Dictionary Learning for Medical Image Segmentation

ANIRBAN MUKHOPADHYAY
THERAPY PLANNING
ZUSE INSTITUTE BERLIN
• Medical Image Segmentation
- Medical Image Segmentation
  - Fully automatic
• Medical Image Segmentation
  ○ Fully automatic
  ○ Arbitrary 3D anatomy and modality
Medical Image Segmentation

- Fully automatic
- Arbitrary 3D anatomy and modality

Deformable model
Deformable Model Recipe

Deformable Model

• Appearance model
• Geometric Regularizer
Deformable Model

- Appearance model
- Geometric Regularizer
Deformable Model
- Appearance model
- Geometric Regularizer

**Main focus:** Systematic approach of generating appearance model
Related Work

Cootes et al., Image Proc. and Analysis 2000 ("PCA")

Kainmüller et al. MICCAI Workshop 3D Segmentation 2007

Lindner et al., TMI13
Related Work

Cootes et al., Image Proc. and Analysis 2000 (“PCA”)

Lindner et al., TMI13

Kainmüller et al. MICCAI Workshop 3D Segmentation 2007

Dictionary Learning:
  • Learn generic appearance model during training
  • Efficient sparse representation during testing
Contribution

- General 3D Segmentation
Contribution

- General 3D Segmentation
- Joint Dictionary Learning (JDL)
Dictionary Learning

- **Image Representation**
  - Image level: High variability, low redundancy
    - ![Image example](image1.png)
    - ![Image example](image2.png)
    - ![Image example](image3.png)
  - Patch level: Low variability, high redundancy
    - ![Patch example](patch1.png)
Dictionary Learning

- Represent image patches using an over-complete dictionary

- Recon. patch: sparse combination of atoms of Dictionary

http://ranger.uta.edu/~huang/R_Cervigram.htm
Samples with intensity features
Rotation Inv. HOG
Training

Samples with intensity features $\Rightarrow$ FG Dictionary $\Rightarrow$ Sparse Rep
Training

Samples with intensity features = FG Dictionary

Sparse Rep
Similarly, Background Dictionary is generated
Cost Function Calculation
Cost Function Calculation
Cost Function Calculation
\[ R_{l,p}^C = \| y_{l,p}^T - D^C \hat{x}_{l,p}^C \|_2^2 \]
Cost Function Calculation

\[ R_{l,p}^C = \| y_{l,p}^T - (D^C \hat{x}_{l,p}^C) \|^2 \]
Cost Function Calculation

\[ P_{l,p} = \lambda (1 - R_{l,p}^B) + (1 - \lambda) R_{l,p}^F \]
Results

Local search. **NO Regularization.**

Liver  CT  Femur  MR

Mukhopadhyay/ZIB
Cardiac Image Segmentation

- Sparse modeling
  - Appearance
  - Motion

![Diagram of cardiac image segmentation](image-url)
<table>
<thead>
<tr>
<th>Methods</th>
<th>Baseline</th>
<th></th>
<th>Ischemia</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard CINE</td>
<td>CP-BOLD</td>
<td>Standard CINE</td>
<td>CP-BOLD</td>
</tr>
<tr>
<td>Atlas-based methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dDEmons [6]</td>
<td>60 ± 8</td>
<td>55 ± 8</td>
<td>56 ± 6</td>
<td>49 ± 7</td>
</tr>
<tr>
<td>FFD-MI [20]</td>
<td>60 ± 3</td>
<td>54 ± 8</td>
<td>54 ± 8</td>
<td>45 ± 6</td>
</tr>
<tr>
<td>Supervised classifier-based methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACRF</td>
<td>57 ± 3</td>
<td>25 ± 2</td>
<td>52 ± 3</td>
<td>21 ± 2</td>
</tr>
<tr>
<td>TACRF</td>
<td>65 ± 2</td>
<td>29 ± 3</td>
<td>59 ± 1</td>
<td>24 ± 2</td>
</tr>
<tr>
<td>Dictionary-based methods</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DDLS [7]</td>
<td>71 ± 2</td>
<td>32 ± 3</td>
<td>66 ± 3</td>
<td>23 ± 4</td>
</tr>
<tr>
<td>RDDL [39]</td>
<td>42 ± 15</td>
<td>50 ± 20</td>
<td>48 ± 13</td>
<td>61 ± 12</td>
</tr>
<tr>
<td>MSDDL [9]</td>
<td>75 ± 3</td>
<td>75 ± 2</td>
<td>75 ± 2</td>
<td>71 ± 2</td>
</tr>
<tr>
<td>UMSS [10]</td>
<td>62 ± 20</td>
<td>71 ± 10</td>
<td>65 ± 14</td>
<td>66 ± 11</td>
</tr>
<tr>
<td>Proposed</td>
<td>77 ± 10</td>
<td>77 ± 9</td>
<td>74 ± 7</td>
<td>74 ± 6</td>
</tr>
</tbody>
</table>
Summary and Future Work

- General model-based 3D segmentation
  - Across anatomies and modalities
- Benefits of Joint Dictionary Learning
  - Traditional PCA-based learning
  - 2D RFRV
- Localized error prone areas
  - Separate/ better strategy
- Experiments on other datasets
Thank You

Questions?
Algorithm 1 Joint Dictionary Learning (JDL)

Input: Training patches for background and the landmarks: $Y^B$ and $Y^F$
Output: Dictionaries for background and the landmarks: $D^B$ and $D^F$

1: for $C=\{B,F\}$ do
2:     Compute $Y^C$
3:     Learn dictionaries with K-SVD algorithm
4: end for

\[
\begin{align*}
&\text{minimize} \left\| Y^C - D^C X^C \right\|_2^2 \quad \text{s. t.} \quad \|X^C_i\|_0 \leq S
\end{align*}
\]
Cost Function Calculation

Algorithm 2 Cost Function Calculation (CFC)

Input: Testing patches along profile of current landmark locations: \( \{Y_{l,p}^T\}_{l=1}^L \), Learnt Shape Model, Dictionaries for background and the landmarks: \( D^B \) and \( D^F \)

Output: Predicted Landmark location

1: for \( l = 1 \ldots L \) do
2:   for \( p = \) each location on the profile of current Landmark \( l \) do
3:     for \( C = \{B,F\} \) do
4:       Compute \( Y_{l,p}^T \)
5:       \[ R_{l,p}^C = \| y_{l,p}^T - D^C \hat{x}_{l,p}^C \|_2^2 \]
6:     end for
7:     \[ P_{l,p} = \lambda (1 - R_{l,p}^B) + (1 - \lambda) R_{l,p}^F \]
8:   end for
9: end for
Rotation Invariant - HOG

- Sample boxes aligned w.r.t. the surface normal
  - Training: Foreground patches can encode the boundary appearance and background patches can encode the completely inside/ outside info
  - Testing: optimization along normal profile ensures that both foreground and background agrees on final position.
- Rotation problem is resolved y the RI-HOG features
  - Any other sophisticated feature and sampling strategy will suffice