Enhanced Resolution of EIT Images based on Restricted ROI

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Abstract

Electrical Impendence Tomography (EIT)[1] has incomparable advantages such as noninvasive, radiation-free, fast imaging speed, cheap cost, etc., attracted more and more researchers to improve its performance, to seek its practical application. Lots of great invention has been done to get more stable and clearer EIT images. However, its blur image, caused by weak measurement signals, limited number of independent measurements and the native ill-posed inverse problem, is always a headache for its application in both medical and industrial area. In this article, the authors try to use pre-knowledge based on the position information and the size information to reduce the interested imaging region, and lock it in the objects and their surrounding region. The simulation results show that the proposed method can get more accurate contour and conductivity of the object. Some phantom experiments are provided to further validated the proposed restricted region of interest (RROI) method. Conclusion and discussion will be given in the end.

Keyword: EIT, restricted region of interest, contour

1. Introduction

The classic Sensitivity Coefficient Method (SCM) is widely used as a stable EIT image reconstruction method. Based on the Compensation Theorem [2,3], it build the sensitivity coefficient matrix[2], with only the first order component in the Taylor's expansion being considered. The iterative procedure shows that the method is convergent and uniqueness. Consequently, in this research, SCM is preferred as the basic algorithm. A new idea with restricted region of interest (RROI) is proposed to improve the "image resolution", and meanwhile do not increase the complexity of the model, and significantly reduce the computation load.

2. Brief Introduction to SCM

Murai and Kagawa[4] proposed to use the Sensitivity Theorem derived by Geselowitz[2] and Lehr to obtain the transfer impedance change ΔZ for the pairs of electrodes (A,B) and (C,D) when the conductivity of the field changes from σ to $\sigma + \Delta\sigma$.

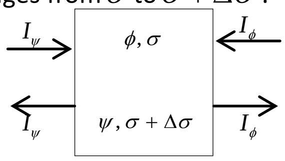


Figure 1. A dual-port model of SCM

It gives the variation of the transfer impedance as

$$\Delta Z = -\int_V \Delta\sigma \frac{\nabla\phi(\sigma)}{I_\phi}\frac{\nabla\psi(\sigma+\Delta\sigma)}{I_\psi} dV \tag{1}$$

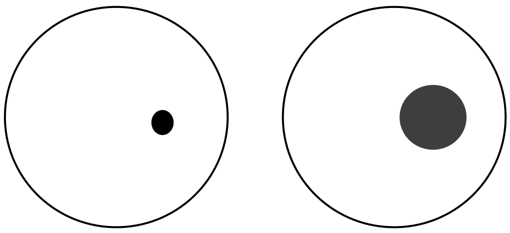
Taylor's expansion is then used to give the simplified form for $\nabla\psi(\sigma+\Delta\sigma)$. The linearized ΔZ is given as [4,5]

$$\Delta Z = -\int_V \Delta\sigma \frac{\nabla\phi(\sigma)}{I_\phi}\frac{\nabla\psi(\sigma)}{I_\psi} dV \tag{2}$$

This shows the general expression of sensitivity coefficient matrix.

3. Restricted Region of Interest (RROI)

Assuming a homogeneous field with a target object in it, the ideal result of the EIT inverse problem is to get a clear target object contour with accurate conductivity value, and other parts of the field (background) have a homogenous conductivity value and do not change during the iterative procedure. However, the background in the reconstructed image is not homogenous because the iteration procedure is impacted by the measurement error and random calculation error and modeling errors, etc. The error in background conductivity will decreases the reconstruction accuracy of the object, both in conductivity and contour. If the error in background is forced to be zero, theoretically the reverse problem should have more accurate solution. In this paper, the region of interest is restricted during the iterative procedure of the image reconstruction based on the priori knowledge of the position and size of the object(s). The idea is explained in Figure 2.



(a) (b)

Figure 2. The model of the restricted region of interest (RROI) method

(a) The model of the real target;

(b) The model of the reverse problem with the rough position and size information

The discrete form of the SCM can be described by the matrix equation given in Eq. (3):

$$[S]_{m\times n}[\Delta\sigma]_{n\times 1} = [\Delta Z]_{m\times 1} \tag{3}$$

where m is the number of independent measurements; n is the number of elements in the finite element model. If there is an object in the field which is surely located in a reduced range covered by p of finite elements, then $\Delta\sigma$ in all other (n-p) elements should be equal to zero in the ideal reconstruction results. If the $\Delta\sigma$ is rearranged that the p elements are next to each other, the new $\Delta\sigma$ can represent by $\Delta\sigma = [\Delta\sigma_1, \ldots \Delta\sigma_p, 0, \ldots 0]^T$. So Eq. (3) can be rearranged as:

$$\begin{bmatrix} S_{m\times p} & 0_{m\times(n-p)} \end{bmatrix} \begin{bmatrix} \Delta\sigma_{p\times 1} \\ 0_{(n-p)\times 1} \end{bmatrix} = [\Delta Z]_{m\times 1} \tag{4}$$

which is equivalent to:

$$[S]_{m\times p}[\Delta\sigma]_{p\times 1} = [\Delta Z]_{m\times 1} \tag{5}$$

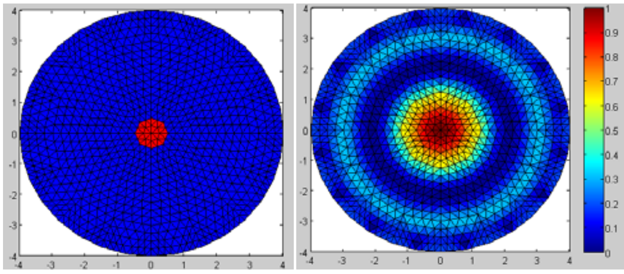
Hence the dimension of SCM algorithm is reduced to the order of p. In theory, if $p \leq m$, the inverse problem should have a defined solution and the image resolution in the ROI is increased.

4. Simulation Results

To test the effects from the restricted region on the SCM image reconstruction process, some conductivity distribution models have been setup via FEM and their forward solutions are used to test the proposed RROI algorithm.

In order to get high accuracy in forward problem solution, a relative dense finite element mesh with 16 electrodes is used in the following study.

(1) A model having a target object with conductivity of 0.13mS/cm in the background of 0.12mS/cm, as shown in Figure 3(a).

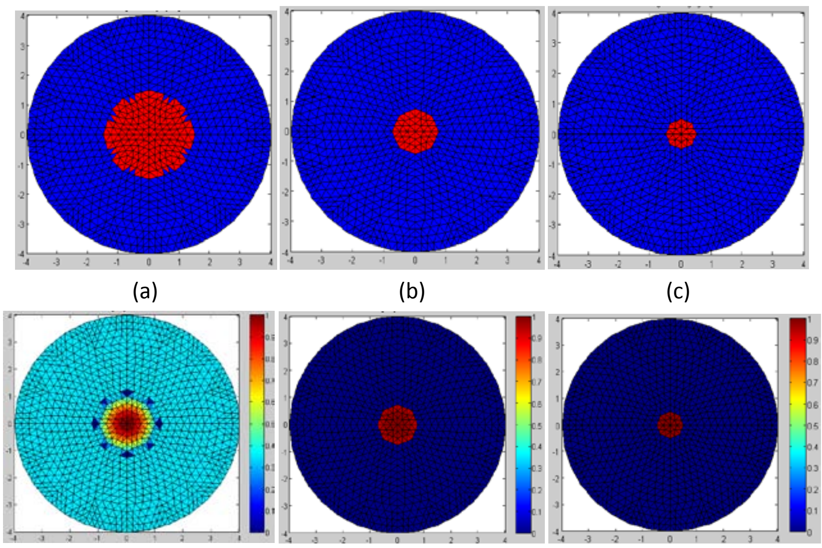


(a) (b)

Figure 3. (a) FEM model; (b) Reconstructed image by SCM algorithm

The Figure 3(b) shows the image from the iterative SCM reconstruction over the entire field. The convergence criterion is $\|\Delta\sigma\| < 0.001$. The boundary of the object is blurring. The average conductivities of the object is 0.1223, which has 5.92% relative error.

From the same FEM model shown in Figure 3(a), images reconstructed by RROI method with ROI defined in Figure 4(a)(b)(c) are shown in Figure 4(d)(e) & (f) respectively. The ROI are obtained with different thresholds from the SCM result.



(a) (b) (c)

(d) (e) (f)

Figure 4. The RROI and reconstructed images of a single object

(a)-(c) the different sizes of restricted ROI;

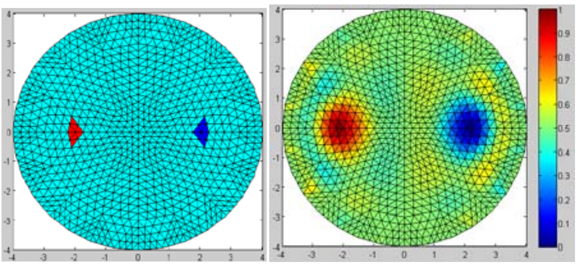
(d)-(e) the reconstructed images from corresponding ROI shown above

Compared with Figure 3(b), Figure 4 (d) (e) & (f) shows better contour accuracy of the object. And the smaller the ROI, the closer the object conductivity is to its true value. The average conductivities of each reconstructed object are listed in Table 1.

Table 1 The reconstructed and true conductivities of the single object

value / case	Reconstructed value	True value	Relative error
Normal	0.1223	0.1300	5.92%
RROI of Figure 4(a)	0.1250	0.1300	3.85%
RROI of Figure 4(b)	0.1245	0.1300	4.23%
RROI of Figure 4(c)	0.1300	0.1300	0%

(2) A FEM model having 2 target objects with conductivities of 0.13mS/cm and 0.11mS/cm respectively in the background of 0.12mS/cm, as shown in Figure 5(a).

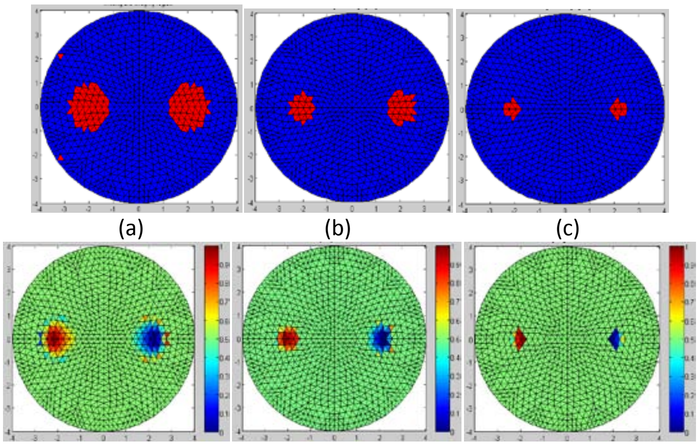


(a) (b)

Figure 5. (a) FEM model; (b)Reconstructed image by SCM algorithm

The corresponding image reconstructed by iterative SCM over the entire field is shown in Figure 5(b), with convergence criterion of $\|\Delta\sigma\| < 0.001$. Again, the boundary of the object is blurring.

Similar to Figure 4, restricted ROI regarding FEM model of Figure 5(a) is defined with different thresholds and shown in Figure 6 (a) (b) & (c).



(a) (b) (c)

(d) (e) (f)

Figure 6. The RROI and reconstructed images of two objects
(a)-(c) the different sizes of restricted ROI;
(d)-(e) the reconstructed images from corresponding ROI shown above

Compared with Figure 5(b), Figure 6 (d) (e) & (f) again shows better contour accuracy of the objects. And the smaller the ROI, the closer the objects' conductivities are to their true values. The average conductivities of each reconstructed object are listed in Table 2.

Table 2 The reconstructed and true conductivities of the two objects

value / case	Reconstructed value		True value		Relative error	
	Object1	Object2	Object1	Object2	Object1	Object2
Normal	0.1219	0.1180	0.1300	0.1100	6.23%	7.27%
RROI of Figure 6(a)	0.1233	0.1165	0.1300	0.1100	5.15%	5.91%
RROI of Figure 6(b)	0.1244	0.1154	0.1300	0.1100	4.31%	4.91%
RROI of Figure 6(c)	0.1293	0.1105	0.1300	0.1100	0.54%	0.45%

The results show in Table 2 reconstructed with the same convergence criterion no matter if it reconstructed over the entire field or a restricted region. The results indicate that the relative errors of the objects conductivities decrease when the size of ROI is reduced. Reconstructions from RROI have higher reconstruction efficiency than reconstruction over the entire field. In other similar simulations, it has been found that the average conductivity of the object will be more close to the real value when the ROI is defined more close to its real shape.

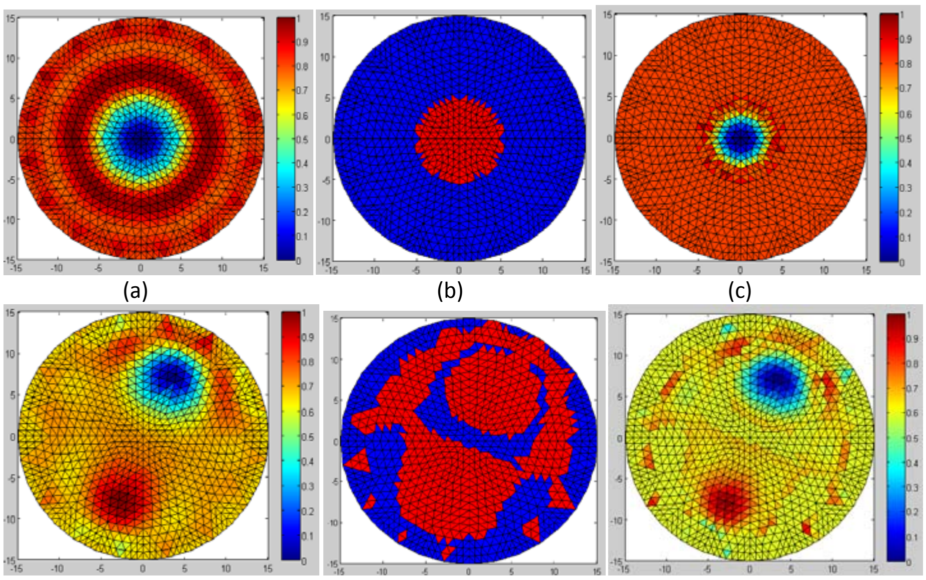
4. Experiment Results

To check the effectiveness of RROI, some phantom experiments using a copper bar and a nylon bar as the objects have been performed.

(a) (b)

Figure 7. Experiment Phantom(d=30cm)

(a) A nylon bar(d=4cm); (b) A nylon bar(d=3cm) and a copper bar(d=2cm)



(a) (b) (c)

(d) (e) (f)

Figure 8. the comparison of normal SCM and RROI

(a) & (d) are reconstructed images by SCM over the entire field; (b) & (e) are the restricted image region defined by the single step SCM with a threshold;

(c) & (f) are the reconstructed images based on RROI defined by (b) & (e) respectively.

Figure 8 shows the SCM reconstruction results over the entire field and over a restricted region (RROI). The results from RROI have relative better contour accuracies compare with the results reconstructed over entire field. However, the measurement noises have significant influence to the image reconstruction with RROI. Although the Tikhonov regularization method[6,7] is used in the image reconstruction, when the RROI decreases to a certain extent, the image reconstruction tends to divergent. The noise suppression and high precise of measurements are critical to the proposed RROI method.

5. Discussion and Conclusion

A new reconstruction method based on RROI is proposed. Variations using FEM simulation results and phantom measurements have demonstrated that RROI has many advantages and summarized in the follows:
(1) RROI decreases the dimension of inverse problem and hence reduces the computation load;
(2) The reconstructed conductivity based on RROI is more close to the true value compared to the reconstruction over the entire field when the same convergence criterion is used;
(3) The measurement noise could make the image reconstruction based on RROI divergent. Noise suppression and highly precise measurement is critical to image reconstruction based on RROI.

In conclusion, the RROI is helpful to make EIT image more accurate and clearer. Demonstrations with tissue models and animal models are necessary and will be performed soon to further validate the effectiveness of the propose image reconstruction method based on RROI.

Acknowledgement

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