# Innovations in CT-Guided Adaptive Radiation Therapy

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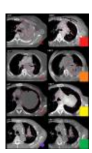
## Disclosures

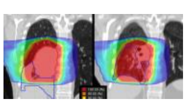
- Employee of Washington University
- Research Grants: NIH, Varian Medical Systems

## Enabling Technologies for Adaptive RT

Onboard Imaging



Decision Making



Replanning

## ART Accuracy and Clinical Efficiency

- High quality ART in the clinic requires accurate and efficient means to:
  - Assess change / decision making (when to adapt)
  - Transfer structures (targets and organs at risk contours)
  - Transfer dose (for accurate assessment of delivered dose)
  - Regenerate the treatment plan

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- Deformable image registration is a key component of these basic elements of ART.

## Topics

- Recent work on improved deformable image registration
- Do we need deformable image registration for adaptive RT?
- Image quality improvements in CT and cone beam CT

## Conventional Deformation

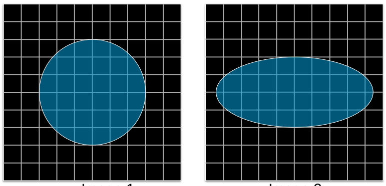

Image 1 Image 2

## Conventional Deformation

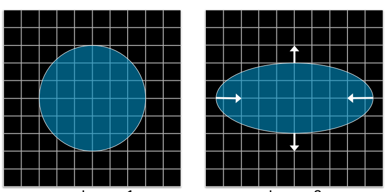

Image 1 Image 2

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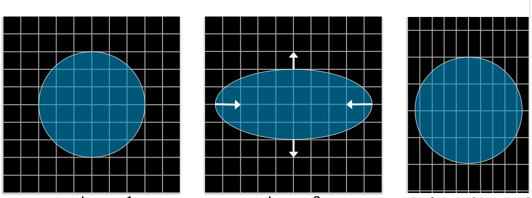


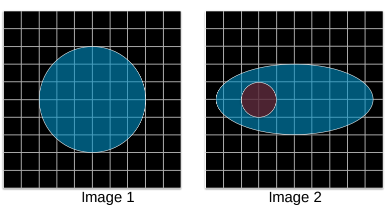
Image 1 Image 2 Deformed Image 2

Topology Preserving: Images can be stretched/squeezed to match without adding or removing image content

## Topology Preserving Deformation

- Articulation / Pose Change
- Breathing Motion

## Challenges – Topological Change

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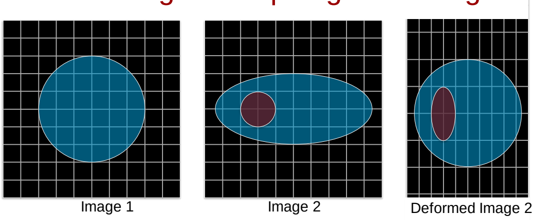


Topology Change: Images can't be stretched/squeezed to match without adding or removing image content

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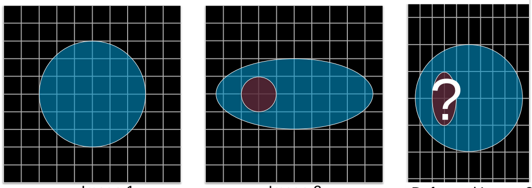
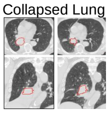



Image 1 Image 2 Deformed Image 2

Topology Change: Images can't be stretched/squeezed to match without adding or removing image content

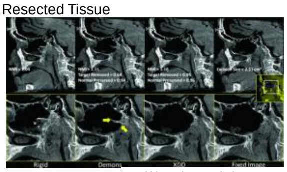
## Topology Change - Examples

Collapsed Lung

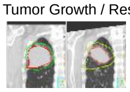


Brachytherapy Applicator

Resected Tissue



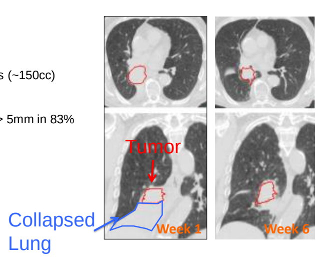
Tumor Growth / Response



S. Nithiananthan, Med Phys 39 2012

## Atelectasis / large tissue change

- Atelectasis (partial collapse)
- Pleural effusion (fluid)
- Large volume changes in atelectasis (~150cc) during RT
- Associated with large tumor shifts (> 5mm in 83% of pts)



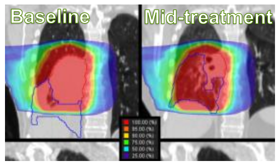

*Guy Med Phys 2016, Tennyson Adv RO 2016*

## Atelectasis / large tissue change

Dose recalculated on mid-treatment image
- Aligned to both bone and carina
- Compared to planned dose

Worst-case estimate

Dose changes can be significant
- Highlights need for ART/DIR




| | | | Bone aligned | | | | Carina aligned | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Structure | Metric | Units | Mean | Stdev | Min | Max | Mean | Stdev | Min | Max |
| Spinal cord | $D_{max}$ | Gy | 0.67 | 2.99 | −2.78 | 10.93 | 0.14 | 1.80 | −2.94 | 4.29 |
| Esophagus | $D_{mean}$ | Gy | 0.99 | 2.69 | −3.72 | 7.92 | 0.77 | 2.95 | −4.56 | 7.07 |
| Lungs | $D_{mean}$ | Gy | 0.50 | 2.05 | −2.89 | 5.69 | 0.06 | 1.71 | −3.35 | 4.56 |

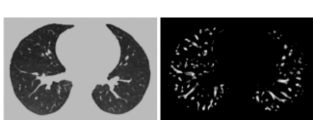
*Guy Med Phys 2016, Tennyson Adv RO 2016*

## Thoracic Registration - Strategies

- Ignore regions with appearance change, identify 'consistent anatomy' between images
- Identify consistent anatomy that can be segmented (vessels, airways, lobes), register these regions
- Model other changes (tumor, atelectasis, pleural effusion, etc.)

## Vessel Registration

- Filters applied to enhance tubular structures
- Produces a 'vesselness measure' image, [0, 1]
- 'Vesselness measure image' registered in parallel with original images



Lung image    Vesselness measure image

*Cao et al., WBIR 2010*

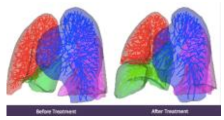
## Vessel Registration

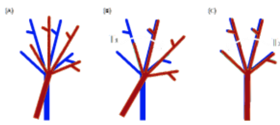
Vessels segmented after enhancement

No 'one to one' match (collapsed lung)

Conventional registration methods may get stuck in 'local minima'.

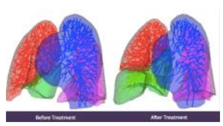
Need an algorithm that can handle global matching

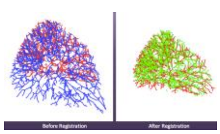


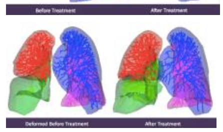



## Vessel Registration

- No one-to-one match
  - Collapsed lung
- 'Varifolds' used for fuzzy matching




Gorbunova, V., Durrleman, S., Lo, P., Pennec, X., & De Bruijne, M. (2009). Curve-and surface-based registration of lung CT images via currents. In *Second International Workshop on Pulmonary Image Analysis*

*Pan CVPR 2016*

## Registering Atelectatic Lobes

Hypothesis:
- Atelectasis is mostly collapsed lung, so re-inflation should approximately preserve the mass of the affected lobe.
- mass-preserving cost function used in atelectatic and normal lung.

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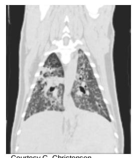
Hypothesis:
- Atelectasis is mostly collapsed lung, so re-inflation should approximately preserve the mass of the affected lobe.
- mass-preserving cost function used in atelectatic and normal lung.

*If mass is preserved, tissue should change intensity when expanded / contracted during registration.*

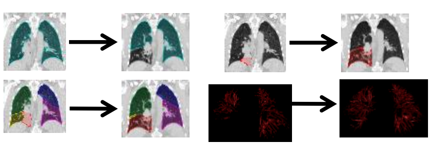


Courtesy G. Christensen

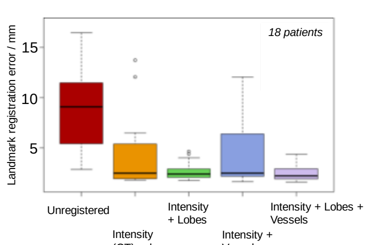
## Lung DIR Algorithm

Multi-resolution B-spline framework (elastix)

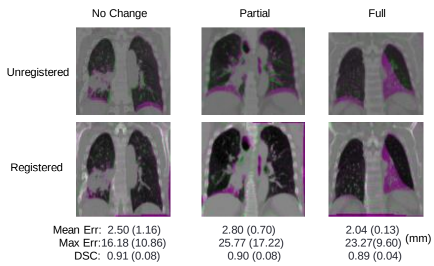
Mass-preserving metric within healthy lung
±
Intensity-based similarity metric within atelectasis
±
Co-registration of lobe label images
±
Co-registration of vesselness measure images



## Lung DIR Algorithm



## Results vs. Resolution Type




## Registration in Cervical Ca RT

- Combined external beam RT and intracavitary BT => large uncertainty in cumulative dose

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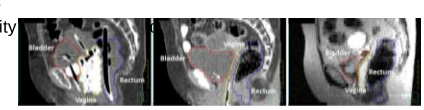
- Combined external beam RT and intracavitary BT => large uncertainty in cumulative dose
- DIR challenges:
  - Images with / without applicator => topology issues
  - Large motion of anatomy in abdomen => complex / large deformations
  - Mixed modality




*S. Oh AAPM 2016*

## Registration in Cervical Ca RT

- Penn approach:
  - EBRT CT to BT CT, with/without EBRT boost
  - Pre-processing to equalize contrast and enhance organ boundaries (bladder, rectum, packing)
  - Contoured applicator
  - Commercial DIR then applied
  - Compared 'parameter adding' of D2cc to DIR-accumulated values between EBRT and BT for risk organs (bladder / rectum)
  - Rectum / bladder D2cc varied by 5% between DIR and parameter adding

*B-K Teo, Radioth Oncol 115, 2015*

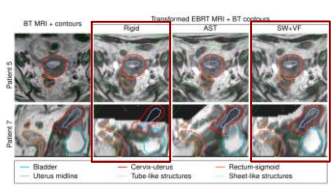
## Registration in Cervical Ca RT

- Rotterdam approach:
  - EBRT MR to BT MR
  - Automated feature extraction near contoured organs (bladder, cervix/uterus, rectum) used for feature-based DIR
    - 'Feature filter' similar to vesselness measure
    - Feature DIR registers points in a 'fuzzy matching' method where point correspondence is unknown
  - Organ, feature, and background transforms combined

*E. Vasquez Ororio, Med Phys 24, 2015*

## Registration in Cervical Ca RT

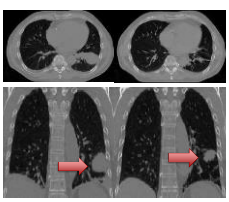
- Rotterdam approach:
- Landmark-based accuracy assessment (mean error):
  - Rigid:
  - 22.4 mm near organs
  - 4.3 mm away from organs
  - DIR:
  - 3.5 mm near organs
  - 3.4 mm away from organs



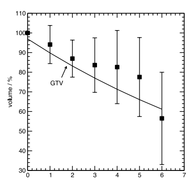

*E. Vasquez Ororio, Med Phys 24, 2015*

## What about the target?

## Tumor Regression



Week 1 Week 7



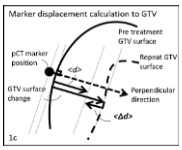

*Glide-Hurst, IJROBP 2010*

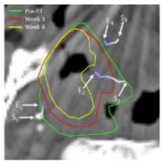
## Tumor Regression

- How to accumulate dose to regressing tumor?
- Where is tissue lost (how to appropriately register)?
- Requires contrast / markers within tumor to study

# Tumor Regression

[HTML] Analysis of GTV reduction during radiotherapy for oropharyngeal cancer: Implications for adaptive radiotherapy
O Hamming-Vrieze, SR van Kranen... - Radiotherapy and ..., 2017 - Elsevier

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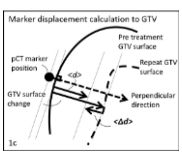
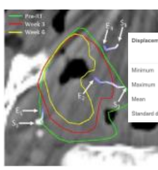


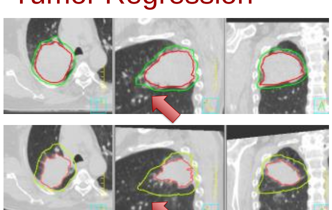




| Displacement (cm) | Week 3 | | | Week 6 | | |
|---|---|---|---|---|---|---|
| | S | $\langle d \rangle_{week}$ | $\langle \Delta d \rangle_{week}$ | S | $\langle d \rangle_{week}$ | $\langle \Delta d \rangle_{week}$ |
| Minimum | −1.0 | −0.9 | −0.6 | −1.9 | −1.3 | −0.9 |
| Maximum | 0.1 | 0.2 | 1.1 | 0.0 | 0.4 | 1.9 |
| Mean | −0.3 | −0.2 | 0.1 | −0.5 | −0.2 | 0.3 |
| Standard deviation | 0.2 | 0.2 | 0.3 | 0.4 | 0.4 | 0.5 |

# Tumor Regression

**Planning Image**

**Week 5, RT**



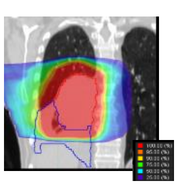
*Hugo et al., IJROBP 2011*

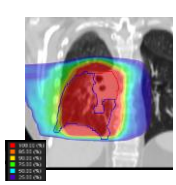
## Cumulative dose in adaptive RT

## ART – Key Questions

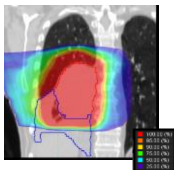
- Image registration – role and need
- Do we need to know the delivered, cumulative dose?

## Adapting the Plan


Original CT, Original Plan


Mid-tx CT, Original Plan

## Adapting the Plan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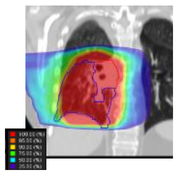
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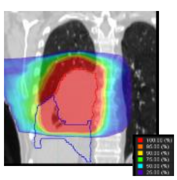
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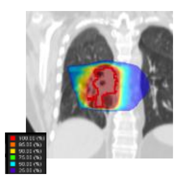
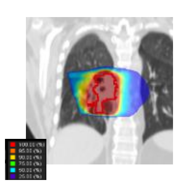
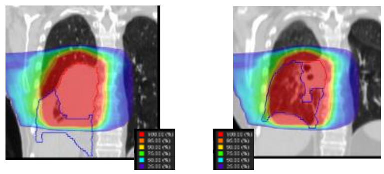

Mid-tx CT, Adapted Plan

## Adapting the Plan


Original CT, Original Plan


Mid-tx CT, Adapted Plan

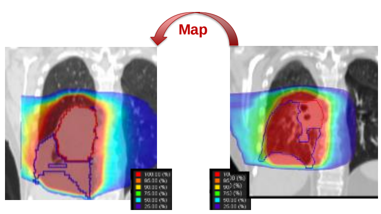
## Cumulative Dose



Original CT, Original Plan

Mid-tx CT, Original Plan

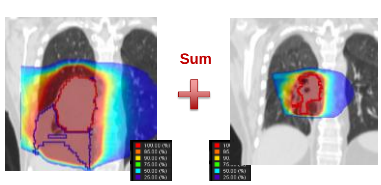
## Cumulative Dose




Original CT, delivered daily Dose

Mid-tx CT, Original Plan

## Cumulative Dose




Original CT, delivered daily Dose

Mid-tx CT, Adapted Plan

## Dose Accumulation

- Use the cumulative, delivered dose to
  - Assess coverage and normal tissue dose (decision support)
  - Avoid hot/cold spots in adaptation
- Is there a need for this?

## Cumulative Dose

- Parameter adding vs. cumulative dose
- 18 patients, single adaptation

| | Mean +/- SD difference / % | Range, difference / % | Number > 5% difference |
|---|---|---|---|
| Mean Lung Dose | 5% +/- 5% | 1% - 16% | 4 / 18 |
| Mean Heart Dose | 4% +/- 3% | 0% - 12% | 6 / 18 |

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- Similar results in cervical ca (other groups)

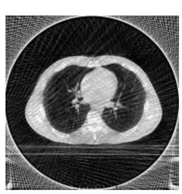
## Cumulative Dose

- Requires clinical trial of 'plan of day' adaptive vs. cumulative dose adaptive to answer the question

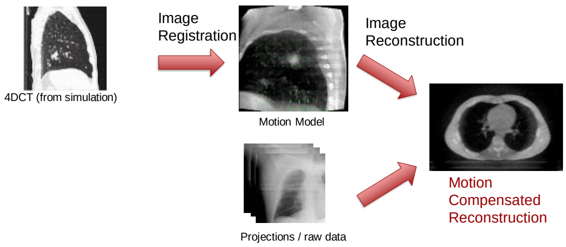
## CT image quality improvements

## Free-breathing CBCT - challenges


Motion Blurring


Streaking (View Aliasing)

## Solution: Motion Compensation

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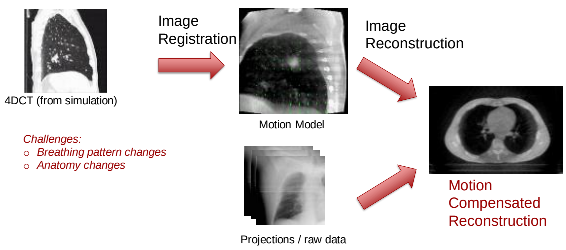


*Challenges:*
- *Breathing pattern changes*
- *Anatomy changes*

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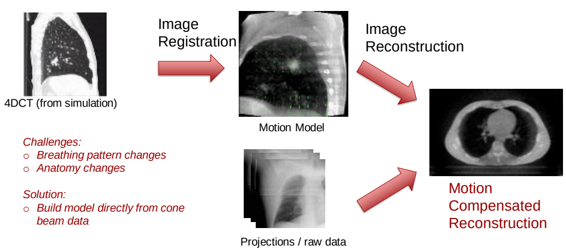


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*Solution:*
- *Build model directly from cone beam data*

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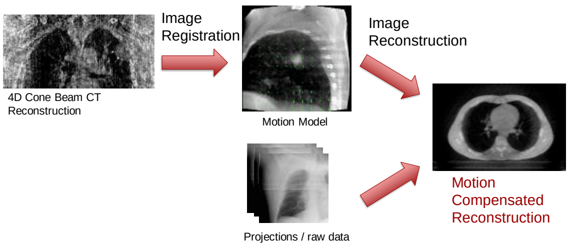
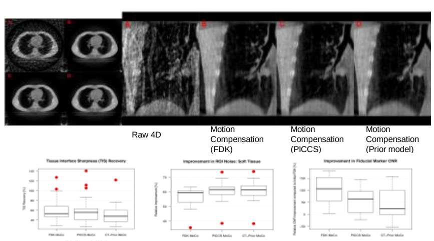



## Results: Clinical Dataset

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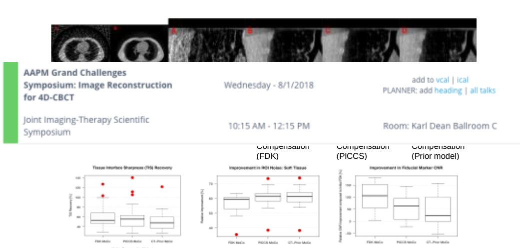
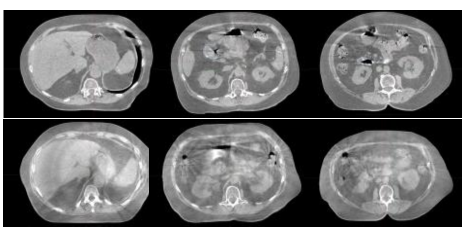


## WashU Halcyon 2.0

2.0 features
- Distal/proximal leaf shaping
- Dynamic beam flattening
- Kilovoltage cone beam CT imaging

## Abdomen – Halcyon vs TrueBeam




## Summary

- Image registration developed to manage large, geometric changes in the thorax.
- Next steps: Test whether cumulative dose is needed
- Image quality is improving for online adaptive radiation therapy

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