ALGORITHMS OF EIT IMAGE RECONSTRUCTION

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Abstract: The aim of this paper is a comparison of two algorithms used in image reconstruction for Electrical Impedance Tomography. The first algorithm presents special implementation of various fuzzy filters based on the Tikhonov regularization method and the second is the algorithm based on the combination of the Tikhonov regularization method and the level set method. They make it possible to determine an internal conductivity distribution for imaging tissues of the head and for determining the relevant brain tissue changes (blood clot). Also, some illustrative examples of local conductivity changes detection are presented. The properties of the reconstruction process are discussed.

Keywords: image reconstruction, fuzzy filter, level set method

1. INTRODUCTION

Electrical Impedance Tomography (EIT) is a method of image reconstruction of an object internal structure using its spatial distribution of conductivity. This method provides an exact and detailed spatial localization of an injury (with the minimal time intake of the research performance) and makes possible of supervision of the tissues status dynamics during a long time in the image reconstruction of biological tissue in the human body.

The internal conductivity distribution is recalculated from the measured voltages on the electrodes attached to the surface of the object by injecting small amounts of electric current (1−10 mA) [1]. Each local conductivity change inside the object causes electric potential changes on the surface of this object. This information about tissue conductivity changes is very useful and important for diagnostics in clinical medicine and also for the therapy related to clinical problems such as pulmonary emboli, breast cancer, cardiac disorder, blood circulation disturbance, and the disturbance of heart function (brain tumours, intracranial hemorrhage, blood clot).

Most described methods of EIT image reconstruction are mainly based on the deterministic approach. Better image reconstruction results can be reached when an additional technique is introduced, for example the level set method (LSM) [2]. There are several alternative techniques, which can be considered for implementation into image reconstruction processes. One of the feasible methods is based on fuzzy logic [3, 4].

2. BASIC THEORY

The image reconstruction is an inverse problem of EIT. The aim is to find the unknown conductivity distribution inside the investigated object. In mathematical terms, the inverse problem can be represented as a minimization of the suitable objective function $\Psi(\boldsymbol{\sigma})$ of $\boldsymbol{\sigma}$. In order to minimize function $\Psi(\boldsymbol{\sigma})$, a deterministic approach based on the method of least squares [1] can be used. Back image reconstruction is a highly ill-posed inverse problem, and therefore it is necessary to apply regularization – the Tikhonov Regularization method (TRM) [1]

$$\min_{\sigma} \Psi(\sigma) = \min_{\sigma}\left[\frac{1}{2}\sum \left\|U_M - U_{FEM}(\sigma)\right\|^2 + \alpha\left\|L\sigma\right\|^2\right]. \quad (1)$$

Here, $\boldsymbol{\sigma}$ is the volume conductivity distribution vector in the object, U_M is the vector of measured voltages on the boundary, and $U_{FEM}(\boldsymbol{\sigma})$ is the vector of computed peripheral voltages relative to $\boldsymbol{\sigma}$, which can be obtained using the FEM; α is a regularization parameter and L is a regularization matrix. A detailed description of procedures enabling us to find the solution of (1) by the help of the Newton-Raphson method is presented in [1].

Although the stability of this algorithm is slightly sensitive to the setting of initial values of conductivity $\boldsymbol{\sigma}_0$, it is very sensitive to the optimal choice of parameter α, which provides balance between the accuracy and the stability of the solution. However, it is likely to be trapped in local minima, notable the common TRM can be used to reach a rough estimate of the regions with a conductivity changes only. Therefore, introduction of an auxiliary technique must be taken into account to help obtain a stable solution with the required higher accuracy of the reconstruction results.

One of these auxiliary techniques is the LSM. The combination of these two methods (the TRM and the LSM) gives the possibility to obtain an algorithm, which will improve the stability and accuracy of EIT reconstructed images. During this iteration process, which is based on minimizing of the objective function $\Psi(\boldsymbol{\sigma})$, the boundary Γ (boundary between regions with different values of $\boldsymbol{\sigma}$) is searched in accordance with the request that the $\boldsymbol{\sigma}$ minimizes the $\Psi(\boldsymbol{\sigma})$, too. We suppose that the unknown conductivity distribution is given by a piecewise constant function $\boldsymbol{\sigma}(NE)$.

This algorithm can be described generally as follows:

1. set constraints for conductivity values;
2. initialize $\boldsymbol{\sigma}(NE) = \boldsymbol{\sigma}_0(NE)$, set parameter α, set $\Psi_0(\boldsymbol{\sigma}) = \Psi(\boldsymbol{\sigma}_0)$;
3. *if* $\Psi(\boldsymbol{\sigma})$ is decreasing, *then*
   - run iteration procedure based on the TRM;
   - set interfaces between subregions with different conductivities based on the LSM;
   - reduce the number of elements with unknown conductivity values considering the constraints;
4. *if* $\Psi(\boldsymbol{\sigma})$ is still decreasing, *then*
   - run new iteration based on the TRM and with interactive updating of interfaces.

Introduce of auxiliary fuzzy filters [3, 4] into the iteration process also makes it possible to provide the stability and accuracy of the EIT reconstruction procedure.

The fuzzy filters are realized by the following functions:

- $\max(\boldsymbol{\sigma})$, $\forall ie \ni \{1,\ldots,NE\} : \boldsymbol{\sigma}(ie) \leq \max(\boldsymbol{\sigma})$;
- $\min(\boldsymbol{\sigma})$, $\forall ie \ni \{1,\ldots,NE\} : \boldsymbol{\sigma}(ie) \geq \min(\boldsymbol{\sigma})$;
- systematic TRM estimation ($\boldsymbol{\sigma}$);
- list of elements given by expected $\boldsymbol{\sigma}_d$;
- list $\boldsymbol{\sigma}_{1L}$ of neighboring elements $\boldsymbol{\sigma}_d$ in the first layer;
- list $\boldsymbol{\sigma}_{2L}$ of neighboring elements $\boldsymbol{\sigma}_d$ in the second layer.

The iteration process can be described by the next five steps:

1. set the initial values of $\boldsymbol{\sigma}_0$ and $\Psi_0 = \Psi(\boldsymbol{\sigma}_0)$;
2. apply the TRM while $\Psi(\boldsymbol{\sigma})$ is decreasing;
3. set $\boldsymbol{\sigma}_0 + \boldsymbol{\sigma}_{1L}$;
4. apply the systematic TRM estimation with $\max(\boldsymbol{\sigma})$ and $\min(\boldsymbol{\sigma})$ while $\Psi(\boldsymbol{\sigma})$ is decreasing;
5. if $\Psi(\boldsymbol{\sigma}) > 1.\text{d-}20$, then set $\boldsymbol{\sigma}_d + \boldsymbol{\sigma}_{2L}$, go to 4.

The proposed filters and their introduction predetermine the possible geometry of unknown regions with conductivity $\boldsymbol{\sigma}_d$ and, also, the value of $\boldsymbol{\sigma}_d$. During the iteration process based on minimizing objective function $\Psi(\boldsymbol{\sigma})$, the geometry and conductivity of region $\boldsymbol{\sigma}_d$ is searched in accordance with the request that the final set $\boldsymbol{\sigma}$(NE) minimizes the $\Psi(\boldsymbol{\sigma})$ too.

3. EXAMPLES

The numerical simulation results were obtained using a 2D FEM model, which represents a simplified horizontal slice of the human head. This FEM model consisting of 2360 elements and 1237 nodes is shown in Fig. 1a. Twenty electrodes have been used for the voltage measurement on the boundary of the investigated object.

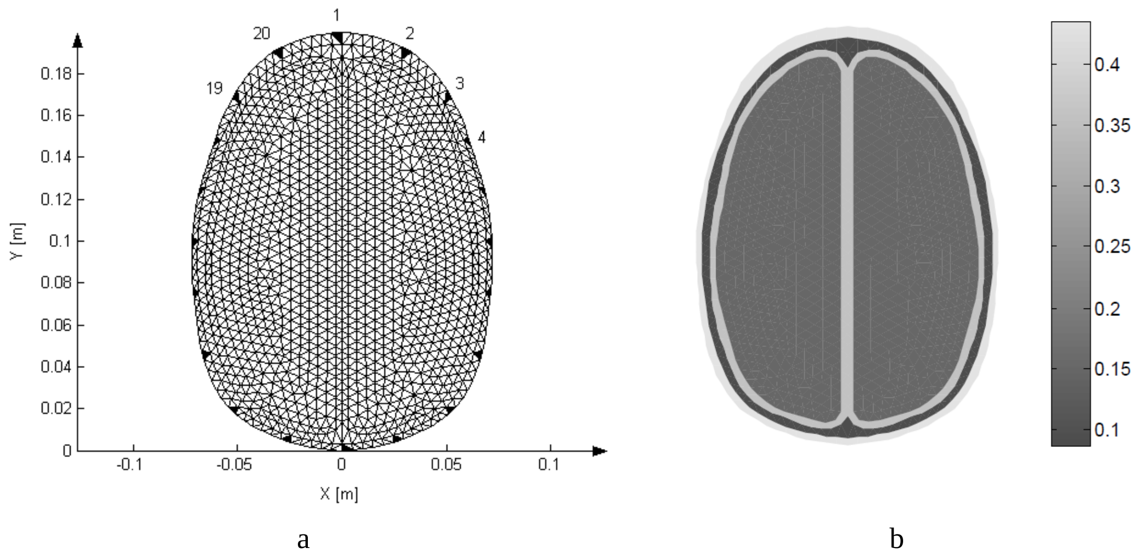

Figure 1: A 2D FEM model for the modeling of brain tissue (a) and the arrangement of health tissue (b).

The model of 2D arrangement with the original conductivity distribution (Fig. 1b) was used to simulate voltage U_M. The information about contact resistance of skin, which should be taken into account in simulation, is presented in [1]. It is a simplified model of the head, which consists of just four homogeneous isotropic layers: scalp, skull, brain (gray and white matter). Therefore, it is necessary to know only the values of average regional conductivities. The conductivity values of different biological tissues used for the following simulations are presented in Table 1; these values were adopted from literature previously published on the topic.

Tissue name	Conductivity σ [S/m]	References
Scalp	0.435	[5]
Skull	0.087	[5]
Gray matter	0.352	[6]
White matter	0.147	[6]

Table 1: The conductivity values of biological tissue.

The following examples demonstrate the results obtained using the foregoing two algorithms, on the condition that the geometry and values of a healthy tissue conductivity are known and complemented with the knowledge of the way a particular disorder affects the tissue conductivity.

Fig. 2a show numerical model which represent a tissue defect, namely blood clots. The conductivity of the inhomogeneity subregion representing a blood clot is 0.3 S/m [7]. These inhomogeneities are supposed to be inside the white matter region, right hemisphere.

Fig. 2b presents conductivity distribution after the application of the TRM: the first part of algorithms for an image reconstruction. And this distribution obtained using the fuzzy filters can be seen in Fig. 2c. The conductivity distribution after using the LSM is shown in Fig. 2e. The final conductivity distributions obtained using the foregoing two algorithms (the second using the TRM) is identical with original distribution in Fig. 2a.

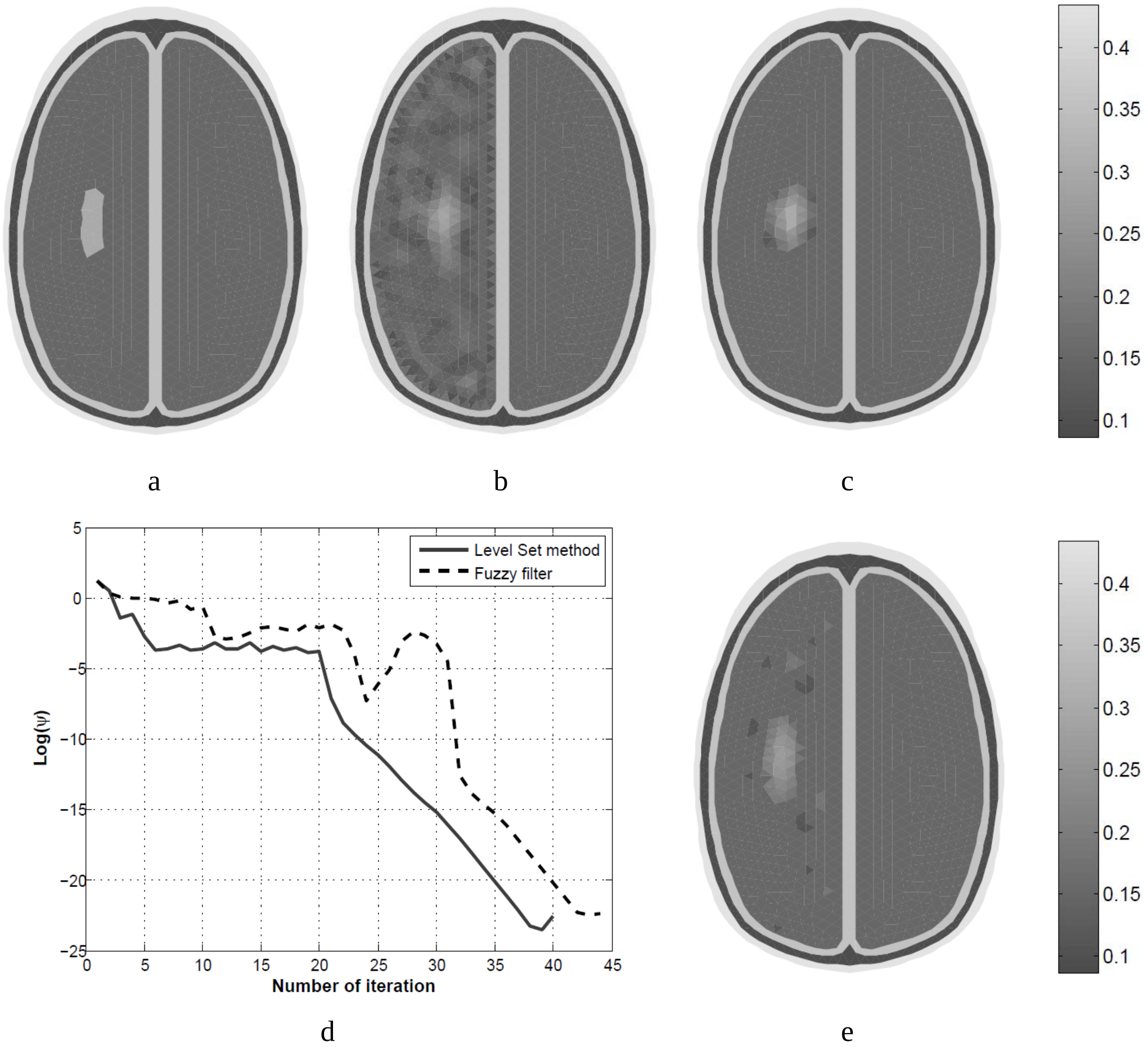

Figure 2: An original conductivity distribution (a);
the conductivity distribution after using the TRM (b), after using fuzzy filtering (c)
and after using the LSM (e); the objective functions during the blood clot detection (d).

The above-presented model with blood clots was used for the testing of two conductivity reconstruction algorithms. For the solution of an inverse problem, the Tikhonov regularization method was applied together with the fuzzy filters (first algorithm) and the level set method (second algorithm). In order to obtain useful reconstruction, it was necessary to set parameter $\alpha = 5{\cdot}10^{-6}$ and parameter $\mathrm{d}\alpha = 0.3$.

	TRM + Fuzzy filter	TRM+LSM
Objective function $\Psi(\sigma)$	3.368e-23	2.946e-24
Number of iteration	44	40

Table 2: Parameters of reconstruction.

During the reconstruction process we focused mainly on the development of an objective function value. The behaviour of these functions for the algorithms based on the combination of the TRM and LSM and combination of the TRM and fuzzy filter respectively is compared in Fig. 2d. All reconstructions were successful and each iteration process ended when the objective function was equal to values, which are presented in Table 2. The unknown conductivity was obtained with relative error less than 3.4% (TRM + LSM) and 4.5% (TRM + Fuzzy filter).

4. CONCLUSION

In this paper, two approaches to the reconstruction of head tissue non-homogeneities have been presented. The main idea of these algorithms lies in introducing an additional technique (the fuzzy filter and the level set method) to the reconstruction process based on the Tikhonov regularization method. Many numerical experiments performed during the above-described algorithm have resulted in the conclusion that the application of the TRM reconstruction algorithm with fuzzy filters or with level set method has an advantage over the TRM in better accuracy and stability of the reconstruction process. The new algorithm is less time-consuming than the algorithm based on TRM and the level set method. These algorithms are used for a significant simplification of the reconstruction process and for saving the time necessary to materialize the solution.

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