Selection of Stimulus and Measurement Schemes

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Abstract: The performance of an EIT system is determined by its ability to detect contrasting changes in a Region of Interest (ROI) (the sensitivity), while not being sensitive to those outside the ROI (the specificity). We propose a framework to measure system performance and show that this can be implemented as a minimax function over a Fisher linear discriminant on the system sensitivity.

1 Introduction

EIT uses patterns of current stimulation and voltage measurement (stim & meas patterns) to create images, and it is clear that the choice of stim & meas patterns is critical to the quality of the reconstructed images. Optimal L_1-, L_2- and L_∞-norm schemes have been considered for circular, two-dimensional domains [1, 2]. Constructing optimal patterns that maximize the distinguishability of a conductivity contrast with a constrained total stimulation power (L_2-norm) results in trigonometric patterns which use many stimulus electrodes simultaneously [3]. A restriction to pair-wise stimulus and measurement electrodes, common to many EIT hardware implementations, results in schemes such as the adjacent-drive and opposite-drive stim & meas patterns.

Sensitivity to a conductivity contrast, the Jacobian J, can be expressed as the change in a measurement δV_m with respect to a small conductivity change $\delta\sigma$, as with the adjoint method

$$J_{i,j} = \frac{\delta V_m}{\delta \sigma_{i,j}} = \int_\Omega \sigma \nabla u \cdot \nabla v \qquad (1)$$

for a voltage distribution between stimulus electrodes u and the voltage distribution if measurement electrodes were used as stimulus electrodes v.

In this work, we develop a generalization of the "distinguishability" approach and show how this can be interpreted as considering sensitivity and specificity across ROIs to achieve an appropriate trade-off between the two criteria.

2 Conceptual Approach

Our conceptual approach is shown in fig. 1. Here, we seek image contrast changes in a "true" ROI, T, while not being confused by changes in nearby "false" ROIs, F_1, F_2, F_3. If the EIT system makes measurements, m_1, m_2, then, including noise, the detected changes from each ROI are shown. Using Linear Discriminant Analysis (LDA), an optimal decision boundary can be defined, and a probability of

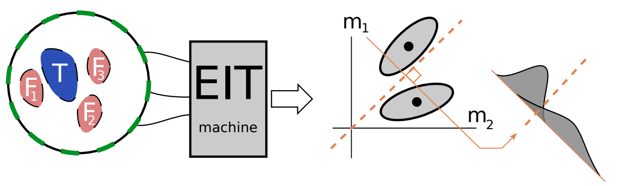

Figure 1: A framework for stim & meas pattern selection; "true" and "false" targets are measured by an EIT machine, an LDA provides an optimal decision boundary separating the two distributions

error, $p(\varepsilon)$, of false detection is calculated. The quality of the pattern is defined by the maximum error probability. Stim & meas patterns can then be compared, where the best pattern minimizes the maximum probability of error $p(\varepsilon)$.

3 Example

As an example, a set of regions (red circles) in an inhomogeneous half-space with 4 electrodes (green circles) are considered (fig. 2). An initial stimulus and measurement pair can be selected based on minimizing the maximum distinguishability z [4], but further choices are needed to balance sensitivity and specificity.

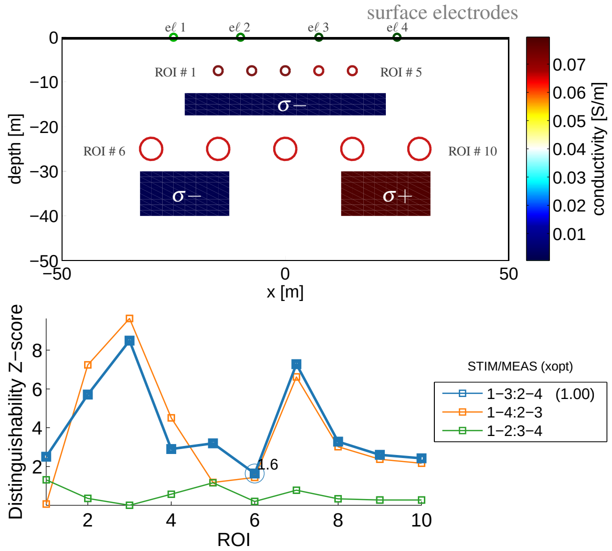

Figure 2: A half-space model with inhomogeneous background conductivity; 4 surface electrodes (green) and 10 regions of interest (red circles); the most widely spaced combination of stim & meas pattern gives the best distinguishability (blue, orange) over adjacent (green).

4 Discussion

The selection of optimal strategies has previously been focused largely on sensitivity. We propose an approach that can be used to select optimal stim & meas patterns that capture the trade-off between sensitivity and specificity.

In the limit, sensitivity is the Jacobian J at a point on the domain. We observe that the concept of specificity is then intimately related to the partial derivatives of the Jacobian

$$\partial_{x,y} J = \nabla(\sigma \nabla u \cdot \nabla v) \qquad (2)$$

$$= \sigma(\nabla^2 u \cdot \nabla v + \nabla u \cdot \nabla^2 v) + \nabla\sigma(\nabla u \cdot \nabla v) \qquad (3)$$

reflecting the variation in sensitivity between nearby points.

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