AN ACCELERATED HYBRID GENETIC ALGORITHM FOR OPTIMIZATOIN OF ELECTROMAGNETIC STRUCTURES

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Abstract. This paper presents a novel optimization technique that combines classical and statistical methods in an innovative and efficient way. In specific, an evolutionary genetic algorithm (GA) has been developed that utilizes a local minimization scheme based on the method of conjugate directions. The proposed optimizer has been applied to the design of planar microwave circuits and printed antenna arrays. The advantages of the proposed technique are illustrated by ample numerical results.

I. INTRODUCTION

The design of electromagnetic structures such as planar microwave components and printed antenna arrays is usually a very challenging task due to the complexity of the models involved. In the majority of cases, there are no simple analytical formulas to describe the performance of microwave components. Oftentimes, a full-wave numerical modeling of the planar structure is necessary to ensure a satisfactory degree of accuracy. However, full-wave optimization can turn out to be excruciatingly exhaustive resulting in very long design cycles.

Optimization techniques have been an area of principal interest to microwave designers. These techniques have been categorically divided into two classes of classical and statistical methods. Representatives of the former class are the conjugate gradient (CG) and Powell's methods. These are based on local minimization of the objective function. Unlike the conjugate gradient method, Powell's method does not require evaluation of the derivative of the objective function, which may be very costly, if not impossible, for most problems of interest in this paper. Optimizers of conjugate directions type perform relatively well when dealing with "well-behaved" problems. However, there is oftentimes the peril of getting trapped in local extrema. Among statistical optimization techniques one can mention the method of simulated annealing and genetic algorithms. In recent years, genetic algorithms have attracted a great deal of attention due to their surprisingly superior performance [1]-[3]. In particular, when treating "stiff" problems with large parameter spaces, these algorithms may provide the only possible solution to the optimization problem. Historically, genetic algorithms used to employ binary strings to encode the solution. Recently, continuous strings in the form of vectors of floating point numbers have been utilized successfully. The latter implementations are sometimes called evolutionary programming.

The rate of convergence of an optimizer and the overall computation time are critical factors in the optimization of planar microwave circuits and printed antenna arrays. Classical methods are normally faster than statistical methods due to the very large population spaces involved in the latter. However, the convergence of classical optimizers is overtly problem-independent. In this paper, we present a novel optimization scheme based on an accelerated evolutionary genetic algorithm. The rate of convergence of a genetic algorithm depends on the quality of the genetic operators involved. In the proposed implementation we introduce operators based on the local minimization of the solution using Powell's

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method. The resulting hybrid operator exhibits a much better convergence performance. The technique has been applied to the design of a number of microwave components and printed antenna arrays.

II. BACKGROUND ON CONVENTIONAL OPTIMIZERS

Optimization is the process of determining the location of the extreme values of a mathematical function $U=U(\mathbf{x})$ commonly called the objective function, error function, or cost function. Most often these values are subject to certain inequality constraints $c(\mathbf{x})\leq 0$ and equality constraints $h(\mathbf{x})=0$. In many cases, $\mathbf{x}$ corresponds to the design parameters and the function U is determined by a simulation algorithm. U is usually formulated so that when U is zero, the problem is solved. Good optimization routines require the least number of function evaluations since the calculation of U can be very expensive. The error function is formulated to take into account design goals along with the usual constraints. Goals are desired values for numerical properties of the entity being optimized. A general implementation of U for frequency-dependent entities has the following form:

$$U(x) = \sum_{j=1}^{N_{band}} \sum_{f=f_{l,j}}^{f=f_{h,j}} \sum_{m=1}^{n_j} W_{m,j}\left(D_{m,j} - S_{m,j}(\mathbf{x}, f)\right)^p, \tag{1}$$

where f is the frequency, N_{band} is the number of frequency bands subject to optimization, the jth frequency band is defined as the range $f_{l}j \leq f \leq f_{h,j}$, index m denotes goals 1 through M_j with M_j being the number of goals defined for the jth frequency band, $W_{m,j}$ is the relative weight given to the mth goal of the jth frequency band, $S_{m,j}$ is the actual value of a particular response to some $\mathbf{x}$ and f, $D_{m,j}$ is the desired value of $S_{m,j}$ over the jth frequency band, and p is an even integer (usually 2).

For an optimization problem with N free parameters, Powell's method will determine a set of N linearly independent, mutually conjugate directions. For this reason, Powell's method is often called a "direction set" method. It is also a direct search method in that it does not require calculation of the gradient of the error function. A set of mutually conjugate directions has the property that minimization along any one direction of the set will not interfere with subsequent minimizations along other directions of the set. This method starts with a set of directions corresponding to unit vectors aligned with the N independent axes of the error domain. From a given starting position P_0, here is the basic main loop:

1. Perform a 1-dimensional line minimization for each direction in the set arriving at a new point P_1.
2. Minimize along the direction $P_1 - P_0$.
3. Substitute the direction from Step 2 for one of the preexisting directions.

The actual implementation includes a robust line minimization algorithm and several heuristics that help ensure the procedure's numerical stability.

Genetic algorithms maintain a set of possible solutions called the population. The initial set can be obtained by some prior calculations, random search, or by some heuristic methods that use problem-specific knowledge. Each generation of new solutions called children are created from the old solutions via genetic operators. These new solutions can either replace or coexist with the prior generation. The population evolves in this way until it finds an optimal solution. Genetic operators can be classified into two categories. The first group performs mutations, whereby some or all parts of an existing member of the population are randomly changed. The second group performs crossover, whereby a new member is created from genetic materials from one or more existing individuals. Many different schemes for population management have been introduced that have an impact on the average rate of convergence and accuracy of the algorithm [4]-[5].

III. ACCELERATED EVOLUTIONARY GENETIC ALGORITHM

When using genetic algorithms for optimization, the most dramatic improvement in performance comes from using problem-specific information to initialize the population and by creating problem-specific genetic operators. The initial set can be obtained by some prior calculations, random search, or by some heuristic methods that use physical or analytical knowledge. For example, in electromagnetic scattering problems the initial population can be introduced in conjunction with a simplified solution based on physical optics (PO) or geometrical theory of diffraction (GTD). For pattern synthesis, one can utilize analytical synthesis techniques such as Chebyscheff, Taylor, Hansen, etc. to generate a set of initial solutions and then use appropriate genetic operators to evolve the population. Due to the very large size of the solution space usually involved, the speed of convergence is highly improved with a good choice of the initial population.

The quality and relevance of the genetic operators also directly influences the speed of a GA-based optimization process. Due to the continuous nature of the problems of interest in this paper, it would be logical to use continuous genes rather than binary genes for encoding the solution. Therefore, instead of bit string operations, one can introduce genetic operators based on a variety of mathematical operations. In addition, to further accelerate the rate of convergence of the GA, a novel genetic operator is introduced based on Powell's method. In the vicinity of a local minimum, Powell's method converges very rapidly toward this minimum. In this hybrid scheme, the genetic operator takes a member of the population as a starting point and locally minimizes the solution. This new solution then replaces the old member of the population. In this way, while the genetic algorithm provides the opportunity to converge toward a global minimum without getting trapped in local minima, the Powell operator speeds up the rate of convergence of the process once the solution approaches such local minima.

IV. NUMERICAL RESULTS

As a test, the newly developed hybrid evolutionary genetic algorithm was utilized to design planar (two-dimensional) arrays of different sizes but all with the goal of achieving a maximum side lobe level of –50dB. The radiating elements are identical in all cases, being a square patch of dimension 40.2cm printed on a grounded substrate of thickness 1.59mm and relative permittivity $\varepsilon_r = 2.57$. The spacing among the radiating elements is uniform along the x- and y-axes and equal half free space wavelength. The optimization is performed at the resonant frequency of the patches, which is 2.28GHz. The element pattern is obtained from a full-wave analysis of the patch structure using the method of moments. Table 1 shows the CPU time for the optimization of the pattern with different array sizes. The results were obtained on a 266MHz Pentium II personal computer. Figures 1 and 2 shows the synthesized patterns of large arrays with 1,024 (32x32) and 10,000 (100x100) elements, respectively. More numerical results for more diverse structures will be presented at the symposium.

Table 1: Comparison of Optimization Times for Array of Different Sizes

Array Size	CPU time
64 (8x8)	1 sec
256(16x16)	6 sec
1024 (32x32)	289 sec
10000 (100x100)	1896 sec

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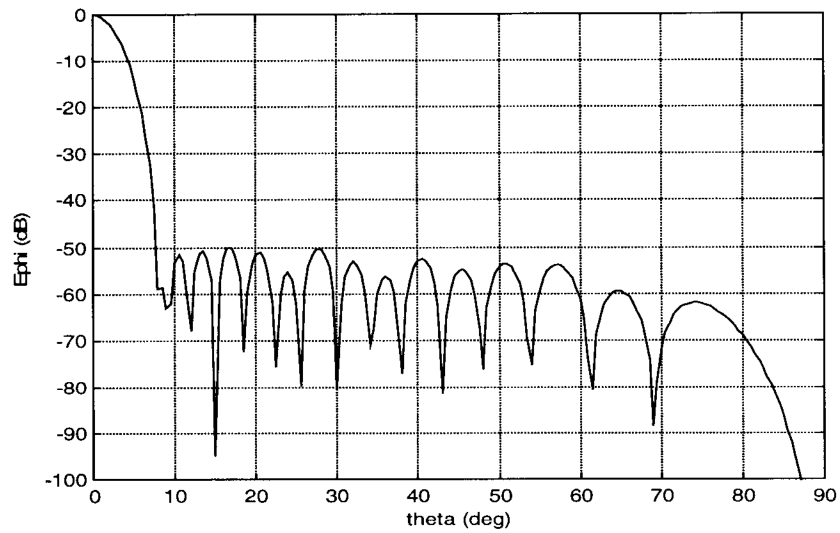

Figure 1: Radiation pattern of an optimized 1,024-element array (θ–polarized) at ϕ=90.

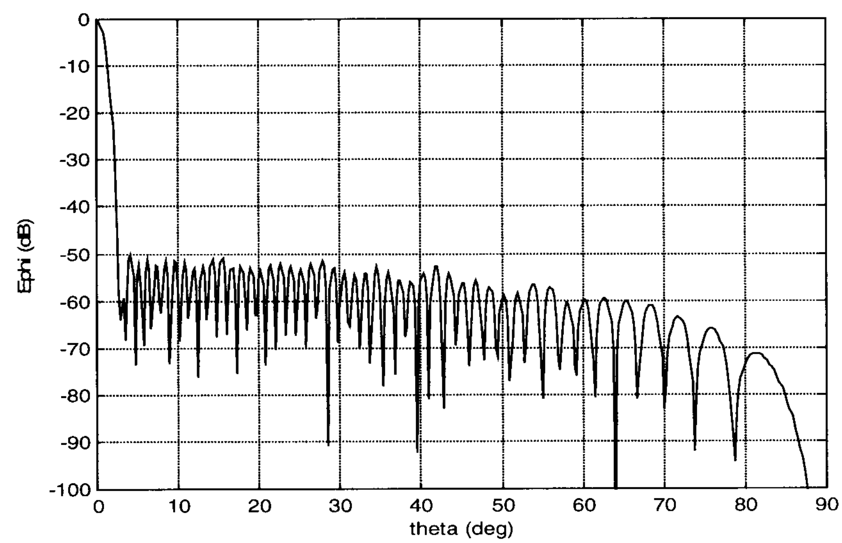

Figure 2: Radiation pattern of an optimized 10,000-element array (θ–polarized) at ϕ=90.