Conformal Antenna Array Pattern Synthesis Using Genetic Learning Particle Swarm Optimization Algorithm

Bin ZHAO\textsuperscript{1,*}, Hai-shi WANG\textsuperscript{1} and Zhi-peng LIANG\textsuperscript{2}

\textsuperscript{1}Chengdu University of Information Technology, Chengdu, Sichuan, China
\textsuperscript{2}University of Electronic Science and Technology of China, Chengdu, Sichuan, China

\textsuperscript{*}Corresponding author

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Abstract. Investigations on conformal phased array pattern synthesis using genetic learning particle swarm optimization algorithm (GL-PSO) are presented in this paper. The hybrid algorithm is composed of two cascading layers, the first for exemplar generation and the second for particle update. Genetic operators are used to generate exemplars from which particles learn and, in turn, historical search information of particles provides guidance to the evolution of the exemplars. The hybrid algorithm is applied to synthesize radiation pattern of a 4x2 cylindrical conformal microstrip antenna. The excitation weights of the conformal array elements are optimized to obtain specific radiation pattern including scanning angle, reduced SLL, limited beamwidth. The influence of mutual coupling and conformal platform are fully considered in the optimization process. Experimental results have verified that the GL-PSO has fast convergence speed and high convergence accuracy when applied to antenna array pattern synthesis.

Introduction

Recently, conformal antenna array has attracted a lot of attention in many applications due to their capacity for beam steering, beam shaping, high gain, visual unobtrusiveness and non-interference with the aerodynamic performance and antenna performance. Various methods including traditional mathematical techniques and optimization algorithms have been proposed to solve complex antenna pattern synthesis problems. But low side-lobe array pattern synthesis techniques developed for planar and linear arrays do not work well with conformal arrays if the array is conformal to a curved surface. This is due to that the elements of conformal array generally direct their radiation beams toward different directions, and not all elements contribute equally to the desired pattern. Therefore, it is desirable to develop an algorithm which is robust and has excellent global optimization performance and fast convergence speed for conformal antenna array pattern synthesis.

As one of the most important global optimization algorithms, the evolutionary optimization algorithm derives from biologic behavior and is especially suitable for solving strongly nonlinear multi-parameter multi-goal problems of conformal array synthesis. Various evolutionary algorithms (EAs) have become more and more popular in this community as they are applicable to both regular and irregular arrays, with or without constraints. Genetic algorithm (GA) and particle swarm optimization (PSO) are two popular kinds of evolutionary optimization algorithms and they are getting much attention due to their efficiency and simplicity [1]. GA uses biologically inspired techniques, such as natural selection, crossover and mutation. The PSO algorithm has only one velocity operator, which renews the current positions of the particles, changes the cooperation or social knowledge of the swarms, and makes the particles move toward a region containing the global or near-optimal optimal solution. However, the disadvantage of these two algorithm when applied to antenna array pattern synthesis is the premature convergence. Hybridisation has been a popular strategy for improving performance of a single algorithm [2-4]. To further improve the performance of PSO, a genetic learning scheme that applies GA for exemplar construction [5] is adopted in this
The hybrid algorithm is composed of two cascading layers, the first for exemplar generation and the second for particle updates. Genetic operators are used to generate exemplars from which particles learn and, in turn, historical search information of particles provides guidance to the evolution of the exemplars. The rest of this paper is organized as follows. In Section 2, the detailed implementation process of the adopted hybrid algorithm is illustrated. The pattern synthesis of a 4×2 cylindrical conformal microstrip antenna array using the hybrid algorithm is studied in Section 3. Final conclusions are drawn in Section 4.

**Genetic Learning Pso**

**Genetic Learning Scheme**

![Figure 1. The flowchart of GL-PSO algorithm.](image)

In order to avoid premature convergence, a genetic learning scheme that applies GA for exemplar construction is adopted [5]. As illustrated in Figure 1, GA and PSO are hybridized in a cascade manner. The main loop of the algorithm is composed of two cascading layers, the first for exemplar generation by GA and the second for particle updates as per a PSO algorithm. In this way, particles in PSO are no longer simply guided by the gbest and pbests, but are guided by the exemplars constructed by GA. GA and PSO are hybridized in a highly cohesive way, which establishes a positive feedback loop to accelerate the population to locate the optimum. The velocity update of the variant PSO operation is adopted [5-6] as follows

\[
v_{i,d} \leftarrow \omega \cdot v_{i,d} + c \cdot r_d \cdot (e_{i,d} - x_{i,d})
\]

Here, replacing the pbest \( P_i \) of particle \( i \) and the gbest \( G_i \) of the whole swarm, a single composite exemplar \( E_i = [e_{i,1}, e_{i,2}, \ldots, e_{i,D}] \) is constructed in phenotype combination to attract particle \( i \). The inertia weight \( \omega \) and the learning factor \( c \) are set to 0.7298 and 1.496. To incorporate genetic operation into a PSO algorithm, the crossover, mutation and selection operator is implemented as follows,

**Crossover:** For each particle \( i \), crossover operation is first conducted on \( P_i \) and \( G_i \) to generate an offspring \( O_i = [o_{i,1}, o_{i,2}, \ldots, o_{i,D}] \)
\[ o_{i,d} = \begin{cases} r_d \cdot p_{i,d} + (1-r_d) \cdot g_d, & \text{if } f(P) < f(P_{k_i}) \\ p_{k_i,d}, & \text{otherwise} \end{cases} \]

where \( r_d \) is a random number uniformly distributed in \([0, 1]\), \( k_i \in \{1, 2, \ldots, M\} \) is the index of a random particle, \( i = 1, 2, \ldots, M \), and \( d = 1, 2, \ldots, D \). Here, without loss of generality, the considered objective \( f \) is for minimization.

**Mutation:** The bred offspring \( O_i \) then undergoes the mutation operation with a probability bounded by probability of mutation (\( pm \)). For each dimension \( d \), a random number \( r_d \in [0,1] \) is generated, and then, if \( r_d \) is smaller than \( pm \), this dimension of \( O_i \) is reinitialized in the search space.

\[ o_{i,d} = \text{rand}(lb_d, ub_d), \quad \text{if } r_d < pm \]

where \( lb_d \) and \( ub_d \) stand for the lower and upper bounds of the \( d \)th dimension.

**Selection:** After applying crossover and mutation to create the offspring, selection is performed to determine whether the offspring or the current exemplar survives in this generation. The following operation is executed:

\[ E_i \leftarrow \begin{cases} O_i, & \text{if } f(O_i) < f(E_i) \\ E_i, & \text{otherwise} \end{cases} \]

For each particle, in summary, it conducts the crossover, mutation, and selection described above once in every generation to construct a promising exemplar and hereafter learns from the exemplar as per the PSO algorithm.

**Preliminary Numerical Experiments**

Two typical test functions which are widely known and used as benchmark functions for optimization strategies are simulated to verify the efficiency of the hybrid algorithm. The test functions are defined as

Rosenbrock:

\[ f_i(x) = \sum_{i=1}^{N} \left[ 100(x_{i+1}^2 - x_i^2) + (1-x_i)^2 \right], \quad |x_i| \leq 30 \]

Rastrigin:

\[ f_i(x) = \sum_{i=1}^{N} \left[ x_i^2 - 10\cos(2\pi x_i) + 10 \right], \quad |x_i| \leq 10 \]

![Figure 2. Average fitness value of test functions using three algorithms over 30 independent runs. (a) Rosenbrock (b) Rastrigin.](image-url)
The performance of the stand GA, PSO and the hybrid GL-PSO are compared using these two functions in 30 dimensions. All experiments are repeated 30 times. The calculated $f(x)$ is defined as the fitness value of the solution. The population size in three algorithms are set to the same $P=50$. The crossover probability and mutation probability in GA are set to 0.8 and 0.08. The personal and social learning factors in PSO are set to 2, 2, and the inertia weight is set from 0.9 to 0.4. The mutation probability in GL-PSO is set to 0.05. Figure 2 presents the variation curve of the average fitness value with the number of iterations. It can be seen that the hybrid GL-PSO algorithm has stronger global search ability and faster convergence speed than the stand GA and PSO.

Pattern Synthesis Of Conformal Antenna Array

As is shown in Figure 3, the platform of a 4×2 conformal array is a cylinder with radius $R$ ($R=4\lambda_0$), where $\lambda_0$ is the wavelength in free space at the operation frequency ($f=2.6$GHz). A typical rectangular microstrip antenna is used as the basic element. All elements are printed on a dielectric substrate with a thickness of 1.5 mm, a relative permittivity of 3 and a dielectric loss tangent of 0.001. The angle $2\alpha$ between the centers of two adjacent elements is 10° along the azimuth direction and the spacing distance $h$ is 80mm. The primary polarization of the conformal antenna array is 45° slant polarization. The whole structure is simulated using HFSS software and the active element patterns of all elements can be extracted from the simulation results. So the array pattern will be obtained according to the superposition principle.

Next, the excitation weights of the conformal array elements are optimized to obtain specific radiation pattern in the x-z plane ($\phi=0°$), including scanning angle ($\theta_i=100°, \phi=0°$), maximum...
side lobe level ($SLL \leq -20\,dB$), maximum half-power beamwidth ($HPBW \leq 25^\circ$). The GA, PSO and GL-PSO algorithm are used to optimize the amplitude and phase of each element to synthesize the desired radiation pattern, respectively. The population size and maximum iterations in three algorithms are set to 50, 500. Comparison of the results using the three methods are shown in Figure 4 and Figure 5. It can be noted from the obtained results that GL-PSO algorithm is superior to GA and PSO algorithm, and our designed goals have been accomplished by using the adopted GL-PSO algorithm.

Summary

The hybrid GL-PSO algorithm has been presented in detail and successfully applied to radiation pattern synthesis of a conformal antenna array. The novelty of GL-PSO lies in that it applies GA to process the pbests and gbest of particles so as to breed the exemplars, which captures the historical search experience with a more global prospective. The experimental results show that the hybrid algorithm is able to achieve the optimum design with fast convergence speed and high convergence accuracy, and is effective and reliable for conformal antenna array pattern synthesis.

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