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

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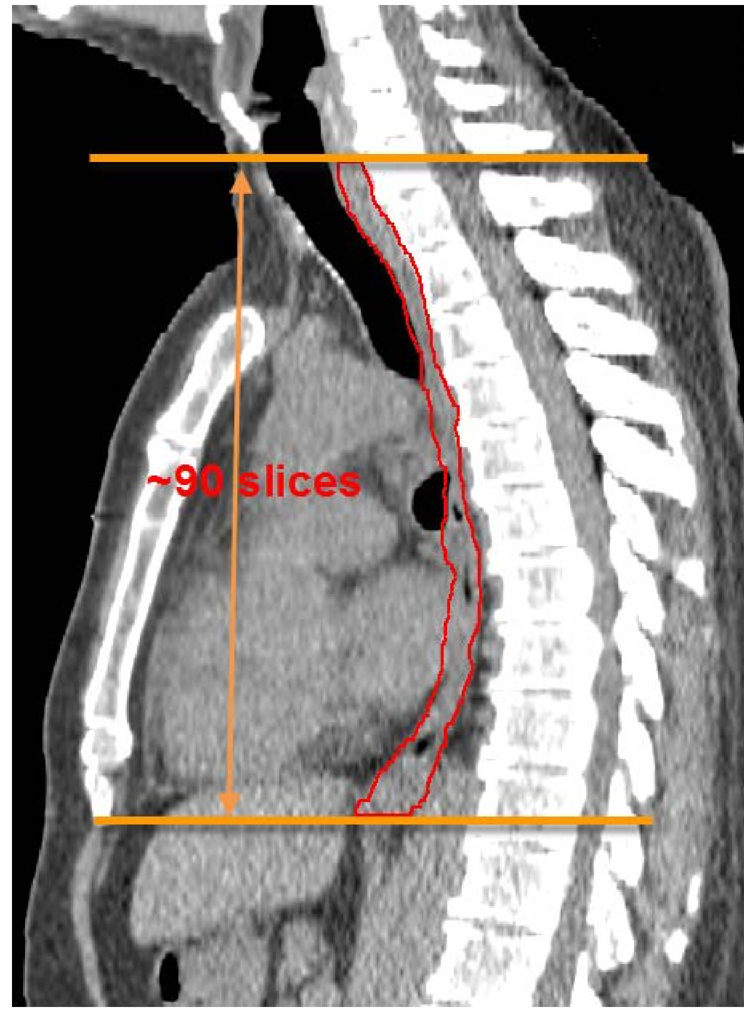
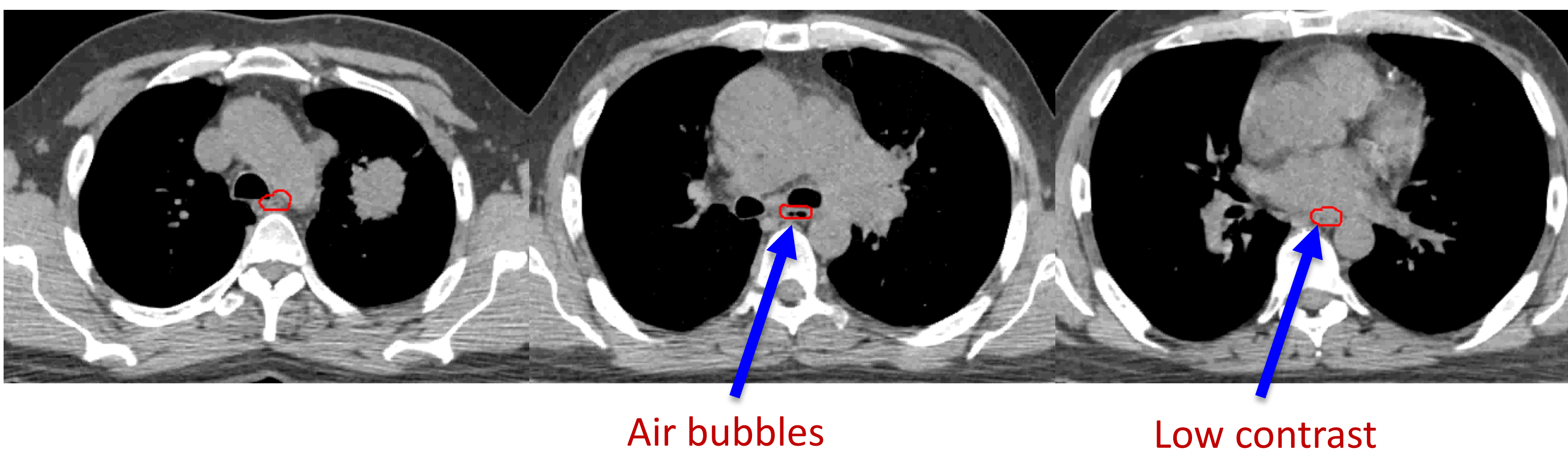
Motivation

- Esophagus is an import organ to spare in thoracic radiotherapy treatment planning
- Manual contouring
  - Labor intensive
  - Observer variability



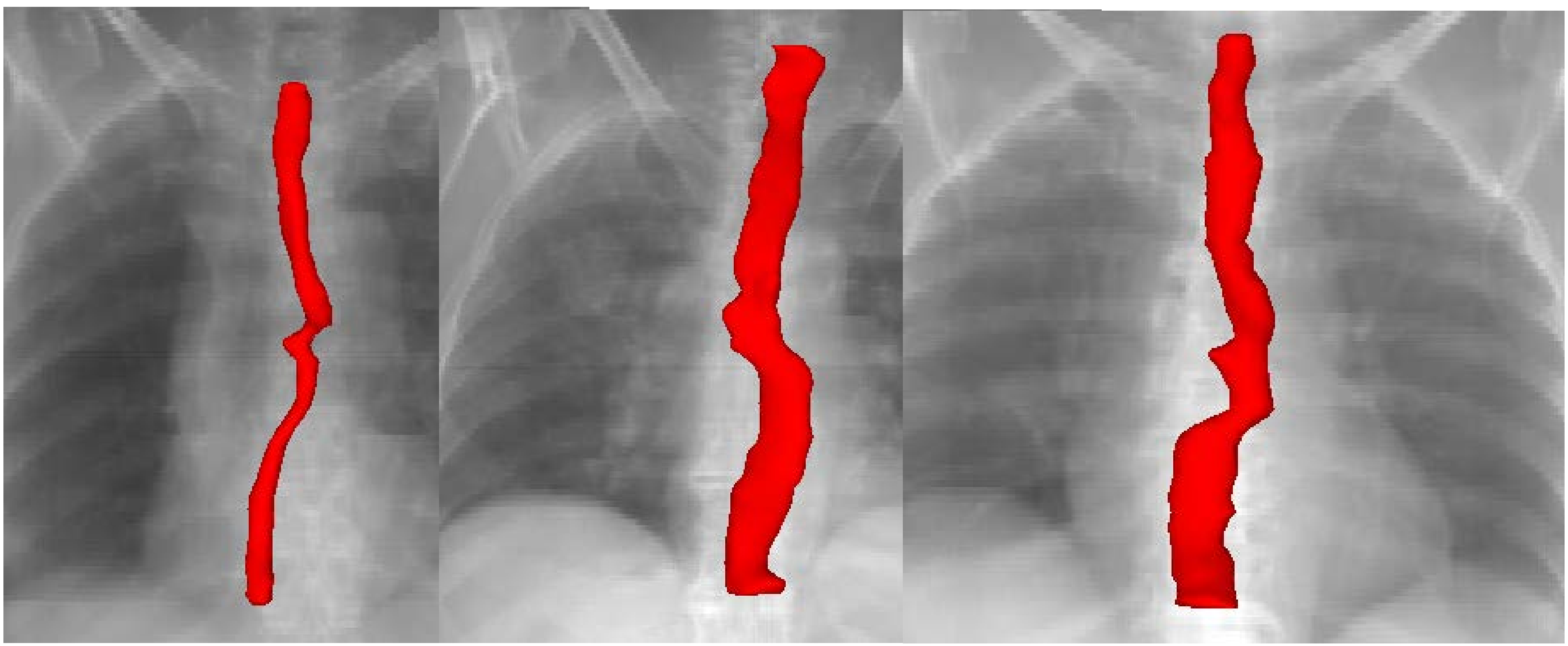
Challenges

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



Challenges

- Complex and variable shapes (Inter-patient variability)



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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
    - Meyer, et al, SPIE Med. Imaging 2011
    - Roussan, et al, SPIE Med. Imaging 2006
  - 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

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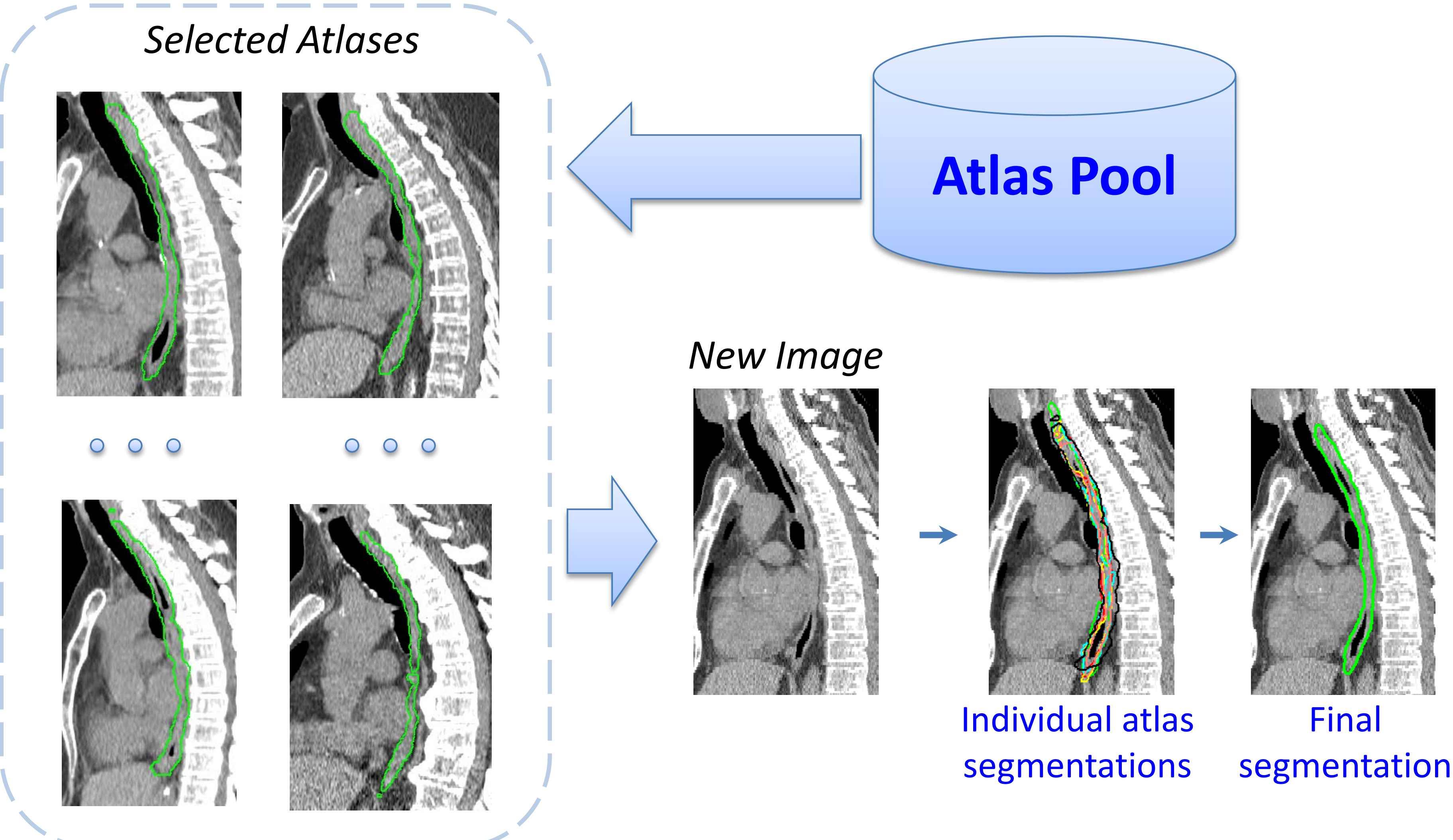
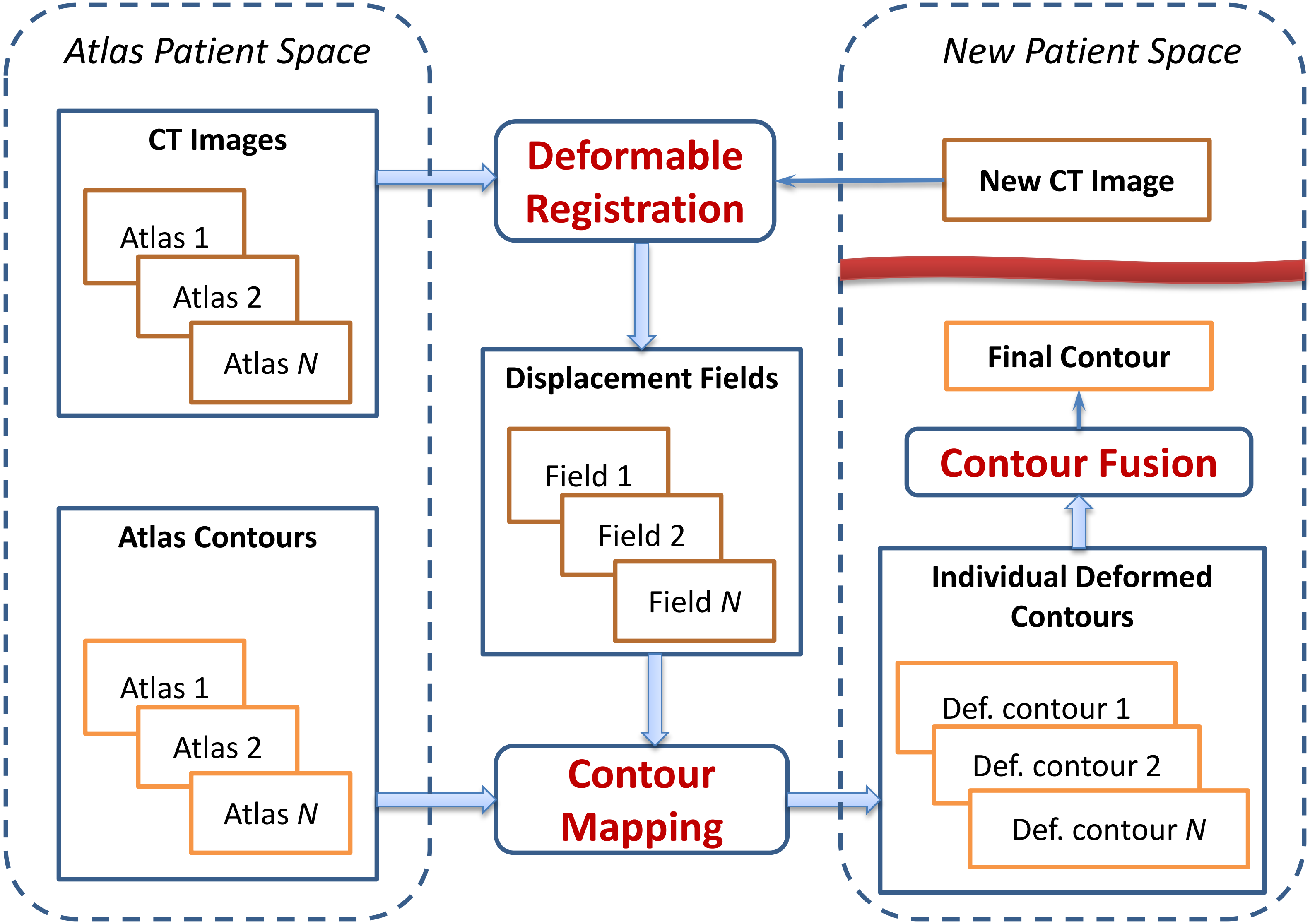
Multi-Atlas Segmentation



Multi-Atlas Segmentation



Multi-Atlas Segmentation

SELECT OPTIMAL ATLAS CANDIDATES

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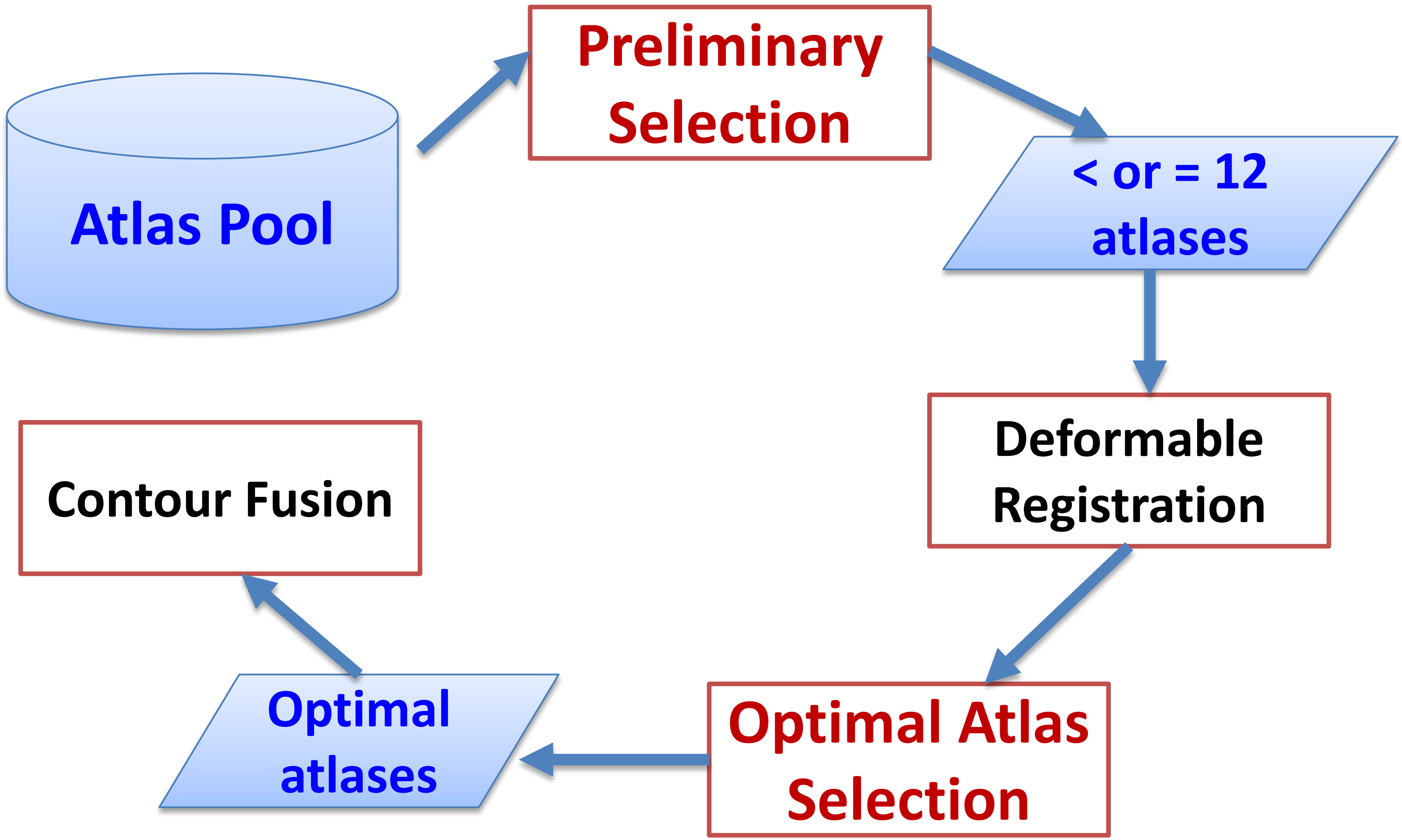
Atlas Selection Process



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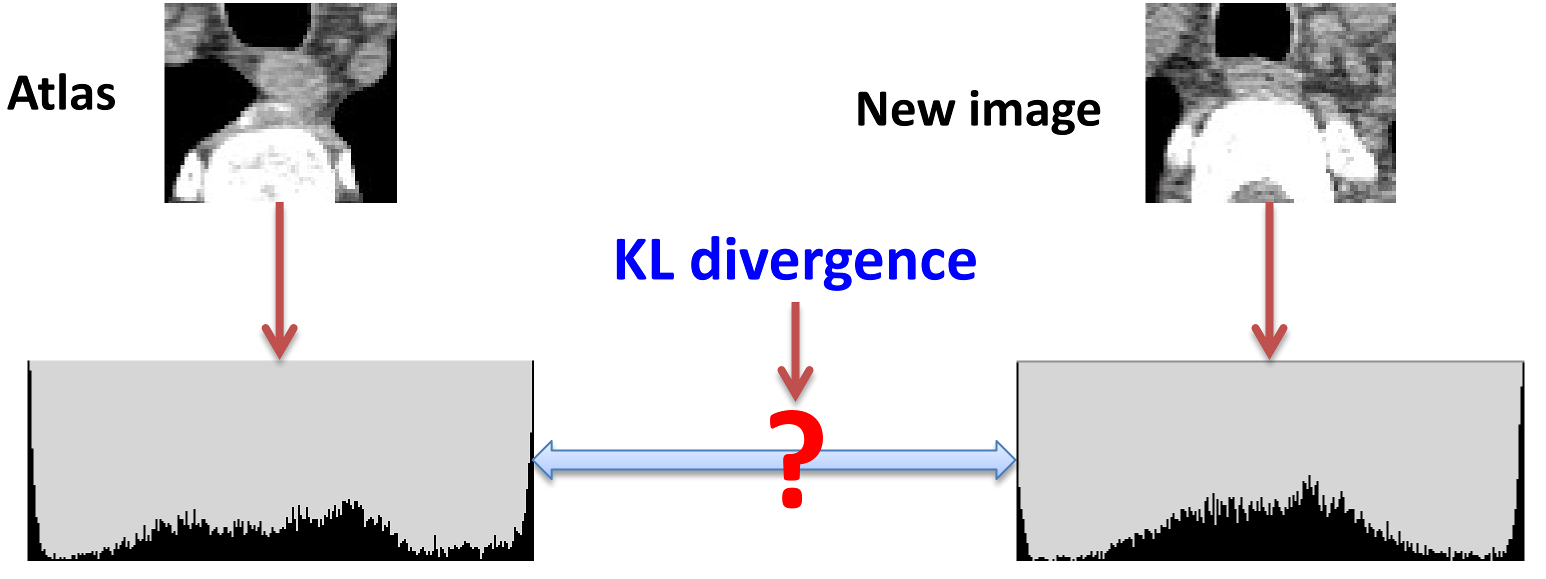
Preliminary Selection

- 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

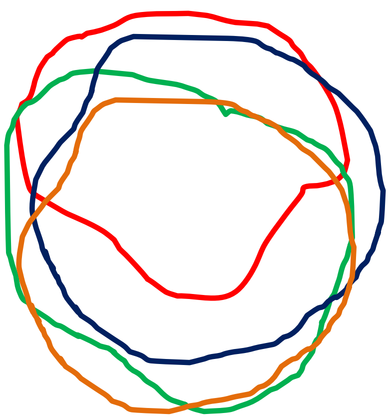
Atlas Ranking

- 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



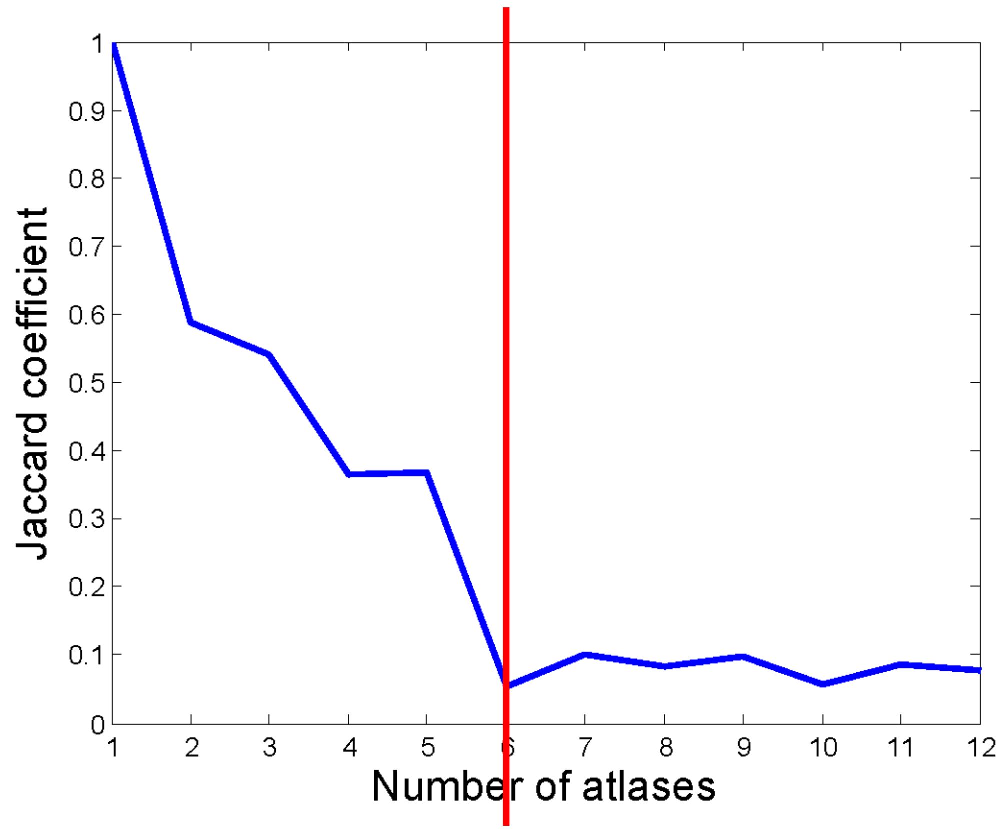
N=1; Jaccard = 1.0

N=2; Jaccard = 0.59

N=3; Jaccard = 0.55

N=4; Jaccard = 0.36

$$Jaccard = \frac{\cap_i A_i}{\cup_i A_i}$$



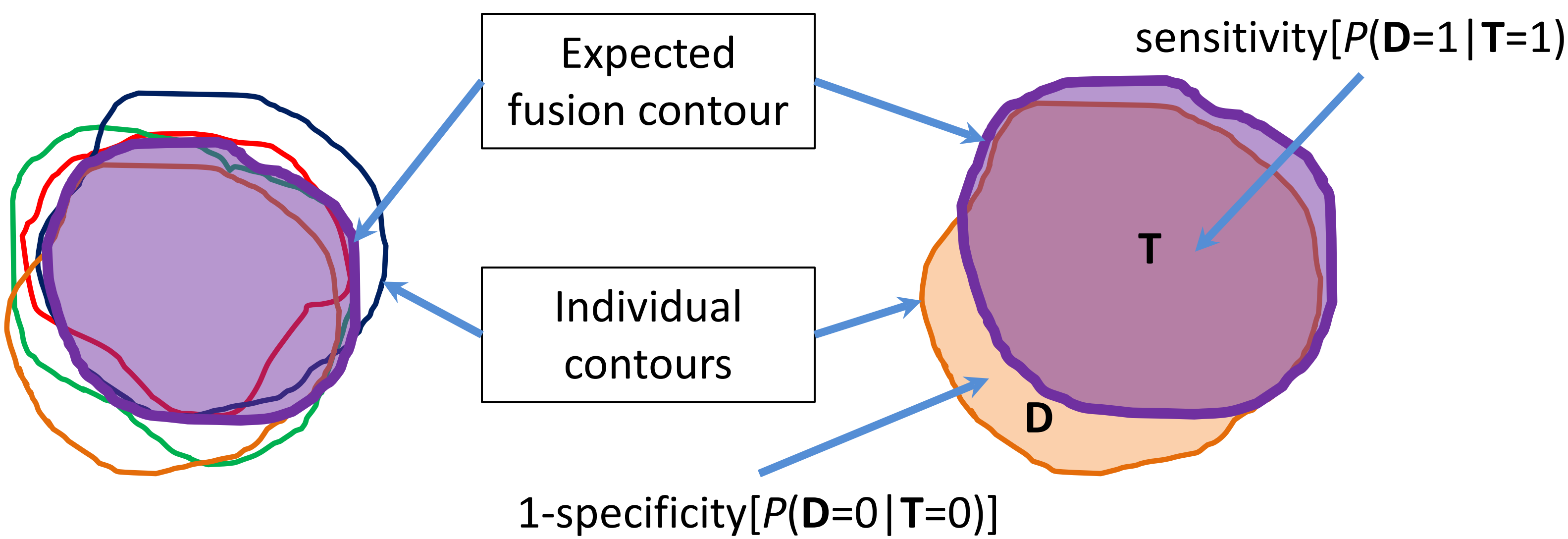
Optimal atlas no. < 6

Multi-Atlas Segmentation

INCLUDE TISSUE APPEARANCE MODEL

Contour Fusion Using STAPLE

- STAPLE: Simultaneous Truth and Performance Level Estimation (Warfield, et al, TMI 2004)
  - Based on the maximum likelihood estimates of sensitivity and specificity of individual contours
  - Fusion contour is the expected truth by estimation



STAPLE Algorithm

- 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**)

$$(\hat{\boldsymbol{p}}, \hat{\boldsymbol{q}}) = \arg\max_{\boldsymbol{p},\boldsymbol{q}} \log f(\mathbf{D}, \mathbf{T} \mid \boldsymbol{p}, \boldsymbol{q})$$

The EM Algorithm

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

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

- E-Step: estimate a conditional expectation

$$f(T_i\,|\,\mathbf{D}_i,\boldsymbol{p}^{(k\text{-}1)},\boldsymbol{q}^{(k\text{-}1)}) = \frac{\prod_j f(D_{ij}\,|\,T_i,p_j^{(k-1)},q_j^{(k-1)})\,\boxed{f(T_i)}}{\sum_{T_i'}\prod_j f(D_{ij}\,|\,T_i',p_j^{(k-1)},q_j^{(k-1)})\,f(T_i')}$$

- M-Step: estimate parameters by maximization

$$(p_j^{(k)},q_j^{(k)}) = \arg\max_{p_j,q_j}\sum_i\sum_{T_i'}[\log f(D_{ij}\,|\,T_i',p_j,q_j)]\cdot f(T_i'\,|\,\mathbf{D}_i,\boldsymbol{p}^{(k\text{-}1)},\boldsymbol{q}^{(k\text{-}1)})$$

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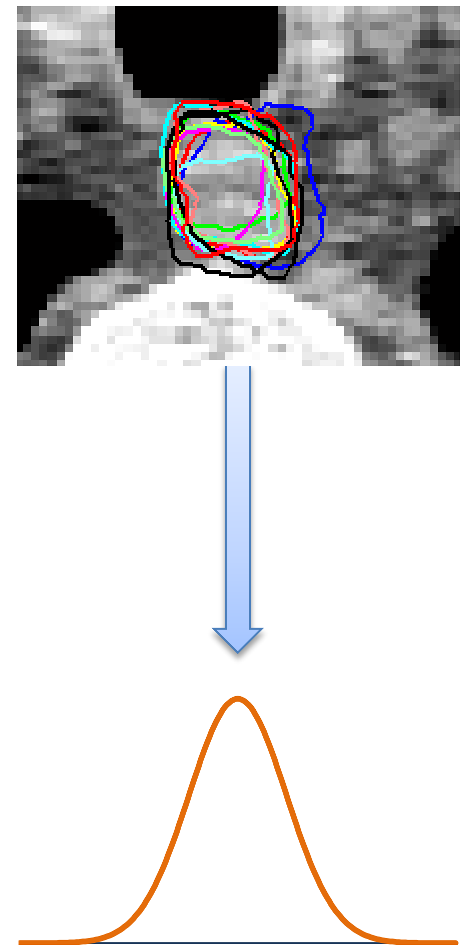
Tissue Appearance Model (TAM)

- 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 μ_p and variance σ_p^2 are estimated from pixels in the union region of individual segmentations



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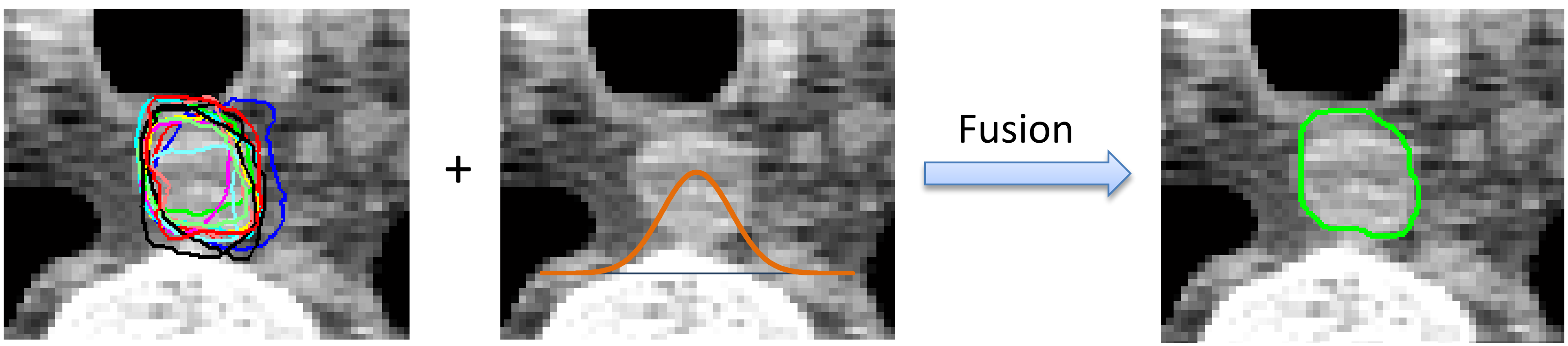
Include Tissue Appearance Model

- Integrate the tissue appearance model into the STAPLE fusion process



Individual segmentations | Tissue appearance model | Final segmentation

Multi-Atlas Segmentation

ESOPHAGUS AUTOSEGMENTATION

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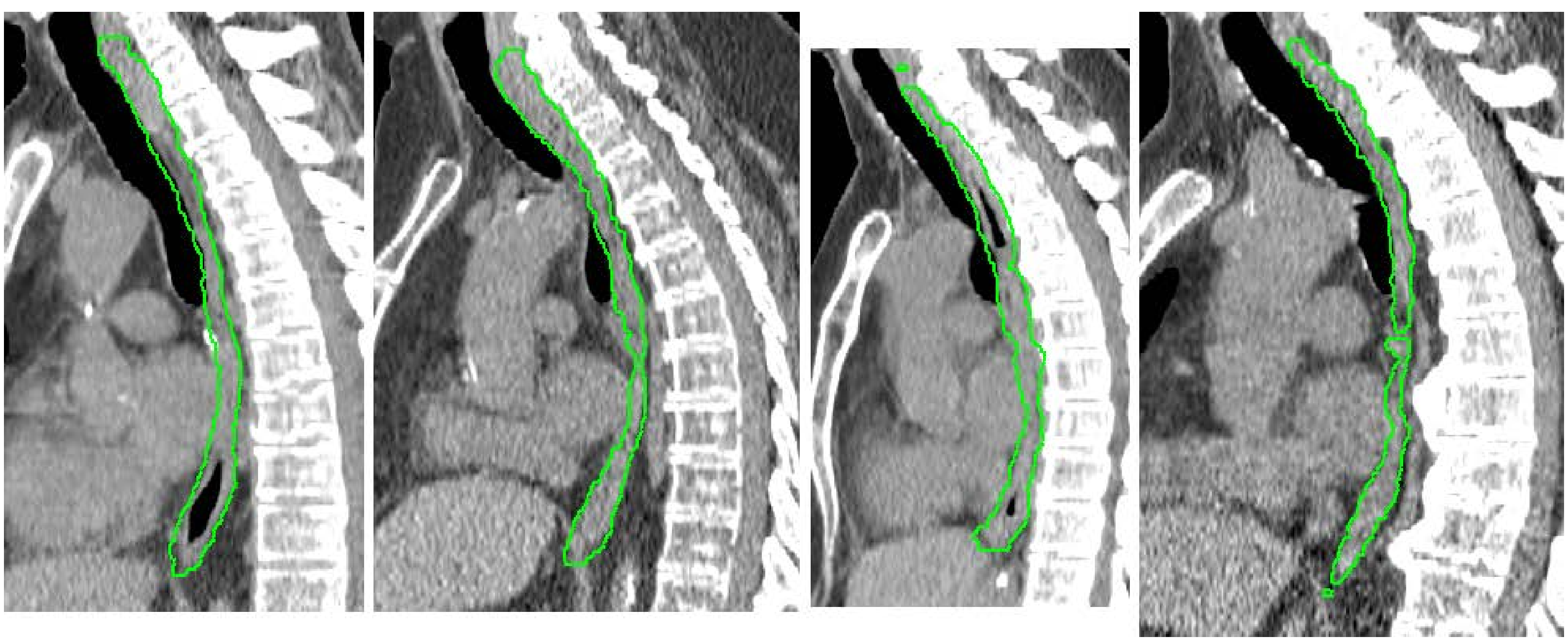
Data Description

- Planning CT of 15 thoracic cancer patients
  - Resolution: 1.0x1.0x2.5mm^3
- Esophagus contours were manually delineated
  - From the top of C6 vertebra to esophagus/stomach junction



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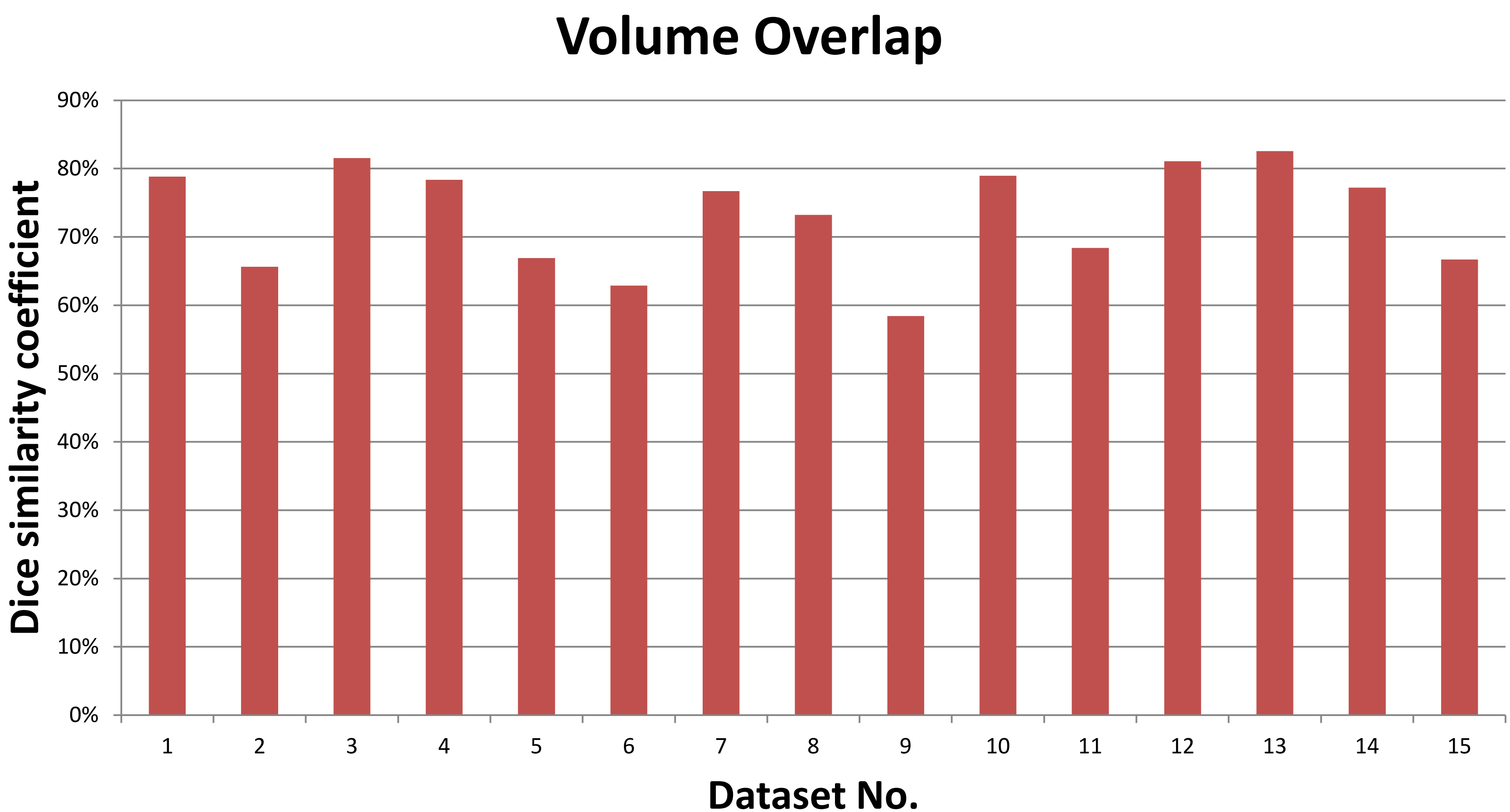
Evaluation Method

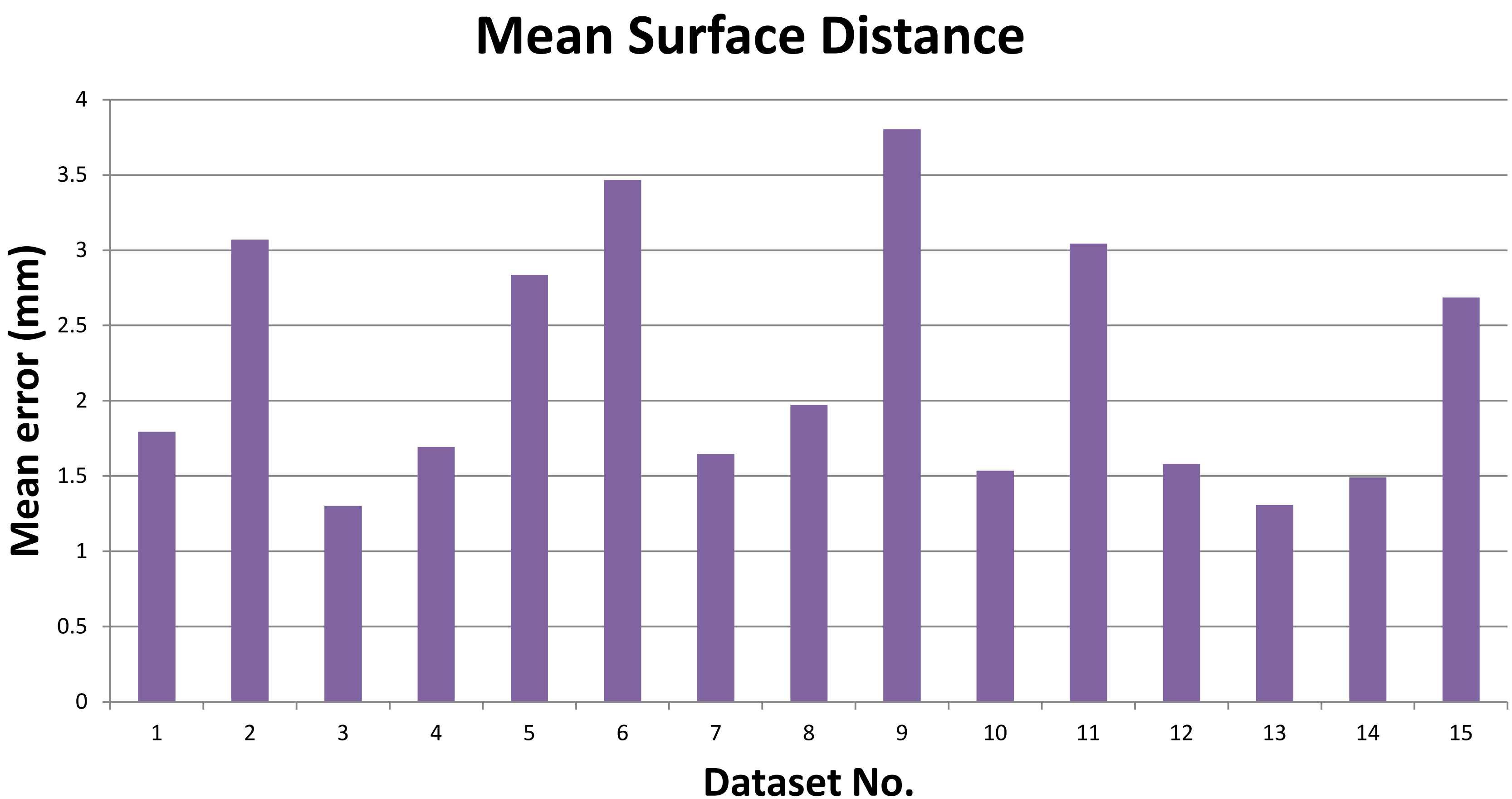
- Performed 15 leave-one-out tests
  - One image as test and the remaining 14 as atlases
  - Number of selected optimal atlases varied from 6 to 12.
- Evaluation metrics (between auto-segmented and manual contours)
  - 3D volume overlap (Dice similarity coefficient)
  - 3D mean surface distance (mean error)
  - 3D Hausdorff distance (max error)

Results



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

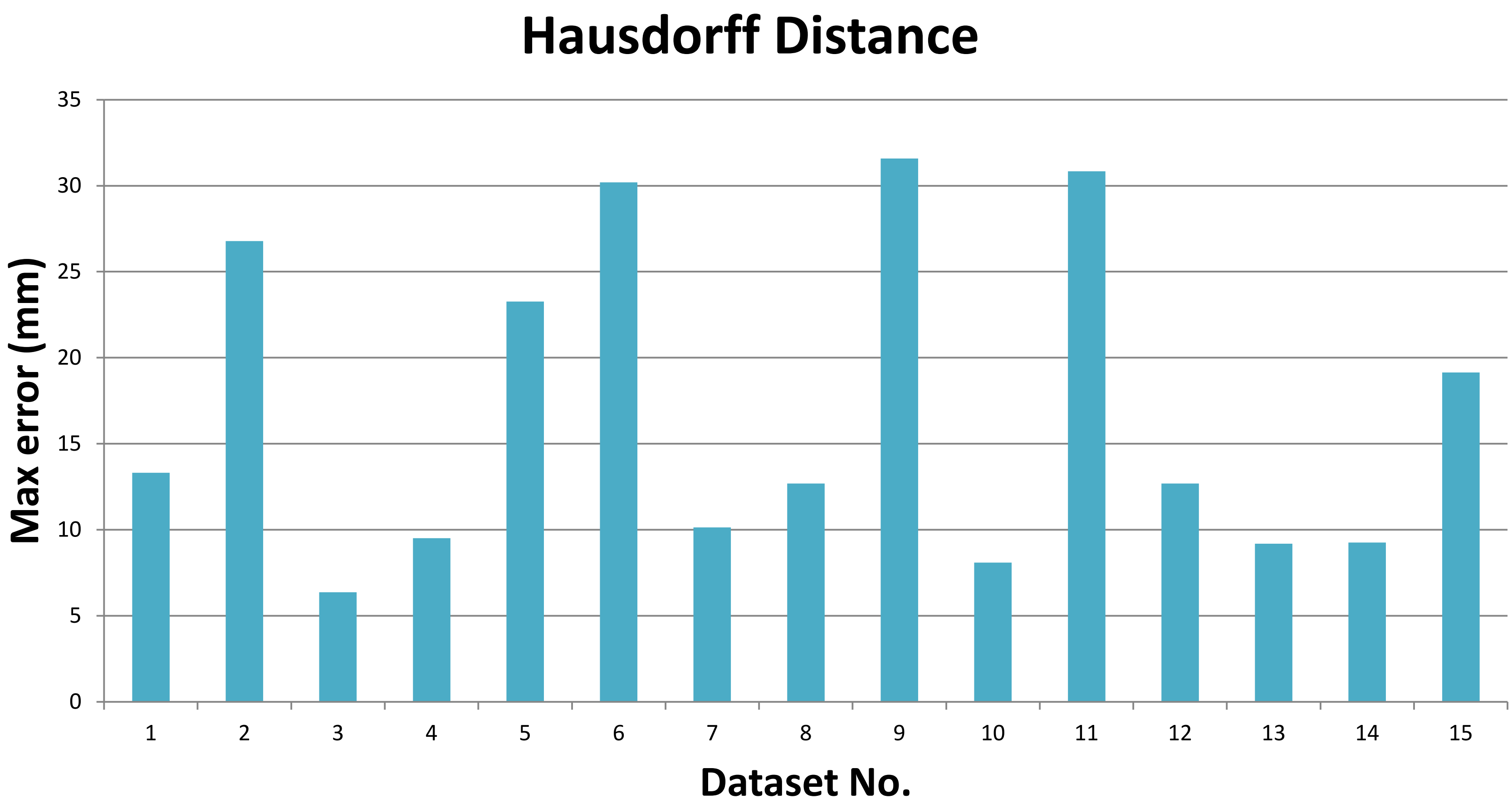
Results



Mean±SD: 2.2±0.8mm

Median = 1.8mm

Results



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

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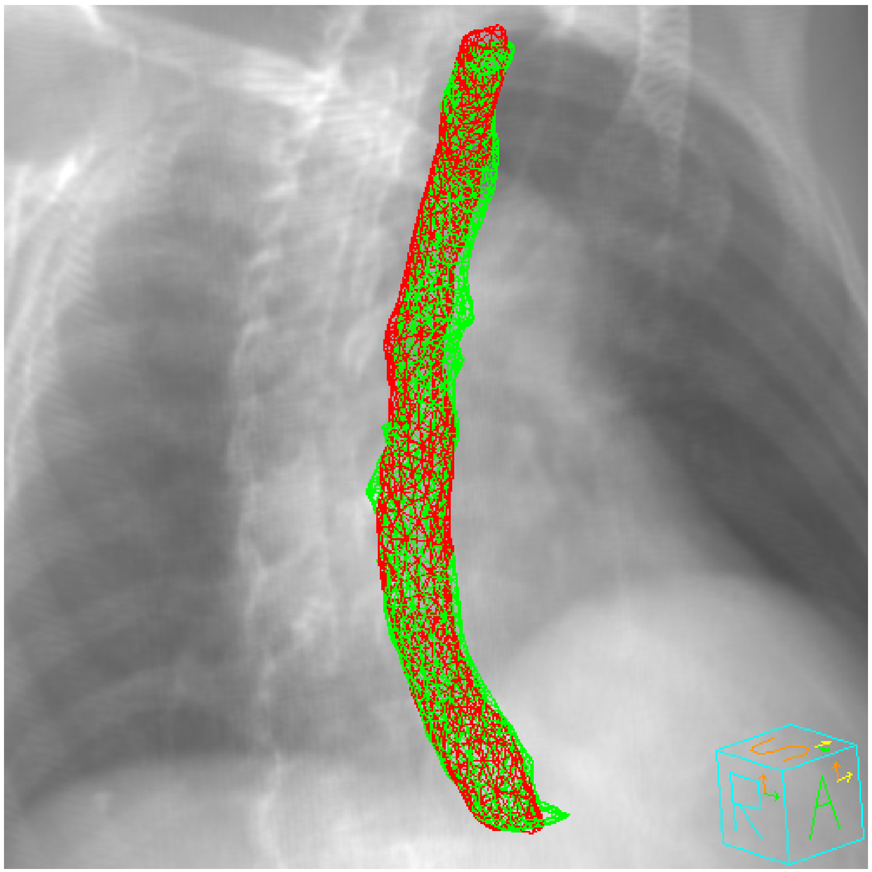
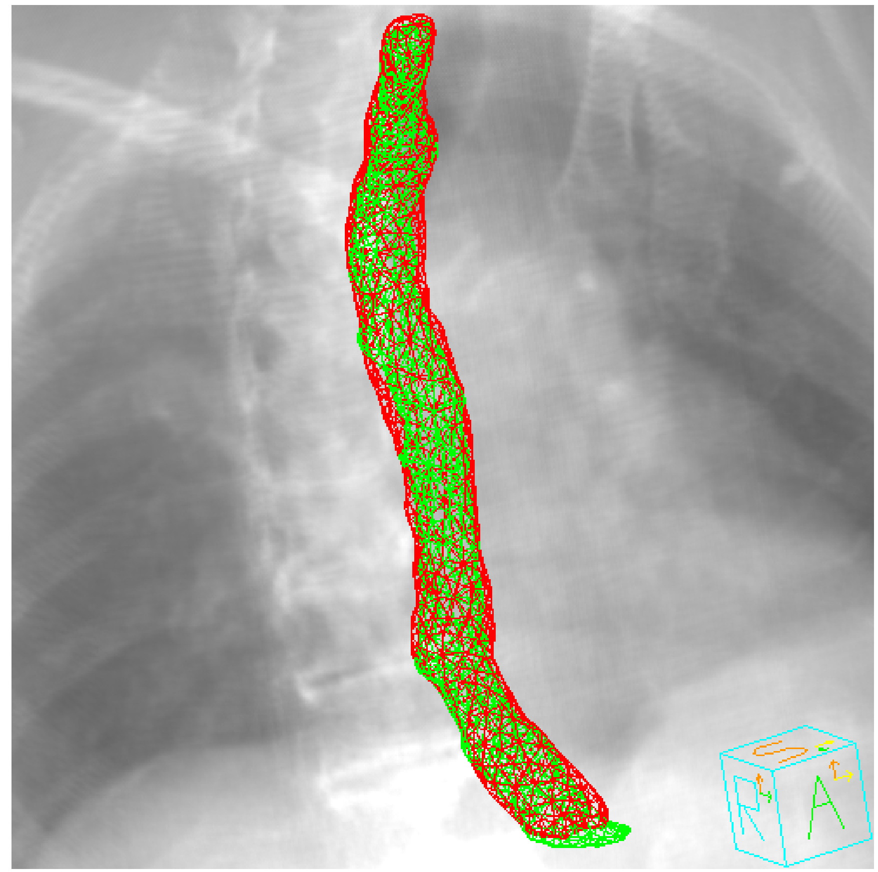
Results



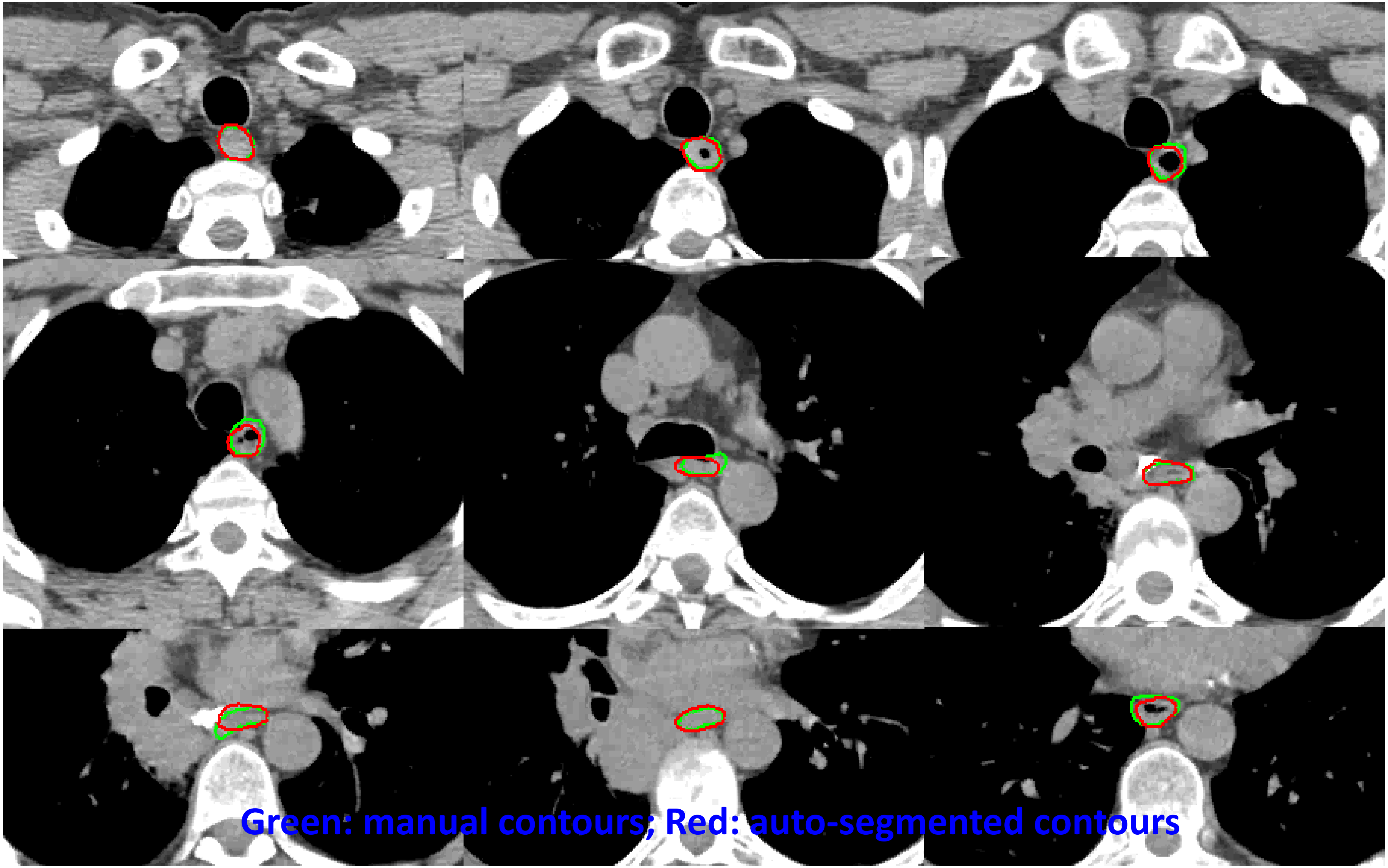
Example 1



Example 2

Green: manual contours; Red: auto-segmented contours

Results



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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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