

Detection of erroneous electrodes in Electrical Impedance Tomography

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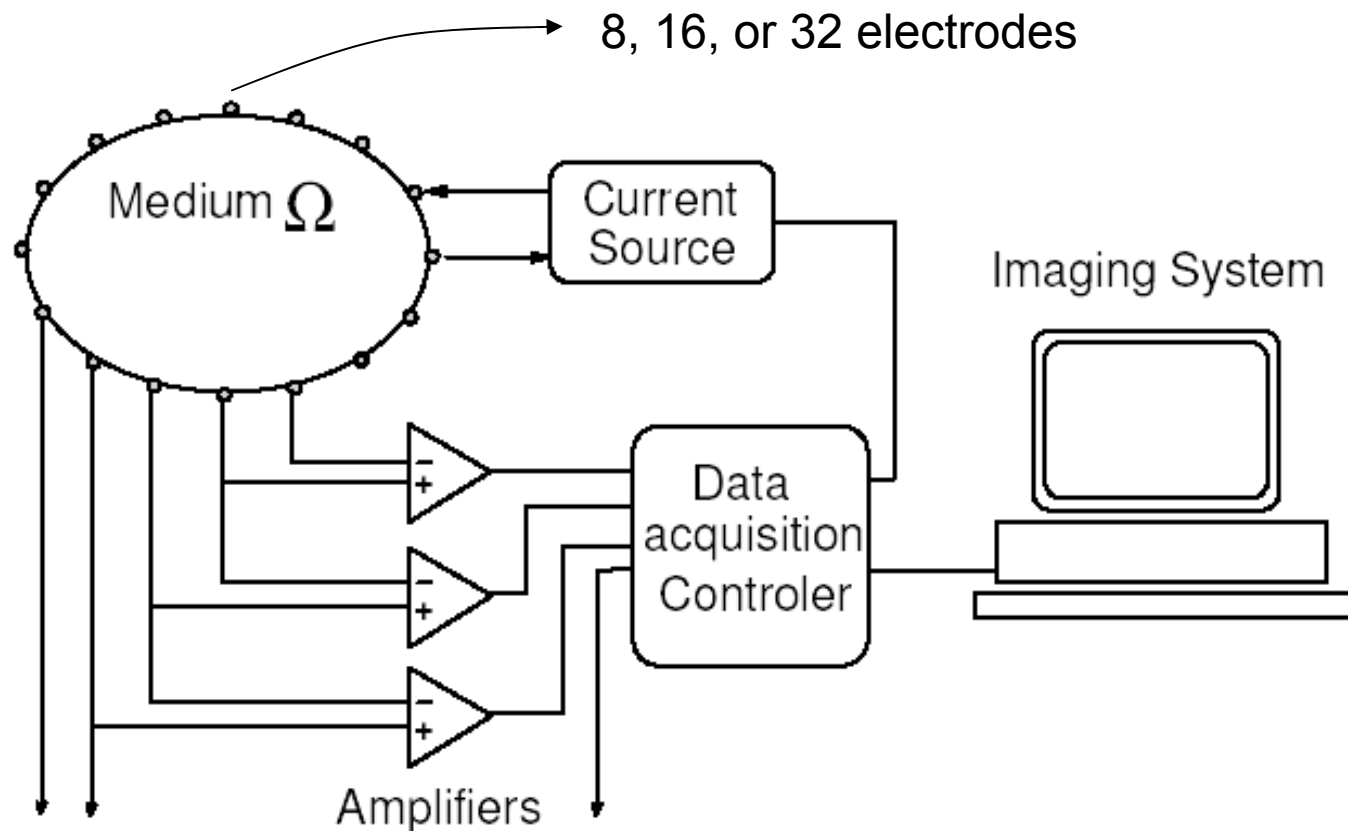
Overview

- Electrical Impedance Tomography
- Electrode errors in EIT
- Electrode error detection
- Result of simulated data
- Result of experimental data
- Discussion

Electrical Impedance Tomography

- Medical Imaging Technique
- Apply current patterns and measure the resulting voltages
- Calculate the resulting conductivity
- Used to monitor movement of conductive fluids and gases
 - Eg. Heart, Lungs and Brain

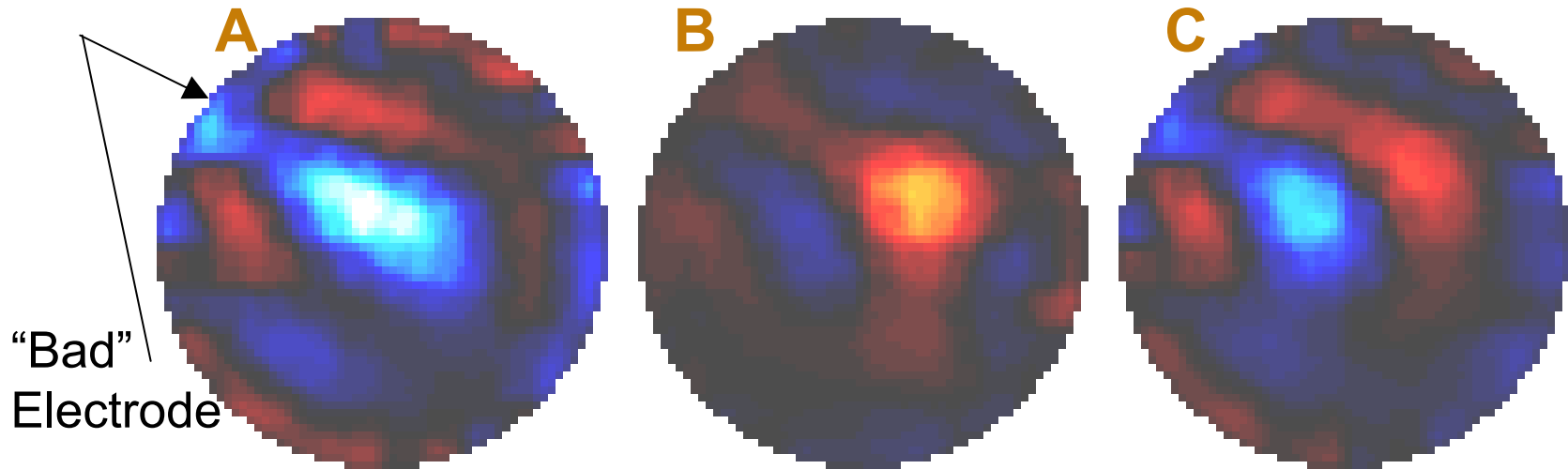
EIT Block Diagram



Problem

- Experimental measurements with EIT quite often show large errors from electrodes
- Causes aren't always clear
 - Electrode Detaching
 - Skin movement
 - Sweat changes contact impedance
 - Electronics Drift?

Example of electrode errors



Images measured in anaesthetised, ventilated dog

- A. Image of 700 ml ventilation
- B. Image of 100 ml saline instillation in right lung
- C. Image of 700 ml ventilation and 100 ml saline

The Problem

- Previously, developed a method to account for erroneous electrode data based on Bayesian Imaging model
 - Model electrode errors as *a priori large measurement noise* on all measurements using affected electrode

The Problem

- Logical step forward is:

How to detect a faulty electrode?

- *Idea:* data from a “bad” electrode are inconsistent with data from “good” electrodes

Imaging Model

Linear forward model:

$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

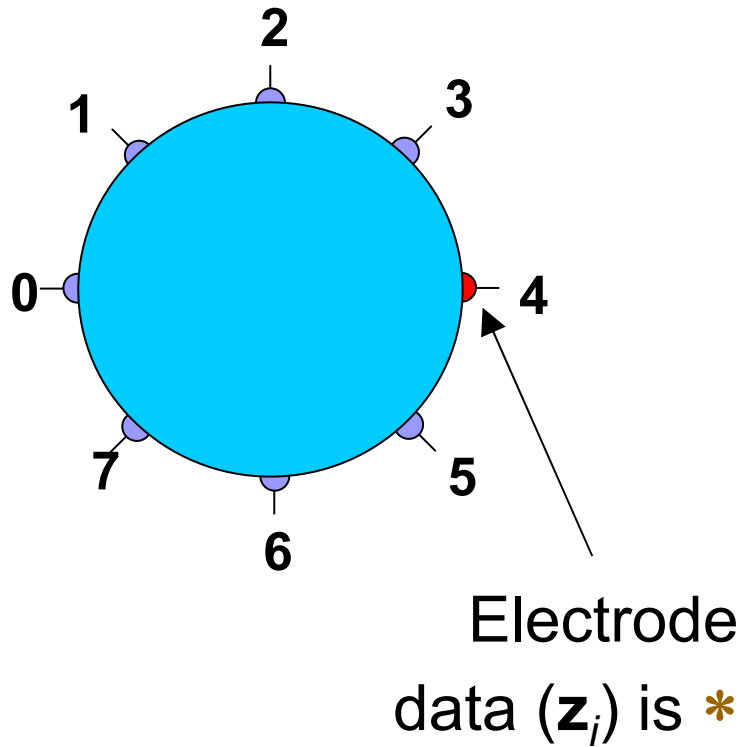
{	\mathbf{z}	measured dynamic signal
	\mathbf{H}	sensitivity matrix
	\mathbf{x}	conductivity change image
	\mathbf{n}	measurement noise

Linear inverse:

$$\hat{\mathbf{x}} = \mathbf{B}\mathbf{z}$$

{	$\hat{\mathbf{x}}$	calculated image
	\mathbf{B}	reconstruction matrix depends on R_n and R_x

Measurements: adjacent drive

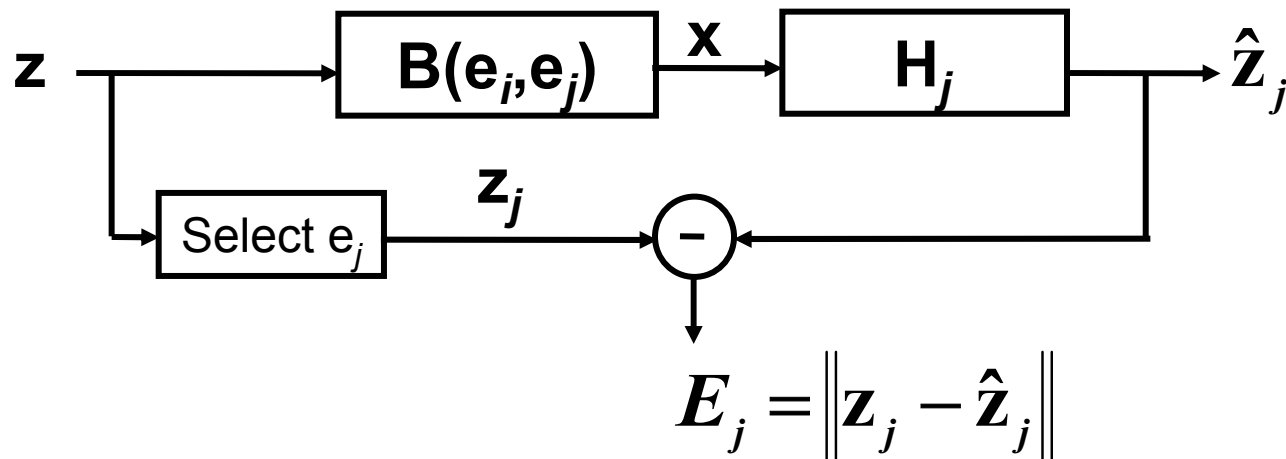


01	X	X		*	*			X
12	X	X	X	*	*			
23		X	X	X	*			
34	*	*	X	X	X	*	*	*
45	*	*	*	X	X	X	*	*
56				*	X	X	X	
67				*	*	X	X	X
70	X			*	*		X	X
	01	12	23	34	45	56	67	70

Our system can't measure at current injection (X)

Estimation Error

- Based on the forward and inverse model we construct an estimation scheme:

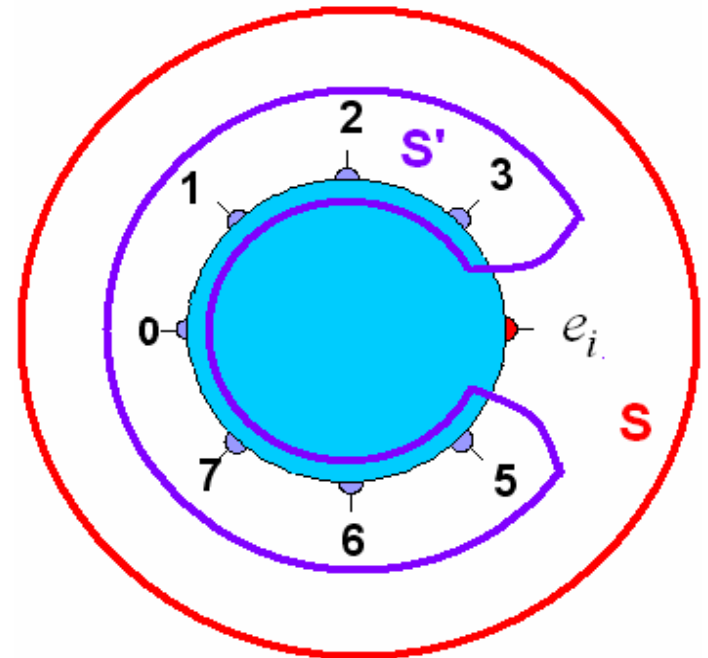


- $\mathbf{B}(\mathbf{e}_i, \mathbf{e}_j)$: reconstruction matrix where data from \mathbf{e}_i , \mathbf{e}_j are removed
- E_j is estimation error for electrode j

Method: outer loop

Goal: construct test for each e_i

- Remove a candidate electrode e_i from set S
- Create a set S' that does not include candidate electrode



Method: inner loop (e_j)

Goal: is data in S' consistent?

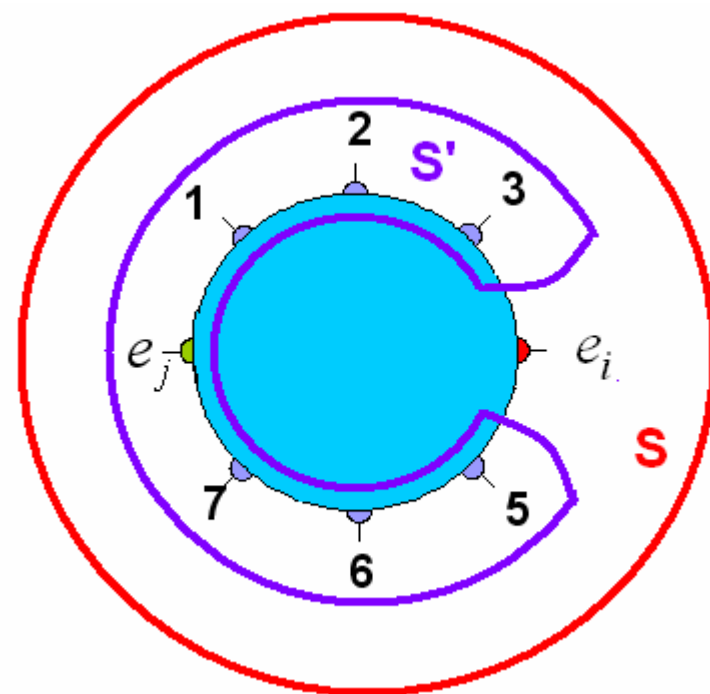
- Estimate \mathbf{z}_j and calculate E_j

$$\begin{aligned} E_j &= \|\mathbf{z}_j - \hat{\mathbf{z}}_j\| \\ &= \|\mathbf{z}_j - \mathbf{H}_j \mathbf{B}(e_i, e_j) \mathbf{z}\| \end{aligned}$$

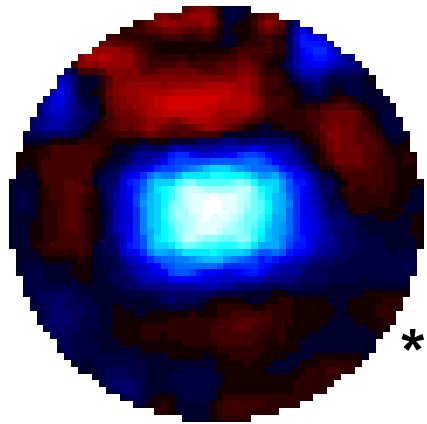
- Sum E_j for electrodes in S' :

$$T_i = \sum_{j=1, j \neq i}^N E_j$$

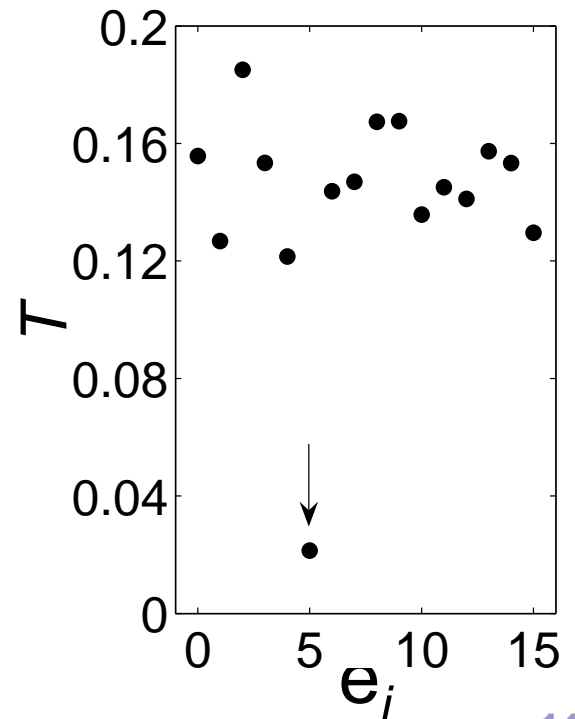
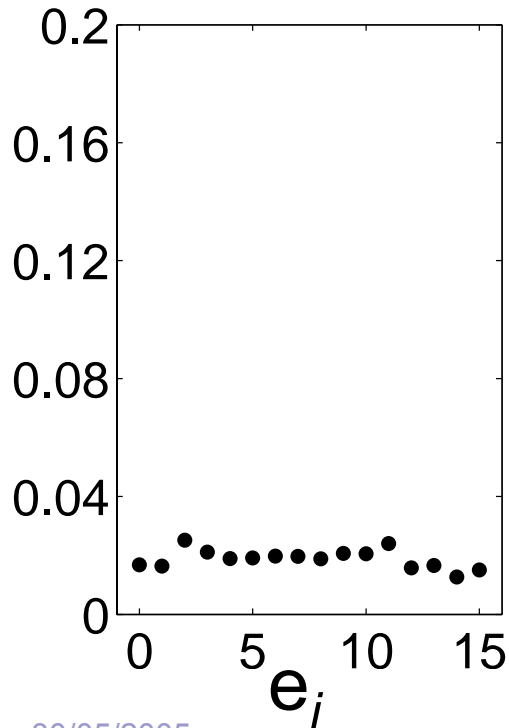
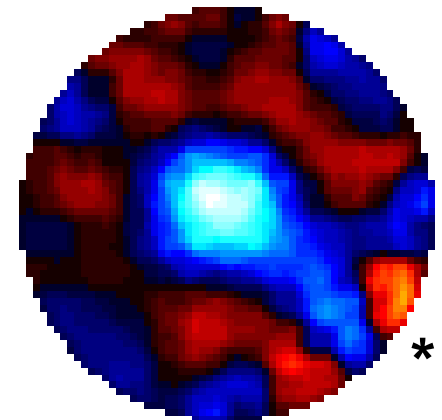
E_j is low if data in S' is consistent



Simulation



→
Add white Gaussian noise to
electrode 5 (*) data
(SNR=-10dB)



Method: *analysis*

■ Case 1: **No bad electrodes**

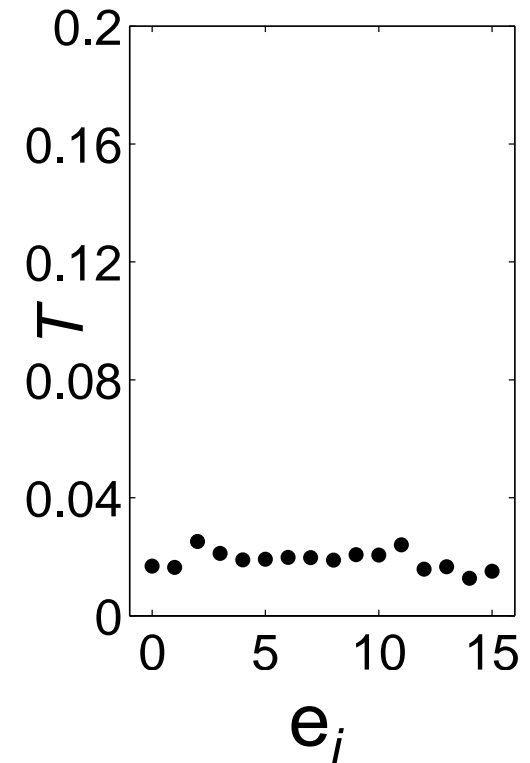
- Data is consistent with estimate
- T will be low for all electrodes

■ Case 2: **One bad electrode**

- *Next slide*

■ Case 3: **More bad electrodes**

- This model doesn't explicitly support



Method: *analysis*

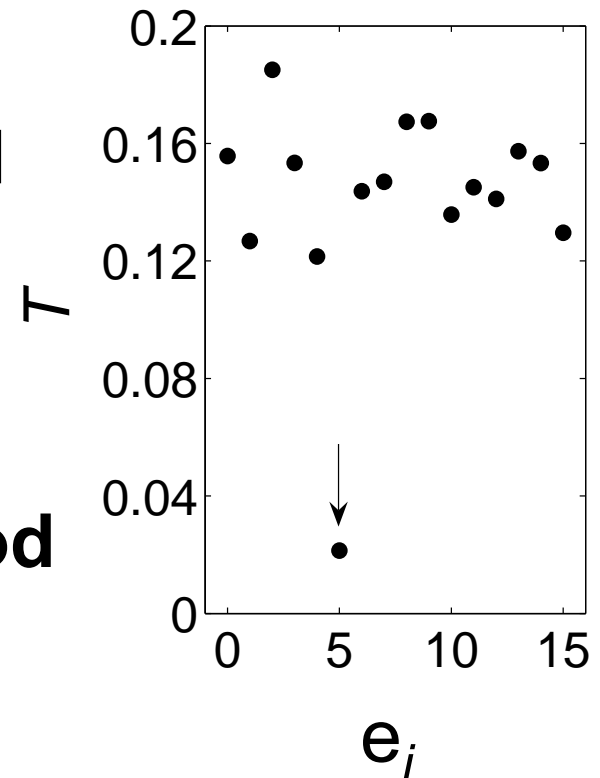
Case 2: One bad electrode

■ Case 2A: electrode (e_i) is bad

- Set S' has good electrodes
- Low estimation error & small T

■ Case 2B: electrode (e_i) is good

- Set S' has a bad electrode
- High estimation error & high T



Method: *decision parameter*

How to decide if there is a bad electrode:

- Distance measure (DM) to test consistency of the T values

$$DM_i = \sum_{j=1}^N |T_i - T_j|$$

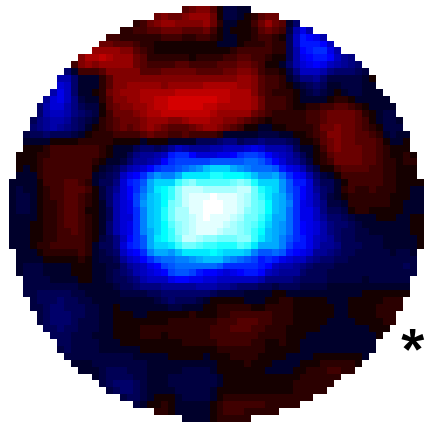
- prediction error ratio (PER)

$$PER = 20 * \log \left[\frac{\min(DM)}{\max(DM)} \right]$$

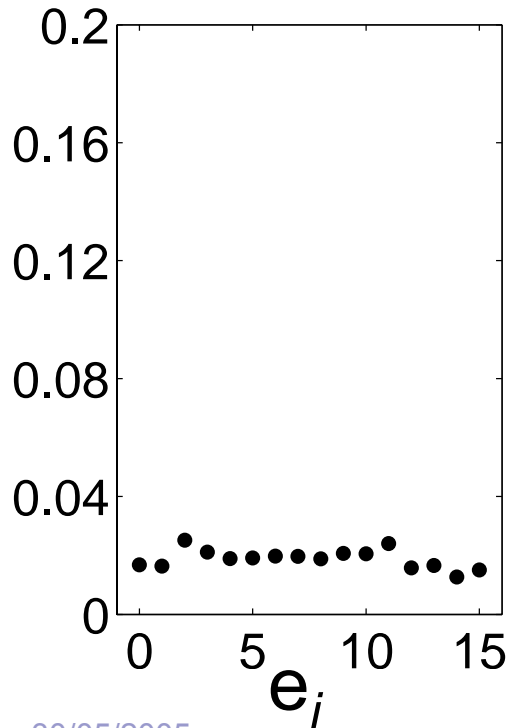
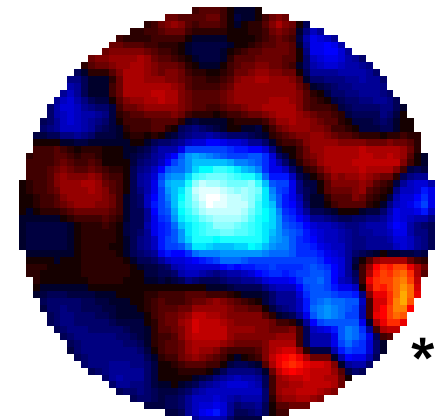
Method: *decision*

- low PER: T values consistent
 - No Erroneous electrode
- high PER: T values not consistent
 - electrode with low T is bad

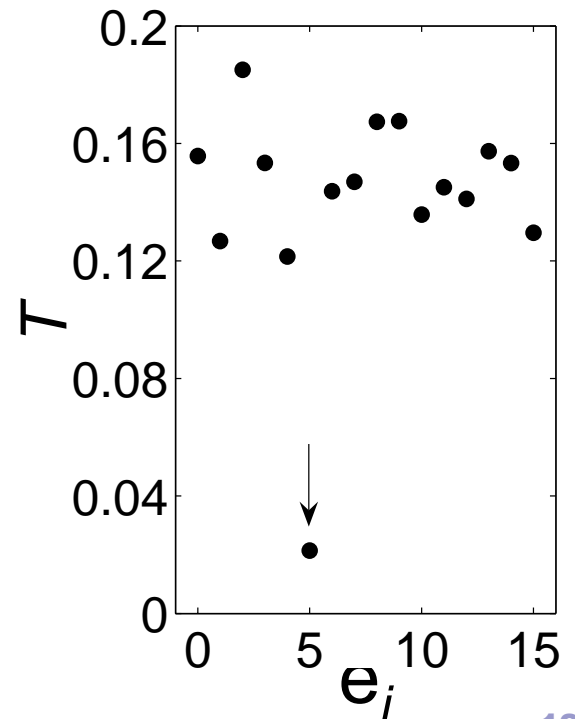
Simulation



→
Add white Gaussian noise to
electrode 5 (*) data
(SNR=-10dB)



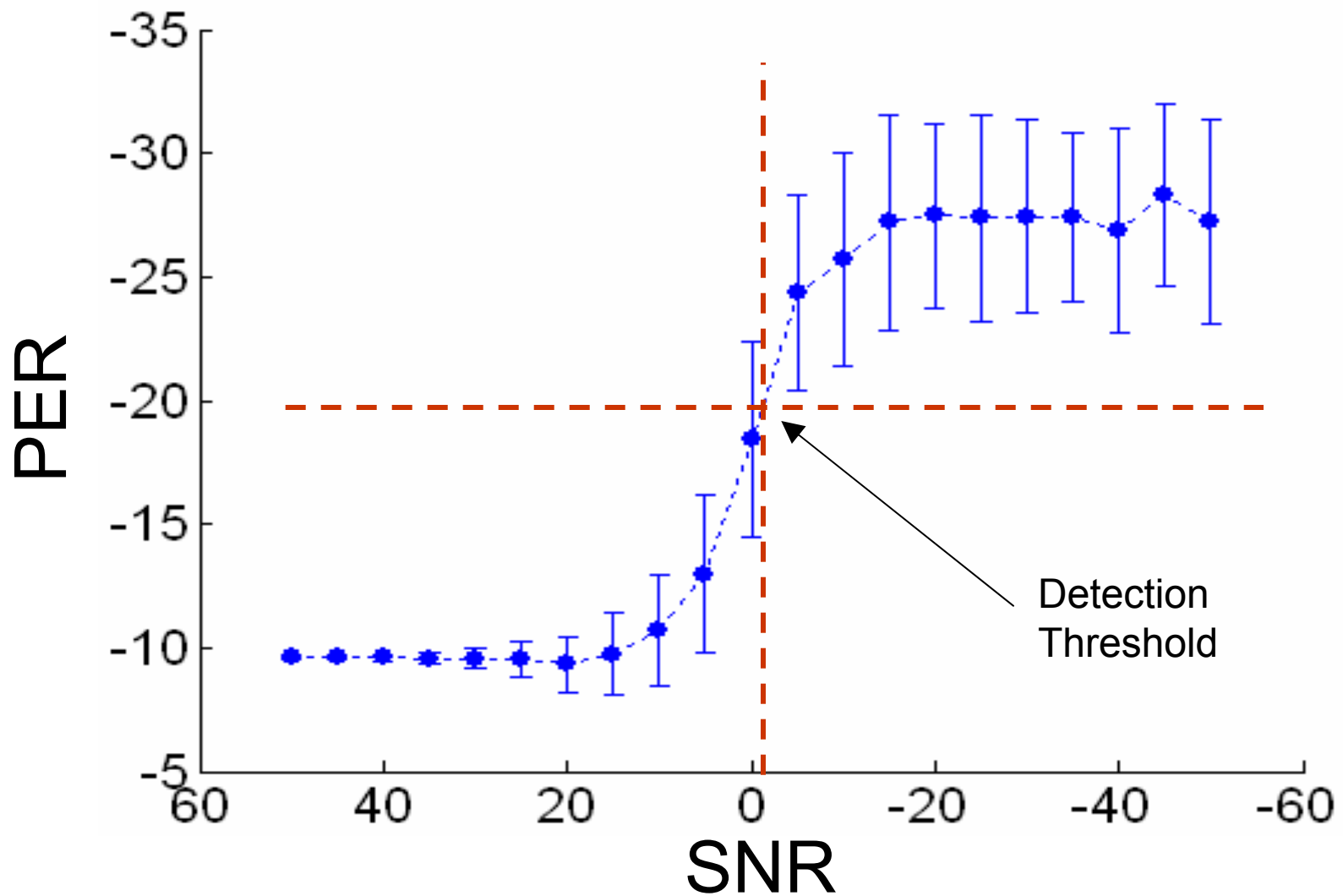
Prediction error ratio:
Original: -13 dB
Noisy: -39.42 dB



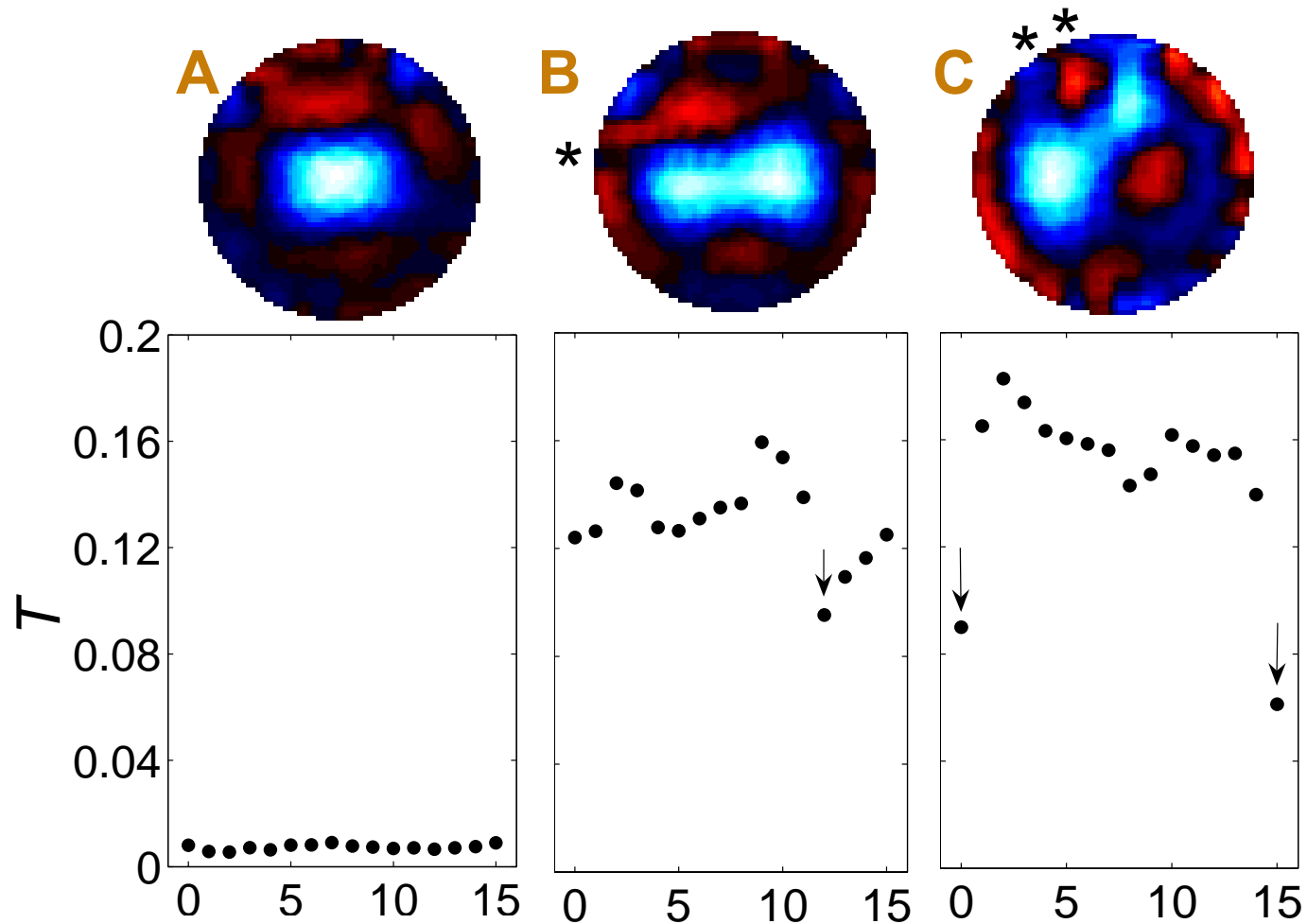
Simulation: *PER* vs *SNR*

- Error detection sensitivity curve
 - Selected representative “clean data”
 - Image of 700 ml ventilation
 - Calculate PER for different noise levels on single electrode
 - 100 simulations per noise level

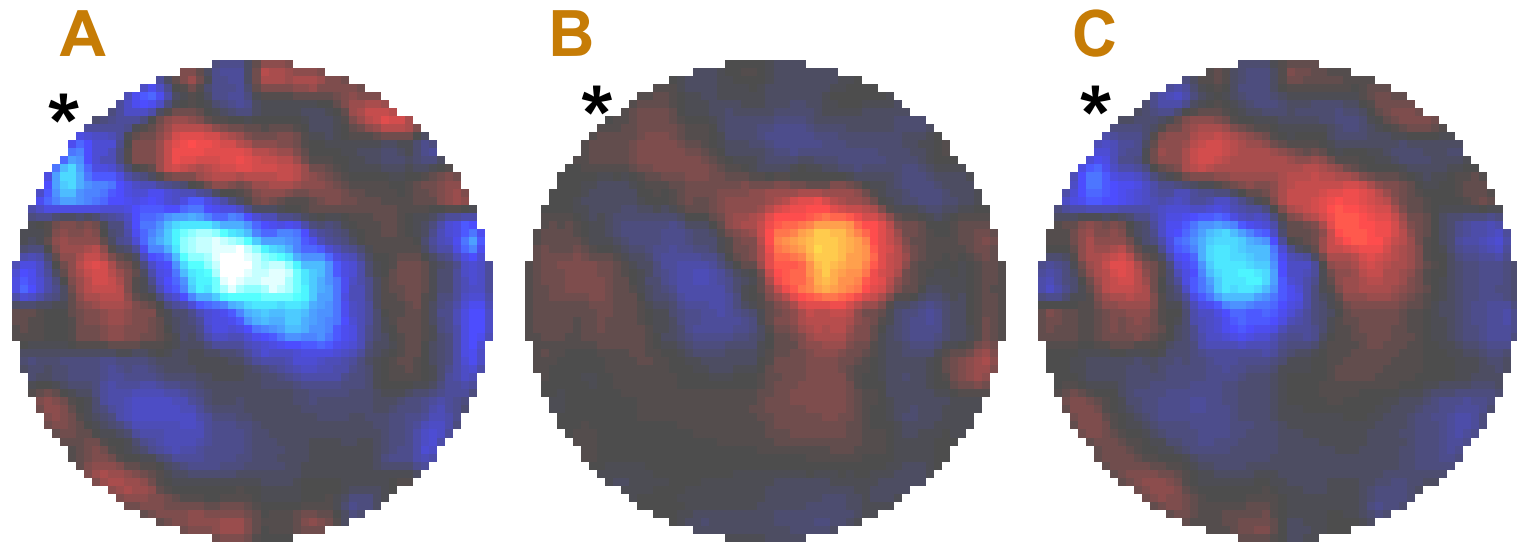
Simulation: *PER* vs *SNR*



How does this work with real erroneous electrode?



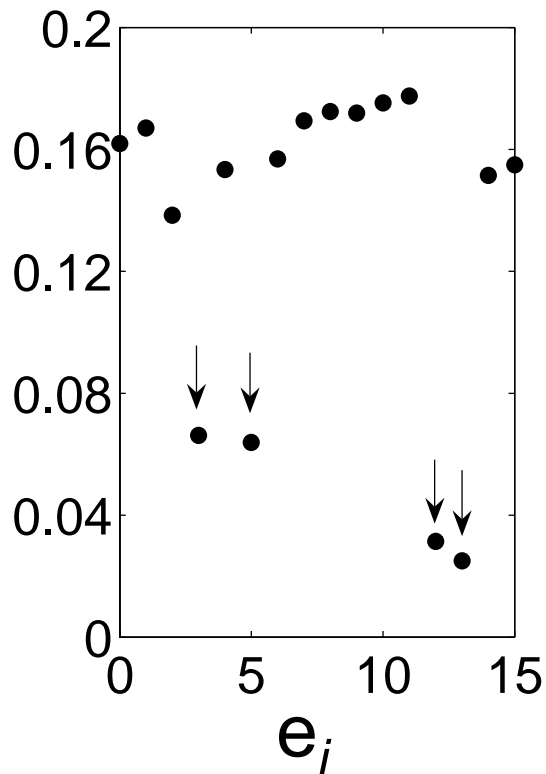
How does this work with real erroneous electrode?



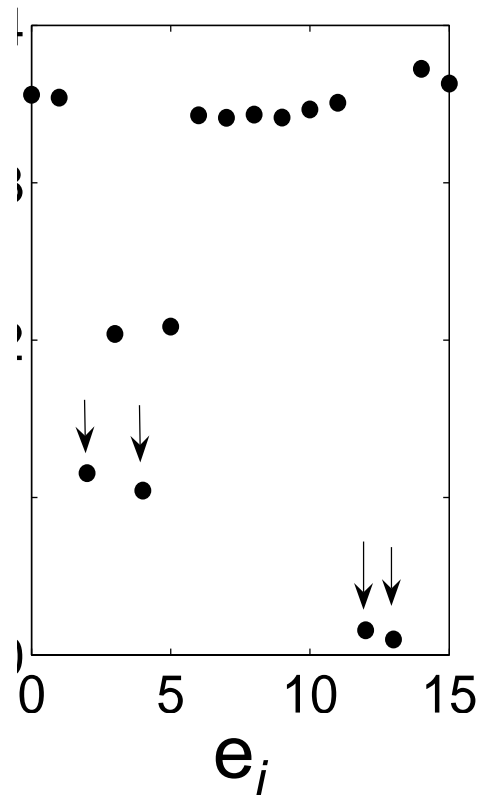
*erroneous electrode

How does this work with real erroneous electrode?

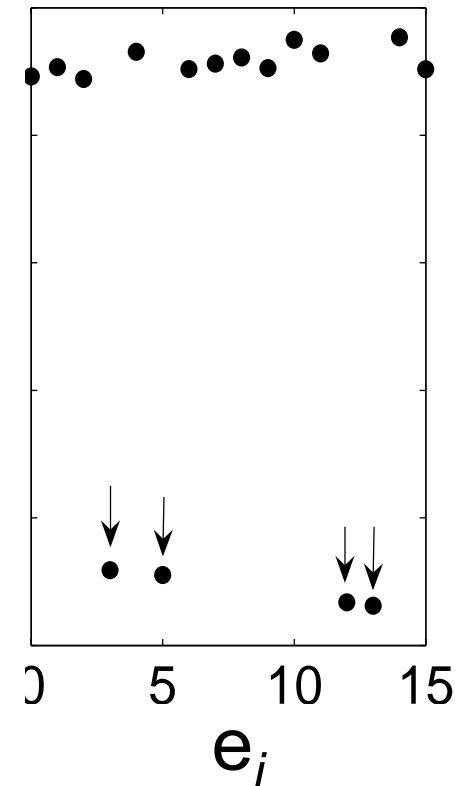
A



B



C



Discussion

- Developed method to detect the presence of single electrode errors in EIT data
- Method is sensitive at SNR < 0dB
- Works well with real data
 - Ability to detect multiple electrode errors with reduced sensitivity
- Method shown to work for 3D EIT using EIDORS 3D

Discussion

- Method extended for detection of multiple erroneous electrodes
 - Tested for two erroneous electrode detection
 - Long computation time
 - Cross validate using a statistical parameter

Publications

■ Three publications:

- Asfaw Y and Adler A (2005) Automatic detection of detached and erroneous electrodes in Electrical Impedance Tomography, *Physiol. Meas.*, IN PRESS
- Asfaw Y and Adler A (2005) Detection of unreliable measurements in multi-sensor devices, IEEE Instrumentation and Measurement Society, Ottawa, Canada, SUBMITTED
- Asfaw Y and Adler A (2004) Automatic detection of detached and erroneous electrodes in Electrical Impedance Tomography, Proceedings of the XII international conference on Electrical BioImpedance and V Electrical Impedance Tomography, Gdansk, Poland, 649-652

AUTOMATIC DETECTION OF DETACHED AND ERRONEOUS ELECTRODES IN ELECTRICAL IMPEDANCE TOMOGRAPHY

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ABSTRACT

Electrical Impedance Tomography (EIT) is an imaging technique which calculates the conductivity distribution within a medium from voltage measurements made at a series of electrodes on the medium's surface. Unfortunately, the electrodes can become detached or poorly connected, such that the measured data cannot be used. This thesis presents an automatic approach to detect such erroneous electrodes via the image reconstruction model. The method calculates an estimate of the data at an electrode, based on the measurements from all other electrodes. In order to detect an erroneous electrode amongst N electrodes, all sets of $N-1$ electrodes are tested, and the set with the best match between measurements and estimate is identified as the one which excludes the erroneous electrode. Tests performed on experimental data for 2D EIT showed similar classification to those made by a trained user. A detection parameter PER is developed, and a detection threshold of -22 ± 2 dB is recommended based analysis of simulated erroneous data. Extension of the method into 3D EIT showed similar results as that of 2D EIT.

Q & A