Distinguishability as a noise performance metric for EIT algorithms

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Abstract: EIT reconstruction algorithms typically offer a trade-off between noise performance and resolution driven by the selection of a hyperparameter. In order to compare algorithms, it is common to choose hyperparameter values such that the noise performance is equal. Many methods exist, but do not work well when the data are incompatible (i.e. different electrode positions). We propose a new metric based on distinguishability.

1 Introduction

We are motivated by the need to compare EIT algorithms and approaches in order to choose optimal algorithms and measurement configurations. Such comparisons are needed to answer questions such as: What skip (spacing) between stimulation patterns is best to measure the lungs? Would it be useful to put a few extra electrodes near the heart? Has algorithm A a lower position error than B?

Such comparisons are not straightforward because most EIT algorithms have at least one tunable parameter (a "hyperparameter", λ) which controls the trade-off between the ability to reject noise (noise performance) and the resolution and other accuracies. The values of λ are chosen based on either heuristic criteria, or using techniques such as the L-curve[1] or cross validation[1]. Another approach is to select λ so that a measure of the noise performance is equal (a common choice is the noise figure, $\text{NF} = \text{SNR}_{\text{data}}/\text{SNR}_{\text{image}}$[2].

Such approaches require data for each tested algorithm to be identical. They are thus not suitable to compare across electrode positions or stimulation strategies. To address this requirement, we propose an approach based on a "distinguishability " metric[3].

2 Methods

The proposed framework estimates the noise performance of an algorithm in terms of the distinguishability of contrasts (Fig. 1). Distinguishability measures the probability of detection of likely targets, H_1, from the background, H_0. Algorithms with equal $p(\text{detection})$ are defined to have equal noise performance.

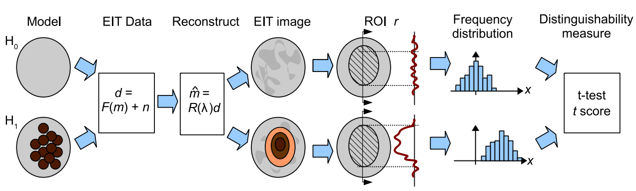

Figure 1: Block diagram of the distinguishability framework.

The approach requires a model of the likely noise, n, characterized by a covariance Π_n (assuming $\bar{n} = 0$). Within H_1, we have a model of likely targets with mean, $\bar{m}$, and covariance, Π_m. Using a linear model, we have $d_1 = Jm_1 + n$, and $d_0 = n$, where d_1, d_0 are the difference EIT measurements (from H_1 and H_0), J is the Jacobian matrix and n is independent uniform Gaussian zero-mean measurement noise with variance σ_n^2. Reconstruction calculates an image, $\hat{m} = R(\lambda)d$ from a linear reconstruction matrix R which depends on a hyperparameter, λ. In a ROI, r, we calculate

$$x = r^t \hat{m} = r^t R(\lambda)(Jm + n) \tag{1}$$

where measure $x \sim \mathcal{N}(\bar{x}, \sigma_x^2)$.

The separation between the H_0 and H_1 distributions is represented by the unequal variances (Welch's) t-test. From t, p-values, sensitivity and specificity can be straightforwardly calculated. This framework can be algebraically developed so distinguishability may be directly calculated from R. In order to use this framework to compare reconstruction algorithms, a t is first chosen. Next, using a bisection search, the λ value is found for each algorithm which corresponds to the given t.

3 Results and Discussion

A simulation of the approach is shown in Fig. 2. In a circular tank with 32 electrodes, skip patterns of 0 (adjacent), 6 (90°) and 14 (180°) are used. Images are reconstructed with a one-step Gauss Newton solver using a Laplace prior. For each reconstruction algorithm, the hyperparameter is adjusted such that the distinguishability $t = 19$. Images are shown for two targets as depicted in Fig. 2 (a). Visual inspection of the images in Fig. 2 (b-d) confirms a comparable noise performance among the three skip patterns.

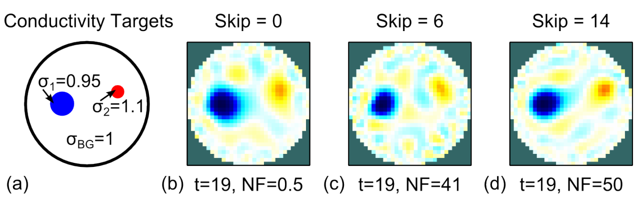

Figure 2: (a) Conductivity targets and (b-d) reconstructed images for different skip patterns with equal distinguishability ($t = 19$).

4 Discussion

We have developed a new framework to compare the noise performance of reconstruction algorithms, based on a statistical measure of the likelihood of distinguishability of targets in a ROI. This has the advantage of allowing comparison between algorithms with incompatible data, such as different electrode positions or stimulation patterns.

References

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