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

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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.

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 ensures consistency between histograms of only the foreground voxels.
- Construct a codebook of features \( \mathcal{F} \) (e.g., using RCB intensities) for images \( T^{(1)} \) and \( T^{(2)} \).
- The histograms on this dictionary are:
  \[ \mathcal{H}^{(1)} = \{ \mathcal{H}^{(1)}_i \} \]
  \[ \mathcal{H}^{(2)} = \{ \mathcal{H}^{(2)}_i \} \]
where \( b \) represents number of histogram bins.
- \( x^{(1)} \) and \( x^{(2)} \) denote the segmentation solutions.
2. Consistency between the foreground regions (after segmentation) is given by:
  \[ \sum_{i=1}^{b} \psi \left( \left( \mathcal{H}^{(1)}_i \cdot x^{(1)} \right), \left( \mathcal{H}^{(2)}_i \cdot x^{(2)} \right) \right) \] (1)

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

Related Work
Different specifications for \( \Psi(\cdot, \cdots) \):
- \( l_1 \) norm with Trust Region based method for optimization (Rother et al., 2006)
- \( l_1 \) norm with Linear Program (impractical for large images) (Makherje 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:
  \[ \min_{x^{(1)}, x^{(2)}} \sum_{i=1}^{b} w_i (x^{(1)}_i - x^{(2)}_i)^2 + \sum_{j=1}^{n} w_j (1 - x^{(2)}_j) \] (2)
  + \( \lambda \sum_{i=1}^{b} \{ \mathcal{H}^{(1)}_i \cdot x^{(1)} \} - \mathcal{H}^{(2)}_i \}^2 \]

2. We reparametrize the above objective to represent it as a Quadratic Pseude 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”.

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 \( 1+\epsilon \)-factor approximation to the energy function. Further, the approximation ratio is tight for this type of rounding.

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

Quantitative evaluations
Dice similarity coefficient:

<table>
<thead>
<tr>
<th>Structure</th>
<th>Our method</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corpus Callosum</td>
<td>0.62 ± 0.04</td>
<td>0.28 ± 0.06</td>
</tr>
<tr>
<td>Interior Capsule</td>
<td>0.57 ± 0.05</td>
<td>0.15 ± 0.02</td>
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</tbody>
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Running time: Our algorithm takes ~ 2 mins per subject while user-guided takes ~ 60s per 3-4 slices.