Deformable Segmentation using Sparse Shape Representation

Shaoting Zhang
Outline

• Introduction

• Our methods
  – Segmentation framework
  – Sparse shape representation

• Applications
  – 2D lung localization in X-ray
  – 3D liver segmentation in whole body PET-CT
  – 3D rat brain structure segmentation

• Conclusions
Introduction
Motivations

- Segmentation (i.e., finding 2D/3D ROI) is a fundamental problem in medical image analysis.
- We use deformable models and shape prior. Shape representation is based on landmarks.
Introduction
Challenges – deformable segmentation

- Good segmentation system:
  - Automatic, accuracy, efficiency, robustness.
  - Handle weak or misleading appearance cues from image information.
  - Discover or preserve complex shape details.
Introduction

Challenges – shape prior modeling

• Good shape prior method:
  – Handle gross errors of the input data.
  – Model complex shape variations.
  – Preserve local shape details.
Methods
Our solutions

• Learning based deformable segmentation.
• Sophisticated shape prior algorithm.
  – Sparse shape composition.

Learn detectors
Methods
Shape prior using sparse shape composition

• Our method is based on two observations:
  – An input shape can be approximately represented by a sparse linear combination of training shapes.
  – The given shape information may contain gross errors, but such errors are often sparse.
Methods
Shape prior using sparse shape composition

• Formulation:
  \[ \min \{ x, \beta \} \| T(y, \beta) - Dx \|_2 \]

• Sparse linear combination:
  \[ \min \{ x, \beta \} \| T(y, \beta) - Dx \|_2, \quad \text{s.t.} \| x \|_0 < k_1 \]
Methods

Shape prior using sparse shape composition

• Non-Gaussian errors:

\[ \min \{ x, e, \beta \} \| T(y, \beta) - Dx - e \|_2, \text{s.t.} \| x \|_0 < k_1, \| e \|_0 < k_2 \]
Methods
Shape prior using sparse shape composition

• Why it works?
  – **Robust**: Explicitly modeling “e” with L0 norm constraint. Thus it can detect gross (sparse) errors.
  – **General**: No assumption of a parametric distribution model (e.g., a unimodal distribution assumption in ASM). Thus it can model complex shape statistics.
  – **Lossless**: It uses all training shapes. Thus it is able to recover detail information even if the detail is not statistically significant in training data.

*Zhang, Metaxas, et.al.: MedIA’11*
Applications – Part I
2D lung localization in X-ray

• Setting:
  – Manually select landmarks for training purpose.
  – 200 training and 167 testing.
  – To locate the lung, detect landmarks, then predict a shape to fit them.
  – Sensitivity (P), Specificity (Q), Dice Similarity Coefficient.
Applications – Part I
2D lung localization in X-ray

- Handling gross errors

<table>
<thead>
<tr>
<th>Detection</th>
<th>PA</th>
<th>ASM</th>
<th>RASM</th>
<th>NN</th>
<th>TPS</th>
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Procrustes analysis, Active Shape Model, Robust ASM, Nearest Neighbors, Thin-plate-spline, Without modeling, "e", Proposed method
Applications – Part I
2D lung localization in X-ray

- Multimodal distribution

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Applications – Part I
2D lung localization in X-ray

- Recover local detail information

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</table>
Applications – Part I
2D lung localization in X-ray

• Sparse shape components

\[ 0.5760 \approx 0.2156 + 0.0982 \]

• ASM modes:

(a) 1st mode  (b) 2nd mode  (c) 3rd mode  (d) 4th mode  (e) 5th mode
Applications – Part I
2D lung localization in X-ray

• Mean values (µ) and standard deviations (σ).

Left lung

Right lung

1)PA, 2)ASM, 3)RASM, 4)NN, 5)TPS, 6)Sparse1, 7)Sparse2
Applications – Part II
3D liver segmentation in low-dose CT

• Setting
  - 3D low-dose CT, low contrast and fuzzy boundaries. 40 training and 27 testing.
  - Use 3D Slicer to segment ground truth.
  - Geometry processing (decimation, smoothing, isotropic remeshing).
  - Use shape registration to guarantee one-to-one correspondence.

Zhang, Wang, Chen, Metaxas, Axel, ISBI’09
Zhang, Uzunbas, Yan, Gao, Huang, Metaxas, FIMH’11
Applications – Part II

3D liver segmentation in low-dose CT

Same landmarks + different shape priors

Initialization

Deformation

Same deformation module

Procrustes analysis
Sparse shape
Ground truth

Same deformation module
Applications – Part II
3D liver segmentation in low-dose CT

Procrustes analysis
Sparse shape
Applications – Part II

3D liver segmentation in low-dose CT

Procrustes analysis
Sparse shape
Applications – Part II
3D liver segmentation in low-dose CT

Procrustes analysis
Sparse shape
Applications – Part II

3D liver segmentation in low-dose CT
Applications – Part II
3D liver segmentation in low-dose CT

• Quantitative comparisons: surface distances.
Applications – Part III

3D rodent brain segmentation in MRM

• Setting
  – Rodents are often used as models of human disease.
  – 3D Magnetic resonance microscopy (MRM).
  – Create complex shape atlas of multiple structures using hierarchical shape priors.
Applications – Part III
3D rodent brain segmentation in MRM

Cerebellum  Striatum  Hippocampus

Regular prior (smoothness)

Hierarchical shape prior
Applications – Part III
3D rodent brain segmentation in MRM

Regular prior (smoothness)
Hierarchical shape prior
Applications – Part III
3D rodent brain segmentation in MRM

Regular prior (smoothness)

Hierarchical shape prior
Applications – Part III
3D rodent brain segmentation in MRM

- Quantitative comparisons: surface distances, relative error of volume magnitude

<table>
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<tr>
<th>Structures</th>
<th>Methods</th>
<th>Distance</th>
<th>Volume</th>
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<td>Independent prior</td>
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<td>Hierarchical prior</td>
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<td>2.69±1.83</td>
<td>0.17±0.05</td>
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<tr>
<td></td>
<td>Hierarchical prior</td>
<td>1.22±1.05</td>
<td>0.06±0.02</td>
</tr>
</tbody>
</table>
Thanks!

Questions and comments