Multi-atlas Segmentation Applied to Esophagus Delineation for Thoracic Oncology Applications

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Motivation

• Esophagus is an important organ to spare in thoracic radiotherapy treatment planning

• Manual contouring
  – Labor intensive
  – Observer variability
Challenges

• Absence of intensity consistency
• Random air bubbles inside
• Low contrast to surrounding tissues
Challenges

• Complex and variable shapes (Inter-patient variability)
Automatic Segmentation

• Capitalize on prior knowledge
  – Prior shape model and appearance model (or centerline model)
    • Feulner, et al, TMI 2011
    • Kurugol, et al, ISBI 2010
  – Air hole model
    • Feulner, et al, TMI 2011
    • Fieselmann, et al, BVM 2008
  – Atlas-based automatic segmentation
• SINGLE ATLAS IS NOT ENOUGH
• USE MULTI-ATLAS SEGMENTATION
  – SELECT OPTIMAL ATLAS CANDIDATES
  – INCLUDE TISSUE APPEARANCE MODEL
Multi-Atlas Segmentation

Selected Atlases

Atlas Pool

New Image

Individual atlas segmentations

Final segmentation
Multi-Atlas Segmentation

**Atlas Patient Space**

- CT Images
  - Atlas 1
  - Atlas 2
  - Atlas N
- Atlas Contours
  - Atlas 1
  - Atlas 2
  - Atlas N

**Deformable Registration**

- Displacement Fields
  - Field 1
  - Field 2
  - Field N

**Contour Mapping**

- Individual Deformed Contours
  - Def. contour 1
  - Def. contour 2
  - Def. contour N

**New Patient Space**

- New CT Image
- Final Contour
- Contour Fusion

**Multi-Atlas Segmentation**
Multi-Atlas Segmentation

SELECT OPTIMAL ATLAS CANDIDATES
Atlas Selection Process

Atlas Pool

Preliminary Selection

< or = 12 atlases

Deformable Registration

Contour Fusion

Optimal atlases

Optimal Atlas Selection
Preliminary Selection

• Purpose
  – Fill out really bad atlases
  – Limit the number of atlases for deformable registration: save some time

• Require rigid registration between each atlas and new image

• Use cross-correlation as similarity measurement

• Measure similarity in a local region containing structures of interest
Atlas Ranking

- Compute local intensity histograms
- Measure similarity using symmetric Kullback-Leibler (KL) divergence
- Rank atlases using measured KL divergence
Atlas Selection

- Check overlap ratio of deformed contours by sequentially adding atlases from the most to least similar

\[ \text{Jaccard} = \frac{\bigcap_{i} A_i}{\bigcup_{i} A_i} \]

- N=1; Jaccard = 1.0
- N=2; Jaccard = 0.59
- N=3; Jaccard = 0.55
- N=4; Jaccard = 0.36

Optimal atlas no. < 6
Multi-Atlas Segmentation

INCLUDE TISSUE APPEARANCE MODEL
Contour Fusion Using STAPLE

  - Based on the maximum likelihood estimates of sensitivity and specificity of individual contours
  - Fusion contour is the expected truth by estimation

![Diagram of contour fusion using STAPLE](image)

- **Expected fusion contour**
- **Individual contours**
- **Sensitivity** $[P(D=1|T=1)]$
- **1-specificity** $[P(D=0|T=0)]$
• Assumption:
  – Individual contours/segmentations $D$ (known)
  – True segmentation $T$ (unknown)
  – Performance parameters of individual segmentation (unknown): sensitivity ($p$) and specificity ($q$)

• Maximum likelihood estimates of ($p, q$) from the complete data ($D, T$)

$$(\hat{p}, \hat{q}) = \arg \max_{p, q} \log f(D, T | p, q)$$
The EM Algorithm

- Expectation-Maximization (EM) algorithm estimates from the incomplete data $D$

$$(p^{(k)}, q^{(k)}) = \arg \max_{p, q} E\left[ \log(f(D | T, p, q) f(T)) \middle| D, p^{(k-1)}, q^{(k-1)} \right]$$

- **E-Step**: estimate a conditional expectation

$$f(T_i | D_i, p^{(k-1)}, q^{(k-1)}) = \frac{\prod_j f(D_{ij} | T_i, p_j^{(k-1)}, q_j^{(k-1)}) f(T_i)}{\sum_{T_i'} \prod_j f(D_{ij} | T_i', p_j^{(k-1)}, q_j^{(k-1)}) f(T_i')}$$

- **M-Step**: estimate parameters by maximization

$$(p_j^{(k)}, q_j^{(k)}) = \arg \max_{p_j, q_j} \sum_i \sum_{T_i'} [\log f(D_{ij} | T_i', p_j, q_j)] \cdot f(T_i' | D_i, p^{(k-1)}, q^{(k-1)})$$
Tissue Appearance Model (TAM)

• The prior probability of $T$ is described by TAM: $f(T_i = 1) = P(i)$

• TAM is a Gaussian model estimated from image intensity:

$$P(i) = \frac{1}{Z} \exp \left( - \frac{(I(i) - \mu_p)^2}{\sigma_p^2} \right)$$

• Mean $\mu_p$ and variance $\sigma_p^2$ are estimated from pixels in the union region of individual segmentations
Include Tissue Appearance Model

- Integrate the tissue appearance model into the STAPLE fusion process

Individual segmentations + Tissue appearance model → Final segmentation
Multi-Atlas Segmentation

ESOPHAGUS AUTOSEGMENTATION
Data Description

• Planning CT of 15 thoracic cancer patients
  – Resolution: 1.0x1.0x2.5mm³

• Esophagus contours were manually delineated
  – From the top of C6 vertebra to esophagus/stomach junction
Evaluation Method

• Performed 15 leave-one-out tests
  – One image as test and the remaining 14 as atlases
  – Number of selected optimal atlases varied from 6 to 12.

• Evaluation metrics (between auto-segmented and manual contours)
  – 3D volume overlap (Dice similarity coefficient)
  – 3D mean surface distance (mean error)
  – 3D Hausdorff distance (max error)
Results

Volume Overlap

Mean±SD: 73.2%±7.4%  Median = 76.7%
Results

Mean Surface Distance

Mean±SD: 2.2±0.8mm  Median = 1.8mm
Results

Hausdorff Distance

Mean±SD: 16.9±8.9mm  
Median = 12.7mm
Results

Example 1

Example 2

Green: manual contours; Red: auto-segmented contours
Results

Green: manual contours; Red: auto-segmented contours
Summary

• Achieved reasonably good results in esophagus autosegmentation for thoracic radiotherapy

• Limitations of our approach
  – Optimal atlas selection highly depends on the image data
  – Similarity comparison of entire long and winding esophagus was not locally accurate in atlas selection
  – Tissue appearance model is subject to the impact of air bubbles
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