An Improved Population-Based Incremental Learning Method for Objects Buried in Planar Layered Media

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***Abstract*—We present an improved Population-Based Incremental Learning (PBIL) to reconstruct the objects that buried in planar layered media. It is essential that fast forward solvers be used to solve the forward scattering problem for the nonlinear inverse scattering methods, since it can avoid errors by approximation. Because PBIL is a predominant all-round optimizing method in the macroscopic simulation of evolution process of species in nature, it provides better solution for nonlinear problems. The PBIL is simpler, both computationally and theoretically, than the genetic algorithm (GA). We discuss how this can be used to calculate the permittivity and conductivity of the targets. We show preliminary results indicating the potential of reconstruction for buried objects. Compared with other methods, the experiment result shows that the PBIL algorithm reduces the number of iteration.**

I. Introduction

The problem of reconstructing three-dimensional objects buried in layered media is an important research issue [1]. It is useful in geophysical exploration, target identification, environmental survey, microwave imaging and nondestructive testing. Previously, many methods have been applied to solve inverse problem, such as genetic algorithm (GA) [2], Born iteration method (BIM) [3][4], and distorted Born iteration method [5]. Population-Based Incremental Learning (PBIL) algorithms [6] are a class of novel stochastic optimization algorithms, which have recently become a hot topic in field of evolutionary computation. Compared with GA, PBIL doesn't need the process of inheritance and variation, so we want to apply the PBIL to this inverse problem.

In the present paper, we propose the application of a new inversion method, which is based on an improved PBIL. The electromagnetic inverse problem is recast as a global optimization problem and discretized by using the moment method.

II. Forward Models

The geometry model of the problem is shown in Fig. 1, where the background medium has M parallel layers with independent permittivity, conductivity, and permeability $(\varepsilon_i, \mu_i, \sigma_i, i=1,\ldots,M)$. The source is located in layer p, the target is completely buried in layer i, while the observation. point is located in layer m; there is no restriction to p, i or m. The electrical properties of the inhomogeneous objects are ε_r, σ_r and μ_i. Our objective in the forward model is to calculate the electromagnetic fields due to a source in such a complex medium.

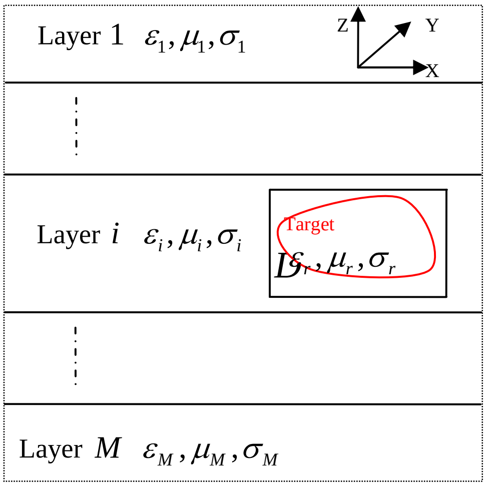

Fig. 1. Typical configuration of an inhomogeneous object in a planar layered medium.

Similar to the scattering problem in a homogeneous background medium, the solution procedure of the volume integral equation method is to find the induced current density inside the object, then the scattered field everywhere can be obtained through the Green's function.

The total electric field $E^{mp}(r)$ in the mth layer is the sum of the incident field $E^{mp}_{inc}(r)$ and the scattered field $E^{mp}_{sct}(r)$,or $E^{mp}(r) = E^{mp}_{inc}(r) + E^{mi}_{sct}(r)$ (1)

where r is the position vector of the observation point.

The scattered electric field $E^{mi}_{sct}(r)$ due to this induced source in the layered medium is given by

$$E^{mi}_{sct}(r) = -j\omega[I + \frac{1}{k_m^2}\nabla\nabla\cdot]A^{mi}_{sct}(r) \qquad (2)$$

while the scattered magnetic vector potential is

$$A^{mi}_{sct}(r) = j\omega\mu_m \int G^{mi}(r,r')\cdot\chi(r')D(r')dr' \qquad (3)$$

where $D(r) = \tilde{\varepsilon}E(r)$ is the electric flux density inside the object (still an unknown at this point), and $\chi(r) = (\tilde{\varepsilon}(r) - \tilde{\varepsilon}_i)/\tilde{\varepsilon}(r)$ is the contrast function of the object, and $G^{mi}(r,r')$ is the dyadic Green's function for magnetic vector potential in a layered background medium. In this paper, the "traditional" form is chosen for the dyadic

Green's function

$$G^{mi}(r,r') = (\hat{x}\hat{x} + \hat{y}\hat{y})G_{xx}^{mi} + \hat{z}\hat{x}G_{zx}^{mi} + \hat{z}\hat{y}G_{zy}^{mi} + \hat{z}\hat{z}G_{zz}^{mi} \quad (4)$$

At this point, the scattered field $E_{sct}^{mi}(r)$ still can't be obtained because *D(r)*, thus $\chi(r')D(r')$ inside the integrand in (3), remains unknown. However, substituting (2) and (3) into (1) yields

A relative error function with respect to the electromagnetic parameters is defined as

$$G(g) = \frac{\sum_{u=1}^{n_t}\sum_{v=1}^{n_r}\sum_{w=1}^{n_s}\left|E^{meas}(t_u,r_v,s_w) - E^{comp}(t_u,r_v,s_w;g)\right|^2}{\sum_{u=1}^{n_t}\sum_{v=1}^{n_r}\sum_{w=1}^{n_s}\left|E^{meas}(t_u,r_v,s_w)\right|^2} \quad (5)$$

where E^{meas} is the result of measured electric field intensity at the observation points, and E^{comp} is the result of the hypothetical parameters g computed by forward model. t_u, r_v and s_w are the incident element, receiver element, and sample point in the frequency domain respectively. n_t, n_r and n_s are the total number of incident, receivers and frequencies, respectively.

III. The Improved PBIL Calculation

Because the PBIL algorithm is a biological evolution algorithm modeling in "macro" level, it has very good performance advantage and its ability that handles nonlinear and large scale problems is better than the "micro" level mathematics iterative method. Compared with the numerical iterative method commonly, it can use the priori information, for example, people know that dielectric constant and conductivity have a scope, so can use this prior information to improve the efficiency of iteration. Numerical results show that the PBIL is better than GA [6] in some examples.

In this validation experiment, we use Gaussian pulse

$$E^{inc} = \hat{x}\exp(-[\frac{4}{T}(t - \frac{r \bullet k}{c})]^2) \quad (6)$$

to reconstruct the objects buried in layered media.

In this paper, our objective is to calculate the electromagnetic parameters of the target. We assume the size of the *D* domain containing the object is $L_x \times L_y \times L_z$. We discrete the *D* domain into $N = N_x \times N_y \times N_z$ uniform cells, with the size of each cell $d_x \times d_y \times d_z$, where $d_x = L_x / N_x$, $d_y = L_y / N_y$, and $d_z = L_z / N_z$. Then, a candidate solution can be written as

$$g = g(\varepsilon_1, \sigma_1, \varepsilon_2, \sigma_2, \cdots, \varepsilon_N, \sigma_N) \quad (7)$$

where $\varepsilon_i, \sigma_i \ (i = 1, 2, \cdots, N)$ are the dielectric constant and conductivity of the *i*th cell, respectively. We can get the domain of every parameter according to our prior knowledge. The solution precision can be written as β, β denotes permittivity ε or conductivity σ. Then the length of every parameter is $L_\beta = (\beta_{\max} - \beta_{\min}) / P_\beta$, $\beta_{\max}$ and $\beta_{\min}$ can be obtained by prior knowledge.

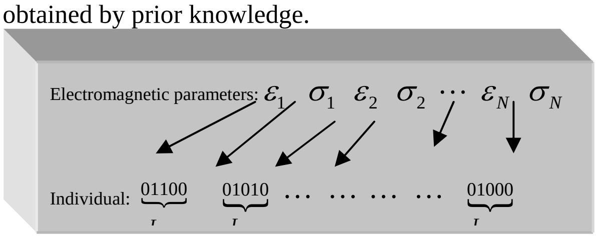

Fig. 4. The structure of an individual

Firstly, we'd better chose a low precision *p*. Because if we chose a high precision, the length of individual will lead to large number of computation. We firstly chose low precision to start, and improve the precision gradually.

In this section, some numerical results are provided. In order to compare the performance of different algorithms, we compare the number of iteration in BIM(DBIM) with generation in PBIL (GA).

TABLE I

PERFORMANCE COMPARION OF DIFFERENT METHODS ON THE RECONSTRUCTION

ACCURACY	BIM	DBIM	GA	PBIL
1%	500	481	473	419
5%	320	300	293	248

IV. Conclusion

Previous empirical work showed that PBIL generally outperformed genetic algorithms, BIM, and DBIM on the problem. Perhaps the most important contribution from this paper is a PBIL way of thinking about reconstruction of objects in layered media using electromagnetic waves. Therefore, the present work provides an attractive alternative to deal with reconstruction of buried objects in layered media.

V. References

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