The importance of shape: thorax models for GREIT

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Abstract: Time difference EIT is useful if the positions of the electrodes are poorly known, as it allows image reconstruction of reasonable quality even when, as is often the case, EIT data from the thorax is reconstructed onto a 2D circular model. However, even though inaccurate models may (and often are) used, there is a significant penalty in terms of reconstructed image accuracy. We focus on developments of the GREIT EIT image reconstruction algorithm. This algorithm represents a novel, optimization based approach to linear EIT reconstruction. So far, results have only been shown for circular thorax geometries, which precludes meaningful definition of conductivity contrast in the models. In this paper, we develop and validate an implementation of the GREIT algorithm for arbitrary thorax shapes. The results are validated on EIT data with simultaneous CT reference data. Results show significant improvements in the anatomical accuracy of reconstructed EIT images, in particular when physiological lung conductivity contrast is taken into account.

1 Introduction

Electrical Impedance Tomography (EIT) is an attractive method for monitoring patients during mechanical ventilation, because it can provide a non-invasive continuous image of pulmonary impedance which indicates the distribution of ventilation. Based on these advantages, there is significant interest in EIT to monitor patients with respiratory compromise.

One limitation is that much clinical and physiological research in lung EIT is done using older and proprietary algorithms; this is an obstacle to interpretation of EIT images because the reconstructed images are not well characterized. Many of these EIT imaging algorithms are based on circular and 2D models of the medium sensitivity and assume homogenous conductivity distribution. Since thoracic EIT data are typically reconstructed with time difference (TD-EIT) algorithms the effect of these limitations are less evident, since TD-EIT is less sensitive to the exact configuration and geometry of the electrodes. However, models with incorrect shape information do result in significant inaccuracies and artefacts in images.

A recent systematic approach to choice of EIT reconstruction for thoracic TD-EIT is a reconstruction algorithm called GREIT (Graz consensus Reconstruction algorithm for EIT)[1]. One limitation of [1] is that it did not clarify the details of how to implement GREIT for arbitrary geometry body shapes. Instead, results were shown for a circular model in order to allow better comparison to the Sheffield backprojection. In this paper we: 1) develop the formulation of GREIT for arbitrary model geometry, and 2) evaluate the effect of using accurate thorax geometries and lung conductivity contrasts using EIT data from pigs with simultaneous CT.

GREIT Framework

The framework for the GREIT algorithm consists of: 1) detailed finite element models of a representative adult and neonatal thorax; 2) consensus on the performance figures of merit for EIT image reconstruction; and 3) a systematic approach to optimize a linear reconstruction matrix to desired performance measures. Consensus figures of merit, in order of importance, are: a) uniform amplitude response, b) small and uniform position error, c) small ringing artefacts, d) uniform resolution, e) limited shape deformation, and f) high resolution. GREIT is designed to calculate a linear reconstruction matrix, $\mathbf{R}$ which performs well against the figures of merit, while maintaining small noise amplification and small sensitivity to electrode and boundary movement.

We represent linear EIT image reconstruction as a matrix, $\mathbf{R} \in \mathbb{R}^{N\times M}$ which maps measurements $\mathbf{y}$ to a reconstructed image $\mathbf{x}$:

$$\mathbf{x} = \mathbf{R}\mathbf{y} \tag{1}$$

where a frame of TD (or normalized TD) EIT data, $\mathbf{y} = \mathbf{v} - \mathbf{v}_r \in \mathbb{R}^M$ is used to reconstruct an image $\mathbf{x} \in \mathbb{R}^N$. The current EIT data frame is $\mathbf{v}$ which is compared to a reference data frame $\mathbf{v}_r$ which is typically averaged over times when the conductivity is stable. Images are represented on N pixel image elements.

The GREIT framework from which the reconstruction matrix, $\mathbf{R}$ is calculated, definition of a forward model, a noise model, and desired performance metrics are illustrated in fig. 1. The *forward* model allows calculation of EIT measurement data $\mathbf{y}_k$ from a conductivity change distribution $\mathbf{x}_k$. The model represents the details of the body geometry, the electrode size and contact impedance, and the reference conductivity around which conductivity changes occur. The *noise* model allows calculation of representative noise (electronic measurement noise and electrode movement artefacts) samples in EIT measurements. Based on the performance metrics defined above, we create a training set of desired images, $\tilde{\mathbf{x}}_k$, centred on each target, but with a blurring corresponding to figures of merit, as illustrated in fig. 1.

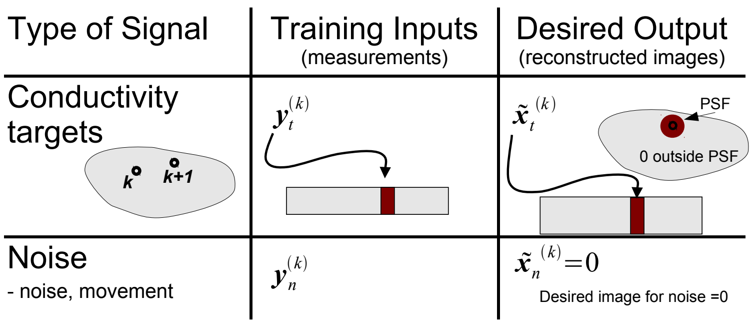

Figure 1: Illustration of signals and training data. Rectangles represents a matrix where column (k) represents a training sample, and the circle represents the corresponding desired image pattern.

Based on the *forward model*, *noise model*, and *desired performance metrics*, the GREIT reconstruction matrix $\mathbf{R}$ which best fits the requirements may be expressed as minimization of the norm

$$\epsilon^2 = \sum_k \|\tilde{\mathbf{x}}_k - \mathbf{R}\mathbf{y}_k\|^2_{\mathbf{W}_k} \tag{2}$$

where $\mathbf{W}_k$ is a diagonal weighting matrix for each sample.

2 GREIT for arbitrary models

In this section, we elaborate on how GREIT is adapted to work with arbitrary models of thorax geometry. 1) The boundary shape, lung tissue outline and electrode positions (if available) are extracted from a CT, CBCT or MRI transverse slice of the thorax (c.f. fig. 2). 2) A 3D FEM for the forward model is built using Netgen [2] by extruding the extracted 2D outlines of the boundary and (optionally) the lungs. The mesh is refined around the electrodes. 3) The forward model is built using either homogenous conductivity or a contrast in the lung region (and others, if available). 4) To calculate the GREIT reconstruction matrix $\mathbf{R}$, the desired solutions for a set of small (less than 5% diameter of the model) contrasting targets are calculated using the forward model and taking into account the desired figures of merit. In contrast to the original formulation in [1], we use uniform, rather than random, distribution of targets covering the entire image (a minimum of 500 are recommended). 5) The GREIT reconstruction matrix is calculated according to eq. 2 with an initial estimate of the noise weighting $\mathbf{W}$. 6) The final value of $\mathbf{W}$ (and the reconstruction matrix $\mathbf{R}$) that results in the desired noise figure (currently 0.5, after [1]) is found iteratively using the simplex search method [3].

This procedure can be used with arbitrary stimulation pattern and number of electrodes, and can produce images beyond the 32-by-32 pixel resolution.

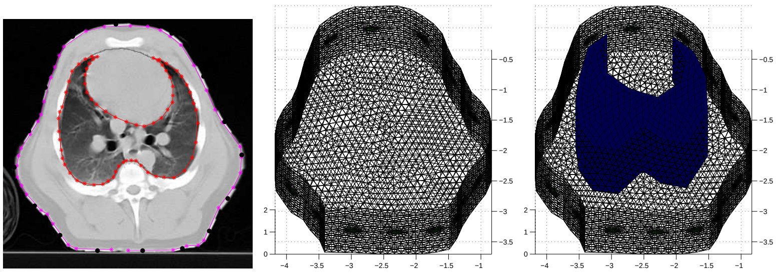

Figure 2: Thorax CT (manually segmented) and the Finite Element Models used.

3 Results

The proposed algorithm was applied to a dataset of EIT and CT data acquired in a 23 kg anaesthesized swine during conventional mechanical ventilation at the University of Mainz under local ethical approval. The boundary shape, lung outline and positions of the electrodes were extracted from a CT slice in the electrode plane and used to build two conforming forward models with a) homogenous conductivity and b) conductivity contrast in the lung region (fig. 2). A 30 s period of ventilation was taken as reference for the reconstruction of two single frames of EIT data corresponding to inspiration and expiration in one breathing cycle with a) the Sheffield backprojection algorithm, b) the original GREIT algorithm using homogeneous circular model [1] and the new algorithm with c) homogenous conductivity distribution as well as lung-to-background conductivity ratios of d) 0.75, e) 0.50 and f) 0.25 (roughly physiological for soft tissue and lung at expiration [4]). The results are presented in fig. 3 as the difference between inspiration and expiration.

Comparing the three reconstructions on homogenous models, the results show that using the correct geometry greatly reduces both the streak and the centre artefacts present in

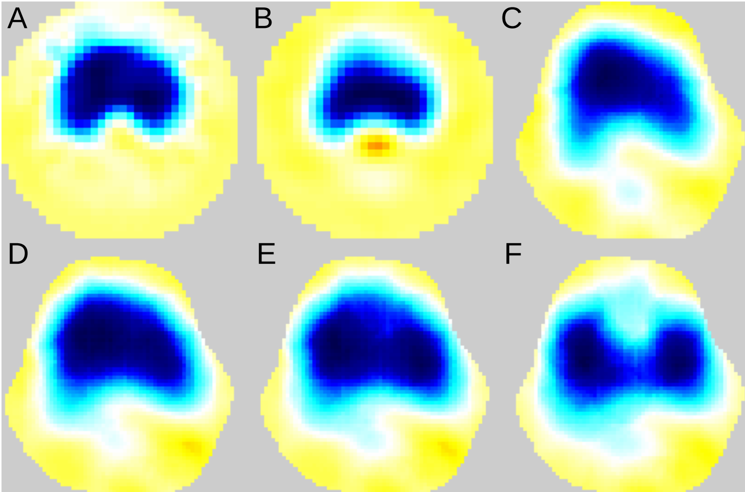

Figure 3: Reconstructed TD-EIT images of ventilation (inspiration minus expiration). *A:* Sheffield backprojection (circular model); *B:* GREIT using circular homogeneous model[1]; *C:* GREIT using conforming FEM model from CT (fig. 2) with homogeneous conductivity; and *D–F:* GREIT using conforming FEM model with lung-to-background conductivity ratio of 0.75, 0.50 and 0.25, respectively. All images represent the same measurement data and are normalised to the same range.

backprojection and GREIT, respectively, and leads to more anatomical shape and position of the lungs (c.f. fig. 3*A–C*). Images in fig. 3*D–F* further demonstrate the increasing ability of the GREIT framework to separate the lungs when provided with more realistic conductivity distribution.

4 Discussion

Our motivation is to develop reconstruction algorithms that provide anatomically correct, and thus more readily interpretable, EIT images. The preliminary results presented here suggest that correct boundary shape and realistic conductivity distribution greatly improve the image quality and are major steps towards achieving this goal. Further research is necessary to establish just how well the boundary shape must be matched to obtain good results and what the effects of changing conductivity distribution are.

References

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