CROSS MODALITY LABEL FUSION
IN MULTI-ATLAS SEGMENTATION

Keyvan Kasiri, Paul Fieguth, David A Clausi
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
BRAIN MRI

- Three-dimensional
- High tissue contrast
- High spatial resolution
- Possible multi-spectral
- Noninvasive quantitative measurements possible
APPLICATIONS

• Clinical applications
  » Detect pathologies,
  » Follow disease evolution,
  » Surgical planning,
  » Visualization,
  » Radiotherapy planning,
  » Volumetric analysis,
    • Brain atrophy, Alzheimer, Schizophrenia, epilepsy

• Research studies
  » Model construction,
  » Statistical studies.
MRI SEGMENTATION

• Partitioning the brain into different regions or structures

• How to segment?
  » Manual segmentation or strongly supervised by a human expert

• Need for automated segmentation process because of
  » Large amounts of data
  » Time required for manual segmentation
  » Inter- and intra-expert variability
ATLAS-BASED SEGMENTATION

- Providing prior knowledge using a reference model
- Atlas: a labeled scan (manually segmented)
ATLAS-BASED SEGMENTATION (2)

• The atlas is matched with the patient’s image, and then atlas labels are propagated to the patient’s image space.

• Basically a registration problem

• Challenges
  » Registration error
  » Need for optimal atlas
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
MULTI-ATLAS-BASED SEGMENTATION

• **Multi-atlas segmentation**
  » Atlas selection: looks for the most similar atlas and propagate its labels
  » Label fusion

• **Scenarios that benefit from multi-modal atlases**
  » MRI acquisition systems with different protocols
  » Multi-spectral MRI data
  » Structure or tissues are represented differently in different modes

• **Goal:**
  » A final segmentation result, which will be generated by combining all propagated labels,
  » The label fusion weighted on the basis of the similarity of the transformed atlases.
PROBLEM FORMULATION

• The atlases and the target image are all warped to the template image $I_T$,
• For the label fusion problem, the target, atlases, and labels are in the common reference frame
• Given
  » $N$ atlases along with their labels,
  » $L$ different classes in the label map,
PROBLEM FORMULATION (2)

\[ F_n = \text{argmin}_F \| I_T, F(I_n) \| \]

\[ F_G = \text{argmin}_F \| I_T, F(I_G) \| \]

\[ L'_n = F_n(L_n) \]

\[ I'_n = F_n(I_n) \]

\[ I'_G = F_G(I_G) \]

Label Fusion

\[ L'_G \]
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
POSSIBLE STRATEGIES

• Majority Voting (MV):
  » Equal contribution for each atlas,
  » Intensity is not considered

• Weighting approaches:
  » Local/global,
  » Weights based on similarities,
  » Assumes consistency of voxel intensities

• Mutual Information (MI):
  » When intensity inconsistency,
  » Problem with inherent non-locality

• Multi-modal approaches,
  » Generative model: models the relation between intensity and the label
PROPOSED METHOD

• Label fusion problem inferred from a MAP estimation framework:

\[
\hat{L}'_G(x) = \arg \max \sum_n p(L'_G(x) \mid L'_n) p(I'_G(x) \mid I'_n)
\]

• \( p(I'_G(x) \mid I'_n) \) is a hint of the relation between these two images (image similarity)

• Different modalities make the relationship complex

• Define a measure to approximate the structural similarity between subject and the atlases
SIMILARITY MEASURE

• Structural Features
  » Based on un-decimated complex wavelet transform
    • Dual Tree Complex Wavelet Transform
    • Log-Lagrange complex transform
  » Computing the phase order at each scale \((\rho_s)\)
    • defined as the normalized weighted summation of phase deviations from its mean value across all scales

• Defining the similarity measure as a function over all scales using mutual information
  \[
  SM(I_1, I_2) = \prod_s MI_s(\rho_{s1}, \rho_{s1})
  \]
• Similarity measure for multi-modal images based on structural features
### STRUCTURAL FEATURES

- Structural features from different MR images

<table>
<thead>
<tr>
<th>Modality</th>
<th>T1</th>
<th>T2</th>
<th>PD</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR Image</td>
<td>![T1 Image]</td>
<td>![T2 Image]</td>
<td>![PD Image]</td>
</tr>
<tr>
<td>Extracted Structural Features</td>
<td>![Extracted T1 Image]</td>
<td>![Extracted T2 Image]</td>
<td>![Extracted PD Image]</td>
</tr>
</tbody>
</table>
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
SIMULATION RESULTS (1)

• Data Description
  » 3D simulated BrainWeb and real LONI databases
  » T1, T2, and PD modalities
  » Three classes of WM, GM, and CSF for segmentation

• Experimental Setup
  » Comparison with MV and MI-based segmentation
  » Artificial deformation using thin-plate spline
  » Registration by SPM framework
  » Quantitative assessment by Dice similarity coefficient

\[
D(A, B) = \frac{2|A \cap B|}{|A| + |B|}
\]
SIMULATION RESULTS (2)

- Multi-modal versus single-mode segmentation

<table>
<thead>
<tr>
<th>T1 target image</th>
<th>T2 training image</th>
<th>Ground truth</th>
</tr>
</thead>
<tbody>
<tr>
<td>MV-single mode 75.2%</td>
<td>MV-multi-mode 77.2%</td>
<td>Seg-multi-mode 80.1%</td>
</tr>
</tbody>
</table>
SIMULATION RESULTS (3)

- Single-mode multi-atlas segmentation results
- Proposed Method (Seg), Majority Voting (MV), and MI-based method (MI).
- Atlas set is T1, target is T2 and PD.

![Graph showing Dice Coefficient % for T2 and PD in CSF, GM, and WM]
SIMULATION RESULTS (4)

- T1 and T2 atlases and PD target mode

<table>
<thead>
<tr>
<th>Tissue</th>
<th>WM</th>
<th>GM</th>
<th>CSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seg</td>
<td>88.6±0.2</td>
<td>88.2±0.2</td>
<td>80.7±0.8</td>
</tr>
<tr>
<td>MI</td>
<td>86.9±0.3</td>
<td>86.1±0.4</td>
<td>78.2±1.2</td>
</tr>
<tr>
<td>MV</td>
<td>85.6±0.4</td>
<td>85.4±0.5</td>
<td>77.6±1.3</td>
</tr>
</tbody>
</table>

- T2 target given real T1 atlases

<table>
<thead>
<tr>
<th>Tissue</th>
<th>WM</th>
<th>GM</th>
<th>CSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seg</td>
<td>80.6±0.4</td>
<td>75.0±0.2</td>
<td>61.2±0.8</td>
</tr>
<tr>
<td>MI</td>
<td>78.9±0.7</td>
<td>75.2±0.4</td>
<td>58.3±1.3</td>
</tr>
<tr>
<td>MV</td>
<td>77.6±0.8</td>
<td>72.4±0.4</td>
<td>55.1±1.7</td>
</tr>
</tbody>
</table>
OUTLINE

• Motivation
• Problem
• Proposed Method
• Simulation Results
• Conclusions
CONCLUSION

• A label fusion method based on a structural similarity measure is proposed,
• Designed
  » to deal with fusing labels across modalities,
  » utilizing single-mode atlas set to segment a target in different mode,
• A similarity measure based on structural features is proposed,
• Based on the results, the proposed label fusion method outperforms the state of the art.