The importance of shape

Thorax models for GREIT

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Introduction

Problems in analysing EIT images

- Poorly characterised images
- Proprietary/older reconstruction algorithms
- Poor anatomical correspondence (circular models)
- Unexplained artefacts

The GREIT algorithm

IOP PUBLISHING — PHYSIOLOGICAL MEASUREMENT

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GREIT: a unified approach to 2D linear EIT reconstruction of lung images

Andy Adler[1], John H Arnold[1], Richard Bayford[3], Andrea Borsic[4], Brian Brown[5], Paul Dixon[6], Theo J C Faes[7], Inéz Frerichs[8], Hervé Gagnon[9], Yvo Gärber[10], Bartłomiej Grychtol[11], Günter Hahn[12], William R B Lionheart[13], Anjum Malik[14], Robert P Patterson[15], Janet Stocks[16], Andrew Tizzard[3], Norbert Weiler[8] and Gerhard K Wolf[2]

Provides:

- Sample FEM models for adult and neonathal thorax
- Consensus performance figures of merit
- A scheme to optimise a linear reconstruction matrix to desired figures of merit
- 32×32 pixels circular images

The GREIT algorithm

Figures of merit (in order of importance)

1. uniform amplitude response
2. small and uniform position error
3. small ringing artefacts
4. uniform resolution
5. limited shape deformation
6. high resolution

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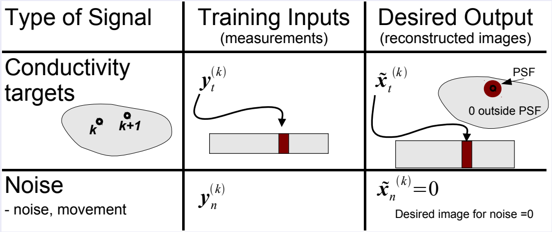
Framework

- Define desired images based on the figures of merit



- Calculate a reconstruction matrix through optimisation

Extension to arbitrary shapes

Procedure

1. Segment the boundary, the lungs and electrode positions from CT, MRI, etc.
2. Build a 3D FEM by extruding the boundary
3. Construct a forward model
4. Calculate desired images for a set of small targets
5. Calculate the GREIT reconstruction matrix

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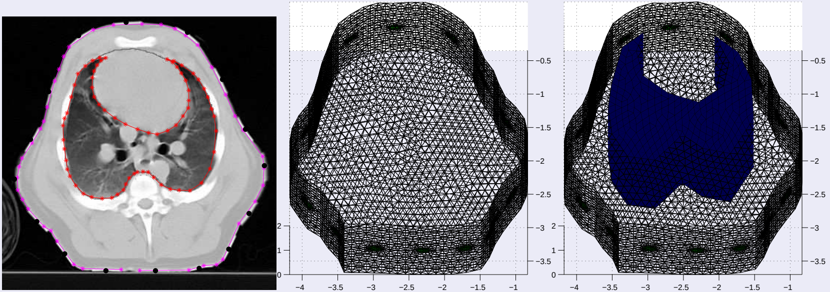
Produces:

- Arbitrary shapes
- Arbitrary resolution

Extension to arbitrary shapes

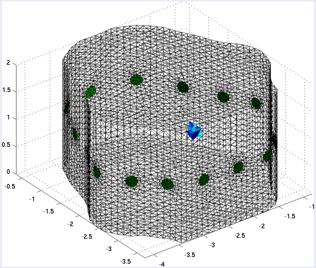
Forward model

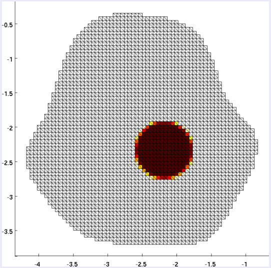


Meshing tool: Netgen.

Extension to arbitrary shapes

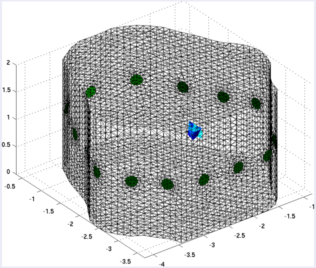
Targets and desired images

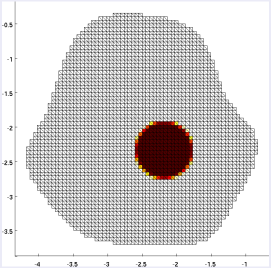




Extension to arbitrary shapes

Targets and desired images



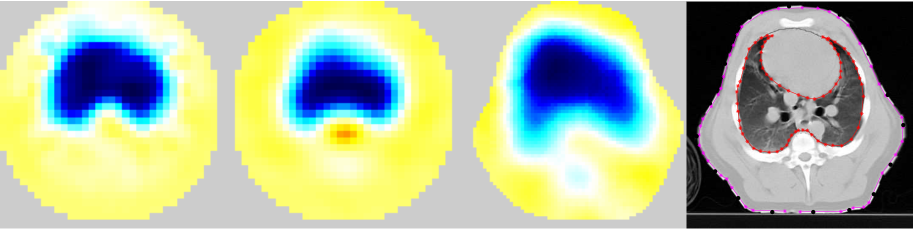


Reconstruction matrix

- Minimises difference between desired and actual images
- Found iteratively such that Noise Figure = 0.5 (hyperparameter)

Comparison with other algorithms

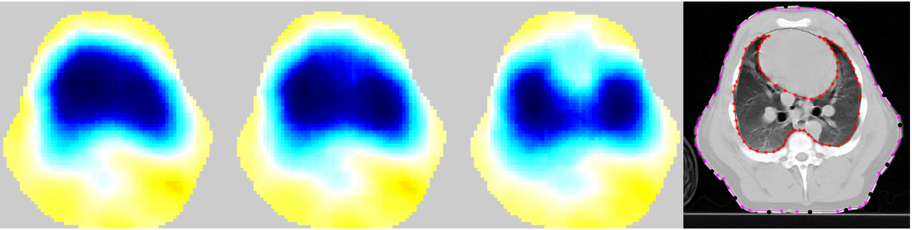
Backprojection GREIT v1.0 GREIT v1.x



Effect of lung contrast in forward model

lung / background ratio =

0.75 0.50 0.25



Simulation study: human thorax

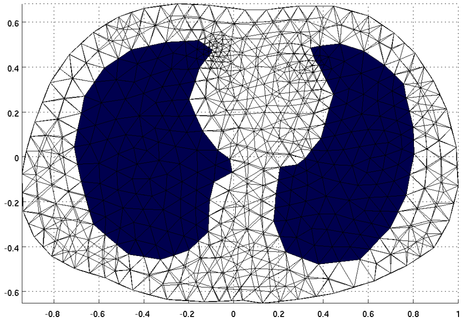


Figure: Forward model (top view)

Simulated measurements

- inspiration and expiration
- 16 electrodes, adjecent drive

Simulation study: human thorax

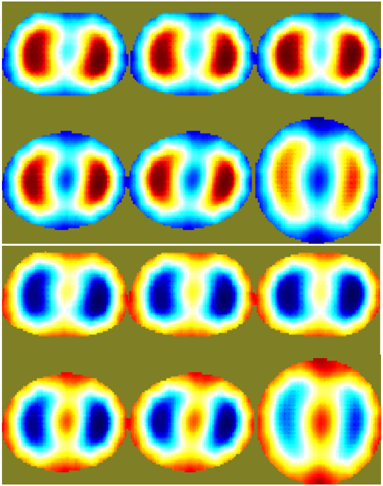


Figure: Reconstructions on progressively rounder shapes

We've worked hard so you don't have to

GREIT model in 7 lines

```
1. fmdl= mk_library_model('adult_male_16el_lungs');      % prepackaged model
2. [fmdl.stimulation, fmdl.meas_select] =
   mk_stim_patterns(16,1,[0,1],[0,1],{'no_meas_current'},1);  % stimulation
3. fmdl.normalize_measurements = 1;
4. img = mk_image(fmdl, 1);                            % background conductivity
5. img.elem_data([fmdl.mat_idx{2};fmdl.mat_idx{3}]) = 0.25; % lung contrast
6. opt.noise_figure = .5;                                          % this is key!
7. imdl=mk_GREIT_model(img, 0.25, [], opt);                      % that was easy!
```

Reconstruct

```
rimg = inv_solve(imdl, ref_data, data);                              % that's it!
```

Conclusion

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- Using the correct shape reduces artefacts
- Using lung contrast improves reconstruction
- It's easy and works GREIT!

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Future work

- Rigorous investigation of GREIT parameters
- Make recommendations for parameter values
- Find a relation between easy to measure parameters and body shape
- How well do we need to know the shape?
- How "anatomical" can EIT become?

Thank You!

Questions?