Joint Segmentation of Image Ensembles via Latent Atlases

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Joint work with **Koen Van Leemput**
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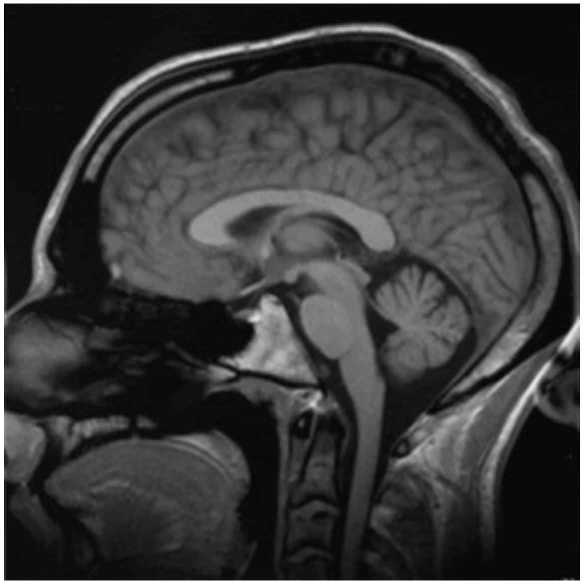
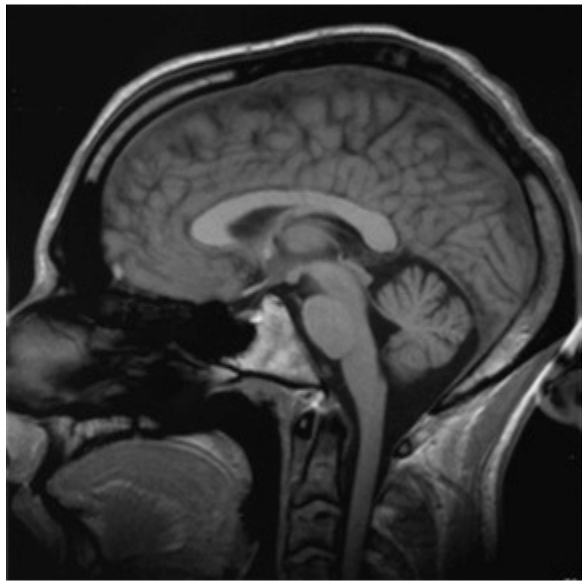
William M. Wells
Polina Golland

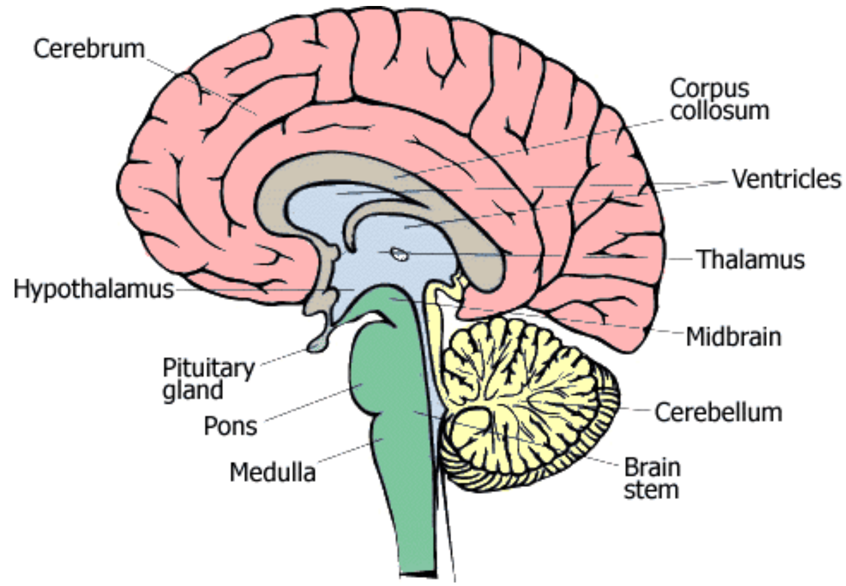
CSAIL

Segmentation of MR Brain Scans



Segmentation of MR Brain Scans





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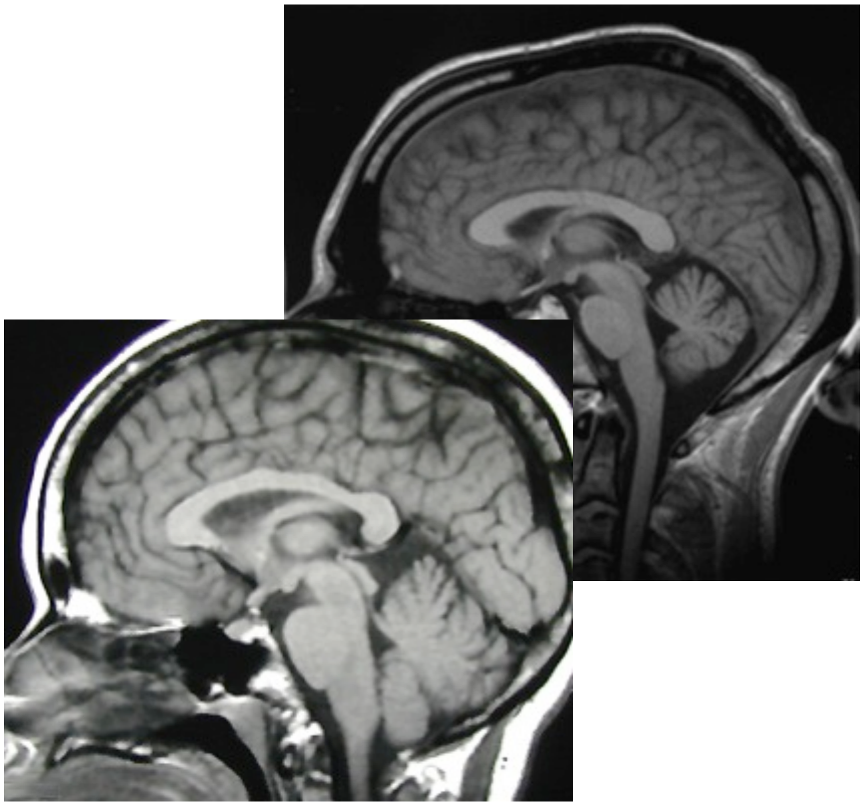

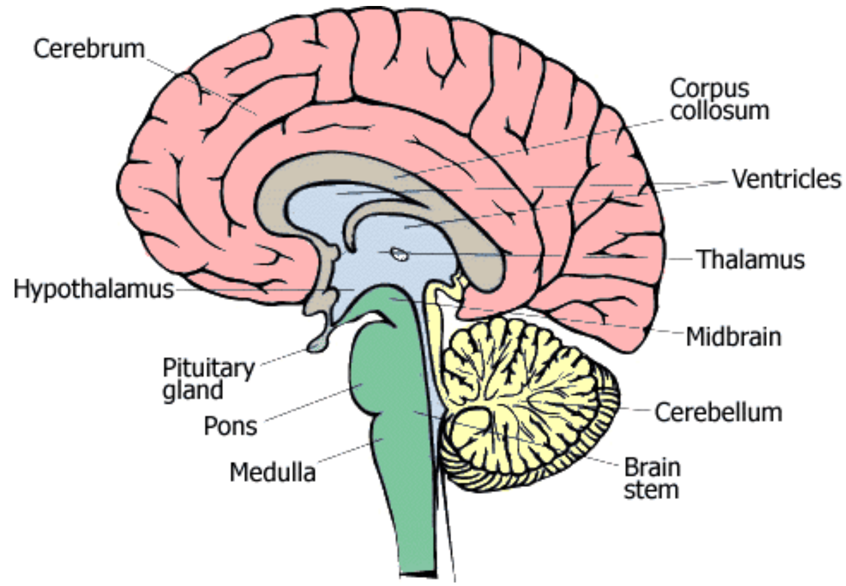

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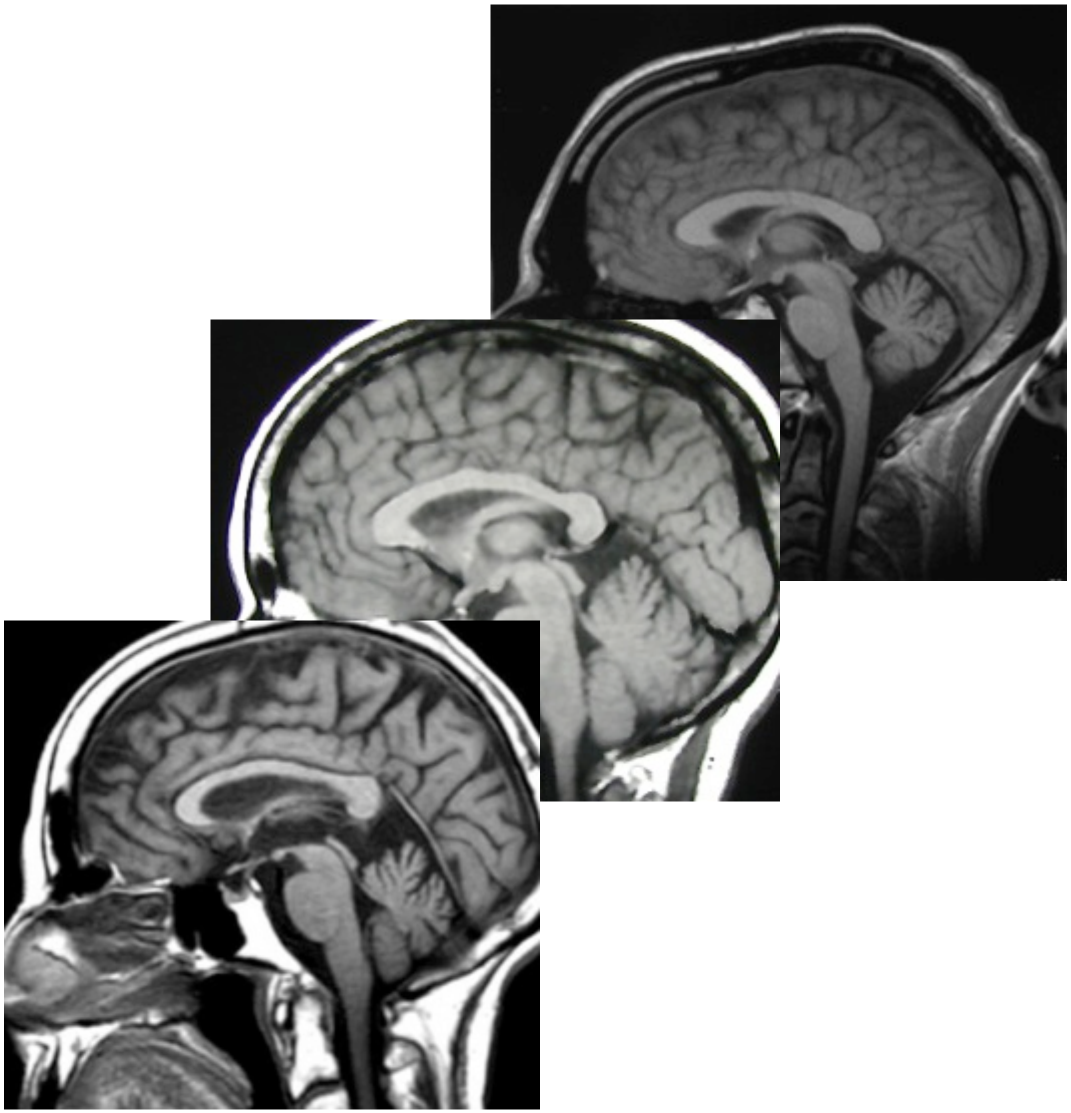

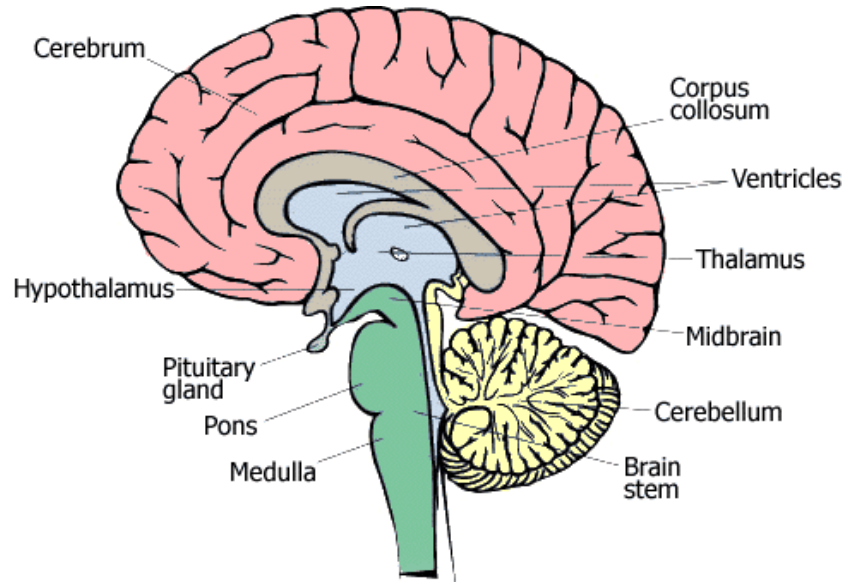

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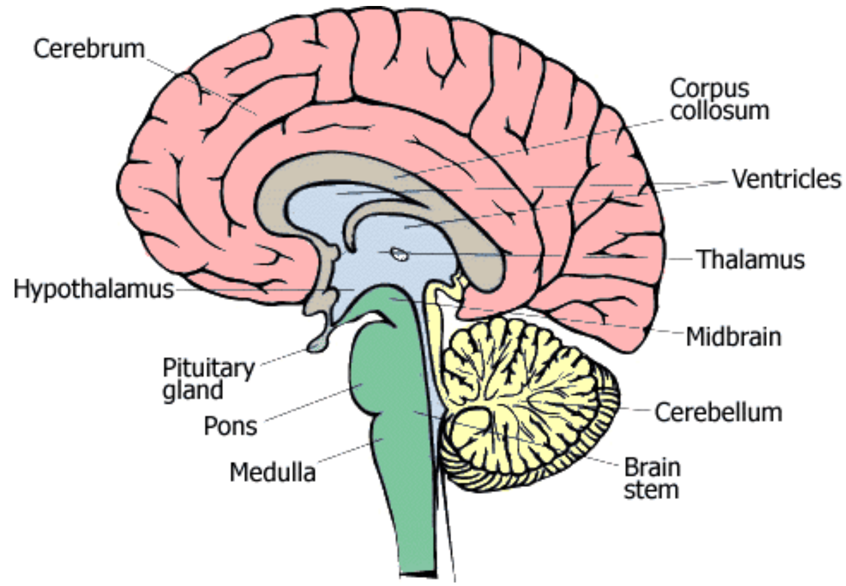

- **Bottom up information:**
  image intensities
- **Top down information:**
  Group: spatial probabilities
  other priors

Atlas based Segmentation

Probabilistic atlas (spatial prior) is obtained by averaging manual segmentations of a population.

Classical approaches

[1] J. Ashburner and K. Friston, Neuroimage 05

[2] B. Fischl *et al*., Neuron 02

[3] K. Pohl *et al.*, Neuroimage 06

[4] K. Van Leemput *et al.,* IEEE TMI 99

Why not Use an Atlas?

✧**Availability** - manual segmentation is laborious.

✧**Compatibility** - e.g. lower resolution

✧**Specificity** - pathologies, pediatric

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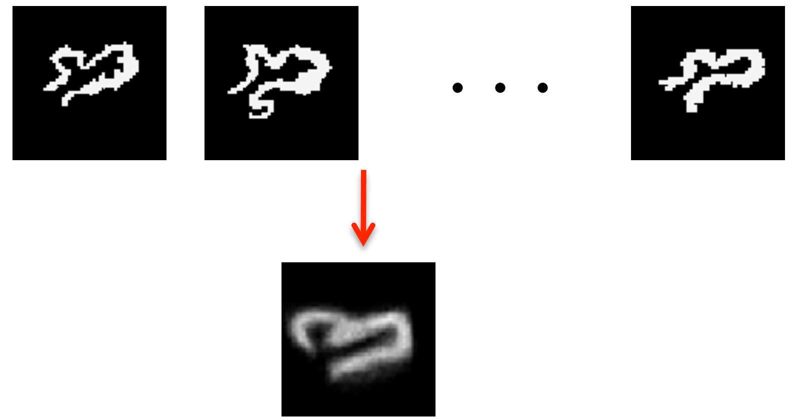
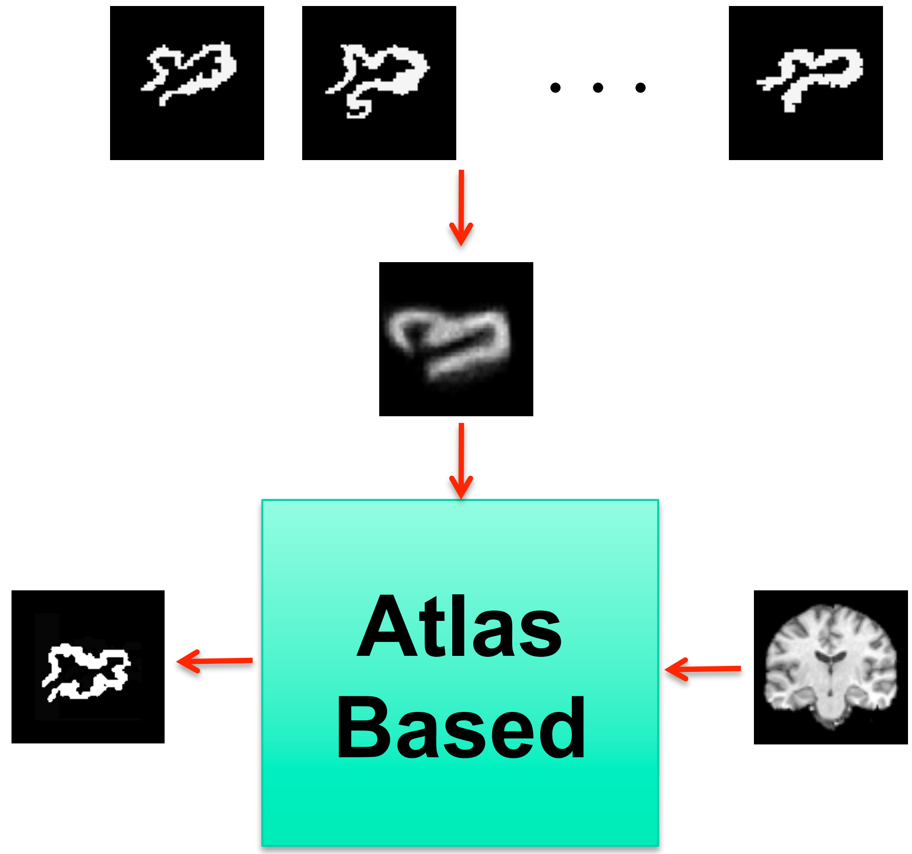
[1] Bhatia et al., MICCAI 07
[2] N.A. Lord, J. Ho, and B.C. Vemuri, ICCV 07

Latent Atlas vs. Known Atlas



Latent Atlas vs. Known Atlas



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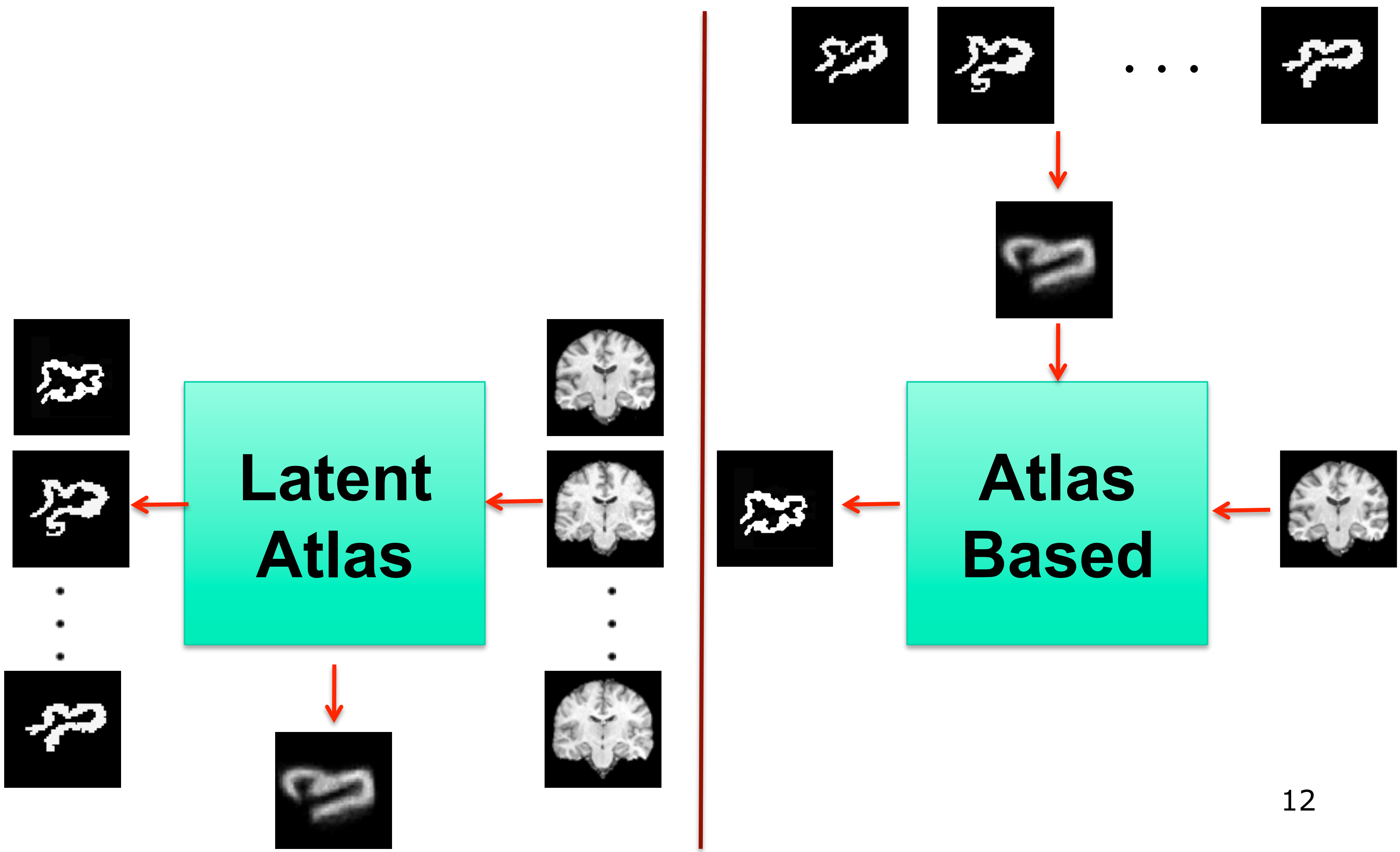

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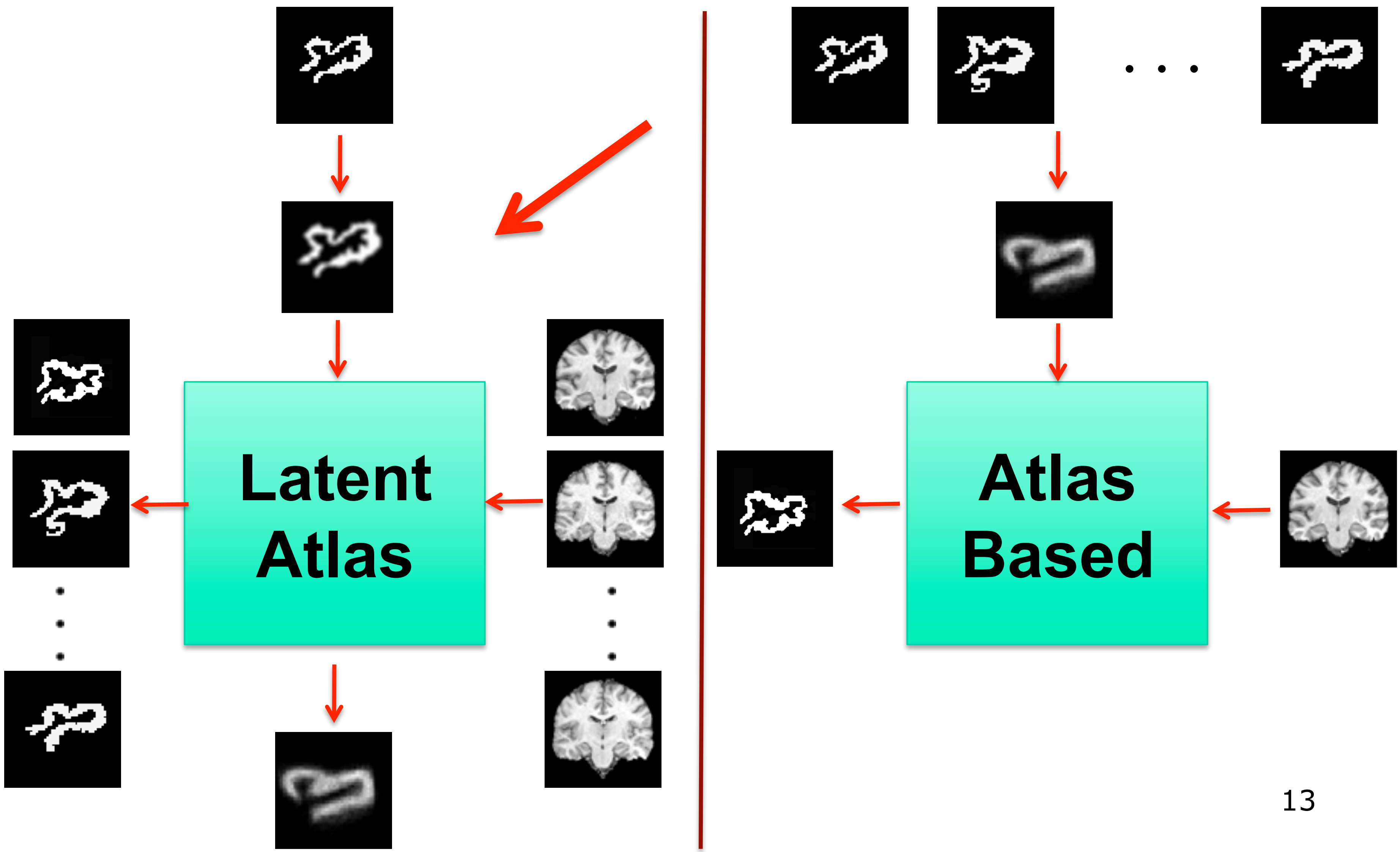
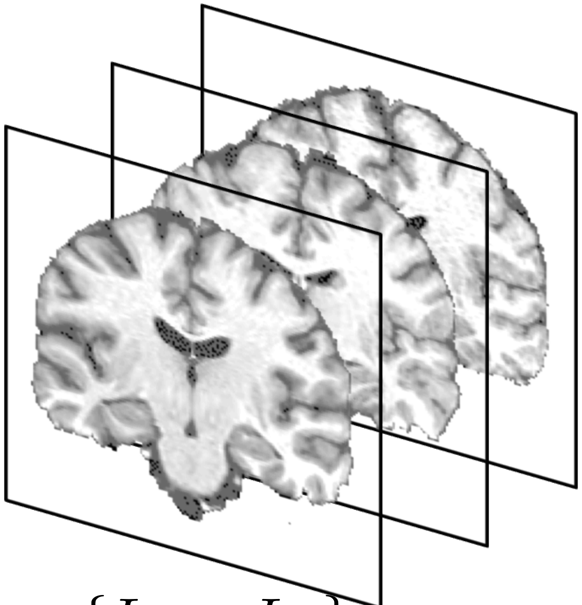


Notation



$\{I_1 \dots I_N\}$

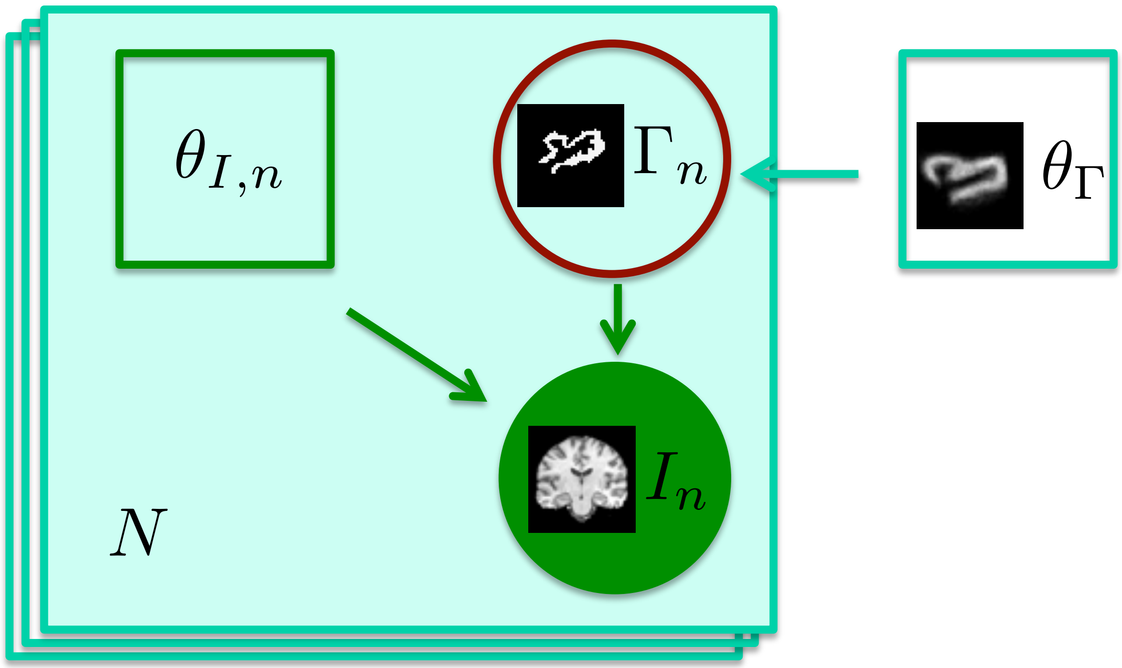
$\Gamma = \{\Gamma_1 \dots \Gamma_N\}$

$\Theta = \{\theta_\Gamma, \theta_{I,1}, \cdots, \theta_{I,N}\}$ unknown model parameters

θ_Γ spatial parameters (latent atlas)

$\{\theta_{I,1} \dots \theta_{I,N}\}$ Intensity (GMM) parameters

Probabilistic Model



$$\{\hat{\Gamma}, \hat{\Theta}\} = \arg \max_{\{\Gamma,\Theta\}} \log p(\Gamma_1 \ldots \Gamma_N, \Theta | I_1 \ldots I_N)$$

$$= \arg \max_{\{\Gamma,\Theta\}} \sum_{n=1}^{N} [\log p(I_n|\Gamma_n, \theta_{I,n}) + \log p(\Gamma_n|\theta_\Gamma)]$$

Probabilistic Model

$$\{\hat{\Gamma}, \hat{\theta}\} = \arg\max_{\{\Gamma,\Theta\}} \sum_{n=1}^{N} [\underbrace{\log p(I_n|\Gamma_n, \theta_{I,n})}_{\text{image likelihood term}} + \underbrace{\log p(\Gamma_n|\theta_{\Gamma})}_{\text{tissue labels term}}]$$

Probabilistic Model

$$\{\hat{\Gamma}, \hat{\theta}\} = \arg\max_{\{\Gamma, \Theta\}} \sum_{n=1}^{N} [\, \log p(I_n | \Gamma_n, \theta_{I,n}) + \log p(\Gamma_n | \theta_\Gamma) \,]$$

image likelihood term tissue labels term

$$\hat{\Theta} = \arg\max_{\Theta} \sum_{\Gamma_1 \cdots \Gamma_N} p(I_1 \cdots I_N, \Gamma_1 \cdots \Gamma_N | \Theta).$$

Probabilistic Model

$$\{\hat{\Gamma}, \hat{\theta}\} = \arg\max_{\{\Gamma,\Theta\}} \sum_{n=1}^{N} [\log p(I_n|\Gamma_n, \theta_{I,n}) + \log p(\Gamma_n|\theta_\Gamma)]$$

image likelihood term tissue labels term

Alternate:

1. Solve N MAP problems:

$$\hat{\Gamma}_n = \arg\max_{\Gamma_n} [\log p(I_n|\Gamma_n, \theta_{I,n}) + \log p(\Gamma_n|\theta_\Gamma)]$$

2. Solve ML problems:

$$\hat{\theta}_{I,n} = \arg\max_{\theta_{I,n}} \log p(I_n|\Gamma_n, \theta_{I,n})$$

$$\hat{\theta}_\Gamma = \arg\max_{\theta_\Gamma} \sum_{n=1}^{N} \log p(\Gamma_n|\theta_\Gamma)$$

Probabilistic Model

$$\{\hat{\Gamma}, \hat{\theta}\} = \arg \max_{\{\Gamma, \Theta\}} \sum_{n=1}^{N} [\log p(I_n | \Gamma_n, \theta_{I,n}) + \log p(\Gamma_n | \theta_\Gamma)]$$

image likelihood term tissue labels term

$$\Gamma_n^v \log \theta_\Gamma^v + (1 - \Gamma_n^v) \log(1 - \theta_\Gamma^v) \quad + \quad f(\Gamma_n^v, \Gamma_n^{\mathcal{N}(v)})$$

spatial (atlas) term

smoothness term

v is the voxel index $\quad v \in \{1 \ldots V\}$ $\quad f(\Gamma_n^v, \Gamma_n^{v'}) = w_{v,v'} (\Gamma_n^v - \Gamma_n^{v'})^2$

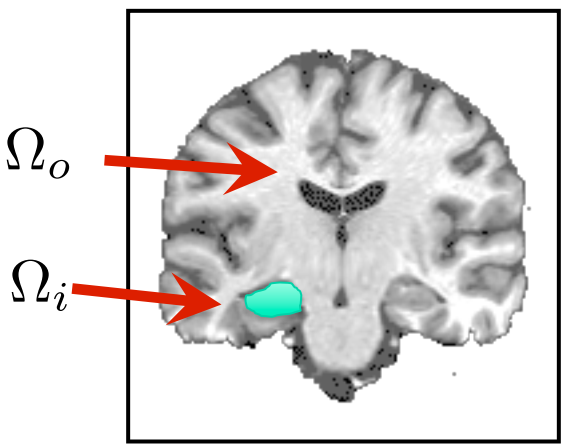
v

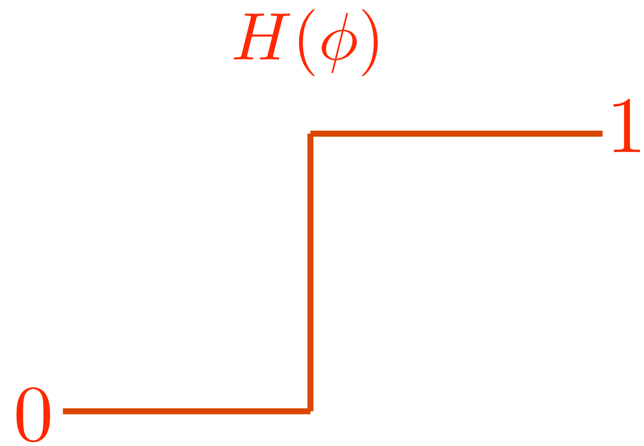
$\mathcal{N}(v)$ the neighborhood of

Probabilistic view of the Level-set Framework

Level-set function $\phi\colon \Omega \rightarrow \mathbb{R}$

ROI boundary, zero level $C = \{\mathbf{x} \in \Omega | \phi(\mathbf{x}) = 0\}$





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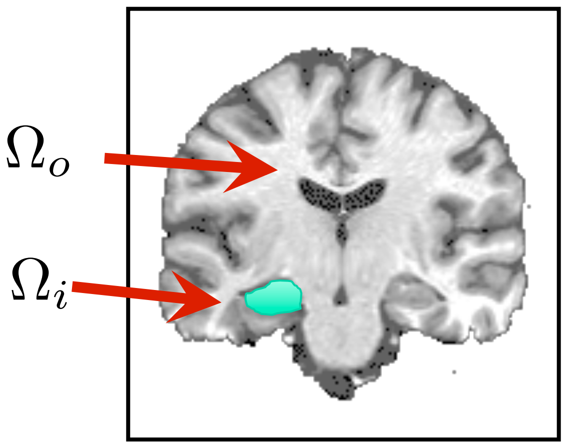

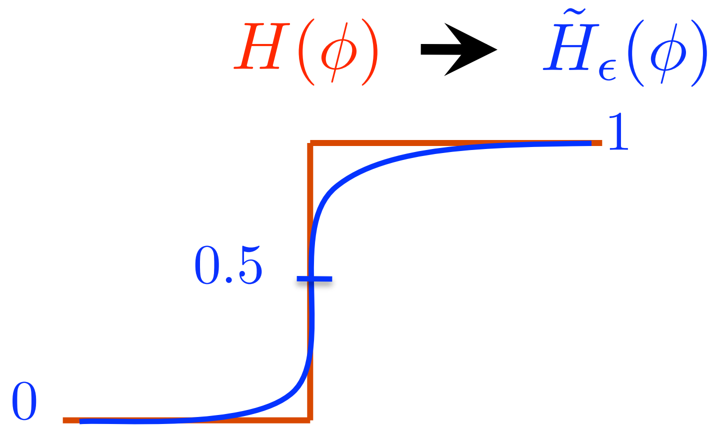

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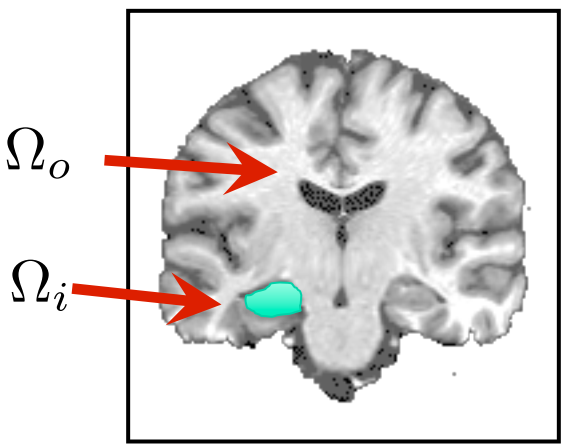

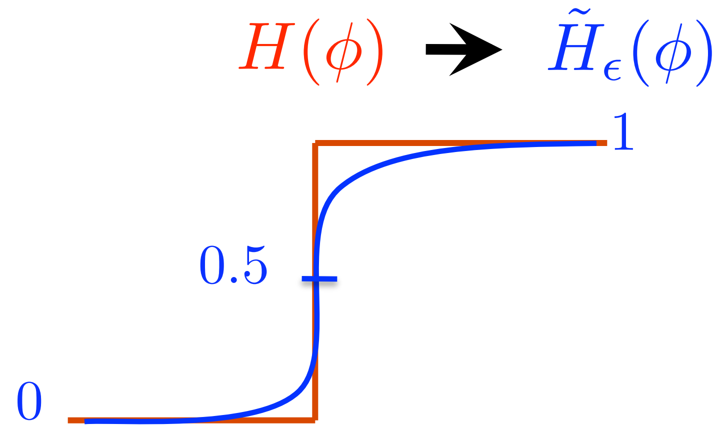

$$\phi(\mathbf{x}) \triangleq \epsilon\ \mathrm{logit}(p) = \epsilon \log \frac{p(\mathbf{x} \in \Omega_i)}{1 - p(\mathbf{x} \in \Omega_i)} = \epsilon\ \log \frac{p(\mathbf{x} \in \Omega_i)}{p(\mathbf{x} \in \Omega_o)}$$

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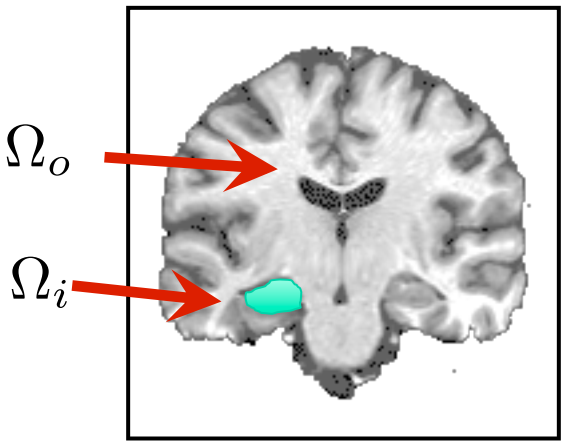

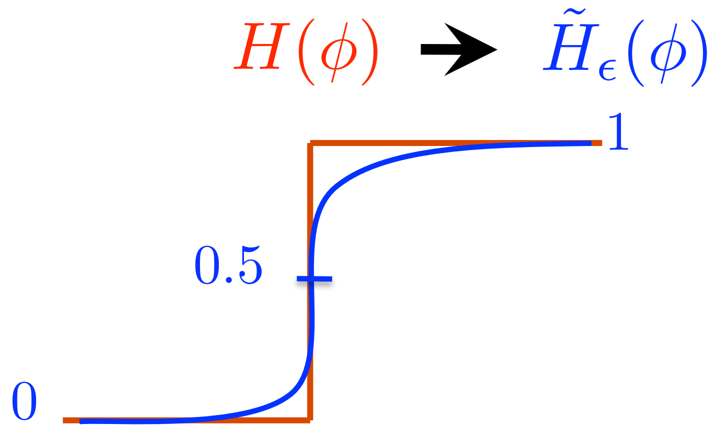

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$$\tilde{H}_\epsilon(\phi) \triangleq \frac{1}{1 + e^{-\phi/\epsilon}} \quad \rightarrow \tilde{H}(\phi(\mathbf{x})) \triangleq p(\mathbf{x} \in \Omega_i)$$

Level-set Framework

$$E(\phi_1 \ldots \phi_N, \Theta) = \sum_{n=1}^{N} [\ \underbrace{E_I(\phi_n, \theta_{I,n})}_{\text{Image likelihood}} + \underbrace{E_S(\phi_n, \theta_\Gamma)}_{\text{Spatial atlas}} + \underbrace{E_{LEN}(\phi_n)}_{\text{Length}}\ ]$$

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Image likelihood　　Spatial atlas　　Length

$$E_I \propto -\log p(I_n | \Gamma_n, \theta_{I,n})$$

image likelihood term

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Image likelihood — Spatial atlas — Length

$$E_I \propto -\log p(I_n | \Gamma_n, \theta_{I,n})$$

image likelihood term

$$E_I = -w_I \sum_{v=1}^{V} [\log p_{in}(I_n; \theta_{I,n}) \Gamma_n^v + \log p_{out}(I_n; \theta_{I,n})(1 - \Gamma_n^v)]$$

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[Chan-Vese IEEE IP 01]

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Image likelihood   Spatial atlas   Length

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Image likelihood — Spatial atlas — Length

$$E_S \propto -\, \Gamma_n^v \log \theta_\Gamma^v + (1 - \Gamma_n^v) \log(1 - \theta_\Gamma^v)$$

spatial (atlas) term

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spatial (atlas) term

$$E_S = -w_S \sum_{v=1}^{V} [\log(\theta_\Gamma^v)\Gamma_n^v + (1 - \log \theta_\Gamma^v)(1 - \Gamma_n^v)]$$

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Image likelihood   Spatial atlas   Length

$$E_{LEN} = w_{LEN} \sum_{v}^{V} f(\Gamma_n^v, \Gamma_n^{\mathcal{N}(v)})$$

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$$|\nabla K|^2 = K_x^2 + K_y^2 + K_z^2 \qquad\qquad K_x(v) \approx \frac{K_{i+1,j,k} - K_{i,j,k}}{h}$$

Level-set Framework

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$$E_I = -w_I \int_\Omega \left[\log p_{\text{in}}(I_n; \theta_{I,n}) \tilde{H}(\phi_n) + \log p_{\text{out}}(I_n; \theta_{I,n}) \tilde{H}(-\phi_n) \right] d\mathbf{x}$$

$$E_S = -w_S \int_\Omega \left[\log \theta_\Gamma(\mathbf{x}) \tilde{H}(\phi_n(\mathbf{x})) + \log(1 - \theta_\Gamma(\mathbf{x})) \tilde{H}(-\phi_n(\mathbf{x})) \right] d\mathbf{x}$$

$$E_{\text{LEN}} = w_{LEN} \int_\Omega |\nabla \tilde{H}(\phi_n(\mathbf{x}))| d\mathbf{x}$$

Alternating Minimization Algorithm

Step 1: Estimation of the model parameters:

Fix the segmentations ϕ_n , estimate of the model parameters Θ :

For each image I_n estimate the intensity parameters:

$$P_{in}(I_n;\theta_{I,n}) = \mathbb{N}(I_n, \mu_n, \sigma_n^2)$$

$$p_{\text{out}}(I_n;\theta_{I,n}) = \text{GMM}(\mu_n^1 \ldots \mu_n^K, \sigma_n^1 \ldots \sigma_n^K, \lambda_n^1 \ldots \lambda_n^K)$$

Estimate the spatial (latent atlas) parameters, ϕ_n given all the current segmentations:

$$\hat{\theta}_\Gamma(\mathbf{x}) = \frac{1}{N}\sum_{n=1}^{N} \tilde{H}(\phi_n(\mathbf{x}))$$

Alternating Minimization Algorithm

Step 2: Evolution of the segmentations

Fix the model parameters Θ , evolve the level-set functions ϕ_n using the corresponding gradient descent equations:

$$\frac{\partial \phi_n}{\partial t} = \tilde{\delta}(\phi_n)\{ w_I \left[\log p_{\text{in}}(I_n; \theta_{I,n}) - \log p_{\text{out}}(I_n; \theta_{I,n})\right] + w_{LEN} \ \text{div} \left(\frac{\nabla \phi_n}{|\nabla \phi_n|}\right) + w_S \left[\log \theta_\Gamma - \log(1 - \theta_\Gamma)\right] \}$$

$$\tilde{\delta}(\phi_n) \triangleq \tilde{\delta}_\epsilon(\phi_n) = \frac{d\tilde{H}_\epsilon(\phi_n)}{d\phi_n}$$

Experiment I

Collaboration: Brigham & Women's Hospital,
Harvard Medical School

Database:
The data set consists of 50 subjects:
17 schizophrenia patients ; 16 affective patients; 17 normal controls
6 cortical and sub-cortical structures (L+R):
Superior Temporal Gyrus ; Amygdala ; Hippocampus
Y. Hirayasu *et al.* , Am J Psychiatry, 1998.

Registration (preprocessing):
Groupwise registration, free-form B-Spline deformation
S. Balci *et al.* , MICCAI Statistical Registration Workshop, 2007

Segmentation Results

Manual

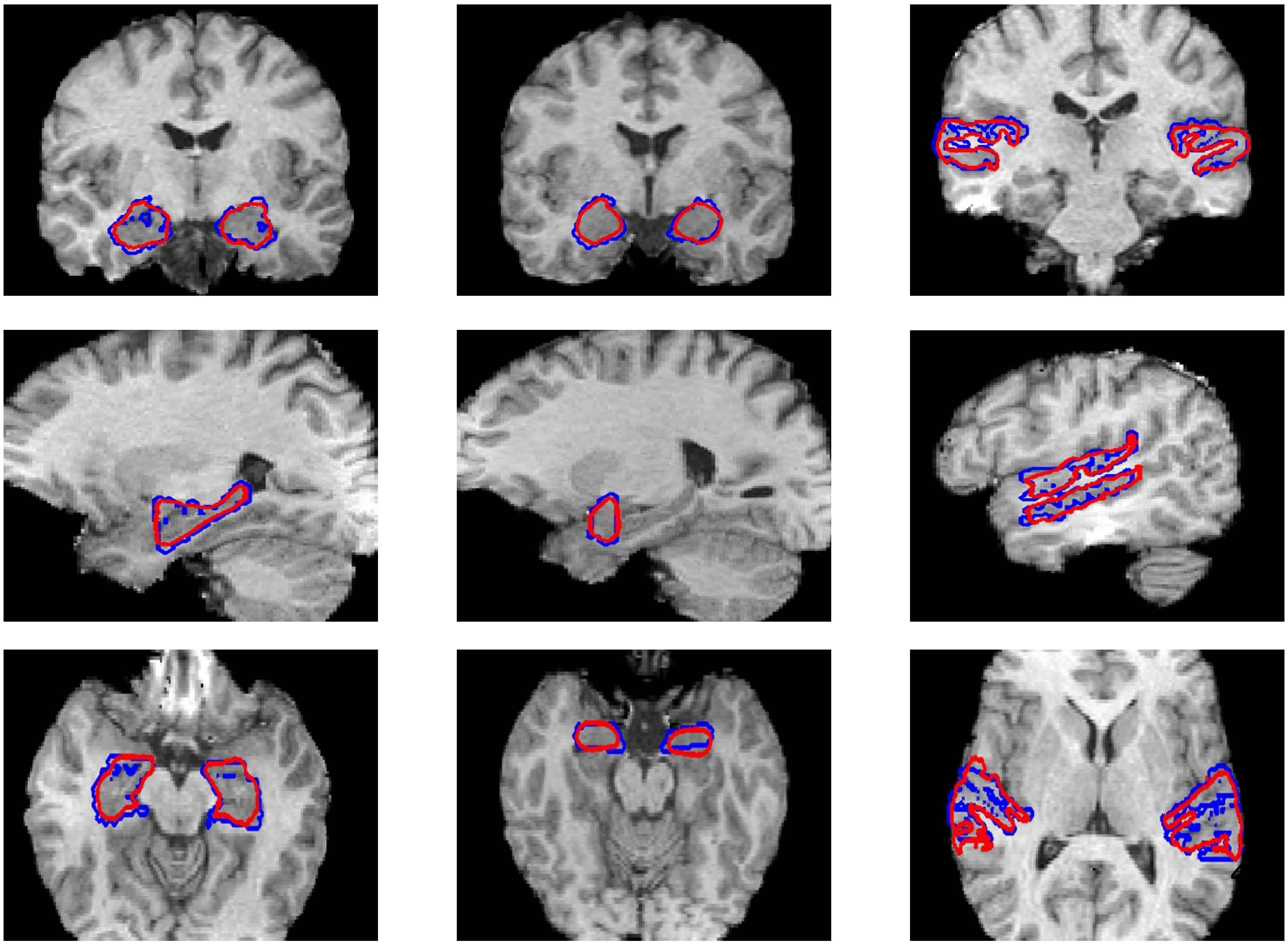
Automatic

HPC AMY STG

Coronal

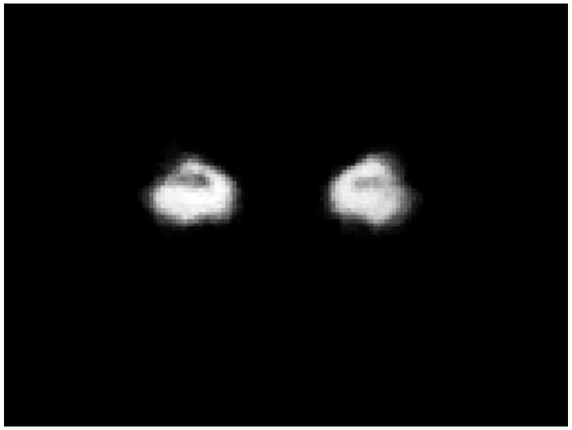
Sagittal

Axial

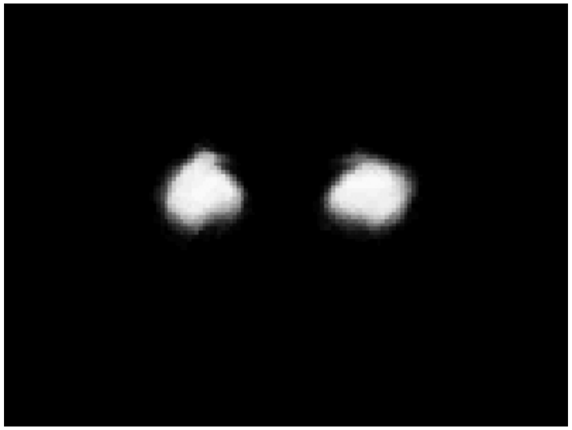


Latent Atlases

HPC



AMY



STG

Experiment II

Collaboration: Mass. General Hospital, Harvard Medical School

Database :

The dataset consists of 39 MR brain scans of different subjects.

Some of the subjects in this set were diagnosed with mild

Alzheimer disease.

T1 MR images ($1\mathrm{mm}^3$,1.5-T GE).

12 sub-cortical structures L+R Hemispheres:

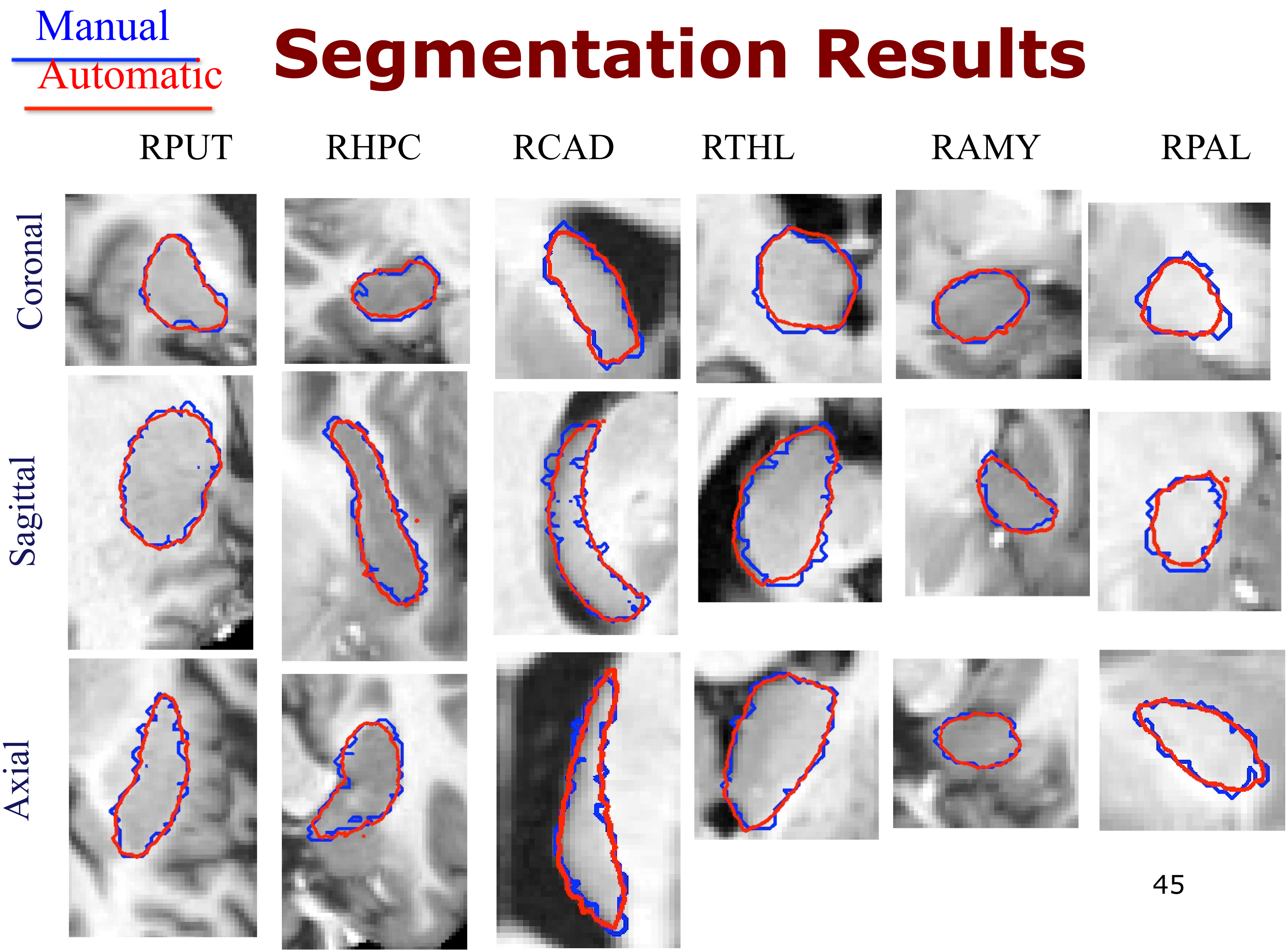
Hippocampus (HPC), Thalamus (THL), Caudate (CAD), Putamen

(PUT), Pallidus (PAD) and Amygdala (AMY).

Registration (preprocessing):

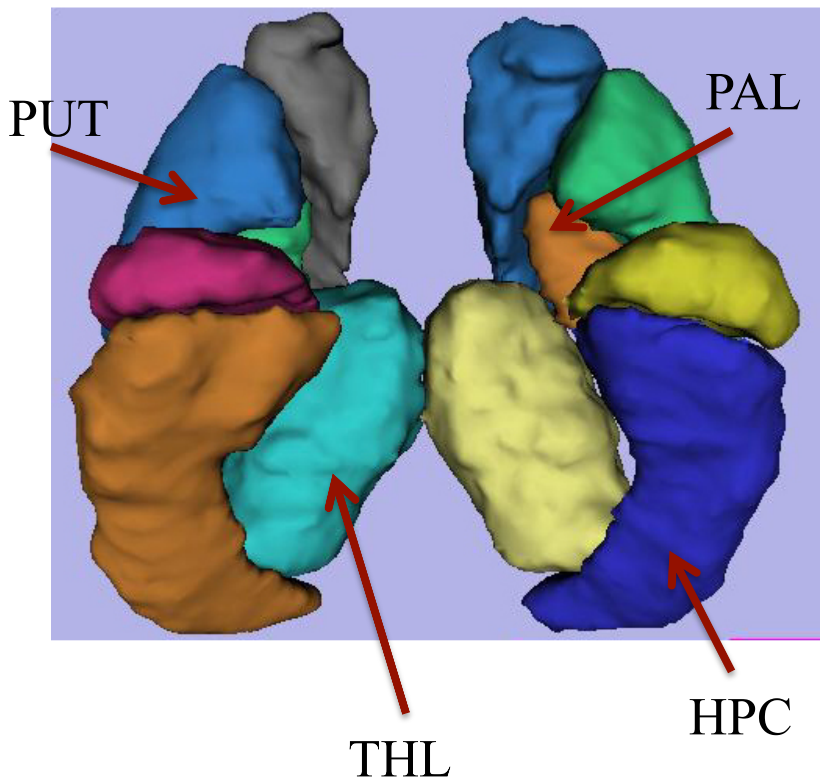
Asymmetric image template registration, M.R. Sabuncu *et al.* , MICCAI , 2009

Segmentation Results

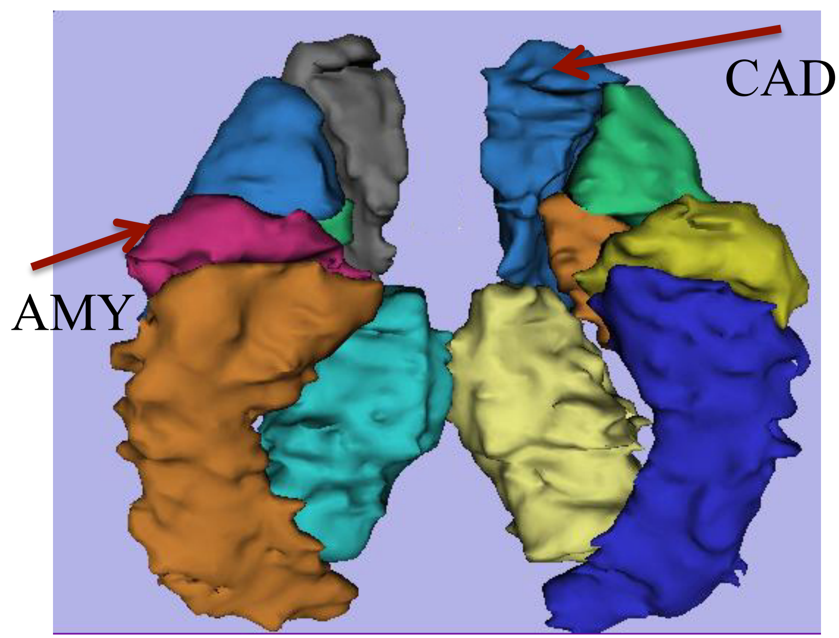


Segmentation Results

Automatic Segmentation

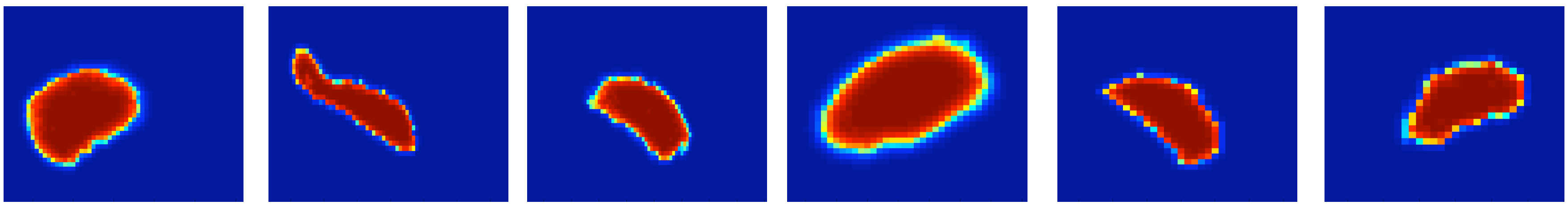


Manual Segmentation

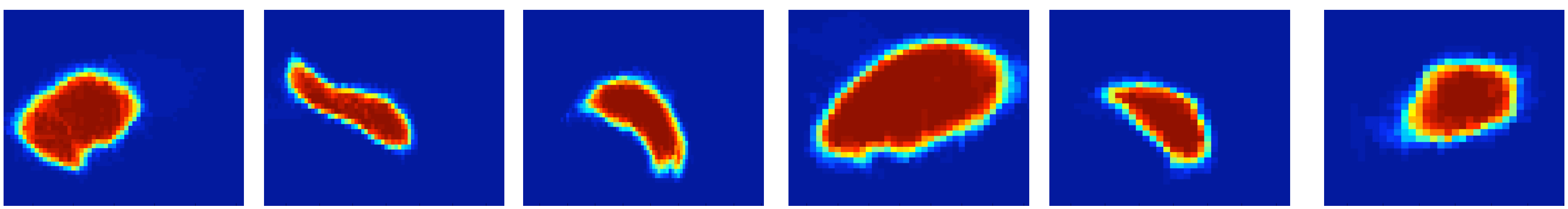


Latent Atlases

RPUT RHPC RCAD RTHL RAMY RPAL

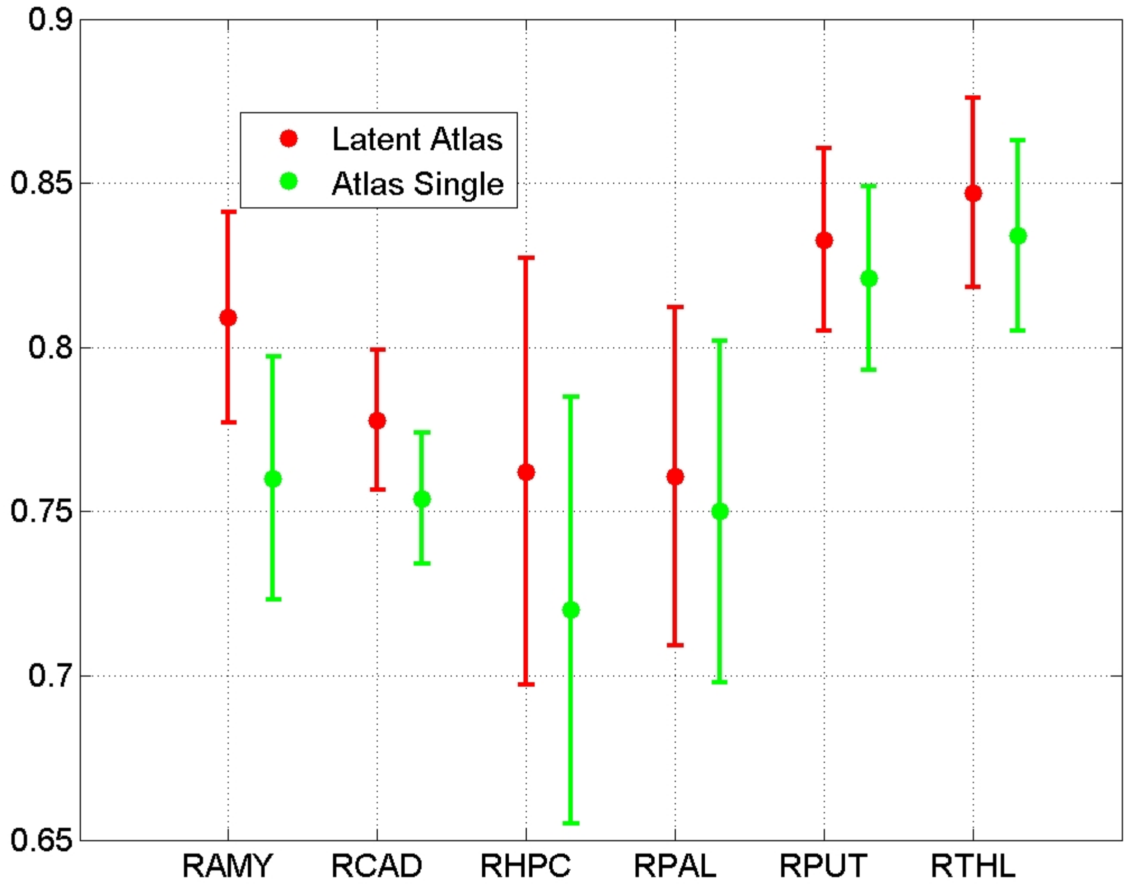


Latent atlases estimated by our method

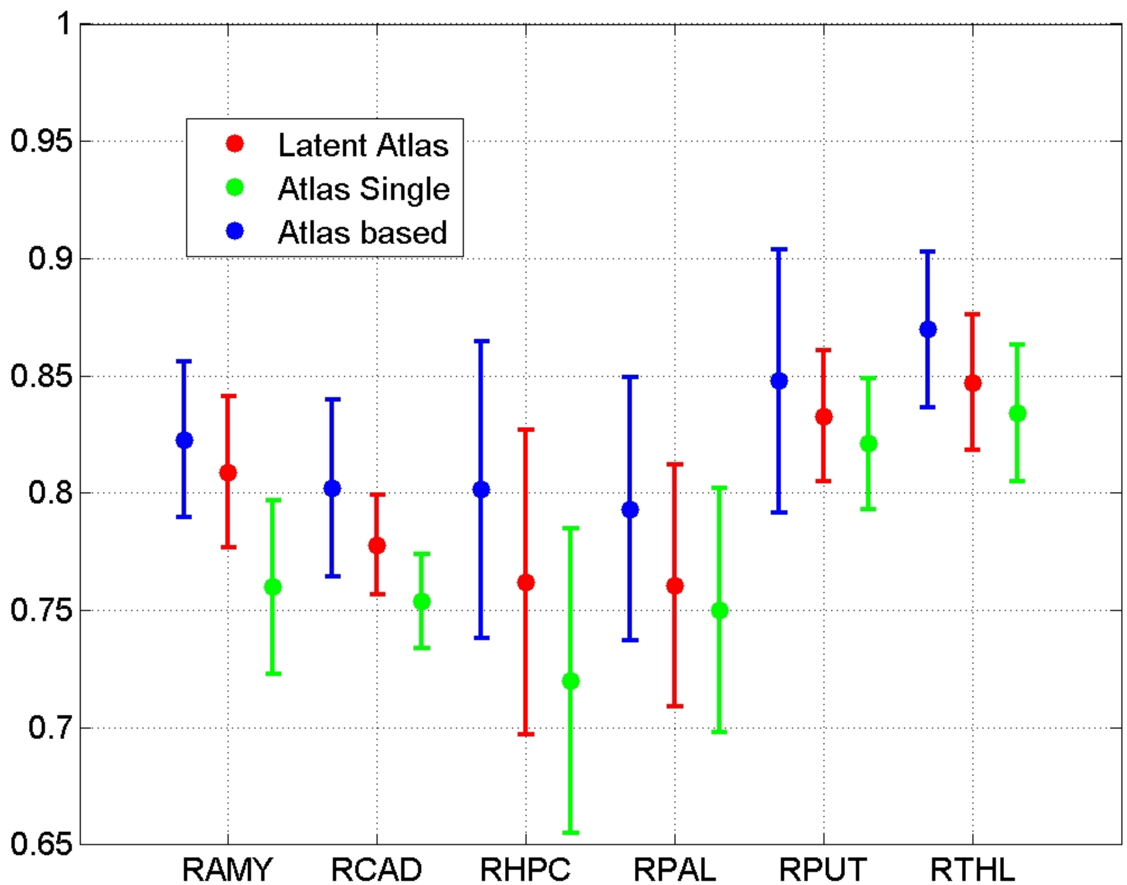


Atlases generated by averaging sets of manual segmentations

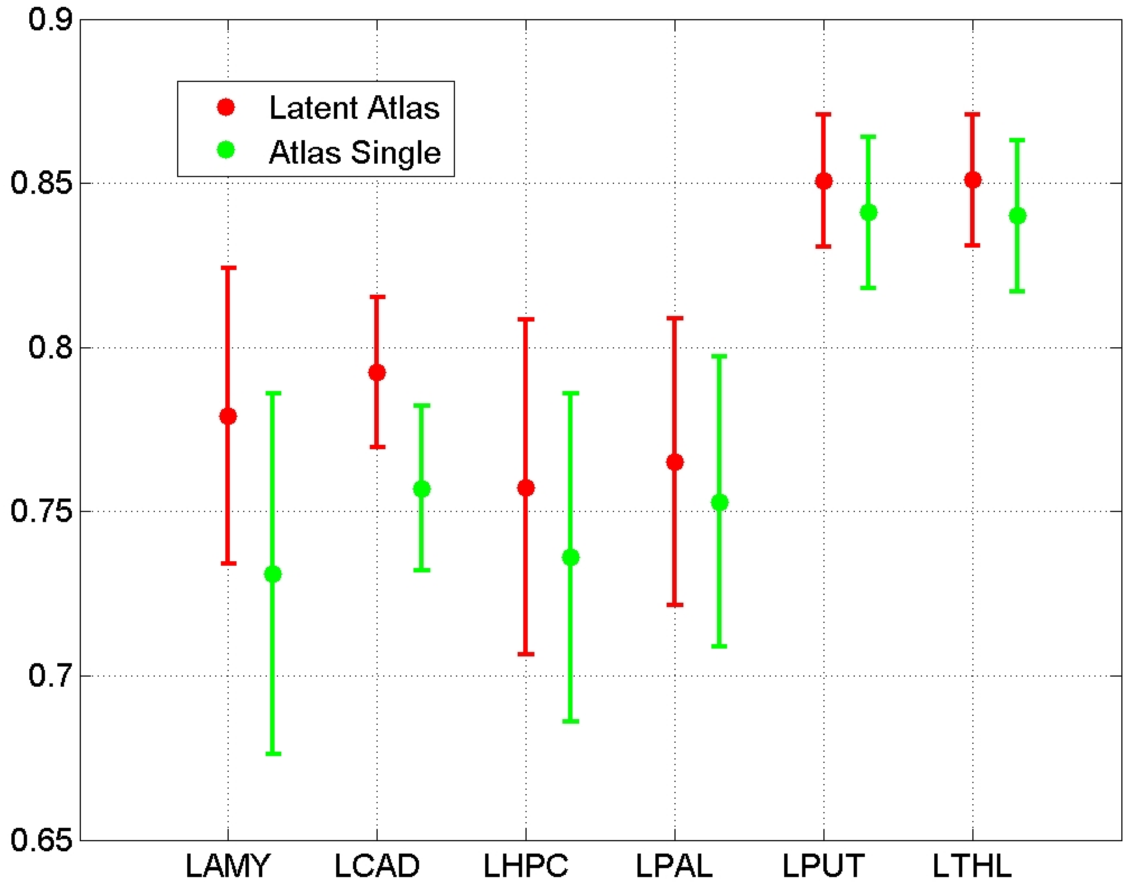
Dice Measures: Right Hemisphere



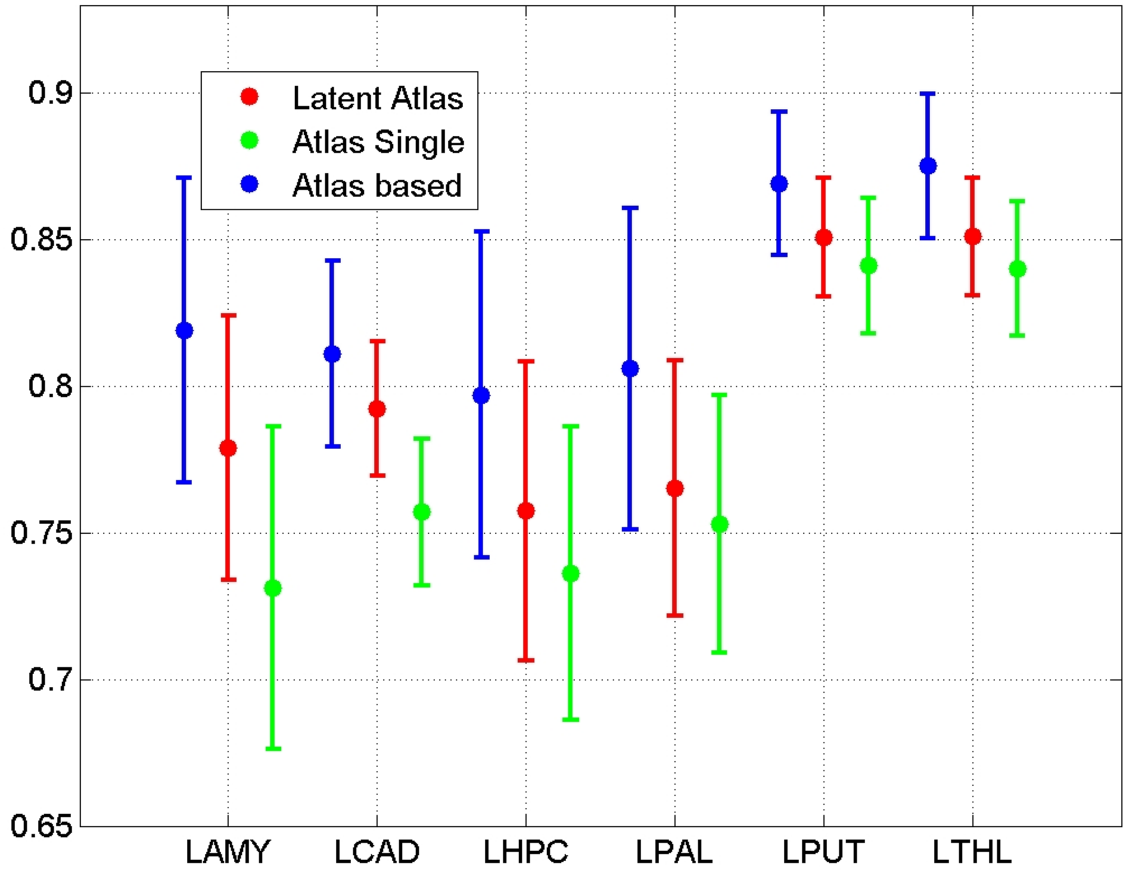
Dice Measures: Right Hemisphere



Dice Measures: Left Hemisphere



Dice Measures: Left Hemisphere



Experiment III

Collaboration: German Cancer Research Center ; INRIA, France

Database :

Single patient, multi-modal, longitudinal study of tumor growth.

44 image volumes of a patient with histologically confirmed low-grade glioma, acquired at 10 different time points.

The volumes were acquired via six imaging protocols:

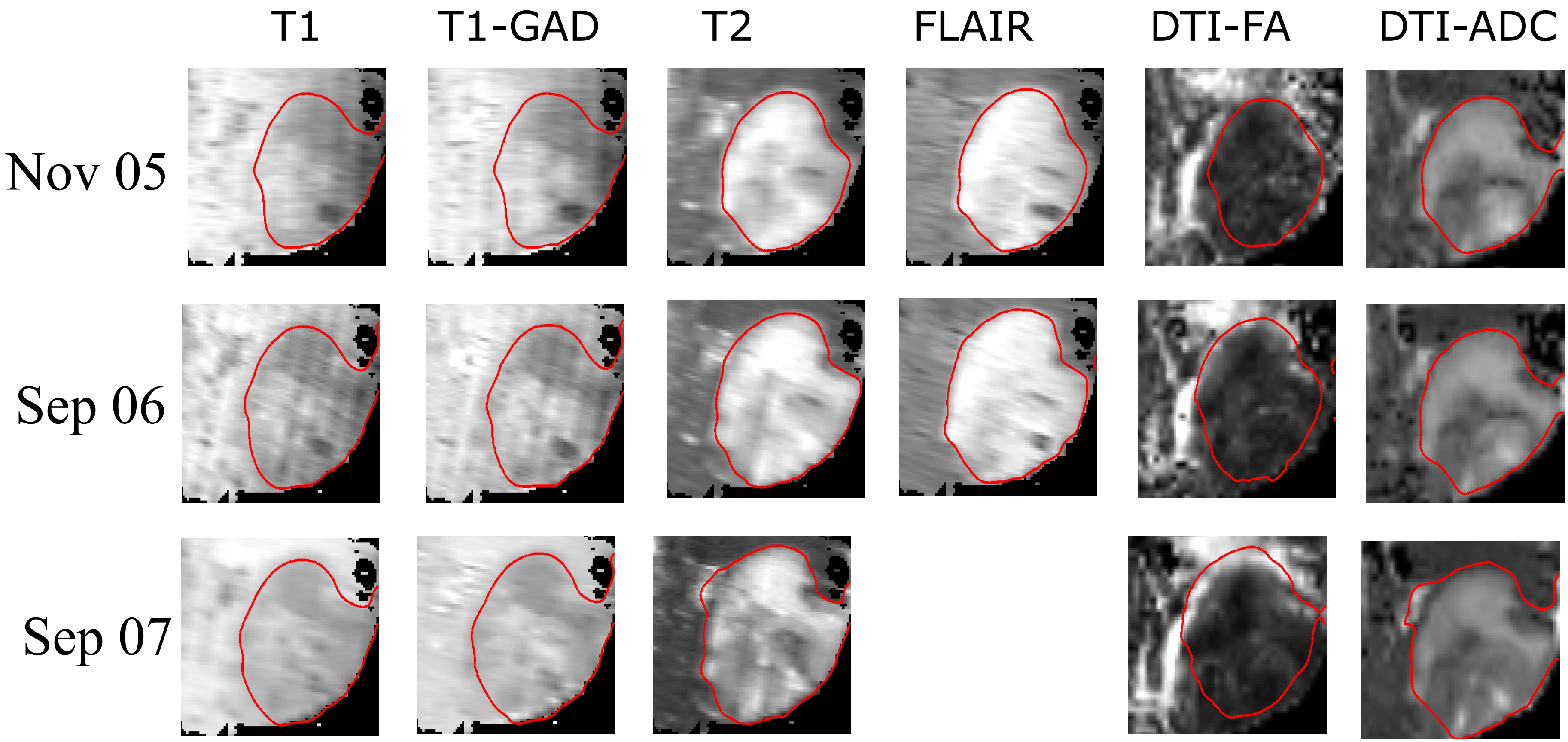
T1, T2, FLAIR, DTI, and contrast-enhanced T1 sequences (T1gd).

Registration (preprocessing):

MedINRIA: Medical Image Navigation and Research Tool by INRIA.

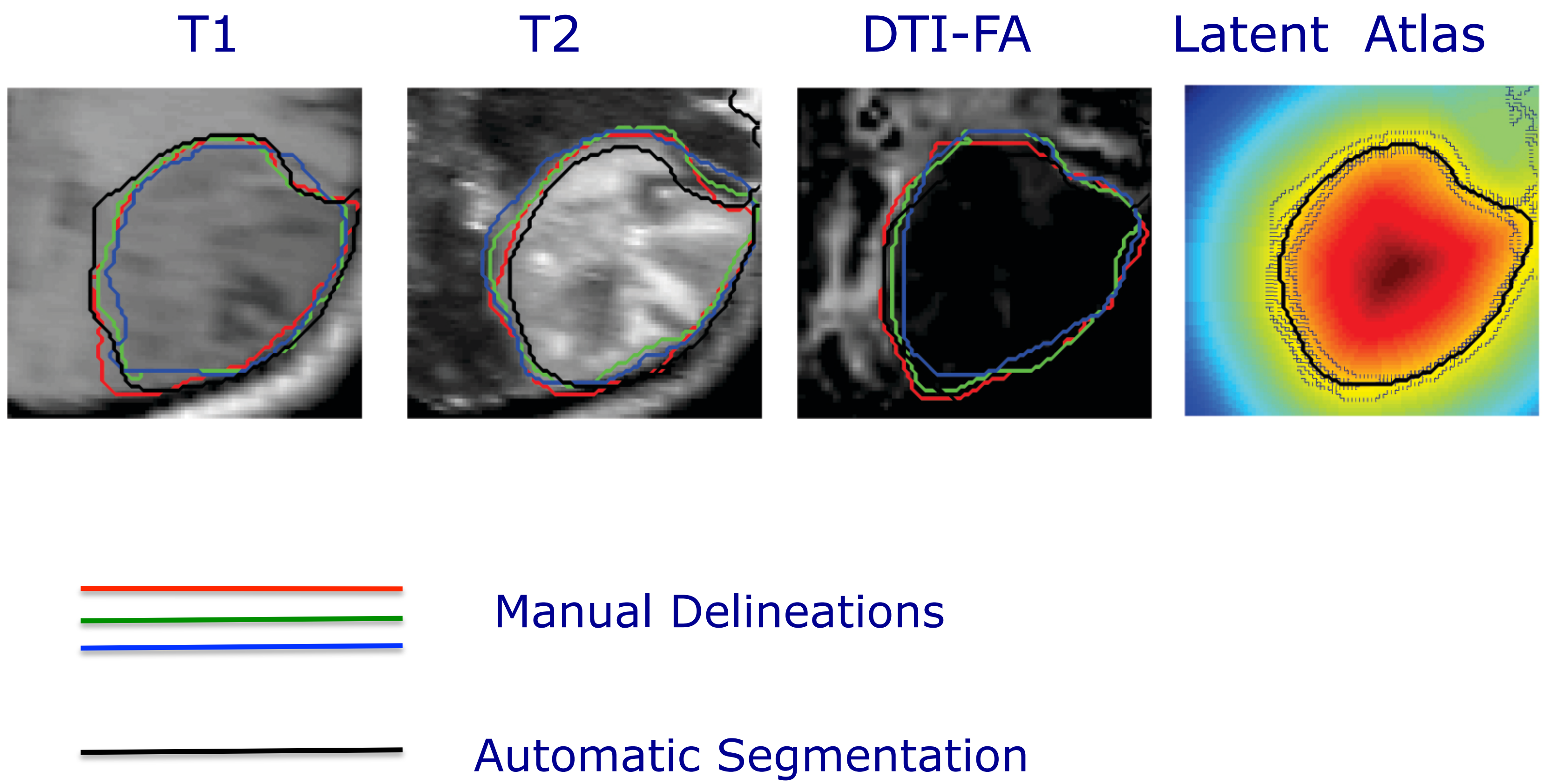
Toussaint et al. Proc. of MICCAI Workshop on Interaction in medical image analysis and Visualization.

Experiment III: Axial Tumor Slice and 3D Segmentation

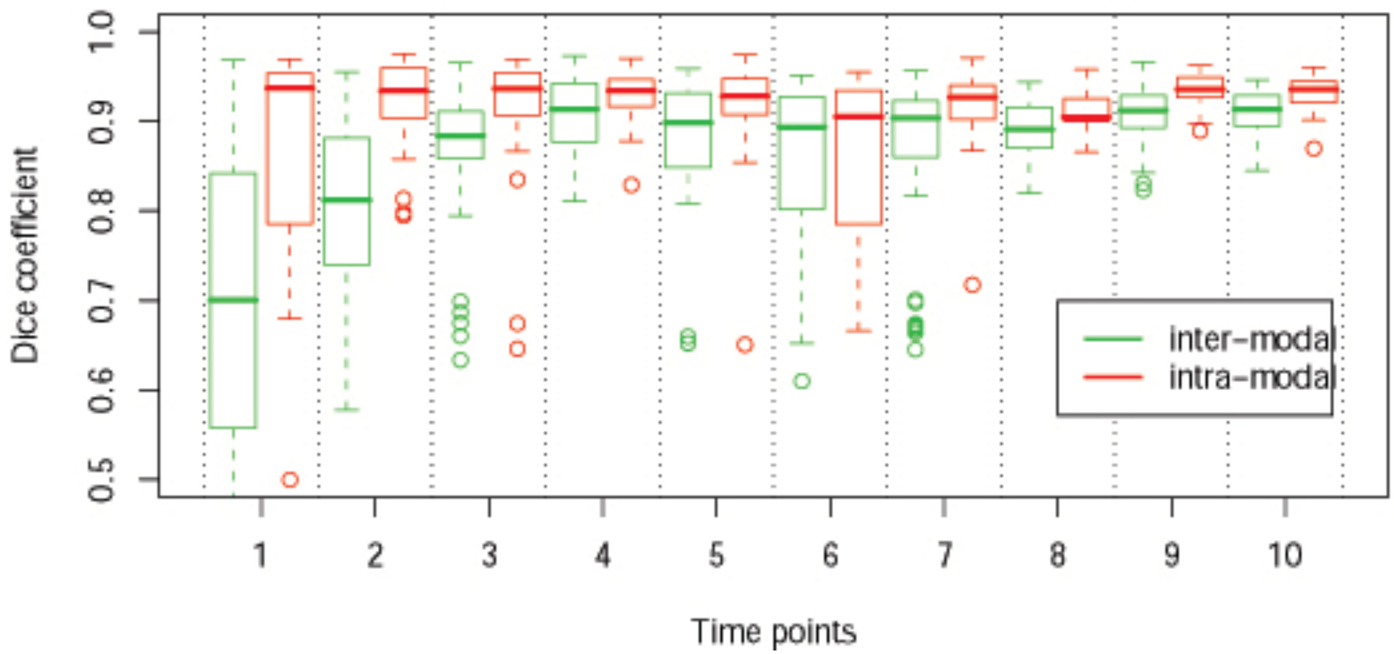


T. Riklin-Raviv, B.H. Menze, K. Van Leemput , B. Stieltjes, M.A. Weber, N. Ayache, W. M. Wells and P. Golland
Joint Segmentation using Patient specific Latent Anatomy Model, PMMIA 09

Manual Vs. Automatic Segmentation

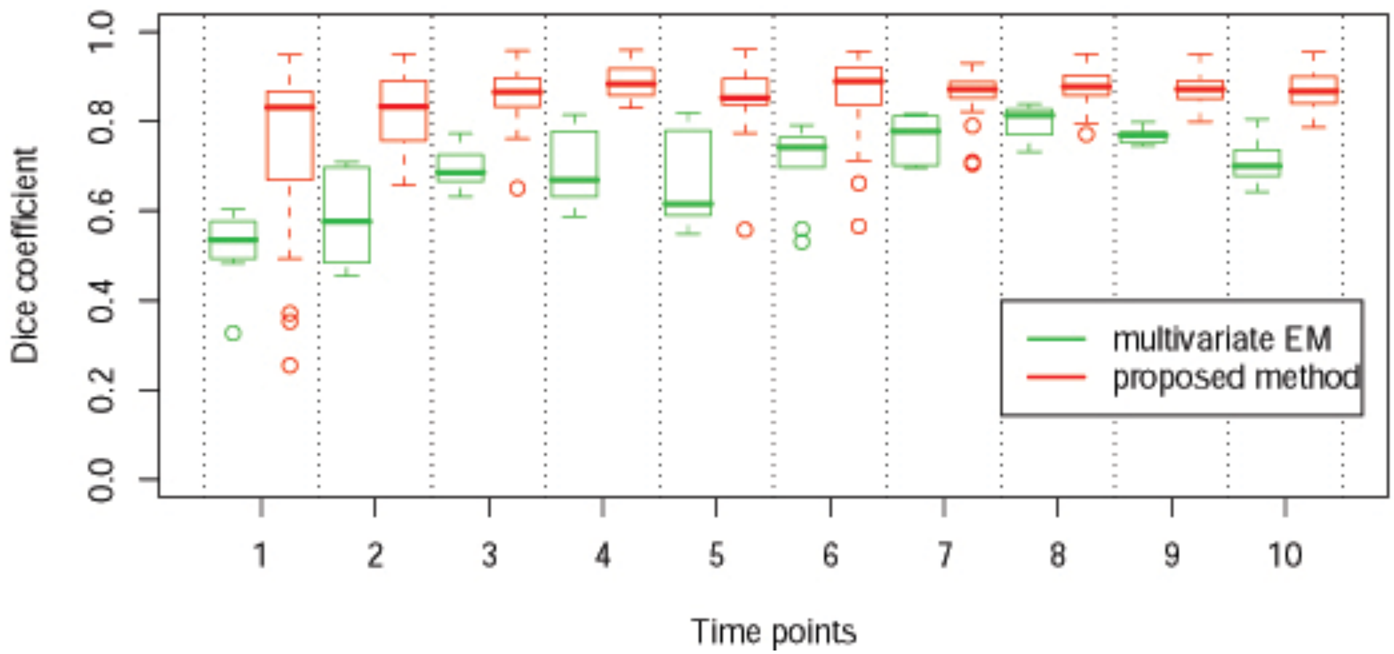


Dice Scores



Dice coefficient
0.5
0.6
0.7
0.8
0.9
1.0
1
2
3
4
5
6
7
8
9
10
Time points
inter-modal
intra-modal

Dice Scores



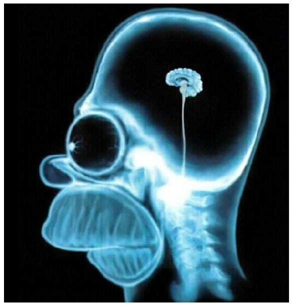
Van Leemput et al. IEEE TMI, 2001

Latent Atlas Concluding Remarks

✧Statistically driven level-set framework for group-wise segmentation of image ensembles.

✧The spatial parameters in the form of a latent atlas are
estimated throughout the segmentation.

✧The latent atlas is used as a part of the model on the tissue labels.



Segmentation of Brain Structures