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Evolutionary Algorithms for Inverse Scattering – Advances and State-of-the-Art Comparisons

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Abstract: This work is aimed at presenting the recent advances and the procedures available in the state-of-the-art for the solution of inverse scattering problems through Evolutionary Algorithms (EAs). The main emphasis is on the use of population-based optimization algorithms used for the retrieval of unknown objects embedded in an inaccessible region when illuminated by a set of microwave radiations. Starting from a description of the general architecture of EAs, advantages and limitation of state-of-the-art approached are pointed out and discussed.

Keywords: Evolutionary Algorithms, Inverse Scattering.

1. Introduction

Evolutionary algorithms [1] are global search approaches able to potentially achieve the global optimum whatever the starting guess. Unlike deterministic methods, they don't require a domain knowledge to avoid being trapped into local minima (i.e., wrong solutions) in case of non-linear and multi-minima functionals. For these reason and thanks to the growing computational resources offered by modern personal computers, this kind of optimization techniques have been effectively applied to inverse scattering problems.

EAs are stochastic iterative procedures which consider at each iteration a pool of trial solutions allowing an efficient sampling of the solution space with respect to single-agent stochastic optimization algorithms (e.g., Simulated Annealing [2]). The trial solutions iteratively updates by means of proper operators until a convergence criterion is reached, usually based on a threshold on the cost function value or on a maximum number of iterations.

The first population-based EAs used as an inversion procedure for electromagnetic diagnostic problems was the Genetic Algorithms (GAs). Several versions of GAs have been implemented and used in electromagnetic inversion to deal with the shape reconstruction of perfectly conducting objects [3][4] as well as the reconstruction of penetrable scatterers [5][6]. In order to cope with the drawbacks of GAs, mainly the low convergence rate, different kinds of evolutionary algorithms has been proposed. In this framework, the Differential Evolution (DE) algorithm [7][8] has been introduced to deal with the optimization of real parameters. Successively, also algorithms inspired by the cooperative behaviour of swarm has been applied in this field. More specifically, the Particle Swarm Optimizer (PSO) [9][10] and, more recently, the Ant Colony Optimizer (ACO) has also been applied [11]. In order to exploit the complementary advantages of EAs to deal with non-convex functional and the converge velocity of gradient-based minimization techniques, a non-negligible number of hybrid approaches has been implemented to improve the convergence rate of global optimizers [12][13].

EAs have shown many attractive features suitable for dealing with inverse scattering problems. As a matter of fact, they are hill-climbing algorithms which not require the differentiation of the cost function unlike gradient-based methods. Moreover, a-priori information can be straight introduced, usually in terms of additional constraints on the actual solution. Furthermore, they can directly deal with real values as well as with a coded representation of the unknowns (e.g., binary coding). As regards to the architecture of the implementation, they can be effectively hybridized with deterministic approaches. Despite several positive advantages, further researches are required in the framework of EAs to overcome the well-known drawbacks affecting these approaches, namely the high computational burden and the low convergence rate when dealing with high-resolution 2D imaging or 3D imaging problems due to the large number of unknowns.

This work is aimed at discussing the advances of evolutionary algorithms on inverse scattering problems and point out advantages and limitation of the state-of-the-art solutions.

2. **EAs for Inverse Scattering**

The aim of evolutionary algorithms is to achieve the global optimum solution. This solution is completely identified when its descriptive characteristics, which quantify the information content of the solution itself, are defined. This can be mathematically done by determining the problem unknowns, namely the coded representation of the solution descriptors, through the optimization of a suitable cost function. Since the descriptors can be either discrete or continuous as well as the number of unknowns to be determined can vary among the optimization problems, the choice of a proper EAs is a key issue and a general rule for the better choice does not exist. Although several EAs exist, they have some common features which can be considered in the design of innovative EA-based optimization techniques.

At the initialization of the EAs, the initial solutions $S_0 = \left\{ \underline{s}_0^{(p)}; p = 1,..., P \right\}$ are usually randomly-generated within the search space or around a reference trial solution exploiting some a-priori information on the solution of problem at hand. Successively, the set of P trial solutions, $S_k = \left\{ \underline{s}_k^{(p)}; p = 1,..., P \right\}$, k being the iteration index, evolves to achieve the final solution of the problem at hand through the optimization of a suitable function $\Psi^{(p)} = \Psi\left(\underline{s}^{(p)}\right)$ which measures how the trial solution fits the problem under given constraints. It should be pointed out that, since the function Ψ is the unique link between optimization and physical problems, great attention should be paid to define it and the reasons are twofold. On the one hand, reliable solutions must be obtained at the end of the optimization process. On the other hand, the complexity in the evaluation of the cost function strongly influence the use of a class of optimization algorithms rather than others. The structure of an EA is then fully described by detailing the following two architecture levels, namely the "Basic level" and the "Control level".

A. Basic Level

The basic level defines the rule for the generation of the succession of trial solutions and it is concerned with the coding of the solutions and the design of the evolutionary operators. The coding of the problem unknowns, $\underline{s} = \left\{ s_n; n = 1,..., N \right\}$, by means of a set of symbols of an alphabet (e.g., discrete or continuous) is a key point since it forces the choice of the evolutionary operators as well as the granularity of the optimization and the accuracy of the final solution. The most frequently used coding strategies are the binary coding [14] and the real coding [6]. Whatever the alphabet, a coding law T is used to map the set of parameters, $\underline{s} = \left\{ s_n; n = 1,..., N \right\}$, from the input space (the so-called phenotype space [15]) to its coded representation, $\underline{c} = \left\{ c_m; n = 1,..., M \right\}$, in the work space (the so-called genotype space [15]), $\underline{c} = \mathrm{T}(\underline{s})$. Then, once a new set of coded solutions is determined in the genotype space, a decoding law is applied to map the updated coded parameters into a new trial solution, $\underline{s} = \mathrm{T}^{-1}(\underline{c})$.

As far as the evolutionary operators are concerned, they are usually inspired by natural paradigms. Representative examples are those modelled on the concepts of natural selection (GAs and DE), cooperation and stigmergy taken from the intelligence of swarms (e.g., PSO and ACO).

B. Control Level

This level is devoted to control the building blocks of the basic level in sampling the solution space to find the global optimum. At this level, the issues related to the setup of the control parameters, the definition of the termination conditions, and the introduction of the problem constraints or boundary conditions on the solutions are addressed.

More specifically, the control parameters define the number of agents (i.e., dimension of the population/swarm), S_k, used at each iteration and the probabilities of applying the evolutionary operators. As for the convergence criteria, termination conditions are generally based on heuristic assumptions and user-defined thresholds on the value of the cost function or on a maximum amount of iterations. Other strategies take into account the stationariness of the cost function value of the optimal solution or quantifying the "diversity" of the solutions of the population.

The boundary conditions are usually related to the physical admissibility of the solution and derive from the a-priori information on the actual solution. Such an information allows one to reduce the dimension of the search space and to improve the convergence towards the global optimum.

3. **Conclusions and Discussions**

As regards the use of EAs to deal with microwave imaging problems, it should be pointed out that the development of evolutionary techniques has received a great boost in the last two decades due the continuous enhancement of the computational resources offered by modern personal computers, but also for their flexibility and features usually very suitable to face with the ill-posedness and nonlinearity of the arising optimization problem. As a matter of fact, EAs are global algorithms thanks to their stochastic nature which allow the straightforward introduction of a-priori information or constraints and are able to deal with floating-point and/or discrete and/or binary unknowns simultaneously. Furthermore, EAs are intrinsically parallel algorithms due to their multiple-agent nature and are easily integrated with local optimizers.

However, some other drawbacks limit their effectiveness besides typical negative issues of inverse scattering problems. For example:

- □ the computational burden, especially dealing with three-dimensional scenarios;
- □ the low convergence rate when approaching the global solution although in its attraction basin;
- □ the dependence on the parameterization of the problem unknowns;
- □ the sensitivity to the calibration parameters.

As regards to the computational issues, some receipts to limit these drawbacks consist in:

- reducing the number of problem unknowns by recurring to a suitable parameterization of the scatterer under test [16] or considering a multi-resolution strategy [17] or a multi-stage reconstruction [18];
- hybridizing the EA with a deterministic optimizer [19];
- computing at each iteration the secondary unknowns (i.e., the field distribution within the investigation domain) by means of fast forward solvers [20];
- exploiting the explicit parallelism of EAs through a parallel implementation [21].

As far as the enhancement of the convergence rate through the reduction of the extension of the solution space to be sampled during the optimization is concerned, the number of iteration strongly reduces whether the amount of a-priori information increases. As a matter of fact, additional information on the location of the attraction basin of the global solution can be exploited by the evolutionary procedure to locate the actual solution as well as the EA designer in defining the optimal parameterization of the problem unknowns.

Another way to save computational resources when applying EAs to inverse scattering problems is to use a succession of inversion procedures, each one concerned with a number of unknowns smaller or equal than the information content of the scattering data in order to "simplify" the cost function to be optimized. The reduction of the complexity of the cost function can be yielded in different ways according to some recently developed strategies. In such a framework, it is worthwhile to mention multi-resolution methods [17] devoted to perform an iterative synthetic zoom on the region where the scatterer is supposed to be located and multi-stage reconstructions [18][22] where each inversion is aimed at identifying different characteristics of the unknown scatterer until its complete knowledge.

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