GREIT: towards a consensus EIT algorithm for lung images

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Abstract **– Recently, electrical impedance tomography (EIT) has begun to see a significant clinical interest for monitoring of ventilated patients. The key capability of EIT is to provide real-time images of the distribution of ventilation in the patient's lungs. However, most clinical and physiological research in lung EIT is done using older and proprietary algorithms; this is an obstacle to interpretation of EIT results because the reconstructed images are not well characterized. To address this issue, we are developing a consensus linear reconstruction algorithm for lung EIT, called GREIT (Graz consensus Reconstruction algorithm for EIT). This algorithm is being developed in three phases: 1) selection of the "ingredients" and evaluation methodology (this paper), 2) evaluation and experience with GREIT variants, and 3) consensus and definition of the GREIT algorithm. Algorithms evaluation criteria are identified to be: a) quantitative output for all positions, b) reconstructed position error (low and uniform), c) resolution (small PSF, uniform, few artefacts), d) good noise performance, e) low sensitivity to electrode and boundary movement, f) good performance on clinical and experimental data. This approach represents the consensus of a large and representative group of experts in EIT algorithm and clinical applications. All software and data to implement and test GREIT will be made available under an open source license which allows free research and commercial use.**

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1 Introduction

Electrical Impedance Tomography (EIT) measures conductivity changes within a body from current stimulation and voltage measurement on the body surface. One of the most promising applications of EIT is for measuring the lungs, since these are large organs which undergo large changes in conductivity during normal functioning. Indeed, lung function measurement was among the first physiological applications of this technology. (Barber and Brown 1984). While there are several medical imaging and instrumentation technologies to measure ventilation, EIT is unique in that it is able to non-invasively and continuously monitor the distribution of ventilation. Based on these advantages, there is significant interest in EIT to monitor patients with respiratory compromise.

One limitation is that most clinical and physiological research on lung EIT is being done using proprietary variants of older image reconstruction algorithms, such as the backprojection algorithm as implemented in the Sheffield (Brown and Seagar, 1987) or Göttingen (Hahn *et al*, 2001) EIT systems. This is an obstacle to clinical use of EIT because: 1) it is difficult to determine whether a given image feature is physiological or an artefact, 2) comparison of regional ventilation is impacted by algorithm spatial non-uniformity and position errors, and 3) multi-centre studies are not possible without a common imaging algorithm. Many approaches to reconstruct EIT images have been proposed, however, it is not easy to compare them, because complete implementation detail are not available. However, there is general consensus amongst experts in EIT image processing of the "ingredients" that should be part of a robust and high performance algorithm.

We plan to address this problem, and to develop a consensus linear reconstruction algorithm for EIT images of the chest. This algorithm is named GREIT, the "Graz consensus Reconstruction algorithm for EIT", since early discussions took place at the 2007 ICEBI conference in Graz, Austria. Our aim is to develop a standard which has broad agreement from experts in the mathematical, engineering, physiological, and clinical EIT communities. This paper is the first step in developing GREIT: we define the selection of "ingredients" in the algorithm and the evaluation methodology. Subsequently, we plan to evaluate and gain experience with GREIT "recipes" based on variants of the ingredients. This will lead to consensus and definition of the GREIT algorithm.

The current work is limited to the reconstruction al-

gorithm. We do not propose calibration tests, data formats or phantoms, standards for image interpretation or EIT based lung parameters; we do not feel there is sufficient experience yet to reach consensus in these areas. It is important to clarify that there is no financial goal to development of this algorithm, and all developed algorithms, software models and simulation and experimental test data used in this algorithm will been made available as part of the open source EIDORS distribution (Adler and Lionheart, 2006).

The goals identified for GREIT are for:

- single and double ring electrode configurations with Sheffield-type EIT systems, using adjacent current injection and measurement.
- linear (real-time) reconstruction of a 2D conductivity change image, based on a 3D forward model
- quantitative reconstructions: given an input in transfer impedance (Ω) units, the output is in impedivity change ($\Omega \cdot m$)
- settings for all parameters: any tunable parameters must have assigned values in the recommended algorithm.
- published reconstruction matrices for a 32×32 pixel array for a single ring of 16, 12 and 8 electrodes, for the shapes: a) neonate chests, b) adult chests (for perhaps several body shapes), and c) cylindrical tank phantoms. For other shapes and electrode configurations, reconstruction matrices may be calculated from the provided source code.
- all software and data to implement and test GREIT to be made available under an open source license which allows royalty free use in both research and commercial applications.

In the remainder of this paper, we clarify two aspects of GREIT: 1) the "ingredients" for the algorithm, and 2) the evaluation methodology.

2 "Ingredients"

There is general agreement that the algorithm features described in this section are the most suitable for linear EIT reconstruction. However, the best selections for the details of each feature are subject to discussion and experimentation. For example, we agree on using regularized image reconstruction, but are not yet certain of the best reconstruction matrix prior. For this reason, we use the metaphor "ingredients" and "recipe".

2.1 Dual Models

A dual reconstruction model uses a fine finite element model (FEM) to implement the forward solution (voltages at electrodes), and a coarse mesh for the inverse solution. For GREIT, the forward model is a 3D FEM with mesh refinement near the electrodes, and the reconstruction model is a square pixel grid (Fig. 1). Given a forward model, F, which calculates a voltage measurement vector, $\mathbf{v}$, from a forward (fine) model conductivity element vector, σ_f, we have $\mathbf{v} = F(\sigma_f)$. The reconstruction (coarse) model is defined on square elements σ_r related by a coarse to fine projection matrix $\mathbf{P}$, where $\sigma_f = \mathbf{P}\sigma_r$.

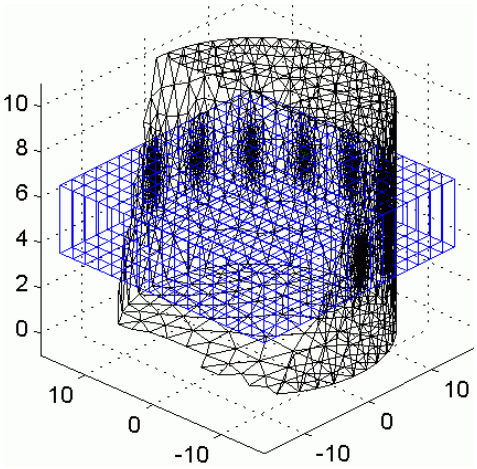

Figure 1: Dual model example. *black:* a cut away view of a cylindrical 3D FEM (fine) forward model (with electrode refinement), *blue:* (coarse) reconstruction model with 2D square pixels of defined height.

2.2 Rasterized Output Image with Units

GREIT output images will be parametrized onto a 2D grid with square pixels (Fig. 2). This differs from many EIT reconstruction algorithms which reconstruct to an arbitrary FEM triangularization. Square pixels are chosen because it allows easier display and analysis of images, and because the resolution limits of EIT are easier to communicate this way. Non-circular reconstruction geometries (for adult and neonate chests) will be represented onto the same 2D grid.

GREIT output images will be in impedivity change units ($\Omega \cdot m$) given input in transfer impedance units (*measured V/stimulation* $I = \Omega$). Assigning units this way requires one length parameter to be measured from the patient. For GREIT, this is the lateral width of the chest (or the diameter of the cylindrical tank).

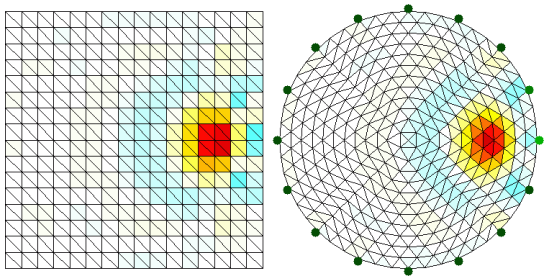

Figure 2: *Left*: Reconstructed image onto 16×16 pixel array using dual model (triangular divisions of pixels is an artefact of EIDORS representation). Precalculated GREIT models will use 32×32 pixel arrays. *Right*: Reconstructed image using a single FEM reconstruction model.

2.3 Regularized GN Reconstruction.

Gauss-Newton (GN) reconstruction seeks a solution $\hat{\mathbf{x}}$

which minimizes

$$\|\mathbf{y} - \mathbf{J}\mathbf{x}\|^2_{\mathbf{W}} + \lambda^2 \|\mathbf{x} - \mathbf{x}_0\|^2_{\mathbf{R}}.$$

$\mathbf{y} = \mathbf{v}^{(b)} - \mathbf{v}^{(a)}$ is the vector of time difference measurements (between times (a) and (b)). The choice of times (a) and (b) depend on the measurement protocol, and often (a) is an average measurement at a time when the patient lung status is stable (ie end-expiration). The selection of times (a) and (b) is out of scope for GREIT. The use of normalized difference measurements ($[\mathbf{y}]_i = [\mathbf{v}^{(b)} - \mathbf{v}^{(a)}]_i / [\mathbf{v}^{(a)}]_i$), has the advantage of compensating for differences between measurement channels, but makes it difficult to assign units to $\hat{\mathbf{x}}$. Both difference and normalized difference measurement schemes will be considered for GREIT. $\mathbf{x} = f(\sigma_r^{(b)}) - f(\sigma_r^{(a)})$ is the (parametrized) conductivity change vector on the inverse model. The parametrization will be chosen to maximize the linear range of the solution; some possible parametrization functions $f(\cdot)$ are logarithmic and linear.

$\mathbf{J}$ is the Jacobian matrix calculated from the fine model and projected on the inverse model, such that

$$[\mathbf{J}]_{ij} = \sum_k \frac{\partial [\mathbf{y}]_i}{\partial [f(\sigma_f) - f(\sigma_{bkg})]_k} \mathbf{P}_{kj},$$

where σ_{bkg} is the background conductivity distribution in the body about which conductivity changes take place. Precalculated GREIT models will assume homogeneous σ_{bkg}, since this assumption is well understood, even though it is not physiologically realistic in the chest. Efficient techniques to compute $\mathbf{J}$ are out of scope for GREIT, since the calculation of the Jacobian is off-line.

GN reconstruction uses the 2-norm ($\|\cdot\|^2$), since this makes image reconstruction linear, and allows precalculation of a reconstruction matrix. Based on this matrix, real-time EIT image reconstruction is implemented using matrix multiplication. It may be possible to increase the computational efficiency of reconstruction using scaled integer multiplication, and with use of hardware which supports parallel computation; however, such implementation details are out of scope for GREIT.

2.4 Image Prior with Spatial Correlations

$\mathbf{W}$ and $\mathbf{R}$ represent the estimates of inverse covariances of the data noise ($\mathbf{\Sigma}_n$) and conductivity change, or image prior ($\mathbf{\Sigma}_x$), such that $\sigma_n^2 \mathbf{W}^{-1} = \mathbf{\Sigma}_n$ and $\sigma_x^2 \mathbf{R}^{-1} = \mathbf{\Sigma}_x$. Here $\lambda = \sigma_n / \sigma_x$, is the regularization *hyperparameter*. Precalculated GREIT models assume uniform uncorrelated Gaussian measurement noise, and thus $\mathbf{W} = \mathbf{I}$, the identity matrix.

Many different approaches have been used to select the image prior $\mathbf{R}$, including scaled diagonal matrices and various forms of spatial high pass filters including discrete Laplacian and Gaussian high pass filters. The choice of $\mathbf{R}$ has several subtle but important implications on reconstructed images, as illustrated in Fig. 3. We identify these undesirable image features as: a) *ringing:* the presence of opposite polarity regions surrounding a reconstructed target (which may be incorrectly interpreted as physiological), b) *position error:* incorrect positioning of a reconstructed target, and c) *blurring:* increased area of a reconstructed target. Clearly, there are compromises to be made between optimizing each feature, such as for *ringing* and *blurring*. Additionally, the uniformity of a feature with spatial position is more important than low average feature errors.

For the evaluation process for GREIT, various proposed reconstruction matrices (and combinations of these matrices) will be tested against the image features. Matrices will be defined directly on the inverse (coarse) grid (and not the forward model).

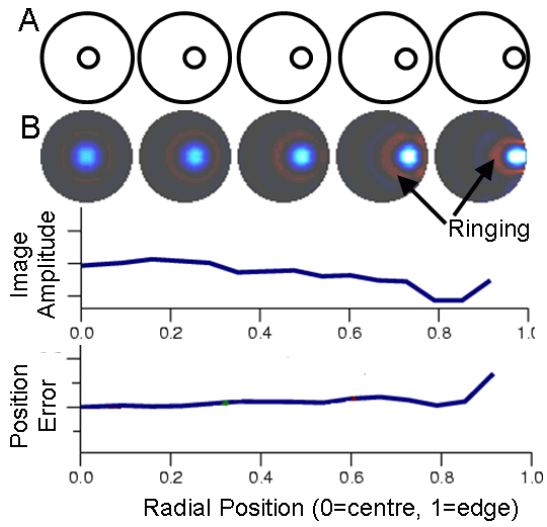

Figure 3: Illustration of several undesirable features affected by the choice of $\mathbf{R}$. *A*: Ground truth simulations of a small non-conductive target. *B*: Reconstructed images. The lower graphs show average image amplitude and position error as a function of simulated radial position.

2.5 Hyperparameter selection method

In many studies, the EIT hyperparameter, λ, is selected manually based on heuristic criteria, probably because automatic techniques, such as the L-curve, work poorly on the EIT problem (Graham and Adler, 2006). Furthermore, these methods select the best λ for each image, rather than for the system configuration.

It is essential that the algorithm define the hyperparameter selection method, as this is necessary for reliable clinical interpretation. Unfortunately, there is little consensus on the best way to choose λ, and thus exploration of this issue will be a major part of the GREIT evaluation process. The criteria for selection are: λ must depend on the EIT equipment (and noise performance) and the expected EIT signal level (of thoracic EIT measurements). We propose to define calibration protocols that may be performed by the equipment maker (or as part of installation) from which an optimal λ may be chosen.

2.6 Electrode Movement and Model Inaccuracy Compensation

Movement of electrodes due to breathing and posture change contributes artefacts to EIT images, which appear as image degradation near the boundary, and a broad artefact that changes image amplitude. Some recent work to correct for movement (Soleimani *et al*, 2006) and general model inaccuracies (Kaipio and Somersalo, 2007) show promising results and may be represented in a linear GN reconstruction, by modifying the data noise model ($\mathbf{\Sigma}_n$) to include both measurement noise and "noise" due to geometrical inaccuracies. Given parameters, $\mathbf{x}_g$, which express electrode movement and other model inaccuracies, we create $\mathbf{\Sigma}_n = \sigma_n^2 \mathbf{W}^{-1} + \mathbf{J}_g \mathbf{R}_g \mathbf{J}_g^t$, where $\mathbf{J}_g$ is the Jacobian of model parameters and $\mathbf{R}_g$ represents the prior covariance between parameters.

Since such techniques are relatively new, they are less well understood than the "ingredients" discussed previously. During the evaluation these techniques may demonstrate their value, or not.

2.7 Temporal reconstruction

Typically, a frame of EIT data is reconstructed assuming that all measurements were made at the same instant. However, EIT systems make sequential measurements for each current pattern. It is possible to take this time difference into account to calculate more accurate EIT images of rapid conductivity changes, such as those due to perfusion or high frequency oscillatory ventilation. This approach may be generalized as a "temporal" image reconstruction (Adler *et al*, 2007) in which measurements from several nearby frames are used. Such an approach may be used to achieve improved noise performance.

3 Evaluation: model data

This paper also defines the evaluation strategy against which GREIT algorithms candidates will be evaluated. Unfortunately, this paper does not provide space to algorithmically define how each evaluation parameter is calculated; instead, the general criteria are listed:

3.1 Amplitude Response

- ◦ output image amplitude is correct
- ◦ the amplitude response is uniform for all radial positions.

3.2 Position Error

- ◦ low average position error
- ◦ uniform position error with radial position

3.3 Resolution

- ◦ small average PSF (point spread function) size
- ◦ uniform PSF size with radial position
- ◦ no (or very little) overshoot in the PSF
- ◦ regular shape (round or oval) PSF (backprojection, with its streaks, does badly here)

3.4 Noise Performance

- ◦ low average noise amplification

3.5 Boundary Shape and Electrode Sensitivity

- ◦ low sensitivity to electrode movement
- ◦ low sensitivity to boundary distortions (with breathing and posture change)

3.6 Performance on *in vivo* data

- ◦ good performance on animal and clinical experimental data. This includes performance monitoring rapid changes with ventilation and perfusion, and slow changes over hours and days of monitoring. Monitoring of slow changes means that GREIT will need to compensate for drift in hardware and electrode behaviour.

The most difficult evaluation criteria will be the last: "experimental data performance" (Faes *et al.* 2005). Our approach is based on a database of experimental EIT data from clinical research groups at Harvard University and the Universities of Kiel and Göttingen. Some of these EIT data sets were measured with simultaneous CT images, which will facilitate developing validation tests of EIT algorithm output. Since the *in vivo* evaluation strategy is still somewhat unclear, we plan to develop these criteria Development of appropriate evaluation criterion as part of the GREIT development process.

4 Discussion

This paper clarifies two aspects of the GREIT algorithm: the technical "ingredients" and the evaluation methodology. Based on this description, we aim to select the best "recipe" for GREIT algorithm as follows: First, algorithm candidates will be built and made available for testing on simulation and experimental data (time frame June – Sept, 2008). Based on this experience, a consensus will be developed and the GREIT algorithm will be defined and published. We anticipate several benefits for this work. It will allow detailed interpretation of EIT images in terms of known algorithm performance, providing a thoroughly characterized baseline against which clinical measurements and newer EIT work may be compared.

References

Adler A and Lionheart WRB 2006 "Uses and abuses of EIDORS: An extensible software base for EIT" *Physiol Meas* 27 S25–S42

Adler A Dai T Lionheart WRB 2007 "Temporal Image Reconstruction in Electrical Impedance Tomography" *Physiol. Meas.*, 28 S1–S11

Barber DC and Brown BH 1984 "Applied potential tomography", *J Phys E: Sci Instrum* 17 723–733

Brown BH and Seagar AD 1987 "The Sheffield data collection system" *Clin Phys Physiol Meas* 8(Suppl A) 91–97

Cheney M Isaacson D Newell JC Simske S and Goble JC 1990 "NOSER: An algorithm for solving the inverse conductivity problem" *J Imaging Syst Technol* 2 66–75

Faes TJC van Genderingen HR and Vonk Noordegraaf A 2006 "Some reflections on the EIT Conference (London UK 22–24 June 2005)" *Physiol. Meas.* 27

Graham B, Adler A 2006 "Objective selection of the hyperparameter for EIT" *Physiol. Meas.* 27 S65-S79

Hahn G Theil F Dudykevych T Frerichs I Gersing E and Hellige G 2001 "Quantitative evaluation of the performance of different electrical tomography devices" *Biomed Tech (Berlin)* 46 91–95

Kaipio J and Somersalo E 2007 "Statistical inverse problems: Discretization, model reduction and inverse crimes" *J Comput Appl Math* 198 493–504

Soleimani M Gómez-Laberge C and Adler A 2006 "Imaging of conductivity changes and electrode movement in EIT" *Physiol. Meas.* 27 S103–S113