September 7. - 9.9.2009
Cheb, Czech Republic

IMPROVEMENT OF IMAGE RECONSTUCTIONS USING LEVEL SET METHOD

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Abstract: *The paper proposes a new approach to image reconstruction problems to improve results applying the level set technique during a reconstruction process, which is based on electrical impedance tomography (EIT). The recently described methods are often based on deterministic or stochastic approach to solve EIT inverse problem, which is nonlinear and highly ill-posed. The suggested approach combines advantages of nowadays used deterministic methods as there is Tikhonov regularization method with advantages of the Level Set method. The new way is applied to the tissue conductivity reconstruction. Numerical results of an image reconstruction based on the proposed new technique are presented and compared with previous results.*

Key words: *FEM, Level Set Method, Inverse Problem, Regularization Methods*

INTRODUCTION

The image reconstruction problem based on electrical impedance tomography is still a widely investigated problem with many applications in physical and biological sciences. Although the back image reconstruction based on EIT is highly ill-posed inverse problem the medical imaging is non-invasive technique and can be used primarily for the detection of pulmonary emboli, non-invasive monitoring of a heart function and a blood flow, or for the breast cancer detection.

The basic theory behind EIT is that by applying current across a material the voltage distribution resulting on the surface will reflect the internal resistivity (or conductivity) distribution. However, intuitively one will understand that multiple resistivity distributions can produce the same voltage distribution at the surface. Therefore the system is stimulated in multiple manners to constrain the possible resistivity distributions.

The EIT system comprises three main areas of development; electrode configuration and connection, data acquisition, and data processing. In this paper we would like to find some new way to improve the quality of the last area. There are two different types of EIT image reconstructions, static and dynamic EIT. In static EIT, only the absolute conductivity in each element is computed and a picture of the internal organs of different conductivity is imaged. In dynamic EIT, temporal variations in conductivity are computed. Both types can be very useful especially in medical applications.

So, the main goal of worthy image reconstructions is to find the very accurate distribution of an unknown conductivity (generally impedivity) inside the region of an investigated object from the currents and voltages measured on the electrodes attached to the surface of this object [1]. There is necessary to use an appropriate regularization and some prior information constraint. Various numerical techniques with different advantages have been developed to solve this problem; the main aim is to find such techniques which offer stable, accurate and no too much time-consuming reconstruction process.

1 THEORETICAL BACKGROUND

There is very well known that the EIT inverse problem searches for parameters in a high-dimensional space. The deterministic approach is based on the Least Squares method. Due to the ill-posed nature of this nonlinear problem, regularization has to be used. First the standard Tikhonov Regularization method (TRM) was applied to solve the inverse EIT problem. So we have to minimize the objective function $\Psi(\sigma)$

$$\Psi(\sigma) = \frac{1}{2}\sum \left\| \boldsymbol{U}_{\mathrm{M}} - \boldsymbol{U}_{\mathrm{FEM}}(\sigma) \right\|^2 + \alpha \left\| L\sigma \right\|^2 \qquad (1)$$

Here σ is the unknown conductivity distribution vector in the object, U_M is the vector of measured voltages on the object boundary, $U_{FEM}(\sigma)$ is the vector of computed peripheral voltages with respect to σ which can be obtained using the FEM, α is a regularization parameter and L is a regularization matrix connecting adjacent elements of the different conductivity values. For the solution of (1) was applied a Newton-Raphson method and after the linearization was used the iteration procedure

$$\boldsymbol{\sigma}_{i+1} = \boldsymbol{\sigma}_i + (\boldsymbol{J}_i^T \boldsymbol{J}_i + \alpha \boldsymbol{L}^T \boldsymbol{L})^{-1} (\boldsymbol{J}_i^T (\boldsymbol{U}_{\mathrm{M}} - \boldsymbol{U}_{\mathrm{FEM}}(\boldsymbol{\sigma}_i)) - \alpha \boldsymbol{L}^T \boldsymbol{L} \boldsymbol{\sigma}_i) \qquad (2)$$

here i is the i-th iteration and J is the Jacobian for forward operator $U_{FEM}(\sigma)$ and it can be calculated very effectively. Additional details are described in [2]. This procedure is commonly used in the EIT inverse problem for its fast convergence and good reconstruction quality. However, it is likely to be trapped in local minima and so additional regularization must be taken into account to obtain the demanded solution. The stability of the TRM algorithm is a bit sensitive to the setting of a starting value of conductivity and to an optimal choice of the parameter α provides balance between the accuracy and the stability of the solution. The value of the parameter α can be adaptively changed during this iteration process. In this way we can obtain the stable solution with required higher accuracy of the reconstruction results.

In recent years is very often used the Level Set method (LSM) to identify regions with different image or material properties [3 - 6]. The distribution of unknown conductivity (or resistivity) σ can be described in terms of level set function F depending on the position of the point r with respect to the boundary Γ between regions with different values of σ

$$\sigma(r) = \begin{cases} \sigma_{\text{int}} \{r : F(r) < 0\} \\ \sigma_{ext} \{r : F(r) > 0\} \end{cases} . \qquad (3)$$
$$\Gamma = \{r : F(r) = 0\}$$

To improve the stability and the accuracy of EIT image reconstructions new algorithm was created. This algorithm uses both of mentioned methods TRM and LSM. During iteration process based on minimizing objective function $\Psi(\sigma)$ the boundary Γ is searched in accordance with request that the $\sigma(r)$ minimizes the $\Psi(\sigma)$, too. New algorithm was applied to the several image reconstructions, with different type of constrains. Further are presented results of conductivity reconstruction for those examples, which were obtained during the reconstruction process.

2 Examples and Results

In this part we restrict a range of tasks to the objects with a biological tissue only. The basic model of the simple 2D arrangement of original conductivity distribution you can see in Fig. 1. The conductivity of homogenous region is 0.333 S/m (represents tissue), the conductivity of one region is 0.1 S/m (dark blue color, represents lungs) and finally the conductivity of the second is 0.667 S/m (brown color, represents heart).

During the reconstruction process the TRM was used to identify the locations and to specify exactly the conductivity values of non-homogenous regions. In the case of an unexpected finishing of iteration process because of non-stability was applied the LSM to specify the locations of non-homogenous regions.

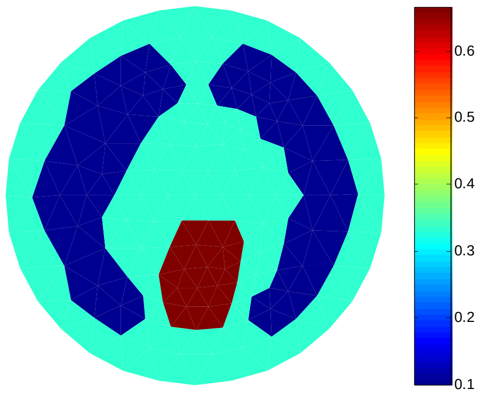

Fig.1: Basic model and original values of conductivity

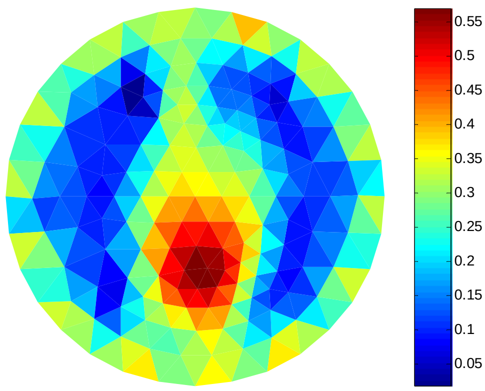

Fig.2: Conductivity distribution after using TRM, LSM

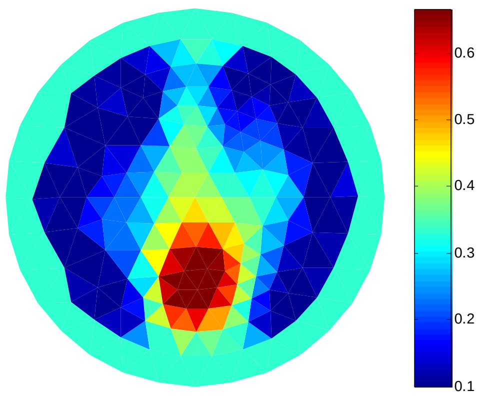

Fig.3: Final conductivity distribution

Finally, the TRM was applied again to specify the conductivity values, but only inside limited regions with non-homogeneity.

Now, let as suppose unknown locations of non-homogeneities, first with unknown values of conductivity. The results after both above mentioned steps are the same, it means after using TRM and after using LSM, you can see them at Fig. 2.

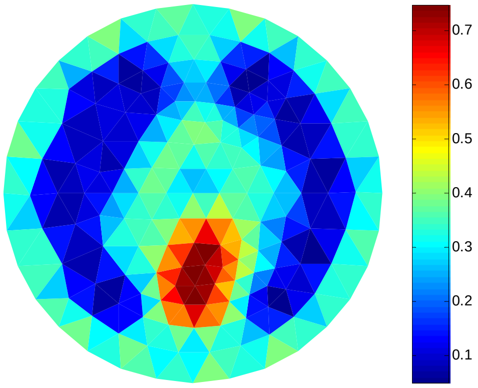

Fig.4: Conductivity distribution after using TRM

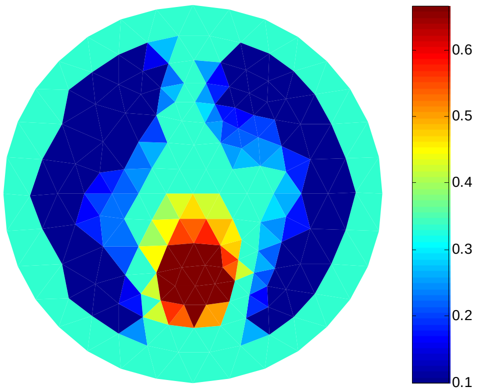

Fig.5: Conductivity distribution after using LSM

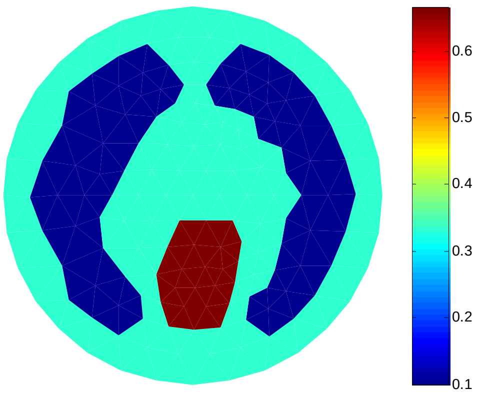

Fig.6: Final conductivity distribution

When we suppose the knowledge of conductivities of all components inside the investigated object (tissue, heart and lungs), the image reconstruction passes to simpler case and it is possible to obtain better results, which are shown in Fig. 4 to Fig. 6. The conductivity distribution after the first step (using TRM) is shown in Fig. 4, the conductivity distribution after the second step (using LSM) is shown in Fig. 5, final results of image reconstruction are shown in Fig. 6. There is evident, that the algorithm works very well in this case, because we obtained the identical distribution as the original.

2.1 *Looking for conductivity changes*

The following aim is to find all local non-homogeneities inside the lungs region or inside the heart region. We suppose the lungs, tissue and heart conductivities knowledge, the location and conductivity value of possible non-homogeneity are unknown.

First we consider the case of non-homogeneities detection inside lung region. New algorithm has to find the sub regions with conductivity different of lungs conductivity. The original conductivity distribution is shown in Fig. 7, three sub regions have 80% conductivity of lungs.

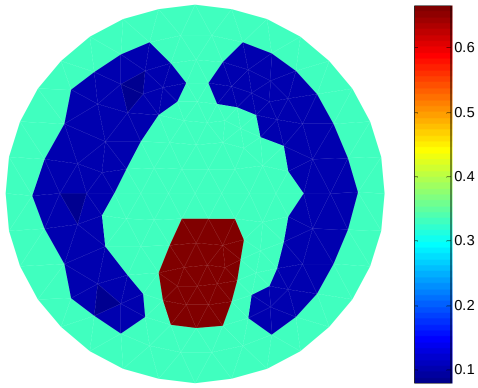

Fig.7: Original (final) values of conductivity

The conductivity distribution after using TRM is shown in Fig. 8, the conductivity distribution after using LSM is shown in Fig. 9, and final conductivity distribution is the same as the original (see Fig. 7)

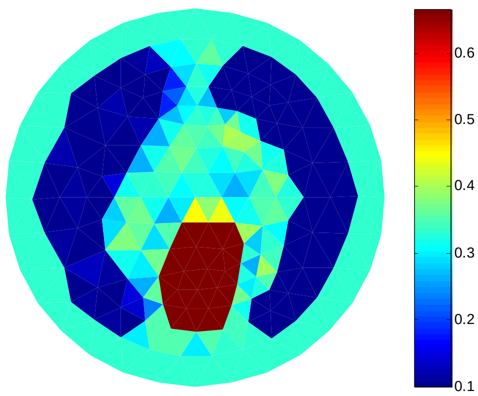

Fig.8: Conductivity distribution after using TRM

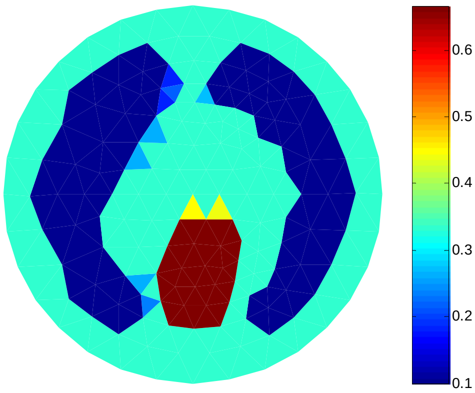

Fig.9: Conductivity distribution after using LSM

In the Figs. 10, 11 and 12 you can see the results of image reconstruction, if the conductivity value of the same non-homogenous sub regions is 120% of lungs conductivity.

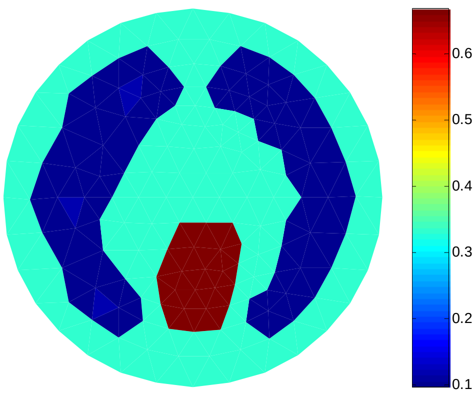

Fig.10: Original (final) conductivity distribution

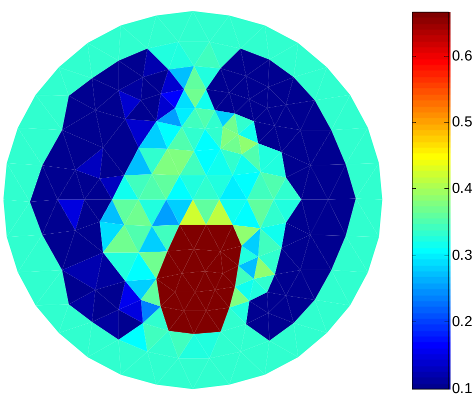

Fig.11: Conductivity distribution after using TRM

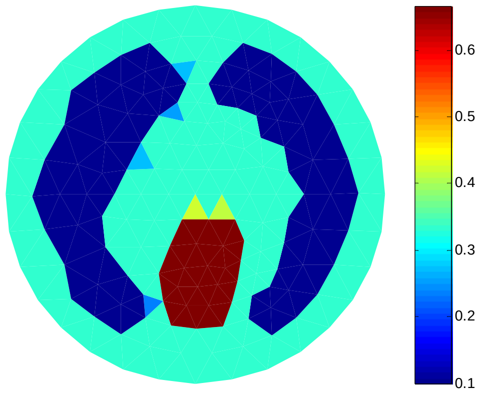

Fig.12: Conductivity distribution after using LSM

The last example represents the non-homogeneities detection inside the heart region. Let as consider again the detection of non-homogenous sub regions with conductivity 80% of heart conductivity. The original conductivity distribution is shown in Fig. 13.

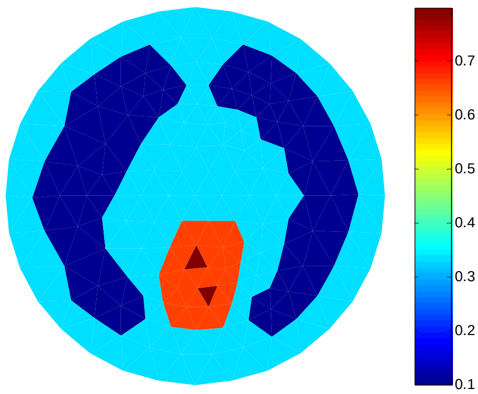

Fig.13: Original conductivity distribution

The conductivity distribution after using TRM is shown in Fig. 14, the conductivity distribution after using LSM is shown in Fig. 15, and final conductivity distribution is in Fig. 16.

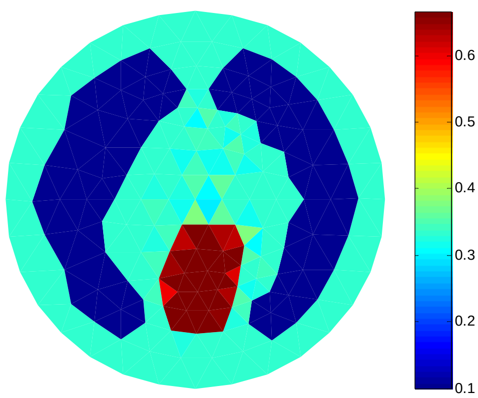

Fig.14: Conductivity distribution after using TRM

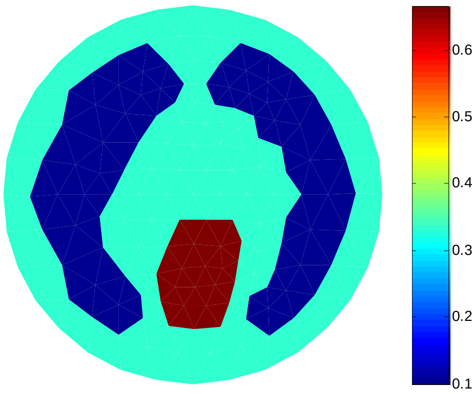

Fig.15: Conductivity distribution after using LSM

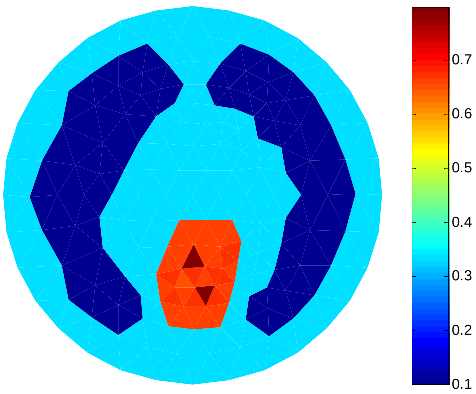

Fig.16: Final conductivity distribution

3 CONCLUSION

There is presented an improved approach to the EIT image reconstruction, which combines advantages of the level set algorithm and Tikhonov regularization method. This new way of an optimization process was used for the acquirement of more accurate reconstruction results in the specific cases. The new approach was tested on different shapes and sizes of non-homogenous regions. Based on appreciable number of realized numerical tests we can summarize, that the proposed algorithm ensures good stability and very often the highest accuracy of reconstruction process in comparison with the algorithm which was based on the TRM only.

ACKNOWLEDGEMENT

The research described in the paper was financially supported by the research program MSM 0021630503.

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