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MICROWAVE IMAGING OF BURIED INHOMOGENEOUS OBJECTS USING PARALLEL GENETIC ALGORITHM COMBINED WITH FDTD METHOD

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Abstract—Microwave imaging of buried objects has been widely used in sensing and remote-sensing applications. It can be formulated and solved as inverse scattering problems. In this paper, we propose a hybrid numerical technique based on the parallel genetic algorithm (GA) and the finite-difference time-domain (FDTD) method for determining the location and dimensions of two-dimensional inhomogeneous objects buried in a lossy earth. The GA, a robust stochastic optimization procedure, is employed to recast the inverse scattering problem to a global optimization problem for its solution. To reduce its heavy computation burden, the GA-based inverse computation is parallelized and run on a multiprocessor cluster system. The FDTD method is selected for the forward calculation of the scattered field by the buried inhomogeneous object because it can effectively model an inhomogeneous object of arbitrary shape. Sample numerical results are presented and analyzed. The analysis of the numerical results shows that the proposed hybrid numerical technique is able to determine the location and dimension of a 2D buried inhomogeneous object, and the parallel computation can effectively reduce the required computation time.

1. INTRODUCTION

Microwave imaging of buried objects is one of the most challenging research topics, and it has been widely used in sensing and remote-sensing applications, such as geophysical exploration, medical imaging, civil engineering, and nondestructive testing. It can be formulated and solved as inverse scattering problems. As pointed out in [1], the inverse scattering problems are nonlinear due to the fact that the scattered field is a nonlinear function of the electromagnetic properties of the objects, and they are ill-posed because the operator that maps the scatterer properties to the scattered field is compact. In general, the nonlinearity of the inverse scattering problems can be coped with by employing iterative optimization technique, and the ill-posedness can be treated by using regularization schemes. In the past, many inversion techniques have been developed to reconstruct the object profile of underground targets. Among these techniques, a number of effective optimization strategies have been proposed. The modified gradient approach has been used to determine the shape and location of a two-dimensional (2D) cylinder embedded in a homogeneous lower half space [2]. The cylinder considered in [2] is assumed to be homogeneous, and its field formulation involves integrals of Green's functions of stratified medium. Also, diffraction tomographic (DT) algorithms have been developed for solving the inverse scattering problem of a 2-D dielectric cylinder [3], and a three-dimensional (3-D) dielectric object [4], buried in a lossy half space. Their formulations are based on the Born approximation that the total field within the object is approximately equal to the incident field under the condition that the electromagnetic parameters (permittivity, permeability, and conductivity) of the buried object have a low contrast compared with the background. In addition, an efficient numerical scheme, based on the distorted Born iterative method (DBIM), has been developed for reconstructing the permittivity and conductivity profile of 2-D dielectric objects buried in a lossy earth [5]. In [3–5], integral equations containing Dyadic Green's functions are formulated, and the numerical results presented are for homogeneous objects. In [6], the inverse scattering of a buried inhomogeneous cylinder is analyzed, making use of an evolutionary algorithm called memitic algorithm. But the analysis is limited to elliptic cylinders only. The Genetic Algorithm (GA) is also a class of popular evolutionary algorithm. It is able to obtain a global solution and can deal with the high non-linearity resulting from a high contrast between the scatter and the lossy earth, which precludes application of the techniques based on the Born-approximation. It has been effectively employed, with integral equation formulations, for determining the inverse scattering of 2-D homogenous objects located in free-space [7–10], and that buried in a stratified region [11, 12]. Also, the GA has been used for determining the conductivity of tissue embedded in a multi-layer biological structure [13].

In this paper, we propose a hybrid numerical technique based on parallel genetic algorithm and finite-difference-time-domain (FDTD) method for determining the inverse scattering of a 2-D *inhomogeneous* object of arbitrary shape. The electromagnetic properties of the buried object may be of high or low contrast to its background material. Its location and dimension are the unknown parameters to be determined. Different from the previously published work [7–12], the FDTD method is employed for the forward calculation of the scattered electric field by the buried object at a number of observation points. Being compared with the integral equation formulation used in the previous research, the FDTD approach is more efficient for modeling inhomogeneous objects and complex geometries. For recovering the profile of a buried object, its scattered field needs to be measured at a number of observation points. In order to obtain sufficient information, the measurement data are acquired at multi frequencies. Then the GA is used in the inverse calculation to recover the location and dimension of the buried inhomogeneous object by recasting the inverse scattering problem to a global optimization problem and then maximizing a fitness function that represents the correspondence between the measured and the calculated scattered electric field at the observation points. Realizing that the forward scattering calculation must be called tens or even hundreds times at each generation in the GA optimization procedure, the computation could be very time-consuming. Since the GA exhibits an intrinsic parallelism and it allows a very straightforward implementation on parallel computers, we implement the GA-based numerical technique into *parallel computation* to make the computation more effective. The computation is parallelized in a master-slave model and is carried out in a multiprocessor cluster system.

To validate the proposed numerical technique based on the parallel genetic algorithm and the FDTD method, sample numerical results are presented and analyzed.

2. THE PROPOSED NUMERICAL TECHNIQUE

Fig. 1 depicts, in cross sectional view, a z-oriented infinitely-long cylindrical object of arbitrary cross section buried below a planar interface separating two homogeneous half-spaces: the air ($\varepsilon_a = \varepsilon_0,\ \mu_a = \mu_0,\ \sigma_a = 0$) and the earth ($\varepsilon_e,\ \mu_e = \mu_0,\ \sigma_e$). The buried object is assumed to be inhomogeneous, and hence its electromagnetic parameters $(\mu_s, \varepsilon_s, \sigma_s)$ may be variable as functions of (x, y). It is illuminated by an electromagnetic wave impinging at the interface, which is taken to be a transverse magnetic (TM) plane wave at normal incidence. We propose to employ a GA-based hybrid numerical technique to determine the location and dimension of the buried object. As pointed out in the previous section, the GA optimization procedure requires knowledge of the measured as well as the computed scattered field at each generation; and in this research, the GA-based numerical

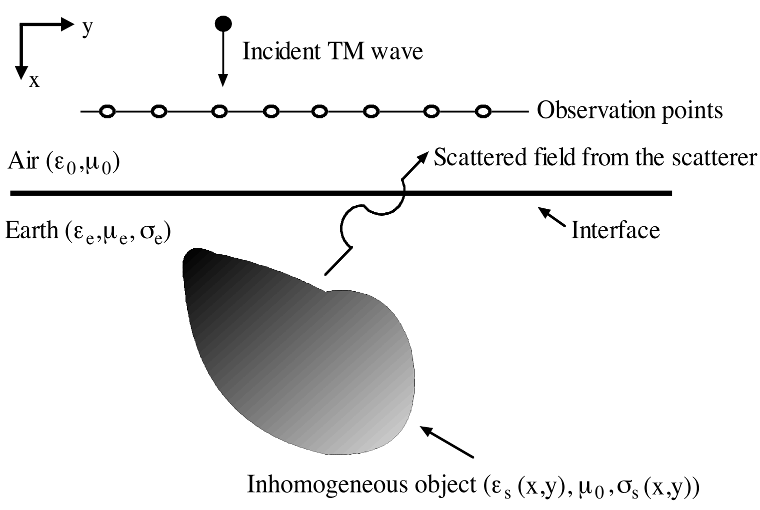

Figure 1. An inhomogeneous 2-D object buried below an air-earth interface.

technique is implemented in parallel computation. In this section, we present the measurement model, the forward computation, the GA-based inverse calculation, and the parallel computation.

2.1. Measurement Model

As illustrated in Fig. 1, the scattered electric field by a buried inhomogeneous object is measured at a large number of observation points along a probing line, which is parallel to and above the air-earth interface. In order to obtain sufficient information, 10 discrete frequencies equally spaced within the 200 MHz–380 MHz frequency range are used for the measurement at each observation point.

2.2. The Forward Computation

The FDTD method [14–19] is employed to compute the scattered electric field at the observation points to provide information needed at each generation in the GA optimization procedure. A FDTD computation domain is formulated as a region of interest, which contains the object, its earth background, and the observation points above the air-earth interface. The computation domain is discretized by Yee's cells [14], and the second-order Mur Absorbing Boundary Condition (ABC) is used on its boundary to simulate that the scattered waves are absorbed as they radiate onto the boundary. Then, after going through a leap-frog solution process, the field can be determined everywhere in the computation domain. In particular, information of the scattered electric field at each observation point is obtained, which is needed for the GA-based optimization procedure described in the next sub-section.

2.3. The GA-Based Inverse Calculation

The Genetic Algorithm (GA) [20–22] is a robust stochastic search and evolution procedure. It starts with a set of randomly constituted trial solutions that is called individuals. In this research, an individual is a set of location and dimension parameters of a trial buried object. A collection of the individuals forms a population. Then, the FDTD method is employed to compute the electric fields scattered by the trial objects, which are represented by the individuals in the population. Such calculated electric fields are then compared with the measured field. The difference between these two sets of data indicates how close the location and dimension parameters of a trial object are, to those of the actual buried object. In order to represent the difference between the calculated and the measured scattered electric field, a fitness function is defined as

$$F = 1 - \sqrt{\frac{\sum_i \sum_j \left(E_{i,j}^{measured} - E_{i,j}^{calculated}\right)^2}{\sum_i \sum_j \left(E_{i,j}^{measured}\right)^2}} \tag{1}$$

where i and j denote the frequency index and the observation point index, $E_{i,j}^{measured}$ and $E_{i,j}^{calculated}$ are the measured and the calculated electric field intensity at the observation points. One observes from this equation that when the field difference goes to zero, the value of the fitness function, namely fitness value, would approach to one. Thus, the inverse scattering problem is converted to a global optimization problem of finding out a trial object, which would result in a fitness value close to 1.

After the selection, crossover, and mutation operations, a new population is generated, which contains better individuals with larger fitness values than those in the previous population. Over a number of generations, the fitness value would be optimized to a value close to 1, and the corresponding best individual would be used as the final solution. To prevent the best individual from being lost during the GA optimization process, the Elitism [7], which copies the best individual directly to the next generation, is employed in the selection operation.

2.4. The Parallel Computation

The GA-based technique developed for determining the inverse scattering of a buried inhomogeneous object could be computationally intensive because it requires a large number of the forward FDTD computations of the scattered field at every generation. Since the GA exhibits an intrinsic parallelism and it allows a very straightforward implementation on parallel computers, we implement the GA-based numerical technique into parallel computation to make the computation more effective. In this work, the Parallel GA (PGA) [23, 24] is adopted and the inverse scattering computation was run in parallel on a PC cluster system, which consists of 16 PCs interconnected by a 100 Mbps fast ethernet switch. It's a homogeneous cluster system with an AMD XP1700+ processor in each PC.

As pointed in [23], the PGA mainly has three parallel models: the master-slave, the coarse grain, and the fine grain model. In this work, the master-slave model is chosen to parallelize the GA in the cluster system. A processor, which is called "master processor", is dedicated for scheduling and assigning tasks (the forward computations) to the other processors called "slave processors". The slave processors carry out the forward computations that are assigned to them and then send the results to the master processor. The flow chart of the proposed master-slave parallel genetic algorithm combined with the FDTD method is illustrated in Fig. 2.

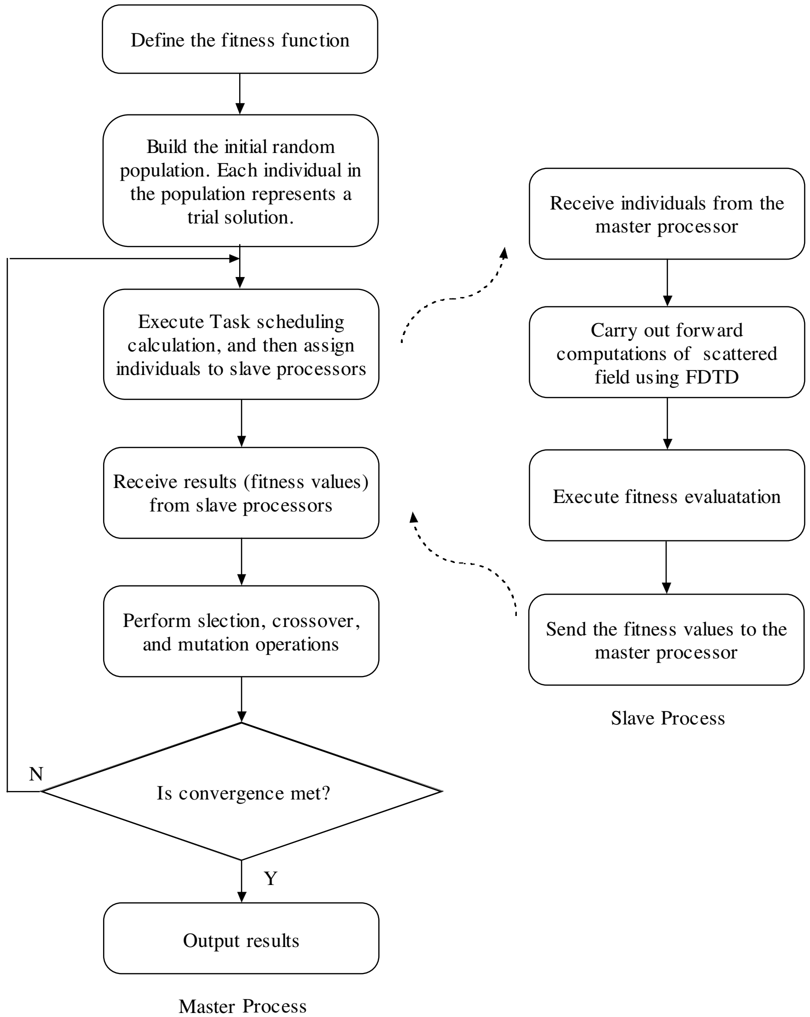

Figure 2. Flow chart of the proposed parallel genetic algorithm combined with FDTD method.

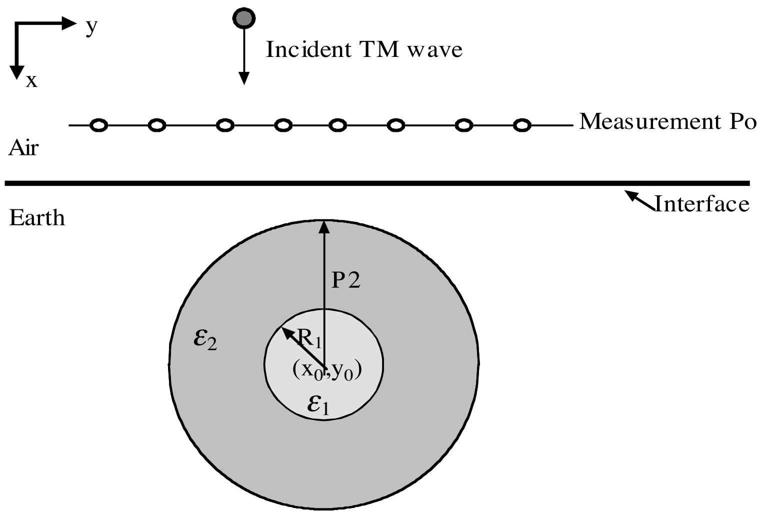

Figure 3. Geometry of a buried circular cylinder with two layers.

3. NUMERICAL RESULTS

To validate the accuracy and the efficiency of the proposed hybrid numerical technique based on parallel genetic algorithm and FDTD method, in this section, sample numerical results are presented and analyzed for buried 2-D objects with layered structures.

The first example is for a buried dielectric circular cylinder of two coaxial layers characterized by ($\varepsilon_1 = 4\varepsilon_0$, $\mu_1 = \mu_0$, $\sigma_1 = 0$) and ($\varepsilon_2 = 8\varepsilon_0$, $\mu_2 = \mu_0$, $\sigma_2 = 0$). As depicted in Fig. 3, the axis of the circular cylinder is located by (x_0, y_0) and the two coaxial layers are of radii R_1 and R_2. The location/dimension parameters x_0, y_0, R_1, and R_2 are the four unknowns to be recovered.

As shown in Fig. 4(a), the reconstruction domain is of cross section containing the buried object. It is divided to $100 \times 100 = 10000$ pixels. The scattered field due to the object, under a TM-wave illumination, is measured at 90 equally-spaced observation points along a probing line, which is parallel to and 0.1-m above the air-earth interface. The measurement is simulated by computation of the scattered field of the buried object with preset electromagnetic parameters, making use of the FDTD method. In the GA inverse calculation, the parameters used are taken to be as the follows. N (the number of individuals in the population) = 100; Pc (the probability of crossover) = 0.5; and Pm (the probability of mutation) = 0.2.

In Figs. 4(b)–4(f) are shown the grey-level images of the

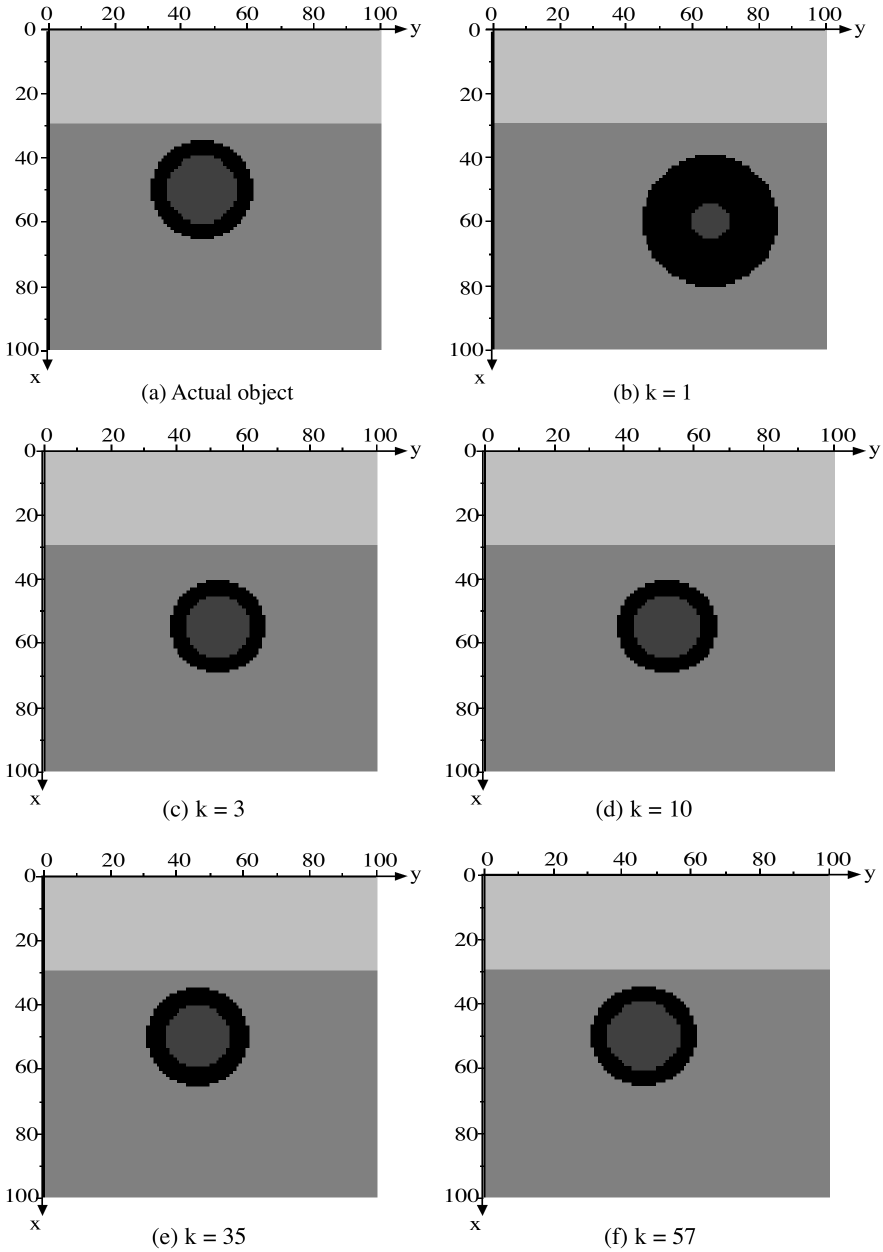

Figure 4. Reconstruction images of the buried circular cylinder at different generations.

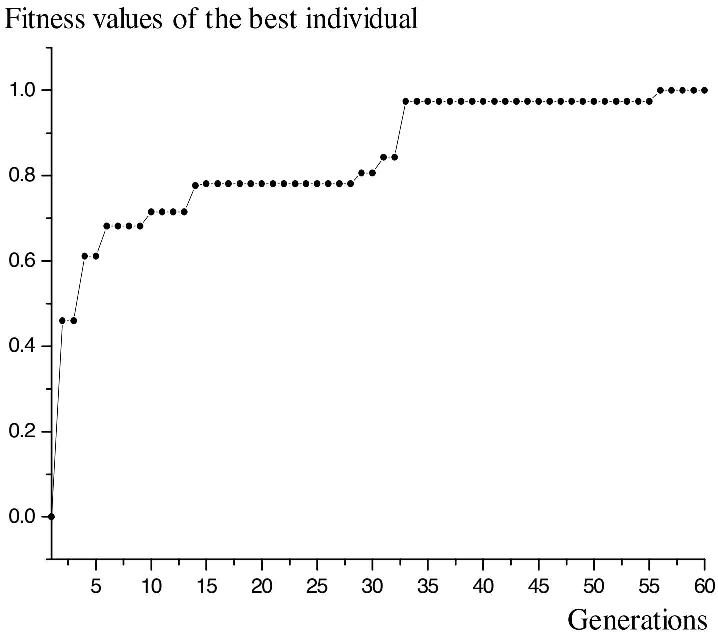

Figure 5. Fitness values of the best individual in different generations.

reconstructed buried object for different generations. For the first generation ($k = 1$), the initial population is created by a set of pseudorandom values. Then, after a number of generations, the population is optimized. A comparison between the image for $k = 57$ depicted in Fig. 4(f) and that for the actual object illustrated in Fig. 4(a) shows a good match between them, indicating that the location/dimension parameters of the buried object have been successively recovered using the proposed hybrid numerical technique.

The values of the fitness function, defined in equation (1), for different generations are shown in Fig. 5. From this figure, one observes that the fitness value increases from generation to generation. At the 57th generation ($k = 57$), it is optimized to 1, which represents a perfect match between the "measured" and the calculated scattered field. Such a match corresponds to a successive recovery of the location/dimension parameters of the buried object, as illustrated in Fig. 4(f).

To further demonstrate the capacity of the proposed hybrid numerical technique, we added 5% random noise to the "measurement" data, and then executed the GA-based inverse calculation. The GA-

Table 1. The location/dimension parameter solutions for different generations.

Generation	x_0	y_0	R1	R2	Fitness value
1	63	30	5	25	0.0
5	54	31	9	15	0.43915
11	55	52	9	14	0.64997
19	55	46	9	14	0.68157
33	52	48	10	15	0.72241
45	50	48	10	15	0.83922
68	50	46	10	15	0.85364

solutions of the location/dimension parameters in different generations, obtained after introducing the noise, are listed in Table 1, for a buried circular cylinder with the preset parameters $x_0 = 50$, $y_0 = 46$, $R_1 = 10$, and $R_2 = 15$ (all in centimeters). As shown in this table, the correct solutions are obtained at the 68th generation. But the fitness value corresponding to the correct solution is only 0.85364, which is due to the noisy measurement background.

The second example is for a buried object of two rectangular layers with electromagnetic parameters ($\varepsilon_1 = 4\varepsilon_0$, $\mu_1 = \mu_0$, $\sigma_1 = 0$) for layer 1 and ($\varepsilon_2 = 8\varepsilon_0$, $\mu_2 = \mu_0$, $\sigma_2 = 0$) for layer 2. As illustrated in Fig. 6, Layer 1 is of length L_1 and width W_1, its upper-left corner is located at (x_1, y_1); and Layer 2 is of length L_2 and width W_2, its

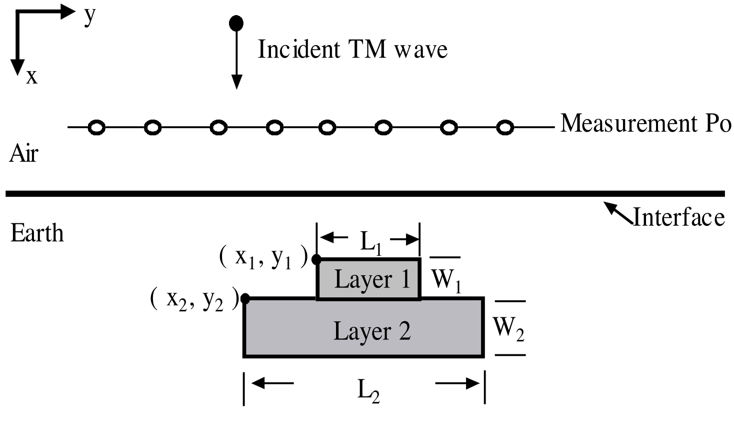

Figure 6. Geometry of a buried rectangular cylinder with two layers.

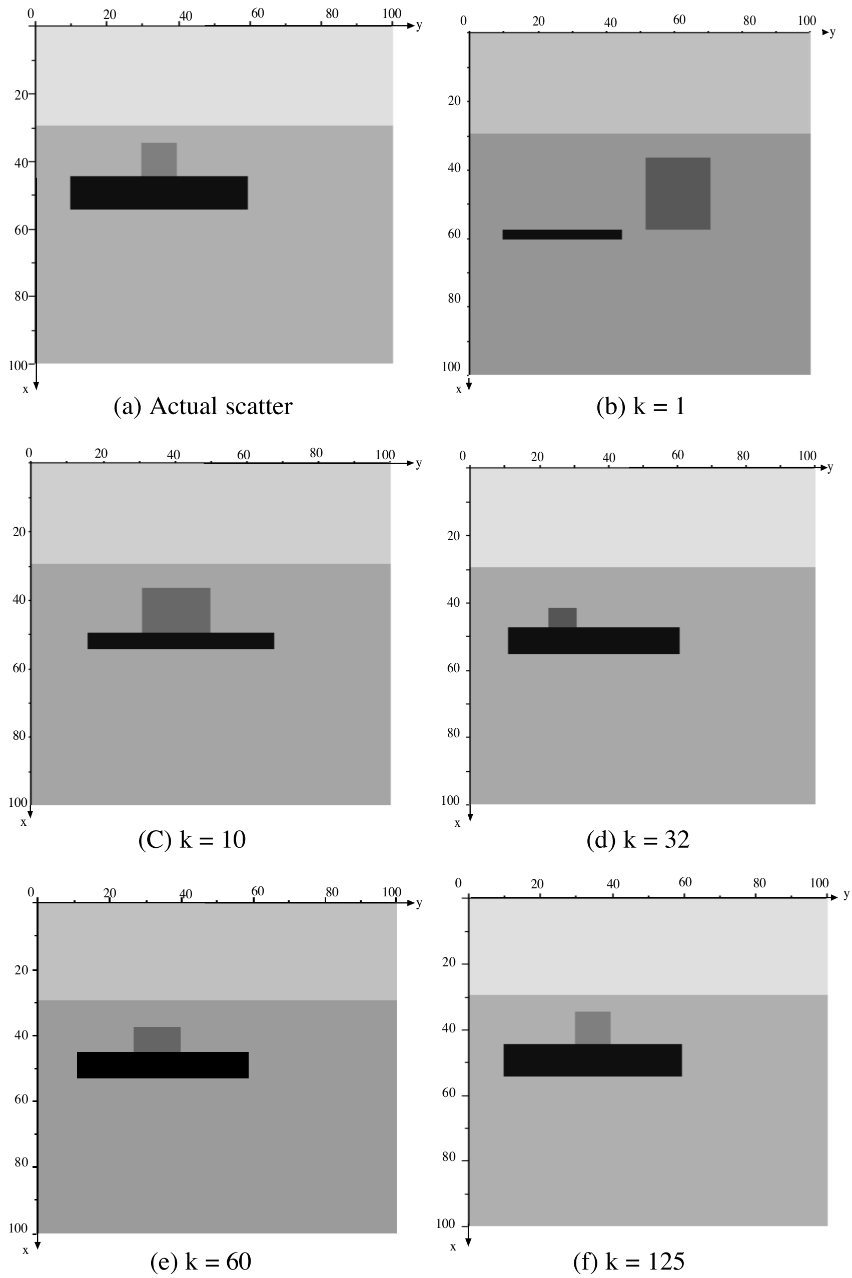

Figure 7. Reconstruction images of the buried rectangular cylinder at different generations.

upper-left corner is located at (x_2, y_2). Since x_2 can be found from $x_2 = x_1 + W_1$, the location and dimension of the buried object can be completely specified by x_1, y_1, y_2, W_1, L_1, W_2, and L_2; these seven location/dimension parameters are the unknowns to be recovered.

In the solution of this inverse scattering problem, the GA-calculation parameters used are the same as those used in the previous example. In Figs. 7(b)–7(f) are shown the grey-level images of the reconstructed buried object for different generations. A good match between the image for $k = 125$ depicted in Fig. 7(f) and that for the actual object shown in Fig. 7(a) indicates that the location/dimension parameters of the buried object have been successively recovered at the 125th generation. One notes that more generations are needed for the GA-based inverse calculation for solving this problem comparing with that used in the previous example (125 vs. 57) because more unknowns are to be reconstructed (7 vs. 4).

To evaluate the efficiency of the proposed numerical technique based on the parallel genetic algorithm, it is of interest to compare its computation time to that without parallel computer configuration. The numerical solution of this example consumes *30 minutes* using the cluster system with 16 processors for the parallel computation. Then, the same problem is solved using sequential computer codes with the parallel communication and overhead removed, and the execution time on one of the computers in the cluster system is found to be *438 minutes*. From this comparison, one observes that a great deal of computer time has been saved owing to the parallel computation.

4. CONCLUSIONS

A hybrid numerical technique based on parallel genetic algorithm (GA) and the FDTD method is proposed for determining the location and dimensions of 2D inhomogeneous objects buried in a lossy earth. The GA employed is a robust stochastic search and optimization procedure suitable for solving the nonlinear inverse scattering problem. To reduce its heavy computation burden, the GA-based inverse computation is parallelized and run on a multi-processor cluster system. The FDTD method is selected for the forward calculation of the scattered field by the buried inhomogeneous object because it can effectively model an inhomogeneous object of arbitrary shape. Sample numerical results are presented for 2-D buried objects with layered structures. An analysis of the numerical results shows that the proposed hybrid numerical technique is able to determine the location and dimension of an inhomogeneous 2D object buried in a lossy earth, and the parallel computation can effectively reduce the required computation time.

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