Harmony Search Heuristics for Quasi-asynchronous CDMA Detection with M-PAM Signalling

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Abstract. Focusing on CDMA (Code Division Multiple Access) uplink communications, this paper addresses the application of heuristic techniques to the multiple user detection problem when dealing with asynchrony between transmitters and bandwidth-limited PAM (Pulse Amplitude Modulation) signals. In such systems it is known that, even for the simplest case of binary modulated signals with perfectly synchronous transmitters, simple Single-User Detection (SUD) techniques (e.g. Rake receiver) are outperformed by Multiple-User Detection (MUD) schemes (based on the Maximum-Likelihood – ML – criteria), at a computational cost exponentially increasing with the number of users. Consequently, Genetic Algorithms (GA) have been extensively studied during the last decade as a means to alleviate the computational complexity of CDMA MUD detectors while incurring, at the same time, in a negligible error rate penalty. In this manuscript, a novel heuristic approach inspired in the recent Harmony Search algorithm will be shown to provide a faster convergence and a better error rate performance than conventional GA's in presence of inter-user asynchrony in bandwidth-limited CDMA communications, specially when the complexity of the scenario increases.

Keywords: CDMA, Multi-user Detection, Genetic Algorithm, Harmony Search.

1 Introduction

From the beginning of wireless communication systems in the late 1970's, huge research has been conduced towards designing efficient transmission and reception techniques aimed at providing ever-growing capacity and/or end-to-end Quality of Service (QoS). A wide variety of problems related to the design and optimization of wireless networks constitute, by themselves, NP-hard problems [1], such as the design of TDMA (Time Division Multiple Access) frame patterns [2], data equalization in dispersive links [3], channel estimation [4], topology design [5], terminal assignment [6] and the Access Node Location Problem (ANLP) [7,8], among others. In NP-hard problems, the dimension of the solution space increases exponentially with the number of inputs, and consequently they cannot be solved in

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polynomial time. Consequently, achieving exact optimum solutions is not feasible in practical scenarios with underlying NP-hard optimization problems.

One of such problems related to wireless communication networks hinges on the joint detection of the data sent by several users over a multiple access channel (also referred to as *uplink* communications). Different multiple access methods have been thoroughly proposed in the literature aimed at separating the signals from the users in some domain, e.g. TDMA (Time), FDMA (Frequency), SDMA (Spatial) and CDMA (Code Division Multiple Access). Let us focus on the latter, where different nodes simultaneously share the channel resources by solely multiplying their data by a set of spreading codes (Figure 1). Note that at reception, the performance of these systems depends roughly on both the method employed to separate the data coming from each node and the orthogonality properties of the set of utilized codes. For instance, the simplest Single-User Detection (SUD) technique just multiplies the received multiplexed signal by the code corresponding to the desired node, which involves considering the signals from undesired nodes (*Multiple Access Interference*, MAI) as noise and, ultimately, an increased effective noise variance. On the contrary, joint Multiple-User Detection (MUD) schemes treat the aforementioned MAI as information rather than noise, which dramatically enhances the error performance of the system at the expense of incrementing the computational complexity of the detection procedure. In this context, the optimum Maximum Likelihood (ML) detector was first proposed by Verdú in [9], whose most elementary implementation is based on exhaustively searching over all possible combinations of the symbols transmitted by the nodes/users. This specific ML search procedure maximizes the computational complexity of the detector exponentially with the number of nodes in the network, hence constituting by itself a NP-hard problem.

For this reason, the research on this field has significantly been devoted to novel optimized heuristic and/or stochastic MUD search procedures offering a good balance between error performance and computational complexity. Juntti *et al* were the first to propose a Genetic Algorithm as an alternate MUD approach [10], work which unchained a plethora of GA-inspired techniques aimed at jointly detecting multiple users in several instances of CDMA networks (e.g. see [11,12,13,14] and references therein). Such genetic algorithms can be regarded as a class of evolutionary methods which employs the natural selection process as a global search technique. In these algorithms the proposed potential solutions are represented by chromosomes so as to constitute the different individuals of the population. The algorithm operates in an iterative manner to produce new generations (i.e. sets of potential solutions) by mimicking the processes of selection, crossover and mutation involved in the natural evolution in species and organisms. The population is updated if new proposed candidate solutions are better – under a certain fitness or cost function evaluation – than those corresponding to previous generations. The above iterative processes are repeated until a termination criterium is satisfied.

Following this research trend, this paper proposes the adaptation of the recent Harmony Search (HS, see [15]) heuristic algorithm to the CDMA MUD

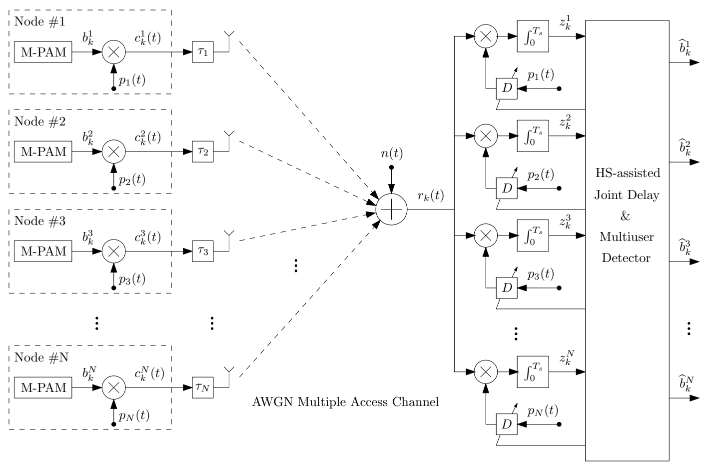


Fig. 1. Block diagram of the N-node quasi-asynchronous CDMA uplink model

detection problem. The HS algorithm mimics the behavior of a music orchestra in the process to compound an harmonious melody, and has been successfully applied to different optimization problems such as water network design [16], multicast routing [17] or even solving the *Sudoku* puzzle [18]. Surprisingly, HS has attracted very marginal attention within the engineering community; to the authors' knowledge, only the recent, independent and almost simultaneous contributions in [19,20] have considered the application of HS to binary-modulated CDMA Multiple-User Detection. The work presented here takes a step further and compares the behavior of a classical Genetic Algorithm and the novel Harmony Search in two CDMA uplink scenarios: 1) quasi-synchronous BPSK modulated transmitters, and 2) M-PAM modulated synchronous transmission. Exhaustive computer simulations conclude that, for a given maximum number of iterations and all the simulated scenarios, HS outperforms GA in terms of end-to-end symbol error rate, specially when the dimension of the solution space increases.

The rest of the manuscript is organized as follows: the mathematical description of the considered CDMA scenarios is presented in Section 2, whereas Section 3 outlines the main characteristics of the proposed HS-based CDMA MUD algorithm. Next, in 4 a comparison study between the algorithms is presented in terms of Symbol Error Rate (SER) and computational complexity. Finally, Section 5 draws some concluding remarks.

2 System Description

We assume the system depicted in Figure 1, i.e. a CDMA network consisting of N nodes which transmit statistically independent data to a common destination. In an equivalent low-pass representation, at time k the n-th node ($n \in \{1, \ldots, N\}$)

generates a M-ary PAM modulated symbol $b_k^n \in \mathcal{B}_M$ at a symbol rate $1/T_s$ symbols/second, where $\mathcal{B}_M \triangleq \{2z-M-1,\, z=1,\ldots,M\}$. Following the previous low-pass representation, each original node symbol b_k^n is CDMA-encoded by using the local signature sequence $p_n(t)$ of duration LT_c, where T_c denotes the chip period. The equivalent low-pass transmitted signal at node n and time k will be therefore given by $c_k^n(t) = b_k^n p_n(t)$. All the nodes' signals are sent over an AWGN multiple access channel, yielding the overall received sequence

$$r_k(t) = \sum_{n=1}^{N} c_k^n(t-\tau_n) + n(t), \tag{1}$$

where $n(t)$ is an additive white random process with zero mean and spectral density amplitude $N_0 = 2\sigma^2$. Note that the transmitted signal at each node n is subject to a random time delay $\tau_n = \xi_n T_c$ ($\xi_n \in \mathbb{N}$). For sake of simplicity we will further assume that $(\max \tau_n) + LT_c < T_s$, i.e. no inter-symbol interference due to temporal delay overlapping is considered in our setup. Observe that this assumption yields $0 \leq \xi_n \leq L-1$ for $n \in \{1,\ldots,N\}$. No a priori information on the delays $\{\tau_n\}_{n=1}^N$ is considered at the sensors or at the common receiver.

At destination, the simplest CDMA SUD (*Single User Detector*) detection strategy would process the received signal $r_k(t)$ through a cascade of $N \cdot L$ matched filters. Each of such filter stages would separate the contribution from each node $n \in \{1,\ldots,N\}$ to the received signal by assuming a certain delay associated to the node at hand. The output ρ_n^l associated to the $((n-1)\cdot L + l)^{th}$ matched filter ($n \in \{1,\ldots,N\}$ and $l \in \{0,...,L-1\}$) would be given by

$$\rho_n^l = \int_0^{T_s} r_k(t) \cdot p_n(t - lT_c), \tag{2}$$

from which the symbol estimation $\widehat{b}_k^n$ for the transmitted symbol b_k^n would be obtained as $\widehat{b}_k^n = \mathrm{HD}_{\widetilde{\mathcal{B}}}[\max_l \rho_n^l]$, with $\mathrm{HD}_{\widetilde{\mathcal{B}}}$ denoting *hard decision* over the constellation $\widetilde{\mathcal{B}} \triangleq \{2Lz - ML - L,\, z = 1,\ldots,M\}$. Despite its simplicity, in this SUD detection technique the information contributed by each node to the received sequence $r_k(t)$ is processed without taking into account the contribution of the information from the other nodes, which ultimately leads to a poor end-to-end performance with dramatically high error floors. This gets even more involved in scenarios with strong Multiple Access Interference (MAI), e.g. when utilizing pseudo-random non-orthogonal spreading sequences and fully-loaded (i.e. $N \approx L$) CDMA setups.

As a means to enhance the performance of the SUD receiver, the optimum Maximum Likelihood (ML) receiver estimates $\mathbf{b}_k \triangleq \{b_k^n\}_{n=1}^N$ as $\widehat{\mathbf{b}}_k$ by maximizing the conditional probability

$$\widehat{\mathbf{b}}_k = \underset{\mathbf{b}_k \in \mathcal{B}^N}{\arg\max}\, Pr\left\{\mathbf{b}_k | z_k^1(\tau_1), \ldots, z_k^N(\tau_N)\right\}, \tag{3}$$

where $z_k^n(\tau_n)$ denotes the output of the decorrelator matched to the sequence $p_n(t-\tau_n)$. Observe that if $\tau_n = 0$ for all n (synchronous CDMA setup), the above expression reduces to the classical CDMA decision rule [21]

$$\tilde{\mathbf{b}}_k = \underset{\mathbf{b}_k \in \mathcal{B}^N}{\arg\min} \left(-\, 2\mathbf{b}_k^H \mathbf{z}_k + \mathbf{b}_k^H \mathbf{R} \mathbf{b}_k \right), \tag{4}$$

where $\mathbf{R}$ denotes the $N \times N$ nonnegative definite cross-correlation matrix between spreading code sequences, and ^{H} denotes hermite conjugate. Unfortunately, even for the simplest case of fully-synchronous transmitters the implementation of the decision rule in expression (4) involves a NP-hard optimization problem which requires evaluating the above metric for $|\mathcal{B}|^N = M^N$ distinct candidate vectors. When turning to the asynchronous case, the search space is further extended to cover, not only all possible symbol vectors $\mathbf{b}_k$, but also all the possible combinations of time delays $\{\tau_n\}$. Therefore, the complexity of an exhaustive search ML detection method is increased by a multiplicative factor $(\xi_{\max})^N$, with $\xi_{\max} \triangleq \max_{n=1,\ldots,N} \xi_n$.

3 Harmony Search CDMA Detector

In order to reduce the computational complexity of the exhaustive search based ML detector, we propose to jointly estimate the symbols sent by the different nodes and the set of corresponding delays $\{\tau_n\}_{n=1}^N$ by means of the Harmony Search (HS) heuristic technique [15]. In general, Harmony Search is a heuristic optimization algorithm based on mimicking the behavior of a music orchestra in the process of seeking the best harmony. In this process a set of candidate solutions or *harmonies* (known as *Harmony Memory*) is evaluated under an aesthetic point of view in much the same way as it is done with the population of *chromosomes* in a standard Genetic Algorithm. The Harmony Memory contains a set of φ harmonies which are iteratively updated in an heuristic fashion until a fixed number of attempts is reached or, alternately, a convergence constraint is met[1]. Regarding the system considered in this paper, and following the nomenclature related to the HS algorithm, we will hereafter refer to a given candidate vector $\mathbf{b}_k \in \mathcal{B}^N$ as *harmony*, whereas each compounding entry b_k^n of $\mathbf{b}_k$ will be denoted as *note*.

In the standard implementation of the HS algorithm by Geem *et al* [15], the improvisation process of the new harmonies is made note by note for all harmonies included in the Harmony Memory. At each iteration, the first improvisation criteria establishes that the new value for a note inside a given harmony can be drawn, with a tunable probability, from the values taken by such note in all the other $\vartheta - 1$ harmonies. In a second step, a fine adjusting pitch over the note vocabulary (also driven by an adjustable probabilistic parameter) is performed on every note of the harmony memory. A third random process allows for the heuristic recovery of note values that could have been lost during the previous steps of the improvisation process. In the last step of each iteration, a new improvised harmony is included in the harmony memory if its metric is better than any of the harmonies remaining from the previous iteration.

[1] One could use metric thresholding or monitor the uniformity of the Harmony Memory to that end, for instance.

In the scenario considered in this manuscript the HS based detection algorithm works sequentially with two distinct harmony memories: the first set of φ N-dimensional harmonies corresponds to the candidate symbol vectors $\mathbf{b}_k$, whereas each N-dimensional harmony contained in the second memory represents a combination of time delays expressed as an natural multiple of the chip period T_c. The main idea of the proposed sequential HS procedure is based on iterating between the symbol harmony memory and the time delay harmony memory, and on applying, at each iteration, an individual HS improvisation procedure onto each of such memories. Notice that the i-th time delay harmony ($i \in \{1, \ldots, \varphi\}$) allows for the computation of the matched filters' outputs $\{z_k^n(\tau_n)\}_{n=1}^{N}$, which will then utilized for computing the i-th metric in the righthand expression of equation (3). In other words, the i-th potential solution of the proposed algorithm will be composed of the i-th harmonies of both the symbol and delay memories.

To be concise, the algorithm flow diagram is depicted in Figure 2, and consists of four steps:

A. The **initialization** process is only executed at the first iteration. At this point, if no a priori knowledge of the solution is assumed, the harmonies of both the symbol and the time delay memories are filled randomly with notes drawn from the corresponding alphabet (i.e. $\mathcal{B}$ for the symbol notes and $\{0, \ldots, L-1\}$ for the time delay notes). It should be made clear that, although the initialization is essential for the performance of the algorithm, in this paper we assume the worst scenario where no a priori knowledge on the best harmonies is considered. Otherwise, the performance of our approach will be significantly improved.

B. Next, the **improvisation** process is sequentially applied to each note of the complete set of symbol and delay harmonies, but note that the metric of the proposed solution is evaluated just φ times per iteration. The proposed method is controlled by three arbitrary parameters, as opposed to the nominal algorithm where only two are used:
   - The Harmony Memory Considering Rate, HMCR $\in [0, 1]$, which establishes the probability that the new value for a note belonging to a given harmony is drawn from the values of the same note in all the other $\varphi - 1$ harmonies in the respective memory.
   - In the present scheme, the random selection of a new value for a given note is controlled by a new parameter, Random Selection Rate (RSR), different than the complementary HMCR probability (1-HMCR) used by the nominal HS algorithm.
   - The Pitch Adjusting Rate, PAR $\in [0, 1]$, which sets the probability that the new note value is picked from its neighbor value in the symbol/delay alphabet.

C. The quality **evaluation** and the harmony memory **update** is made at each iteration based on the fitness function in expression (4). At each iteration φ new candidate harmonies (symbols and delays) are improvised and evaluated, but will be included in the harmony memory only if they improve the quality (fitness) of the φ harmonies remaining from the previous iteration.

D. The proposed scheme includes a **perturbing** criterium when all harmonies of any of the two harmony memories (either symbols or delays) becomes uniform, i.e. populated with the same harmony. In this case, as a means to increase the diversity of the algorithm, the perturbing criterium changes randomly the value of a fixed number of notes (denoted as ϱ) in the $\varphi - 1$ worse harmonies of the uniform harmony memory. The best candidate in the given memory is kept unmodified. The resulting harmonies are always accepted disregarding the quality of their fitness.
E. The algorithm stops the iterative process when 1) the metric of the best harmony falls below a certain threshold which, in the simulations presented in this paper, is set to a multiplicative factor κ of the noise standard deviation σ; or 2) a fixed number of iterations $\mathcal{I}$ is reached. The selected stop criterium is an important task for the tradeoff between computational complexity and error performance of the algorithm. If the stop criterium is not satisfied, the algorithm continues the iterative process from point B.

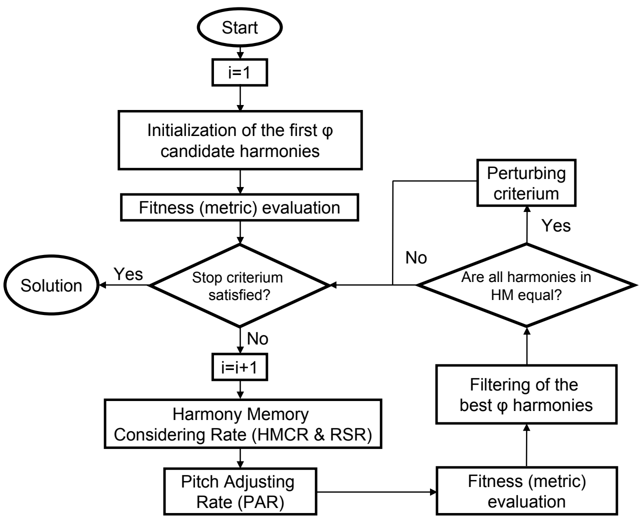


Fig. 2. Flow diagram of the proposed CDMA MUD detector (i denotes iteration)

When comparing the Harmony Search with the classical Genetic Algorithm, essential differences arise mainly based on the improvisation process for the new harmonies. In the case of genetic algorithms, new genes for a chromosome are obtained from the genes of two parents. In the case of Harmony Memory, however, new values for notes are taken from the value of this note in all the other harmonies included in the harmony memory. Intuitively, from this observation one infers that HS is a more *explorative* heuristic optimization algorithm when compared to the more *exploitative* genetically-inspired search.

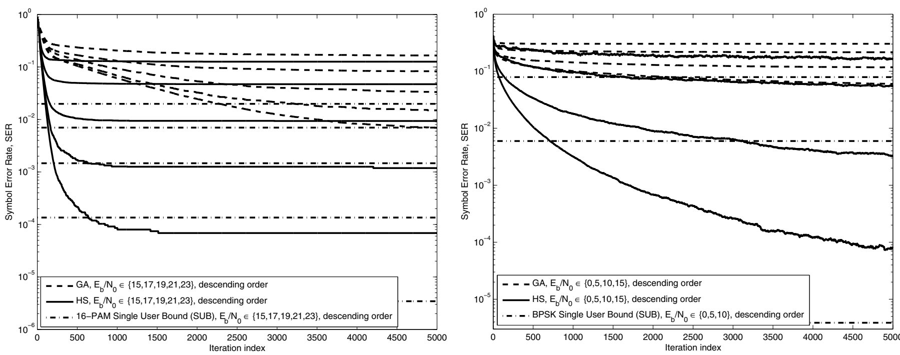
4 Simulation Results

In order to assess the performance of the proposed detector, intensive computer simulations have been carried out by comparing the convergence of both HS- and GA-based MUD detectors in two different scenarios, as described in the following:

- The first scenario consists of $N = 7$ fully-synchronous CDMA transmitters transmitting 16-PAM modulated data to a central receiver. The spreading sequences are pseudo-randomly generated at the beginning of the Monte Carlo simulation, with a spreading factor of $L = 12$ chips. The parameters of the proposed HS-based detector are set to $(\text{HMCR}, \text{RSR}, \text{PAR}) = (0.9, 0.1, 0.1)$, and the size of the harmony memory is equal to $\vartheta = 16$. For the GA-based detector, a population of 16 *chromosomes* with an elite pool size of 8 individuals has been used, whereas the selection process is based on the Roulette-Wheel criterium [22] with an uniform crossover rate [23] of $P_c = 0.9$ and a mutation probability of $P_m = 0.3$. It should be noted that the choice of the values for all parameters has been done after intensive simulation-based optimization studies. Also note that in this scenario the complexity of an ML detector based on exhaustive search would be $M^N = 268,435,456$ metric evaluations.
- The second scenario is composed of $N = 5$ quasi-asynchronous nodes transmitting BPSK ($M = 2$) modulated data to the common destination, with L kept fixed to 12, pseudo-randomly generated CDMA codes, and a maximum delay factor $\xi_{\max} = 4$. Therefore, the delays $\{\tau_n\}_{n=1}^{N}$ are randomly and independently drawn from the set $\{0, \ldots, 4T_c\}$ at every symbol period T_s. The parameters of the HS-based MUD detector are given by $(\text{HMCR}, \text{RSR}, \text{PAR}) = (0.99, 0.2, 0.2)$, with again $\vartheta = 16$ candidates in the harmony memory. Regarding the GA-based detector, the sizes of the population and elite pools are set to 16 and 8 individuals and P_c and P_m are equal to 0.7 and 0.3, respectively. The values for these parameters (i.e. HMCR, RSR, PAR, P_m and P_c) are set identical for both symbol and delay harmony memories. In this case, the complexity of the optimum ML detector is $(\xi_{\max})^N \times M^N = 32,768$ metric evaluations.

In both simulated scenarios, the maximum number of iterations of the HS and GA detection algorithms is $\mathcal{I} = 5,000$ and the number of notes affected by the perturbing criterium detailed in Section 3 is given by $\varrho = 5$. The alternate stop criterium based on thresholding the metric by a multiple of the channel noise standard deviation uses $\kappa = \sqrt{N}$, which accounts for the fraction of σ per user. It should also be noted that in all cases, no a priori information on the delays and/or the harmonies is assumed at the receiver.

Having said this, Figure 3.a depicts the Symbol Error Rate (SER) as a function of the iteration index for the first simulated scenario, a range of energy per bit to noise spectral density amplitude $E_b/N_0 \in \{15, 17, 19, 21, 23\}$ (in dB), and both considered heuristic detection algorithms. Also are included in the plot horizontal asymptotes corresponding to the SER values of a point-to-point single-user 16-PAM transmission over an AWGN channel with $E_b/N_0 \in \{15, 17, 19, 21, 23\}$. For the sake of clarity no markers are included in the plot, where it should be read that the curves are drawn in descending order from $E_b/N_0 = 15$ dB (upper set of curves) to $E_b/N_0 = 23$ dB (lower set of curves). Observe that the HS-based MUD detector proposed in this paper not only outperforms the GA-assisted detector significantly in terms of SER, but also converges in much fewer iterations. For instance, when $E_b/N_0 = 17$ dB the HS-based detector converges to $SER \approx 4.8 \cdot 10^{-2}$ in roughly 400 iterations, as opposed to the GA-based approach whose SER reaches $8.5 \cdot 10^{-2}$ at $2,300$ iterations. For this E_b/N_0 level, these SER values are attained at an complexity of $13,920$ (HS) and $25,200$ (GA) average metric evaluations, which are computed as the product of ϑ (equivalently, population size) and the average number of iterations within the corresponding algorithm converges.



(a) (b)

Fig. 3. (a) SER convergence versus iteration index of the two considered heuristic MUD detection techniques for (a) the first simulated scenario (16-PAM, synchronous); (b) the second simulated scenario (BPSK, quasi-synchronous)

Let us now focus on Figure 3.b, where the SER curves corresponding to the second simulated scenario are plotted in a similar arrangement to Figure 3.a. In this case, although the distance to the BPSK single-user SER bound increases for both HS-based and GA-based detection algorithms, the SER performance gap between such techniques augmentates dramatically while maintaining the reduced average computational complexity of the first commented scenario. For instance, at $E_b/N_0 = 15$ dB the HS-based detector requires on average $1,136$ metric evaluations, in comparison to the $15,568$ average evaluations of the objective function in the GA approach. Future research will be conducted towards narrowing the performance gap to the single-user SER bound of the proposed HS-based detector in this second scenario.

5 Conclusions

In this paper we have proposed a novel heuristic MUD technique for quasi-asynchronous CDMA systems employing multilevel amplitude signalling. The proposed detector is based on the Harmony Search heuristic algorithm, and sequentially iterates between a pool of φ candidate symbol vectors (symbol harmony memory) and φ sets of time delay candidates (delay harmony memory). The progressive refinement of these sets is governed by a set of parameters controlling the convergence behavior of the proposed detector. The presented simulation results state that the HS-based detector here proposed is able to outperform alternate MUD detection approaches based on classical Genetic Algorithms in terms of end-to-end Symbol Error Rate while requiring, at the same time, much less complexity.

Further work on this topic will gravitate around optimizing the perturbing criterium utilized to escape from the local minima, combining the HS-based procedure with concepts drawn from Tabu Search [24,25], and improving the a priori information fed to the detector in order to enhance the starting state of the algorithm. Investigations will be also focused on jointly optimizing the symbol and delay harmonies, as opposed to the sequential approach adopted in this work.

Acknowledgments

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