

A Layered Reconstruction Algorithm for Cerebral Electrical Impedance Tomography

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1 Introduction

Our previous studies have shown that electrical impedance tomography (EIT) is a promise method that could be used to monitor brain pathological process continuously and provide diagnostic information as an innovative functional image modality with lack of radiation, minimal cost, and high sensitivity^{[1][2][3]}. To promote clinical application, we have introduced an optimized strategy for EIT, in which the EIT/CT fusion image can be achieved to present more anatomical information^[4]. Recently, we improved the method for cerebral EIT by adopting a more accurate brain reconstruction model, which not only includes the boundary of the head but also the internal structure within the head. Although encouraging results have been acquired, the influence of skull needs further consideration. In some situations, the impedance change region of EIT may cover the skull region, which is supposed to remain unchanged. It will be difficult to interpret this kind of image to clinician. In addition, due to incorporating skull prior information in the reconstruction model, the scalp disturbance, such as electrode movement, perspiration, etc, would exert greater influence on the image and cover the target. The problem described above is hard to solve by improving the reconstruction model. In this paper, we developed a novel layered reconstruction (LR) algorithm to reduce the influences of skull and scalp and to highlight the target in cranial cavity. For simplicity, relevant evaluations were performed using numerical simulation data.

2 Methods

2.1 Traditional algorithm

At low frequencies and small field strengths, the relationship between the conductivity distribution and the electric potential field within domain Ω can be described by Laplace's equation:

$$\nabla \cdot \sigma \nabla \phi = 0 \quad \text{within } (x, y) \in \Omega \quad (1)$$

where $\sigma = \sigma(x, y)$ denotes the conductivity distribution inside the body and $\phi = \phi(x, y)$ is the electrical potential distribution. In the forward problem of EIT, the boundary shape, the injecting current and the change of the impedance distribution are known. The changes in voltage on the body surface can be represented as^[5]:

$$\Delta \mathbf{v} = \mathbf{S} \Delta \mathbf{p} \quad (2)$$

where $\mathbf{p} = \frac{1}{\sigma}$ is the impedance distribution. \mathbf{S} is the linearized sensitivity matrix.

For the inverse problem of EIT, we consider that the data might be contaminated with errors. Therefore, equation (2) is described as

$$\Delta \mathbf{v} = \mathbf{S} \Delta \boldsymbol{\rho} + \mathbf{e} \quad (3)$$

where \mathbf{e} is an unknown parameter indicating the error or noise vector. The classic damped least squares (DLS) solution is given as^[6]:

$$\Delta \hat{\boldsymbol{\rho}} = [\mathbf{S}^T \mathbf{S} + \lambda \mathbf{R}]^{-1} \mathbf{S}^T \Delta \mathbf{v} = \mathbf{B} \Delta \mathbf{v} \quad (4)$$

where $\mathbf{R} = \text{diag}(\mathbf{S}^T \mathbf{S})$ is the regularization matrix, λ is the regularization parameter, and \mathbf{B} is the reconstruction matrix.

2.2 Layered reconstruction model

For simplicity, the CSF layer is ignored, and the reconstruction model is divided into three layers: scalp layer Ω_{scalp} , skull layer Ω_{skull} , and cranial cavity layer Ω_{brain} (Fig. 1). Then the reconstructed value $\Delta \hat{\boldsymbol{\rho}}$ is correspondingly divided into $\Delta \hat{\boldsymbol{\rho}}_{\text{scalp}}$, $\Delta \hat{\boldsymbol{\rho}}_{\text{skull}}$, and $\Delta \hat{\boldsymbol{\rho}}_{\text{brain}}$. In vector form, it will be:

$$\Delta \hat{\boldsymbol{\rho}} = \begin{bmatrix} \Delta \hat{\boldsymbol{\rho}}_{\text{scalp}} \\ \Delta \hat{\boldsymbol{\rho}}_{\text{skull}} \\ \Delta \hat{\boldsymbol{\rho}}_{\text{brain}} \end{bmatrix} \quad (5)$$

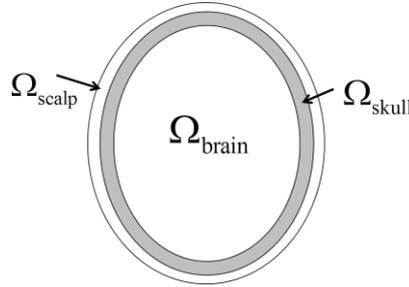


Fig. 1. A sketch map of layered reconstruction model

2.3 Layered reconstruction algorithm

In order to attenuate the influences of skull and scalp, the layered reconstruction (LR) algorithm involves three steps:

LR Step 1. Consider Ω_{skull} : The impedance of Ω_{skull} is supposed to be unchanged since most brain pathological process rarely changes the skull impedance. The prior information will be:

$$\Delta \rho_j = 0 \quad j \in \Omega_{\text{skull}} \quad (6)$$

Introduce a constraint matrix \mathbf{D} , equation (6) can be rewritten in matrix form:

$$\mathbf{D} \Delta \boldsymbol{\rho} = \mathbf{h} \quad (7)$$

where \mathbf{h} is a zero vector. Then equation (2) can be rewritten as:

$$\tilde{\mathbf{S}} \Delta \boldsymbol{\rho} = \begin{bmatrix} \mathbf{S} \\ \mathbf{D} \end{bmatrix} \Delta \boldsymbol{\rho} = \begin{bmatrix} \Delta \mathbf{v} \\ \mathbf{h} \end{bmatrix} \quad (8)$$

The misfit vector will be:

$$\mathbf{e} = \begin{bmatrix} \Delta \mathbf{v}_{obs} \\ \mathbf{h} \end{bmatrix} - \begin{bmatrix} \Delta \mathbf{v}_{pre} \\ \mathbf{h}_{pre} \end{bmatrix} \quad (9)$$

where $\Delta \mathbf{v}_{obs}$ is measurement value, $\Delta \mathbf{v}_{pre}$ is prediction value. \mathbf{h} is ideal value, \mathbf{h}_{pre} is prediction value. The DLS solution is then given as:

$$\Delta \hat{\boldsymbol{\rho}} = (\mathbf{S}^T \mathbf{S} + \lambda \mathbf{D}^T \mathbf{D} + \mu \mathbf{R})^{-1} \mathbf{S}^T \Delta \mathbf{v} = \mathbf{B}_L \Delta \mathbf{v} \quad (10)$$

where λ is constraint parameter. If \mathbf{h} is ideal zero, the constraint parameter has to take a large value, and then the reconstructed value $\Delta \hat{\boldsymbol{\rho}}_{skull}$ will be a very small value.

LR Step 2. Consider Ω_{scalp} : The impedance change within Ω_{scalp} have great influence over reconstruction and should be eliminated or attenuated. Using space prior information, the influence vector $\Delta \hat{\boldsymbol{\rho}}_s$ can be easily obtained:

$$\Delta \hat{\boldsymbol{\rho}}_s = \begin{bmatrix} \Delta \hat{\boldsymbol{\rho}}_{scalp} \\ \mathbf{0} \end{bmatrix} \quad (11)$$

LR Step 3. Consider Ω_{brain} : The impedance change within Ω_{brain} is the target that we want to reconstruct, which can be calculated with:

$$\Delta \hat{\boldsymbol{\rho}}_b = \mathbf{B}_L (\Delta \mathbf{v} - \mathbf{S} \Delta \hat{\boldsymbol{\rho}}_s) \quad (12)$$

where:

$$\Delta \hat{\boldsymbol{\rho}}_b = \begin{bmatrix} \boldsymbol{\varepsilon} \\ \Delta \hat{\boldsymbol{\rho}}_{brain} \end{bmatrix} \quad (13)$$

$\boldsymbol{\varepsilon}$ is a small residual vector.

Equation (13) shows that influences of skull and scalp have been greatly attenuated.

3 Results

The reconstruction model was established as displayed in Fig. 2(a). Fig. 2(b) and (c) show the simulation models. They were limited to two dimensions and the boundary was circular. 16 equidistant spacing nodes marked with red bold line were used as electrodes. The $\boldsymbol{\rho}_{scalp}$, $\boldsymbol{\rho}_{skull}$, and $\boldsymbol{\rho}_{brain}$ were set to 0.44S/m, 0.01 S/m, and 0.2 S/m. The target conductivity was set to 0.67S/m. Fig. 2(b) has a single target, while Fig. 2(c) contains scalp influence(0.67S/m). The data was generated with 0.01% noise.

Fig. 2(d) and (e) were constructed with the traditional algorithm. Fig. 2(f) and (g) were constructed with layered reconstruction algorithm after the first step. Fig. 2(h) and (i) were constructed with layered reconstruction algorithm after all three steps. For traditional algorithm, when the target was located near the skull, as illustrated in Fig. 2(d), the skull region shows a false impedance change, and after a scalp influence is set, as illustrated in Fig. 2(e), the target is covered by the influence of scalp. For layered reconstruction algorithm, as illustrated in Fig. 2(h)-(i), it provides superior results.

The influences of skull and scalp have been greatly attenuated.

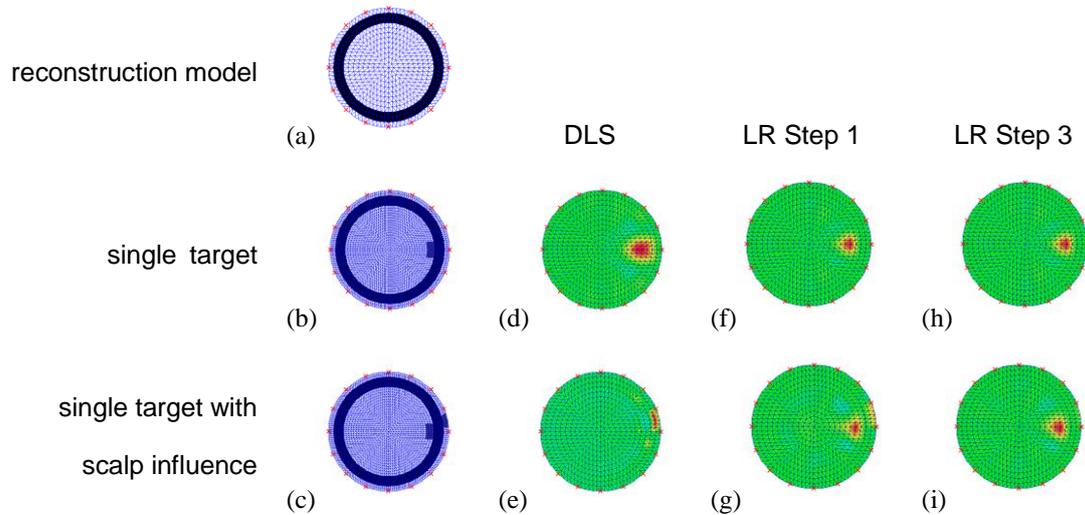


Fig. 2. (a) Reconstruction model, (b) simulation model with a single target, (c) simulation model with scalp influence, (d)-(e) images reconstructed by traditional DLS algorithm, (f)-(g) images reconstructed by LR algorithm after the first step, (h)-(i) images reconstructed by LR algorithm after all three steps.

4 Discussion and Conclusions

In this study, we proposed a novel layered reconstruction algorithm for cerebral EIT. Through preliminary evaluation of simulation data, it is shown that this algorithm can reduce the influences of skull and scalp and produces more precise images as compared to traditional DLS method. Ongoing studies include accurate head numerical model and test of clinical data.

Acknowledgment

This work is partially supported by the National Key Technology R&D Program of China under grant NO. 2011BAI08B13, 2012BAI20B02, 2012BAI19B01, National Natural Science Foundation of China under grant NO. 50937005, 61071033, and Natural Science Foundation of Shaanxi Province under grant NO. 2012JQ4012.

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