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Electrical Impedance Tomography in medical research

***Abstract**. This paper presents the applications of the Electrical Impedance Tomography (EIT) in medical imaging, selecting perfusion lung and female breast. In a study of breast to ensure a stable contact of electrodes indicated on the indirect method consisting in immersing the breast suitably measurements intermediate fluid container. Basic parameters are defined in medical imaging of impedance tomography method. The preferred method solutions of the inverse problem are linear algorithms based on finite element method approximating of the tested objects. The conductivity values in different regions are determined by the finite element method.*

***Streszczenie**. W pracy przedstawiono zastosowania tomografii impedancyjnej w badaniach medycznych wybierając obrazowanie perfuzji płuc oraz badanie piersi kobiet. W badaniach piersi dla zapewnienia stabilnego kontaktu elektrod wskazano na metodę pośrednią polegającą na zanurzeniu piersi w odpowiednio opomiarowanym pojemniku z płynem pośrednim. Preferowaną metodą rozwiązania zagadnienia odwrotnego są algorytmy liniowe oparte na metodzie elementów skończonych przy aproksymacji badanych obiektów. Określono podstawowe parametry w obrazowaniach medycznych metodą tomografii impedancyjnej. (**Tomografia impedancyjna w badaniach medycznych**)*

Keywords: electrical impedance tomography, finite element method, inverse problem, medical research
Słowa kluczowe: tomografia impedancyjna, metoda elementów skończonych, problem odwrotny, badania medyczne

Introduction

Research on electrical impedance tomography (EIT) was developed from the beginning of the seventies of the twentieth century and led to many interesting solutions and results. With such advantages as: non-invasive, low cost, ease of use and practicality, this method has been used in many areas. EIT can be very fast, able to generate thousands of images per second. Its main drawback and restriction is small spatial resolution. It stems primarily from insufficient changes values measured voltage in relation to the distribution of conductivity of the test object. At low resolution method also affects the non-linear distribution of electricity, and a limited number of measurements.

EIT might be helpful in clinical studies, such as an empty stomach contents or secretions collecting in them, lung ventilation, non–invasive monitoring heart rate and blood circulation, determining various premenstrual syndrome based on the amount of fluid inside and outside the cell, the detection of cancerous changes in the cells of the skin and breast, the detection of internal bleeding, the study of local increase temperature associated with hypothermia treatment, and results in the improvement of ECG and EEG. Their usefulness in clinical studies, this method is based on the electrical properties of healthy and diseased tissues. Depending on the state of change the values of the conductivity and dielectric permittivity, which is based on the method described. Modern measurement systems used in EIT are built using professional equipment, sensors, data acquisition cards, A/D converters, computers and software. Functional diagram of a universal system contains the necessary components to enable running relevant research, calculation and visualization.

EIT in medical research is to measure changes in conductivity in the body, determined by measuring the voltage at the electrodes placed on the surface of the body. Voltages on the electrodes caused by stimulation of the body in many different places small harmless electric currents (Fig. 1). One of the most promising applications of tomography is the relationship of physiological events in the chest. The thorax is composed of several organs, in which during normal operation, occur extreme changes in conductivity. EIT is able to non-invasively examine impedance changes of the interior of the thorax, giving a continuous picture of the distribution of ventilation. Very similar to relationship exists with emptying of stomach contents study.

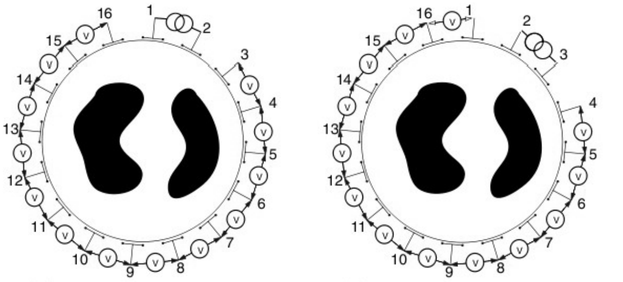

Fig. 1. The team electrodes and measuring techniques used in the imaging of lung ventilation and gastric emptying of contents

Methods for measuring 3D objects

Location positioning of the electrodes and the processes occurring between the interface electrodes and test object are still a major problem. For example, in studies of lung tomography, the changes of conductivity near electrodes in many cases lead to a misinterpretation as changes in conductivity within the body. There are various ways to provide a good and stable electrode contact with the patient body. The study of women's breasts often uses a set of electrodes attached to the surface of sufficient size cone or hemisphere (Fig. 2).

To eliminate the problem of imperfect location or unstable electrode contact, studies can be used an additional container which is equipped with a properly stable electrodes with a well-defined location, filled with a liquid with a known conductivity. In this container, immerse the tested object and make typical tomographic measurements. Electrodes problem disappears if we use a special technique of research by an intermediate container that is already prepared the appropriate equipment to ensure the proper and stable parameters. The tested object is placed in a intermediate container filled with liquid of known and properly chosen conductivity.

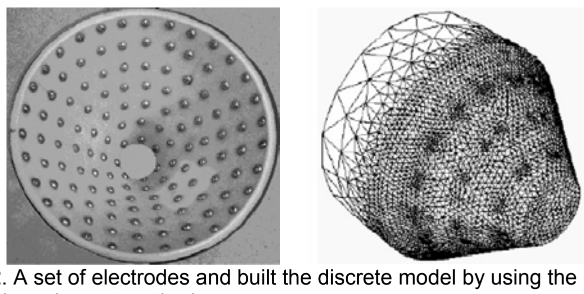
Fig. 2. A set of electrodes and built the discrete model by using the boundary element method

Linear algorithms for the solution of the reconstruction problems

Described in this part Gauss-Newton algorithm for the approach to reconstruction is widely used in EIT. The solution is a linear reconstruction of the matrix, which allows fast real-time visualization, and allows using of advanced regularization models for the inverse problem of EIT. For small changes in conductivity within the σ_r reference, the relationship between σ and V might be linear:

$$\text{(1)} \quad \Delta\sigma = (\mathbf{J}^T\mathbf{J})^{-1}\mathbf{J}^T\Delta V = (\mathbf{J}^T\mathbf{J})^{-1}\mathbf{J}^T[V_m - V(\sigma)] ,,, \ \Delta V \geq \xi$$

$$\boldsymbol{\sigma} = \boldsymbol{\sigma} + \alpha\,\Delta\boldsymbol{\sigma}$$

where $\mathbf{J} \in \Re^{n_M \times n_N}$ is the Jacobi or the Sensitivity matrix, $\boldsymbol{n} \in \Re^{n_M}$ is a measure of the noise, which is assumed as uncorrelated the white noise with a Gaussian distribution. Jacobi matrix $\mathbf{J}$ is calculated as $[J]_{ij} = \left.\frac{\partial[V]_i}{\partial[\sigma]_j}\right|_{\sigma_r}$, it depends on MES, at present are pattern of beats stimuli referenced to the conductivity electrode models. This algorithm is indeterminate for $n_N > n_M$. Regularization are required in order to calculate the estimates of conductivity changes of the x vector, which is attached to both y measurement and "*a priori*" knowledge of restriction image. Inverse problem solution algorithm EIT in general Tikhonovs regularization is expressed as the minimum sum of squared norms. Dependence is reduced to the problem of optimization of regularization:

$$\text{(2)} \quad \|\boldsymbol{y} - \mathbf{J}\,\boldsymbol{x}\|^2_{\sum_n^{-1}} + \|\boldsymbol{x} - \boldsymbol{x}^o\|^2_{\sum_n^{-1}}$$

where $\boldsymbol{x}^o$ represents the expected value of the element conductivity changes, which are zero in the EIT. Σ_n is matrix of the n measurement noise covariance. As the *n* is correlated, Σ_n is a diagonal matrix with the elements, where is the noise in the *i*-th measurement. $\sum_x \in \Re^{n_M \times n_N}$ is expected image covariance.

Voltage model and the accuracy of the measurement For uncorrelated noise, each diagonal matrix element is proportional to the signal and noise. Regularization P matrix can be understood as a model for the probability of picture elements and their interactions. Minimizing the goal function of the linearization leads to solve the inverse problem in one step [2,3].

It is worth noting that in the tomography used many other solutions, such as TSVD and SIRT. All of these methods are linear and structurally similar. However, the relation defined in equation (1) clearly exhibits a selection of image reconstruction parameters. Typically covariance matrixes Σ_n and Σ_x are not directly calculated, but are heuristically modeled. Characters $V = \sigma_n^2 \sum_n$ and $\mathbf{P} = \sigma_x^2 \sum_x$, where σ_n is the average amplitude of the measurement noise, and σ_x is founded "*a'priori*" amplitude changes in conductivity.

Inverse problem:

$$\text{(3)} \quad \hat{\boldsymbol{x}} = \left(\mathbf{J}^T \frac{1}{\sigma_n^2} V^{-1}\mathbf{J} + \frac{1}{\sigma_n^2}\mathbf{P}^{-1}\right)^{-1} \mathbf{J}^T \frac{1}{\sigma_n^2} V^{-1}\boldsymbol{y} = \left(\mathbf{J}^T V^{-1}\mathbf{J} + \lambda^2\mathbf{P}^{-1}\right)^{-1}\mathbf{J}^T V^{-1}\boldsymbol{y}$$

where P is the matrix of the linear image reconstruction σ_n TI, $\mathbf{R} = \left(\mathbf{J}^T V^{-1}\mathbf{J} + \lambda^2\mathbf{P}^{-1}\right)^{-1}\mathbf{J}^T V^{-1}$ $\lambda = \sigma_n/\sigma_x$ is often called hyper parameter regularization that controls the resolution and suppressing noise in the reconstructed image. Matrix $\mathbf{R} = \mathbf{PJ}^T\left(\mathbf{JPJ}^T + \lambda^2 V\right)^{-1}$ is a linear one-step inverse transformation about size $n_N \times n_N$.

Often we use the Wiener filter, and then the $\mathbf{R}$ matrix takes the form: $\left[\mathbf{P}^{-1}\right]_{i,i} = \left[\mathbf{J}^T\mathbf{J}\right]_{i,i}$. In this relationship $\mathbf{R}$ matrix is reduced to the dimension of the $n_M \times n_M$. If parts of the image are considered to be independent, then equation (1) uses the Tikhonov zero-order regularization. For EIT such solutions tend to increase the sensitivity of the measurement data and are much more sensitive to the elements around the edge of the image. Instead, the P matrix can be scaled with the sensitivity all the elements, so that each *i*-th diagonal element dependency satisfy. To improve the smoothness of the image in the entire area, proposed many improvements based on the discrete Laplace'a filter, Gaussian filter, or on the basis of uniformity of variance reduction. This algorithm is a representative for a group of structurally similar procedures, which are widely used in the EIT, because often leads to good results.

Tikhonov's regularization

Another way the reconstruction might be used pseudo-inverse matrix $\mathbf{J}^+$:

$$\text{(4)} \quad \mathbf{J}^+ = \mathbf{J}^T(\mathbf{J}\mathbf{J}^T)^{-1} = (\mathbf{J}^T\mathbf{J})^{-1}\mathbf{J}^T$$

which solves the equation $\boldsymbol{\sigma} = \mathbf{J}^+\boldsymbol{V}$. Unfortunately, this equation is numerically ill-conditioned, which often leads to a lack of solutions or considerable errors. Only use an additional member of regularization allows get the correct solution:

$$\text{(5)} \quad \boldsymbol{\sigma}_{Tik} = (\mathbf{J}^T\mathbf{J} + \alpha^2\mathbf{1})^{-1}\mathbf{J}^T\boldsymbol{V}$$

or by using the Tikhonov classical regularization:

$$\text{(6)} \quad \Delta\sigma = (\mathbf{J}^T\mathbf{J} + \alpha^2\,\mathbf{R}\mathbf{R}^T)^{-1}\mathbf{J}^T\Delta\boldsymbol{V}, \text{ for } \alpha > 0$$

Quality of the solution depends largely on the choice of the parameter α. For small α values we get a good quality of reconstruction, but also prone to significant measurement errors and disturbances, which can lead to defective and unacceptable results. The high value of this parameter causes lower quality of reconstruction, by the same time more resistant to errors. In practice, the regularization parameter is chosen experimentally. Calculation of regularization component is time-consuming, but it can be done before starting the measurements. This makes the method is fast and can be used in the on-line reconstruction.

Iterative methods of the inverse problem solution

Supposing, we know the F function, which is based on the decomposition of the material parameter solves the forward problem, in other words sets the measurement vector:

$$\text{(7)} \quad \boldsymbol{V} = F(\boldsymbol{\sigma})$$

The solution of the equation due to the vector σ can be reduced to minimize the mean square error between the measured $\boldsymbol{V}_o$ vector and $\boldsymbol{V}_P$ vector derived from the image of F function:

$$\text{(8)} \quad e = [F(\boldsymbol{\sigma}) - \boldsymbol{V}_O]^T[F(\boldsymbol{\sigma}) - \boldsymbol{V}_P]$$

Minimizing the mean square error can be obtained using an iterative Newton-Raphson algorithm:

(9) $$\widehat{\boldsymbol{\sigma}}_{k+1} = \widehat{\boldsymbol{\sigma}}_k - (\mathbf{J}_k^T \mathbf{J}_k)^{-1} \mathbf{J}^T (\boldsymbol{V}_O - \boldsymbol{V}_P)$$

where: $\widehat{\boldsymbol{\sigma}}_{k+1}$ is reconstructed conductivity of the material in the next step iteration, Jk, sensitivity matrix calculated on the basis of the distribution of material $\widehat{\boldsymbol{\sigma}}_k$, V_O is a vector of voltages obtained from the solution of the forward problem, V_P – vector of measured voltages. Often is used to modify the Tikhonov regularization, and then the algorithm takes the form:

(10) $$\widehat{\boldsymbol{\sigma}}_{k+1} = \widehat{\boldsymbol{\sigma}}_k - (\mathbf{J}_k^T \mathbf{J}_k - \alpha \mathbf{1})^{-1} \mathbf{J}^T (\boldsymbol{V}_O - \boldsymbol{V}_P)$$

Another iterative algorithm is Landweber algorithm where the goal function is minimalized:

(11) $$e = [\mathbf{J}\boldsymbol{\sigma} - \boldsymbol{V}_P]^T [\mathbf{J}\boldsymbol{\sigma} - \boldsymbol{V}_P]$$

The solution of the problem leads to an iterative algorithm expressed Landweber's relationship:

(12) $$\widehat{\boldsymbol{\sigma}}_{k+1} = \widehat{\boldsymbol{\sigma}}_k - \alpha \mathbf{J}^T (\mathbf{J}_k \widehat{\boldsymbol{\sigma}}_k - \boldsymbol{V}_P)$$

where α is relaxation parameter.

As previously presented algorithms Jk sensitivity matrix is calculated at each step based on the previous iteration result. In practice, due to the large time-consuming to apply a constant sensitivity matrix calculated, for example for a homogeneous distribution. In this case the reconstruction a bit deteriorates, but for small changes is acceptable in the distribution coefficient of the material. This increases the speed of the algorithms, which allows real-time reconstruction.

Our method is based on the idea called dual meshing. Fine mesh is used to determine Jacobian in the forward problem and a coarse mesh is for the inverse problem. The forward problem is well posed, so the high mesh density allows for a high accuracy of the computations. Described algorithms are in many ways similar to each other and therefore can be generalized to the following form:

(13) $$\widehat{\boldsymbol{\sigma}}_{k+1} = \widehat{\boldsymbol{\sigma}}_k - \alpha F_{\mathrm{odw}} (F_{\mathrm{pro}} \widehat{\boldsymbol{\sigma}}_k - \boldsymbol{V}_P)$$

where: F_{odw} – matrix describes inverse problem, F_{pro} – matrix describes forward problem, $\boldsymbol{V}_P$ – measurement vector, α – relaxation parameter.

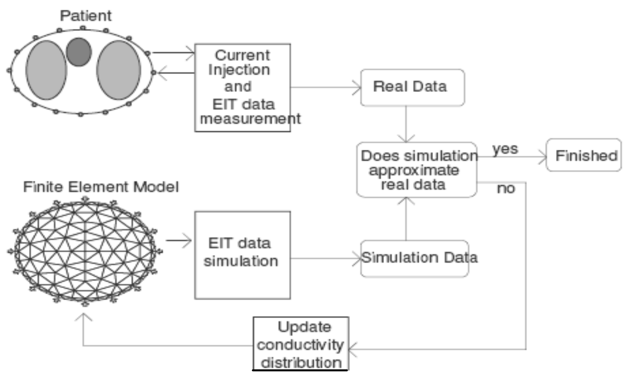

Fig. 2. Shows a diagram of the EIT using iterative algorithms

It is worth noting that such a generalized iterative reconstruction algorithm is flexible and can be easily adapted to specific tasks – it takes into account "a priori" knowledge of the process. The speed and precision of the algorithm depends mainly on the choice of functions through forward and inverse problem. In order to get high speed can use the simplest linear projection of the forward and backward linear projection. Both methods are fast, but less precise, however, their use in an iterative process leads to a substantial increase in the quality of the reconstruction compared to non-iterative methods.

Experimental studies of lung ventilation

The paper presents experimental studies of lung ventilation, and their visualization by means of inverse algorithms. Sample images of lung studied are shown in Fig. 3b.

Main advantages of EIT, such as safety, short imaging time low cost are still valid for presented setup.

a) b)

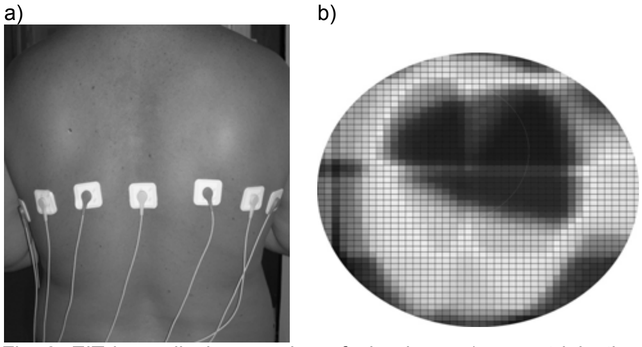

Fig. 3. EIT in medical research perfusion lung: a) current injection and data measurement, b) reconstruction image of the object (measured data)

On Fig 3b was presented the first reconstruction image of the real measure data. The image was obtained using the finite element method. Bell function was used to solve inverse problem. We used mesh with 4096 elements. The obtained results allow to conclude, that used this methods is possible to obtained of reconstruction lung ventilation and other medical problems.

REFERENCES

[1] Ackerman M.J.: *The Visible Human Project*, Proc. IEEE 86, 1998, pp. 504-511.

[2] Adler A., Arnold J.H., Bayford R., Borsic A.,Brown B., Dixon P., Faes T.J.C., Frerichs I., Gagnon H., Garber Y., Grychtol B., Hahn G., Lionheart W.R.B., Malik A., Patterson R.P, Stocks J., Tizzard A., Weiler N., Wolf G.K..: *GREIT: a unified approach to 2D linear EIT reconstruction of lung images*. Physiol. Meas. 30 (2009) pp. 35-55.

[3] Filipowicz S.F.: *Nowe metody i algorytmy tomografii procesowej*. Bell Studio, Warszawa, 2011.

[4] http://www.princeton.edu/~ktchu/software/lsmlib/lsmlib_doc/index.html

[5] Sawicki B., Grzywacz T.: Electrical Impedance Tomography through an ambitne fluid as a solution for electrode contact problem, Przegląd Elektrotechniczny R. 88 NR 6/2012

[7] Rymarczyk T.: *Zastosowanie metody zbiorów poziomicowych w tomografii impedancyjnej.* Rozprawa doktorska 2010.

[8] Zhang J., Patterson R.P.: EIT images of ventilation: what contributes to the resistivity changes? Physiol. Meas. 26, 2005, pp. 81-92.

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