Microwave Imaging of Three-Dimensional Dielectric Objects Employing Evolution Strategies

*Payam Rashidi[1], Magda El-Shenawee[1], Demetrio Macías[2], Eric Miller[3]
[1]Department of Electrical Engineering, University of Arkansas
Fayetteville, AR 72701, USA, Email: prashid@uark.edu
[2]Laboratoire de Nanotechnologie et d'Instrumentation Optique -CNRS FRE 2671
Université de Technologie de Troyes,
12 rue Marie Curie, B.P. 2060,10010 Troyes, France
[3]Department of Electrical and Computer Engineering, Northeastern University
Boston, MA 02115, USA

ABSTRACT

This paper investigates the performance of an evolutionary algorithm in the reconstruction of the shape and location of an arbitrary three-dimensional (3-D) dielectric object immersed in air. An evolution strategy optimization technique is combined with the method of moments to estimate, in terms of a multidimensional optimization problem, the unknown parameters that determine the shape and the location of the object. The reconstruction is performed through the minimization of an error function between the synthetic measurements and simulated scattered data. The results show a potential of the algorithm in estimating the shape and location of 3-D objects.

I. INTRODUCTION

Microwave imaging modality has an important potential in medical applications, especially in the detection of small malignant breast tumors. This method takes advantage of the significant contrast between malignant and breast tissue at the microwaves frequency range. The analysis of the intensity of the scattered waves (electric fields) leads to information regarding the shape, size, electrical properties, and location of the tumor [1]. A technique employing evolution strategies is proposed to reconstruct the shape and location of the malignant tumor. For simplicity, to illustrate the principles of the method, this work will focus on the reconstruction of the shape and location of 3-D dielectric objects immersed in air.

Section II discusses the formulations of the evolution strategies, Section III discusses the numerical results, and Section IV summarizes the concluding remarks.

II. FORMULATIONS

An evolution strategy is an iterative optimization technique inspired on Darwin's theory of evolution [3]. The numerical implementation we consider in this work draws on some inspiration from the inversion procedure described in [4]. The step before starting the evolutionary loop is the random generation of an initial population given by the set:

$$P_{\mu}^{g} = \{p_1^g, p_2^g, ..., p_n^g\} \text{ with n=1,…,μ.} \quad (1)$$

where g is a given iteration, μ is the size of the parent population. Thus, p_i^g represents the i^{th} component in the g^{th} iteration of the μ^{th} set in the parent population.

In the first step of the evolutionary loop, the elements of the initial population are modified through the introduction of random changes by means of the genetic operators of recombination and mutation. The resulting set of modified elements is known as secondary or intermediate population, depending on the strategy employed, and has the form:

$$P_{\lambda}^{g} = \{\tilde{p}_1^g, \tilde{p}_2^g, ..., \tilde{p}_n^g\} \text{ , with n=1,…, } \lambda. \tag{2}$$

where $\tilde{p}_i^g$ represents the i^{th} component in the g^{th} iteration of the λ^{th} set in the secondary population. The tilde in Eq.(2) indicates that each element has been generated employing the genetic operators.

The role of the recombination operation is to exchange information between the elements of the population and it is defined as:

$$\left\langle p'^{g}_{l,i} \right\rangle = \frac{1}{\rho} \sum_{r=1}^{\rho} p_{r,i}^{g} \tag{3}$$

where $i = 1, 2,…, n$ and $l = 1, 2,…, \lambda$ with n and λ being the number of elements and the size of the secondary population respectively, and where ρ determines the number of parent population sets that take part into the creation of one set of the secondary population.

The mutation operator is used to avoid premature convergence over local minima by exploring the search space through the introduction of new information into the population set [5]. A typical implementation of this operation, known as “self-adaptive mutation” is given by [4]:

$$\tilde{\sigma}_{l,i} = \sigma'_{l,i} \exp[\tau' N_l^{(0)}(0,1) + \tau N_l^{(1)}(0,1)], \tag{4}$$

$$\tilde{p}_{l,i} = p'_{l,i} + \tilde{\sigma}_{l,i} N_i^{(2)}(0,1), \tag{5}$$

where σ is a “strategy parameter” whose main function is the adaptation of the mutation step sizes through the evolutionary loop. According with the notation employed in Eqs. (3) and (4), it is clear that in a ‘self-adaptive’ scheme the genetic operators are applied simultaneously to the objective variables p, which represent the physical values of the secondary population, and to the strategy parameters σ. The function $N(0,1)$ is a normally distributed Gaussian random variable with zero expectation and variance of one. Finally, the two exogenous parameters τ and τ' are known as “learning rates” and they are defined as follows [4]:

$$\tau' \propto \left(\sqrt{2n}\right)^{-1}, \qquad \tau \propto \left(\sqrt{2\sqrt{n}}\right)^{-1}. \tag{6}$$

It is worth mentioning that the determination of the learning rates depends on the features of the cost function and on the number of object variables.

In order to evaluate the potential of the elements within the secondary population, a cost value is associated to each of them. For this end, the forward problem is solved through a rigorous, approximate or numerical method, depending on the problem that is being studied. Then, the closeness between the resultant scattering data corresponding to each element is compared with those corresponding to the object to be reconstructed through a cost function that we have defined as follows:

$$C(P) = \sum_{j=1}^{N_r} | \overline{E}_j^{True}(P) - \overline{E}_j^{Sim}(P) |^2 \tag{7}$$

where $\overline{E}_j^{True}(P)$ represents the scattered electric fields from the target object and $\overline{E}_j^{Sim}(P)$ represents the scattered electric fields from the reconstructed object. The total number of receivers is denoted by N_r. The vector components $\boldsymbol{P}(p_1, p_2, \ldots, p_n)$ represent the unknown parameters to be retrieved. In the present work we employ the method of moments (MOM) described in ref. [2] to calculate both, the "target" data that serves as input for the method and the fields scattered from dielectric objects generated with the elements of the population that is being evaluated.

Once this error is obtained, depending on the selection strategy employed, only those μ elements with the lowest associated cost value will be selected to be the parents for the next iteration. This process is repeated until convergence is achieved or a termination criterion is fulfilled.

III. NUMERICAL RESULTS

The reconstruction of several dielectric objects such as spheres, spheroids and ellipsoids were investigated. In all these cases three unknown parameters were used to determine the coordinates of the center of the object. For brevity, only those results corresponding to the reconstruction of an ellipsoid will be presented in this work. In this case, 6 parameters describing the shape and location will be estimated (i.e. a, b, c, x_0, y_0, z_0). The target values of the center coordinates are $4\lambda_0$, $4\lambda_0$, and $-0.4\lambda_0$ for the x-, y- and z-directions, respectively. Also, the three coefficients that determine the shape of the target object are set to $a = 0.156\lambda_0$, $b = 0.356\lambda_0$, and $c = 0.556\lambda_0$, where λ_0 is the free space wavelength of the incident s-polarized plane wave employed to illuminate the object. The dielectric constant of the target ellipsoid is $\varepsilon_r = 5.071 - j0.591$. The object is discretized, according to the MOM, into triangular patches with 15 nodes in the θ-direction and 20 nodes in the ϕ-direction. A total of 2176 point receivers surround the object. The receivers are positioned at $x = 2.5\lambda_0$, $x = 5.5\lambda_0$, $y = 2.5\lambda_0$, $y = 5.5\lambda_0$, and at $z = -1.68\lambda_0$. The spacing between the point receivers in the x- and y-directions is $0.1\lambda_0$ while $0.12\lambda_0$ is used in the z-direction.

The reconstruction results are shown in figure 1 where the dark color represents the reconstructed object and the light color represents the original object. The reconstructed object is plotted after 1, 30, 60, and 100 iterations to show the convergence of the algorithm. It is observed that after 60 iterations the object has almost converged to the true one. In this case, the required CPU time is approximately 11 hours.

IV. CONCLUSION

The evolution algorithm is combined with the method of moments to reconstruct 3-D dielectric objects immersed in air. The results show promising potential for estimation of the shape and location of malignant tumors immersed in normal breast tissue as a future application. The algorithm is currently under modification to improve the CPU time. For practical considerations, less number of point receivers will be utilized in the future.

ACKNOWLEDGMENT

This research was sponsored by the Arkansas Biosciences Institute award no. ABI-103, and in part by the National Science Foundation Center for Subsurface Sensing and

Imaging Systems (CenSSIS) at Northeastern University in Boston award No. EEC-9986821. D. M. gratefully acknowledges ``Le Ministère de la Jeunesse, de l'Education Nationale et de la Recherche'' and the``Conseil Régional de Champagne-Ardennes" for financial support.

REFERENCES

[1] Susan C. Hagness, Allen Taflove, Jack E. Bridges, "Three Dimensional FDTD analysis of a pulsed microwave confocal system for breast cancer detection: design of an antenna-array element," *IEEE Trans. on Antennas and Propag.*, vol. 47, no. 5, pp. 783-791, May 1999.

[2] L. Medgyesi-Mitschang, J. Putnam, and M. Gedera, "Generalized method of moments for three-dimensional penetrable scatters," *J. Opt. Soc. Amer., A,* vol. 11, no. 4, pp. 1383-1398, Apr. 1994.

[3] H.P. Schwefel, "Evolution and Optimum Seeking", John Wiley & Sons Inc., New York, 1995.

[4] Demetrio Macías, Alexandre Vial, Dominique Barchiesi, "Application of evolution strategies for the solution of an inverse problem in the near-field optics," *J. Opt. Soc. Amer., A*, vol. 21, no. 8, pp. 1-7, August 2004.

[5] Tao-Yuan Huang, Yung-Yaw Chen, "Modified Evolution Strategies with a Diversity-Based Parent-Inclusion Scheme," *Proceedings of the 2000 IEEE International Conference on Control Applications*, Anchorage, Alaska, USA, pp. 379-384, September 25-27, 2000.

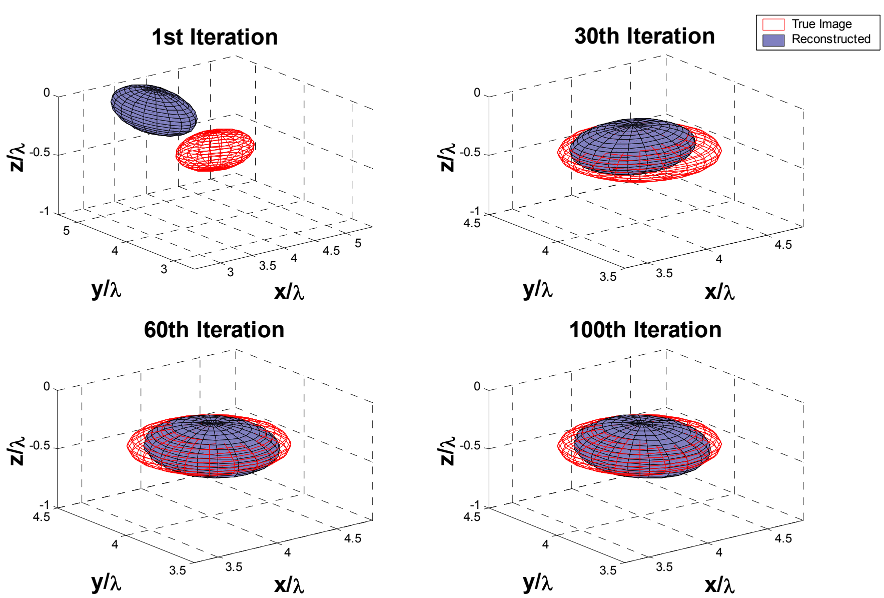

Figure 1 The reconstructed object at different inversion iterations using Gaussian