Seminar:

Review of a landmark-based approach for atlas creation and segmentation of head-and-neck regions

Chris Micek

Group 10

Computer Integrated Surgery II

Mentors: Dr. Todd McNutt, Dr. Russel Taylor, Sierra Cheng

4/18/2017

Goal and Clinical Significance

Goal: Design, implement, and evaluate an algorithm that creates spatially dependent dose features at the inter-organ level

Significance: Identify specific areas of the head and neck that are more or less critical and sensitive to radiation damage to improve radiotherapy planning and reduce negative outcomes
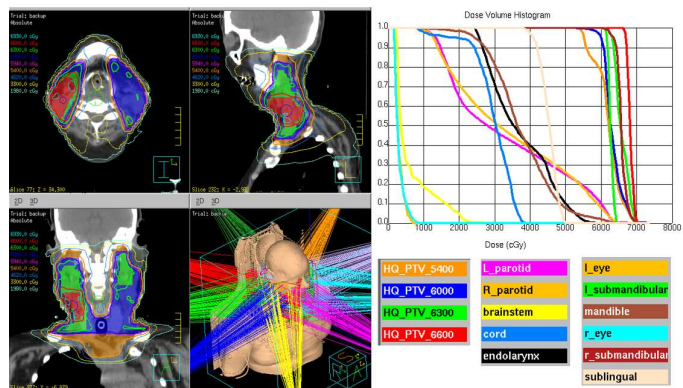

Fig. 1: View of sample radiotherapy treatment plan and the associated dose volume histograms for affected anatomical structures

Paper Selection

Title: Validation of automatic landmark identification for atlas-based segmentation for radiation treatment planning of the head-and-neck region

Authors: Claudia Leavens, Torbjørn Vik, Heinrich Schulz, Stéphane Allaire, John Kim, Laura Dawson, Brian O'Sullivan, Stephen Breen, David Jaffray, and Vladimir Pekar

Rationale:

- Attempts to solve a similar problem (generate an atlas to define regions in patient space)
- Includes elements we may be able to use to increase accuracy/decrease runtime

Us:

Deformable Registration → Atlas Creation → Dose-Feature Information

Problem: Manual Contouring is Difficult

Solution:

Pipeline to automatically segment head/neck anatomy:

1. Automatic landmark identification in the image dataset of interest
2. Automatic landmark-based initialization of deformable surface models to the patient
3. Adapt of these models to patient-specific anatomical boundaries of interest

In addition, introduce way of determining which patient anatomy produces a more robust atlas

Technical Approach: Atlas Creation

- 27 anatomical landmarks manually chosen by radio oncologists in all 20 patient CT datasets
- Set of 10 patients used for atlas creation
- In addition to size/shape/location/orientation, want to describe expected/permitted variation of these

Use PCA:

- Align landmarks with Procrustes
- Calculate covariance matrix:

$$\mathbf{C} = \frac{1}{N-1} \sum_{i=1}^{N} (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T$$

- Eigenvectors $\mathbf{q}_j, j = 1, \dots, M$ of $\mathbf{C}$ are M principle modes of variation ($M = 5$)

Atlas Registration/Model Transfer

- Find optimal transformation mapping landmarks from atlas to test patient using controlled random search, restricted to lie in domain of PCA modes

$$T_{opt} = \arg \min_T \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{G_i} |g_k - \hat{g}_k|$$

- Transformations of the form

$$T(\mathbf{x}, \mathbf{p}) = \mathbf{R}\mathbf{x} + \sum_{j=1}^{M} w_j \mathbf{q}_j$$

- G_i = # voxels around the grey-value template of i-th landmark ($30 \times 30 \times 30$ mm^3)
- g_k, $\hat{g}_k$ = grey values of k-th voxels of the patient/atlas templates

- $\mathbf{R}$ = rigid isotropic scaling transformation
- Right addend is deformation using PCA variation modes

Optimization

- Want to find combination of patients that would be most robust to variability in target volumes

- Hypothesized that atlases with larger eigenvolumes (product of nonzero eigenvalues from PCA) would be more robust than those with smaller values, since this indicates a larger eigenspace in which to search for landmark correspondences

- 20 datasets available, 16 viable for atlas creation, use 10 per atlas

- Find eigenvolumes of all 8008 atlas combinations, compare 10 with highest e-volumes to those with 10 lowest.

Results

- Register each of the 10 atlases to the 10 left out patients, compute mean RMS distance of registered points to ground truth:

	Large Eigenvolume: Mean RMS dist (mm)	Small Eigenvolume: Mean RMS dist (mm)
Total:	9.5 ± 0.6	11.0 ± 0.9

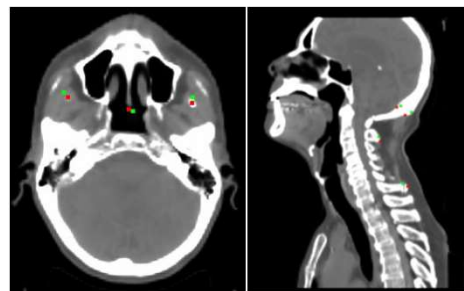- CRS took 60 seconds using 3.4 GHz Intel PC and 1 GB RAM

Fig 1: Comparison of landmarks transformed from atlas (green) to ground truth in target (red)

Discussion

- Apparent confirmation of hypothesis regarding eigenvolumes & atlas robustness
- Landmarks with best performance had high contrast with background, unique appearances
- Those with worse performance were located on nonrigid structures and had a large amount of ground-truth variability
- State that improving number of iterations may improve robustness for landmarks with greater variability

Positives

- Paper easy to follow
- Included efficiency information
- Used PCA to reduce dimensionality of data and include information about variation
- Metric for evaluating robustness of atlas patients
- Despite differences in the underlying dataset, registration & atlas creation relevant for our project

Negatives

- Used gray-valued CT data
- Lots of unanswered questions:
  - How would these results generalize to larger datasets?
  - Why 27 landmarks? No experiment comparing performance with number of landmarks.
  - Is 9.5 mm error actually acceptable? Is the 1.5 mm difference between large and small eigenvolumes significant?
  - No quantitative measurement of ground truth variability and how it relates to performance.
  - No data on how number of iterations affects accuracy.

What We Can Use

- Could potentially use PCA to include information about variation in patient anatomy/more efficiently register using thin-plate splines
- Can test which patients would be optimal for atlas creation by comparing eigenvolumes

References

1. Leavens, C., Vik, T., Schulz, H., Allaire, S., Kim, J., Dawson, L., ... & Pekar, V. (2008, March). Validation of automatic landmark identification for atlas-based segmentation for radiation treatment planning of the head-and-neck region. In *Medical Imaging* (pp. 69143G-69143G). International Society for Optics and Photonics.