An efficient transport back-transport framework for EIT

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Abstract: Implementation of efficient methods to handle calculations in EIT is a key issue to address 3D electrical property reconstructions. Following a transport back-transport method, we develop in this work an adjoint approach and define explicit forward and back-projection operators. It allows reducing the size of matrices involved in reconstruction. This framework has been tested on experimental data acquired in vitro on a saline phantom.

1 Introduction

Forward problem solution and sensitivity computations are the fundamentals of Electrical Impedance Tomography (EIT) [1]. Standard approach is to use Finite Element Methods (FEM) to derive both admittance matrix and Jacobian from an elemental discretization of conductivity. Calculation parallelization [2] and deduction of nodal Jacobian [3] offer ways to enhance calculus efficiency.

In most EIT systems, the same measurement configuration is used per injection configuration. Then, following a transport back-transport method [4], we explicitly define forward and back-projection operators from potential gradients. It allows using inversion algorithms without explicit Jacobian assembly. Matrix size involved in reconstruction is proportional to the number of electrodes E instead of the number of measurements.

2 Methods

We elaborate our framework supposing the electric potential $\mathbf{v} \in \mathbb{R}^{N_n}$ linear per element and considering a piecewise constant conductivity discretization $\boldsymbol{\sigma} \in \mathbb{R}^{N_e}$.

2.1 Sensitivity calculations, adjoint framework

Classical estimation of Jacobian coefficient is based on the perturbation approach [5]. Two configurations are considered: the actual measurement configuration, and a virtual measurement configuration in which source and detector have been interchanged. In this work, the Jacobian matrix is factorized with matrices containing elemental potential gradients. They can be determined by standard FEM formulation [6]. Using only the gradient matrices, a forward operator is defined and solves a direct transport problem. A back-projection operator is also defined and transports back residuals into the imaging domain. The profit of such a formulation relies upon the size of gradient matrices $\mathbf{G} \in \mathbb{R}^{N_e \times E}$ used in inversion, versus the larger size of standard Jacobian matrix, typically $\mathbf{J} \in \mathbb{R}^{N_e \times E^2}$. Inversion is then done with a standard preconditioned conjugate gradient (PCG).

2.2 Experimental device

Experimental measurements are performed on a saline phantom of 4cm diameter featuring 14 equally-spaced copper electrodes with a custom-built EIT system [7].

2.2.1 Reconstruction approach

The implementation of the framework, adapted from the EIDORS library [8], is first validated on simple test cases in 2D before exploring reconstructions from noisy simulated measurements. Reconstructions are then performed against experimental data.

3 Results

Reconstructions from simulated data (Figure 1) exhibit a correct behaviour of the framework and PCG algorithm used for inversion. The framework performs also well in experimental situation (Figure 2).

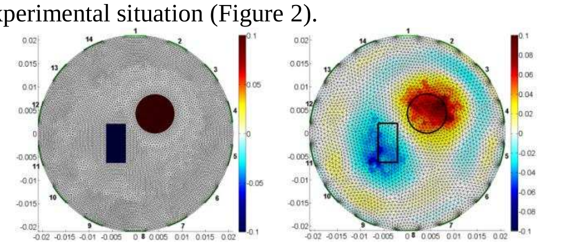

Figure 1: 2D difference reconstructions from simulated data with 5% additive Gaussian noise

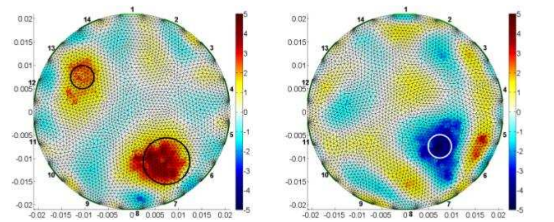

Figure 2: 2D difference reconstruction from experimental data, with estimated 5% noise

4 Discussion

The framework presented in this work allows inversion without explicit Jacobian calculations, working only with potential gradient matrices for injection and measurement configuration. It has been validated against both simulated and in vitro experimental measurements.

Further investigation might consider reconstructions that favour sparse solutions and make use of non-linear inversion algorithms.

References

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