Head and Neck Lymph Node Region Delineation with Auto-segmentation and Image Registration

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Outline

- Introduction
- Related Work
- Lymph Node Region Contouring with Image Registration
- Automatic Segmentation of Landmark Structures
- Geometrical Feature Based Similarity
- Results
- Conclusion
Context

- **3D Conformal Radiotherapy** (beams are shaped to match the tumor)
- **Intensity Modulated Radiation Therapy** (controls intensity in small volumes)
Target Volumes

- GTV / CTV / PTV

- Gross tumor volume
- Clinical target volume
- Planning target volume
- Lymph nodes
Motivation

- Improve the process of target volume delineation for radiation therapy planning.

Objective:
- Auto-contour lymph node regions.
- Initial focus on head and neck.
Problem

- Where are the lymph nodes?
- Where are the lymph node regions?

none of the structures are lymph nodes
Solution

- Create reference (canonical) models.
- Map reference nodal regions to patients.
System Overview

Target CT Images

Segmentation of Landmark Structures

3D Volume and Mesh of Mandible, Hyoid, ...

Retrieve Similar Reference Models

Image Registration

Projected Lymph Node Regions

Reference Models with Lymph Node Regions
Image Registration

- Align the transformed reference image $f_R \circ g$ to the target image $f_T$.
- Find the optimal set of transformation parameters $\mu$ that maximize an image similarity function $S$:

$$\mu_{\text{optimal}} = \arg\max_{\mu} S(\mu)$$
Mattes’ Method

- Similarity Function
  \[ S(\mu) = -\text{mutual\_information}(f_R \circ g, f_T) \]

- Transformation Function
  \[ g(x|\mu) = R(x - x_C) - T(x - x_C) + D(x|\delta) \]
  \[ x = [x, y, z]^T \text{ in the reference image coordinates.} \]
Deformable Transformation

- Control points \((15*15*11)\).
- Each control point is associated with a 3-element deformation vector \(\delta\), describing \(x\)-, \(y\)-, \(z\)-components of the deformation.
Project Target Lymph Regions

- Image registration aligns reference and target CT sets.
- Apply result transformation $g$ to reference lymph node regions.
- Incorporate anatomical landmark correspondences.
- Use surface mesh of outer body contour, mandible, hyoid ...
Surface Warping

- Shelton’s method used to find correspondences between surfaces.
- Energy based surface mesh warping.

\[ E(C) = E_{\text{sim}}(C) + \alpha E_{\text{str}}(C) + \beta E_{\text{pri}}(C) \]

\( C \) is the function which maps points from reference surface \( S_R \) to target surface \( S_T \).
\( E_{\text{sim}}(C) \) is similarity, \( E_{\text{str}}(C) \) is structural, \( E_{\text{pri}}(C) \) is prior information.
Landmark Correspondence

- The deformation $\zeta$ at landmark points $z_k$

$$\zeta_k = \bar{v}_k - v_k$$

$v_k$: points from reference surface mesh $S_R$.

$\bar{v}_k$: corresponding locations on transformed reference surface $S_R \circ C$ matching the target surface mesh $S_T$. 
Surface $S_R$

$S_R \circ C$

Surface $S_T$

$\zeta_k = \omega_k - \upsilon_k$
Using Landmark Correspondence

- Deformation vectors $D(\lambda_j)$ are modified according to landmark correspondences $\zeta_k$ in the proximity of the control points $\lambda_j$.
- Landmark structures align better.
- Faster convergence.
Compare Image Registration Results

Reference  Mattes  w/ Landmark  Target
Automatic Segmentation of Landmark Structures

- **Given**: Cancer radiation treatment patient’s head and neck CT image.
- **Find**:
  - Skull base & thoracic inlet.
  - Anatomical structures:
    - cervical spine (white)
    - respiratory tract (dark green)
    - mandible (turquoise)
    - hyoid (yellow)
    - thyroid cartilage
    - internal jugular veins (pink)
    - carotid arteries (dark yellow)
    - sternocleidomastoid muscles (light green, orange)
Method

- 2D knowledge-based segmentation
  - Based on Kobashi’s work
  - Dynamic thresholding
  - Progressive landmarking

- Combined with 3D active contouring
  - Does not require successful 2D segmentation on every axial slice
  - Initialized with 2D segmentation result
2D Segmentation Results
2D/3D Iteration

Identify objects that are easy to find, use them to find harder ones.
Geometrical Feature-Based Similarity

- **Given**: A stored database $DB$ of CT scans from prototypical reference head and neck cancer patients and a single query CT scan $Q$ from a target patient.

- **Find**: Similarity between $Q$ and each database image $d$ in $DB$ in order to find the most similar database images $\{d_s\}$. 
Structures

- Outer body contour
- Mandible
- Hyoid
- Internal jugular veins
Feature Types

- **Simple** numeric 3D regional properties: volume and extents.
- **Vector** properties: relative location between structures.
- **Shape** properties: surface meshes of structures.
Features for Similarity Measure

- Volume and extents of the overall region
- Normalized centroid of hyoid and mandible
- 3D centroid difference vector between mandible and hyoid
- 2D centroid difference vectors between hyoid and jugular veins
- Surface meshes of mandible and outer body contour
Mesh Feature Distance

- Register reference mesh $S_R$ and target mesh $S_T$ with Iterative Closest Point (ICP), result $T$.

- **Hausdorff distance** between two aligned surface meshes, $TS_R$ and $S_T$

$$d_h(TS_R, S_T) = \max_{p \in S_R} d(Tp, S_T)$$

The Hausdorff distance is the maximum distance from any point in the transformed reference image to the test image.
Feature Vector Distance

- Given feature vectors $F_d$ and $F_Q$ for model $d$ and query $Q$ in the feature vector space $\mathbb{R}^N$.

$$D_F(F_d, F_Q) = \left[ \sum_{i=1}^{N} w_i d_i(F_{di}, F_{Qi})^2 \right]^\frac{1}{2}$$
Evaluation

- Surface mesh distance after full image registration $D_H$ – slow.
- Feature vector distance $D_F$ – fast.

$$\text{corr\_coef}(D_H, D_F) = 0.72$$

Images with small feature vector distance should produce the best results after registration.
Experiment Results

- 50 head and neck patient CT sets.
- 34 subjects are segmented.
- 20 subjects with lymph node regions drawn by experts.
- Image registration
  \[20 \times (20 - 1) = 380 \text{ total cases.}\]
Auto-segmentation Results

- Correct Segmentations
Auto-segmentation cont.

- Incorrect Segmentations

- Carotid artery misidentified as jugular vein due to surgery.
- Hyoid partly missing due to too low inter-slice resolution.
Auto-segmentation cont.

<table>
<thead>
<tr>
<th>Structure</th>
<th>Successs</th>
<th>Failure</th>
<th>Incorrect</th>
<th>% of success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cervical Spine</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td>Respiratory Tract</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td>Mandible</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td>Hyoid</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>100.00%</td>
</tr>
<tr>
<td>Thyroid Cartilage</td>
<td>33</td>
<td>0</td>
<td>1</td>
<td>97.06%</td>
</tr>
<tr>
<td>Left Internal Jugular Vein</td>
<td>27</td>
<td>3</td>
<td>4</td>
<td>79.41%</td>
</tr>
<tr>
<td>Right Internal Jugular Vein</td>
<td>31</td>
<td>1</td>
<td>2</td>
<td>91.18%</td>
</tr>
<tr>
<td>Left Carotid Artery</td>
<td>25</td>
<td>9</td>
<td>0</td>
<td>73.53%</td>
</tr>
<tr>
<td>Right Carotid Artery</td>
<td>30</td>
<td>4</td>
<td>0</td>
<td>88.24%</td>
</tr>
<tr>
<td>Left SCM</td>
<td>24</td>
<td>10</td>
<td>0</td>
<td>70.59%</td>
</tr>
<tr>
<td>Right SCM</td>
<td>25</td>
<td>9</td>
<td>0</td>
<td>73.53%</td>
</tr>
</tbody>
</table>
# Image Registration Results

## Success/Failure

<table>
<thead>
<tr>
<th>Method</th>
<th>Total cases</th>
<th>Successful</th>
<th>Success rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mattes method</td>
<td>380</td>
<td>367</td>
<td>96.57%</td>
</tr>
<tr>
<td>New method using landmark correspondence</td>
<td>380</td>
<td>380</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

## Time of Convergence

<table>
<thead>
<tr>
<th>Method</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mattes method</td>
<td>32 minutes</td>
<td>6 minutes</td>
</tr>
<tr>
<td>New method using landmark correspondence</td>
<td>26 minutes</td>
<td>5 minutes</td>
</tr>
</tbody>
</table>
Quantitative Evaluation - Surface Mesh Distance

\[ D_H(S_R \circ g, S_T, n) : \text{Hausdorff distance} \]

\[ n : \text{lymph node region} \]

Projected Region \( S_R \circ g \)

Color is distance to truth.

Ground Truth: Expert Drawn Target Region \( S_T \)
\[ D_H(S_R \circ g, S_T, 1B) \] for all \( S_R, S_T \).

<table>
<thead>
<tr>
<th>Method</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mattes method</td>
<td>2.85</td>
<td>1.44</td>
</tr>
<tr>
<td>New method using landmark correspondence</td>
<td>2.12</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Measurement in centimeter.

Mattes distance larger than landmark distance.
\textit{Mean\_distance}(S_R \circ \mathbf{g}, S_T, \mathit{1B}) \text{ for all } S_R, S_T.

<table>
<thead>
<tr>
<th>Method</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mattes method</td>
<td>1.02</td>
<td>0.51</td>
</tr>
<tr>
<td>New method using landmark correspondence</td>
<td>0.59</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Measurement in centimeter.
Similarity Evaluation

- $R_H(i, Q)$: the $i^{th}$ ranked reference subject for target $Q$ based on the image registration results, $D_H$.
- $R_F(i, Q)$: the $i^{th}$ ranked reference subject based on geometrical features, $D_F$.

$$P(R_F(1, Q) = R_H(1, Q)) = 80\%$$
$$P(R_F(1, Q) = R_H(2, Q)) = 10\%$$
$$P(R_F(1, Q) = R_H(3, Q)) = 4\%$$
Similarity Evaluation

Examples

corr_coef(D_H, D_F) = 0.74

corr_coef(D_H, D_F) = 0.68
# Similarity Evaluation – Surface Mesh Distance

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_H$ for the closest reference subject to each target based on feature distance</td>
<td>1.28</td>
<td>0.31</td>
</tr>
<tr>
<td>$D_H$ for all reference and target subjects</td>
<td>2.59</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Measurement in centimeter. 

So its better to find the closest subject.
Qualitative Evaluation – 1.1

- Clinically acceptable target projection.

Mattes                  Expert           w/ Landmark

Clinically acceptable target projection.
Qualitative Evaluation – 1.2

- Clinically acceptable target projection.

Mattes

Expert Drawn

w/ Landmark
Qualitative Evaluation – 1.3

- Clinically acceptable target projection.

Mattes
Expert Drawn
w/ Landmark
Qualitative Evaluation – 2

- Clinically **unacceptable** target projection.
Conclusion

- Inter-subject image registration technique shows promise for lymph node region auto-contouring.
- Knowledge-based auto-segmentation is useful for head and neck CT.
- Fast similar subject search is possible and critical as reference database grows.
Future Work

- Integrate and evaluated in a clinical environment.
- Generalize to other types of cancer.
- Regional lymphatic involvement prediction.
- Improve image registration results.
- Improve auto-segmentation results.
  - Validation logic
  - Knowledge-based 3D active contour constraints
Acknowledgement

- Linda Shapiro
- Ira Kalet
- Jim Brinkley
- David Haynor
- David Mattes
- Mark Whipple
- Jerry Barker
- Carolyn Rutter
- Rizwan Nurani
Contributions

- The first auto target contouring tool for radiation therapy. *(AMIA 2002)*

- An auto-segmentation method combining 2D dynamic thresholding and 3D active contouring. *(IEEE CBMS 2006)*

- An image registration method using landmark correspondences in conjunction with mutual information optimization. *(IEEE ISBI 2006)*

- A patient similarity measurement using 3D geometrical features of anatomical structures. *(IEEE ISBI 2007)*