Invasive Weed Optimization Method Based Blind Multiuser Detection for MC-CDMA Interference Suppression over Multipath Fading Channel

Ho-Lung Hung , Chien-Chi Chao
The Department of Electrical Engineering,
Chien-Kuo Technology University,
Changhua County, Taiwan
e-mail: hlh@ctu.edu.tw

Chia-Hsin Cheng, *Member,IEEE*
The Department of Electrical Engineering,
National Formosa University
Yunlin County, Taiwan
e-mail: chcheng@nfu.edu.tw

Yung-Fa Huang*, *Member,IEEE*
The Department of Information and Communication Engineering,
Chaoyang University of Technology
Township, Taichung County, Taiwan
*e-mail: yfahuang@mail.cyut.edu.tw

Abstract—**The paper presents a novel constrained constant modulus (CMA) approach for the blind suppression of multiuser interference in multi-carrier code division multiple access (MC-CDMA) systems. In this paper, we put forward a novel receiver, which combines CMA blind adaptive multiuser detection with Invasive weed optimization (IWO) for MC-CDMA interference suppression over multipath fading channel. To work around potentially computational intractability, the proposed scheme exploits heuristics in consideration of both global and local exploration the step size of the CMA. The computer simulation results show that compared with the various CMA developed previously, the proposed IWO method obtains the most desirable bit error rate performance with low computational complexity.**

***Keywords*—Invasive weed optimization, Constant Modulus Algorithm, Blind Multiuser Detection, Multi-carrier Code Division Multiple Access component, formatting**

I. INTRODUCTION

For future high-data-rate wireless applications, multi-carrier code division multiple access (MC-CDMA) has emerged as the most promising multiple access scheme due to its numerous advantage over conventional code division multiple access in both uplink and downlink communications. [1-2]. In uplink transmission, the base station receives the signals from different mobile terminals through different paths and every user's signal experiences independent random amplitude and phase distortions result in the loss of orthogonality at the receiver. This in turn gives rise to multiple access interference (MAI) which limits the capacity and performances of the system. Multiuser detection [3] is a powerful technique to combat MAI and increase the capacity of the system. Many multiuser detection approaches have been proposed in literature [3-5]. Recently, blind adaptive multiuser detection has received special attention and several detectors have been proposed [5-14]. The main motivation for employing a blind detector is to avoid the requirements of a training sequence, which is commonly required in most of the adaptive multiuser detectors proposed previously. For the analogy between inter-symbol interference (ISI) and MAI, some blind adaptive multiuser detection [5-14] has been receiving a great deal of research recently, and it requires no additional knowledge than conventional single user receiver, that is, the desired user's signature waveform and its timing. In wireless communications system, the conventional CMA [4] for blind multiuser detection has some disadvantages such as slow convergence speed and phase rotation. In order to overcome these shortages, a modified constant modulus algorithm was developed for blind multiuser detector. A faster converging CMA similar in form to the recursive least squares method is the orthogonalzed CMA. The signed error version of CMA (SE-CMA) is shown to improve the computational efficiency of the traditional CMA algorithm resulting in low cost design [5]. To improve the tracking capability, the use of the linearly constrained constant modulus algorithm (LCCMA) to capture desired user instead of an interfering one was reported in [6-7]. However, their convergence is more easily influenced by the step-size. A dither signed error algorithm (DSECMA) [8] is put forward, which results in robustness properties closely resembled to standard CMA. But, both CMA and DSECMA are phase-blind. Consequently, the equalizer output signal constellation suffers from an arbitrary phase rotation. In time varying channel, randomly rotating phase distortion may seriously degrade the performance of the algorithms.

Comparisons of the performance of the conventional CMA show that the LCCMA generally achieves high SIRs, but is show that in convergence and weak in robustness when the working environment channel abruptly. A faster converging CMA is the least squares CMA (LSCMA) [9]. The authors of [10] have studied steepest-descent CMA (SDCMA) blind multiuser methods. Yan Meng *et al.* [11], Chern *et al.*[12] , Kimet al.[13] and Sanchez *et al.* [14], and S. Chen *et al.* [20] study that CMA blind multiuser detection is applied in MC-CDMA systems. Yan Meng *et al.* [11] and J. Namgoong [15] suggests that subspace-based linear MMSE detection be used in MC DS-CDMA systems. The subspace-based method has

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much matrix computation which makes complexity increase. SDCMA renews weight vectors with the minus gradient descent direction as the searching direction and its implementation is very simple. For a stochastic gradient (SG) [16] adaptive algorithm, such as the training-based least mean square (LMS), the step size must be sufficiently small to avoid divergence. Within the range of the step size values that ensures convergence, a smaller step size achieves a better steady-state performance at the expense of slower convergence speed, while a larger step size improves convergence speed with a poorer steady-state performance. A constant step-size LMS algorithm thus has to trade off between the steady-state performance and convergence speed when choosing the step size value. In attempts to optimize both the steady-state performance and convergence speed, techniques based on fuzzy logic (FL) tuning of LMS's step size have been developed [16–21]. The CMA is a stochastic gradient blind adaptive algorithm, and its step size has to be chosen with extreme care, much more than the training-based LMS algorithm.

Based on points above, we state our interest to employ a novel CMA technique based on the invasive weed optimization (IWO) [22-25] to suppress the MAI in the MC-CDMA signal through this paper. Meanwhile, the algorithm adaptively varies the step-size in order to minimize the constant modulus criterion. The algorithm is blind in the sense that no training data are required. Specifically, this paper proposes an improved CMA algorithm by utilizing the error function, which is deduced from CMA philosophy, in the sign operation of the IWO based CMA to speed the convergence process and reduce computational complexity. Against this background, the main contribution of the proposed algorithm is to minimize the computational complexity with the optimum weight factor and suppress multiple access interference. Simulation results confirm these improvements achieved by the proposed algorithm. The outline of the paper is as follows. The system model is introduced in Section II. Invasive weed optimization (IWO) assisted CMA blind detection in multipath fading domain is demonstrated in Section III. In Section IV simulations and performance analysis are given. Conclusions are drawn in Section V.

II. SYSTEM MODEL

Consider a synchronous BPSK-modulated MC-CDMA communication system in additive white Gaussian noise with K active users. The BPSK-Modulated symbols $b_k \in (-1,+1)$ are spread using a spreading sequence $a_k = (a_k^1, a_k^2, \cdots a_k^N)$ of length N. Then N consecutive chips of the spreading sequences were mapped N different subcarriers by the inverse Fast Fourier Transform (IFFT). This signal is transmitted through a multipath fading channel, which is assumed to have L paths, hence the channel impulse response (CIR) can be expressed as

$$s_k(t) = \sum_{l=1}^{L} a_k^l p_c(t - (n-1)T_c), \qquad t \in [0, T_s]$$

(1)

where T_c is the chip interval. T_s is the symbol interval. $(a_k^1, a_k^2, \cdots a_k^N)$ is the spreading code of the k-th user, taking the value +1 or -1. $N = T_s / T_c$ is the spreading gain. $p_c(t)$ is the chip waveform. The energy of $s_k(t)$ is normalized, i.e., $\int_0^{T_s} s_k^2(t)dt = 1$. The k-th user, for $1 \le k \le K$, generates a stream of mapped data symbols $b^k = (\cdots, b_0^k, b_1^k, b_2^k, \cdots)$. The baseband model of transmitted signal of the kth user is expressed as

$$y_k(t) = \sum_{m=1}^{M} A_k \{\sum_{i=\infty}^{\infty} b_i^k s_k(t - iT_s)\} \exp[j2\pi \frac{m-1}{M} t]$$

(2)

where A_k and b_i^k respectively denote the amplitude and the complex symbol of the k-th user signal. M denotes the number of parallel branches, and it is also the number of subcarriers. Each subcarrier is assumed to experience slowly varying flat fading and adjacent subcarriers are assumed not to interfere with each other. The received signal can be expressed as

$$r(t) = \sum_{k=1}^{K} \sum_{m=1}^{M} A_k \alpha_{k,m} \{ \sum_{i=-\infty}^{\infty} b_i^k s_k(t - iT_s) \}^*$$
$$\exp(j2\pi \frac{m-1}{M} t) + n(t)$$

(3)

parameter $\alpha_{k,m}$ accounts for the overall effects of phase shifts and fading for the mth carrier of the kth user, and $n(t)$ is the zero-mean complex Gaussian Noise. For $k = 1, 2, \ldots, K$ and $m = 1, 2, \ldots, M$, $\alpha_{k,m}$ can be modeled as complex i.i.d. Gaussian random variables with zero-mean, so that the amplitude of each carrier is Rayleigh distributed. The received signal $r(t)$ is first demodulated and then passed through a chip-matched filter, as illustrated in Fig.1 where $\omega_1, \omega_2, \cdots \omega_M$ denote different carrier frequencies. The output of the chip matched filter on each branch is sampled at chip rate. The output signal in one symbol interval is denoted as

$$\mathbf{r} = \sum_{k=1}^{K} \mathbf{A}_k b_k \mathbf{D}_k \boldsymbol{\gamma}_k + \mathbf{n}$$

(4)

where

$$\mathbf{D}_k = \mathrm{diag}\left\{ \underbrace{\alpha_{k,1}, \cdots \alpha_{k,1}}_{N}, \cdots, \underbrace{\alpha_{k,M}, \cdots \alpha_{k,M}}_{N} \right\} \tag{5}$$

$$\boldsymbol{\gamma}_k = \left[\underbrace{y_k^T \ \cdots \ y_k^T}_{M} \right]^{\mathrm{T}}$$

(6)

$$y_k = \frac{1}{\sqrt{N}} \left[a_k^1 \quad a_k^2 \ \cdots a_k^N \right]^T$$

(7)

where T denotes transposition; $\boldsymbol{n}$ is an AWGN vector with the size of $MN \times 1$. Equation 4 denotes signals of all subcarriers after demodulation at the receiver, which can be viewed as signal in frequency domain.

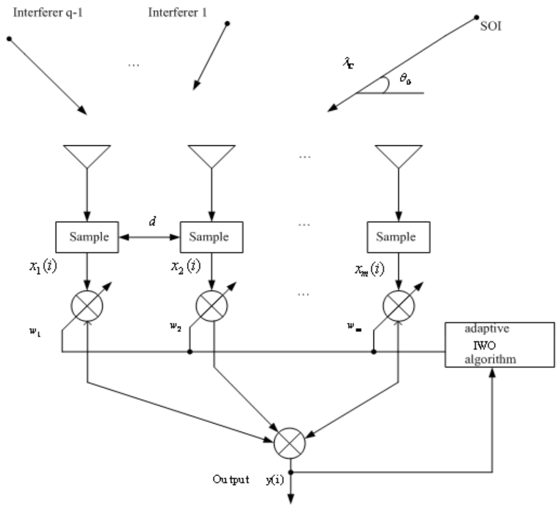

Figure 1 Block diagram of system receiver

To implement blind detection of MC DS-CDMA systems, Equation 4 is slightly changed to

$$\mathbf{r} = \sum_{k=1}^{K} \mathbf{A}_k b_k \boldsymbol{\beta}_k \boldsymbol{\alpha}_k + \mathbf{n}$$

(8)

where $\boldsymbol{\beta}_k$ is the diagonal matrix with the spreading code of the k-th user as the diagonal elements,

$$\boldsymbol{\beta}_k = \begin{bmatrix} \underbrace{\begin{matrix} y_k & & & \\ & \mathrm{y}_k & & \\ & & \ddots & \\ & & & y_k \end{matrix}}_{M} \end{bmatrix}$$

(9)

parameter β_k denotes a vector consisting of M elements of complex fading on M subcarriers of the k-th user,

$$\beta_k = \left[\beta_{k,1} \ \ \beta_{k,2} \ \cdots \beta_{k,M} \right]^T \tag{10}$$

In order to recover original signals, Equation 8 is first despread for partly eliminating MAI, followed by constant modulus algorithm (CMA) blind detection. In the Conventional CMA, a linear receiver is chosen comprising a weight vector $\mathbf{w}$ that operates on the vector $\mathbf{r}$ to yield the output y. the weight vector $\mathbf{w}$ is chosen to minimize the deviation of the receiver's output form a constant modulus. Assuming the user 1 is the desired user, according to the above idea the cost function can be defined by

$$J(w) = E\left[\left| \mathbf{w}^H \beta_1^H r \right| - 1 \right]^2 \tag{11}$$

Where $\beta_1^H r$ is the despread signal for the user 1. $\mathbf{w} = [w_1 \ w_2 \cdots w_M]^T$ is the weigh vector. H denotes the conjugate transposition. The optimum weight vector $\hat{w}$ of CMA blind detection is

$$\hat{w} = \arg\min_{w} J(w)$$

(12)

The disadvantage of the CMA is that it may capture a constant modulus signal other than the desired one. The problem stems from the fact that the CMA cost function doesn't have a unique minimum, and that it will be minimized for any constant modulus filter output. The other disadvantage is that the CMA may be too slow for a practical wireless application. To find a good tradeoff between the CMA performance on BER reduction and the complexity in the process of weight factor selection, we propose a novel IWO algorithm based CMA which is useful in solving combinatorial optimization problem. The objective of the technique is to find the weight factors that achieve blind detection statistic close to that of the CMA technique with reduced search complexity and little performance degradation. Basically, the EM based CMA technique described below can be implemented by appropriated changing the optimization weight factor (OWF) for w block in Fig. 1.

Let's first consider the Steepest-Descent CMA (SDCMA) [10], it is deducted from Least mean square. The restrictive function of mean square error as follow

$$J(w) = E\left\{ \left| b(i) - w^T r(i) \right|^2 \right\} \tag{13}$$

where $b(i)$ is the transmit signals of expected user, $r(t)$ is the receive signal, $w^T r(i)$ is the estimation of the transmit signal. The self-adoption expression of w

$$w(i) = w(i+1) + \mu(i) v(i-1) \tag{14}$$

$w(i)$ is the weight vector of the ith refresh; $\mu(i)$ is the step of the ith compute; $v(i-1)$ is the refresh direction vector and equal to the negative gradient of $J\left[w(i-1)\right]$. SDCMA has advantages, such as better stability and BER performance, but its convergence is slower. The optimum weight vector of SDMCA blind detection is

$$\hat{w} = \arg\min_{w} J(w) \tag{15}$$

There, the specific algorithm of SDCMA detection is as follows.

The output $y(i)$ of the detector is given by

$$y(i) = w^H(i) V_1^H r(i) \tag{16}$$

The error information $e(i)$ is denoted as $e(i) = y(i) - y(i)/|y(i)|$. The renewing formula of the weight vector w with the stochastic gradient descent approach is expressed by

$$w(i+1) = w(i) - \mu V_1^H r(i) e^*(i) \tag{17}$$

where w is initialized, and the initial value of w is $w = [111\cdots111]^T$. Then Eq. (16) to Eq. (17) are repeated until w converges. The method is simply implemented and need not complex matrix computation.

The LSCMA[9] is a technique for minimizing the $J(1,2)$ cost function given by

$$J(w) = J(1,2) = E[(|y|-1)^2] \tag{18}$$

The least squares CMA (LSCMA) is shown to be globally stable and convergent for any linearly independent set of input data and converge faster than some conventional CMA. The LSCMA is a technique for minimizing and the F(1,2) cost function is given by:

$J(w) = J(1,2) = E[(|y|-1)^2]$ subject to

$$w^T s_1 = 1 \tag{19}$$

The linearly constrained constant modulus (LCCMA) [6,13] cost function is given by

$$\min_w J(w) = E\left[(|y|^2 - 1)^2\right], \tag{20}$$

subject to the linear constraint $w^T s_1 = 1$, where s_1 is the received desired user.

III. INVASIVE WEED OPTIMIZATION BASED MUD

Invasive weed optimization (IWO), first designed and developed by Mehrabian and Lucas [24], is a relatively novel numerical stochastic optimization algorithm inspired from colonization of invasive weeds. The algorithm is simple but has shown to be effective in converging to optimal solution by employing basic properties, e.g. seeding, growth and competition, in a weed colony [23]. A weed is any plant growing where it is not wanted; any tree, vine, shrub or herb may qualify as a weed, in any specified geographical area, depending on the situation. Weeds have shown a very robust and adaptive nature that renders them undesirable plants in agriculture. In a D-dimensional search space, a weed which represents a potential solution of the objective function is represented by $W = (w_1, w_2, \cdots, w_m)$. Firstly, M weeds, called a population of plants, are initialized with random growth position, and then each weed produces seeds depending on its fitness and the colony's lowest fitness and highest fitness to simulate the natural survival of the fittest process. The number of seeds each plant produce increases linearly from minimum possible seed production to its maximum; Fig.1 illustrates the procedure. The generated seeds are being distribution randomly in the search area by normal distribution with mean equal to zero and a variance parameter decreasing over the number of iteration. By setting the mean parameter equal to zero, the seeds are distributed randomly such that they locate near to the parent plant and by decreasing the variance over time, the fitter plants are grouped together and inappropriate plants are eliminated over times.

To model and simulate the colonizing behavior of weeds in order to introduce a novel optimization algorithm, some basic properties of the colonization process are considered:

1. A finite number of seeds are being dispread over the *d*-dimensional problem space with random positions (initializing a population)
2. Every seed grows to a flowering plant and produces seeds depending on their fitness (reproduction): a member of the colony of weeds is allowed to produce seeds depending on its own and the lowest and highest fitness values of the colony, where the number of seeds each plant produces increases linearly from a possible minimum to its maximum; in other words, a plant will produce seeds based on its fitness and the lowest and highest fitness values of the colony to ensure that the increase is linear. The procedure is illustrated in Fig. 2. This step adds a significant property to the search algorithm. In evolutionary algorithms that are adopted to solve optimization problems, intuitively, the infeasible individuals are not allowed to be reproduced, and feasible individuals could be thought to be the ones with better fitness values than infeasible individuals, although it is possible that some of the infeasible individuals carry more useful information than feasible individuals during the evolution process; in the reproduction method, this chance is given to infeasible individuals to survive and reproduce similar to the mechanisms that occur in nature.

3. The produced seeds are being randomly dispread over the search area and grow to new plants (spatial dispersal): the generated seeds are being randomly distributed over the d-dimensional search space by normally distributed random numbers with a mean equal to zero but with a varying variance of w^2]. Thus, seeds will be randomly distributed such that they abide near the parent plant. The SD of the random function is reduced from a previously defined initial value $w_{initial}$ to a final value w_{final}, in every step (generation). In simulations, a nonlinear alteration has shown satisfactory performance [22]

$$W_{iter} = \left[\frac{iter_{MAX} - iter}{iter_{MAX}}\right]^n (w_{initial} - w_{final}) + w_{final} \tag{21}$$

where $iter_{MAX}$ is the maximum number of iterations, w_{iter} the SD at the present time step and *n* the nonlinear modulation index. This alteration ensures that the probability of dropping a seed in a distant area decreases nonlinearly at each time step, which results in grouping fitter plants and the elimination of inappropriate plants.

4. This process continues until the maximum number of plants is attained by fast reproduction. At this stage, only the plants with higher fitness can survive and produce seeds, whereas others are eliminated (competitive exclusion). In this process, after the maximum number of weeds in a colony is reached, each weed is allowed to produce seeds, spread them over the search area, and find their position and rank together with their parents. Next, weeds with lower fitness values are eliminated in order to attain the maximum allowable population in a colony. The course continues until the maximum iterations are reached and hopefully the plant with the best fitness is the closest to the optimal solution. It is worth mentioning that the IWO has some distinctive properties when compared with the traditional GA and other numerical search algorithms, such as reproduction, spatial dispersal and competitive exclusion. In addition, no genetic operators are employed in the proposed algorithm, which makes it more dissimilar from the GA. In the Appendix, a pseudo-code for an IWO algorithm is introduced and some simulations are reported to show the ability of the algorithm in locating the global minimum of two benchmark functions. Extensive simulations are reported to compare the performance of the IWO algorithm with that of other algorithms like GA, PSO and MA for different low- and high-dimension functions in [22], where it is shown that the IWO algorithm is competitive with other numerical stochastic optimization algorithms.

IV. EXPERIMENT RESULTS

In this section, we present the results of Monte Carlo computer simulations, carried out over 100 independent trials, aimed at assessing the performance of the proposed method and providing a comparison with other blind techniques in all the experiments, unless otherwise specified, the following simulation setting is assumed. The desired signal is QPSK, which corresponds to a dispersion coefficient to be used in the CMA cost function, whereas the interference is QPSK. The spreading code is Gold 31 and the spreading gain is N=31.The number of subcarriers is 64. The number of active users is K=16, 32 and the user 1 is the desired user. The amplitude of fading of every subcarrier has Rayleigh distribution and the phase has uniform distribution. Figure 2 illustrates the average bit error rate (BER) against input SNR for different algorithms. The performance measure is signal to interference plus noise ratio (SIR):

$$Q_{SIR} = \frac{E^2\left\{\beta^T r\right\}}{\mathrm{var}\left\{\beta^T r\right\}} \tag{21}$$

With the step size reduced to be 10^{-4}, Fig. 2 compares the performance achieved by various algorithms. It is observed that when a strong MAI enters the channel, the LCCMA is affected severely, i.e. its SIR is significantly reduced and fails to trace the system changes, as shown in Fig. 2 in which curve 3 stops at symbol index 5000. The SIRs versus number of iterations for the algorithms are shown in figure 2. The signal to noise ratio is 20 dB.it can be concluded that the IWO-CMA performs better than the LCCMA, SDCMA, AND GA-CMA on convergence speed, and has higher SIRs than the CMA. Finally, Figs. 4 -5 illustrate the average bit error rate against input SNR for different algorithms. The parameter settings are exactly the sane as those used for Fig. 2. The BER of the IWO-CMA is substantially better than that of other algorithm. For the same detection method its performance is getting worse with increasing MAI. In addition, the noticeable point is that the CMA and SDCMA have error floor at high SNRs, which does not occur in the IWO-CMA method.

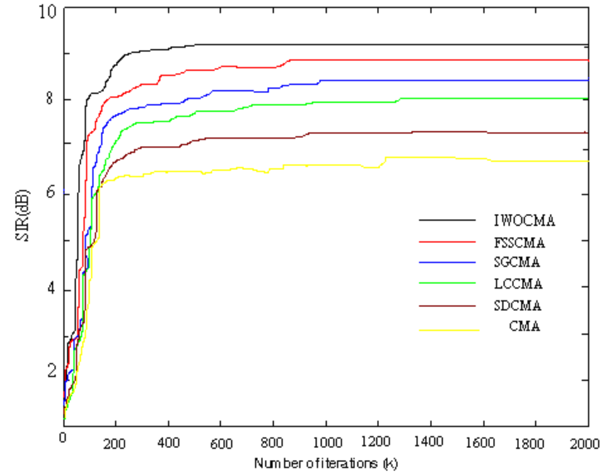

Figure 2 Comparison of CMA, SDCMA in MAI=30dB suppression and SNR=24dB

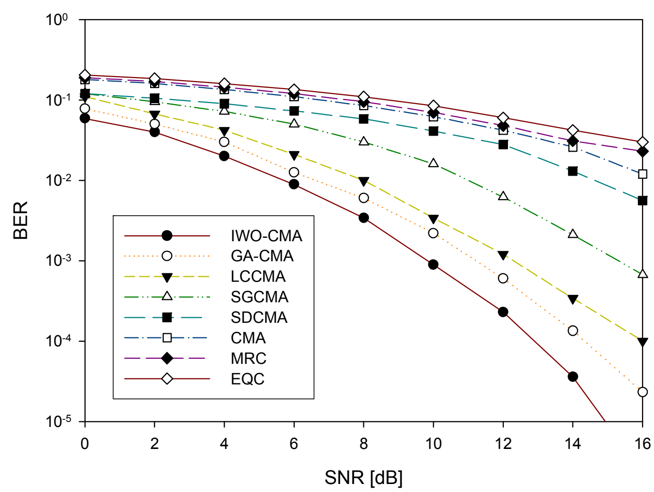

Figure 3 BER performance curves of the various detectors considered: CMA, SDCMA, GA-CMA and 1WO-CMA blind detection methods and K=16 users.

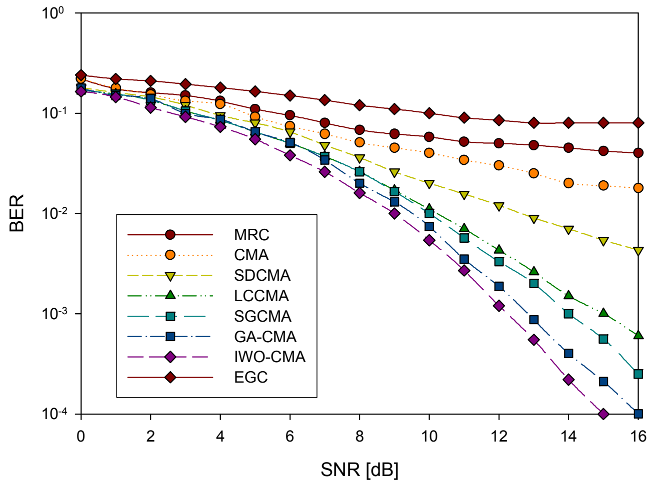

Figure 4 BER performance curves of the various detectors considered: CMA, SDCMA, GA-CMA and IWO-CMA blind detection methods and K=32 users.

V. Conclusions

In this paper, we have devised a new robust IWO algorithm for MAI suppression to achieve desired performance in the MC-CDMA system for multiuser detection under fading channel. An IWO method is designed to adjust the step-size in order to minimize the constant modulus criterion, and the potential benefits of using this adaptive size approach are investigated. In addition, the convergence analysis of the proposed algorithm is also presented. As compared with the various CMA schemes developed previously, the simulation results showed that the performance of the proposed IWO method can not only achieve perfect BER performance but also enjoy complexity advantages. Particularly, it is more significant when the algorithm is implementd in limit precision environments. Therefore, it is very suitable to be employed for future wireless multimedia communications to achieve high data rate transmission.

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