Computer Vision for Medical Imaging

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CSAIL/EECS

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Medical Vision Group
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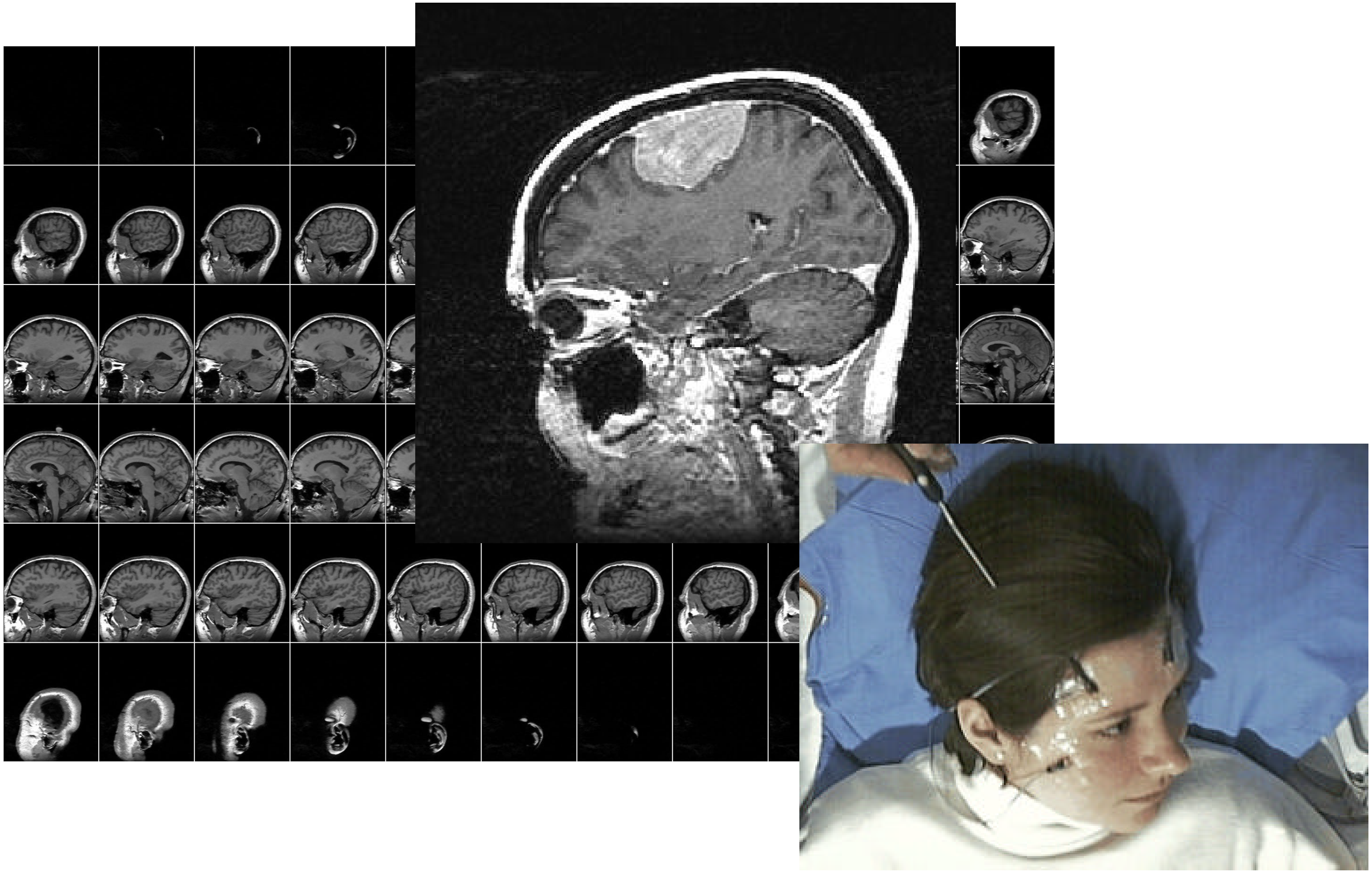
Sandy Wells, John Fisher
And many, many students
CSAIL, MIT

Medical Imaging



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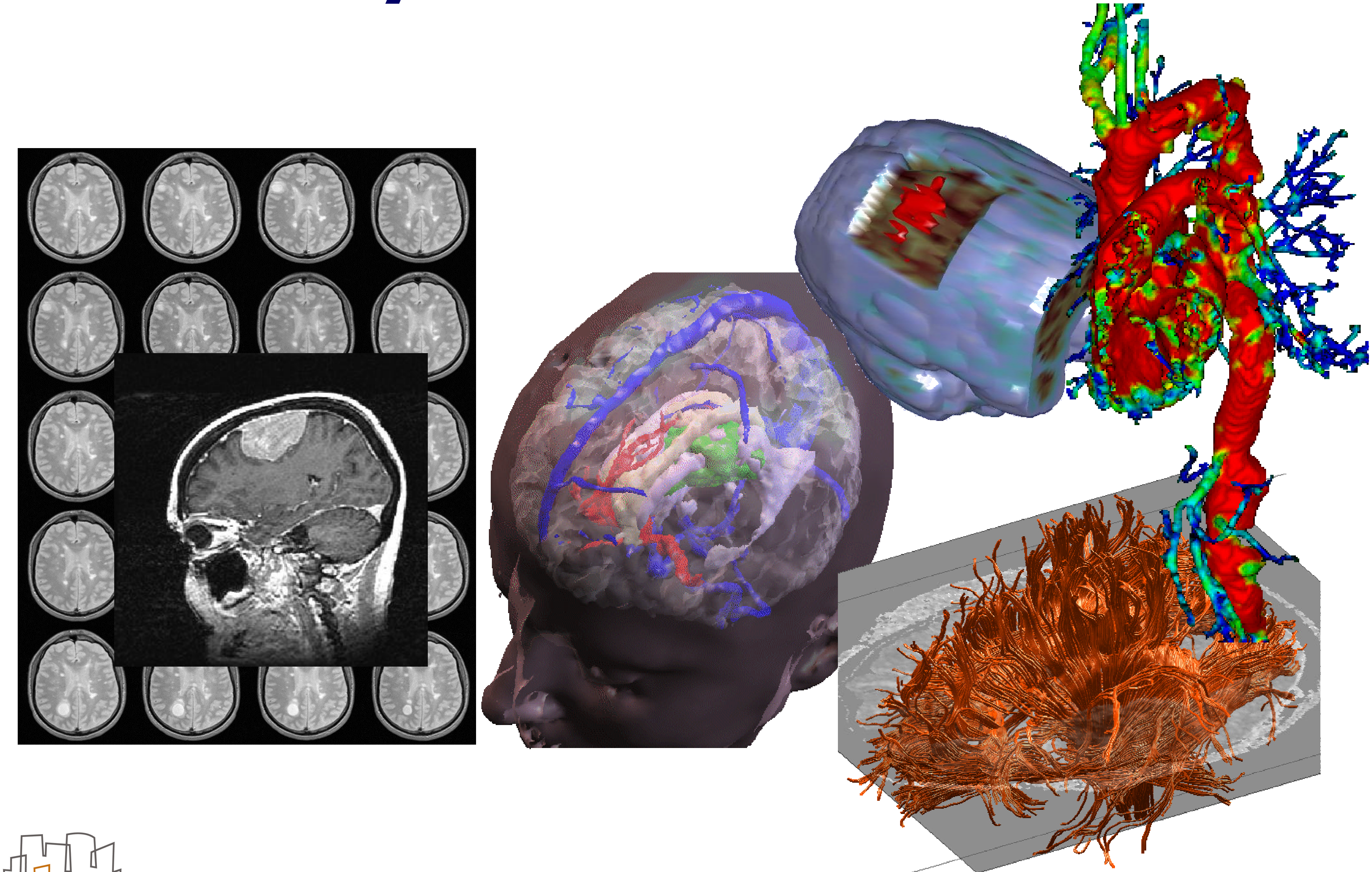
Analysis + Visualization



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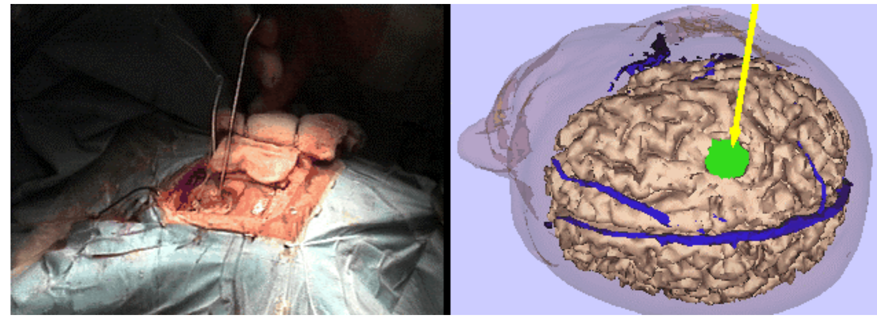
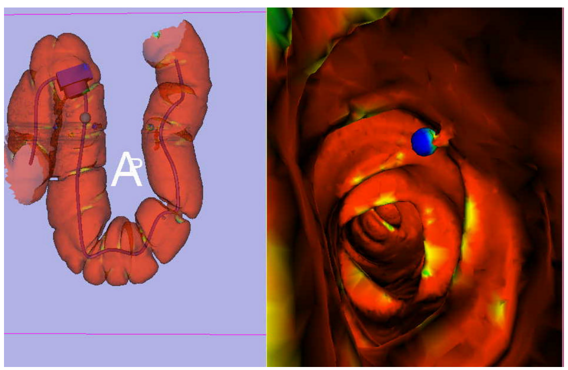
Medical Vision

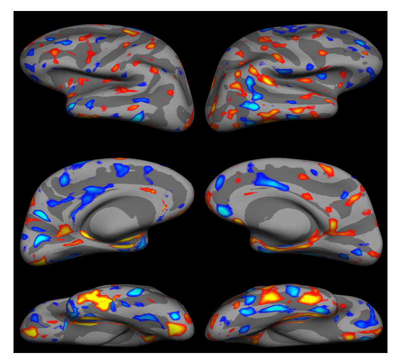
Surgical planning and navigation



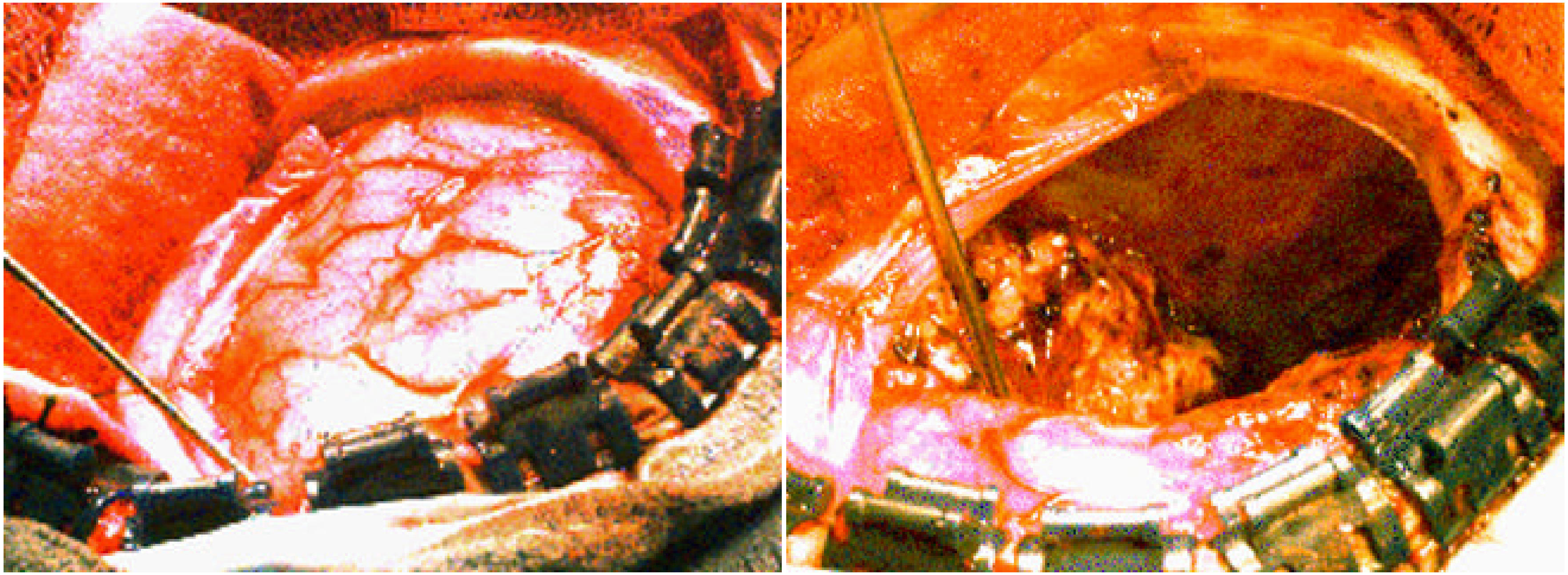


Simulation

Population modeling

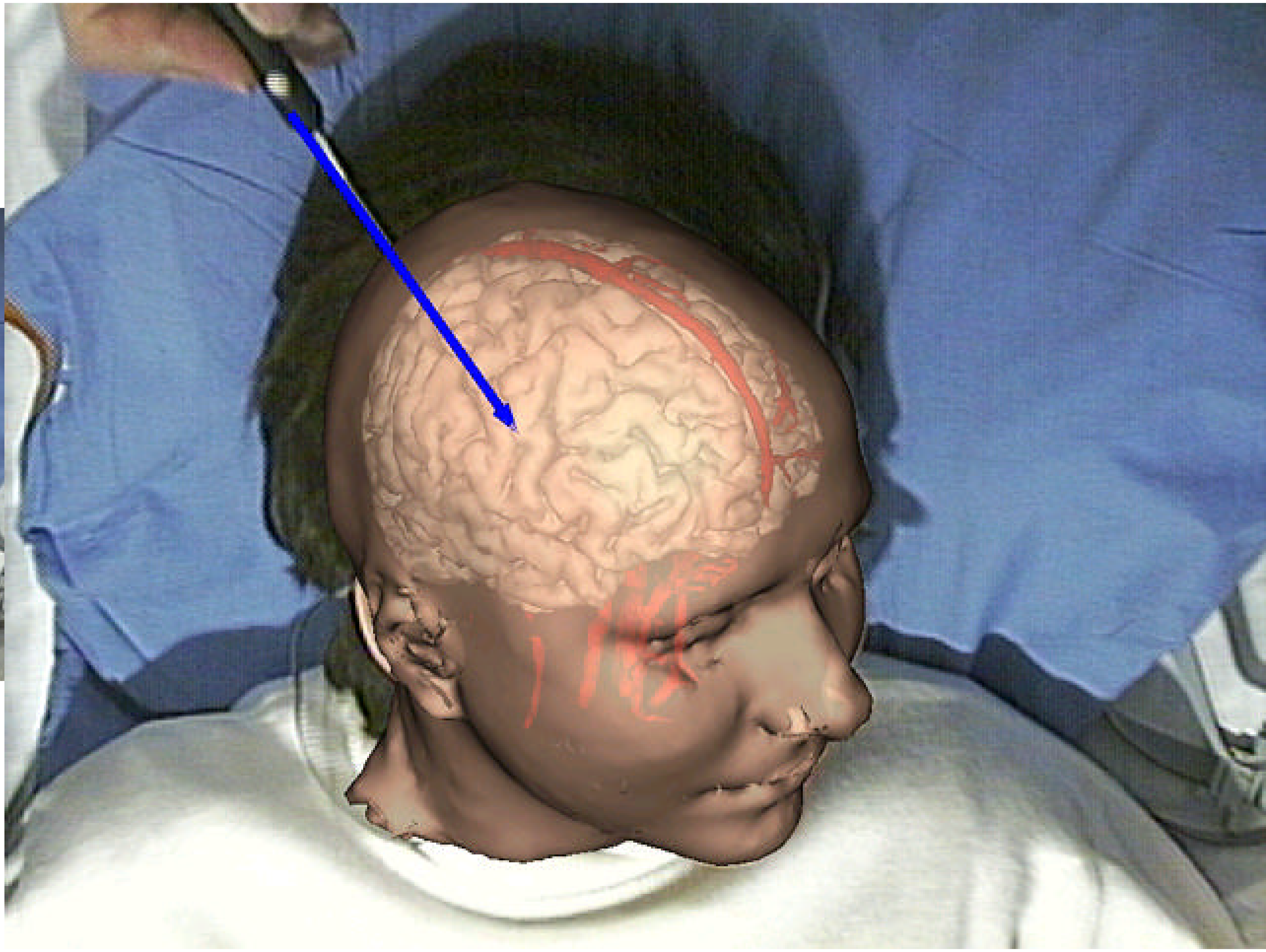


Conventional Surgery: See the surface



Provided by Nakajima, Atsumi et al.

Image Guided Surgery: See under the surface



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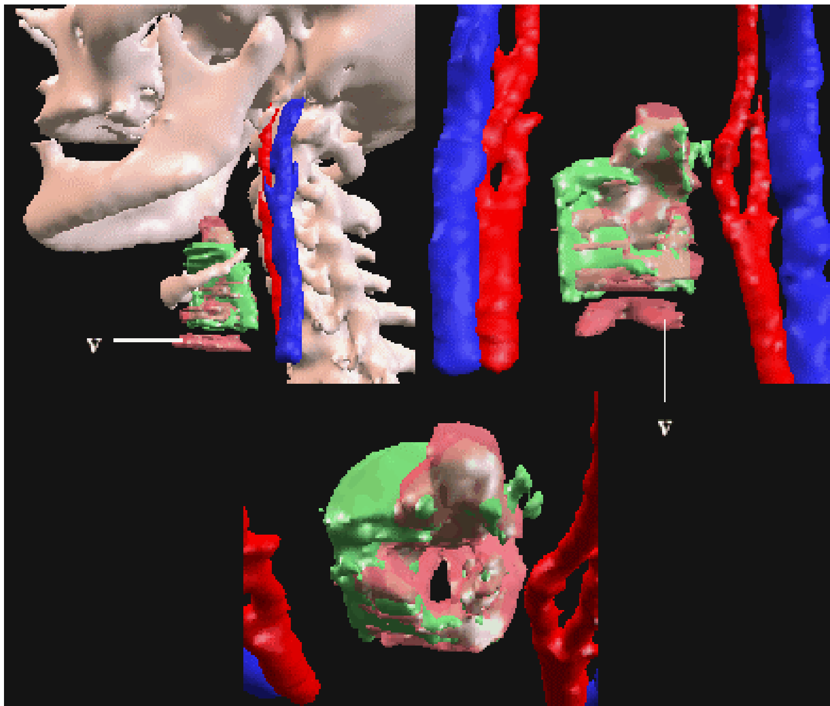
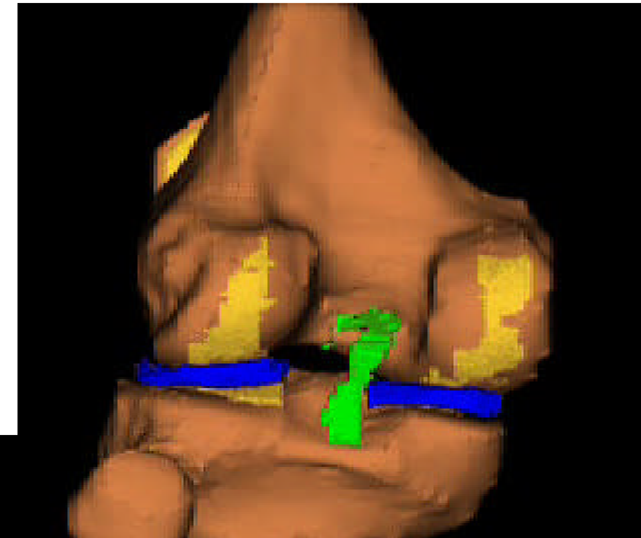
Intelligently aiding the surgeon

- Convert medical images into models of patient’s:
  - Structural anatomy
  - Functional anatomy
  - Vascular structure

Example patient specific models





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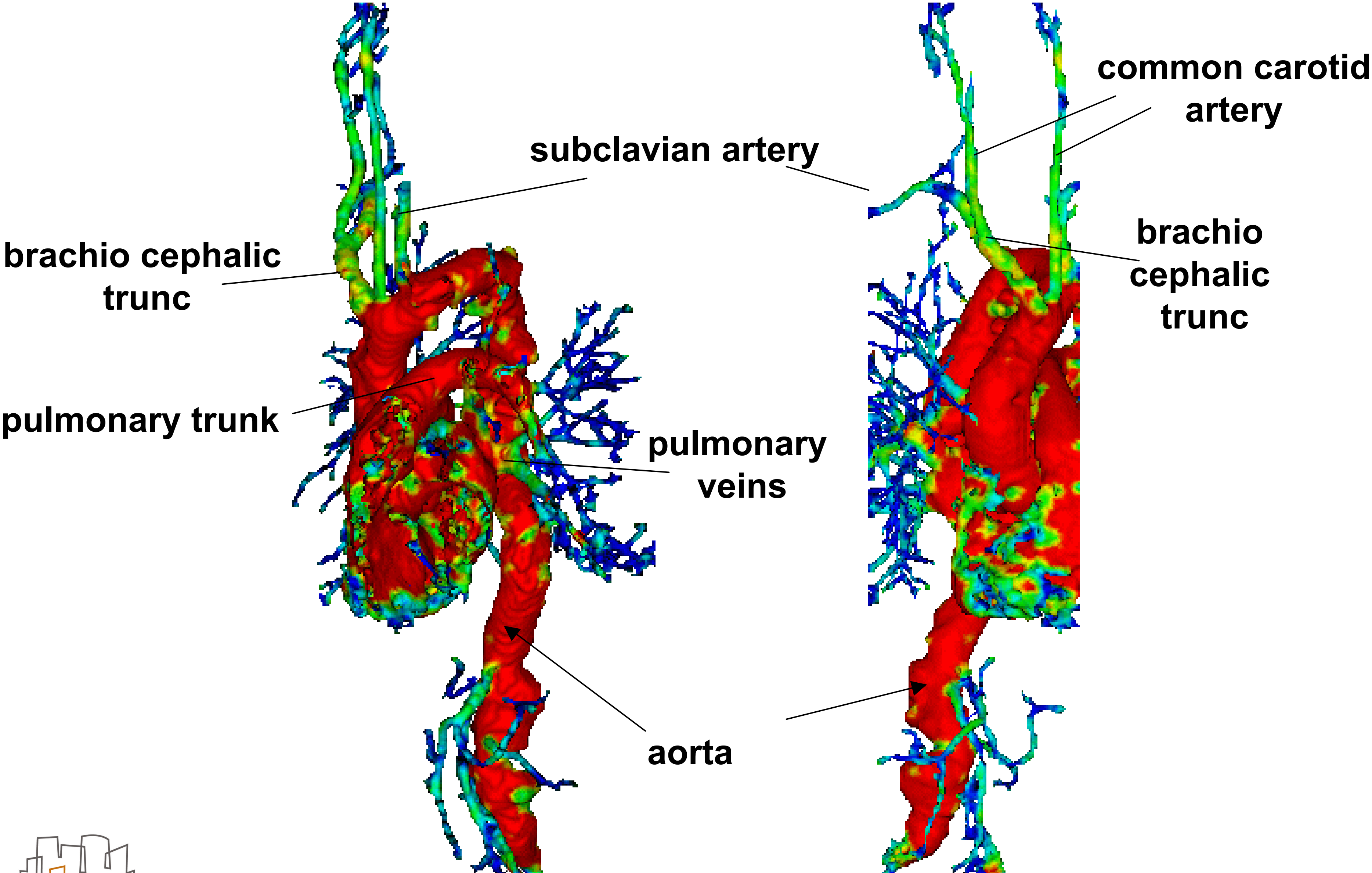
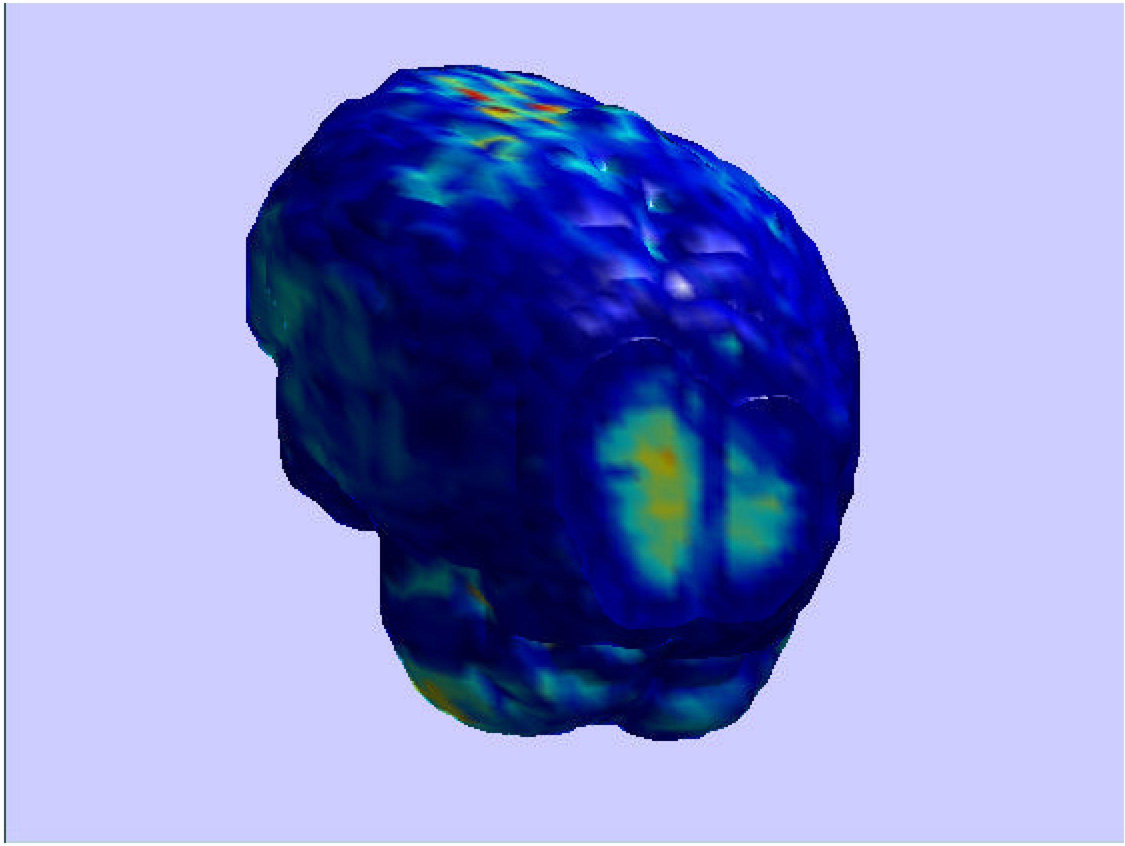
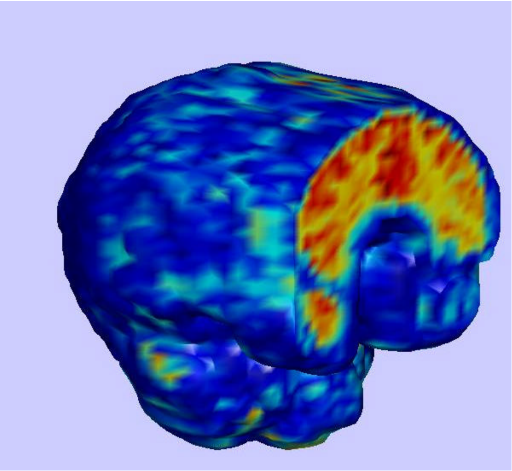
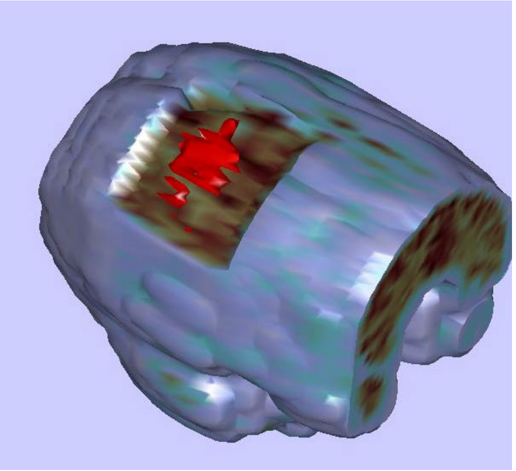
Central Vessels



Functional information



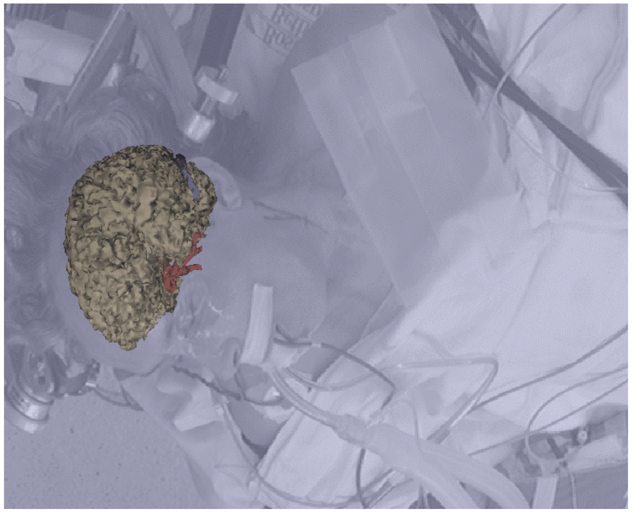


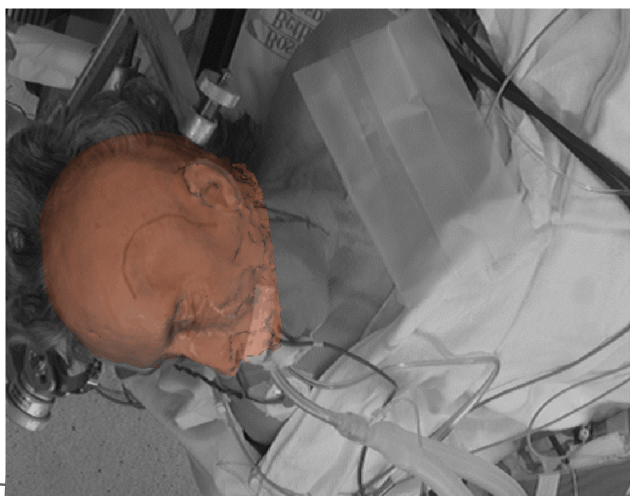


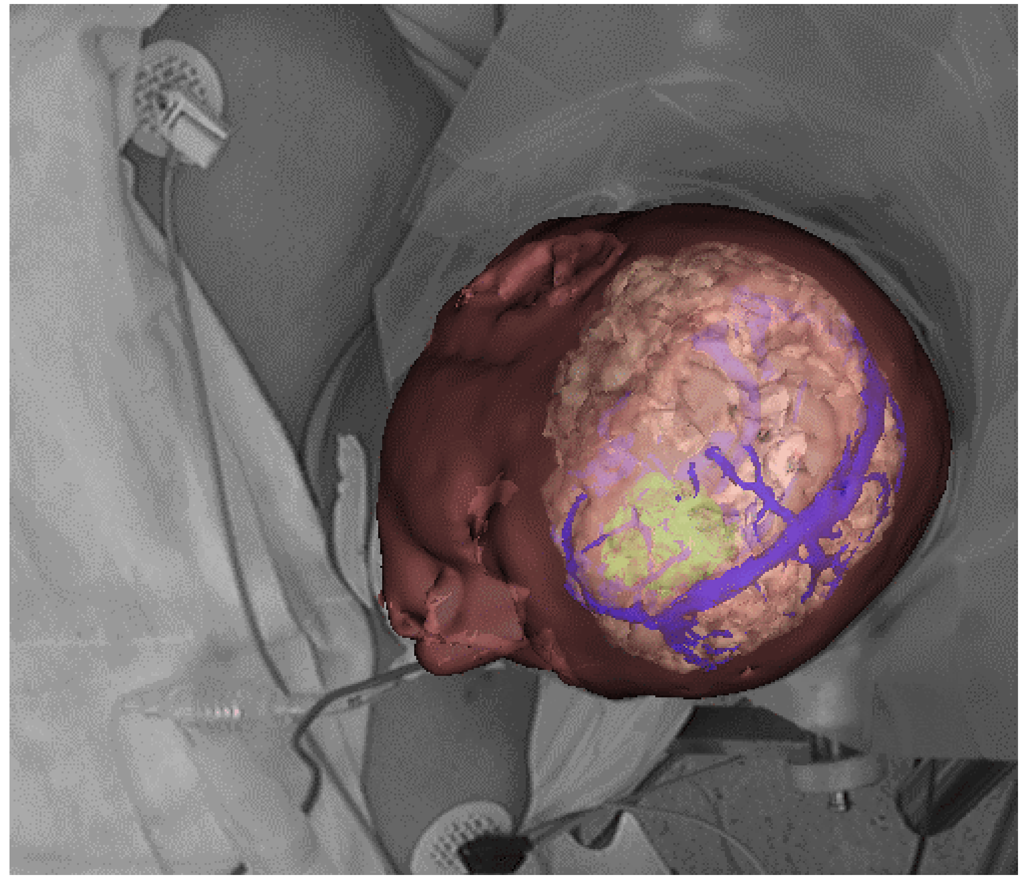
Visualizing the surgical site

- Augmented reality visualizations
  - combine with real imagery
- Surgical guidance
  - planning and navigation
- Simulation of surgical navigation
  - Use image information for diagnostics

Augmented Reality







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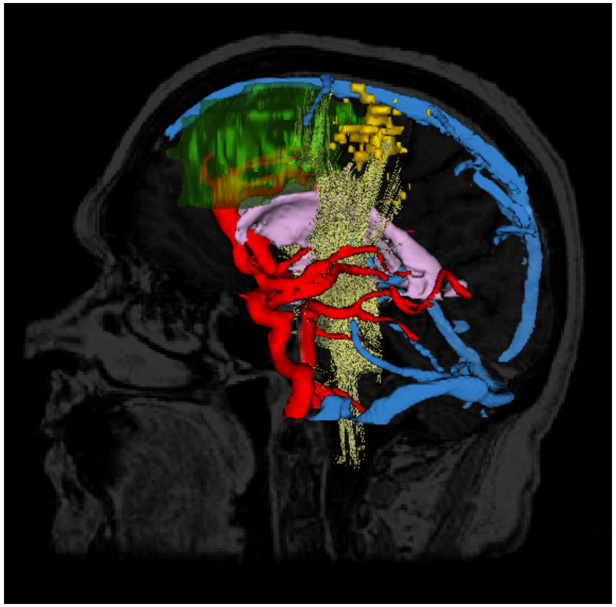
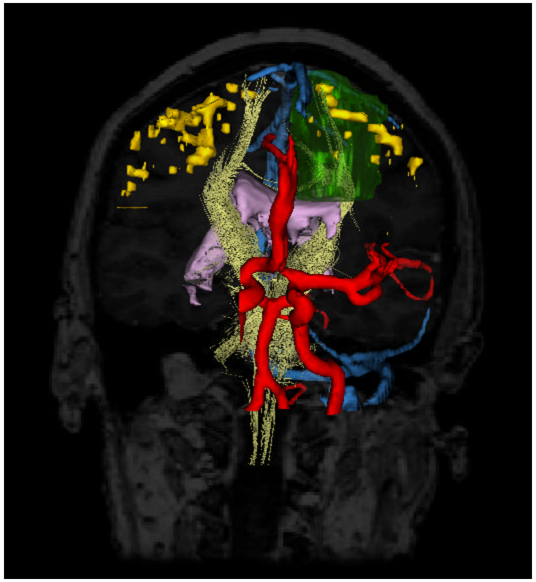
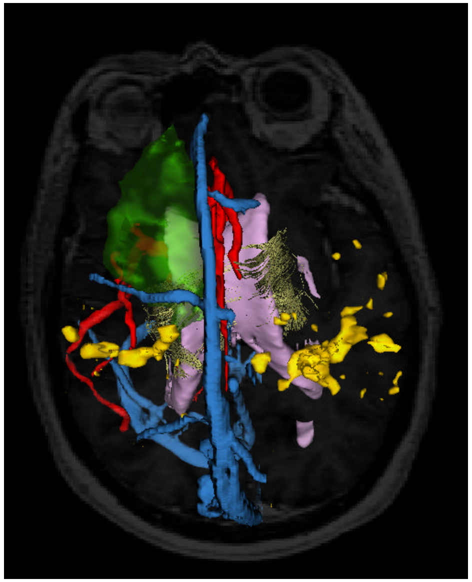
Multi-modal Modeling







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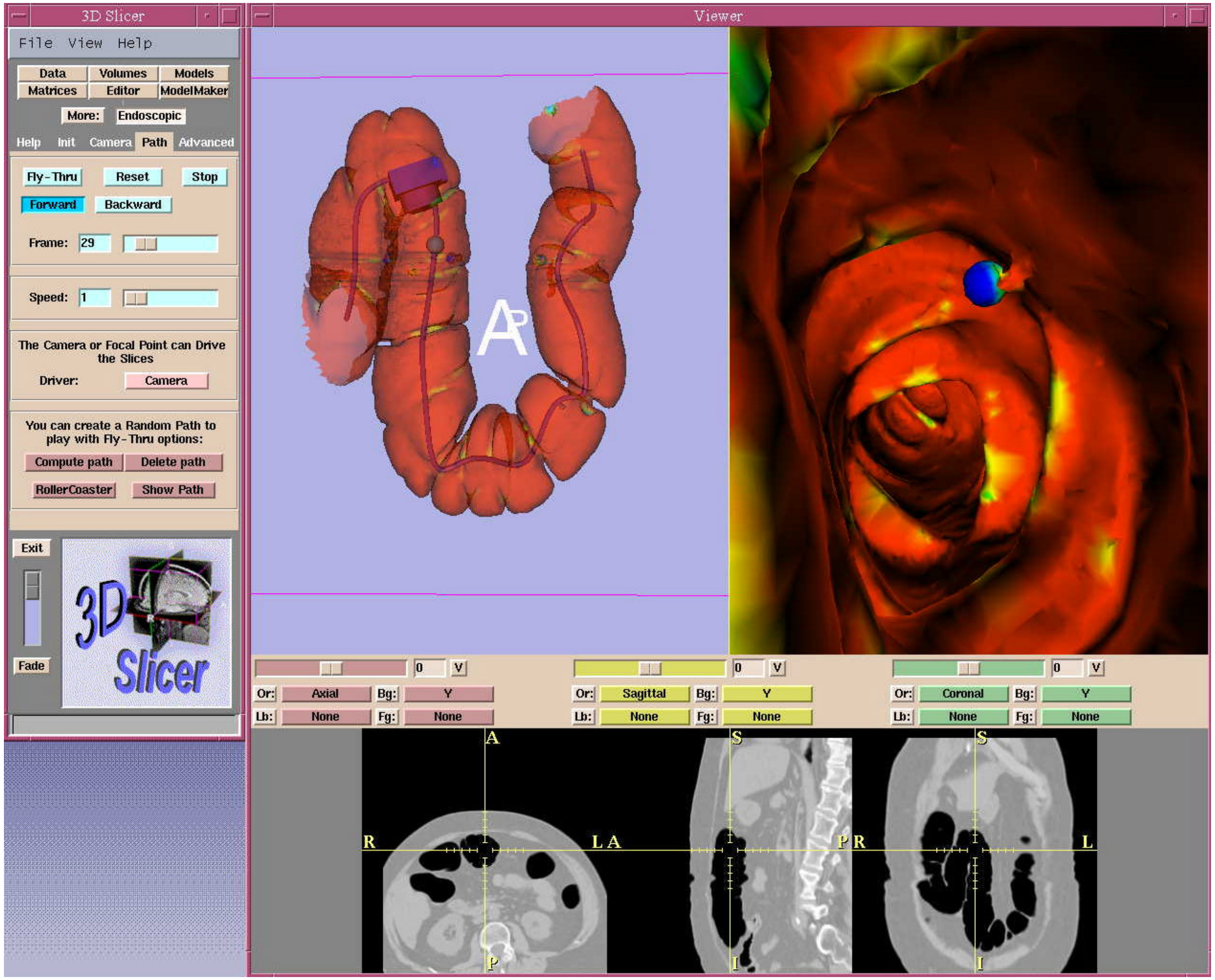
Surgical guidance

Joint with Brigham and Women's Hospital

Simulation: Virtual Endoscopy



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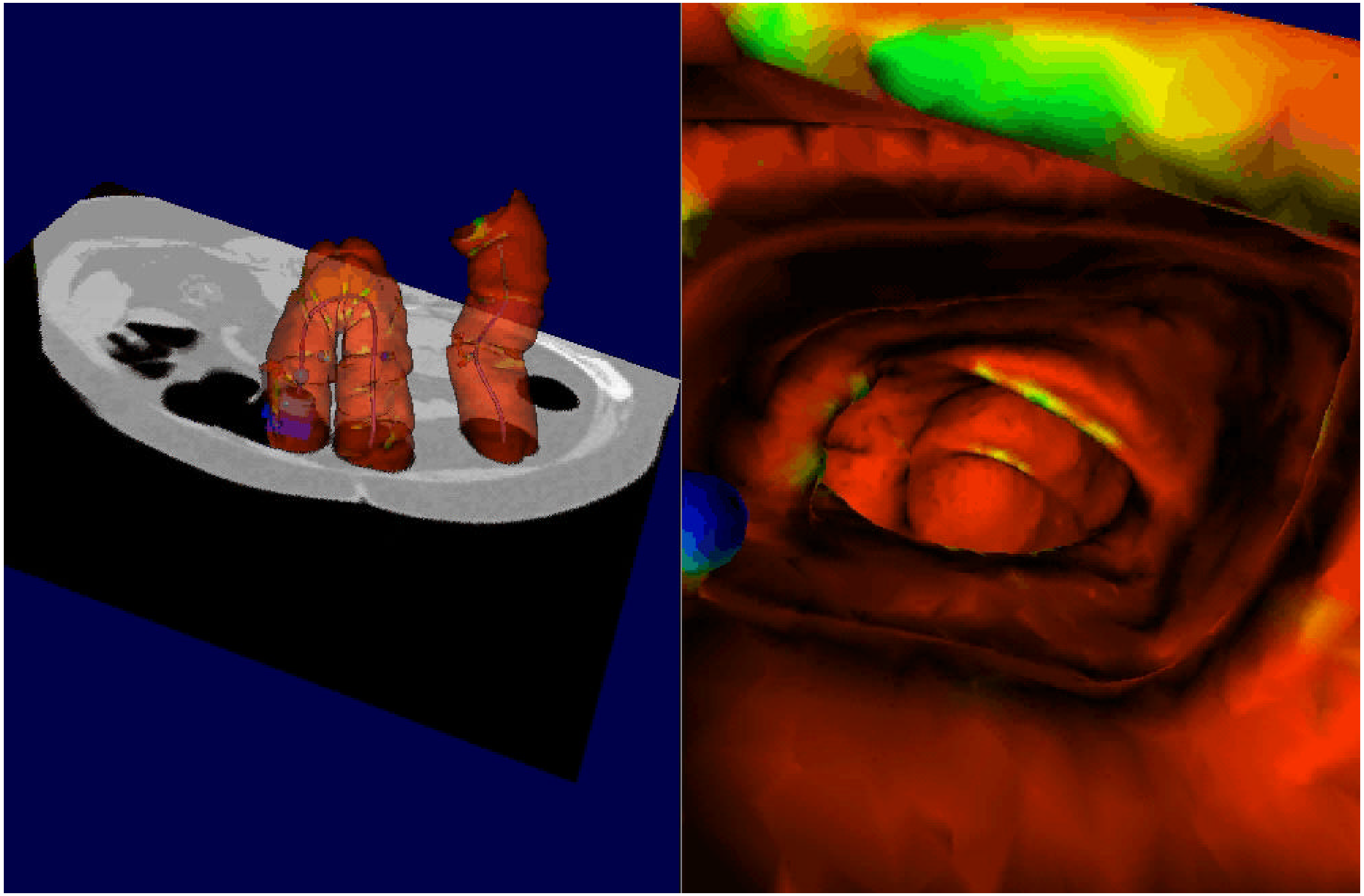
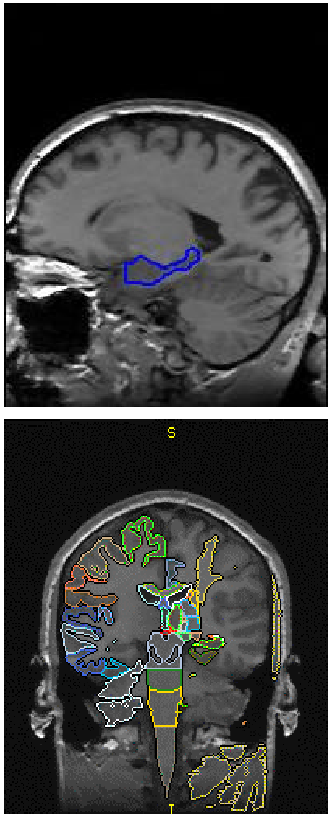
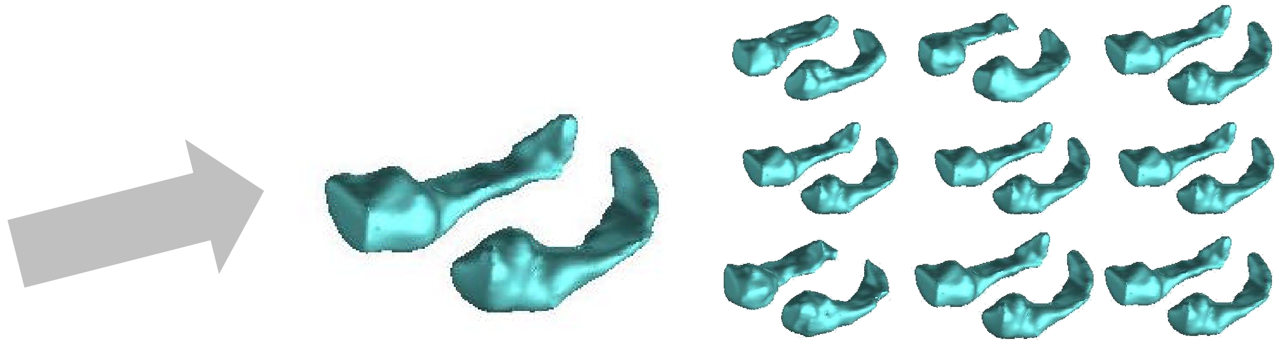
Virtual Endoscopy

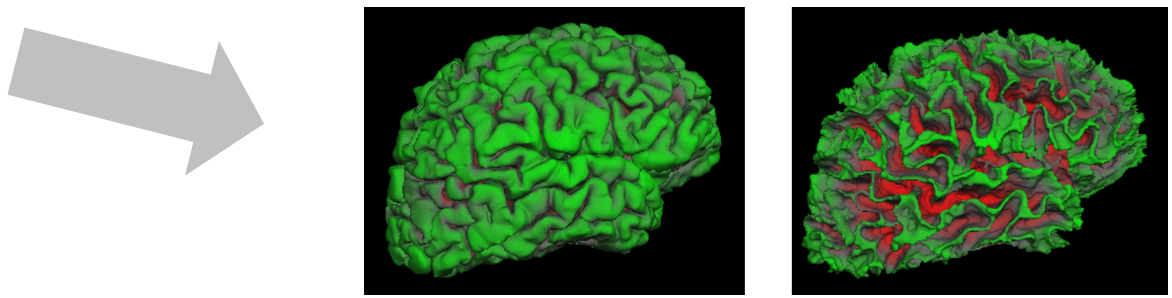


Joint with Brigham and Women's Hospital

Population Studies



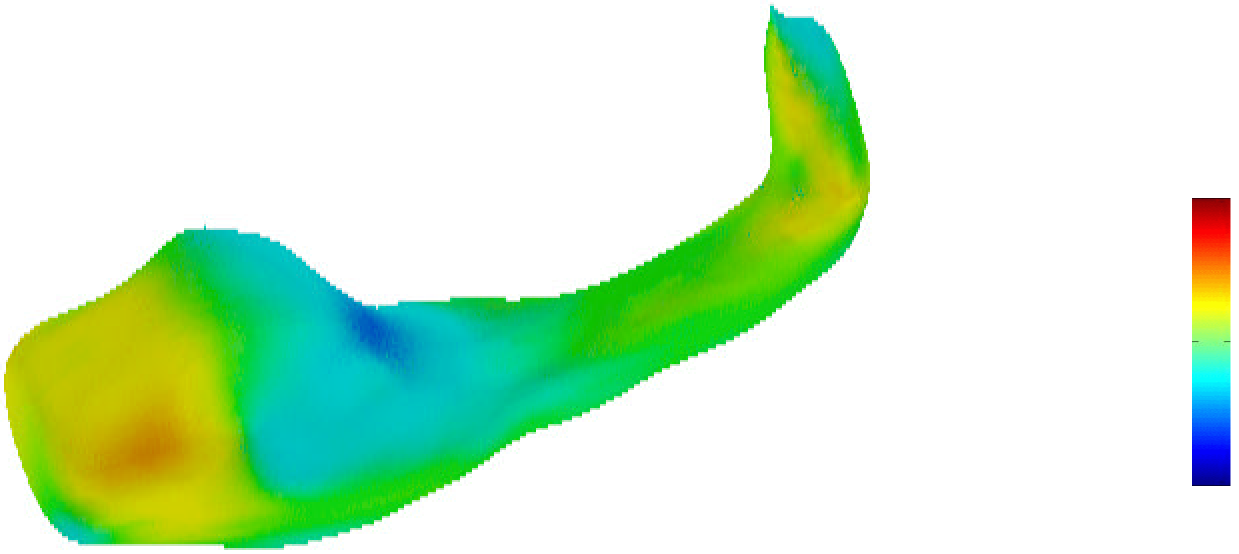




How does the brain develop?

How does a disease affect anatomical shape?

Hippocampus in Schizophrenia



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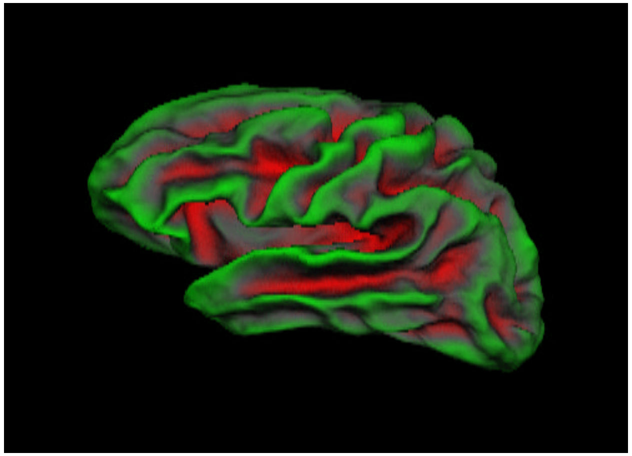
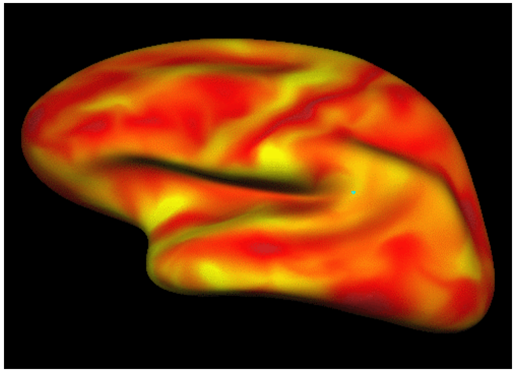
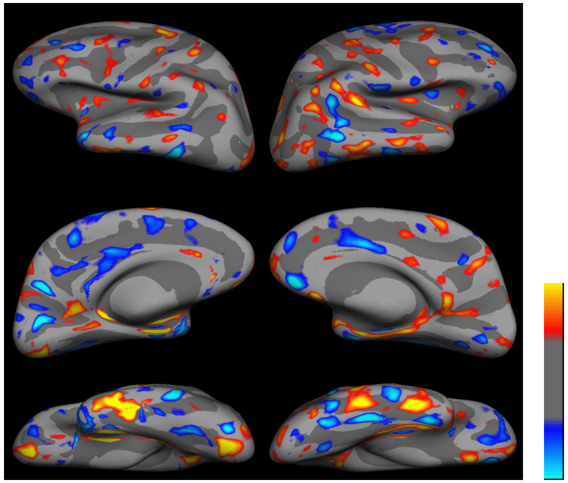
Cortical Thickness

Cortical thickness in Alzheimer's disease



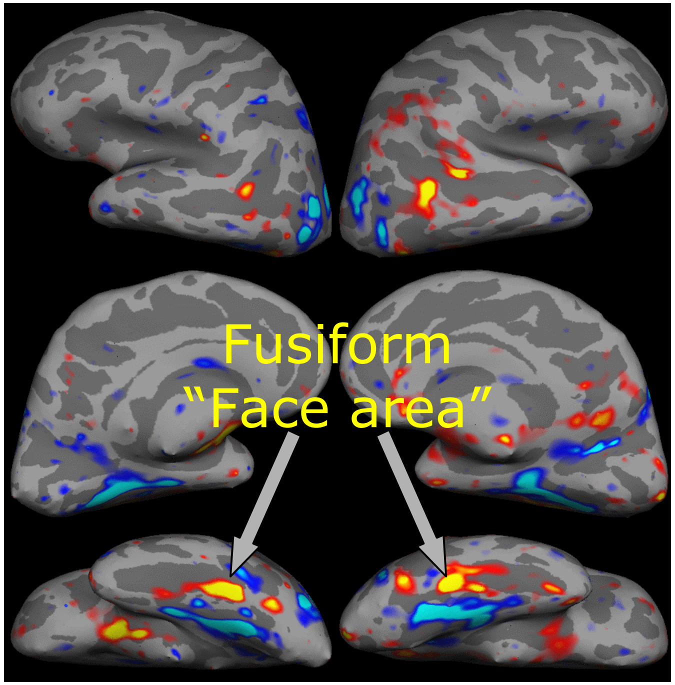




Joint with Mass General Hospital

fMRI Analysis

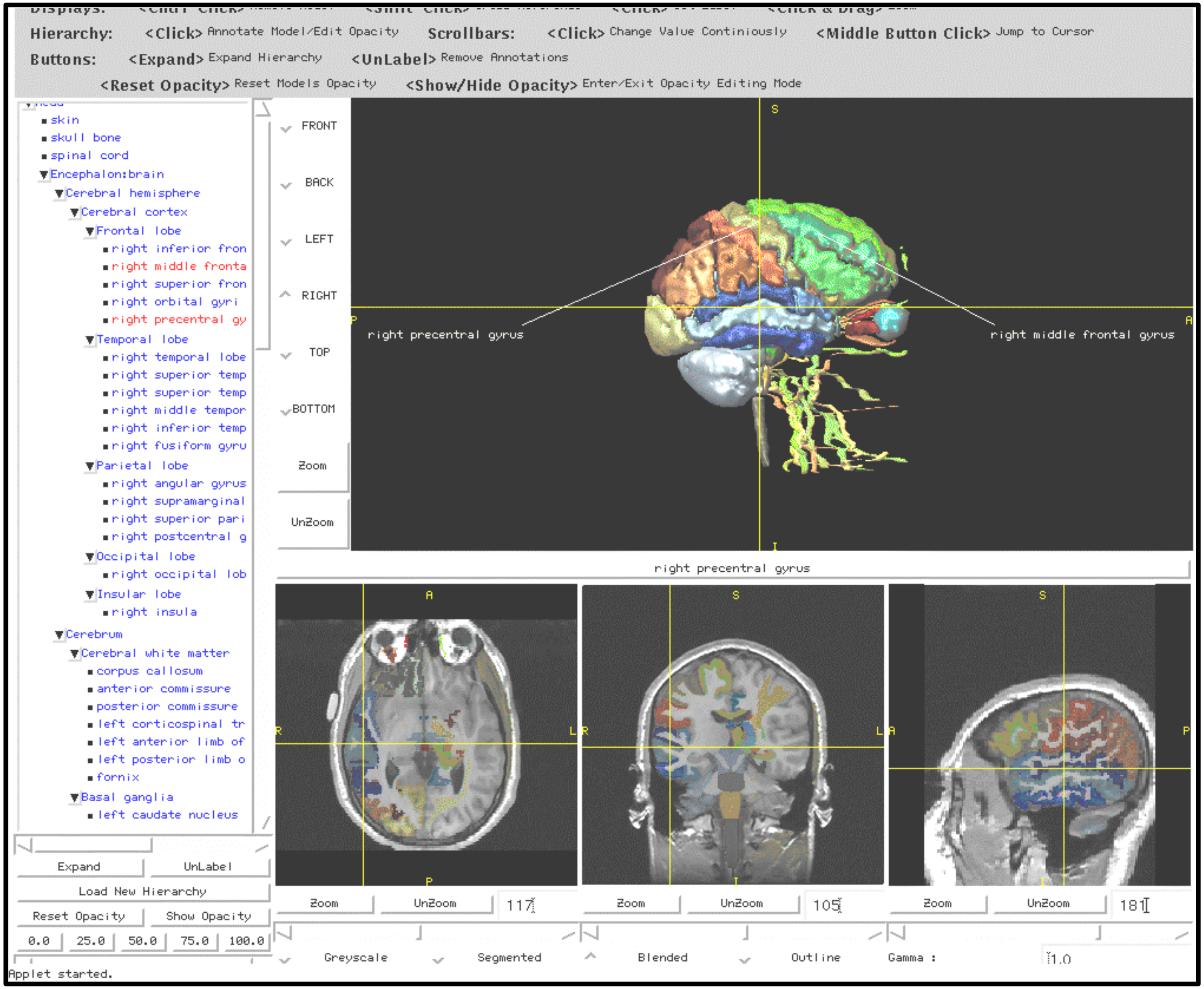
- Brain activation
- Faces vs. other objects



94%, $p < .03$

Joint with Mass General Hospital and BCS, MIT

Back to Visualization



Methods

- Segmentation
- Shape Analysis
- DTI Analysis

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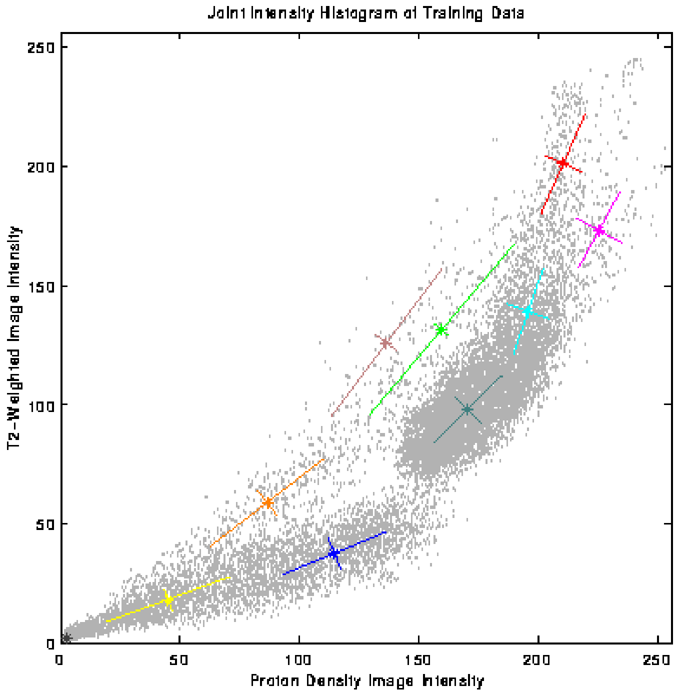
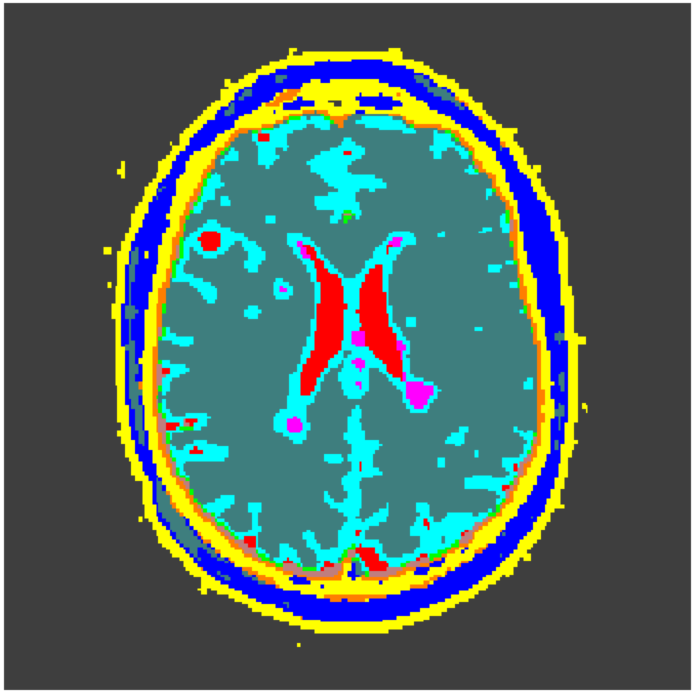
Image interpretation: voxel classification

- Measure distribution of intensities for each class
- Classify each voxel based on its intensity





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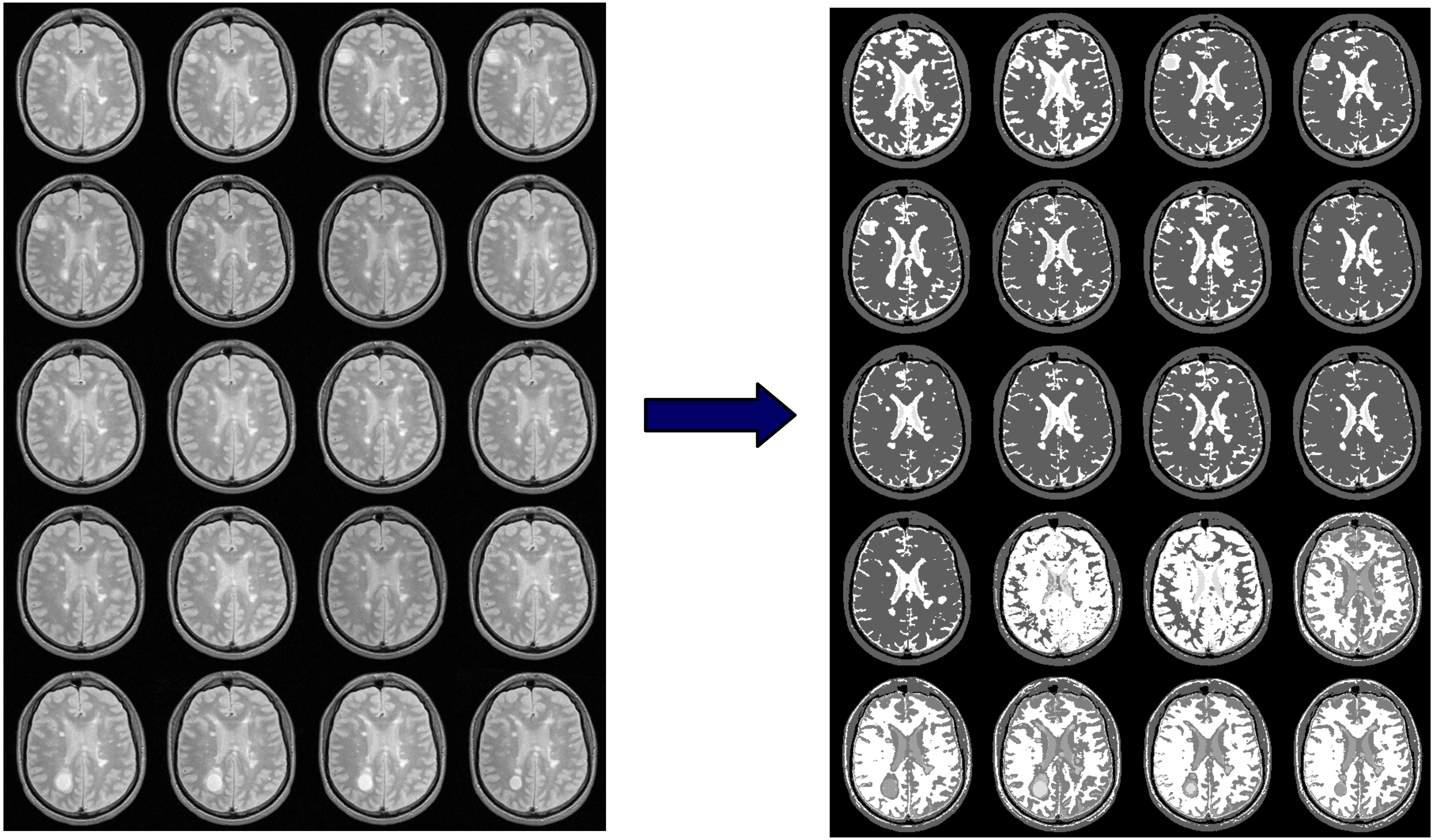
Problem: Bias (gain) field



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Solution: EM segmentation [Wells 1994]

- If one knew the gain field
  - correct image and use standard statistical methods
- If one knew the tissue types
  - could predict the image and find the gain field correction

- Solution:
  - Expectation Maximization (EM) method
  - iteratively solve for gain field and tissue class using probabilistic models

EM-Segmentation

- Observed Variables Y
  - log transformed intensities in image
- Hidden Variables W
  - indicator variables for classification
- Model Parameters b
  - the slowly varying corrupting bias field

(Y_s, W_s, b_s refer to variables at voxel s in image)

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EM-segmentation

E-Step

Compute tissue posteriors using current intensity correction.

$$\widetilde{P}^{(t)}(W) = P(W \mid Y, \mathbf{b}^{(t-1)})$$

M-Step

Estimate intensity correction using residuals based on current posteriors.

$$\mathbf{b}^{(t)} = \arg\max_{\mathbf{b}'} E_{\widetilde{P}^{(t)}}[\log P(\mathbf{b}' \mid W, Y)]$$

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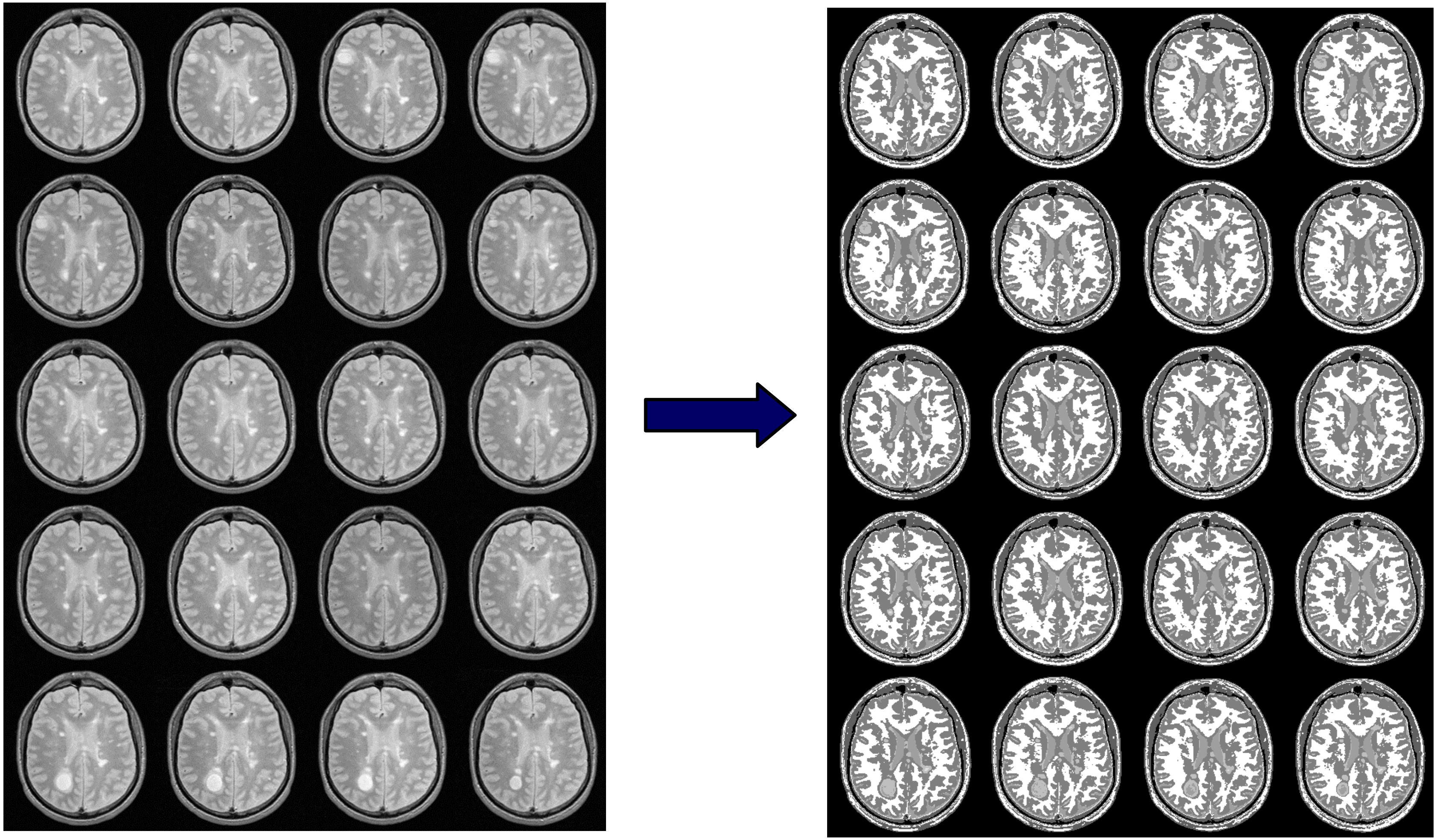
EM Segmentation



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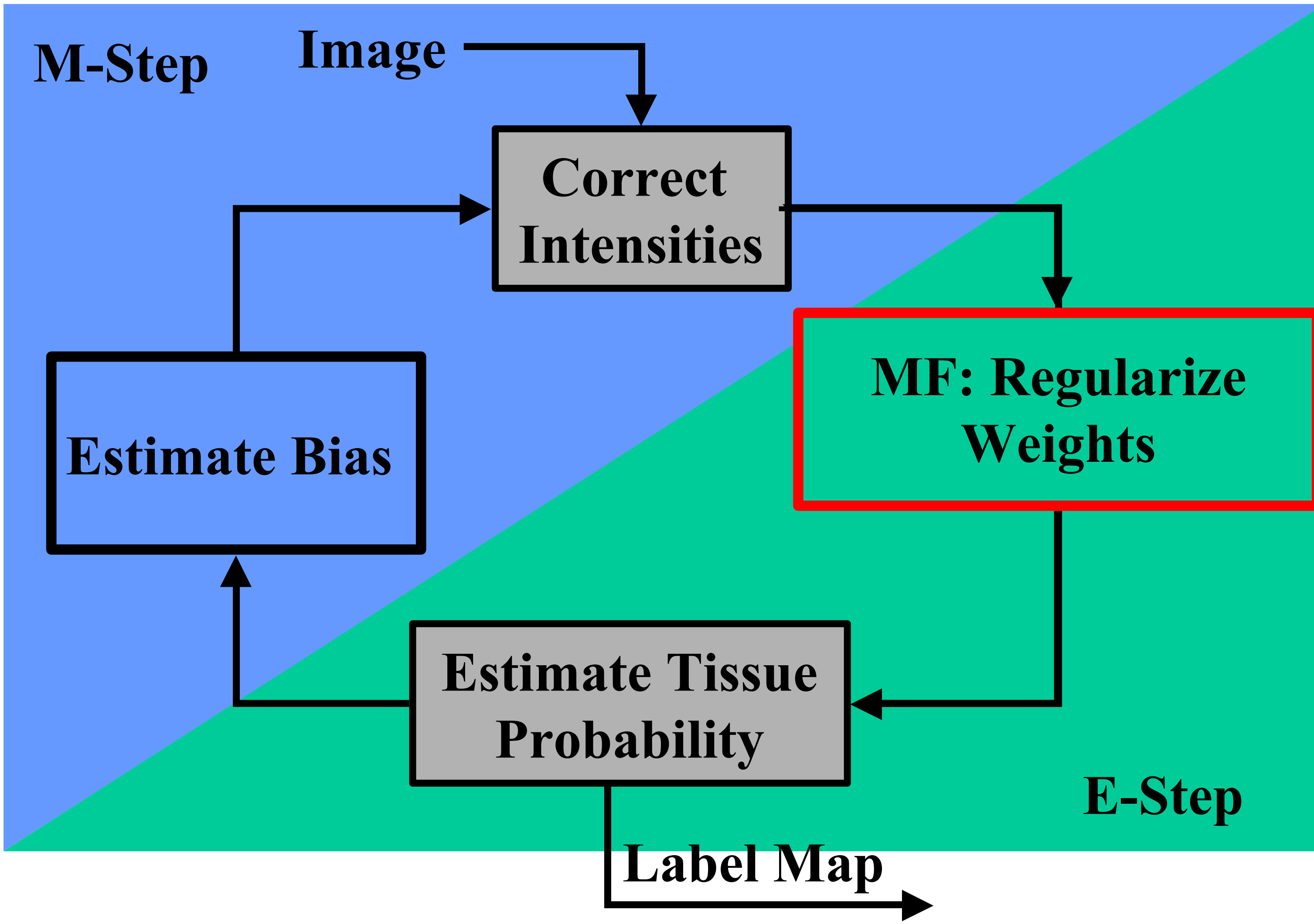
Handling local interactions: Markov Random Fields

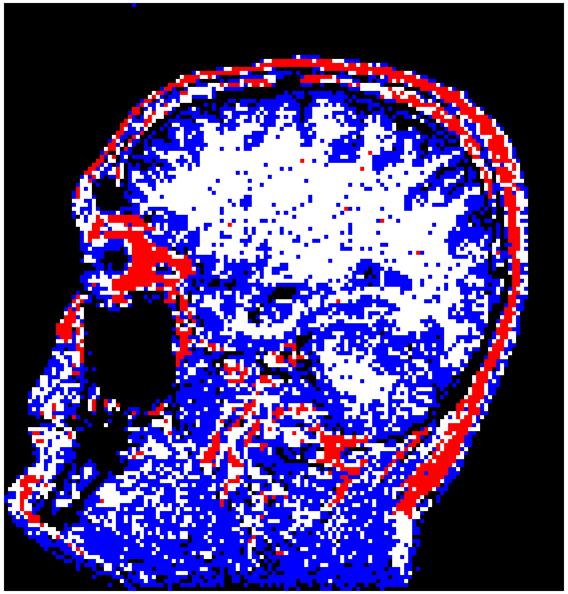
- Prior in EM-Segmentation:
  - Independent and Spatially Stationary
- Markov Random Field (MRF)
  - probability model on a lattice
  - partially relaxes independence assumption to allow interactions between neighbors
  - used in image restoration [Geman&Geman 84]
- Use mean field approximation for MAP estimation of the label-map

EM-MF Algorithm [Kapur 1998]

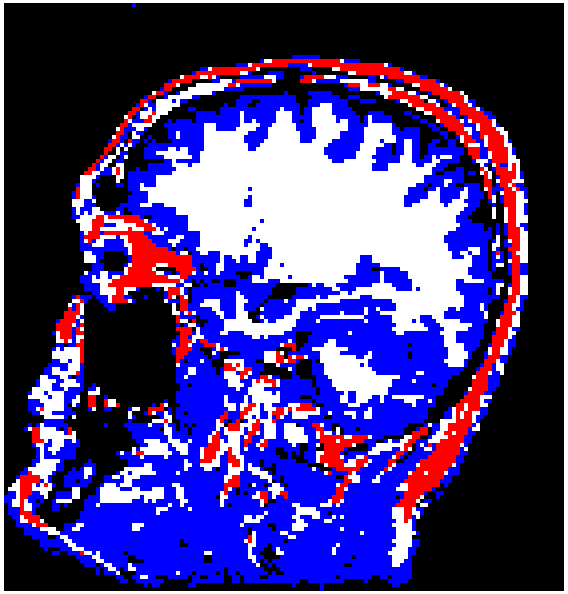


Example Results

Noisy MRI



EM Segmentation

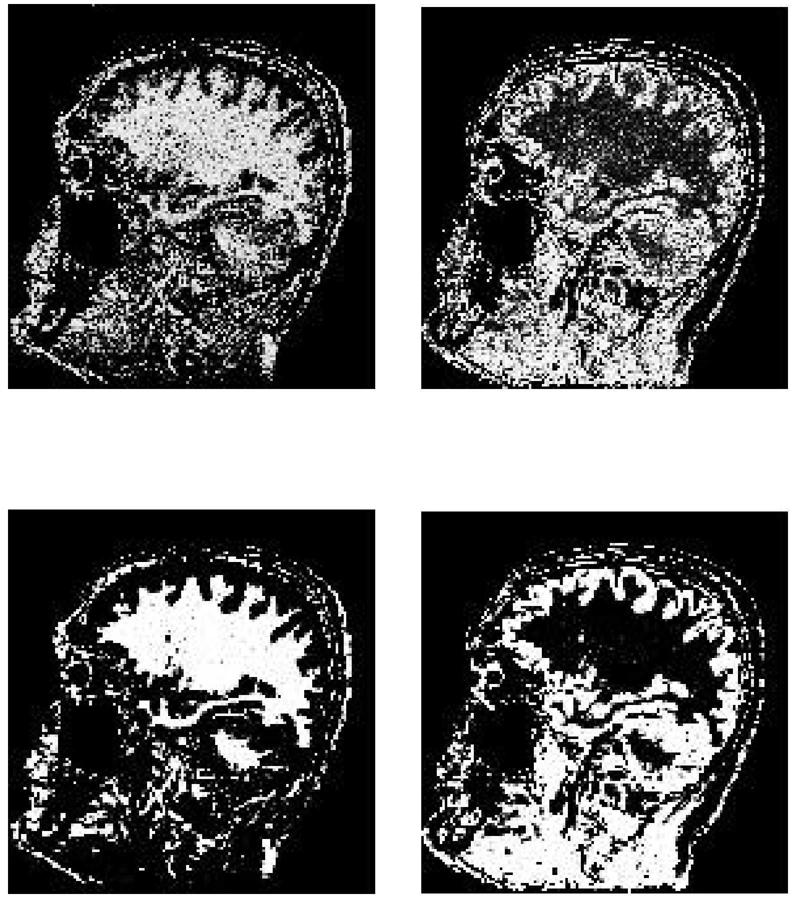


EM-MF Segmentation

Posterior Probabilities

EM

EM-MF



White matter Gray matter

Evolution of the Model [Pohl 2002]

New E-Step:

W(T):= $P_x(T) \cdot P(I \mid T, B) \cdot \exp[-\text{Energy}(T \mid \text{Neighbors})]$

EM Algorithm **MF** **Local Prior**

T - Labelmap
I - Log Image
B - Image Inhomogeneities

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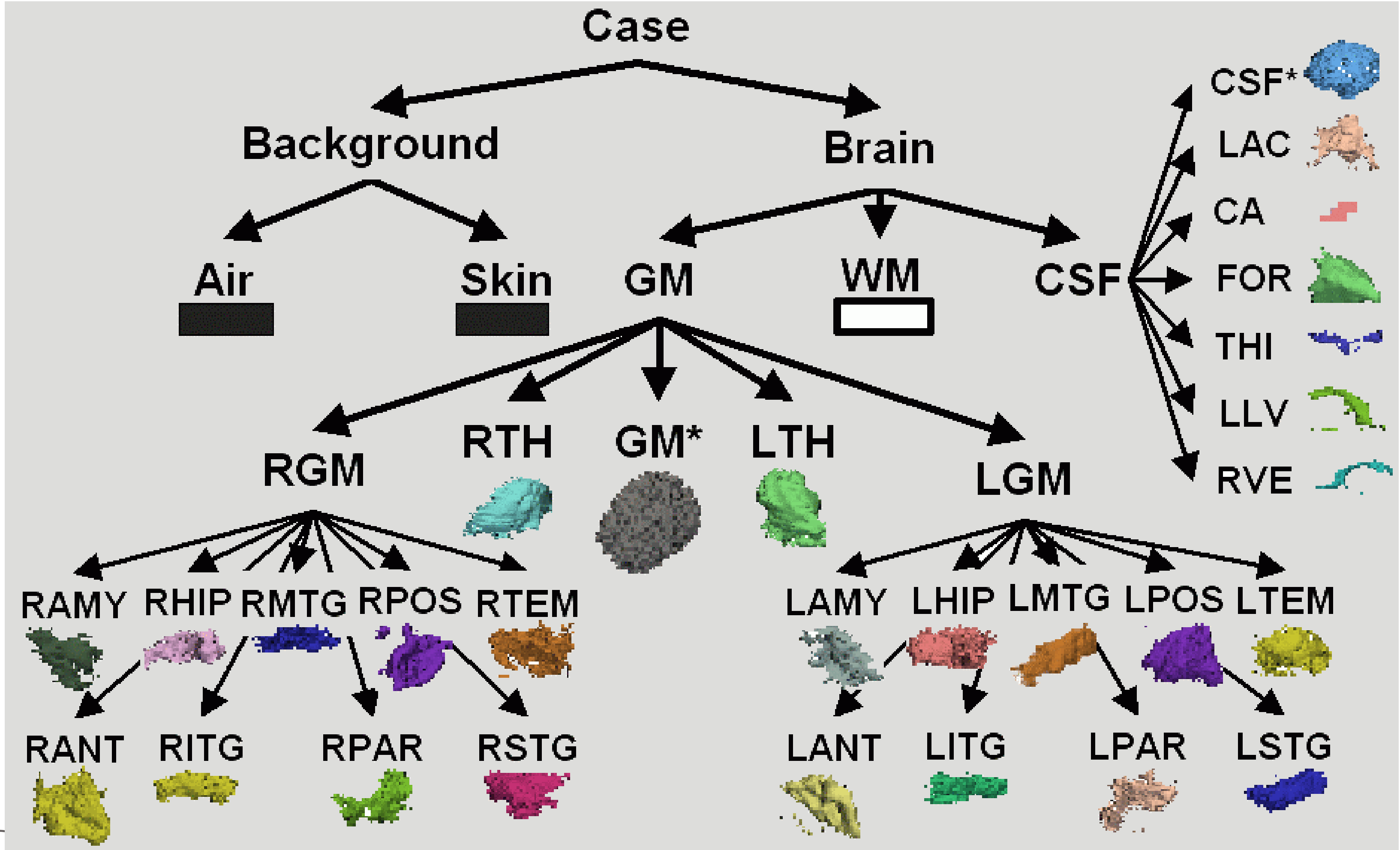
Segmentation of 31 Structures [Pohl 2004]



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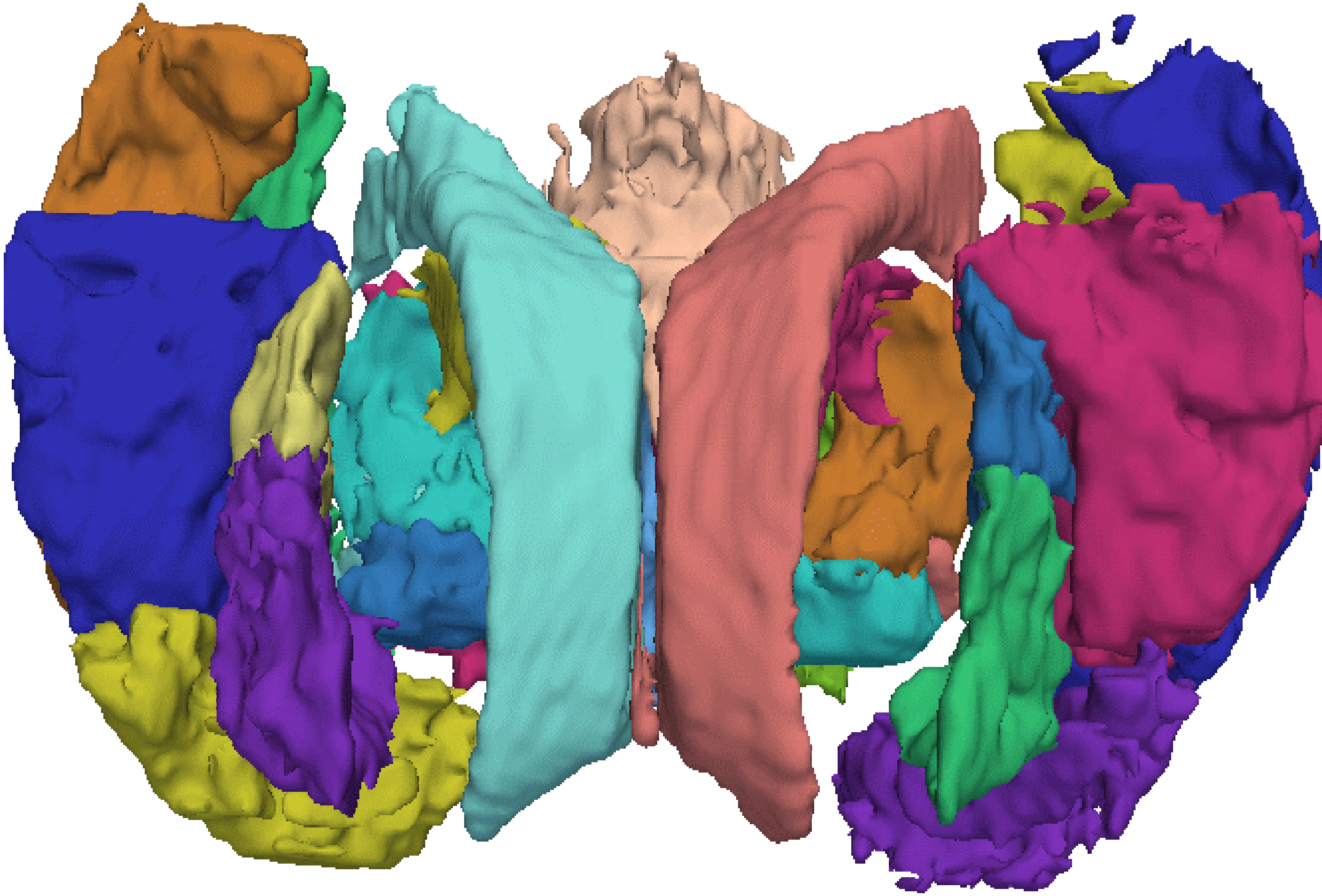
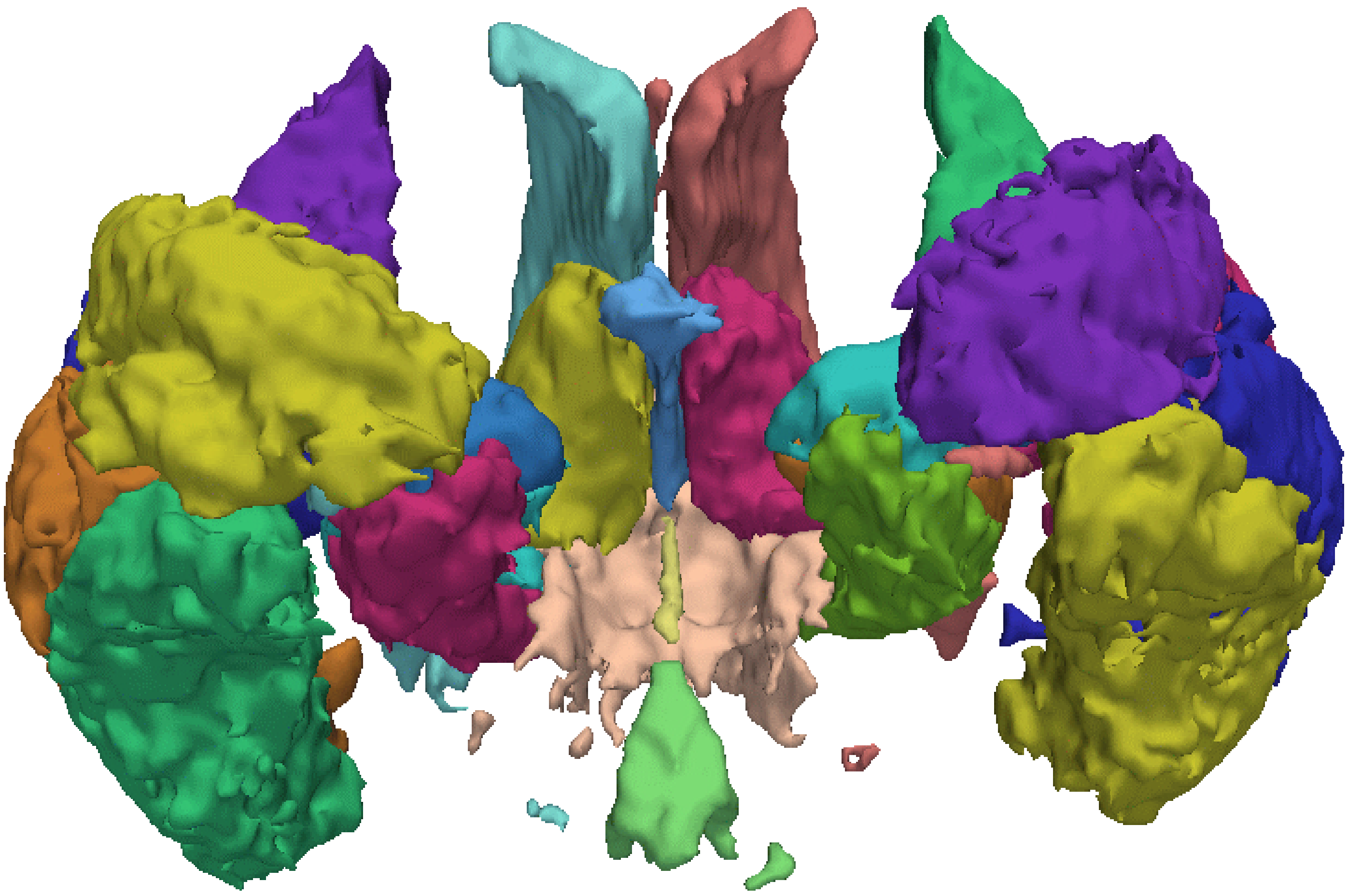
Segmentation of 31 Structures



Upper Front

Segmentation of 31 Structures



Lower Front

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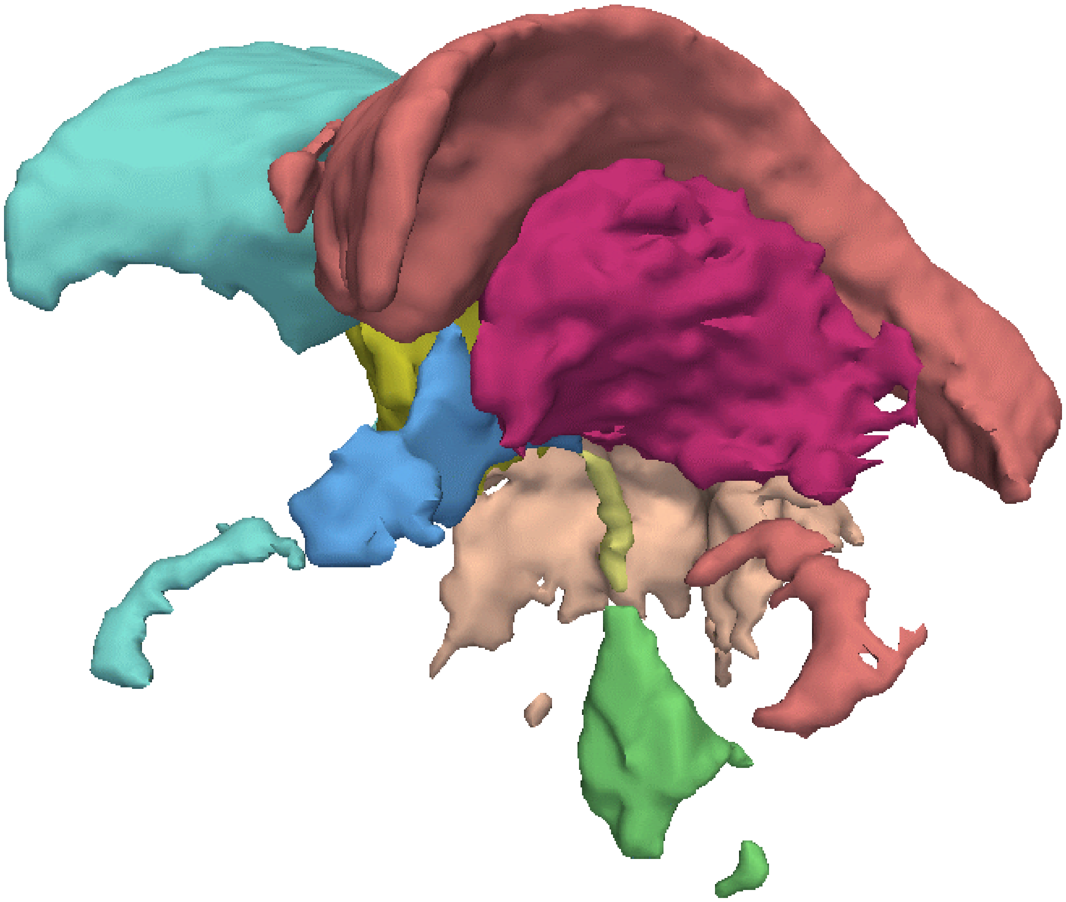
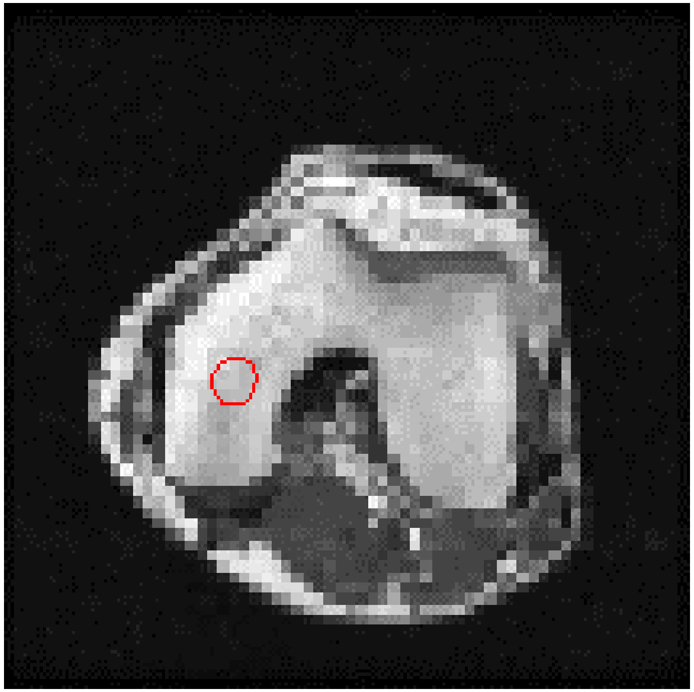
Segmentation of 31 Structures



Ventricles

Boundary Localization

- Active Contours, 'Snakes', Level Sets



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Geodesic Active Contours

- Snake methodology defines an energy function E(C) over a curve C as

$$E(\mathcal{C}) = \beta \int |\mathcal{C}'(q)|^2 dq - \lambda \int |\nabla I(\mathcal{C}(q))| dq$$

- Caselles, *et al.* reduced the minimization problem to the expression.

$$\min_{\mathcal{C}(q)} \int g(|\nabla I(\mathcal{C}(q))|)\ |\mathcal{C}'(q)|\ dq$$

where g is a function of the image gradient of the form $\frac{1}{1+|\nabla I|^2}$.

- The following curve evolution equation can be derived using Euler-Lagrange.

$$\frac{\partial \mathcal{C}(t)}{\partial t} = g\kappa\mathcal{N} - (\nabla g \cdot \mathcal{N})\mathcal{N}$$

where κ is the curvature and $\mathcal{N}$ is the normal.

- By defining an embedding function u of the curve C, the update equation for the higher dimensional surface is given by (Osher, Sethian '88):

$$\frac{\partial u}{\partial t} = g\ \kappa\ |\nabla u| + \nabla u \cdot \nabla g$$

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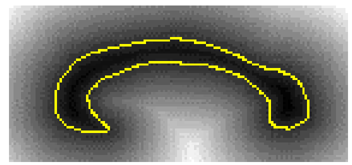
Shape Prior for Segmentation [Leventon 2001]

- Train on a set of shapes
  - Mean shape
  - PCA-based model of variation

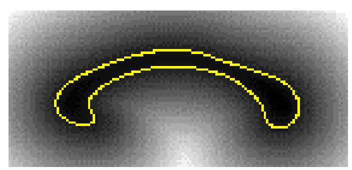
- Bias the segmentation towards likely shapes

Training Data

- The training set, T, consists of a set of surfaces: $T = \{u_1, u_2, \ldots, u_n\}$

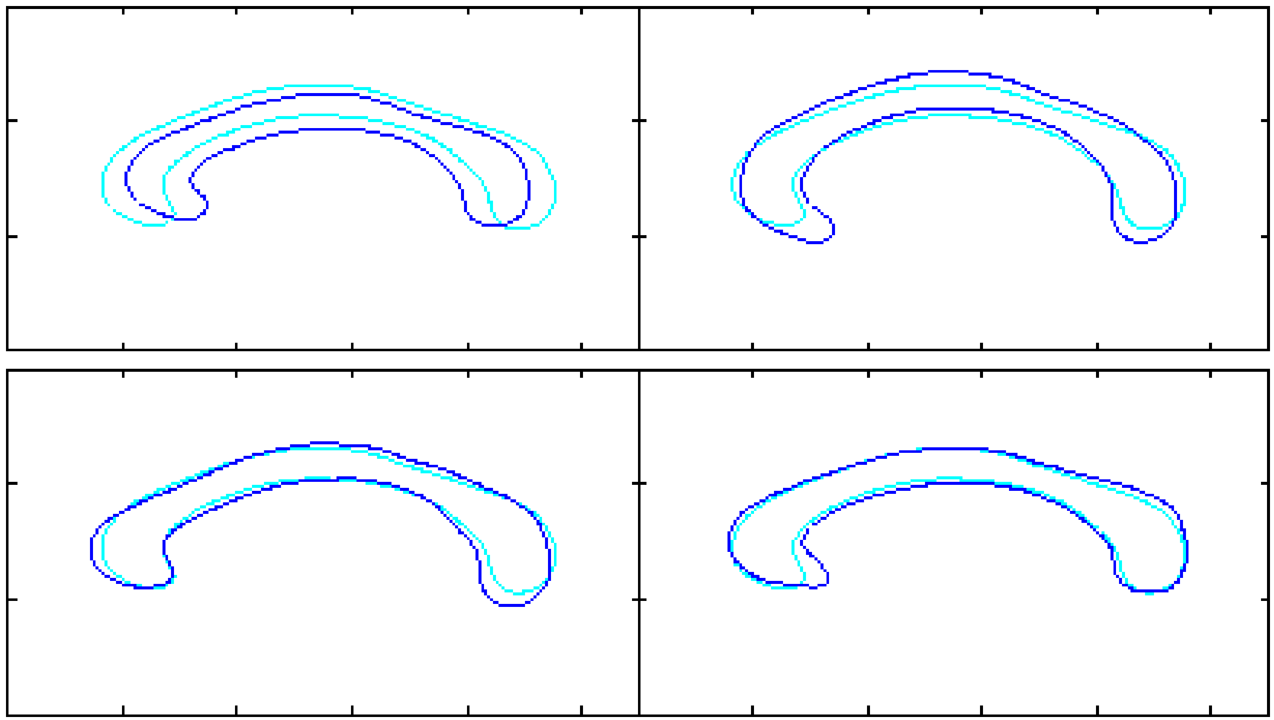
$T = \{$  $, \ldots\}$

- The mean shape

$\mu =$ 

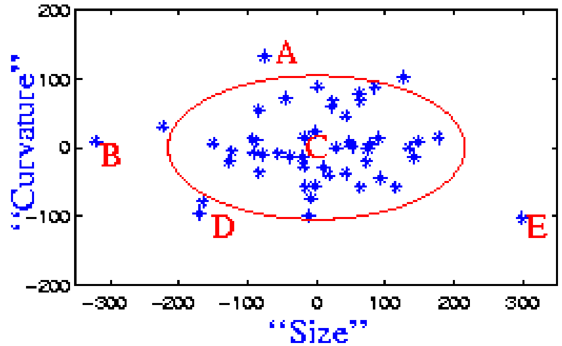
Principal Modes of Variation
(using PCA)

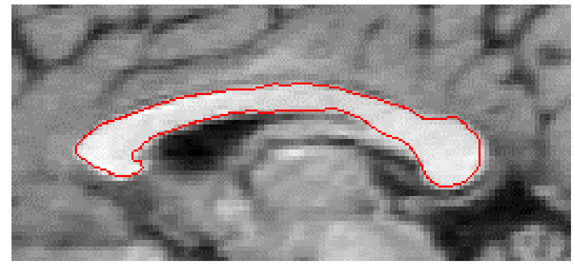
1st Mode — 2nd Mode



3rd Mode — 4th Mode

Shape Distribution





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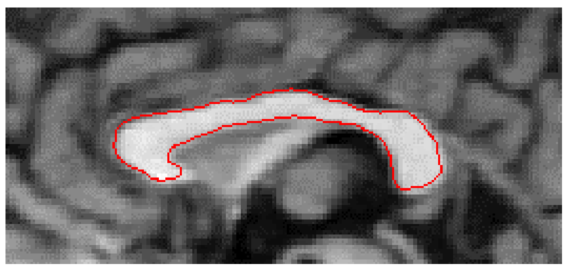

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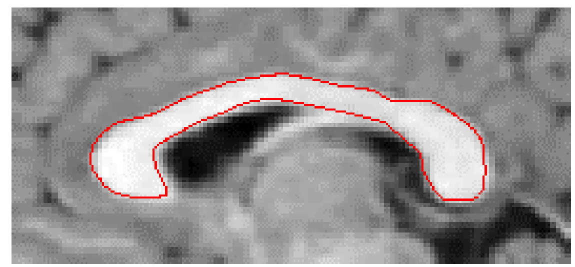
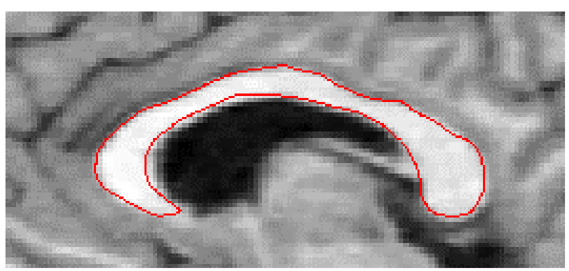
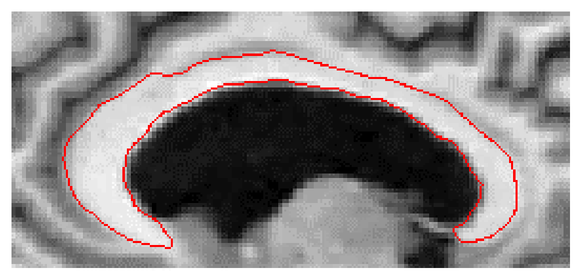


C



D



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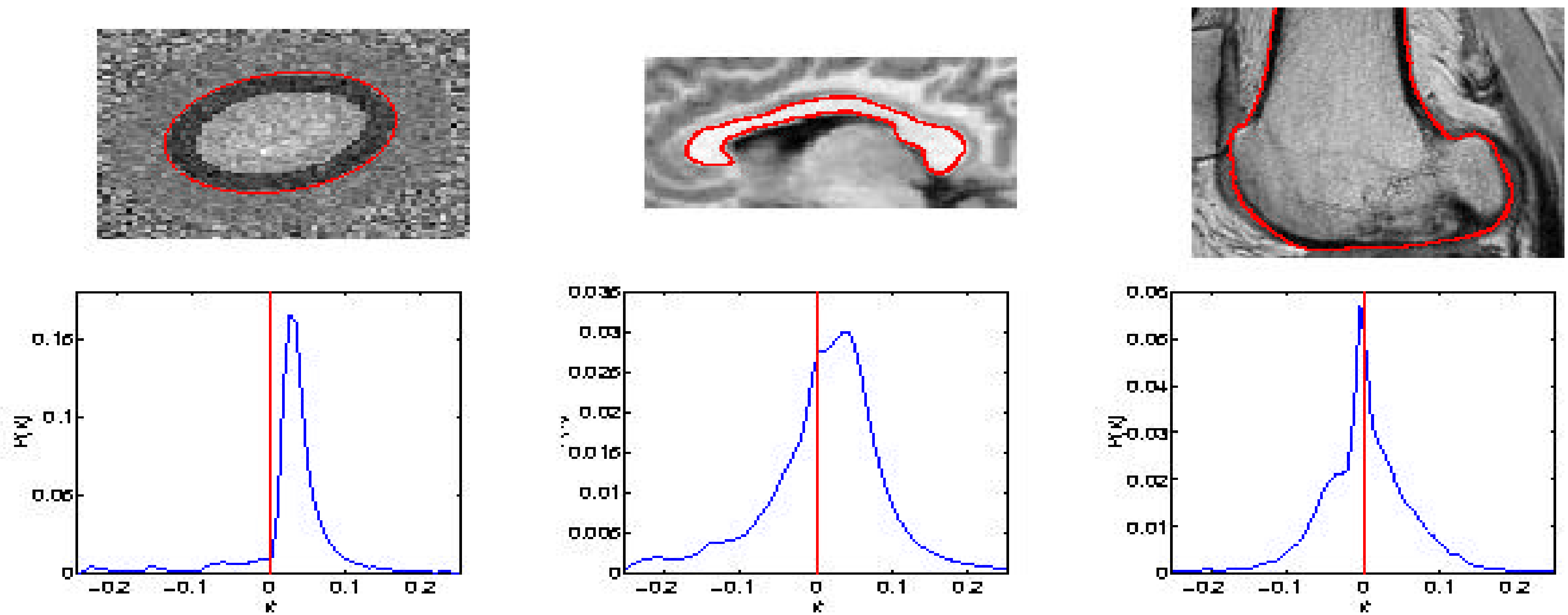
Regularization

Prior Model of Curvature



Histograms of the Curvature of the training objects

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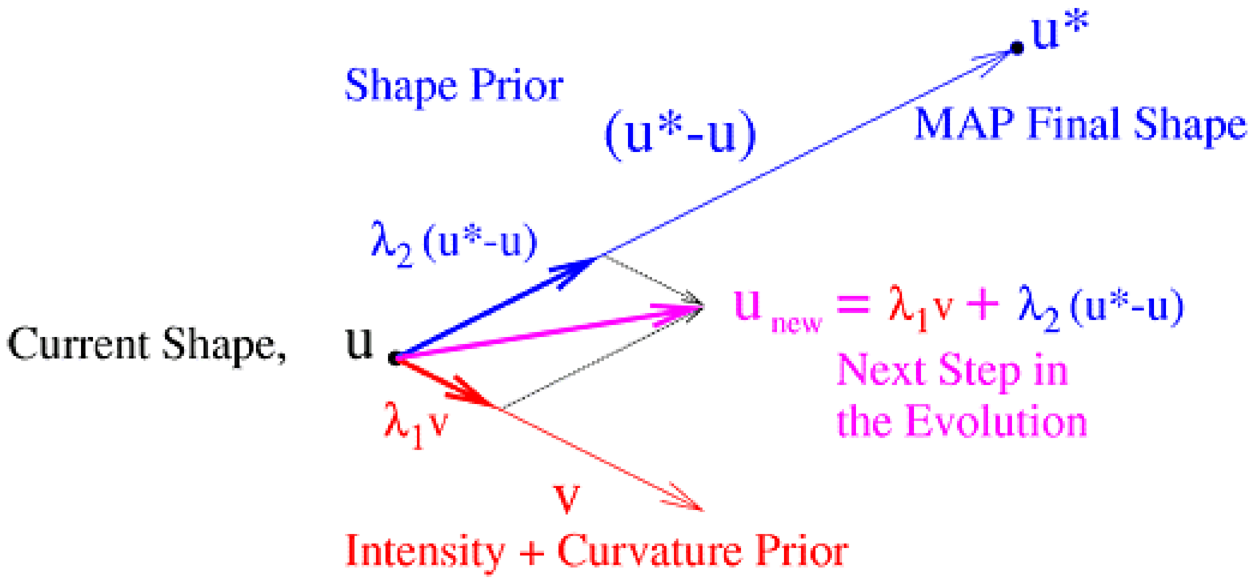
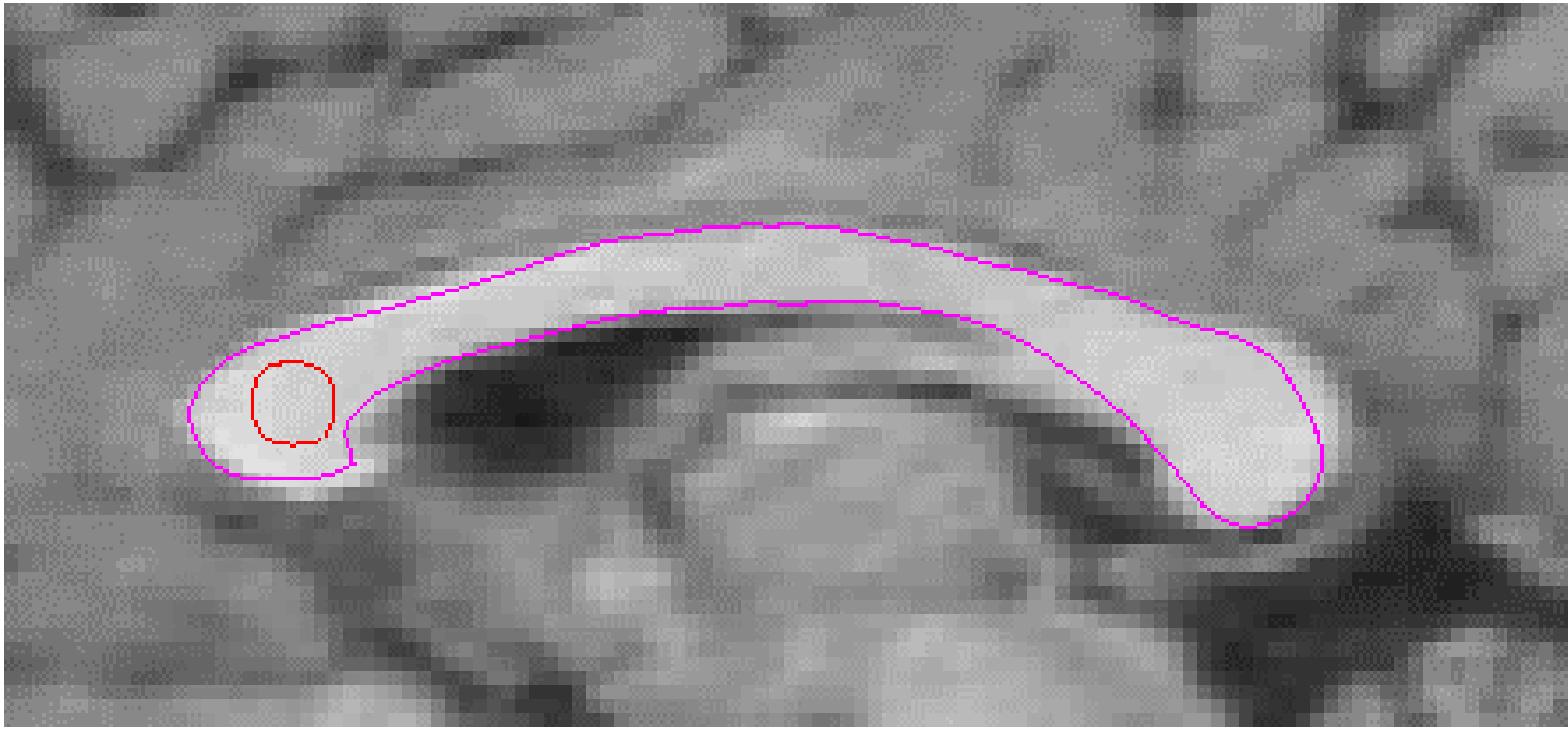
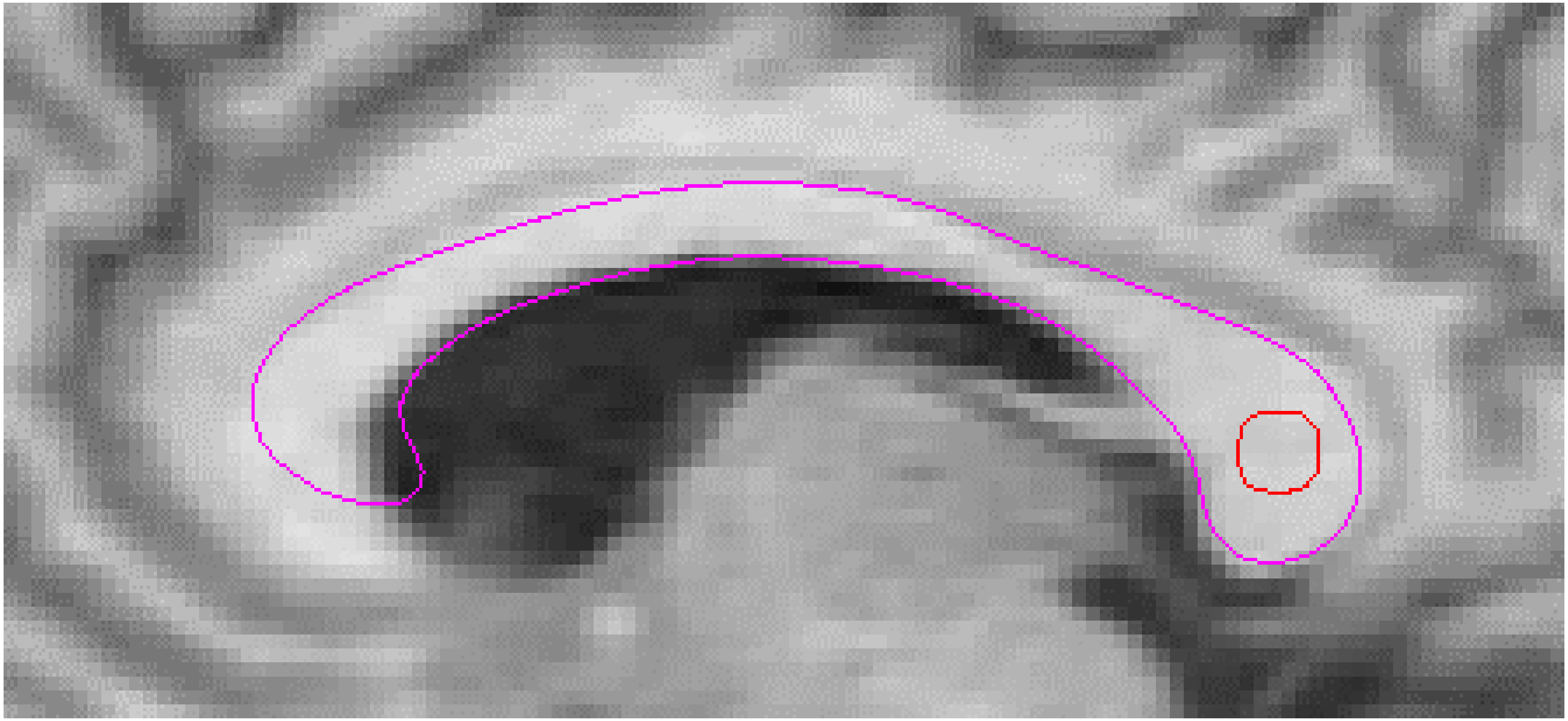
Modified Evolution Equation



Corpus Callosum Segmentation

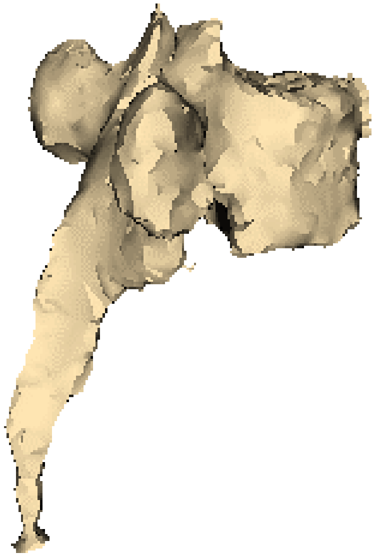


Corpus Callosum Segmentation



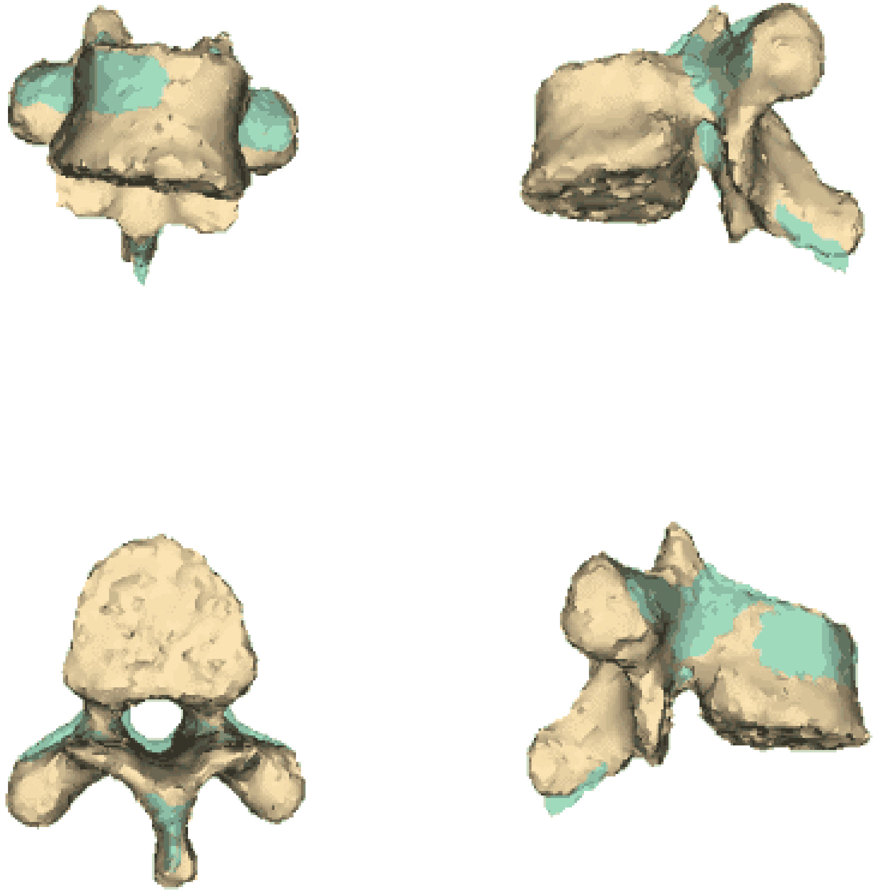
Spine Modes

- 3D Models of seven thoracic vertebrae (T3-T9)

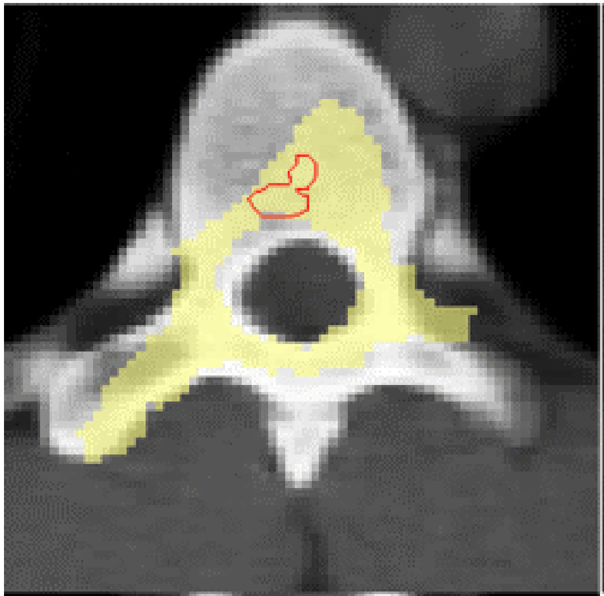


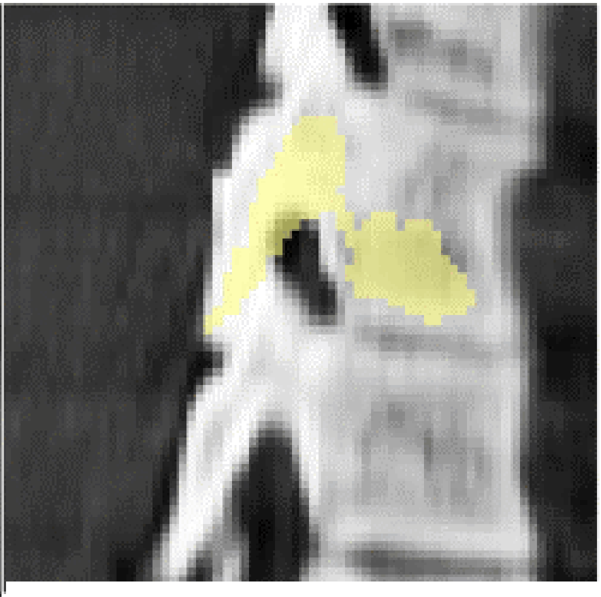
Spine Mean Shape

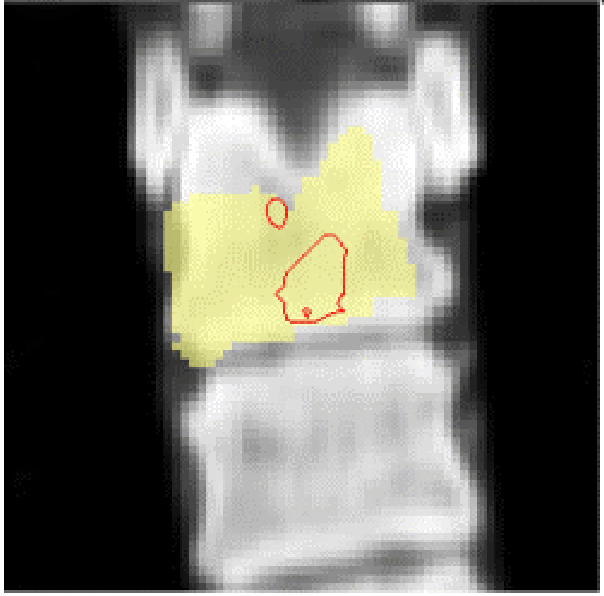
Spine 1st Mode of Variation



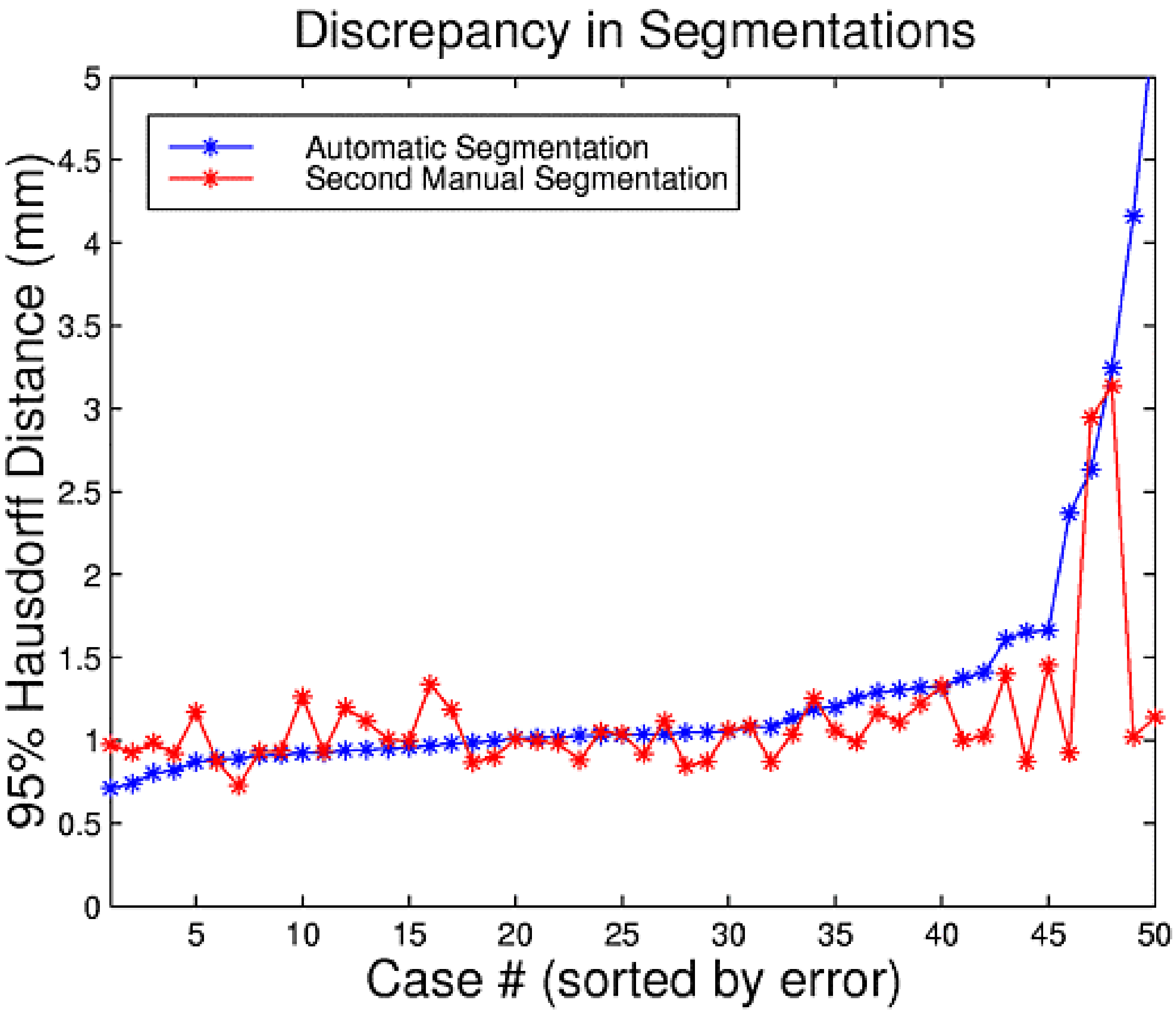
Segmentation of the Vertebrae







Comparison to human expert



Leventon
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Segmentation Summary

- EM for bias field correction
- MRFs for spatial priors on image labelings
- Shape and appearance priors for segmentation

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Learning Shape from Images

- Building quantitative models of natural shapes and their variability from images.

- Creating useful representations and visualizations of the learned concepts.

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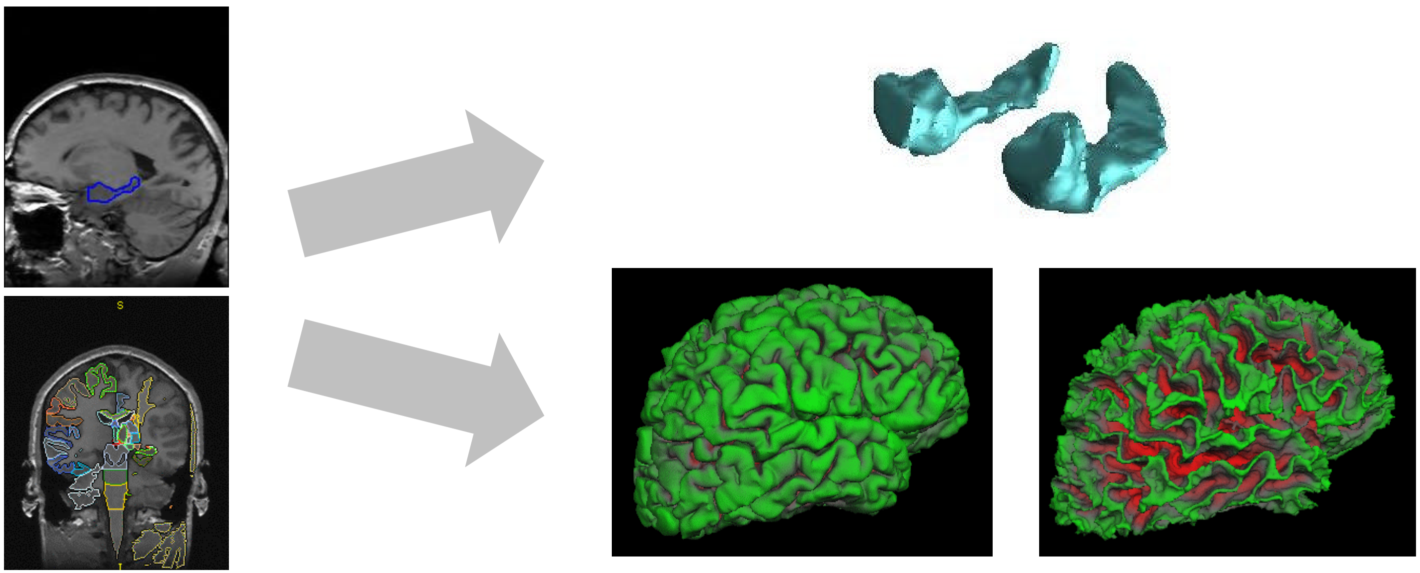
Neuroimaging Studies



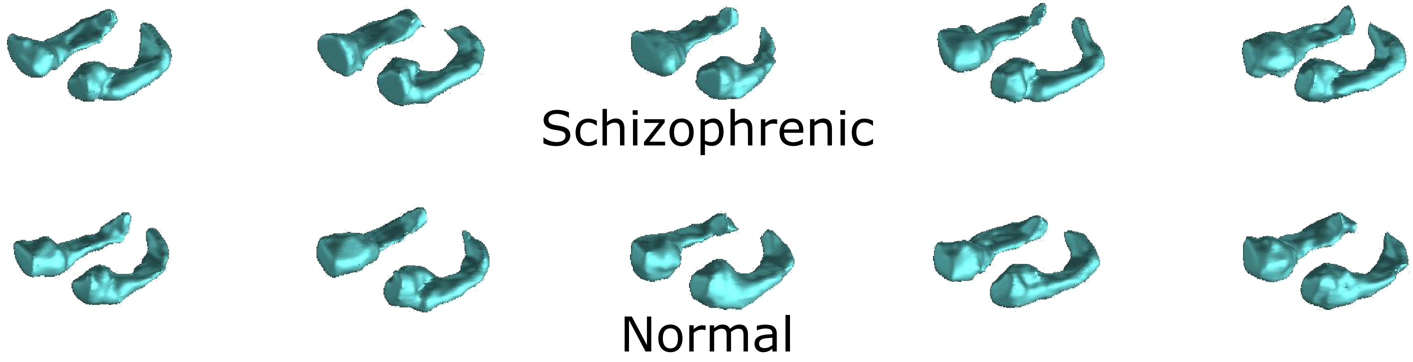
How does the brain develop?

How does a disease affect its structure and function?

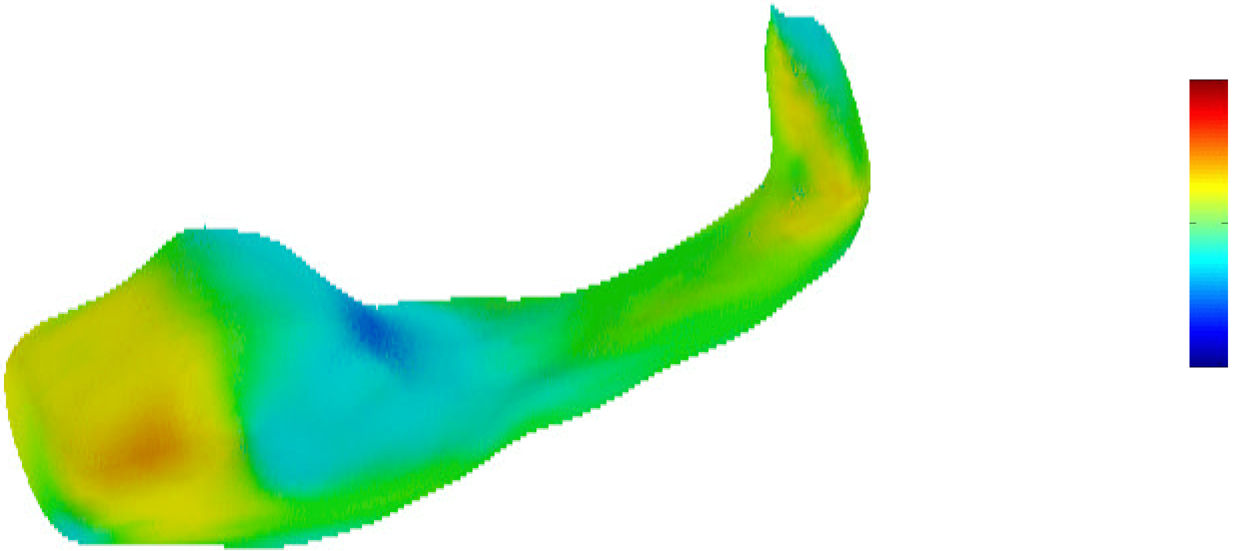
Learn from observing the population.

Problem:

Given two (small) sets of shapes, what are the differences, if any?



Solution



Discriminative direction

Challenges

- Complexity of shapes
  - rich representations
  - classification framework
- Visualization of the statistical model
  - discriminative direction
- High dimensionality of data
  - need less data than suggested by conventional analysis

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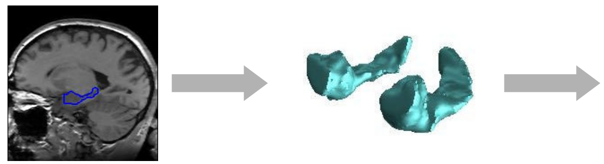
Analysis Framework

1. Feature extraction

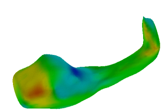


$\boldsymbol{x}$

2. Statistical modeling

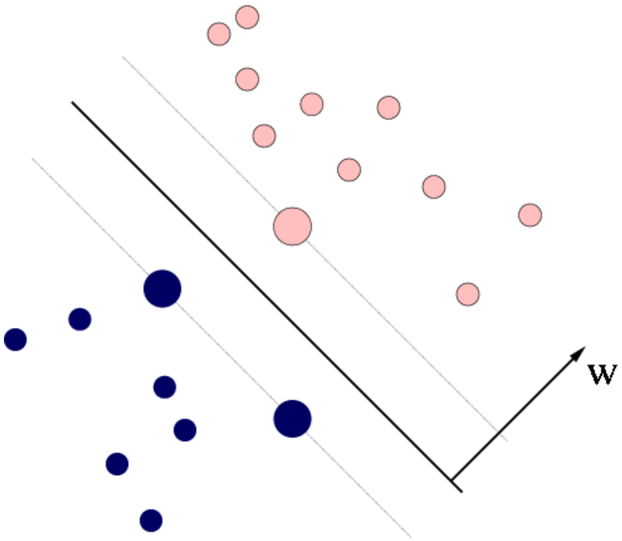
$$f(\boldsymbol{x})$$

3. Classifier analysis
   - discriminative direction
   - statistical significance



Discriminative direction [Golland 2001]

Move the input example towards the other class without introducing irrelevant changes.



- Linear case

$$f\left(\boldsymbol{x}\right) = \langle \boldsymbol{x} \cdot \boldsymbol{w} \rangle + b$$

- Discriminative direction is $\boldsymbol{w}$.

- *General case:* search for direction $d\boldsymbol{x}$ that minimizes irrelevant changes with respect to $f(\boldsymbol{x})$.

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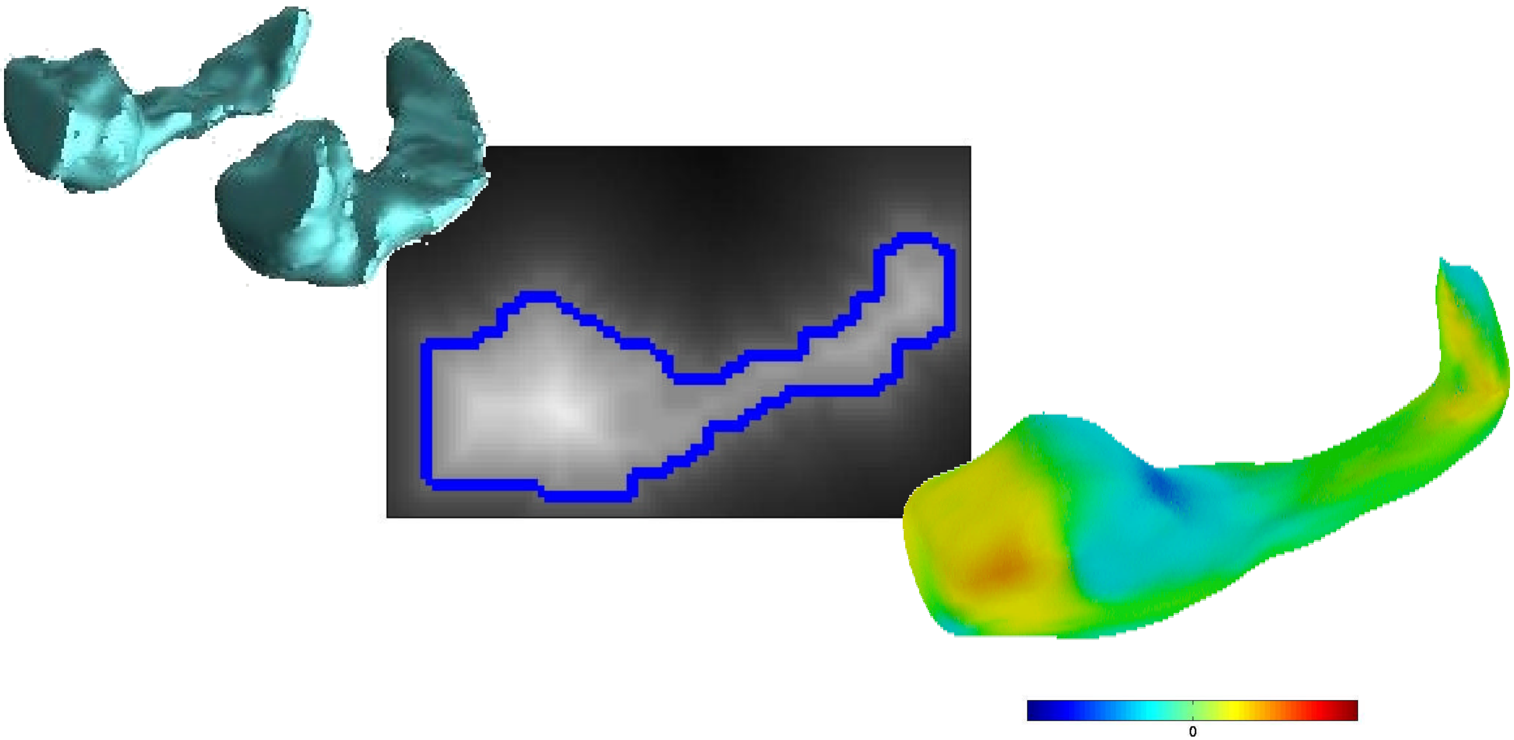
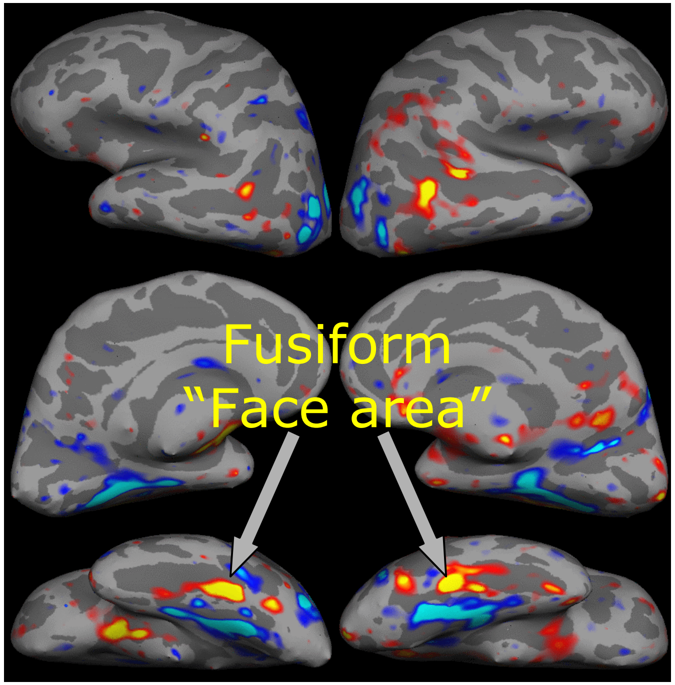
Study of shape

Hippocampus shape in schizophrenia



fMRI Analysis [Golland et al 2003]

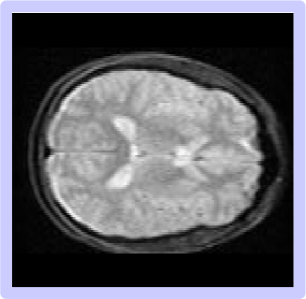
- Brain activation
  - fMRI analysis
  - visual stimuli
- Faces vs. other objects

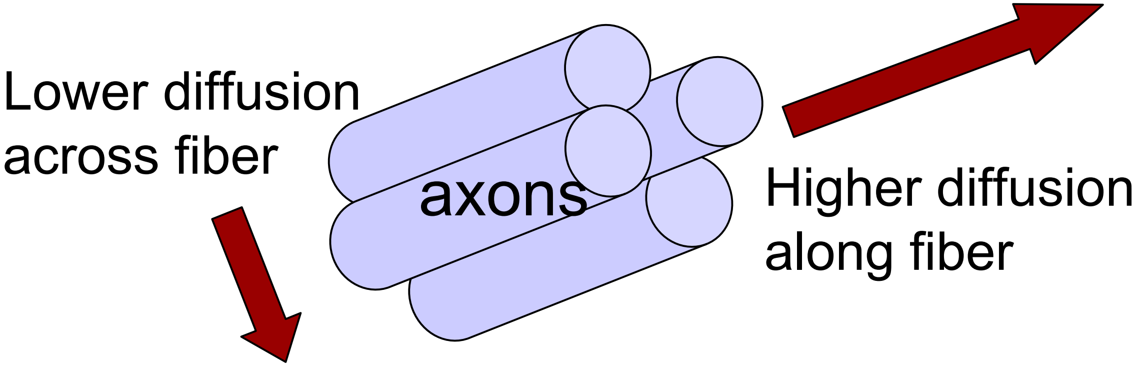


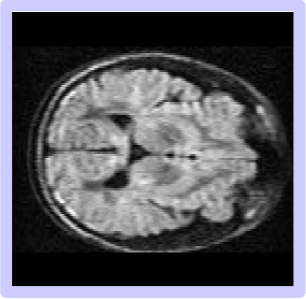
94%, $p < .03$

DTI: Neural Structure and MRI

- MRI signal is from protons in water
- Membranes restrict water diffusion
- Diffusion causes MRI signal loss
- 3D shape of water diffusion







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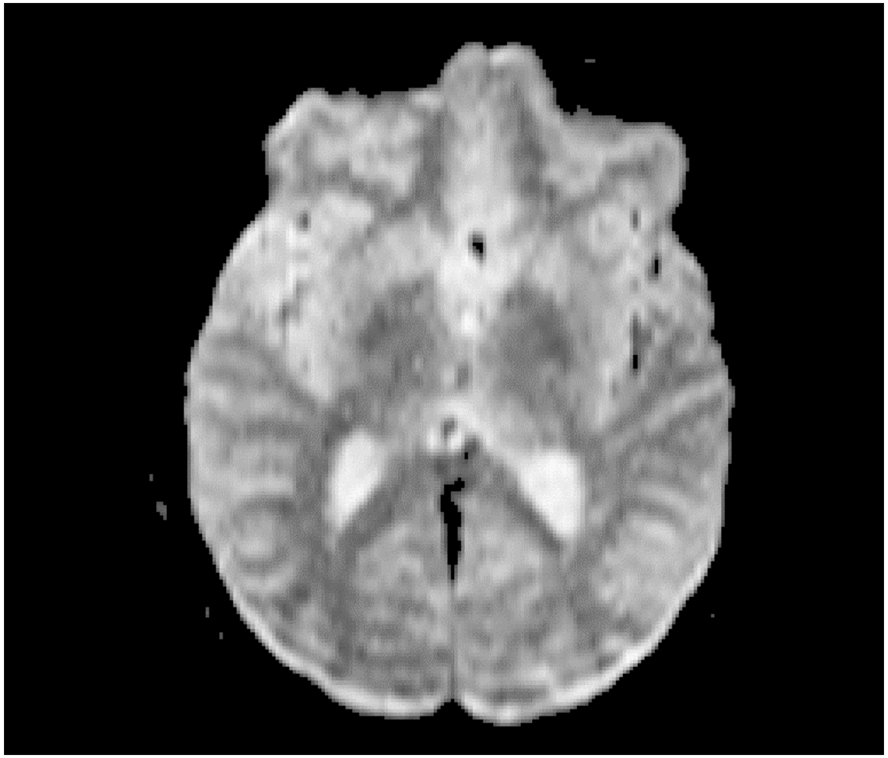
Diffusion tensor MRI

- Complex data can only be partially visualized
  - Show subset of diffusion measurements (eigenvector)



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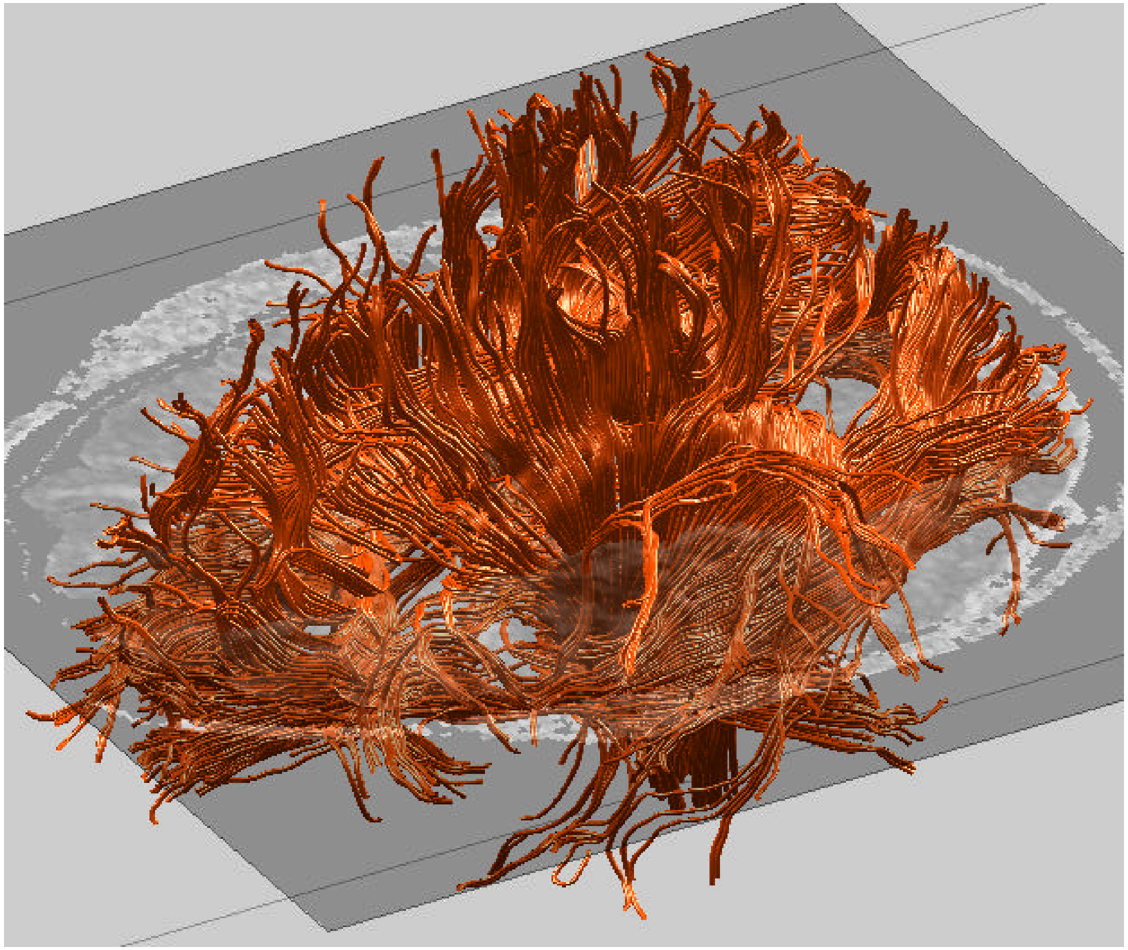
DT-MRI Tractography



H.J. Park, M.E. Shenton, C.-F. Westin

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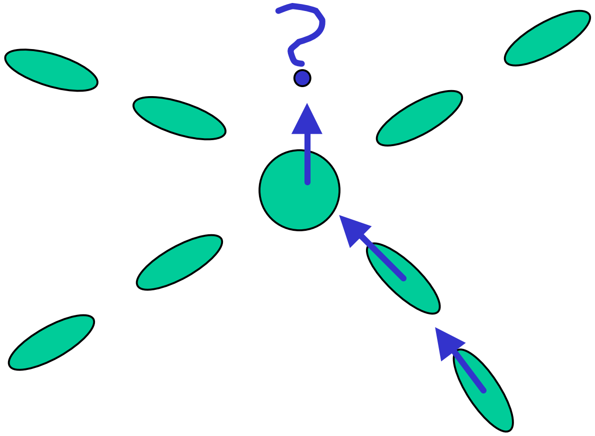
Issues in Tractography



- Single path:
  - shows strongest connection only
- Errors accumulate
- Fiber crossing:
  - ambiguous path due to local decisions

Diffusion-Based Connectivity [O'Donnell 2002]

- Use anisotropic diffusion equation
  - Sources and sinks in the tensor field
  - Steady-state concentration and flow

$$j = -D\nabla u$$

the diffusion tensor

- Flow along a path reflects connectivity

$$\int_S | j^T t | \, ds$$

flow vector

unit tangent vector

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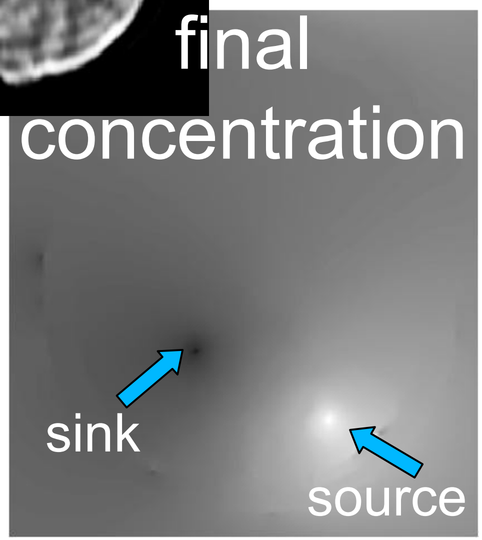
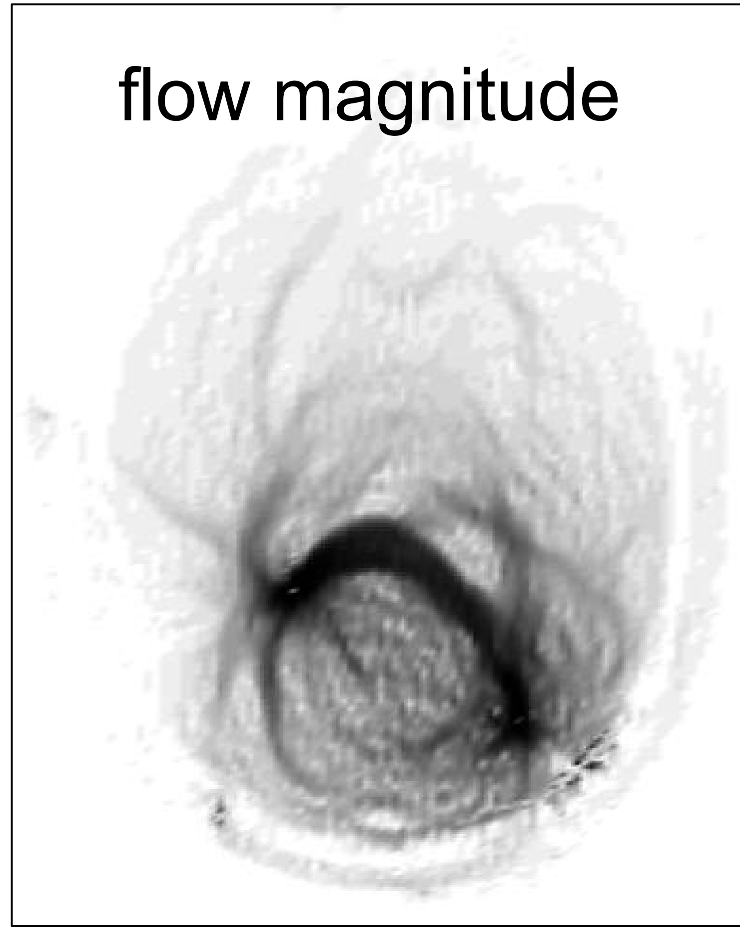
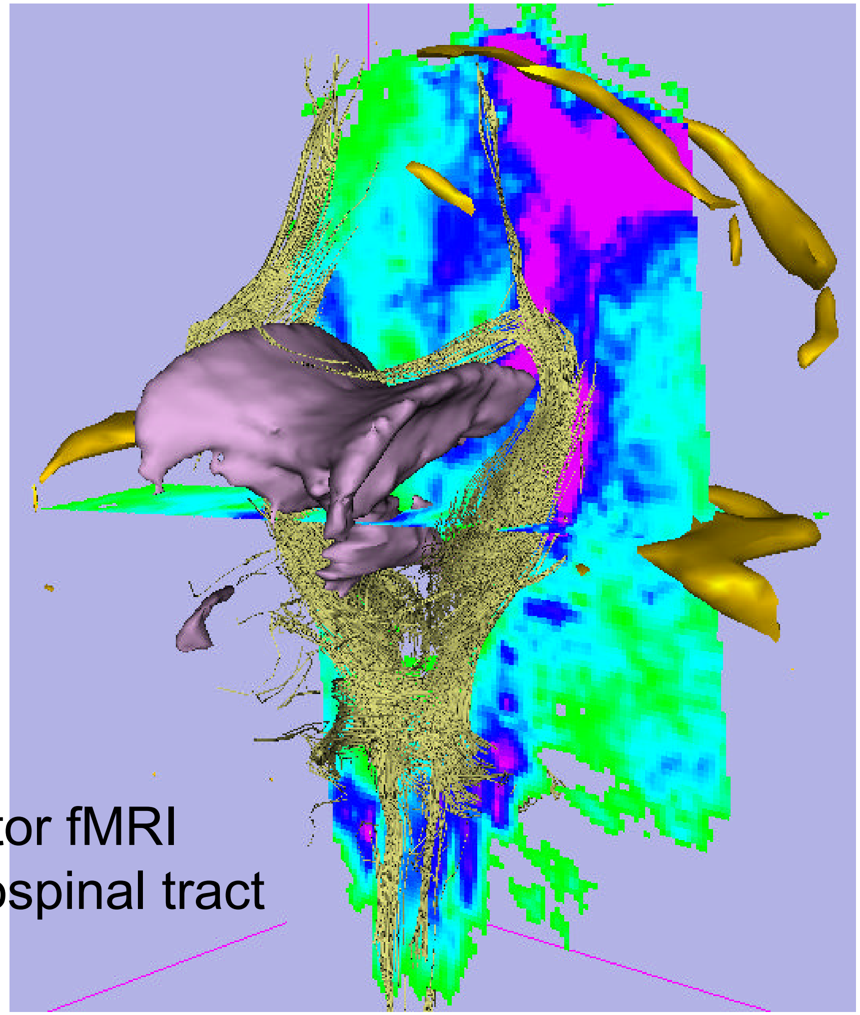
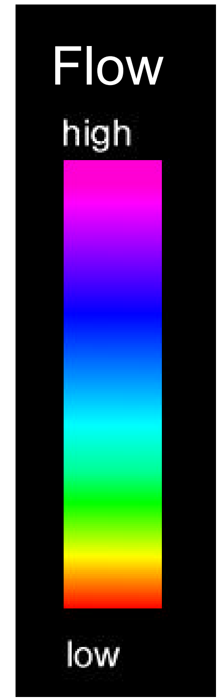
Steady-State Flow





Diffusion-Based Connectivity



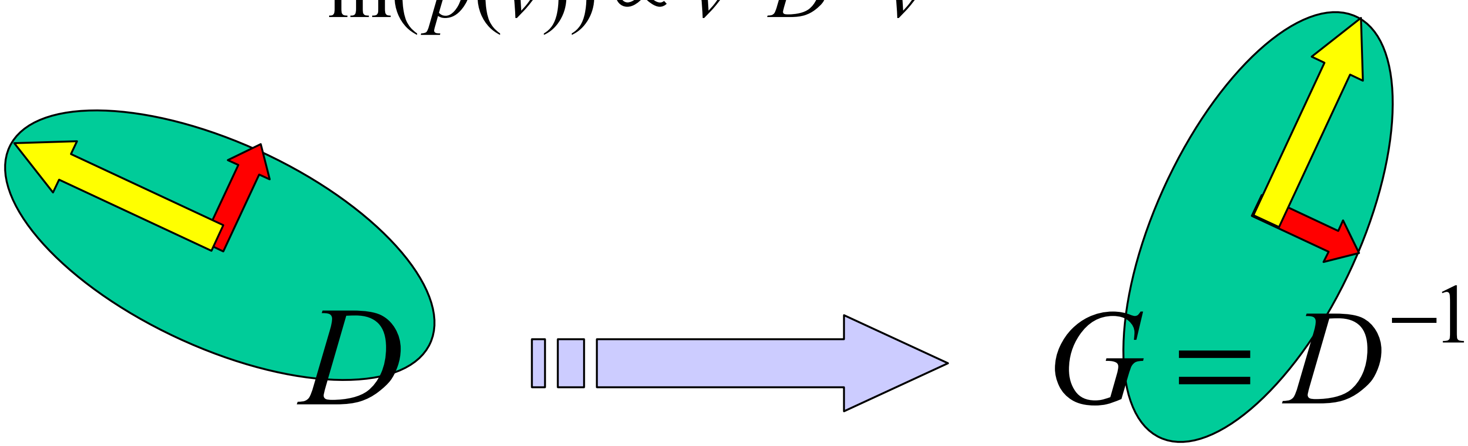


- Source: motor fMRI
- Sink: corticospinal tract

Distance-Based Connectivity [O'Donnell 2002]

- Connectivity should be proportional to distance in some metric space $$|v|_G^2 = v^T G v$$
- Probabilistic interpretation:

$$\ln(p(v)) \propto v^T D^{-1} v$$

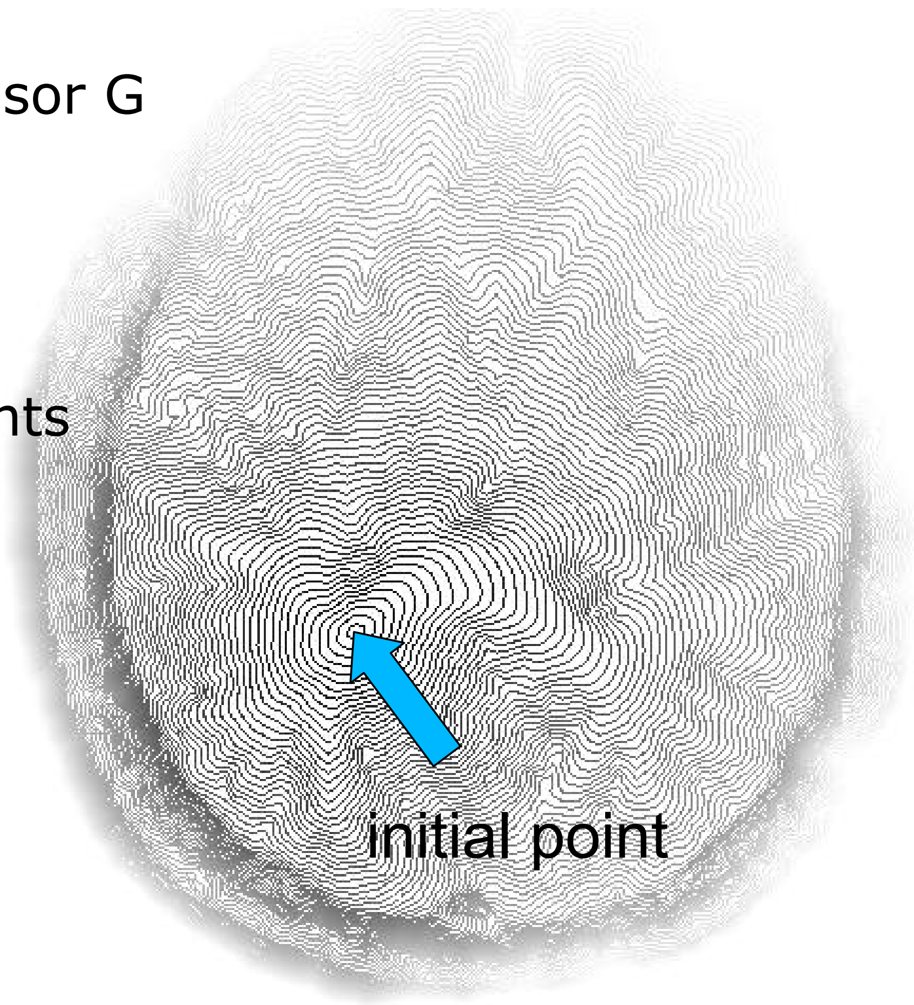


Diffusion Tensor

Metric Tensor

Distance Map

- Input:
  - Riemannian metric tensor G
  - initial point
- Output:
  - geodesic paths
  - distances between points



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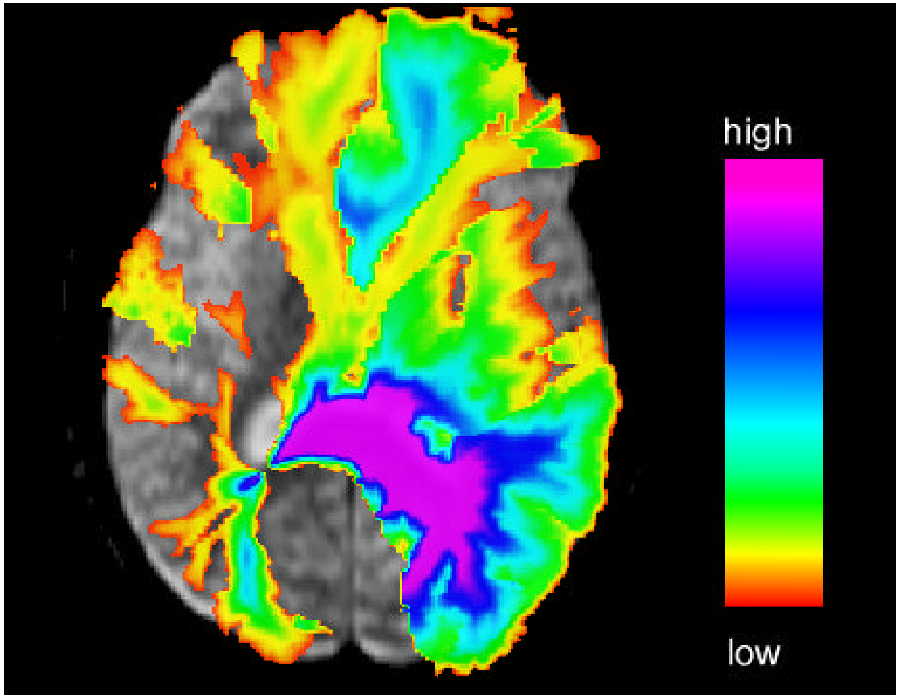
Distance-Based Connectivity

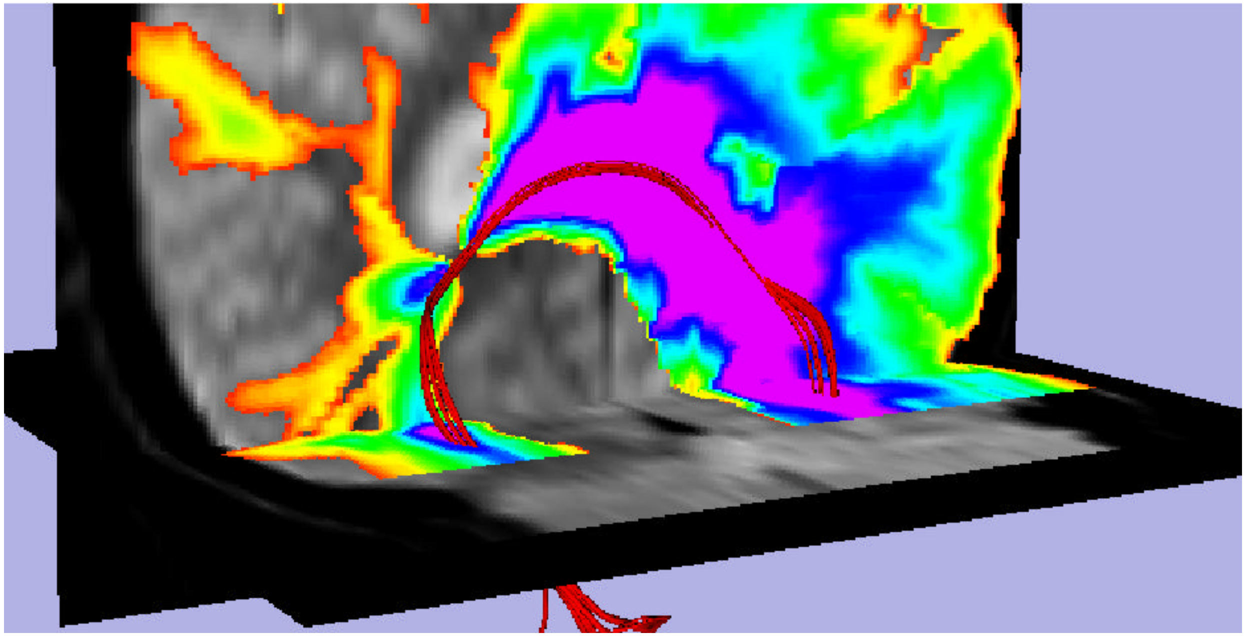
- Proportional to length of the geodesic
- Normalize by Euclidean length

$$C = \frac{L_{Euclidean}}{L_{Geodesic}}$$



Distance-Based Connectivity

- Computed connectivity measure in 3D
- Tractography: highest-connectivity region



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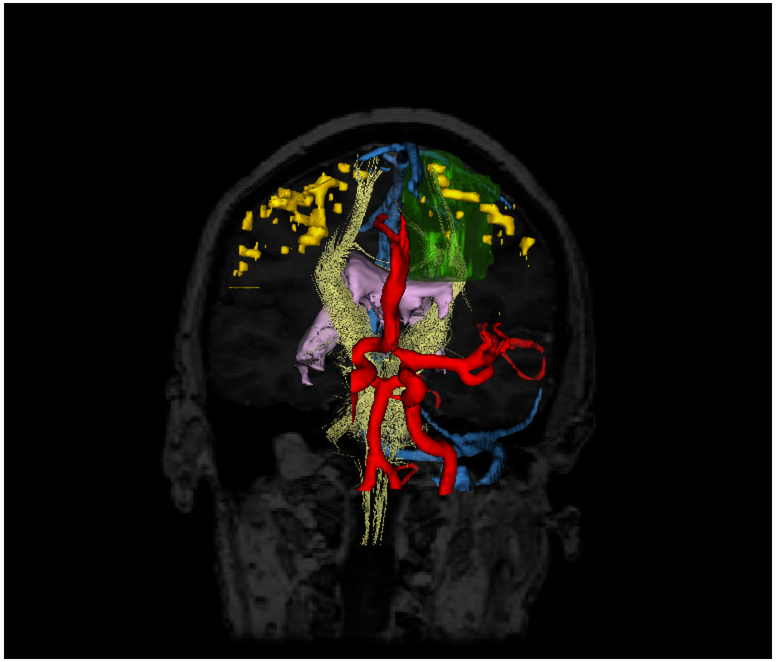
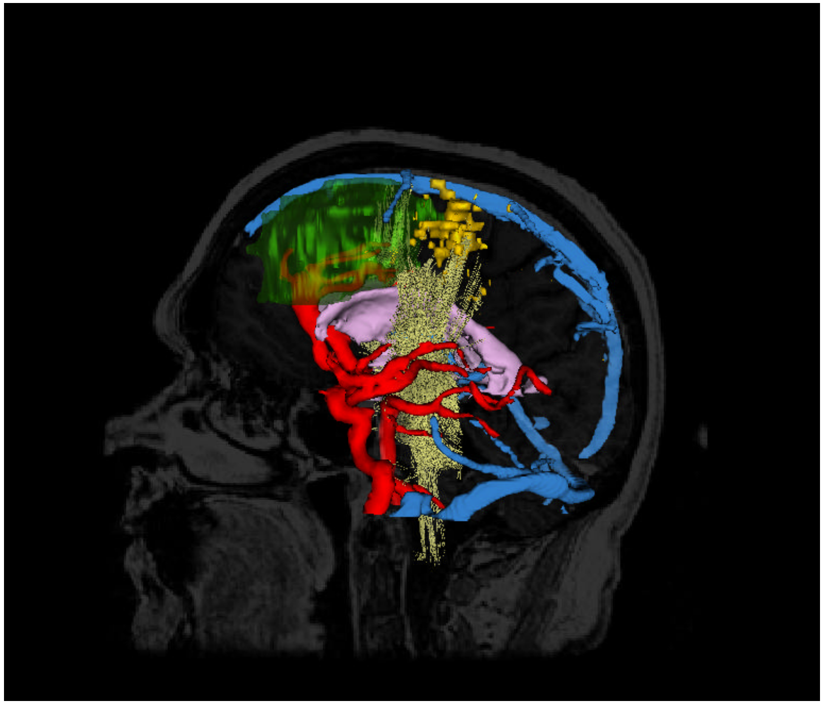
Multi-modal Pre-operative model





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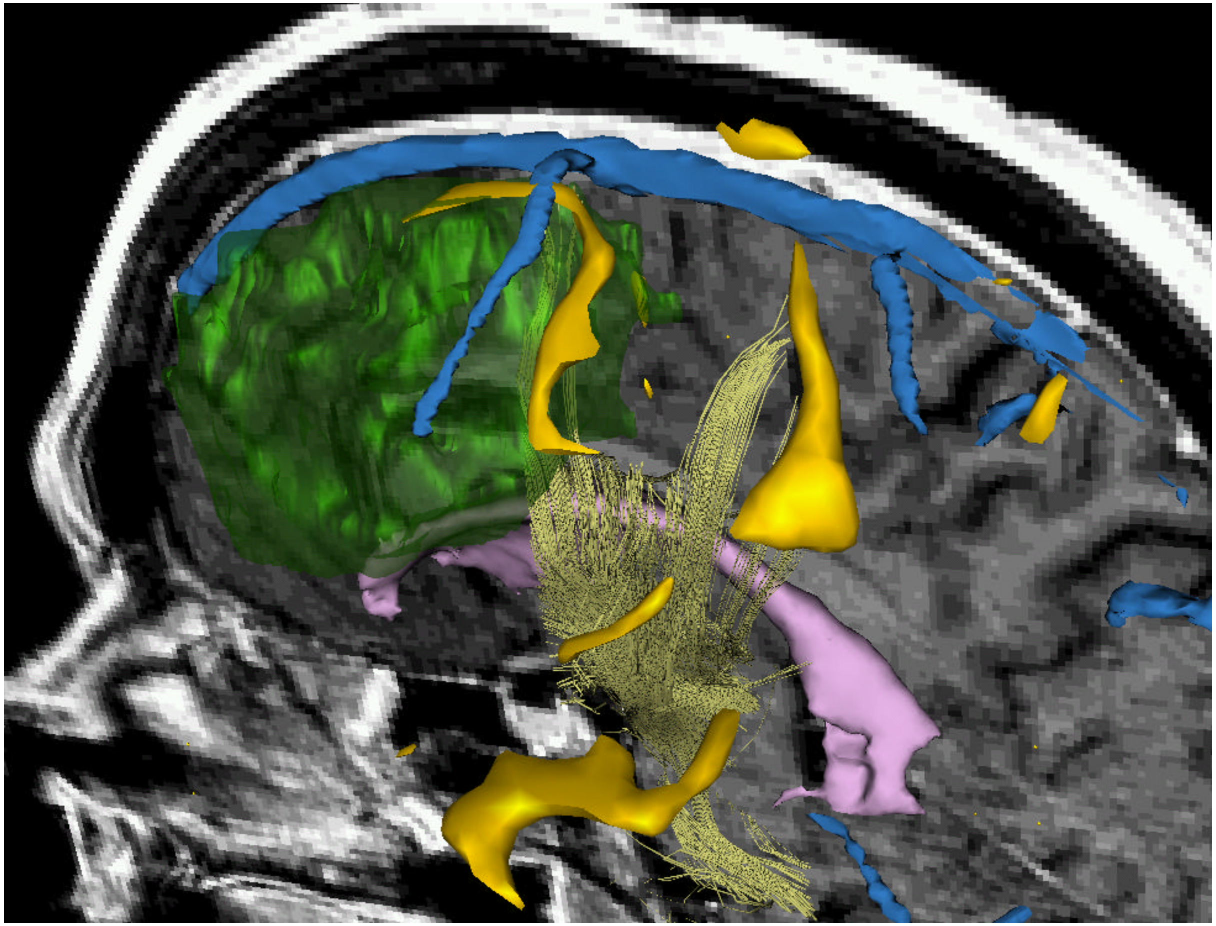
Visualization of DTI and fMRI



Summary

- Interesting, hard problems looking for principled methods

- Methods
  - Segmentation
  - Shape analysis
  - fMRI, DTI analysis

- Applications
  - Surgical planning
  - Neuroscience

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