Imaging in Radiotherapy

- Modalities of Interest
  - CT: gold standard for RT planning; reference for dose
  - MRI: better visualization of soft tissues (e.g., prostate), segmentation of the organs at risk (OAR)
  - PET, SPECT, ICT, fMRI: visualization of tumor metabolism and organ function
  - 4D CT, Cine MR: tumor and normal tissue motion characterization and tracking

- Two major tasks: segmentation & registration

Image Segmentation & Contouring

- Goal: find the location and boundary of anatomical structure(s) or tumor

Structure Segmentation for RTP

- Many Structures to Delineate
  - Takes 2-4 hours for a HN patient

- Manual Segmentation
  - Subjective
  - Suffers from large intra- and inter-rater variability

- Motivation: need efficient and automatic image segmentation method

Common Challenges

- Imaging noise
- Low image contrast
- Partial volume effects
- Shading and other artifacts
- Incomplete or missing information

Outline

- Introduction
- An Atlas-based Auto-segmentation Method (ABAS)
  - Atlas registration method
  - Atlas selection strategy
  - Acceleration with GPU
- Some Validation Results
- Conclusion & Future Work
Image Segmentation Methods

Available Methods
- Thresholding & Edge detection
- Watershed
- Region growing
- Graph methods
- Mathematical morphology
- Fuzzy-connectedness
- Livewire
- Artificial neural networks
- Markov random field
- Atlas-based methods
- Deformable models
- Others

Atlas-based Auto-Seg. (ABAS)

Two important components
- Atlas/image registration method
- Atlas selection/construction strategy

Image Registration

Goal: finding optimal mapping between points in two images, to achieve biological, anatomical, or functional correspondence.

Transformation Model — Degrees of Freedom

- Rigid (6 parameters): rotation, translation
- Affine (12 parameters): rotation, translation, scale, shear
- Deformable transformation, non-linear
  - Parametric models: B-Splines, RBFs, $\delta$
  - Vector displacement fields

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Transformation Model \& Degrees of Freedom

- **Rigid, Affine**
  - Very few parameters, simpler to compute
  - Only suitable for intra-subject, global alignment

- **Deformable, non-linear**
  - Necessary for inter-subject alignment
  - More difficult to estimate due to high DOFs
  - Extra regularization is critical
    - Smoothness, diffeomorphism

Similarity Metric

- **Feature-based Methods** (Geometric)
  - External markers
  - Anatomical or geometrical landmarks
  - Edges, lines, surfaces
  - Requires reliable feature detection and correspondence estimation

- **Intensity-based**
  - Many forms
    - Sum of Squared Differences (SSD), \( \sum |I(x) - J(T(x))| \)
    - Basis for the Demons method
      - Assumes \( I(x) = J(T(x)) + \text{noise} \)
      - Only valid for same modality, may require intensity normalization as in the case of MR
    - Normalized Cross-Correlation (CC)
      - Assumes \( I(x) = a J(T(x)) + b + \text{noise} \)
      - Can account for image contrast change, e.g., between CT and CBCT
    - Mutual Information (MI)
      - Only assumes statistical dependence
      - Works for both intra- and inter-modality cases

Optimization Methods

- Gradient Descent
- Conjugate Gradient, Gauss-Newton
- Evolution algorithms
- Stochastic Gradient Descent [Klein et al. IJCV 2009]
- Block Matching [Suarez et al. MICCAI 2002]
- Discrete MRF with Linear programming [Glocker et al. IPMI 2007] [wikipedia.org]

Challenges for Atlas Registration

- Large inter-subject anatomical differences \( \Rightarrow \) correspondence may not even exist (e.g. tumor)
- Intensity variations, e.g., due to contrast agents; make SSD/Demons method unsuitable
Hierarchical Registration Strategy

- Gradually increase degrees-of-freedom
- Incorporate atlas structure shape information when possible to improve registration robustness

Poly-smooth Def. Reg.

- The volume registration is driven by smooth alignment of major structures in the atlas
- Iterates over 4 major steps till convergence

Poly-smooth Reg. Demo

- Poly-smooth registration driven by Skin, Mandible, Brain-stem, and Spinal-cord

Linear Registration

- Linear transformation to align gross shape and size (12 DOF): composition of rotation, translation, scaling, and shearing

\[
T(x) = A \cdot x + t = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}
\]

- Maximize global mutual information (MI)

\[
T = \arg \max_{T} \text{MI}(I, J \circ T)
\]

- Solution computed using a multi-resolution stochastic gradient descent algorithm

- Takes a few seconds normally

Shape-constrained Dense Deformable Registration

- Free-form dense transformation model: \( T(x) = x + U(x) \)

\[
E(I, J \circ T) = E_{\text{sim}}(I, J \circ T) + E_{\text{reg}}(T)
\]

- Hybrid image similarity metric

\[
E_{\text{sim}}(I, J \circ T) = \text{MI}(I, J \circ T) - \lambda \cdot \text{SSD}(\tilde{I}, J \circ T)
\]

- Shape-constrained regularization

\[
E_{\text{reg}}(U) = \int_{S} \left( \lambda \frac{\nabla^2 U}{\mu_S} \right)^2 dS + \mu_S \left| \nabla U \right|^2 dS
\]
Dense Def. Reg. Similarity Metric

\[ E_{\text{sim}}(I, J \circ T) = \text{MI}(I, J \circ T) - \text{SSD}(\tilde{I}, \tilde{J} \circ T) \]

\[ \tilde{I}(x) = \frac{I(x) - \mu}{\sigma^2} \]

\[ \mu = \frac{1}{\Omega} \int_{\Omega} I(x) \, dx \]

\[ \sigma^2 = \frac{1}{\Omega} \int_{\Omega} [I(x) - \mu]^2 \, dx \]

\[ \text{SSD}(\tilde{I}, \tilde{J} \circ T) = \sum_{x \in \Omega} \left( \tilde{I}(x) - \tilde{J}(T(x)) \right)^2 \]

- Improves alignment of image details

Refinement using Deformable Model

- Segmentation result may be poor if atlas and subject differ significantly in shape

- Deformable model method can very well improve results for structures with good contrast

Atlas Selection Strategies

- Multiple atlases and segmentation fusion!
  - Use the STAPLE Algorithm [Warfield et al., TMI 2004]

- Use the average of a group of subjects
  - not biased by a single subject
  - cross subject averaging removes potentially useful information in the atlas, thus limiting the accuracy

- Multiple atlases and segmentation fusion!
  - Use the STAPLE Algorithm [Warfield et al., TMI 2004]

GPU vs. CPU

- Graphics hardware performance is roughly doubling every six months.
- GPU performance outpaces Moore’s Law!
**GPUs vs Supercomputers on Desktop**

- **NVIDIA GTX 480 for PC**
  - 480 processors @ 1.4GHz
  - 1350 GFLOPS (billions of floating-point operations per second)
  - Up to 3 cards can be used together (NVIDIA SLI technology) to get 2.8X performance
  - ~$300

- **Intel Core i7-980X**
  - Six-core processor @ 3.33 GHz
  - 108 GFLOPS
  - ~$1000

**NVIDIA CUDA (Computer Unified Device Architecture)**

- C programming language on GPUs
- Requires no knowledge of graphics APIs
- Easy to get started and get real performance benefits
- Stable, available for free, documented and supported
- For both Windows and Linux
- Exposes the different types of memory available
  - Easier to get maximal performance out of the hardware

**Acceleration of ABAS with GPU**

- Atlas/image registration is highly parallelizable, well suited for GPU acceleration
- GPU has 32-bit floating point precision texture and output buffers
  - As accurate as conventional CPU-based methods
- Texture memory with hardware accelerated tri-linear interpolation
  - Optimal for image re-sampling and warping
- 25 to 30X speed up easily obtainable

<table>
<thead>
<tr>
<th></th>
<th>Single Atlas</th>
<th>10 Atlases</th>
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<tr>
<td>One GTX 280 GPU</td>
<td>19 sec</td>
<td>&lt; 4 min</td>
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<tr>
<td>Quad-core CPU</td>
<td>8 min</td>
<td>1.3 hours</td>
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**Validation vs Compare ABAS Results with Manual Segmentation**

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<th>ABAS Result</th>
<th>Manual</th>
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**Quantitative Evaluation**

- ABAS results compared against manual segmentation using the Dice overlapping coefficient for each structure:

\[
\text{Dice} = \frac{\text{Overlap Volume}}{\text{Average Volume}}
\]

- 0 ⇒ no overlap
- 1 ⇒ perfect match
- .7 considered good

**A H&N Validation Study vs Single v.s. Multiple-atlases**

- 10 random subjects
  - Manually labeled
  - Both N0 and N+
  - Differ in tumor stage and location
  - Differ in IV-Contrast Uptake
- Leave-one-out
  - for each subject, remaining 9 are used as candidate atlases

[Han et al., MICCAI 2008]
**Clinical Validation - Design**

- **Data**
  - 12 clinically IMRT treated H&N patients
  - 10 lymph node levels (5 each side) and 19 OARs were manually labeled with labeling time recorded

- **Ran ABAS Software (Elekta Inc.), followed by expert editing**
  - Editing time recorded

- **Evaluation of quality of ABAS results suitable for editing**
  - 0 = poor; 1 = major deviation; 2 = minor deviation, editable; 3 = perfect

- **Evaluation of contour quality of edited and original manual contours by a separate expert panel**
  - 0 = poor; 1 = moderate; 2 = good

**Clinical Validation - Results**

- **Quality of ABAS results for editing**
  - 100% of node levels rated as minor-deviation-editable or better

- **Contouring Time Comparison**
  - 180 minutes (average) as the initial contouring time
  - 66 minutes (average) if editing ABAS results, 63% reduction

- **Accuracy Evaluation (mean Dice coefficients)**
  - 0.7/0.8 (nodes/OARs) against original contours
  - 0.8/0.9 if compared against edited contours

- **Evaluation of final contour quality by a separate expert panel**
  - 88% of edited contours scored as good
  - 83% of original manual contours scored as good

**Conclusion**

- **Atlas-based Auto-segmentation is promising in helping solving contouring problem in RTP**

- **Hierarchical registration scheme and incorporating atlas object shape info helps robust atlas registration and segmentation**

- **Using multiple atlases significantly improve accuracy of ABAS**

- **GPU-acceleration makes computation feasible in practice**

- **ABAS significantly reduces manual contouring time and improve consistency in clinics**

**Future Work**

- **Improving DIR methods**
  - Site-specific considerations and design
  - Combine intensity-based with feature-based techniques
  - Integrate statistical models of organ shape and deformation across population

- **Efficient atlas query and selection methods**

- **Multi-modality Atlas-based Segmentation**
  - Combined CT/MR atlases
# Acknowledgments

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<th>Å Erasmus Medical Center</th>
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<tr>
<td>Peter Levendag</td>
<td>Virgil Willcut</td>
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<td>Mischa Hoogemann</td>
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<td>Peter Voet</td>
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