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Multiuser Detection Based on Adaptive LMS and Modified Genetic Algorithm in DS-CDMA Communication Systems

Abdulhamid Zahedi · Hamidreza Bakhshi

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Abstract In this paper, we present an efficient evolutionary algorithm for the multi-user detection (MUD) problem in direct sequence-code division multiple access (DS-CDMA) communication systems. The optimum detector for MUD is the maximum likelihood (ML) detector, but its complexity is very high and involves an exhaustive search to reach the best fitness of transmitted and received data. Thus, there has been considerable interest in suboptimal multiuser detectors with less complexity and reasonable performance. The proposed algorithm is a combination of adaptive LMS Algorithm and modified genetic algorithm (GA). Indeed the LMS algorithm provides a good initial response for GA, and GA will be applied for this response to reach the best answer. The proposed GA reduces the dimension of the search space and provides a suitable framework for future extension to other optimization algorithms. Our algorithm is compared to ML detector, Matched Filter (MF) detector, conventional detector with GA; and Adaptive LMS detector which have been used for MUD in DS-CDMA. Simulation results show that the performance of this algorithm is close to the optimal detector with very low complexity, and it works better in comparison to other algorithms.

Keywords Direct sequence-code division multiple access (DS-CDMA) · Multiuser detection · Adaptive LMS algorithm · Genetic algorithm

1 Introduction

In a direct sequence-code division multiple access (DS-CDMA) system, the receiver is a matched filter bank (MFB), which comprises the conventional detector (sign detector). This

A. Zahedi (✉)
Faculty of Engineering, Science and Research Branch, Islamic Azad University,
Tehran, Iran
e-mail: H.zahedi.62@gmail.com

H. Bakhshi
Department of Electrical Engineering, Shahed University, Persian Gulf Highway,
Tehran, Iran
e-mail: bakhshi@shahed.ac.ir

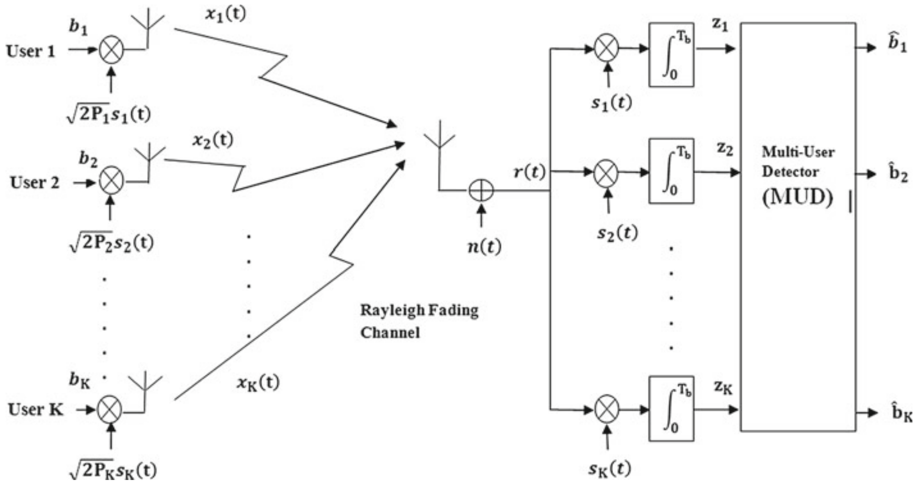


Fig. 1 Baseband DS-CDMA block diagram, receiver with MUD [1]

type of receiver is unable to optimally recover the signal when the channel is contaminated by additive white Gaussian noise (AWGN), and suffers from flat or frequency selective fading; because the DS-CDMA signal is affected by multiple access interference (MAI) and also by the near-far ratio (NFR) [1]. In fact, the signature signals of different users are not completely orthogonal to each other, and cross correlation among these signals results in multiple access interference. Therefore, the conventional MF detector [2,3], as in single user communication, is no longer effective and causes many problems. In 1986, Verdu in [2] proposed the optimum multiuser detector (OMUD) which consists of a bank of matched filters followed by a maximum likelihood sequence estimator (MLSE). The MLSE detector generates a maximum likelihood sequence, $\hat{b}$, which is associated with the transmitted sequence, as presented in Fig. 1 [1]. The vector b is estimated in order to maximize the sequence transmission probability given that $r(t)$ is received; where $r(t)$ is extended for all messages, considering all the transmitted messages with the same transmission probability [1]. The OMUD has a computational complexity which grows exponentially with the number of users. Thus, since CDMA systems could potentially have a large number of users, the OMUD is impractical to implement for them. Therefore, many researches have focused on sub-optimum detectors with less complexity and a performance which is almost as high as the OMUD. Alternative detectors for OMUD include the Decorrelator proposed by Verdu in [2] and the MMSE recommended by Poor and Verdu in [4]. These algorithms have reasonable computational complexity, and their performance is comparable to that of the optimum receiver, but they yield a degraded communication system in sense of BER [1].

According to the problem of ML detector, many methods for suboptimal detection have been proposed. Some heuristic methods have been developed, such as genetic algorithm (GA). The first GA-based multiuser detector (GA-MUD) was proposed by Juntti et al. [5] where the analysis was based on a synchronous CDMA system communicating over an AWGN channel. After that in [6–11], the new approach of GA is proposed. Tabu search algorithm [12] and simulated annealing algorithm (SAA) [13] are the other new approaches of multiuser detectors. Also some novel techniques, such as particle swarm optimization (PSO) and wavelet transform have been used [14–17]. Moreover, the PSO-based multiuser detection (MUD) has been combined with Rake processing to overcome the multipath fading and multi access interference in [18]. Ant Colony-based MUD for suboptimal detection is applied in [19,20].

For better implementation of multiuser detection, adaptive algorithms are used for MUD implementation such as LMS and RLS algorithms. In [21] a new method, LBER, for MUD in CDMA system is applied. Channel estimation using LMS and RLS and other adaptive algorithms is discussed in [22]. Moreover in [23,24] LMS detector for multiple access system is given. In adaptive algorithms by using of weight updating process, it is tried to decrease the error between received and desired signal. With this property and due to the goal of this paper (minimizing the detection error) we combined adaptive LMS algorithm and GA to suggest sub-optimum method for multiuser detection. Our method is applied in two steps: first using adaptive LMS to achieve a good initial response for GA and then in second step, applying GA and repeating several generations to achieve the best result for multiuser detection.

We compare our proposed method to the ML detector, MF detector, conventional detector with GA and Adaptive LMS detector and we show that the performance of the proposed method is better with less complexity.

The remainder of this paper is organized as follows: Sect. 2 describes our asynchronous CDMA system model; Sect. 3 highlights the algorithm used to implement our proposed detector. The simulation results are presented in Sect. 4, while Sect. 5 provides comparison of the complexities associated with our algorithm and several effective methods. Finally, some conclusions are drawn in Sect. 6.

2 System Model

In a DS-CDMA system with binary phase-shift keying modulation (BPSK) shared by k asynchronous users, as illustrated in Fig. 1, the k-th user transmitted signal is given by [25]:

$$x_k\,(t) = \sqrt{2P_k}\sum_i b_k^{(i)} s_k\,(t - iT_b)\cos\,(\omega_c t)\,. \tag{1}$$

where P_k represents the k-th user transmitted power; $b_k^{(i)}$ is the i-th BPSK symbol with period T_b; ω_c is the carrier frequency and $s_k(t)$ corresponds to the spreading sequence defined in the interval [0, T_b):

$$s_k\,(t) = \sum_{n=0}^{N-1} c_{k,n}\,p(t - nT_c); \quad 0 \le t < T_b. \tag{2}$$

where $c_{k,n} \epsilon \{+1, -1\}$ is the n-th chip of the sequence with length N used by the k-th user; T_c is the chip period and the spread spectrum processing gain, $\frac{T_b}{T_c}$ is equal to N; the pulse shaping $p(t)$ is assumed rectangular with unitary amplitude in the interval [0, T_C) and zero outside.

Assuming a frame with I bits for each user propagating over L independent slow Rayleigh fading paths, the baseband received signal in the base station is [25]:

$$r\,(t) = \sum_{i=0}^{I-1}\sum_{k=1}^{K}\sum_{l=1}^{L} A_k b_k^{(i)} s_k(t - \tau_k) * h_k^{(i)}\,(t) + w\,(t)\,. \tag{3}$$

where K is the number of active users, $t \epsilon$ [0, T_b) , the amplitude A_k is assumed constant for all I transmitted bits, $b_k \epsilon \{+1, -1\}$ is the transmitted information bit, s_k denotes a copy of the signature sequence assigned to the k-th user and τ_k representing the random delay associated to the k-th user; the complex low-pass impulse response of the channel for the k-th user over the i-th bit interval can be written as [25]:

$$h_k^{(i)}(t) = \sum_{(l=1)}^{L} a_{(k,l)}^{(i)} \delta(t - \lambda_{k,l}). \tag{4}$$

where $\lambda_{k,l}$ is the propagation delay and $a_{k,l}^{(i)}$ is the complex channel coefficient whose amplitude has Rayleigh distribution, and its phase is uniformly distributed over $[0, 2\pi]$; finally, $w(t)$ represents the AWGN with bilateral power density equal to $\frac{N_0}{2}$.

Using vectorial notation, Eq. (3) can be stated as:

$$r(t) = \sum_{i=0}^{I-1} \boldsymbol{s}^T (t - iT_b) \boldsymbol{A}\boldsymbol{a}^{(i)}\boldsymbol{b}^{(i)} + w(t) \tag{5}$$

where $\boldsymbol{A} = diag[A_1\boldsymbol{I}, A_2\boldsymbol{I}, \ldots, A_K\boldsymbol{I}]$ is the diagonal matrix for the users' amplitude including the path losses and shadowing effects, and $\boldsymbol{I}_{L\times L}$ is the identity matrix with a dimension equal to L; $\boldsymbol{s}$ is the vector of users signature sequence, and $\boldsymbol{a}$ is the diagonal channel gain matrix as:

$$\boldsymbol{a}^{(i)} = diag\left[a_{1,1}^{(i)}, \ldots, a_{1,L}^{(i)}, a_{2,1}^{(i)}, \ldots, a_{2,L}^{(i)}, \ldots, a_{K,L}^{(i)}\right] \tag{6}$$

And the data vector is given by:

$$\boldsymbol{b}^{(i)} = \left[b_1^{(i)}, b_2^{(i)}, \ldots, b_K^{(i)}\right]^T \tag{7}$$

Representing the $1\times L$ k-th user bit vector.

If we use the conventional Rake receiver which consists of a bank of KL filters matched to the users' signature sequence, then the output for the i-th bit interval can be expressed as [25]:

$$y_{k,l}^{(i)} = \int_{-\infty}^{+\infty} r(t)\, s_k\left(t - iT_b - \tau_{k,l}\right) dt = A_k T_b \rho_{k,l}^{(i)} b_k^{(i)} + I_{k,l}^{(i)} + n_{k,l}^{(i)}. \tag{8}$$

where the first term corresponds to the desired signal, the second term refers to the MAI over the l-th multipath component of the k-th user, and the last term represents the filtered AWGN. Notice that we neglect the auto-interference term for simplicity. MAI is the result of cross correlation between signature signals of users as expressed [25]:

$$R_{j,k}(\tau, i) = \int_0^{T_b} s_j(t)\, s_k(t + iT_b + \tau)\, dt. \tag{9}$$

If we use the Rake receiver as in [26], we need to estimate some parameters such as channel coefficients and delay (τ). When the number of users increases, the significance of interference rises and owing to this fact, the conventional detector performance in MUD is degraded. As mentioned in the previous section, we use the optimum detector to solve this problem. The optimum detector is the maximum likelihood sequence detector that selects the most likely sequence of transmitted bits given by the observations at the receiver. In this context, the K-user, L-paths, I-frame and asynchronous channel scheme can be viewed as a *KLI*-user synchronous channel scheme, and then the *KLI*-user vector B can be written as [25]:

$$B = \left[b^{(0)^T}, b^{(1)^T}, \ldots, b^{(I-1)^T}\right]^T. \tag{10}$$

Based on [27], Verdu proved that in order to select the maximum likelihood sequence B, we must maximize the log likelihood function (LLF):

$$f(B) = 2Re\left\{B^T \boldsymbol{a}^H Ay\right\} - B^T \boldsymbol{a} ARA \boldsymbol{a}^H B \tag{11}$$

where y is the output vector and R is the cross correlation matrix that having the toeplitz property:

$$y = [y^{(0)^T}, y^{(1)^T}, \ldots, y^{(I-1)^T}]^T \tag{12}$$

$$R = \begin{bmatrix} R[0] & R^T[1] & 0 & \cdots & 0 & 0 \\ R[1] & R[0] & R^T[1] & \cdots & 0 & 0 \\ 0 & R[1] & R[0] & \cdots & 0 & 0 \\ & \vdots & & \ddots & \vdots & \\ 0 & 0 & 0 & \cdots & R[1] & R[0] \end{bmatrix} \tag{13}$$

Neglecting the channel effect, we can state (11) in a simple form as [25]:

$$f(B) = B^{\mathrm{T}} r - B^{\mathrm{T}} RB. \tag{14}$$

where r is the received signal and B is the transmitted sequence to be guessed and we neglect other parameters in (11) due to the channel effect. The complete frame with the estimated transmitted bits for all K users can be obtained through optimization of (14), resulting [25]:

$$\hat{B} = arg\left\{\max_{\mathrm{B}\epsilon\{+1,-1\}^{\mathrm{IK}}}[f(B)]\right\} \tag{15}$$

The OMUD attempts to find the best vector of data bits but because of high complexity and unfeasible implementation, it is an inefficient method for multiuser. Because the optimization associated with the OMUD is high dimensional, the dimension of the search space needs to be restricted; hence, all suboptimal algorithms try to find a solution following an objective function which is able to improve the performance of multiuser detection. These attempts try to reduce the complexity of OMUD and maximize the DS-CDMA mean performance. As a matter of fact, most efforts concentrate on approaching the performance of ML algorithm with less complexity and reliable applicability along with the least possible error. In the next section, we propose our algorithm to achieve this goal and compare our algorithm to other efficient algorithms available in the literature.

3 Proposed Algorithm

It is well-known in the evolutionary computation literature that basic GAs (and even many other modified evolutionary algorithms) bear some deficiencies in solution of large scale problems. It is worthwhile to devise a dimension reducing algorithm to surmount the so-called "curse of dimensionality". One of the most important features of GAs is their ability to find the global optimum of a cost function [28,29]. Many of the modifications performed on the conventional GA's have targeted this issue [30].

Our proposed method in this paper not only modifies GA, but also guarantees the stability and fast convergence of that. This method is adaptive and composed of two steps:

3.1 LMS Algorithm

In the first step for using the LMS algorithm, the initial weights must be determined. For this subject the sequence of pilot data is transmitted and due to this fact that the desired output must be the same as the transmitted data, it is tried to minimize the error between received and transmitted pilots iteratively as in [31]. In this paper we use LMS with variable step size and this variation is as follow (VSS algorithm [32]):

$$\mu(n+1) = \alpha\mu(n) + \gamma e^2(n). \tag{16}$$

where μ is the step size, e is the error between output and desired signal, $0 < \alpha < 1$ and $\gamma > 0$. Also $\mu(n+1)$ is limited between $\mu_{\min}$ and $\mu_{\max}$. The advantage of variable step size is that when the step is large, the convergence speed is much but probability of missing the optimum point is high and if the step size is small, the convergence occurs late. The variable step size has both advantages of these two cases.

Thus with this iterative and adaptive algorithm, the proper weights for minimizing input-output difference are set and in other words the system is trained. The output is obtained and then applied as initial response to GA. This output signal is near the optimum answer. The simplicity and good performance of the LMS algorithm make it the benchmark against which other optimization algorithms are judged. The use of LMS presents a proper initial condition for applying GA.

3.2 Genetic Algorithm

In step 2, regarding to the fixed weights from previous step, it is tried to obtain the minimum detection error with GA and LLF criterion.

It is trivial that the optimization algorithm performs better when the number of parameters is fewer. Thereby, decomposition of a large scale problem into small parts is of substantial interest. Such ideas are strong motivations for introducing a novel GA which tries to simplify optimization problems and decompose them into simpler problems, since the probability of finding the solution reduces when the number of the parameters increases. For example, to elaborate more, consider the following cost function [30]:

$$F(\vec{x}) = 0.5 + (sin^2|\vec{x}| - 0.5)e^{-0.2|\vec{x}|}, \vec{x} = (x_1, x_2, \ldots, x_l) \tag{17}$$

In which $\vec{x}$ is the vector of the parameters of the problem. Obviously, the global minimum of the cost function is located in $\vec{x} = 0$ and its value is 0. First, consider $\vec{x} = x_1$. As shown in Fig. 2, in order to reach the global optimum, it is necessary for a chromosome to be placed in the best region, which is highlighted in Fig. 2. This region occupies a ratio of $\frac{L_1}{L}$ of the search space, which is a significant part of the space. There are many precise tools which can assist the GA to reach this global optimum easily. Now, consider the following situation:

$$\vec{x} = (x_1, x_2) \tag{18}$$

The function is illustrated in Fig. 3. Observe that the portion of the search space occupied by the attraction domain of the global optimum is proportional to $(L_1/L)^2$ rather than $\frac{L_1}{L}$. Since $\frac{L_1}{L} < 1$, this fact directly causes a reduction in the chance of finding the global optimum. When the number of parameters proliferates, the chance decreases exponentially.

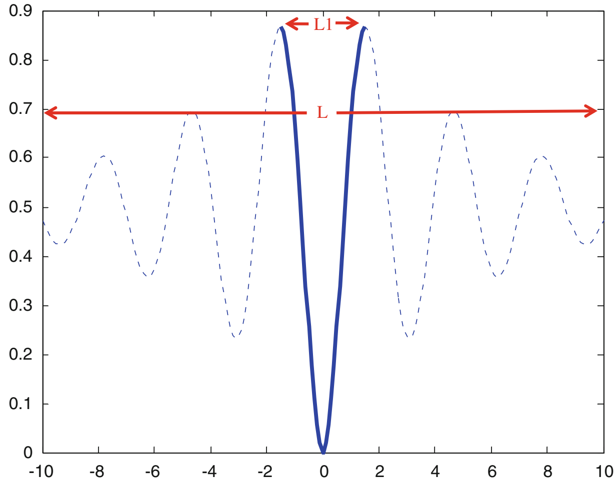


Fig. 2 The function $F(\vec{x})$ in $\vec{x} = x_1$ [29]

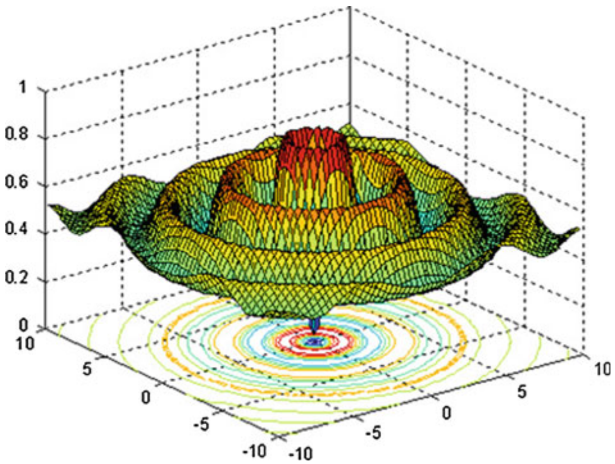


Fig. 3 The function $F(\vec{x})$ in $\vec{x} = (x_1, x_2)$ [29]

This fact is firstly realized by a naive idea, i.e. neglecting some of the parameters of the problem in the optimization procedure. However, such an approach is not mathematically feasible when the steps towards the optimum points of the objective function are selected regularly. In contrast, the random nature of the GAs makes the implementation of this idea possible. The algorithm allows every parameter to change. The main difference of the algorithm with conventional GA's is that in each iteration, the algorithm is performed over subset of the parameters while the other parameters are kept constant. In the next iteration, different set of parameters are selected to be constant. The set of changeable parameters are selected according to a procedure described in the sequel. With a sufficient number of repetitions, one can make sure that an appropriate searching strategy is selected for the whole search space which reduces the dimension of the parameters in each iteration of the conventional GA. It is heuristically justifiable to initialize the algorithm by a "sufficiently good" solution which is determined by adaptive LMS algorithm as previous section.

Next, let us take a closer look at the objective function. Considering Eqs. (11) and (14), the objective function is comprised of the two parts: $B^T r$ and $B^T RB$. In the $B^T r$ part, considering the fact that each element of B can only take the values of either 1 or -1 (as many as the number of transmitted bits), it is enough for each element of B to to be either 1 or -1, according to the corresponding member in r. Since the $B^T RB$ term is a square matrix, if the non-diagonal elements were small, it would practically equal to $B^T B$. In this case it is indifferent if the values of the elements of B are either 1 or -1. The main problem is that in some cases, some non-diagonal matrix elements are not considerably small and cannot be assumed as negligible. Because the matrix R is symmetric, these elements add terms of the type $2R_{ij} B_i^T B_j$ to the objective function. In this case if R_{ij} is negative, the fact that B_i^T and B_j bear the same sign helps increase the value of the objective function, and if R_{ij} is positive, their difference in sign helps this fact. In other words, the problem variables are no longer independent, and their interaction is influential. The variable showing more interaction with other variables is considered to be a more significant variable. In other words, the following criterion is proposed:

$$id_k = \sum_{j=1}^{K} abs(R_{kj}) \tag{19}$$

where K is the number of transmitted bits. Any element of B with higher value id is a more significant and effective variable. As discussed, a number of variables (say M) are selected for optimization in the proposed algorithm, and the rest $(K - M)$ are kept constant at the previous value. As we discussed, those variables with lower id are more likely to be at their optimal value, provided by the adaptive LMS detector from previous section. Thus, it is better to take advantage of a probabilistic algorithm for selection of M, so that the variables with higher id are more likely to be selected. Accordingly, the Roulette Wheel can be used in each iteration for selection of variables with a probability proportional to their *id* value. However, we take advantage of a method with less computational cost. This is done through selection of a random number for each variable, having uniform distribution between zero and the id corresponding to that variable. Then, the M variables possessing larger random numbers are picked out. This action, on one hand, makes all the variables likely to be selected, and on the other hand, makes those with higher id more likely to be chosen. In the next step, a chromosome is created using these M variables, and the conventional GA is performed on it once. Subsequently, the best answer is saved as the new values of these M variables, and this process continues again. The different parts of this conventional GA are as follows:

3.2.1 Fitness Function Evaluation

In each generation, the fitness values are computed for each chromosome. Due to (14), the fitness function is as follow:

$$f(B) = B^T r - B^T RB \tag{20}$$

3.2.2 Selection

In order to preserve better chromosomes (solutions) to yield better offspring, we employ the truncated selection scheme, through retaining only some of the parent chromosomes in the population, which possess larger fitness values and reproduce them in the mating pool from which the two parent chromosomes are randomly selected for the following crossover step [28,33].

3.2.3 Crossover

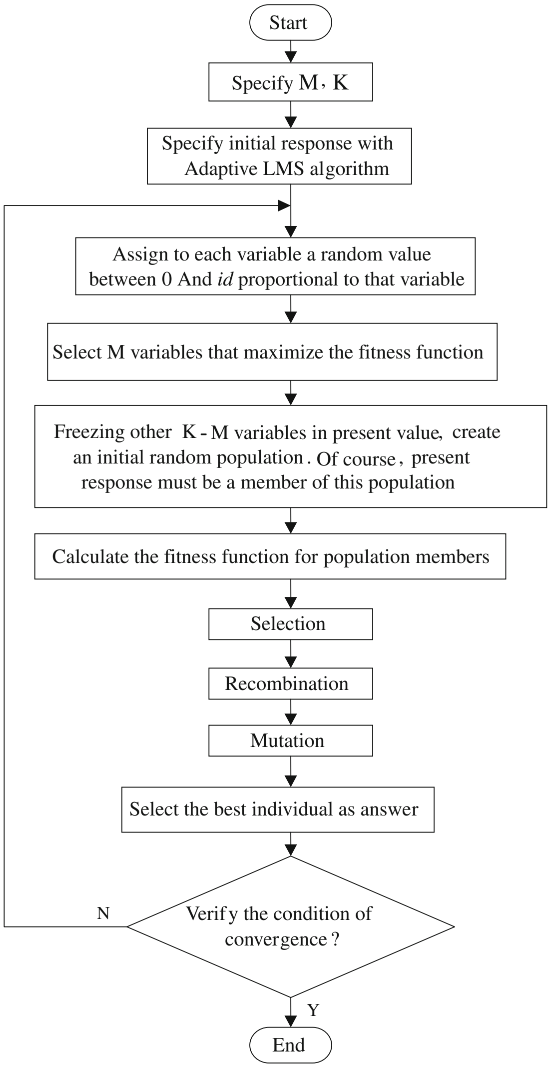
The bits of the parent vectors are then exchanged using the uniform crossover process in order to produce two offspring. The process of uniform crossover invokes a crossover mask, which is a sequence consisting of randomly generated 1s and 0s [28,33].

3.2.4 Mutation

The mutation process [28,33] refers to the alteration of the value attributed to a bit in the offspring from 1 to −1 or vice versa, with a probability pm. Here, we set $pm = 1/K$, such that on the average, only one bit in each individual is mutated.

The flowchart is provided in Fig. 4.

Fig. 4 The flowchart of proposed algorithm



The algorithm seems to have another advantage. Fine tuning algorithms for GA's such as Tabu search and other types of local search are more efficient in escaping from the local minima when the dimension of the search space is low. Thereby, this algorithm is more likely to perform better when combined with fine-tuning algorithms.

4 Numerical Results

In this section, the performance of the algorithm described in Sect. 3 is compared with optimum ML detector and ordinary GA with conventional detector considering the BER as the main figure of merit. The convergence of the algorithm versus optimization parameters is also considered. It is assumed that the communication system is asynchronous DS-CDMA MUD, over slow Rayleigh fading AWGN channel. The system performance is evaluated for both BPSK and QAM modulations. The numerical results were obtained based on the averaging of 1,000 simulation runs; these results were attained in identical systems and channel conditions in order to provide fair comparison with other algorithms. In all simulations, the parameters are as follows in Table 1.

The spread sequences are selected as pseudo-noise (PN) m-sequence; the number of active asynchronous users in the system is $K = 20$ and $M = 4$; the processing gain is $N = 63$. In all simulations, it was assumed that the phases, amplitudes, channel gains and random delays of all users are perfectly known in the receiver, and users' power is according to:

$$E\left[\sum_{l=1}^{L}\left|a_{k,l}^{(i)}\right|^{2}\right] = 1, \ \ for\ k = 1, 2, \ldots, K \tag{21}$$

L is the number of signal paths. In all simulations, the population of GA has been selected as 10 and the iteration has been chosen as 100. In these simulations as will be seen, our proposed method is more effective and better in comparison to other algorithms presented before.

First the main parameter of each communication system, BER, is discussed. In Fig. 5, this property of the proposed algorithm for BPSK modulation is compared to the other algorithms and also to the comprehensive search in the space of parameters known as ML and the worst case as MF. It is revealed that although in low SNR, there is no main difference among the methods; the proposed algorithm in high SNR converges to OMUD and the BER of this method is less than others. In this figure, it is concluded that adaptive LMS detector with step size 0.01 has a low performance in high SNR and so does conventional genetic method, but

Table 1 Simulation parameters

Modulation	BPSK/QAM
Spreading code	m-sequence with 63 chips
Communication system	Uplink asynchronous CDMA
User number (K)	20
Channel	AWGN with slow Rayleigh fading
Path number (L)	4
Path loss variance	−5 dB
α (LMS)	0.9
γ (LMS)	0.1

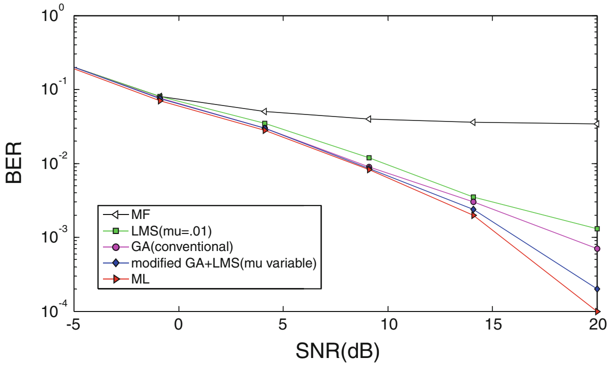


Fig. 5 BER of the proposed algorithm in comparison with other methods versus SNR, (BPSK mode)

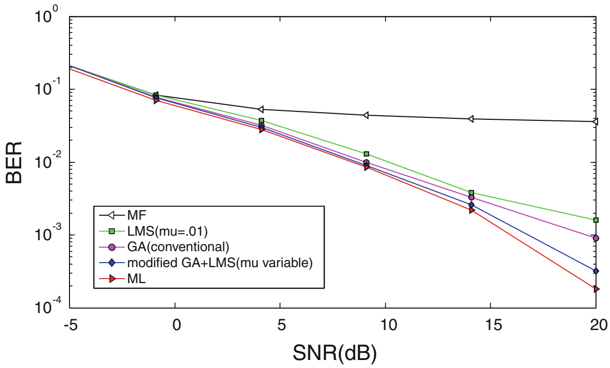


Fig. 6 BER of the proposed algorithm in comparison with other methods versus SNR, (4-QAM mode)

the proposed algorithm which combines adaptive variable step size LMS with modified GA, has an excellent performance close to optimum detector. Figure 5 shows the unsuitability of the MF form MUD.

In Figs. 6 and 7, the performance of the proposed algorithm compared to other algorithms is presented for system with 4-QAM and 64-QAM modulations. In these figures, the similar results such as those in the previous figure (Fig. 5) are obtained but with BER more than that in the previous figure because the error of QAM modulations is more than that in BPSK ones.

In Fig. 8, the effect of increasing the number of users on BER is analyzed for all mentioned algorithms. On the basis of this figure, we see that the proposed adaptive genetic-based algorithm performance is better than others and BER of this algorithm does not considerably increase with increasing user numbers and is almost near ML detector. We also see that the performance of the classic MF method is degraded substantially, and this fact shows that for Multiuser detection, single user detector is not an effective method. This simulation is carried out with SNR $= 12$ dB.

In Fig. 9, the BER of the proposed algorithm versus SNR with different step sizes is implemented, and the numerical results are depicted. It is observed that with the variable step size, the algorithm converges to OMUD and has a little error. Of course, for step sizes 0.01, 0.05, convergence occurs with an error. This figure shows that variable step size LMS

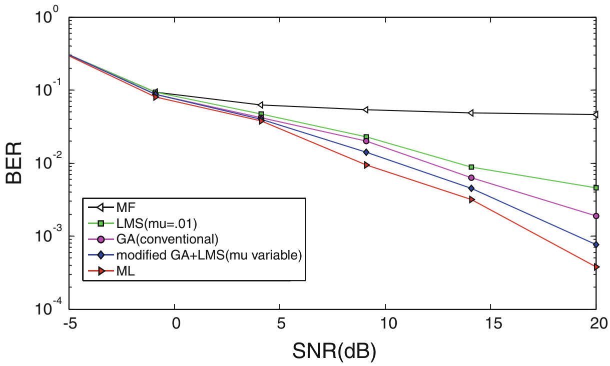


Fig. 7 BER of the proposed algorithm in comparison with other methods versus SNR, (64-QAM mode)

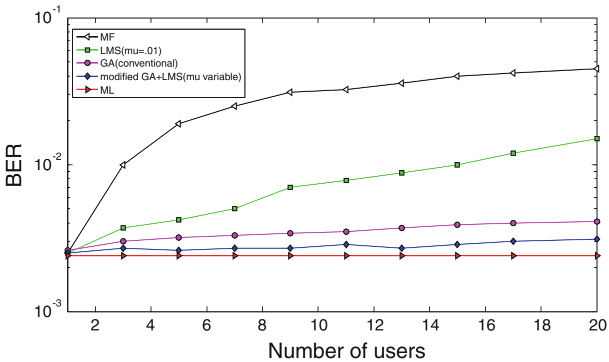


Fig. 8 BER of the proposed algorithm versus number of users in comparison with other methods. SNR is fixed at 12 dB

has better convergence and less error in comparison with fixed step size LMS. Moreover the limits of fixed step size LMS are suppressed.

In Fig. 10, BER versus the number of generations in different population sizes is illustrated, and it is revealed that the proposed algorithm with population size 15 converges faster in comparison to other two population sizes 10, 5. This property is very important, as the complexity of calculations is decreased to a great extent by the proposed algorithm and noticeably the cost of the detector and hardware bears the least quantity possible. This figure shows that our algorithm is comparable with ML algorithm, and its convergence is fast with lower complexity. This simulation was conducted in SNR $= 15$ dB.

5 Computational Complexity

In order to express the complexity of the analyzed algorithms, it is essential to determine which instructions are carried out and how many times they are processed. For the fitness value calculation, Eq. (11), the set of operations $F_1 = a^H Ay$ and $F_2 = aA\boldsymbol{R}Aa^H$ can be obtained before the optimization loop of each algorithm. If the number of transmitted bits is I and number of users is K, the complexity of genetic section of the proposed algorithm is in the

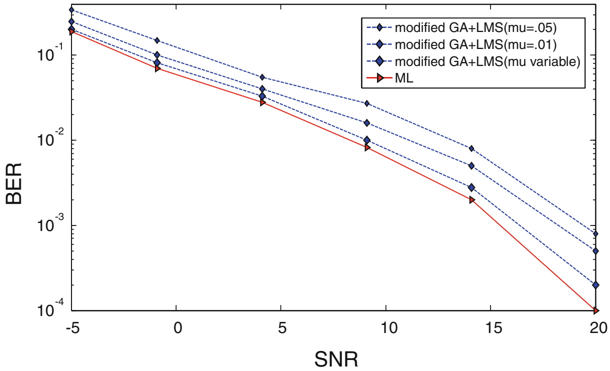


Fig. 9 BER of the proposed algorithm versus SNR in different step sizes

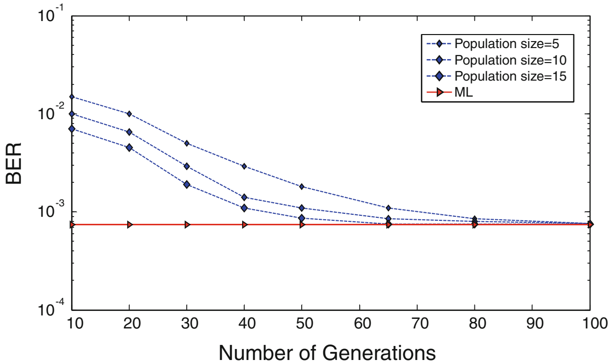


Fig. 10 BER versus the number of generations in proposed algorithm in different step sizes 15, 10, 5, and ML and SNR = 15 dB

order of $(KI)^2$ as most GAs [6]. This relation is because both the number of Generations and the number of Populations is proportional to KI, and the complexity of GAs is proportional to the product of these two parameters. Moreover the complexity of LMS section is in order of KI [22]. So the complexity of the proposed algorithm is in order of $(KI)^3$ in the worst case mode (in the sequel it is explained why the worst case mode is said). Of course this order is valid for the BPSK modulation and in QAM modulation, this complexity exists in two dimensions such as in 4-QAM. So, the complexity of 4-QAM or 4-PSK is two times more than BPSK mode complexity and in higher order modulation, the complexity grows almost linearly. But for OMUD, the number of operations increases exponentially with the number of users, i.e. 2^{KI}. For example, in case with user numbers as 10 and the transmitted bits equal to 4, the complexity of our proposed algorithm is compared with other methods in Table 2.

As said in above, the complexity order $(KI)^3$ is valid in the worst case mode. Indeed in proposed algorithm, the computation order is less than that in the Table 2 because the LMS algorithm is not needed to apply completely and after some iterations, it proposes a good initial response for the modified GA as the next step. So the computation order of modified GA is decreased because it relates with approximately good response from previous step and it needs fewer numbers of generations and populations to converge. Fur-

Table 2 Comparison of the complexity of our proposed algorithm with other methods ($K = 10$, $I = 4$)

Methods	O (order of computation)
MF	$K = 10$
LMS	$KI = 10 \times 4 = 40$
GA (conventional)	$(KI)^2 = (10 \times 4)^2 = 1,600$
Modified GA+LMS	$(KI)^3 = (10 \times 4)^3 = 64,000$
OMUD	$(2)^{KI} = 2^{(10\times4)} = 1.0995e + 12$

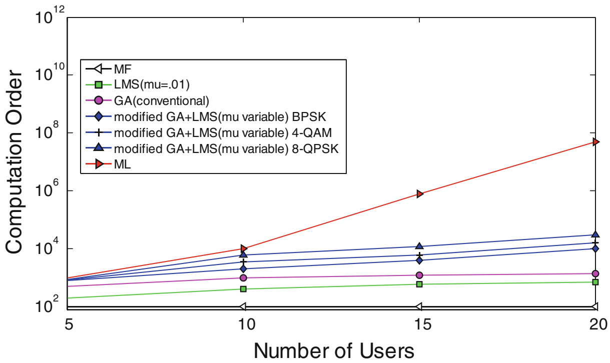


Fig. 11 Computation order of the proposed method in various modulations versus the number of users, comparison to LMS, GA (conventional), ML and MF method

thermore, modified GA has less complexity than conventional GA. In numerical aspect by using of averaging, it can be said that each step complexity of the proposed algorithm is approximately reduced to half of its value and complexity order $(KI)^3$ is converted to $\frac{KI}{2} \times (\frac{KI}{2})^2 = \frac{(KI)^3}{8}$. Due to this new order, the computation order 64,000 in Table 2 is changed to 8,000 for the proposed algorithm and due to this discussion, the real complexity of proposed algorithm is near the other algorithms but its performance is much better than others. From this table, the complexity of OMUD is much more than the proposed algorithm even with higher order modulations. In Fig. 11, we assumed the number of users as k= [5,10,15,20] and the number of transmitted bits as $I = 4$. From this figure, although LMS receiver has less complexity in comparison to our algorithm but it is generally less performing than adaptive GA-LMS and is strongly influenced by the step size parameter setting.

6 Conclusions

In this paper, multiuser detection based on adaptive LMS combined with modified GA was implemented, and through presentation of a new search method, the desirable optimization method was achieved. In addition to complexity view point, there are three main novelties in this work: First, we have used LMS algorithm with variable step size as initial response for GA which has shown a good performance in the paper. Second, we have applied a modification of GA which is powerful against high dimension problems. This is very important, since we know that the curse of dimensionality is the main cause of failure in high dimension problems optimization. On the other hand multiuser detection in DS-CDMA systems is certainly a high dimension problem with many optimization variables. Third, we have defined a way to find more important variables in DS-CDMA systems, i.e. we have proposed that users with higher cross-correlation have more important role in the final cost function. So the optimization procedure should be applied on them more than the others.

When compared to sub-optimal algorithms such as conventional GA and LMS receiver, the new algorithm shows better performance, and in some cases, rapidly approaches the optimal ML algorithm. The present paper is also novel from complexity viewpoint. By using the proposed method, the complexity is decreased considerably by the decomposition of the problem into several problems with lower dimensions as presented in this paper.

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Author Biographies

Abdulhamid Zahedi was born in Kermanshah, Iran, in 1983. He received the B.Sc. degree in electrical engineering from Amirkabir university of technology (Tehran Polytechnic), Tehran, Iran in 2005. He received his Master's degree in communication engineering from shahed university, Tehran, Iran in 2008. He is currently pursuing his Ph.D. degree in communication engineering in Science and Research branch of Tehran, Islamic Azad university, Iran. His interest fields of research are Multiuser Detection and wireless communication, specially CDMA and MIMO-OFDM communications.

Hamidreza Bakhshi received the B.Sc. of electrical engineering in Tehran university of technology in Iran in 1993 and M.Sc. in Tarbiat Modarres university in Iran in communication engineering in 1996. He began his Ph.D. in 1997 in Tarbiat Modarres university in Iran and received his degree of Ph.D. in 2001. Now he is the faculty of shahed university in electrical engineering department. his interest fields are wireless telecommunication, array antenna, CDMA and MUD and MIMO-OFDM communications.