Significance of Neighborhood Topologies for the Reconstruction of Microwave Images Using Particle Swarm Optimization

Tony Huang, Student Member, IEEE, and Ananda Sanagavarapu Mohan, Member, IEEE
Microwave and Wireless Technology Research Laboratory, Information and Communication Group, Faculty of Engineering, University of Technology, Sydney
PO Box 123, Broadway NSW 2007, Australia

Abstract—Recently, the use of the particle swarm optimization (PSO) technique for the reconstruction of microwave images has been reported. However, the standard version of the PSO technique may suffer from the problem of premature convergence, as the particles are communicating through a fully connected social structure. In this paper, different social structures have been considered for better performances of the PSO technique, and simulation results have shown that neighborhood topologies such as the lbest and von Neumann topologies should be considered for global optimization problems such as the reconstruction of microwave images.

I. INTRODUCTION

The particle swarm optimization (PSO) technique is a relatively new technique for antennas and microwave communities. It has received a huge attention and popularity due to its algorithmic simplicity and effectiveness for solving design problems such as antenna design [1], [2]. Recently, the application of PSO has been extended to the reconstruction of microwave images and excellent results have been reported in the literature [3], [4].

Although it has been reported that the PSO technique can be effectively applied to various electromagnetic applications, it should be noted that the nature of microwave image reconstruction problem is very different to most of the design problems. For example, in antenna design problems the goal is to design an antenna that meets its required specifications, e.g. bandwidth, radiation pattern, physical dimensions, etc. Hence, the optimization process is set to terminate whenever a design meets its requirements, and this means that for a particular design specification there could be a number of potential solutions exist in the problem space, regardless of whether it is a local solution or not. For image reconstruction problems, on the other hand, it differs in the way that it does not have multiple solutions in its problem space. In fact, in order to reconstruct the correct image and avoid artifacts, the PSO technique is used to bypass local minimums and search for the global minimum.

Another problem for applying the PSO technique to the reconstruction of microwave images is the possibility of particles suffering from premature convergence in a complex high dimensional problem space, which is another cause of unwanted artifacts. As this issue has yet to be addressed in the literature for microwave imaging applications, this paper attempts to investigate the use of different neighborhood topologies and compare their performances for the reconstruction of microwave images.

The paper is organized as follows. In Section II, the fundamental concept of the PSO technique and its neighborhood topologies are introduced. In Section III, we implement the PSO technique with each of the neighborhood topology and compare their performances based on a complex microwave image reconstruction problem, and finally the conclusion of this paper is presented in Section IV.

II. PARTICLE SWARM OPTIMIZATION

A. Fundamental Concept

The PSO technique is an innovative stochastic global optimization technique originally proposed by Eberhart and Kennedy [5], [6]. It is formulated based on the inspiration of search abilities from biological examples such as a flock of birds or a swarm of bees, where the collaborated search abilities of such natural systems appear to excel the ability of each individual agent in the system. Hence, based on this cooperative strategy, the PSO technique can be distinguished from many other well known optimization techniques such as genetic algorithms (GAs) where the solution is found using the competitive strategy.

In the context of the language used in PSO, the terms “swarm” and “particles” are used to refer to the population and individual solutions, respectively. At the initialization stage, a swarm is initialized by generating a set of random particles within the problem space. These particles are then randomly initialized with a velocity vector and set to fly through the problem space to search for the global optimum solution.
The basic operations of the PSO technique are explained as follows [7]. By assuming an $N$-dimensional problem space, and a swarm consisting of $M$ particles, the position and the velocity of the $i^{th}$ particle, $1 \leq i \leq M$, can be both expressed as $N$-dimensional vectors, that is

$$X_i(t) = [x_{i1}(t), x_{i2}(t), \cdots, x_{iN}(t)]$$

$$V_i(t) = [v_{i1}(t), v_{i2}(t), \cdots, v_{iN}(t)]$$

where $x_{i,n}(t)$ and $v_{i,n}(t)$ denotes the position and velocity of the $i^{th}$ particle in the $n^{th}$ dimension.

At the end of each iteration process, the trajectories of particles are updated based on their new velocities defined by the personal best success of each particle, $p_{i,best}$, and the best success achieved by the swarm, $g_{best}$, which can be expressed as

$$v_{i,n}(t + 1) = w v_{i,n}(t) + c_1 r_1 [p_{i,best} - x_{i,n}(t)] + c_2 r_2 [g_{best} - x_{i,n}(t)]$$

$$x_{i,n}(t + 1) = x_{i,n}(t) + v_{i,n}(t + 1)$$

where $w$ is the inertia weight used to control global exploration and local exploitation of the particles, and is usually varied linearly from 0.9 to 0.4 in a decreasing order throughout the simulation. $c_1$ and $c_2$ are the acceleration constants that act as weights to provide the relative pull for each particle towards $p_{i,best}$ and $g_{best}$ positions. $r_1$ and $r_2$ are two uniformly distributed random variables in the range [0,1] to provide a stochastic variation in the relative pull towards $p_{i,best}$ and $g_{best}$.

In most cases, to reduce the likelihood of particles escaping the problem space, a parameter $V_{max}$ that acts as an upper limit for the velocity of particles is used. However, it has been noted in [1] that the particles may still occasionally fly to a position beyond the defined problem space, and hence produce an invalid solution. To further complicate the problem, the dimensionality and the location of the optimum solution with respect to problem space boundaries can both have a great effect on the search performance of the PSO technique [3]. Hence, to provide a remedy to this problem, a novel hybrid boundary condition known as the damping boundary was proposed in [3] to offer a more robust and consistent search performance for the PSO technique.

The damping boundary is formed based on the combination of features offered by both the existing absorbing and reflecting boundaries [1]. With the damping boundary, whenever a particle tries to escape the search space in any one of the dimensions, part of the velocity in that dimension is absorbed by the boundary and the particle is then reflected back to the search space with a damped velocity along with a reversal of sign. In terms of equations, the updated velocity of the dampened particle can be expressed as

$$v_{i,n}(t + 1) = \Delta d \cdot v_{i,n,ref}(t + 1)$$

where $\Delta d$ is a random variable uniformly distributed between [0,1] to create the damping effect, $v_{i,n,ref}(t + 1)$ is the velocity of the reflected particle as if the reflecting boundary were imposed at the boundary of the search space. It has been shown in [3] that the damping boundary is more suited for the PSO technique in microwave imaging applications, where the burden on choosing a suitable boundary condition for the PSO technique is removed.

Once the boundary condition is applied, before commencing the next velocity update, each particle is substituted directly/indirectly into the objective function ($OF$) to evaluate its fitness, and the $p_{i,best}$ and $g_{best}$ are updated based on the conditions below:

$$p_{i,best}(t + 1) = \begin{cases} p_{i,best}(t) & \text{if } OF\{X_i(t+1)\} \geq OF\{p_{i,best}\} \\ X_i(t) & \text{if } OF\{X_i(t+1)\} < OF\{p_{i,best}\} \end{cases}$$

$$g_{best}(t + 1) = \text{arg}\min\{OF\{p_{1,best}(t+1)\}, 1 \leq i \leq M\}$$

where $OF$ is assumed to be minimized, and $\text{arg}(.)$ and $\min(.)$ are functions used to find the argument and minimum of a function, respectively. These operations are repeated until the termination criteria has been met, which can be defined as the maximum number of iterations and/or a targeted $OF$ value. Fig. 1 shows the flow chart of these PSO operations.

**B. Neighborhood Topologies**

In the implementation of the standard PSO technique, each particle’s velocity is updated based on the inertia, cognition and social components in (3). It has been reported that the structure of the social network modeled by the social
component can have a great influence on the overall performance of the PSO technique.

The original velocity update equation, where \(g_{\text{best}}\) is utilized in the social component, represents a fully connected social network structure that the entire population is treated as each individual’s neighborhood. This structure is generally known as the gbest topology, and through the instantaneous communication among all particles this topology can offer a rapid rate of convergence for the PSO technique. However, the major disadvantage of this topology is the possibility that particles may converge prematurely, and this could occur when the position of \(g_{\text{best}}\) is not updated regularly.

To overcome this problem, other neighborhood topologies have been proposed to impede the communication among particles and preserve the swarm diversity [8]. This change in the neighborhood topology is implemented by replacing the original velocity update equation with the following

\[
v_{i,n}(t+1) = wv_{i,n}(t) + c_1r_1[p_{i,\text{best}} - x_{i,n}(t)] + c_2r_2[N_i,\text{best} - x_{i,n}(t)]
\]

where \(N_i,\text{best}\) is the best solution found so far in the neighborhood of the \(i\)th particle.

Currently, the lbest and von Neumann topologies are the two most common topologies used for gaining a better performance for the PSO technique. For the lbest topology the neighborhood of the \(i\)th particle is comprised of its two adjacent neighbors, and this ring like topology offers the slowest, most indirect communication pattern for the particles. The von Neumann topology, on the other hand, connects the particles in a grid structure where each particle is connected to its four immediate neighbors. In other words, the von Neumann topology can be described as a square lattice whose extremities are connected as a torus. Fig. 2 shows an example of how 12 particles are connected under the gbest, lbest and von Neumann topologies.

III. SIMULATION RESULTS

To investigate the effect of different neighborhood topologies on the PSO performance for solving microwave image reconstruction problems, we have considered a typical microwave imaging scenario shown in Fig. 3, where a lossless homogeneous dielectric scatterer of \(\varepsilon = 4\) is located inside a cubic free space investigation domain of side length \(\lambda_0\). The dimension of the scatterer is \(0.2\lambda_0 \times 0.2\lambda_0 \times 0.6\lambda_0\).

To reconstruct the spatial distribution of dielectric properties inside the investigation domain, we have partitioned the investigation domain into 125 equal sized sub-cells and assume the dielectric scatterer occupies three of the sub-cell, which is illustrated as the shaded area in Fig. 3.

For our simulation, we have surrounded the investigation domain with five uniform circular arrays (UCAs) for purpose of measuring the fields scattered by the scatterer. Each of the UCA is consisted of 36 equally spaced antenna elements and the radius of these UCAs are equal to the free space wavelength, \(\lambda_0\), of our incident plane wave of frequency \(f_0 = 2.45\text{GHz}\). The plane wave is propagating along the \(x\)-axis, while the electric field vector is polarized along the \(y\)-axis.

For the implementation of PSO, we have used 25 particles to form our swarm. Each particle is a vector of dimension of 125, and each dimension represents the relative dielectric permittivity of a sub-cell inside the investigation domain. The fitness of each particle is determined by the normalized root mean square error (RMSE) between the measured and computed values of the scattered field \(\vec{E}^s\), i.e.

\[
OF = \frac{1}{V} \sum_{v=1}^{V} \frac{\left|\vec{E}_{\text{meas}}^s(\rho_v, \phi_v, z_v) - \vec{E}_{\text{comp}}^s(\rho_v, \phi_v, z_v)\right|^2}{\left|\vec{E}_{\text{meas}}^s(\rho_v, \phi_v, z_v)\right|^2}
\]

where \(V\) is the total number of receivers used in the imaging system and \(\vec{E}_{\text{meas}}^s(\rho_v, \phi_v, z_v), \vec{E}_{\text{comp}}^s(\rho_v, \phi_v, z_v)\) are the measured and computed values of \(\vec{E}^s\) at location \((\rho_v, \phi_v, z_v)\), respectively.

In our simulations, we have considered the use of the damping boundary condition and the optimization process is set to terminate at the end of the 1000th iteration. The neighborhood topologies considered in our simulations are the gbest, lbest and von Neumann topologies.

Finally, as PSO is a stochastic optimization technique, to obtain a realistic result, we have performed 10 independent simulation runs and taking the final result as the average of these 10 simulation runs.

Fig. 4 shows the comparison of the PSO performance offered by the three neighborhood topologies when the signal-to-noise ratio (SNR) is equal to 30dB. It can be seen that although the gbest topology has the fastest rate of convergence, its solution is inferior to the one found by the lbest and von Neumann topologies. The best performance is offered by the lbest topology and it is followed by the von Neumann and gbest topologies. This has demonstrated that the use of a slower communication scheme can reduce the risk of particles converging prematurely. Fig. 5 shows the comparison between the actual distribution of dielectric properties inside the investigation domain and the images reconstructed by the three neighborhood topologies.
IV. CONCLUSION

In this paper we have investigated the significance of neighborhood topologies for the reconstruction of microwave images using the PSO technique.

In the standard implementation of the PSO technique, the $g_{best}$ topology is employed to ensure a fast convergence rate for the particles. However, this topology is not always the best choice for the PSO technique as it also increases the risk of particles converging prematurely, which would in turn pose a serious problem for the correct image to be reconstructed.

From our simulation results we have shown that the risk of premature convergence can be minimized by adopting different types of neighborhood topologies such as the $l_{best}$ and von Neumann topologies. Both the $l_{best}$ and von Neumann topologies allow each individual particle to be influenced by a smaller number of adjacent particles as compared to the $g_{best}$ topology. With these slower communication schemes, the diversity within the swarm can be maintained and particles are encouraged to converge to the global solution. Hence, for global optimization problems such as the reconstruction of microwave images, we strongly recommend the use of neighborhood topologies other than the traditional $g_{best}$ topology to be considered.

Finally, we would like to emphasis that although the results shown in this paper have indicated that the $l_{best}$ topology is the better choice for the PSO technique, we would also like to recommend the use of von Neumann topology as it offers a more consistent performance for various other types of problems.

ACKNOWLEDGMENT

The work reported in this paper is supported by the Australian Research Council through a Discovery Project Grant DP0346540.

REFERENCES