A New Divide and Conquer Method for Three-Dimensional Electrical Impedance Tomography

Sébastien Martin[1] and Charles T. M. Choi[1,2], *Senior Member, IEEE*

[1]Department of Electrical and Computer Engineering, National Chiao Tung University, Hsinchu, 300 Taiwan, sebastien1606.eed01g@nctu.edu.tw
[2]Institute of Biomedical Engineering, National Chiao Tung University, Hsinchu, 300 Taiwan, c.t.choi@ieee.org

Electrical Impedance Tomography (EIT) is a patient safe approach for imaging applications, and is a promising technology for biomedical imaging. By applying an electrical current to a living tissue and measuring the electrical potential at different points of the boundary of the tissue, it is possible to solve the inverse problem and allow us to generate a map of the conductivities of the tissue. Although it is a promising method, the reconstruction process remains a complicated task and therefore real-time nonlinear image reconstruction algorithms are not widely adopted yet. Recently, use of Artificial Neural Network (ANN) to solve an EIT inverse problem has been proposed. ANNs can give a nonlinear conductivity distribution. Although several works have been published on 2-dimensional FE models, very little work has considered three-dimensional problems. In this paper, a solution based on Divide and Conquer and ANNs is used to solve the non-linear inverse problem without any linearization. The solution presented here aims to reduce the difficulty of training a large ANN, which is commonly required to solve a 3D-EIT problem with Artificial Intelligence (AI) algorithms.

***Index Terms*— Artificial Neural Networks, Complexity, Electrical Capacitance Tomography, Inverse Problems.**

I. Introduction

In Electrical Impedance Tomography (EIT), one aims to obtain the distribution of the internal electrical conductivities of living tissues by measuring the electrical potential at the boundary of the body [1]. In biomedical applications, this technique allows both inexpensive and radiation free tomography [2]. In EIT, internal conductivities can be obtained from the voltages measured at the boundary of the Finite Element (FE) model by solving a nonlinear inverse problem. This problem is very challenging since the commonly used inverse solvers tend to linearize the problem [3].

Some researchers proposed the use of Artificial Intelligence (AI) algorithms to solve the inverse problem. Artificial Neural Networks (ANNs) are the most commonly used [4]. Several papers studied ANN as a replacement of the linear inverse solver for Two-Dimensional (2D) problems [4][5], but the available literature on solving three-dimensional (3D) problems is still limited. This limitation can be due to the difficulties of efficiently training an ANN which is capable of solving the EIT problem in 3D with greater accuracy.

This paper introduces an original method to divide the EIT reconstruction problem into manageable subtasks to allow the reconstruction of 3D EIT images more efficiently. The FE model is divided into several parts and each part of the FE model is solved by a different ANN. This approach limits the number of outputs of the ANN, and consequently reduces the number of weights and biases present in each individual ANN, which makes the training process much faster and gives greater global convergence.

II. Method

EIT problems can be simulated in two steps, commonly known as the forward problem and the inverse problem. In the forward problem, given a conductivity distribution within a FE model, the goal is to determine the corresponding voltages at the boundary. This step can be solved linearly by using a linear solver [1]. On the other hand, a specific set of measurements may correspond to several different conductivity distributions, making the inverse problem severely ill-posed [6]. To reduce this ill-posedness, one common practice is to assume that the conductivity of one element approximates the conductivity of its neighbors. This assumption allows one to utilize a linear inverse solver to solve the problem.

Although this assumption gives good results, it cannot reconstruct an exact result when the change in conductivity is abrupt. In real applications, the electrical current passes through several different tissues and each of these tissues present rough boundaries, at which the conductivity change is abrupt. Different algorithms have been proposed to replace the linear inverse solver. For instance, ANNs are capable of very good approximations and can be used to solve the EIT inverse problem in 2D [7]. However, the complexity of a 3D FE model, in terms of the number of available measurements and the number of nodes, will automatically lead to an exponential growth of the ANN in terms of input and output neurons. Training such a large ANN usually takes more time, requires a greater number of training data. After training the ANN, the testing phase shows that, when having a large number of neurons, the ANN usually has a lower convergence, and the risk of falling into local minima is increased.

Previous work has shown that it is possible to reduce the complexity of the training process by dividing the problem into several ANNs using Divide and Conquer (D&C) [8]. Here, the FE model is divided into several 'sub meshes', and each of these sub-meshes is solved with a specific ANN. By doing this, it is possible to significantly reduce the number of weights and biases in each network, allowing a more efficient training, in terms of accuracy and computation requirement. In other words, the proposed method avoids the curse of dimensionality.

III. RESULTS

The FE model was divided into 64 'sub meshes', each of them containing a variable number of output neurons, between 400 and 500. The division of the original FE model was done in a way that each ANN will be assigned to a specific region of the mesh. The mesh was divided along the XY plane and the Z axis. The whole mesh contained 27333 elements, and 4 layers of 8 electrodes, allowing up to 928 different measurements. Each ANN was given the set of 928 measured voltages as input data, and gave the conductivity distribution of a specific sub-mesh at its output. The output of the ANNs corresponds to the estimate of the electrical conductivity within the FE model. It was possible to combine the output of each ANN to obtain the reconstructed image.

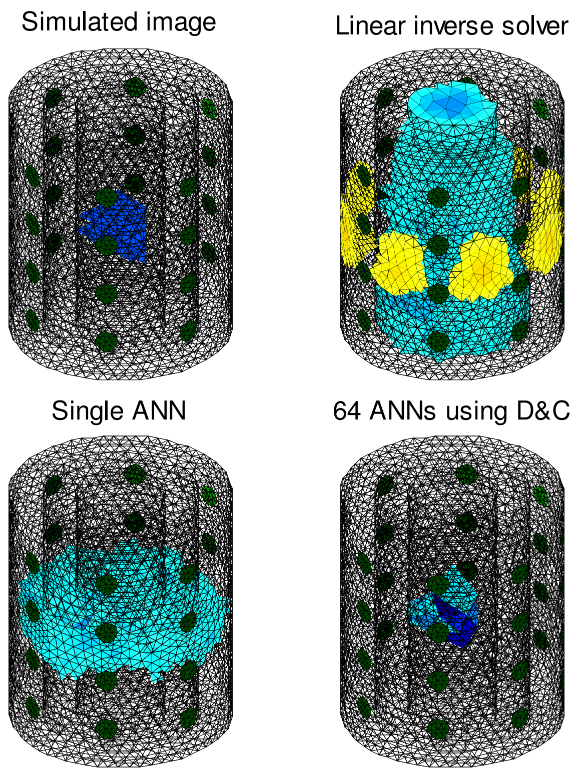

Fig. 1 Comparison of 3D-EIT images obtained with a linear solver, one ANN and the proposed method with 64 ANNs

Fig. 1 shows a simulated EIT image. The forward and inverse problems were solved without considering the presence of noise. Corresponding reconstructions obtained with linear inverse solver (Gauss Newton One Step), one ANN, and several ANNs with the proposed D&C ANN algorithm. It can be seen that the training algorithm had difficulties in training the ANN with 27333 outputs. The proposed method gives a higher accuracy than the linear inverse solver or the single ANN.

After reconstruction and normalization, a corresponding Root Mean Square (RMS) error is calculated based on the conductivity of each element in the FE model. The resulting errors are reported in Table1. It can be seen that the proposed method significantly reduces the RMS error obtained on the image reconstruction. Basically, this is a consequence to the non-linear behavior of the neural networks. The images obtained with the proposed algorithm show that the artifacts resulting from linearization are significantly reduced when the inverse problem is solved with ANN.

TABLE 1
RMS errors obtained for 3D-EIT reconstructions using the linear inverse solver, one ANN and the proposed method (64 ANNs with D&C)

Linear inverse solver	one ANN	Proposed Multiple ANNs, D&C
31.48 %	15.10 %	5.83%

Another interesting advantage of using ANN to solve the EIT inverse problem is their strong ability to deal with noisy input data. Previous studies have shown that training an ANN with PSO algorithm and noisy input data offers a great resistance to noise in measurements and deformations of the 2D mesh, an important source of errors in real life applications.

IV. CONCLUSION

To conclude, the proposed D&C method in which the 3D problem is divided into several 'sub-problems', in conjunction with ANN algorithm, allows the 3D-EIT inverse problem to be solved by a fully nonlinear algorithm with a very high degree of accuracy, better than simple ANN algorithm and traditional inverse solver. Using a D&C method reduces the difficulty of training a large ANN, which increases the global convergence of the reconstruction.

Compared to other widely used reconstruction methods, the solution proposed in this paper also shows good resistance to noise. ANNs trained with noisy data are capable of solving the inverse problem with a noisy input. This ability to solve the inverse problem with noisy data is very important for real-world measurements, where an extremely low-current is injected, and the noise may become an important source of errors in the reconstruction process.

REFERENCES

[1] D. S. Holder, *Electrical Impedance Tomography: Methods, History and Applications*. London, U.K.: Institute of Physics Publishing, 2005.
[2] R. Bayford and A. Tizzard, "Bioimpedance imaging: an overview of potential clinical applications.," *Analyst*, vol. 137, no. 20, pp. 4635–4643, Oct. 2012.
[3] W. R. B. Lionheart, "EIT reconstruction algorithms: pitfalls, challenges and recent developments," *Physiol. Meas.*, vol. 25, no. 1, pp. 125–142, Feb. 2004.
[4] J. Lampinen, A. Vehtari, and K. Leinonen, "Application of Bayesian neural network in electrical impedance tomography," in *IJCNN'99. Int.Joint Conf. on Neural Networks.*, 1999, vol. 6, pp. 3942–3947.
[5] J. H. Kim, B. C. Kang, B. Y. Choi, M. C. Kim, S. Kim, and K. Y. Kim, "Phase boundary estimation in electrical resistance tomography with weighted multilayer neural networks," *IEEE Trans. Magn.*, vol. 42, no. 4, pp. 1191–1194, Apr. 2006.
[6] L. Borcea, "Electrical impedance tomography," *Inverse Probl.*, vol. 18, no. 6, pp. R99–R136, Dec. 2002.
[7] A. Adler and R. Guardo, "A neural network image reconstruction technique for electrical impedance tomography.," *IEEE Trans. Med. Imaging*, vol. 13, no. 4, pp. 594–600, Jan. 1994.
[8] C.-C. Chiang and H. Fu, "A divide-and-conquer methodology for modular supervised neural network design," in *Int.Conf. on Neural Networks (ICNN'94)*, 1994, vol. 1, pp. 119–124.