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Black-Hole PSO and SNO for Electromagnetic Optimization

Matteo Ruello, Alessandro Niccolai, Francesco Grimaccia, Marco Mussetta, Riccardo E. Zich
Dipartimento di Energia
Politecnico di Milano
Via La Masa 34, 20156 Milano, Italy
riccardo.zich@polimi.it

***Abstract*—In the past years Particle Swarm Optimization (PSO) has gained increasing attention for engineering and real-world applications. Among these, the design of antennas and electromagnetic devices is a well-established field of application. More recently, Social Network Optimization (SNO) has been introduced, inspired by the recent explosion of social networks and their capability to drive people's decision making process in everyday life. "Black-hole" is a novel operator, which is here considered for both PSO and SNO. It is based on the concept of repulsion among agents when they get stuck in local optima. The design of a planar array antenna is here addressed in order to assess its performances on a benchmark EM optimization problem. Reported results show its effectiveness in dealing with antenna optimization.**

I. INTRODUCTION

The optimization of electromagnetic devices is usually a difficult task since the interaction of many parameters, complex boundary conditions, and width/peak gain relation [1]. Among these the design of antennas and micro to sub-millimetre wave components is a potential field of application. In this field, multi-objective problems are quite common: in these cases there is no a single solution, but the real challenge is to find a good trade-off solution that represents the best compromise among the considered objectives. To address this complexity, the use of Evolutionary Optimization algorithms it is now well assessed also in the Antennas community [2], where the most known procedures are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO).

In this paper a new operator suitably developed for the PSO method, namely the Black-hole operator, is presented and its performances are assessed over classical benchmark functions and antennas problems. Moreover, its application is extended also to another evolutionary algorithm, recently developed, namely the Social Network Optimization (SNO). The new proposed approaches are called Black-Hole PSO (bhPSO) and Black-Hole SNO (bhSNO).

II. BASIC PSO ALGORITHM

Particle Swarm Optimization (PSO) is a well known evolutionary algorithm based on a model of social interaction between independent agents (particles) that uses social knowledge (also called swarm intelligence, *i.e.* the experience accumulated during the evolution) in order to find the global maximum or minimum of a function [3]. This computational technique, adopts a pseudo-biological approach and takes its origin from the simulation of social behaviors such as those related to synchronous bird flocking and fish schooling; it is similar to other population-based algorithms, like GAs, but it operates emulating social interaction between independent agents and utilizes swarm intelligence to achieve the goal of optimizing a specific fitness function in a way easy to understand and implement [4]. In fact, any set of coordinates in the M-dimensional space is a particular position of an agent and represents a solution; it corresponds to a particular value of the fitness function. Each particle also has an associated velocity, that takes into account the best position reached by all ones and the best position, resulting in a migration of the swarm towards the global optimum.

The standard PSO algorithm is an iterative procedure in which a set of $i = 1, \ldots, N_p$ particles, or agents, are characterized by their position $\vec{X}_i$ and velocity $\vec{V}_i$, defined in the M-dimensional space domain of a cost function $F(\vec{X})$.

At the beginning positions and velocities have completely random values $\vec{X}_i^0$ and $\vec{V}_i^0$, then they are updated iteratively according to the rules:

$$\vec{V}_i^{k+1} = \omega_k \vec{V}_i^k + \phi\eta_1(\vec{P}_i - \vec{X}_i^k) + \phi\eta_2(\vec{G} - \vec{X}_i^k) \quad (1)$$

$$\vec{X}_i^{(k+1)} = \vec{X}_i^{(k)} + \vec{V}_i^{(k+1)} \quad (2)$$

where $\vec{P}_i$ the best position so far attained by particle i itself (personal knowledge) and $\vec{G}$ is the best position so far attained by the whole swarm (social knowledge); ω_k is a friction factor slowing down particles (it can depend on k, as shown in [5]), η_1 and η_2 are positive parameters tuning the pulls towards the personal and global best positions and ϕ is a random number of uniform distribution in the $[0, 1]$ range.

III. BLACK-HOLE PSO

As previously reported [1], standard PSO usually gets stuck because exploitation outperform exploration and, when a local best is found, there is a high probability of bouncing around this point. In fact the agent that found this point has two out of three vectors pointing the same point, which is, indeed, its own personal best ($\vec{P}_i$) and global best ($\vec{G}$).

In order to improve the algorithm's exploration capability, black-hole concept is here introduced; its main ideas (briefly summarized in Figure 1) are the following:

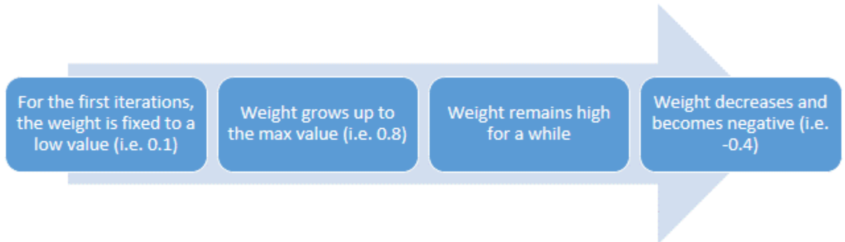

Fig. 1. A view of the black-hole operator here proposed and implemented with variable weight concept.

- Around the global best a suitable hyper-sphere can be defined (radius ρ);
- Every particle moving within the hyper-sphere around the global best is then randomly reinitialised in the parameter space.

Moreover, the introduced variation affects the usual velocity update rule: which is updated as:

$$\vec{V}_i^{k+1} = \omega_k \vec{V}_i^k + w_p(\vec{P}_i - \vec{X}_i^k) + w_g(\vec{G} - \vec{X}_i^k) \quad (3)$$

where $\vec{P}$ is the position of the best value found by the single particle, w_p is its weighting coefficient, $\vec{G}$ is the position of the best value found by all agents, w_g is its weight. It is worth noticing that, since random search (*i.e.* exploration) is guaranteed by the new Black-Hole operator, having other random coefficient ϕ is useless.

In particular, in our black-hole implementation, a variable weight system can be introduced: since global best stagnation is avoided by the black hole it is better to use an high value for w_g, but this is not good at an early stage of search. In fact only "stable" best should attract the particles. So it is good having a low w_g value in the beginning and then making it increase with iterations. After a certain number of iterations in which the global best is stable, we can assume that all the information linked to that point has been used, so we should explore other parts of the domain, similarly to the concept of *implicit restart* introduced firstly in [6]. To help this, the global best weight starts lowering and becomes negative, thus rejecting other particles from its region. Every time a new global best is found the cycle starts over.

Of course, a new randomly generated position can easily be slightly worst than the best one found so far; nevertheless, it could contain more useful information than the current global best, thus we should give a chance to these new points to be considered. This is provided by increasing (or decreasing if we are founding a maximum) the value of the stored global best cost by a small percentage during the last part of the procedure shown in Figure 1.

In the following figures, a preliminary analysis of the performances of bhPSO compared to traditional PSO is presented: in particular, the considered functions are Ackley (Figure 2) and Rastrigin (Figure 3) with a $M = 10$ dimension space

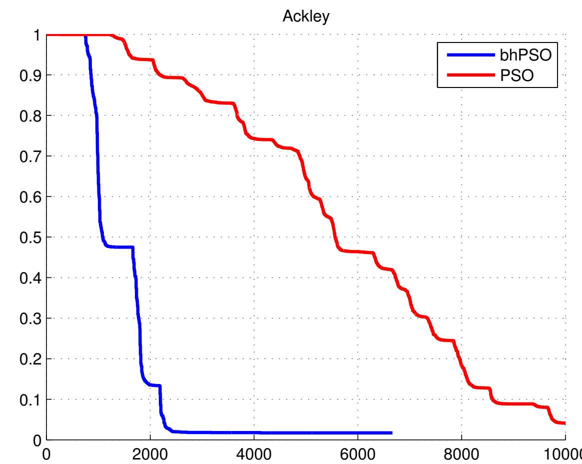

Fig. 2. bhPSO and PSO performances over the Ackley benchmark function (Average over 20 independent trials; $M = 10$).

and 50 individuals. The benchmark functions are those made available on Prof. D. Simon's website [7].

IV. Basic SNO Algorithm

In the last decade, the diffusion of multimedia platforms Internet connection and Social Networks have dramatically modified the human life style with a direct impact on everyday life behavior and decisional process. This context has affected different research fields as for example computer science, economy and sociology creating novel paradigms inspired by social networks with interesting results related to pervasive diffusion of heterogeneous data and an increasing capacity in computation and information exchange.

To address this complexity, after creating a hybrid method between GAs and particle swarms ten years ago, the authors recently created the SNO algorithm as a population based algorithm inspired to the social network knowledge sharing and decision making process.

The optimization process of engineering problems in many fields of science is a complex task since the interaction between multiple physical parameters and not trivial boundary conditions affect the structure of the objective function and related algorithm convergence. In order to face this complexity,

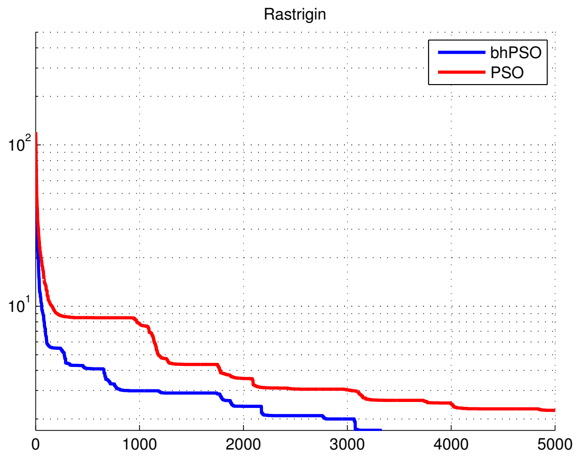

Fig. 3. bhPSO and PSO performances over the Rastrigin benchmark function (Average over 20 independent trials; $M = 10$).

the authors introduced a new algorithm called SNO, first presented in [8] in a simplistic way and further developed to enhance its performance, essentially built as a population based algorithm inspired to the social network knowledge sharing and emulating the decision making process recently introduced by these networks.

In this algorithm in fact, each individual represents a social network member characterized by a proper social environment (a specific position in the solution space), a proper character, a personal reputation recognized by his group and a personal interest which can be compared to a sort of taste or liking shared among his relational network. The personal interest can be seen as preferred direction in the space domain due to both stronger and weaker characters or particular opinion leaders.

In the SNO population, each single individual has his personal life style as in the any day life of every people. Besides, any single person, which accumulates experience during his or her life, can be influenced by interaction with other members of the social network, in particular by some opinion leader that frequently have eccentric characters. Thus each person is described by the surrounding social environment and its personal character, and both these elements change during the time due to aging and multiple interactions. The combination of social environment and personal propensity or taste can be considered as experience which leads actions in all our lives and can certainly evolve during time in a dynamic context. Moreover, nowadays this lived experience is often shared in social networks in order to avoid mistakes, suggest places to visit, express likes and dislikes.

Therefore the social network has two main impacts: the knowledge sharing and the influence on other peoples choice: this means that in the social network environment all the situations shared and previously evaluated by other people can influence the way a person choose and act in the future. The SNO operators emulates also the past experiences that are published on common social networks and we call this characteristic as *memory*.

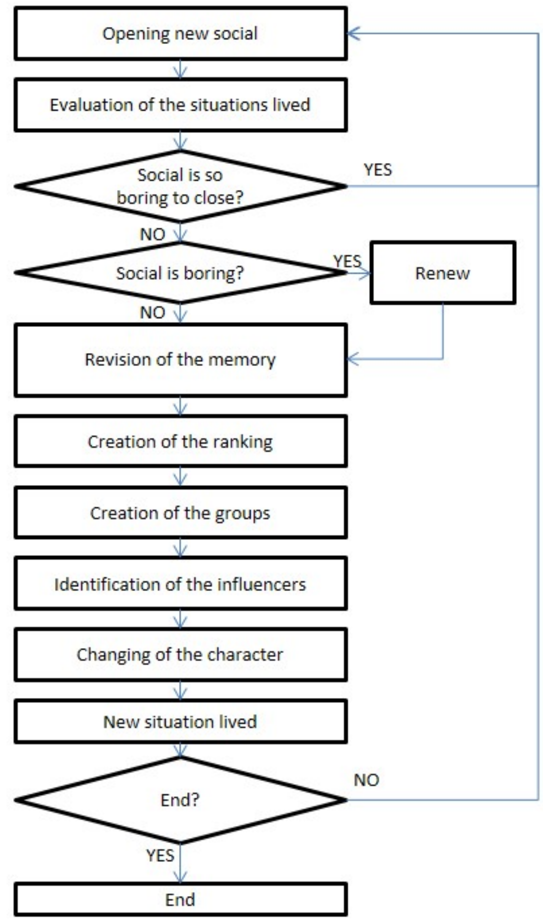

Fig. 4. A flowchart description of basic SNO operators

The flow chart in Figure 4 represent how SNO change the characteristics of the agents during run time. It also summarize the main aspect of SNO such as situation, memory, ranking groups and influencers, explained in detail in [9].

V. Black-hole SNO

To emulate social networks' behavior different operators have been previously introduced in SNO algorithm [9], [10]. In this section we describe the option of an additional one in order to test the relative algorithm behavior. The most important operator for SNO was the personal character c whose role explains the interaction between people among a social group, but in this paper a Black-Hole operator was introduced and tested to be compared with the PSO case.

When in SNO algorithm a black-hole operator is introduced to test its efficiency a potential improvement can be found in the performance. The operator changes the rule of attraction towards solutions that are stored since more than an arbitrary value of t_1 iterations. Normally the rule of attraction for a specific solution can be written as:

$$att = p_{infl} - p \tag{4}$$

where *att* is the attraction operator, p the position of attracted solution in the domain and p_{infl} the position of influencer. The Black-Hole operator modifies the eq. 4 in:

$$att = -\frac{cr}{p_{infl} - p} \tag{5}$$

A full simulation campaign was performed with different values of cr and t_1 and in some cases the introduction of BH operator improved the overall performance even if the authors observed its efficiency is greater in PSO case.

VI. Electromagnetic application and conclusion

In this paper, the proposed algorithm has been used for the optimization of the array factor of a planar array. The considered geometry consists of $(2N_e + 1) \times (2N_e + 1)$ identical elements whose position and excitation (both amplitude and phase) are free to vary.

As shown in [1], each element is characterized by its excitation $I_{i,j}$ and position $(x_{i,j}, y_{i,j})$, with $i = -N_e, \ldots, N_e$ and $j = -N_e, \ldots, N_e$.

The array is considered symmetrical both on x and y, therefore $I_{i,j} = I_{-i,j} = I_{-i,-j} = I_{i,-j}$, $x_{i,j} = -x_{-i,j} = -x_{-i,-j} = x_{i,-j}$, and $y_{i,j} = y_{-i,j} = -y_{-i,-j} = -y_{i,-j}$.

For what concerns position optimization constraints, we chose $x_i \in [x_i^{\min}, x_i^{\max}]$ with:

$$x_i^{\min} = i \cdot \lambda/2 \tag{6}$$

$$x_i^{\max} = i \cdot \lambda \tag{7}$$

The central element is taken as a reference and is characterized by $x_0 = 0$, $a_0 = 1$ and $\beta_0 = 0$.

The aim of the optimization is to design a 11×11 BS array ($N_e = 6$) with a $\theta_{3dB}/2 = 3.8°$ and a side lobe level (SLL) envelope below -20 dB for $\theta > 9°$. This is of course a multi-objective problem and the cost function has been defined to take into account both objectives by considering 90 sampling points in the far-field pattern.

Dealing with the planar array optimization, Figure 5 shows the array factor of an optimized configuration in $\phi = 0°$ and $45°$ planes. The array factor in the $\phi = 90°$ plane is identical to the one in the $\phi = 0°$ plane due to symmetry reasons, as shown in Figure 6.

It is worth noticing that trying to achieve this array pattern with only 11×11 elements leads to a total number of elements equal to 121, much lower than the number of 144 requested by an equivalent Tseng-Cheng array [11], as shown in [1], with a corresponding significant reduction in array and feeding network complexity. These preliminary reported results confirm the effectiveness of the application to PSO of the newly developed Black Hole operator in addressing complex EM optimization problems.

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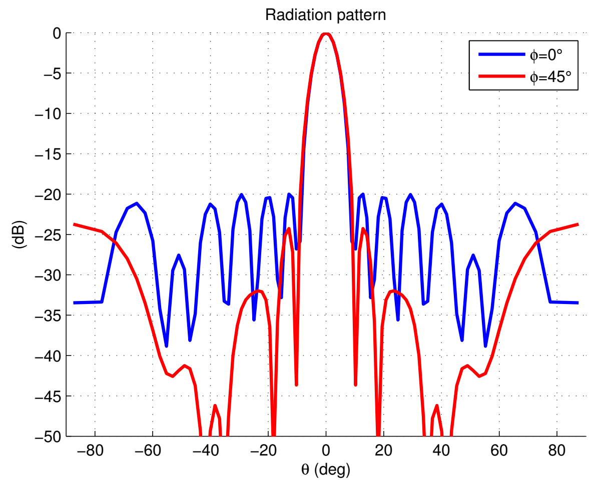

Fig. 5. Resulting array factor

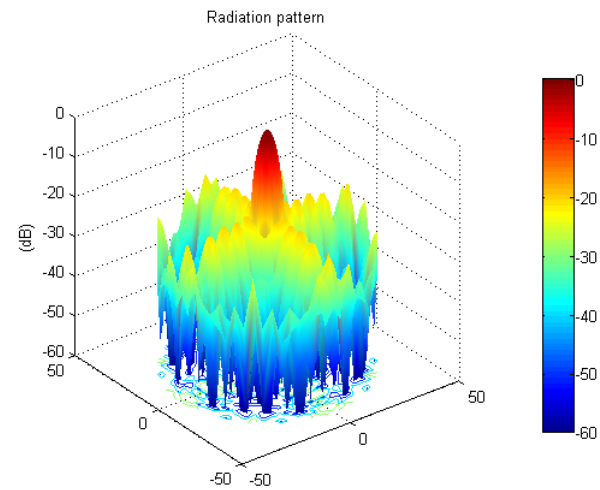

Fig. 6. 3D array factor

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