Selection of Stimulus and Measurement Schemes

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Problem

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).

Contributions

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.

Method

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.

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 error, $p(\epsilon)$, 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 $p(\epsilon)$.

An Initial stimulus and measurement pair can be selected (fig. 3) for a particular geometry (fig. 2) based on minimizing the maximum distinguishability z [4], but further choices are needed to balance sensitivity and specificity.

References

[1] Lionheart WRB, Kaipio J, McLeod C. *Physiol Meas* **22**(1):85–90, 2001

[2] Adler A, Gaggero P, Maimaitijiang Y. *Physiol Meas* **32**(7):731–744, 2011

[3] Isaacson D. *IEEE Trans Med Imag* **5**(2):91–95, 1986

[4] Boyle A, Mamatjan Y, Adler A. In *Workshop on 100 Years of Electrical Imaging, Paris, France*. 2012

Framework

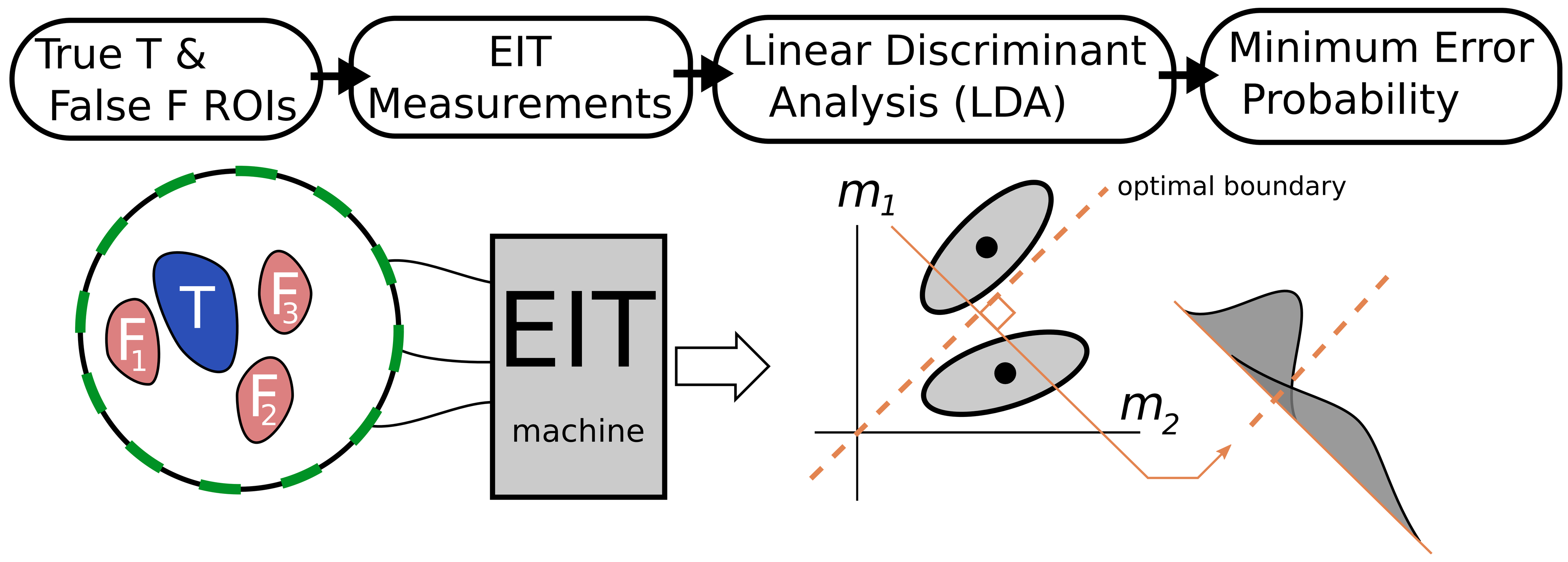

Figure 1: A framework for stim & meas pattern selection; "true" and "false" targets are measured by an EIT machine, an LDA provides an optimal decision boundary separating the two distributions

A Model

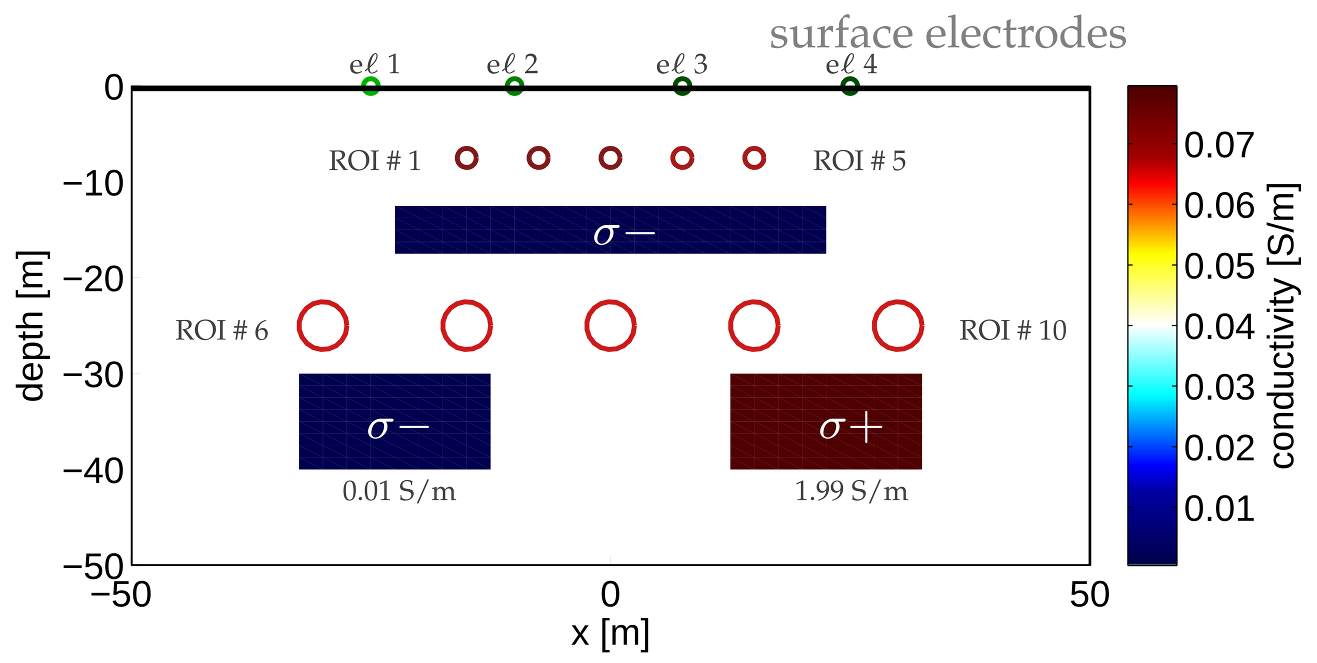

Figure 2: A half-space model with inhomogeneous background conductivity; 4 surface electrodes (green) and 10 regions of interest (red circles)

Sample Results (Sensitivity)

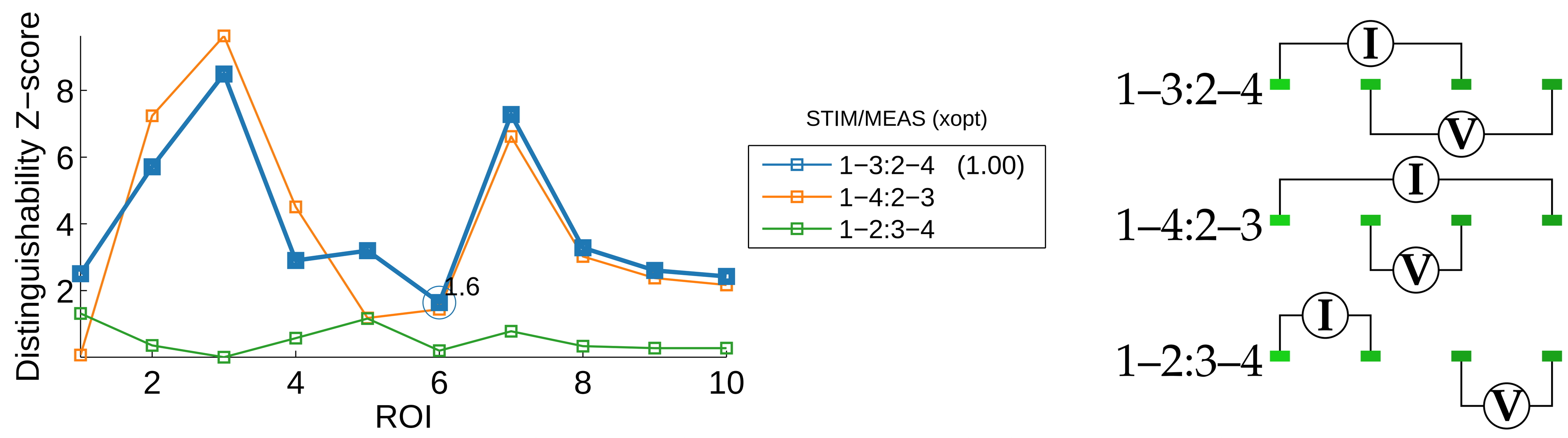

Figure 3: Based on sensitivity alone, the most widely spaced combination of stim & meas pattern gives the best distinguishability (blue, orange) over adjacent (green).

Sensitivity

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.

Specificity

In the limit, regional sensitivity is the Jacobian J at a point on the domain. If we define specificity as the ability to reject nearby changes, 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.