Inverse Problems, Design and Optimization Symposium
Rio de Janeiro, Brazil, 2004

A METHOD TO BUILD IMAGES FROM ELECTRICAL IMPEDANCE TOMOGRAPHY TECHNIQUE BASED ON TOPOLOGY OPTIMIZATION

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ABSTRACT

Electrical Impedance Tomography (EIT) is a recent monitoring technique that allows us to obtain images representing a transversal plane of human body section. The images are obtained by applying a sequence of low intensity electrical currents, through electrodes positioned around human body. The EIT deals with inverse problem solution. In this work, the main objective is to apply Topology Optimization Method (TOM) to obtain images of body section by using EIT. The TOM is an iterative method whose computational algorithm combines Finite Element Method and an optimization algorithm. TOM applied to obtain images of body consists of finding the conductivity distribution in the body section domain that minimizes the difference between electric potential measured on electrodes and electric potential calculated by using a computational model. This work contributes on development of image reconstruction algorithms applied to monitor accurately mechanical ventilation of lungs. Image reconstruction results obtained by using numerical data are shown.

Keywords: Electrical Impedance Tomography, Topology Optimization, Finite Element Method, Sequential Linear Programming.

INTRODUCTION

During the last years of century XX, modern techniques have been developed to observe the interior of human body with strong tendency to minimal invasive surgical intervention. Ever since, the tomography techniques became the most important way to obtain medical images. Among all of them, the tomographies by x-ray and by magnetic resonance are the most common techniques. However, since the beginning of 90´s years, other technique called Electric Impedance Tomography (EIT) has been studied as an interesting alternative for obtaining images in clinical applications. Essentially, EIT consists in obtaining images that represent any transversal plane section of human body (head, thorax, thigh, etc), where each pixel in the image is related to its corresponding value of electrical conductivity. A sequence of low intensity electrical currents is applied to the body section, through electrodes positioned around the patient's body and aligned in a plane corresponding to a transverse section of the body, as illustrated in Fig. 1.

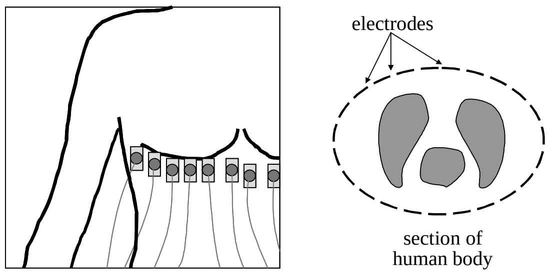


Figure 1 – Electrodes positioned around the body.

In EIT, an inverse problem must be solved [1], that is, by injecting known amounts of electrical current, according to an excitement pattern (adjacent), and measuring the electrical potential field (voltages) at electrodes on the boundary of the body, it estimates and construct a map of the conductivity distribution of region of the body probed by the electric currents.

Although EIT image quality is expected to have relatively poor resolution, compared to other tomography techniques, it has some very attractive features for clinical applications such as monitoring lung fluid, monitoring of heart function and blood flow, detecting tumors and others [1]. The technology for EIT is safer and cheaper than other techniques, as resonance magnetic tomography. Moreover an EIT device is short and portable which allows its installation for continuous monitoring of bedridden patients, which avoids dangerous patient transportation from ICU (Intensive Care Unit) to the exam room. In this technique the patient does not have exposition to any type of radiation, just to the low electrical current levels that do not cause any harm to the patient [2].

This work presents results obtained from computational algorithm that applies the Topology Optimization Method (TOM) to reconstruct images of body section by using EIT technique. TOM tries to find systematically a material distribution inside of a design domain (the section of body), to satisfy an objective function requirement and specified constraints. The problem of applying TOM to obtain an image of body section consists in finding a conductivity distribution in the body section domain that minimizes the difference between electric potential measured on electrodes and electric potential calculated by using a computational model. Conductivity distribution is related to material distribution inside of the domain and thus to the voltage values measured on electrodes positioned at domain boundary. The solution of the topology optimization problem is obtained by combining Finite Element Method (FEM) and an optimization algorithm called Sequential Linear Programming (SLP).

The next sections show some related works in EIT and TOM, the FEM model for the conductive medium, the topology optimization problem formulated to obtain image by using EIT, the numerical implementation to solve that optimization problem and the sensitivity analysis of the topology optimization problem. Image reconstruction results by using numerical data of well-know domains are also shown. Finally, in the last section, the conclusions are given.

SOME FEATURES ABOUT EIT AND TOM

The first studies and theoretical formulations for implementation of image reconstruction algorithms that constructed the foundation for EIT in practical applications medicine emerged in the 80’s years in the University of Sheffield (England). Researchers of this university studied the EIT technique and described its practical application in medicine such as the monitoring of lung, heart and gastric functions, for instance. They are practically the pioneers in the formulation of theories and data, which built the EIT foundation until the present moment, and developed the first commercial EIT device based on the Backprojection method [3]. This device has a scheme called APT system (Applied Potential Tomography), which is composed by a simple source of electric current with 16 electrodes and it uses the adjacent pattern for application of the electrical current. This APT system has the advantage of simplicity of design, but its image quality is intrinsically limited. Although this APT system just allows us to obtain images of low resolution, it has been used in studies of several medical procedures as the monitoring of the blood flow in the thorax and lung problems. In the 90’s years, researchers of Rensselear Polytechnic Institute (USA) designed and built another EIT device that it has a scheme called ACT system (Adaptive Current Tomography) with 32 electrodes, which is able to obtain 20 static images per second [1]. This device uses a “fast” method for image reconstruction, which is based on the One-Step Newton method. In Brazil, the development of a EIT device has been studied by researchers of the University of São Paulo in a thematic project whose objective is to study algorithms reconstruction for EIT to monitor accurately the mechanical ventilation of lungs [2] and to diagnose when any portion of lungs is damaged (obstructed or collapsed) during mechanical ventilation process.

The application of Topology Optimization Method (TOM) [4] is not recent and it began in the mechanical structural area, where the method demonstrated its great potentiality in the design of mechanical parts with maximum stiffness and smaller weight. Thus, it had been used broadly in the design of optimized parts at the automotive and aeronautics industries in the United States, Japan and Europe. In addition, TOM was applied recently to design compliant mechanisms and piezoelectric actuators [5]. TOM is a generic and systematic and iterative method that combines optimization algorithms with an analysis method, in general the Finite Element Method (FEM), to distribute the material inside of a fixed design domain (region limited by the boundary conditions) to maximize or to minimize a specified objective function. In the TOM, the fixed design domain is divided into several finite elements and its FEM mesh is not changed during the optimization process. The material in each point of the fixed design domain can change from a material type A to another one type B, assuming intermediate materials between A and B in according to material model, which defines the mixture of two or more materials.

In this work, the material model used is known as Density Method [5]. Thus, considering the domain has been discretized in N finite elements, the conductivity properties ($\mathbf{c}_i$) of each element can be given in the following way:

$$\mathbf{c}_i = \rho_i^{\,p}\mathbf{c}_A + (1-\rho_i)^p\,\mathbf{c}_B\ ;\ 0 \le \rho_i \le 1,\ i = 1...N \qquad (1)$$

where $\mathbf{c}_A$ and $\mathbf{c}_B$ are the conductivity properties of the base materials that compose the domain. In that case the material A could be air, for instance, and the material B could be the tissue of the lungs. The values of each ρ_i can change from 0 (only material B) to 1 (only material A). Excess of mixture of the two materials (values between 0 and 1) is not interesting in the final result and should be avoided by use of penalization parameter *p*, whose value must be adjusted [5].

FEM MODEL

In this work, the design domain is discretized by four nodes quadrilateral elements, where the electric potentials in all nodes are obtained by using FEM analysis considering application of electric currents to the boundary nodes of the domain. The FEM formulation applied to conductive medium [6] is generated from electrical conductivity equations, which are given by:

$$div(\sigma\nabla\phi) = 0\ ;\ \begin{cases} \mathbf{I} = \sigma\nabla\phi \\ \mathrm{I}_n = \sigma\nabla\phi.\mathbf{n} = \sigma\dfrac{\partial\phi}{\partial \mathrm{n}} \end{cases} \qquad (2)$$

where ϕ is the electric potential, σ is the electric conductivity, $\mathbf{n}$ is a normal vector to the boundary of domain, $\mathbf{I}$ is the electrical current vector (in ampere per square meter), I_n is a component of the electrical current in the direction $\mathbf{n}$, *div* is the divergent operator and ∇ is the gradient operator.

Thus, the FEM formulation consists in substituting approximation functions of the electric potential into the integral form of the electric conductivity equations of Eq. (2) to calculate the electric potentials distributed in the discretized domain through a system of equilibrium equations, whose matrix formulation is given by [7]:

$$\mathbf{K}\,\boldsymbol{\Phi} = \mathbf{I} \qquad (3)$$

where $\mathbf{K}$ is the global FEM electric conductivity matrix of discretized domain, $\boldsymbol{\Phi}$ is a vector of nodal electric potential and $\mathbf{I}$ is a vector of nodal electric current.

The nodal electric potential is obtained from electric current applied to metal electrodes positioned on the boundary design domain. In addition to represent the distribution of the electric field for the contact resistance of these electrodes an electrode model, proposed by Hua et al. [8], has been used. In that model, the electric potential for nodes 4, 5 and 6 of the electrode elements (see Fig. 2) are assumed to be equal ($\phi_4 = \phi_5 = \phi_6$).

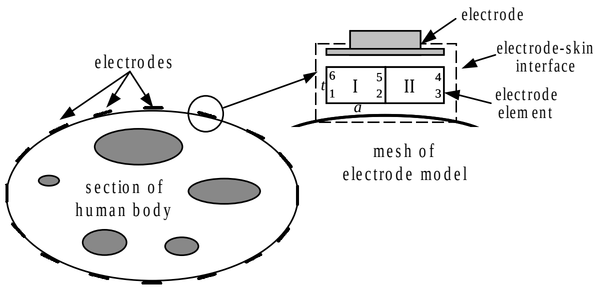


Figure 2 – Electrode model.

The electrical conductivity matrix ($\mathbf{k}_{el}$) of the electrode element is given by:

$$\mathbf{k}_{el} = \frac{1}{\rho\, t}\begin{bmatrix} \frac{a}{2} & 0 & 0 & -\frac{a}{2} \\ & a & 0 & -a \\ sim. & & \frac{a}{2} & -\frac{a}{2} \\ & & & 2a \end{bmatrix} \qquad (4)$$

where a is the half width of an electrode, t is the thickness of the contact interface (electrode-skin) and ρ is the resistivity (inverse of the conductivity) value of the contact interface. The product $\rho\, t$ is known as contact impedance of electrode elements. Each electrode element matrix $\mathbf{k}_{el}$ is inserted in the global matrix $\mathbf{K}$ in according to its connectivity.

TOPOLOGY OPTIMIZATION PROBLEM APPLIED TO EIT

The image reconstruction by EIT using TOM can be interpreted as a problem of finding the material distribution inside the domain that reproduces the measured electric potential values at electrodes. In that way, the optimization problem whose solution has been studied with TOM, could be:

$$\text{Minimize:} \quad F = \frac{1}{2}\sum_{j=1}^{ne}\sum_{i=1}^{np}\left(\phi_{ij} - \phi_{ij0}\right)^2 \qquad (5)$$

Such that: *electrical conductivity equation*

$$0 \leq \rho_i \leq 1 \quad i = 1...N$$

where F is the objective function related to the difference between the values of electric potential measured on the electrodes (ϕ_{ij0}) and calculated in the computational model of the domain (ϕ_{ij}). The *ne* and *np* values are the number cases of applied current load and the number of measurement points (electrodes), respectively, and ρ_i are the design variables related to the amount of material in each element of the domain. The optimization problem above is an ill-posed problem, which finds different distributions of conductivities in the domain that yield the same voltage values on electrodes. However, the application of TOM to this problem makes possible the inclusion of several constraints in the reconstruction image problem, restricting the solution space easily and avoiding images without clinical meaning.

NUMERICAL IMPLEMENTATION

The solution of topology optimization problem shown in Eq. (5) is obtained numerically by iterative algorithm optimization which steps are shown in Fig. 3. The FEM model of the design domain is supplied to the algorithm as initial data. By analysis of the FEM model, the electric potentials are calculated, allowing us to obtain the objective function and constraints values. In next step, the optimization is done, by using the gradients of the objective function and constraints, relative to design variables. The optimization algorithm is started with a uniform distribution of material for whole design domain and it supplies a new material distribution (design variable), which is updated in the FEM analysis. The iteration steps continue until the convergence for the objective function value is achieved.

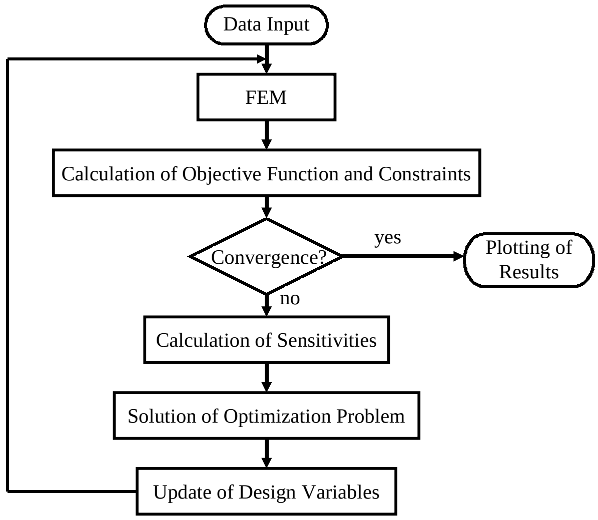


Figure 3 – Flowchart of the TOM algorithm.

In this work, the optimization algorithm used to solve the optimization problem of Eq. (5) is known as Sequential Linear Programming (SLP), which has been successfully applied to topology optimization. The SLP allows us to work with a large number of design variables and complex objective functions, and solves a non-linear optimization problem considering it as a sequence of linear sub-problems, which can be solved with Linear Programming (LP). The non-linear optimization problem of Eq. (5) is linearized by writing a Taylor series expansion for the objective function considering only the terms with derivative of first order. For that approach to be valid it is necessary to limit the variation of value of the design variables in each linear sub-problem by using of moving limits [9]. In each iteration of topology optimization process, the SLP algorithm finds the optimum value for the design variables, that it will be used in the subsequent iteration as initial value. Thus, this process continues successively until convergence of the solution.

SENSITIVITY ANALYSIS

The gradients of the objective function and constraints are known as sensitivities of topology optimization problem. These gradients are used in the SLP for obtaining the linear sub-problems and its mathematical formulation is obtained by using the mutual energy concept.

Applying the chain rule to the Eq. (5), the derivative of the objective function in relation to design variables (ρ) of the optimization problem, can be written in the following form:

$$\frac{\mathrm{dF}}{\mathrm{d}\rho} = \frac{\partial \mathrm{F}}{\partial \phi_{\mathrm{ij}}} \frac{\partial \phi_{\mathrm{ij}}}{\partial \rho} = \sum_{\mathrm{j}=1}^{ne} \sum_{\mathrm{i}=1}^{np} \left(\phi_{\mathrm{ij}} - \phi_{\mathrm{ij0}}\right) \frac{\partial \phi_{\mathrm{ij}}}{\partial \rho} \tag{6}$$

The derivative of the Eq. (6) is determined by using the extension of Maxwell's reciprocity theorem [10] where if a body is submitted simultaneously to two cases of applied electric current load and using FEM formulation, we can say that:

$$\mathbf{I}_1^{\mathrm{T}} \mathbf{\Phi}_2 = \mathbf{I}_2^{\mathrm{T}} \mathbf{\Phi}_1 \tag{7}$$

where **I** is the applied electric current vector, **Φ** is the electric potential vector, the index $_1$ and $_2$ indicates first and second case of applied current load and $^{\mathrm{T}}$ indicates the transposition of the vector.

Initially, we admit a fictitious excitement as a electric current vector of second case load ($\mathbf{I}_2$) whose only non-zero component is a unit current applied to one point of the body. Thus, using equilibrium equation from FEM formulation (Eq. (3)) and using the Eq. (7), we obtain:

$$\mathbf{\Phi}^{\mathrm{T}}_1 \mathbf{K} \, \mathbf{\Phi}_2 = \phi_1 \tag{8}$$

where **K** is the symmetric global matrix. From derivation of two sides of the Eq. (8) relative to design variables of the problem optimization, we obtain:

$$\frac{\partial\left(\mathbf{\Phi}^{\mathrm{T}}_1 \mathbf{K} \, \mathbf{\Phi}_2\right)}{\partial \rho} = \frac{\partial\left(\phi_1\right)}{\partial \rho} \tag{9}$$

The gradient of the left side of the Eq. (9) is the derivative of the mutual energy of the system, which is developed in the following form:

$$\frac{\partial \mathbf{\Phi}_1^{\mathrm{T}}}{\partial \rho} \mathbf{K} \, \mathbf{\Phi}_2 + \mathbf{\Phi}_1^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_2 + \mathbf{\Phi}_1^{\mathrm{T}} \mathbf{K} \frac{\partial \mathbf{\Phi}_2}{\partial \rho} \tag{10}$$

Deriving the equilibrium equation $\mathbf{K} \, \mathbf{\Phi}_1 = \mathbf{I}_1$ (first load case) relative to design variables and considering that the electric current $\mathbf{I}_1$ does not change with design variables, we have:

$$\frac{\partial \mathbf{\Phi}_1}{\partial \rho} = -\mathbf{K}^{-1} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_1 \tag{11}$$

Thus, transposing the Eq. (11), we obtain:

$$\frac{\partial \mathbf{\Phi}_1^{\mathrm{T}}}{\partial \rho} = -\mathbf{\Phi}_1^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{K}^{-1} \tag{12}$$

Likewise, deriving the equilibrium equation of second load case, and substituting this derivative and the result of Eq. (12) in Eq. (10) and simplifying, we obtain:

$$\frac{\partial\left(\mathbf{\Phi}_1^{\mathrm{T}} \mathbf{K} \, \mathbf{\Phi}_2\right)}{\partial \rho} = -\mathbf{\Phi}_1^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_2 \tag{13}$$

Thus, the Eq. (9) can be written in the following way:

$$-\mathbf{\Phi}_1^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_2 = \frac{\partial \phi_1}{\partial \rho} \tag{14}$$

In the EIT, some measurements around of the body section (i = 1 to *np*) in different points are made for all cases (j = 1 to *ne*) of applied current load. Thus, we consider the first measurement point (i = 1) and the fictitious electrical excitement to be a vector whose components are:

$$\mathbf{I}_{1\mathrm{j}}^{\mathrm{T}} = \left\{(\phi_{1\mathrm{j}} - \phi_{1\mathrm{j}0}) \quad 0 \quad 0 \quad \cdots \quad 0\right\} \tag{15}$$

where the electric current vector above produces in the domain Ω a potential field $\mathbf{\Phi}_{1\mathrm{j}}$. It is known that the electric current ($\phi_{1\mathrm{j}} - \phi_{1\mathrm{j}0}$) is constant during the load case. Thus, applying the Eq. (14) we have:

$$-\mathbf{\Phi}_{\mathrm{j}}^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_{1\mathrm{j}} = (\phi_{1\mathrm{j}} - \phi_{1\mathrm{j}0}) \frac{\partial \phi_{1\mathrm{j}}}{\partial \rho} \tag{16}$$

Then, if the procedure is repeated in analogous way to the first measurement until *np* measurement points, we have:

$$-\mathbf{\Phi}_{\mathrm{j}}^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \mathbf{\Phi}_{np\mathrm{j}} = (\phi_{np\mathrm{j}} - \phi_{np\mathrm{j}0}) \frac{\partial \phi_{np\mathrm{j}}}{\partial \rho} \tag{17}$$

Now, the development of the first summation (1 to *np*) of the Eq. (6) is:

$$\frac{\mathrm{dF}}{\mathrm{d}\rho} = \sum_{\mathrm{j}=1}^{ne} \left[\left(\phi_{1\mathrm{j}} - \phi_{1\mathrm{j}0}\right) \frac{\partial \phi_{1\mathrm{j}}}{\partial \rho} + \left(\phi_{2\mathrm{j}} - \phi_{2\mathrm{j}0}\right) \frac{\partial \phi_{2\mathrm{j}}}{\partial \rho} + \cdots + \left(\phi_{np\mathrm{j}} - \phi_{np\mathrm{j}0}\right) \frac{\partial \phi_{np\mathrm{j}}}{\partial \rho}\right] \tag{18}$$

By comparison of the Eq. (18) with the

development for obtain Eq. (17) and considering *np* measurement points and grouping the similar terms, we conclude that:

$$\frac{\partial \mathrm{F}}{\partial \rho} = -\sum_{\mathrm{j}=1}^{ne} \mathbf{\Phi}_{\mathrm{j}}^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \underbrace{\left(\mathbf{\Phi}_{1\mathrm{j}} + \mathbf{\Phi}_{2\mathrm{j}} + \cdots + \mathbf{\Phi}_{np\mathrm{j}} \right)}_{\mathbf{\Phi}_{\mathrm{j}}^{''}} \qquad (19)$$

As the FEM formulation is linear, we can obtain the summation of electric potentials of Eq. (19) by applying electric current to all *np* measurement points simultaneously, as illustrated in Fig. 4.

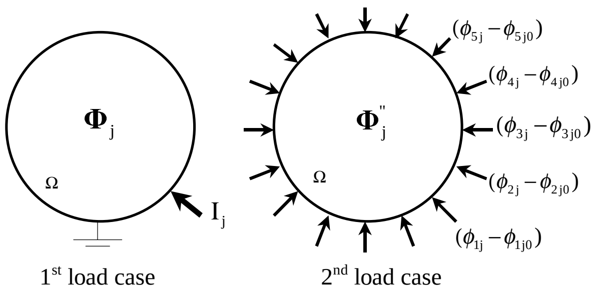


Figure 4 – Application of all measurement point.

Thus, the vector $\mathbf{\Phi}_{\mathrm{j}}^{''}$ can be calculated through the equilibrium equation $\mathbf{K}\,\mathbf{\Phi}_{\mathrm{j}}^{''} = \mathbf{I}_{\mathrm{j}}^{''}$.

Therefore, considering *ne* applied load cases and *np* measurement points, the expression to calculate of derivative of the objective function is given by:

$$\frac{\mathrm{dF}}{\mathrm{d}\rho} = \sum_{\mathrm{j}=1}^{ne} \sum_{\mathrm{i}=1}^{np} \left(-\,\boldsymbol{\phi}_{\mathrm{j}}^{\mathrm{T}} \frac{\partial \mathbf{K}}{\partial \rho} \boldsymbol{\phi}_{\mathrm{ij}}^{''} \right) \qquad (20)$$

Thereby, the procedure described above saves a lot of computational time to calculate the gradients of objective function.

RESULTS

The topology optimization problem for obtaining image by EIT is implemented in a software which is programmed using C language. In this section, some examples will be presented to illustrate image reconstruction. For all examples, the applied electric current load is considered equal to 1 mA. Moreover, in these examples, the topology optimization algorithm uses penalization coefficient value (p) equal to 2, and it assumes 0.15 as initial value for design variables at starting of the SLP.

The images reconstructed here are shown in Fig. 5. In this case, the dark and clear region simulates a material with low conductivity ($10^{-6}(\Omega.\mathrm{m})^{-1}$) and high conductivity ($5.882\times10^{-2}(\Omega.\mathrm{m})^{-1}$), respectively. In practice, this situation would be equivalent to obtain some regions with presence of air in the tomography of a water-like domain, for instance.

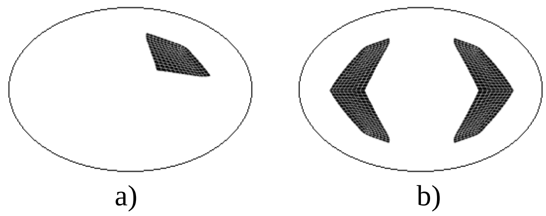


Figure 5 – Images to be reconstructed: a) one region; b) two regions.

The images are obtained from elliptical domain whose major axis is 400 mm. In this work, numerical data is used for image reconstruction. Thus, two different FEM models were built. Their meshes use quadrilateral finite elements (with thickness equal to 35 mm) and are generated by using mesh generator of ANSYS software.

First model has a fine mesh (3072 elements) and it is used to simulate accurately the electric potential distribution inside of the elliptical domain (numerical phantom). The electric potential distribution, considering the elliptical domain without regions or with one and two regions (see Fig. 5), are calculated through this phantom which are used in image reconstruction procedure as the electric potential measured ($\phi_{\mathrm{ij}0}$). In this case, a chosen value equal to $100(\Omega.\mathrm{m}^2)^{-1}$ is considered as parameter $1/\rho\, t$ (inverse of contact impedance) of matrix $\mathbf{k}_{\mathrm{el}}$ of Eq. (4).

The second model has a coarse mesh (1120 elements, see Fig. 6) and it is used for image reconstruction, having fewer design variables which saves computational time. Moreover, if the software reconstructs the desired image in a coarse mesh by using information of a refined mesh, it demonstrates that implemented algorithm is robust to deal with error of electric potential values, simulated here by two different discretizations of the domain.

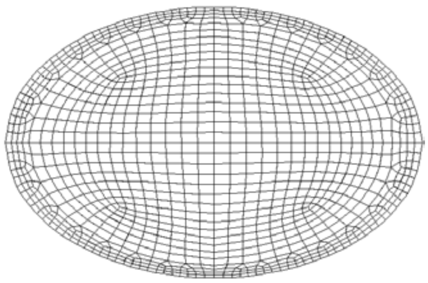


Figure 6 – Discretized domain (mesh with 1120 quadrilateral elements)

In this work, to obtain a good quality image for clinical applications in EIT, 32 electrode elements (whose width equal to 10 mm) are uniformly positioned along the boundary of the design domain [11]. To find the nodal electric potentials in these electrode elements a pair of them is excited electrically, following an adjacent pattern, where one of them is made to be null potential (“ground”) and other (neighbor) receives the low intensity electric current. Thereby, for obtaining the image desired in the EIT, the pair of electrodes (electrically excited) is changed successively until enough number of observations under different angles is obtained. Therefore, in total, a sequence of 32 patterns of electrical excitement of the same type (adjacent) is applied to obtain the desired image here.

Following, image reconstruction procedure is described. This procedure is divided in two steps: obtaining of contact impedance values of the electrode elements and obtaining desired image.

Obtaining of contact impedance values

The contact impedance values of the electrode elements (product of ρ and t in Eq. (4)) must also be obtained through the software implemented. In this case, the contact impedance values are design variables, which are obtained numerically through the iterative topology optimization algorithm. The obtained electric potential distribution inside of the numerical phantom, containing just one material (without regions), is initially considered. After that, by using these electrical potentials as the electric potential measured (ϕ_{ij0}) and the coarse mesh (1120 elements, see Fig. 6), the software obtains the contact impedance values of the electrode elements considering any initial guess of contact impedance values in the optimization process. In this example, we expect to recover the contact impedance values adopted for the numerical phantom. The obtained values ($1/\rho\, t$) in this simulation are shown in Table 1.

electrode	$1/\rho\, t$	electrode	$1/\rho\, t$	electrode	$1/\rho\, t$	electrode	$1/\rho\, t$
1	51.0	9	62.3	17	34.0	25	84.3
2	103.0	10	93.1	18	93.3	26	93.1
3	93.1	11	93.3	19	84.3	27	93.1
4	84.3	12	84.3	20	93.3	28	93.1
5	84.3	13	93.3	21	93.1	29	93.1
6	84.3	14	84.3	22	93.1	30	93.0
7	68.9	15	84.3	23	84.3	31	103.0
8	126.0	16	100.0	24	93.1	32	114.0

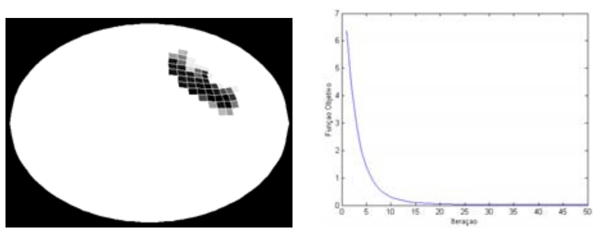
Table 1 – Contact impedance values.

According to table above, the most of contact impedance values were obtained closer than the expected values ($100(\Omega.m^2)^{-1}$ for all electrode elements). The errors between the obtained and the expected contact impedance values are justified, since the software obtains the optimal contact impedance values for the coarse mesh.

Obtaining Desired Image

In this step the software reconstructs the desired image by using the information about electric potentials calculated through the numerical phantom as electric potential measured (ϕ_{ij0}), considering the domain with one and two regions. The contact impedance values obtained in previous step are also used.

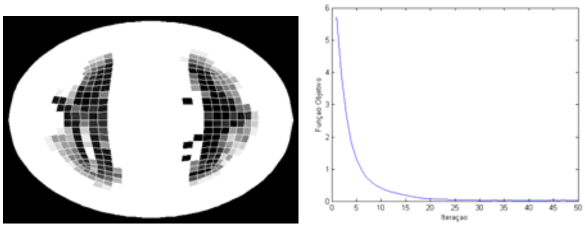
Following the images obtained by applying adjacent pattern are shown. First, Fig. 7 shows image and convergence curve obtained of desired image with one dark region. The obtained image and convergence curve of desired image with two dark regions are shown in Fig. 8.



a) tomography image b) convergence curve

Figure 7 – Obtained image and convergence curve (one region).

According to convergence graphs, shown in Fig. 7b) and Fig. 8b), it is verified that the objective function fell quickly to a minimum value (20 iterations approximately), however they



a) tomography image b) convergence curve

Figure 8 – Obtained image and convergence curve (two regions).

continue iteration by iteration with very small oscillation until the best image for the tomography examination is found (~50 iterations). It is noticed the objective function converges to a minimum value equal to 0.0245 for image with one region and 0.0285 for image with two regions. The absolute electric conductivity values of elements in the dark region are closer than the expected original value (approximately an average of 90%). This optimization result corresponds to a local optimum and we believe that it could be improved.

CONCLUSIONS

An algorithm of Topology Optimization Method (TOM) applied to Electrical Impedance Tomography (EIT) was proposed for image reconstruction. The software, written in C language, was implemented to accomplish the iterative process of TOM. According to obtained results, the software is able to obtain, from numerical data, in some sets of ten iterations and with a certain level of acceptable precision, the contact impedance values of interface electrode-skin and the values of absolute conductivity of two materials inside of the domain and consequently the desired image. Some improvement is still necessary to work with experimental data, where noise is considered. However, since good results were obtained by using a coarse mesh, it demonstrates that implemented method is robust, and we believe that it will be succesful to deal with experimental data. The TOM algorithm, studied in this work, could be improved for obtaining images of the lung through EIT device. The TOM allows us to include some constraints in the problem of image reconstruction limiting the solution space in tomography examination and avoiding images without clinical meaning. For instance, it is possible to limit in the design domain the area where presence of air in the lung can occur, and in addition it allows us to work with known areas inside the domain (bone, heart, etc).

ACKNOWLEDGEMENT

First author thanks the financial support of FAPESP through doctoral scholarship (n^{o}. 02/01625-0).

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