Medical Image Analysis

(Multi)Atlas-Patch based Segmentation

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With slide credits
D. Rueckert
L. Wang
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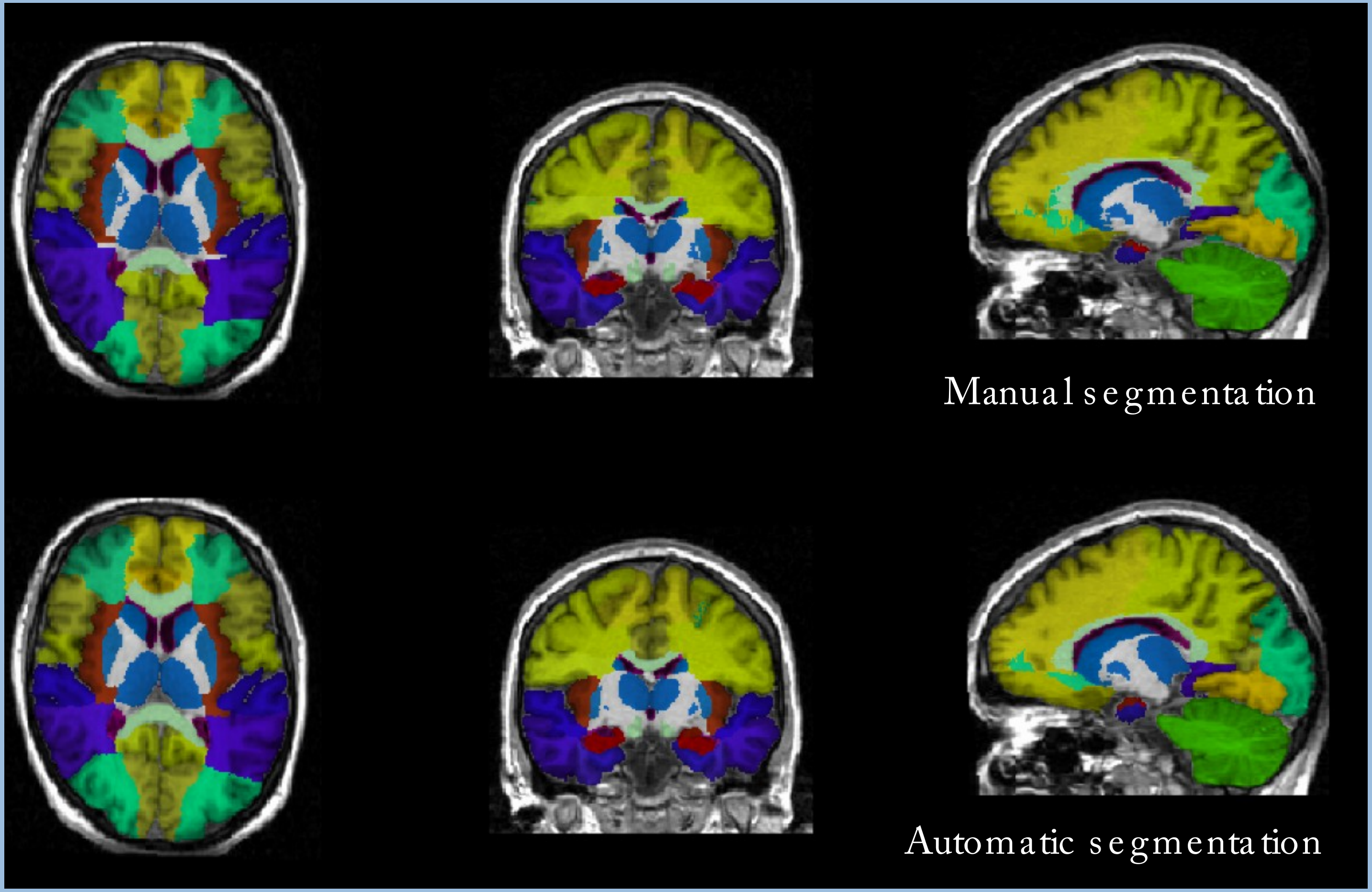
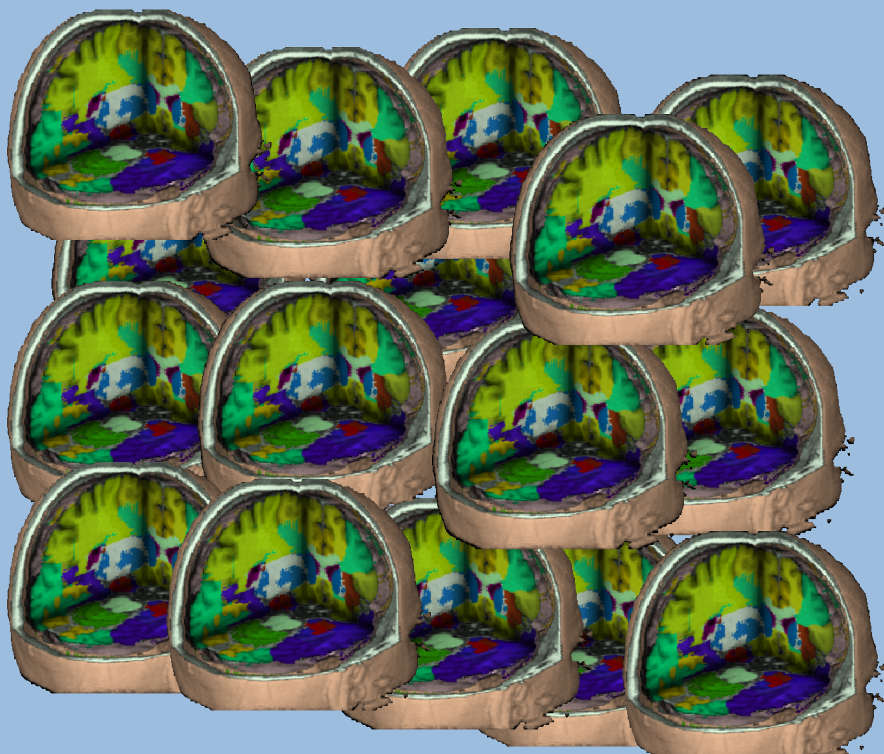
Segmentation using registration



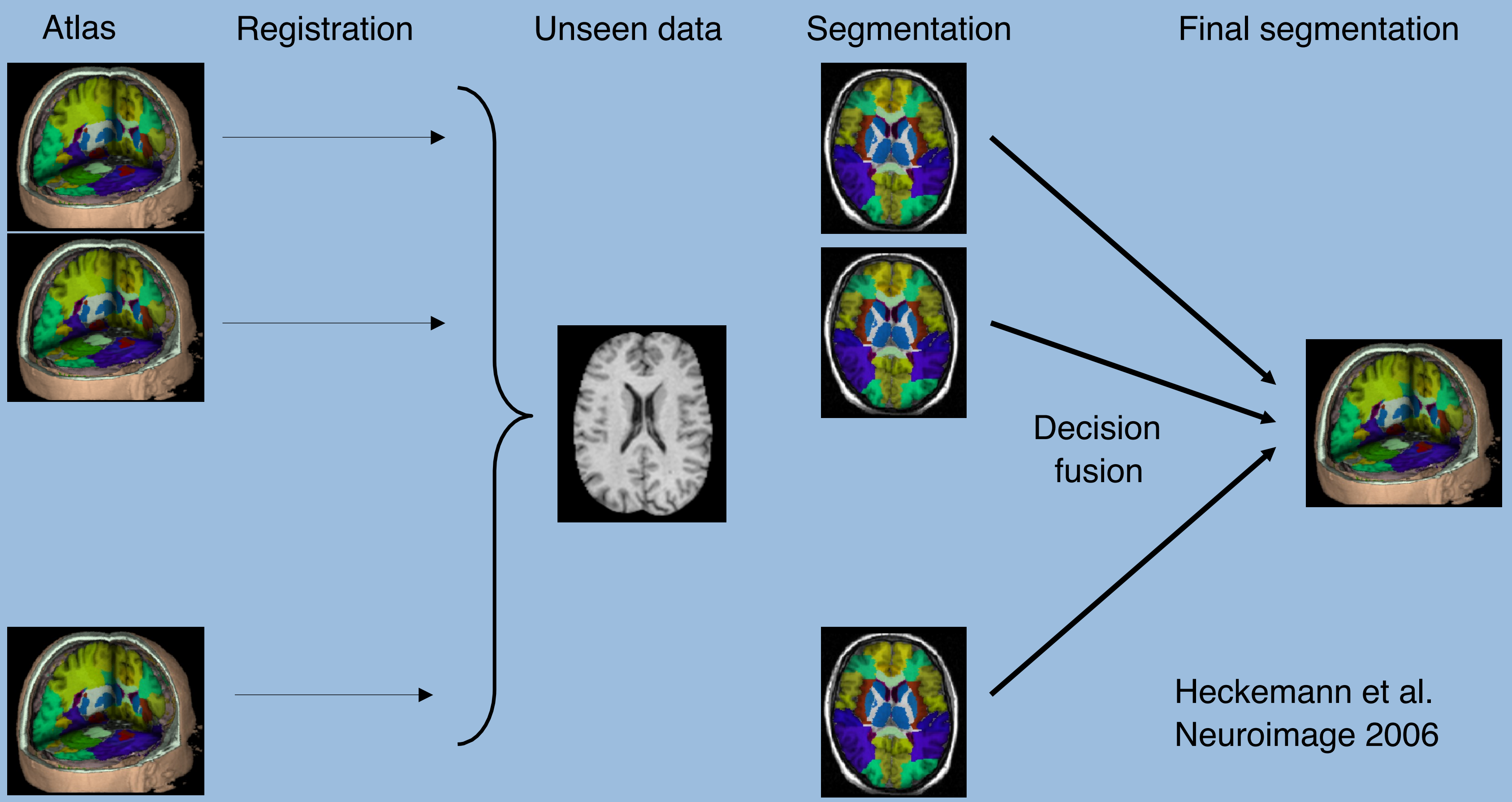
Multi-Atlas based segmentation



A. Hammers *et al*. Three-dimensional maximum probability atlas of the human brain, with particular reference to the temporal lobe. Human Brain Mapping, 19(4):224-247, 2003.

- T1-weighted MR images from 30 volunteers (age range 20-54 years, median age 30.5 years, 15 male, 15 female)
- 256 x 256 x 124 volumes (resolution 1.25 × 0.94 × 1.50 mm)
- Each image is manually segmented in 83 anatomical structures

Multi-atlas segmentation using classifier fusion

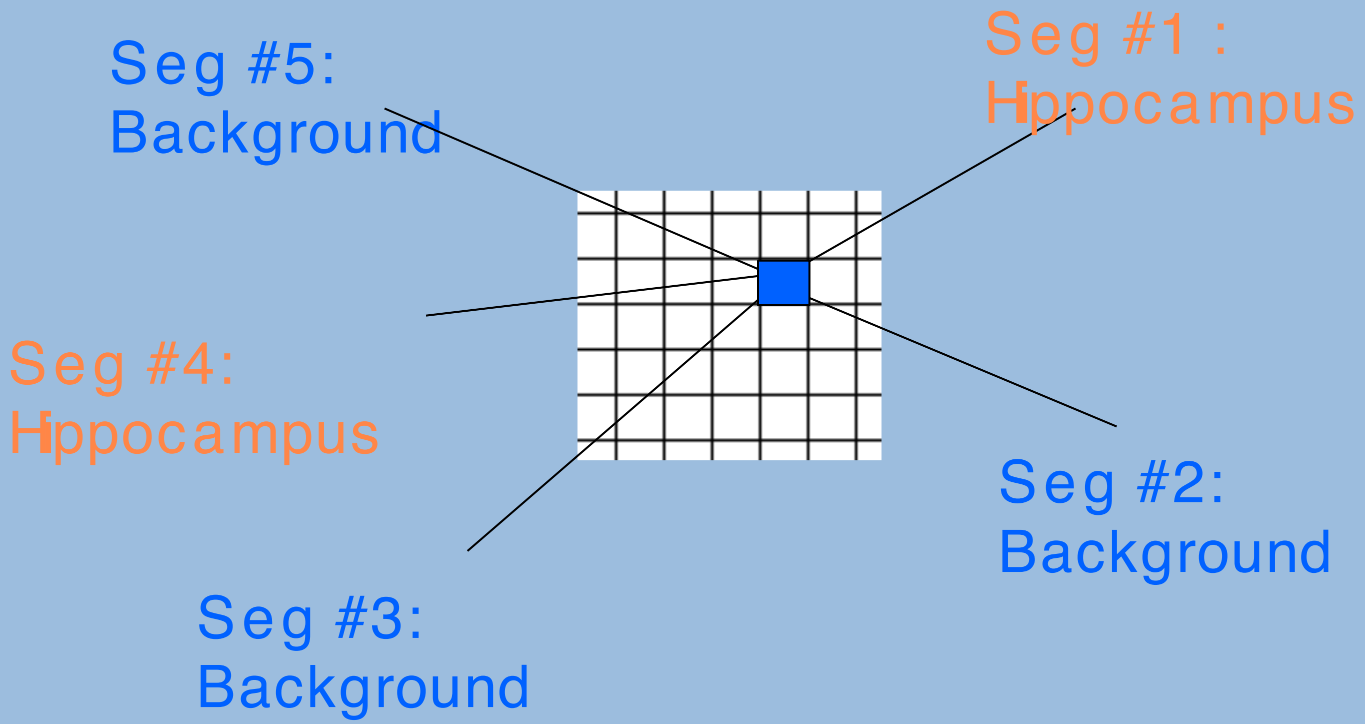


Heckemann et al.
Neuroimage 2006

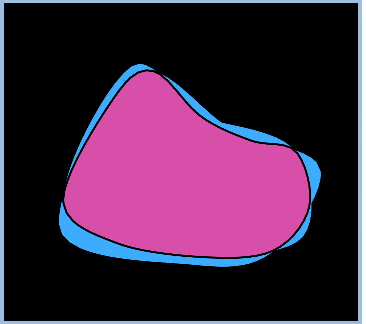
How do you fuse?

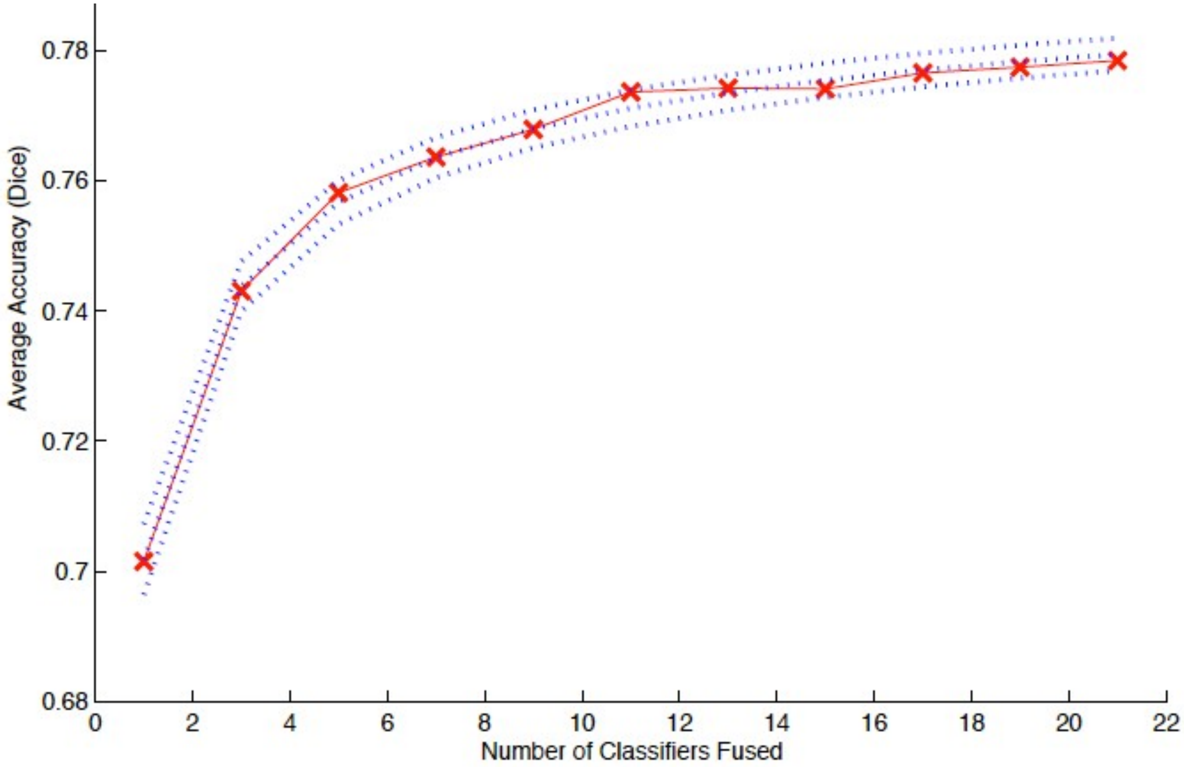
- Global fusion strategies:
  - Majority voting
  - Weighted voting
- Local fusion strategies:
  - Locally weighted fusion
  - Simultaneous Truth And Performance Level Estimation (STAPLE)
- Shape Based Averaging

Combining multiple segmentations: Simple majority voting



Multi-atlas segmentation using classifier fusion

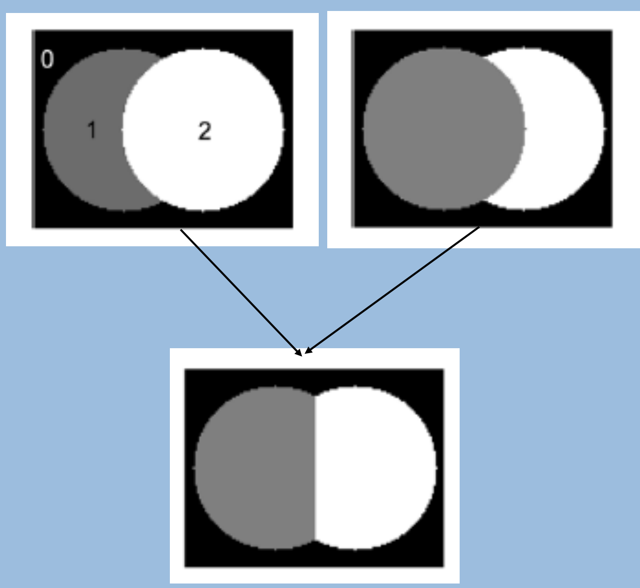


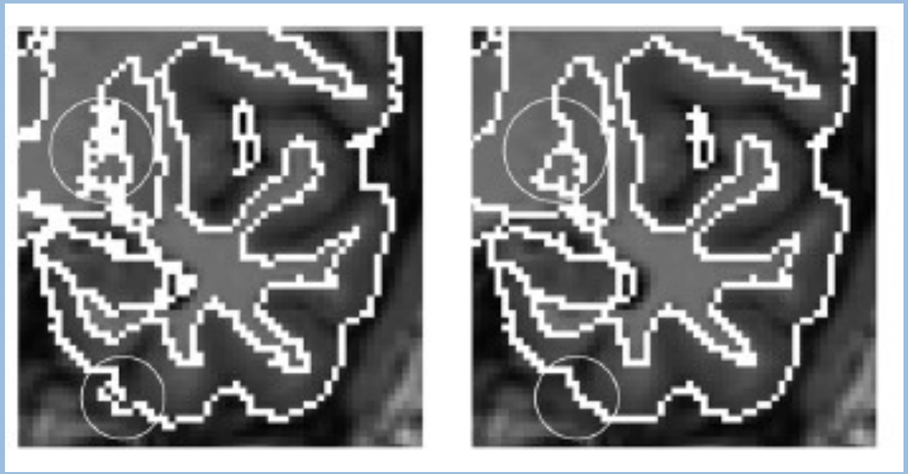


Heckemann et al.
Neuroimage 2006

Combining multiple segmentations: Shape- based averaging

- Average the shapes of the segmentations
  - Based on averaging the distance transforms of the segmentations



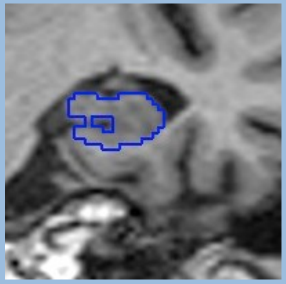


VOTE SBA

Combining multiple segmentations: STAPLE

Probabilistic approach

What is the **most probable** underlying true segmentations when you see the above segmentations?

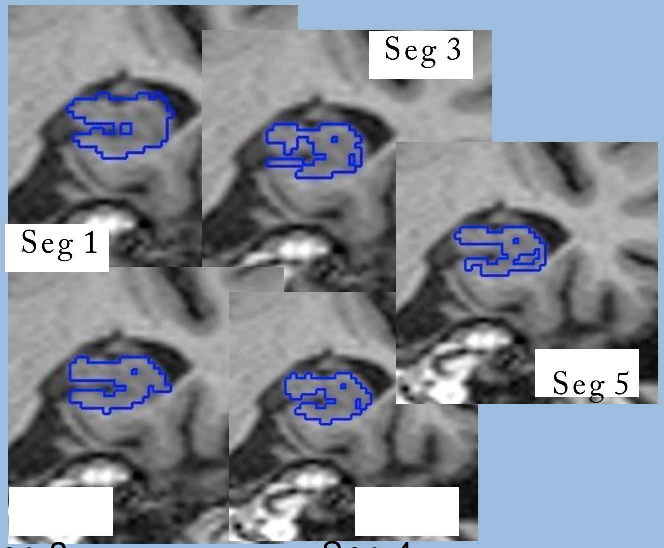


- At the same time, it tells you the performance (sensitivity and specificity) of each segmentation.
- Sensitivity p: true positive fraction Specificity q: true negative fraction

Combining multiple segmentations: STAPLE

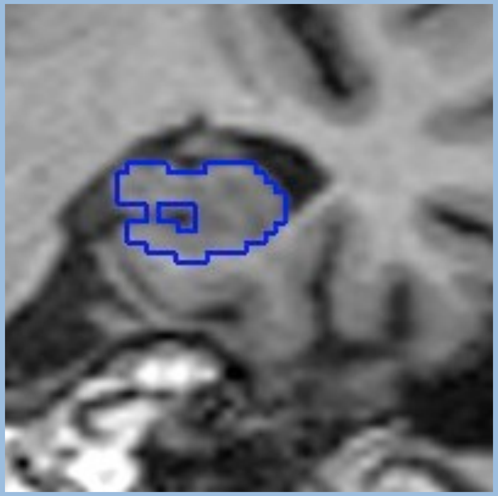
- Can we find the performance of each segmentation (p, q) and the ground truth (T) that maximises the likelihood of observing the segmentations (D)?

D (Data/expert segmentations we want to merge) known



Seg 2 Seg 4

T (the ground Truth) unknown

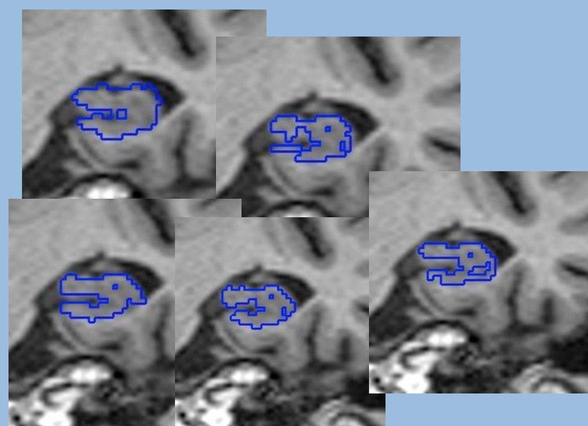


p, q (performance of each segmentation), unknown

Combining multiple segmentations: STAPLE

Solved iteratively by Expectation-Maximization (EM) (Warfield et al., 2004)

D (Data/expert segmentations you want to merge)
known



T (the ground Truth)
unknown

p, q (performance of each segmentation),
unknown

$f\,(T \mid D, p^{(0)}, q^{(0)})$

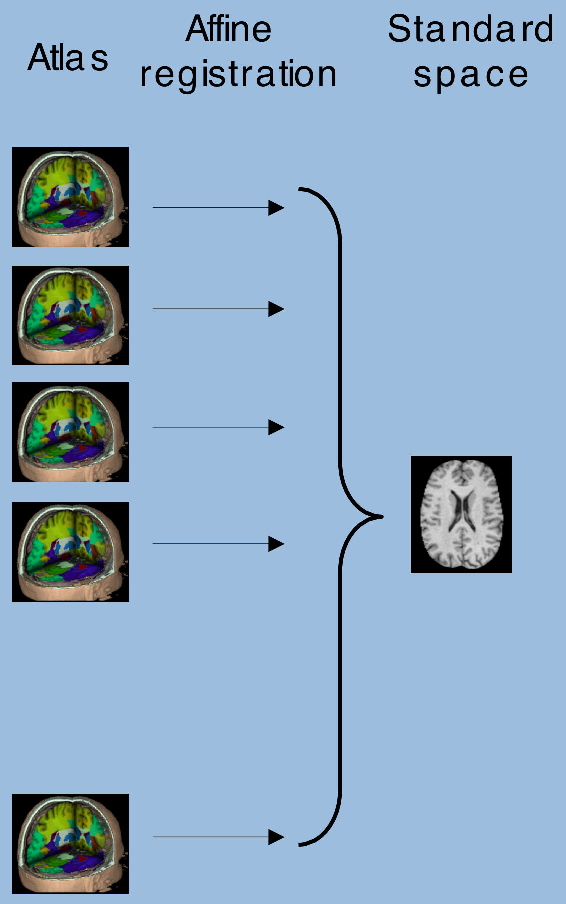
$p^{(0)}, q^{(0)}$: initial estimate

E-step

$p^{(1)}, q^{(1)}$: next estimate

M-step : use the current ground truth to estimate the next $p^{(1)}, q^{(1)}$.

Multi-atlas segmentation using classifier **fusion and selection**



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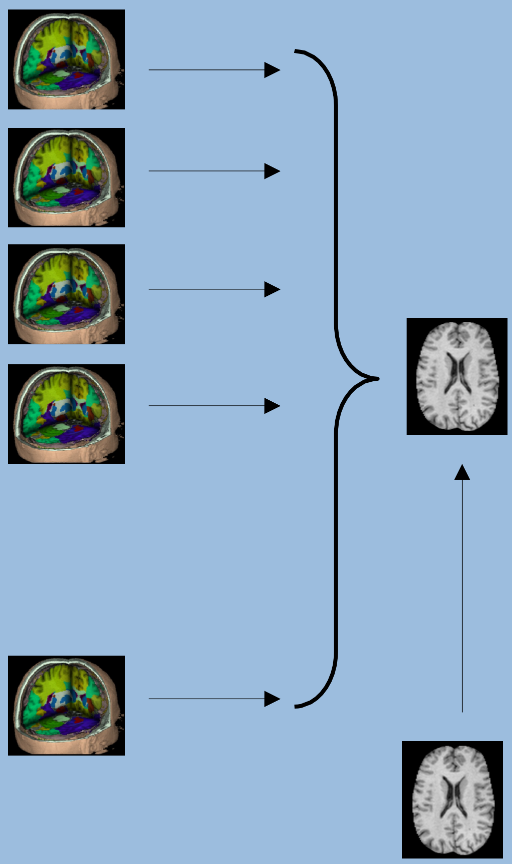

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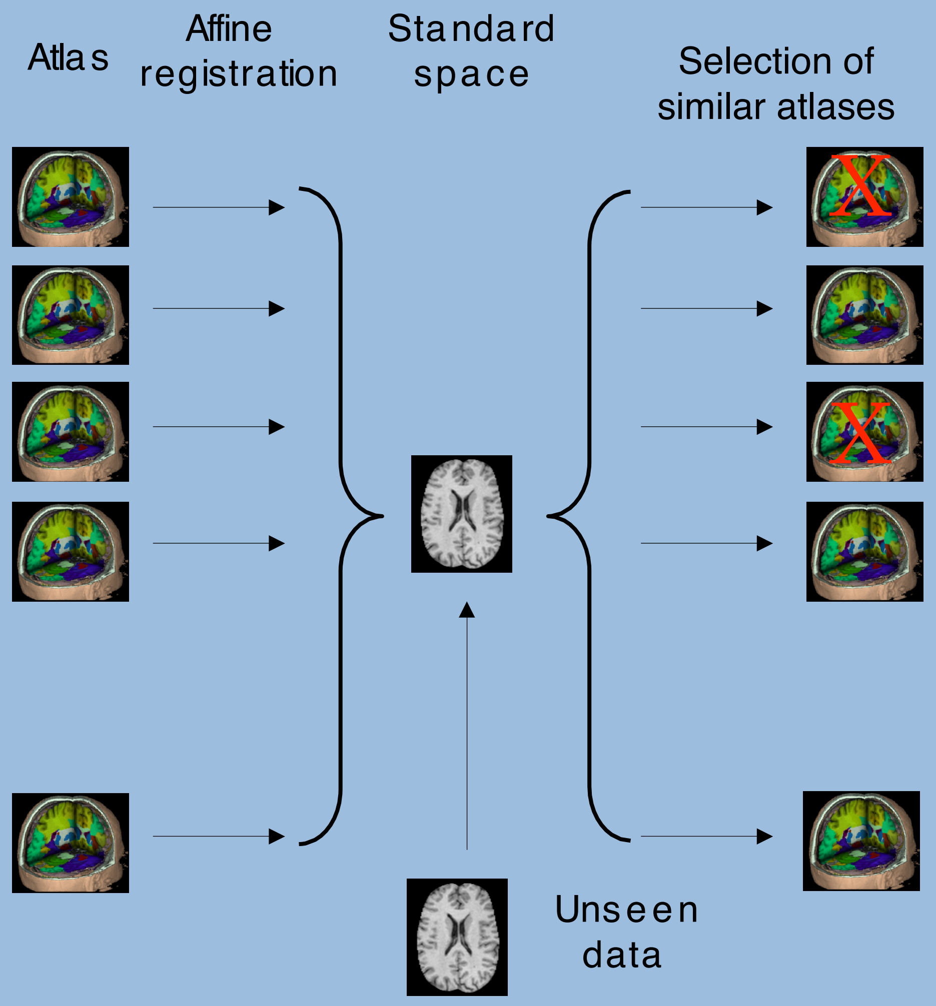
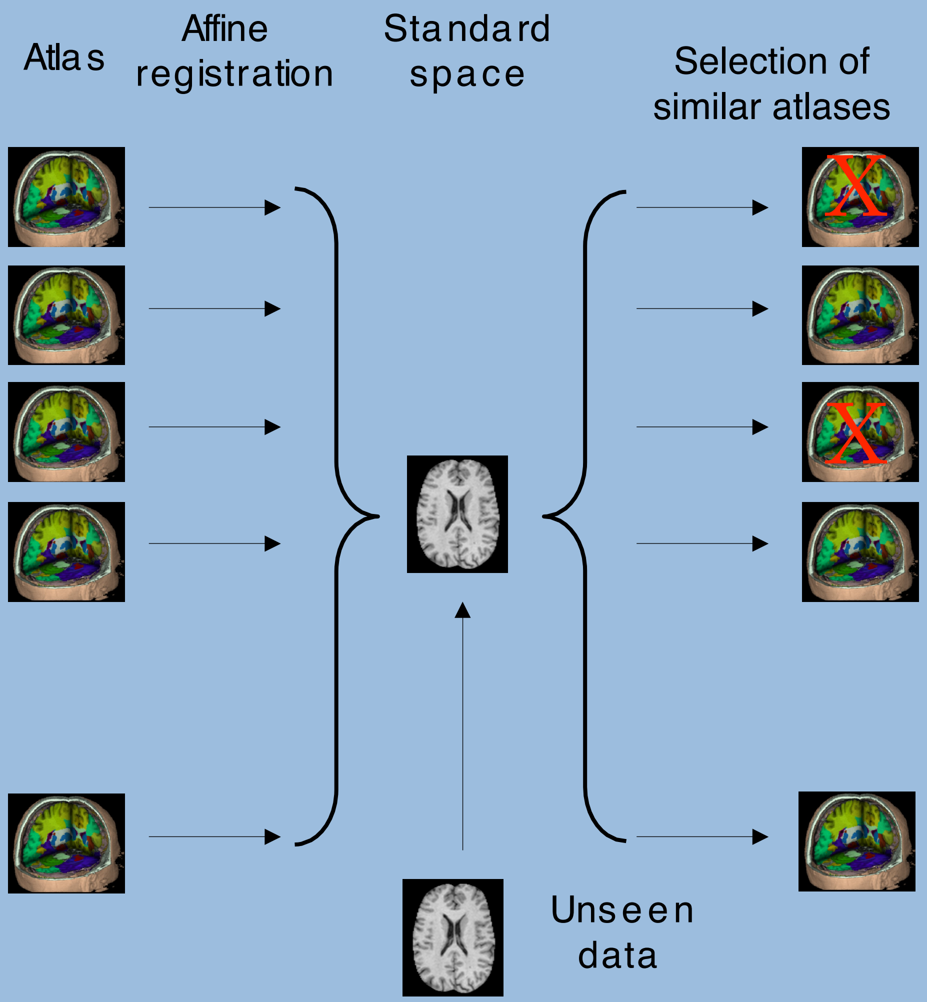


Multi-atlas segmentation using classifier **fusion and selection**



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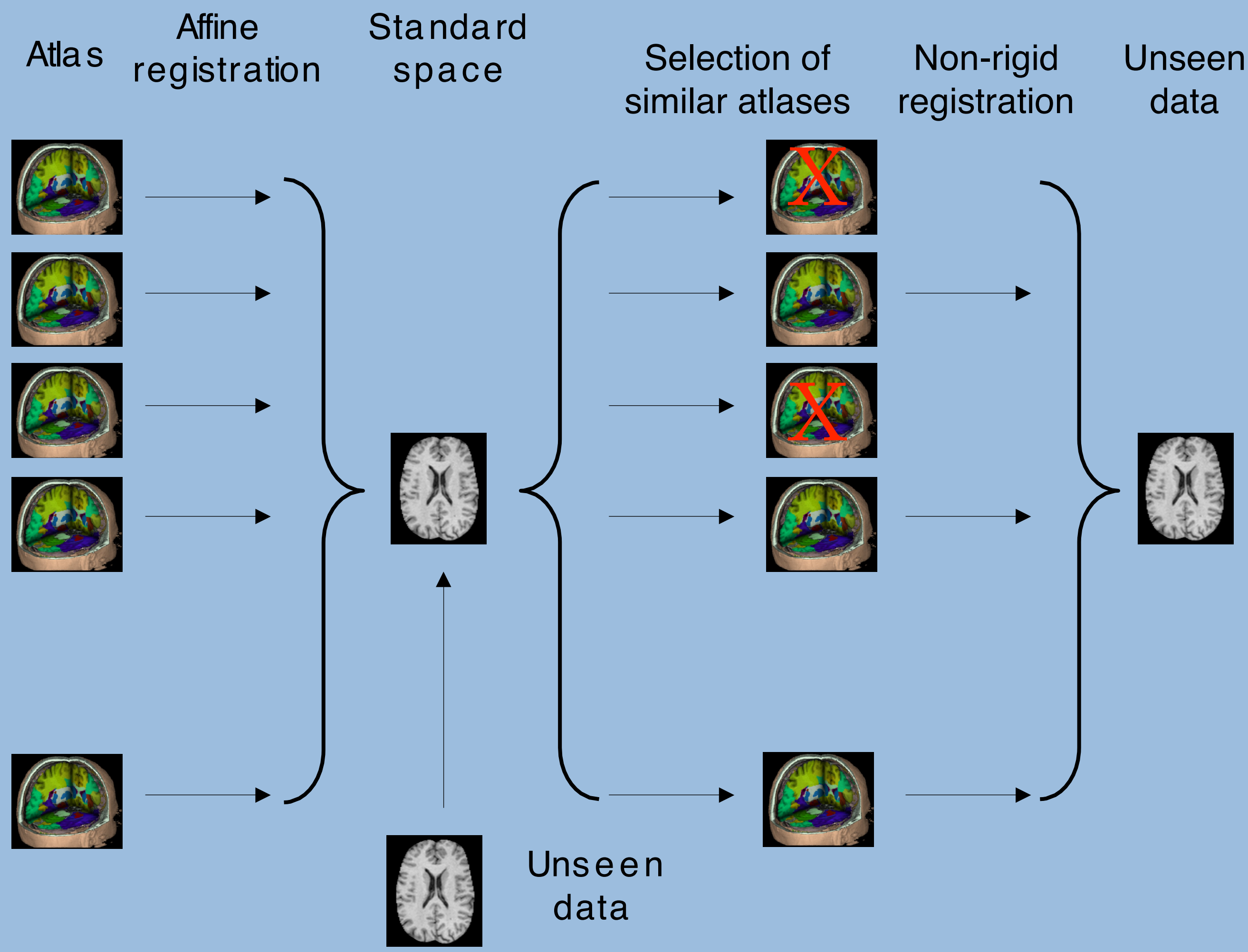

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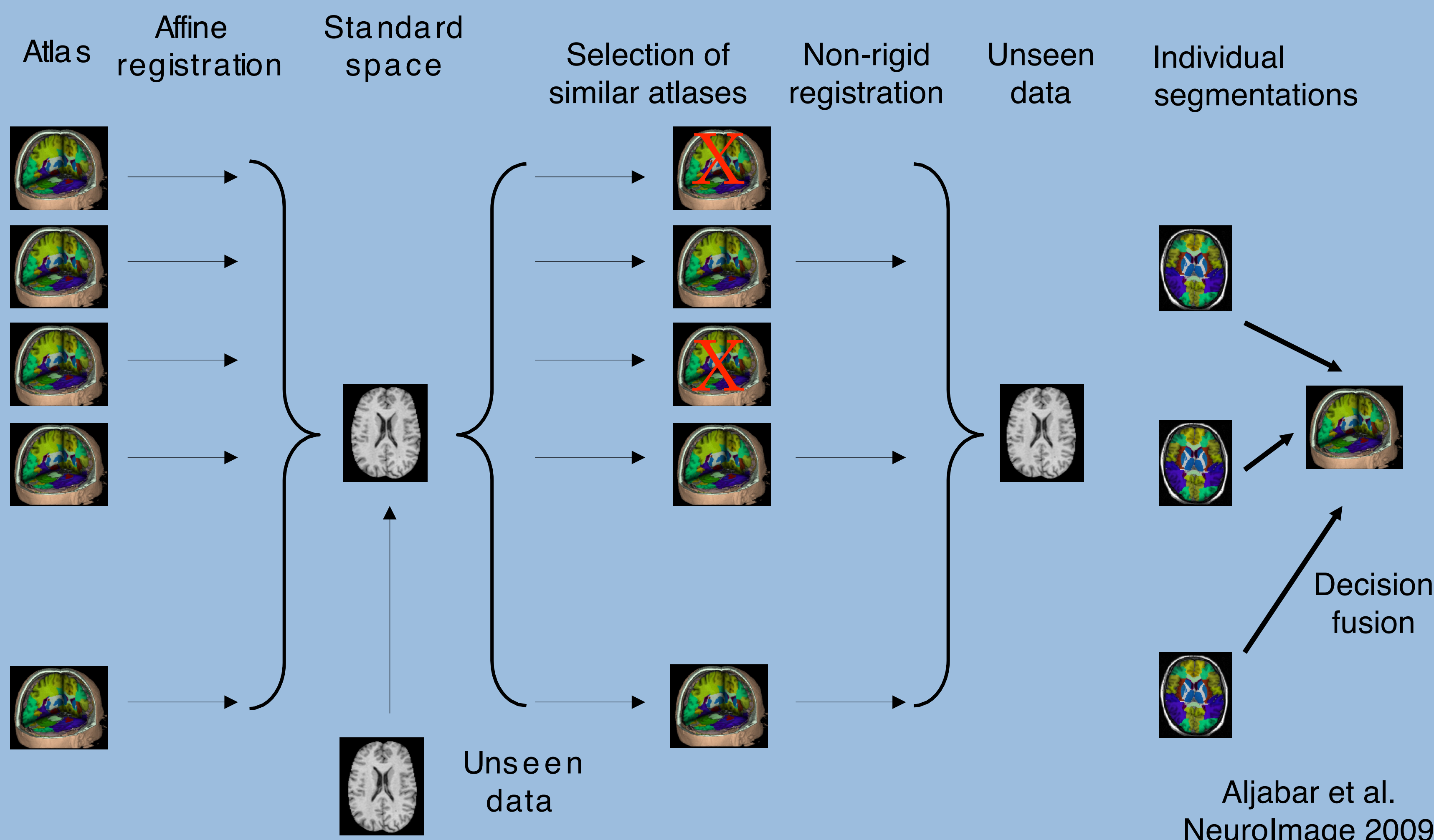
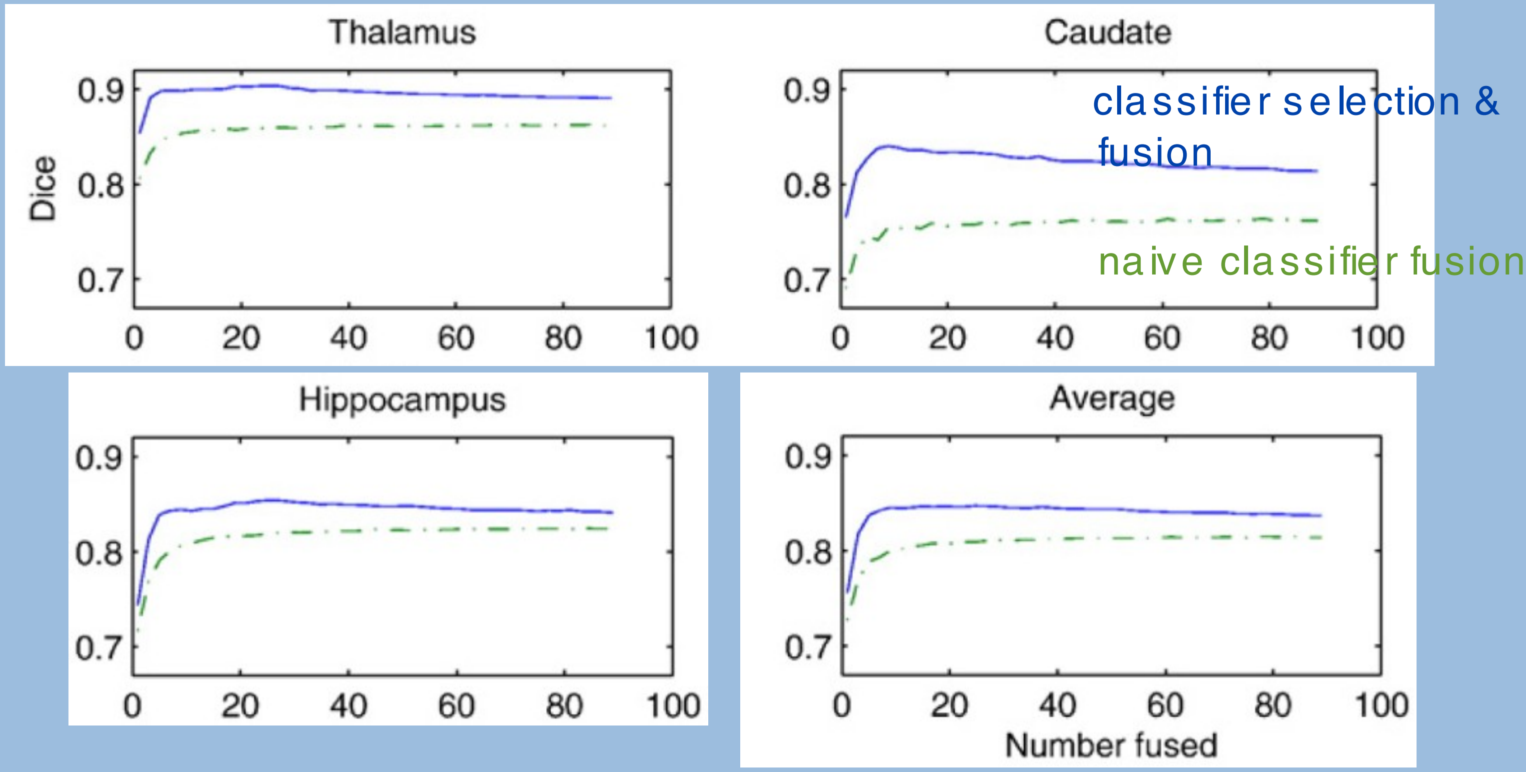


Aljabar et al.
NeuroImage 2009

Multi-atlas segmentation using classifier **fusion and selection**



Aljabar et al.
NeuroImage 2009

Patch-based segmentation

- Patch-based methods have been popular in the computer vision community, e.g.
  - texture synthesis (Efros and Freeman, 2001)
  - in-painting (Criminisi et al., 2004)
  - restoration (Buades et al., 2005)
  - single-frame super resolution (Protter et al., 2009).
- Basic idea:
  - only coarse registration required (e.g. rigid or affine registration)
  - use the same concept as label fusion

Patch-based denoising

- Buades et al. 2005
  - uses a neighborhood averaging strategy called non-local means (NLM)
  - assumes that every patch in a natural image has many similar patches in the same image.

$$\forall \mathbf{x} \in \Omega,\ I_{nlm}(\mathbf{x}) = \frac{\sum_{\mathbf{y}\in\Omega} w(\mathbf{x},\mathbf{y}) I(\mathbf{y})}{\sum_{\mathbf{y}\in\Omega} w(\mathbf{x},\mathbf{y})}$$

Denoised image

Original image

Self-similarity

Patch-based denoising

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$$\forall \mathbf{x} \in \Omega,\ I_{nlm}(\mathbf{x}) = \frac{\sum_{\mathbf{y}\in\Omega} w(\mathbf{x},\mathbf{y}) I(\mathbf{y})}{\sum_{\mathbf{y}\in\Omega} w(\mathbf{x},\mathbf{y})}$$

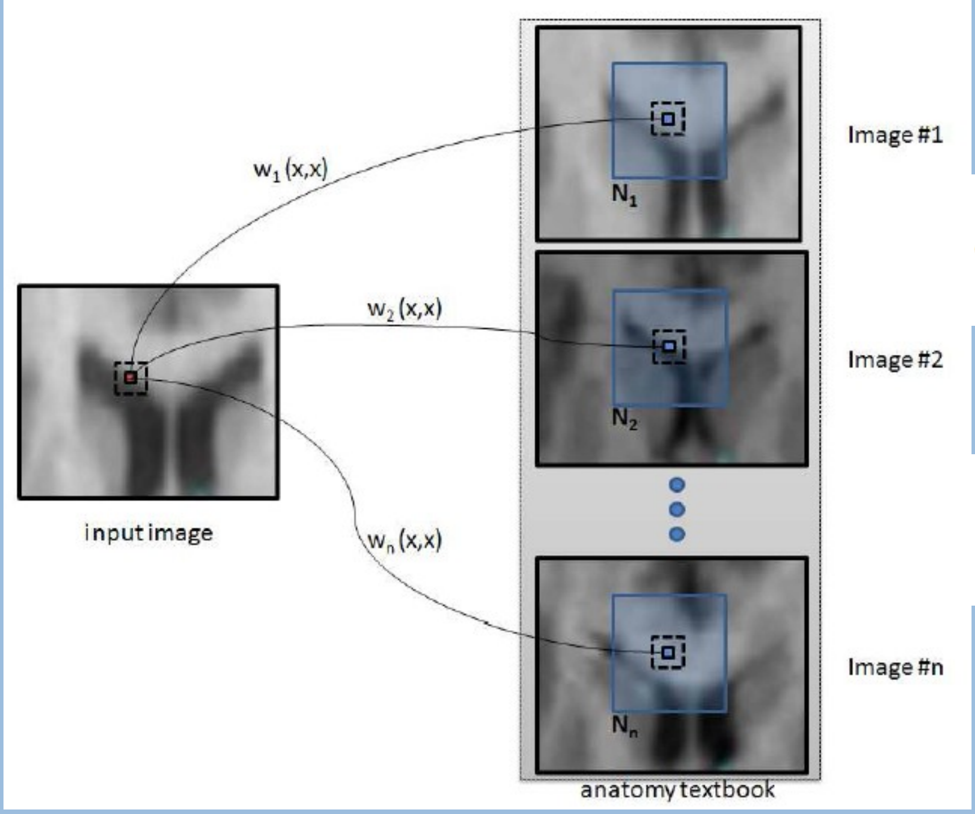
$$w(\mathbf{x},\mathbf{y}) = f\left(\frac{\sum_{\mathbf{x}'\in\mathcal{P}_I(\mathbf{x}),\mathbf{y}'\in\mathcal{P}_I(\mathbf{y})} \left(I(\mathbf{x}') - I(\mathbf{y}')\right)^2}{2N\beta\hat{\sigma}^2}\right)$$

Weighting function
usually: exp(-x)

Bandwidth for smoothing

Patch-based denoising

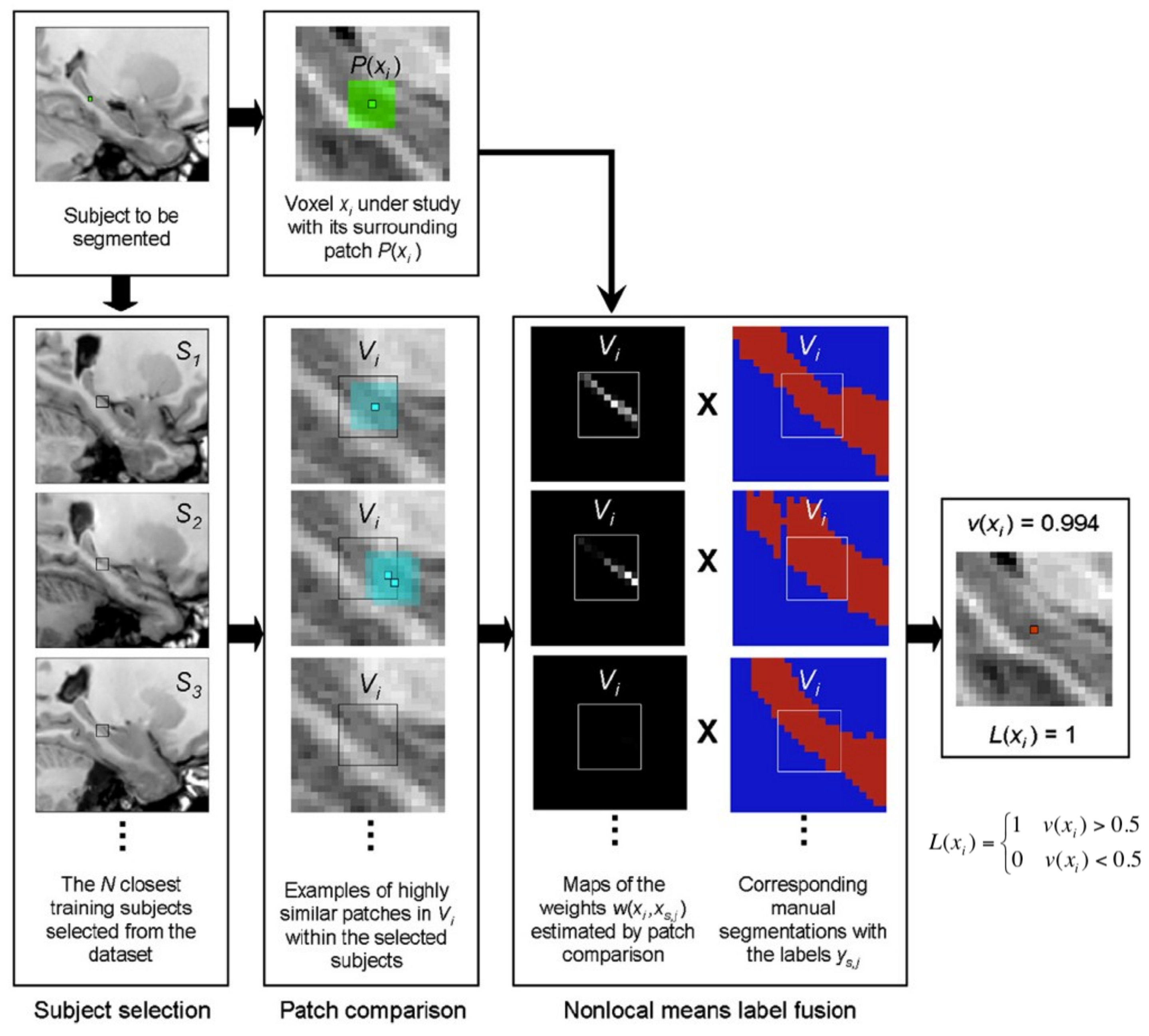
- Apply the same idea as in denoising to label fusion:
  - Simultaneously proposed by Rousseau et al. and Coupe et al. in 2011



$$w_i(\mathbf{x},\mathbf{y}) = f\left(\frac{\sum_{\mathbf{x}'\in\mathcal{P}_I(\mathbf{x}),\mathbf{y}'\in\mathcal{P}_{\mathcal{I}_i}(\mathbf{y})}\left(I(\mathbf{x}')-\mathcal{I}_i(\mathbf{y}')\right)^2}{2N\beta\hat{\sigma}^2}\right)$$

$$\forall \mathbf{x}\in\Omega, L(\mathbf{x}) = \frac{\sum_{i=1}^{n}\sum_{\mathbf{y}\in\mathcal{N}(\mathbf{x})} w_i(\mathbf{x},\mathbf{y})\mathcal{L}_i(\mathbf{y})}{\sum_{i=1}^{n}\sum_{\mathbf{y}\in\mathcal{N}(\mathbf{x})} w_i(\mathbf{x},\mathbf{y})}$$

Rousseau et al. 2011

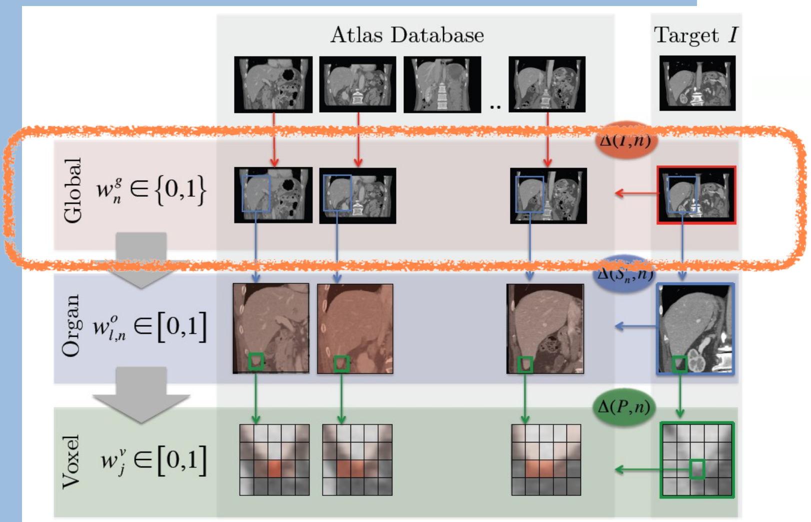


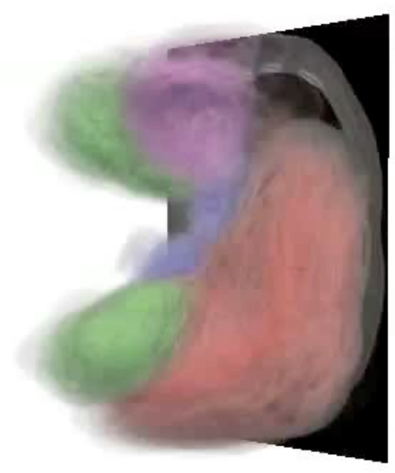
Coupe et al. 2011

Patch-based multi-organ segmentation of abdominal CT

- Segmentation of CT scans from 150 subjects
- Hierarchical, patch-based label fusion process

Structure	Dice	Jaccard
Kidneys	92.5 (7.2) [51.5 98.2]	86.8 (10.5) [34.6 96.4]
Liver	94.0 (2.8) [81.4 97.3]	88.9 (4.8) [68.7 94.9]
Pancreas	69.6 (16.7) [6.9 90.0]	55.5 (17.1) [3.6 83.3]
Spleen	92.0 (9.2) [26.4 98.2]	86.2 (12.7) [15.2 96.4]





Wolz et al, IEEE-TMI, 2013

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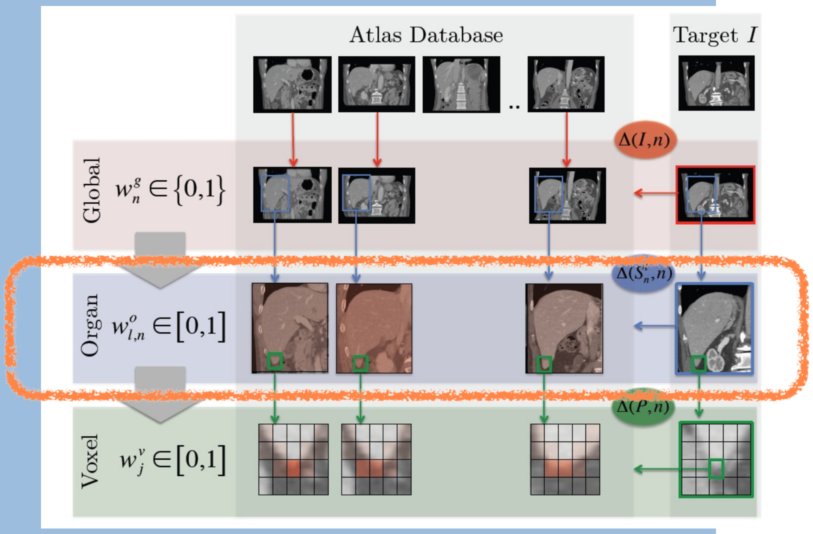

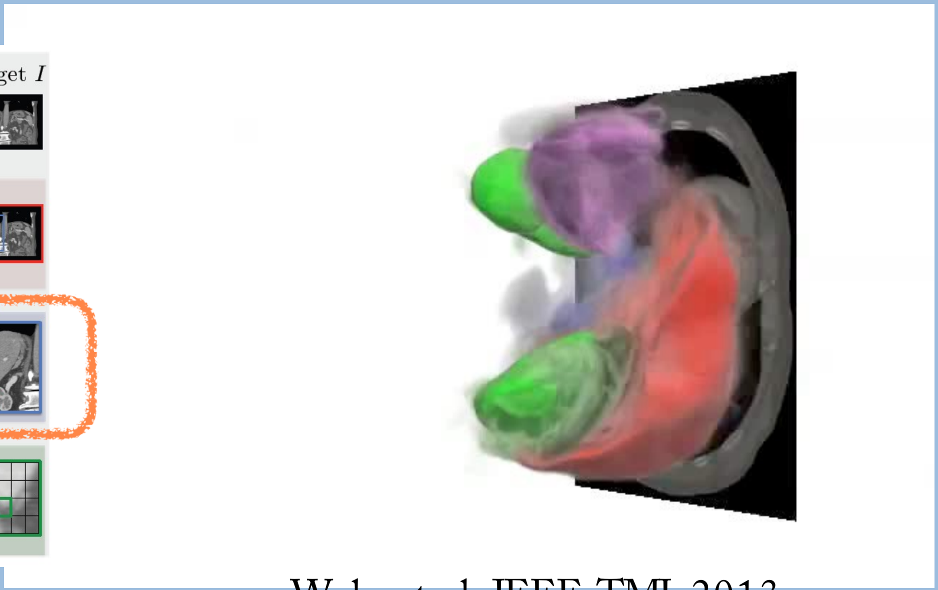

Wolz et al, IEEE-TMI, 2013

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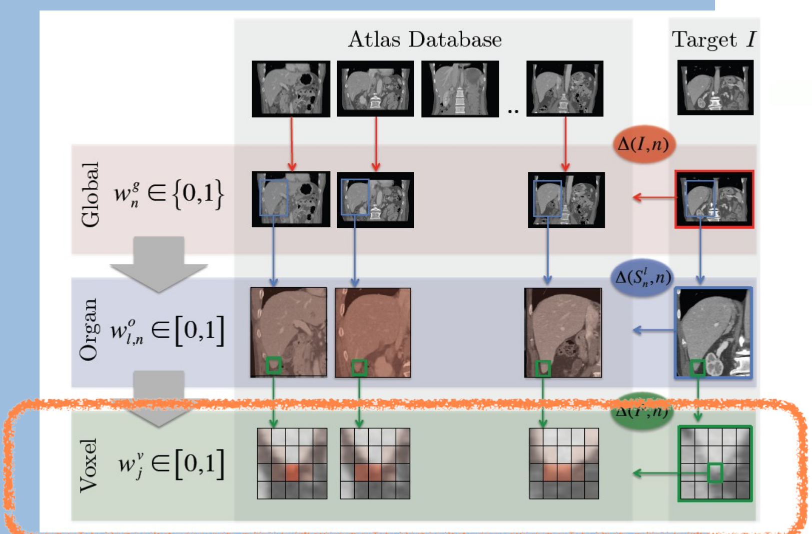

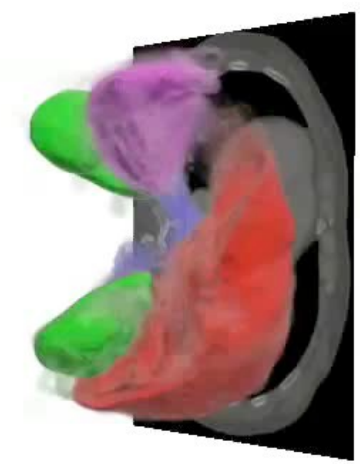

Wolz et al, IEEE-TMI, 2013

Patch-based multi-organ segmentation of abdominal CT

- Segmentation of CT scans from 150 subjects
- Hierarchical, patch-based label fusion process plus graph-cut refinement

Structure	Dice	Jaccard
Kidneys	92.5 (7.2) [51.5 98.2]	86.8 (10.5) [34.6 96.4]
Liver	94.0 (2.8) [81.4 97.3]	88.9 (4.8) [68.7 94.9]
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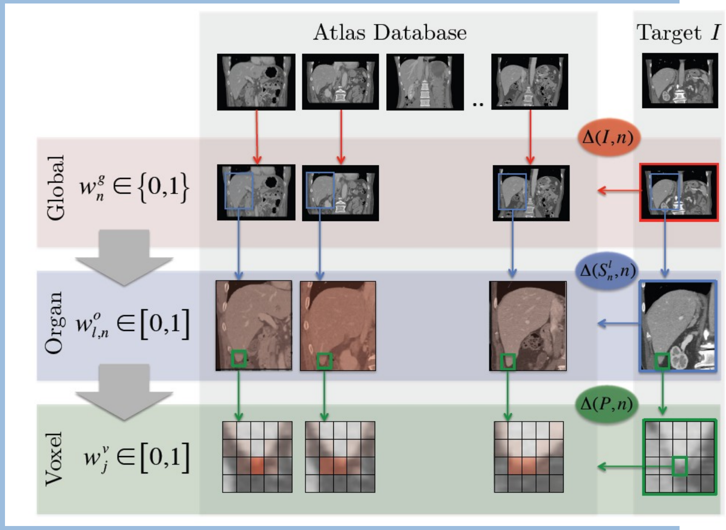
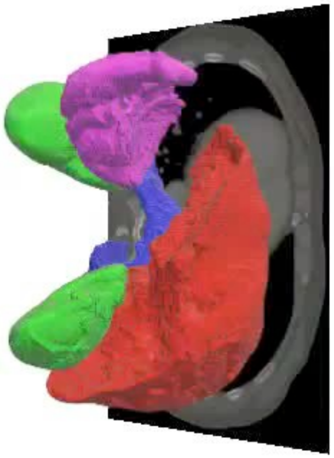
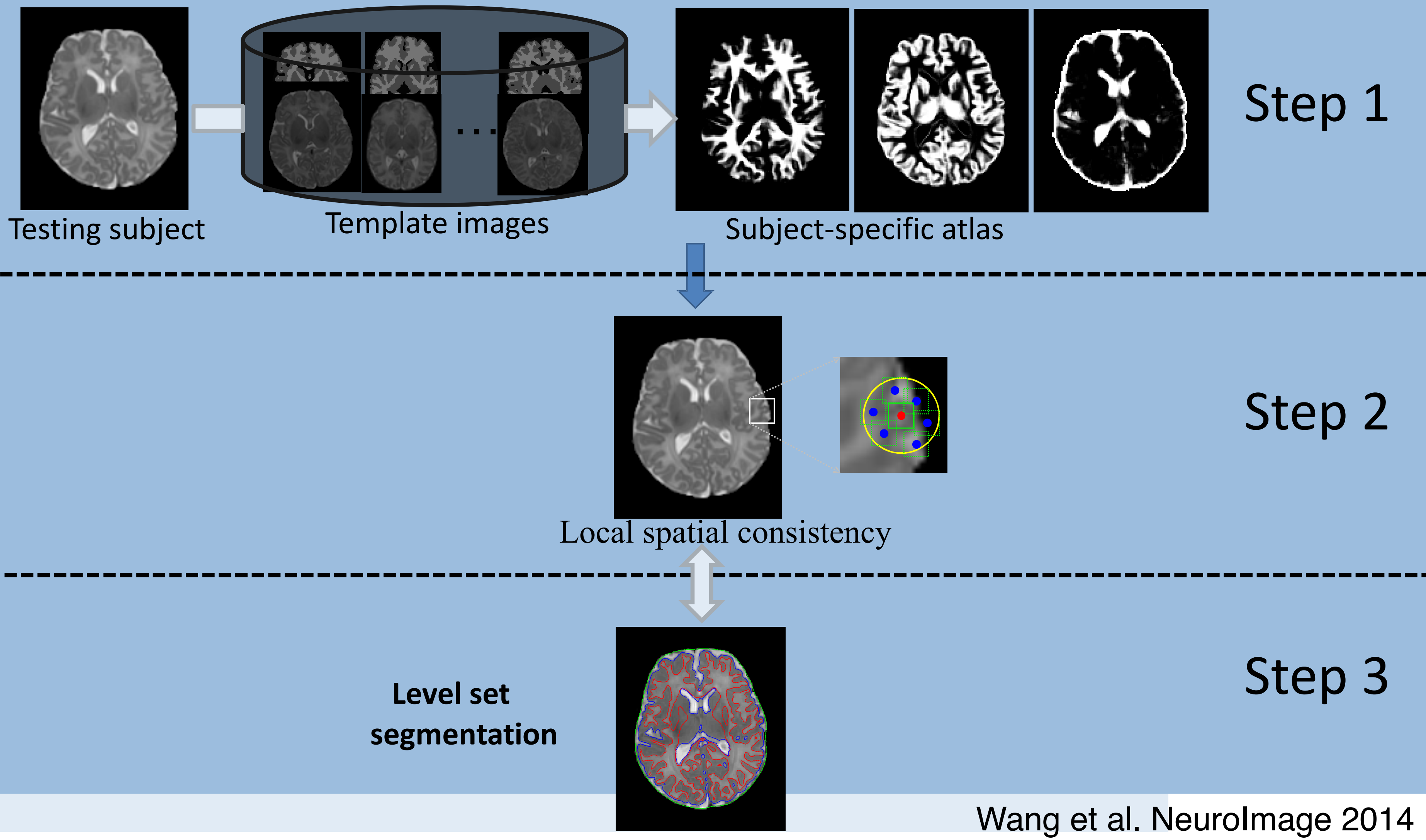




Wolz et al, IEEE-TMI, 2013

Patch-based multi-organ segmentation of brain structures



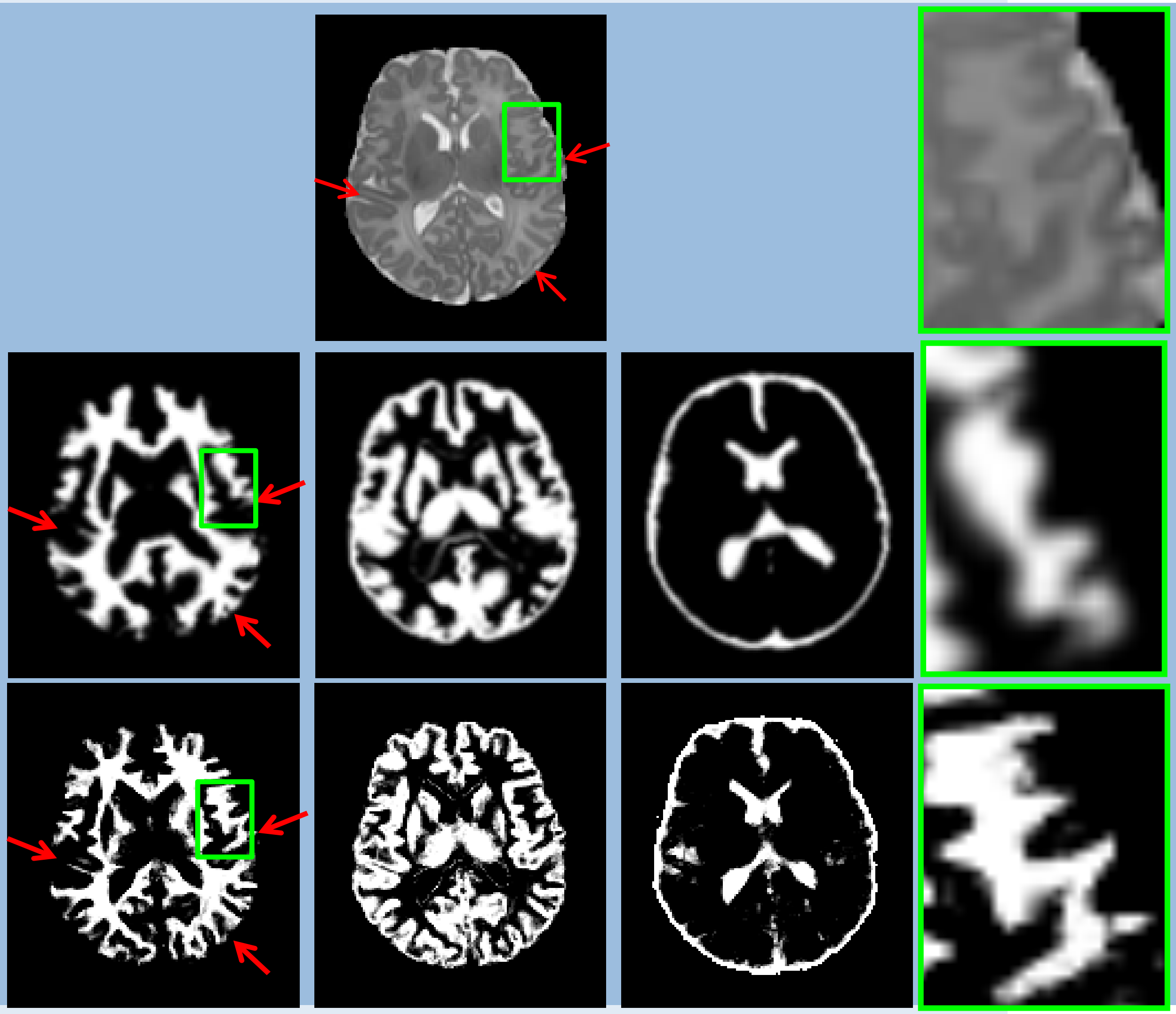
Wang et al. NeuroImage 2014

Patch-based multi-organ segmentation of brain structures

Original T2 image

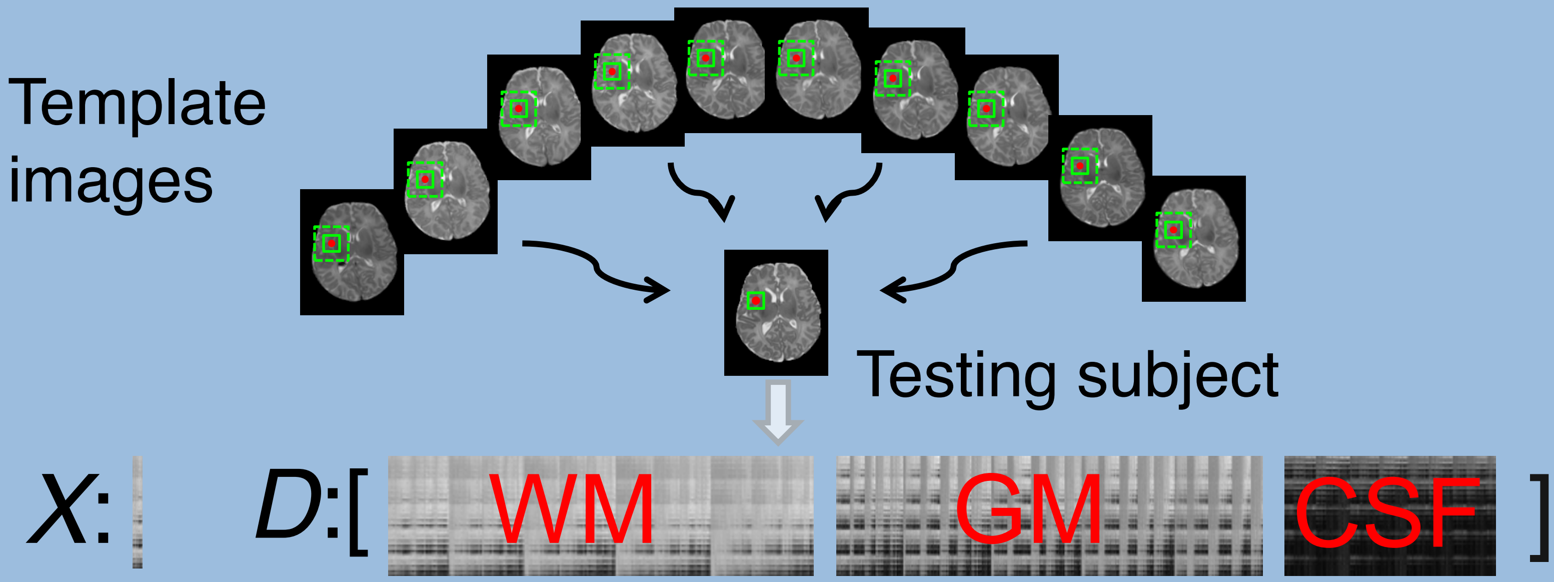
Population-based atlas

Subject-specific atlas



Wang et al. NeuroImage 2014

Patch-based multi-organ segmentation of brain structures



$$\min_{\alpha \geq 0} \frac{1}{2}\|X - D\alpha\|_2^2 + \lambda_1\|\alpha\|_1 + \frac{\lambda_2}{2}\|\alpha\|_2^2$$

Wang et al. NeuroImage 2014

Patch-based multi-organ segmentation of brain structures

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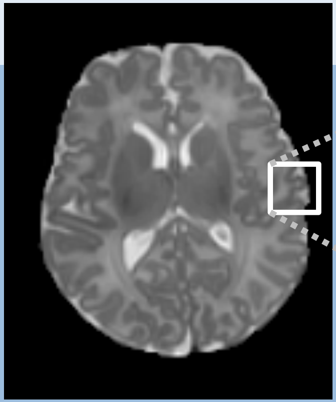
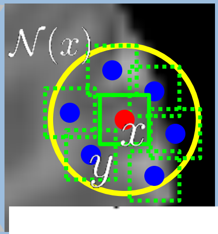




$$P_j^{Patch\_L}(x) \propto \frac{1}{Z}\sum_{y\in\mathcal{N}(x)} \underbrace{\alpha'_y}_{\substack{patch\\ similarity}} \underbrace{p_{j,y}\big(I(x)\big)}_{LGD}$$

$$\min_{\alpha'\geq 0} \frac{1}{2}\left\|X - D'\alpha'\right\|_2^2 + \lambda_1\left\|\alpha'\right\|_1 + \frac{\lambda_2}{2}\left\|\alpha'\right\|_2^2$$

$$p_{j,y}\big(I(x)\big) = \frac{1}{\sqrt{2\pi}\sigma_j(y)}\exp\left(-\frac{\big(u_j(y) - I(x)\big)^2}{2\sigma_j^2(y)}\right)$$

$$P_j^{Patch\_L\_Prior}(x) = \underbrace{P_j(x)}_{prior} P_j^{Patch\_L}(x)$$

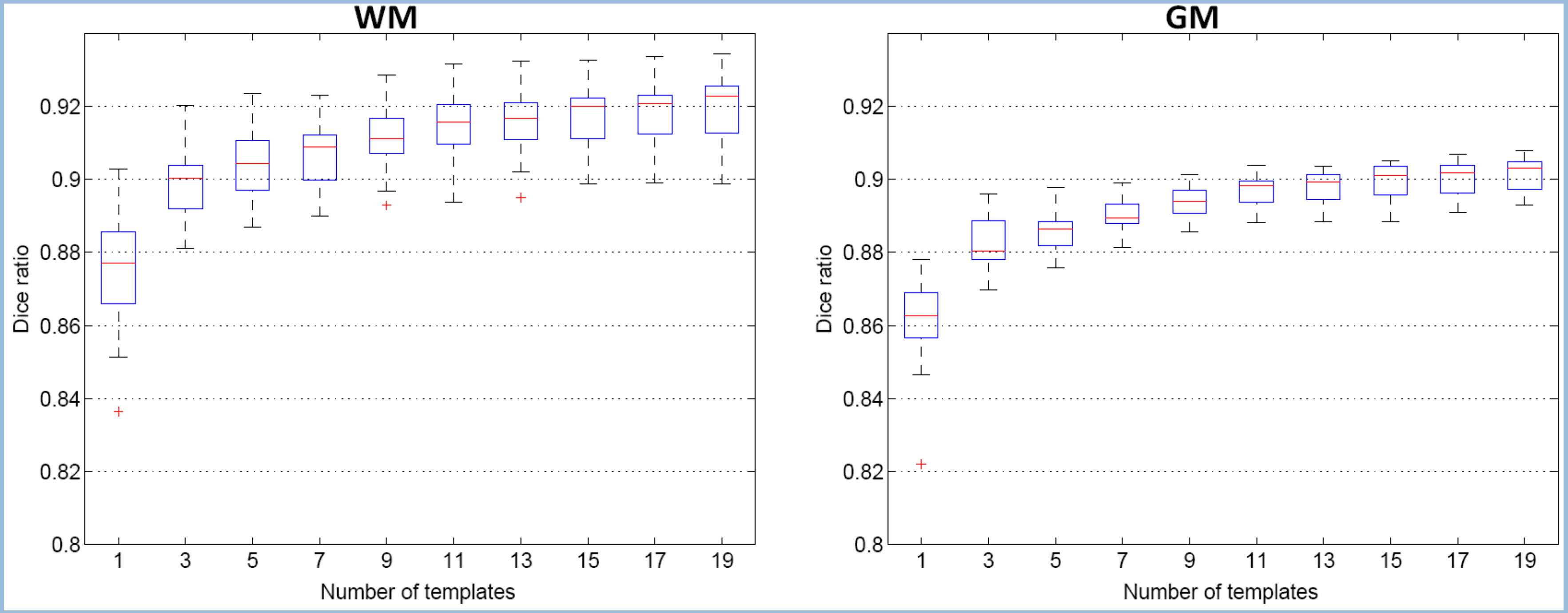
Step 1: subject-specific atlas

$$\varepsilon = -\sum_{j=1}\int_{x\in\Omega_j} log\ P_j^{Patch\_L\_Prior}(x)\ dx$$

Wang et al. NeuroImage 2014

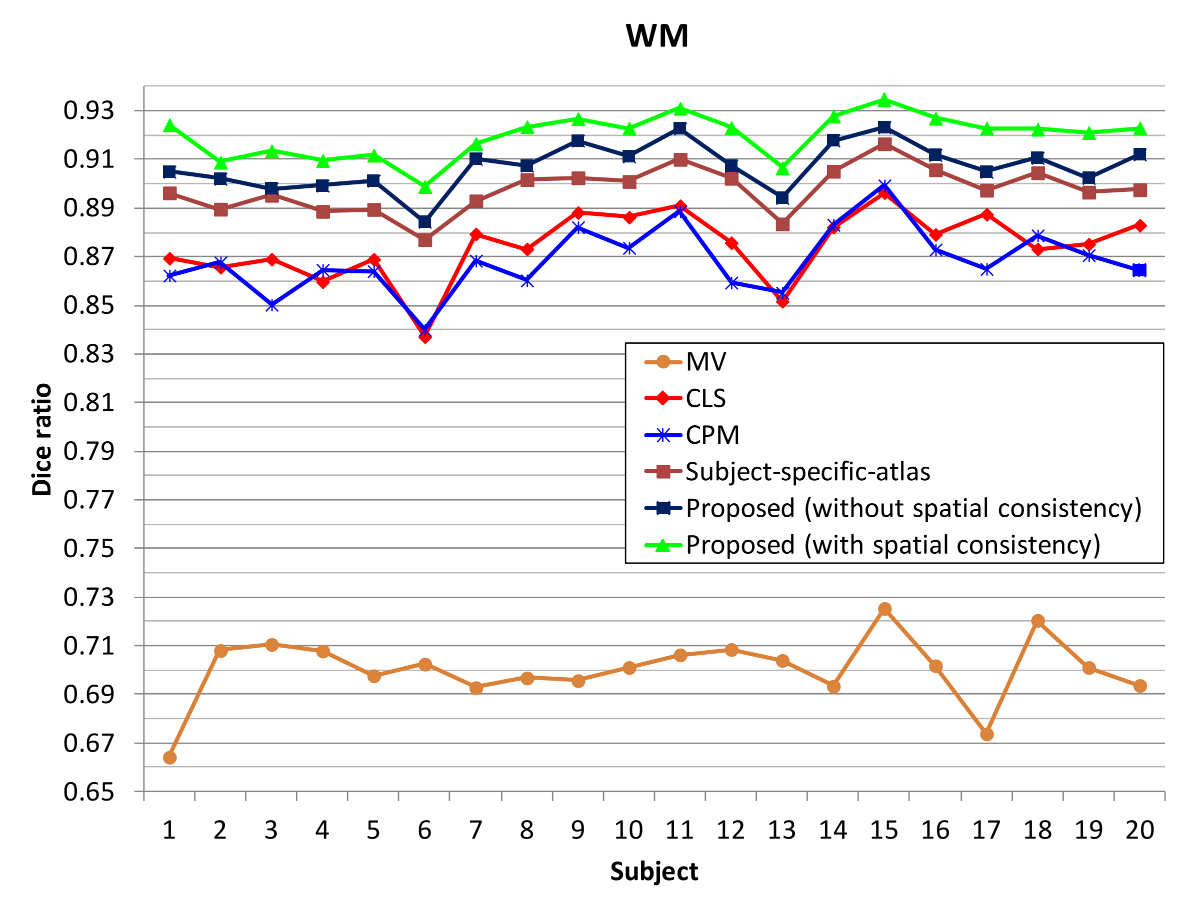
Template numbers?

How many template images are needed to generate a good segmentation?



Box-whisker plots of Dice ratio of segmentation using an increasing number of templates from the library. Experiment is performed by leave-one-out using the library of 20 templates.

Leave-one-out cross validation on 20 subjects



M V: *Majority voting*
CLS (Coupled level sets): *Wang, L., et al., 2011. NeuroImage*
CPM (Conventional patch-based method): *Coupe, P.,et al., 2011. NeuroImage*

8 testing subjects with manual segmentations

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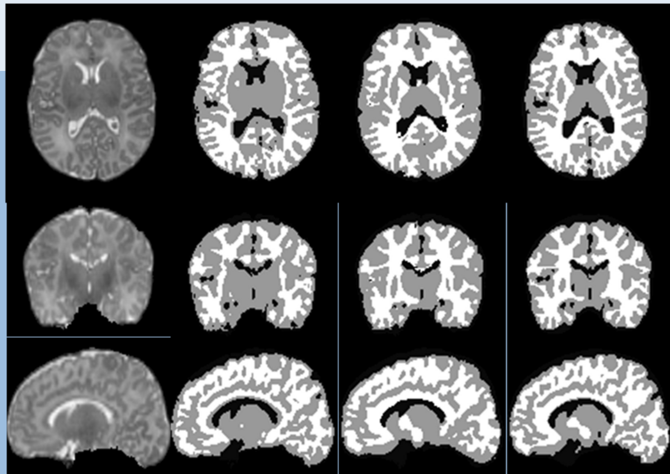
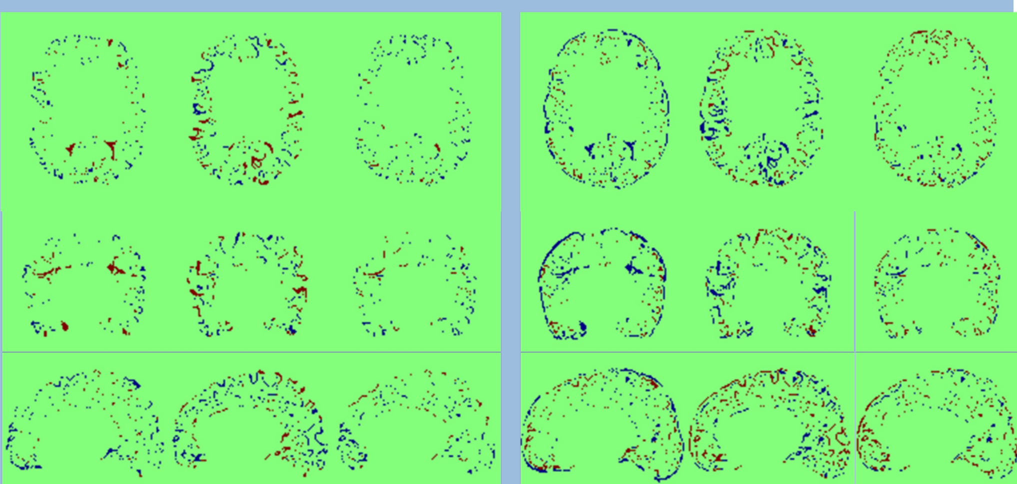
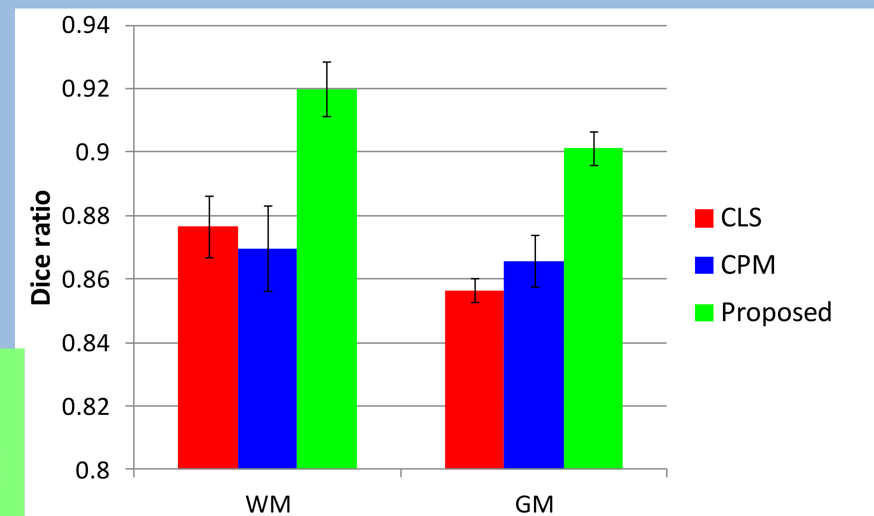


(a) Original (b) CLS (c) CPM (d) Proposed



(e) CLS (f) CPM (g) Proposed (h) CLS (i) CPM (j) Proposed

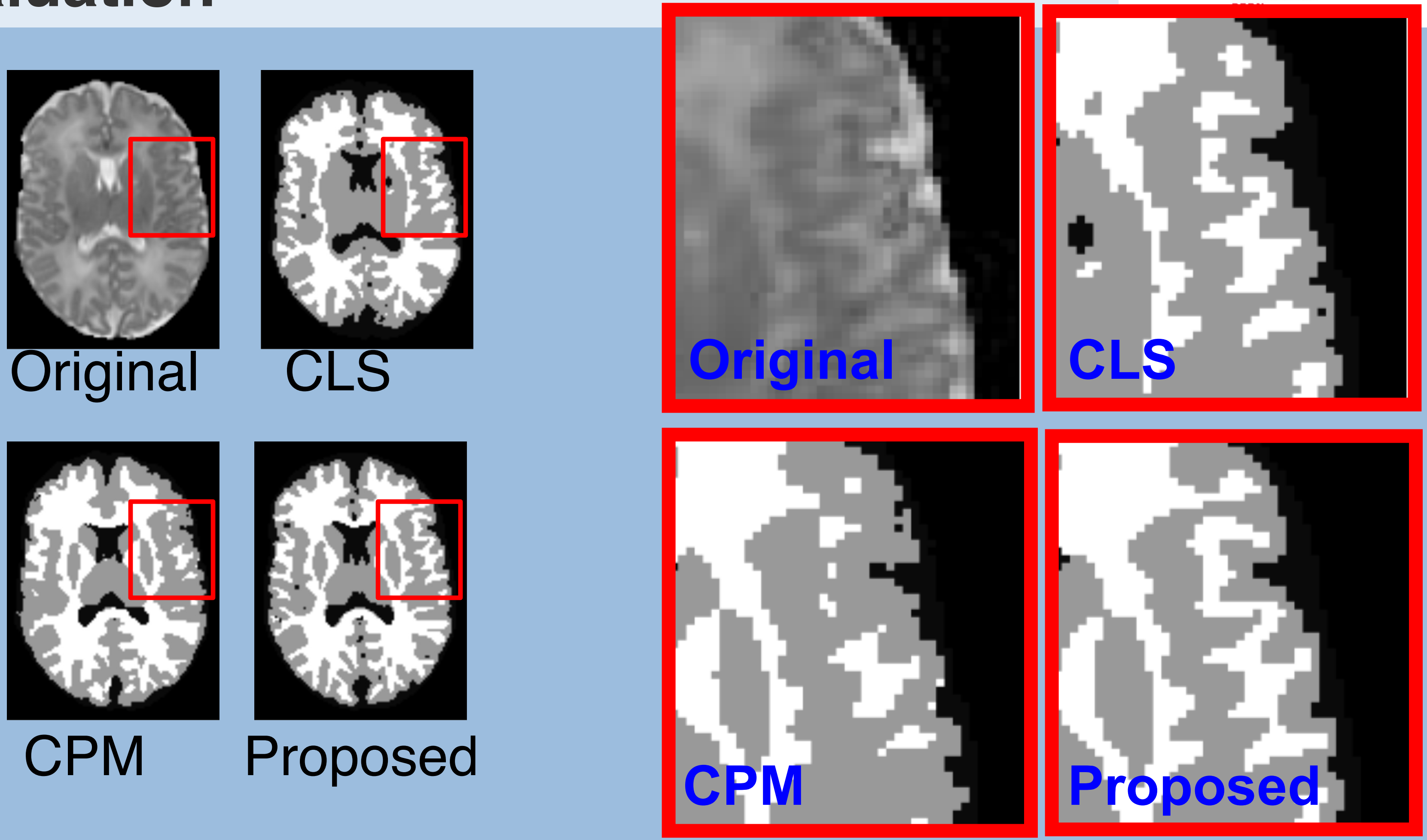
WM difference GM difference



CLS: Coupled level set

CPM: Conventional patch-based method

94 testing subjects for qualitative evaluation



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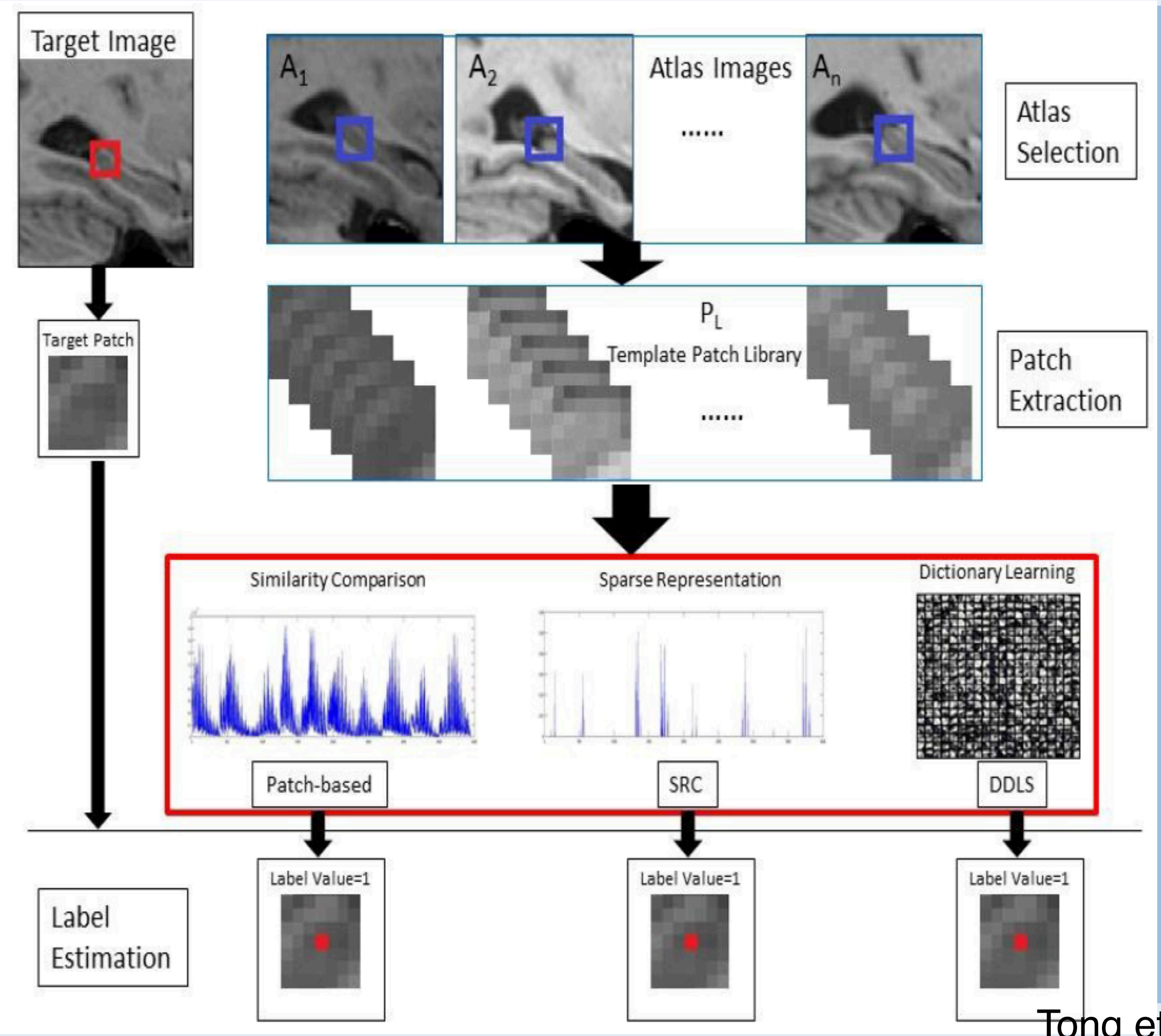
CPM: Conventional patch-based method

Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)



Tong et al. Neuroimage 2013

Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)

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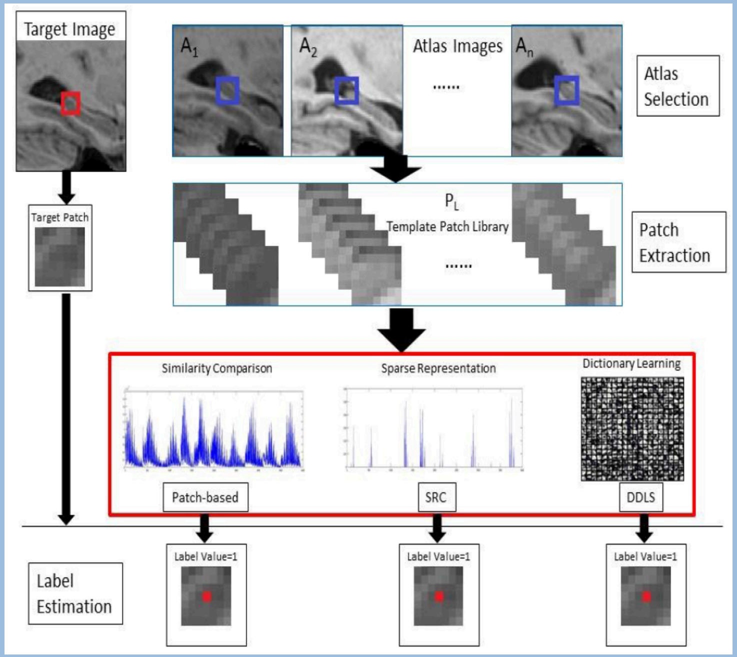
- SRC assumes a target patch represented by a few representative patches
- DDLS adds a learned linear classifier



Target patch

$$p_t = a_1 p_1 + a_2 p_2 + \cdots + a_n p_n$$

a_i: coefficient; sparse

p_i: patch library

$$\hat{\mathrm{a}} = \min_{\mathrm{a}} \frac{1}{2} \|\mathrm{p_t} - \mathrm{P_L a}\|_2^2 + \lambda_1 \|\mathrm{a}\|_1 + \frac{\lambda_2}{2} \|\mathrm{a}\|_2^2$$

Elastic-Net problem

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Patch-based Labeling vs.
Sparse Representation Classification (SRC) vs.
Discriminative Dictionary Learning for Segmentation (DDLS)

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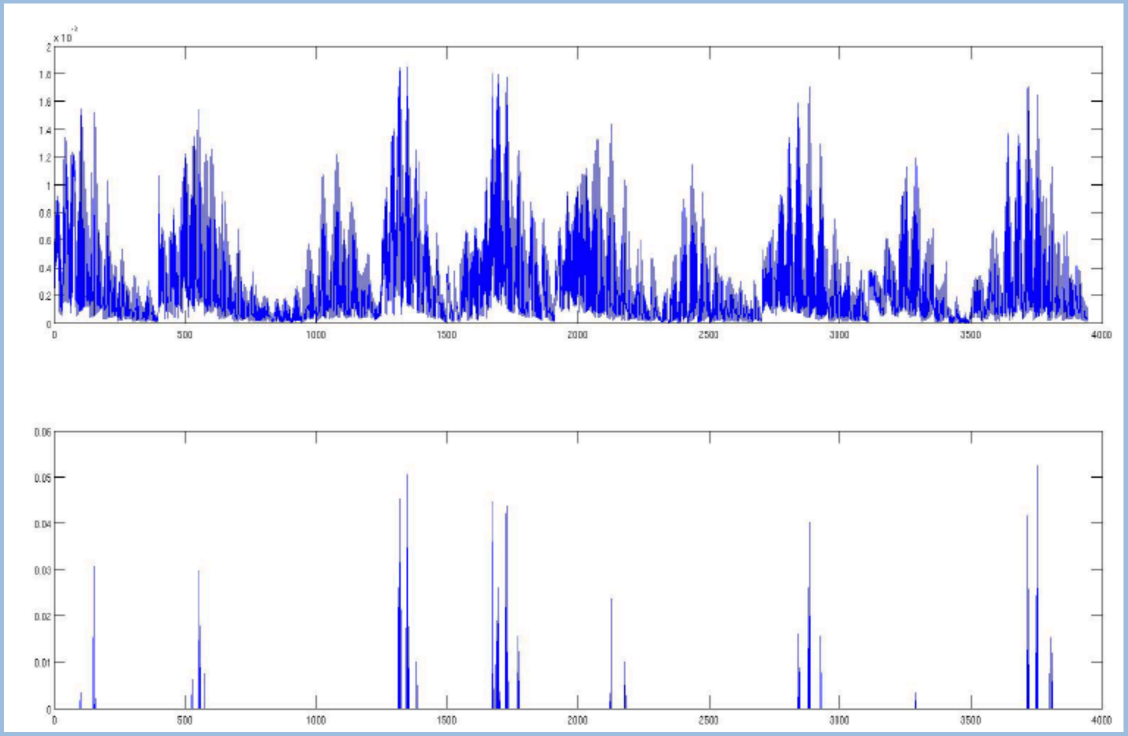

Patch-based

SRC

Tong et al. Neuroimage 2013

Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)

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- DDLS:
  - Decrease computational burden via smaller-size dictionary
  - Better exploit discriminative power of patch library

$$\langle D, W, \alpha \rangle = \underset{D,W,\alpha}{\arg\min} \underbrace{\boxed{\|\mathrm{P_L} - D\alpha\|_2^2}}_{\text{Reconstruction error}} + \beta_1 \underbrace{\boxed{\|H - W\alpha\|_2^2}}_{\text{Classification accuracy}}$$

$$\text{subject to} \quad \|\alpha\|_0 \leq T$$

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Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)

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- DDLS:
  - Decrease computational burden via smaller-size dictionary
  - Better exploit discriminative power of patch library

$$\langle D, W, \alpha \rangle = \underset{D,W,\alpha}{\arg\min} \|\mathrm{P_L} - D\alpha\|_2^2 + \beta_1 \|H - W\alpha\|_2^2 \quad \text{subject to} \quad \|\alpha\|_0 \leq T$$

$$\langle D, W, \alpha \rangle = \underset{D,W,\alpha}{\arg\min} \left\| \begin{pmatrix} \mathrm{P_L} \\ \sqrt{\beta_1} H \end{pmatrix} - \begin{pmatrix} D \\ \sqrt{\beta_1} W \end{pmatrix} \alpha \right\|_2^2 \quad \text{subject to} \quad \|\alpha\|_0 \leq T$$

Grouping patch and label information

$$\left\langle \tilde{D}, \alpha \right\rangle = \underset{\tilde{D},\alpha}{\arg\min} \left\| \tilde{\mathrm{P}}_\mathrm{L} - \tilde{D}\alpha \right\|_2^2 + \beta_2 \|\alpha\|_1$$

$$\tilde{D} = (D^t, \sqrt{\beta_1} W^t)^t, \; \tilde{\mathrm{P}}_\mathrm{L} = (\mathrm{P_L}^t, \sqrt{\beta_1} H^t)^t$$

Impose sparsity

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Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)

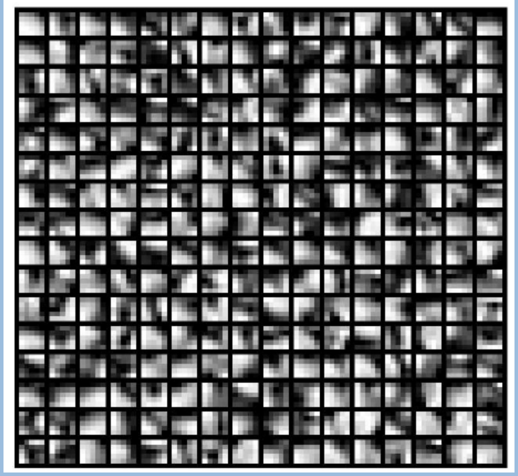
- DDLS:
  - Decrease computational burden via smaller-size dictionary
  - Better exploit discriminative power of patch library

$$\tilde{D}_t = \left\{ \begin{pmatrix} \tilde{d}_1 \\ \sqrt{\beta_1}\tilde{w}_1 \end{pmatrix}, \begin{pmatrix} \tilde{d}_2 \\ \sqrt{\beta_1}\tilde{w}_2 \end{pmatrix}, \cdots, \begin{pmatrix} \tilde{d}_K \\ \sqrt{\beta_1}\tilde{w}_K \end{pmatrix} \right\}$$

Normalized voxel-wise dictionaries and classifiers

$$\hat{D}_t = \left\{ \frac{\tilde{d}_1}{\|\tilde{d}_1\|_2}, \frac{\tilde{d}_2}{\|\tilde{d}_2\|_2}, \ldots, \frac{\tilde{d}_K}{\|\tilde{d}_K\|_2} \right\} \quad \hat{W}_t = \left\{ \frac{\tilde{w}_1}{\|\tilde{d}_1\|_2}, \frac{\tilde{w}_2}{\|\tilde{d}_2\|_2}, \ldots, \frac{\tilde{w}_K}{\|\tilde{d}_K\|_2} \right\}$$

Final {D,W}



Example of dictionary:
The dictionary has 16x16 atoms of size 53

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- Three-steps for DDLS:

1.- Extract patch p

2. Solve for:

$$\hat{\alpha}_t = \arg\min_{\alpha_t} \left\| p_t - \hat{D}_t \alpha_t \right\|_2^2 + \beta_2 \|\alpha_t\|_1$$

3.- Label voxel using classifier

$$\begin{cases} h_t = \hat{\mathrm{W}}_t \hat{\alpha}_t \\ v = \arg\max_j h_t(\mathrm{j}) \end{cases}$$

h_t: class label vector

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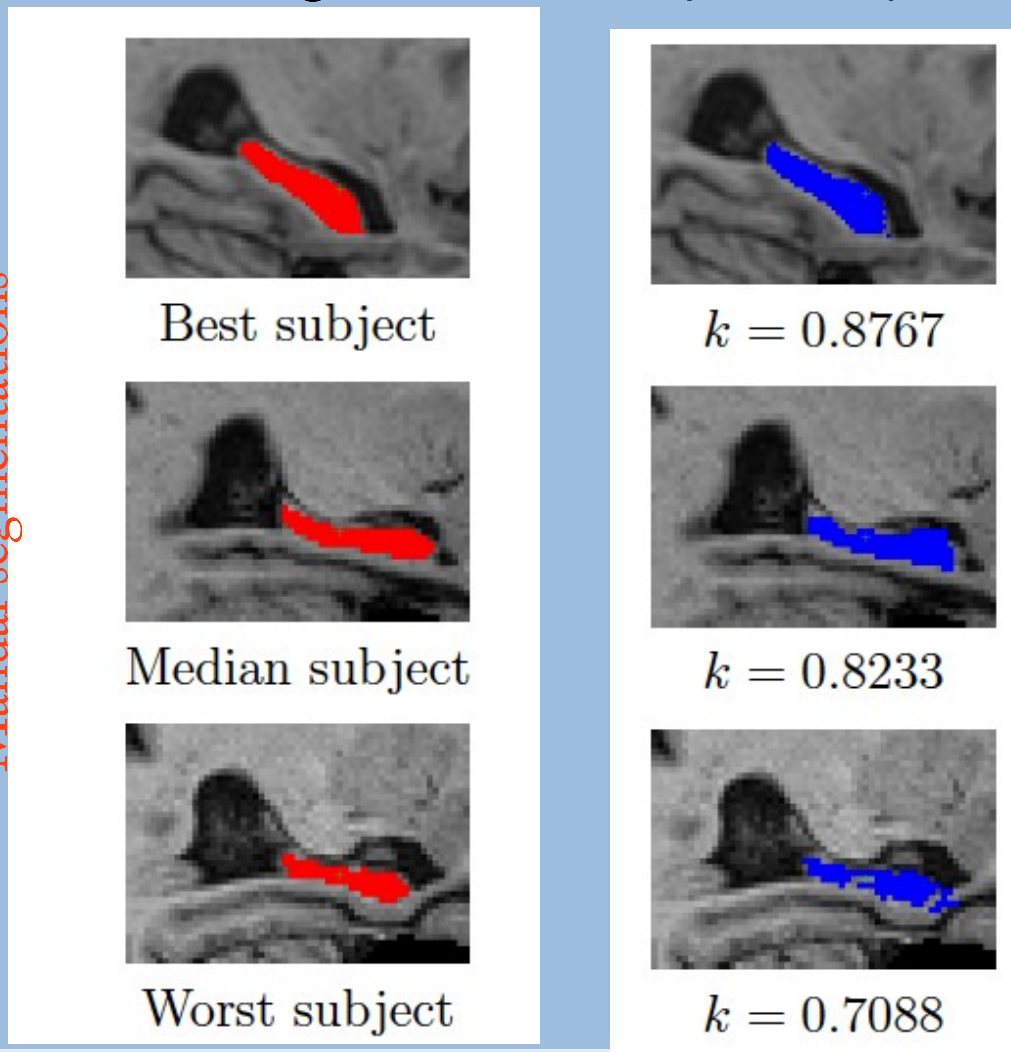
Discriminative Dictionary Learning for Segmentation (DDLS)

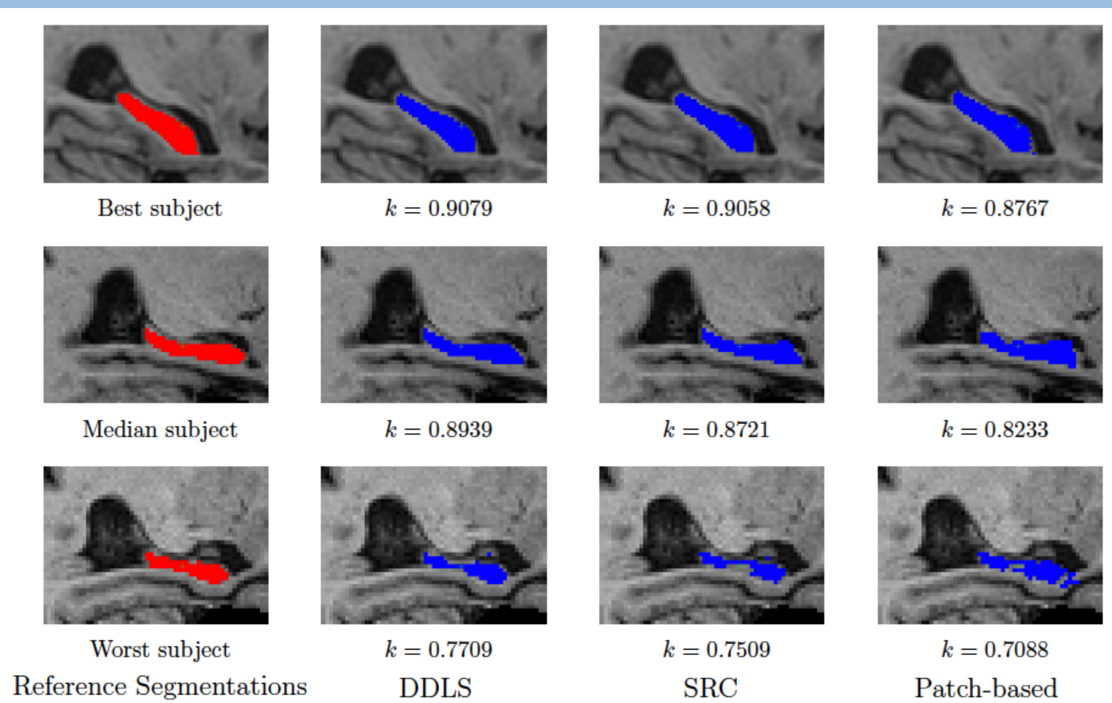
Manual segmentations

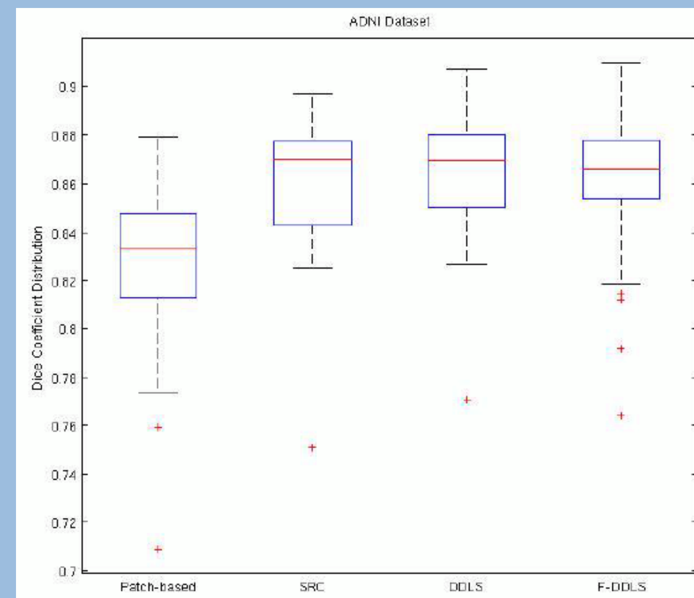


Automatic segmentations

Patch-based Labeling vs. Sparse Representation Classification (SRC) vs. Discriminative Dictionary Learning for Segmentation (DDLS)

Comparison of methods on ADNI dataset using Dice





Patch-based SRC DDLS

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Medical Image Analysis

(Multi)Atlas-Patch based Segmentation

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ARTORG Center Biomedical Engineering / Insel Data Science Center, Univ. Hospital Bern
Medical Image Analysis Group