

Respiratory Motion Models of the Lungs for Radiotherapy

Jamie McClelland

Overview

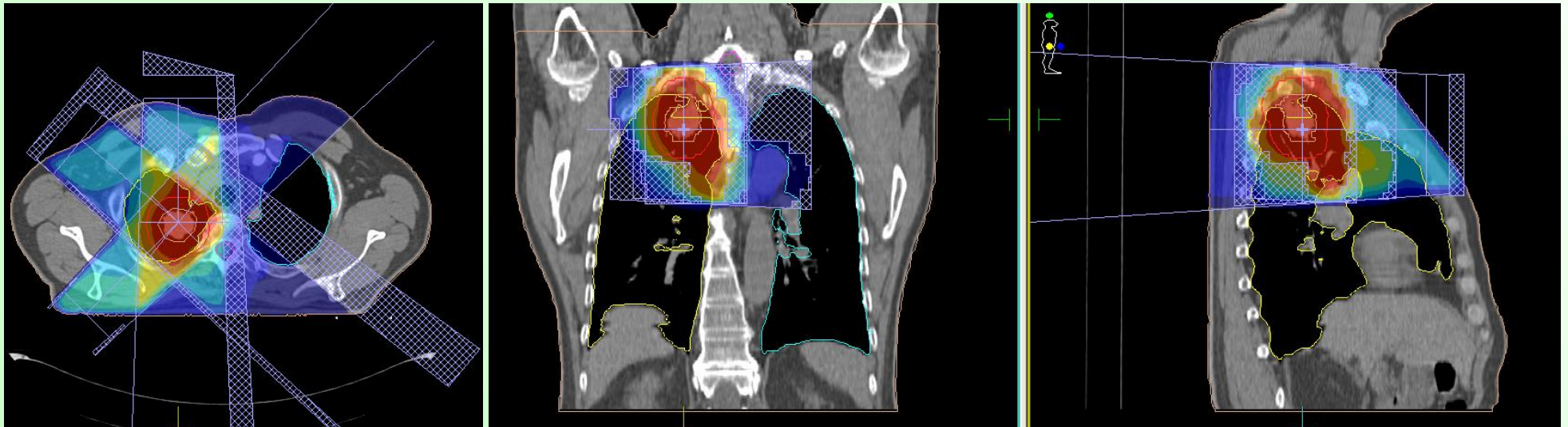
- Introduction,
- Data,
- Deformable registrations,
- Correspondence models,
- Validation,
- Using the motion models,
- Conclusions and future work,
- Group project.

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Introduction

- Aim of Radiotherapy (RT) is to deliver high dose of radiation to tumour,
- Also want to minimise dose to surrounding healthy tissue,



Introduction

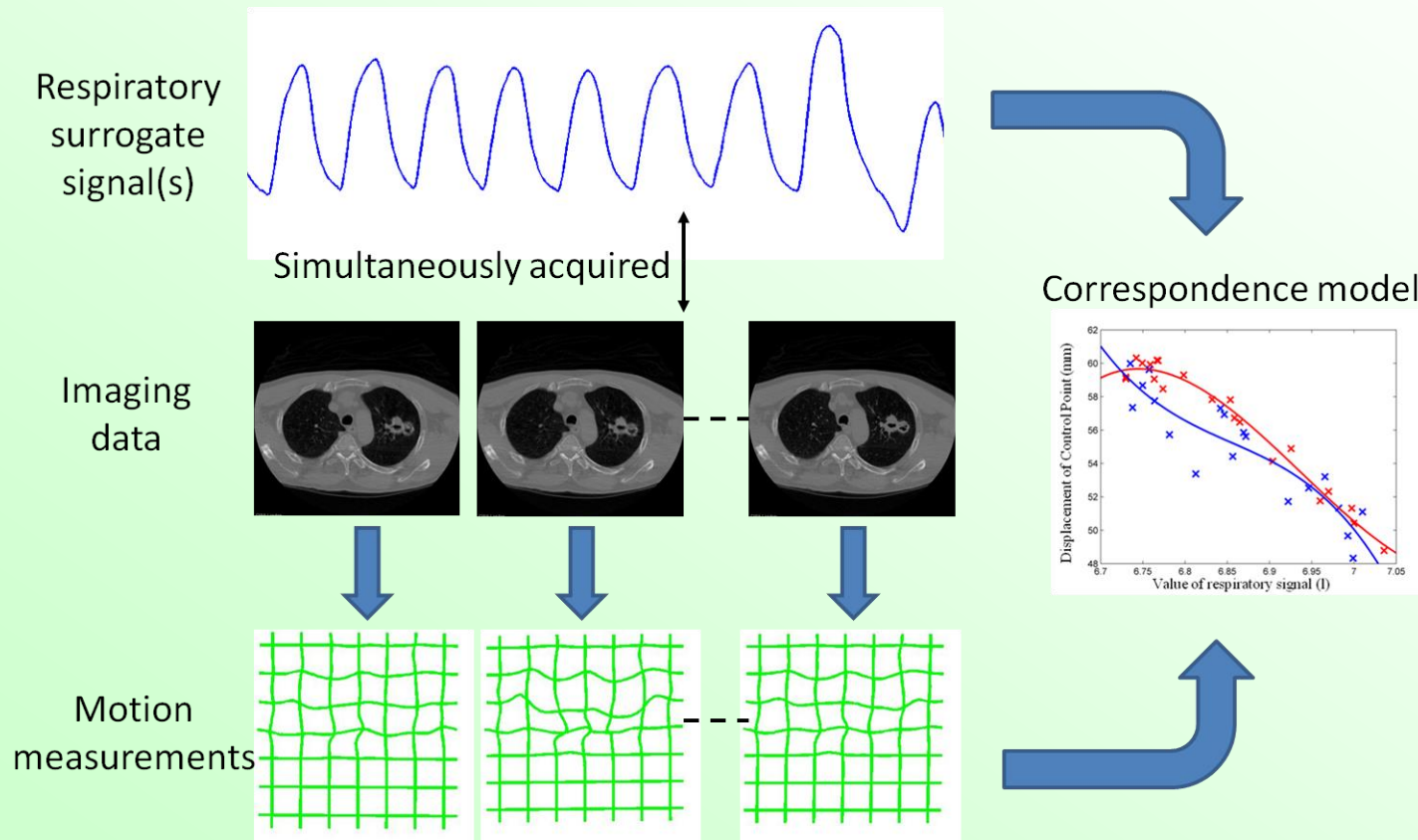
- Respiratory motion can cause errors and uncertainties when planning and delivering RT.
- Knowing motion before treatment helps make more accurate plans,
- Knowing motion during treatment enables gated or tracked treatment delivery,

Introduction

- Difficult to directly image respiratory motion during RT treatment.
- But respiratory surrogate signals easy to measure.
- Developed respiratory motion models,
 - Model relationship between internal motion and surrogate signal,
 - Can estimate internal motion from surrogate signal.

Introduction

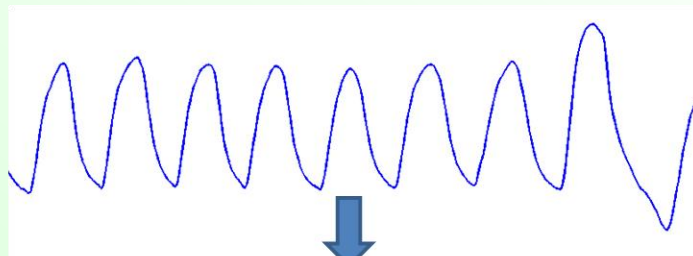
Building a motion model



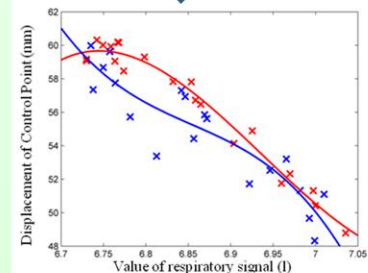
Introduction

Using a motion model

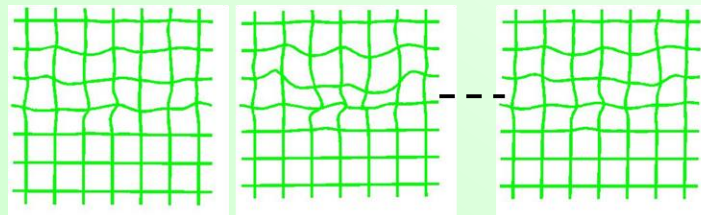
Respiratory
surrogate
signal(s)



Correspondence model



Motion
estimates

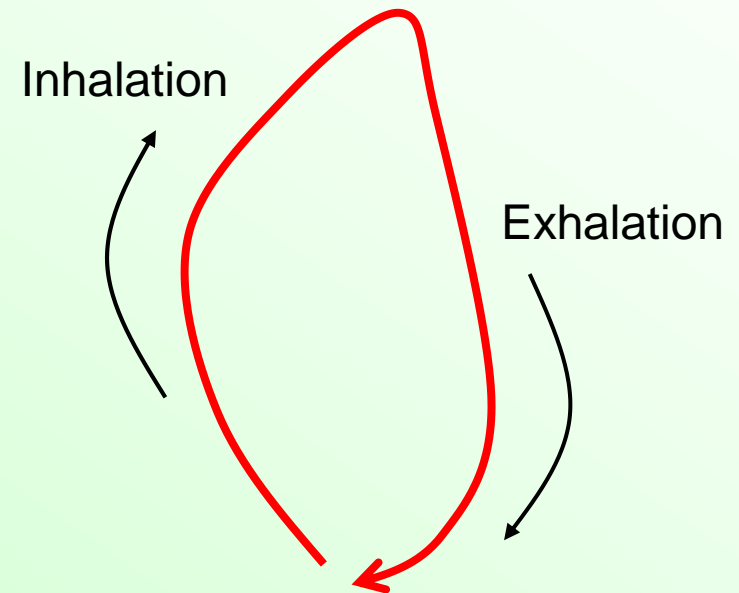


Introduction

- Respiratory motion is only ‘quasi-periodic’,
 - Intra-cycle variation,
 - Inter-cycle variation,
 - Inter-fraction variation.

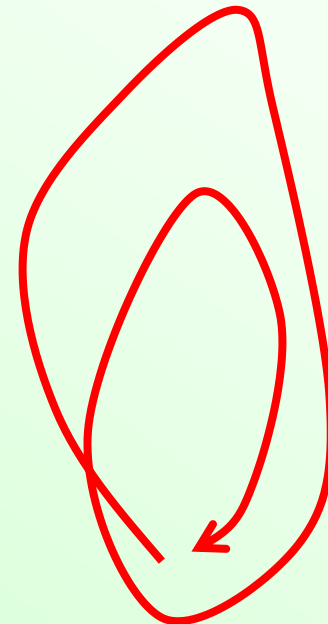
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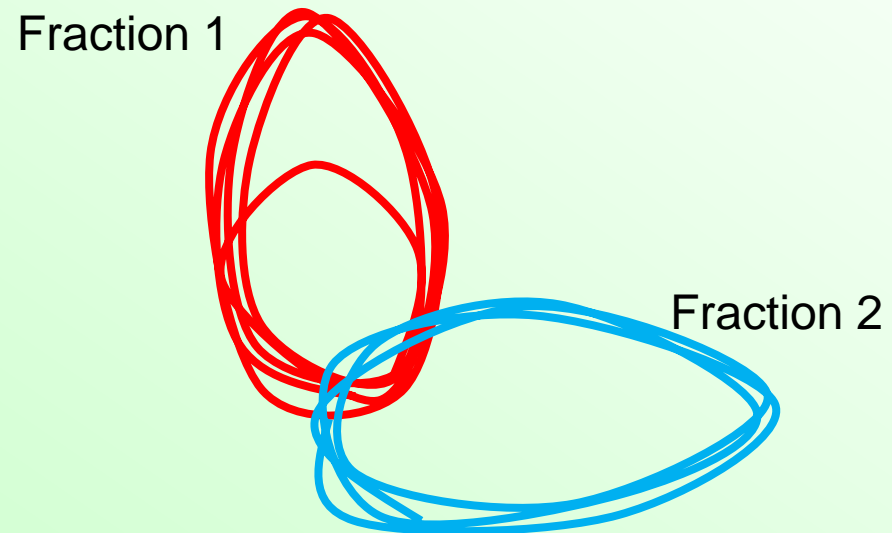
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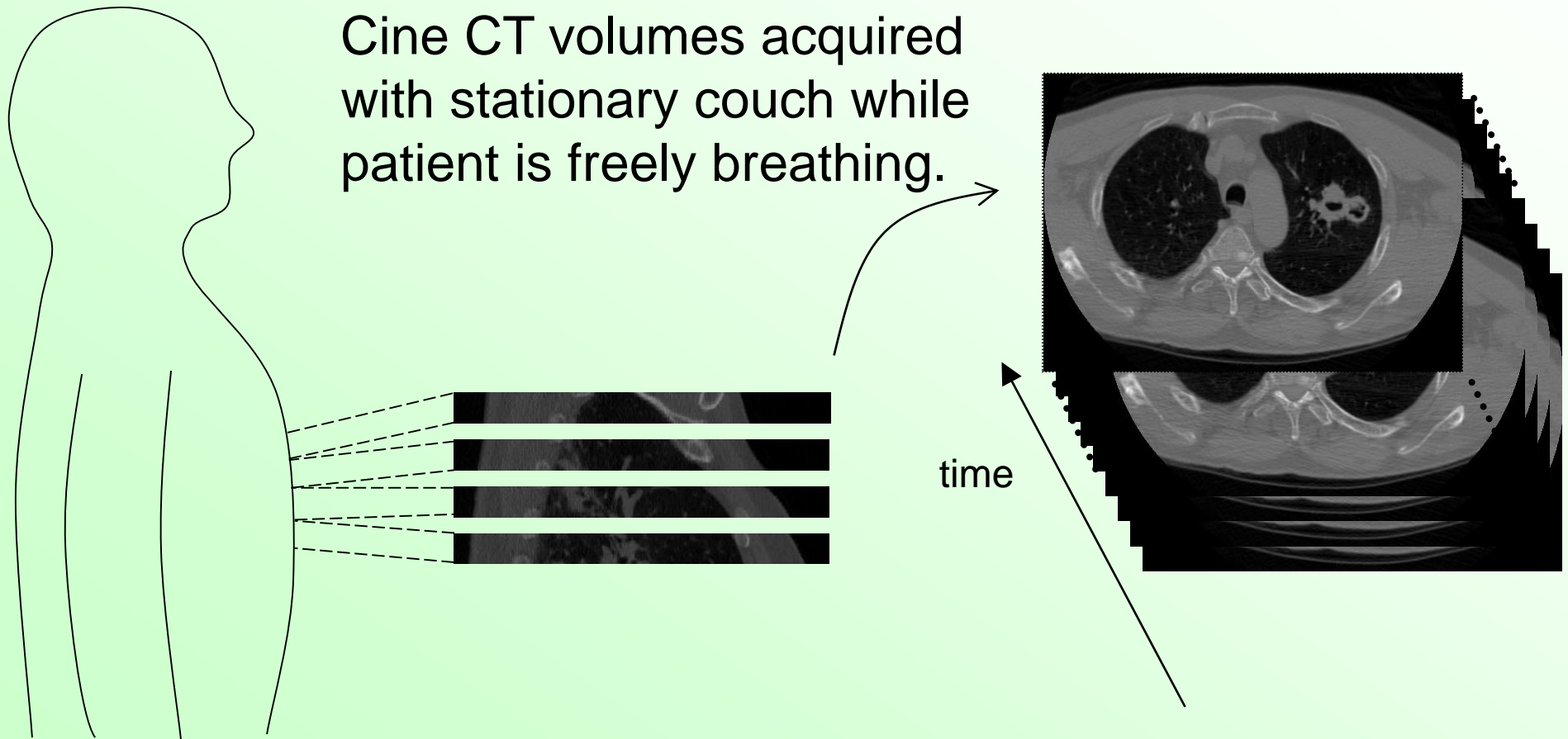


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Cine CT data

Cine CT volumes acquired with stationary couch while patient is freely breathing.

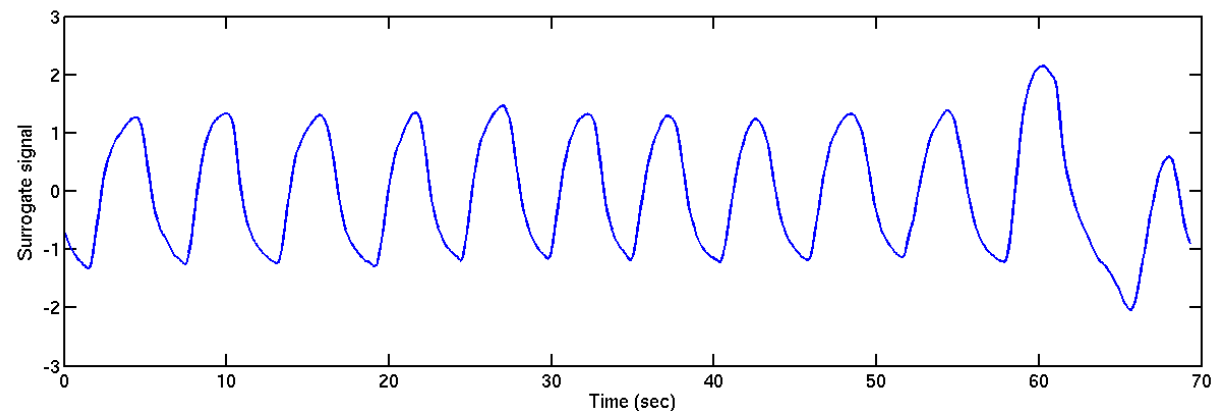


Data acquired

- Cine CT data acquired at 7 couch positions,
 - 40 Cine CT volumes acquired over 20 seconds at each couch position,
 - 12 x 2.4 mm slices per volume.
- Respiratory surrogate signal simultaneously acquired,
 - Use Vision RT 3D skin surface data.

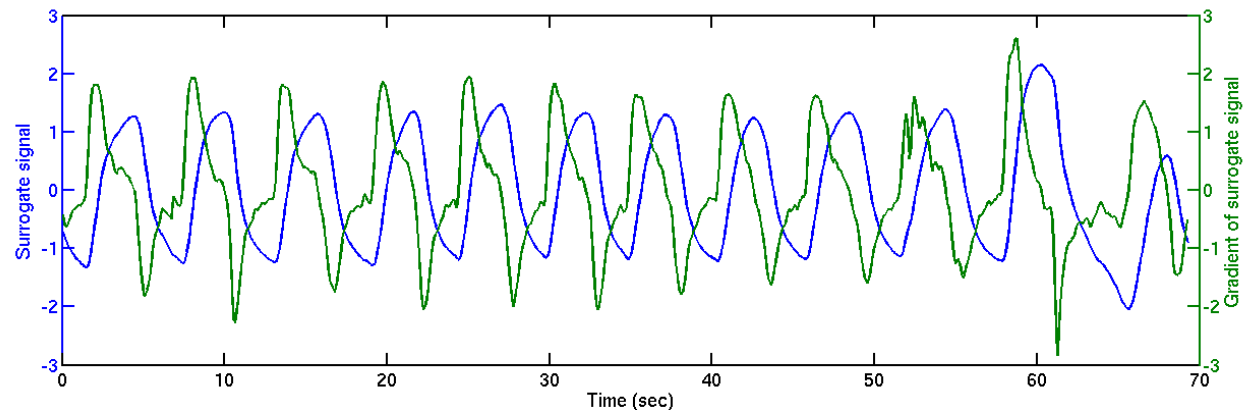
Processing Vision RT data

- Vision RT data used to generate surrogate signal
 - Find volume between surface and couch.
 - Shown to be similar to spirometry signal,
 - Also use gradient of signal and respiratory phase



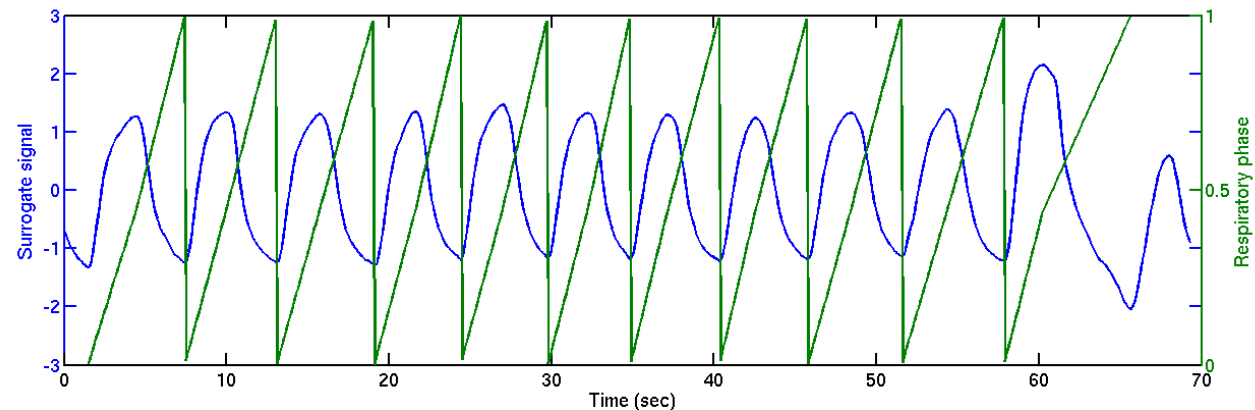
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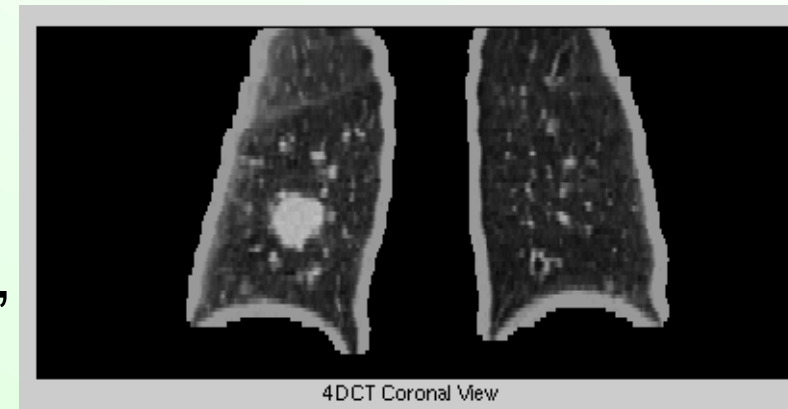


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Registering CT data

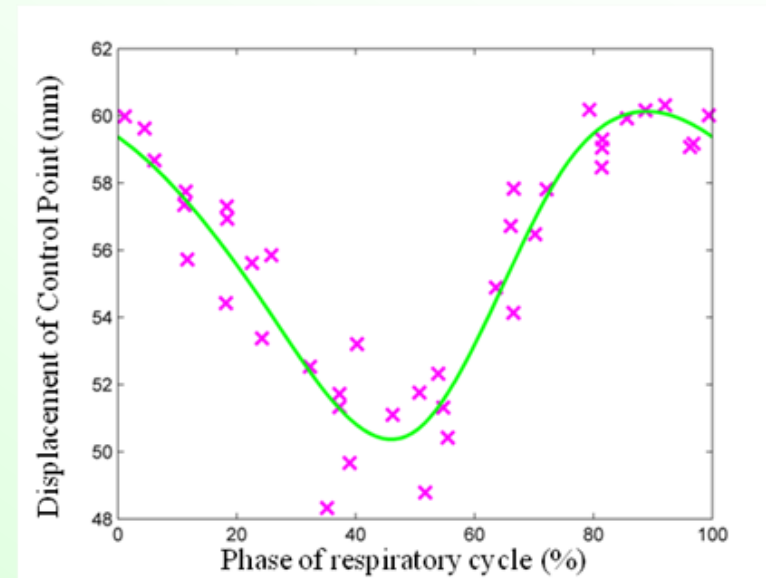
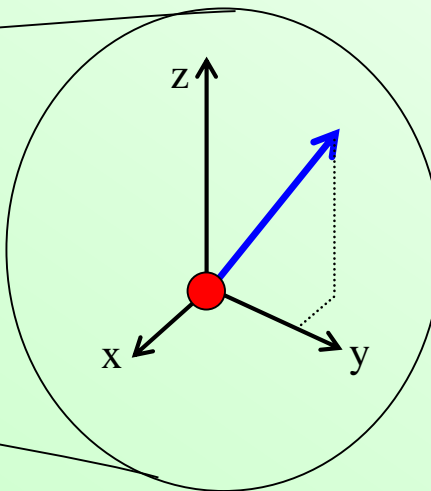
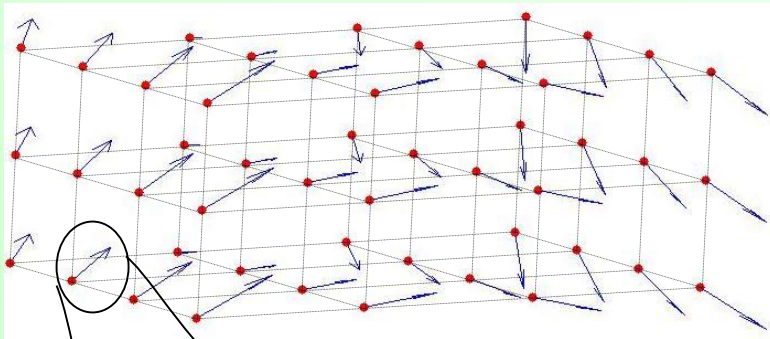
- End exhale 4DCT volume used as reference volume,
- Lungs can slide past chest wall,
 - Segment lungs,
 - Only registered and modelled lungs,
- Registered to each Cine CT volume,
 - NiftyReg software,
 - B-spline registration algorithm,
 - Defines transform using a grid of control points (CPs).



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Relating registration results to the surrogate signal



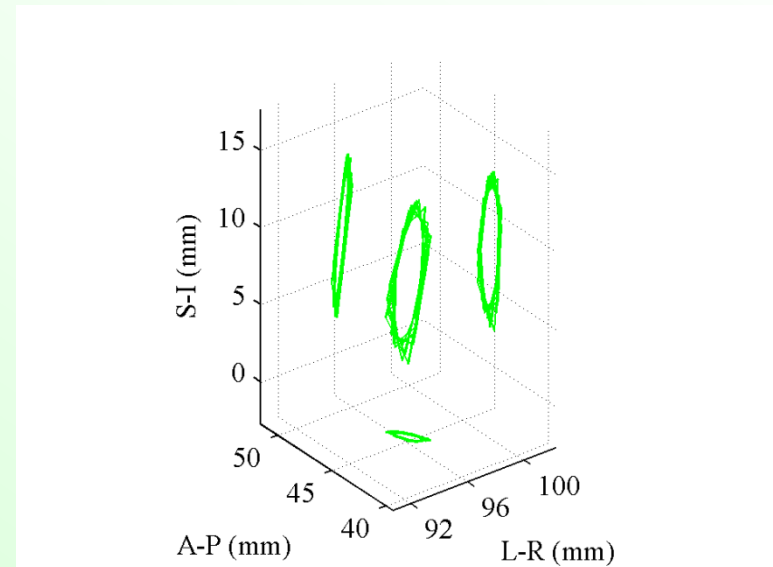
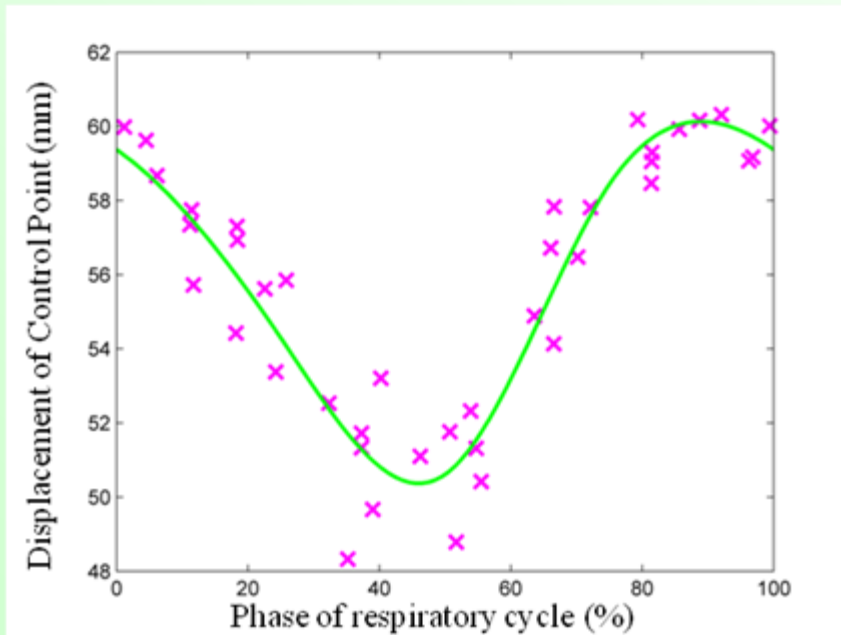
Correspondence models

- Investigated several different models,
- 3 most promising models relate the registrations to:
 - Model 1: respiratory phase using a cyclic B-spline,
 - Model 2: value of signal using 3rd order polynomials,
 - Model 3: value and rate of change of signal using 2D linear function.

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Model 1

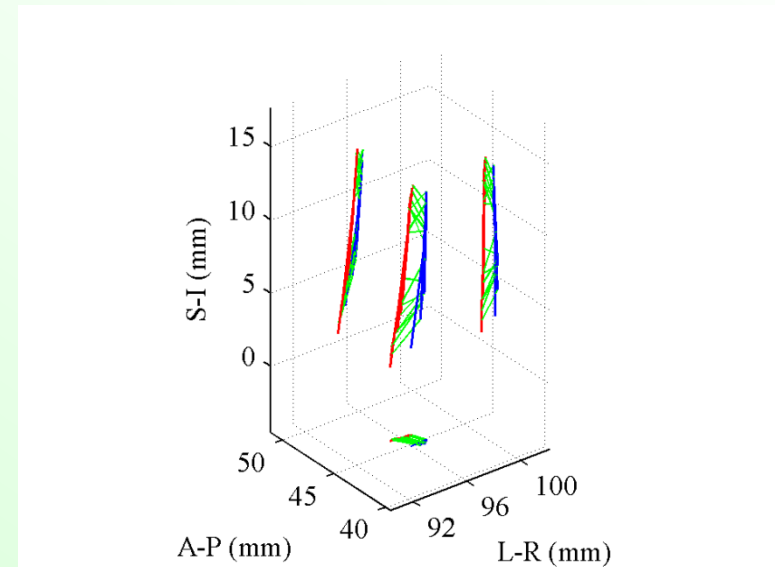
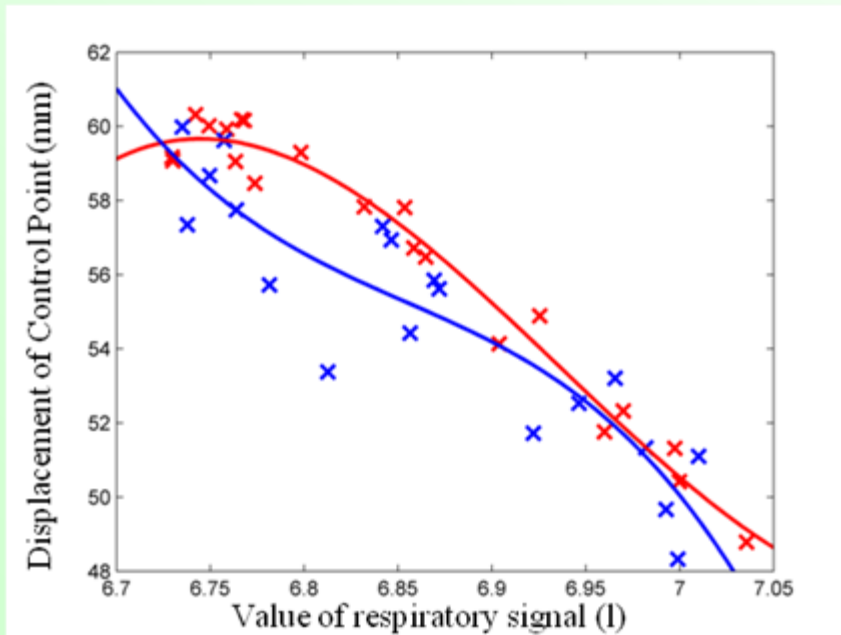


$$x(\vartheta) = \sum_{i=0}^3 B_i(j) c_{(i+k)(\text{mod } N_\vartheta)}$$

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Model 2

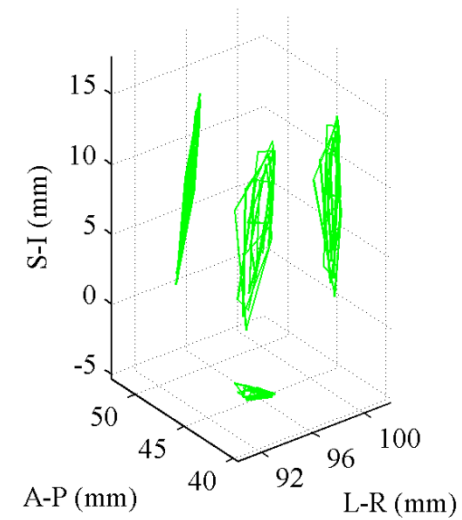
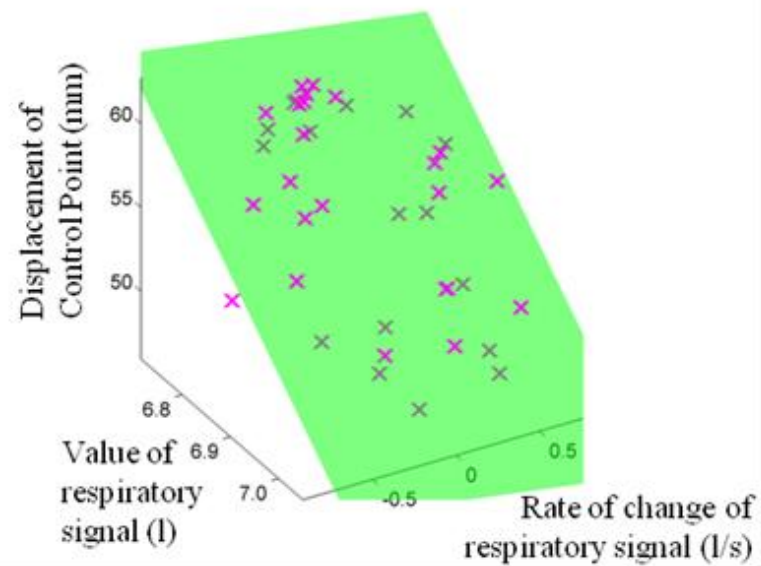


$$x(s) = c_3 s^3 + c_2 s^2 + c_1 s + c_0$$

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Model 3



$$x\left(s, \frac{\partial s}{\partial t}\right) = c_2 s + c_1 \frac{\partial s}{\partial t} + c_0$$

Fitting correspondence models

- Initial approach:
 - Loop through all CP displacements,
 - Use non-linear least squares curve fitting (`lsqcurvefit`).
- Improvements:
 - Linearise models,
 - Models are linear combination of surrogate signal terms.
 - Fit all CP displacements at once,
 - Surrogate signal terms are the same for all CP displacements.

Fitting correspondence models

- E.g. 3rd order polynomial model with N CP displacements and 40 registrations

$$x(s) = c_3 s^3 + c_2 s^2 + c_1 s + c_0$$

$$\mathbf{X} = \mathbf{S}\mathbf{C}$$

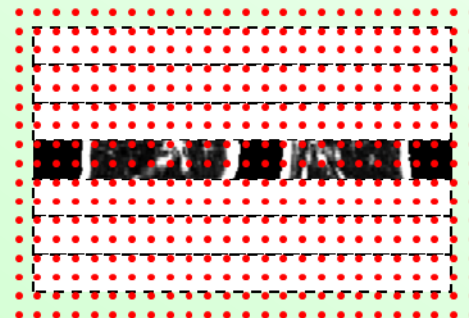
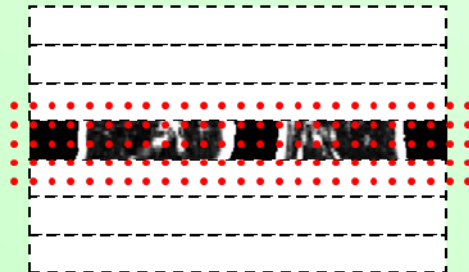
$$\begin{bmatrix} x_{0,0} & x_{1,0} & \cdots & x_{N,0} \\ x_{0,1} & x_{1,1} & \cdots & x_{N,1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{0,40} & x_{1,40} & \cdots & x_{N,40} \end{bmatrix} = \begin{bmatrix} s_0^3 & s_0^2 & s_0 & 1 \\ s_1^3 & s_1^2 & s_1 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ s_{40}^3 & s_{40}^2 & s_{40} & 1 \end{bmatrix} \begin{bmatrix} c_{3,0} & c_{3,1} & \cdots & c_{3,N} \\ c_{2,0} & c_{2,1} & \cdots & c_{2,N} \\ c_{1,0} & c_{1,1} & \cdots & c_{1,N} \\ c_{0,0} & c_{0,1} & \cdots & c_{0,N} \end{bmatrix}$$

$40 \times N$
 40×4
 $4 \times N$

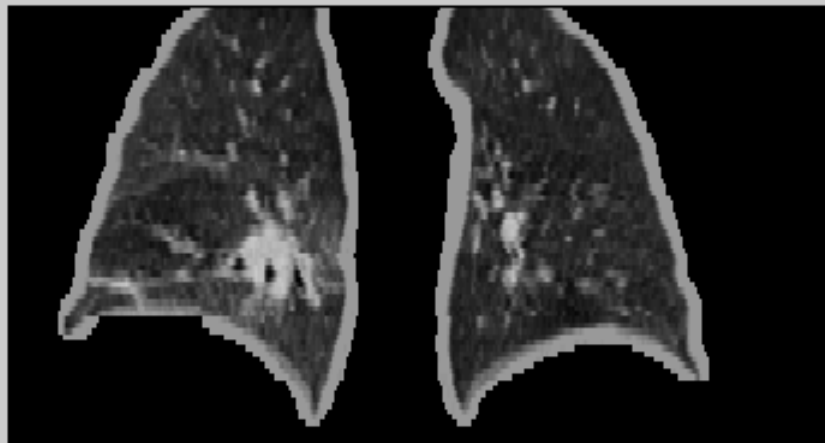
- To fit model: $\mathbf{C} = \mathbf{S}^{-1}\mathbf{X}$ (mldivide '\')

Combining Model Predictions

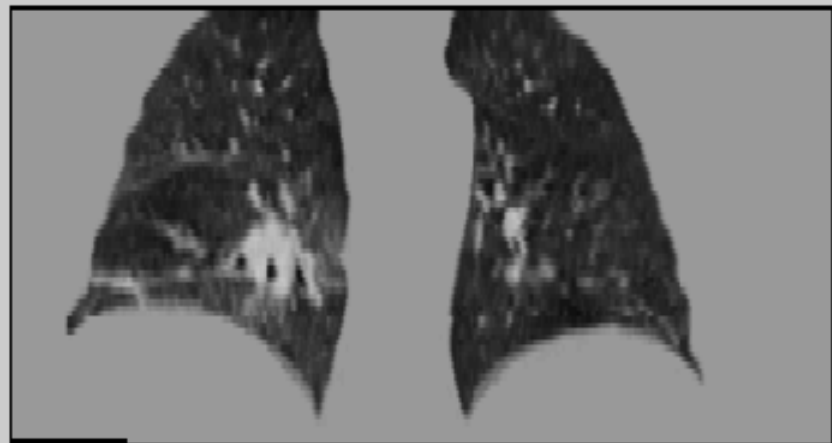
- Combine model predictions from each couch position into single continuous transform,
 - Use extended control point grid for registrations,
 - Form weighted average of model predictions,
 - Weight proportional to contribution that control points make to registration,
 - Predicted volumes appear artefact free.



Motion Model vs 4DCT



4DCT Coronal View



Model Coronal View

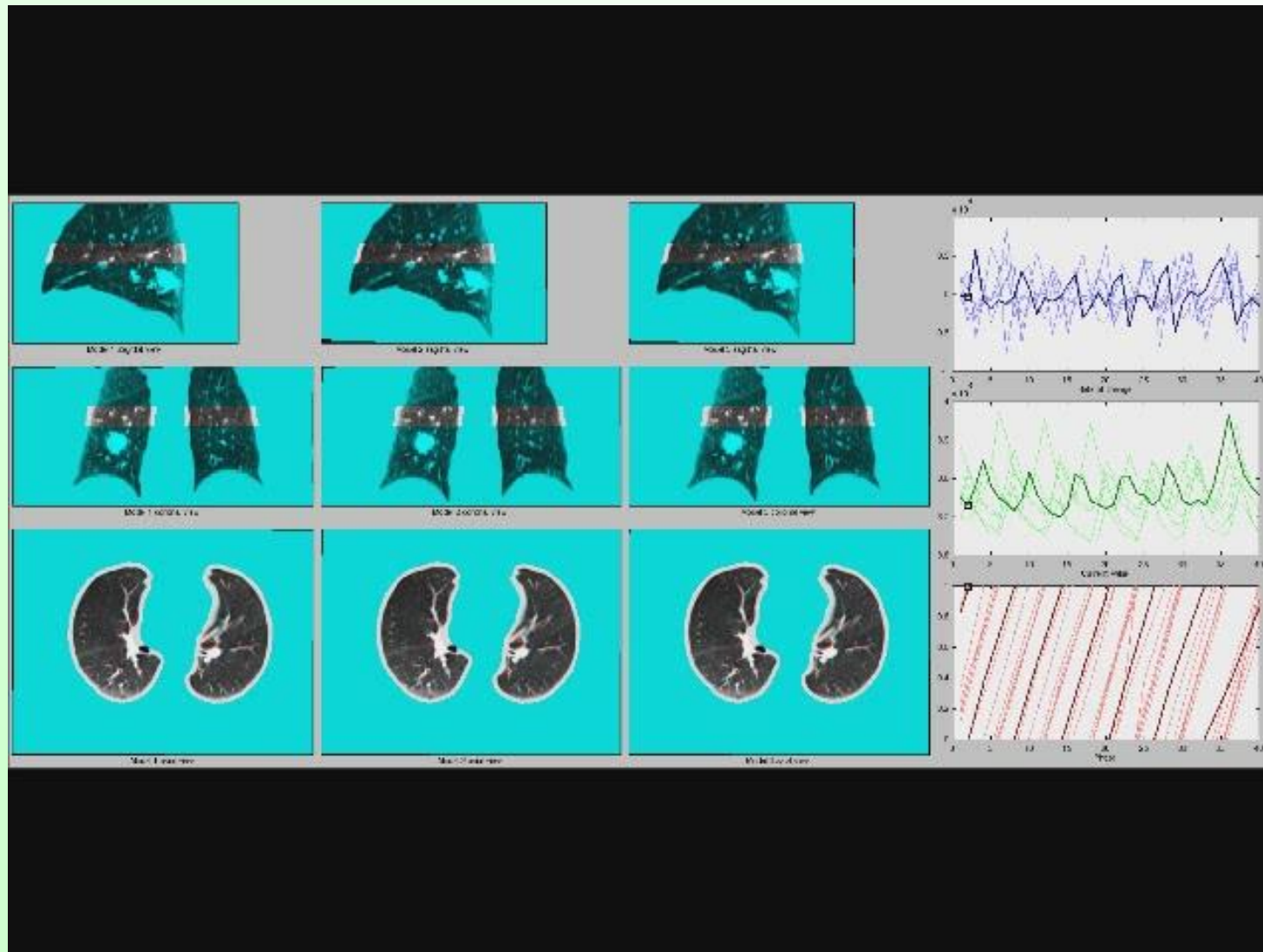
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Validation

- Limited amount of data,
 - Used leave-one-out approach.
- Assessed model estimates:
 - By comparing to registration results,
 - Using CP displacements,
 - Using deformation fields.
 - By comparing to Cine CTs,
 - Visually,
 - Using anatomical landmarks identified by a clinician,
 - Can also assess registration results.

Visual assessment



Landmark assessment

- Results for 10 datasets (from 5 patients)

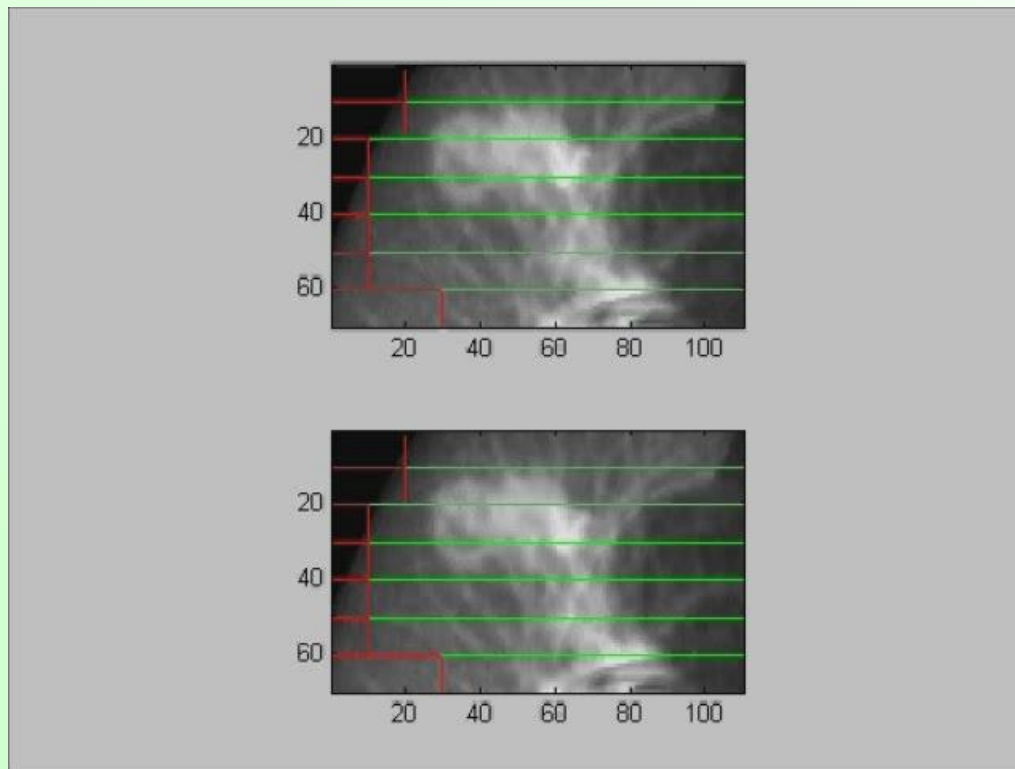
	Ref. Error (mm)	Reg. Error (mm)	Model Error (mm)		
			Model 1	Model 2	Model 3
Mean	2.8	1.0	1.2	1.2	1.2
95 th Percentile	9.7	2.3	3.0	2.8	2.7
99 th Percentile	15.3	3.2	4.5	3.9	3.7

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Tracked IMRT treatment

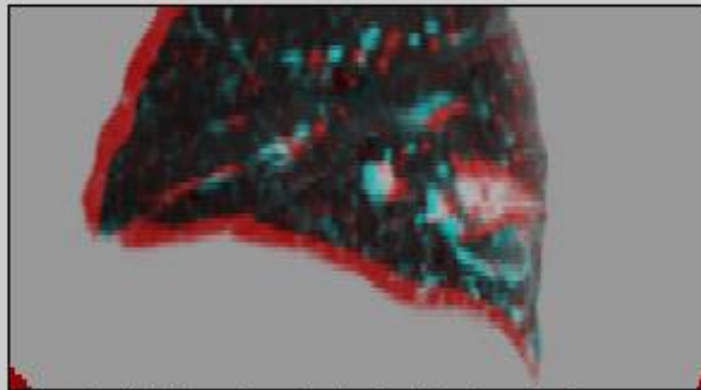
- Initial study using simplified simulation,
- Still many problems to overcome before clinical reality.



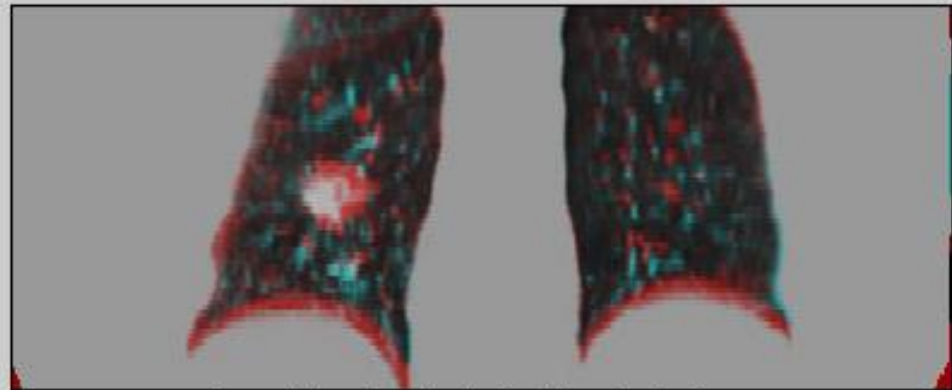
Study of inter-fraction variation

- Acquire full dataset at planning and end of RT treatment,
 - Used data from 5 patients.
- Build models from both datasets,
- Models poor at predicting motion in other dataset,
- Mostly due to 'base-line shifts',
- Relationship between surrogate and motion varied for some patients,
- Anatomical variations also observed.

Change to type of breathing

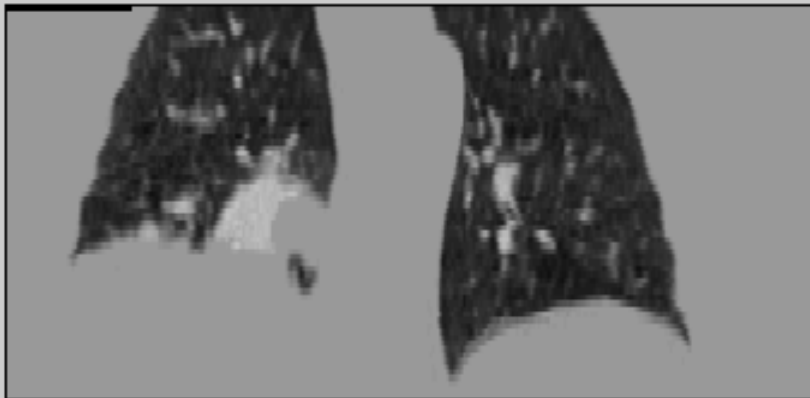


Sagittal view: Session 1 - Red, Session 2 - Cyan

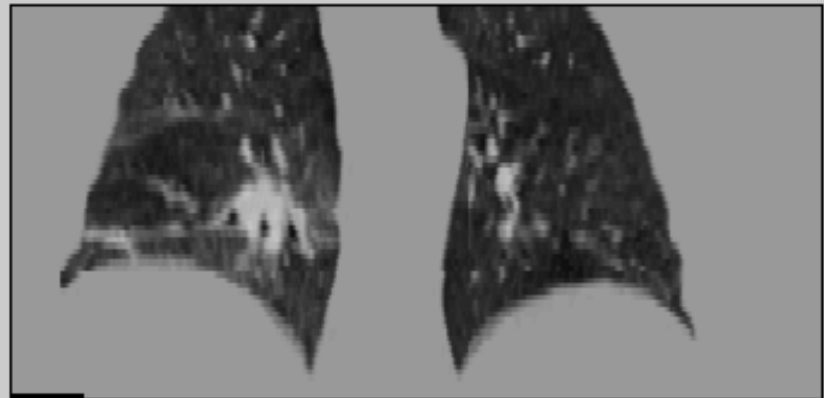


Coronal view: Session 1 - Red, Session 2 - Cyan

Large anatomical change



Session 1 Coronal View



Session 2 Coronal View

Overview

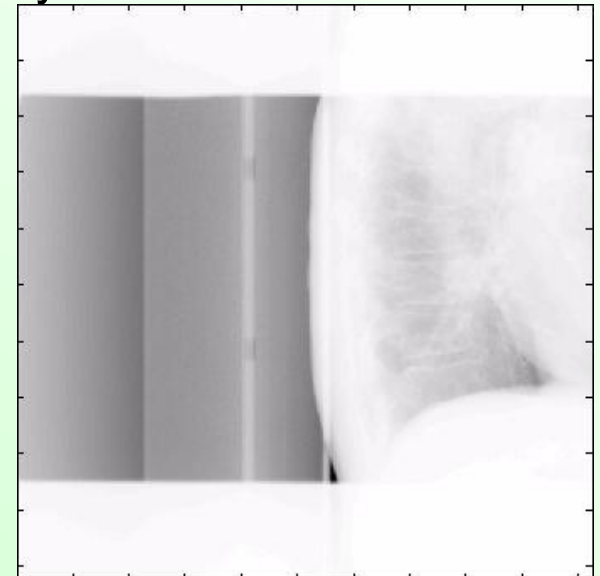
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Conclusions

- Developed models to relate internal respiratory motion to an easily measured respiratory surrogate signal,
- Used to model lung motion for RT.
- Investigated different models,
 - But all had similar performance,
 - Models are accurate for short time frame (20 sec) but are invalidated by inter-fraction variation.

On-going / future work

- Build models from Cone Beam CT data,
 - New model can be built just before each fraction of RT.
 - Need to use projection data,
 - Only 2D,
 - Difficult to distinguish tumour and other anatomy.
 - Simultaneously fit model and estimate motion for all projections.
 - Iterate with image reconstruction.



On-going / future work

- Generalised framework to combine DIR and motion modelling into single optimisation
 - Directly optimise motion model on image data
 - Can use many different:
 - Image data (including ‘partial’/‘raw’ data)
 - 3D volumes, individual slices, projections, k-space
 - Registration algorithms
 - Similarity measure, constraint terms, transformation models
 - Motion models
 - Surrogate signal(s), correspondence model
- Can combine with motion compensated image reconstruction in iterative approach

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Group project

- I will give you registration results and corresponding surrogate signal values.
- You will:
 - Assess registrations,
 - Fit correspondence models,
 - Simple, more complex, own ideas, using different fitting methods.
 - Assess models
 - Compare to registrations, compare to Cine CTs, use anatomical landmarks.
 - Calculate confidence intervals

References

- [1] McClelland et al, 'Respiratory motion models: A review' Medical Image Analysis, 2013
- [2] McClelland, 'Estimating internal respiratory motion from respiratory surrogate signals using correspondence models,' chapter in book: '4D Motion Modeling: Estimation of Respiratory Motion for Radiation Therapy,' editors Ehrhardt and Lorenz.
- [3] McClelland et al, 'Inter-fraction variations in respiratory motion models' Physics Medicine and Biology 2011

Thank you...

...any question?