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COMPLEX SYNTHESIS OF ANTENNA STRUCTURES THROUGH
EVOLUTIONARY-OPTIMIZATION TECHNIQUES

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Complex Synthesis of Antenna Structures through Evolutionary-Optimization Techniques

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Abstract – In this paper, three antenna problems concerned with both the synthesis and the control (i.e., a real-time synthesis) are formulated and solved by using innovative and ad-hoc versions of evolutionary optimization techniques. In order to assess the effectiveness of the proposed techniques, some representative results are compared with those obtained with standard versions of optimizers or state-of-the-art deterministic approaches.

1 INTRODUCTION

Nowadays, the solution of antenna problems by means of evolutionary optimization techniques is a topic of great interest in electromagnetics. These approaches allow one to define new and satisfactory solutions fitting in a very effective fashion the requirements of the modern wireless communication systems as the adaptation to time-varying scenarios, the integration of different services, the size and the costs. Moreover, they usually outperform the solutions obtained with gradient-based or conventional techniques.

In the following, three test cases concerned with antenna synthesis and control are discussed. In particular, Particle-Swarm-Optimizer (PSO) based strategies are used for phased array control (Section 2.1) and synthesis of pre-fractal antennas (Section 2.2). Moreover, a synthesis approach based on the Ant Colony Optimizer (ACO) is profitably adopted for synthesizing array monopulse antennas (Section 2.3).

2 FORMULATION AND NUMERICAL VALIDATION

2.1 Real-Time Control of Array Antennas through a Memory-Enhanced PSO

The ever-growing diffusion of wireless communications requires Tx/Rx systems able to adapt themselves to the time-varying environment conditions in order to guarantee a suitable Quality-of-Service (QoS). When dealing with adaptive arrays, several control techniques have been proposed for interference suppression. The adaptive real-time control of array weights is generally performed either through analytical procedures (e.g., [1]) or by means of optimization strategies [2][3][4].

In such a framework, a PSO-based optimization has been successfully applied in [5] dealing with complex scenarios by considering both linear and planar array geometries. In order to speed up the convergence rate (i.e., the re-adaptation of the system to the changing conditions) and for facing with a scenario where jamming sources are located both in near [7] and far-field, an enhanced version of the standard PSO (called Particle Swarm Optimizer with Memory - PSOM) that exploits the memory of the optimization process, has been preliminary presented in [6].

Let us consider a set of J narrow-band signals impinging on an array of N elements. The received signal is given by

$$\underline{s}^{(r)}(t) = \underline{s}^{(d)}(t) + \sum_{j=1}^J \underline{s}_j^{(i)}(t) + \underline{\eta}(t) \quad (1)$$

where $\underline{s}_j^{(i)}$ is a jamming and $\underline{\eta}$ indicates the background uncorrelated noise. Moreover, $\underline{s}^{(i)}(t) = \alpha^{(i)}(t)\underline{h}^{(i)}$, where $\alpha^{(i)}$ stands for the envelope and $\underline{h}^{(i)} = [\exp(j\phi_1^{(i)}), \dots, \exp(j\phi_N^{(i)})]^T$ ($t = r, d, i$). By considering both near and far-field interferences at each snapshot t_i , the phase term of the j -th interferer can be expressed as follows

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$$\begin{aligned} \varphi_{n,j}^{(i)} &= \\ &= \frac{2\pi}{\lambda} \left[d_j^{(i)} - \sqrt{(d_j^{(i)} u_j^{(i)} - x_n)^2 + (d_j^{(i)} v_j^{(i)} - y_n)^2 + (d_j^{(i)} q_j^{(i)} - z_n)^2} \right] \end{aligned} \quad n=1,\dots,N, \quad j=1,\dots,J \quad (2)$$

$d_j^{(i)}$ being the distance of the j -th jamming source from the antenna center, (x_n, y_n, z_n) is the position of the n -th array element, and $u_j^{(i)} = \sin \theta_j^{(i)} \cos \phi_j^{(i)}$, $v_j^{(i)} = \sin \theta_j^{(i)} \sin \phi_j^{(i)}$, $q_j^{(i)} = \cos \theta_j^{(i)}$.

Under these assumptions, the maximization of the signal-to-interference-plus-noise ratio (SINR) at the receiver is usually carried out by maximizing the following fitness function [4]

$$\mathfrak{J}(\underline{w}) = \frac{|\underline{w}^T \underline{h}^{(d)}|^2}{|\underline{w}^+ \underline{\Theta}^{(r)} \underline{w}|^2} \quad (3)$$

where $\underline{\Theta}^{(r)} = \underline{\Theta}^{(d)} + \underline{\Theta}^{(i)} + \underline{\Theta}^{(n)}$ is the covariance matrix of the received signal and $\underline{w} = \{w_n \exp(j\beta_n)\}_{n=1,\dots,N}$ is the weights vector. Towards this end, at each snapshot t_l , the optimal weights \underline{w}_{opt} are determined by means of an iterative PSO-based procedure. The process starts from the choice of a suitable global-best particle from a buffer of trial solutions of size M , $\{\underline{c}_m; m=1,\dots,M\}$, which defines the so-called ‘‘memory’’ of the optimization process (the exchange of particles between the memory and the swarm is managed through the ‘‘Resurrection Operator’’ and the ‘‘Storage Operator’’ detailed in [6]). Unlike standard PSO, the velocity is updated as follows

$$\begin{aligned} v_{b,s,n}^{k_l+1} &= \Lambda \left\{ w v_{b,s,n}^{k_l} + c_1 r_1 (p_{b,s,n}^{k_l} - x_{b,s,n}^{k_l}) + \right. \\ &\quad \left. + c_2 r_2 (g_{b,s,n}^{k_l} - x_{b,s,n}^{k_l}) + c_3 r_3 A_{b,n} \right\} \end{aligned} \quad (4)$$

where $s \in [1,\dots,S]$ is the index of the particle of the swarm of size S and $b \in [1,\dots,B]$ indicates the b -th bit coding the n -th phase term β_n .

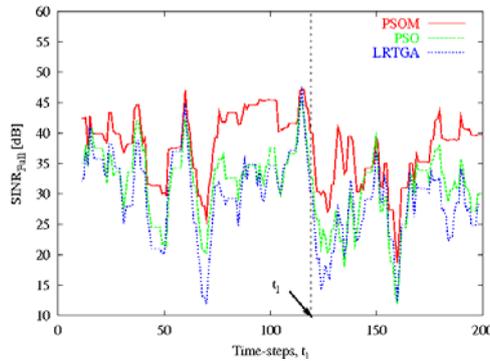


Figure 1: SINR versus time-step index, t_l .

In (4), the first term on the right side is the ‘‘self-knowledge’’, the second one is the ‘‘group-knowledge’’ term, and $A_{b,n}$ is the ‘‘ambient-knowledge’’ term that depends on storage solutions and given by

$$A_{b,n} = \frac{\sum_{m=1}^M [c_{b,m,n} \exp(-H \frac{m-1}{M})]}{M} \quad (5)$$

where H is an integer heuristically-defined. At each time-step t_l , the PSOM terminates when a maximum number of iterations or a user-defined SINR threshold is reached.

As an example, Figure 1 shows the behavior of the SINR versus the snapshot index t_l when using a planar array [8] and in correspondence with a scenario characterized by near/far-field interferences with random directions and arrival times characterized by a Poisson-like distribution [6] ($S = 30$, $M = 20$, $B = 8$). As it can be observed, the PSOM overcomes other optimization strategies (i.e., standard PSO [5] and LRTGA [8]) thanks to a more effective exploitation of the memory buffer. In order to further point out the effectiveness of the proposed approach, Figure 2 shows the beam pattern at $\phi = 88$ synthesized when a jammer with power 30 dB over the desired signal and located at $(d_1^{(i)}, \theta_1^{(i)}, \phi_1^{(i)}) = (62, 88, 32)$ impinges on the planar array. Both LRTGA and PSO are able to reject the interference signal placing a null of -66 dB and -117 dB in depth, respectively, but the PSOM places a deeper null (-140 dB).

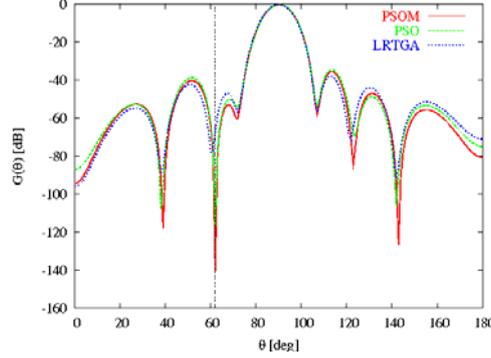


Figure 2: Beam pattern synthesized at t_l , $l = 119$.

2.2 PSO-Based Strategy for Pre-Fractal Multi-Band Antenna Synthesis

In the last years, besides devices able to adapt themselves to time-varying electromagnetic environments, a growing interest and researches have been attracted towards the synthesis of antenna systems able to contemporarily qualify different services on the wireless channel. In this framework, fractal antennas seem to be an effective solution [9] due to their implicit multi-band behavior and miniaturization properties. However, since fractal shapes present a harmonic-frequency rather than a multi-band behavior [10], an innovative fractal-based methodology has been proposed for synthesizing fractal-like antennas with (in principle) unconstrained multi-band behaviors [11]. Towards this end, reference pre-fractal shapes are iteratively modified according to a PSO-based optimization procedure aimed at minimizing the following cost function

$$\phi(\chi) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{t=0}^{T-1} \left\{ \max \left[0, \frac{G_{\min}(t\Delta\theta, n\Delta\phi, m\Delta f) - \Gamma(t\Delta\theta, n\Delta\phi, m\Delta f)}{G_{\min}(t\Delta\theta, n\Delta\phi, m\Delta f)} \right] \right\} + \sum_{v=0}^{V-1} \left\{ \max \left[0, \frac{\Psi(v\Delta f) - VSWR_{\max}(v\Delta f)}{VSWR_{\max}(v\Delta f)} \right] \right\} \quad (6)$$

where suitable constraints on dimensions and electrical requirements are imposed (e.g., gain values Γ greater than G_{\min} , and impedance matching at the input port of the antenna, i.e., synthesized voltage-standing-wave-ratio values Ψ smaller than $VSWR_{\max}$).

As a representative result, the synthesis of a dual-band antenna allowing L_1 -GPS and *Wi-Fi* services is discussed. As far as the geometrical and electrical requirements are concerned, the following constraints have been imposed: (a) $\Psi \leq VSWR_{\max} = 2.0$, (b) a gain greater than $G_{\min} = 3.0 \text{ dB}_i$ at $\theta = 0^\circ$ and $\Gamma \geq G_{\min} = -4.0 \text{ dB}_i$ at $\theta = 70^\circ$ in the L_1 -GPS band by taking into account the presence of a 20 dB preamplifier, (c) an hemispherical coverage in the *Wi-Fi* band, and (d) a physical dimension larger than $\lambda_{L1}/4 \times \lambda_{L1}/4$.

Starting from a reference geometry generated by applying two-times ($i = 1, 2$) the so-called *Hutchinson* operator on a *Sierpinski*-like fractal shape [12], the minimization of (6) has been carried out by integrating the PSO with a Method-of-Moments (*MoM*) electromagnetic modeling tool for carefully simulating the presence of the support dielectric slab and of a reference ground plane. Figure 3 shows the cost function behavior versus the iteration index. For completeness, the plots of the corresponding *VSWR* values are reported (Fig. 4), as well.

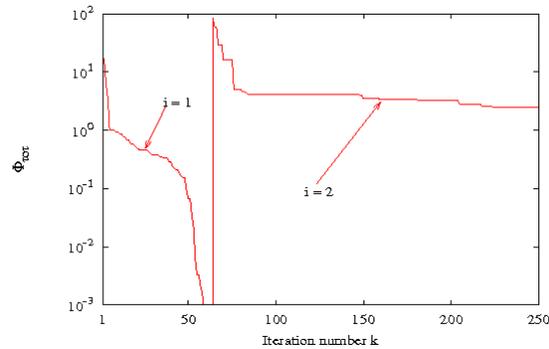


Figure 3: Cost function versus the iteration number.

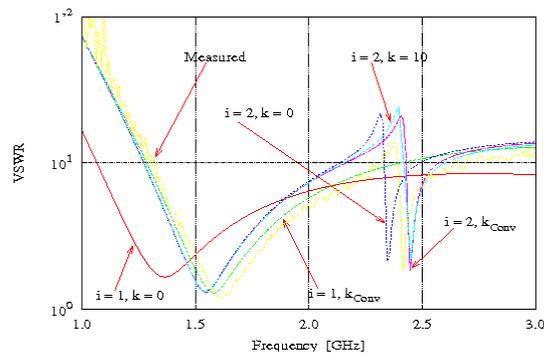


Figure 4: Measured and simulated *VSWR* values.

Finally, the prototype of the synthesized dual-band *Sierpinski*-like pre-fractal antennas is shown in Figure 5.



Figure 5: Antenna prototype.

2.3 ACO for Tree-Searching-based Synthesis of Monopulse Array Antennas

Another interesting topic in the field of antenna design is concerned with radar applications and the synthesis of monopulse arrays. In particular, the definition of an optimal compromise among sum and difference patterns through sub-arraying techniques has been widely studied and innovative solutions based on evolutionary techniques have been recently proposed [13].

In such a case, the synthesis problem can be stated as follows “for a fixed array geometry and a given optimal sum mode, defining the elements aggregation and the sub-array weights such that compromise excitations afford a difference pattern as close as possible to the optimum difference in the Dolph-Chebyshev fashion”. Towards this purpose, an effective optimal matching method has been preliminary presented in [14]. By exploiting the relationship between independently optimal sum $\underline{A}^{opt} = \{\alpha_n; n=1, \dots, N\}$ and difference $\underline{B}^{opt} = \{\beta_n; n=1, \dots, N\}$ excitations, a non-complete binary tree that identifies the whole set of admissible sub-array aggregations $\underline{C} = \{c_n; n=1, \dots, N\}$, $c_n \in [1; Q]$, is defined and a cost value is assigned to each tree branch

$$\Psi(c_n, w_q) = \sum_{q=1}^Q \sum_{n=1}^N \alpha_n^2 \left| \frac{\beta_n}{\alpha_n} - \delta_{c_n, q} w_q \right|^2. \quad (7)$$

The optimal solution is then defined as the minimum of (7) to be identified by effectively sampling the solution tree. Accordingly, an optimization procedure based on the ACO [15] aimed at looking for the minimum-cost path is used and the sub-arrays gains are

$$w_q = \frac{\sum_{n=1}^N \alpha_n^2 \delta_{c_n, q} v_n}{\sum_{n=1}^N \alpha_n^2 \delta_{c_n, q}} \quad (8)$$

$\delta_{c_n, q}$ being the Kronecker delta ($\delta_{c_n, q} = 1$ if $c_n = q$, $\delta_{c_n, q} = 0$ otherwise) and $v_n = \frac{\beta_n}{\alpha_n}; n=1, \dots, N$. More in detail, each ant $f_i, i=1, \dots, I$ codes a vector of integer values, namely the aggregation vector $\underline{C} = \{c_n; n=1, \dots, N\}$ and the ants are moving from the root to the leaves.

At the first iteration, the same cost value is assigned to every branch of the solution-tree. Then the probability of exploring a branch is modified according the *pheromone update* and *evaporation*, as detailed in [15].

As an example, a $N=100$ elements array has been considered and the number of sub-arrays has been set to $Q=6$. Furthermore, the optimal difference pattern has been chosen equal to the Zolotarev beam with -30 dB sidelobe level (*SLL*). For comparison purposes, Figure 6 shows the pattern synthesized with the ACO-based strategy and that determined by means of a deterministic method called *Border Element* (BE) [14]. It is worth noting that the ACO method guarantees a *SLL* of -26 dB more than 3 dB better than that of the *BE* solution.

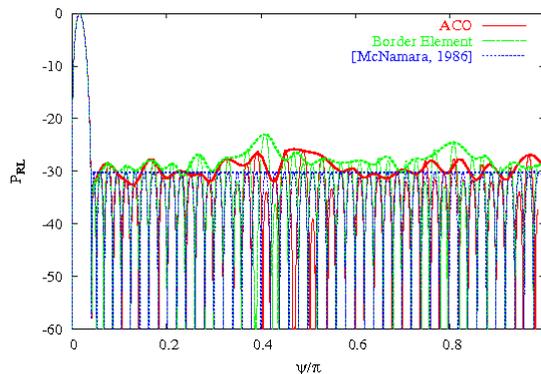


Figure 6: Compromise difference patterns.

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