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Frontiers in Multiple-Agents Evolutionary Techniques Applied to Adaptive Arrays Design

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This paper proposes an innovative approach to control phased arrays. Starting from the adaptive array theory, a particle swarm strategy is used to tune the phase coefficients of the array in order to adaptively minimize/avoid the effects of interfering signals at the receiver. The effectiveness of the proposed approach is assessed through a comparison with state-of-the-art methods.

Introduction

In the last years there has been a growing interest in the design and application of reconfigurable phased-array antennas. In the scientific literature (see [1][2] and the references cited therein), several methodologies for the adaptive phase-array control have been proposed. However, to limit the cost of the hardware equipment, there is the need of operating in the digital domain by only acting on the phase terms of the array elements.

Within such a framework, effective approaches have been proposed. The problem has been reformulated in an optimization one and it has successively solved through an evolutionary strategy based on a Genetic Algorithm (GA) [3]-[6]. Recently, a new stochastic algorithm called particle swarm optimizer (PSO) [7] has been shown to be a valuable addition to the electromagnetic design engineer's toolbox [8]. One advantage of the PSO over the GA is its algorithmic simplicity. Moreover, another key-issue for the application of a PSO-based procedure to the phased-array real-time tuning lies in its ability to control the convergence of the optimization as well as its stagnation. As pointed out in [9] and detailed in [8], although crossover and mutation rate can affect the convergence of the GA, the PSO allows a more significant level of control by decreasing the inertial weight during the optimization process. To evaluate the effectiveness of the PSO in dealing with the real-time control of planar array, this paper proposes a computational approach based on a binary version of the PSO.

Mathematical Formulation

Let us consider an array whose M elements are arbitrarily located on the (x, y) plane at $\bar{r}_m = (x_m, y_m, z_m)$, $m = 0,...,M-1$ that generates the following radiation pattern:

$$b(u,v) = \sum_{m=1}^{M} \mathrm{w}_\mathrm{m} \exp\{jk(\bar{r}_m \cdot \bar{r})\} \tag{1}$$

where $w_m = \hat{w}_m \exp(j\phi_m)$, $m = 0,...,M-1$ are the array weights, $k = 2\pi/\lambda$, and $\bar{r} = (u, v, s)$ indicates the direction of arrival (DOA) of the desired signal being $u = \sin\theta\cos\varphi$, $v = \sin\theta\sin\varphi$, and $s = \cos\theta$.

Under the assumption of narrowband conditions and co-channel interference (i.e., the desired and interfering signals are centered on the same working frequency), according to Applebaum's theory [1], the SINR can be defined as follows

$$SINR(\mathbf{w}) = a^2 \frac{|b(u,v)|^2}{\mathbf{w}^{\mathrm{T}*}\Phi_u \mathbf{w}} \tag{2}$$

where Φ_u is the undesired covariance matrix $\Phi_u = \Phi_i + \Phi_n$ (Φ_i and Φ_n being the interference and noise covariance matrices, respectively).
As pointed out in [1][4], the computation of (2) is not possible since Φ_u is an unknown quantity and it cannot be directly measured. Nevertheless, it has been demonstrated [4] that the *SINR* maximization is equivalent to the maximization of the following cost function

$$\Psi(\mathbf{w}) = a^2 \frac{|b(u,v)|^2}{\mathbf{w}^{T*} \Phi_r \mathbf{w}} \tag{3}$$

where Φ_r is given by $\Phi_r = \Phi_u + \Phi_d$ (Φ_d, being the desired signal covariance matrix) and can be easily computed at the receiver. In order to maximize (3), a suitable PSO-based strategy is adopted as described in following Section.

PSO-Based Adaptive Control Strategy

The PSO is a multiple-agents optimization algorithm developed by Kennedy and Eberhart [7]. A standard PSO implementation considers a swarm of P trial solutions (called *particles*) that fly in the solution space by improving their positions according to suitable updating equations. To deal with phase-only adaptive arrays control, the PSO-based approach can summarized as follows.

Step 0 - Coding. Since the m-th element of the array is controlled through a L-bits digital phase shifter, the p-th binary trial solution is $\overline{\zeta}^{\,p} = \{\varphi_m^{p,l}; l = 1,...,L; m = 1,...,M\}$ where $\varphi_m^{p,l}$ is the binary bit at the l-th place along the gene corresponding to the ϕ_m^p parameter. At each "position" vector $\overline{\zeta}^{\,p}$ is associated a velocity vector $\overline{v}^{\,p} = \{v_m^{p,l}; l = 1,...,L; m = 1,...,M\}$, where $v_m^{p,l}$ is the probability of $\varphi_m^{p,l}$ taking value 1.

Step 1 - Initialization. At $k = 0$, the positions of the P particles of the swarm $\Xi_0 = \{\overline{\zeta}_0^{\,p}; p = 1,...,P\}$ as well as their velocities $V_0 = \{\overline{v}_0^{\,p}; p = 1,...,P\}$ are randomly generated according to the following rules

$$\varphi_{m,0}^{p,l} = \begin{cases} 1 & if \;\; \rho_{m,0}^{p,l} \\ 0 & otherwise \end{cases}, \qquad v_{m,0}^{p,l} = \sigma_{m,0}^{p,l} v_{\max} \tag{4}$$

where $\rho_{m,k}^{p,l}$ and $\sigma_{m,0}^{p,l}$ are random numbers between 0 and 1 .

Step 2 - Fitness evaluation. At each iteration the cost function values are computed: $\Psi_k^p = \Psi\{\mathbf{w}(\overline{\zeta}_k^{\,p})\}$ and the "*previous best*" particle $\overline{\xi}_k^{\,p} = \arg\left(\max_{h=1,...,k}\left[\Psi\{\mathbf{w}(\overline{\zeta}_h^{\,p})\}\right]\right)$ as well as the "*global best*" particle $\overline{\varsigma}_k = \arg\left(\max_{p=1,...,P}\left[\Psi\{\mathbf{w}(\overline{\zeta}_k^{\,p})\}\right]\right)$ are stored. To improve the "*reaction*" of the algorithm to environmental changes occurring between consecutive timesteps, optimal particles are stored $\overline{\gamma}_c = \overline{\varsigma}_{k-c}$, $c = 1,...,C$ (C being the buffer length). The iteration index is updated, $k = k + 1$.

Step 3 - Termination criterion. If the maximum number of iterations K (admissible in a timestep t) is reached ($k = K$) or if the optimal fitness is under a given threshold η , then the optimization process is stopped and $\overline{\varsigma}_k$ is assumed as the problem solution. Otherwise, the *Step 4* is done.

Step 4 - Velocity updating. The velocity of each particle is updated according to the following relation:

$$v_{m,k}^{p,l} = \begin{cases} v_{\max} & if \;\; v_{m,k}^{p,l} > v_{\max} \\ -v_{\max} & if \;\; v_{m,k}^{p,l} < -v_{\max} \\ v_{m,k}^{p,l} & otherwise \end{cases} \tag{5}$$

where $v_{\max}$ is a constant clamping value [7] generally set at 4.0 and similar to the mutation rate in GAs. Moreover,

$$v_{m,k}^{p,l} = \chi v_{m,k-1}^{p,l} + a_1\rho_1\left\{\xi_{m,k}^{p,l} - \varphi_{m,k}^{p,l}\right\} + a_2\rho_2\left\{\delta_m^{l} - \varphi_{m,k}^{p,l}\right\} \tag{6}$$

where $\bar{\delta} = \arg\left(\max_{c=1,\dots,C}\left[\Psi\{\mathbf{w}(\bar{\gamma}_c)\}\right]\right)$; ρ_1 and ρ_2 are two positive random numbers drawn from a uniform distribution with a predefined upper limit often set so that $\rho_1 + \rho_2 = 4.0$; a_1 and a_2 are constants called *cognition* and *social* acceleration [7], respectively. Moreover, χ is the inertial weight [8].

Step 5 - Position updating. The particle position is then updated as follows

$$\varphi_{m,k}^{p,l} = \begin{cases} 1 & if \;\; \rho_{m,k}^{p,l} < \left(1 + e^{-v_{m,k}^{p,l}}\right)^{-1} \\ 0 & otherwise \end{cases}. \tag{4}$$

Then go to *Step 2*.

Numerical Assessment and Comparative Analysis

The proposed approach has been evaluated by considering a planar array of elliptical geometry ($M = 160$) shown in Fig. 1(*a*) and working in a realistic scenario characterized by a background Gaussian noise of 30 *dB* below the desired signal (coming from $\theta_d = 0°$) and interferences of amplitudes 30 *dB* above the desired signal uncorrelated with each other, the desired signal, and the noise. The directions of jamming signals have been modeled as in [5]. For comparison purposes, the obtained results have been reported with those obtained with other state-of-the-art procedures: (*a*) the Applebaum's approach [1], (*b*) the Applebaum's approach with quantized phases (DPA), (*c*) the customized GAs-based strategy [6] (CGA), and (*d*) the Least-Mean-Square algorithm [2] (LMS). The array weights have been set to $\hat{w}_m = 1.0$, $m = 1,\dots,M$, while the phase coefficients have been iteratively tuned making use of digital phase shifters characterized by $L = 6$ bits as in [4]. Concerning GAs and PSO, a population of $P = M$ trial solutions has been considered and $K = 20$. The PSO control parameters have been set to: $a_1 = a_2 = 2.0$, $C = (P/10)$, and χ linearly varying from 0.9 to 0.4 over the course of the optimization run. On the other hand, the same parametric configuration chosen in [6] has been adopted for the GA-based procedure.

As a representative result of the comparative study, Fig. 1(*b*) shows the behavior of the average SINR (computed by calculating a running average over 50 past timesteps) during $T = 250$ timesteps. As can be noticed, the PSO-based approach generally outperforms other techniques since, starting from the quiescent pattern shown in Fig. 1(*c*), the PSO-based procedure is able to place nulls exactly in correspondence with interfering signals (as pictorially shown in Fig. 1(*d*) where an example of the synthesized beam patterns – computed at t=205 – is displayed), while other methodologies (without considering the optimal synthesis) generally make an error of some degrees compared with the correct position or reduce the null depth.

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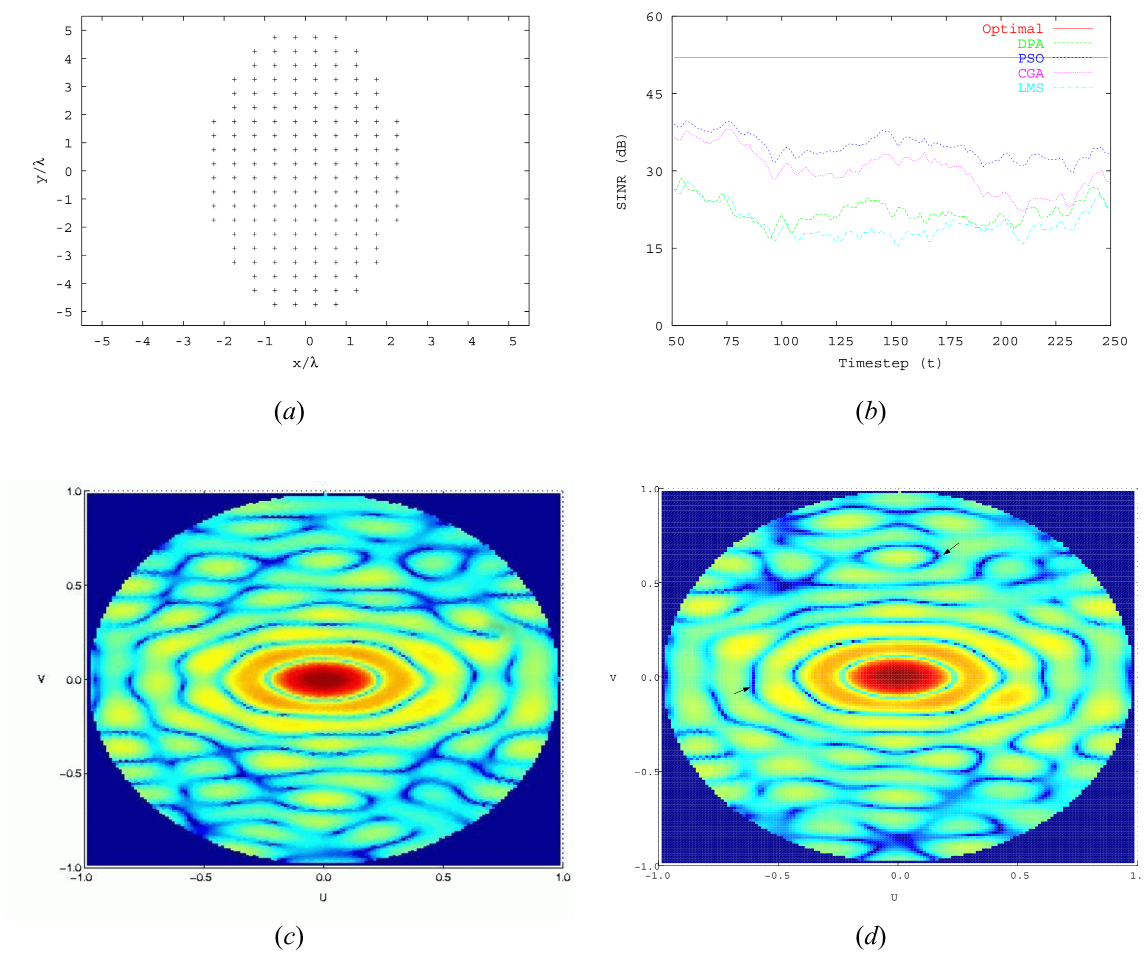

Figure 1. Eliptical array layout ($M = 160$) (*a*). (*b*) Running average of the *SINR* versus *t* obtained with the Applebaum's method (solid line), the DPA method (dashed line), the LMS approach (point-dashed line), the CGA-based technique (dotted line), and the PSO strategy (small dashed line). (c) Quiescent beam pattern. (*d*) Sample of the synthesized beam pattern ($t = 205$).