GREIT: Consensus EIT algorithm for lung images

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Outline

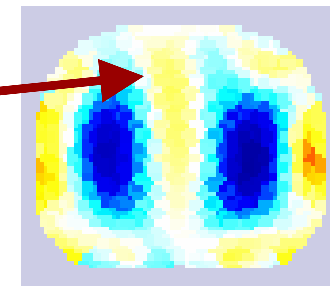
- Why do we need GREIT
- “Roadmap”
  - Step 1: agree on “ingredients” – present at Dartmouth EIT conf
  - Step 2: try “recipes” & evaluate
  - Step 3: algorithm consensus – paper for special issue
- Ingredients and evaluation

Why do we need a new algorithm?

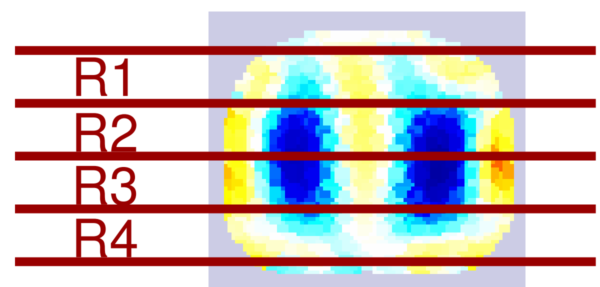
- EIT shows significant clinical potential to monitor ventilated patients.
- EIT can non-invasively image the lungs to better manage the patient’s ventilation.
- Clinical and physiological research in lung EIT being done with old, poorly understood, ill-defined algorithms.

Example Problems

- Is that image feature physiological or artefact?
  - Implemented algorithm is uncalibrated (and is proprietary)



- Can we compare regional ventilation?
  - Implemented alg varies between regions



Are there better algorithms?

- Yes, lots, but:
  - Most work in mid-90’s. Researchers working on “harder” problems.
- Problems with algs:
  - No careful measurement of performance and errors
  - No consensus on the choice of parameters
  - No detailed exposition including all the “secret sauce”

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

stands for:

Graz consensus
Reconstruction
algorithm for
Electrical
Impedance
Tomography

- Initial work at Graz EIT conf.
- Easy to pronounce

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

- Aim is to get large representation of math/engineering and physiological communities.
- This will encourage EIT system vendors to provide it as standard
- Allows multi-centre EIT trials

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

What's in it for participants?

- There is no financial interest here. We not trying to achieve lock-in to benefit commercially

Benefits are:

- Intra-centre comparison
- Helping EIT perception
- Name on a cited paper.

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

This work is limited to the reconstruction algorithm.

- No image interpretation
- No clinical/physiological tests specified

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

Linear algorithm for time difference imaging.

- Fast reconstruction allowing real time
- Linear algs are better understood with noisy data
- No absolute reconstruction
- No advanced (eg. total variation) schemes

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

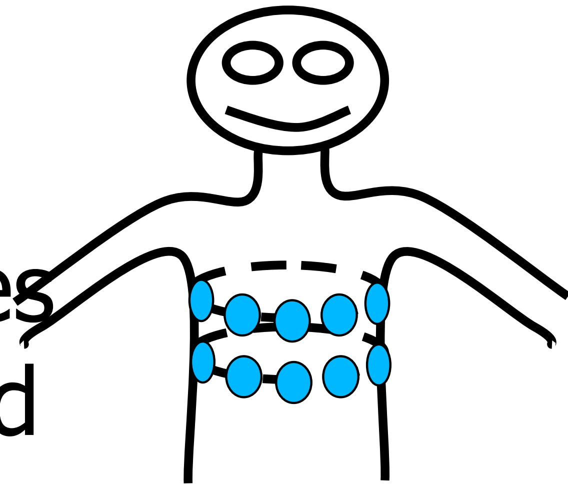
Algorithm units:

- Input: Transfer impedance ($V/I = \Omega$) at time t1 and t2
- Output: Conductivity change (S-m)

GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

2 & 3 ring electrode placement

- 16x1 and 8x2 electrodes planes around chest
- Model is 3D, but output image is 2D
- Method suitable for arbitrary electrodes/planes

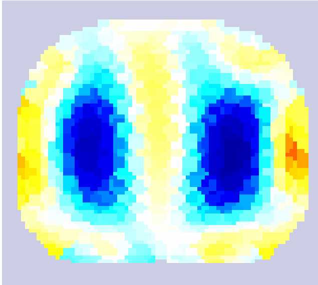


GREIT: a consensus linear reconstruction algorithm for EIT images of the chest

Algorithm is focused on lung EIT.

Geometric models for

- Adult thorax
- Neonate thorax
- Cylindrical Phantom



Difference adult/neonate is electrode size

“Roadmap”

Step 1: Propose on “ingredients” in alg
- paper at Dartmouth EIT conf. (April)

Step 2: Discussions/experience
- Test algorithm “recipes” (May-Sept)

Step 3: Consensus where possible
- publish paper and software (Oct-Nov)

Expected outcomes

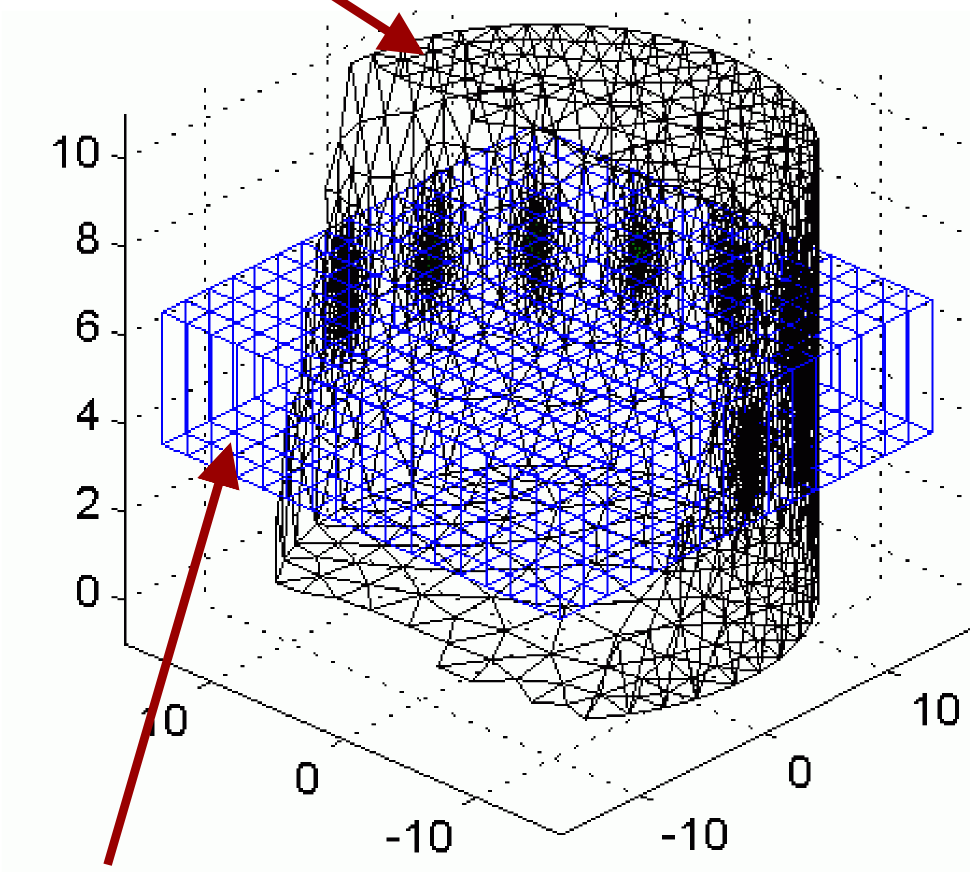
- Agreement on issues AND solutions
- Agreement on issues but NOT solutions
  - Eg. Strategies to calibrate systems,
    Managing contact impedance
- Some remaining disagreement issues
  - Hopefully few. Can establish research questions to determine

Step 1A: “basic ingredients”

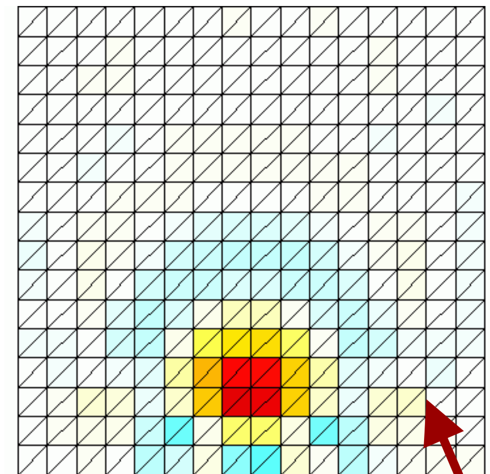
- Dual model (2D coarse / 3D fine)
- Gauss Newton reconstruction
- Image prior with spatial filter
- Scaling for spatial uniformity
- Hyperparameter selection method

Dual Models

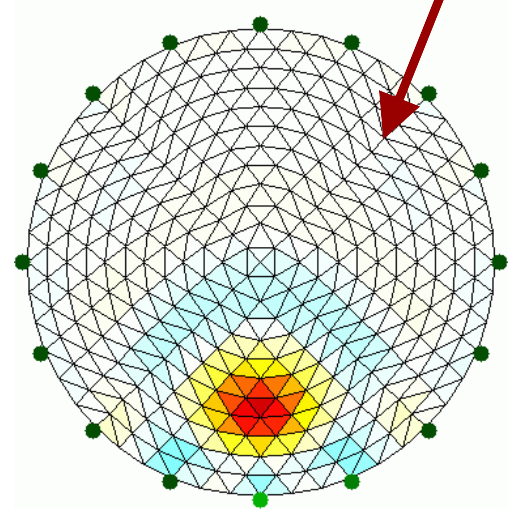
Fine Mesh: fwd_model
(with complete electrode model)

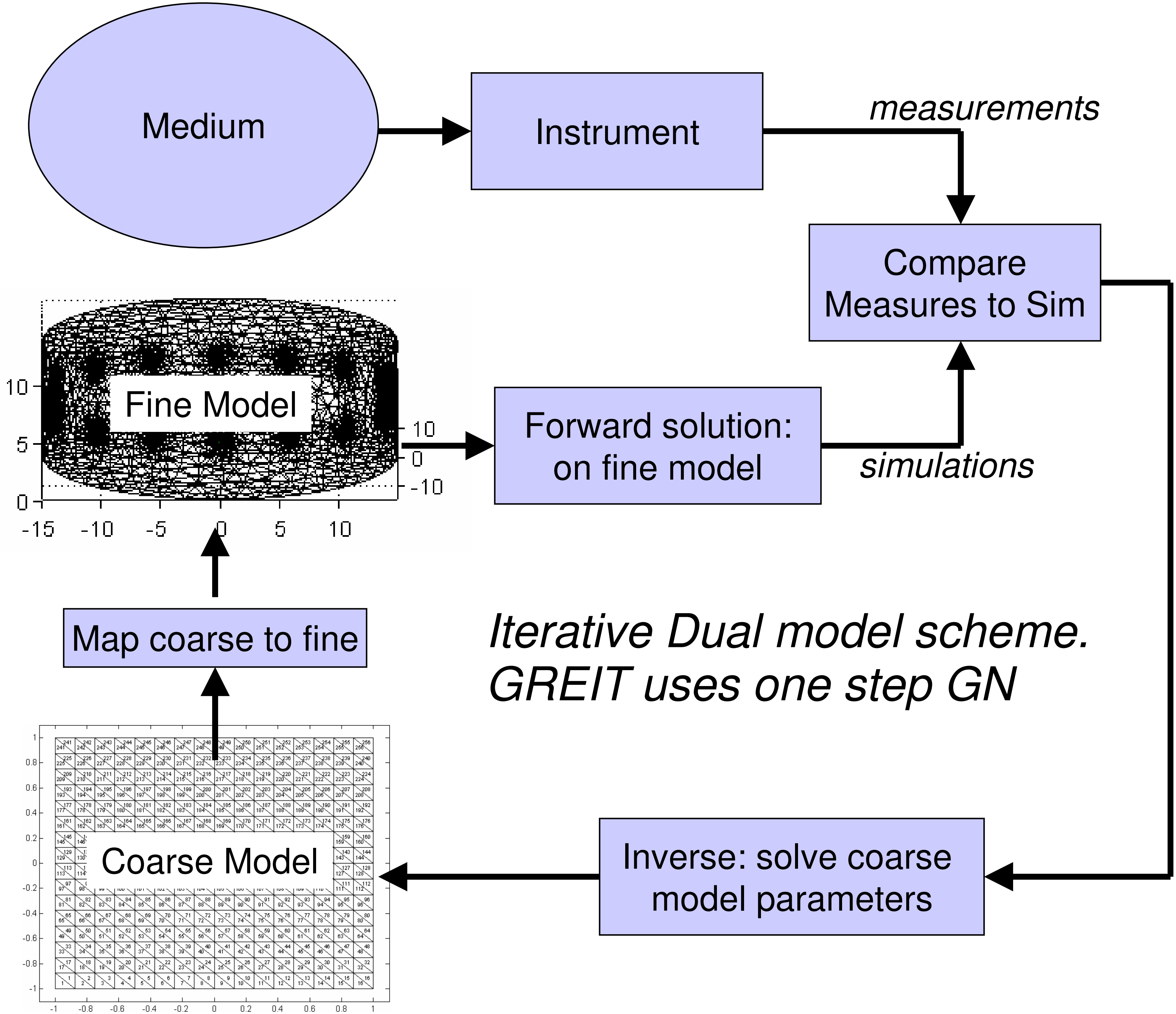


Square mesh: rec_model



We reconstruct to square pixels, not FEM elems





Iterative Dual model scheme.
GREIT uses one step GN

Gauss Newton Reconstruction

$$\hat{\mathbf{x}} = \left(\boldsymbol{\Sigma}_x \mathbf{J}^t (\mathbf{J}\boldsymbol{\Sigma}_x \mathbf{J}^t + \lambda^2 \boldsymbol{\Sigma}_n)^{-1}\right)\mathbf{y}$$

Tikhonov form

$$\hat{\mathbf{x}} = \left((\mathbf{J}^t \boldsymbol{\Sigma}_n^{-1} \mathbf{J} + \lambda^2 \boldsymbol{\Sigma}_x^{-1})^{-1} \mathbf{J}^t \boldsymbol{\Sigma}_n^{-1}\right)\mathbf{y}$$

Wiener filter form

Post scaling for units & spatial uniformity

Quantity	symbol
Difference Measurements:	$\mathbf{y} = \mathbf{v}^1 - \mathbf{v}^2$
Conductivity image:	$\hat{\mathbf{x}}$
Image prior covariance:	$\boldsymbol{\Sigma}_x$
Measurement covariance:	$\boldsymbol{\Sigma}_y$
Jacobian:	$\mathbf{J}$
hyperparameter:	λ

Image Prior: spatial filter

- Spatial filter priors are more flexible

Spatial filter type prior

1	-½				
-½	1	-½			
	-½	1	-½		
		-½	1	-½	
			-½	1	-½
				-½	1

Diagonal type prior

1					
	1				
		1			
			1		
				1	
					1

- Recommend exponential relationship with rate = 10% diameter

Image Prior: requirements

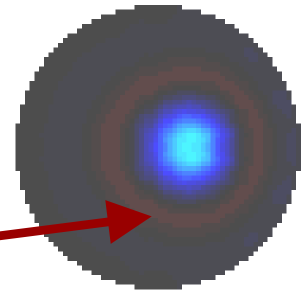


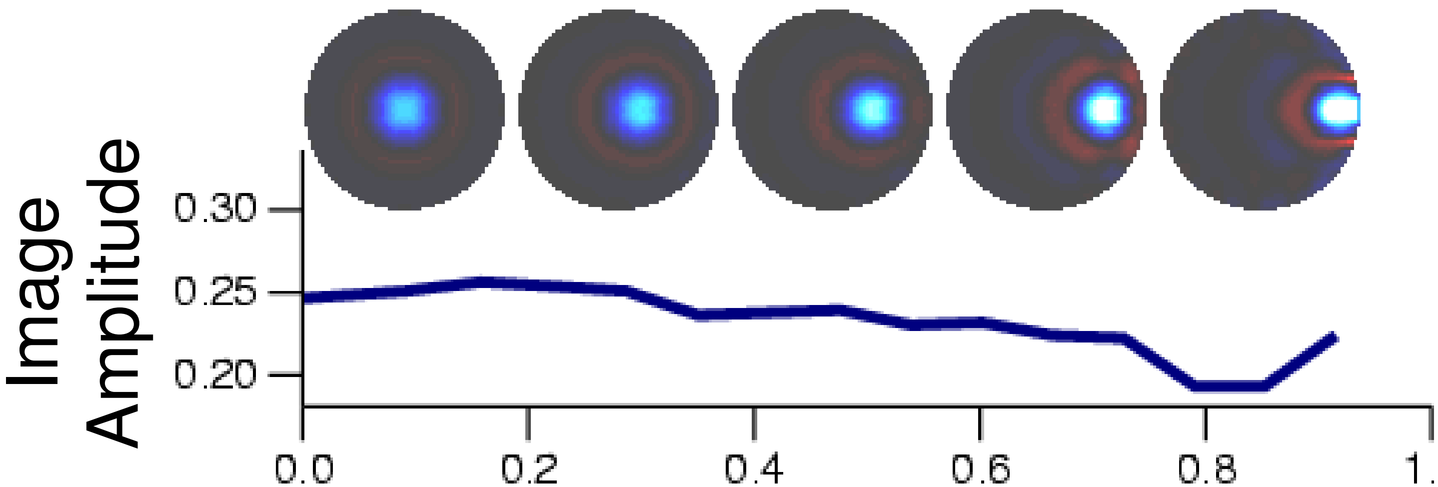
Image Prior choices

- Ringing
- Position error (ie. NOSER tends to "push" toward centre)
- Reconstructed shape

- Need to try many different priors
- Can add different priors into "recipe"

Scaling for spatial uniformity

- Total image amplitude must not vary with radial position



- Reconstruction matrix must be scaled to prevent (otherwise misinterpretation)

Hyperparameter selection

- We can’t have user selectable λ
- We can’t have λ depend on each image
- λ must depend on the equipment and configuration. It is chosen
  - mfg calibration
  - calibration via defined test procedure (with well defined phantom)

Hyperparameter selection

- I propose Noise Figure

$$NF = \frac{SNR_x}{SNR_y} = \frac{\frac{E[\|\mathbf{x}\|]}{std(\mathbf{x})}}{\frac{E[\|\mathbf{y}\|]}{std(\mathbf{y})}}$$

  - NF depends only on λ and reconstruction parameters
- Another approach is to define image SNR for standard target
- Need to build consensus on λ selection strategy. This might be difficult

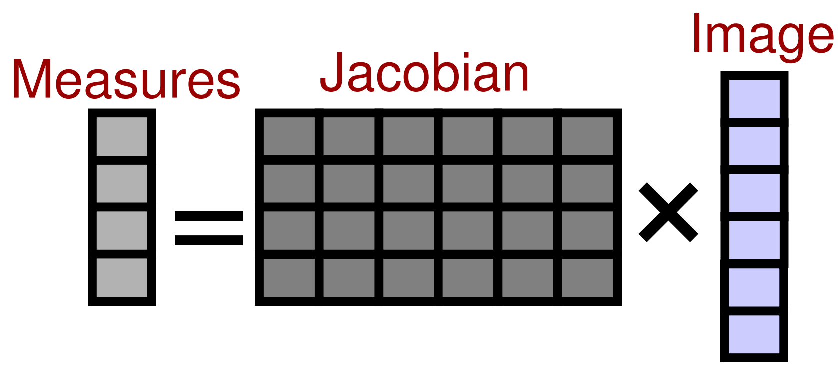
Step 1B: “advanced ingredients”

- Reconstruct at each stim pattern
  - Vauhkonen et al 1998, Adler et al 2006
- Electrode movement compensation
  - Soleimani et al, 2005

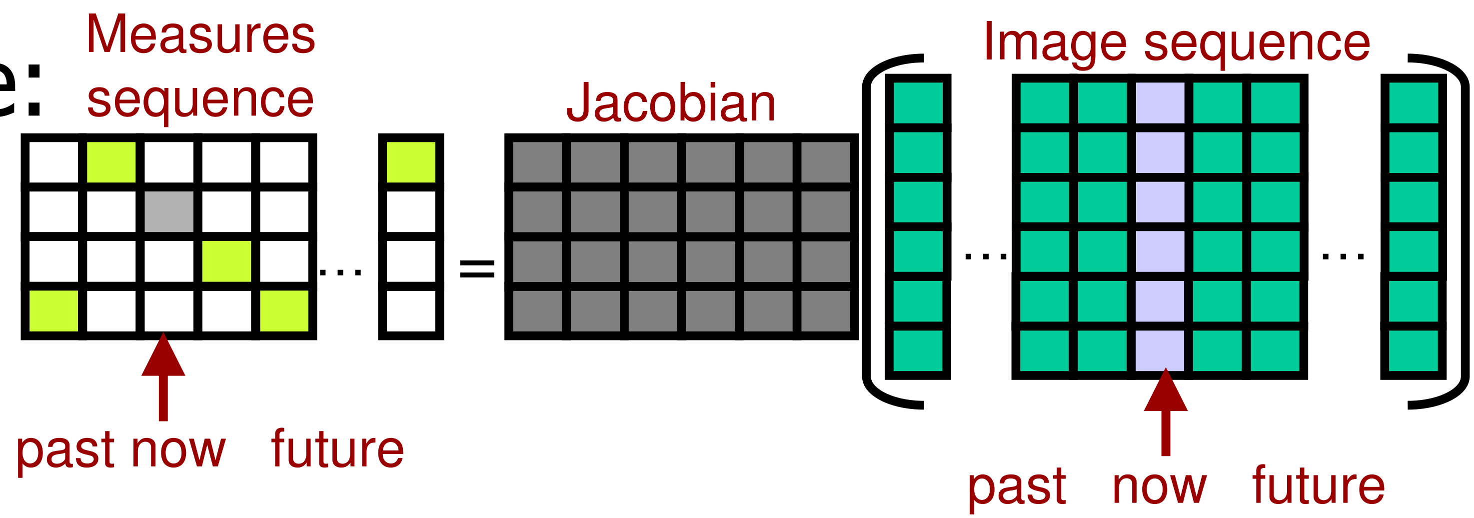
Update at each stimulation

Each stimulation occurs at different time.

Instead of:



We have:



Update at each stimulation

- Reformulate problem as Temporal reconstruction (using augmented data and image terms)
- Reconstruct image at each stimulation in sequence

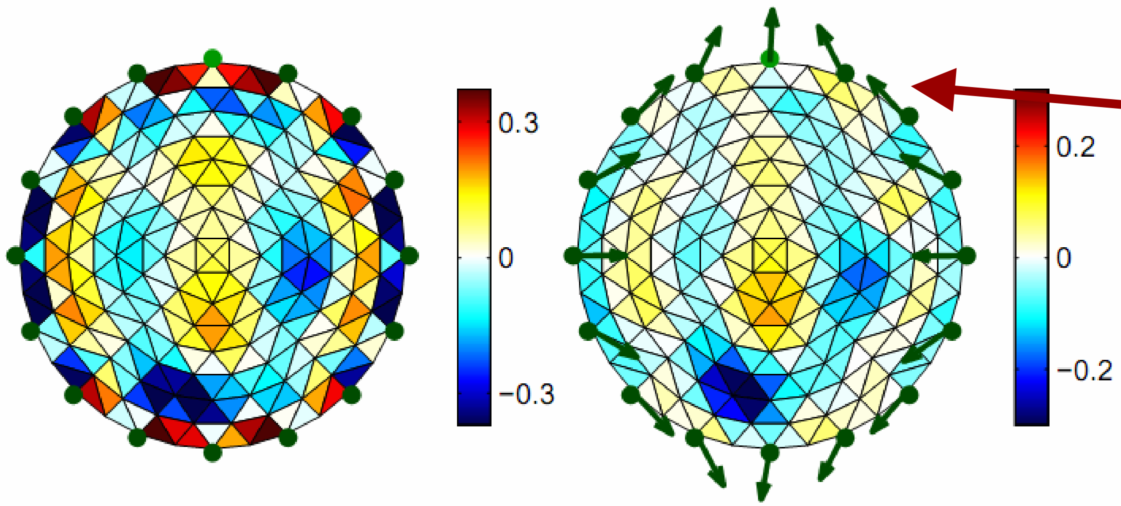
- *General:* should we use temporal reconstruction with nearby few data frames?

Electrode Movement artefacts

From Soleimani et al (2006)

$$\hat{\mathbf{x}} = \left(\mathbf{J}^t \frac{1}{\sigma_n^2} \mathbf{W} \mathbf{J} + \frac{1}{\sigma_c^2} \mathbf{R}_c + \frac{1}{\sigma_m^2} \mathbf{R}_m \right)^{-1} \mathbf{J}^t \frac{1}{\sigma_n^2} \mathbf{W} \mathbf{z}.$$

define $\mathbf{R} = \mathbf{R}_c + \mu^2 \mathbf{R}_m$, and rewrite (6) as (using $\mathbf{W} = \mathbf{I}$),



Arrows aren't accurate (conformal problem), but artefacts dramatically reduced

Figure 2. Reconstructed images (256 element mesh) for phantom data with two non-conductive objects: one on the positive x-axis, the other on the negative y-axis. Arrows indicate each electrode's movement, and are scaled by 10×. *Left*: Reconstructed image with standard method using $\lambda = 10^{-2}$ (AAM = 0.134). *Right*: Reconstructed image including electrode movement using $\lambda = 10^{-2}$ and $\mu = 10$ (AAM = 0.0273).

Step 1: “ingredients”

– Dual model (2D coarse / 3D fine)
– Gauss Newton reconstruction
– Image prior with spatial filter
– Scaling for spatial uniformity
– Hyperparameter selection method
– Update at each stimulation
– Electrode movement compensation

Paper for Dartmouth EIT conf

This algorithm is proposed for discussion:

- Ingredients
- Parameters for Algorithm
- Licensing
- Evaluation Methods

Important issues we defer for later:

- Contact impedance estimation
- Reciprocity error / electrode error detection
- Calibration protocols and phantoms
- Complex reconstruction and contact impedance

Features: parameters

Parameters for operator to set

- Distance (Lateral) across chest

Parameters for manufacturer:

- Regularization parameter (based on measured noise level)
- Electrode size

Licensing

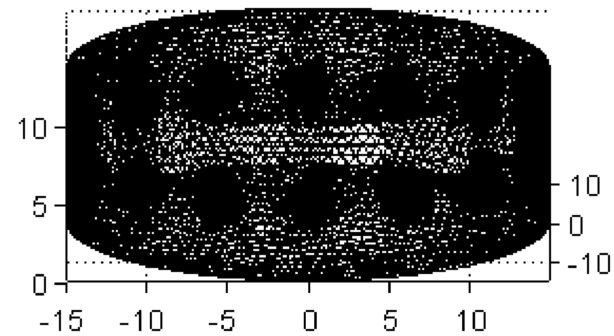
- All algorithms, models and test data to be made available under an open source
  - Algorithm: as part of EIDORS (GPL)
  - Models/Data: Creative Commons - Attrib
- Reconstruction algorithm (output of algorithm) is *public domain*.
- Authors disclaim any warranty
- Authors will state intention not to patent *this algorithm*

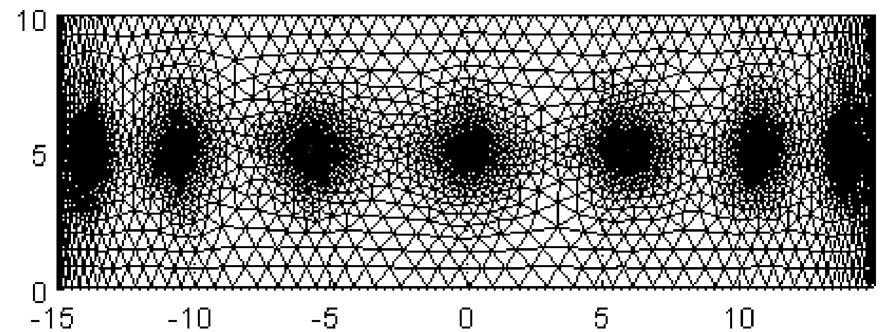
Evaluation Methods

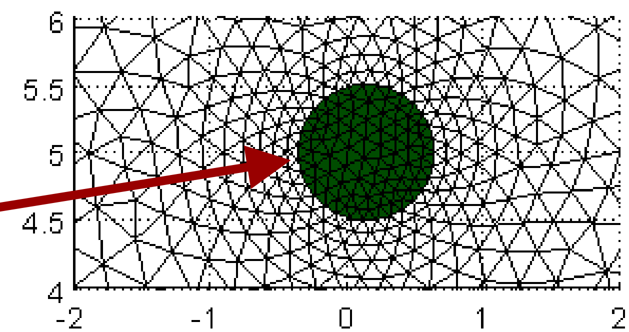
1. Generate data
   - Numerical Models
   - Clinical sample studies
2. Develop test criterion
3. Develop/Collect algorithm candidates
4. Evaluate/Score results

Methods: Generate Data

1. Numerical Models
   - Adult
   - Neonate
   - Cylindrical tank

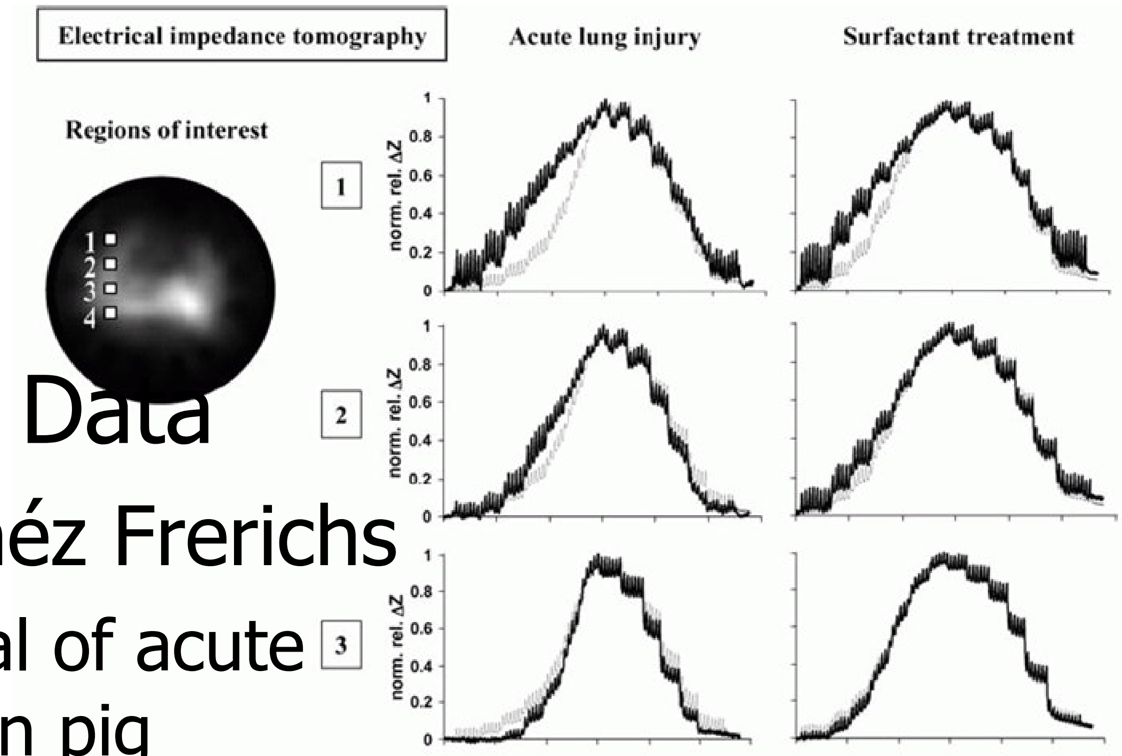






3D models with High Resolution Electrodes

Methods: Data



2. Experimental Data
    - Data from Inéz Frerichs
      EIT of PEEP trial of acute lung injury in pig
    - Data from Günter Hahn
      Instillation of air/fluid into pleural cavity in pig

Methods: Evaluation

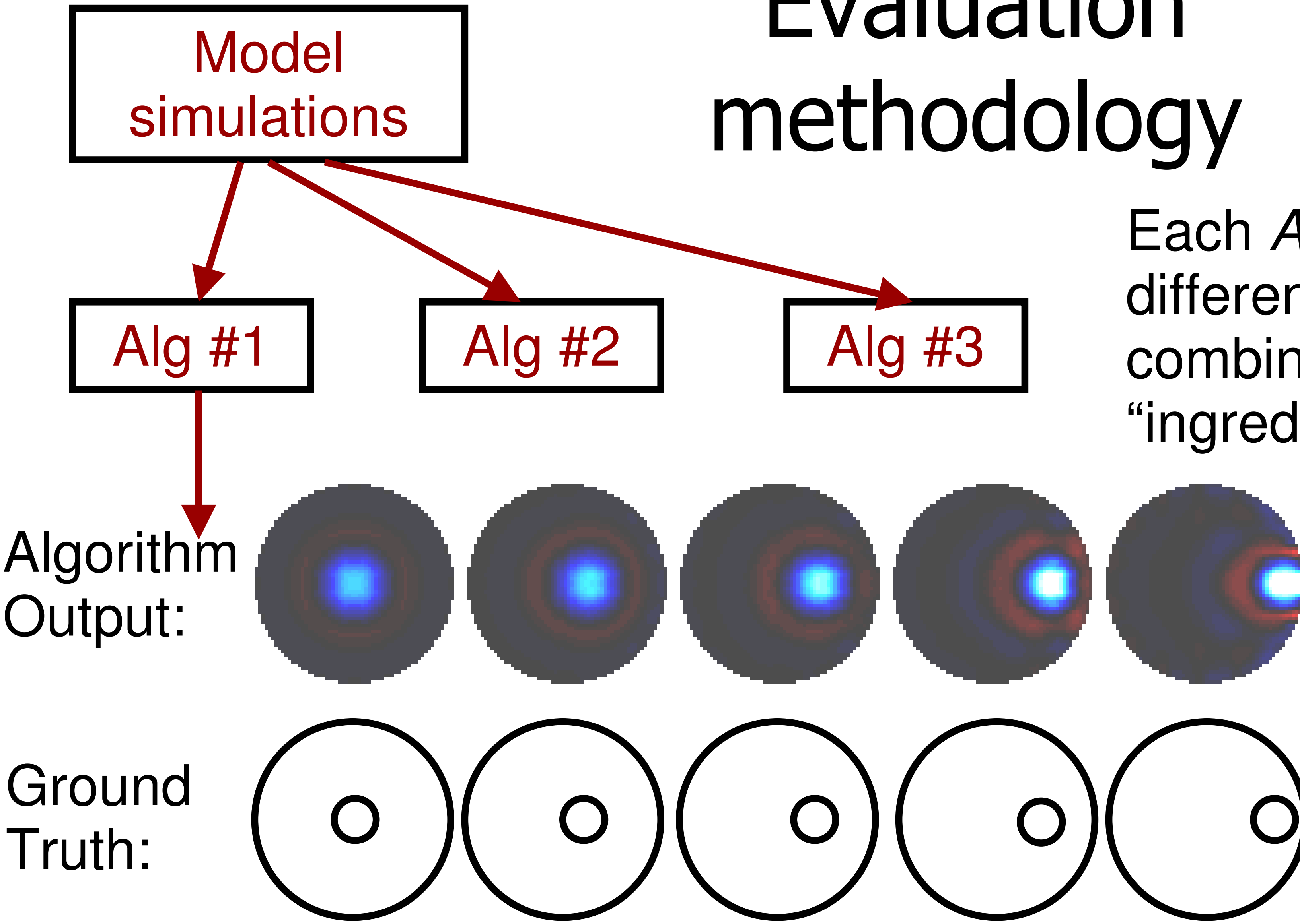
- Amplitude Response
- Position Error
- Resolution
- Noise Performance
- Boundary shape and electrode sensitivity
- Experimental data performance

Model data

Experim-
ental data

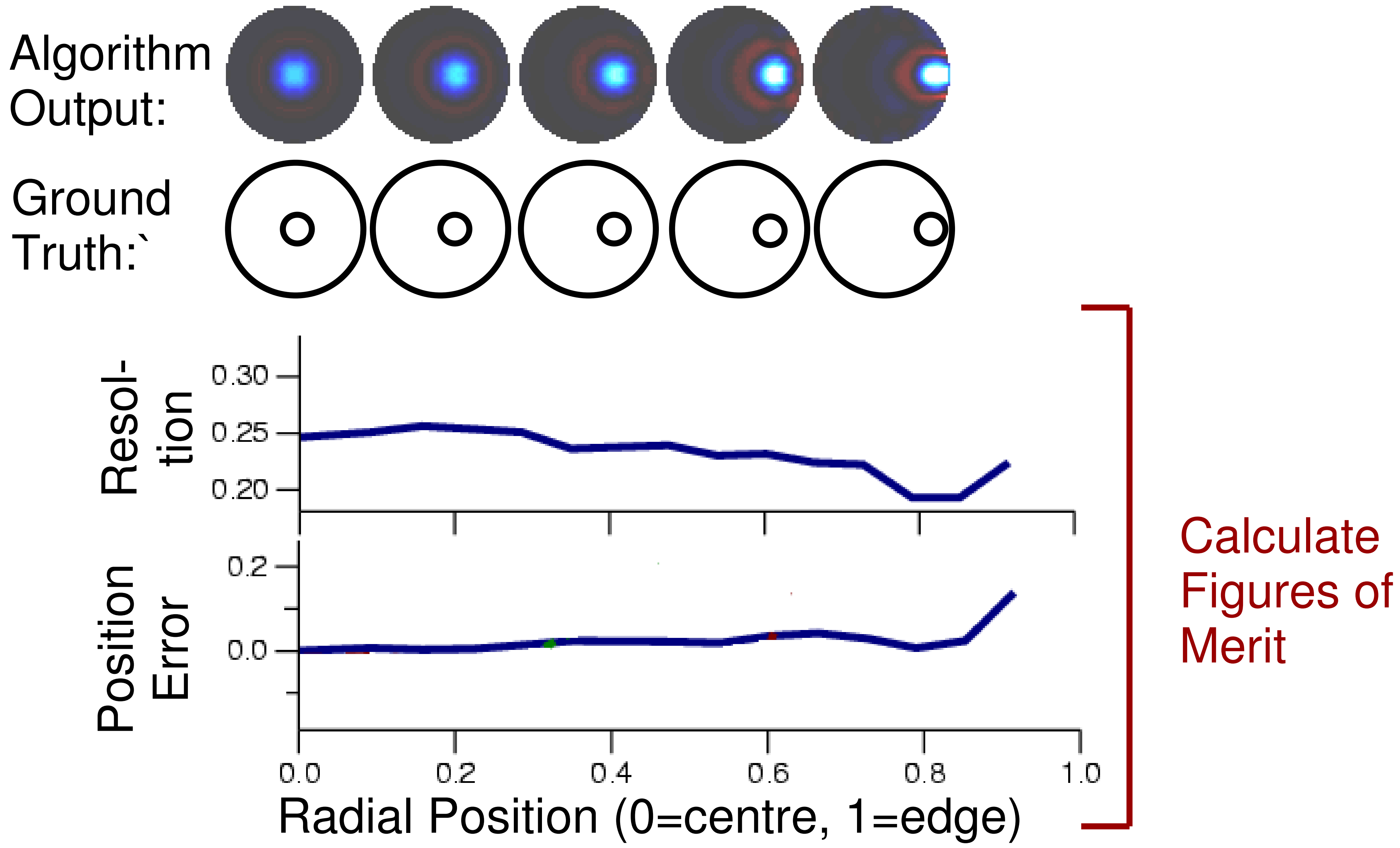
we need to figure out how to objectively evaluate experimental data performance

Evaluation methodology



Each *Alg* is a different combination of “ingredients”

Evaluation methodology



Evaluation: selection

Criterion	**Score**	**Expert Weightings**		Avg Weight	Weighted score
Amplitude Response	?	Expert #1	Expert #2		
Position Error	?				
Resolution	?				
Noise Performance	?				
Boundary shape	?				
Experimental data	?				
Overall					