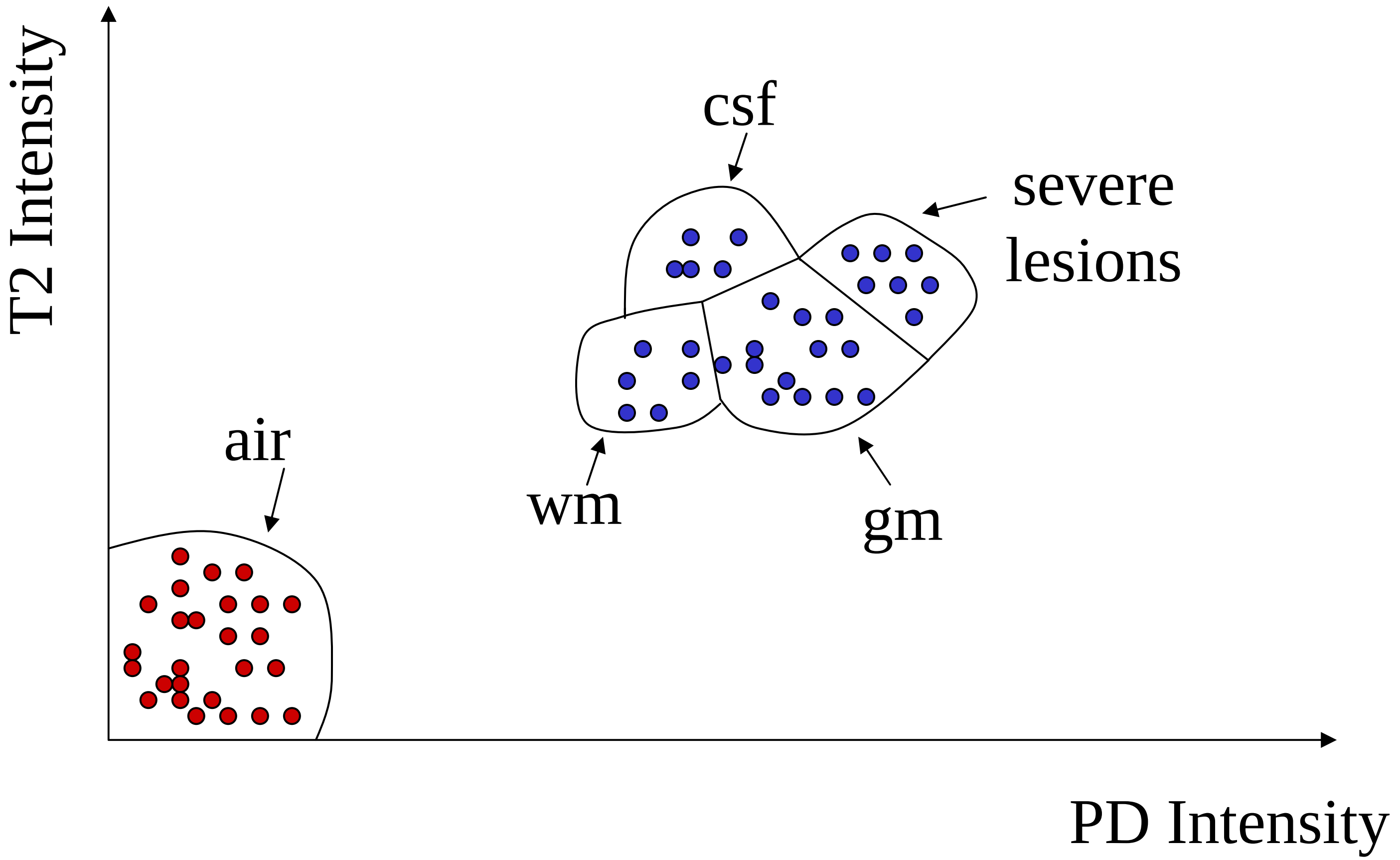
PDw T2w

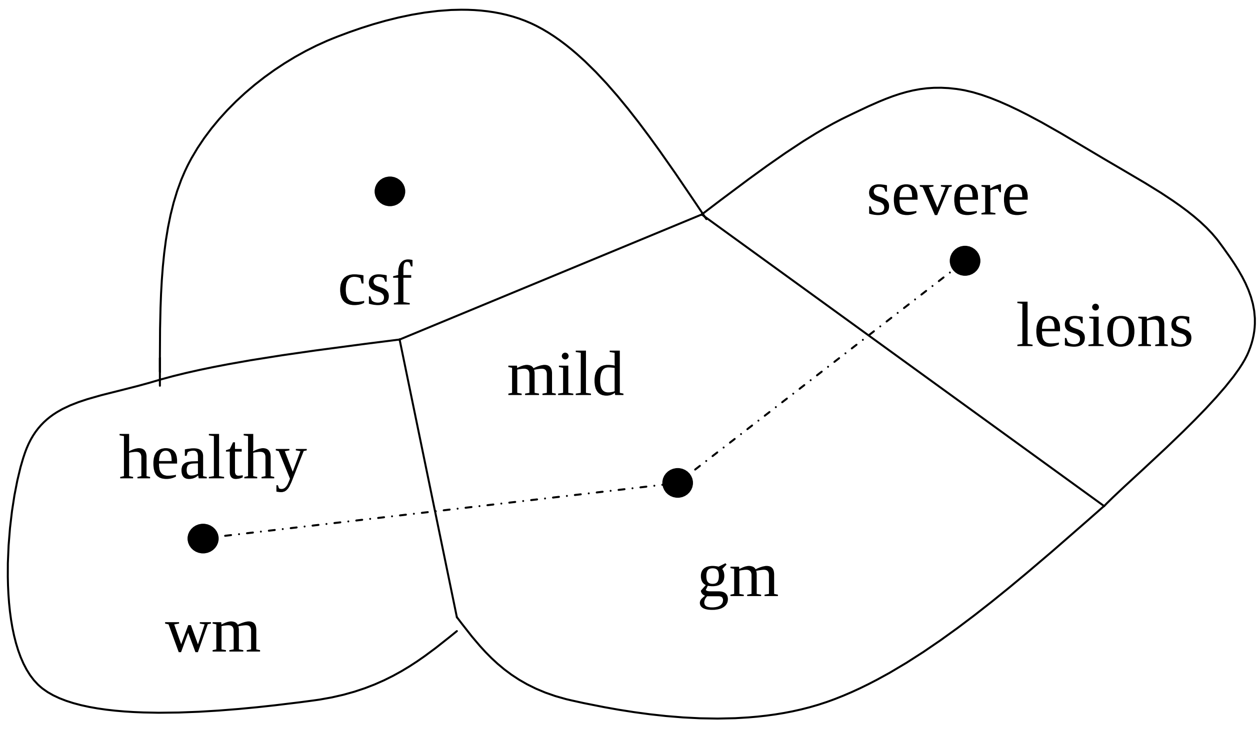
Provided by S Warfield

Dual Echo MRI Feature Space

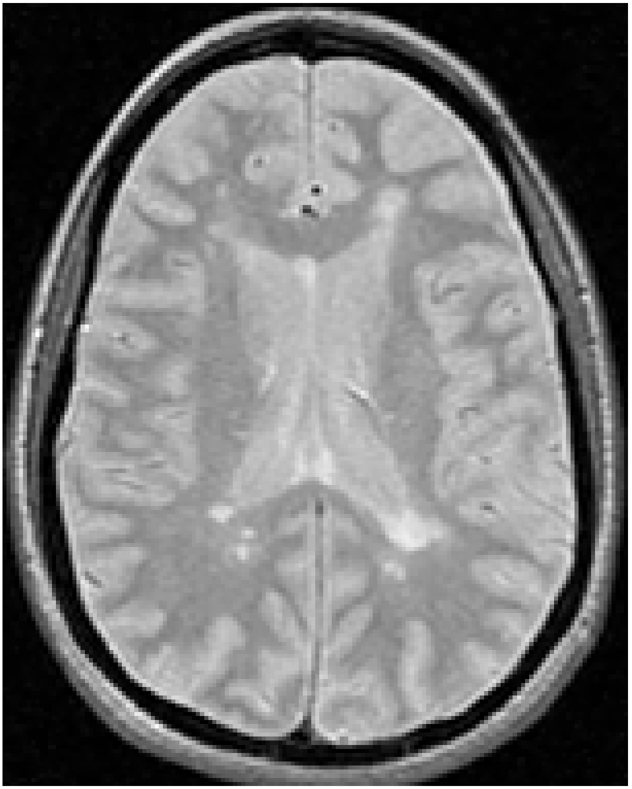


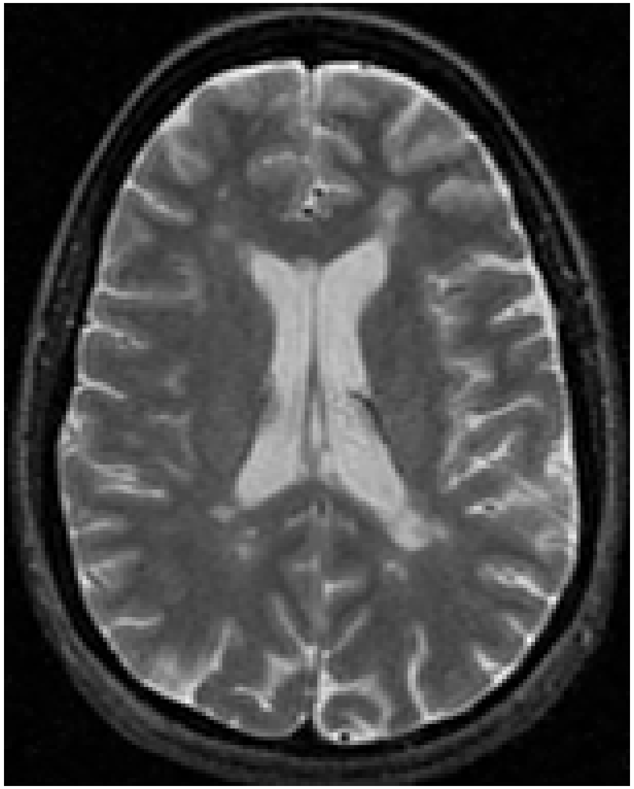
Detail

- MS Lesions are “graded phenomenon” in MRI, and can be anywhere on the curve



Multiple Sclerosis





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PDw

T2w

Segmentation

Background: Intensity Inhomogeneities in MRI

- MRI signal derived from RF signals…
- Intra Scan Inhomogeneities
  - “Shading” … from coil imperfections
  - interaction with tissue?
- Inter Scan Inhomogeneities
  - Auto Tune
  - Equipment Upgrades

EM-Segmentation

E-Step

Compute tissue posteriors using current intensity correction.

Estimate intensity correction using residuals based on current posteriors.

M-Step

Provided by T Kapur

Dual Echo Longitudinal Study

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PDw

T2w

Tissue classification

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No Intensity Correction

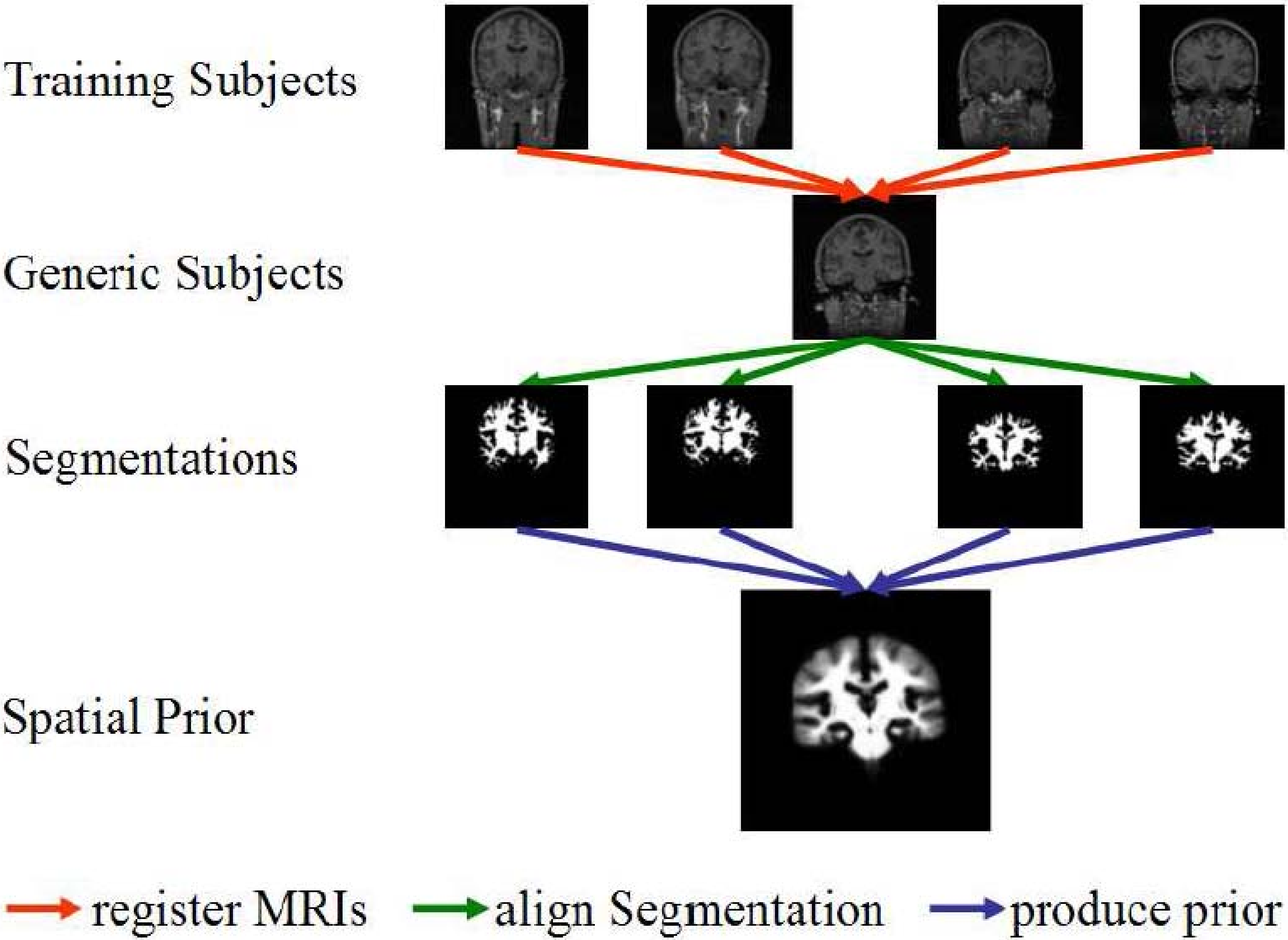
EM Segmentation

Prior Models

- Average Brain
- Structurally-Conditioned Models
- Markov Random Fields (MRF)
  - Ising
  - Potts

Average Brain Models

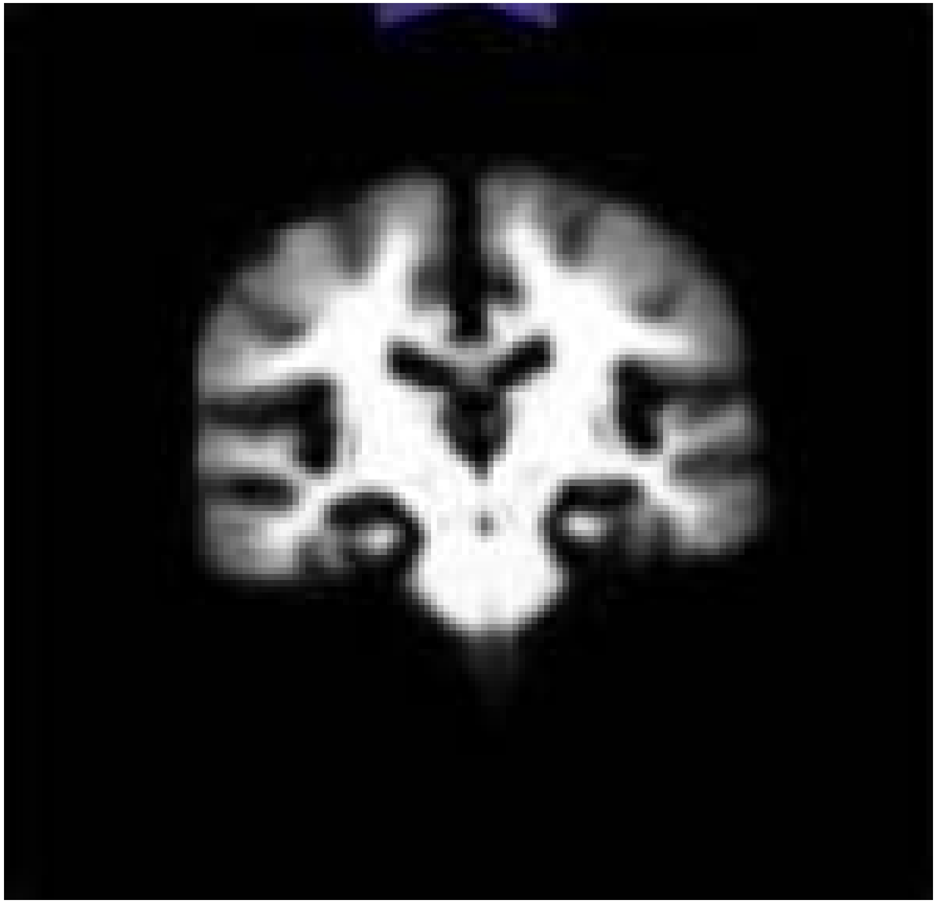
- Construct a spatial prior model by averaging tissue distributions over a population [MNI].



Provided by Kilian Pohl

Source: Pohl, Kilian M. "Prior Information for Brain Parcellation." MIT Ph.D. thesis, 2005.

P(white matter | x y)



Provided by Kilian Pohl

Source: Pohl, Kilian M. "Prior Information for Brain Parcellation." MIT Ph.D. thesis, 2005.

Structurally-Conditioned Prior Models

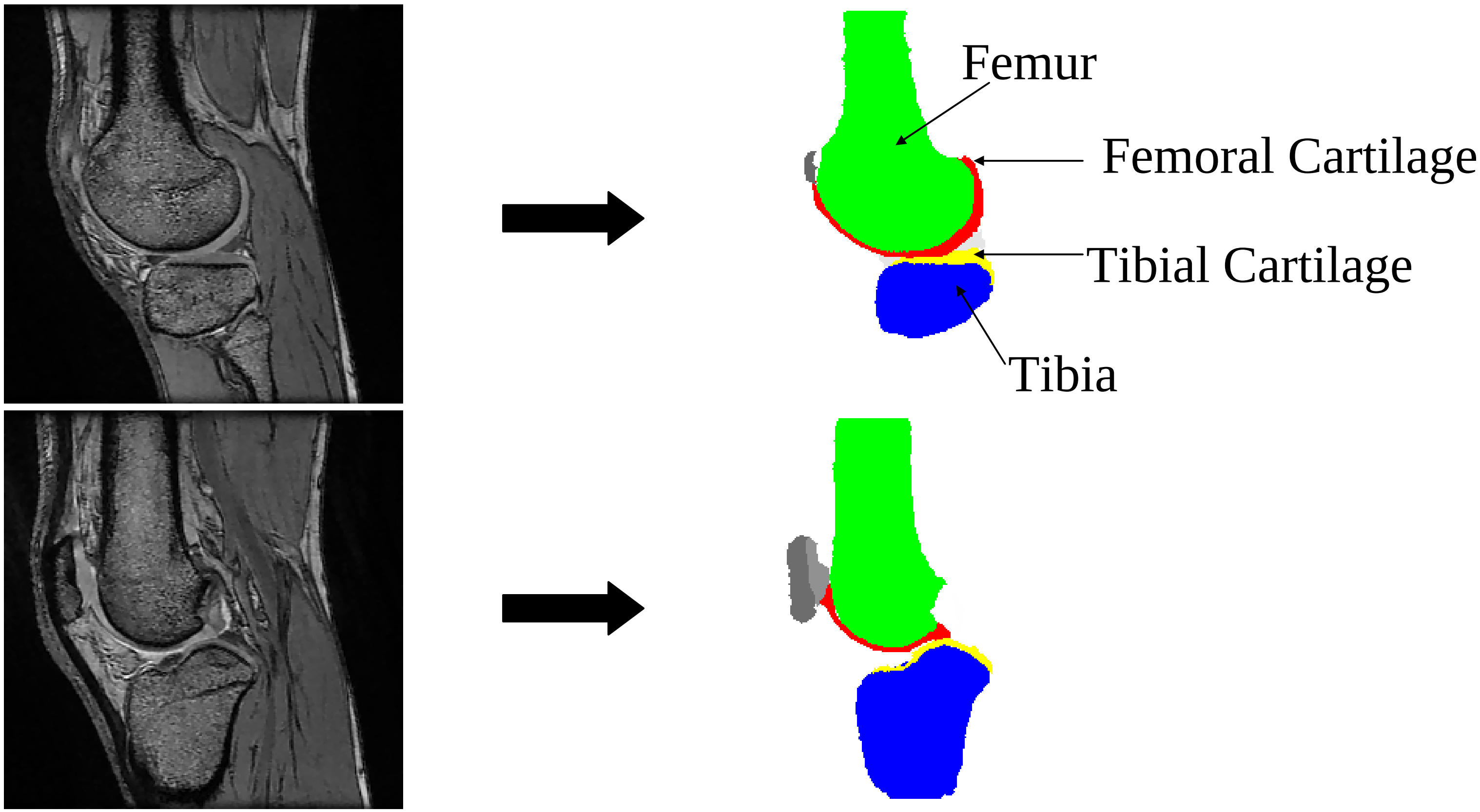
- From (Kapur 1999)
  - Modeling Global Geometric Relationships between Structures

Modeling Global Geometric Relationships between Structures

- Relative Geometry Models
- Motivate Using Knee MRI
- Brain MRI Example

MERL, SPL, MIT, CMU
Surgical Simulation
(Sarah Gibson, PI)

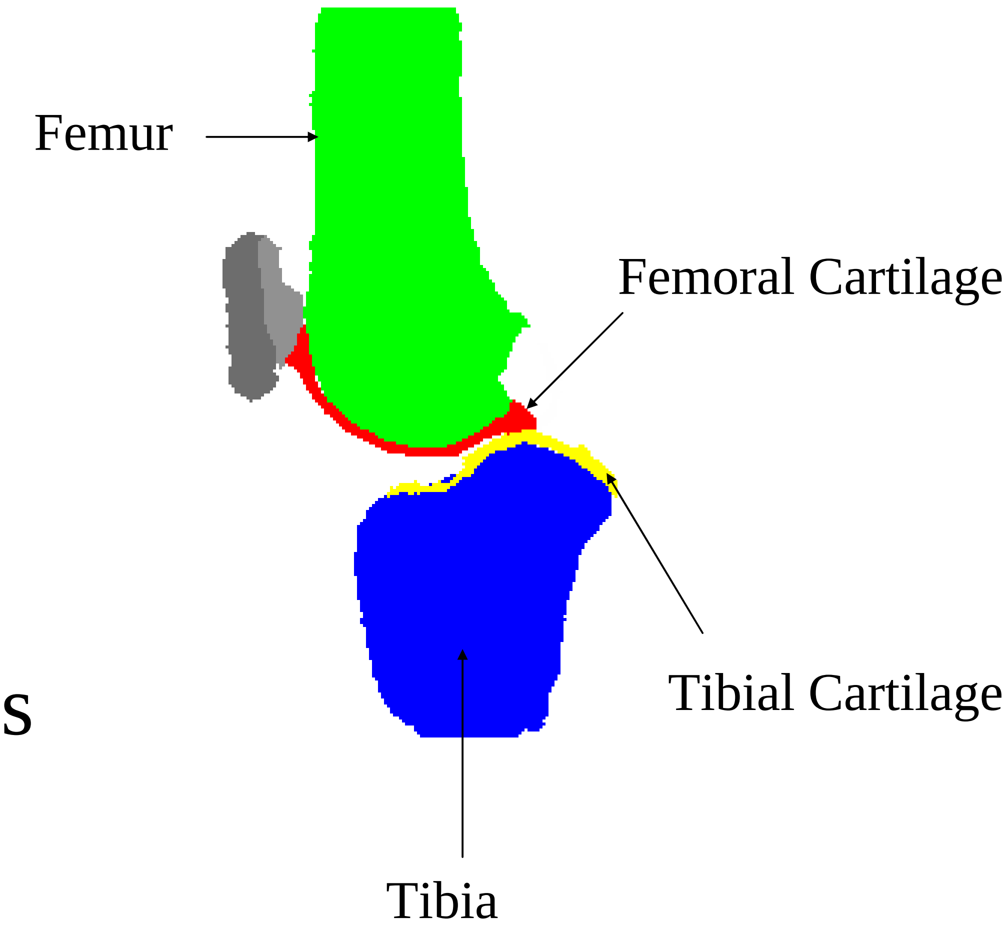
Segmented Knee MRI



Source: Kapur, Tina. “Model based three dimensional medical image segmentation.” MIT Ph.D. thesis, 1999.

Motivation

- Primary Structures
  - image well
  - easy to segment
- Secondary Structures
  - image poorly
  - relative to primary



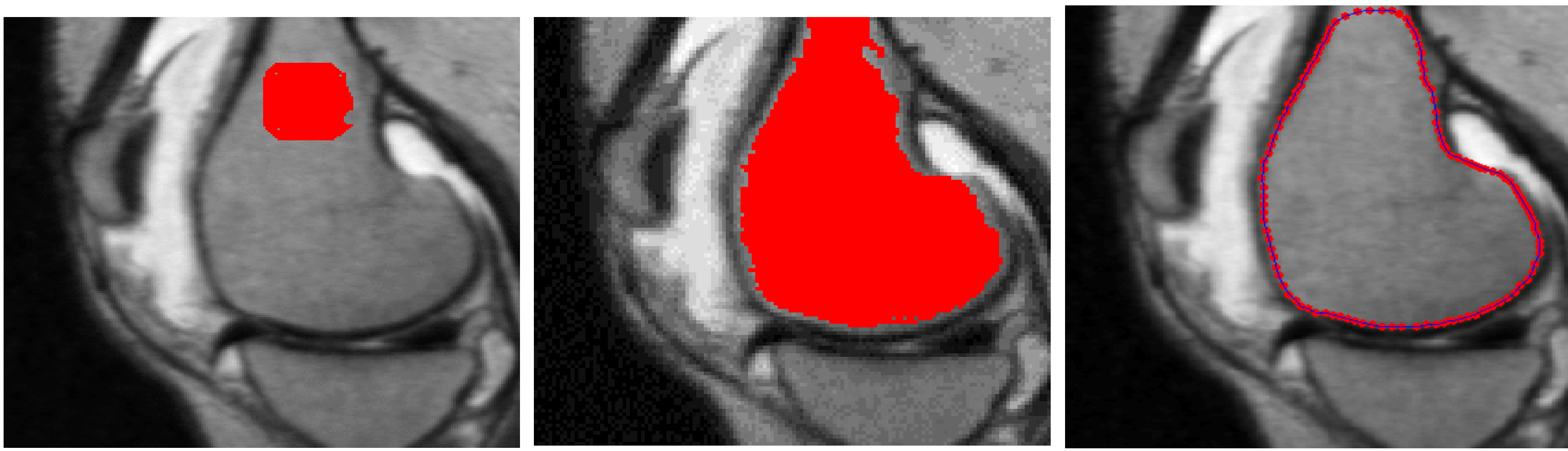
Source: Kapur, Tina. “Model based three dimensional medical image segmentation.” MIT Ph.D. thesis, 1999.

Relative Geometric Prior Approach

- Select primary/secondary structures
- Measure geometric relation between primary and secondary structures from training data
- Given novel image
  - segment primary structures
  - use geometric relation as prior on secondary structure in EM-MF Segmentation

Provided by T Kapur

Segment Primary Structures: Femur, Tibia



Seed Region Growing Boundary Localization

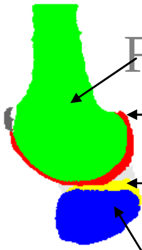
Source: Kapur, Tina. “Model based three dimensional medical image segmentation.” MIT Ph.D. thesis, 1999.

Status

- Have Bone
- Want Cartilage

Provided by T Kapur

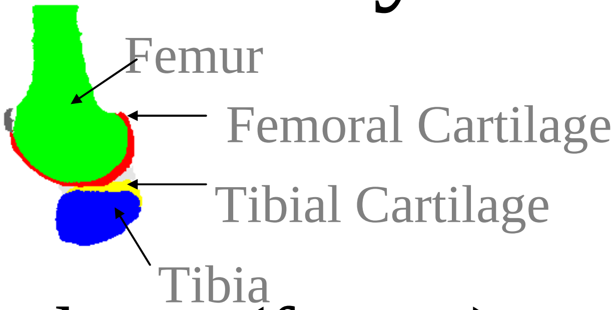
Measure Geometric Relationship between Primary and Secondary Structures



- Using primitives such as
  - distances between surfaces
  - local normals of primary structures
  - local curvature of primary structures
  - etc.

Provided by T Kapur

Measure Geometric Relationship between Primary and Secondary Structures



$$\rho_s \equiv \text{distance to closest point on bone (femur)}$$

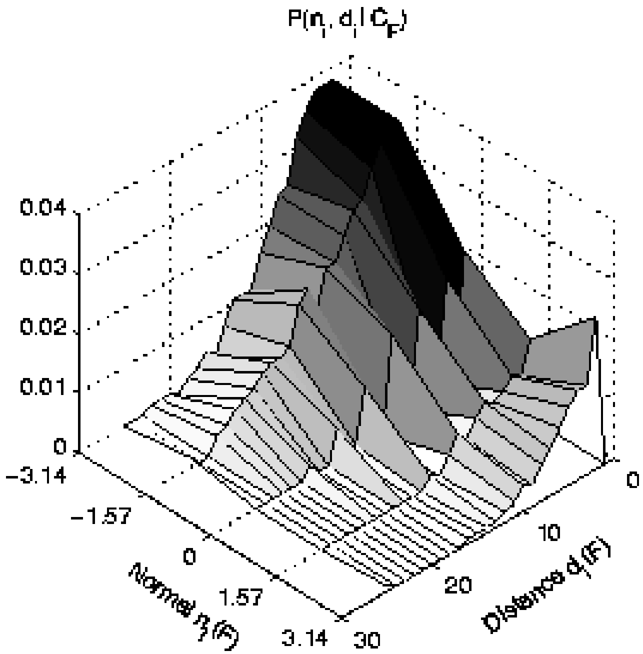
$$n_s \equiv \text{normal to bone (femur) at closest point}$$

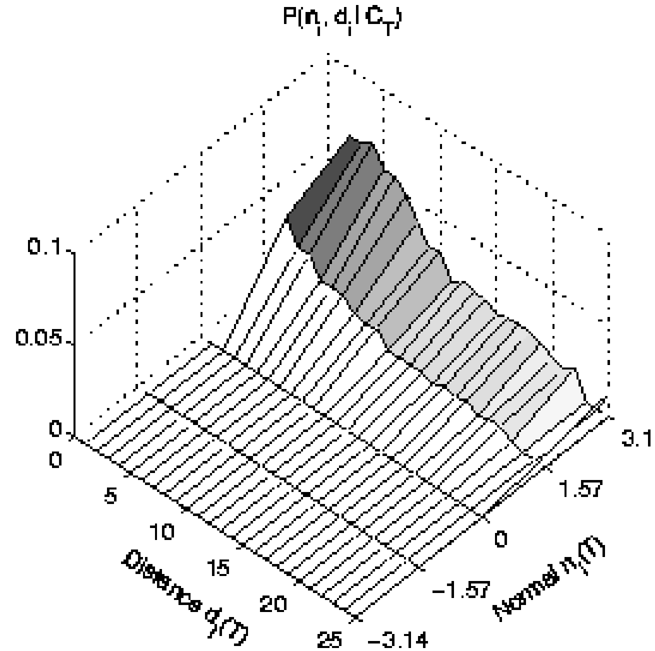
$$P(x_s \in \text{Cartilage} \mid \text{Bone})$$

$$\cong \frac{P(\rho_s, n_s \mid x_s \in \text{Cartilage})P(\text{Cartilage})}{Z}$$

Provided by T Kapur

Estimate of $P(\rho_s, n_s \mid x_s \in \text{Cartilage})$

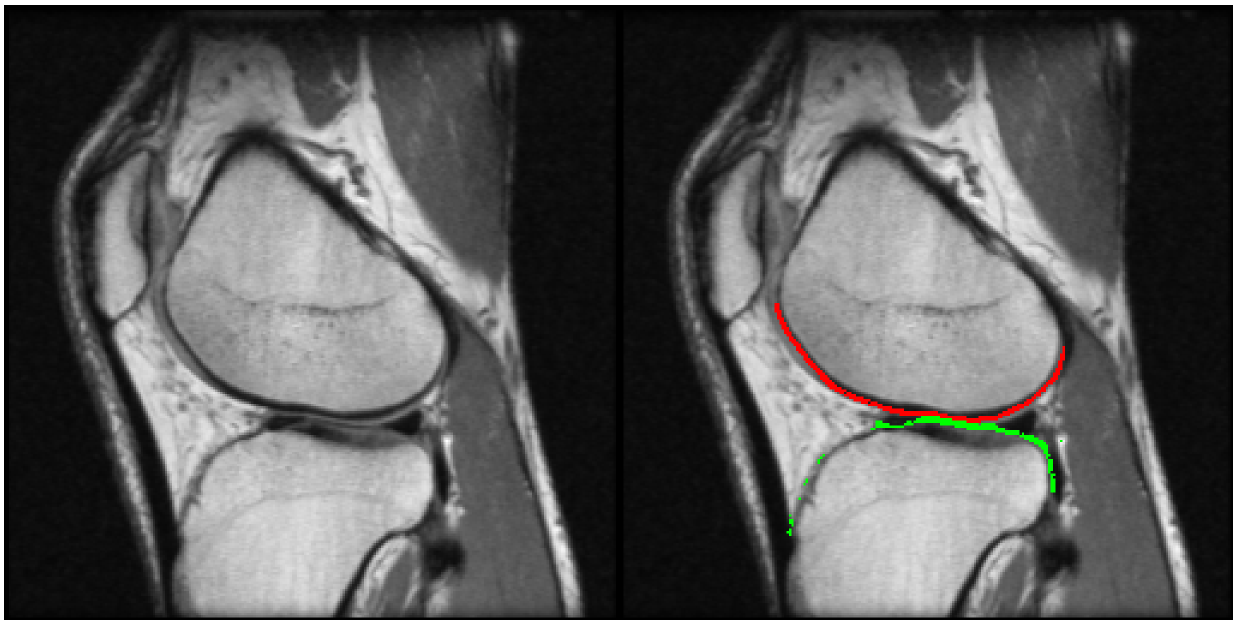


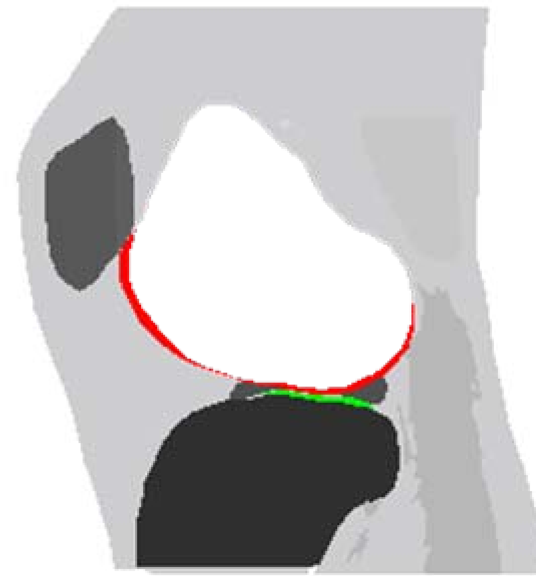


$P(\rho_s, n_s \mid x_s \in \text{Fem. Cartilage})$ $P(\rho_s, n_s \mid x_s \in \text{Tib. Cartilage})$

Source: Kapur, Tina. “Model based three dimensional medical image segmentation.” MIT Ph.D. thesis, 1999.

Results: Segmentation of Femoral & Tibial Cartilage





MRI Image

Model-Based Segmentation

Manual Segmentation

Source: Kapur, Tina. "Model based three dimensional medical image segmentation." MIT Ph.D. thesis, 1999.

kNN combined with Atlas

- Simon Warfield
- Use Atlas to control kNN Classifier
  - Resolve contrast failure

Overlapping distributions

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Lesion classification

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Lesion classification

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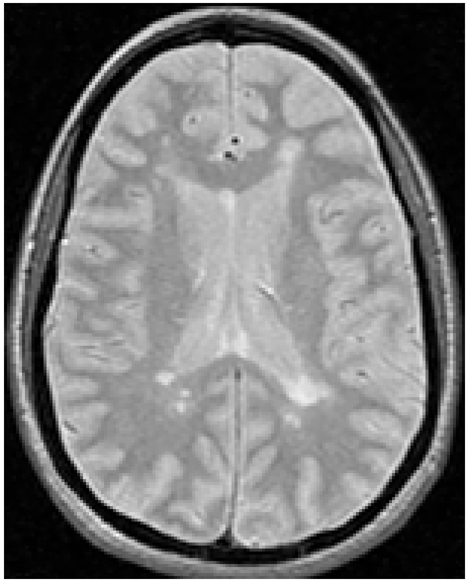
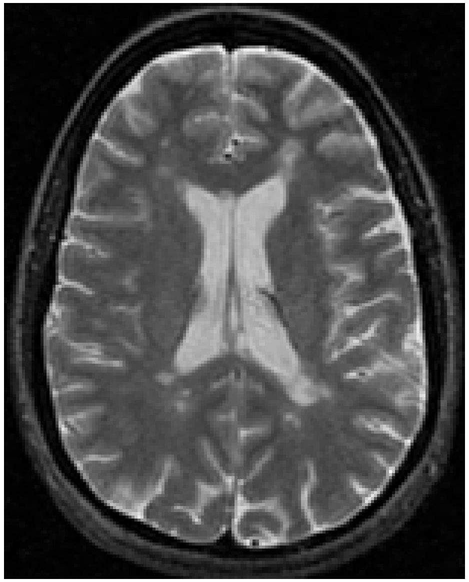
Multiple Sclerosis



PDw



T2w

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Morphological Operations

- Erosion
- Dilation
- Opening
- Closing

- [Haralick + 1989]

Morphological Operators...

- Ubiquitous simple tools. Useful for ad-hoc clean-up of results from Statistical Classification.

Dilation

- Binary (or Boolean) images
- Represent image by a set of coordinate vectors of pixels with value 1

image

$$A \oplus B \equiv \{c \mid c = a + b, \text{for some } a \in A, b \in B\}$$

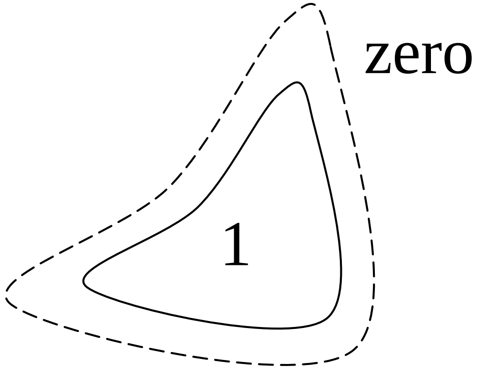
vector addition

Typical structure elements:

$$\left\{ \begin{array}{cc} 1 & 1 \\ 1 & 1 \end{array} \qquad \begin{array}{ccc} & 1 & \\ 1 & 1 & 1 \\ & 1 & \end{array} \right.$$

Dilation

- Continuous analogy
- Makes structures *fatter*



Erosion

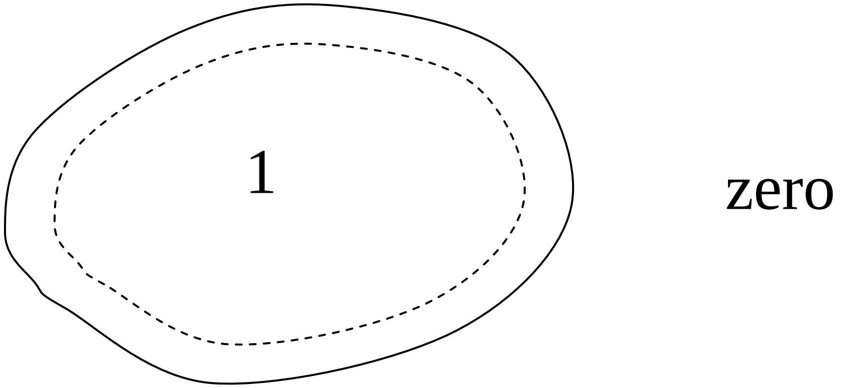
- Erosion is dual of dilation
  - complement A
  - reflect B (negate coordinates)
  - dilate
  - complement result

$$\boxed{A \otimes B = \overline{\overline{A} \oplus \hat{B}}}$$

•Frequently, B is symmetric and then reflection can be ignored

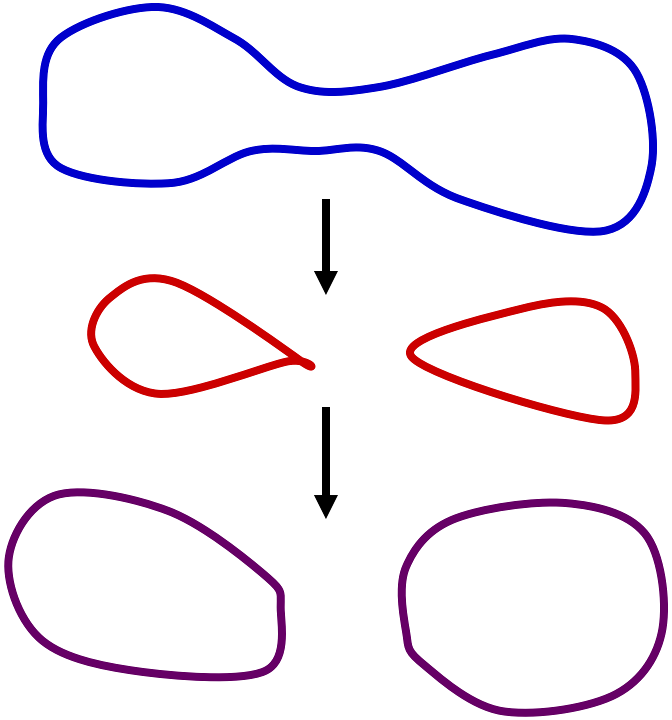
Erosion

- Erosion by simple S.E.'s makes structures thinner
- Analog analogy:



Opening

- Opening = Erode <u>then</u> Dilate



Break thin connections

Removes small junk

Closing

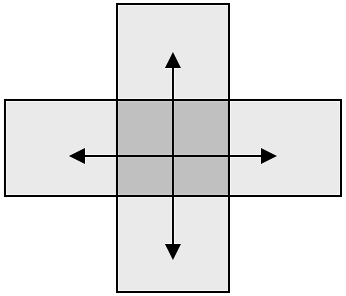
- Closing = Dilate then Erode
- Can attach objects that have become fragmented

Erosion and Dilation

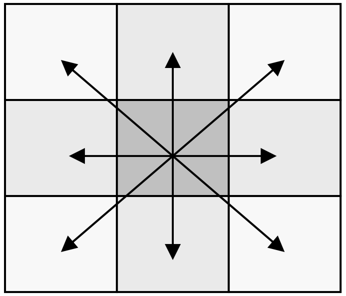
- Common trick in brain isolation “de-scalping”
  - Erode “it”
    - to disconnect brain from head
  - Dilate “it”
    - But ***only*** mark pixels that were originally “brain”

Connectivity

- Define neighbor relation



4-neighbor



8-neighbor

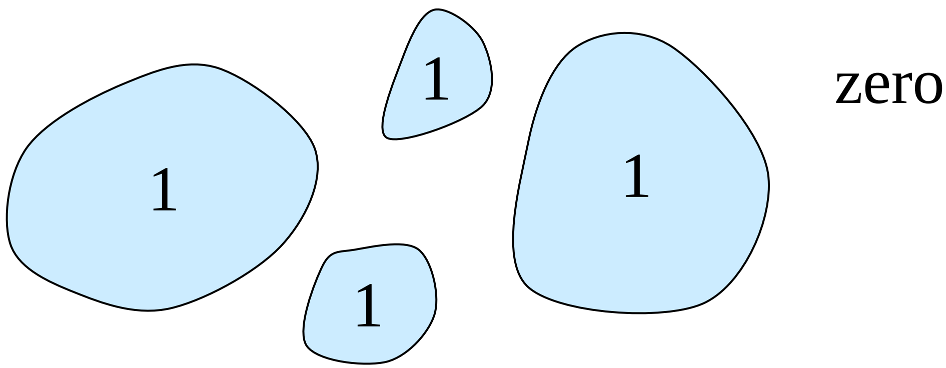
  – There are some inconsistencies that a 6-neighbor relation can fix

Finding Connected Components

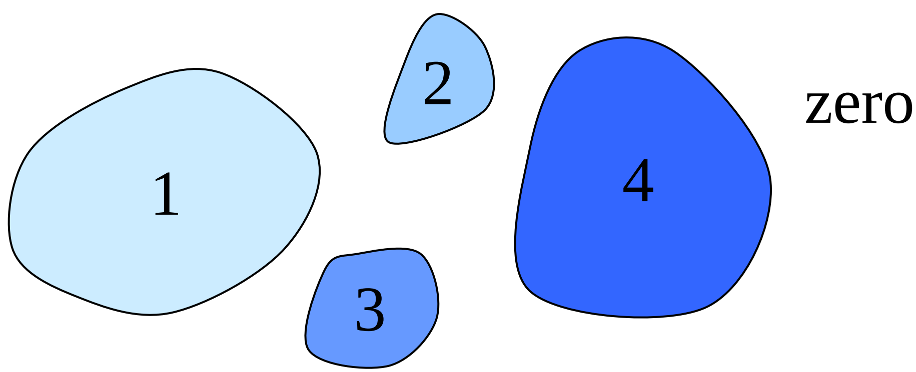
- N = 1
- Repeat until all pixels are labeled
  - Pick an unmarked *1* pixel
  - Label it, and all of its *1* neighbors, N
  - N $\leftarrow$ N + 1

Connected Components: Example

- Boolean image



- Each separate object get a unique label



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