Surface-Based Coordinate System

- Establish a 2-D coordinate system on cortical surface
  - Every point in cortex should have a (unique) coordinate
  - Every coordinate should refer to a point in cortex
- Inter-subject alignment of cortical folding patterns
- Improve alignment of *functional* areas

Surface-Based Coordinate Systems:
what 'space' to use?

- Flat maps (Van Essen and Drury).
  + simple computationally
  - cuts in coordinate system
  - nonconvex

2. Ellipsoids (Sereno, et al).
   + closed surface (no cuts)
   + minimal distortion in mapping from cortex
   - difficult space to work in computationally.

3. Spheres (Fischl, et al; Thompson and Toga)
   + closed surface (no cuts)
   + tractable computationally
   - a bit more distortion required in mapping.
     (but less than cross-subject variability)

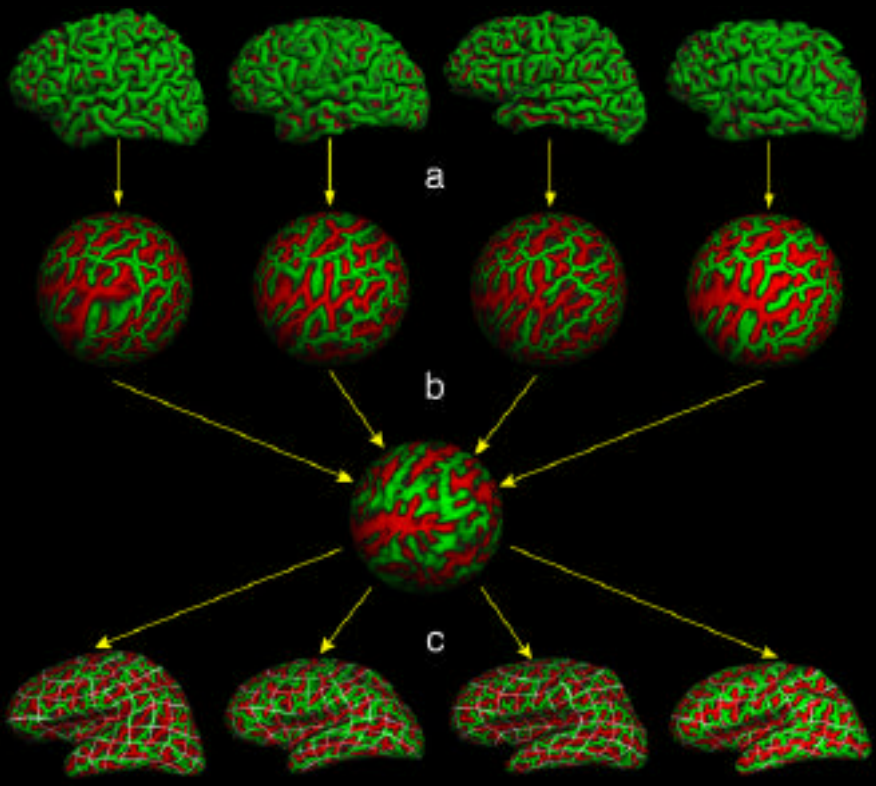
Surface-Based Coordinate Systems

Two Different Approaches

- **Manually define corresponding points across subjects, force them to align, and interpolate every where else (Van Essen and Drury, Thompson and Toga).**

- **Automatically align entire folding pattern across subjects (Fischl, Sereno, Tootell and Dale).**

A Surface-Based Coordinate System



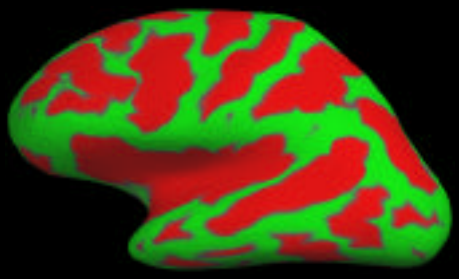
Spherical Transformation: Equations

Energy Functional: $J_d+\lambda_T J_T$

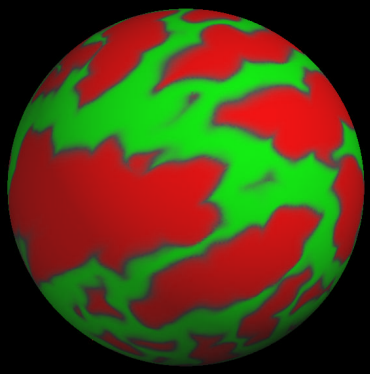
J_d: Metric Distortion (macroscopic distances)

J_T: Topology preservation (oriented area)

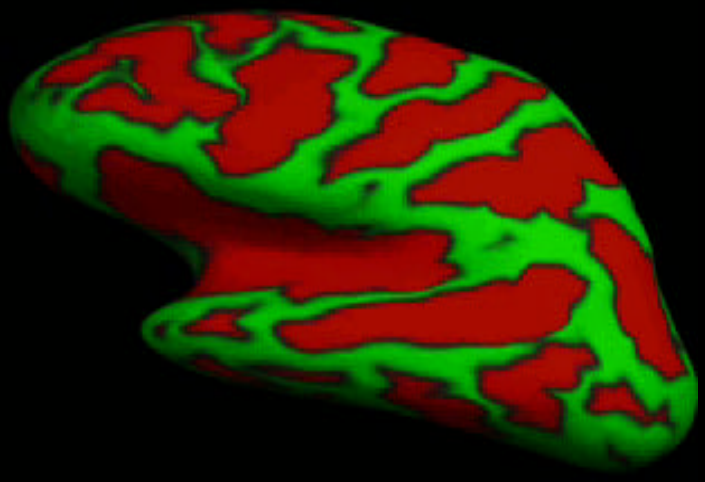
Maximally Isometric Spherical Mapping



Inflated Surface



Transformed Surface



Spherical Morphing: Equations

Energy Functional: $J_c+\lambda_d J_d+\lambda_T J_T$

- J_c: Correlation error (aligns folding patterns)
- J_d: Metric distortion (constrains allowable shape differences)
- J_T: Topology term (forces mapping to be invertible)

How does one pick value of λ_d?

Spherical Morphing: Equations

Average Folding Pattern:

$$\bar{C}(\varphi,\theta) = \frac{1}{N}\sum_{i=1}^{N} C_i(\varphi,\theta)$$

Variance of Folding

$$\sigma^2(\varphi,\theta) = \frac{1}{N-1}\sum_{i=1}^{N} (C_i(\varphi,\theta) - \bar{C}(\varphi,\theta))^2$$

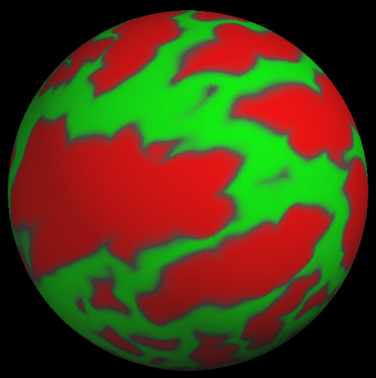
Maximum Likelihood Term:

$$J_c = \frac{1}{2V}\sum_{v=1}^{V} \left(\frac{G_\alpha * (C_v - \bar{C}(\phi(v),\theta(v)))}{\sigma(\phi(v),\theta(v))}\right)^2$$

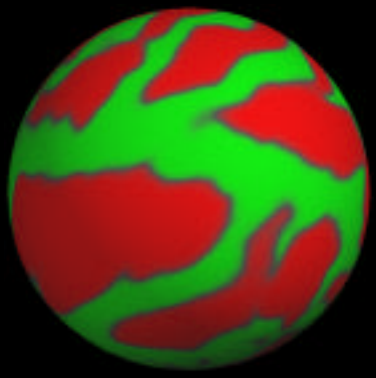
Complete Energy Functional:

$$J = J_c + \lambda_T J_T + \lambda_d J_d$$

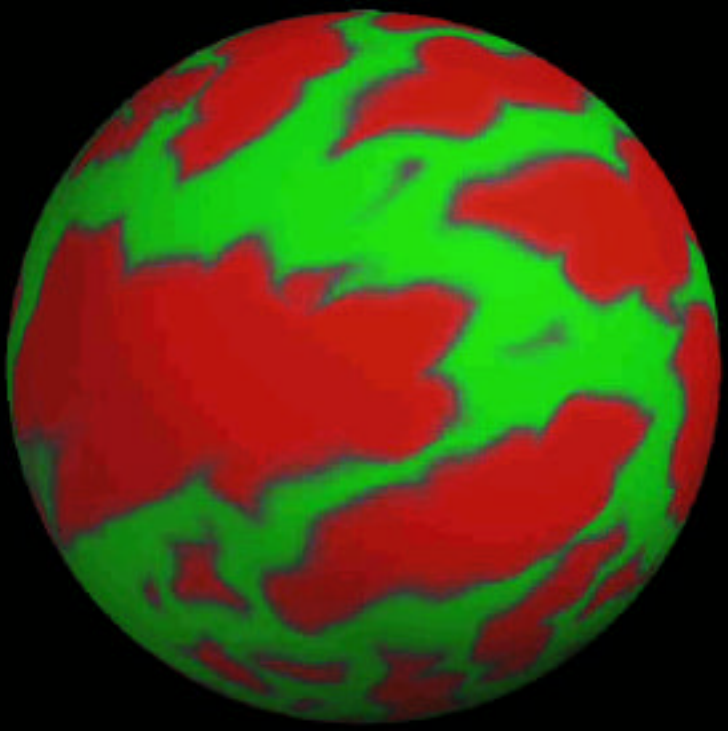
Inter-Subject Morphing



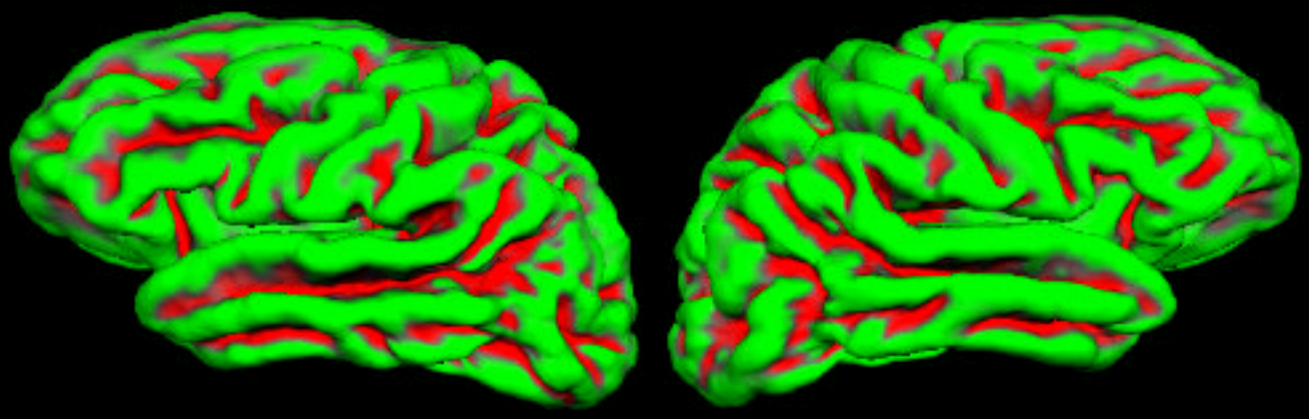
Individual Subject



Average (Target)



Surface-Based Averaging



Average surface created from 30 subjects

Applications

- Increased statistical power for inter-subject averaging
- Automatic functional/anatomical labeling
- Inter-subject averaging of morphometric properties
- Statistical analysis of morphometric properties
  - aging
  - neurodegenerative diseases
  - longitudinal studies of structural changes
  - hemispheric asymmetry

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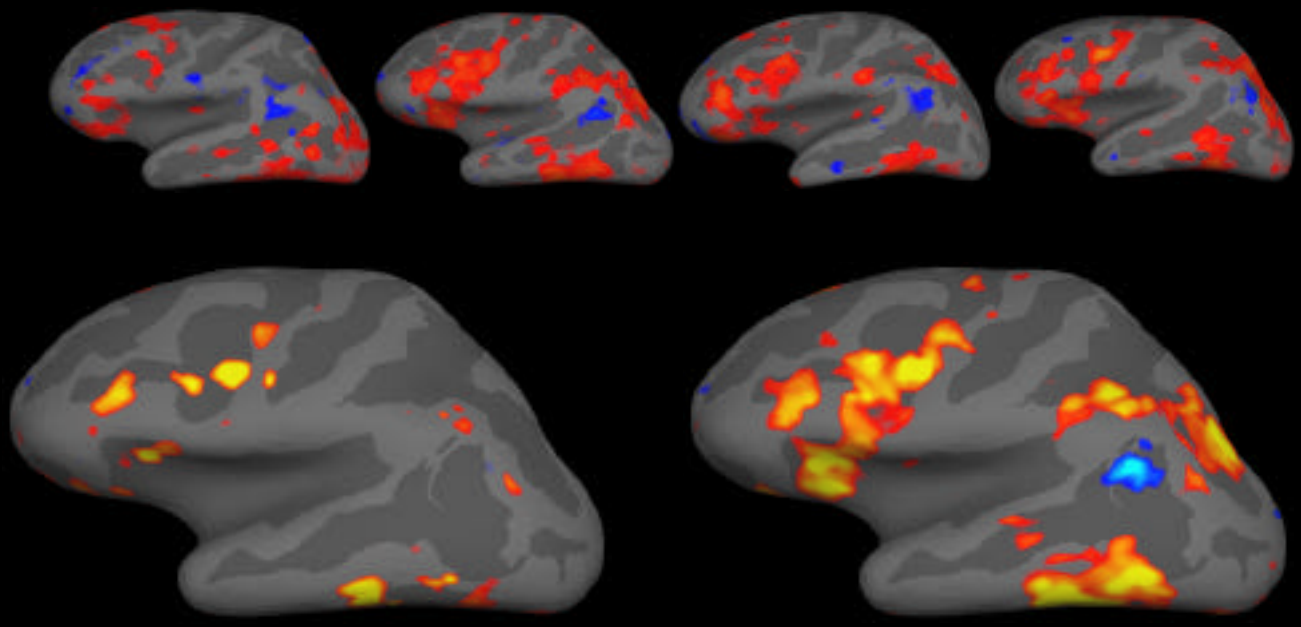
Inter-Subject Averaging of Activations



Talairach Average

Spherical Average

Applications

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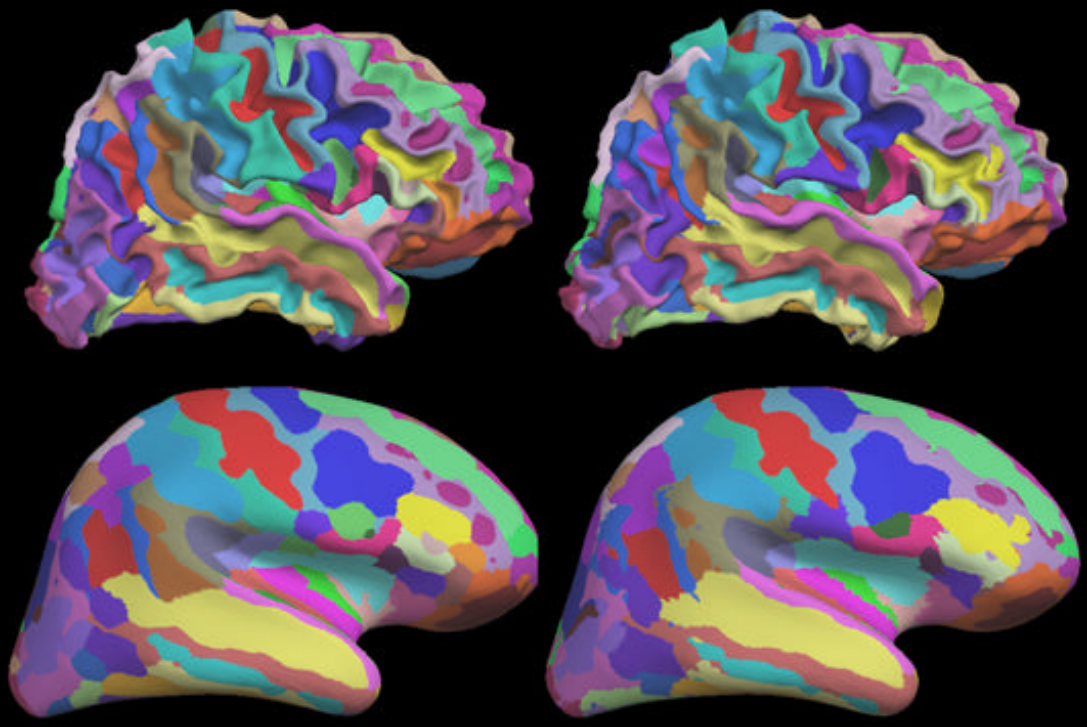
Cortical Parcellation: Manual vs. Automated



Manual Parcellation Automatic Parcellation

Thanks to Christophe Destrieux for this slide.

Applications

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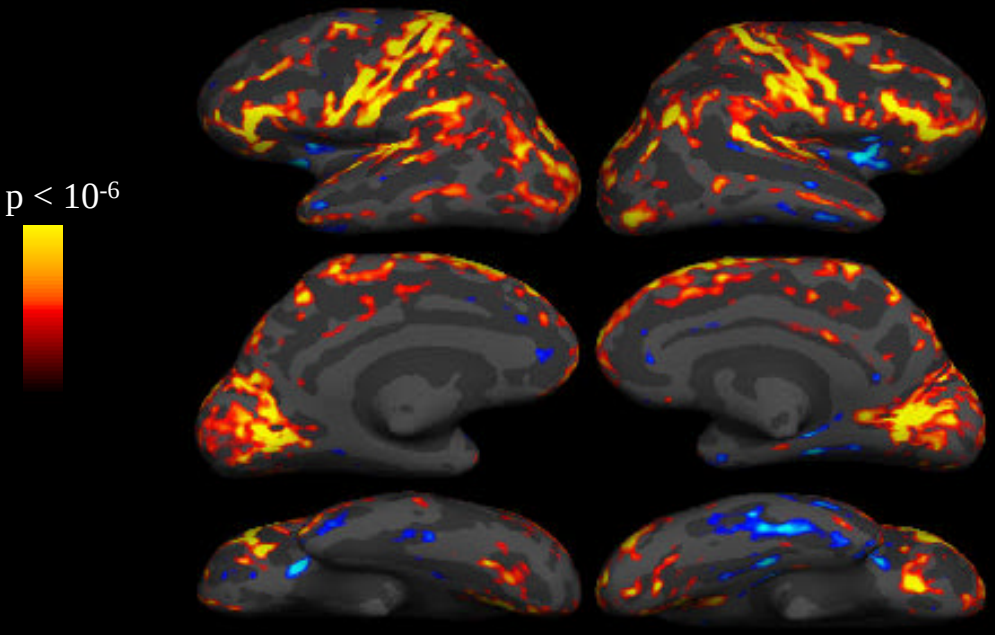
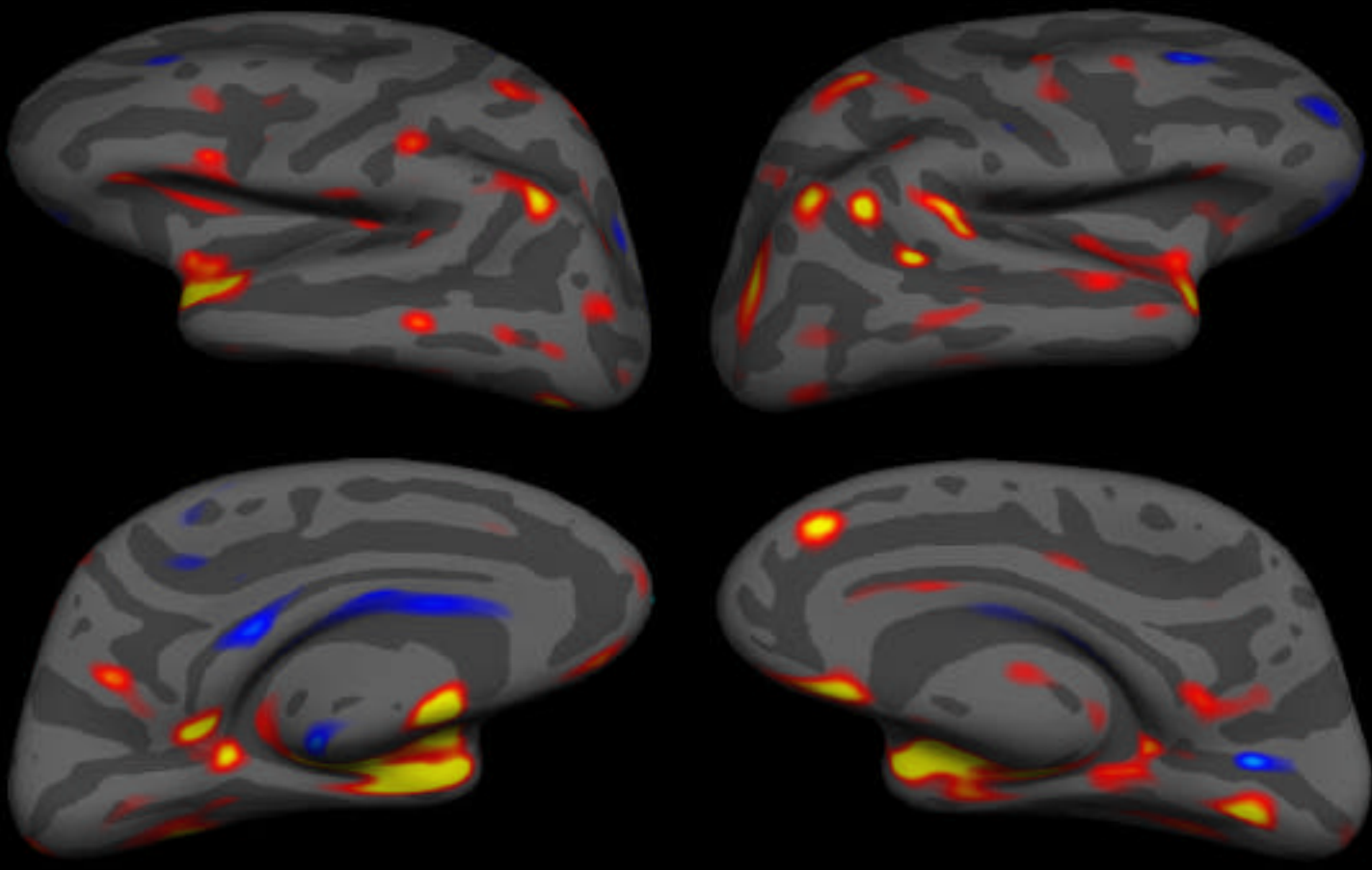
Statistical Map of Cortical Thinning: Aging



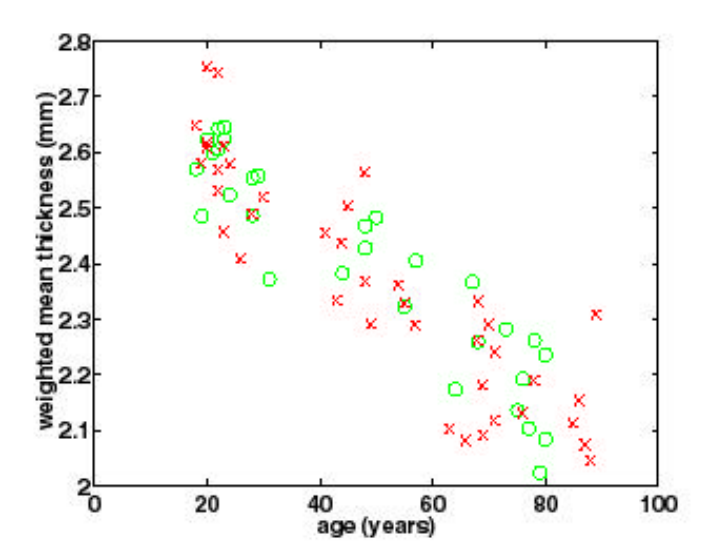
Thanks to Drs. Randy Buckner and David Salat for supplying this slide.

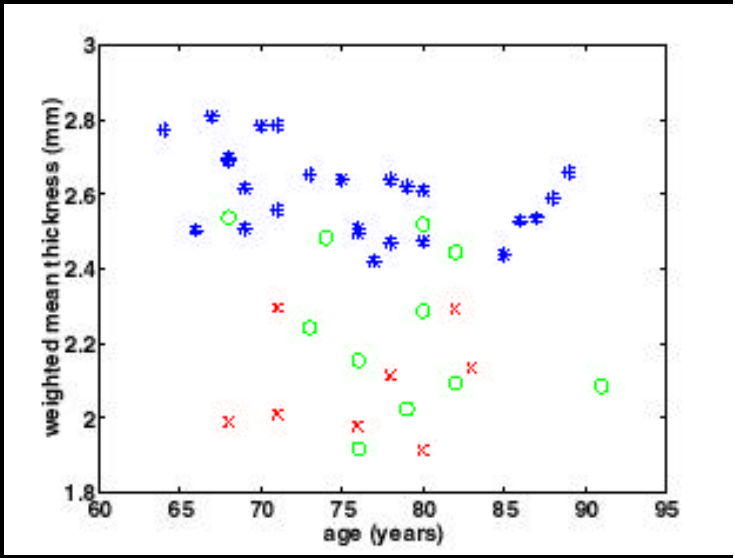
Cortical Thickness AD vs. Controls



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

Cortical Thinning with Aging and AD





Thanks to Anders Dale for this slide.

Data Courtesy of Randy Buckner, WUSTL

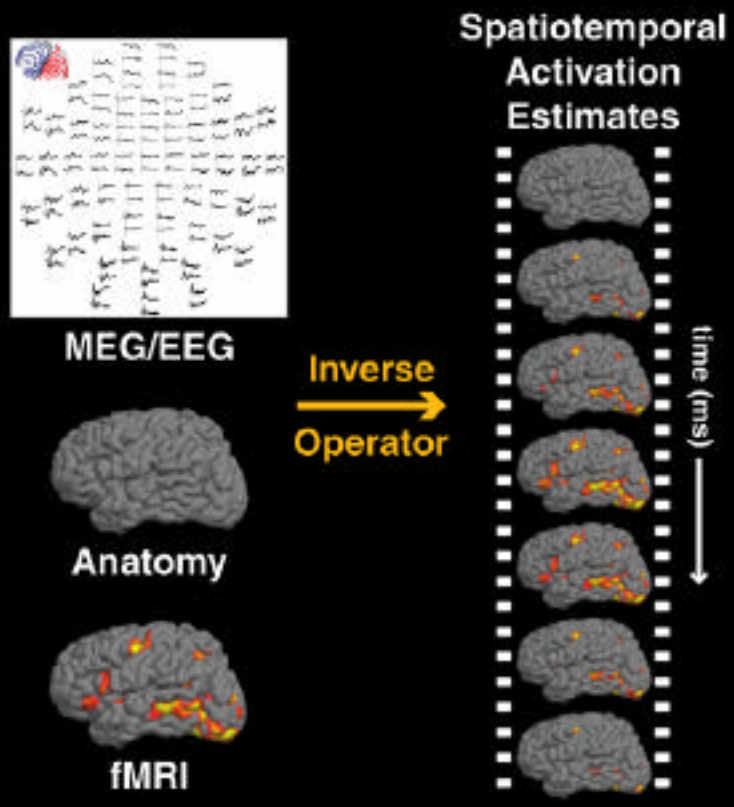
Multi-Modality Integration

How to infer the distribution of currents in the brain that gave rise to a measured electromagnetic field (EEG or MEG)?

Problem: measuring hundreds of variables and trying to solve for potentially millions – ill-posed (need constraints).

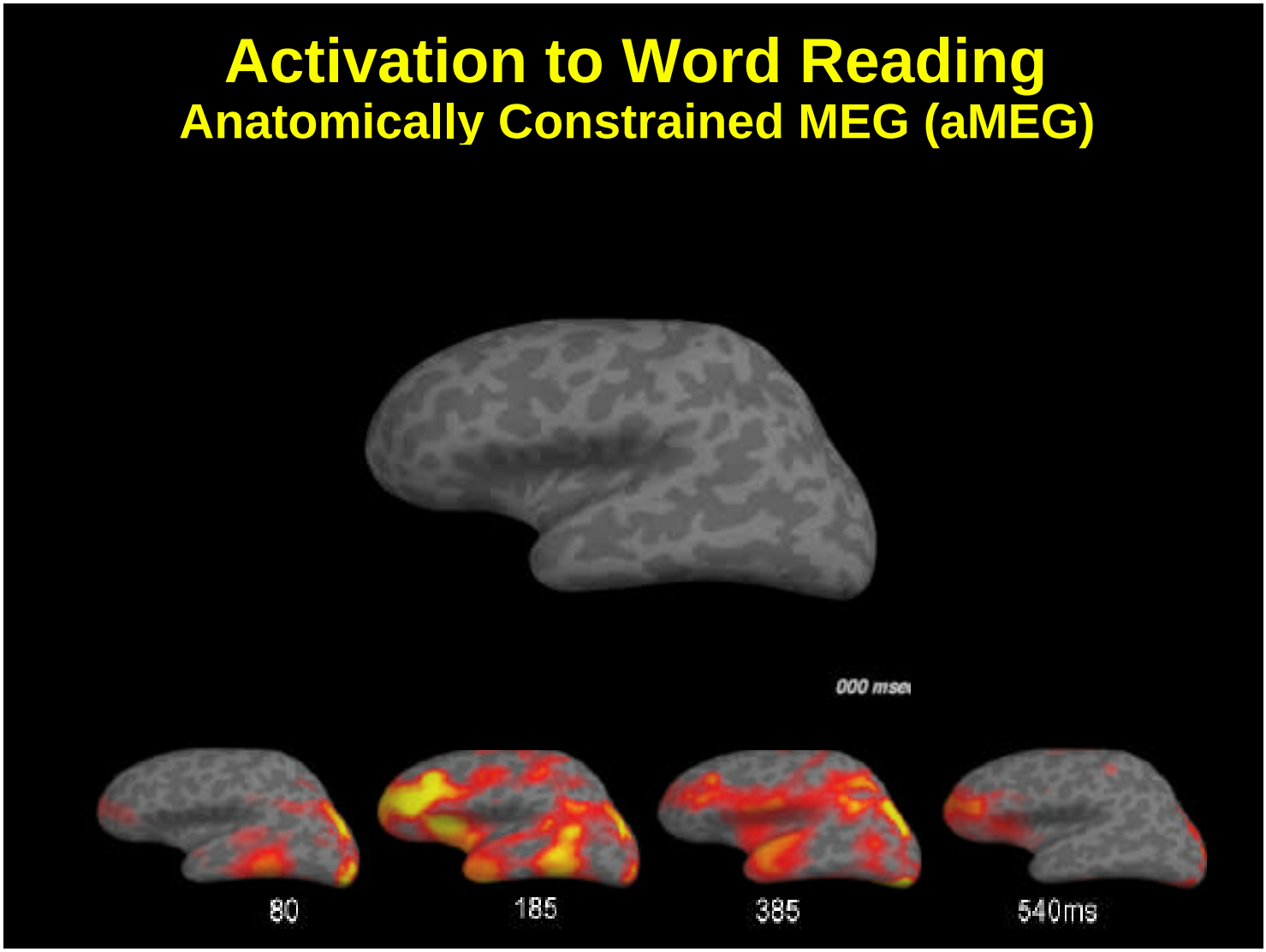
One solution (Dale and Sereno, 1993) – assume majority of signal comes from pyramidal neurons in cortex. If one has a cortical model, then position and orientation of sources is known and the problem becomes linear.

Multi-Modality Integration

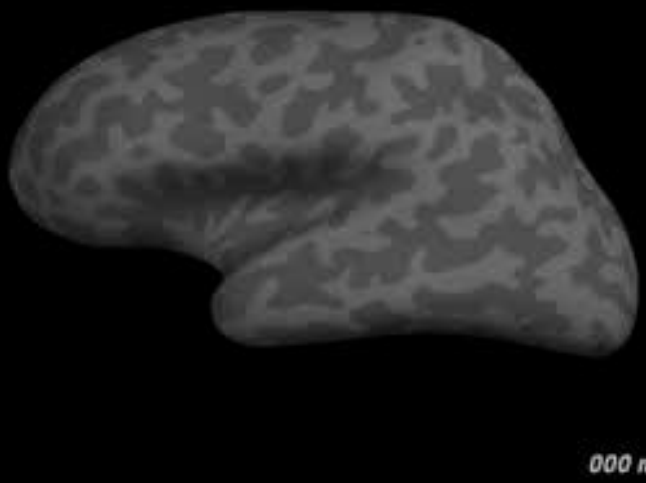


Thanks to Drs. Anders Dale and Arthur Liu for supplying the next 3 slides

Activation to Word Reading
Anatomically Constrained MEG (aMEG)



Sequence of Activation to Word Repetition: Anatomically and fMRI (fMEG) Constrained MEG



Thanks to Drs. Anders Dale, Eric Halgren and Arthur Liu for supplying this slide

Talk Outline

- The Spatial Structure of Retinotopic Cortex.
- Cortical Analysis.
- Subcortical Analysis.

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Whole-Brain Segmentation

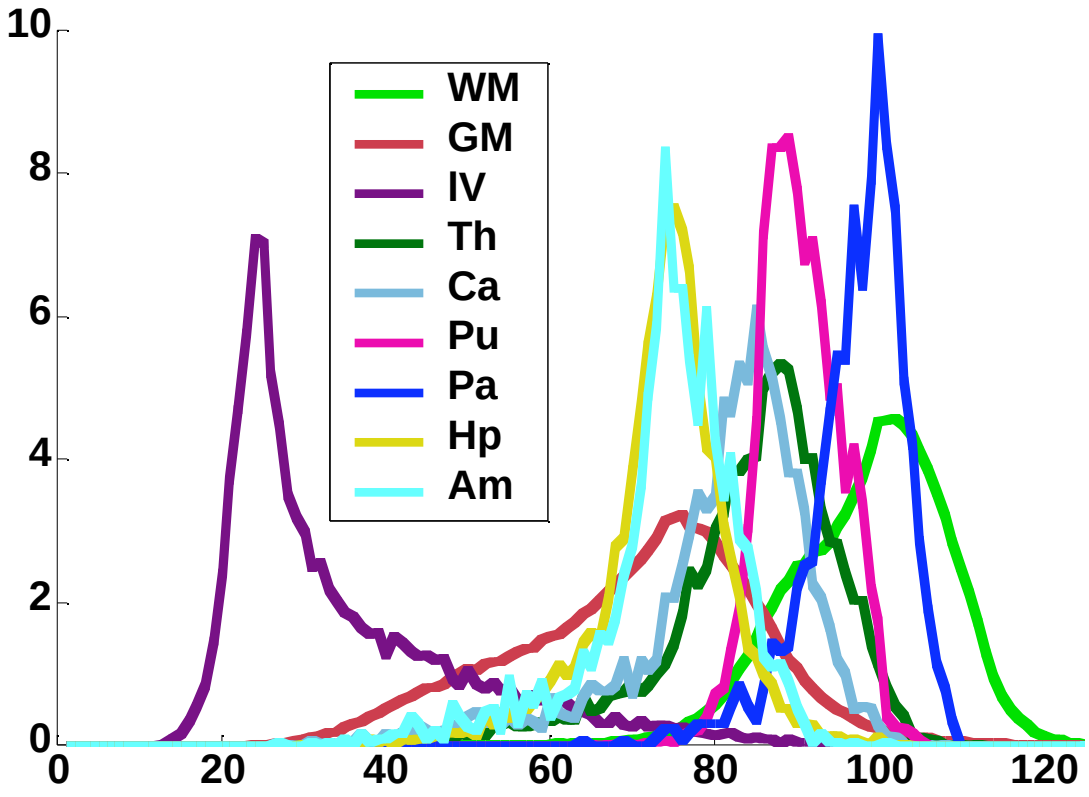
Goal: Segment T1-weighted MRI into anatomically and semantically meaningful structures (e.g. caudate, putamen, etc…).

Requirements:

- Insensitive to pathology.
- Insensitive to varying pulse sequences.

Prerequisite: registration with anatomically meaningful space (e.g. Talairach)

Why Segmentation is Hard!



Some Definitions Revisited

p(I|C) is called the ***likelihood*** of the image given the classification. Since ***p(I|C)*** is frequently assumed to be Gaussian in form, the log of the likelihood is commonly used.

The classification ***C*** that maximizes ***p(C|I)*** is called the ***maximum a posteriori*** (MAP) estimate of ***C***.

The classification ***C*** that maximizes ***p(I|C)*** is called the ***maximum likelihood*** estimate (MLE) of ***C***.

How can we compute the MAP estimate of C?

Bayes Rule

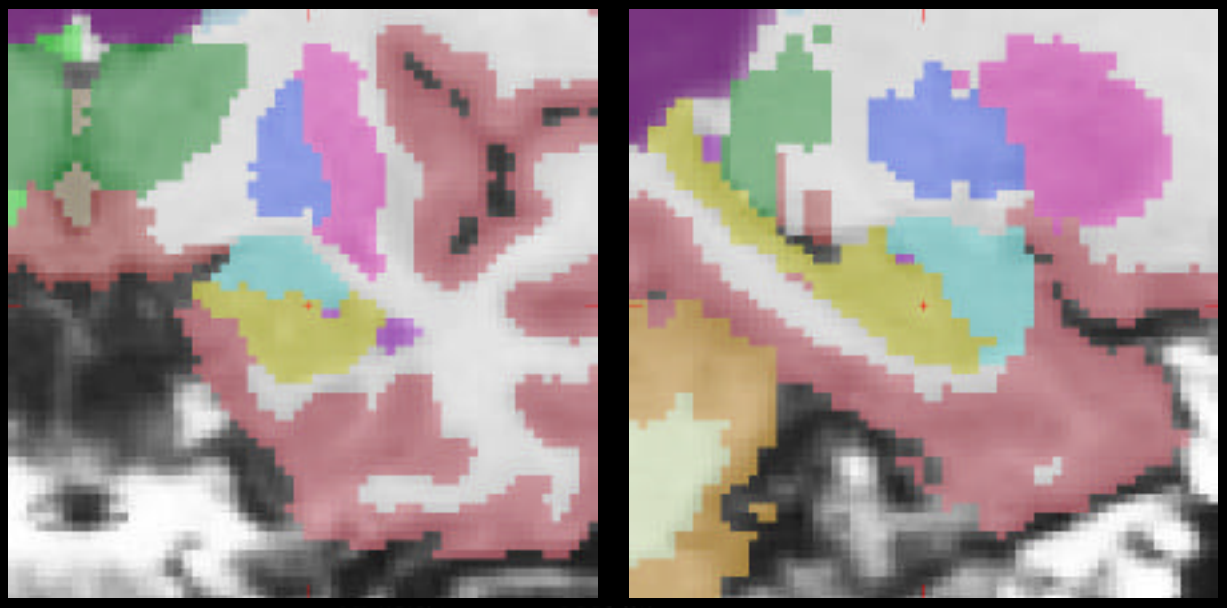
What is the most likely classification ***C*** of an image ***I***, given some prior information we have about what kinds of classifications are allowable (***p(C)***) and a model for how an image is formed? That is, what is the ***C*** that maximizes ***p(C|I)*** (I.e. what is the MAP estimate)?

$$p(I,C) = p(I \mid C)\,p(C) = p(C,I) = p(C \mid I)\,p(I)$$

Thus

$$p(C \mid I) = \frac{p(I \mid C)\,p(C)}{\cancel{p(I)}}$$

Segmentation Results: CMA Labeling



- Cerebellar cortex
- Cerebellar WM
- 4th ventricle
- RH cerebral WM
- LH cerebral WM
- Hippocampus
- LH pallidum
- Thalamus
- Cerebral cortex
- Misc.
- Lateral ventricle
- Caudate
- Amygdala

Tissue Segmentation

Given a transform *L* into an atlas space, *C* can be estimated using a Maximum a Posteriori (MAP) approach: what is the most likely tissue classification *C* given the observed image *I* , the transformation *L*, and prior information about *C*?

$$C = \arg\max_{C'} p(C' \mid I, L)$$

$$p(C' \mid I, L) \sim p(I \mid C', L)\, p(C')$$

Tissue Segmentation

The probability distribution of each voxel is modeled as an independent *nonstationary* Gaussian (because it is a function of ***r***):

$$p(I \mid \mathbf{L}, C) = \prod_{\mathbf{r} \in R} p(I(\mathbf{r}) \mid \mathbf{L}, C(\mathbf{r}), \mathbf{r})$$

Forward Model of Image Formation:

$$p(I(\mathbf{r}) \mid \mathbf{L}, C(\mathbf{r}) = c, \mathbf{r}) = \frac{1}{\sigma_c(L\mathbf{r})\sqrt{2\pi}} \exp\left(-\frac{(I(\mathbf{r}) - \mu_c(L\mathbf{r}))^2}{\sigma_c(L\mathbf{r})^2}\right)$$

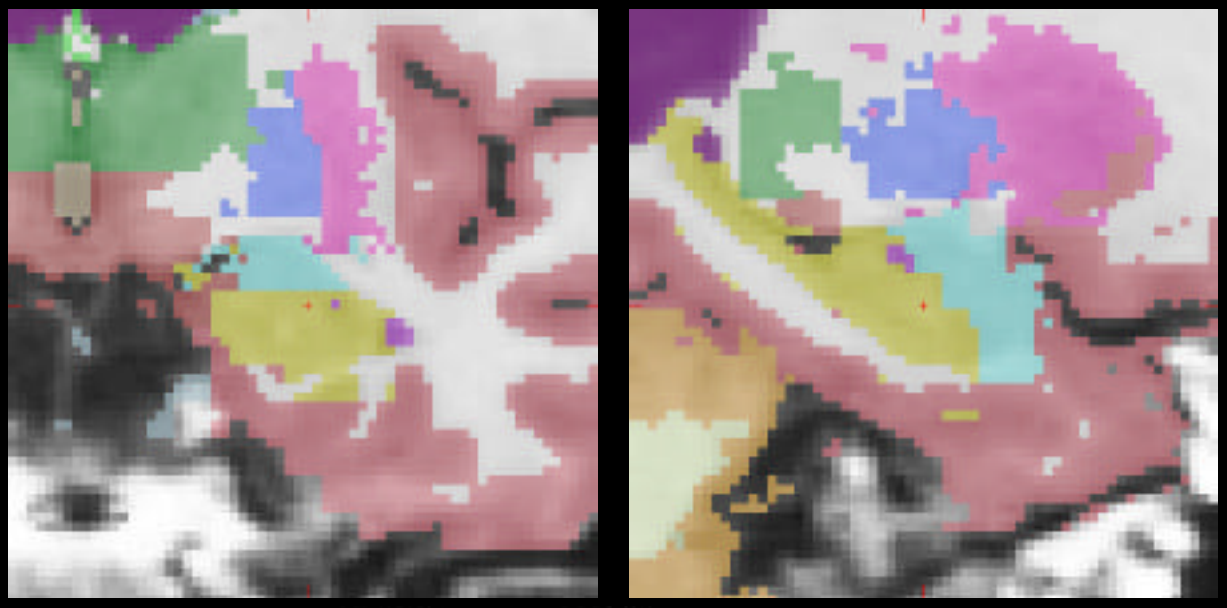
Segmentation: Independent Spatial Priors

If the probability distribution of the labels is assumed to be spatially independent, the probability of a segmentation C can be expressed as:

$$p(C) = \prod_{\mathbf{r} \in R} p(C(\mathbf{r}) \mid \mathbf{r})$$

$$p(C(\boldsymbol{r}) \mid \boldsymbol{r}) = \frac{\#\text{ of times class } C(\boldsymbol{r}) \text{ occurred at location } \boldsymbol{r}}{\#\text{ of times any class occurred at } \boldsymbol{r}}$$

Segmentation Results: Independent Spatial Priors



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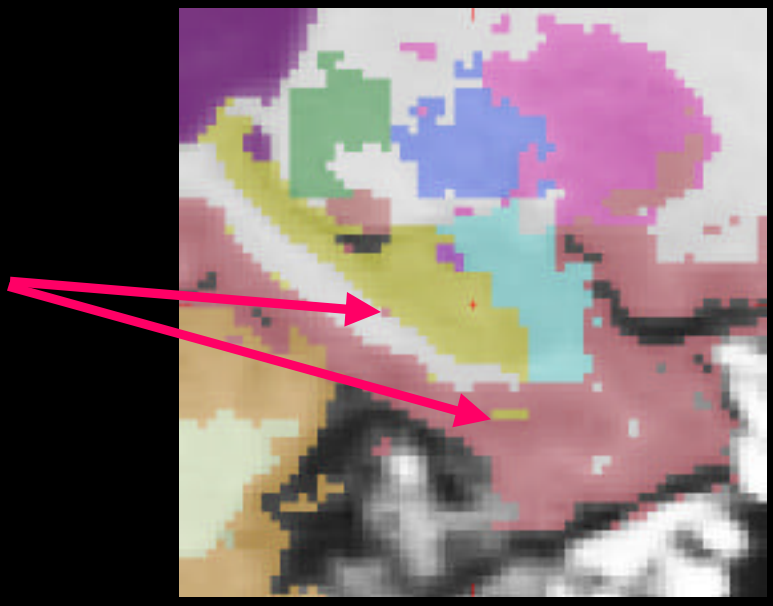
Gibbs Priors: Motivation

What is the probability that cortical gray matter occurs inferior to hippocampus?



Markov Random Fields

Modeling the segmentation as a *Markov Random Field (MRF)* means:

$$p(C(\mathbf{r}) \mid \text{the rest of the labels}) = p(C(\mathbf{r}) \mid \text{the labels in a neighborhood around } \mathbf{r})$$

Modeling the segmentation as an MRF means we can express the prior probabilities using a *Gibbs distribution*

(don't worry too much about this)

Segmentation: Gibbs Priors

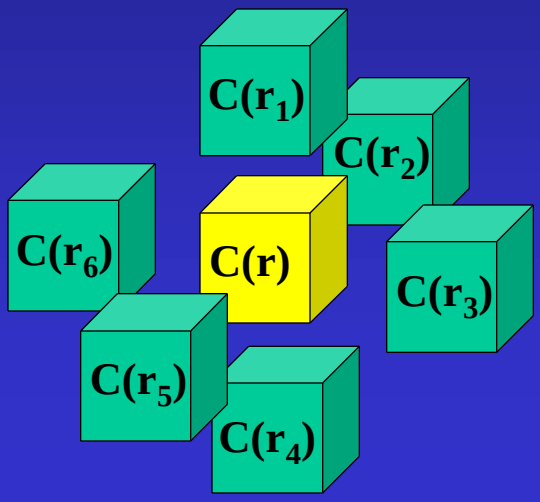
Problem: the segmentation is fractured because no spatial smoothness constraints are encoded in model.

Solution: incorporate prior probability of one tissue class being the neighbor of another into model:

$$p(C) \prod_{\mathbf{r} \in R} p(C(\mathbf{r}) \mid \mathbf{r}) \prod_{\mathbf{r}_i \in N(\mathbf{r})} p(C(\mathbf{r}_i) \mid C(\mathbf{r}), i, \mathbf{r}, \mathbf{r}_i)$$

Segmentation: Gibbs Priors

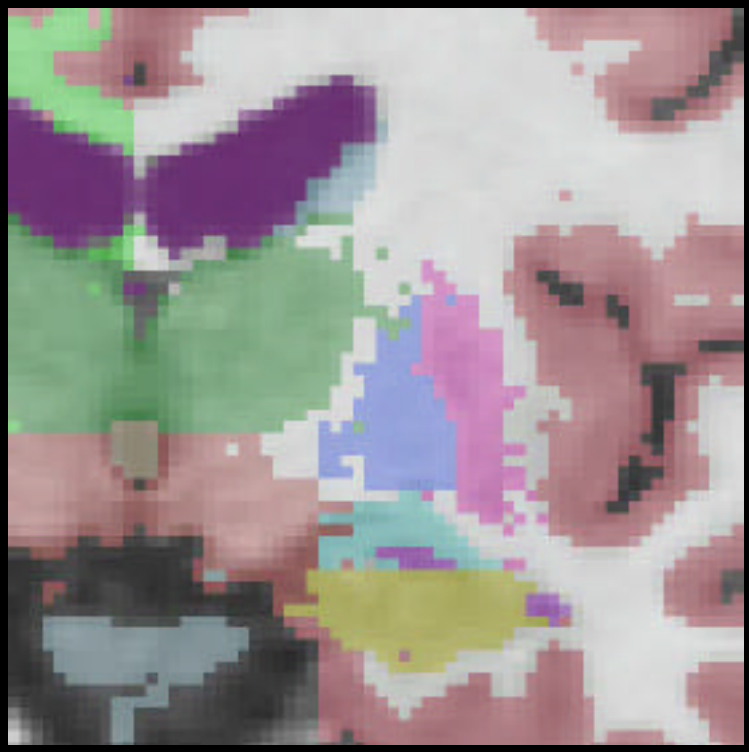
$p(\mathrm{C}(\boldsymbol{r}_i)|C(\boldsymbol{r}), I, \boldsymbol{r},\boldsymbol{r}_i)$ encodes the probability that tissue class $\mathrm{C}(\boldsymbol{r}_i)$ occurs at spatial location r_i when tissue class $C(\boldsymbol{r})$ occurred at $\boldsymbol{r}$. The segmentation is thus modeled as an *anisotropic* nonstationary *Markov Random Field (MRF)*.



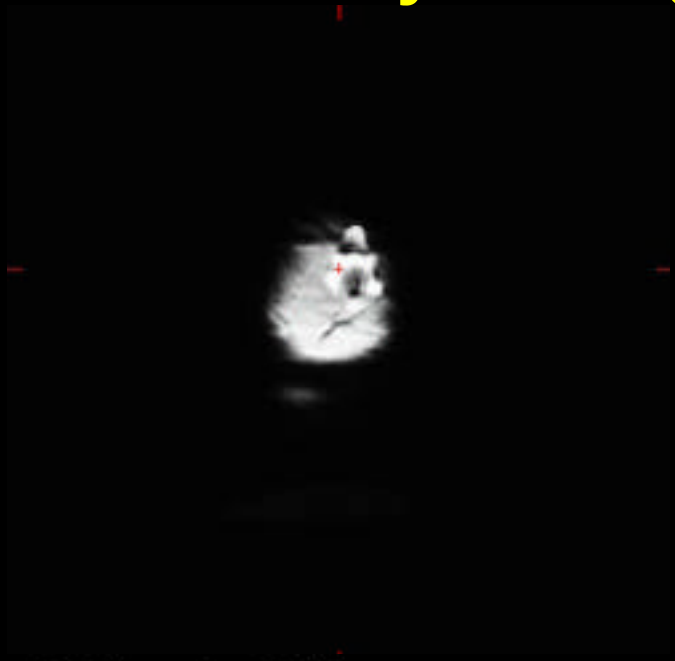
Segmentation: Gibbs Priors

Preliminary Segmentation

Final Segmentation



Segmentation with Gibbs Priors: Fly Through



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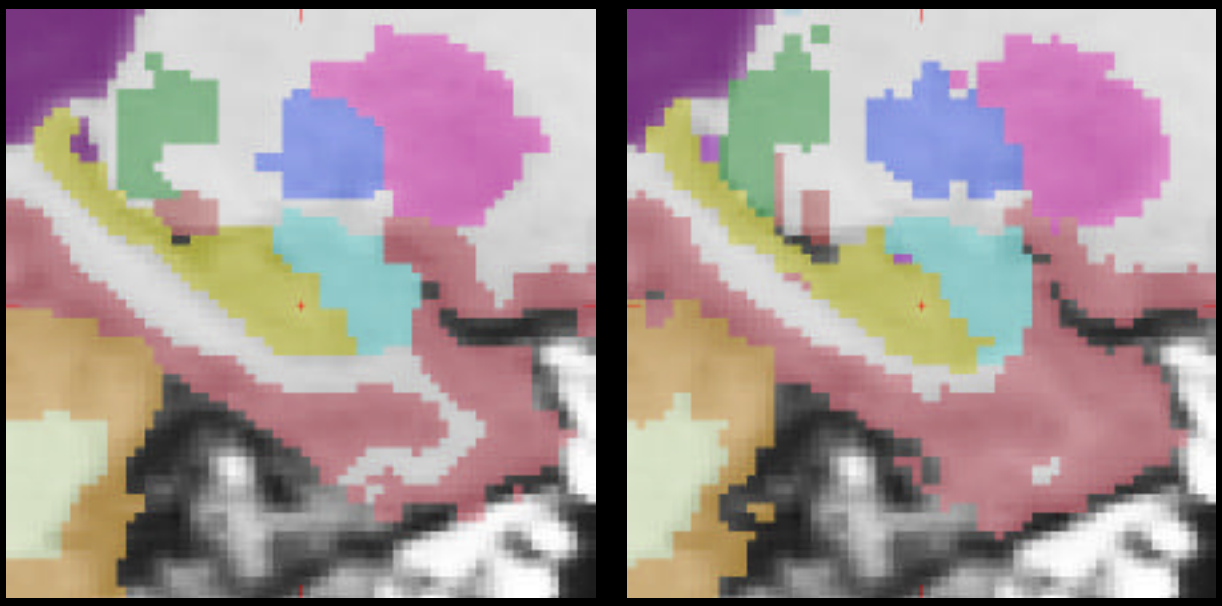
4th ventricle
RH cerebral WM
LH cerebral WM
Hippocampus
LH pallidum
Thalamus
Cerebral cortex
Misc.
Lateral ventricle
Caudate
Amygdala

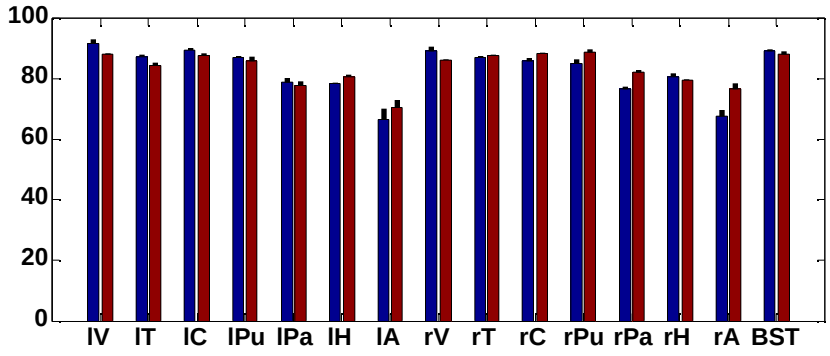
Segmentation Comparision: Automated vs. Manual



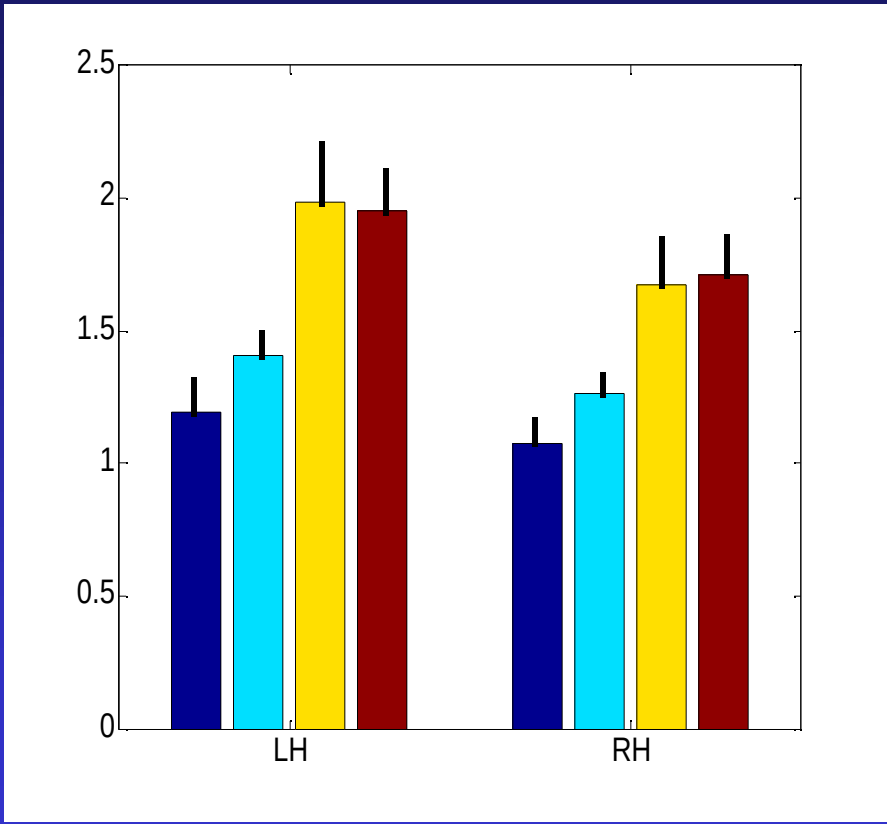
Automatic Manual

Manual (red) vs Automated (blue)

%Volume Difference %Volume Overlap

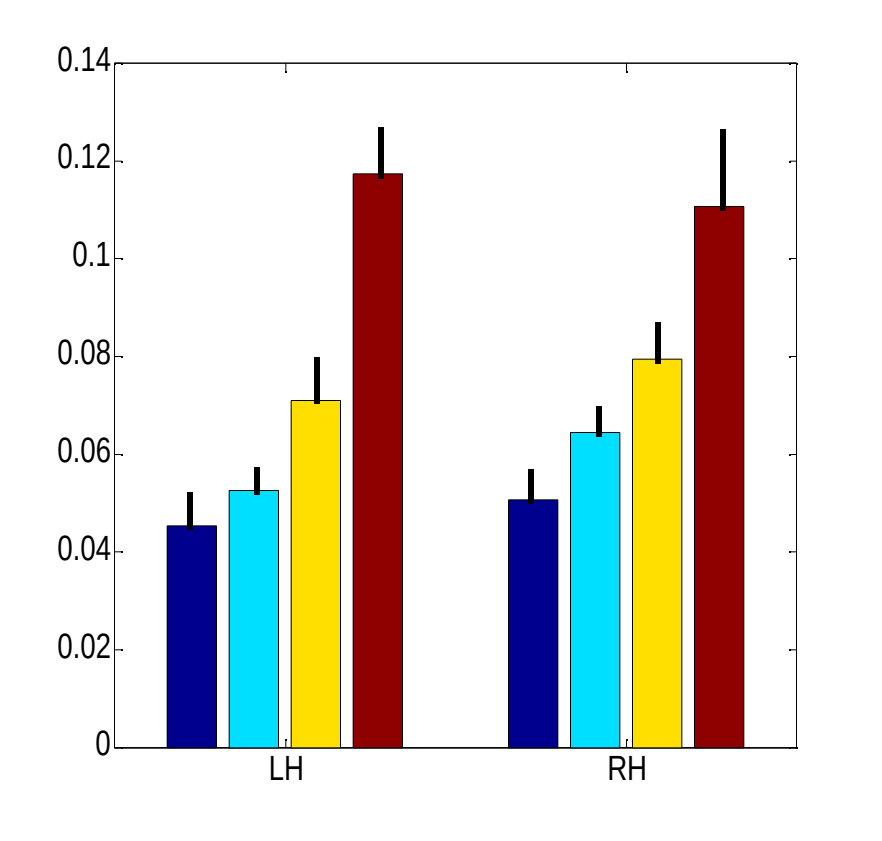


Results: Ventricular Volume



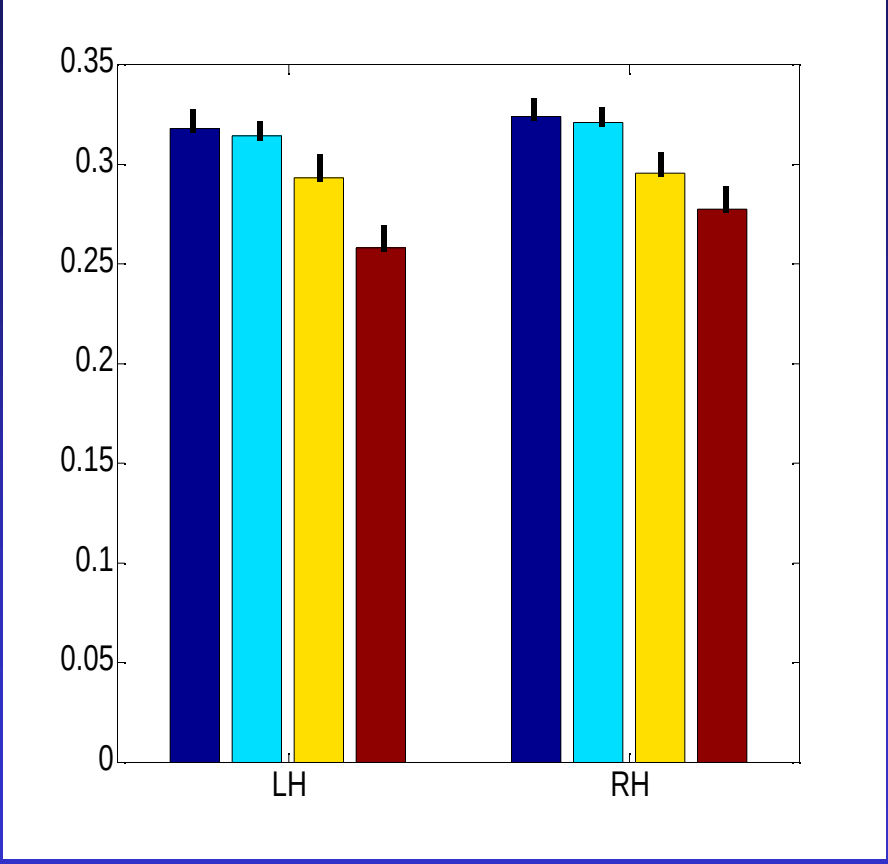
Data courtesy of Dr. Marilyn Albert

Results: Temporal Horn of Ven.



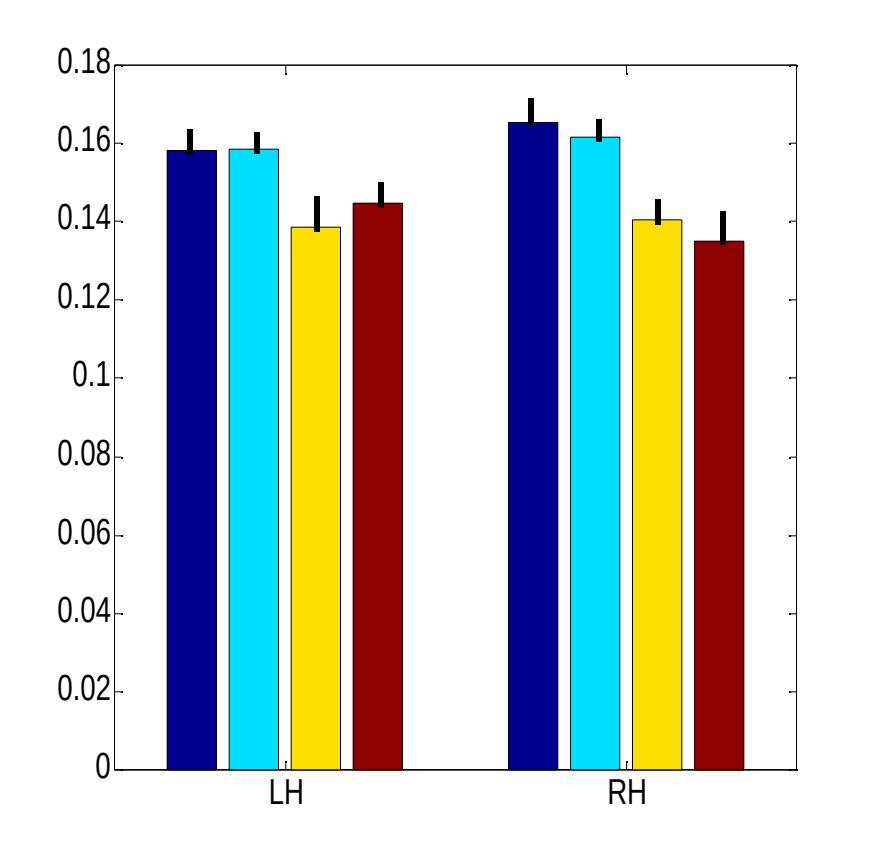
Data courtesy of Dr Marilyn Albert

Results: Hippocampal Volume



Data courtesy of Dr Marilyn Albert

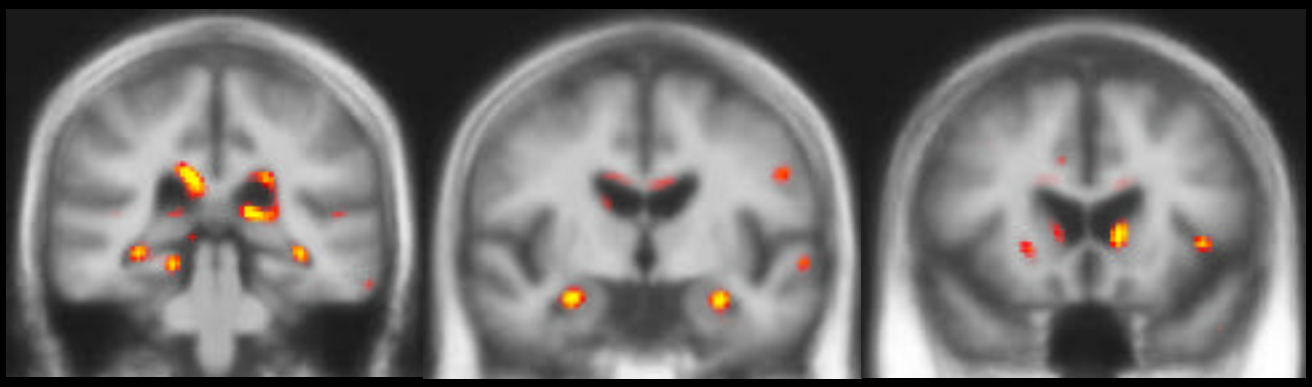
Results: Amygdala Volume



Data courtesy of Dr. Marilyn Albert

AD vs. Normal: Statistical Map*

25 controls vs 17 probable AD



POSTERIOR MID ANTERIOR

$p<10^{-4}$

Data courtesy of Dr. Marilyn Albert

Pulse sequence independence

Forward model of image formation (solution of SPGR/FLASH Bloch equations):

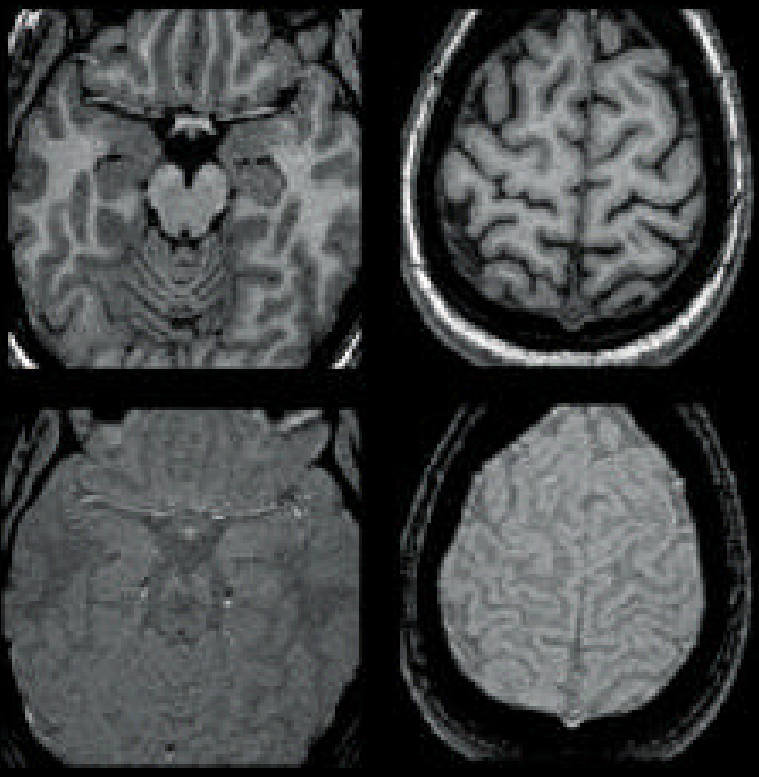
$$S(TR, TE, \alpha, T_1, T_2, P) = P \sin\alpha \left(\frac{1 - e^{-TR/T_1}}{1 - \cos\alpha e^{-TR/T_1}}\right) e^{-TE/T_2}$$

Varying acquisition parameters (*TR*, *TE*, α) allows the maximum likelihood estimation of intrinsic tissue parameters.

FLASH data

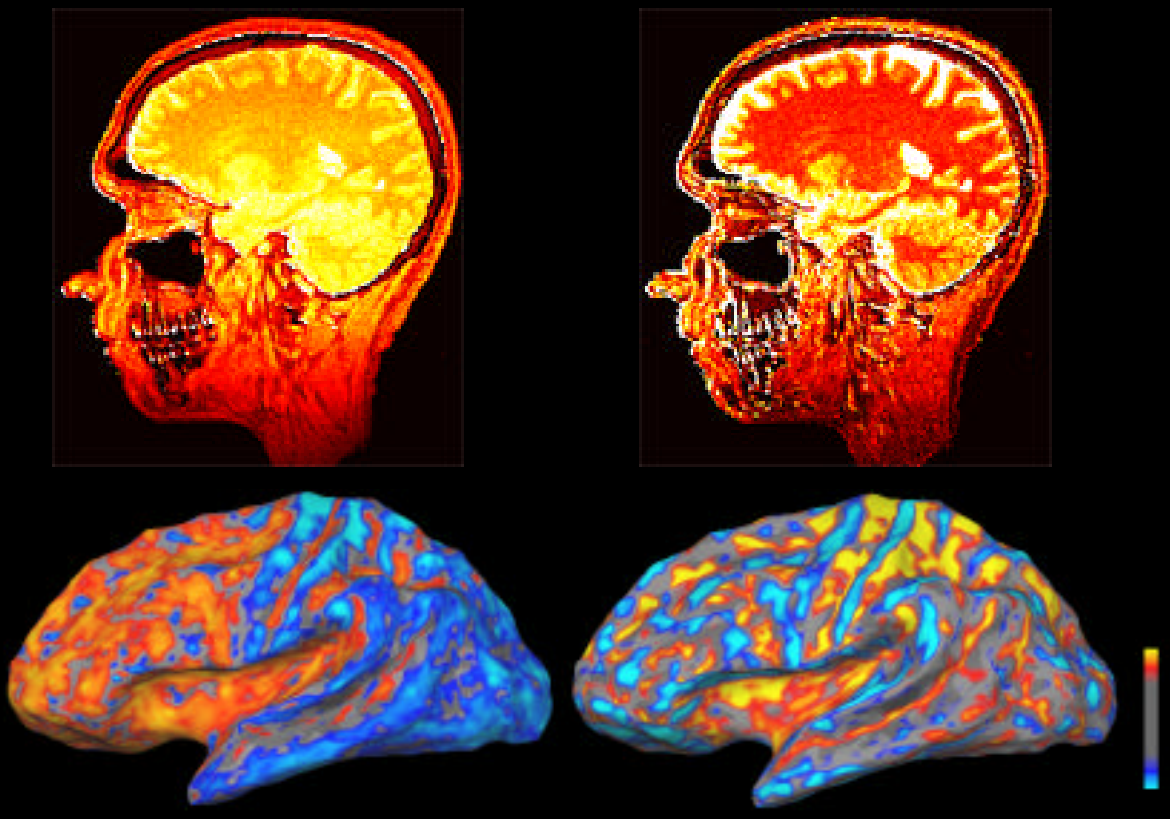
$\alpha=30^{o}$ (T_1-weighted)

$\alpha=5^{o}$ (PD-weighted)



Inferior Superior

Tissue Parameter Mapping



Proton Density T_1

Tissue Parameter Mapping