Atlas-based Auto-Segmentation for RTP

Xiao Han, Ph.D.
Elekta Inc.
Xiao.Han@Elekta.com

ELEKTA

Outline

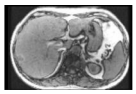
- Introduction
- An Atlas-based Auto-segmentation Method (ABAS)
  - Atlas registration method
  - Atlas selection strategy
  - Acceleration with GPU
- Some Validation Results
- Conclusion & Future Work

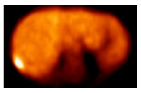
ELEKTA

Imaging in Radiotherapy

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


CT


MRI

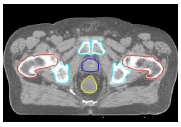

PET

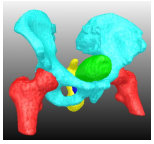
- Two major tasks: segmentation & registration

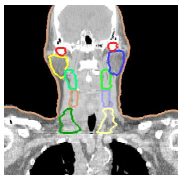
ELEKTA

Image Segmentation ï Contouring

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



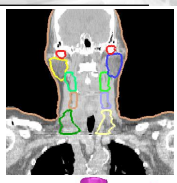




ELEKTA

Structure Segmentation for RTP

- Many Structures to Delineate
  - Takes 2 ï 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

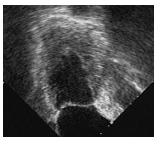


7/29/2011

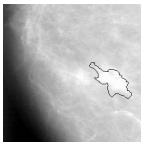
ELEKTA

Common Challenges

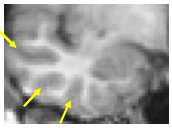
Imaging noise



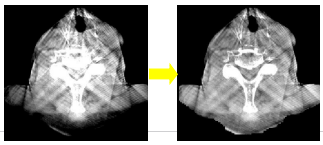
Low image contrast



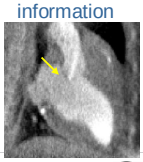
Partial volume effects



Shading and other artifacts



Incomplete or missing information



ELEKTA

Image Segmentation Methods

Thresholding & Edge detection

Region growing

Watershed

Mathematical morphology

Fuzzy-connectedness

Livewire

Available Methods

Graph methods

Markov random field

Artificial neural networks

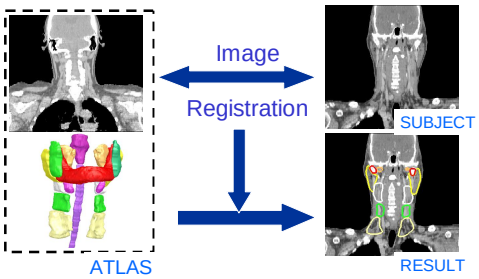
Deformable models

Atlas-based methods

Others

ELEKTA

Atlas-based Auto-Seg. (ABAS)

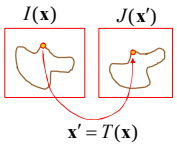


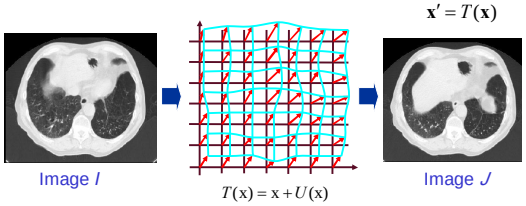
- Two important components
  - Atlas/image registration method
  - Atlas selection/construction strategy

ELEKTA

Image Registration

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



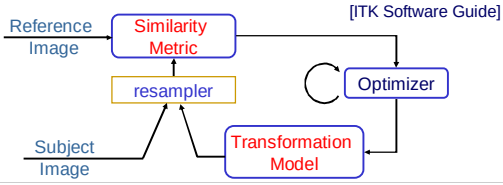


ELEKTA

Image Registration ï Common Framework

- Three major components for every registration method
- Optimal design is usually application dependent
  - Generic (general) methods highly desired, but performance usually limited

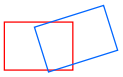
[ITK Software Guide]



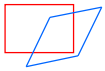
ELEKTA

Transformation Model ï Degrees of Freedom

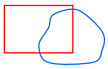
- Rigid (6 parameters): rotation, translation
- Affine (12 parameters): rotation, translation, scale, shear
- Deformable transformation, non-linear
  - Parametric models: B-Splines, RBFs, é
  - Vector displacement fields



translation + rotation



Affine transform

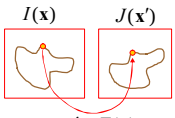


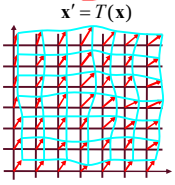
Non-linear deformation

ELEKTA

Transformation Model ï Degrees of Freedom

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





deformation field model

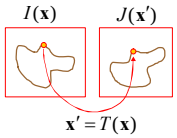
$T(\mathrm{x}) = \mathrm{x} + U(\mathrm{x})$

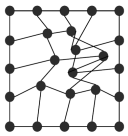
ELEKTA

Transformation Model ï Degrees of Freedom

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

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





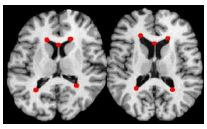
Invalid Deformation

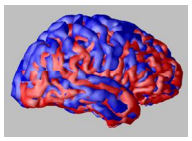
ELEKTA

Similarity Metric

Å Feature-based Methods (Geometric)
- ï External markers
- ï Anatomical or geometrical landmarks
- ï Edges, lines, surfaces

Å Requires reliable feature detection and correspondence estimation





ELEKTA

Similarity Metric ï Intensity-based

Å Many forms
- ï Sum of Squared Differences (SSD), $\sum \|I(\mathbf{x}) - J(T(\mathbf{x}))\|^2$ basis for the *Demons* method
  - Assumes $I(\mathbf{x}) = J(T(\mathbf{x})) + \text{noise}$
  - Only valid for same modality; may require intensity normalization as in the case of MR
- ï Normalized Cross-Correlation (CC) $\sum \frac{(I-\bar{I})(J-\bar{J})}{\sigma_I \sigma_J}$
  - Assumes $I(\mathbf{x}) = a\,J(T(\mathbf{x})) + b + \text{noise}$
  - Can account for image contrast change, e.g., between CT and CBCT
- ï Mutual Information (MI)
  - Only assumes statistical dependence
  - Works for both intra- and inter- modality cases

ELEKTA

Similarity Metric ï Mutual Information

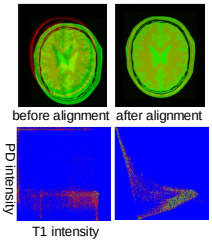
Å MI is a fundamental concept from information theory
- ï measure of statistical dependence of two r.v.s
- ï amount of info one r.v. contains about the other

Å MI is a function of the joint and marginal intensity probabilities

$$\mathrm{MI}(I,J) = \sum_{i,j} p_{IJ}(i,j) \log \frac{p_{IJ}(i,j)}{p_I(i)\,p_J(j)}$$

Å MI is maximal at registration => Joint histogram is more clustered

[Collignonô95; Violaô95]



ELEKTA

Optimization Methods

Å Gradient Descent

Å Conjugate Gradient, Gauss-Newton

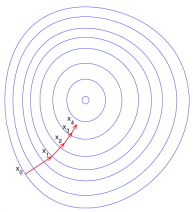
Å Evolution algorithms

Å Stochastic Gradient Descent [Klein et al. IJCV 2009]

Å Block Matching [Suarez et al. MICCAI 2002]

Å Discrete MRF with Linear programming [Glocker et al. IPMI 2007]

Å é

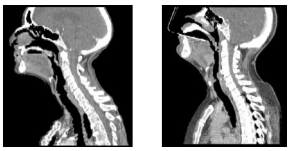


[wikipedia.org]

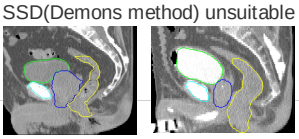
ELEKTA

Challenges for Atlas Registration

Å Large inter-subject anatomical differences ï correspondence may not even exist (e.g. tumor)

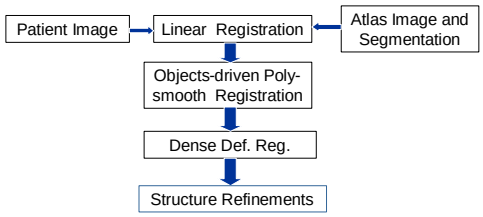


Å Intensity variations, e.g., due to contrast agents; make SSD(Demons method) unsuitable



ELEKTA

ABAS ï Hierarchical Registration Strategy



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

ELEKTA

ABAS ï Linear Registration

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

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

- Maximize global mutual information (MI)

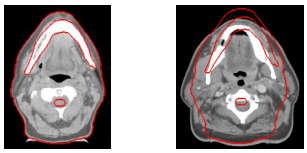
$$T = \arg\max_{T} \mathrm{MI}(I, J \circ T)$$
$$= \arg\max_{T: \mathbf{x} \to \mathbf{y} = T(\mathbf{x})} \int_{\Omega} p(I(\mathbf{x}), J(\mathbf{y})) \log \frac{p(I(\mathbf{x}), J(\mathbf{y}))}{p(I(\mathbf{x}))p(J(\mathbf{y}))} d\mathbf{x}$$

- Solution computed using a multi-resolution stochastic gradient-descent algorithm
- Takes a few seconds normally

ELEKTA

ABAS ï 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

Update Deformation → Surface Regularization → Volume Extrapolation → Volume Regularization

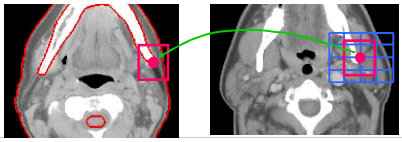
ELEKTA

ABAS ï Poly-smooth Def. Reg.

Update Deformation → Surface Regularization → Volume Extrapolation → Volume Regularization

- Block-wise Mutual Information as local image similarity measure [Suarez et al. 2003]

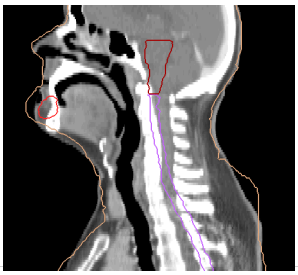
$$\mathrm{BMI}_{\mathbf{x}}(I, J, U(\mathbf{x})) = \int_{B(\mathbf{x})} \log \frac{p(I(\tilde{\mathbf{x}}), J(\tilde{\mathbf{x}} + U(\mathbf{x})))}{p_I(I(\tilde{\mathbf{x}}))p_J(J(\tilde{\mathbf{x}} + U(\mathbf{x})))} d\tilde{\mathbf{x}}$$



ELEKTA

ABAS ï Poly-smooth Reg. Demo

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

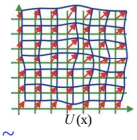


ELEKTA

ABAS ï Shape-constrained Dense Deformable Registration

- Free-form dense transformation model: $\mathbf{T}(\mathbf{x}) = \mathbf{x} + \boldsymbol{U}(\mathbf{x})$

$$E(I, J \circ \mathbf{T}) = E_{\mathrm{sim}}(I, J \circ \mathbf{T}) + E_{\mathrm{reg}}(\mathbf{T})$$



- Hybrid image similarity metric

$$E_{\mathrm{sim}}(I, J \circ \mathbf{T}) = \mathrm{MI}(I, J \circ \mathbf{T}) - \lambda \cdot \mathrm{SSD}(\tilde{I}, \tilde{J} \circ \mathbf{T})$$

- Shape-constrained regularization

$$E_{\mathrm{reg}}(U) = \int_{\Omega \setminus S} \|\nabla U\|^2 d\mathbf{x} + \mu \int_S \|\nabla_S U\|^2 dS$$

ELEKTA

Dense Def. Reg. ï Similarity Metric

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

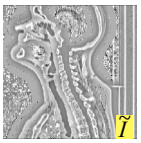
Å Generalized SSD

$$\text{SSD}(\tilde{I}, \tilde{J} \circ \mathbf{T}) = \sum_{\mathbf{x} \in \Omega} (\tilde{I}(\mathbf{x}) - \tilde{J}(\mathbf{T}(\mathbf{x})))^2$$

$\tilde{I}(\mathbf{x}) = \frac{I(\mathbf{x}) - \bar{I}}{\sigma_I(\mathbf{x})}$: normalized local offset image

$\bar{I}(\mathbf{x}) = G_\sigma * I$: local mean

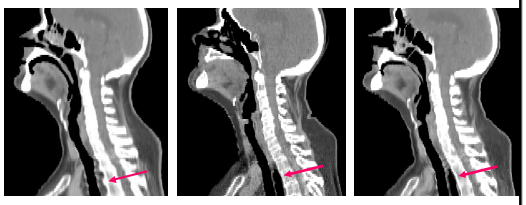
$\sigma_I^2 = G_\sigma * (I - \bar{I})$: local variance



Å Improves alignment of image details

ELEKTA

ABAS ï Shape-constrained Dense Def. Reg.

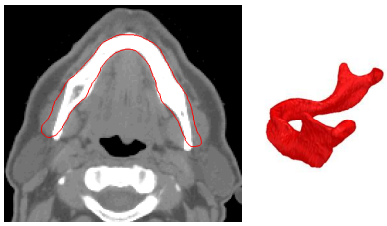


Subject after Poly-smooth Reg. | Atlas Image | Subject after Dense Def. Reg.

ELEKTA

Refinement using Deformable Model

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



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

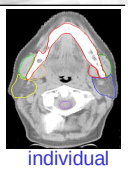
ELEKTA

Atlas Selection Strategies

Å Choose a single segmented image as the atlas

ð can represent anatomical structures at as fine a scale as the imaging technology allows

ð may not be representative

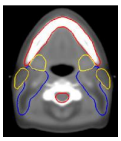


individual

Å Use the average of a group of subjects

ð not biased by a single subject

ð cross subject averaging removes potentially useful information in the atlas, thus limiting the accuracy



average

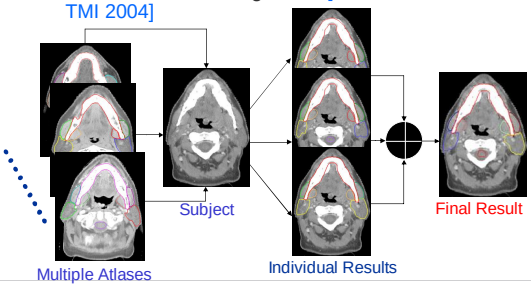
[Commowick et al., RO 2008]

ELEKTA

Atlas Selection Strategies

Å Multiple atlases and segmentation fusion!

ï Use the STAPLE Algorithm [Warfield et al., TMI 2004]



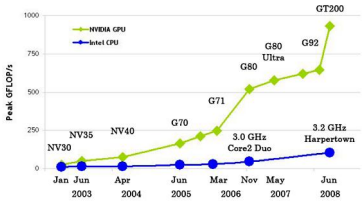
Time Is the Only Issue !

ELEKTA

GPUs vs. CPUs

Å Graphics hardware performance is roughly doubling every six months.

Å GPU performance outpaces Mooreôs Law!



[NVIDIA CUDA Userôs Guide]

ELEKTA

GPUs ï 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

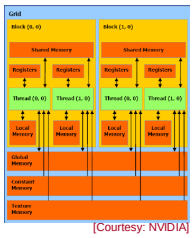
GTX 480

NVIDIA SLI Model

ELEKTA

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



[Courtesy: NVIDIA]

CUDA Memory Model

ELEKTA

Acceleration of ABAS with GPU

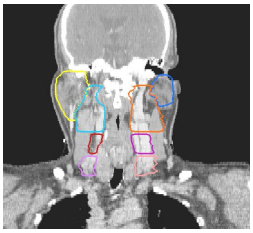
- Atlas/image registration is highly parallelizable, well suited for GPU acceleration
- GPU has 32-bit floating point precision texture and output buffers
  - As accurate as conventional CPU-based methods
- Texture memory with hardware accelerated tri-linear interpolation
  - Optimal for image re-sampling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

Size: 256×256×128

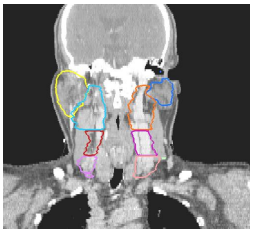
	Single Atlas	10 Atlases
One GTX 280 GPU	19 sec	< 4 min
2.66 GHz Quad-core CPU	8 min	1.3 hours

ELEKTA

Validation ï Compare ABAS Results with Manual Segmentation



ABAS Result



Manual

ELEKTA

Quantitative Evaluation

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

$$\text{Dice} = \frac{\text{Overlap Volume}}{\text{Average Volume}}$$

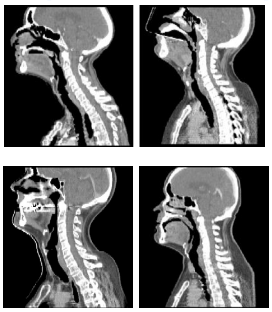
- 0 ⇒ no overlap
- 1 ⇒ perfect match
- .7 considered good

ELEKTA

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

[Han et al., MICCAI 2008]

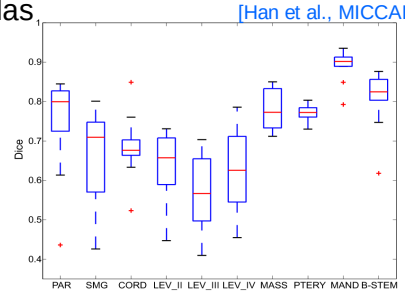
- 10 random subjects
  - Manually labeled
  - Both N0 and N+
  - Differ in tumor stage and location
  - Differ in IV-Contrast Uptake
- Leave-one-out
  - for each subject, remaining 9 are used as candidate atlases



ELEKTA

Validation Result ï Single ñOptimalò Atlas

[Han et al., MICCAI 2008]

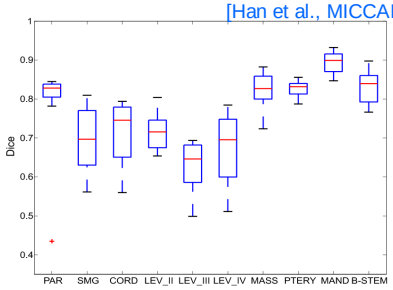


- OARs mostly above 0.7; node levels around 0.6

ELEKTA

Validation Result ï Multiple Atlases

[Han et al., MICCAI 2008]



- Multiple atlases significantly improves accuracy
- 5 of 7 OARs above 0.8; all above 0.65

ELEKTA

Clinical Validation ï Design

[Teguh et al. IJROBP 2011]

- 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

ELEKTA

Clinical Validation ï Results

[Teguh et al. IJROBP 2011]

- 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

ELEKTA

Conclusion

- Atlas-based Auto-segmentation is promising in help 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

ELEKTA

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

ELEKTA

Acknowledgments

- Erasmus Medical Center
  - Peter Levendag
  - Mischa Hoogemann
  - Peter Voet
  - David Teguh
  - Ben Heijmen
- Elekta Inc.
  - Virgil Willcut
  - Lyn Hibbard
  - Nicole O'Connell

ELEKTA