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Immune-inspired Dynamic Optimization for Blind Spatial Equalization in Undermodeled Channels

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***Abstract*—In this work, we propose an evolutionary-like approach to the problem of blind adaptive spatial filtering that is based on the decision-directed criterion and on the dopt-aiNet, an artificial immune network conceived to perform multimodal search in dynamic environments. The proposal was tested under static and time-varying undermodeled channel models, and, in all cases, its ability to find and track a solution close to the Wiener global optimum was attested. The obtained results reveal that the dopt-aiNet may decisively enhance the performance of adaptive arrays in scenarios built from elements that are representative of some aspects of real-world communication systems.**

I. Introduction

IN many real-world applications, it is of particular relevance to separate signals associated with multiple users of a given systemic resource or to restore an information signal corrupted by the presence of interferers and noise. The fulfillment of these objectives depends on the availability of a number of distinct measurements, the role of which is to engender some sort of *diversity*. In purely spatial problems, this diversity emerges from the placing of an adequate number of sensors in different positions, since the physical properties of the environment will be responsible, as a rule, for combining the signals in a manner that will tend to be different for each element. Therefore, it might be possible, by processing the sensor outputs in a rational way, either to model the medium through which the messages are sent or to extract the subjacent sources of information.

In digital communications, problems of this kind are very common due to the pervasive requirement that several users share limited resources in an orderly way, i.e., without degenerating into a noxious interference process. A widespread solution to achieve this aim is the use of an *adaptive antenna array*, a device formed by a set of antennas ordered in a chosen geometry (usually linear or planar) and endowed with adjustable gains, as shown in Fig. 1.

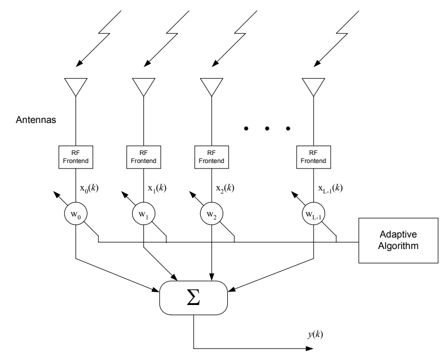

Fig. 1. Adaptive antenna array

It can be said that the array works as a *spatial filter*, because an adequate choice of its parameters can either amplify or cancel signals coming from distinct directions. Consequently, the structure is able to separate signals of interest from undesirable interferers, exactly in the spirit of the problem we posed.

Albeit the described array is a potentially useful tool, a crucial issue is yet to be addressed: how can its parameters be adjusted in order to produce a certain desired response or behavior? An immediate possibility is, given the directions of arrival (DOAs) of all signals, build, in conformity with some mathematical criterion, a response that conveniently captures or cancels each one of them. This is, for instance, the essence of the Frost [1] and Applebaum [2] criteria. Another possibility is to formulate a criterion in which a desired signal is used to adapt the array parameters via a conventional mean-square error (MSE) cost function, which is, in simple terms, the *modus operandi* that characterizes the Wiener approach [3]. Both strategies, nevertheless, share a crucial inconvenient property: they are essentially dependent on information that is not necessarily available at the receiver. In some cases, it can be impossible or undesirable from a systemic point of view to have access to information that is not necessarily available at the receiver.

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Therefore, it is quite appealing to consider the possibility of employing an adaptive criterion that depends exclusively on generic statistic features, being, therefore, unsupervised. Fortunately enough, criteria of this kind exist and have been applied to the spatial filtering problem with success [4]. Perhaps the most widely used class of blind criteria is that of the Bussgang algorithms [5], of which the decision-directed (DD) and the constant modulus (CM) techniques are emblematic representatives.

Although Bussgang techniques are undeniably solid paradigms for spatial filtering, their use, nevertheless, requires attention, particularly in an *undermodeled case*, in which there are more source signals than elements of the antenna array. In this case, the involved cost functions will possess local minima, i.e., some source signals will be more easily extracted than others and, moreover, some signals may not be recoverable at all. This means that the optimization problem associated with the spatial filtering task will be multimodal in essence, wherefore conventional gradient-based optimization algorithms may become inappropriate if optimal performance is required.

In addition to the problem of multimodality, in mobile communications there is another practical difficulty: the channel may be time-varying, i.e., the characteristics of the signals that arrive at the spatial filter may change with time. This may occur, for instance, due to the existence of *fading* [6], a phenomenon that may significantly reduce the amplitude of some or even all of the incident signals.

In this work, we propose the use of an artificial immune network, called *dopt-aiNet* [7], to tackle these two problems. The dopt-aiNet is particularly suited to this task for two reasons: (*i*) it is an optimization tool conceived to solve highly multimodal problems; and (*ii*) it contains mechanisms devised to work with time-varying cost functions. Thus, the joint employment of the dopt-aiNet and a Bussgang cost function may produce a filtering paradigm in which the best solution is attained and tracked in an undermodeled and time-varying scenario. The performance of this proposal will be firstly tested in terms of global convergence in a static environment and, afterwards, a dynamic element will be introduced to allow the tracking capabilities of the dopt-aiNet to be put to the test.

The work is organized as follows. In section II, we present the fundamentals of the spatial filtering problem together with an explanation of the proposed approach. In section III, the dopt-aiNet is explained in detail, while, in section IV, the results are presented. Finally section V contains the conclusions and final remarks.

II. Blind Spatial Filtering

In accordance with the description provided by Fig. 1, the output of an antenna array can be written as a linear combination of the signals captured by its *N* elements:

$$y(n) = \sum_{k=0}^{N-1} w_k x_k(n) \quad (1)$$

where $x_k(n)$ is the signal captured by the *k*-th antenna of the array and w_k is the complex gain associated therewith. Equation (1) can be rewritten as

$$y(n) = \mathbf{w}^T \mathbf{x}(n) \quad (2)$$

where $\mathbf{w} = [w_0\ w_1\ \ldots\ w_{N-1}]^T$ is the *parameter vector* of the array, $\mathbf{x}(n) = [x_0(n)\ x_1(n)\ \ldots\ x_{N-1}(n)]^T$ is its *input vector* and $(.)^T$ is the transpose operator. In a purely spatial environment, the input vector can be related to the transmitted information signals $\mathbf{s}(n)$, to which we shall also refer as *sources*, through the expression

$$\mathbf{x}(n) = \mathbf{H}\mathbf{s}(n) \quad (3)$$

where

$$\mathbf{H} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \exp(-j\Phi_1) & \exp(-j\Phi_2) & \cdots & \exp(-j\Phi_M) \\ \vdots & \vdots & \ddots & \vdots \\ \exp[-j(N-1)\Phi_1] & \exp[-j(N-1)\Phi_2] & \vdots & \exp[-j(N-1)\Phi_M] \end{bmatrix} \quad (4)$$

and

$$\Phi_i = 2\pi \frac{d}{\lambda} \sin(\theta_i) \quad (5)$$

where *d* is the distance between the elements of the array, λ is the wavelength of the carrier used to modulate the transmitted signals and θ_i is the direction of arrival of the *i*-th signal; the vector

$$\mathbf{s}(n) = \begin{bmatrix} s_1(n) \\ s_2(n) \\ \vdots \\ s_M(n) \end{bmatrix} \quad (6)$$

contains samples of all M sources taken at instant *n*. Careful attention should be paid to the $N \times M$ matrix $\mathbf{H}$; its *i*-th column corresponds to the so-called *steering vector* associated with the DOA of the *i*-th source signal. The steering vector is a direct expression of the manner whereby the disposition of the antennas in the array (in this work, we will always assume that this disposition is linear and uniform) defines the time of propagation between different antennas and the phase delay it originates.

A crucial problem in the above context is that of finding the parameter vector $\mathbf{w}$ which propitiates the recovery of a given source $s_i(n)$. As we have outlined in the introduction, there are basically two classes of techniques capable of achieving this aim: that of supervised techniques, of which the Wiener criterion is the main representative, and that of blind techniques, among which we highlight the decision-directed (DD) criterion.

A. The Wiener Approach

The Wiener criterion, which can be considered the cornerstone of the optimal filtering theory, is founded on a measure of mean-square error between a desired signal, d(n), and the actual output of the array, y(n). The cost function that incorporates this idea is [3]:

$$J_W = E\left[|d(n) - y(n)|^2\right] \quad (7)$$

being E[.] the statistical expectation. It can be demonstrated that the parameter vector which minimizes J_W is

$$\mathbf{w_o} = \mathbf{R}^{-1}\mathbf{p} \quad (8)$$

the so-called *Wiener solution*. In (8),

$$\mathbf{R} = E[\mathbf{x}(n)\mathbf{x}^H(n)] \quad (9)$$

is the correlation matrix, where $(.)^H$ denotes the Hermitian transpose, and

$$\mathbf{p} = E[d^*(n)\mathbf{x}(n)] \quad (10)$$

is the cross-correlation vector. It is important to remark that, when the Wiener criterion is applied to a spatial filtering problem, the desired signal can be chosen to be any of the existing sources $s_i(n)$: in fact, there will be *M* possible Wiener solutions.

When $N \geq M$, i.e., in the case in which there is a number of elements in the array greater than or equal to the number of transmitted signals, it is possible to choose a set of parameter vectors that allows a *perfect recovery* of all existing sources. Therefore, under these circumstances, all Wiener solutions will be associated with a null residual mean-square error. On the other hand, when $N < M$, that is, in an undermodeled case, the multiple Wiener solutions will no longer be equivalent; as a matter of fact, some solutions will be better (in the MSE sense) than others, and it is possible that some sources be irrecoverable. This reveals that an undermodeled scenario gives rise to a multimodal Wiener filtering problem, a fact that will be of great importance in our subsequent reasoning.

B. *The Decision-Directed Criterion*

The Wiener approach, a theoretical construct of undeniable solidity, possesses, notwithstanding, a feature that can make its application rather difficult in some practical cases: *the need for a reference signal*. This very feature is behind the proposal of *blind* or *unsupervised* techniques, the objective of which is to employ statistical information instead of pilot samples as the main reference in the optimization task.

A member of the class of Bussgang techniques will be of particular interest to us in this work: the decision-directed (DD) criterion, whose cost function is [3][5]:

$$J_{DD} = E\{\mathrm{dec}[y(n)] - y(n)\}^2 \quad (11)$$

where dec(.) represents the mapping performed by the decision-device of the communication system. The rationale of the DD cost function is to replace the unavailable pilot signal with the estimate generated by the decision-device, whose aim is to recover the "digital character" of the signal processed at the receiver. J_{DD} is known to be a multimodal function with two classes of minima: "good" minima, which correspond to Wiener solutions capable of perfectly restoring one of the sources, and spurious minima, which are solutions that do not allow the proper recovery of any source [5].

The "good" Wiener-like solutions, which are the only configurations of practical value, emerge when the estimate produced by the decision-device is identical to one of the sources, i.e.,

$$\mathrm{dec}[y(n)] = s_i(n) \quad (12)$$

When $N \geq M$, all solutions of this kind are ideal Wiener solutions; in such case, $J_{DD} = J_W = 0$. Thus, the DD cost function will be formed by these minima and some spurious minima for which $J_{DD} > 0$ – we do already envisage a scenario in which a gradient-based technique may lead to unsatisfactory performance.

However, an even more complex scenario takes place when $N < M$. Under this condition, some of the Wiener solutions, albeit not ideal, appear in the DD cost function as "good minima". Moreover, once more, the class of spurious minima, which are worse than the "good" minima, will be present. Therefore, we have a scenario in which there are multiple minima and only one Wiener-like solution is globally optimal.

The problem of spatial filtering generates a particularly challenging optimization task in the undermodeled case, and, as a consequence, any global search requirement will be more stringent therein. Furthermore, this case has a considerable practical appeal, as a methodology that is robust to undermodeling should work well in a great number of cases of interest.

C. *The Proposed Approach*

Let us consider for a while the steps we have taken so far. After having defined the necessary models, we presented the Wiener criterion, which straightforwardly revealed the characteristics of the spatial problem: it is multimodal, since there are several sources that can be recovered and, in addition to that, when there are more sources than sensors, each solution is, as a rule, associated with a distinct MSE. This state of things is also manifest in the decision-directed criterion, which contains spurious solutions that, in a certain sense, "enhance the multimodality" of the spatial filtering problem.

We may thus infer from this initial explanation that an approach devised to ally robustness to optimal performance in generic environments would have to possess the following features:

1) To be unsupervised, as a wide scope of application is highly desirable.
2) To contain global search mechanisms, since the blind spatial filtering problem can be, particularly if undermodeled scenarios are considered, highly multimodal.

The accomplishment of these requirements certainly generates an efficient methodology, but, if we want to increase significantly its applicability to problems of a more realistic nature, it is desirable to include a third feature:

3) The subjacent global search procedure must be robust to changes in the cost function.

Such a demand can be justified in practical terms: in many communication systems, the characteristics of the medium responsible for conveying the information signals may possess a strongly variant character [6]. Another important issue arises, for instance, in mobile communications: it is likely that the number of sources vary in time, which would modify the signal model described in Eq. (3). These considerations lead us to a conclusion: any viable approach should be prepared to deal with time-varying systems and models [8].

In this work, we propose a formulation that is potentially able to meet the entirety of these demands. The proposal is founded on two pillars: a) the DD cost function, which, as discussed above, contains, *inter alia*, the best available Wiener solutions; and b) the *dopt-aiNet* [7] – an artificial immune system capable of performing global search with great efficiency and, moreover, endowed with mechanisms devised to enhance its performance in time-varying problems. Our goal is to obtain a methodology that is efficient in static and dynamic environments and that performs well in terms of global convergence in undermodeled scenarios. However, before we proceed to a detailed performance analysis, let us study in detail the dopt-aiNet.

III. AN ARTIFICIAL IMMUNE NETWORK FOR OPTIMIZATION IN DYNAMIC ENVIRONMENTS

The field of research of *artificial immune systems* (AIS) [9] has followed the tendency of evolutionary algorithms and devoted major efforts to the proposal and validation of robust techniques for solving multimodal and dynamic optimization problems. This can be justified on two bases: (*i*) the importance of the application domain; and (*ii*) the fact that the vertebrate immune system, which inspired the development of AIS, is very efficient in adapting itself to dynamic environments. Disease-causing agents continually change their shapes, forms of attack and many other attributes aiming at invading the organism. Based on some of the biological immune mechanisms of host defense, simple evolutionary-like immune algorithms have been devised and studied in the context of global, multimodal and dynamic optimization [7][10][11][12].

In de França et al. [7], the optimization version of an immune network model (opt-aiNet) was improved and extended to deal with multimodal dynamic environments. The modified algorithm, named dopt-aiNet (opt-aiNet for dynamic environments) is depicted in Fig. 2.

The algorithm starts by initializing a random population of cells containing $N_{initial}$ solution vectors of dimension D (each vector contains the real and imaginary part of the N coefficients of the array; thus, D = 2N) and an initial rank number that will be explained later. Inside the main loop, every cell is evaluated and then each one generates Nc clones (exact copies) of themselves.

```
Function [C] = dopt-aiNet(Nc,range,σs,f,max_cells)
    C = random(range)
    While stopping criterion is not met do
        fit = f(C)
        C' = clone(C,Nc)
        C' = mutate(C',f)
        C = select_clones(C',f)
        C' = clone(C,Nc)
        C' = one-dimensional(C',f)
        C = select_clones(C',f)
        C = gene_duplication(C,f)
        For each cell c from C do,
            If c improved,
                c.rank = c.rank + 1
            Else
                c.rank = c.rank – 1
            End
            If c.rank == 0,
                Mem = [Mem, c]
            End
        End
        Avg = average(f(C))
        If the average error does not stagnate
            return to the beginning of the loop
        else
            cell_line_suppress(C, σs)
            C = [C; random(range)]
        End
        If size(C) > max_cells,
            suppress_fitness(C)
        End
    End
End
```

Fig. 2. The dopt-aiNet algorithm

For every clone, a Gaussian random mutation is performed:

$$c' = c + \alpha G \qquad (13)$$

where G is a vector composed of random elements generated by a Gaussian distribution with zero mean and standard deviation $\sigma = 1$. Additionally, α represents a step-size calculated via a line search algorithm called "golden section" [13], which is, in theory, capable of finding a value close to the optimal one.

Subsequently, each cell (or solution vector) is improved with two other mutations introduced in [7]: the *one-dimensional mutation* and the *gene duplication mutation*. The one-dimensional mutation treats one direction at a time, thus making a finer search on the area surrounding the cell. The directions are defined by a diagonal matrix with a Gaussian random number on its non-zero elements and the unitary vectors +**1** (vector with all elements equal to 1) and **–1**. The gene duplication mutation replaces the current value of a given element in the cell by the value of another randomly selected element if this action improves the fitness. When this process ends, the final vector is a new cell that will be introduced in the cell population.

After the mutation procedures, each cell will have an increase or decrease on its rank value depending on whether it has been improved or not, and, when this rank reaches zero, this cell will be moved to a separate population called "Memory Population" and will remain there only for the suppression process and the final results.

At this point, the average results of the present and previous iteration are used to measure the stagnation of the algorithm, and, if it is still improving its results, the process is repeated from the beginning of the loop. Otherwise, the cell similarities are calculated and those which present a high similarity are suppressed. After suppression, new cells are randomly created and introduced in the population. *The Cell Line Suppression algorithm*, introduced and better described in [7], is based on the fact that cells belonging to the same local optimum should be detected and submitted to suppression, so that only the best one remains. In the maximization problem illustrated in Fig. 3, the points P_1 and P_2 are associated with the same local optimum, while P_3 is associated with a different one and must remain after the suppression phase. P_1 will be eliminated even receiving a better individual evaluation when compared to P_3.

The notation "line suppression" is motivated by the initiative of estimating the relative position of every pair of points by comparing the functional values at intermediate points with the corresponding values produced by a straight line between the points under analysis. Indeed, returning to the illustrative example of Fig. 3, the straight line connecting P_1 and P_3 and the straight line connecting P_2 and P_3 have nothing to do with the original function, which can easily be detected by sampling intermediate points. On the other hand, the straight line connecting P_1 and P_2 will be very close to the original function, and this fact can be used to infer that they belong to the same local optimum.

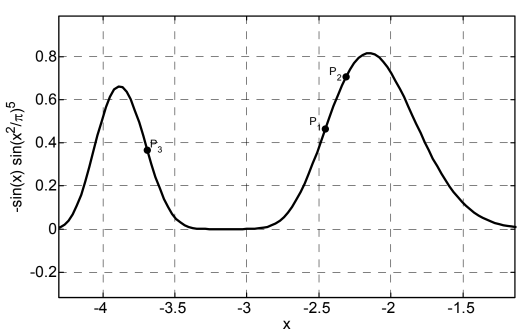

Fig. 3. Illustrative example of the Cell Line Suppression algorithm in a multimodal scenario.

Finally, if the population size grows enough to reach a certain maximum number of cells, the worst individuals will be removed from the population for the sake of performance.

IV. Simulation Results and Discussion

Simulations under two different scenarios were carried out in order to evaluate the performance of the proposed approach to the problem of spatial filtering using a linear adaptive antenna array. The first scenario (sc1) is characterized by the presence of signals (Sigs. 1 to 4) coming from angles with elevation of 30°, 0°, 45°, and 60°. The second one (sc2), a critical scenario due to the proximity of the involved directions of arrival, is formed by signals coming from elevation angles of 30°, 35°, 40°, 45° and 50° (Sigs. 1 to 5). Firstly, both scenarios will be analyzed in a context in which the channel model is static; afterwards, they will be modified to emulate time-varying environments, in which the desired signals have their amplitudes altered during the observation time.

In all cases, the linear antenna array is formed by isotropic elements uniformly spaced with half of the wavelength, and there are more incoming signals than elements in the array. This case, as discussed in Section II, is 'undermodeled', and it is important to remark that it poses a difficult problem to the adaptive algorithms classically utilized in spatial filtering, insofar as global convergence is concerned. In both instances (static and dynamic) of the first scenario, the array has 3 elements, while, in the second scenario, 4 elements were employed.

In all simulations, the signal-to-noise ratio (SNR) is set to 20dB, and we assume that the transmitted samples are i.i.d. (independent identically distributed) and belong to a 2-PAM (Phase-Amplitude Modulation) constellation (−1/+1) with unit power. The decision-directed (DD) cost function is estimated by means of a time window composed of 50 consecutive samples of the received signal. Other important parameters are shown in Table I.

TABLE I
General Settings

Parameters	Static Scenario	Dynamic Scenario
Initial population	10	10
Number of clones per mutation	10	10
Maximum number of cells in the population	80	80
Iterations	650(sc1) and 450(sc2)	650
Number of runs	20	1

Since, in this work, all the transmitters are assumed to produce signals with identical amplitude, any variation in their gain could be related to static attenuation or fluctuations due to fading, both of which are typical phenomena in communication systems [6]. In the static channel model that forms the basis of the first scenario, all signals have unit gain, except for the signal whose DOA is 45°, the amplitude of which is 0.6. In the static model of the second scenario, all signals have unit gain, except for the one associated with the DOA of 60°, whose gain is 0.4.

The time-varying channel model was built from abrupt amplitude variations. In the first scenario, they occur every 150 iterations (starting from n = 100), and, in sc2, after 250 iterations and, subsequently, every 150 iterations. The time evolution of the amplitudes is given in Tables II and III. In accordance with the link between DD and Wiener criteria, discussed in Section II, we evaluate the performance of the proposed strategy having the best Wiener solution as the main reference.

TABLE II
TIME EVOLUTION OF THE AMPLITUDES – FIRST SCENARIO

Sig	Angle	Amplitude 1 – 100	Amplitude 101 – 250	Amplitude 251-400	Amplitude 401-end
1	30°	1	0.9	0.85	0.8
2	0°	1	0.6	0.2	0.1
3	45°	0.6	0.8	0.92	1
4	60°	1	1	1	1

The performance of the optimization algorithm will be assessed in three different ways: 1) by observing the time evolution of the gain of the spatial filter whose parameters are those associated with the best individual for all DOAs; 2) by comparing the radiation pattern produced by the best individual with that originated by the best Wiener solution; and 3) by considering the convergence profile of the DD cost during the course of the simulation.

TABLE III
TIME EVOLUTION OF THE AMPLITUDES – SECOND SCENARIO

Sig	Angle	Amplitude 1 – 250	Amplitude 251-400	Amplitude 401-end
1	30°	1	0.4	0.1
2	35°	1	0.8	0.7
3	40°	1	0.7	0.6
4	45°	1	0.4	0.4
5	50°	0.4	1	1

A. First Scenario – Static Case

Firstly, let us analyze the performance of the dopt-aiNet in the static version of the first scenario. In this case, it is possible to demonstrate that the best Wiener solution is originated by the choice of Sig. 2 as the desired signal. We ran the dopt-aiNet algorithm 20 times and, in all trials, the best individual produced a configuration very close to the optimal. In order to illustrate this assertion, let us study in more detail one particular run, which we consider to be representative of the average behavior of the optimization tool. In Fig. 4, we show the time evolution of the gains associated with the best individual of the population in the DOAs of the four sources.

As Fig. 4 reveals, a configuration close to the optimal was attained in less than 25 iterations: the best individual captures Sig. 2 with a gain close to unity and significantly attenuates the other sources. Fig. 5 contains the radiation patterns generated with the best individual and with the optimal Wiener solution. In both cases, Sig 2 is adequately recovered and the other signals are almost completely cancelled; furthermore, the similarity between these curves attests the efficacy of the optimization process.

In Fig. 6, we present the evolution of the decision-directed (DD) cost of the best individual in an average of 20 runs. This figure confirms the convergence profile delineated by Fig. 4 and, moreover, reveals that the quality of the solution attained after the transients is similar to that of the best Wiener solution (the optimal Wiener cost is, in this case, equal to 0.0038). Therefore, we conclude that the dopt-aiNet performed very well in this initial test.

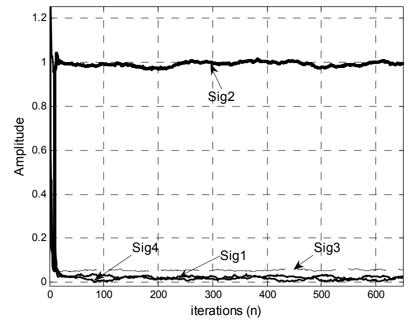

Fig. 4 Time evolution of the spatial response– First scenario (static)

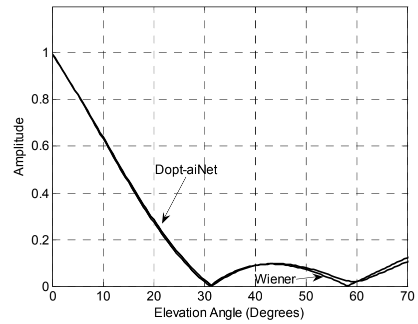

Fig. 5 Radiation patterns – First scenario (static)

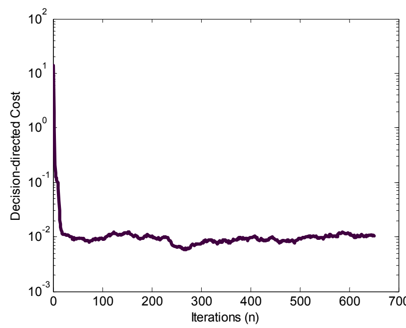

Fig. 6. Evolution of the DD cost – First scenario (static)

B. Second Scenario – Static Case

Now, let us analyze the simulation results obtained in the static version of the second scenario. In this case, the optimal Wiener solution is the one that corresponds to a situation in which Sig. 1 is the desired signal. Once more, in all 20 runs the performance of the best individual generated by dopt-aiNet was close to the optimal. In Fig. 7, the time evolution of the best individual in a typical simulation is shown; it is noticeable that the proximity of the DOAs gave rise to a harder optimization task: the ideal configuration is attained only after 100 iterations.

In Fig. 8, the radiation patterns of the best individual and of the optimal Wiener solution are presented. They are similar, but not as similar as those presented in Fig. 5; this discrepancy has not precluded the capture of Sig. 1 (that was done in the correct direction but with smaller amplitude) and, moreover, is justifiable in the light of the closeness between the DOAs. It is also important to observe the pattern produced by the dopt-aiNet in the angles associated with the others signals and compare it with the one generated by the Wiener solution in the same directions. Only at 35º and 45º the dopt-aiNet produces an amplitude that is higher than the Wiener amplitude, but the values are, notwithstanding, such that the signals are properly cancelled. It is relevant to keep in mind that, in this situation, restriction-based methods such as the one proposed by Frost [1] would not be practical due to undermodeling.

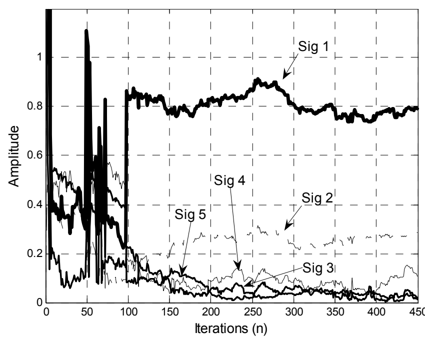

Fig. 7. Time evolution of the spatial response– Second scenario (static)

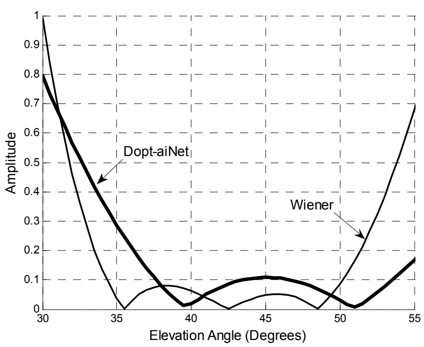

Fig. 8 Radiation patterns – Second scenario (static)

At last, in Fig. 9, we present the evolution of the DD cost in an average of 20 runs. The curve confirms the convergence behavior anticipated by Fig. 7 and, moreover, its steady-state behavior confirms our analysis of Fig. 8.

C. First scenario – Dynamic Case

The static analysis we have just carried out confirmed that the dopt-aiNet is an optimization tool capable of performing multimodal search with very high global convergence rates. Now, we will attempt to verify if its efficiency is preserved in the time-varying scenarios described in Tables II (first scenario) and III (second scenario). It is important to remark that, in this dynamic stage of our analysis, we will not make use of multiple runs to assess the performance of the optimization tool.

Firstly, let us assume that the communication channel obeys the model described in Table II. The amplitudes are supposed to vary stepwise. In order to facilitate our study, we present, in Table IV, the MSE of the best Wiener solution in all regions of the time-varying model, as well as the desired signal that generates them.

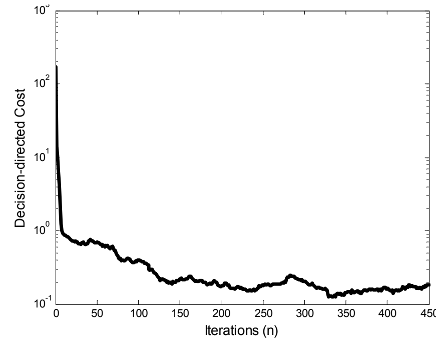

Fig. 9. Evolution of the DD cost – Second scenario (static)

TABLE IV
MSE OF THE BEST WIENER SOLUTION-FIRST SCENARIO

Iteration	1-100	101-250	251-400	401-end
MSE-Wiener	0.0038	0.0158	0.1285	0.0932
Captured Sig	2	2	4	4

In Fig. 10, we present the time evolution of the gains associated with the best individual. It is interesting to notice how the dopt-aiNet responds promptly and adequately to the variations: the algorithm converges in a few iterations to a situation in which the correct signal (Sig. 2) is recovered; after the first transition, the algorithm takes 50 iterations to attain, once more, a solution close to the ideal; the second transition introduces a more dramatic change – the optimal desired signal changes from Sig. 2 to Sig. 4 – but the algorithm appropriately modifies the radiation pattern of the spatial filter in no more than 20 iterations; finally, the last transition barely alters the curves. This good convergence behavior is confirmed by Fig. 11, which shows the evolution of the DD cost. This figure also reflects the differences between the residual MSEs shown in Table IV.

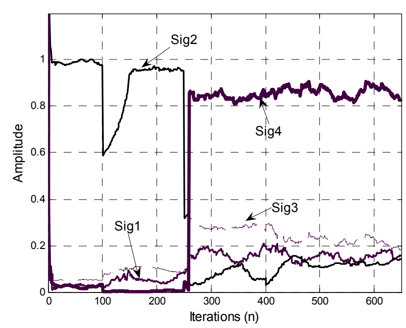

Fig. 10 Time evolution of the spatial response– First scenario (dynamic)

D. Second Scenario – Dynamic Case

In Fig. 12, we have the evolution of the response of the adaptive array when the communication channel obeys the model described in Table III. Once more, the dopt-aiNet had a good performance: after an initial convergence similar to that presented in Fig. 8, the expected signals were properly recovered. The characteristics of the best Wiener solutions are as shown in Table V. Notice that, in accordance with the ideal case, Sig. 1 and then Sig. 5 are recovered in their respective intervals.

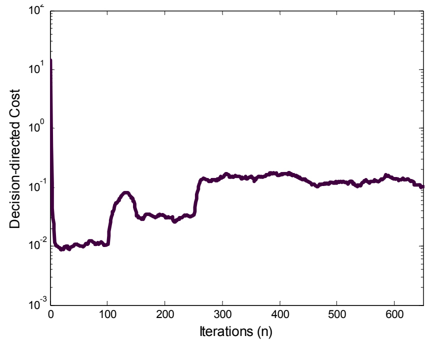

Fig. 11 Evolution of the DD cost – First scenario (dynamic)

TABLE V
MSE OF THE BEST WIENER SOLUTION-SECOND SCENARIO

Iteration	1-250	251-400	401-end
MSE-Wiener	0.0088	0.0116	0.0052
Captured Sig	1	5	5

The first transition, which modifies the desired signal, generates a transient of approximately 30 iterations, after which the algorithm captures Sig. 5 with a gain close to unity and attempts to cancel the other signals; when the second transition takes place, the algorithm demands approximately 50 iterations to converge again to a good solution. Fig. 13 reveals that the DD cost is almost constantly kept in a low level.

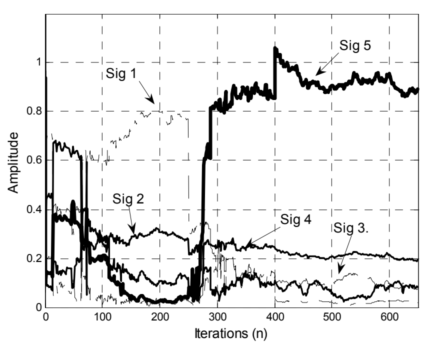

Fig. 12 Time evolution of the spatial response– Second scenario (dynamic)

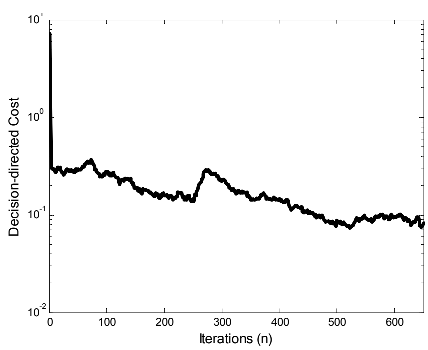

Fig. 13. Evolution of the DD cost – Second scenario (dynamic)

V. CONCLUDING REMARKS

The objective of this work was to present a new evolutionary-like approach to the problem of adapting the parameters of an antenna array in undermodeled and time-varying scenarios. In order to achieve this aim, we proposed the use of the DD criterion and of a multimodal search tool specially tailored to operate under dynamic cost functions – the dopt-aiNet. A conjunction of this sort is very promising, since it allies an unsupervised formulation to an algorithm that is capable of avoiding local minima. Firstly, the proposal was tested in two distinct static scenarios, and, in both cases, a solution with characteristics similar to those of the optimal Wiener solution was obtained in all runs, indicating the solidity of the search technique. In a second stage, the performance of the dopt-aiNet was studied under two dynamic channel models and, in both cases, the immune-inspired algorithm proved itself capable of allying search potential to a very satisfactory tracking ability. Therefore, we are led to conclude that the approach is sound and can be useful in practical applications in which optimal performance is a stringent requirement; on the other hand, it is important to remark that the computational cost of the dopt-aiNet is significantly higher than the cost of a gradient-based algorithm, which establishes a compromise that must be taken into account by the system engineer.

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