Accounting for erroneous electrode data in Electrical Impedance Tomography

or, Salvaging EIT Data

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The Problem

- Experimental measurements with EIT quite often show large errors from one electrode
- 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

Measurements: adjacent drive





Our system can't use same 01 12 23 34 45 56 67 70 electrode for current injection and voltage measurement

Measurements = $N \times (N-3)$

Measurements with "bad" electrode



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

One "bad" electrode: Measurements = $(N-4)\times(N-3)$

Possible solution: zero erroneous data

- Set all measurement and injection data on "bad" electrodes to zero
- "Traditional solution" in the sense I've used it. I'm not aware of any formal description

Solution: zero erroneous data

Issues

- Reduces amplitude of contrasts
- Error in reconstructed contrast Position
- Decreases image resolution

Proposed solution: Bayesian Imaging model

- Maximum a posteriori (MAP) models allow incorporation of known constraints into regularized image calculation
- Model electrode errors as a priori large measurement noise on all measurements using affected electrode

Regularized Imaging Model

Linear forward model:

$$z = Hx + n$$

- z measured dynamic signal
- H sensitivity matrix
- x conductivity change image
- n measurement noise

MAP inverse estimate:

$$\hat{\mathbf{x}} = \left(\mathbf{H}^{t}\mathbf{R}_{n}^{-1}\mathbf{H} + \mathbf{R}_{x}^{-1}\right)^{-1}\mathbf{H}^{t}\mathbf{R}_{n}^{-1}\mathbf{z}$$

 $\begin{cases} \hat{\mathbf{x}} & \text{calculated image} \\ \mathbf{R}_n & \text{measurement correlations} \\ \mathbf{R}_r & \text{image element correlations} \end{cases}$

Regularized Imaging Model

Parameters R_x, R_n, represent a priori statistical knowledge of problem

$$\mathbf{R}_{\mathbf{n}} = E[\mathbf{n}^{t}\mathbf{n}] = \begin{bmatrix} \sigma_{1}^{2} & 0 & \cdots \\ 0 & \sigma_{2}^{2} & \\ \vdots & \ddots \end{bmatrix}$$

If a σ² = ∞, then inverse matrix will have 0 in corresponding position



Data simulated with 2D FEM with 1024 elements – not same as inverse model

Simulation results for adjacent drive



Zero Affected Measurements



Bayesian Inverse



Simulation results for opposite drive



Zero Affected Measurements



Bayesian Inverse



Position error vs. radial position



Resolution (psf) vs. radial position



How does this work with real data?

Β



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

"Bad"

Electrode

Discussion

Image Approaches to Electrode Errors

- Set "bad data" to zero
 - Works reasonably well > 25% diameter from electrode
- MAP model
 - □ Works well up to 15% diameter from electrode
 - □ Close to no errors for opposite drive
 - Natural extension of Bayesian prior info
- However, should also try to better understand the causes of electrode errors ...

Accounting for Erroneous electrode data in Electrical Impedance Tomography, Andy Adler (adler@site.uottawa.ca), School of Information Technology and Engineering, University of Ottawa, Ontario, Canada

Abstract

An unfortunate, but not unusual, occurrence in experimental measurements with Electrical Impedance Tomography, is electrodes which become detached or poorly connected, such that the measured data cannot be used. We propose an image reconstruction methodology which allows use of the remaining good measurements. A finite element model of the EIT dynamic imaging forward problem is linearized as z=Hx, where z is the vector change in measurements and x the vector of change in finite element log conductivities. Image reconstruction is represented in terms of a Maximum a Posteriori (MAP) estimate as x=inv(H'*inv(Rn)*H +inv(Rx))*H'*inv(Rn)*z, where () represents the transpose operator, and Rx and Rn represent the a priori estimates of image and measurement noise cross correlations, respectively. Using this formulation, missing electrode data can be naturally modelled as infinite noise on all measurements using the corresponding electrodes. Simulations were conducted of a small contrasting target at different radial positions as a function of the position of the problem electrode. Contrast position error, point spread function, and total image amplitude were calculated. All values are close (±10%) to those calculated without missing electrode data as long as the target was further from the problem electrode than 10% of the medium diameter. When the target was closer than this limit, all error values increased significantly, but the reconstructed image still represented a reasonable "best effort". Application of this technique to experimental data shows similar results. In comparison, simulations were made of the simple approach of setting measurements from problem electrodes to zero. Results show significant errors for targets 25% of the medium diameter from the electrode. The increase in point spread function size above the value for no electrode errors was three times greater for this simple approach than for the MAP estimate.