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Blind Search for Optimal Wiener Equalizers Using an Artificial Immune Network Model

Romis Ribeiro de Faissol Attux
DSPCOM, DECOM, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: romisri@decom.fee.unicamp.br

Murilo Bellezoni Loiola
DSPCOM, DECOM, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: mloiola@decom.fee.unicamp.br

Ricardo Suyama
DSPCOM, DECOM, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: rsuyama@decom.fee.unicamp.br

Leandro Nunes de Castro
DCA, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: lnunes@dca.fee.unicamp.br

Fernando José Von Zuben
DCA, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: vonzuben@dca.fee.unicamp.br

João Marcos Travassos Romano
DSPCOM, DECOM, FEEC, State University of Campinas, C.P. 6101, Campinas, SP, Cep 13083-970, Brazil
Email: romano@decom.fee.unicamp.br

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This work proposes a framework to determine the optimal Wiener equalizer by using an artificial immune network model together with the constant modulus (CM) cost function. This study was primarily motivated by recent theoretical results concerning the CM criterion and its relation to the Wiener approach. The proposed immune-based technique was tested under different channel models and filter orders, and benchmarked against a procedure using a genetic algorithm with niching. The results demonstrated that the proposed strategy has a clear superiority when compared with the more traditional technique. The proposed algorithm presents interesting features from the perspective of multimodal search, being capable of determining the optimal Wiener equalizer in most runs for all tested channels.

Keywords and phrases: blind equalization, constant modulus algorithm, evolutionary computation, artificial immune systems, immune network model.

1. INTRODUCTION

The constant modulus (CM) criterion [1, 2, 3] is a broadly studied blind equalization technique. The last 20 years have seen the proposal of many relevant works scrutinizing the basis of the CM criterion and its relation to other criteria.

These works pointed out two aspects that deserve to be highlighted [3, 4]:

(1) the CM cost function is multimodal;
(2) there is an intimate relationship between CM minima and some Wiener optima.

In particular, the literature indicates a one-to-one relationship between the best Wiener solutions and the minima of the CM criterion.

From these considerations, it is possible to make a strong claim: *if one can determine the CM global minima, then the best possible Wiener receiver can also be evaluated.*

This suggestion opens an exciting perspective: *the possibility of obtaining the best equalizer (in the mean square error sense) without a desired signal, that is, by using a blind or unsupervised search strategy*. To achieve this goal, it is necessary to propose a method capable of locating, over a set of local minima, the best CM minimum in most of the runs performed by the algorithm. Evolutionary algorithms (EAs) are particularly suitable to determine the optimal Wiener equalizer because they present a high capability of performing an exploratory search when a priori knowledge is not available.

This paper proposes to apply the optimization version of an artificial immune network model, named opt-aiNet [5], to the problem of determining the optimal Wiener solution. By combining the CM criterion with the opt-aiNet algorithm, this paper introduces a novel framework (CM + opt-aiNet) to obtain the optimal receiver.

Different channel models and filter orders were used to evaluate the potential for finding the global Wiener minimum. In some cases, the proposed strategy was compared with an approach based on genetic algorithms with niching [6], which proved to be a valuable tool to solve this problem, and thus benchmark the proposed technique. In all cases, the obtained results validated the framework, demonstrating that it is possible to find the optimal equalizer for a given channel by using a powerful blind search technique.

The paper is organized as follows. Section 2 presents some theoretical considerations on the equivalence between the CM minima and Wiener solutions, a cornerstone of this work. Section 3 introduces the immunologically inspired algorithm, named opt-aiNet, and places it in the context of other search techniques, with particular emphasis on EAs. Section 4 presents the simulation results and discusses the performance of the algorithm by comparing it with a genetic algorithm with niching. The final remarks and future trends are presented in Section 5.

2. ADAPTIVE CRITERIA: THEORETICAL BASIS

The main goal of communications engineering is to provide adequate message interchange, through a certain channel, between a transmitter and a receiver. Nevertheless, the channels introduce distortion in the transmitted message, what usually leads to severe degradation. A device named *equalizer* filters the received signal in order to recover the desired information. Figure 1 depicts the schematic channel and equalizer representation in a communication system, together with their respective input and output signals.

From Figure 1, it can be inferred that the main goal of the equalizer is to obtain an output signal as similar as possible to the transmitted signal, except for a gain K and a delay d, that is,

$$y(n) = K \cdot s(n-d), \tag{1}$$

which is the well-known *zero-forcing* (ZF) condition.

In most applications, the equalizer is implemented using a *finite impulse response* (FIR) filter, which is a mathematically simple and inherently stable structure. Its input-output relationship is given by

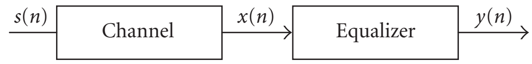

Figure 1: Elements of a communication system.

$$y(n) = \mathbf{w}^T \cdot \mathbf{x}(n), \tag{2}$$

where $\mathbf{w}$ is the equalizer coefficient vector of length L and $\mathbf{x}(n) = [x(n)x(n-1)\cdots x(n-L+1)]^T$ is the input vector.

Consequently, the central problem is to adjust the vector $\mathbf{w}$ in order to obtain a good equalization condition, that is, a condition as close as possible to the ZF (1). If it is possible to count on a priori knowledge of the channel impulse response, the task becomes purely mathematical. When this is not the case, it is necessary to determine a suitable optimization criterion.

When information about the transmitted signal is, at least for some time, at hand, it is possible to make use of the *Wiener criterion*, based on the following *mean square error* (MSE) cost function:

$$J_W = E\left\{\left[s(n-d) - y(n)\right]^2\right\}, \tag{3}$$

where d is the previously defined *equalization delay*. If this delay is known a priori, J_W has a single minimum, named the *Wiener solution*. As a rule, each Wiener solution possesses a distinct MSE. This accounts for an important assertion: *if the equalization delay is a free parameter of* (3), then J_W *has several minima (multiple local optima)*. Among these many optima, there is, usually, a single *optimal Wiener solution*, associated with an optimal delay.

As can be deduced from the comparison between (1) and (3), the Wiener criterion is strongly related to the ZF condition. Hence, the determination of the optimal Wiener solution is very important and has a great practical appeal. However, there are two main difficulties: the use of samples of the transmitted signal and the choice of d.

The drawback associated with the dependence on a "pilot signal" was the main motivation behind the proposal of blind techniques, that is, criteria which do not make use of samples of $s(n)$. Among these, the CM criterion has received special attention in the last twenty years. Its cost function is given by

$$J_{CM} = E\left\{\left[R_2 - |y(n)|^2\right]^2\right\}, \tag{4}$$

where

$$R_2 = \frac{E\left[|s(n)|^4\right]}{E\left[|s(n)|^2\right]}. \tag{5}$$

The cost function presented in (4) has multiple minima, except in some trivial cases. Recent works [3, 4] have pointed in the direction of an intimate relationship between these minima and some Wiener solutions (the best ones). This is the core of the CM part of the framework proposed here.

2.1. Relationship between CM minima and Wiener optima

The rationale of this work is to find an optimal method for the design of blind equalizers. Since the notion of optimality can be related to the concept of supervised adaptive filtering, it is important to discuss the relationship between Wiener and CM minima. This discussion relies on the following assumptions.

Assume that the best Wiener solutions are close to the best CM minima so that each minimum of the former class can be achieved from a minimum of the latter class through a simple steepest descent algorithm (that will be further described). Therefore, *to find the CM global optimum is equivalent to determining the optimal Wiener solution*. We will always assume that there is at least one good Wiener solution, that is, one that provides perfect recovery in the absence of noise. Such assumption is not reasonable only in a few particular cases (e.g., when there is a channel zero at ± 1).

The main result of this claim is that it becomes feasible to determine the best possible equalizer *without supervision*, that is, by using a blind search strategy.

The key to accomplish such a demanding task on the CM cost function is to use strategies capable of performing not only global search but also multimodal search, such as EAs with niching and the immunologically inspired technique to be discussed in the next section.

Therefore, it is important to choose a method capable of providing a good balance between exploration and exploitation of the search space. This balance allows for the algorithm to exploit specific portions of the search space without compromising its global search potentialities. These features were found in EAs with niching and a technique inspired by some theories of how the human immune system works.

The last step of the framework is to refine the CM solution through the decision-directed (DD) algorithm in order to compensate for the inherent difference between this and the Wiener solution. The iterative expression of the DD algorithm is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \cdot \{\operatorname{dec}[y(n)] - y(n)\}\mathbf{x}(n), \quad (6)$$

where $\operatorname{dec}[y(n)]$ is simply the slicer output.

In a previous work, the same task has been performed using a genetic algorithm with niching, and good results were reported [6], which will serve as a basis for comparison in Section 4.

3. IMMUNOLOGY, ARTIFICIAL IMMUNE SYSTEMS, AND AN IMMUNE NETWORK MODEL

Together with many other bodily systems, such as the nervous and the endocrine systems, the immune system plays a major role in maintaining life. Its primary functions are to defend the body against foreign invaders (e.g., viruses, bacteria, funguses, etc.) and to eliminate the malfunctioning self cells and debris.

The interest in studying and understanding the immune system gave rise to immunology, a science with approximately 200 years of age. More recently, however, computer scientists and engineers have found several interesting theories concerning the immune system and its functioning that could be very helpful in the development of artificial systems and computational tools capable of solving complex problems. The new field of research that emerged from this interdisciplinary research on immunology, computer science, engineering, and others, is named *artificial immune systems* [7].

3.1. The clonal selection and the immune network theories

Among the many theories used to explain how the immune system works, two were explored in the development of the algorithm used in this paper: (1) the clonal selection theory [8] and (2) the immune network theory [9].

According to the clonal selection theory, when a disease-causing agent, named pathogen, enters the organism, a number of immune cells capable of recognizing this pathogen are stimulated and start replicating themselves. The number of copies each cell generates is directly proportional to the quality of the recognition of the pathogen, that is, the better a cell recognizes a pathogen, the more copies of itself will be generated. During this self-replicating process, a mutation event with high rates also occurs such that the progenies of a single cell are slight variations of the parent cell. This mutational process of the immune cells has the remarkable feature of being inversely proportional to the quality of the pathogenic recognition; the higher the quality of the recognition, the smaller the mutation rate, and vice versa.

The clonal selection theory, briefly described above, is broadly used to explain how the immune system defends the body against pathogens. With a revolutionary view of the immune system, Jerne [9] proposed a novel theory to explain, among many other things, how the immune system reacts against itself. Jerne suggested that the immune cells are naturally capable of recognizing each other, and the immune system thus presents a dynamic behavior even in the absence of pathogens. When an immune cell recognizes another immune cell, it is stimulated and the recognized cell is suppressed. In the original network theory, the results of stimulation and suppression were not clearly defined. Therefore, different immune network models present distinct ways of accounting for network stimulation and suppression.

The discussion to be presented in Section 3.2 is restricted to the specific artificial immune network model used in this work, which combines clonal selection with the immune network theory.

3.2. An artificial immune network model to perform multimodal search

In [10], de Castro and Von Zuben proposed an artificial immune network model, named aiNet, inspired by the clonal selection and network theories of the immune system. This algorithm is demonstrated to be suitable to perform data compression and clustering with the aid of some statistical and graph theoretical strategies.

The aiNet adaptation procedure was further improved in [5], and transformed into an algorithm to perform multimodal search, named opt-aiNet. Several features of opt-aiNet can be highlighted. (1) It is a population-based search technique, in which each individual of the population is a real-valued vector represented according to the problem domain. (2) The size of the population, that is, the number of individuals in the population, is dynamically adjusted. (3) It is capable of locating multiple optima by making a balance between exploitation (through a local search technique based on clonal selection and expansion) and exploration (through a dynamic diversity maintenance mechanism).

In a simplified form, the opt-aiNet algorithm can be summarized with the procedure below.

(1) *Initialization*. Randomly initialize a population with a small number of individuals.

(2) *While* stopping criterion is not met, do the following.

(2.1) *Fitness evaluation*. Determine the fitness (goodness or quality) of each individual of the population and normalize the vector of fitness.

(2.2) *Replication*. Generate a number of copies (offsprings) of each individual.

(2.3) *Mutation*. Mutate each of these copies inversely proportionally to the fitness of its parent cell, but keep the parent cell. The mutation

$$c' = c + \alpha N(0, 1),$$
$$\alpha = \frac{1}{\beta} \exp(-f^*) \quad (7)$$

follows, where c' is a mutated individual c, $N(0, 1)$ is a Gaussian random variable of zero mean and standard deviation $\sigma = 1$, β is a parameter that controls the decay of an inverse exponential function, and f^* is the fitness of an individual normalized in the interval $[0, 1]$. A mutation is only accepted if the mutated individual c' is within its range of domain.

(2.4) *Fitness evaluation*. Determine the fitness of all new (mutated) individuals of the population.

(2.5) *Selection*. For each clone—group formed by the parent individual and its mutated offspring—select the individual with highest fitness and calculate the average fitness of the selected population.

(2.6) *Local convergence*. If the average fitness of the population is not significantly different from the one at the previous iteration, then continue, else return to step (2.1).

(2.7) *Network interactions*. Determine the affinity (degree of similarity measured via the Euclidean distance) of all individuals of the population. Suppress (eliminate) all but the highest fitness of those individuals whose affinities are less than a suppression threshold σ_s and determine the number of network individuals, named *memory cells*, after suppression.

(2.8) *Diversity introduction*. Introduce a percentage $d\%$ of randomly generated individuals and return to step (2).

(3) *EndWhile*.

The original stopping criterion proposed for the algorithm is based on the number of memory cells. After the network interactions (step (2.7)), a certain number of individuals remain. If this number does not vary from one iteration to the other, then the network is said to have a stable population size. In such condition, the remaining individuals are all memory cells corresponding to local optima solutions. However, in accordance with the classical modus operandi in adaptive equalization, a maximum number of iterations was adopted as the stopping criterion.

For a more computational description of the immune algorithm presented, the reader is invited to visit the website http://www.cs.ukc.ac.uk/people/staff/jt6/aisbook/ais-implementations.htm, from where the original Matlab code for the opt-aiNet and many other immune algorithms can be downloaded.

3.3. How opt-aiNet works?

The behavior of the opt-aiNet adaptation procedure can be simply explained. In steps (2.1) to (2.5), a local search is being performed based on the clonal selection theory. At each iteration, a population of individuals is locally optimized through reproduction, affinity proportional mutation, and selection (exploitation of the search space). The fact that no parent individual has a selective advantage over the others contributes to the multimodal search of the algorithm.

Steps (2.6) to (2.8) check for the convergence of the local search procedure, eliminate redundant individuals, and introduce diversity in the population. When the initial population reaches a stable state (determined by the stabilization of its average fitness), the cells interact with each other in a network form, that is, the Euclidean distance between each pair of individuals is determined, and some of the similar cells are eliminated to avoid redundancy. In addition, a number of randomly generated individuals are added to the current population, allowing for a broader exploration of the search space, and the process of local optimization restarts in step (2.1).

To illustrate the behavior of the opt-aiNet algorithm, assume the simple bidimensional function

$$f(x, y) = x \sin(4\pi x) - y \sin(4\pi y + \pi) + 1 \quad (8)$$

to be maximized.

Figure 2a depicts $f(x, y)$ and an initial population of 13 individuals after the local search part of the algorithm was completed for the first time (steps (2.1) to (2.6)). Note that all the remaining 13 individuals are positioned in peaks of the function. Figure 2b depicts the function to be optimized after the convergence of the algorithm. In this case, nearly all peaks

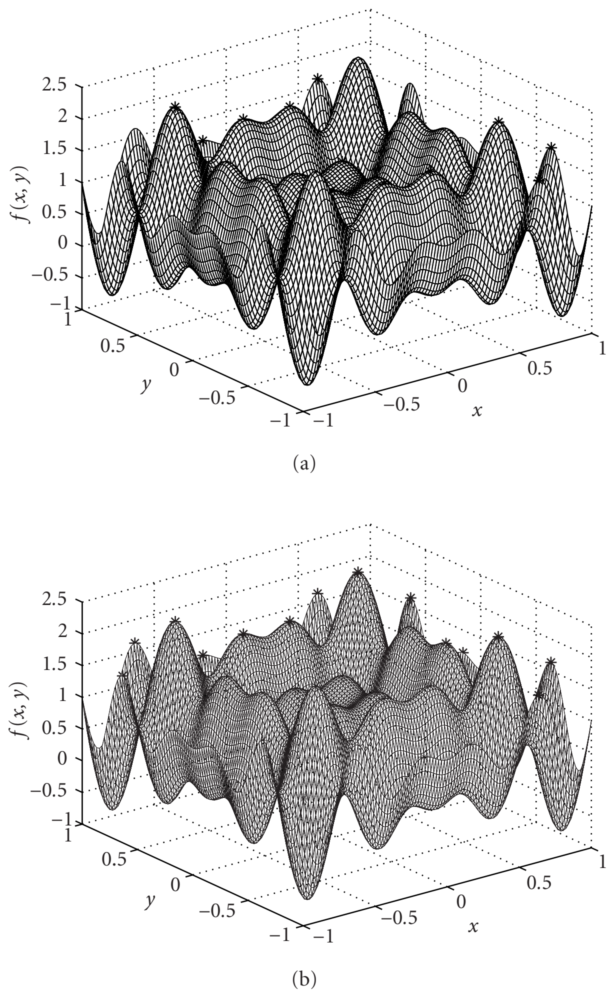

Figure 2: Illustrative performance of the opt-aiNet algorithm when applied to the function described in (8).

of the function were determined, including the four global optima and all local optima of very low values in comparison with the highest peaks.

3.4. Opt-aiNet and other search techniques

The algorithm described in this paper is most often characterized as an immune algorithm since it is inspired in the immune system. Nevertheless, the similarities between some immune and EAs are striking and deserve remarks.

EAs can be defined as search and optimization strategies with their origins and inspiration in the biological processes of evolution [11]. For an algorithm to be characterized as evolutionary, it has to present a population of individuals that are subjected to reproduction, genetic variation, and selection. Therefore, most EAs are comprised of the following main steps: (1) reproduction with inheritance, (2) selection, and (3) genetic variation [12].

If one looks into the clonal selection theory of the immune system, briefly reviewed in Section 3.1 and used as a part of the opt-aiNet algorithm, it is clear that the main steps of an EA (reproduction, selection, and variation) *are embodied in the clonal selection procedure*. Steps (2.1) to (2.3) of the opt-aiNet algorithm correspond to the clonal selection principle of the immune system. These can be likened to a genetic algorithm [13] with no crossover and elitist selection, or to the evolution strategies originally proposed by Schwefel [14].

However, it is important to remark that a number of differences exist among them, in addition to their sources of inspiration. For instance, in opt-aiNet, no coding of the individuals is performed, as in the case of genetic algorithms, the mutation rate of each individual is inversely proportional to fitness (an original approach inspired by some immune mechanisms), and a deterministic and elitist selection scheme is adopted.

Another remarkable difference between the opt-aiNet and any EA is the presence of direct interactions (connections) between the network individuals (cells). In opt-aiNet, as individuals are connected with each other in a network-like structure, a dynamic control of the population size can be performed. We are not going much further into specific differences between these algorithms, but the interested reader is invited to refer to [5, 15] for additional discussions.

Since all the evolutionary steps are embodied in the adaptive procedure of opt-aiNet, it is possible to consider EAs to be particular cases of opt-aiNet. Taking into account an opposite viewpoint, it is possible to claim that the opt-aiNet algorithm is nothing but a new type of evolutionary approach inspired by the immune system, for it contains the main steps of reproduction, variation, and selection, which an algorithm needs to be characterized as evolutionary. Regardless of which algorithm can be viewed as a particular case of the other, it is important to note that both are adaptive systems suitable for exploratory search. There is a main difference in performance, however, once the opt-aiNet is intrinsically suitable for performing multimodal search, while EAs require modifications to tackle such problems.

Empirical comparisons could also be performed between the opt-aiNet algorithm and other search procedures, such as simulated annealing [16] and particle swarm optimization techniques [17]. However, as the nature of the optimal Wiener equalizer problem requires an algorithm capable of efficiently locating multiple solutions to the problem, the performances of these algorithms are supposed not to be competitive with the ones presented by EAs with niching and the opt-aiNet algorithm. However, empirical investigation must still be undertaken in order to validate this claim.

4. SIMULATION RESULTS

In order to evaluate the performance of the opt-aiNet algorithm when applied to search for the optimal Wiener equalizers, three different channels (C1, C2, and C3) were

Table 1: Simulation parameters.

Parameter	Value
Initial population	5
Suppression threshold (σ_s)	0.35
Number of offsprings per cell	10
β (equation (7))	50
Maximum number of iterations	1000
Number of runs	100

Table 2: Results of C1 and 8-coefficient equalizer.

Solution	MSE	Freq. (GA + niching)	Freq. (opt-aiNet)
$\mathbf{W}_{\text{opt}}$	0.1293	48%	82%
$\mathbf{W}_2$	0.1397	22%	17%
$\mathbf{W}_3$	0.1445	12%	1%
$\mathbf{W}_4$	0.1533	10%	—
$\mathbf{W}_5$	0.1890	4%	—
$\mathbf{W}_6$	0.1951	4%	—

considered. Their transfer functions are as follows:

$$H_{C1} = 1 + 0.4z^{-1} + 0.9z^{-2} + 1.4z^{-3},$$
$$H_{C2} = 1 + 1.2z^{-1} - 0.3z^{-2} + 0.8z^{-3}, \quad (9)$$
$$H_{C3} = 1 + 0.6z^{-1} - 0.7z^{-2} + 2.5z^{-3}.$$

C1 and C2 are nonminimum phase channels and C3 has maximum phase. The equalizer, as mentioned in Section 2, is always an FIR filter with L coefficients. We estimate the CM cost function through time averaging and use the mapping

$$J_{\text{FIT}} = \frac{1}{1 + J_{\text{CM}}} \quad (10)$$

to generate the fitness. The basic idea behind this conversion is to transform minima into maxima.

We used the immune network model, as discussed in Section 3.2, to obtain *the CM global minimum* for these channels. The best individual was refined by the aforementioned DD algorithm (6) and compared with the Wiener solutions. This procedure allows a direct verification of the potentialities of the proposed method. The results are presented in terms of convergence rates to different minima, which favors a straightforward performance analysis.

The default values for the parameters used to run the opt-aiNet algorithm are presented in Table 1.

The first test was performed with channel C1 and an 8-coefficient equalizer. The results are summarized in Table 2, together with the equivalent outcome produced by the GA benchmark [6]. In all tables, $\mathbf{W}_{\text{opt}}$, $\mathbf{W}_2$, $\mathbf{W}_3$, and so forth stand for the various Wiener minima (ranked according to their MSE).

The results demonstrate that the immune network was able to find the global optimum in most cases, thus surpassing the GA by a great margin. It is also relevant to observe that when global convergence did not occur, the rule was to pick $\mathbf{W}_2$, contrarily to what the benchmark outcome reveals.

Table 3: Results of C2 and 7-coefficient equalizer.

Solution	MSE	Freq. (GA + niching)	Freq. (opt-aiNet)
$\mathbf{W}_{\text{opt}}$	0.0312	48%	100%
$\mathbf{W}_2$	0.0458	40%	—
$\mathbf{W}_3$	0.0917	8%	—
$\mathbf{W}_4$	0.0918	2%	—
$\mathbf{W}_5$	0.1022	2%	—

Table 4: Results of C3 and 12-coefficient equalizer.

Solution	Residual MSE	Freq. (opt-aiNet)
$\mathbf{W}_{\text{opt}}$	0.0071	66%
$\mathbf{W}_2$	0.0075	32%
$\mathbf{W}_3$	0.0104	2%

Table 5: Results of C3 and 12-coefficient equalizer.

Solution	Residual MSE	Freq. (opt-aiNet)
$\mathbf{W}_{\text{opt}}$	0.0071	84%
$\mathbf{W}_1$	0.0075	16%

The second test was carried out with channel C2 and a 7-coefficient equalizer. The results are presented in Table 3, together with the GA performance.

In this case, the results are even more impressive; the immune network was capable of determining the best minimum in all runs. Again, the proposal led to results far superior to those achieved by the GA.

Finally, channel C3 and a 12-coefficient equalizer were considered. We chose this equalizer length to increase the size of the search space, thus increasing the problem difficulty. There is no available benchmark in this case. Table 4 presents the results for the opt-aiNet algorithm.

The global convergence rate is lower than that of the previous test cases. However, simulation performances such as the one illustrated in Section 3, and previous experience with machine-learning techniques, encouraged us to try to improve the performance of the algorithm by varying some of its adaptation parameters. Based upon the discussion presented in [5, 10], concerning the importance of each parameter, beta was changed to $\beta = 100$. This choice would lead to a more precise local search, that is, capability of dealing with the MSE similarity between $\mathbf{W}_{\text{opt}}$ and $\mathbf{W}_2$. Table 5 depicts the results.

By simply fine-tuning the local search of opt-aiNet, a greater improvement in its performance could be observed. The method once more proved itself capable of achieving optimal performance in the vast majority of trials.

The results presented so far are good indicators of the opt-aiNet potentiality to locate the global optima solutions. However, it is known that this algorithm is capable of determining most local optima solutions of a given problem, as illustrated in Figure 2b. To study how the multimodal search of opt-aiNet works on problems C1 to C3, assume, without

Table 6: Individuals of the population and associated Wiener receivers.

Individuals of the population				Close to
[0.1740	−0.1297	−0.0852	−0.1882	$\mathbf{W}_{\text{opt}}$
0.4516	0.1137	−0.1007	0.0860]	
[−0.1805	0.1303	0.0967	0.1862	$\mathbf{W}_{\text{opt}}$
−0.4559	−0.1021	0.0949	− 0.0781]	
[0.1113	−0.0377	0.0297	−0.2622	$\mathbf{W}_2$
0.2195	0.0414	0.2687	−0.5315]	
[−0.1041	0.0394	−0.0205	0.2460	$\mathbf{W}_2$
−0.2160	−0.0475	−0.2449	0.5218]	
[−0.0094	0.2060	−0.1512	−0.0991	$\mathbf{W}_3$
−0.2261	0.4798	0.1023	−0.0547]	
[0.0045	−0.2133	0.1477	0.1002	$\mathbf{W}_3$
0.2389	−0.4794	−0.1108	0.0527]	
[0.0025	0.0025	−0.2134	0.1518	$\mathbf{W}_4$
0.0773	0.2414	−0.4720	−0.0815]	
[−0.0019	0.0036	0.2117	−0.1416	$\mathbf{W}_4$
−0.0747	−0.2416	0.4692	0.0835]	
[−0.0795	−0.0877	−0.1181	0.3541	$\mathbf{W}_6$
0.1515	−0.1279	0.1087	− 0.0761]	
[0.0824	0.0959	0.1175	−0.3742	$\mathbf{W}_6$
−0.1458	0.1282	−0.1022	0.0508]	
[−0.1197	−0.1265	0.3463	0.1777	$\mathbf{W}_5$
−0.1494	0.1260	−0.1174	0.0538]	
[0.1355	0.1127	−0.3420	−0.1769	$\mathbf{W}_5$
0.1485	−0.1198	0.1248	− 0.0601]	
[−0.1768	0.3269	0.1402	− 0.0967	$\mathbf{W}_7$
0.1024	−0.1249	0.0497	0.0252]	

loss of generality, the particular case of channel C1. The first column of Table 6 presents some of the individuals of a typical run of opt-aiNet when applied to C1. In the vicinity of each individual, we find an associated Wiener solution, presented in column 2 of Table 6 (eventual sign discrepancies are inevitable in blind equalization). A close inspection reveals seven different Wiener optima, including the global minimum. This property of diversity maintenance confirms the capability of multimodal exploration, inherent to the immune network approach.

5. DISCUSSION AND FUTURE TRENDS

This work started claiming that there is a strong relationship between the CM global optima and some of the Wiener solutions so that such solutions can be attained by refining the CM minima using a simple DD technique. On the other hand, the CM global optimum can be easily reached by means of a blind search procedure, such as an EA. Therefore, the combination of the CM criterion with an efficient global search procedure gives rise to a framework to design optimal Wiener filters. This is the core of our proposal.

Our approach uses an immune-based algorithm, named opt-aiNet, to optimize the parameters of the equalizer, and benchmarks its performance against those obtained by using a genetic algorithm with niching. Different channels and filters were used for evaluation and comparison. The results were much favorable to the opt-aiNet algorithm, which can also be understood as an evolutionary search technique inspired by the immune system.

These investigations support the establishment of CM-based evolutionary search as a *strong paradigm for optimal blind equalization*.

A natural extension of this work is the testing of the opt-aiNet algorithm with its automatic stopping criterion so that the amount of user-defined parameters of the algorithm [10, 15] could be reduced. Further studies also involve the use of the opt-aiNet in the context of nonlinear equalization, prediction, and identification.

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Romis Ribeiro de Faissol Attux was born in Goiânia, Brazil, in 1978. He received the B.S. and M.S. degrees, both in electrical engineering, from the State University of Campinas (Unicamp), Campinas, Brazil, in 1999 and 2001, respectively. Currently, he is a doctorate student at the same institution. His main research interests are blind equalization and identification, adaptive nonlinear filtering, evolutionary computation, and dynamical systems.

Murilo Bellezoni Loiola was born in São Paulo, Brazil, in 1979. In 2002, he received his B.S. degree in electrical engineering from the State University of Campinas (Unicamp), Campinas, Brazil, where he is currently an M.S. student. His main research interests include turbo equalization, smart antennas, artificial neural networks, and evolutionary algorithms.

Ricardo Suyama was born in São Paulo, Brazil, in 1978. He received the B.S. degree in electrical engineering from the State University of Campinas (Unicamp), Campinas, Brazil, where he is currently an M.S. student. His research interests include adaptive equalization, adaptive nonlinear filtering, smart antennas, and evolutionary algorithms.

Leandro Nunes de Castro received the B.S. degree in electrical engineering from the Federal University of Goiás, Goiânia, Brazil, in 1996, and M.S. degree in control engineering and Ph.D. degree in computer engineering from the State University of Campinas, Campinas, São Paulo, Brazil, in 1998 and 2001, respectively. He was a Research Associate with the Computing Laboratory at the University of Kent, Canterbury, UK from 2001 to 2002, and is currently a Visiting Lecturer at the School of Computer and Electrical Engineering at Unicamp. His research interests include artificial immune systems, artificial neural networks, evolutionary algorithms, and artificial life. Dr. de Castro is a member of the IEEE, and the SBA (Brazilian Society of Automation). He has been a referee for a number of conferences and journals related to computational intelligence, such as the Soft Computing Journal, IEEE Transactions on Evolutionary Computation, and IEEE Transactions on Neural Networks.

Fernando José Von Zuben received his B.S. degree in electrical engineering in 1991. In 1993, he received his M.S. degree and his Ph.D. degree in 1996, both in automation, from the Faculty of Electrical and Computer Engineering at the State University of Campinas, SP, Brazil. Since 1997 he is an Assistant Professor in the Department of Computer Engineering and Industrial Automation, at the State University of Campinas, SP, Brazil. The main topics of his research are artificial neural networks, artificial immune systems, evolutionary algorithms, nonlinear control systems, and multivariate data analysis. F. Von Zuben is a member of IEEE, INNS, and AAAI.

João Marcos Travassos Romano was born in Rio de Janeiro in 1960. He received the B.S. and M.S. degrees in electrical engineering from the State University of Campinas (Unicamp) in Brazil in 1981 and 1984, respectively. In 1987, he received the Ph.D. degree from University of Paris XI. In 1988, he joined the Communications Department of the Faculty of Electrical and Computer Engineering, Unicamp, where he is now a Professor. He served as an Invited Professor in the University René Descartes in Paris during the winter of 1999, and in the Communications and Electronic Laboratory in CNAM, Paris, during the winter of 2002. He is the responsible of the Signal Processing for Communications Laboratory. His research interests concern adaptive and intelligent signal processing and its applications in telecommunications problems like channel equalization and smart antennas. Since 1988, he is a recipient of the Research Fellowship of CNPq, Brazil. Professor Romano is a member of the IEEE Electronics and Signal Processing Technical Committee and an IEEE senior member. From April 2000, he is the President of the Brazilian Communications Society (SBrT), a Sister Society of ComSoc, IEEE.