Comparison of Steady-State Genetic Algorithm and Asynchronous Particle Swarm Optimization on Inverse Scattering of a Partially Immersed Metallic Cylinder

Chi Hsien Sun* , Chien-Hung Chen††, Chung-Hsin Huang††, Ching-Lieh Li‡, En-Nung Chiu‡, and San Liang Lee*

*Department of Electronic and Computer Engineering, National Taiwan University of Science and Technology, Taipei City, Taiwan, R.O.C.
Email: laisingsun@yahoo.com.tw
†Taipei College of Maritime Technology, Department of Information Technology and Mobile Communication, New Taipei City, 25137 Taiwan
††Department of Marine Engineering, Taipei College of Maritime Technology, New Taipei City, Taiwan, R.O.C.
‡Electrical Engineering Department, Tamkang University Tamsui, Taiwan, R.O.C

***Abstract* —The inverse problem under consideration is to reconstruct the characteristic of scatterer from the scattering E field. Steady-state genetic algorithm (SSGA) and asynchronous particle swarm optimization (APSO) are stochastic-type optimization approach that aims to minimize a cost function between measurements and computer-simulated data. Thus, the shape of metallic cylinder can be obtained by minimizing the objective function. After an integral formulation, a discretization using the method of moment (MoM) is applied. Numerical results indicate that the asynchronous particle swarm optimization (APSO) outperforms steady-state genetic algorithm (SSGA) in terms of reconstruction accuracy and convergence speed.**

***Index Terms* —Inverse Scattering, Asynchronous Particle Swarm Optimization, Partially Immersed Conductor.**

I. INTRODUCTION

Microwave imaging is an application of electromagnetic inverse scattering that is capable of performing noninvasive evaluation on a test object and determining its shape and/or material properties. The application of electromagnetic scattering to retrieve the shape, location, and the property of an unknown scatterer embedded in a homogeneous space or buried underground has shown great potential in several application areas such as medical tomography, geophysics, non-destructive testing and object detection [1]-[5].

From a mathematical point of view, inverse problems are intrinsically ill-posed and nonlinear. Hence, only a finite number of parameters can be accurately retrieved. To stabilize the inverse problems against ill-posedness, usually various kinds of regularizations are used which are based on a priori information about desired parameters. On the other hand, due to the multiple scattering phenomena, the inverse-scattering problem is nonlinear in nature. Therefore, when multiple scattering effects are not negligible, the use of nonlinear methodologies is mandatory.

Inverse scattering problems are usually cast into optimization ones. There are usually two types of optimization schemes to solve the inverse scattering problems: the deterministic one and the stochastic one. The former has been developed for decades, such as the contrast source inversion conjugate-gradient method [6], distorted Born iterative method (DBIM) [7] and other gradient-type methods [8] etc. The stochastic methods usually employ a group of initial guesses and use certain stochastic procedure to minimize the cost function, such as the genetic algorithm (GA) [9]-[10] and various evolutionary optimization ones. The application of population-based optimization techniques increases the capability of finding the global minimum rather than being trapped in a local minimum as the deterministic optimization techniques are. Stochastic procedure provides a more robust and efficient approach for solving inverse scattering problems. Particle swarm optimization (PSO) has proven to be a useful method of optimization for difficult and discontinuous multidimensional engineering problems due to its efficiency of exploring the entire search space. Besides, PSO had been applied for inverse scattering problems [11]-[12]. In additions, GA and PSO were utilized to search the global extreme of the inverse scattering problem to overcome the drawback of the deterministic methods.

Recently, inverse scattering problems are usually considered in optimization-based procedures on transverse magnetic (TM) cases [9]-[14]. It's been recognized that the 2-D TE problems include two orthogonal electric field components in the transverse plane and thus leads to a vectorial mathematical formulation. Therefore, the computational load for exploiting such positive features is unavoidably increased as compared to the TM case with only one electric field component. In other words, the TE-polarized case includes polarization charges at dielectric discontinuities, which are more difficult to model numerically. However, there are advantages of utilizing the TE-polarized data (as compared the TM-polarized ones) since they may contain more useful information about the object of interest data. It should be noted that these two polarizations are physically uncoupled and they provide independent information about the object being imaged [15].

In this paper, the inverse scattering problem of the partially immersed perfectly conducting cylinder by TE wave illumination is investigated. We use the APSO to recover the shape of a partially immersed perfectly conducting cylinder.

II. Direct Problem

Let us consider a perfectly conducting cylinder which is partially immersed in a lossy homogeneous half-space, as shown in Fig. 1. Media in regions 1 and 2 are characterized by permittivities and conductivities $(\varepsilon_1, \sigma_1)$ and $(\varepsilon_2, \sigma_2)$ respectively. In our simulation, a priori information is assuming that scatterer is a metallic cylinder. A perfectly conducting cylinder is illuminated by a TE plane wave. The cylinder is of an infinite extent in the z direction, and its cross-section is described in polar coordinates in the x, y plane by the equation $\rho = F(\theta)$. We assume that the time dependence of the field is harmonic with the factor $e^{j\omega t}$. Let $\vec{H}^{inc}$ denote the incidence field form region 1 with incident angle ϕ_1 as follow:

$$\vec{H}^{inc} = e^{-jk_1(y\cos\phi_1 + x\sin\phi_1)}\hat{z} \qquad (1)$$

Owing to the interface between regions 1 and 2, the incident plane wave generates two waves that would exist in the absence of the conducting object. Thus, the unperturbed field is given by

$$\vec{H}^i = \begin{cases} [e^{-jk_1(y\cos\phi_1 + x\sin\phi_1)} + \vec{H}_1 e^{-jk_1(-y\cos\phi_1 + x\sin\phi_1)}]\hat{z} & , y \le -a \\ \vec{H}_2 e^{-jk_2(y\cos\phi_2 + x\sin\phi_2)}\hat{z} & , y > -a \end{cases} \qquad (2)$$

where

$$\vec{H}_1 = \left(\frac{Z_1 - Z_2}{Z_1 + Z_2}\right)e^{2jk_1 a\cos\phi_1}$$

$$\vec{H}_2 = \frac{2Z_1 e^{jk_1 a\cos\phi_1} e^{-jk_2 a\cos\phi_2}}{Z_1 + Z_2}$$

$$\phi_2 = \sin^{-1}\frac{k_1}{k_2}\sin\phi_1$$

$$Z_1 = \eta_1\cos\phi_1 \ ,\ Z_2 = \eta_2\cos\phi_2 \ ,\eta_1 = \sqrt{\frac{\mu_1}{\varepsilon_1}} \ ,\ \eta_2 = \sqrt{\frac{\mu_2}{\varepsilon_2}}$$

The total magnetic field at any point in measured space can be expressed as:

$$\vec{H}(x,y) = \begin{cases} \vec{H}_1^i(x,y) + \vec{H}_1^s(x,y), y \le -a \\ \vec{H}_2^i(x,y) + \vec{H}_2^s(x,y), y > -a \end{cases} \qquad (3)$$

Where $\vec{H}_1^s(x,y)$ and $\vec{H}_2^s(x,y)$ are the scattering field of region 1 and region 2, respectively.

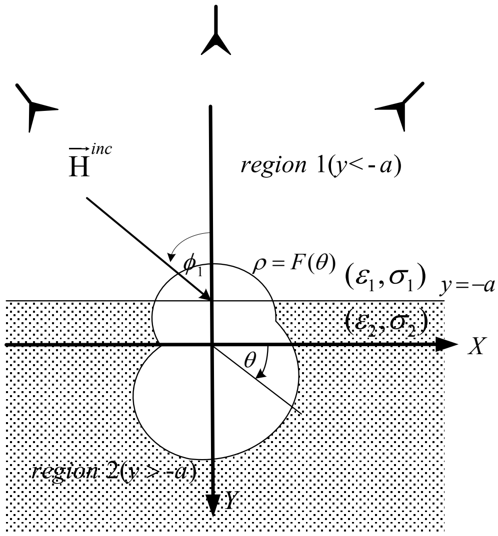

Fig. 1. Geometry of the problem in (x,y) plane

For a perfectly conducting scatterer, the total tangential electric field at the surface of the scatterer is equal to zero.

$$\hat{n} \times \left(\frac{1}{j\omega\varepsilon}\nabla \times \vec{H}^{tot}\right) = 0 \qquad (4)$$

with $\vec{H}^{tot} = \vec{H}^i + \vec{H}^s$, where $\hat{n}$ is the outward unit vector normal to the surface of the scatterer and $\vec{H}^s$ is the scattered field.For the direct scattering problem, the scattered field $\vec{H}^s$ is calculated by assuming that the shape is known. For the inverse problem, assume the approximate center of scatterer, which in fact can be any point inside the scatterer, is known. Then the shape function $F(\theta)$ can be expanded as:

$$F(\theta) = \sum_{n=0}^{N/2} B_n \cos(n\theta) + \sum_{n=1}^{N/2} C_n \sin(n\theta) \qquad (5)$$

where B_n and C_n are real coefficients to be determined, and N+1 is the number of unknowns for the shape function. More details about the Fourier expassion can be found in [16]. In the inversion procedure, the SSGA and APSO are used to minimize the following cost function

$$CF = \left\{\frac{1}{M_t}\sum_{m=1}^{M_t}\left|\vec{H}^s_{exp}(\vec{r}_m) - \vec{H}^s_{cal}(\vec{r}_m)\right|^2 / \left|\vec{H}^s_{exp}(\vec{r}_m)\right|^2\right\}^{1/2} \qquad (6)$$

where M_t is the total number of measurement points. $\vec{H}^s_{exp}(\vec{r}_m)$ and $\vec{H}^s_{cal}(\vec{r}_m)$ are the measured and calculated scattered fields, respectively.

III. INVERSE PROBLEM

APSO starts with an initial population of potential solutions that is composed by a group of randomly generated individuals. Each individual is a D-dimensional vector consisting of D optimization parameters. Clerc suggested the use of a different velocity update rule, which introduced a parameter called constriction factor [17]. The role of the constriction factor is to ensure convergence when all the particles tend to stop their movement. The velocity update rule is then given by

$$v_j^{k+1} = 0.729 \cdot \left(v_j^k + c_1 \cdot \phi_1 \cdot \left(x_{pbest_j}^k - x_j^k \right) + c_2 \cdot \phi_2 \cdot \left(x_{gbest}^k - x_j^k \right) \right) \quad (7)$$

$$x_j^{k+1} = x_j^k + v_j^{k+1},\ j = 0 \sim N_p - 1 \quad (8)$$

$$\phi = c_1 + c_2 \geq 4$$

c_1 and c_2 are the learning coefficients used to control the impact of the local and global component in velocity equation (5), φ_1 and φ_2 are both random numbers between 0 and 1. More details about the APSO algorithm can be found in [17].

IV. NUMERICAL RESULTS

We illustrate the performance of the proposed inversion algorithm and its sensitivity to random noise in the scattered field. Let us consider a perfectly conducting cylinder buried in a lossless half-space ($\sigma_1 = \sigma_2 = 0$). The permittivity in each region is characterized by $\varepsilon_1 = \varepsilon_0$ and $\varepsilon_2 = 2.7\varepsilon_0$, respectively. The frequency of the incident wave is chosen to be 3GHz with incident angles ϕ_1 equal to -45°, 0° and 45°, respectively. The wavelength λ_0 is 0.5 m. To reconstruct the shape of the cylinder, the object is illuminated by incident waves from three different directions and 8 measurements are made for each incident angle at the points equally separated on a semi-circle with the radius of 3m in region 1 along the interface $y = -a$, which is considered here as a test configuration for future application of landmine detection. The related coefficients of the APSO are set below. The learning coefficients c_1 and c_2 are set to 2.8 and 1.3, respectively [18]. The mutation probability is 0.1 and the population size is set to 70. The operations coefficients for the NU-SSGA algorithm are set as below: The crossover probability and the mutation probability are set to be 0.02 and 0.05 respectively. The population size *Np* is the same with APSO. The searching range for the unknown coefficients is chosen from 0 to 1.0.

It should be noted that the termination criterion is set to 1000 generations in our simulation based on our empirical rule.

The relative error of shape function (RE) of the reconstructed shape is defined as

$$RE = \{\frac{1}{N'}\sum_{i=1}^{N'}[\bar{F}^{cal}(\theta_i) - \bar{F}(\theta_i)]^2 / \bar{F}^2(\theta_i)\}^{1/2} \quad (9)$$

In the example, the shape function is chosen to be $F(\theta) = (0.1 + 0.04\cos 2\theta)$ m. The statistical performances (of 20 runs) of two algorithms applied for example. In this case, the best final reconstructed shapes by NU-SSGA algorithm and APSO scheme at the 1000th generation are compared to the exact shape in Fig. 2. Fig. 3 shows that the reconstruction relative error versus the number of iterations by NU-SSGA algorithm and APSO, respectively. The APSO outperforms the NU-SSGA regarding the reconstruction accuracy. The reason for this is following: being a population-based algorithm, APSO maintained it's individuals/particles distinct from each other, while SSGA loses its gene diversity of the gene pool by reproducing more offspring from the best-fitted chromosomes.

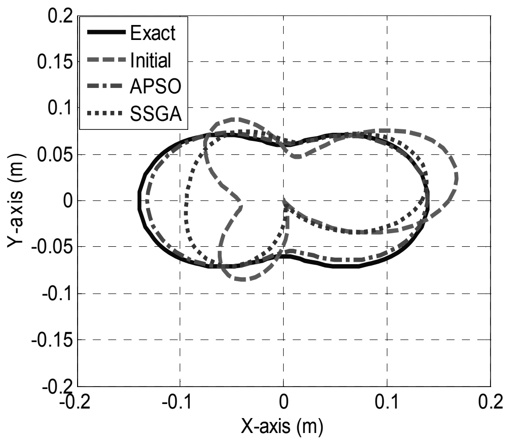

Fig.2.The reconstructed shape of the cylinder for example

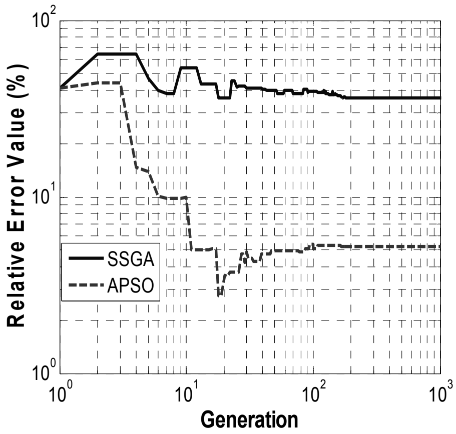

Fig. 3. Shape function error in each generation.

V. CONCLUSIONS

We have presented a study of applying the APSO and NU-SSGA to reconstruct the shapes of a partially immersed conducting cylinder illuminated by TE waves. The inverse problem is reformulated into an optimization one. Numerical result shows the APSO has better reconstructed result compared with NU-SSGA when the same number of iterations is applied, and the APSO outperforms the NU-SSGA in terms of the reconstruction accuracy. More tests about these evolutionary algorithms will exam to 3-D cases in the future researches.

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