Recent Advances in Evolutionary Optimization Techniques in Applied Electromagnetics

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Abstract—This presentation will focus on: \(\textbf{(a)}\) a tutorial introduction to GA, PSO and CMA-ES by describing in a novel fashion the underlying concepts and recent advances for those who have used these techniques and for those who have not had any experiences in these areas, \(\textbf{(b)}\) a unique approach in performing fundamental comparative studies among these algorithms, \(\textbf{(c)}\) demonstration of the potential applications of these algorithms to a variety of electromagnetic and antenna designs, and \(\textbf{(d)}\) assessment of the advantages and the limitations of these techniques.

I. INTRODUCTION

Broadly defining, optimization is the process of adjusting a set of pertinent input parameters to characterize a device, a mathematical process, or an experiment with the objective to finding the minimum or maximum desired output quantities as depicted in Fig. 1. The input typically consists of parameters; the process or function is known as the cost function, objective function, or fitness function, and the output is the cost or fitness.

![Fig. 1. Optimization adjusts the pertinent input parameters in order to either minimize or maximize the desired output quantities of interest.](image1)

Among various EO’s, nature inspired techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and the Covariance Matrix Adaptation (CMA) Evolution Strategies (ES) have attracted considerable attention. GA utilizes an optimization methodology which allows a global search of the cost surface via the mechanism of the statistical random processes dictated by the Darwinian evolutionary concept (adaptation, selection, survivability and mutation). PSO is a robust stochastic evolutionary computation technique based on the movement and intelligence...
II. GENERAL OVERVIEW OF EACH ALGORITHM

A. Genetic Algorithms

The GA technique has been shown to be suitable for optimizing a broad class of problems of interest to the electromagnetic community. Genetic-algorithm optimizers are robust, stochastic search methods, modeled on the principles and concepts of natural selection and evolution. As an optimizer, the powerful heuristic of the GA is effective at solving complex, combinatorial and related problems. During a GA optimization, a set of trial solutions, or individuals, is chosen, and then evolved toward an optimal solution, under the selective pressure of the fitness function. In the simple, typical genetic-algorithm optimizer, this set of trial solutions are initiated by filling an initial population with a number of encoded, usually randomly created, parameter strings, or chromosomes. In the literature, these chromosomes have also been termed the individuals, and the set of individuals is called the current generation. Each individual in the set is assigned a fitness value by evaluating the fitness function for each individual. The current generation is then used to produce children by selecting parents, crossing over genes, and mutating the genes to produce offspring, as shown in Fig. 1. The selection, crossover, and mutation operations are repeated until enough children have been generated.

of swarms of bees looking for the most fertile feeding location applying their cognitive and social knowledge. The CMA-ES technique is based upon the evolution of a population of individuals, capitalizing on the ideas of survival of the fittest, recombination, and mutation, and this version of ES has only been recently introduced to the applied electromagnetic community. This algorithm has certain similarities in comparison to the standard Genetic Algorithms; however the selection and recombination/crossover operators have some key differences. In particular, the notion of average performance among the individuals is an important theme in the evolution processes for this algorithm.

This presentation will focus on: (a) a tutorial introduction to GA, PSO and CMA-ES by describing in a novel fashion the underlying concepts and recent advances for those who have used these techniques and for those who have not had any experiences in these areas, (b) a unique approach in performing fundamental comparative studies among these algorithms, (c) demonstration of the potential applications of these algorithms to a variety of electromagnetic and antenna designs, and (d) assessment of the advantages and the limitations of these techniques.

Fig. 3. Evolution of the chromosome population utilized in GA where selection, crossover, and mutation are used to further evolve the population.

Fig. 4. Graphical depiction of the PSO technique searching the solution space utilizing each particle's (bird's) social and cognitive memory [5].
to fill the new generation. In some GAs, the temporary population completely replaces the current generation, however there do exist slightly more complicated GA implementations where the newly updated generation can be of a different size than its predecessor, thus allowing overlap between the new generation and the old generation.

B. Particle Swarm Optimization

PSO is an Evolutionary Optimization technique based on the movement and intelligence of swarms (swarm of bees, a flock of birds, or a school of fish). In many scientific studies on bee swarm social behavior, it has been conjectured that the collective intelligence of the swarm directs them to look for the most fertile feeding location. The PSO technique utilizes the swarm’s searching mechanisms in an effort to find the solution of electromagnetic problems. The global optimization problem is tackled by creating a group (or swarm) of particles (often represented by bees or birds) whose position in the solution space represents a possible trial solution and whose velocity represents the rate of change in the variables between iterations. Each particle has two distinct memories: 1. it remembers the best seen point by the group (social memory) and 2. it remembers the best seen point in its own history (cognitive memory). These points are often termed gBest and pBest, respectively. During each iteration, the velocity of each particle is updated to guide it towards those previously best seen points, as shown in Fig. 2. Consequently, each particle is innately driven toward the pBest and the gBest locations. Overall, the particle swarm algorithm presents an intuitive strategy for searching the solution space based on a swarm’s social behavior and memory.

C. Covariance Matrix Adaptation Evolution Strategies

The Evolution Strategies (ES) works by evolving a population of individuals, where each iteration represents one generation. New generations are born through operators known as recombination and mutation. ES also makes use of the evolutionary concept of survival-of-the-fittest, and this is accomplished through the use of a weighted selection operator. In particular, the CMA-ES technique employs the use of Gaussian distributed random numbers to spawn new members of the population. In other words, the CMA-ES population can be described by the population mean \( \langle \mathbf{x} \rangle \) and the covariance matrix \( \mathbf{C} \). The population distribution adapts its mean and covariance matrix based on the group's previous experience, and this adaptation has been demonstrated to enhance the performance to a rapid global convergence.

![Graphical depiction of CMA-ES](image)

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Fig. 5. Graphical depiction of CMA-ES, which can be interpreted as an evolving population whose offspring are generated from the weighted best average of the group.

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especially for convex fitness functions. In particular, the covariance matrix can change shape in order to better emphasize certain optimization parameters that play a bigger role in the fitness function. It is also interesting to compare CMA-ES to both GA and PSO. Many of the operators resemble those in GA while also exploiting the social information from a group similarly to PSO. For instance, the recombination operator bears some similarities to the crossover operator in GA, however it exploits the group history through a weighted average as opposed to two individuals as in GA.

III. FUNDAMENTAL TASKS USED IN EACH ALGORITHM

An evolutionary algorithm forms an optimization heuristic based upon processes often observed in nature, such as evolution and survival-of-the-fittest. While the processes being modelled by a given algorithm may be similar, the implementation of the process may be fundamentally different. This can lead to a different global search mechanism
altogether, and therefore it is important to highlight the key tasks inherent in each algorithm.

D. Seven Basic Tasks in GA Implementation
1. Encode the solution parameters as genes.
2. Create a string of the genes to form chromosome.
3. Initialize a starting population by creating a set of specific chromosomes, usually in a randomized manner.
4. Evaluate and assign fitness values to individuals in the population.
5. Perform reproduction through the fitness-weighted selection of individuals form the population.
6. Perform recombination and mutation to produce individuals of the next generation.
7. Terminate the iteration process by either the number of desired iterations or by accepted results satisfying the design objectives.

E. Seven Basic Tasks in PSO Implementation
1. Define the solution space (upper and lower boundaries of each parameter).
2. Initialize the swarm by generating each particle's velocity \( V_i \) and position \( X_i \).
3. Evaluate and assign fitness values to particles in the swarm.
4. If the fitness is better than the previous pBest and/or gBest locations, then replace them with the current location.
5. Update the particle velocity by directing the particles to move towards the new pBest and gBest locations using the formulas in [3].
6. Update each particle's position with the newly generated velocity.
7. Terminate the iteration process by either the number of desired iterations or by accepted results satisfying the design objectives.

F. Seven Basic Tasks in CMA-ES Implementation
1. Define the solution space of interest (upper and lower boundaries of each parameter).
2. Initialize population mean \( \langle X \rangle \) and covariance matrix \( C \) as shown in [4].
3. Generate population positions \( X_i \) from the Gaussian distribution \( \mathcal{N}(\langle X \rangle, C) \).
4. Evaluate and assign fitness values to individuals in the population.
5. Sort individuals by best fitness and update the population mean \( \langle X \rangle \).
6. Update the covariance matrix \( C \) according to the best seen positions to emphasize the most critical parameters.
7. Terminate the iteration process by either the number of desired iterations or by accepted results satisfying the design objectives.

IV. APPLICATIONS OF GA, PSO, AND CMA-ES
There exist a wide variety of applications within electromagnetics where evolutionary optimization techniques thrive over standard design techniques. In many design scenarios, the global best solution tends to be non-intuitive and unclear, and these optimization techniques provide a systematic methodology to find a sufficient solution. Fig. 6 and Fig. 7 show some representative applications where these global optimization techniques were quite successful. Further references on these optimization techniques can be found in [1] and [5].

REFERENCES