A GREIT-type linear reconstruction algorithm for EIT using eigenimages

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Abstract. Reconstruction in electrical impedance tomography (EIT) is a nonlinear, ill-posed inverse problem. Based on point-shaped training and evaluation data, the "Graz consensus Reconstruction algorithm for EIT" (GREIT) constitutes a universal, homogenous method. While this is a very reasonable approach to the general problem, we ask the question if an optimized reconstruction method for a specific application of EIT, i.e. thoracic imaging, can be found. Instead of point-shaped training data we propose to use spatially extended training data consisting of eigenimages. To evaluate the quality of reconstruction of the proposed approach, figures of merit (FOMs) derived from the ones used in GREIT are developed. For the application of thoracic imaging, lung-shapes were segmented from a publicly available CT-database (www.dir-lab.com) and used to calculate the novel FOMs. With those, the general feasibility of using eigenimages is demonstrated and compared to the standard approach. In addition, it is shown that by using different sets of training data, the creation of an individually optimized linear method of reconstruction is possible.

1. Introduction

Electrical Impedance Tomography (EIT) seeks to reconstruct the electrical impedance distribution inside a body from measurements on its surface. It has proven to be a valuable tool in various areas, including medical science [1, 2]. One great advantage of EIT is its high temporal resolution with up to 50 frames per second, a drawback of this technology is it relatively poor spatial resolution. This is due to the fact that the problem of reconstruction, i.e. the calculation of the underlying impedance distribution from the measured voltage data, is ill-posed. As such, it is very sensitive to noise and can only be solved incorporating a-priori knowledge. Several iterative [3, 4] and non-iterative reconstruction algorithms exist. While the former show advantageous behavior in terms of reconstruction non-smooth impedance distributions, they are expensive from a computational point of view. Algorithms of the latter type have the advantage of being computationally inexpensive and can be calculated on-line, supporting EITs high frame rate. The first algorithm of this type is the "Sheffield Backprojection" algorithm. Though its basic assumptions are borrowed from Computed Tomography (CT) and hold only very limited in EIT, it showed reasonable results and was widely used in the clinical and experimental EIT community. More rigorous approaches are based on the regularized inversion of the forward-problem, i.e. the calculation of resulting voltage data from the known impedance distribution. The "Newton’s One Step Error Reconstructor (NOSER)" algorithm [5] inverts a well-posed modification of the Jacobian; other regularization methods demand the solution to be smooth.
(Laplace) or small (Tikhonov). An implementation of the different algorithms can be found in the EIDORS-package [6].

A recent development in the category of non-iterative reconstruction algorithms is the "Graz consensus Reconstruction algorithm for EIT" (GREIT) [7]. Here, instead of directly inverting the forward problem, a set of impedance distributions and the associated voltage data are used to learn a linear reconstruction matrix, i.e. indirectly inverting the forward problem. Special attention needs to be given to the handling of noise by incorporating it as virtual measurements. Several metrics are implemented to assess the quality of the GREIT-algorithm and showed its superior performance and homogeneity compared to other linear reconstruction algorithms.

The training data used in GREIT consists of point-shaped changes in the homogenous background impedance. If we assume the impedance-space to be discretized, we can consider these changes in impedance as a set of unit vectors. As such, they form an orthonormal set that spans the impedance-space. This renders the training data neutral, as they are equally distributed through the whole impedance-space and give no advantage to a specific location or shape. On the other hand, this choice of training data is an arbitrary one with respect to real world medical applications, where the observed impedance distribution will likely be spatially extended and not point-shaped. Due to the ill-posed non-linear nature of the problem, it is reasonable to assume that the choice of an application specific set of training data will result in an application specific improvement of the quality of reconstruction. To assess this, the following steps were undertaken in this work: Section 2.1 Definition of a realistic test data set & FOMs, Section 2.2 Development of a modular framework, Section 2.3 Finding of realistic training data.

2. Materials & Methods
2.1. Realistic Test Data Set & FOMs
As a potential area of application, pulmonary EIT is chosen. To assess the quality of the reconstruction algorithm objectively, a novel shape-based evaluation scheme is created. On the one hand, a point-based evaluation method as used in GREIT is likely to favor a reconstruction algorithm that was trained using point-shaped training data. At the same time, as argued above, the occurrence of point-shaped impedance distributions is not a realistic scenario in pulmonary EIT applications. Thus, the algorithms real-world performance may not be evaluated objectively. To counter this, an evaluation set of lung-shapes was created from a publicly available set of human thorax CT scans (www.dir-lab.com, [8]). The database consists of 4DCT scans of 10 patients, from which a total of 5518 lung shapes were segmented automatically and rescaled to 32 by 32 pixels using a custom algorithm. Figure 1 shows a selection of 60 shapes, sorted by size. The extreme changes in size origin from the different position of the transversal slices and the differently sized patients.

Since the evaluation data is not of point-shaped nature, the FOMs defined in [7] need to be adapted:

![Figure 1. Examples of automatically segmented lung shapes from the 4DCT-database available at www.dir-lab.com, sorted by area.](image-url)
Table 1. Novel FOMs, their correspondent in [7] and description.

| Novel FOM          | Similar to       | Description                                                                 |
|--------------------|------------------|-----------------------------------------------------------------------------|
| Widening           | Resolution       | Ratio of area of reconstructed to test shape (mean)                         |
| Overshoot          | Ringing          | Ration of neg. to pos. signal in reconstructed image (mean)                 |
| Distortion         | Shape            | Absolute difference of reconstructed shape and original shape over area of original shape (mean) |
|                    | Deformation      |                                                                             |
| Dislocation        | Position         | Euclidian distance of reconstructed shape to true position of test data (mean, relative to diameter of background) |
|                    | Error            |                                                                             |
| Area/Impedance     | Amplitude        | Quotient of size of test shape and sum of impedances in reconstructed image (standard deviation (std) over mean) |
| Ratio              | Response         |                                                                             |

2.2. Modular Framework

The algorithm is implemented using MATLAB and the EIDORS framework. The training data is defined on the 32 x 32 pixel impedance-image-space. From this, an interpolation to a 2D FEM-mesh is done, which in turn allows the calculation of the resulting voltage vectors. These sets of impedance-images are spatially filtered and with the voltage vectors used to calculate the reconstruction matrix. A noise figure optimization as described in [7] is implemented, for all calculations a noise figure of 0.5 was chosen.

2.3. Training Data

GREIT-PT In order to compare the approach to the GREIT-algorithm, a set of point-shaped training data was created. Here, the conductivity of one of the 1024 pixels is increased against the background. Since only changes inside a circular region are considered, the resulting dataset consists of 748 impedance-images.

GREIT-SVD-GT To create the non-point-shaped training data, the singular value decomposition (SVD) is used on the 5518 lung-shape test data. This yields to a set of eigenimages, which also form an orthonormal set. Since the number of linear independent voltage measurements is limited to 104 per frame when using a configuration of 16 electrodes, it is sufficient to use the first 104 eigenimages.

GREIT-SVD-DR As a second source of spatially extended training data, the same approach was used on a set of 4800 frames from a pulmonary EIT sequence. These frames were acquired in an animal trial using the Dräger EIT Evaluation Kit 2 and the proprietary method of reconstruction. Thus, they represent a set of training data completely independent of the test data.

An overview of the respective first 20 eigenimages can be found in Figure 2.

Figure 2. First 20 eigenimages of the test data set (top row, GREIT-SVD-GT) and the pulmonary EIT sequence (bottom row, GREIT-SVD-DR).
Table 2. Comparison of GREIT-PT, GREIT-SVD-GT and GREIT-SVD-DR using the novel FOMs (less is better). Values printed boldly denote the optimum.

| FOM                              | GREIT-PT | GREIT-SVD-GT | GREIT-SVD-DR |
|----------------------------------|----------|--------------|--------------|
| Widening [area ratio]            | 1.8589   | 1.4929       | 1.7961       |
| Overshoot [impedance ratio]      | 0.0038   | 0.0015       | 0.0063       |
| Distortion [area ratio]          | 1.8595   | 1.4958       | 1.7970       |
| Dislocation [distance ratio]     | 0.0257   | 0.0198       | 0.0246       |
| Area/Impedance Ratio [std/mean]  | 0.1219   | 0.1350       | 0.1108       |

3. Results
In Table 2, a comparison of the three different GREIT-type algorithms can be found. For most FOMs, using eigenimages calculated from the test data yield the best results. In addition, using spatially extended data that is completely independent of the test data also leads to an improvement in some FOMs. It is interesting to observe that especially the Area/Impedance Ratio seems to benefit from using the GREIT-SVD-DR training data set.

4. Conclusion & Future Work
Firstly, the general feasibility of using spatially extended, orthonormal training data can be deduced. In addition, it can be stated that a-priori information about the morphology of the impedance distribution to be reconstructed can be incorporated into a GREIT-type algorithm by the use of eigenimages. Interestingly, the Area/Impedance Ratio shows the best results when neither point-shaped nor the decomposed evaluation data but a completely independent training data set is used. One explanation could be found when examining Figure 2: The eigenimages used for GREIT-SVD-GT show sharp edges as one finds in point-shaped training data. The ones used for GREIT-SVD-DR, however, show a much smoother behavior. Thus, smoothness of the training data might be an important factor when the Area/Impedance Ratio is to be optimized.

While the proposed FOMs suggest an increased quality of reconstruction for a specific application, the practical value of this approach has yet to be proven. This could be achieved by retrospectively re-evaluating animal trials using the proposed method of reconstruction. In addition, an extension of the approach to a 2.5D-FEM-model as well as a full integration into the EIDORS/GREIT framework seems reasonable.

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