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Detection Algorithm for Two Air Holes in Underground Using Particle Swarm Optimization

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1. Intruduction

A technology to image a state of an underground by using a ground penetrating radar (GPR) over a ground is one of the effective techniques for a detection of underground objects. Since this technique can obtain measured data at low cost and in short time, a further innovation of the technique is expected. In a popular radar system for underground objects with the GPR, the system visualizes an internal state of the ground by focusing on the difference in response time of measured scattered electromagnetic wave. However, it is well known that a clear image is not obtained easily by this technique. Therefore, many methods that give a reconstructed image of the underground objects are proposed [1]-[3].

In recent years, stochastic optimization methods such as genetic algorithm (GA) [4] have been proposed and have attracted many attentions from workers. Particle swarm optimization (PSO) is also one of the stochastic methods and is modeled after group behaviors of a swarm of birds or fishes [5]. Since PSO searches an optimal solution for the problem by using the agent swarm as well as genetic algorithm, the method can search the solution for broad estimation area simultaneously. Therefore, it is expected that the application of PSO to the optimization problems in various fields of engineering. We have also proposed a PSO based detection algorithm for the underground objects [6].

This manuscript presents a detection algorithm for the underground objects using PSO. It is assumed that cylindrical dielectric objects are buried in a lossy homogeneous soil. Some line sources and receiving antennas are located over a ground surface and the scattered waves are measured from the soil contains the objects. Introducing FDTD method [7], we can obtain scattered electromagnetic waves from the soil. A cost functional for an inverse scattering problem is defined using measured electromagnetic components and calculated ones for estimated parameter of the objects. Applying our detection algorithm that based on PSO to a minimization of the functional, we can obtain estimated parameters for the objects. For the purpose of enhancing a convergence of the algorithm to the optimal solution, we have modified the original PSO formulation using the excellent agents in successive generation. In order to avoid local minima in the early stage of the estimation, we have employed a technique similar to a mutation in GA and a reducing method of the estimation region gradually. For a case of two air holes with circular cross sections in the soil, we estimate the location, dimension, and relative permittivity of the holes. From the numerical results, we can show validity of our algorithm.

2. Theory

Figure 1 illustrates geometry of the problem. It is assumed that cylindrical dielectric objects with arbitrary cross sections are buried in a homogeneous lossy soil. The parameters ε and σ show permittivity and conductivity of the objects and the parameters ε_s and σ_s correspond to those of the soil. Furthermore, permeabilities of objects and soil are assumed to be μ_0 and the parameter μ_0 is a permeability in free space. Some line sources and receiving antennas are located over the smooth soil surface and E-polarized pulsed waves are generated from the sources. Uniaxial perfectly matched layer (UPML) [8] is introduced as an absorbing boundary for electromagnetic wave and is terminated with perfect electric conductor (PEC) wall. Using FDTD method, we have the scattered electromagnetic waves from the soil.

Noting components of the scattered electromagnetic field, we define

$$F(\mathbf{p}) = \int_0^T \sum_{p=1}^{P}\sum_{q=1}^{Q} \Psi(t)\Big[|E_z(\mathbf{p},\mathbf{r}_p,\mathbf{r}_q,t) - \widetilde{E}_z(\mathbf{r}_p,\mathbf{r}_q,t)|^2 + \eta_0^2\, |H_x(\mathbf{p},\mathbf{r}_p,\mathbf{r}_q,t) - \widetilde{H}_x(\mathbf{r}_p,\mathbf{r}_q,t)|^2$$
$$+ \eta_0^2\, |H_y(\mathbf{p},\mathbf{r}_p,\mathbf{r}_q,t) - \widetilde{H}_y(\mathbf{r}_p,\mathbf{r}_q,t)|^2\Big]\, dt, \quad (1)$$

where the parameters $\widetilde{E}_z$, $\widetilde{H}_x$, and $\widetilde{H}_y$ are components of measured scattered electromagnetic field and E_z, H_x, and H_y are calculated one's components for estimated parameters of the cylinders. Moreover, T is a measurement time and $\mathbf{r}_p(p = 1, 2, \cdots, P)$ and $\mathbf{r}_q(q = 1, 2, \cdots, Q)$ show the locations of the source and receiving antenna, respectively. The parameter η_0 is the intrinsic impedance in free space and $\mathbf{p}$ is a vector composed with estimated parameters about the objects and $\Psi(t)$ is a weighting function. Minimizing the cost functional, we can obtain the estimated parameters of the underground objects.

For the i-th $(i = 1, 2, \cdots, I)$ agent in the PSO swarm, our update equations for the velocity vector component $v_{i,d}^{k+1}$ and the estimated parameter vector component $p_{i,d}^{k+1}$ are as follows [6]:

$$v_{i,d}^{k+1} = wv_{i,d}^{k} + c_1r_1\left(pbest_{i,d} - p_{i,d}^{k}\right) + c_2r_2\left(gbest_d - p_{i,d}^{k}\right) + c_3r_3\left(best1_d - p_{i,d}^{k}\right)$$
$$+ c_4r_4\left(best2_d - p_{i,d}^{k}\right) \quad (2)$$
$$p_{i,d}^{k+1} = p_{i,d}^{k} + v_{i,d}^{k+1} \quad (3)$$

where d and k are the numbers of dimension and generation. The parameter w is an inertia weight and $c_\alpha(\alpha = 1, 2, \cdots, 4)$ denotes a weighting coefficient. The parameter $pbest$ is an agent's personal best and $gbest$ corresponds to the swarm's global best at the generation, respectively. The parameter r_α is a random number between 0 and 1. The parameters $best1$ and $best2$ are the 1st and 2nd excellent agents that are obtained until the k-th generation.

In order to increase the efficiency of the optimal solution search and decrease the computation time, we introduce a method that reduces the estimation regions for each parameter gradually. Therefore, we set up some thresholds for the method. The regions are narrowed down when the value of the functional is smaller than these thresholds.

Our detection algorithm for the underground objects is composed with the following steps.

Step 1 Generate initial value $\mathbf{p}_i^{(0)}(i = 1, 2, \cdots, I)$ of each agent with random numbers.

Step 2 Solve the forward problem for $\mathbf{p}_i^{(k)}(k = 0, 1, 2, \cdots, K)$.

Step 3 Calculate value of the cost functional for $\mathbf{p}_i^{(k)}$. Examine convergence criterion given by threshold value. Continue if not satisfied.

Step 4 Judge the reduction of estimation regions with the prescribed threshold. If the condition is satisfied, determine new regions and generate new agents with random number. Return to **Step 2**.

Step 5 Update p_{best} and g_{best}, if necessary.

Step 6 Renew $best1$ and $best2$, if necessary.

Step 7 Update for $\mathbf{p}_i^{(k+1)}$ with Eqn. (2) and (3).

Step 8 Revise $\mathbf{p}_i^{(k+1)}$ if one of the components of $\mathbf{p}_i^{(k+1)}$ is outside the estimation region. Return to **Step 2**.

3. Numerical Results

It is assumed that there are two cylindrical air holes with circular cross sections in the soil. We estimate the location, radius and relative permittivity of the holes. A situation for numerical results is illustrated in Fig. 2. We set an 80×40 cells area that is enclosed with dotted line as an estimation region and assume that these holes are in the region. Note that the number of the holes is given as *a priori* information. Initial estimation regions for each parameter of the holes are given by:

- $0 \leqq \dfrac{x}{\Delta x} \pm \dfrac{R}{\Delta x} \leqq 80$,
- $0 \leqq \dfrac{y}{\Delta y} \pm \dfrac{R}{\Delta y} \leqq 40$,
- $1 \leqq \dfrac{R}{\Delta u} \leqq 10$,
- $1 \leqq \varepsilon_r \leqq 10$,

where and R and ε_r denote a radius and relative permittivity of each hole. Furthermore, $\Delta x = \Delta y = \Delta u$ and $\Delta u = 0.01$ (m). Thus the vector **p** in Eqn. (1)-(3) is given by

$$\mathbf{p} = (x_1, y_1, R_1, \varepsilon_{r1}, x_2, y_2, R_2, \varepsilon_{r2})^t, \tag{4}$$

where the subscripts 1 and 2 denote the object numbers for the holes and the superscript t represents the transpose. The numbers of the sources and antennas are 4 and 8 and heights of these from the ground surface are $h_1 = 0.1$ (m) and $h_2 = 0.05$ (m), respectively. The relative permittivity and conductivity of the soil are 5.0 and 1.0×10^{-3} (S/m) and these parameter also used as *a priori* information. The weighting function $\Psi(t)$ in Eqn. (1) is

$$\Psi(t) = \sin\left(\frac{\pi t}{T}\right), \tag{5}$$

where $T = 500\Delta t$ (ns) and $\Delta t = 1.0$ (ns). On the other hand, The inertia weight w is expressed by

$$w = 0.5 + \frac{[0,1]}{2}, \tag{6}$$

where $[0,1]$ represents a random number between 0 and 1 [9]. The parameters $c_1 = c_2 = c_3 = c_4 = 2$. Moreover, the parameter $K = 400$ and the number of agents I is 150.

We also focused on the positional relationship between two holes since the relationship strongly affects the value of the functional. We quantify the relationship between the two objects in the i-th agent by the following equation:

$$\beta(i) = \left|\frac{x_1(i)}{\Delta x} - \frac{x_2(i)}{\Delta x}\right| + \left|\frac{y_1(i)}{\Delta y} - \frac{y_2(i)}{\Delta y}\right| + \left|\frac{R_1(i)}{\Delta u} - \frac{R_2(i)}{\Delta u}\right| + |\varepsilon_{r1}(i) - \varepsilon_{r2}(i)|. \tag{7}$$

Quantified values for the excellent agents are referred to as the upper and lower limit values when the agents are updated. Furthermore, in order to maintain a variety of the swarm, we also introduce a method that is similar to a mutation in GA [4]. In this method, some agents in the swarm are updated by the random numbers based on the mutation rate rather than the proposed equations. Then we set the mutation rate as 0.05. In addition, when the value of the functional is not smaller than the threshold for the estimation region reduction after some generations, we produce all agents using random number newly.

Tables 1 and 2 show the true and estimated values of these holes. We perform 10 times trial and show the maximum, the minimum, and the average values of the solutions in 6 times from which the optimal solutions are obtained. From these results, we can obtain good estimation results for these parameters of the holes.

4. Conclusion

We have considered the estimation algorithm using PSO for the detection of underground objects. Noting the cost functional measured scattered waves and calculated ones for the estimated parameters of the objects, we proposed the detection algorithm with PSO for an optimization problem that is minimized the functional. In order to raise a convergence of the algorithm to the optimal solution, we introduced modified update equations of PSO and a technique to narrow down estimation regions for the objects to progressively. Furthermore, the method to maintain a variety of the swarm and the technique to avoid local minima are employed in the algorithm. For a case of two cylindrical air holes with circular cross sections, we estimate the location, radius, and relative permittivity of these holes. We also pay attention to the positional relationship between two holes in numerical calculation. Numerical results confirm the effectiveness of the proposed algorithm for the detection of the air holes in underground.

Study on the numerical consideration for various buried objects remains a topic for future work.

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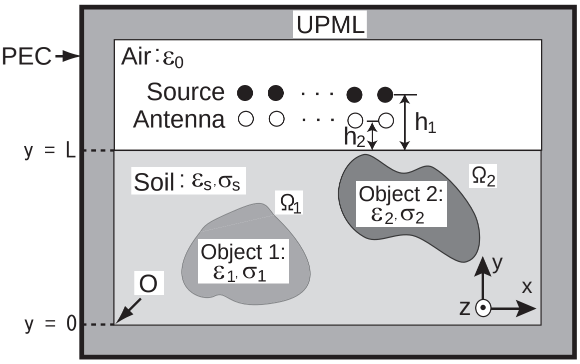

Figure 1: Geometry of the problem.

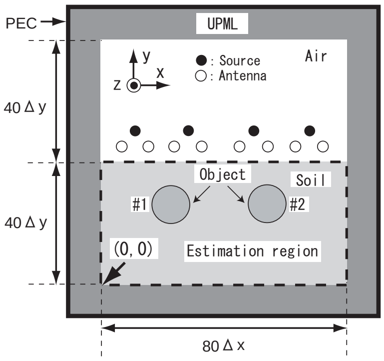

Figure 2: Situation for numerical simulations.

Table 1: True and estimated values for air hole 1.

	$x_1/\Delta x$	$y_1/\Delta y$	$R_1/\Delta u$	ε_{r1}
True	30	22	6	1
Maximum	30	25	8	2
Minimum	28	20	4	1
Average	29.2	22.3	5.8	1.2

Table 2: True and estimated values for air hole 2.

	$x_2/\Delta x$	$y_2/\Delta y$	$R_2/\Delta u$	ε_{r2}
True	50	22	6	1
Maximum	51	22	7	1
Minimum	49	21	6	1
Average	50.0	21.5	6.3	1.0