Nonlinear Electrical Impedance Tomography reconstruction using Artificial Neural Networks and Particle Swarm Optimization

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

Recent medical imaging technologies, such as Electrical Impedance Tomography (EIT), offer the advantages of being noninvasive and it does not generate ionizing radiation. The main difficulty in applying EIT is to solve a very ill-posed nonlinear inverse problem. Given a set of electrical voltages measured at the boundary of a finite elements model, the goal is to identify the materials present in the domain by determining their electrical conductivities. However, since EIT is a nonlinear problem, various algorithms proposed in the literature can only approximate real conductivity distribution. Nonlinear algorithms, especially Artificial Neural Networks (ANN), have been proposed to solve this inverse problem, but these algorithms are usually limited by slow convergence issues during the training phase of an ANN. In this paper, the Particle Swarm Optimization method (PSO) is used to train an ANN to solve the EIT problem. PSO algorithm has recently been used to train ANN. It has been proven that, compared to the classical Back-Propagation (BP) algorithm, PSO is capable of generating both faster and higher convergence. In addition, this paper also shows that the proposed method is capable of dealing with noisy data and imperfections in the Finite Element (FE) discretization, an important source of errors in EIT imaging.

***Index Terms*—Artificial Neural Network, Electrical Impedance Tomography, Finite Element Method, Inverse Problems, Particle Swarm Optimization.**

I. INTRODUCTION

ELECTRICAL IMPEDANCE TOMOGRAPHY (EIT) is a technology based on injecting electrical current into a body via two electrodes located at the boundary of a Finite Element (FE) model of the body, while other electrodes are being used to measure the resulting voltages at different boundary points of the domain [1]. Given a set of measured voltages, the conductivity distribution of the different elements in the FE model is determined by solving an inverse problem. This inverse problem is usually solved by linear inverse solvers [1]. However, such linear algorithms cannot give an exact reconstruction in case of nonlinear conductivity distribution, which is usually the case at the boundaries of the objects that are crossed by the electrical current.

More recently, Artificial Neural Networks (ANNs) [2], are being used to solve the EIT inverse problem. These algorithms are capable of approximating highly nonlinear problems, and therefore are able to determine the exact conductivity distribution of the elements within an FE model [3]. The results obtained with ANN show a nonlinear conductivity distribution and objects having rough boundaries.

This paper introduces an optimal method to train an ANN while maintaining a high convergence rate within a limited number of iterations. Particle Swarm Optimization (PSO) is a relatively recent optimization algorithm, which is capable of training ANN. Compared to the classic Back-Propagation (BP) algorithm, training an ANN with PSO gives a higher convergence when approximating a function [4]. In EIT applications, ANNs are very sensitive to measurement errors and errors in the boundary's shape. The results show that, when these practical imperfections are considered during training of the ANN, the resulting network can still give a good reconstruction in case of noisy data. This paper also introduces a method to model noise present in measured data and to efficiently train the ANN to solve real EIT problems.

II. THEORY

A. Electrical Impedance Tomography

In EIT problems, the goal is to determine the electrical impedance of the objects present within a FE domain based on current injections and voltages measurements at the boundary of the domain. This is the most challenging problem in EIT, basically a result of the nonlinear and ill-posed aspects of the inverse problem. While linear algorithms can only give an approximation of nonlinear conductivity distribution, nonlinear algorithms appear to be capable to estimate the real conductivity distribution with a very high accuracy. Since EIT inverse problem is nonlinear, minor difference in the measured voltages may result in a very large difference in the corresponding conductivity distribution. While linear algorithms are not sensitive to nonlinearities, nonlinear methods might be more sensitive to noisy data. Consequently, for phantom experiments, it is important to model the noise and measurement errors that are present in the hardware system to train the ANN.

B. Artificial Neural Networks

ANNs are nonlinear algorithms inspired by the human brain, and are capable of approximating the response of a nonlinear system. Technically, an input signal (here, the voltages measured by the electrodes at the boundary of the FE domain) goes through several layers of simple and linear mathematical functions called neurons. Between each layer, the signal is adjusted with different weights and biases, previously determined during the training process. This training process plays a very important role in the convergence of an ANN. A poorly trained ANN will not correctly adjust the signal between each layer, and therefore the output will not converge to the desired result.

C. *Particle Swarm Optimization*

PSO algorithm has been proved to be capable of training an ANN with a limited number of iterations [5], and can be used to train an ANN to solve the EIT inverse problem. This algorithm is based on social behavior of a swarm. Therefore, each particle will look for the best solution and automatically adjust its flight according to its own previous direction and the direction of the whole swarm. This particularity gives both global and local convergence to PSO algorithm.

III. Experiments and Result

PSO algorithm was used to train an ANN to solve the EIT inverse problem. The advantage of using PSO for training an ANN to approximate a nonlinear function is that it approaches the desired convergence rate quickly. After training the ANN is used to solve the EIT inverse problem. Reconstructions were made from simulated voltages, obtained numerically from a given conductivity distribution. The inverse problem was solved using both the classic linear inverse solver and the proposed method based on ANN and PSO. Each reconstruction was compared to the original conductivity distribution. The Position Error (PE) [6] and Root Mean Square (RMS) error were both calculated. The PE corresponds to the Euclidean distance from the center of gravity of the reconstructed object and the center of gravity of the real target, and was calculated by the equation (1):

$$PE = r_t - r_q \tag{1}$$

where r_t is the center of gravity of the target object, from which the forward problem has been solved, and r_q is the center of gravity of the reconstructed object. The RMS error was calculated according to (2).

$$RMS = \sqrt{\sum_{elements} \left| target \text{ - } output \right|^2} \tag{2}$$

Fig. **1** shows a simulated conductivity distribution, with a target object having rough boundaries. Starting from this conductivity distribution, the corresponding voltages at the boundary were simulated numerically by solving a linear problem. Then, the inverse problem was solved twice, using the linear inverse solver, and using the proposed method based on ANN trained with PSO algorithm. Fig. **1** shows that solving the EIT inverse problem with a nonlinear algorithm resulted in a nonlinear conductivity distribution, which reduced the presence of smoothness (artifacts) in the final image. The RMS error and the PE were calculated for each resulting image. The resulting errors, presented in Table 1, clearly show that the proposed method is capable to give an accurate reconstruction, closer to the reconstruction obtained with the classic linear inverse solver.

In real applications the shape of the FE model is not fixed but varies randomly. Since the voltage distribution is sensitive to the shape of the FE model, a variation in the boundary's shape may result in an incorrect conductivity distribution. To overcome this difficulty, the ANN is trained with several different elliptical shapes instead of a single circular shape, and tested with several shapes. The resulting RMS errors show that the proposed ANN method can solve the EIT inverse problem under noisy data and with an unknown boundary shape.

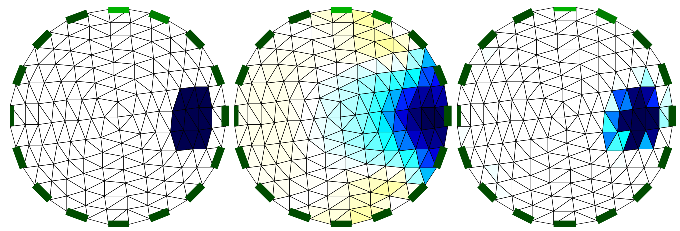

Fig. 1 **Comparison of the original conductivity distribution (left), the reconstruction using linear inverse solver (middle), and the proposed method using ANN and PSO (right)**

Table 1. Comparison of RMS error and position errors for the reconstructions using linear inverse solver and the proposed method based on ANN trained with PSO algorithm

	Linear solver	Proposed ANN
RMS error (%)	20.1	9.5
Position error (%)	15.0	2.0

Finally, after adding the effect of white Gaussian noise and band pass filter to the simulated voltages measured in , an existing data acquisition system and to obtain training data similar to the measurement data obtained with this system. Measurements were made from real phantom experiments, and sent to the ANN trained with noisy voltages to solve the EIT inverse problem. This final experiment showed that the proposed method gives a lower error than the linear method, and is applicable for real EIT application.

IV. Conclusion

The proposed method, based on ANN and PSO, is capable of solving EIT problems, with a much higher accuracy than the linear inverse solver. Modelling real cases and additional sources of errors will later lead to an ANN capable of solving EIT problems in medical applications.

References

[1] D. S. Holder, *Electrical Impedance Tomography: Methods, History and Applications*. London, U.K.: Institute of Physics Publishing, 2005.

[2] 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.

[3] M. GhasemAzar and B. V. Vahdat, "Error Study of EIT Inverse Problem Solution Using Neural Networks," in *2007 IEEE International Symposium on Signal Processing and Information Technology*, 2007, pp. 894–899.

[4] V. G. Gudise and G. K. Venayagamoorthy, "Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks," in *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS'03 (Cat. No.03EX706)*, vol. 2, no. 1, pp. 110–117.

[5] A. Roy, "Training Artificial Neural Network using Particle Swarm Optimization Algorithm," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 3, no. 3, pp. 430–434, 2013.

[6] A. Adler, J. H. Arnold, R. Bayford, A. Borsic, B. Brown, P. Dixon, T. J. C. Faes, I. Frerichs, H. Gagnon, Y. Gärber, B. Grychtol, G. Hahn, W. R. B. Lionheart, A. Malik, R. P. Patterson, J. Stocks, A. Tizzard, N. Weiler, and G. K. Wolf, "GREIT: a unified approach to 2D linear EIT reconstruction of lung images," *Physiol. Meas.*, vol. 30, no. 6, pp. S35–S55, Jun. 2009.