MEDICAL IMAGING INFORMATICS: Lecture # 6

Segmentation

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Overview

- Definitions
- Role of Segmentation
- Segmentation methods
  - Intensity based
  - Shape based
  - Texture based
- Summary & Conclusion
- Literature

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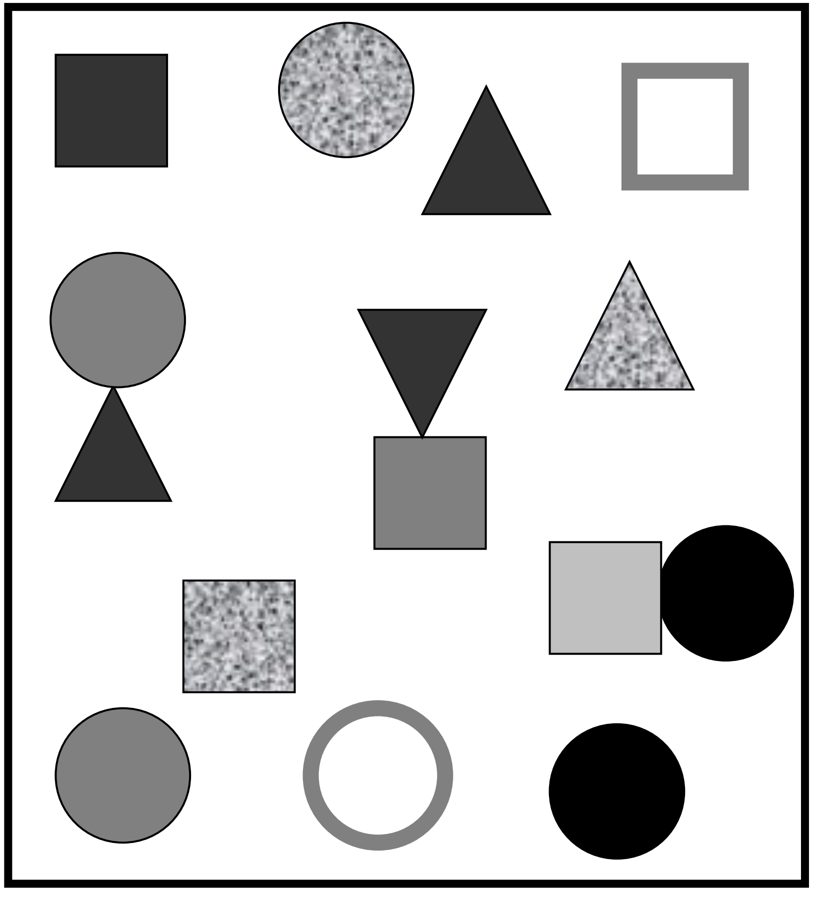
The Concept Of Segmentation

Identify classes (features) that characterize this image!



Intensity: Bright - dark

Shape: Squares , spheres, triangles

Texture: homogeneous – speckled

Connectivity: Isolated - connected

Topology: Closed - open

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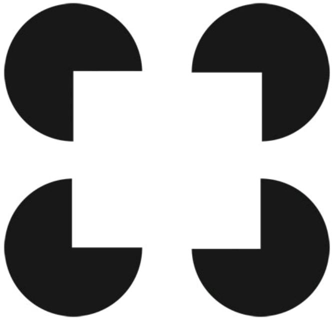
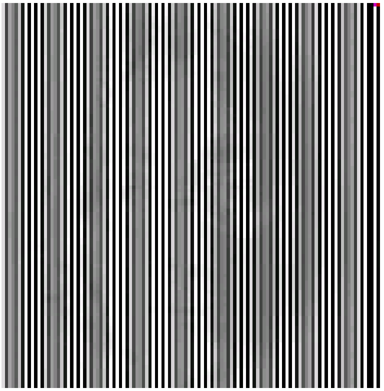
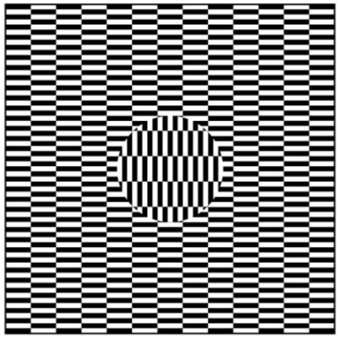
More On The Concept Of Segmentation

Can you still identify multiple classes in each image?







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Segmentation Of Scenes

Segment this scene!
Hint: Use color composition and spatial features

By J. Chen and T. Pappas; 2006, SPIE; DOI: 10.1117/2.1200602.0016

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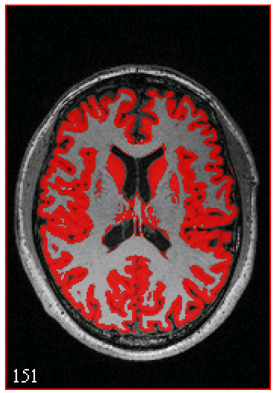
Examples: Intensity and Texture

By intensity

Gray matter segmentation



By texture

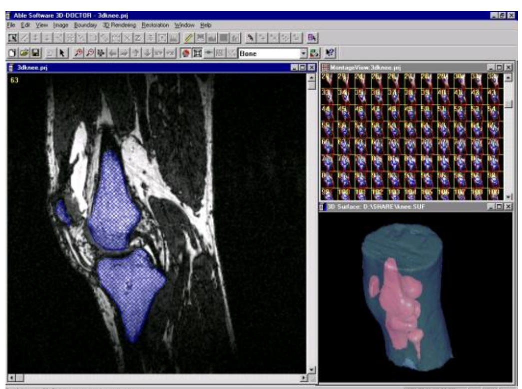
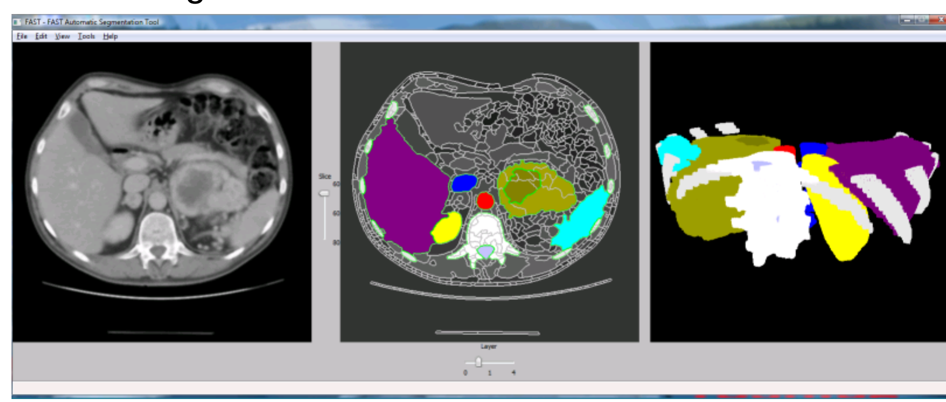


image at: www.ablesw.com/3d-doctor/3dseg.htm

Segmentation of abdominal CT scan



Stephen Cameron. Oxford U, Computing Laboratory

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Definitions

- Segmentation is the partitioning of an image into regions that are homogeneous with respect to some characteristics.

In medical context:

- Segmentation is the delineation of anatomical structures and other regions of interest, i.e. lesions, tumors.

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Formal Definition

If the domain of an image is Ω, then the segmentation problem is to determine sets (classes) Z_k, whose union represent the entire domain

$$\Omega = \bigcup_{k=1}^{N} Z_k$$

Sets are connected:

$$Z_k \bigcap Z_j = \alpha; k \neq j$$

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More Definitions

- When the constraint of connected regions is removed, then determining the sets Z_k is termed pixel classification.

- Determining the total number of sets K can be a challenging problem.

- In medical imaging, the number of sets is often based on a-priori knowledge of anatomy, e.g. K=3 (gray, white, CSF) for brain imaging.

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Labeling

- Labeling is the process of assigning a meaningful designation to each region or pixel.

- This process is often performed separately from segmentation.

- Generally, computer-automated labeling is desirable

- Labeling and sets Z_k may not necessarily share a one-to-one correspondence

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Dimensionality

- Dimensionality refers to whether the segmentation operates in a 2D or 3D domain.

- Generally, 2D methods are applied to 2D images and 3D methods to 3D images.

- In some instances, 2D methods can be applied sequentially to 3D images.

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Characteristic and Membership Functions

- A characteristic function is an indicator whether a pixel at location j belongs to a particular class Z_k.

$$\chi_k(j) = \begin{cases} 1 \; if .. j \in Z_k \\ 0 \; otherwise \end{cases}$$

- This can be generalized to a membership function, which does not have to be binary valued.

$$0 \le \chi_k(j) \ge 1, \; for \quad all \quad j,k$$

$$\sum_{k=1}^{N} \chi_k(j) = 1, \; for \quad all \; j$$

- The characteristic function describes a "deterministic" segmentation process whereas the membership function describes a "probabilistic" one.

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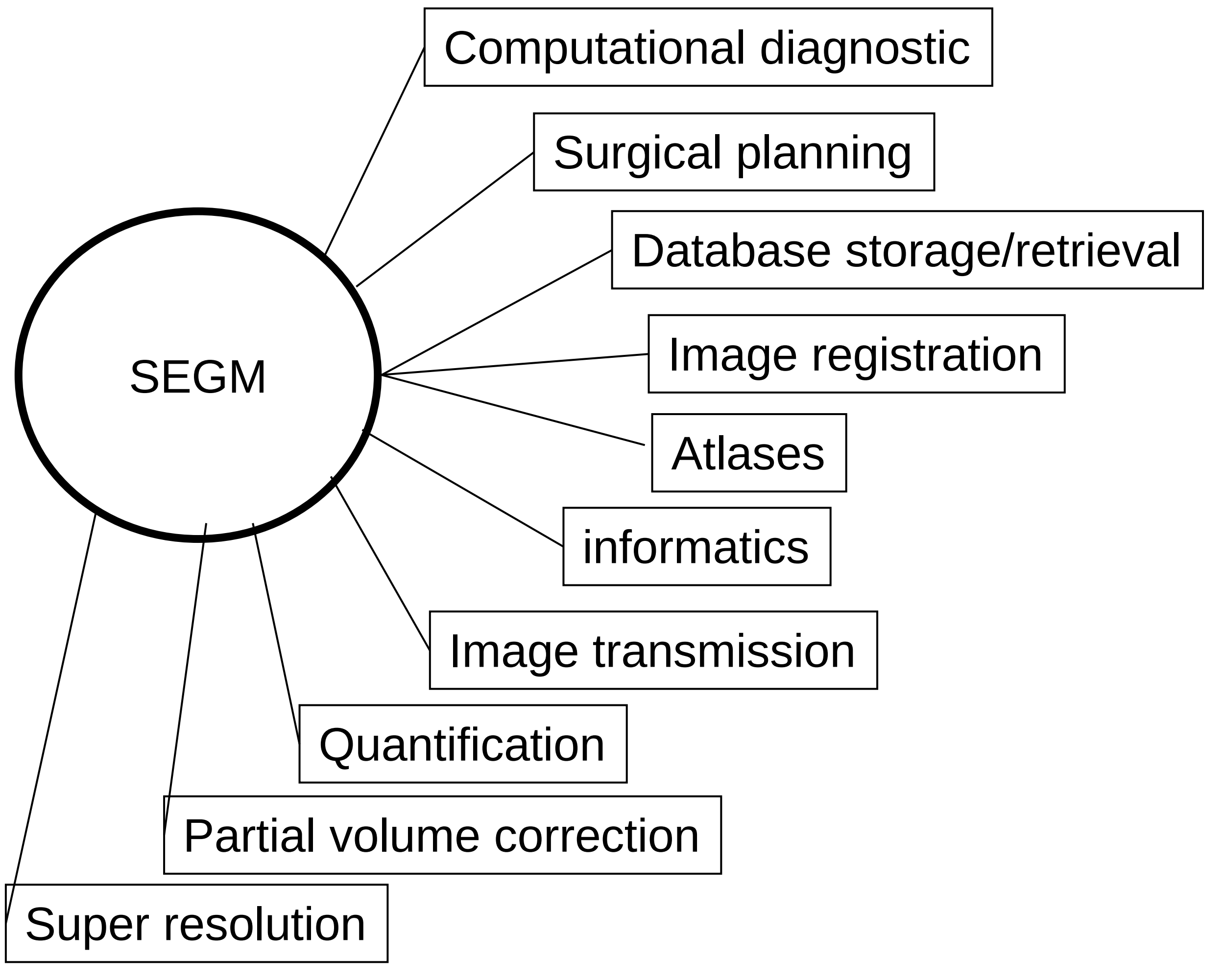
Segmentation Has An Important Role



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Segmentation Methods

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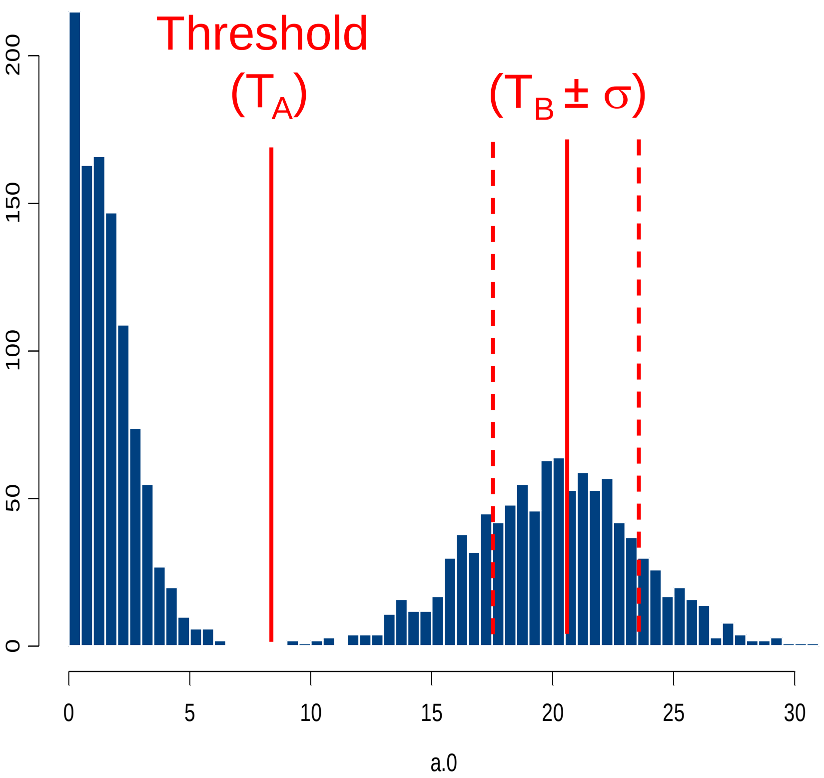
Threshold Method

Angiogram showing a right MCA aneurysm

Dr. Chris Ekong;
www.medi-fax.com/atlas/brainaneurysms/case15.htm

Histogram (fictitious)



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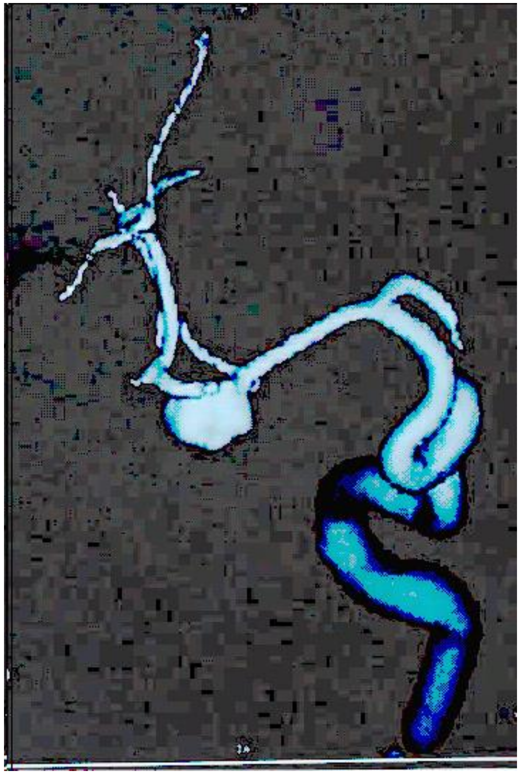
Threshold Method

Original

Threshold min/max



Threshold standard deviation

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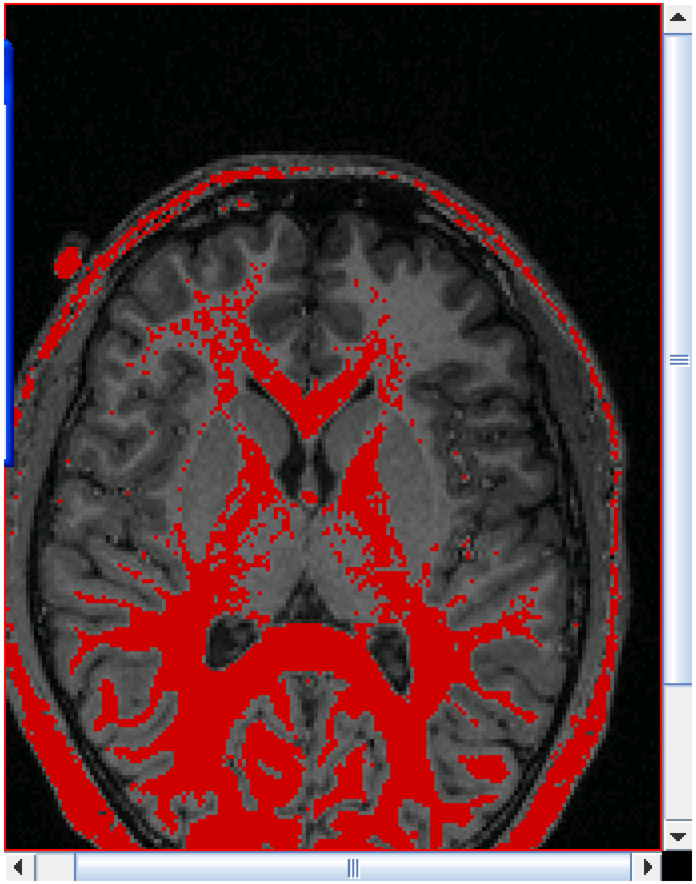
Threshold Method Applied To Brain MRI

White matter segmentation



- •Major failures:
  - •Anatomically non-specific
  - •Insensitive to global signal inhomogeneity

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Threshold: Principle Limitations

- Works only for segmentation based on intensities
- Robust only for images with global uniformity and high contrast to noise
- Local variability causes distortions
- Intrinsic assumption is made that the probability of features is uniformly distributed

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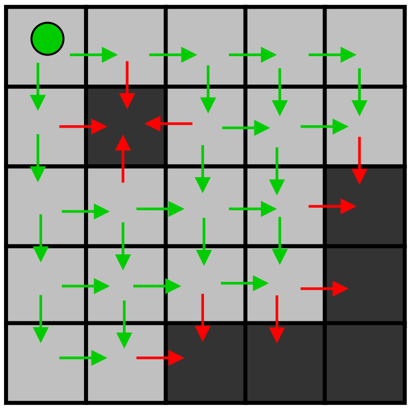
Region Growing - Edge Detection

Seed point



Guided e.g. by energy potentials:

Similarity: $V(i,j) = \frac{I_i - I_j}{\sigma_{i,j}}$

Edges: $V(i,j) = \frac{1}{I_i - I_j}$

- Region growing groups pixels or subregions into larger regions.
- A simple procedure is pixel aggregation,
- It starts with a "seed" point and progresses to neighboring pixels that have similar properties.
- Region growing is better than edge detection in noisy images.

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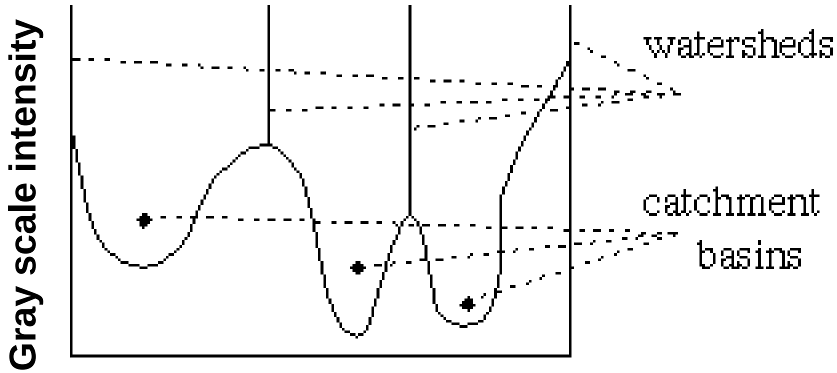
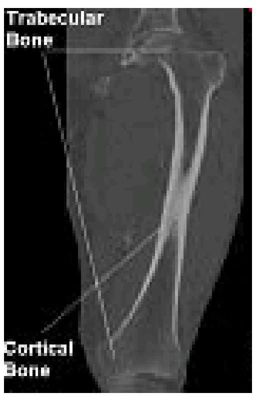
Region Growing – Watershed Technique

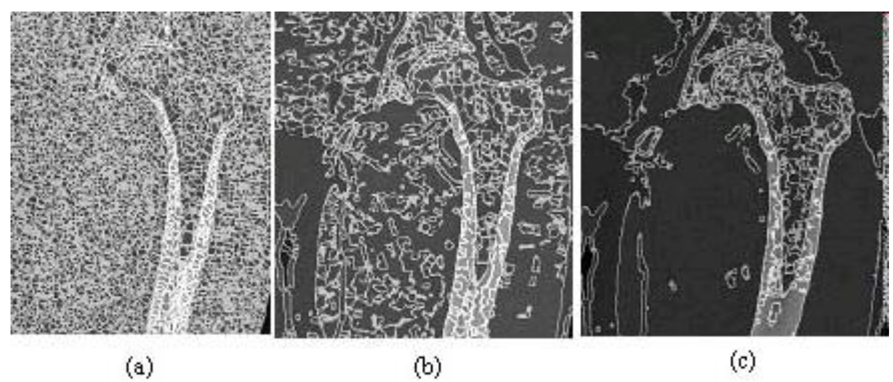


CT of different types of bone tissue (femur area)



M. Straka, et al. Proceedings of MIT 2003

(a) WS over-segmentation
(b) WS conditioned by regional density mean values
(c) WS conditioned by hierarchical ordering of regional density mean values



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Region Growing: Principle Limitations

- Segmentation results dependent on seed selection
- Local variability dominates the growth process
- Global features are ignored

- Generalization needed:
  – Unsupervised segmentation (i.e.insensitive to selection of seeds)
  – Exploitation of both local and global variability

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Clustering

- Generalization using clustering
- Two commonly used clustering algorithms
    - K-mean
    - Fuzzy C-mean

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Definitions: Clustering

- Clustering is a process for classifying patterns in such a way that the samples within a class Z_k are more similar to one another than samples belonging to the other classes Z_m, $m \neq k$; $m = 1 \ldots K$.

- The ***k*-means algorithm** attempts to cluster *n* patterns based on attributes (e.g. intensity) into *k* classes $k < n$.
- The objective is to minimize total intra-cluster variance in the least-square sense:

$$\sigma = \sum_{k=1}^{K} \sum_{\chi_j \in S_k} \left(\chi_j - \mu_k \right)^2$$

- *for k* clusters Z_k, $k = 1, 2, \ldots, K$. μ_i is the mean point (centroid) of all pattern values ⍰$_j \in Z_k$.

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Fuzzy Clustering

- The ***fuzzy C*-means algorithm** is a generalization of K-means.
- Rather than assigning a pattern to only one class, the ***fuzzy C*-means** assigns the pattern a number m, $0 <= m <= 1$, described as membership function.

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K- means

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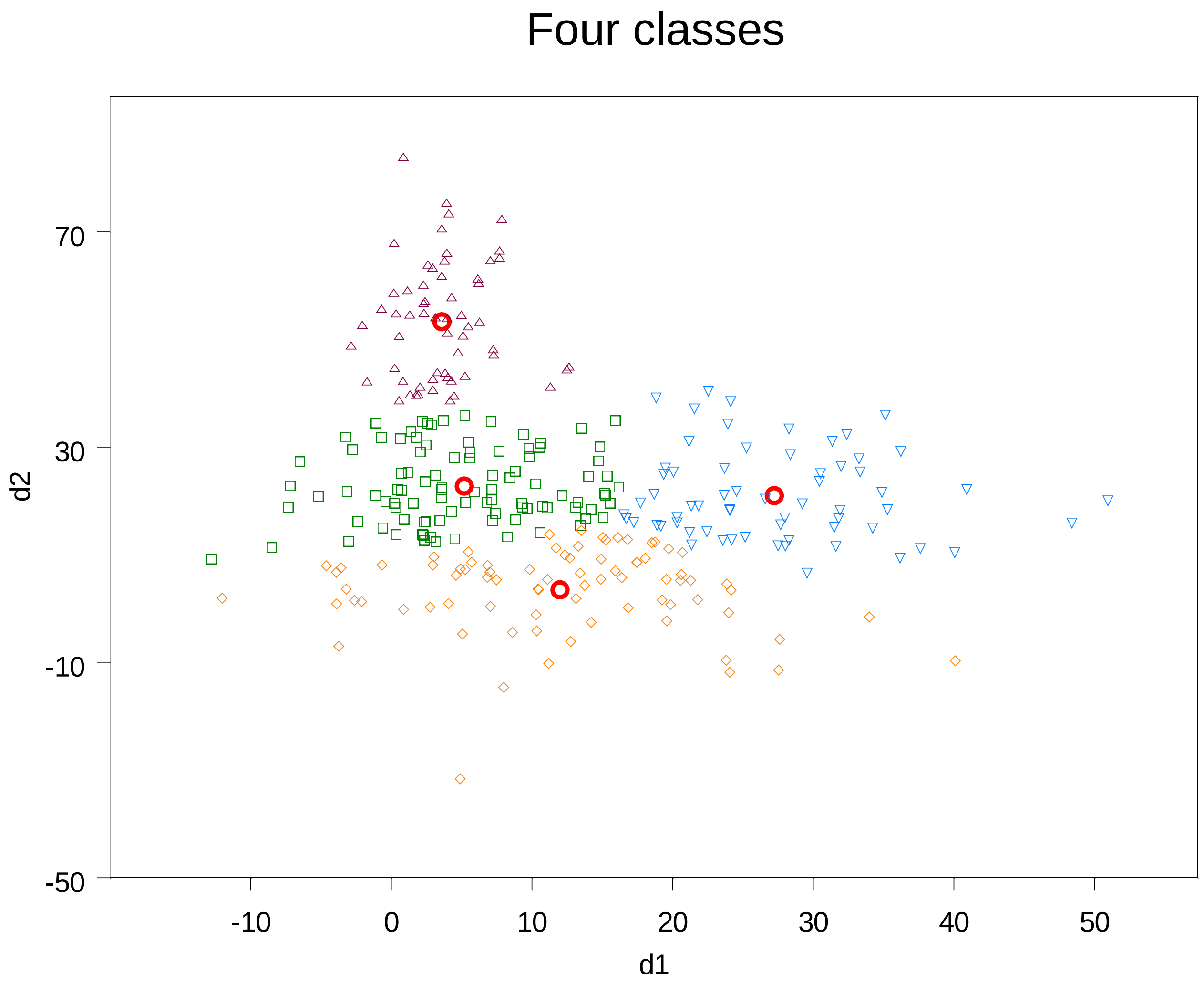
K - means



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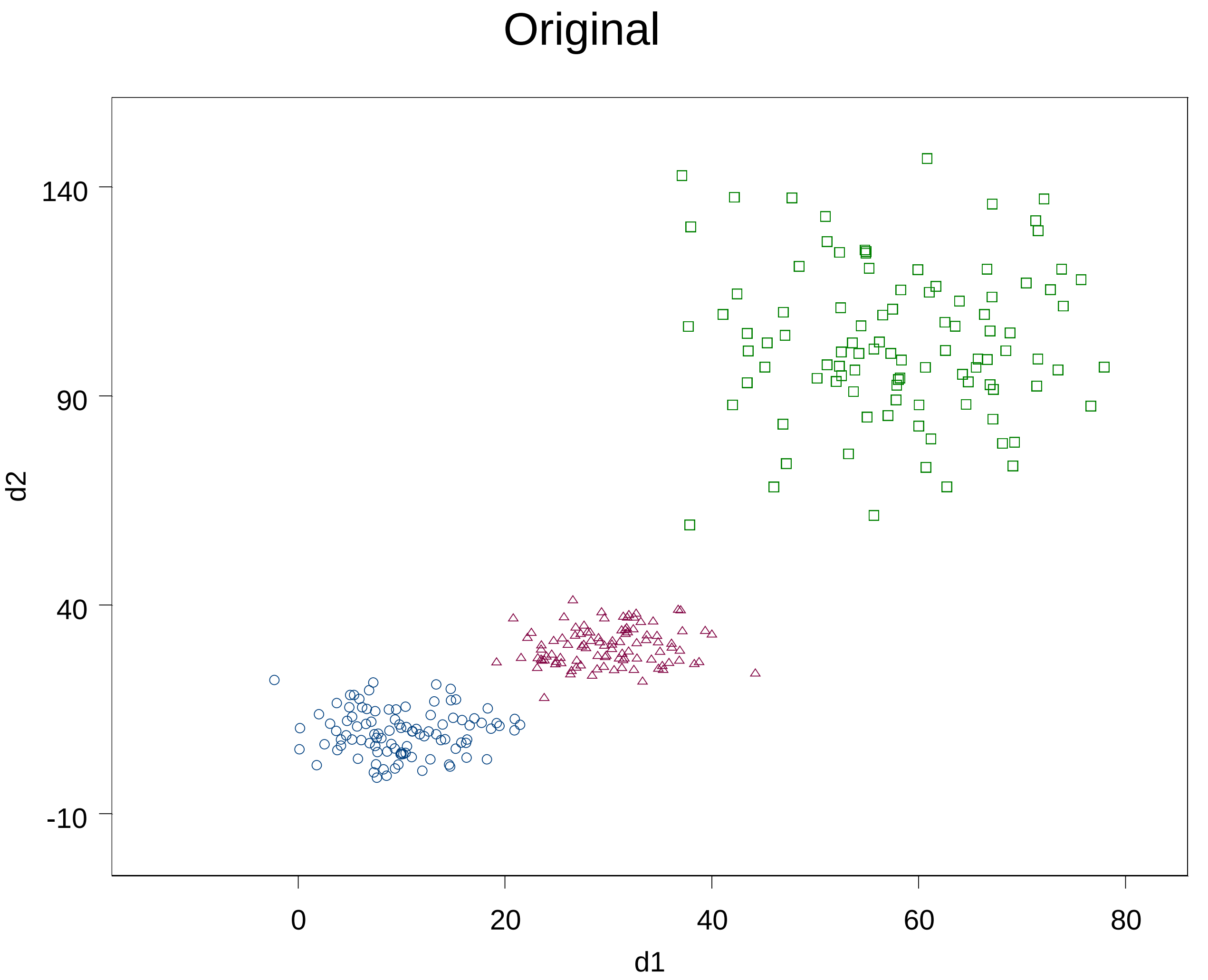
K - means



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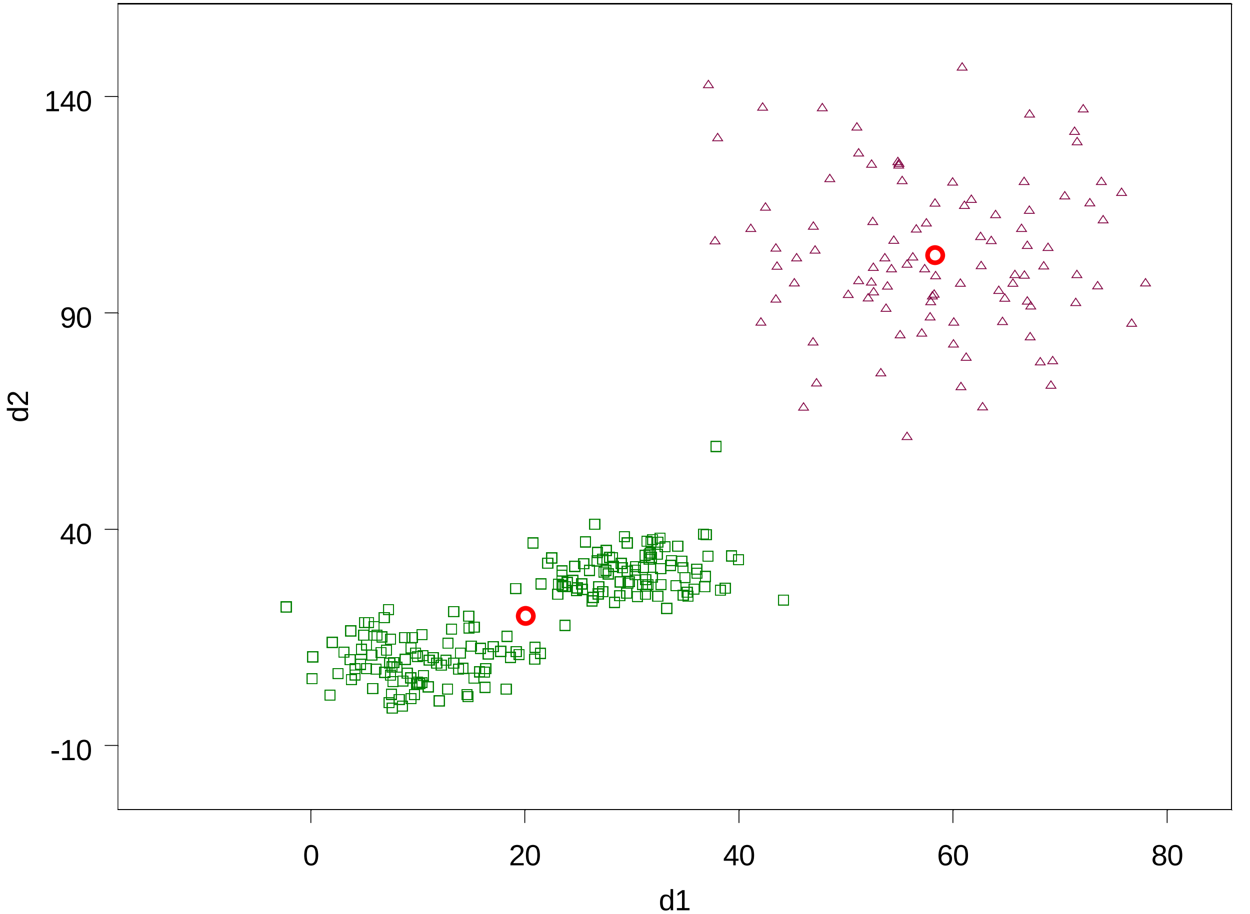
K - means

2 clusters



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K - means

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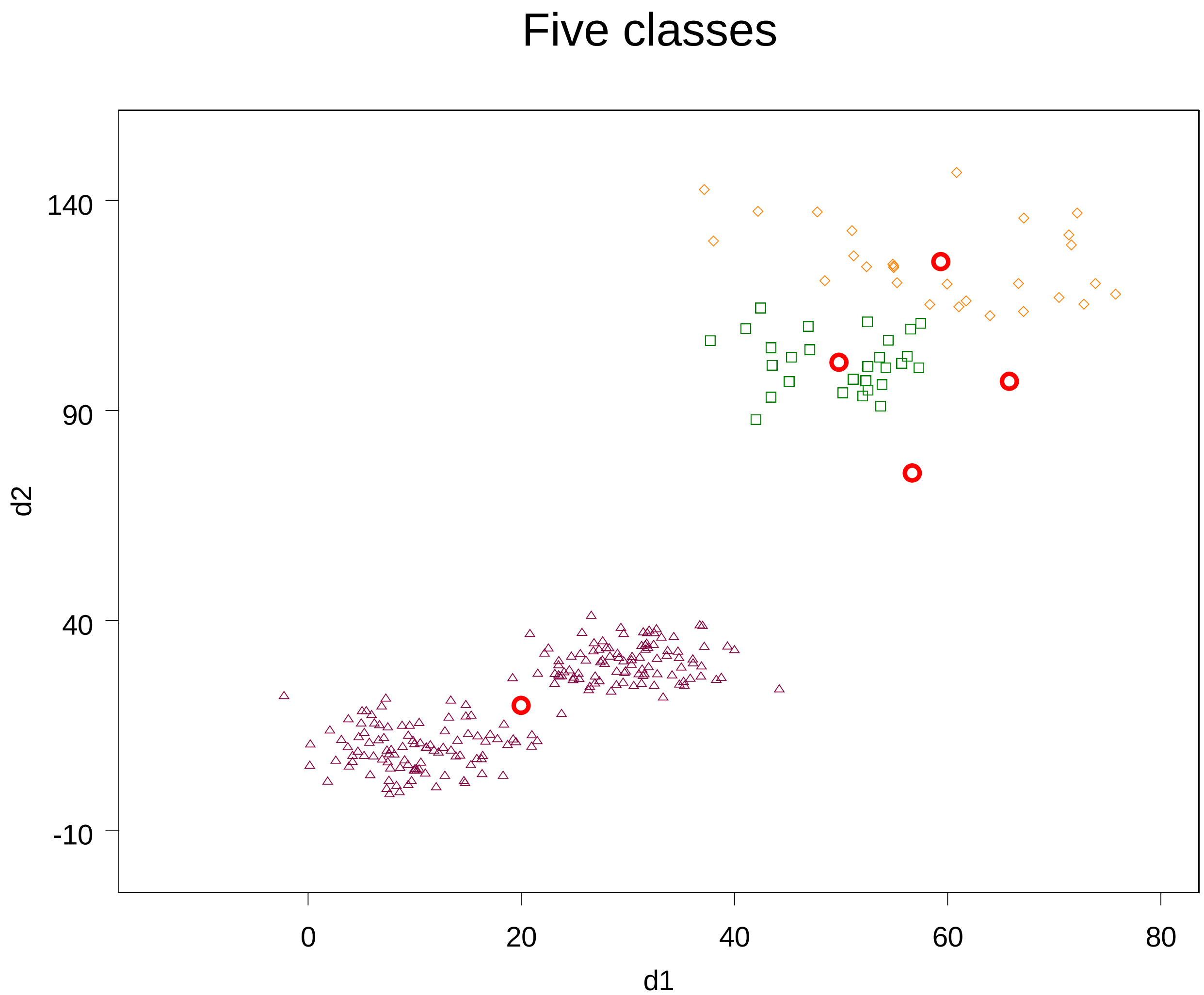
K – means: TRAPPED!



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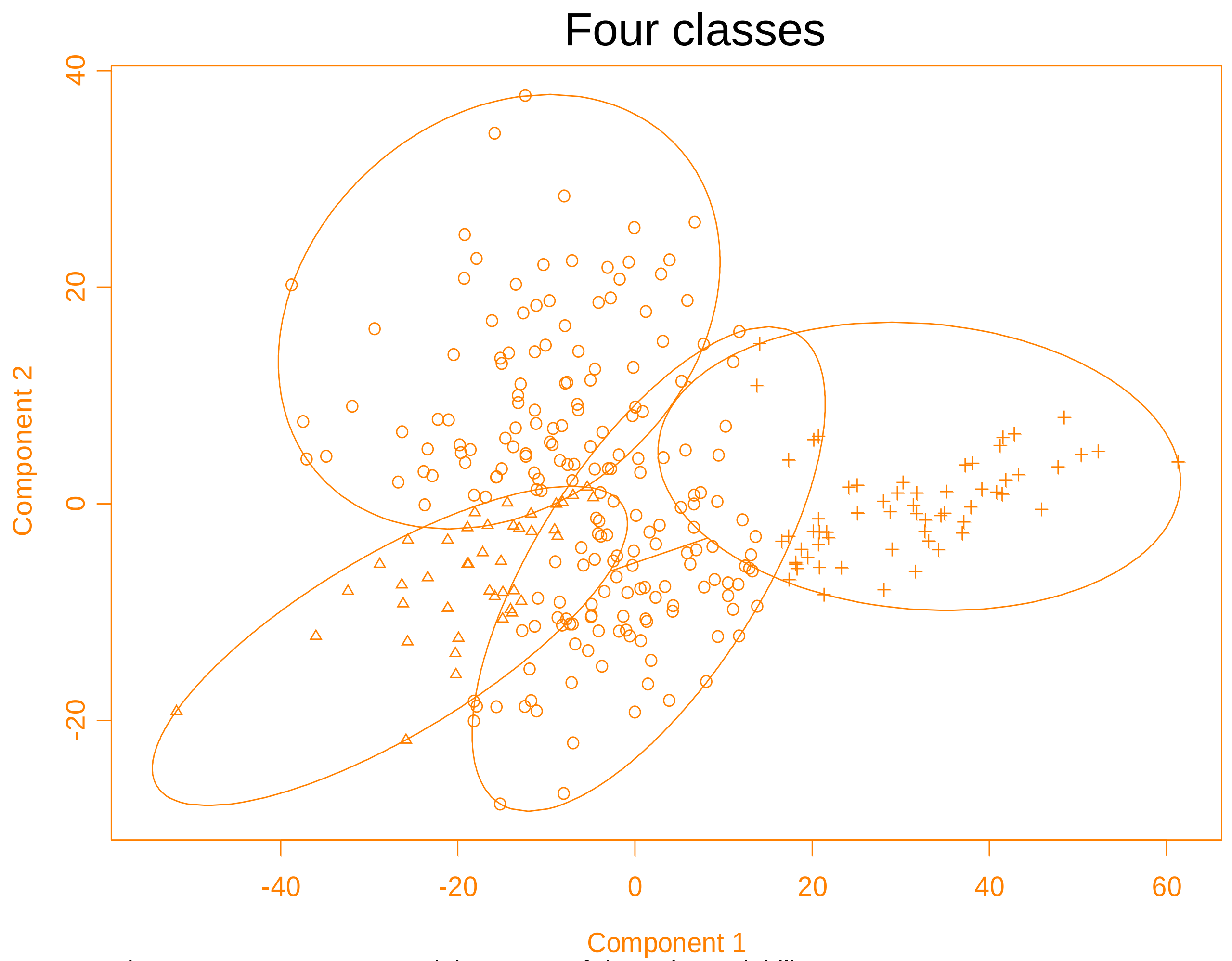
Fuzzy C - means



These two components explain 100 % of the point variability.

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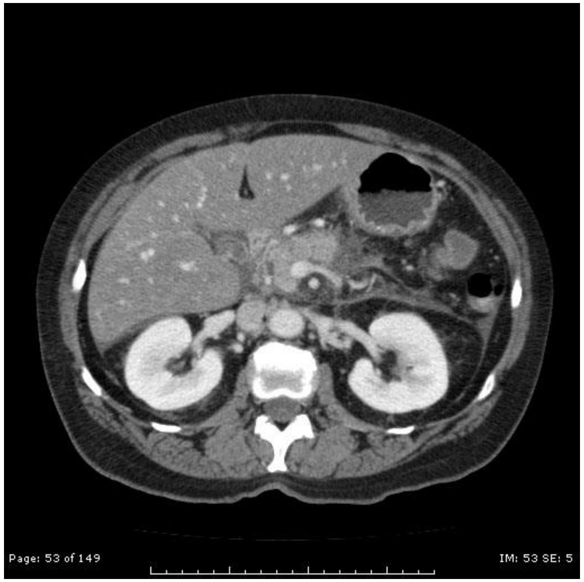
Fuzzy C- Means Segmentation I

Two classes

Original



Class I

Class 2

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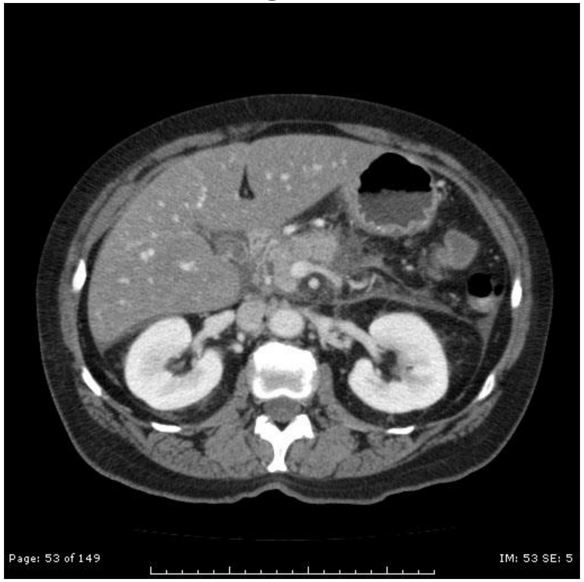
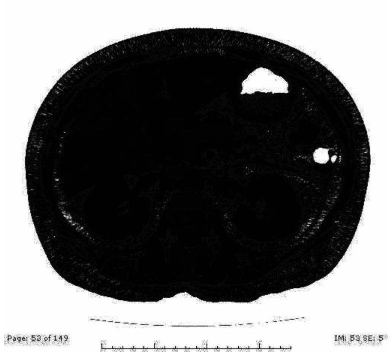
Fuzzy Segmentation II

Four classes

Original



Class I



Class 2

Class 3

Class 4

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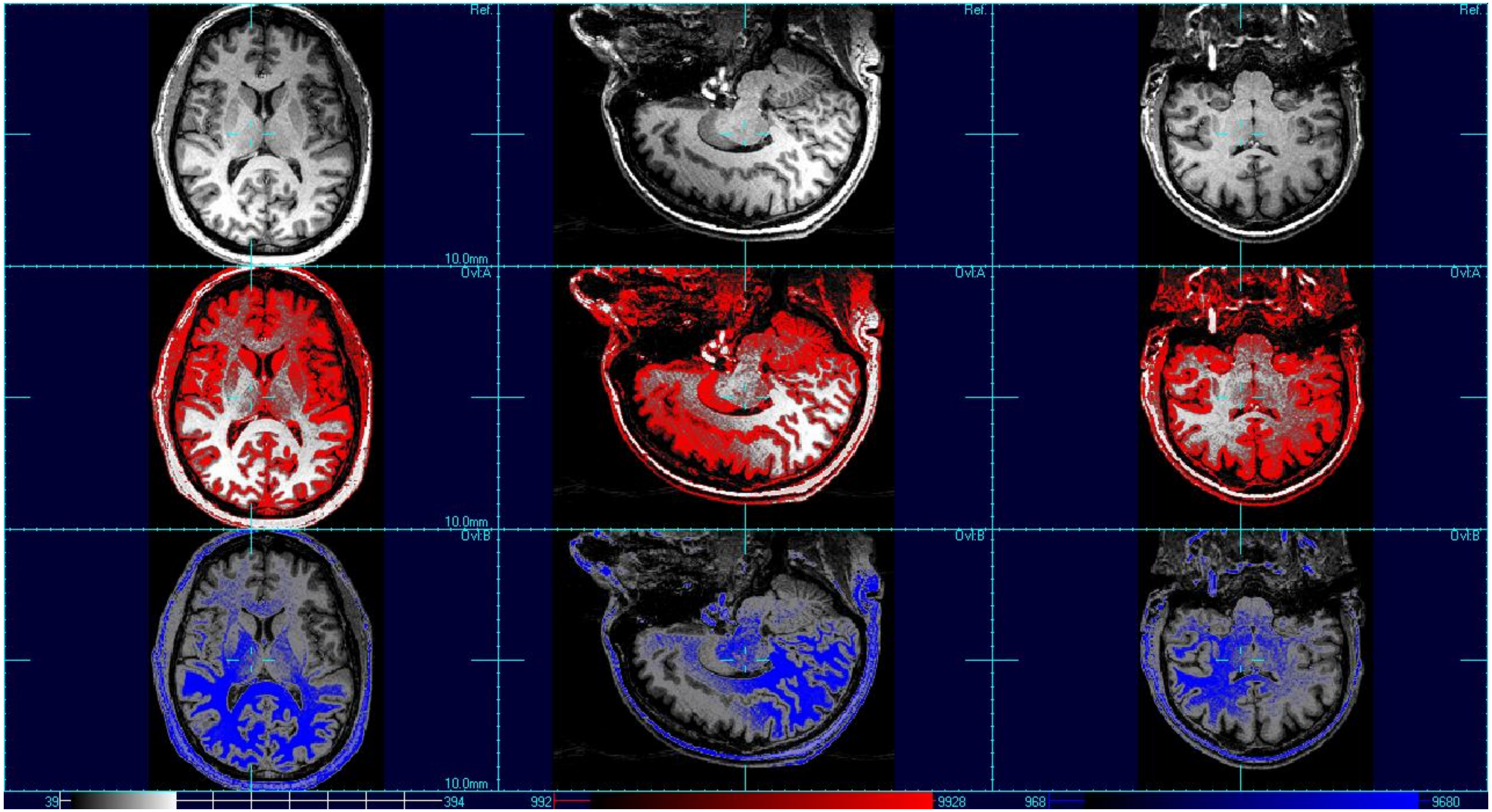
Brain Segmentation With Fuzzy C-Means



4T MRI, bias field inhomogeneity contributes to the problem of poor segmentation

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Clustering: Principle Limitations

- Convergence to the optimal configuration is not guaranteed.
- Outcome depends on the number of clusters chosen.
- No easy control over balancing global and local variability
- Intrinsic assumption of a uniform feature probability is still being made

- Generalization needed:
  - Relax requirement to predetermine number of classes
  - Balance influence of global and local variability
  - Possibility to including a-priori information, such as non-uniform distribution of features.

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Segmentation As Probabilistic Problem

- Treat both intensities **Y** and classes **Z** as random distributions
- The segmentation problems is finding the classes that maximize the likelihood to represent the image
- Segmentation in Bayesian formulation becomes :

$$p(Z\,|\,Y) = \frac{p(Z) * f(Y\,|\,Z)}{p(Y)}$$

- where
  - Y is the observed image (values $y_1 \ldots. y_n$)
  - Z is the segmented image (classes $z_1 \ldots. z_K$)
  - p(Z) is the prior probabillity
  - p(Y|Z) the observation probability
  - and p (Y) is the observation and hence stable

Treat As Energy Minimization Problem

- Since p(Y) is stable, it follows:

$$\ln\left[p(Z\,|\,Y)\right] \propto \ln\left[p(Z)\right] + \ln\left[f(Y\,|\,Z)\right]$$

- The goal is to find the most probably distribution of p(Z|Y) given the data

- Since the log probabilities are all additive, they are equivalent to distribution of energy

$$E_{Z|Y} = \alpha \cdot E_Z + \beta \cdot E_{Y|Z}$$

- segmentation becomes an ***energy minimization problem***.

- This means in particular that no probabilistic point of view is finally required.

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Probability In Spatial Context

- Use the concept of Markov Random Fields (MRF) for segmentation

- Definition:
  - Classes Z are a MRF on Y if
    - p(z) > 0 for all $z \in Z$
    - p(z) at a location depends only on the neighboring locations
    - p(y|z) (observed data) is a random process following a distribution of many degrees of freedom (Gibbs distribution).

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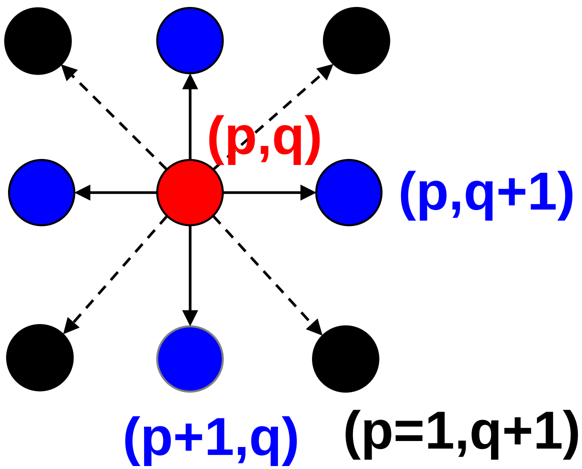
MRF Based Segmentation

1st and 2nd order MRFs



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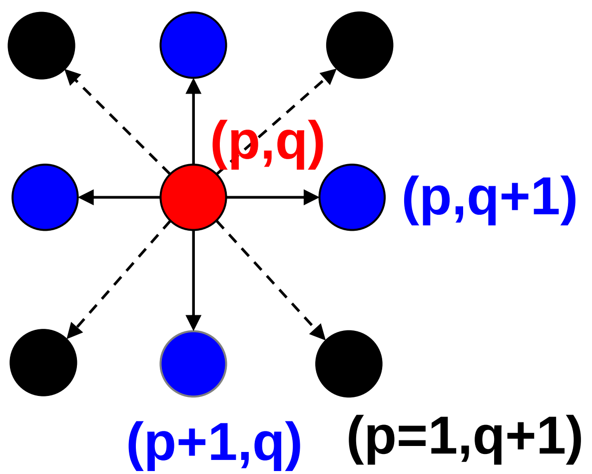
MRF Based Segmentation

1st and 2nd order MRFs



- Step I: Define prior class distribution energy:

$$E_z\left(p,q\right) \propto \sum_{t \in N_s} \delta\left(z_s, z_t\right)$$

$$\delta\left(z_s, z_t\right) = \begin{cases} -1, & z_s = z_t \\ +1 & z_s \neq z_t \end{cases}$$

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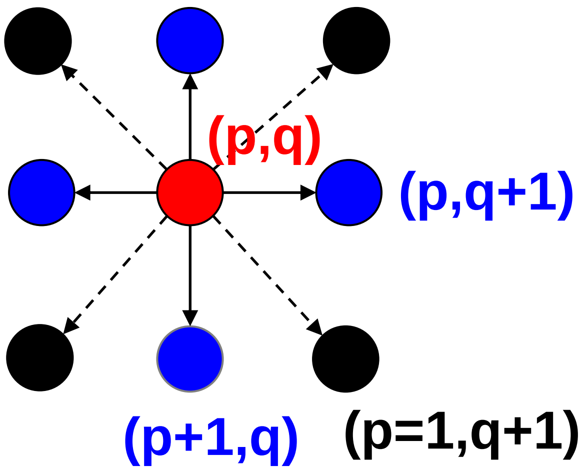
MRF Based Segmentation

1^{st} and 2^{nd} order MRFs



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- Step II: Select distribution of conditional observation probability, e.g gaussian:

$$E_{y|z}(p,q) \propto \frac{\left(y_{p,q} - \mu_z\right)^2}{2\sigma_z^2} + const.$$

  - $Y_{p,q}$ is the pixel value at location (p,q)
  - μ_z and σ_z are the mean value and variance of the class z

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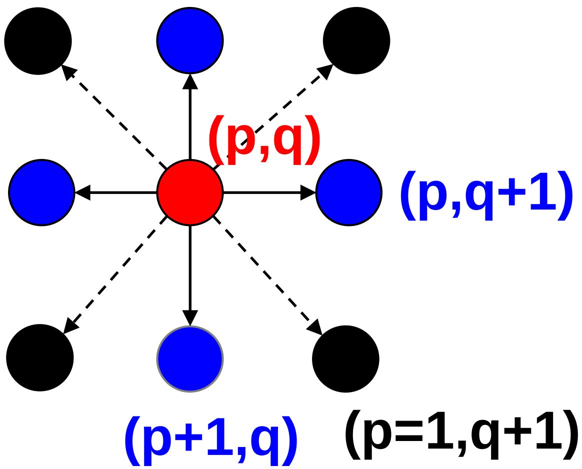
MRF Based Segmentation

1st and 2nd order MRFs



Step III: Solve (iteratively) for the minimal distribution energy

$$\arg\min E_{z|y}(p,q) \propto \underbrace{\sum_{t\in N_s} \delta(z_s, z_t)}_{\text{assignment}} + \underbrace{\frac{\left(y_{p.q} - \mu_z\right)^2}{2\sigma_z^2}}_{\text{similarity}} + const.$$

energy

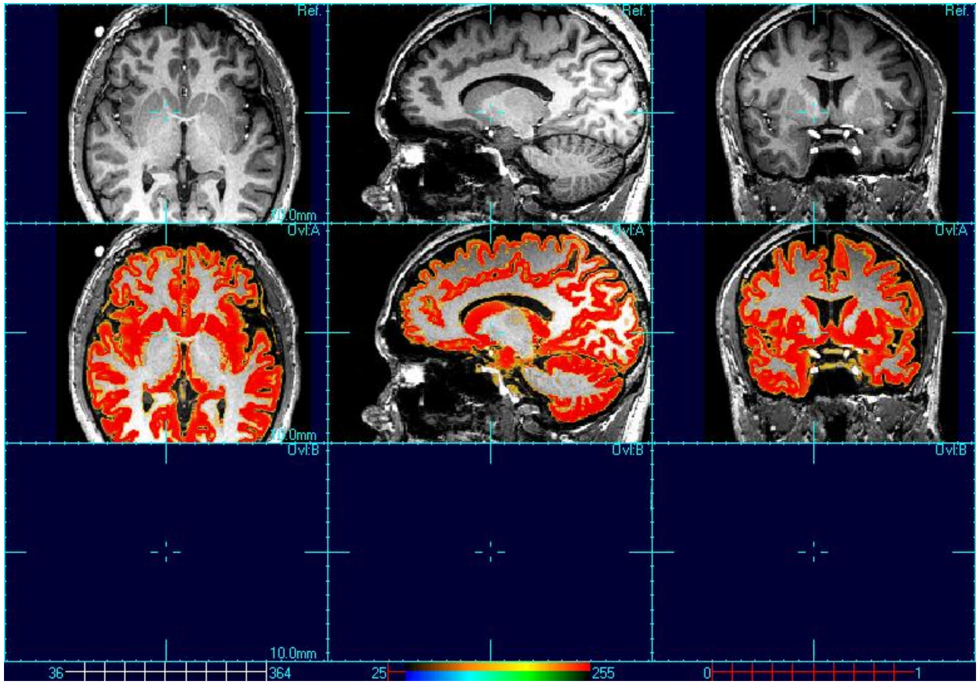
How To Obtain A Prior Of Class Distributions?

Average Gray Matter Map
Of 40 Subjects

Register to

Segment

Individual MRI



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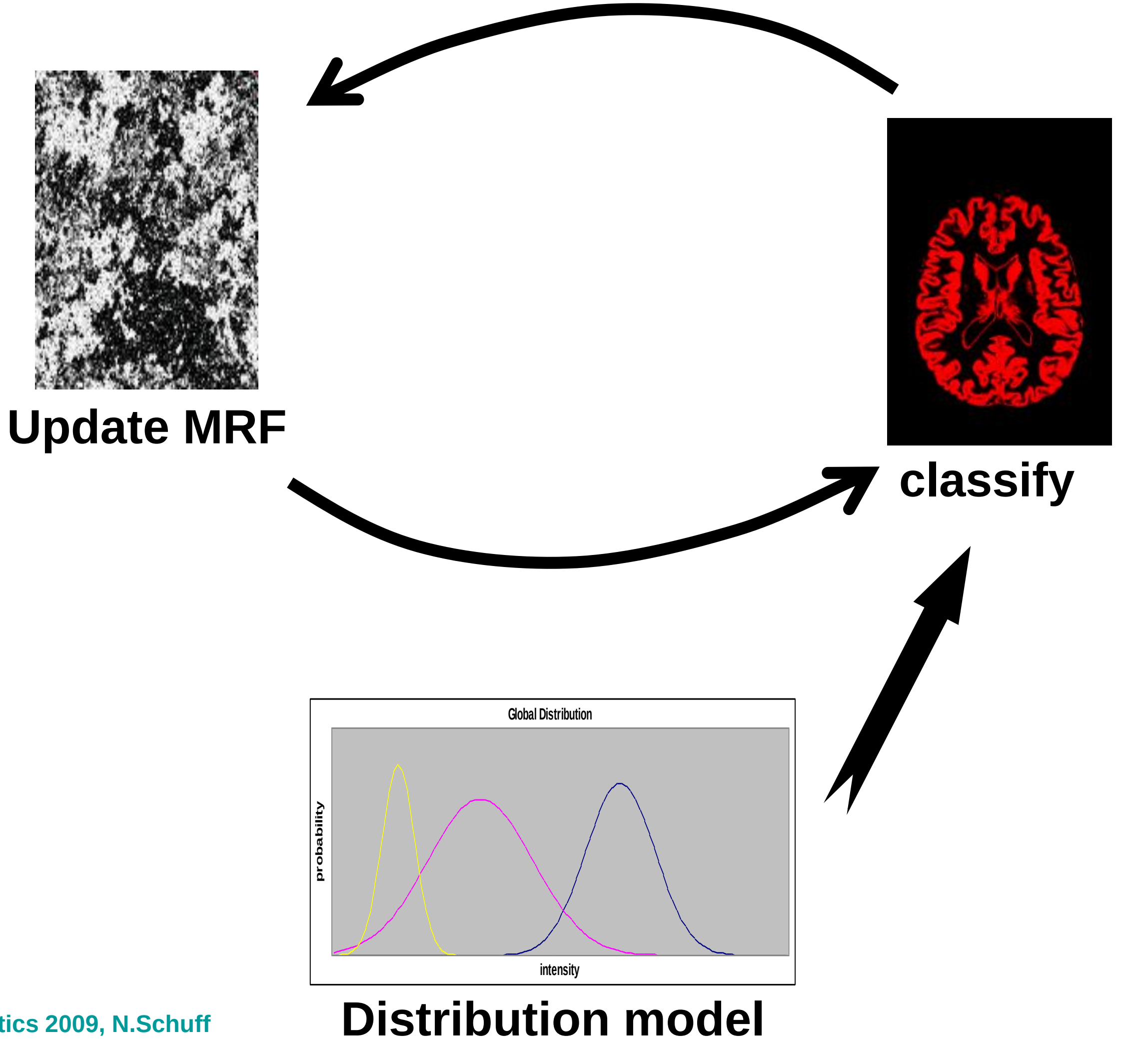
The Process of MRF Based Segmentation



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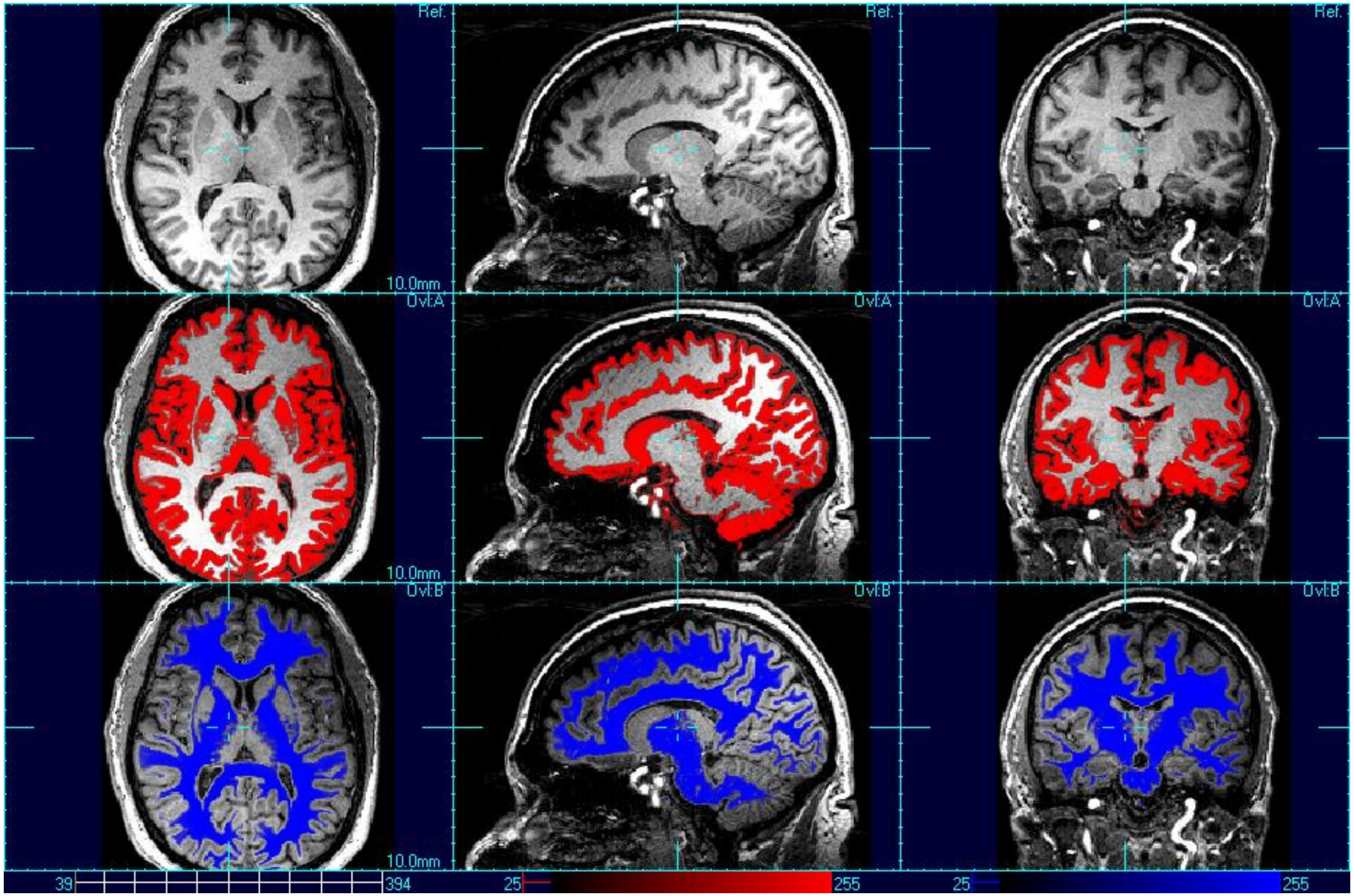
MRF Based Segmentations



4T MRI, SPM2, priors for GM, WM based on 60 subjects

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Generalization to Mixed Gaussian Distributions

$$\arg\min E_{z|y}\left(p,q\right) \propto \sum_{t\in N_s} \delta\left(z_s, z_t\right) + \frac{\left(y_{p,q}-\mu_{z_s}\right)^2}{2\sigma_{z_s}^2} + \frac{\left(y_{p,q}-\mu_{z_t}\right)^2}{2\sigma_{z_t}^2} + const.$$

Find solution iteratively using Expectation Maximization (EM)

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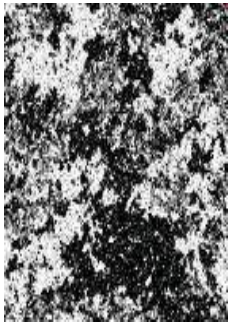
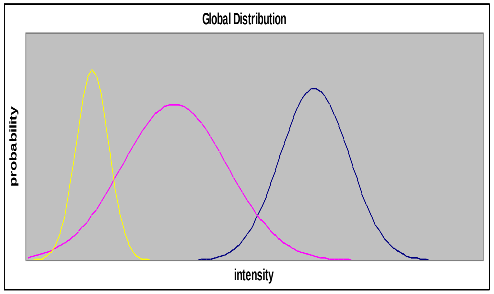
EM Of MRF Based Segmentation



UpdateMRF

classify



Update distribution model

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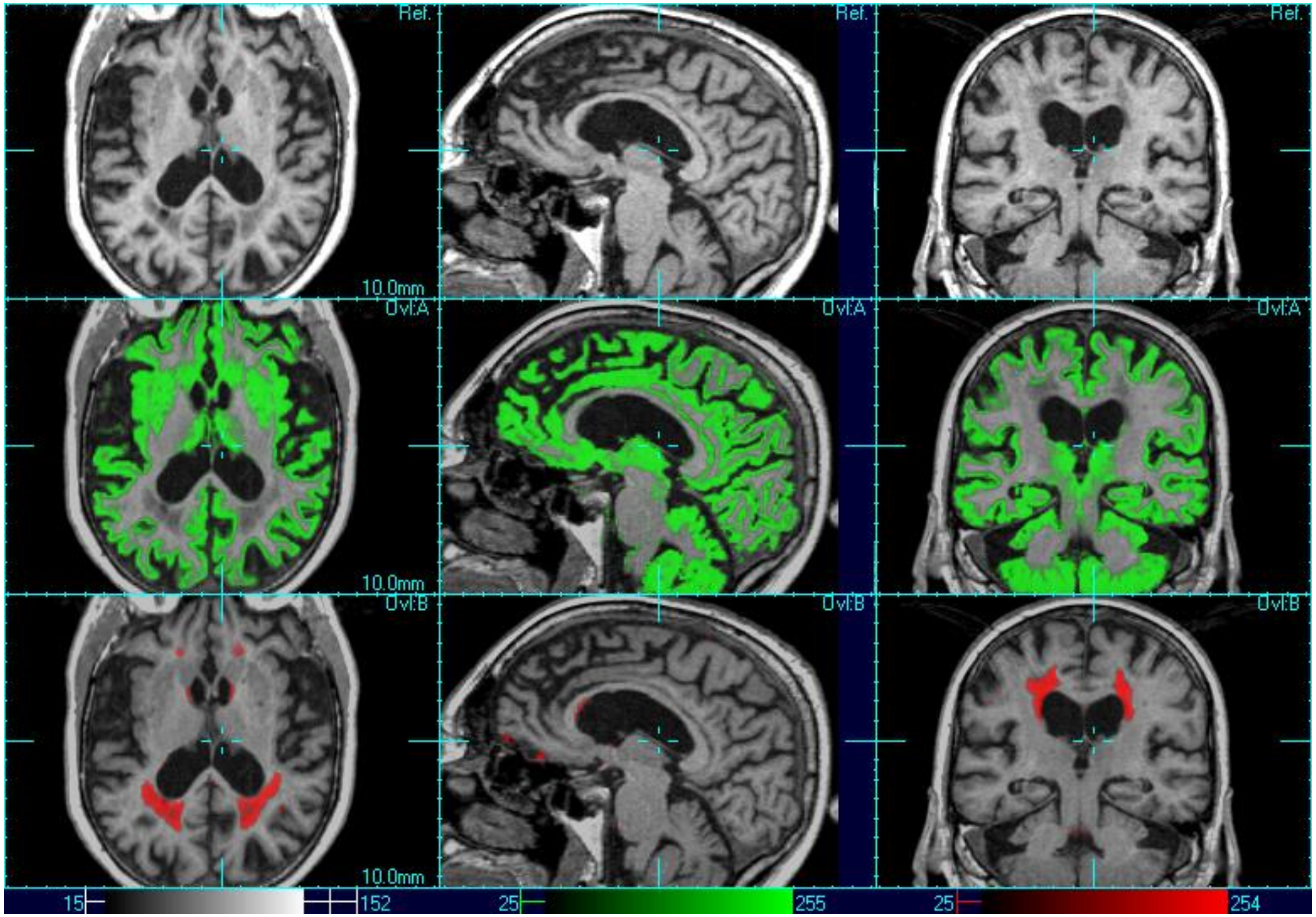
EMS



1.5 MRI, SPM2, tissue classes: GM, WM, CSF, WM Lesions

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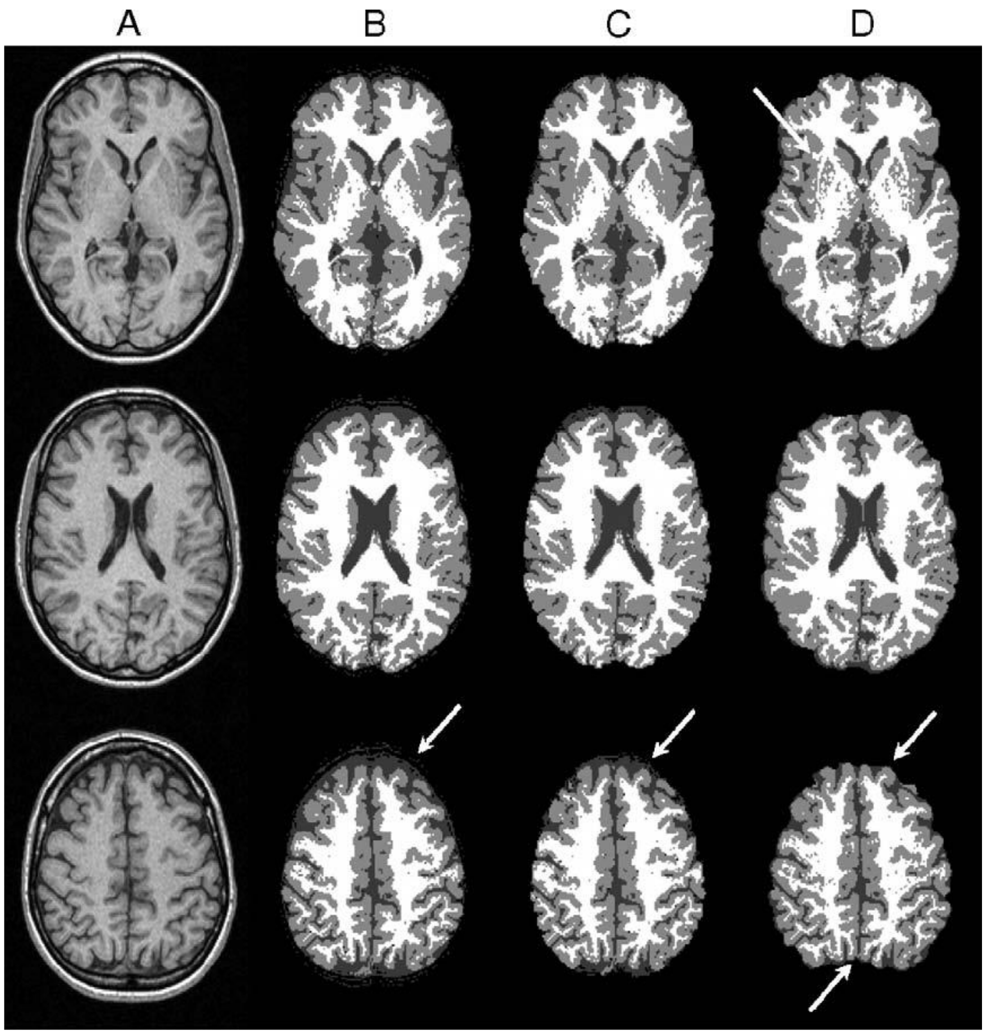
MRF Based Segmentation Using Various Methods



A: Raw MRI
B: SPM2
C: EMS
D: HBSA

from
Habib Zaidi, et al,
NeuroImage 32
(2006) 1591 – 1607

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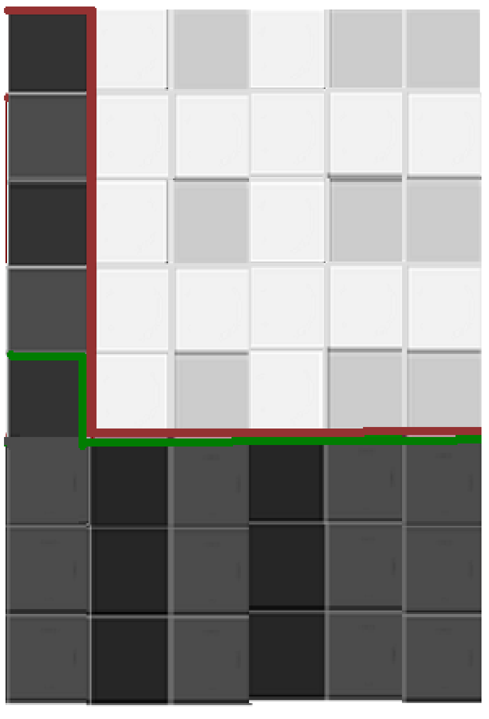
Geo-Cuts Algorithm for 3D Brain MRI Segmentation

Jie Zhu and Ramin Zabih
Cornell University

Principle Limitations Of MRF



Case where a simple energy minimization might not work:

- green: wrong segmentation
- red: correct segmentation

The segmentation energy of green might be smaller than that of red based on simple separation energy

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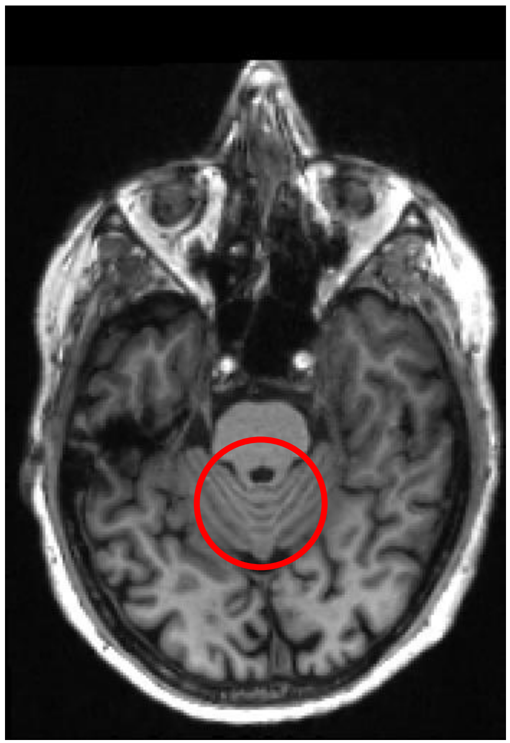
A Case As Motivation

- EMS

EMS gray matter segmentation



  – areas where EMS have problems.

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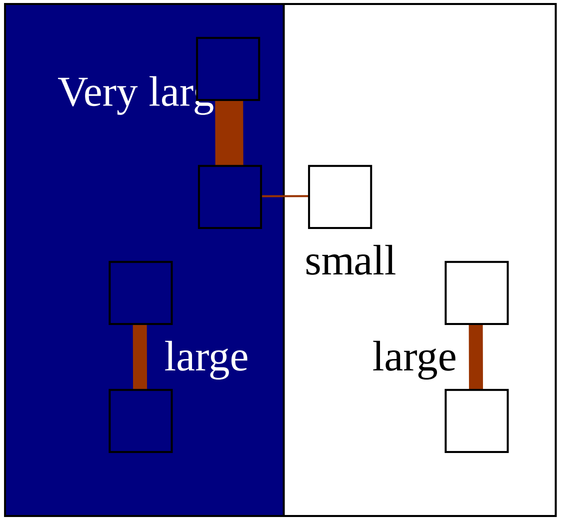
How Geo-cuts Works

- The separation penalty is defined based on magnitude and direction of image gradient:
  - Small gradient magnitude:
    - separation penalty: large (all directions)

$$E(p,q) = \frac{1}{\nabla\left(I_p - I_q\right)}$$

  - Large gradient magnitude
    - separation penalty :
      - small in direction of gradient.
      - very large in other directions.



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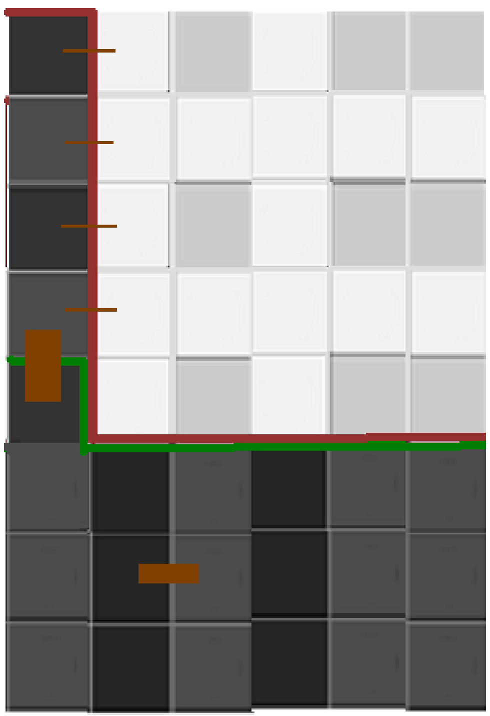
Why Use Geo Cuts



Case where simple separation energy did not work:

- green: wrong segmentation
- red: correct segmentation

Using Geo-cuts leads to

- Higher separation energy for green *than for red.*
- *→ Correct segmentation*

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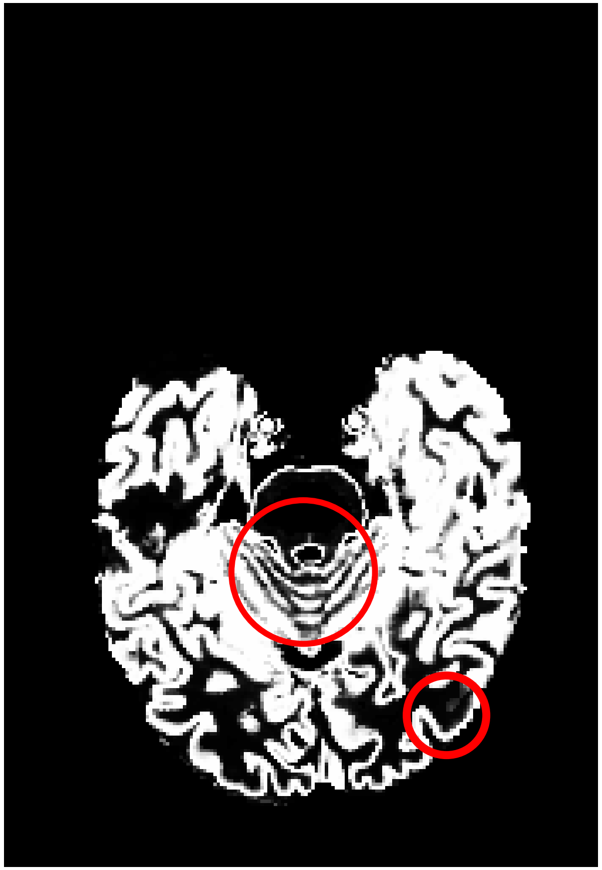
EMS vs. Geo Cuts

EMS gray matter

Geo-Cuts gray matter



Geo-Cuts white matter

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Deformable Models

- So far segmentation methods have not exploited knowledge of shape.
- In shape based methods, the segmentation problem is again formulated as an energy-minimization problem. However, a curve evolves in the image until it reaches the lowest energy state instead of a MRF.
- External and internal forces deform the shape control the evolution of segmentation.

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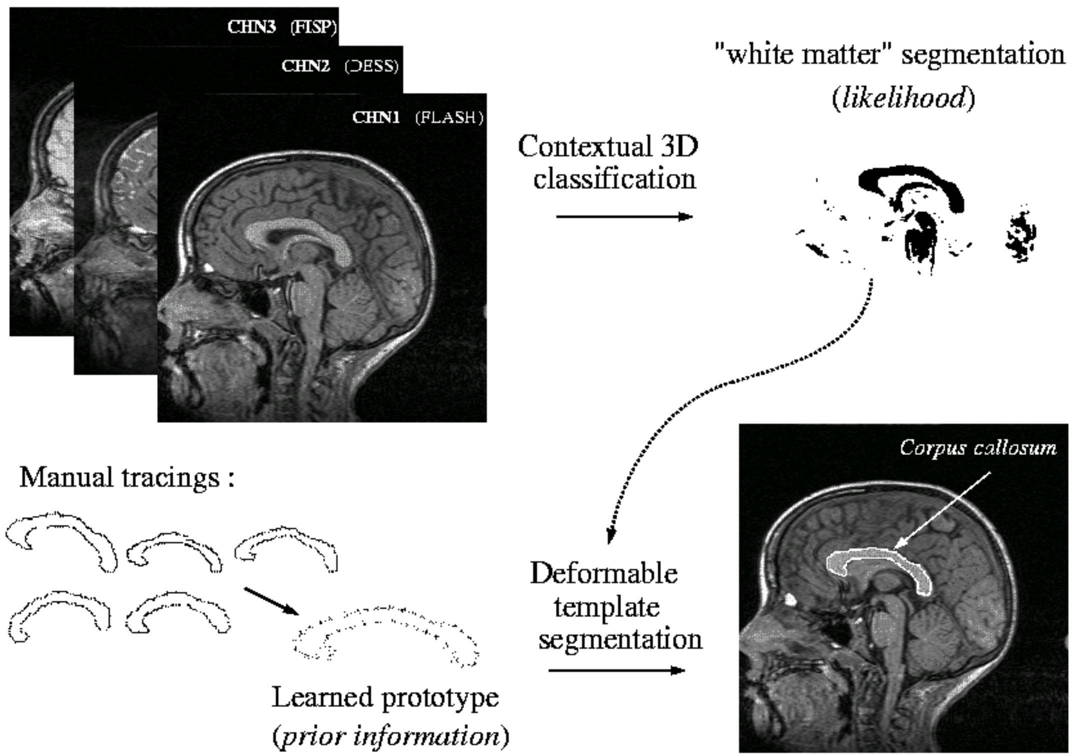
Deformable Template Segmentation



A. Lundervold et al.
Model-guided Segmentation of Corpus Callosum in MR Images
www.uib.no/.../arvid/cvpr99/cvpr99_7pp.html

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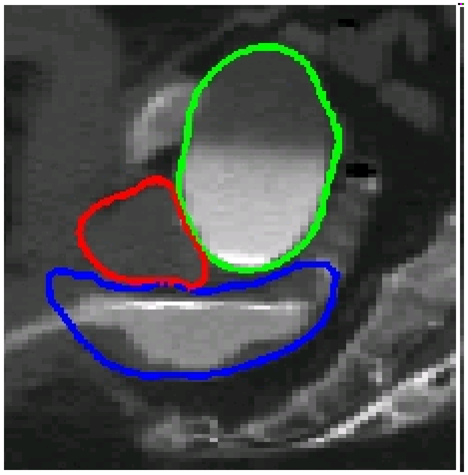
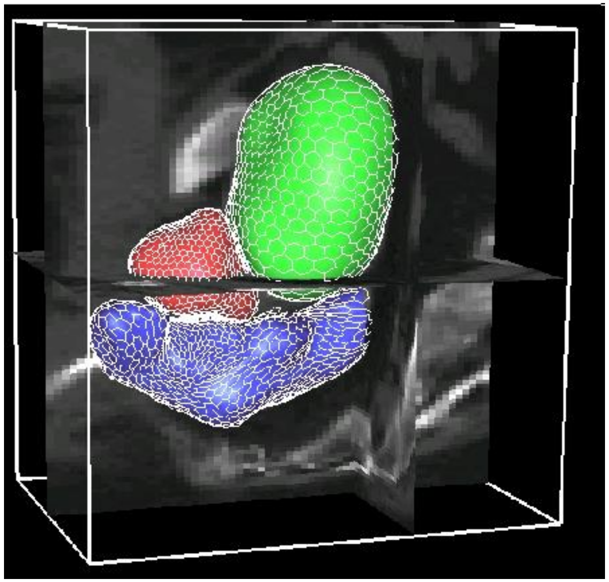
3D Deformable Surfaces

Automated Delineation of Prostate Bladder and Rectum





Costa, J. École Nationale Supérieure des Mines de Paris
www.jimenacosta.com/Jime.Publications.MICCAI0

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Segmentation Via Texture Extraction

- Two classical methods for feature extraction
  - Co-occurrence matrix (CM)
  - Fractal dimensions (FD)

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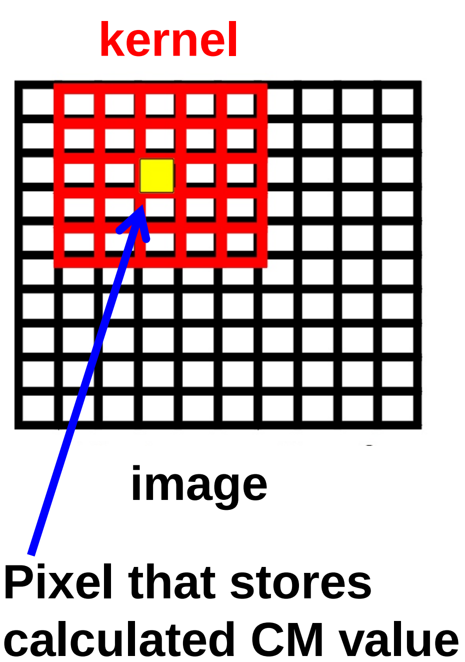
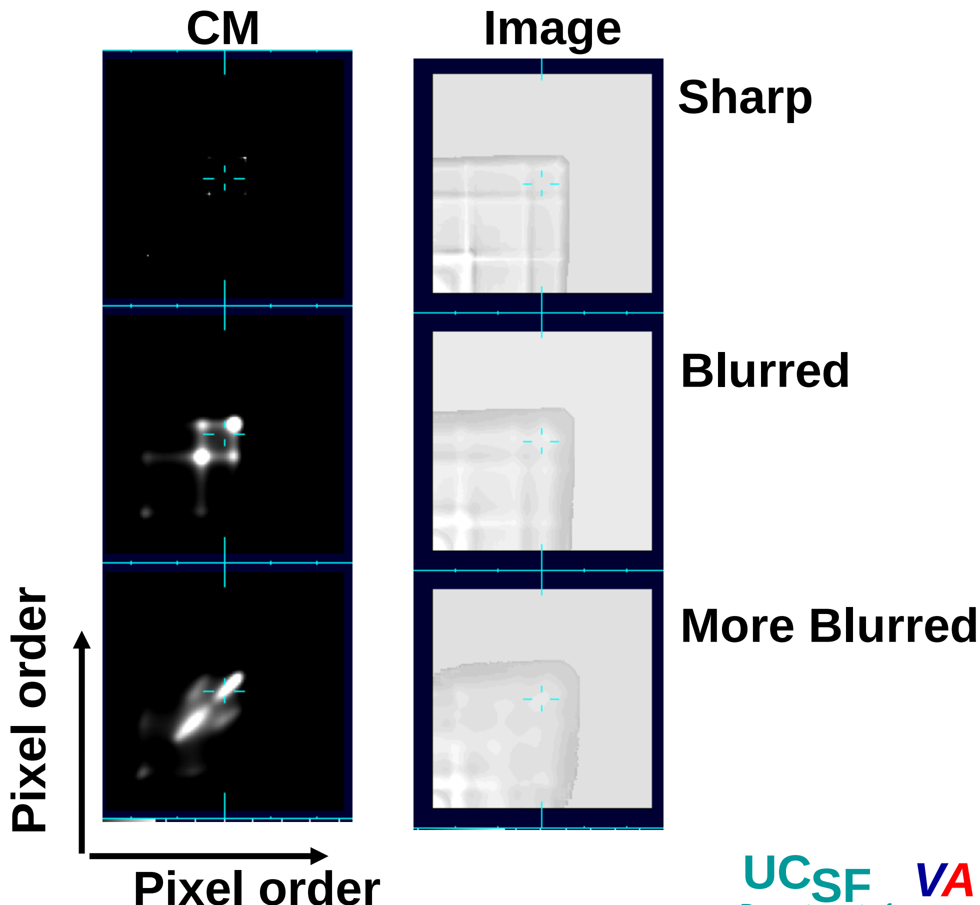
Co-Occurrance Matrix (CM)

Definition: The CM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in an image.





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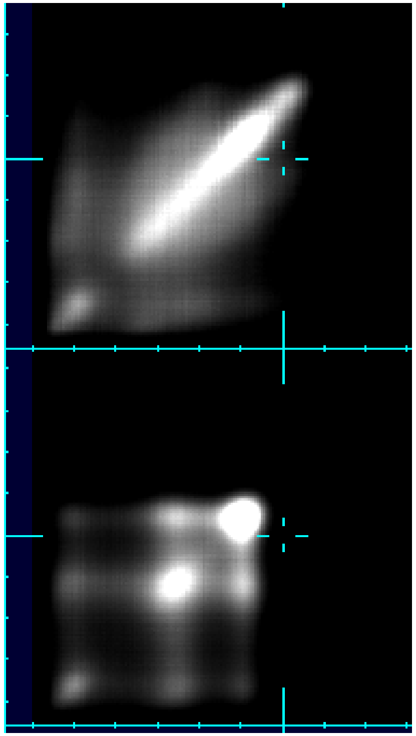
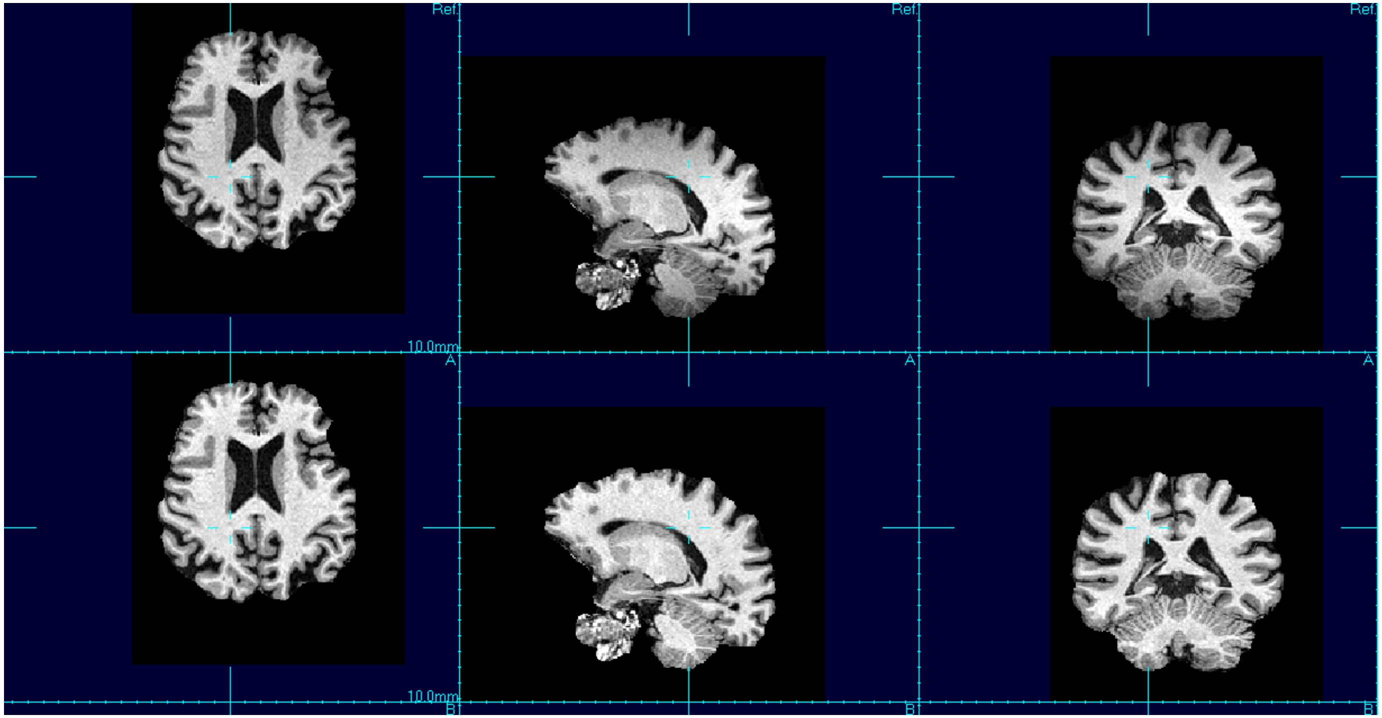
Evaluation of CM

CM



MRI with spatially varying intensity bias



MRI with spatially homogenous intensity bias

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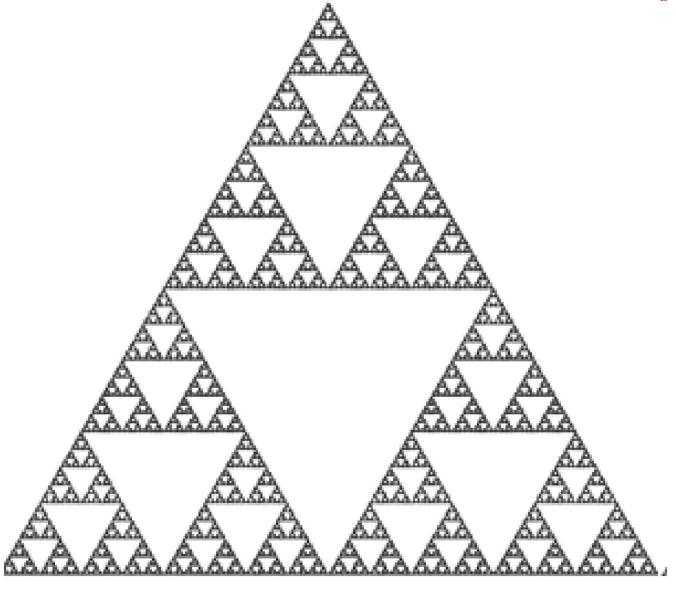
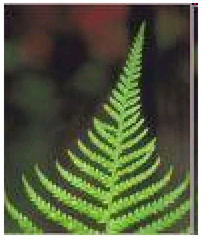
Fractal Dimensions

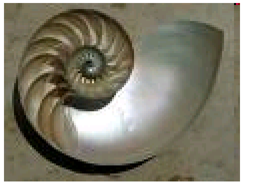
Intuitive Idea:

Many natural objects have structures that are repeated regardless of scale. Repetitive structures can be quantified by fractal dimensions (FD).



Sierpinski Triangle





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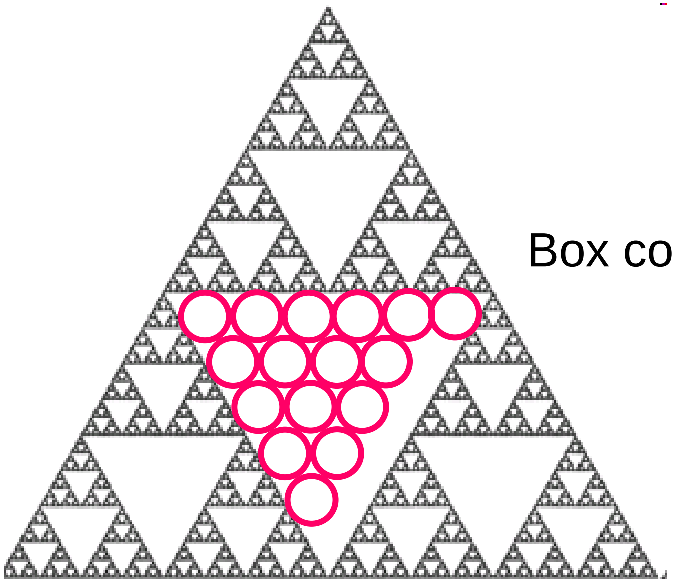
Fractal Dimensions

Definition:

$$N \cdot \varepsilon^{D} = 1$$



Box counting

Sierpinski Triangle

$$D = \lim_{\varepsilon \to 0} \frac{\ln\left[N(\varepsilon)\right]}{\ln\left[\frac{1}{\varepsilon}\right]}.$$

ε

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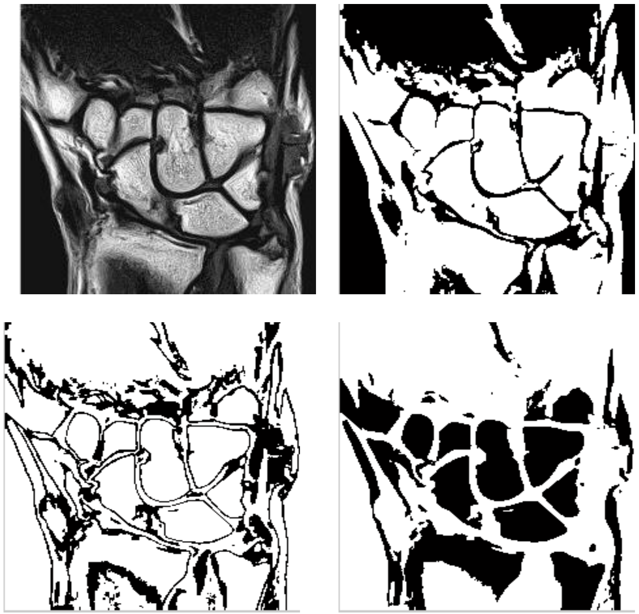
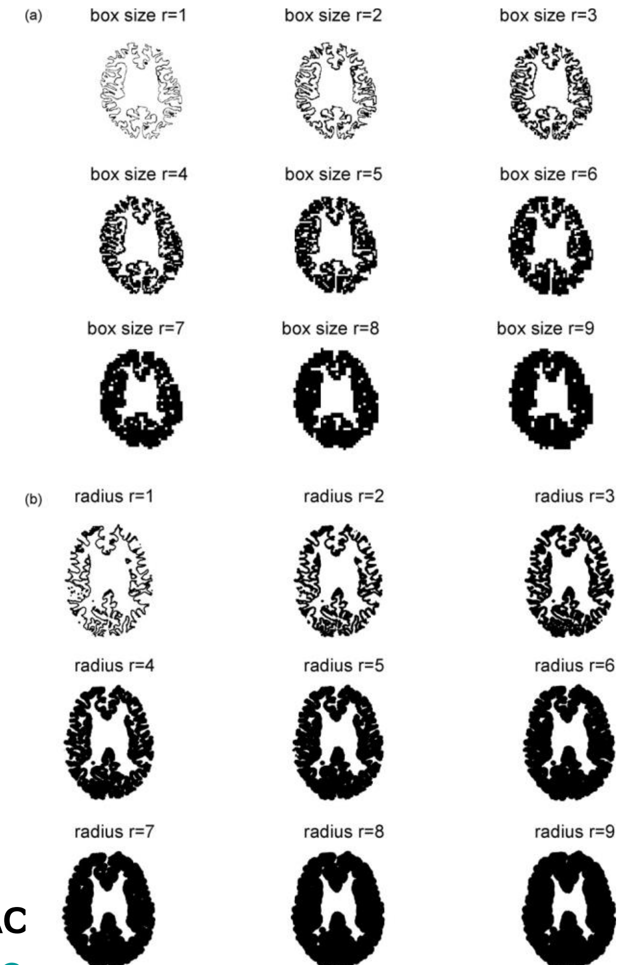
Fractal Dimensions





MEDICAL IMAGE SEGMENTATION USING MULTIFRAC

Soundararajan Ezekiel; www.cosc.iup.edu/sezekiel/Publications/Medical

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Summary

Automated	Semi-automated	Initializing	Manual
Threshold MRF Shape Models Fractal Dimensions	Region growing K-means Fuzzy C-Means	Co-occurrence	Tracing

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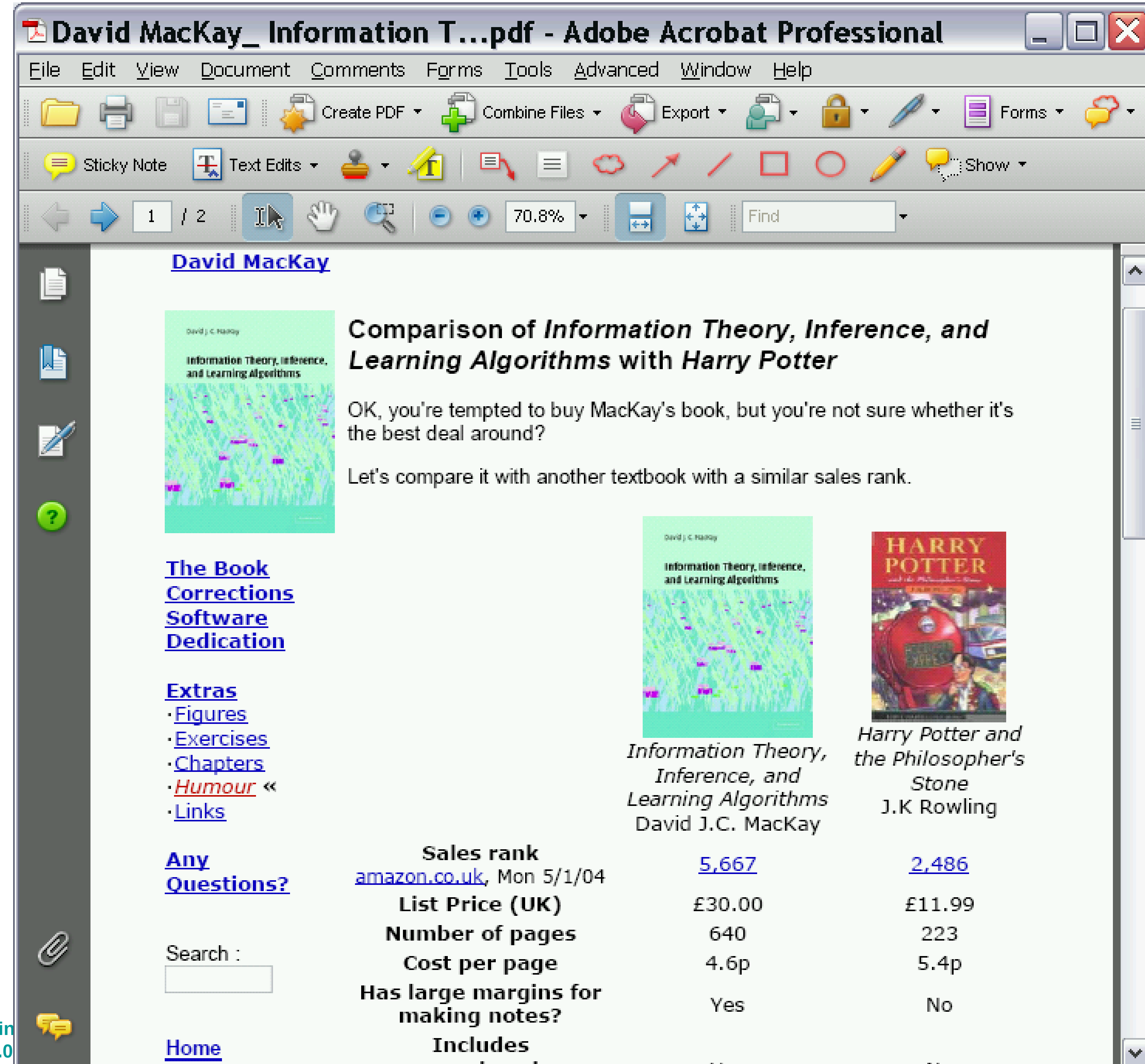
Literature

1. Segmentation Methods I and II; in Handbook of Biomedical Imaging; Ed. J. S. Suri; Kluwer Academic 2005.
2. WIKI-Books: http://en.wikibooks.org/wiki/SPM-VBM
3. FSL- FAST:http://www.fmrib.ox.ac.uk/fsl/fast4/index.html



David MacKay_ Information T...pdf - Adobe Acrobat Professional

David MacKay

Comparison of *Information Theory, Inference, and Learning Algorithms* with *Harry Potter*

OK, you're tempted to buy MacKay's book, but you're not sure whether it's the best deal around?

Let's compare it with another textbook with a similar sales rank.

	Information Theory, Inference, and Learning Algorithms David J.C. MacKay	*Harry Potter and the Philosopher's Stone* J.K Rowling
Sales rank amazon.co.uk, Mon 5/1/04	5,667	2,486
List Price (UK)	£30.00	£11.99
Number of pages	640	223
Cost per page	4.6p	5.4p
Has large margins for making notes?	Yes	No
Includes		

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Extras
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