Segmentation, a (short) review of progress and pitfalls.

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Acknowledgements

- Image Science group UCL (CS and Medphys)
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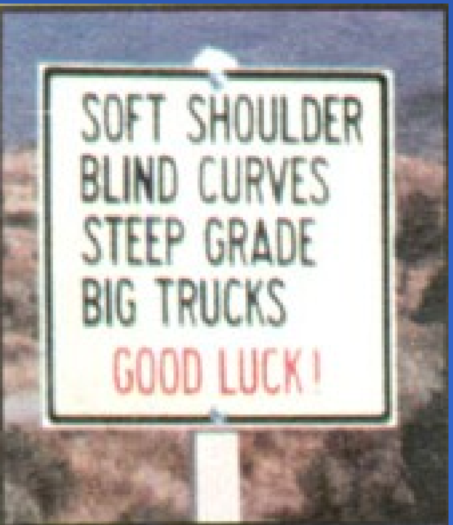
- Yale (J. Duncan)
- and many others

Outline

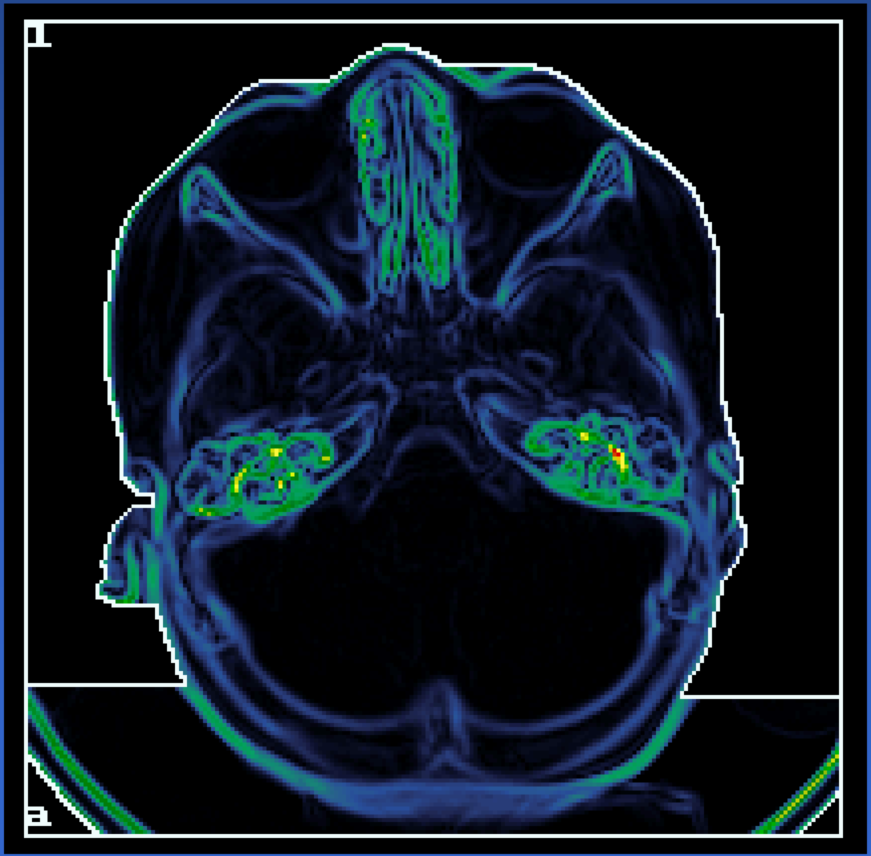
- Some methods of segmentation
- Modelling
- Assymmetry
- A target application
- Questions of validation



A road map

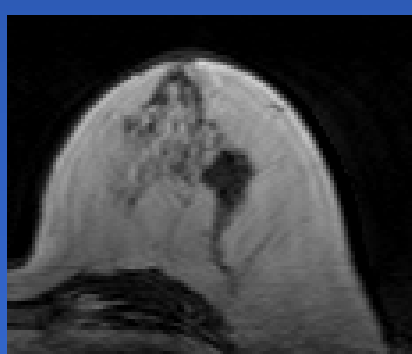
Segmentation

- Classic ‘edge detection’ methods
  - Gradient (Sobel etc), zero crossing of Laplacian
  - Canny
  - Marr Hildreth
- Phase congruency
- Model based
  - Medial axis
  - Active shape
- Clustering
  - Split merge
  - K-Means
  - Affinity
- etc

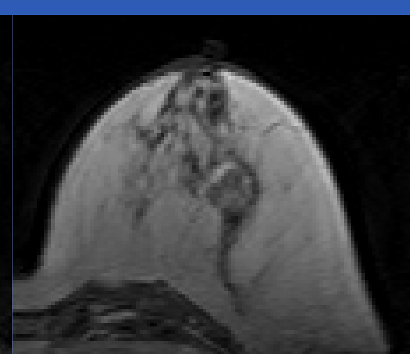


Three research strands

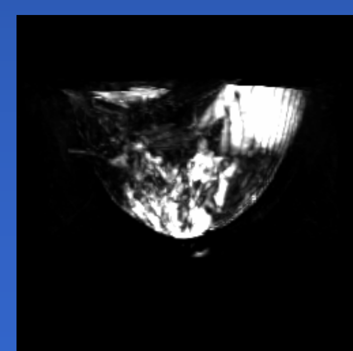
- Non-rigid registration
  - change detection
  - voxel-based morphometry
  - segmentation



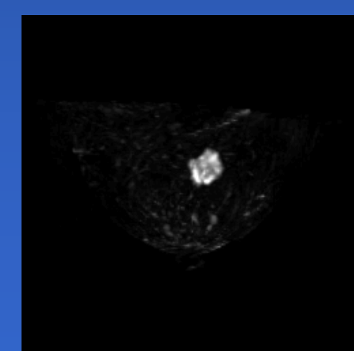
Pre-contrast



Post-contrast



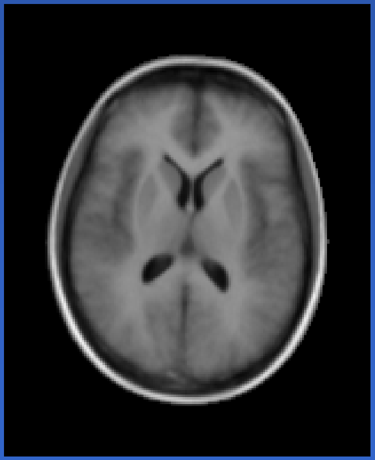
Subtract



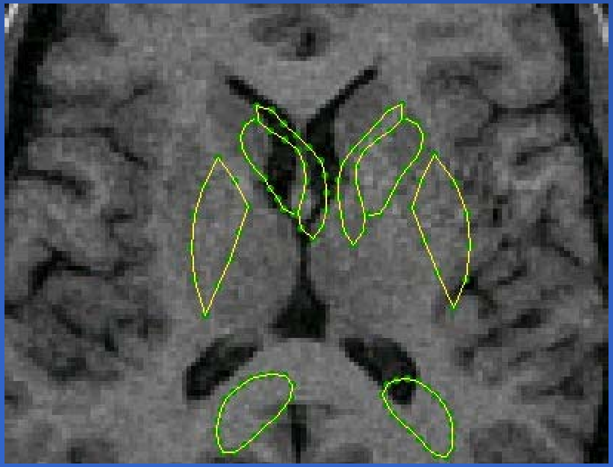
Subtract NRR

2^{nd} strand

- Non-rigid registration
- Shape and appearance models
  - segmentation
  - normal variation and pathology



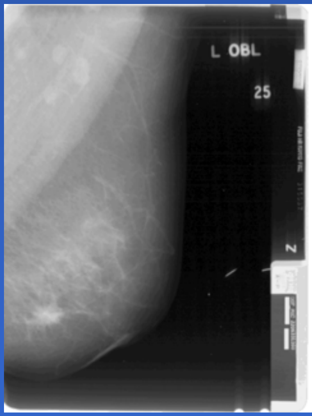
Appearance Model



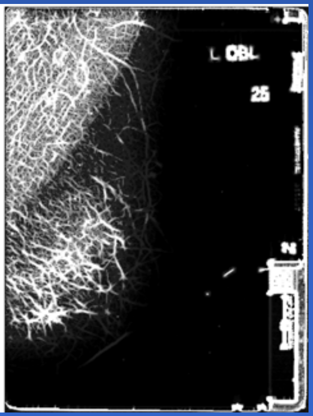
Model-based Segmentation

3^{rd} strand

- Non-rigid registration
- Shape and appearance models
- Feature detection
  - ‘interesting’ structure
  - abnormal structure

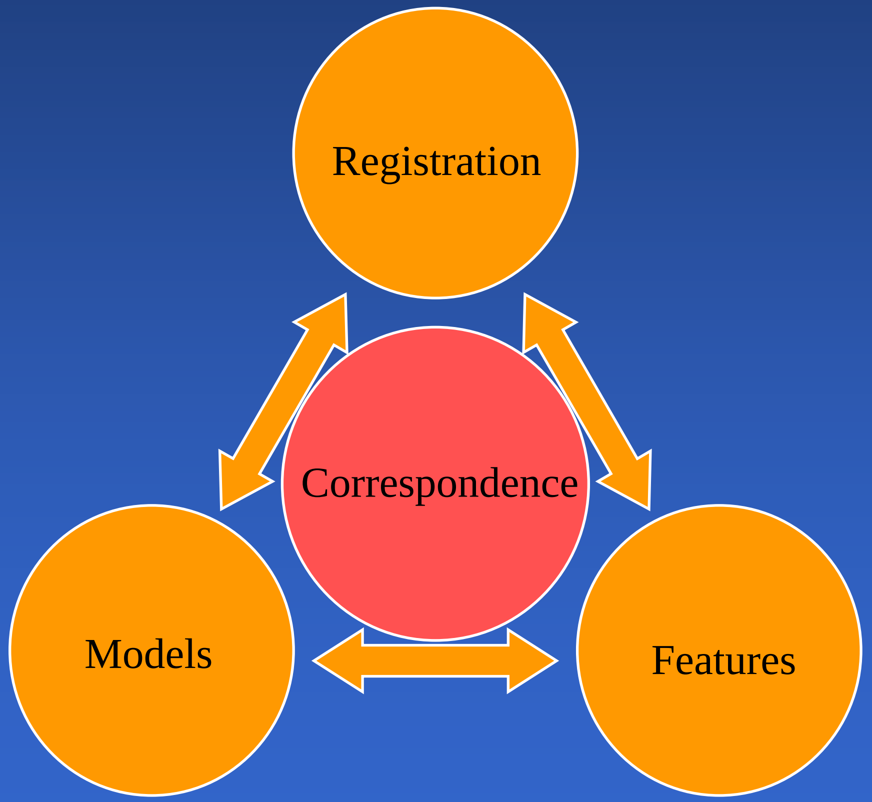


Mammogram



Linear features

A Unified View

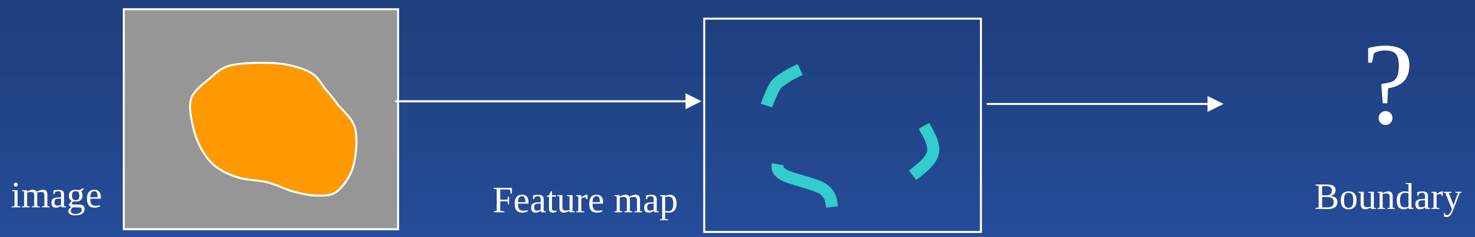


Underlying unity not currently exploited

- Models ⇔ Registration
  - NRR to build models
  - models to constrain NRR
- Registration ⇔ Features
  - features to improve NRR
  - NRR defines corresponding features
- Features ⇔ Models
  - features to enrich models
  - models to locate features

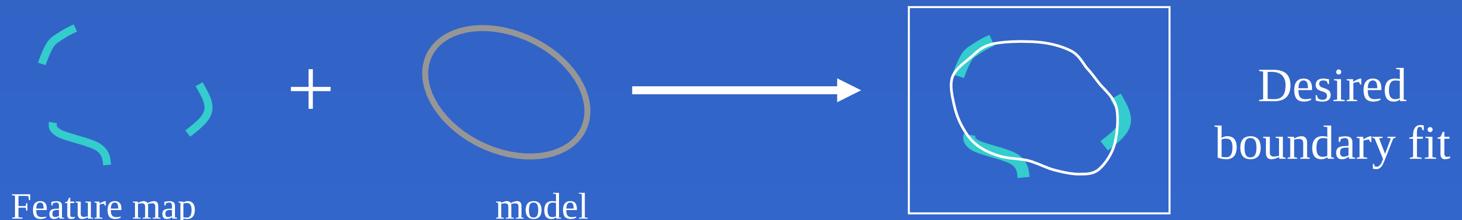
Models in Biomedical Image Analysis

- Lack of image quality and/or features often limit the recovery of quantitative information from images.



- Overall, these problems can be seen as ill-posed

- Models can help constrain solutions in plausible ways:



The Deformable contour model

- Deformable contour model (or “snake”) can be represented by a set of controls points developed through the solution of energy minimization using variational calculus
- This model requires initial control points which roughly delineate the volume of interest on several slices
- New Control points on each slice are generated from cubic spline interpolation to obtain continuity and smoothness

Contd. Deformable contour model

The total energy of snake can be represented by

$$E_{total} = \int_0^1 E_{snake}[v(i)]\,di = \alpha E_{\text{int}}\big[v(i)\big] + \beta E_{image}\big[v(i)\big]$$

The internal energy is

$$\alpha E_{\text{int}}[v(i)] = \alpha_1 \left|v_i - v_{i-1}\right|^2 + \alpha_2 \left|v_{i-1} - 2v_i + v_{i+1}\right|^2$$

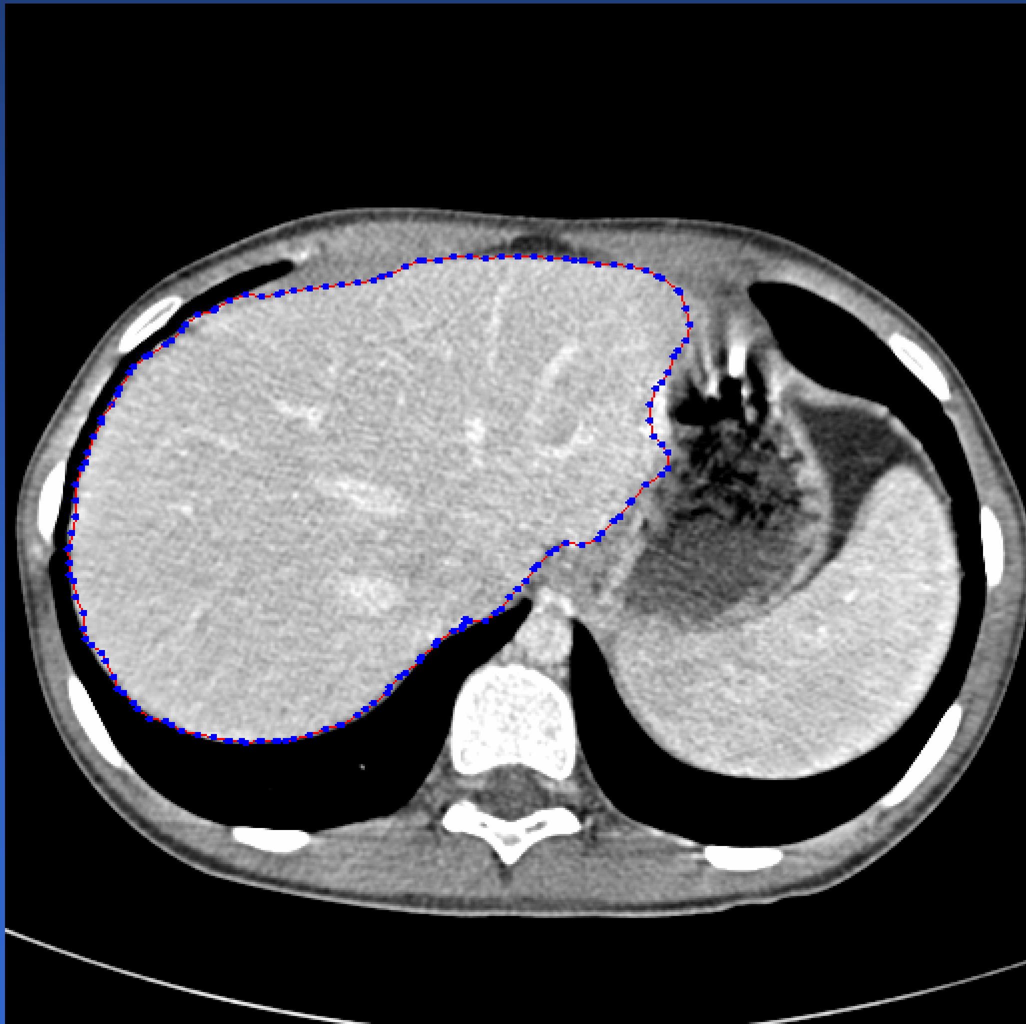
The external energy is

$$\beta E_{image} = \beta_1 E_{\text{int}\, en}[v(i)] + \beta_2 E_{grad}[v(i)]$$

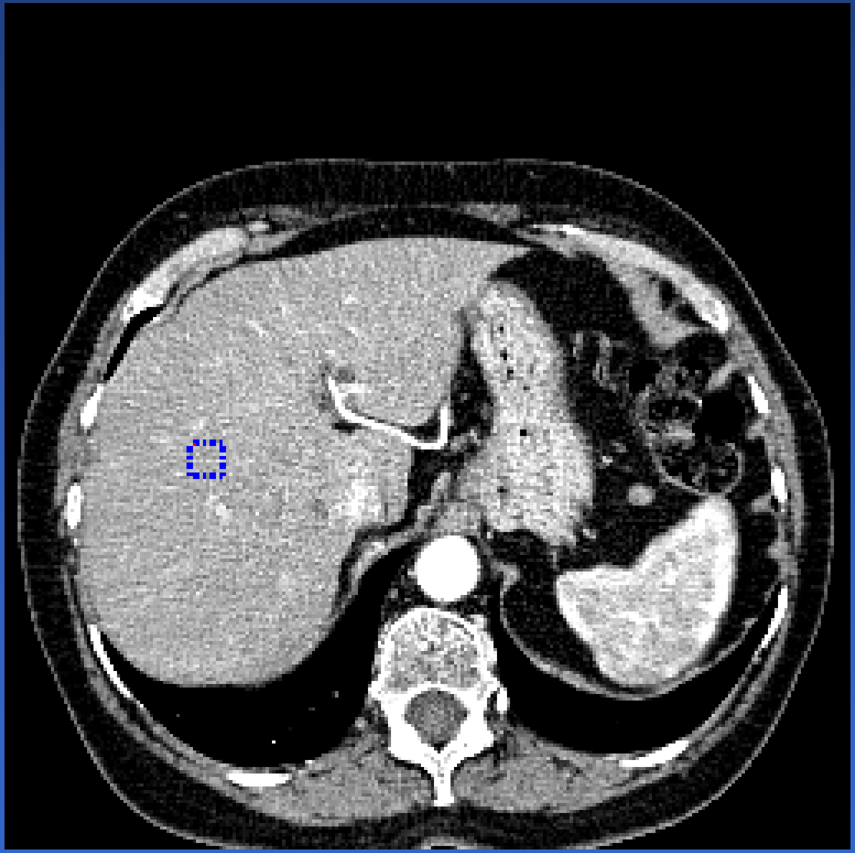
In this process, modified greedy optimisation technique has been used

Snakes

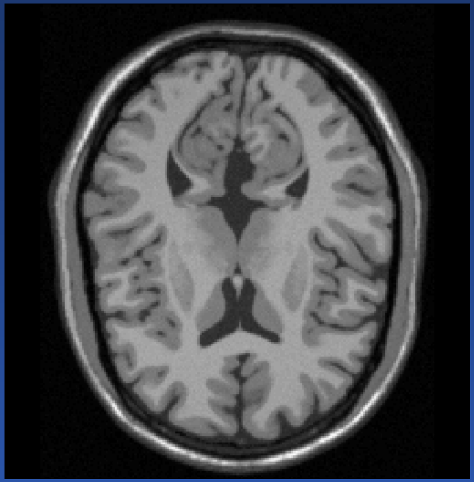
- Balloons
- Shrink wrapping
- Gsnakes
- Tsnakes
- 2-D to 3-D



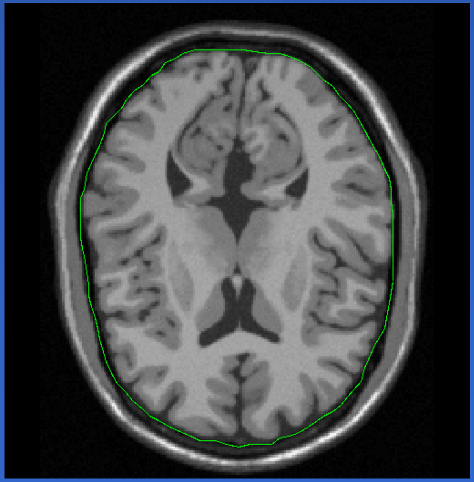
Reparameterization



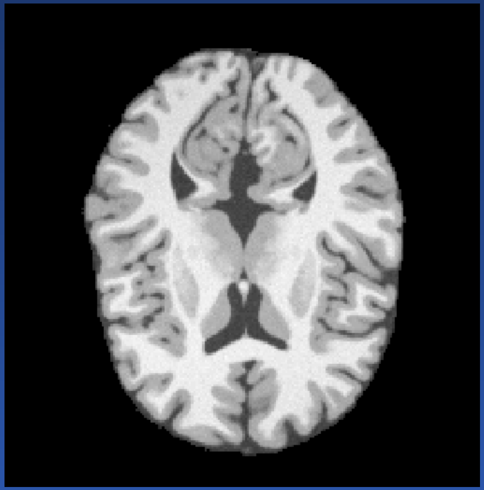
Examples of separate brain and CSF from non-brain tissues of a volume data set



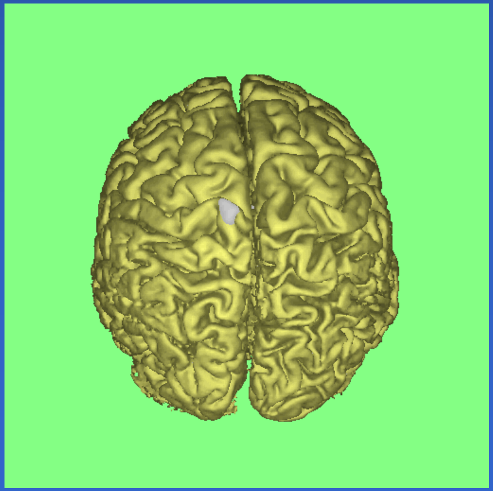
(a)



(b)



(c)



(d)

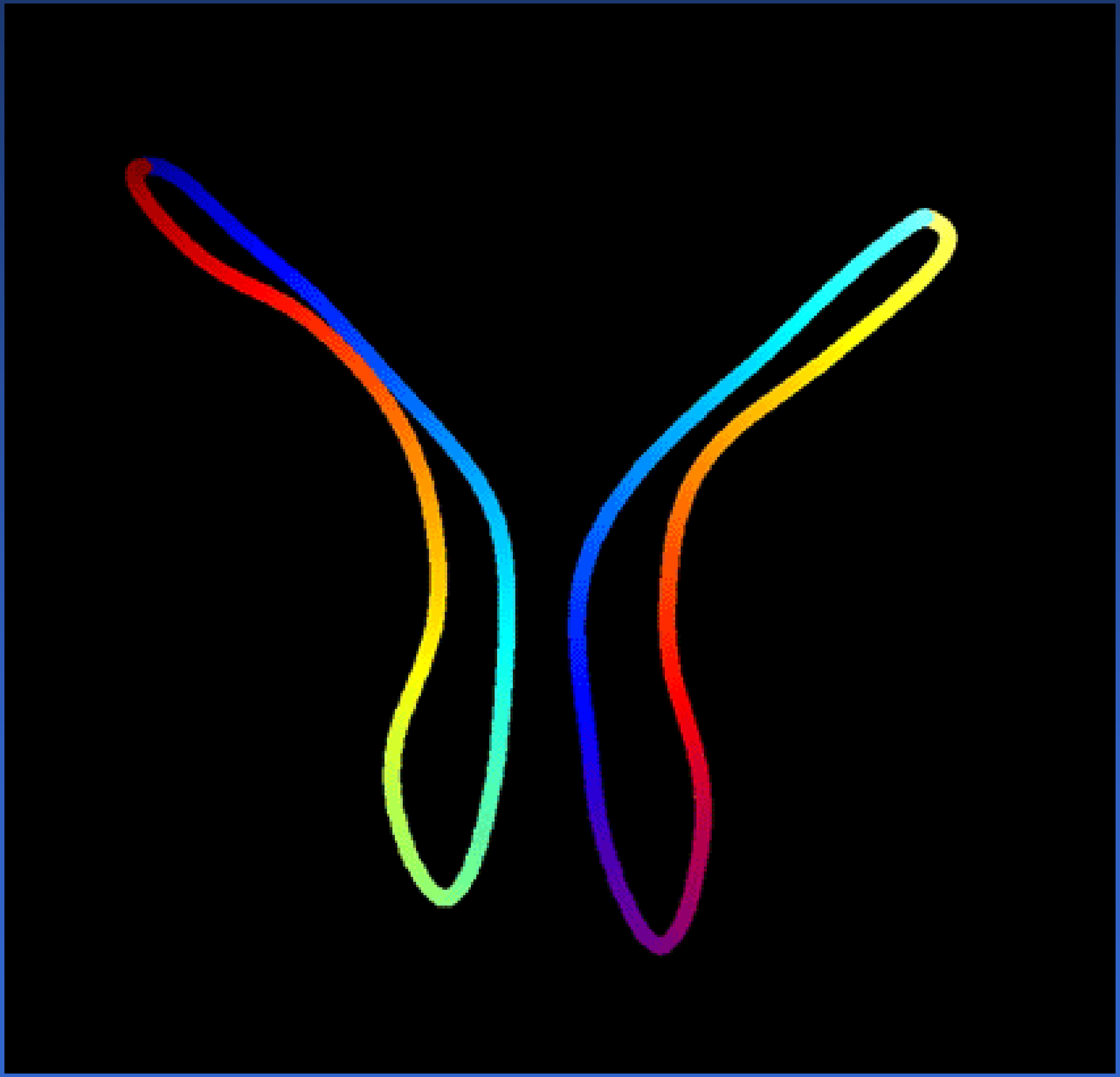
(a) The whole brain image

(b) Final deformable contour Model fit to extract brain and CSF from non-brain tissues

(c) brain and CSF has been Separated from non-brain tissues

(d) Separate brain and CSF From non-brain tissues of a Volume data set

SSM Built from Annotation



Fuzzy Classification and Fuzzy Connectedness

- Segmentation and classification
- Classification can lead to segmentation and vice-versa.
- Classification refers to the labelling of pixels in an image that may result in the segmentation of objects or regions.
- The grey level intensity value is the most common feature. Texture is an alternative.
- Pixels with similar feature vectors form clusters in the feature space that can be separated by lines or curves.
- In reality, partitioned regions do overlap at the border and the classes are not separable which brings fuzzy Clustering.
- Fuzzy membership functions has been assigned a pixel to classes with any value between 0 and 1.
- Any pixel can be assigned to more than one class simultaneously where the membership value of a pixel i to each class k is

$$\mu_{ik} \in [0,1] \ \ and \ \sum_{k} \mu_{ik} = 1$$

Fuzzy Clustering works as follows:

1. Initialise c cluster centres
2. Begin iteration

   i. Calculate distance function

$$d_{ik} = \left\| x_i - m_k \right\|$$

   ii. Assign a fuzzy membership value to each pixel x_i for each cluster

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{ij}} \right)^{2(m-1)}}$$

   iii. Re-calculate cluster centres

$$m_k = \frac{\sum_{i=1}^{n} (\mu_{ik})^m x_i}{\sum_{i=1}^{n} (\mu_{ik})^m}$$

   iv. At each iteration, recalculate the membership value

3. Stop iteration when appropriate stopping criterion is satisfied.

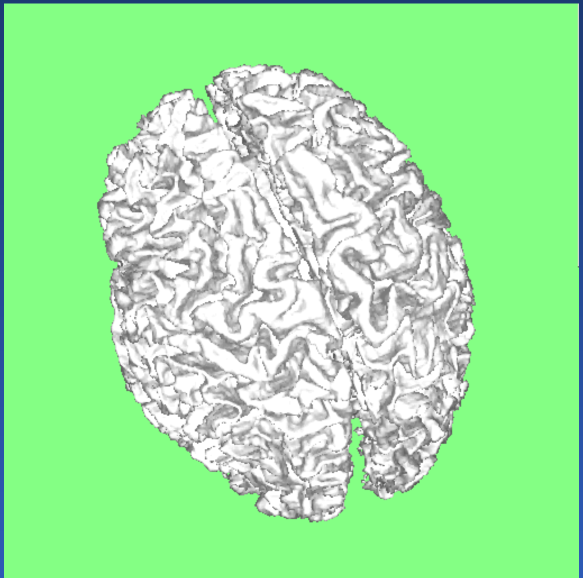
Contd. Fuzzy clustering and fuzzy connectedness

- The overall objective function by this classification process is given by

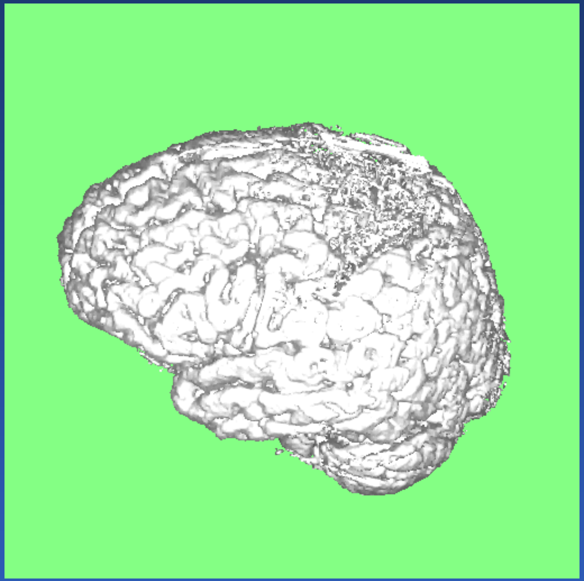
$$F_m = \sum_{i=1}^{n} \sum_{k=1}^{c} \left(\mu_{ik}\right)^m \left(\left\| x_i - v_k \right\|\right)^2$$

- Using spatial information, image elements that constitute a region can be called as "accumulated voxels". These voxels can be determined by the similarity of image elements and of intensity-based features associated with image elements as well as by their spatial connectivity.
- Fuzzy connected object is that object in an image where every pixel is spatially adjacent, homogenous in pixel intensities and their fuzzy membership values are high.
- An image element will be considered to belong to that object whose strength of connectedness is highest.

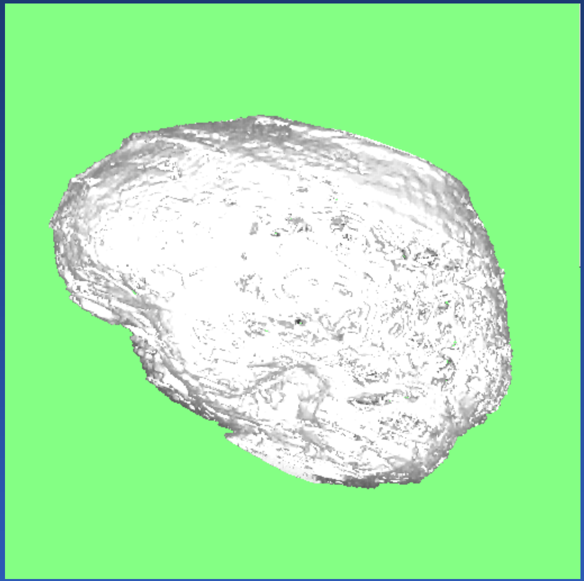
Examples of WM, GM and CSF which are segmented by applying relative fuzzy connectedness are shown below:



(a) Segmented volume WM



(b) Segmented volume GM

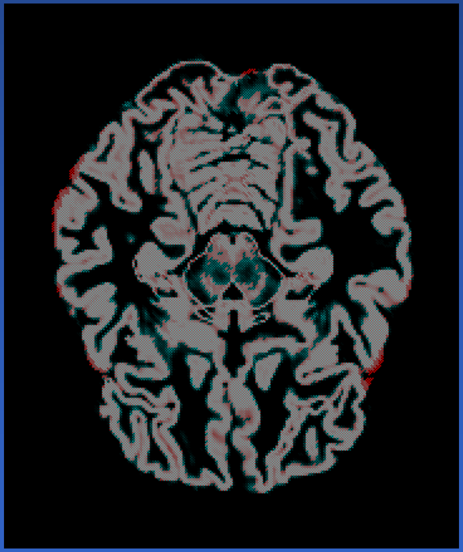


(c) segmented volume CSF

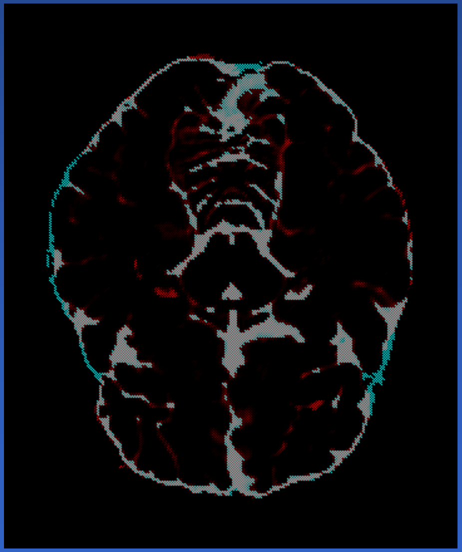
Comparison between segmented matter with simulated segmented matter

To create a colour overlay model to make an objective comparison by merging segmented WM with simulated WM, segmented GM with simulated GM and segmented CSF with simulated CSF

(a) Matched WM



(b) Matched GM



(c) matched CSF

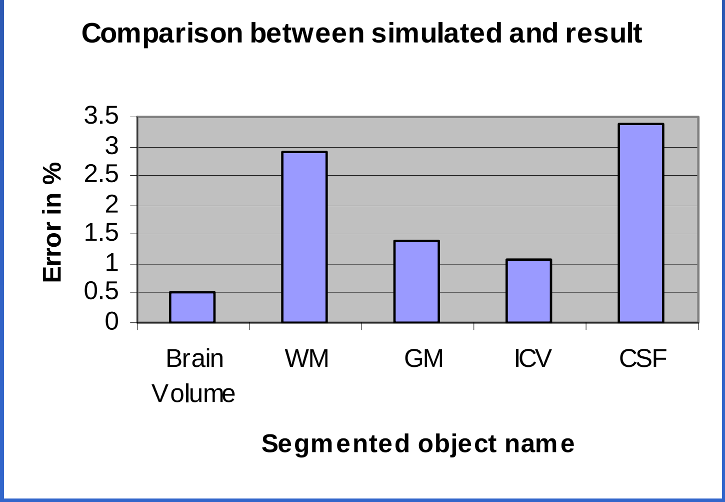
Comparison Contd.

Simulated segmented tissue volumes:	WM volume = 674777	GM volume = 902912	Total brain volume = 1577689	CSF volume= 371945	Total ICV = Brain vol. + CSF vol. = 1949634
Obtained result using simulated data based:	694944	890611	1585555	384750	1970305
Error (%)	2.9%	1.4%	0.5%	3.4%	1.06%

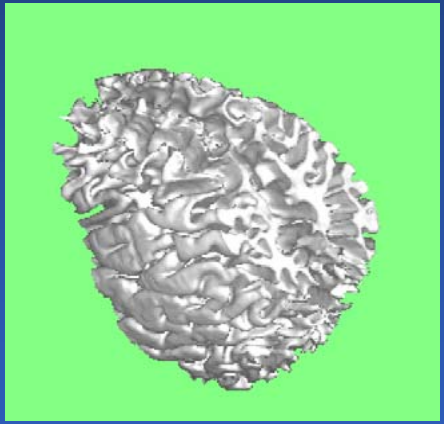
Error in Brain Volume = 4% (1999)

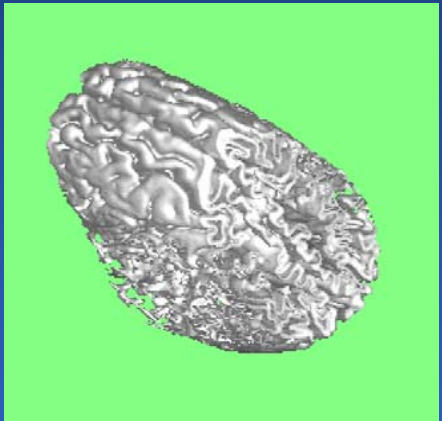
Error in WM = 3% (2001)

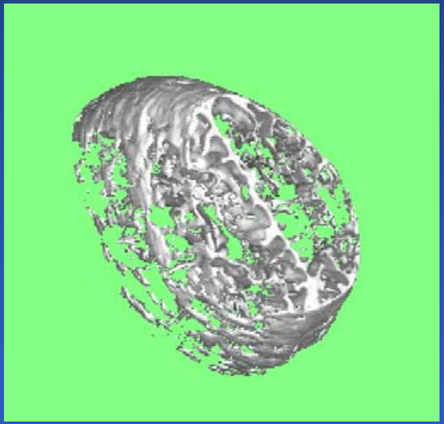
Error in ICV = 4% (1998)



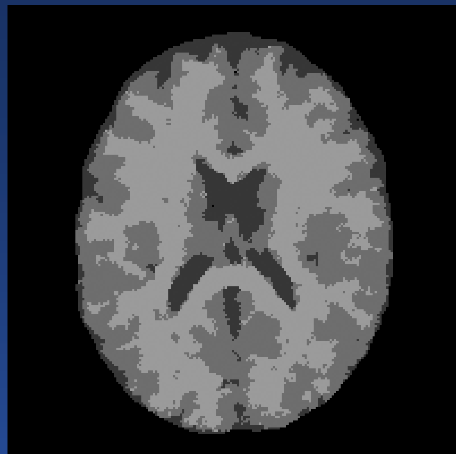
Examples of clinical data samples

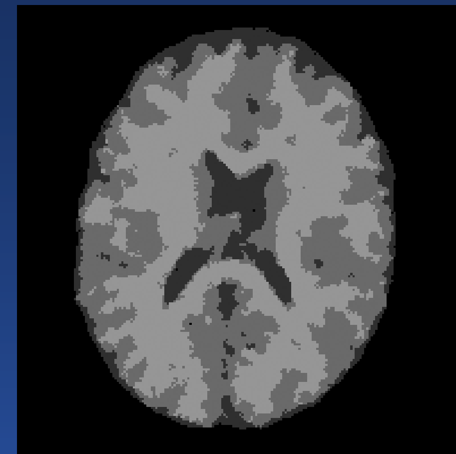

(a) Segmented WM


(b) Segmented GM

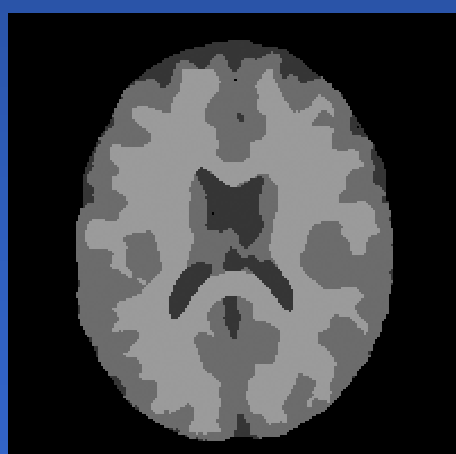

(c) segmented CSF

Ack. Oxford





Separate segmentation of left and right images

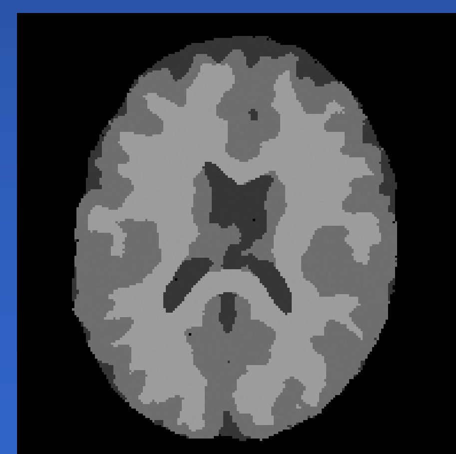


→

4.95º

←

4.97º



Rotation 5º

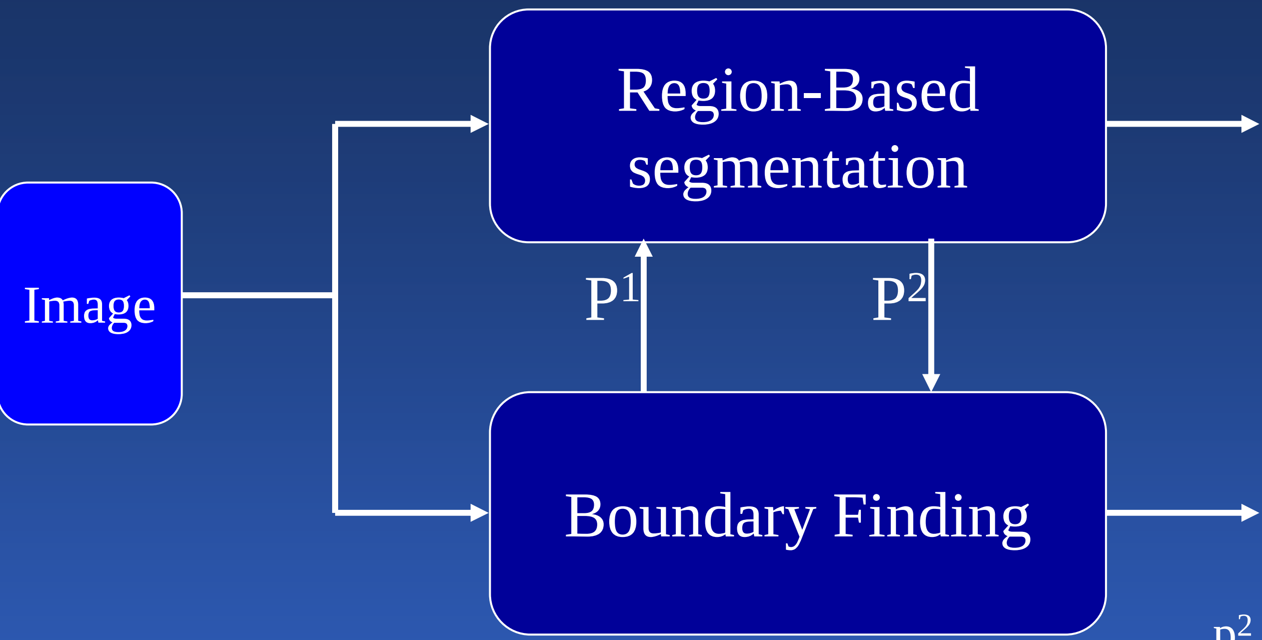
Simultaneous segmentation & estimation of transformation

Model based fitting

- Shape Priors: Cootes and Taylor (IPMI93) ; Grenander/ Miller (atlases/templates- 1991) ; Vemuri, et al. (MedIA97); Leventon, Grimson, et al. (CVPR00)
- Integrated Methods: Region grow w/ edges- Pavlidis and Liow (PAMI91); Zhu and Yuille (ICCV95) ; Ahuja (PAMI96) ; level sets - Tek and Kimia (ICCV95)
- Segmenting Cortical Gray Matter: Macdonald and Evans (SPIE95) ; Davatzikos and Prince (TMI95); Davatizikos and Bryan (TMI96); Teo and Sapiro (TMI97) ; Xu and Prince (MICCAI98) ;
- Multiple Objects/Level Sets and Priors: Tsai, Wells, Grimson, Willsky (IPMI03); Leventon, Grimson,Faugeras (CVPR00);

Integrated Segmentation via Game Theory

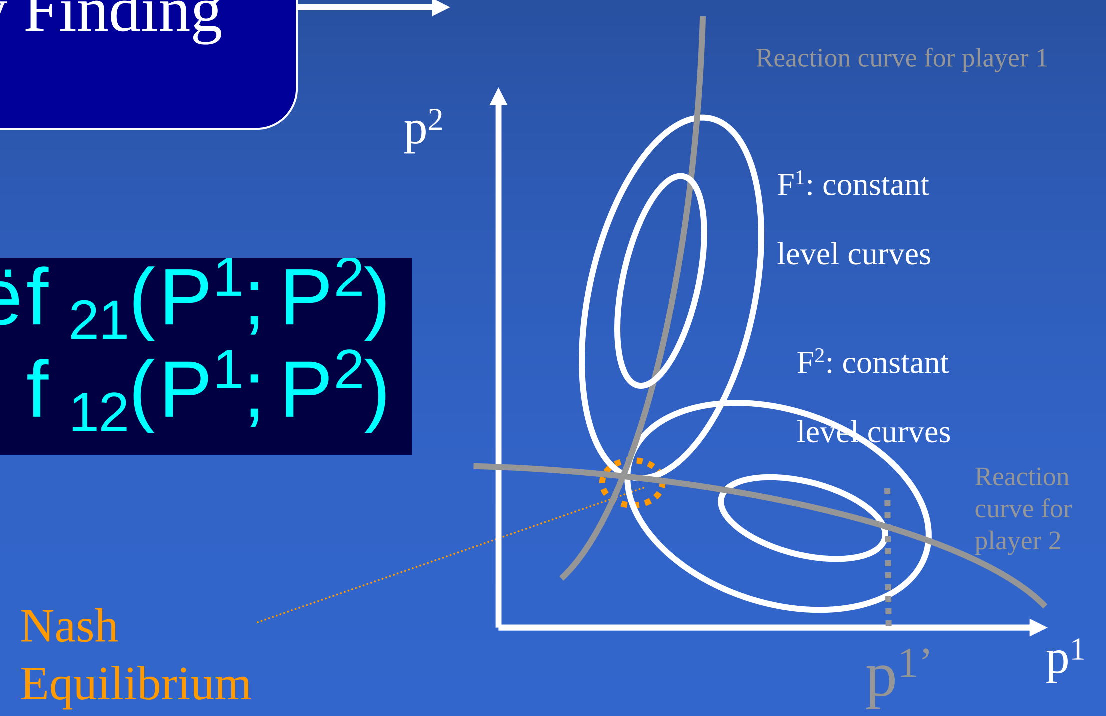
(Chakraborty & Duncan, PAMI 99)



$P^{1*} = X$
(classified pixels)

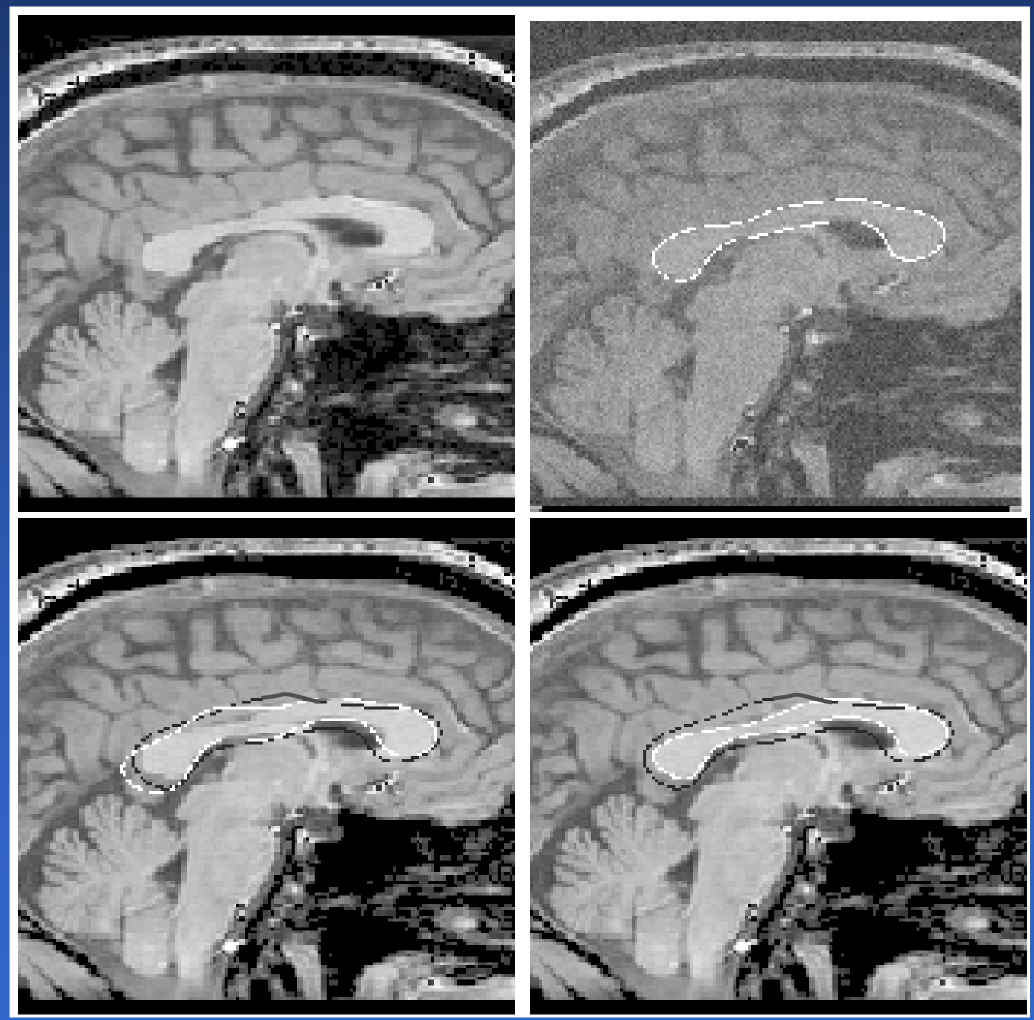
$P^{2*} = p$
(boundary parameters)

$$F^1(P^1; P^2) = f_1(P^1) + \text{ë}f_{21}(P^1; P^2)$$
$$F^2(P^1; P^2) = f_2(P^2) + \text{ì}\, f_{12}(P^1; P^2)$$



Corpus Callosum Result

Sagittal MR ($1mm^3$ gradient echo)



Expert-traced contour

Black = initial contour

White = gradient-based boundary finding

Black = initial contour

White = game-theory result

Ack. Duncan

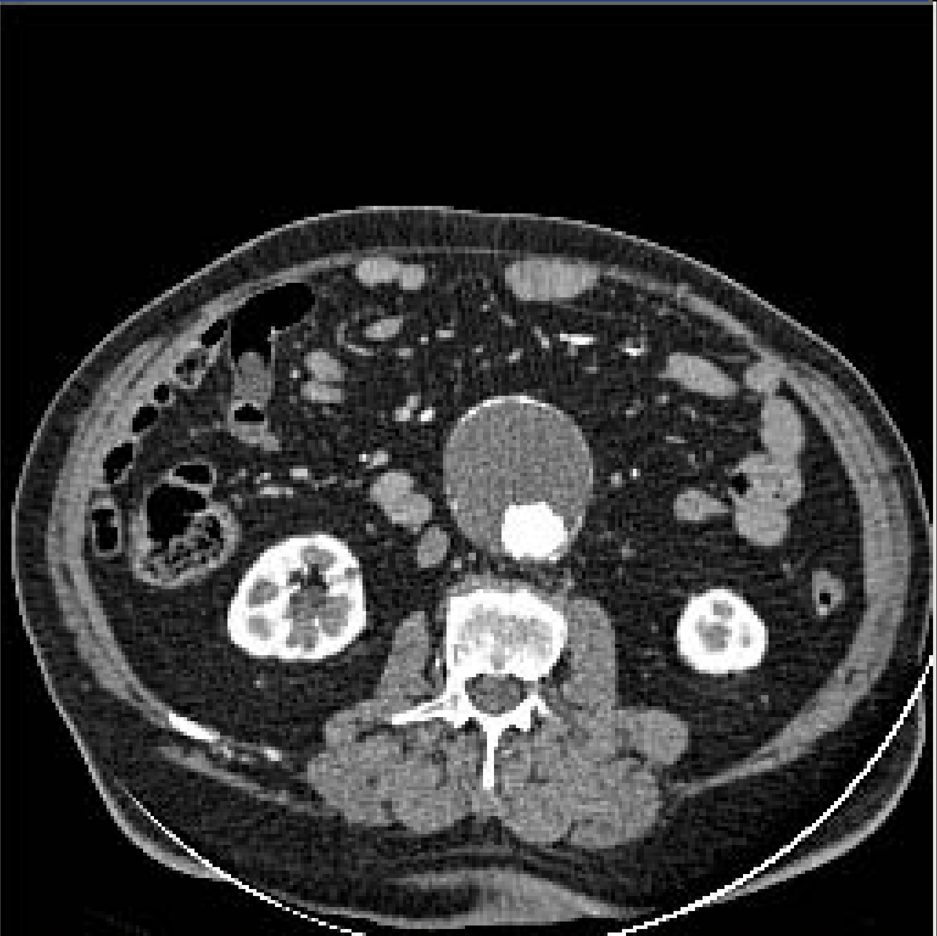
3D Coupled Surfaces Segmentation vs. Human Expert Tracing

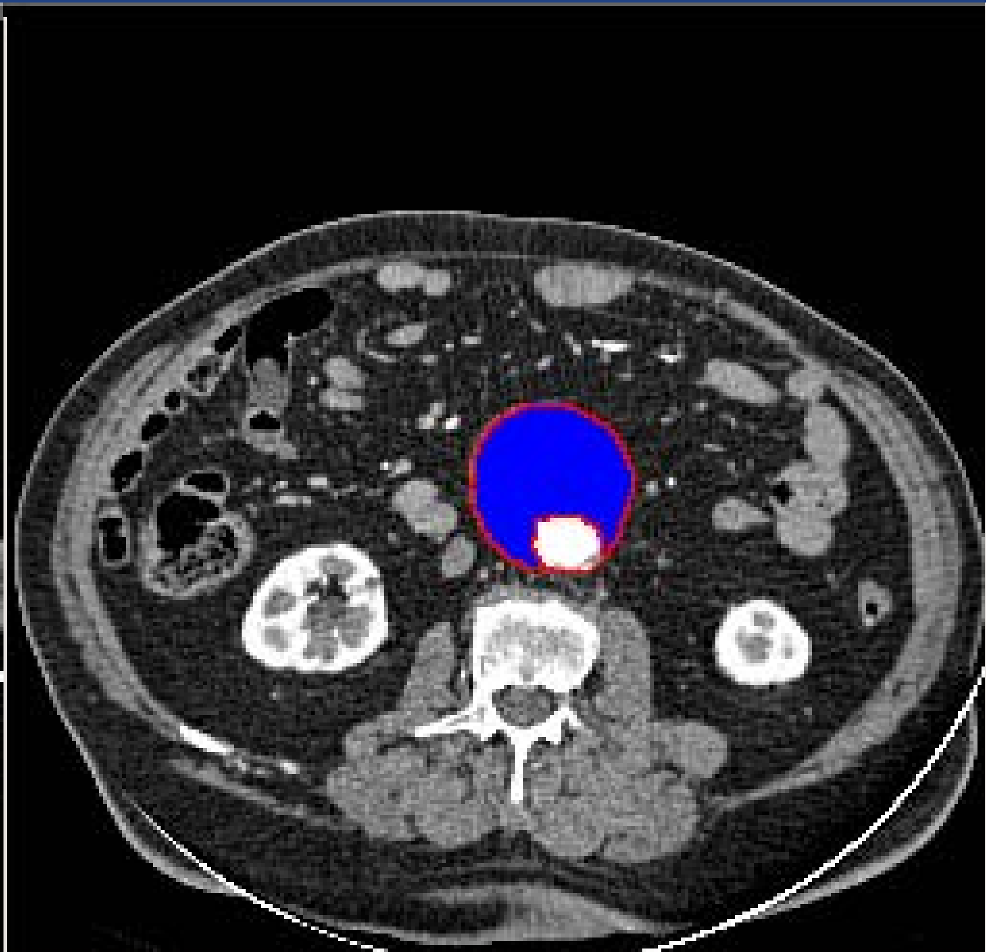
Original Expert Algorithm

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Brain TP	94.3	93.4	95.3	95.4	94.6	97.2	95.3	95.5	95.6	95.0	94.0	94.5	95.3	97.2
Brain FP	3.2	3.8	4.0	3.3	5.1	5.1	3.9	3.7	3.8	3.4	2.0	4.8	4.0	3.9
Cort. TP	86.9	87.1	87.0	86.2	83.7	88.2	87.3	86.6	88.6	87.9	89.7	87.0	84.7	87.0

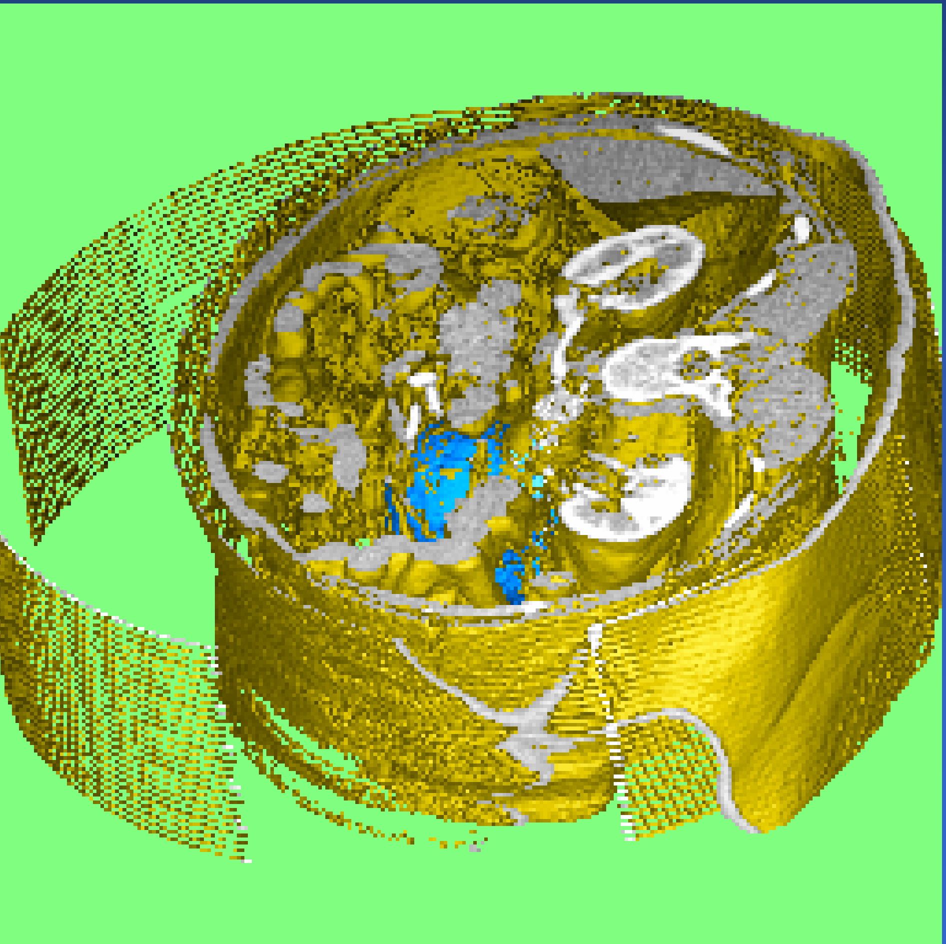
TP = true positive rate (%) ; FP = false positive rate (%) ; 14 brains studied in terms of VOLUME

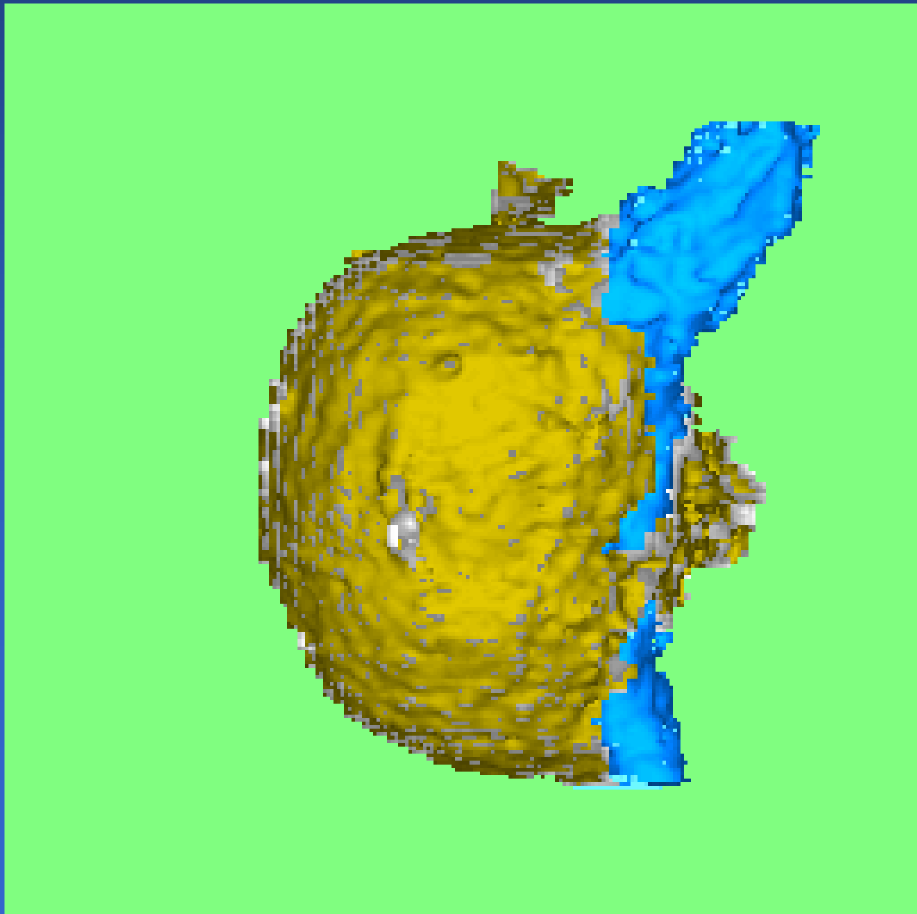
Watersheds



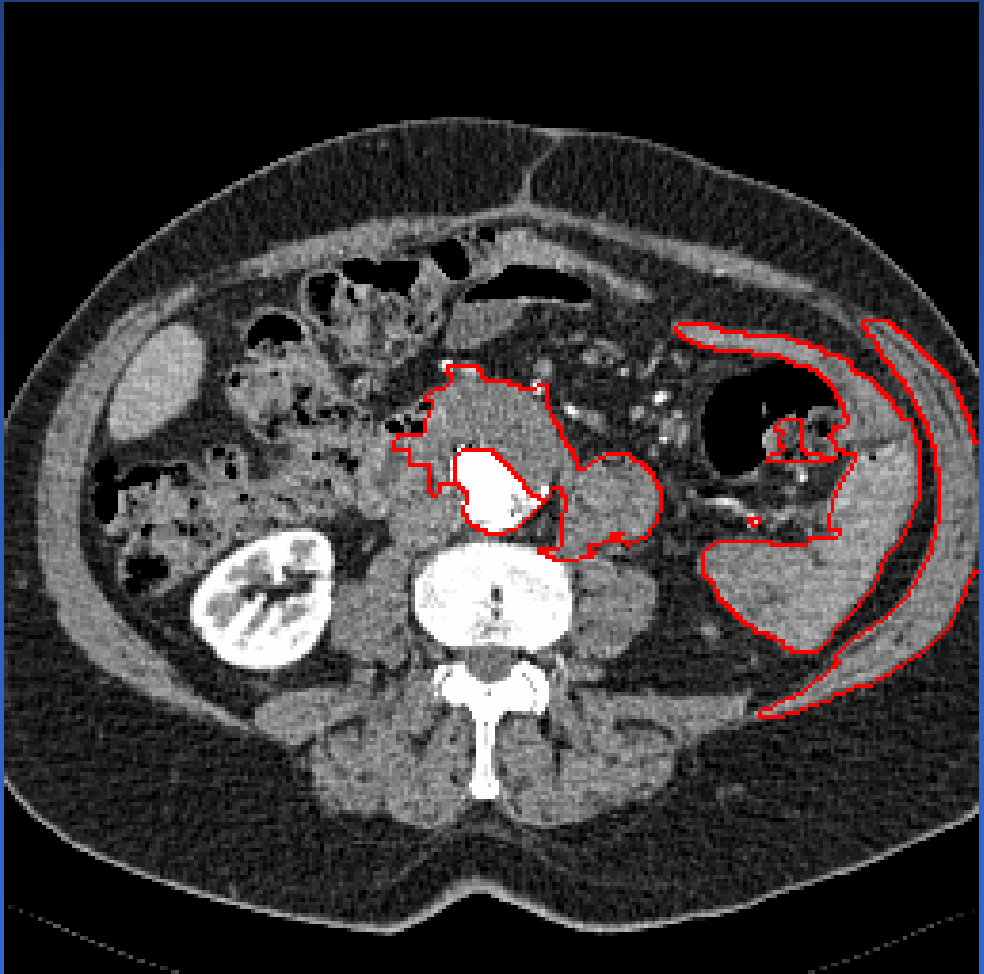


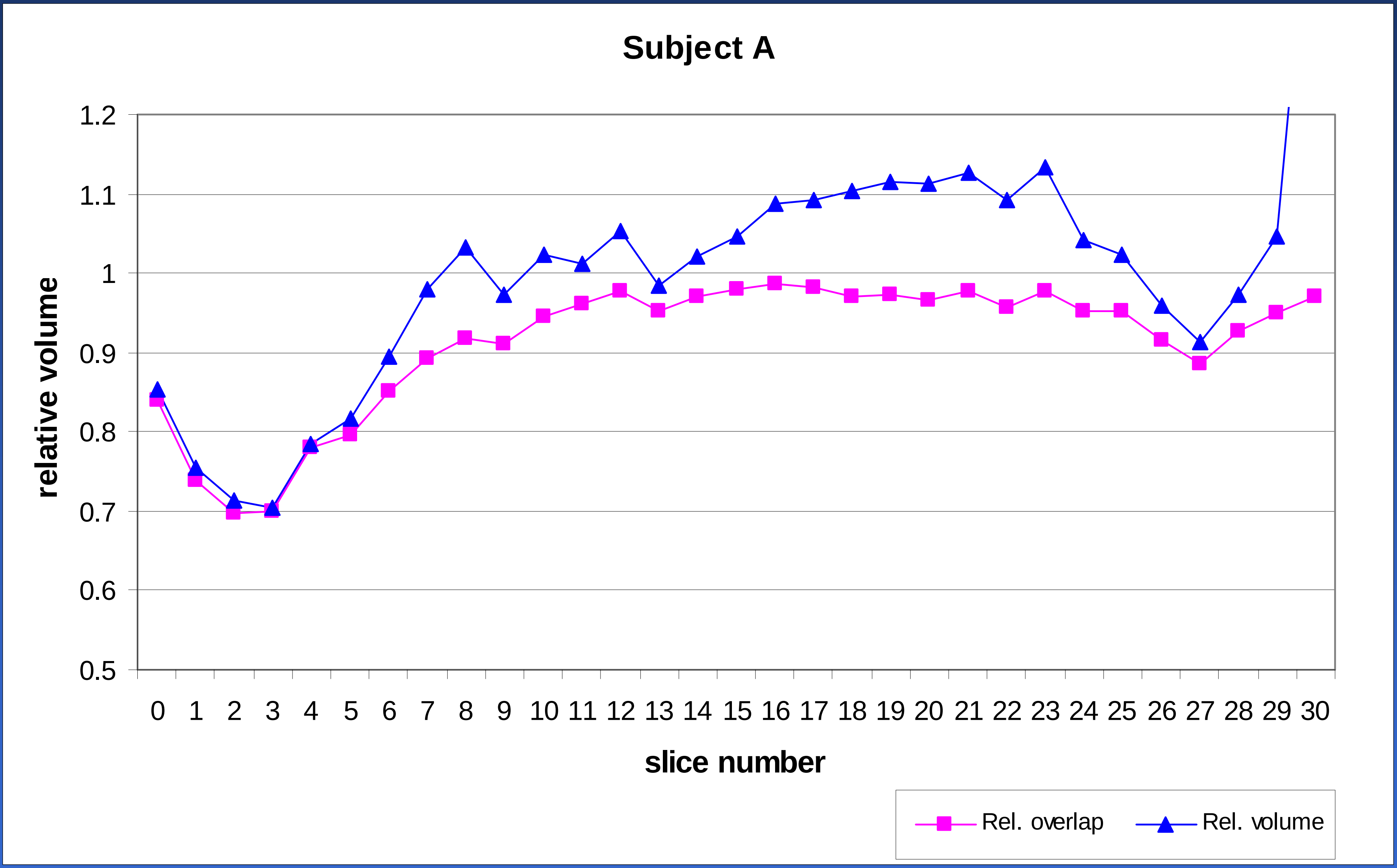
3D task



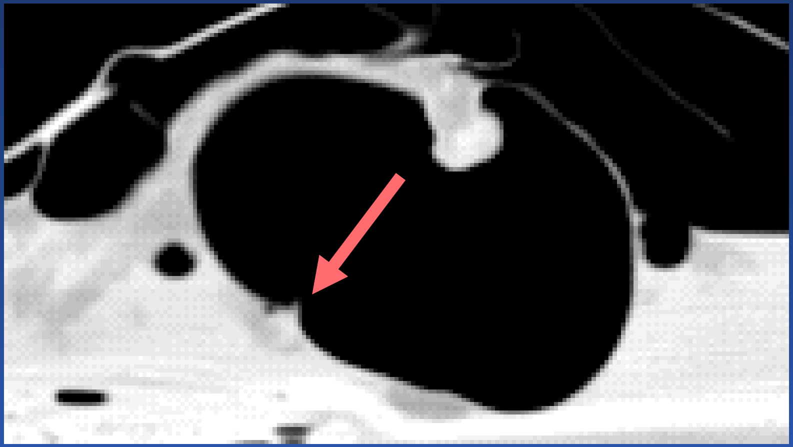


Leakage

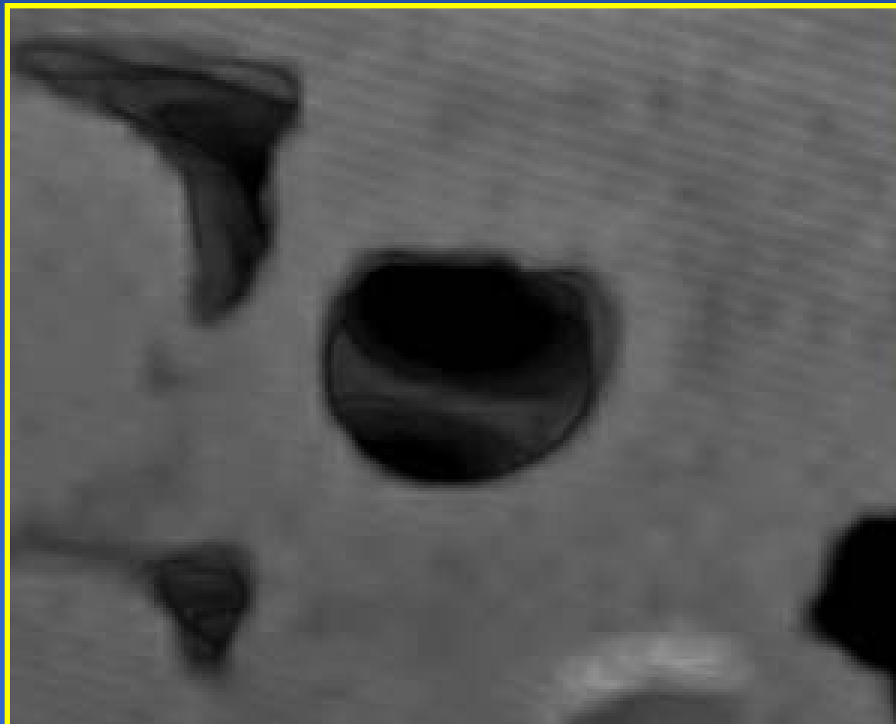



Subject A
relative volume
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
slice number
Rel. overlap
Rel. volume

Colon segmentation

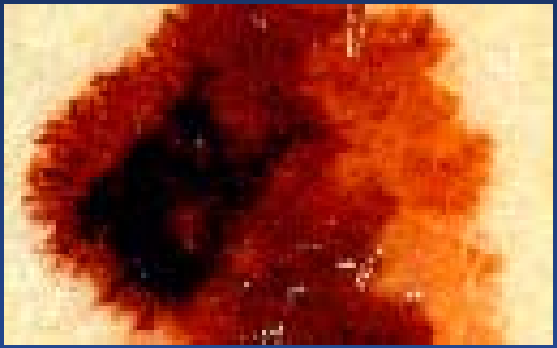


Ack Sorantin



Key question: how much
does the tumour invade
The colonic wall.

Characterisation of skin tumours



Sharp edges

Network of pigment

Radial stripes

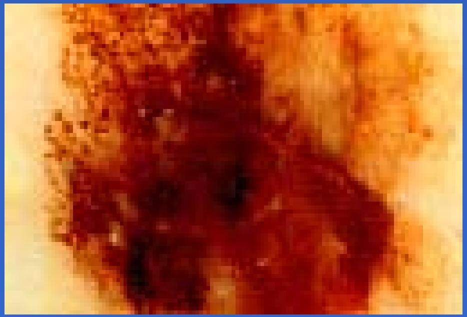
Grey-blue veil

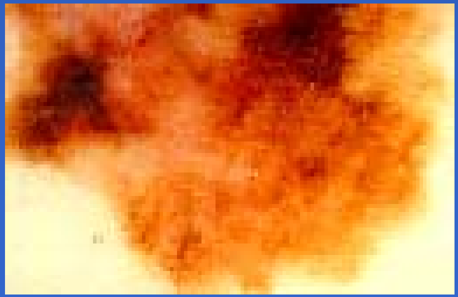
symmetry

pseudopods

inhomogeniety

Erythemous regression





- Differential diagnosis

→ Detection, visual inspection by dermatologist

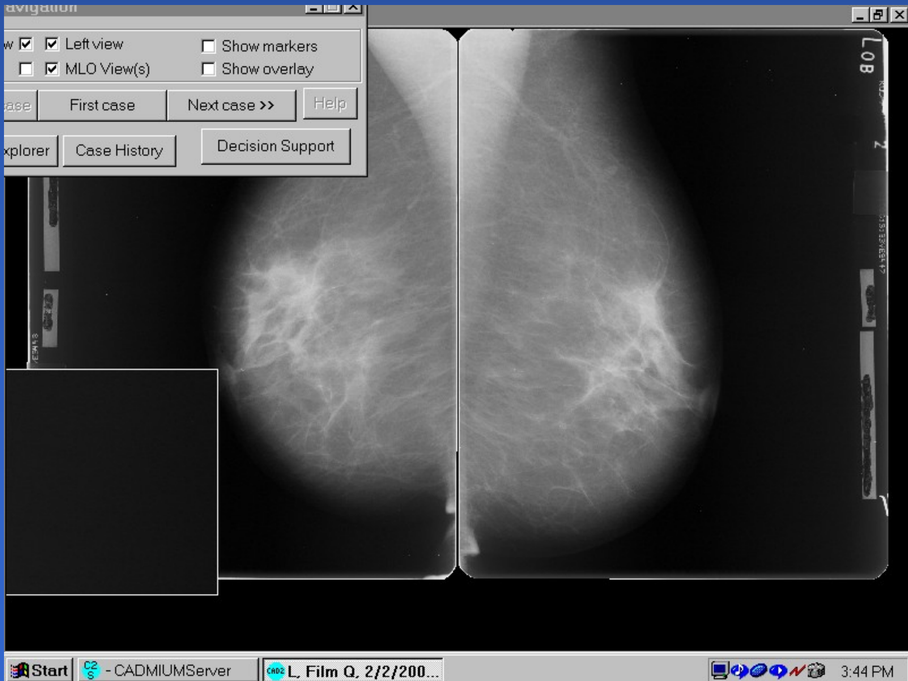
→ Dermatoscope

→ ANN

Breast

- Micro-calcification detection
- Lesion detection
- Asymmetry detection

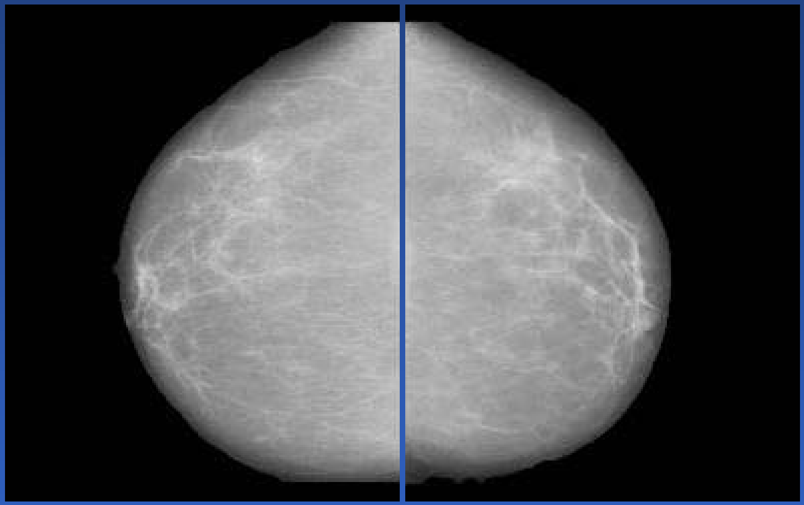
- Problem is false positives



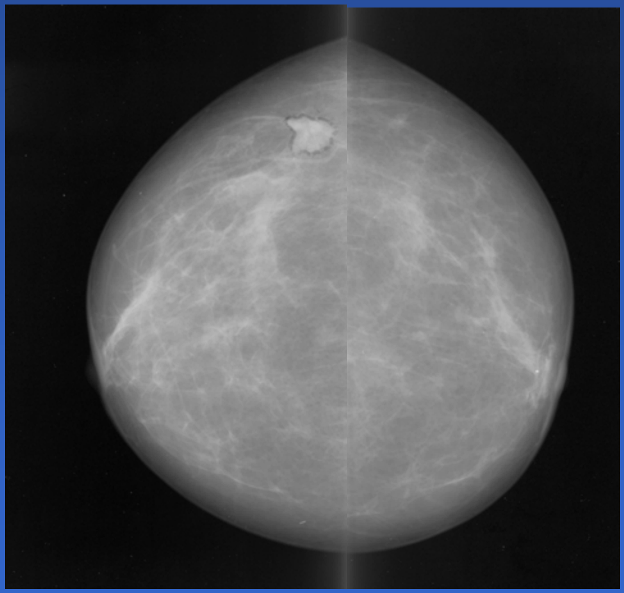
What do we mean by asymmetry?

To identify abnormal asymmetry, first model normal asymmetry

Need very large samples: eDiamond



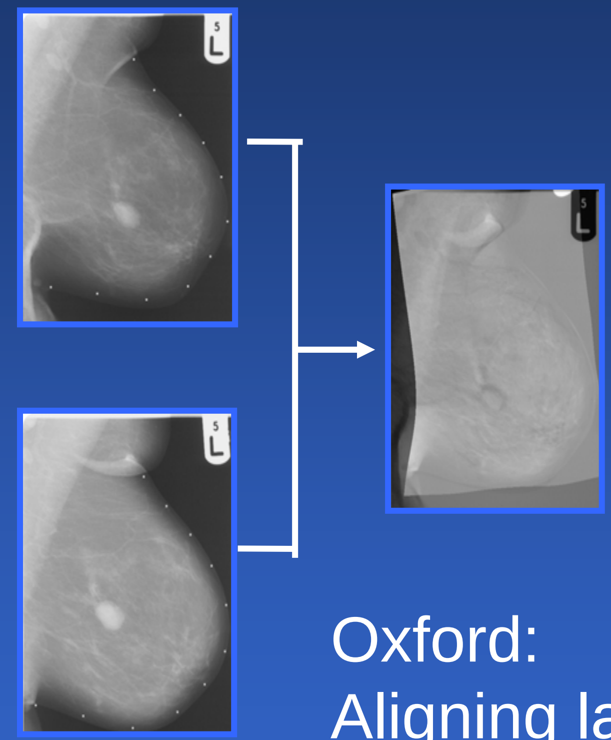
normal



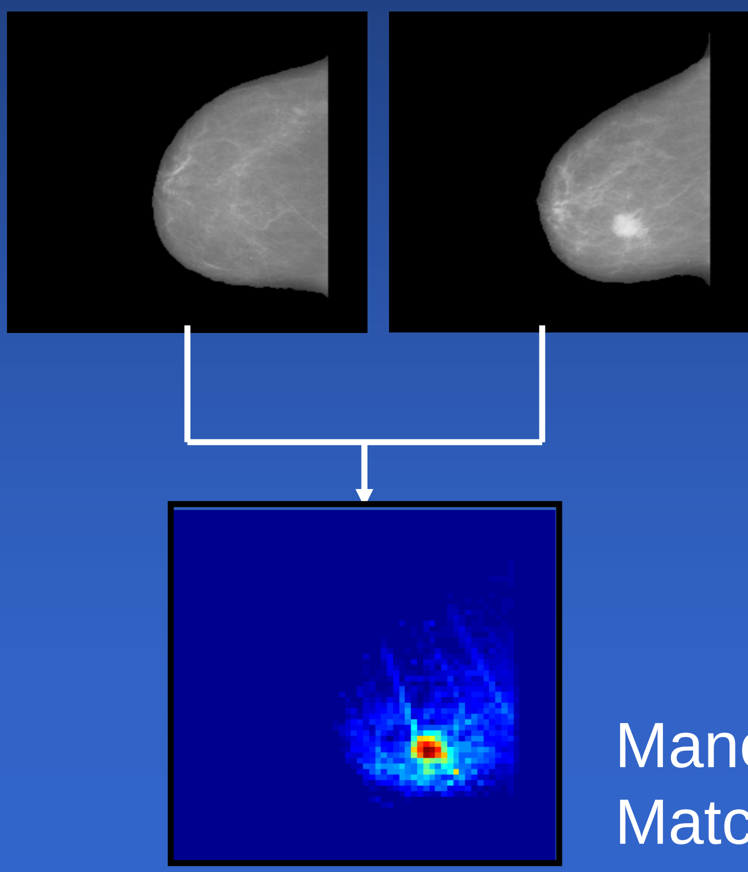
abnormal

UCL: analyse radiologists' assessments of asymmetry

How can we compare left and right breasts?

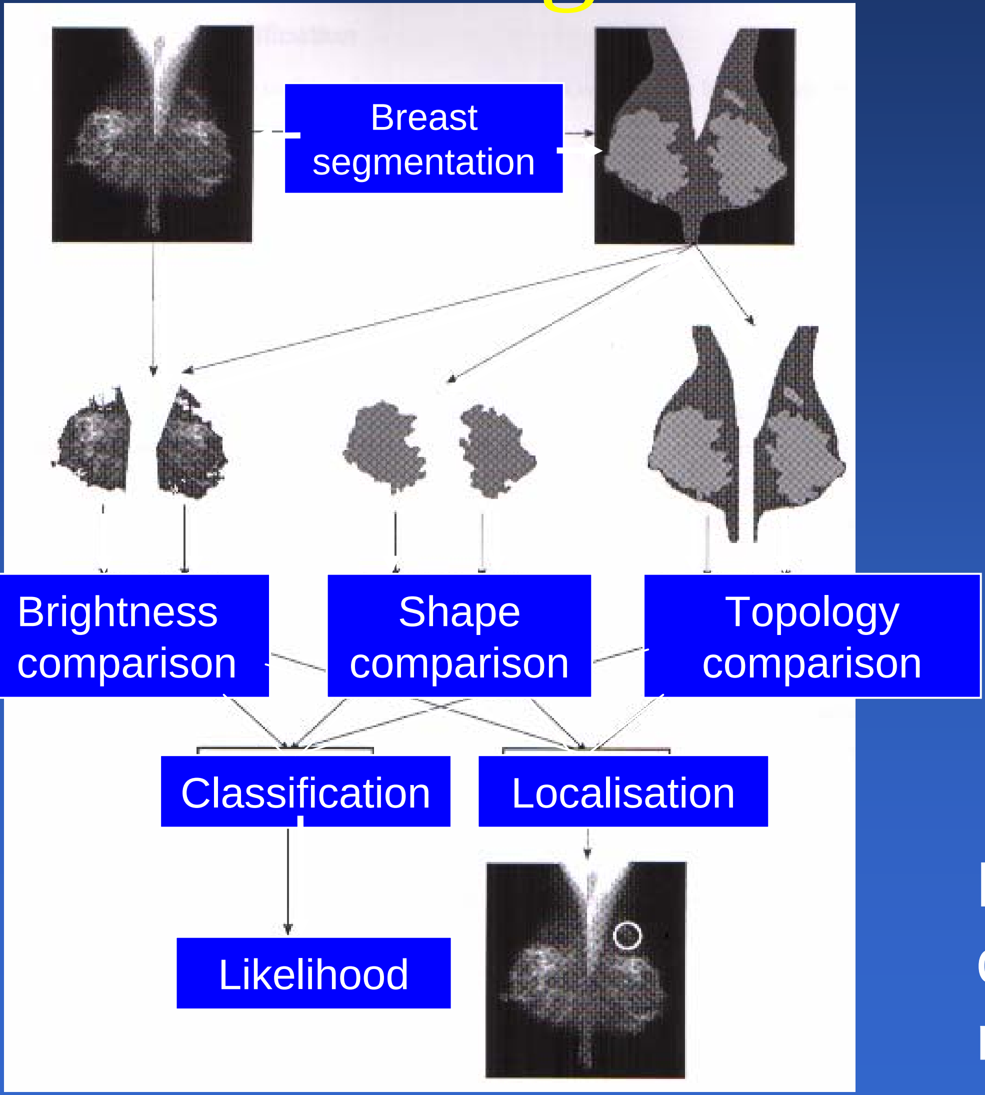


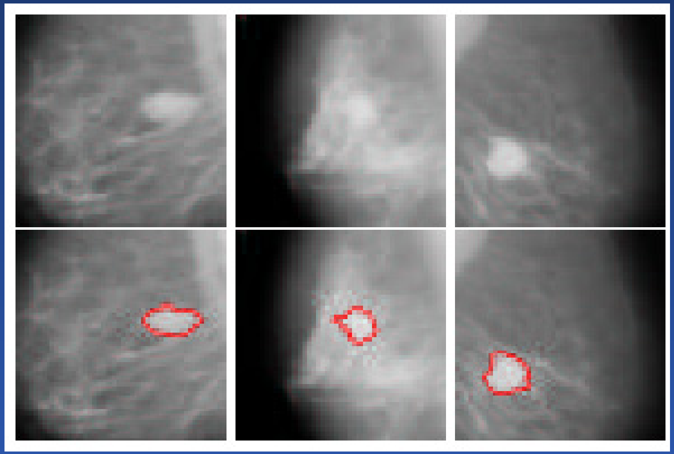
Oxford:
Aligning landmarks at multiple scales



Manchester:
Match based on minimisation of transportation cost

How can we identify salient regions?

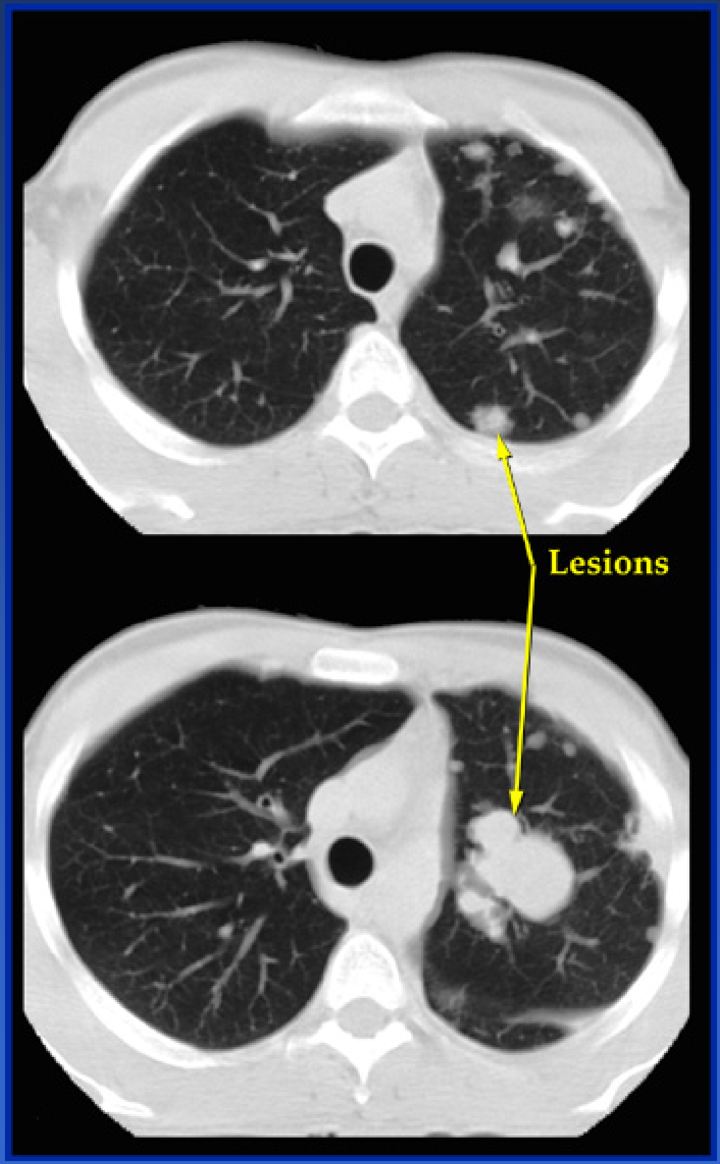




Oxford: Topological reasoning on a contour representation

Manchester: Bayesian classification from multiple comparisons

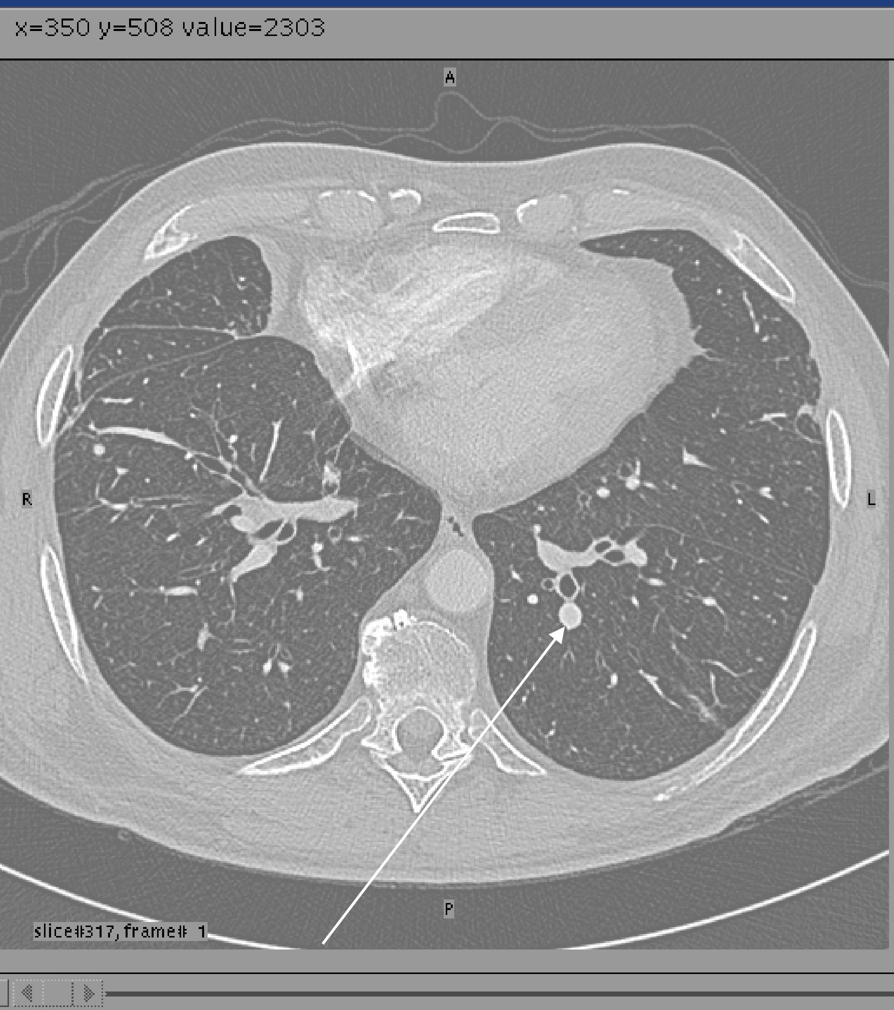
CT Lung lesions

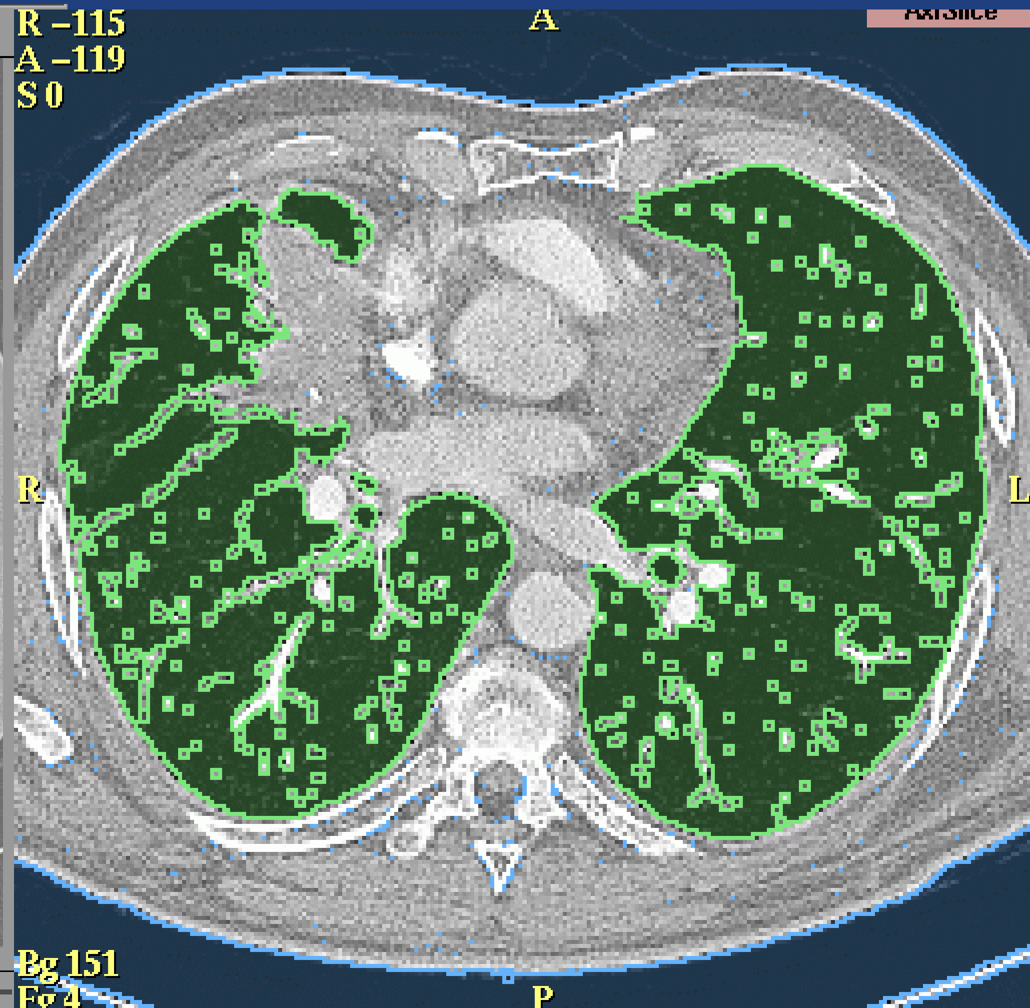


Aims and objectives

- Automating analysis of multiple slices
- Isolating lung field
- Identifying structures
- Eliminating blood vessels and airways
- Classification of nodules on 3-D
- Determination of extent in 3-D
- Problem is false positives

Simulated nodule insertion
Classification using ANNs





Neighbor-Constrained Segmentation

(Yang, Staib, Duncan, IPMI03)

Observation:

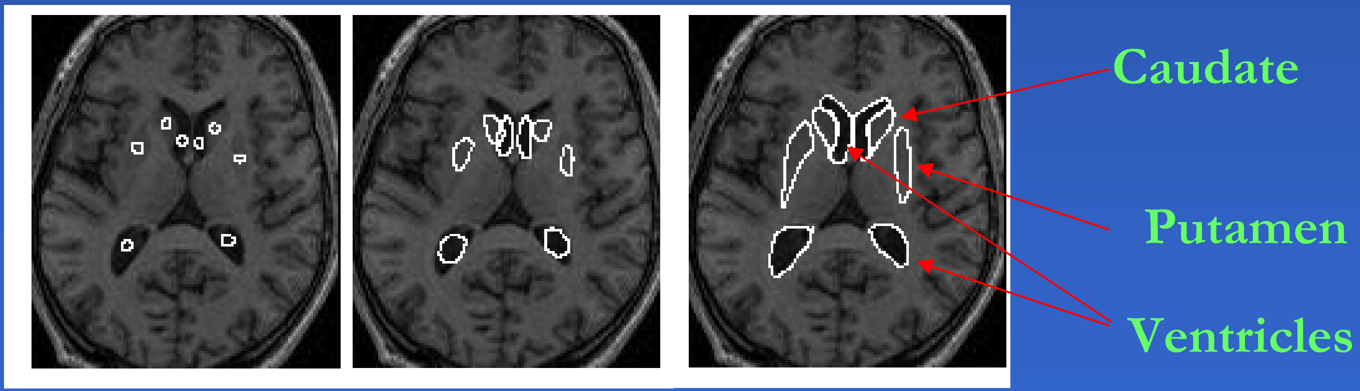
- Neighboring structures often have a consistent image location and shape ;
- Relative positions or shapes among neighbors can be modeled based on statistical information from a training set.

•Maximum A Posterior (MAP) framework:

Assume image I has M objects of interest: $S_1, S_2, \ldots S_M$

$$\hat{S}_i = \arg\max_{S_i} p(S_1, S_2, \ldots, S_M / I)$$

$$= \arg\max_{S_i} \underbrace{p(I / S_1, S_2, \ldots, S_M)}_{\text{image gray level info}} \underbrace{p(S_1, S_2, \ldots, S_M)}_{\text{neighbor (shape + distance) prior info}} \qquad i = 1, 2, \ldots, M$$



Detection of 8 sub-cortical structures using neighbor priors

Segmentation for RT planning

- Lesions can be identified and classified
- Different tissue types can segmented
- How do we determine penumbra?

- Desirability of feedback during treatment
- Interventional and image guided methods

Conclusions

- Many different segmentation methods available
- More interesting rely on model fitting and hence iterative minimisation of some cost function
- Evaluation is hindered by absence of gold standard