Modified regularized Newton-Raphson algorithm for Electrical Impedance Tomography in Region Of Interest

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Abstract: Newton-Raphson is most used algorithm in EIT(electrical impedance tomography), cross-sectional distribution of resistivity is reconstructed by mean of both generating and sensing electrodes attached onto the surface of the object. EIT has been suffered from the severe ill-posedness which is caused by the inherent low sensitivity of boundary measurements to any changes of internal resistivity values. In this paper, we propose modified cost function and weighting factor that compensate for low sensitivity between boundary measurements and internal resistivity and improve performance of Newton-Raphson for EIT in region of interest.

Keywords: Region of interest, Initial value, Regularization, ill-posedness.

1. INTRODUCTION

EIT(electrical impedance tomography) is internal resistivity distribution estimation that is earned by current injection into attached small electrodes around object and measuring voltages on electrodes. EIT has cheaper hardware expenses, worse spatial resolution of reconstructed image but better temporary resolution, more securities about human body than CT. it is used monitoring tools in chemical engineering, geotechnology, and material engineering. And used assistant equipments in medical engineering.[1,2]

EIT system consists of two part, one is hardware part, current is injected into object and voltage is measured. the other is image reconstruction algorithm that estimates internal resistivity distribution using measured voltage. Image reconstruction process obtains from iterative solution of forward problem and inverse problem based on mathematical model of electromagnetic equation where, forward problem is process that inject currend into electrode and then measure voltage, inverse problem is process that estimate resistivity distribution using injected current and measured voltage, then reconstruct image. We assume internal initial resistivity distribution, and then improve internal resisitivity from iterative operation forward problem and inverse problem, when computed voltage lie in permissible voltage error range, obtain final image. EIT has problems those are ill-posedness from low sensitivity of external measured voltage comply with change of internal resistivity. Various regularization methods have been proposed to solve these ill-posedness problem and are still matter of concern. Akaike proposed reduction of condition number by elimination of small eigenvalue of hessian in 1974, Murai et al introduced SVD method in 1944, Levenverg in 1944 and Marquardt in 1963 introduced matrix coefficient method, and Cohen-Bacrie proposed regularization method using variance uniformization constraint, Vauhkonen used Tikhonov method and subspace regularization method in 1996, 1998. [3-9]

This paper assumes to be comparative small anomaly in homogeneous background. Object aim value replace as constant initial value using modified Newton-Raphson method and grouping method. And then estimates object more exactly using Tikhonov regularization method in ROI. It increases operation to obtain initial value but improves compensation of low sensitivity and accuracy. This paper is verified image reconstruction performance of proposed algorithm computer simulation

2. METHOD

2.1 ROI and Initial value setup

We use a modified Newton-Raphson method to estimate the resistivity distribution of the object and then find out position and region by estimated image. so we use this for the use of region of interest. For the estimation of resistivity distribution of the object, the cost functional to be minimized necessitates regularization such that

$$\Phi(\rho) = \frac{1}{2}[U - V(\rho)]^T[U - V(\rho)] + \frac{1}{2}\alpha\rho R^T R\rho \tag{1}$$

where $U \in \Re^{L\times(L-1)}$ is the measured voltage on each electrode about current pattern, $V(\rho) \in \Re^{L\times(L-1)}$ is the computed voltages about current pattern, $R^T R = diag(J^T J)$ and α are regularization parameters. Solution of minimized resistivity as follows

$$\rho_{i+1} = \rho_i + \left(J_i^T J_i\right)^{-1} J_i^T \left(U - V(\rho_i)\right) \tag{2}$$

where J is Jacobian at $\rho = \rho_i$ form as

$$J \equiv \frac{\partial V(\rho_i)}{\partial \rho} \tag{3}$$

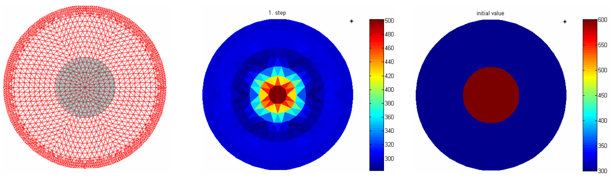
This paper has assumption, there are comparatively small anomaly in homogeneous background. We reconstruct image using 1 frame information from equation (2) and obtain region of interest and initial value from this reconstructed image by simple classification criterion as follows

$$\mu_j = \frac{\rho_j}{\rho_{avg}} \tag{4}$$

$$\rho_{avg} = (\sum \rho_j)/N_e \tag{5}$$

where ρ_{avg} is average value of resistivity from image obtained by 1 frame information, N_e is number of elements. After computing μ_j by equation (5), each element is classified into two group, ROI group and background group. If μ_j of each element is larger than μ_{TH} or smaller than μ_{TL} it belongs to ROI group, else it belongs to background group. where μ_{TH} and μ_{TL} are threshold values which are grade of group decision. Elements of ROI and BG are grouped by average of each group. And then are used initial value to proposed algorithm .

(b) of Fig 1. is 1 iteration result from modified Newton-Raphson method for sake of ROI and initial value of proposed method, (a) is estimated ROI from (b) and (c) is initial value for proposed method. Fig 2. is flow chart for ROI and initial value.



(a) (b) (c)

Fig. 1 (a) ROI, (b) 1iteration result of mNR, and (c) initial value

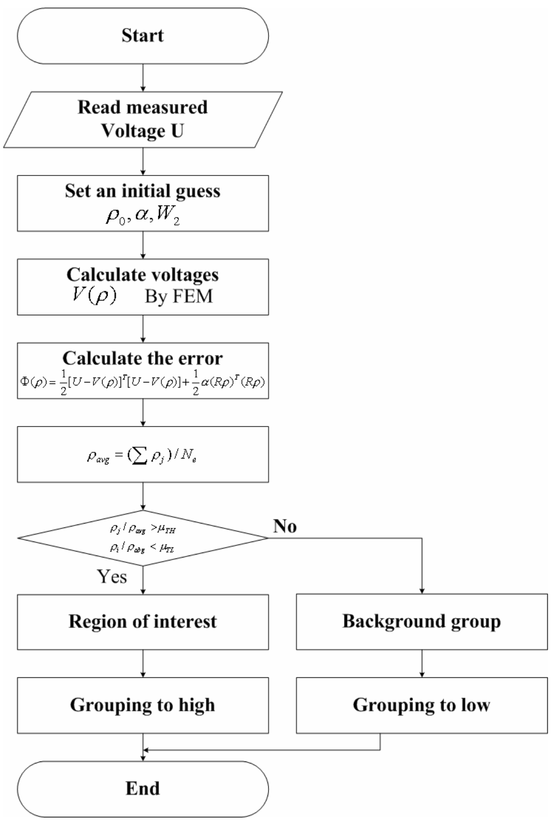


Fig. 2 Flow chart for ROI and initial value

2.2 Modified regularized NR

There are iterative operation for image reconstruction, case of background that has homogeneous resistivity and comparatively small anomaly, background is affected itself in previous value, roughly region of object, ROI distinguished itself in change of voltage. We propose cost function for verification of change in ROI. That is

$$\Phi(\rho)=\frac{1}{2}[U-V(\rho)]^T[U-V(\rho)]+\frac{1}{2}\alpha[\rho-\rho_i]^T W[\rho-\rho_i] \tag{6}$$

where $U \in \Re^{L\times(L-1)}$ is the measured voltage on each electrodes about current pattern, $V(\rho)\in\Re^{L\times(L-1)}$ is the computed voltages about current pattern, α and W are regularization parameter and matrix.

Iterative resistivity as follow

$$\rho_{i+1}=\rho_i+\left(J_i^T J_i+\alpha W\right)^{-1}\left(J_i^T(U-V(\rho_i))\right) \tag{7}$$

where $W=diag(J^T J)$ in NOSER algorithm, $W=I$ in Levenberg-Marquardt algorithm. [5],[6],[10]

In this paper, for more accurate estimation of object, W is smaller than 1 in ROI and the other region $W=1$, and then resistivity in ROI is more sensitive to change of voltages. Resistivity in back ground affected previous value so we can find out more accurate object. Fig 3. is Flow chart for proposed algorithm.

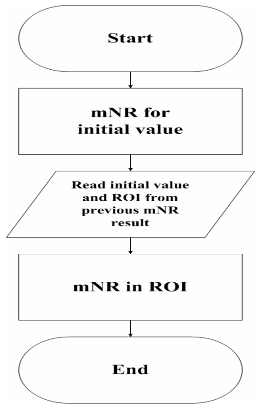


Fig. 3 Flow chart for proposed algorithm

3. SIMULATION

We have compared static EIT image reconstruction algorithm mNR with proposed algorithm and analyzed performance. Two type of object are used for simulation case1 : there is a circle in center and case2 : there is a shield shape object between boundary and center. Meshs of forward problem are FEM meshes having 3104 elements and 1681 nodes. We must decide proper element of mesh because of increase of operation. So FEM meshs are 1/4 smaller than forward problem that have 776 elements and 453 nodes. The number of electrode is 32, radius of phantom is 8 cm, impedance of background is $300\Omega cm$, impedance of object is $600\Omega cm$ and regularization parameter is $\alpha = 0.000005$.

For comparison and evaluation, we define RMSE as follow

$$RMSE \equiv \sqrt{[U_k-V_k(\rho_k)]^T[U_k-V_k(\rho_k)]} \tag{8}$$

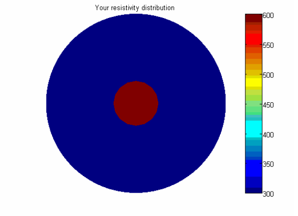
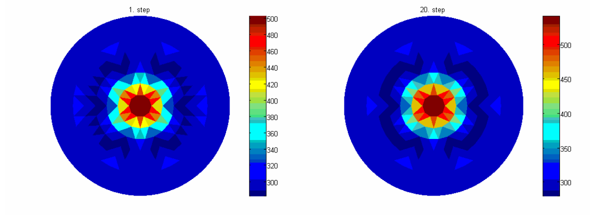


Fig. 4 true image of case1



(a) (b)

Fig. 5 mNR (a) result of 1st iteration, (b) result of 20th iteration

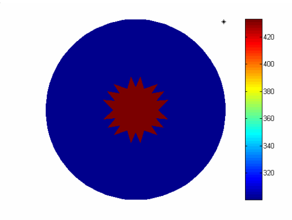
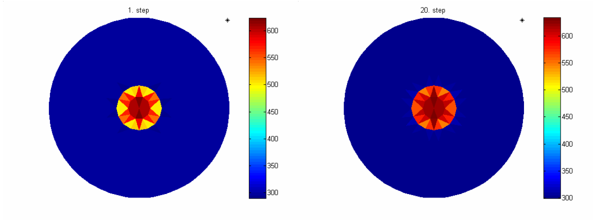


Fig. 6 initial value of case1 using proposed algorithm.



(a) (b)

Fig. 7 proposed algorithm (a) result of 1st iteration, (b) result of 20th iteration

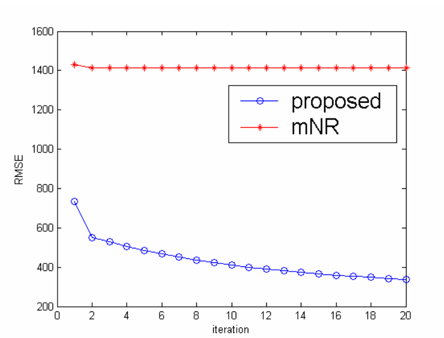


Fig. 8 RMSE for case1

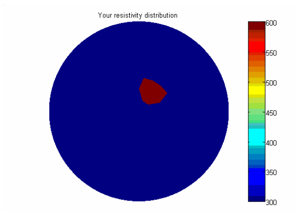
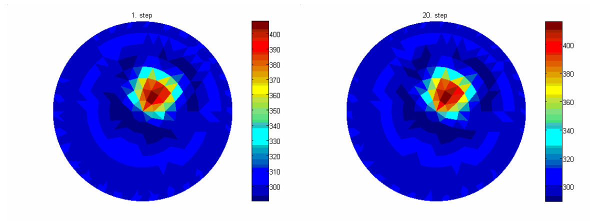


Fig. 9 true image of case2



(a) (b)

Fig. 10 mNR (a) result of 1st iteration, (b) result of 20th iteration

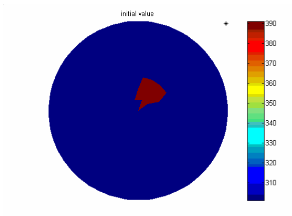
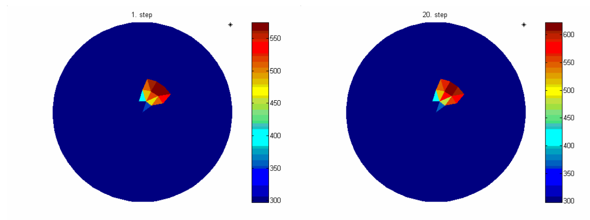


Fig. 11 initial value of case2 using proposed algorithm.



(a) (b)

Fig. 12 proposed algorithm (a) result of 1st iteration, (b) result of 20th iteration

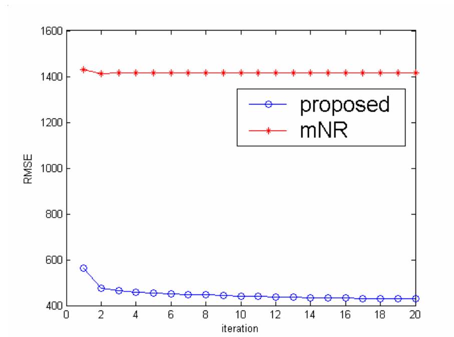


Fig. 13 RMSE for case2

Fig.4 and fig.9 are true object image for each case, fig. 5 and fig. 10 are results of mNR, fig. 6 and fig. 11 are initial values that are obtained from 1 frame information of mNR. For this process $\mu_{TH} = 1.15$, $\mu_{TL} = 0.5$ are used. Fig.10 and fig. 12 are results of image reconstruction by proposed method. Fig.8 and fig. 13 are RMSE for mNR and proposed method respectively for each case. By these results, we can verify that proposed method has better performance than mNR's.

4. CONCLUSION

This paper express that proposed method using ROI, initial value and regularized NR has better convergence performance than mNR. These ROI and initial value are estimated from reconstructed image by 1 frame information of mNR. By computer simulation, we compare and analyze performance of each EIT image reconstruction algorithm using imaginary data. By results of RMSE, proposed method is the more increase their frame the smaller error than mNR.

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