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Particle Swarm Optimization for Real-Time Adaptive Array Control

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Abstract. *This paper describes the application of the particle swarm optimizer (PSO) to the real-time adaptive antenna control. The PSO is an evolutionary procedure similar to genetic algorithms, but generally it requires only few parameters to be calibrated. Furthermore, the PSO optimizer is much easier to be implemented. To assess the performance of such a technique as compared to state-of-the-art methods, a set of selected experiments is carried out and the obtained results are deeply analyzed from a computational point of view as well as in terms of the numerical performance.*

1. INTRODUCTION

The *PSO* was developed in 1995 [1] by Eberhart and Kennedy and it simulates the behavior and distributed intelligence of swarms. Such a numerical procedure is simple and it can be applied to a wide range of electromagnetics applications [2]. Recently, *PSO* has been successfully applied to antenna design [3][4] and to inverse scattering problems [5]. This paper is aimed at assessing the effectiveness of such an approach in dealing with a complex and time-varying problem as the on-line control of adaptive array antennas. Within this framework, the *PSO* is used to adaptively tune the array weights in order to separate the desired signal from noise and interfering sources by maximizing the *SINR* at the receiver. This task is obtained maximizing the Signal-to-Interference-plus-Noise-Ratio (*SINR*).

The paper is organized as follows. In Section 2, the mathematical details of the application of the *PSO* to the real-time adaptive array control are presented. Then, a numerical assessment of the proposed procedure is presented and the results compared with those of reference methods (Sect. 3). Finally, some conclusions follows in Sect. 4.

2. MATHEMATICAL FORMULATION

Let us to consider a linear array where M isotropic elements are equally spaced with an inter-element distance equal to $d = \frac{\lambda}{2}$, λ being the free space wavelength. Under narrow-band conditions and the assumption of co-channel interference, the signal-to-noise-plus-interference ratio (*SINR*) at the receiver can be optimized by maximizing the following cost function arising from the Applebaum theory [6]

$$\phi(\bar{w}) = \frac{\left|[\alpha(\theta_d)]^t\,\overline{w}\right|^2}{[\overline{w}]^{t*}\,C_T\overline{w}} \tag{1}$$

$\alpha(\theta_d)$ being an array-column which jth element is given by $\alpha_m(\theta_d) = e^{jm\frac{2\pi}{\lambda}dsen(\theta_d)}$, $m = 0, ..., M-1$; θ_d is the incident angle indicating the impinging direction of the desired signal (*DOA*); $\overline{w} = \{w_m = c_m e^{j\varphi_m};\ m = 0, ..., M-1\}$, and C_T is the measurable desired-plus-undesired covariance matrix. By assuming constant amplitude coefficients c_m, the antenna array is controlled by continuously tuning the phase coefficients φ_m for maximizing (1) and according to a *PSO*-based procedure.

More in detail, the *PSO* is an evolutionary procedure, which operates on symbolic representations (called *particles*) of trial solutions. The algorithm considers a set of S particles (or *swarm*), $D =$

$\{P_s;\ s = 1, ..., S\}$, and it operates following social interaction rules. in order to achieve the goal of minimizing or maximizing a suitable fitness function that determines the quality of the solution of the problem at hand. Each particle P_s is located at the position $\overline{x}_s = \left\{\varphi_m^{(s)};\ m = 0, ..., M-1\right\}$ and moves in the solution space with a velocity $\overline{v}_s = \left\{v_m^{(s)};\ m = 0, ..., M-1\right\}$. Successively, iteration by iteration (k being the iteration number), the particle flies from current position $\overline{x}_s(k)$ to another position $\overline{x}_s(k+1)$ in order to effectively sample the searching space according to the following updating relation:

$$\varphi_m^{(s)}(k+1) = \varphi_m^{(s)}(k) + v_m^{(s)}(k+1) \tag{2}$$

where

$$v_m^{(s)}(k+1) = I_w v_m^{(s)}(k) + C_1 U_1 \left\{p_m^{(s)}(k) - \varphi_m^{(s)}(k)\right\} + C_2 U_2 \left\{g_m(k) - \varphi_m^{(s)}(k)\right\} \tag{3}$$

$\overline{p}_s(k)$ being the location with the highest fitness value discovered by the sth particle up till now ($\overline{p}_s(k) = arg\left\{max_{h=1,...,k}\left[\phi(\overline{x}_s(h))\right]\right\}$) and $\overline{g}(k)$ is the position in the solution space of highest global fitness ($\overline{g}(k) = arg\left\{max_{s=1,...,S}\left[\phi(\overline{p}_s(h))\right]\right\}$); U_1 and U_2 are random numbers selected between 0 and 1; C_1 and C_2 are positive constants called *acceleration coefficients*: they model the "cognition" and "social" weight of the swarm pushing each particle $\overline{x}_s(k)$ towards $\overline{p}_s(k)$ and $\overline{g}(k)$. Finally, the inertial weight I_w is a scaling factor of the velocity $\overline{v}_s(k)$.
The iterative process is repeated until $\overline{g}(K) \leq \eta$ where η is a fixed threshold and K is the iteration of the convergence of the optimization procedure.

3. NUMERICAL ASSESSMENT

In order to asses the effectiveness of the PSO-based real-time control strategy, a linear array consisting of $M = 20$ isotropic elements was considered. The weight amplitudes c_m was chosen according the Dolph-Chebyschev criterion. As far as the time-varying environment is concerned, the interference scenario was modeled according to the stochastic model described in [7]. In particular, the life-time of the interfering signals was chosen $L_t = 5$ and the Poisson frequency of the interference arrival was assumed to be equal to $1\,Hz$. Moreover, the amplitude of the interfering signals s_i, $i = 1, ..., I$ (I being the number of the interfering signals) was assumed to be $30\,dB$ above the desired signal s_d. Such a reference signal was considered to impinge on the mechanical bore-sight of the array antenna. Finally, a background noise s_n of about $30\,dB$ below the level of s_d was added at the received signal.
As an example, Fig. 1 gives a representative plot of the stochastic interference scenario by showing the distribution of the angles of arrival of the interfering signals during the iterative process. Concerning the PSO parameters, the following values was heuristically determined: $S = 40$ (*swarm dimension*), $C1 = C2 = 2.0$ (*acceleration terms*), and the constant inertial weight equal to $I_w = 0.4$. For comparison purposed, the same scenario was deal with other state-of-the-art control methods in order to point out the advantages and possible limitations of the proposed approach. Within such a framework, the optimal theoretical strategy or the optimal Applebaum's methods [6] as well as a deterministic procedure based on the least mean square error criterion (LMS) [8] was taken into account. Moreover, for completeness, a modified version of a Genetic Algorithm, called *Learned Real-Time Genetic Algorithm* ($LRTGA$) and detailed in [9], was considered, as well.

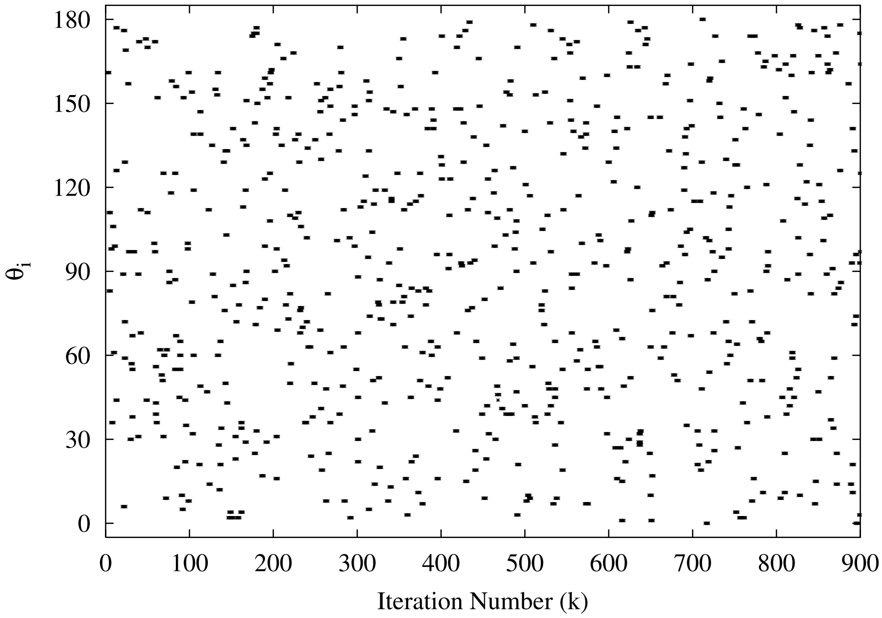

Figure 1. Angles of arrival (θ_i, $i = 1, ..., I$) of the interfering signals versus the iteration number k.

The strategy based on the PSO generally outperformed other methodologies in terms of convergence rate as well as robustness to the noise-interferences. In terms of empirical tuning of meta-heuristic parameters, the calibration phase required a very short time as compared to that of other stochastic procedures being the number of control parameters very limited.

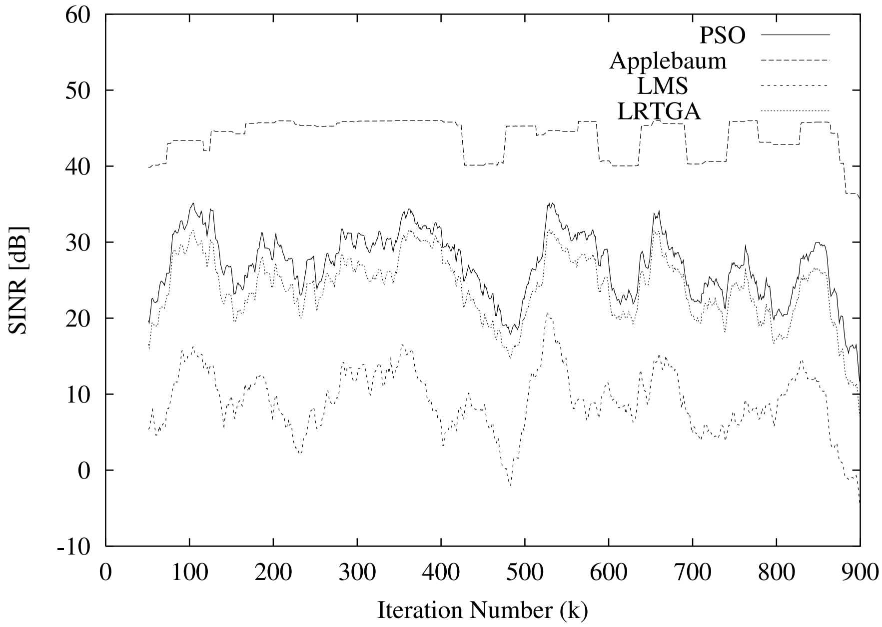

Figure 2. Comparisons of the behavior of the SINR obtained by using different kinds of minimization procedures.

As a representative example, Figure 2 shows the behavior of the $SINR$ during the iterative process for different strategies. It can be observed that on average the performance of the PSO turns out to be greater of about $4\,dB$ than that of the best numerical method (namely the $LRTGA$).

4. CONCLUSIONS

An optimization method based on the Particle Swarm Optimizer has been applied to the real-time control of linear antenna arrays. By means of some preliminary numerical experiments, the effectiveness of the proposed approach has been pointed out and the achieved results have been compared with reference closed-form solutions as well as with other reference numerical methods. Future work will aimed at extending the proposed procedure to the adaptive control of various array geometries and to further assess the ability of the control strategy in dealing with more realistic environments.

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