Epitome driven 3-D Diffusion Tensor image Segmentation: on extracting *specific* structures

Kamiya Motwani[†§] Nagesh Adluru[§] Chris Hinrichs[†§] Andrew Alexander[‡] Vikas Singh[§†]

[†]Department of Computer Sciences [§]Department of Biostatistics & Med. Informatics [‡]Department of Medical Physics

THE UNIVERSITY of WISCONSIN MADISON

Objective:
Segmenting *specific* white matter structures of interest from Diffusion Tensor (DT-MR) brain images.

Contributions

1. Combinatorial approximation algorithms to incorporate domain specific constraints (global advice) for Markov Random Field (MRF) based image segmentation.
2. Analysis of the solution quality.
3. Evaluate performance on extracting specific structures of interest in Neuroimaging.

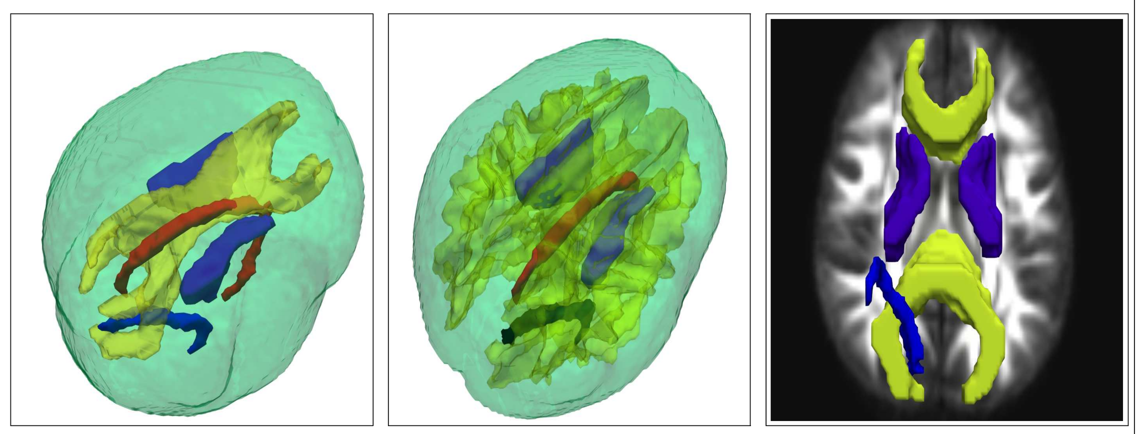

Fig 1. Specific white matter structures such as Corpus Callosum, Interior Capsules, and Cingulum Bundle within the entire white matter. Our objective is to segment such structures from DTI images.

Motivation

1. Study variations between clinically disparate groups by analyzing segmented *specific* structures of interest.
2. Investigate how specific structures of the brain network topology respond to disease and treatment.

Difficulties

- Interactive expert guided segmentation is tedious for large datasets.
- Directly using off the shelf toolboxes to learn a classifier does not work well — local spatial context at each tensor voxel is not sufficiently discriminative.

Problem Statement

Given:
A DTI image and a known appearance model (over a bag of codebook features) for a *specific* structure.

Determine:
Segment the given image (using MRFs, normalized cuts), while ensuring the extracted foreground to match the known appearance model.

Cosegmentation to Epitome-based MRFs

1. Cosegmentation : concurrent segmentation of the images with a global constraint that enforces consistency between histograms of *only* the foreground voxels.

- Construct a codebook of features $\mathcal{F}$ (e.g., using RGB intensities) for images $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$.
- The histograms on this dictionary are:

$$\mathcal{H}^{(1)} = \{\mathcal{H}_1^{(1)}, \cdots, \mathcal{H}_\beta^{(1)}\}$$

$$\mathcal{H}^{(2)} = \{\mathcal{H}_1^{(2)}, \cdots, \mathcal{H}_\beta^{(2)}\}$$

where b represents number of histogram bins.

- $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$ denote the segmentation solutions.

2. Consistency between the foreground regions (after segmentation) is given by :

$$\sum_{b=1}^{\beta} \Psi\left(\langle\mathcal{H}_b^{(1)}, \mathbf{x}^{(1)}\rangle, \langle\mathcal{H}_b^{(2)}, \mathbf{x}^{(2)}\rangle\right). \qquad (1)$$

3. In Epitome-based MRF, $\mathcal{H}_b^{(2)}$ is the *given* epitome.

Related Work

Different specifications for $\Psi(\cdot,\cdot)\ldots$

- ℓ_1 norm with Trust Region based method for optimization (*Rother et al., 2006*)
- ℓ_2^2 norm with Linear Program (impractical for large images) (*Mukherjee et al., 2009*)
- "Carrot/stick" motivated reward function (*Hochbaum and Singh, 2009*)

Our Approach

1. MRF objective + additional regularization term to penalize histogram dissimilarity using sum of squared differences :

$$\min_{\mathbf{x},\mathbf{z}} \sum_{i\sim j} c_{ij} z_{ij}^{(1)} + \sum_{j=1}^{n} w_{j0}(1 - x_j^{(1)}) + \sum_{j=1}^{n} w_{j1} x_j^{(1)} \qquad (2)$$
$$+ \lambda \sum_{b=1}^{\beta} (\langle\mathcal{H}_b^{(1)}, \mathbf{x}^{(1)}\rangle - \underbrace{\hat{\mathcal{H}}_b}_{\langle\mathcal{H}_\mathbf{b}^{(2)}, \mathbf{x}^{(2)}\rangle})^{\mathbf{2}}$$

2. We reparametrize the above objective to represent it as a Quadratic Psuedo boolean function.
3. Using concepts from Psuedo-boolean Optimization (*Boros and Hammer, 2002; Rother et al., 2007*): construct an appropriate graph and optimize the energy function by computing a maximum flow/ minimum cut.
4. Provides a 'half-integral' solution with $\{0, 1, \frac{1}{2}\}$ entries.
5. The variables assigned $\{0, 1\}$ values are "persistent".

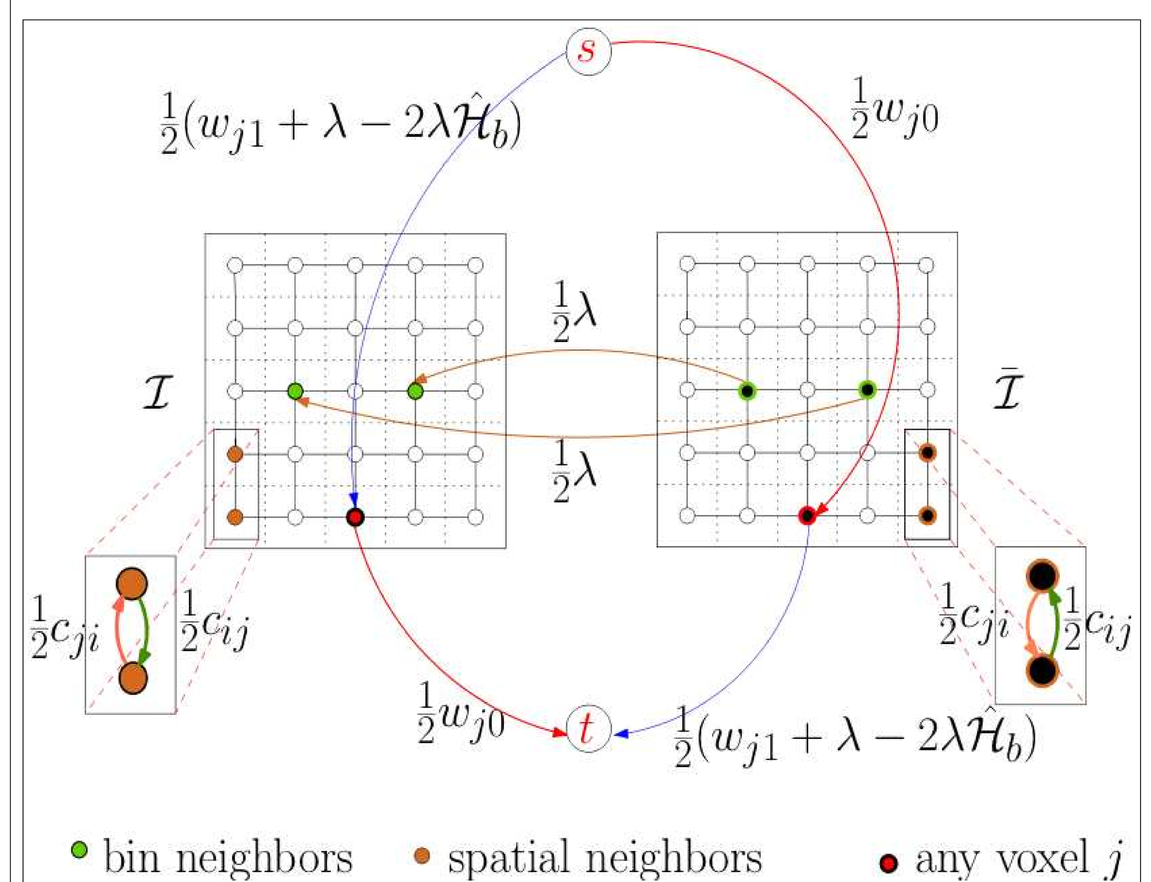

Fig 2. A graph to optimize the objective function.

Rounding Strategy

- Round up all $\frac{1}{2}$-valued variables up to 1.

Theorem 1. *The round-up scheme above gives a feasible solution; the solution is a 4-factor approximation to the energy function. Further, the approximation ratio is tight for this type of rounding.*

Experimental Results

Dictionary generation: Similar to HOG or SIFT in tensor space.

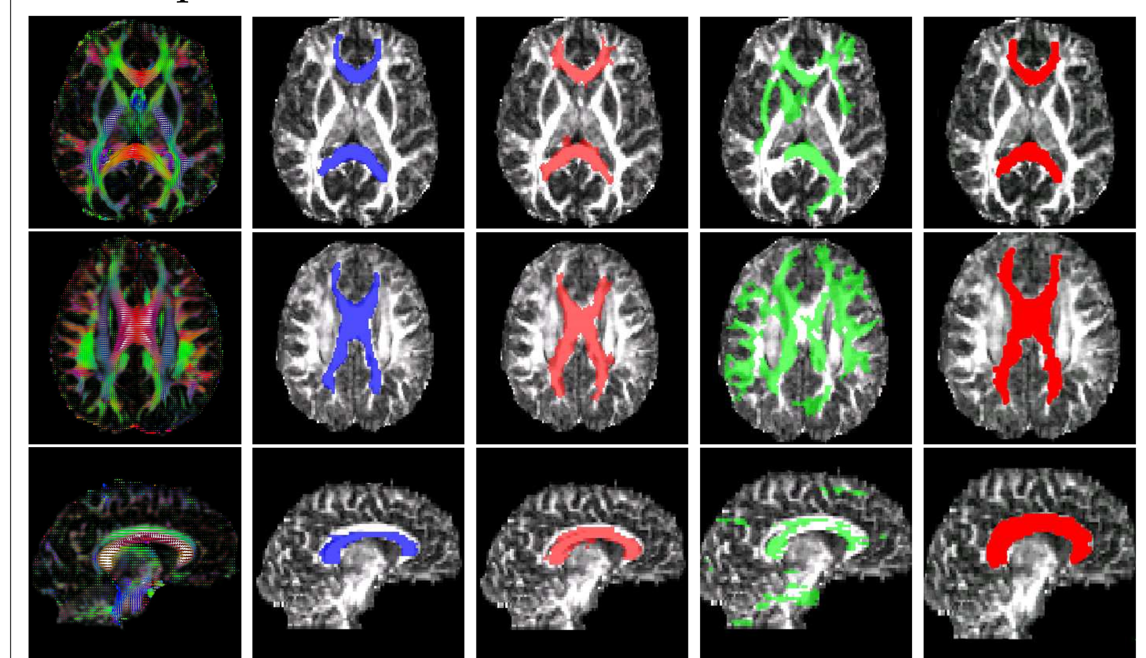

Fig 3. A segmentation of the Corpus Callosum. (1) Input (2) Ground truth (3) Ours (4) SVM (5) User-guided

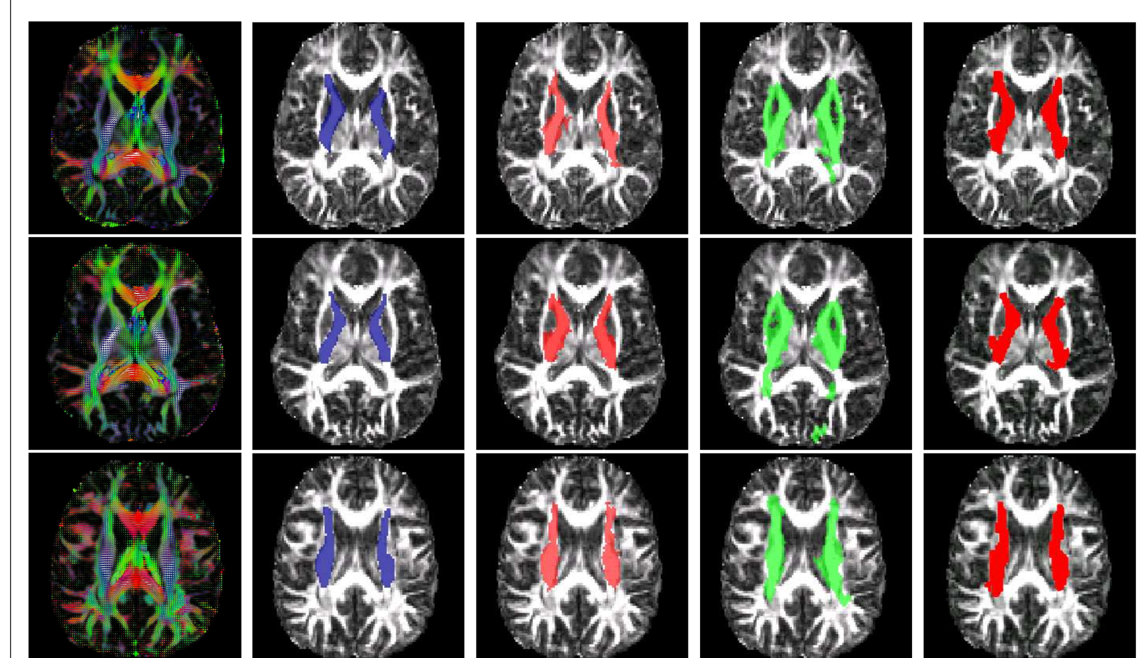

Fig 4. A segmentation of the Interior Capsules. (1) Input (2) Ground truth (3) Ours (4) SVM (5) User-guided

Quantitative evaluations

Dice similarity coefficient:

Structure	Our method	SVM
Corpus Callosum	0.62 ± 0.04	0.28 ± 0.06
Interior Capsule	0.57 ± 0.05	0.15 ± 0.02

Running time: Our algorithm takes ~ 2 mins per subject while user-guided takes $\sim 60s$ per 3-4 slices.

Conclusions

- The model may serve to incorporate epitomes (or global advice) for general segmentation problems on natural images.

Neural Information and Processing Systems (NIPS), December 2010.