A Permittivity Range Profile Reconstruction Technique for Multilayered Structures by a Line Process-Augmented Genetic Algorithm

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This paper presents a technique to reconstruct the permittivity range profile of a layered medium using noisy backscattering data. Working on an ill-posed problem, inverse scattering normally provides either unstable or oversmoothed results. Our method tries to obtain an accurate reconstruction using a two-step genetic algorithm employing a regularization constraint with an explicit line process and a local deterministic optimization strategy.

Introduction

In inverse scattering, an unknown scattering object is probed with known waves to estimate its structure by measuring the scattered fields. Noninvasive imaging inspection by electromagnetic probing radiations is very appealing in several areas from civil and industrial engineering to nondestructive testing and biomedical applications. In spite of this great importance, most microwave tomographic techniques are still far from solving practical problems. In fact, there are theoretical aspects hard to manage, such as the nonlinear and nonconvex relationship between the scattered field and the object structure and the robustness of the inversion algorithms against noise.

Some of the authors who tried to solve the inverse scattering problem by new computational paradigms resorted to evolutionary computing, namely, to different versions of genetic algorithms (GAs) [1][2]. Since these approaches proved to be able to efficiently find a global optimum in a fitness landscape, we attempted to exploit this feature in order to get both stable and locally smooth solutions, preserving possible discontinuities. Our specific problem regards the reconstruction of the permittivity range profile of a lossless layered object from measurements of its complex reflection coefficient within a certain frequency band. The inversion is achieved by a hybrid GA, which evolves in two distinct phases. In the first one, the solution is only regularized by a global smoothness constraint; in a second phase, the fitness function is augmented by an explicit line process (LP) in its regularization part [3]. After the activation of the LP, a local deterministic optimizer is used to improve the fitness value before creating the new generation for the GA scheme. In this paper, we give some details on our formulation of the range profile reconstruction problem, its genetic solution with local smoothness constraints, and discuss some of the results from our early experimentation.

Genetic Algorithm Implementation

Let us consider a lossless dielectric wall of thickness *L* surrounded by air and probed with a plane-wave electromagnetic field in the microwave range. The incidence is supposed to be normal. The complex reflection coefficient is measured at *n* frequencies within the chosen bandwidth and stored in a complex vector. Our aim is to estimate the wall permittivity as a function of the depth coordinate *z*. To solve this problem, we discretize the wall into a finite number *M* of homogeneous layers of equal thickness. The GA has to find the configuration of layers that gives the best fit between the measured and the computed reflection coefficients, subject to suitable regularizing constraints. The forward solver implemented in the code evaluates the total reflection coefficient of any structure composed by a finite number of layers for each of the *n* frequencies used in the probing session. The fitness function to be optimized in the first stage is the following:

$$F_1(\varepsilon) = dist\left(\Gamma_{meas}, \Gamma_{GA}\right) + \lambda \sum_{m=1}^{M-1} \left(\varepsilon_{m+1} - \varepsilon_m\right)^2,$$

where *dist* is a suitable distance between the two *n*-element arrays of the measured (Γ_{meas}) and the calculated (Γ_{GA}) reflection coefficients. The second term is the quadratic penalization given by the global smoothness constraint, which prevents the permittivities of any two adjacent layers from being too different. Although the optimizing function F_1 is only able to provide smooth profiles, it allows us to obtain a first rough approximation of the actual permittivity profile. After a fixed number of GA generations, a further regularization term is activated in the fitness function whose form now becomes:

$$F_2(\varepsilon) = dist\left(\Gamma_{meas}, \Gamma_{GA}\right) + \lambda \sum_{m=1}^{M-1} \left(\varepsilon_{m+1} - \varepsilon_m\right)^2 \left(1 - l_m\right) + \alpha l_m \ ,$$

where the new variables l_m are introduced to preserve abrupt permittivity variations where these are likely to occur. When $l_m=1$, any difference between the permittivities of two adjacent layers is not penalized, except for a constant contribution α that is added to the fitness function. When $l_m=0$, the difference between ε_{m+1} and ε_m is quadratically penalized, and the algorithm prevents to consider solutions with a significant permittivity discontinuity between the two layers. The *l* array, which represents the values of the LP, is encoded in the last part of each chromosome. The α and λ parameters influence the discontinuity values which can be accounted for.

According to the selection strategy we adopted, any chromosome is assigned with a probability to enter in the next generation that is proportional to its fitness value and the introduction of simple elitism prevents the loss of the current best solution. The mutation operator is only allowed to affect the three less significant bits of each gene. The crossover takes place between any two chromosomes, which could exchange a gene. The algorithm chooses one gene in a chromosome and one in the other and makes the change. This means that a certain layer is passed from one configuration to another. During the edge-preserving optimization phase a deterministic operator manipulates the best solution found at that moment before letting a new generation be created. From the best chromosome in the current generation, we build a new l array as follows. Starting from the first, a single l_m bit is fixed to 0 and the fitness function of the best chromosome with this new l array is calculated. Then, the same is made fixing the bit to 1. The first bit is then chosen according to best fitness value found. This procedure is followed for all the l_m bits. At the end, we have a new LP set for the best chromosome. This solution is compared to that of the actual best. If we have found a better one, this new chromosome replaces the old best chromosome in the evolutionary process.

Discussion of Results

The described method seems to provide good results. All the following reconstruction are elaborated by using M=12 layers and n = 100 frequencies in the range 0.8 GHz – 3 GHz. The assumed SNR is 25 dB. The reconstructed profile for a concrete wall (ε_r=10) of thickness L=24 cm with an air inclusion inside is shown in Fig. 1. In Fig. 2 the algorithm is facing a wall of the same depth but with a discontinuity of 4 cm in the rightmost part. The last result (Fig. 3) was obtained in the case of a discontinuity that does not match the lattice of the assumed layered model. The reconstruction is still quite good.

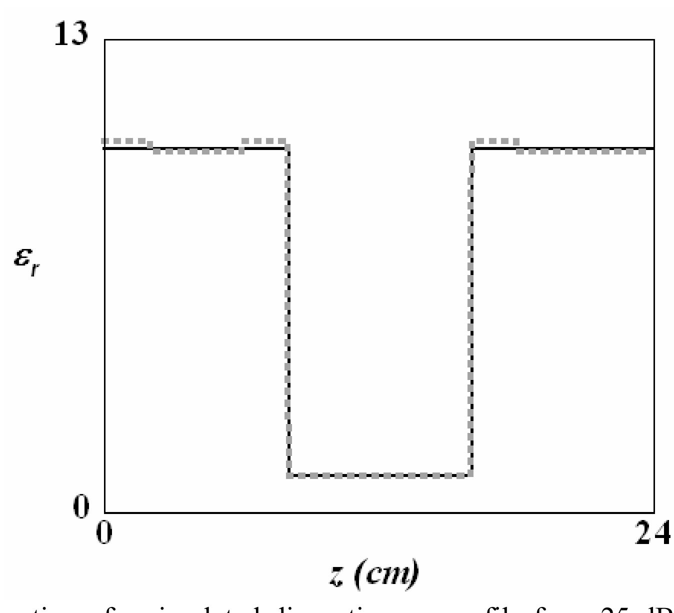

Fig.1- Reconstruction of a simulated discontinuous profile from 25 dB-SNR data. The solid line shows the original profile while the dashed one represents the reconstruction.

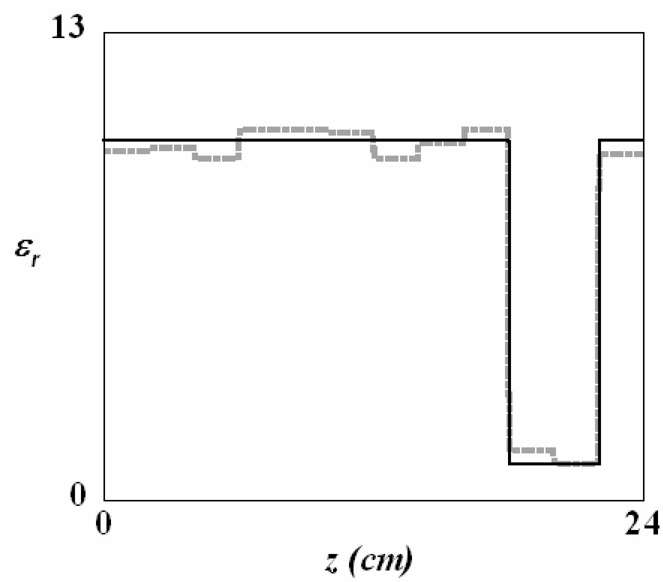

Fig.2 – Reconstruction of a profile with a discontinuity in the rightmost side of the wall. The SNR is 25 dB. Original (solid) and reconstructed (dashed) profiles.

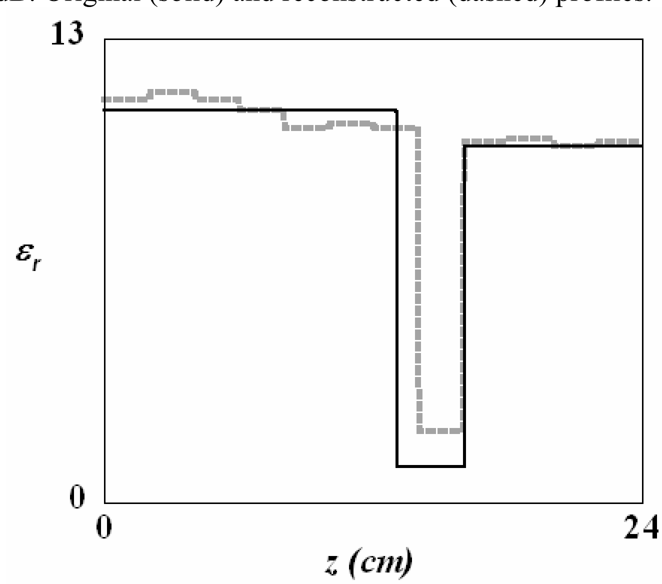

Fig.3 – Result obtained in a case where the discontinuities do not fit the reconstruction lattice. The SNR is 25 dB. Original (solid) and reconstructed (dashed) profiles.

References

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