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

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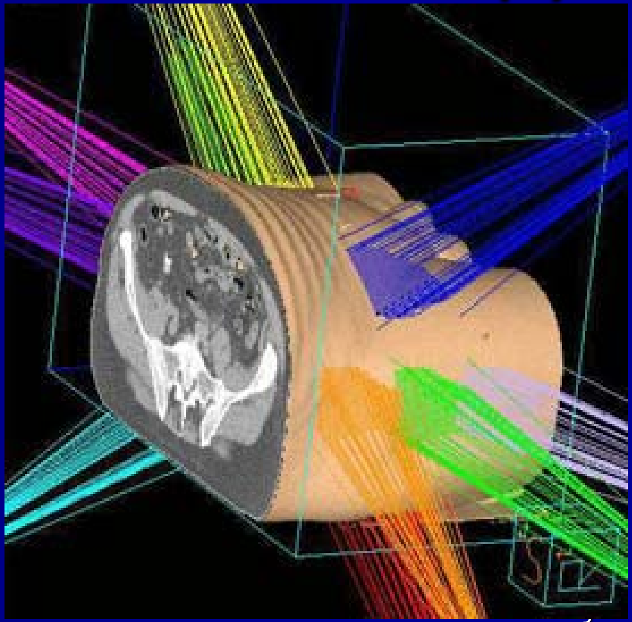
Outline

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

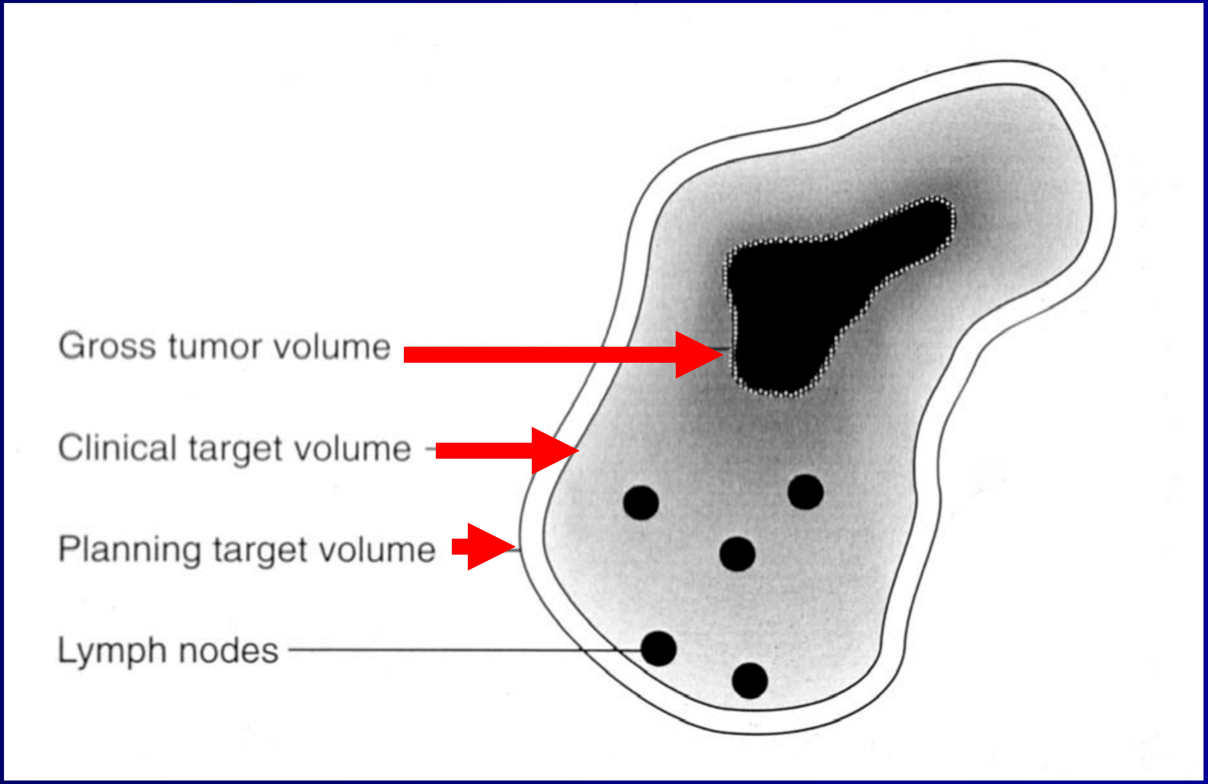
Context

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



Target Volumes

- GTV / CTV / PTV

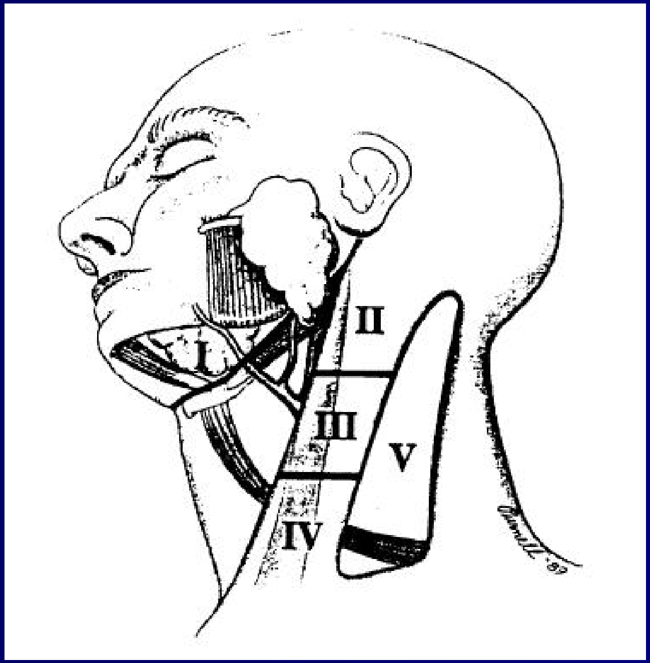


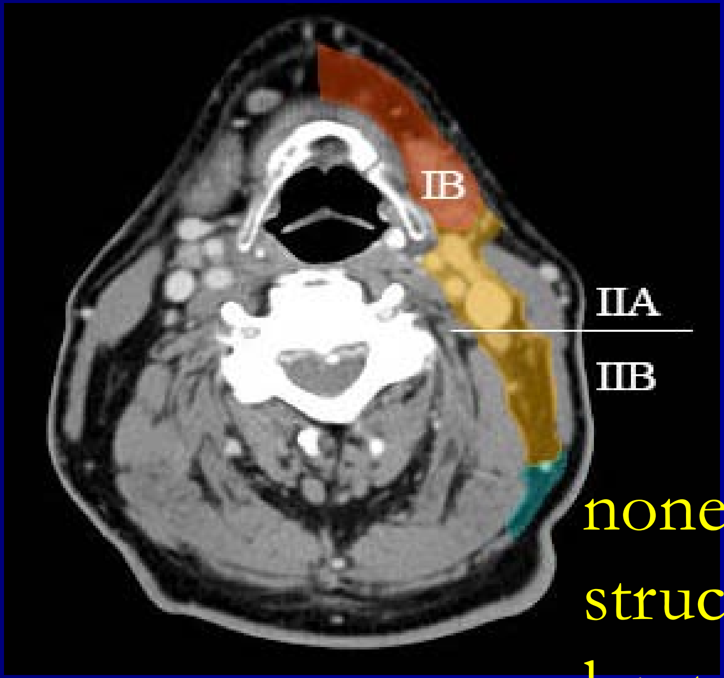
Motivation

- 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?

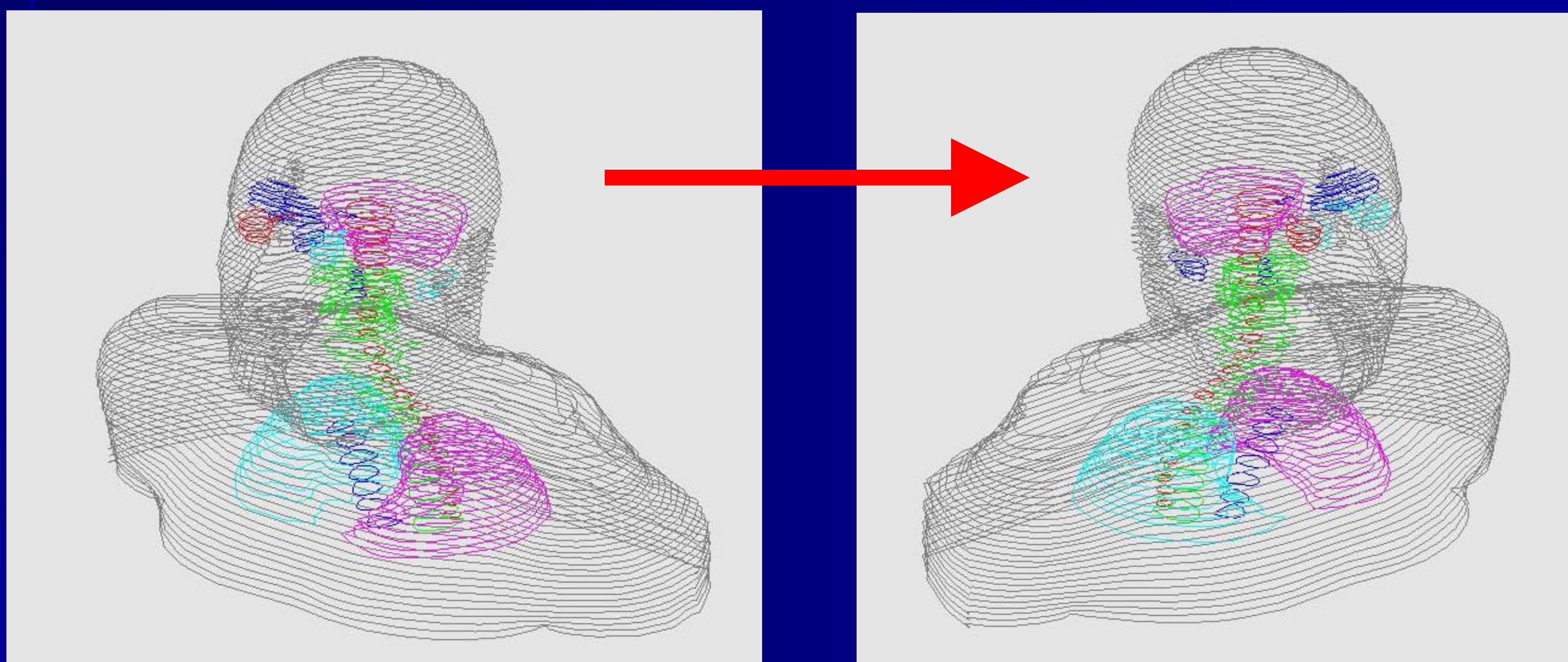




none of the structures are lymph nodes

Solution

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



System Overview

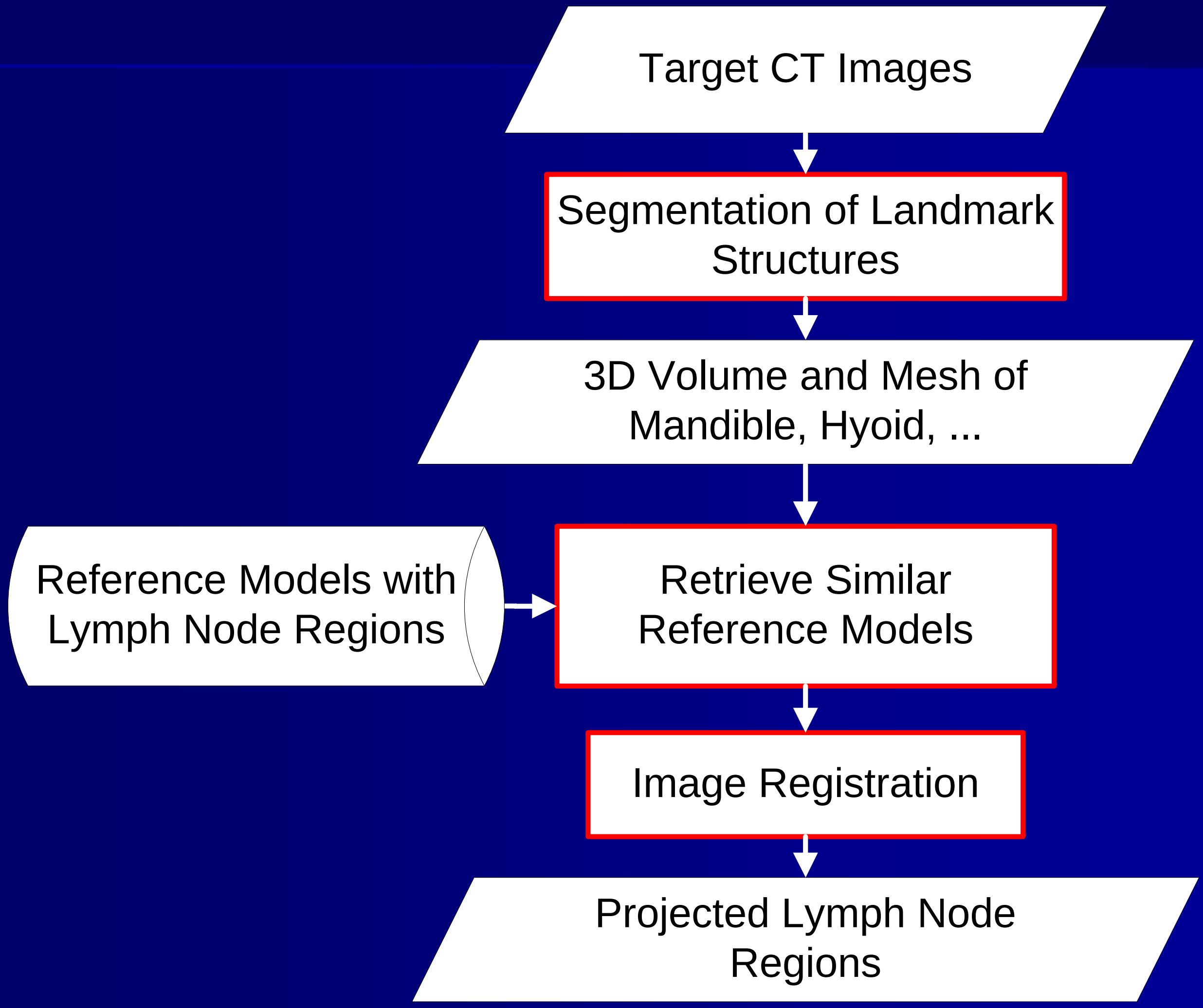
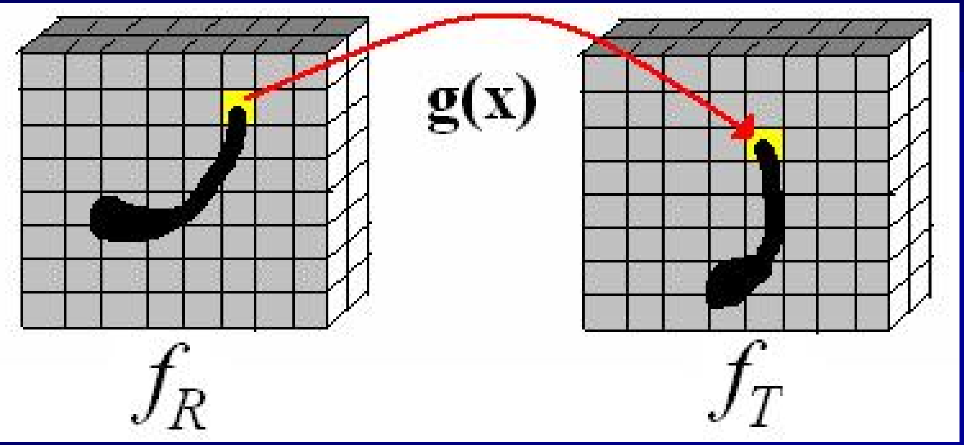


Image Registration



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

$$\mu_{\text{optimal}} = \text{argmax}_{\mu} S(\mu)$$

Mattes' Method

- Similarity Function

$$S(\mu) = -\,mutual\_information(\, f_R \circ \mathbf{g} \,,\, f_T \,)$$

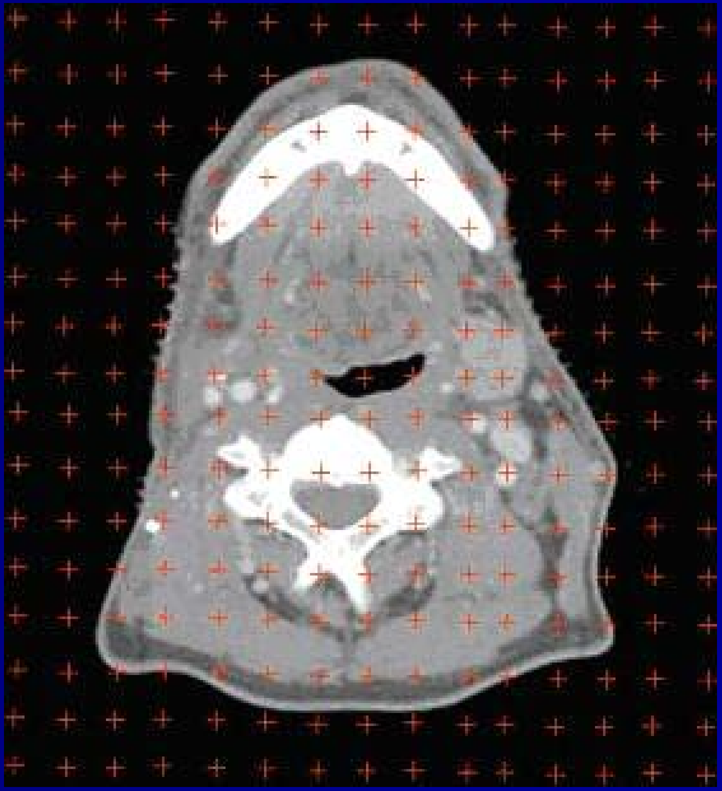
- Transformation Funciton

$$\mathbf{g}(\mathbf{x}|\mu) = \mathbf{R}(\mathbf{x} - \mathbf{x}_C) - \mathbf{T}(\mathbf{x} - \mathbf{x}_C) + \mathbf{D}(\mathbf{x}|\delta)$$

$\mathbf{x} = [x, y, z]^T$ in the reference image coordinates.

Deformable Transformation

- Control points (15*15*11).
- Each control point is associated with a 3-element deformation vector δ, 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.

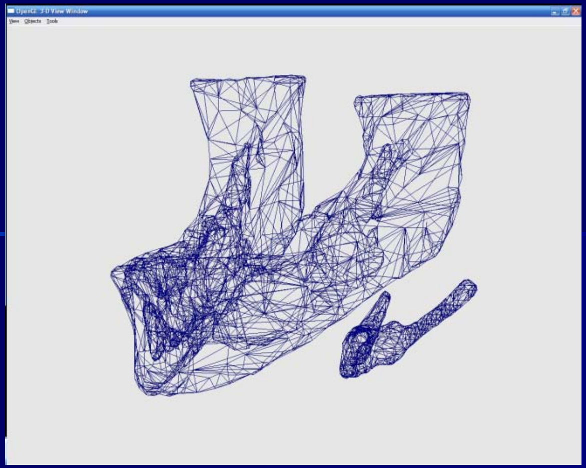
Landmark Correspondence

- The deformation ζ at landmark points

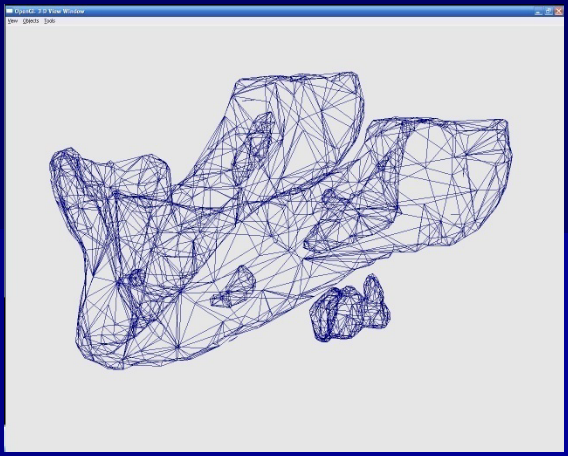
  $\zeta_k = \varpi_k - \upsilon_k$

υ_k : points from reference surface mesh S_R.

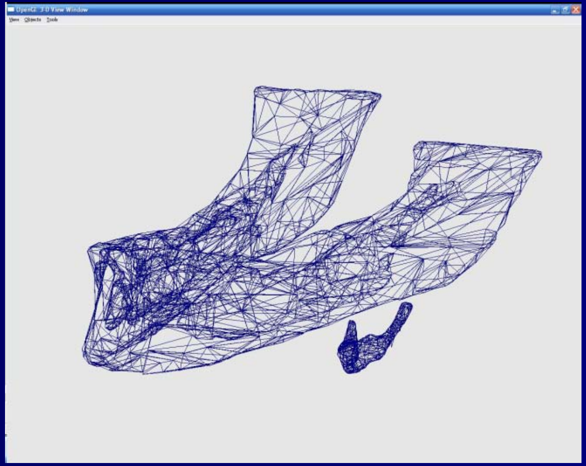
ϖ_k : corresponding locations on transformed reference surface $S_R \circ C$ matching the target surface mesh S_T.



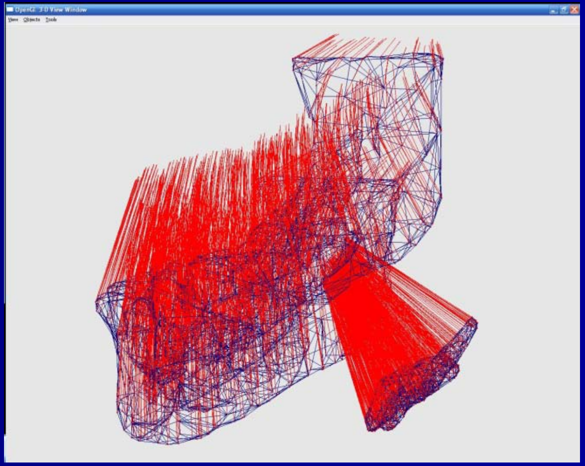
Surface S_R



Surface S_T



$S_R \circ C$

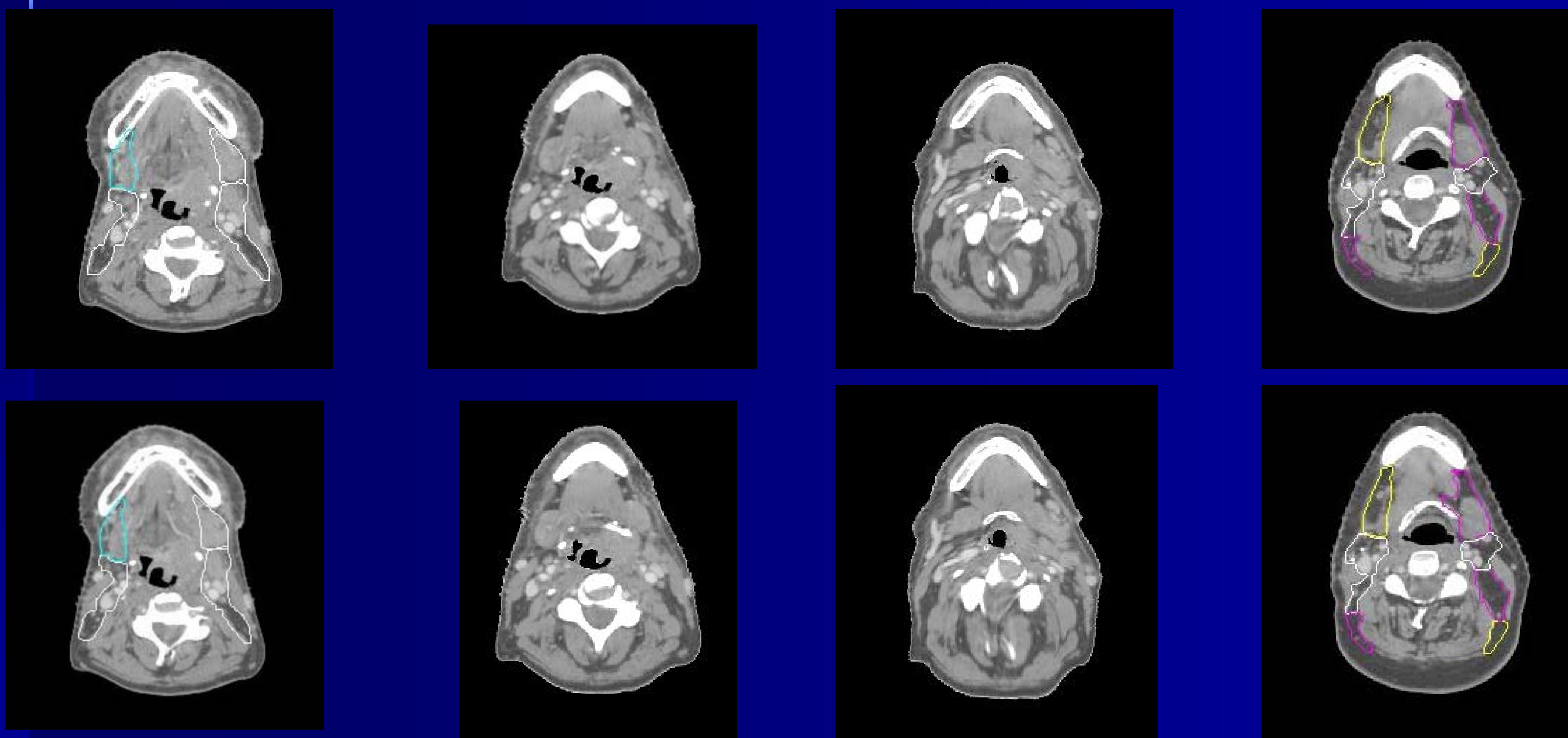


$\zeta_k = \varpi_k - \upsilon_k$

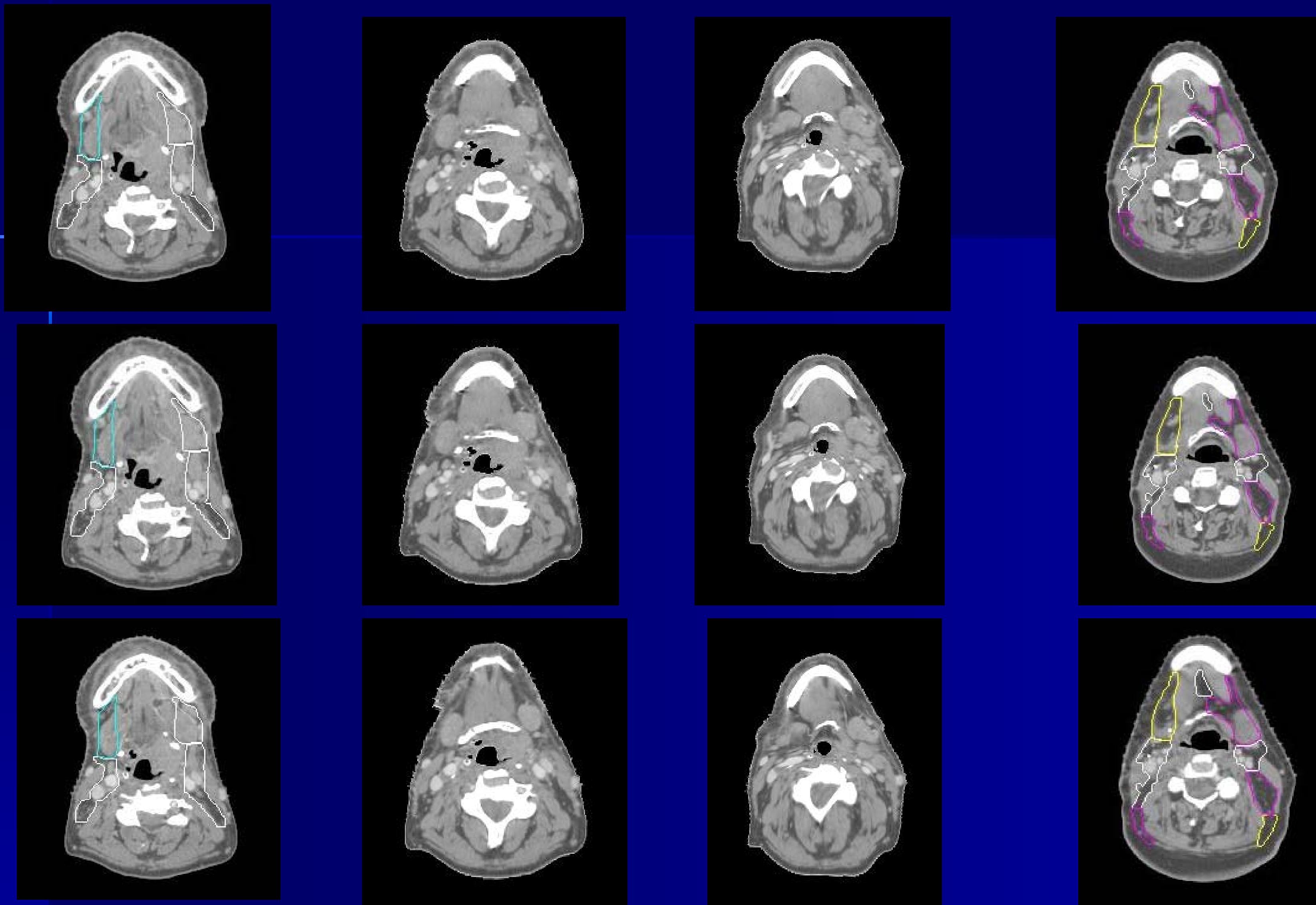
Using Landmark Correspondence

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

Compare Image Registration Results



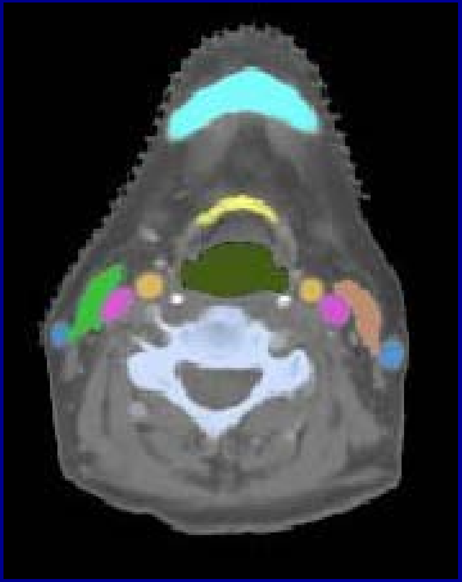
Reference Mattes w/ Landmark Target



Reference Mattes w/ Landmark Target

Automatic Segmentation of Landmark Structures

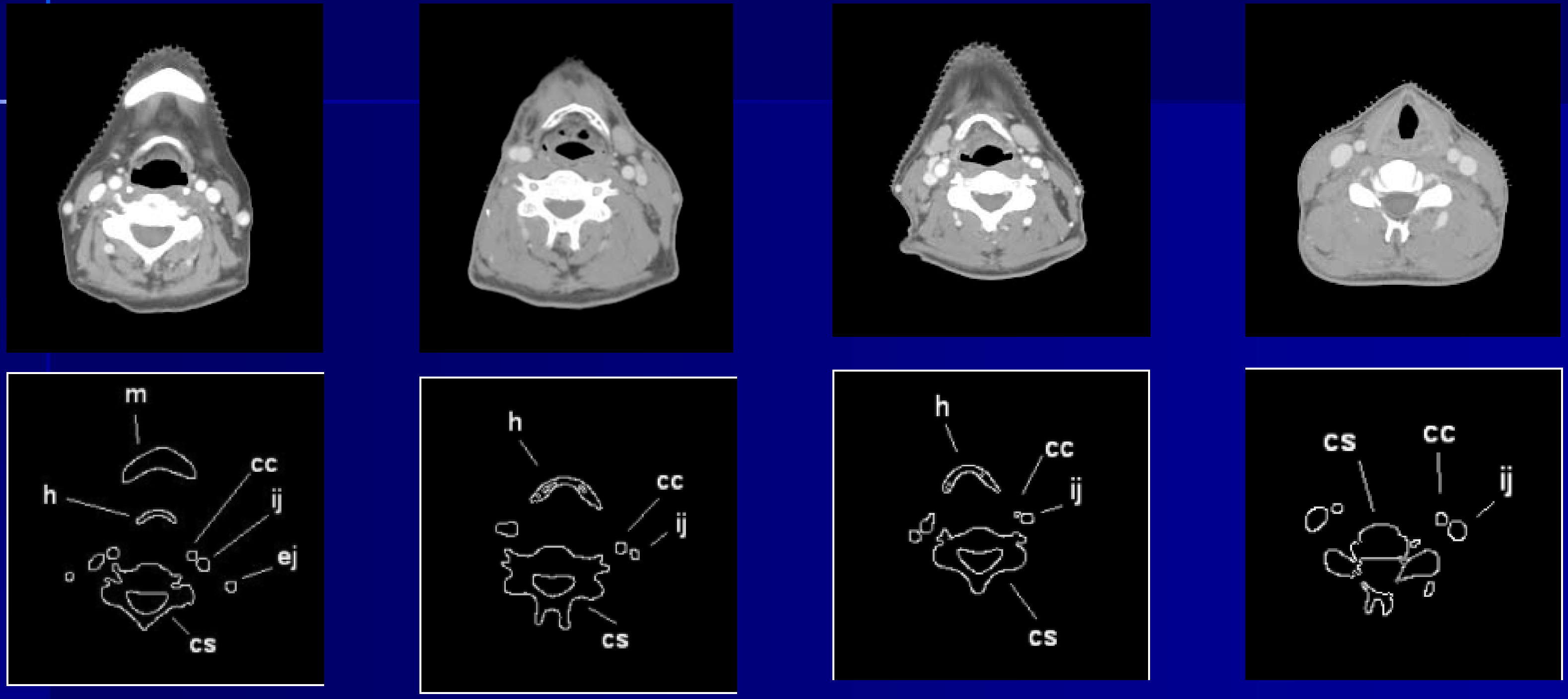
- **Given**: Cancer radiation treatment patient's head and neck CT image.
- **Find**:
  - Skull base & thoracic inlet.
  - Anatomical structures:
    - cervical spine (white)
    - respiratory tract (dark green)
    - mandible (turquoise)
    - hyoid (yellow)
    - thyroid cartilage
    - internal jugular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



Method

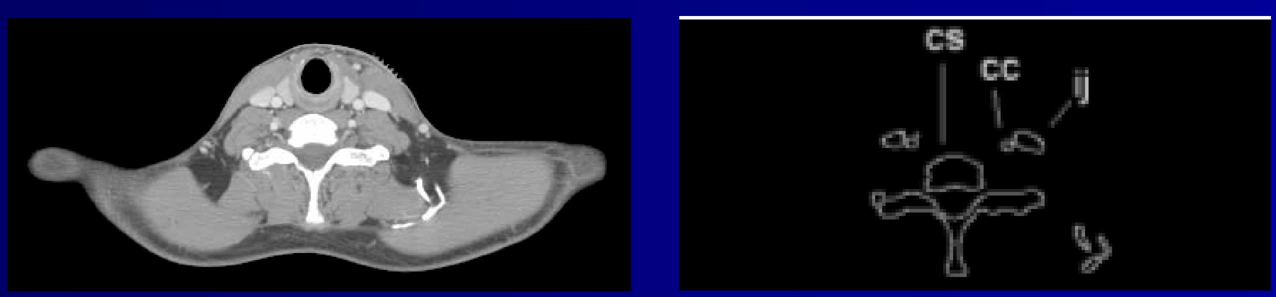
- 2D knowledge-based segmentation
  - Based on Kobashi’s work
  - Dynamic thresholding
  - Progressive landmarking
- Combined with 3D active contouring
  - Do not require successful 2D segmentation on every axial slice
  - Initialize with 2D segmentation result

2D Segmentation Results



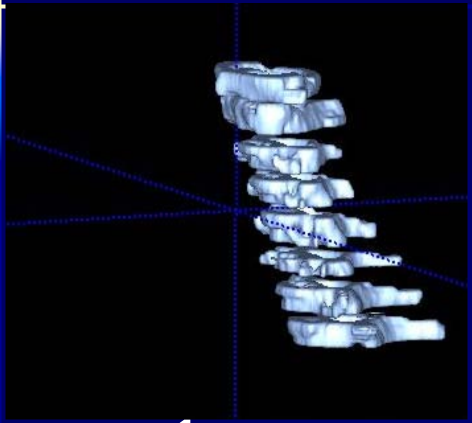
A B C D

E



2D/3D Iteration

Identify objects that are easy to find, use them to find harder ones.



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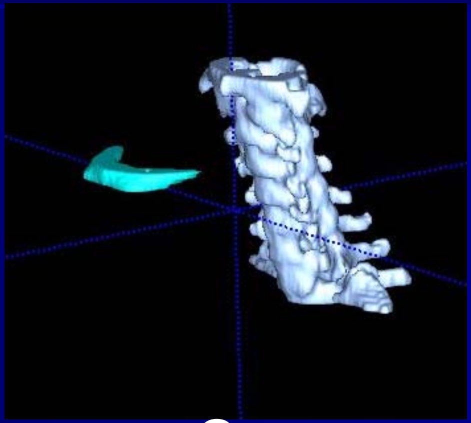

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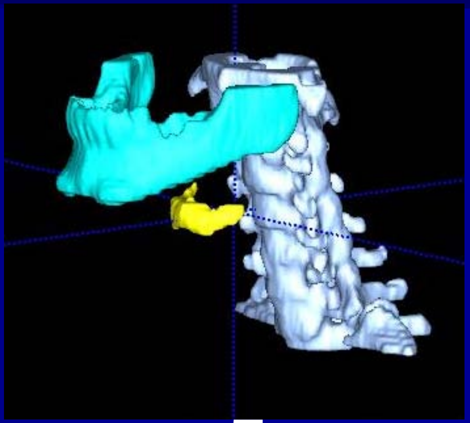

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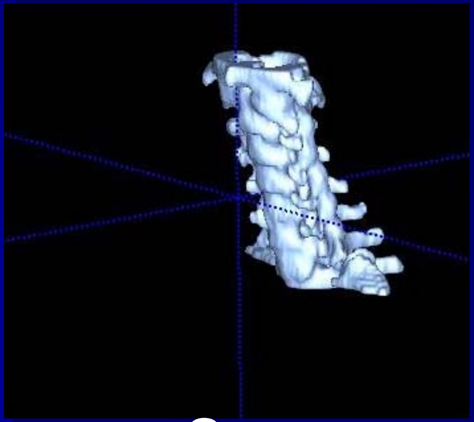

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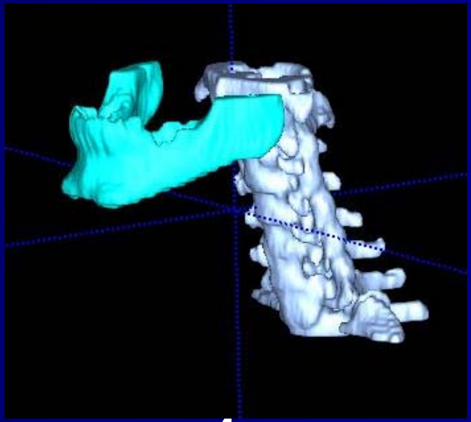

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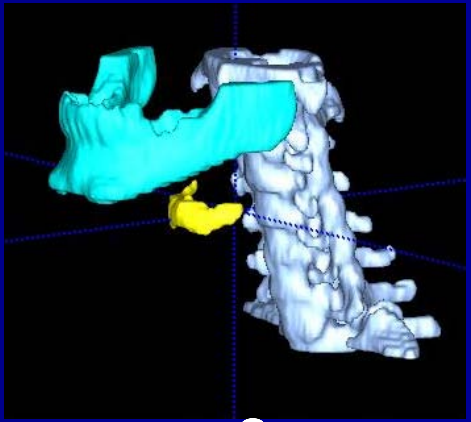

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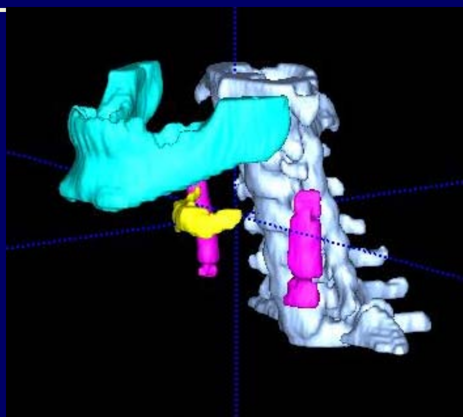
2D/3D Iteration – cont.



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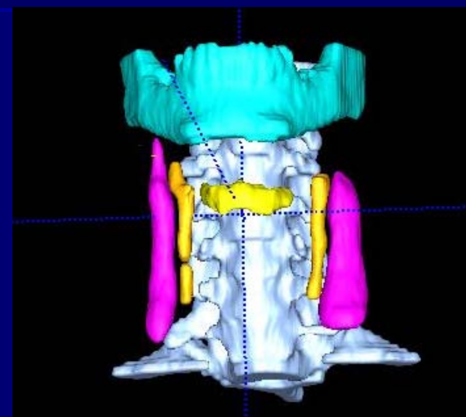

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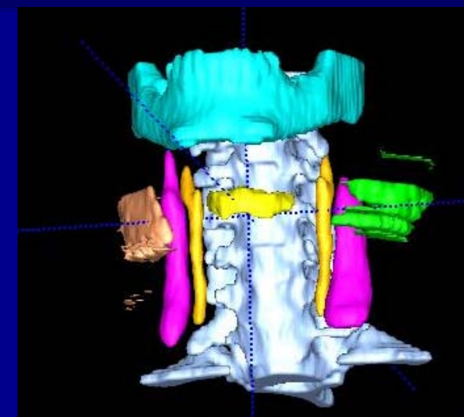

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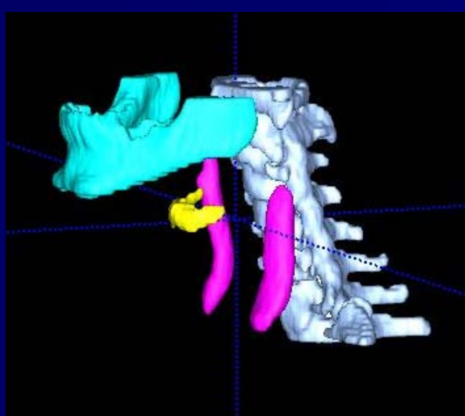

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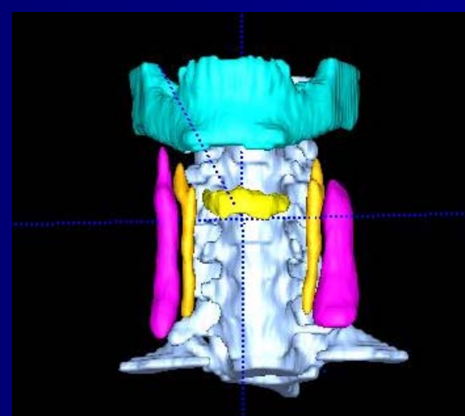

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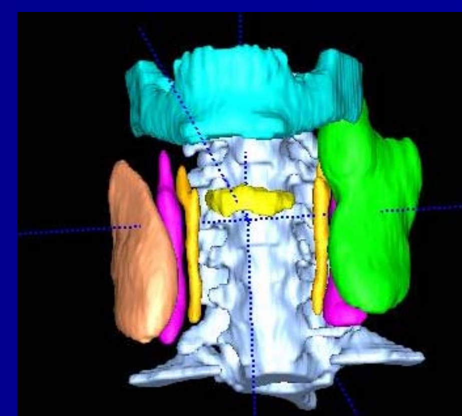

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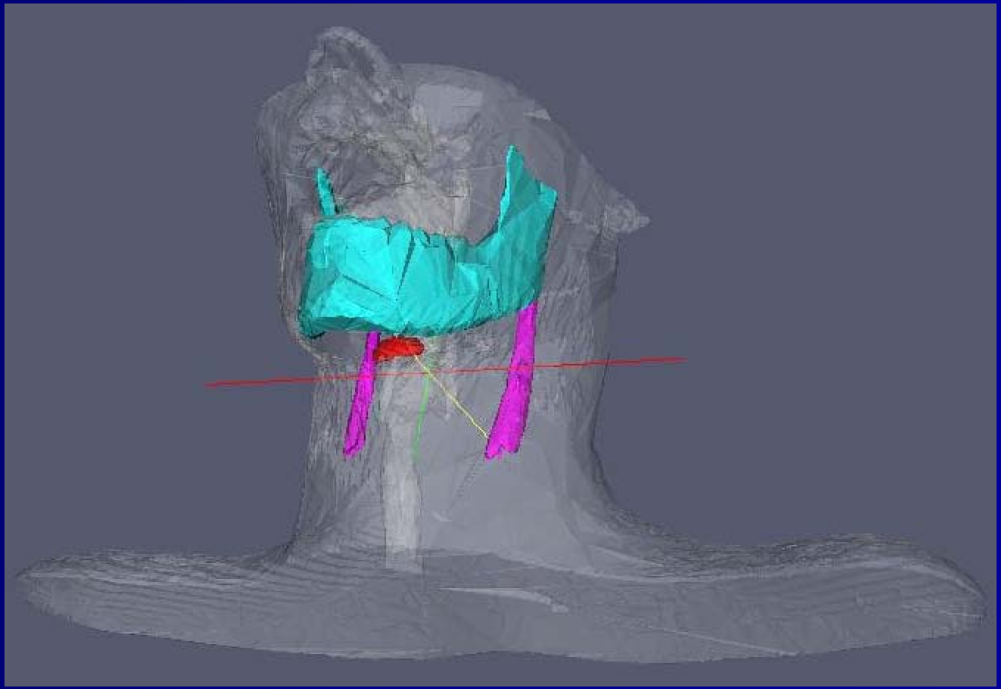
Geometrical Feature-Based Similarity

- **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

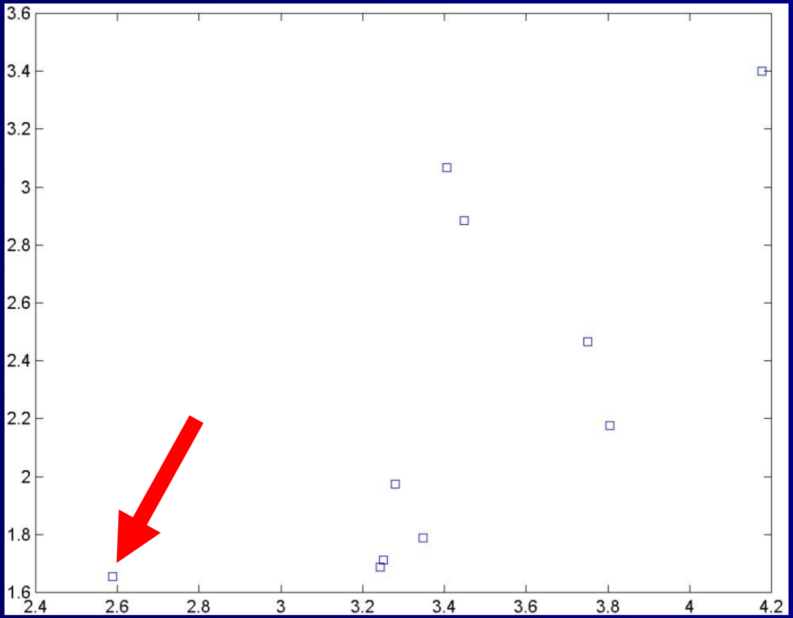
- Given feature vectors F_d and F_Q for model ***d*** and query ***Q*** in the feature vector space R^{N}.

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

Evaluation

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

D_H



D_F

corr_coef(D_H, D_F) = 0.72

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

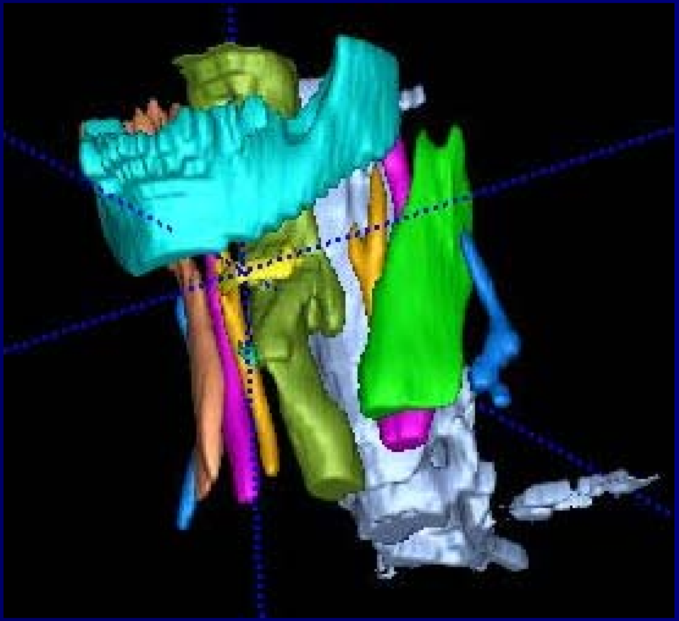
Experiment Results

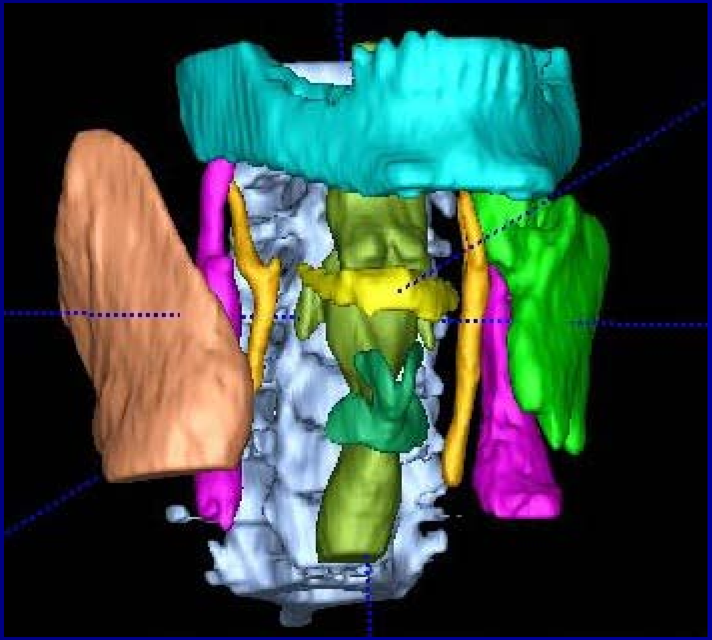
- 50 head and neck patient CT sets.
- 34 subjects are segmented.
- 20 subjects with lymph node regions drawn by experts.
- Image registration

  20 * (20 – 1) = 380 total cases.

Auto-segmentation Results

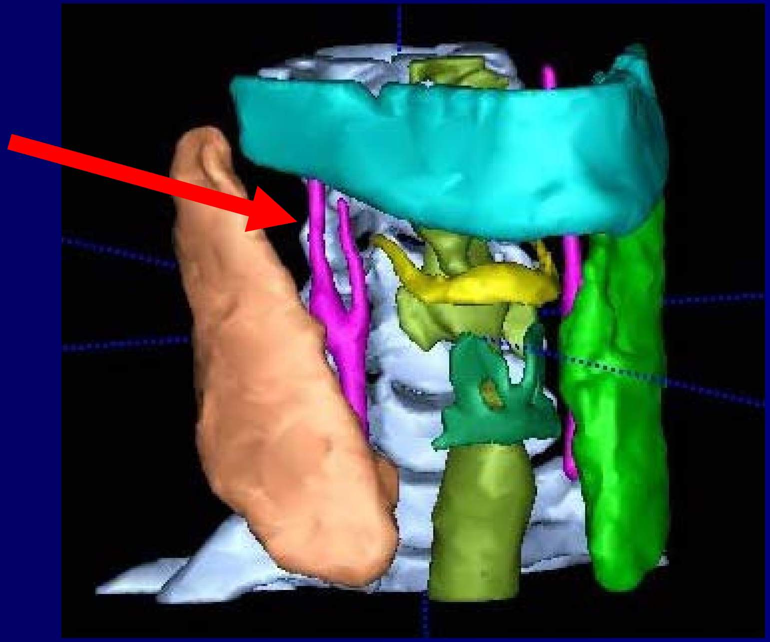
- Correct Segmentations



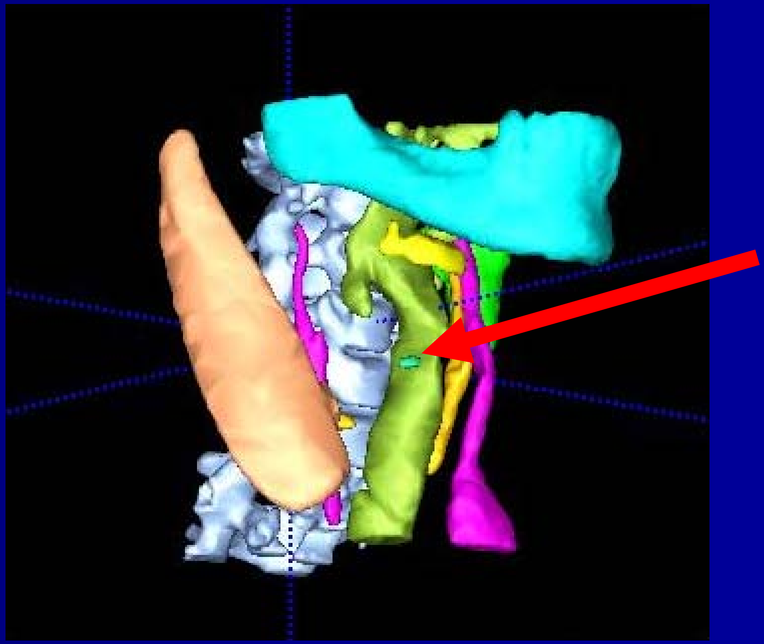


Auto-segmentation cont.

- Incorrect Segmentations



Carotid artery misidentified as jugular vein due to surgery.



Hyoid partly missing due to too low inter-slice resolution.

Auto-segmentation cont.

	Successs	Failure	Incorrect	% of success
Cervical Spine	34	0	0	100.00%
Respiratory Tract	34	0	0	100.00%
Mandible	34	0	0	100.00%
Hyoid	34	0	0	100.00%
ThyroidCartilage	33	0	1	97.06%
Left Internal Jugular Vein	27	3	4	79.41%
Right Internal Jugular Vein	31	1	2	91.18%
Left Carotid Artery	25	9	0	73.53%
Right Carotid Artery	30	4	0	88.24%
Left SCM	24	10	0	70.59%
Right SCM	25	9	0	73.53%

Image Registration Results

Success/Failure

	Total cases	Successful	Success rate (%)
Mattes method	380	367	96.57%
New method using landmark correspondence	380	380	100.00%

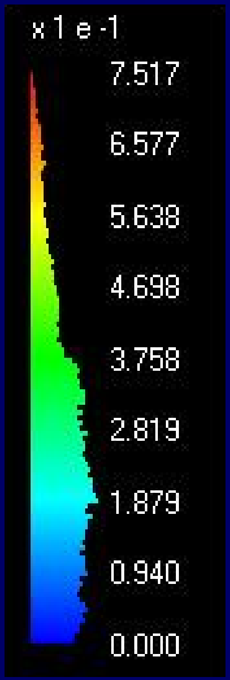
Time of Convergence

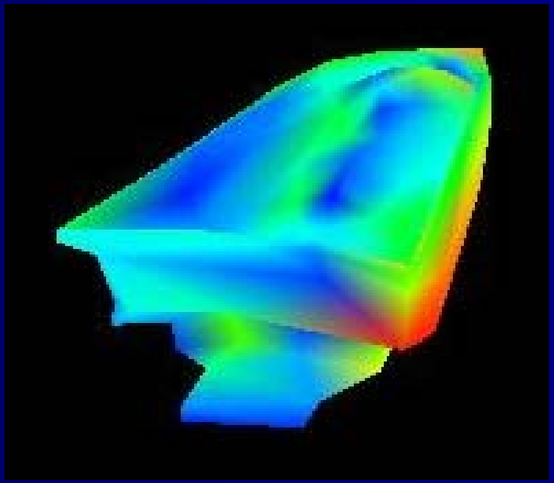
	Average	Standard deviation
Mattes method	32 minutes	6 minutes
New method using landmark correspondence	26 minutes	5 minutes

Quantitative Evaluation - Surface Mesh Distance

$D_H(S_R \circ \mathbf{g}, S_T, n)$: Hausdorff distance

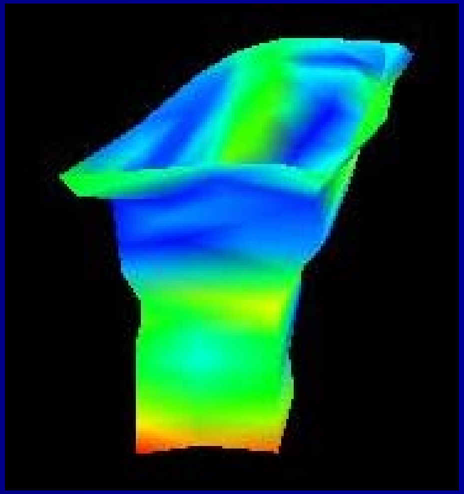
n : lymph node region



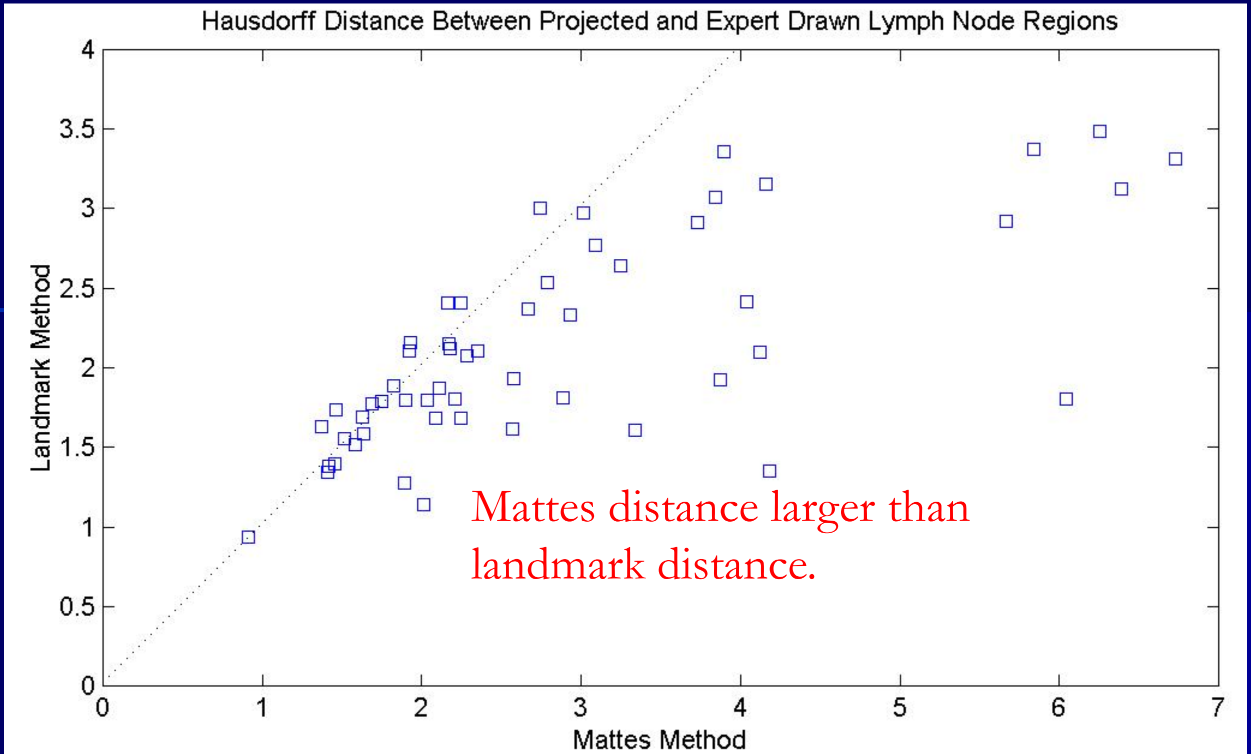


Projected Region $S_R \circ \mathbf{g}$

Color is distance to truth.



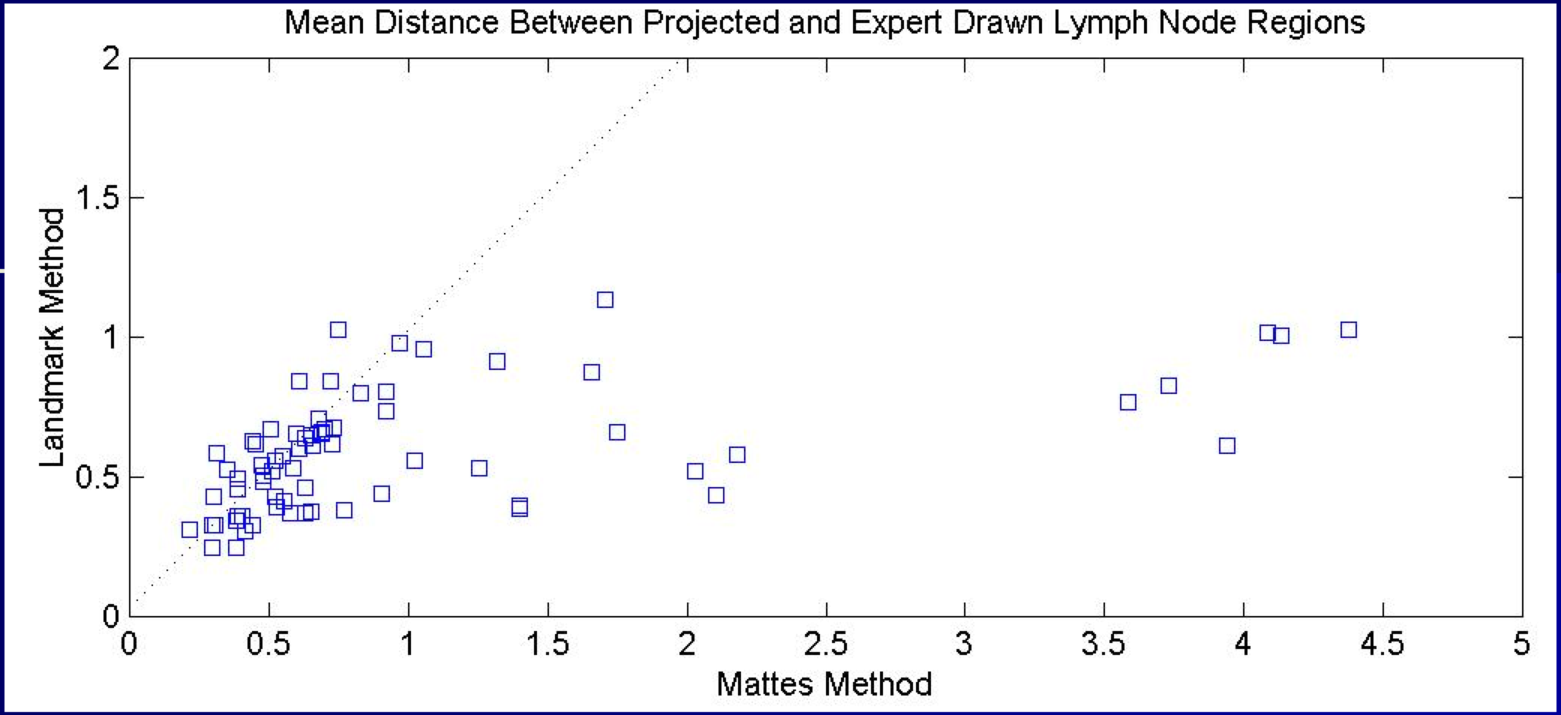
Ground Truth: Expert Drawn Target Region S_T



$D_H(S_R \circ \mathbf{g}, S_T, 1B)$ for all S_R, S_T.

	Average	Standard deviation
Mattes method	2.85	1.44
New method using landmark correspondence	2.12	0.64

Measurement in centimeter.



$Mean\_distance(S_R \circ \mathbf{g}, S_T, 1B)$ for all S_R, S_T.

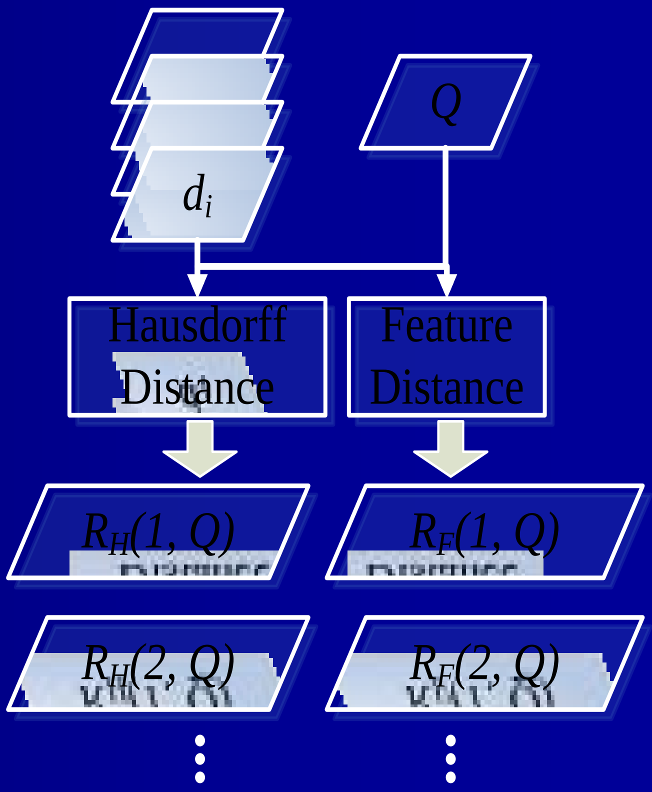
	Average	Standard deviation
Mattes method	1.02	0.51
New method using landmark correspondence	0.59	0.21

Measurement in centimeter.

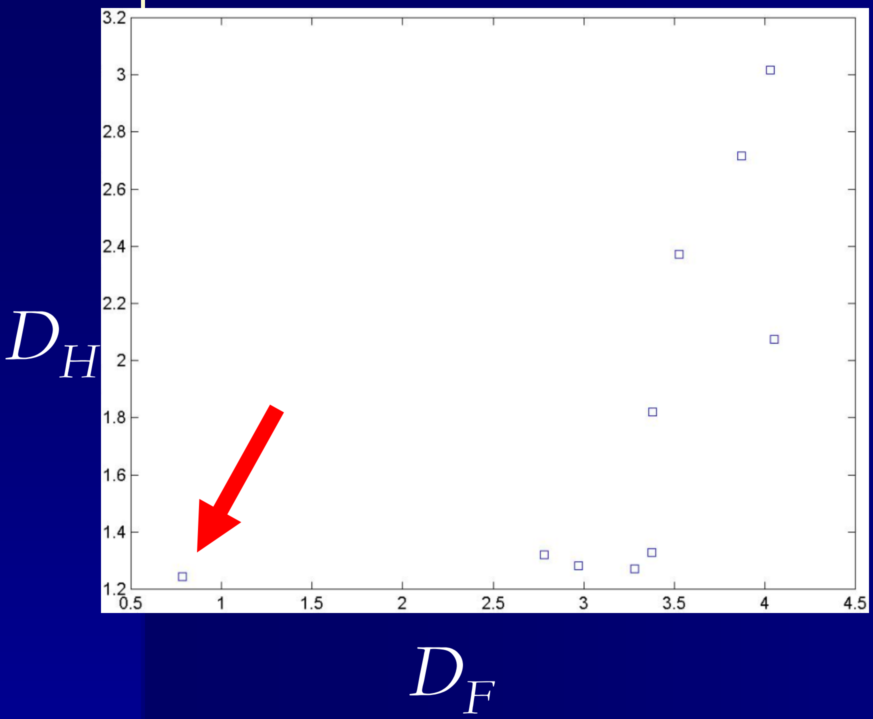
Similarity Evaluation

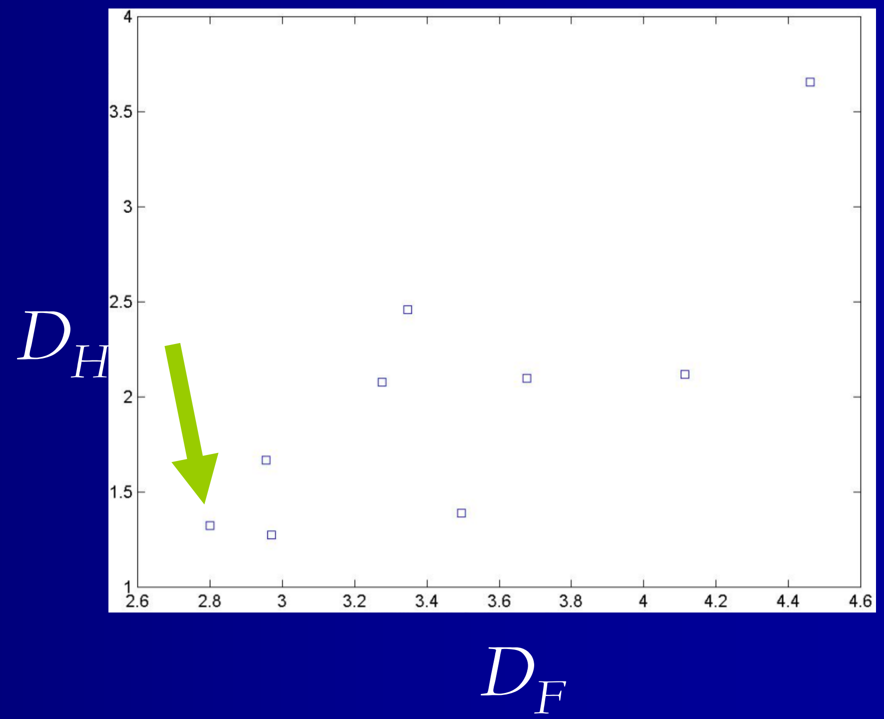
- $R_H(i, Q)$: the i^{th} ranked reference subject for target Q based on the image registration results, D_H.
- $R_F(i, Q)$: the i^{th} ranked reference subject based on geometrical features, D_F.

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



Similarity Evaluation Examples





corr_coef(D_H, D_F) = 0.74

corr_coef(D_H, D_F) = 0.68

Similarity Evaluation – Surface Mesh Distance

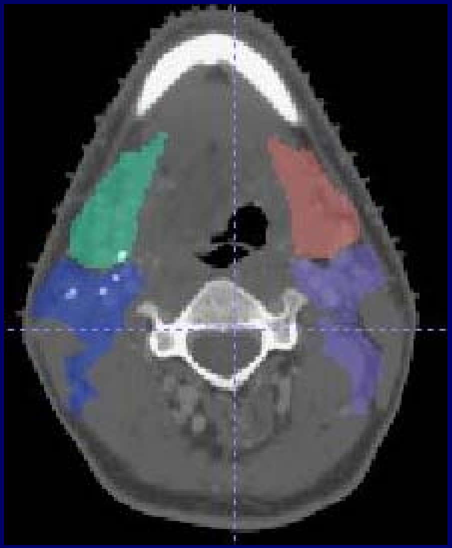
	Average	Standard deviation
D_H for the closest reference subject to each target based on feature distance	1.28	0.31
D_H for all reference and target subjects	2.59	0.90

Measurement in centimeter.

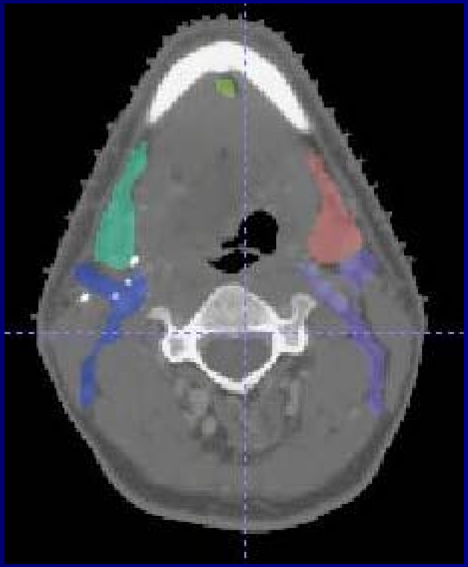
So its better to find the closest subject.

Qualitative Evaluation – 1.1

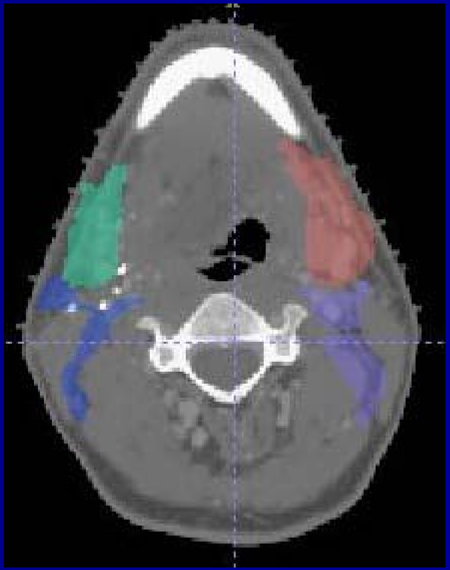
- Clinically acceptable target projection.



Mattes



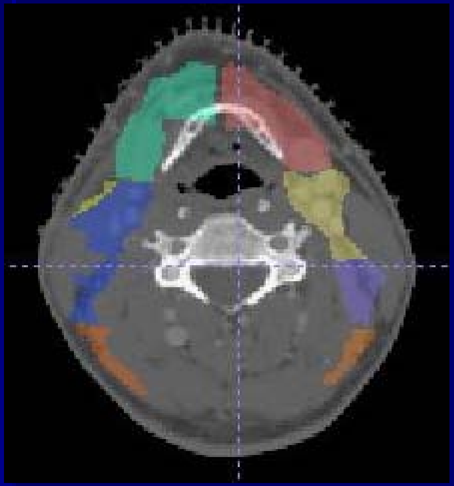
Expert Drawn



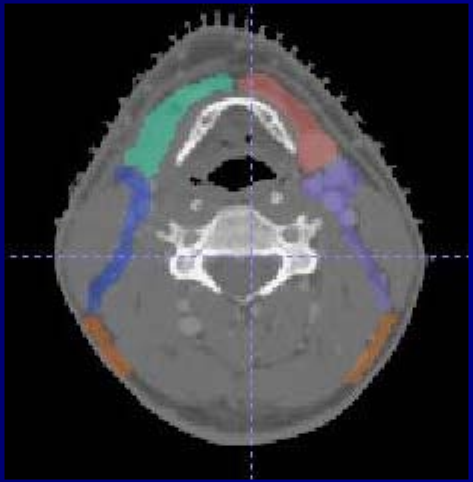
w/ Landmark

Qualitative Evaluation – 1.2

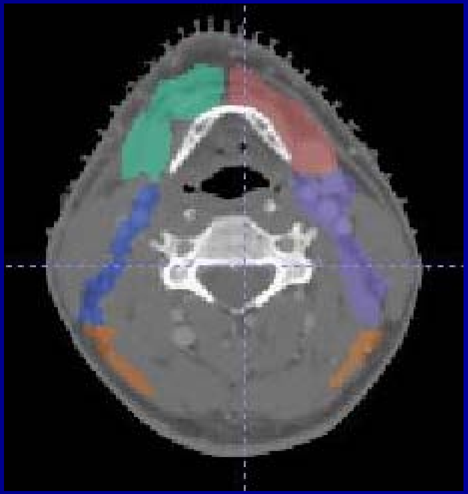
- Clinically acceptable target projection.



Mattes



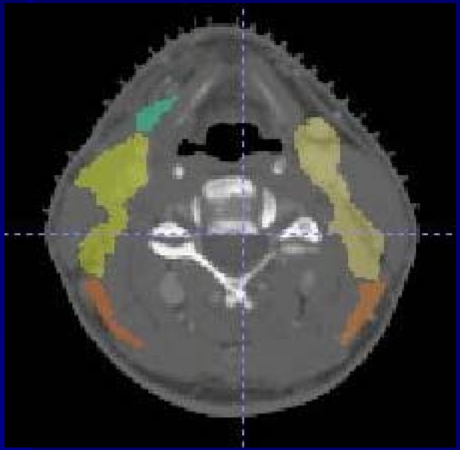
Expert Drawn



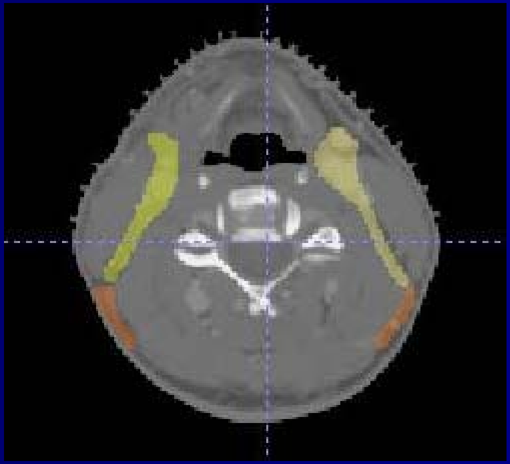
w/ Landmark

Qualitative Evaluation – 1.3

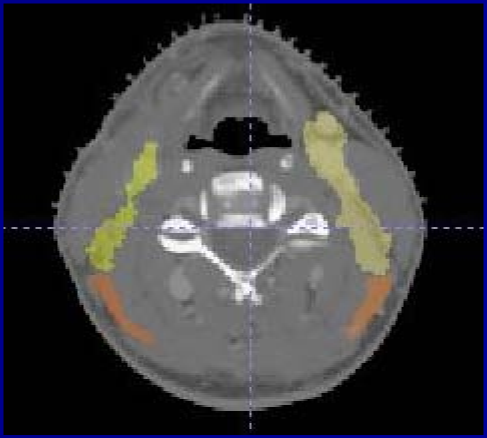
- Clinically acceptable target projection.



Mattes



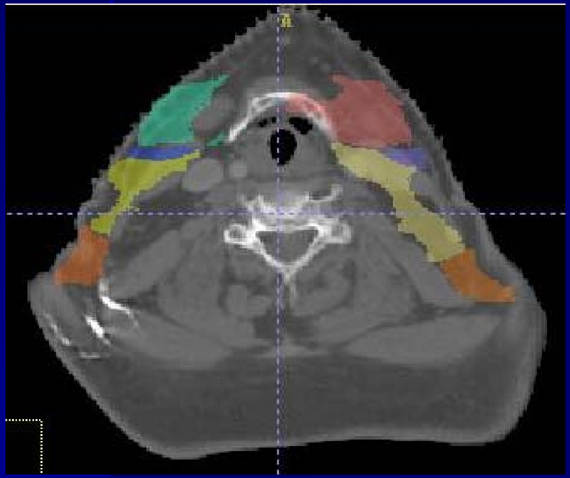
Expert
Drawn



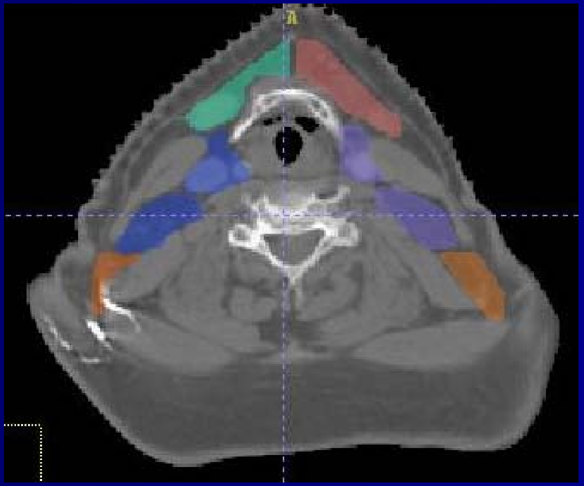
w/ Landmark

Qualitative Evaluation – 2

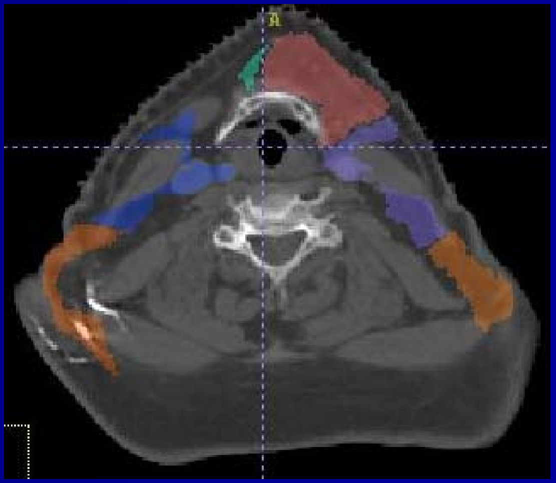
- Clinically unacceptable target projection.



Mattes



Expert Drawn



w/ Landmark

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

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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)*