Effective electrode positions and stimulation patterns for head EIT

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Abstract: The objective of this study is to find an effective stimulation and measurement strategy to improve distinguishability for head EIT. To better understand the relationship between distinguishability and various strategies (stimulation/measurement patterns) for a set of electrodes, we evaluated a realistic head model and a range of common strategies.

1 Introduction

Electrical Impedance Tomography (EIT) of the head has the potential to image cerebral edema and stroke, and to assist the EEG inverse problem. To effectively utilize an EIT system for human head, there is a need for maximizing sensitivity and increasing detectability by choosing an appropriate stimulation pattern and electrode placement strategy. Fabrizi et al [1] conducted simulation study for brain imaging using a realistic finite element (FE) model of the head, but only a limited evaluation was carried out due to high computational cost, where only 14 protocols were tested for both homogeneous model and a realistic head model. The objective of this study is to find an effective strategy to use a given EIT system for head EIT by systematically assessing possible stimulation and measurement patterns.

2 Methods

This paper (i) implements a realistic head model with 73 electrodes in standard EEG positions, (ii) provides quantified values and demonstrates the specific relationship between distinguishability and target position for different stimulation / measurement strategies, and (iii) makes recommendations for 16, 32, 64 electrode systems using standard EEG caps. The results are analyzed using the distinguishability formulation proposed by [3].

A realistic FE mesh of an adult head with 73 electrodes in standard EEG positions was built based on the mesh SAH262 contributed to EIDORS by [2]. Using EIDORS's interfaces to Netgen and Gmsh, the scalp was re-meshed to include 73 circular electrodes with local mesh refinement [4]. After defining Nasion and Inion landmarks, the positions of the remaining 71 electrodes were calculated as an extension of the 10-20 standard.

We choose $N = 16$, 32 and 64 electrodes for simulations, numbering them front-to-back in a zig-zag fashion starting from the left-most electrode (Fp1). We denote the measurement strategy by $\Delta s\text{-}m$ where the distance between the two stimulating electrodes is $s = 1,\ldots,N$ and that between measuring electrodes is $m = 1,\ldots,N$. Thus, the typical adjacent measurement and stimulation pattern is denoted by Δ1-1. For each total number of electrodes, we evaluate all strategies where $s = m$ for only 64 electrodes due to high computation time.

Distinguishability is defined as the ability to distinguish between a hypothesis H_1 (conductivity change) and the null hypothesis H_0 (no conductivity change) within a region of interest (ROI) according to measure m [3]. The maximum likelihood estimate [3] of the conductivity change $\arg\min ||\Delta\mathbf{d} - \mathbf{R}\Delta\sigma|| + P(\cdot)$ for the hypothesis m within an ROI of area A_R is $m = A_R\Delta\hat{\sigma}_R$. The probability that the null hypothesis is rejected is determined by the z-score [3]:

$$\bar{z} = \frac{\hat{m} - m_0}{\text{std}(m)} = \frac{A_R\Delta\hat{\sigma}_R}{(\mathbf{R}_R\Sigma_n\mathbf{R}_R{}^{\intercal})^{\frac{1}{2}}} = A_R\Delta\hat{\sigma}_R\sqrt{\mathbf{J}_R{}^{\intercal}\Sigma_n{}^{-1}\mathbf{J}_R} \quad (1)$$

where $\hat{m}$ is the maximum likelihood estimate for m, the null hypothesis is m_0 and $\text{std}(m)$ is the standard deviation of m.

2.1 Results

Fig. 1 shows $\bar{z}$ distinguishability values for 16, 32 and 64 electrode systems and 8 different object positions from Nasion to Inion for the best and worst measurement strategies. Δ25-25 with 64 electrode model produced highest $\bar{z}$ values for different object positions, while the adjacent patterns Δ1-1 produced lowest $\bar{z}$ values for all 3 electrode configurations. For Δ1-1, 32 electrodes performed better than both 16 and even 64 electrodes.

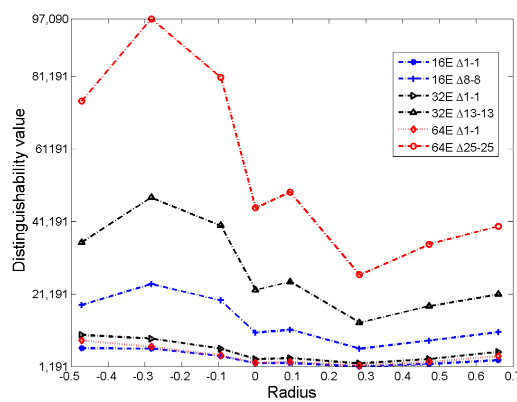

Figure 1: Distinguishability values for 16, 32 and 64 electrodes with 8 object positions for the stimulation and measurement patterns of Δ1-1 (adjacent) and $\Delta s\text{-}m$ with maximum average $\bar{z}$ values.

3 Conclusions

Our results indicate that distinguishability increases throughout the model with average distance between the two stimulating/measuring electrodes. Future work will address the impact of changing electrode numbering and ways of finding optimum electrode positioning and measurement strategy to maximise distinguishability in a particular region of interest.

References

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