# 3-D Electrical Impedance Tomography Reconstruction Using $\ell_1$ Norms Regularization

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**Abstract:** An $\ell_1$ norm reconstruction algorithm which has the merits of reducing the sensitivity to data outliers and avoiding edge blurring is applied in this paper to solve a 3-D EIT problem. The iterative imaging method allows flexible choice of norms by simply choosing different norm value. A cluster analysis is implemented for labelling targets using the morphology technique.

## 1 Introduction

Electrical Impedance Tomography (EIT) is a soft field imaging modality due to the diffusive propagation of electrical current. Reconstruction of the internal conductivity distribution from boundary measurements is severely ill-conditioned. Most reconstruction algorithms are based on $\ell_2$ norm regularization (e.g. one-step GN method) which is believed to blur image outlines and be sensitive to measurement noises. These difficulties can be greatly alleviated if $\ell_1$ norm reconstruction technique is involved [1-5]. An $\ell_1$ norm applied on the measurements residue term reduces the sensitivity to data outliers, while an $\ell_1$ norm on the image prior term avoids edge blurring. An $\ell_1$ norm iterative method is applied in this paper to solve a 3-D EIT problem, which is designed to detect breast cancer from women patients. In the post-processing stage, a cluster analysis is applied for labelling reconstructed targets using the morphology technique. Simulative and phantom experiments showed the advantages of $\ell_1$ norm reconstruction and the validity of the clustering method.

## 2 Methods

A weighted and regularized inverse seeks an estimate solution $\hat{\mathbf{x}}$ by minimizing

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} \|\mathbf{y} - \mathbf{J}\mathbf{x}\|^{p_n}_{\Sigma_n^{-1}} + \|\mathbf{x} - \mathbf{x}^{\mathrm{o}}\|^{p_x}_{\Sigma_x^{-1}} \qquad (1)$$

Where $p_n$ and $p_x$ are the data and image norms respectively. With $p_n = 2$, $p_x = 2$ it models the $\ell_2$ norm regularization; while with $p_n = 1$ , $p_x = 1$ , $\ell_1$ norm reconstruction can be achieved. In this paper, a general iterative method for solving (1) is applied, which allows flexible choice of norms by simply choosing different $p_n$ and $p_x$ value. Details can be found in [5], and will not be elaborated here.

When EIT reconstruction is completed, image filtering technique is implemented to remove noises, and then a cluster analysis based on the morphology is involved for labelling targets.

## 3 Results

### 3.1 Numerical simulation

The forward model was a funnel-shaped applicator. 64 electrodes were located surrounding the outside surface. Inside, there were two targets with conductivity $1.2 \times \sigma_h$, while the background had conductivity $\sigma_h = 1$. In order to accurately simulate forward model and make inverse solution less ill-conditioned, dual model was applied, which means a fine mesh for the forward and coarse mesh for the inverse. Gaussian white noise was added to the simulation data with noise level SNR=20dB. When reconstruction was completed, cluster analysis was implemented. The two targets were marked by different colours (red and yellow) as shown in Fig. 1.

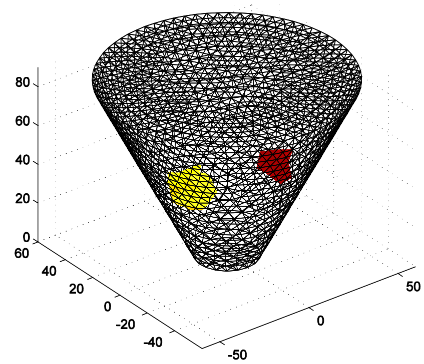


**Figure 1:** Image reconstructed using $\ell_1$ norm and labelled by cluster analysis.

### 3.2 Phantom experiment

The saline phantom was fabricated the same as described in the previous section. Small biological tissues such as potato, apple and porcine liver were statically suspended in the saline solution. Similar results were obtained.

## 4 Conclusions

EIT images reconstructed using $\ell_1$ norm regularization give two distinct advantages: edge preservation and noise robustness. However, the disadvantage is that the $\ell_1$ norm formulation cannot be realized as a linear one-step algorithm due to non-differentiability. In this paper, we extended Dai's previous work [5] from 2-D to 3-D problem, and proved that the iterative process for solving (1) is effective in 3-D scenario as well. Moreover, the cluster analysis based on the morphology technique was involved and successfully separated targets from the background, which is important in clinical applications.

## References

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