

An Automatic Neural-Networks Based Mesh Refinement Method for Electrical Impedance Tomography

Sébastien Martin¹ and Charles T. M. Choi^{1,2}, *Senior Member, IEEE*

¹Department of Electrical and Computer Engineering, National Chiao Tung University, Hsinchu, 300 Taiwan

²Institute of Biomedical Engineering, National Chiao Tung University, Hsinchu, 300 Taiwan, c.t.choi@ieec.org

In real life applications, inverse problems, such as the electrical impedance tomography problem, usually have a limited accuracy, and require huge computation resources to be solved correctly. In electrical impedance tomography, the goal is to obtain the electrical properties of different materials (typically living tissues) by applying an electrical current and measuring the resulting potential difference at the boundaries of the domain. While the maximum numerical accuracy is technically limited by the size of the elements within the finite element mesh, using a fine mesh will result in a computationally demanding reconstruction, especially when the location of the target is unknown. However, this situation is different when the location of the target is known in advance. In this case, one can easily refine the finite element model around the target, allowing a greater accuracy around the region of interest. In this paper, a novel approach estimates the location of the target object before solving the inverse problem, so that it becomes possible to refine only a specific area of the element domain. An artificial neural network is used to determine the location of the target directly from voltages measured at the boundary of the domain. This location is then used to refine the mesh at this specific location, which increases the accuracy without significantly affect the computation resources necessary to solve the inverse problem. Since linear inverse solvers give a linear conductivity distribution, it was decided to use the h-method to refine the mesh around the target object.

Index Terms—Adaptive Mesh Refinement, Artificial Neural Network, Electrical Impedance Tomography, Inverse Problem

I. INTRODUCTION

ELECTRICAL IMPEDANCE TOMOGRAPHY (EIT) is the most recent technique used for medical imaging [1]. Given the electrical voltages measured at the boundaries of a domain, the inverse problem aims to retrieve the electrical conductivity of the different elements within a Finite Element (FE) model. Several linear and nonlinear techniques have been proposed to obtain this electrical conductivity [2], but most of them can only give an approximation of the real conductivity distribution. In EIT, these approximations are basically due to the underlying assumptions made by the linear algorithms [3], but also to the size of the elements in the FE model. An accurate 3D FE model may easily reach more than 50,000 nodes, and then computing the inverse problem requires enormous computation resources. The challenge is to reduce the size of this problem while maintaining accuracy.

Recently, non-linear algorithms have been proven to be capable of accurate EIT reconstructions [4], with a very limited smoothness in the resulting image. These algorithms, usually based on Artificial Neural Networks (ANN) or Evolutionary Algorithms (EA), perform well in 2D applications, but the additional dimension of a 3D FE model usually makes the training phase more challenging. Although it is complicated to create an accurate reconstruction, ANNs are still capable of giving a correct approximation of target size and location. Different methods to automatically refine the FE model have been proposed [5], but these methods are based on the reconstructed image, requires solving the inverse problem several times, with several different meshes, before converging to an accurate reconstruction. In 3D-EIT, this step can be very long, and therefore this solution is not suitable for real-time 3D applications.

In this paper, an automatic method to refine 2D and 3D meshes without any prior reconstruction is proposed. The

method, based on ANN, determines the locations and sizes of the targets directly from the voltages measured at the boundaries. After that, it becomes possible to refine the FE model before solving the inverse problem. This local refinement allows greater accuracy around the target boundaries. Given the voltages measured at the boundaries, an ANN gives an approximation of the size, and another ANN estimates the location, which is used to refine a coarse FE model. Then this refined mesh is used to solve the EIT inverse problem with a linear inverse solver.

II. DESCRIPTION OF EXPERIMENTS

One of the problems in 3D EIT is the large computation resources required to solve the inverse problem with a high degree of accuracy. A 3D FE model comprised of 4 layers of 8 electrodes on the boundary was used in this experiment. Two adjacent electrodes in the same layer were used to inject an electrical current into the EIT domain, while all the other pairs of adjacent electrodes were being used to take the measurements in the same layer. This configuration allows a satisfactory degree of accuracy, but it has been shown that additional electrodes or additional independent injections can enhance the accuracy of the system. On the other hand, an accurate 3D model contains a large number of nodes, making the reconstruction very demanding (it usually requires several GB to compute).

ANNs are powerful algorithms capable of approximating a solution to a non-linear problem. In this application, they were used to find the size and position of the target image, directly from the measured voltages at the boundary. To do so, a set of 1000 EIT images, containing spherical objects with different sizes and different locations, was used to train the ANN. In EIT, the forward problem is linear and can be solved numerically. Its solution gives the resulting voltages at the

electrodes. These voltages were used to train the ANNs, using the gradient descent algorithm. The ANNs can then be used to estimate the size and location of new targets directly from the measured voltages. At this point, an error, defined as the Euclidean distance from the estimated position and the real position, is determined.

Once the size and location of the target are known, it is possible to refine the mesh at the boundary of the object. Since linear inverse solvers usually generate some smoothness in the resulting image, it was decided to refine all the elements located at a certain distance from the boundary of the target. In both 2D and 3D models, the refinement was done by applying the h-method and vertex bisection.

After refining the mesh, it is possible to solve the EIT inverse problem with a high degree of accuracy without increasing the computational resource demand significantly, since the dimension of the whole FE model should not be strongly affected by the local refinement. After solving the inverse problem, the conductivities obtained were mapped into a fine mesh, used to solve the forward problem. Although this final step has a limited relevance in real applications, it allows one to compare the results and calculate the Root Mean Square (RMS) error for the different images.

III. RESULT

Experiments were conducted for both 2D and 3D EIT. First, the Euclidean distance from the original location of the target and its estimated location was used to measure the efficiency of the ANN. The radius of the tank was normalized to 1. In this application, the Euclidean distance between these two points is below 0.1, meaning that the estimated location is close to the real location.

After refinement, the results obtained with a coarse mesh, a locally refined mesh, and a fine mesh are compared. The computation time and required memory are compared for these three different configurations. As shown in Table 1, solving the problem with the proposed locally refined mesh is more than 100 times faster than solving with the fine mesh, and reduces the memory required by 100 times. This result can be explained by the number of nodes in the different FE models. The fine FE model used to solve the forward problem has more than 10000 nodes, while the locally refined meshes have only 499 nodes.

Table 1. Comparison of reconstruction using coarse mesh, fine mesh, and an automatically locally refined mesh

	Fine mesh	Coarse mesh	Proposed locally refined mesh
time (s)	1090	2.9	8.1
RMS error (%)	8.4	15.9	8.8
Memory (Gb)	40	0.04	0.4
# nodes	10197	98	499

Finally, the resulting images were mapped into the initial FE model, previously used to simulate a target object and solve the EIT forward problem. This mapping allowed a comparison of the different EIT images obtained with the

different meshes. The RMS errors show that the proposed method improves the quality of the reconstruction, and the resulting error is close to the error obtained with a completely fine mesh. Fig. 1 shows the conductivity distributions obtained with the coarse, fine, and locally refined meshes.

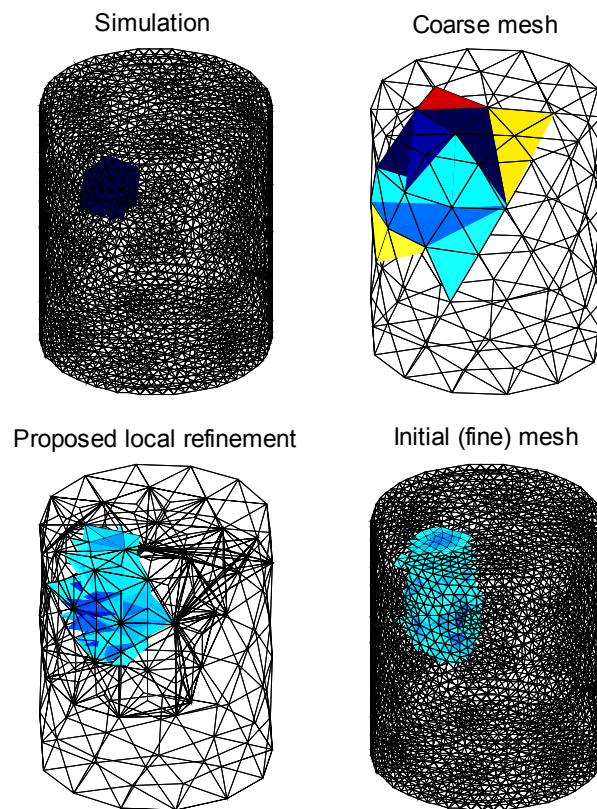


Fig. 1. Comparison of reconstructions using a coarse mesh, fine mesh, and a mesh refined by the proposed method

IV. CONCLUSION

The proposed method uses an ANN to locate the target prior to solving the inverse problem, using a locally refined mesh. This mesh can be used to solve the EIT problem in a shorter time and requires less computation resource while maintaining a high degree of accuracy. This digest introduces the idea over a very simple case. Future work will focus on the modelling of multiple targets and more realistic shapes that are very likely to be met in real EIT applications.

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