Blind Multiuser Detection for UWB Systems Based on Differential Evolution Algorithm with Constant Modulus Scheme

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Abstract—**A novel blind iterative detection approach that the linearly constrained constant modulus algorithm (LCCMA) is a blind multiuser detector (MUD) solution to multiple access interference (MAI) suppression that is widely investigated in direct-sequence ultra-wideband (DS-UWB) systems. However, the conventional constant modulus algorithm (CMA) based on the stochastic gradient descent (SGD) has slow convergence speed. In this paper, a new adaptive step-size CMA based on differential evolution (DE) algorithm for multiuser UWB receiver is presented for application in indoor channel. DE is essentially a novel population-based heuristic search algorithm. It is based on human understanding and searching capability for finding an optimum solution. The algorithm is derived upon the basis of adapting the step-size to minimize the constant modulus criterion and its convergence is varied analytically. Our research introduces an approximation of DE into LCCMA for better convergence speed in DS-UWB system. Using computer simulations, we showed that faster convergence can be achieved with this SOA based LCCMA, compared with the previous constant step size CMA and least mean square (LMS)-based CMA algorithms.**

Keywords: Ultrawideband system; constant modulus algorithm; Differential evolution algorithm, blind multiuser detector

I. INTRODUCTION

Ultra-wideband (UWB) wireless transmission is a promising technology for wireless personal area networks (WPANs). Two alternative physical layer for WPANs based on UWB technology are supported by various industry groups and have been considered by the IEEE 802.15.3a task group [1] for standardization: direct-sequence spreading based UWB (DS-UWB) systems [2] and UWB systems based on multiband orthogonal frequency-division multiplexing (MB-OFDM) [3]. Hence, UWB achieves much higher data rates at very low transmit power levels due to its large unlicensed bandwidth. UWB technology [4-9] which can achieve very high data rates is a promising shortrange wireless communication technique. Constitute a range of promising alternatives that may be deployed for home, personal area, sensor network, and other applications, where the communication devices are required to have low complexity, high reliability, and minimum power consumption [4-6]. However, in pulse-based UWB systems, the spreading factor is usually very high. The UWB channels are usually very sparse, which results in a large number of low-power resolvable multipaths [7-9]. The large number of resolvable multipaths can provide significant diversity gain if they are efficiently exploited but generates severe multiuser interference (MUI) and intersymbol interference (ISI) as well. Hence, to attain the promised diversity gain, an UWB receiver has to efficiently deal with the lowpower resolvable multipath signals and mitigate the MUI and ISI that they generated.

The optimal receiver for a multiple access system jointly decodes the signals of all users. The optimal multiuser detection [10-11] however is very complex and usually infeasible to implement. A simple suboptimal receiver is the conventional matched-filter (MF) receiver composed of a linear filter matched to the received signal followed by a bit slicer. The performance of matched filter receiver depends on the statistical properties of multi-access interference (MAI). However, there exist numerous challenges in the design of UWB receivers, such as ISI and MAI in multiuser environments with multipath fading channels. Moreover, MAI is the primary performance degradation factor in systems based on UWB technology. Multiuser detection (MUD) schemes, such as interference cancellation (IC), can be used to effectively solve this problem.

Blind adaptive MUD [12-17] has been the hot point studied recently, and it requires no more know ledge than does the conventional single user receiver: the desired user's signature waveform and it's timing [13-14]. An important problem in digital communications is the recovery of the data symbols transmitted through a distorting medium. The constant modulus algorithm (CMA) criterion is arguably the most widespread blind channel equalization principle [13-14]. The main advantage of CMA is that it is a blind adaptive algorithm, i.e., it does not require a training sequence. The conventional CMA is based on a stochastic gradient descent (SGD) form [15]. However, the conventional CMA based on SGD has slow convergence speed. Moreover, the stochastic gradient CMA drops the expectation operator and approximates the gradient of the criterion by a one-sample estimate, as in least mean square (LMS)-based algorithms. This rough approximation generally leads to slow convergence and poor misadjustment, even if the step size is carefully

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chosen. For improvement on the tracking capability, the use of the linearly constrained constant modulus algorithm (LCCMA) to capture the desired user instead of an interfering one was reported in [10–12]. Consequently, the blind algorithms for the adaptive multiuser detector (MUD) have attracted much attention to improve the bandwidth efficiency. In [15], a linearly constrained constant modulus algorithm (LCCMA) detector based on the SGD algorithm, which could achieve output performance the same as that of the minimum mean-square error (MMSE) receiver, was proposed. Therefore, our research mainly focuses on the proposition of recursive least square (RLS) -LCCMA for MUD and performance analysis.

This paper discusses the application of the Low-complexity blind receiver designs can be obtained by solving constrained optimization problems based on the constrained constant modulus (CCM) algorithm or evolution algorithm criterion [15-17]. The most of the above algorithms show the problems of fixing algorithm's control parameters, premature convergence, stagnation and revisiting of the same solution over and again.

Conventional mathematical/numerical methods may fail to achieve an optimal design due to the high degree of nonlinearity and nonconvexity of the objective functions, which make the optimization problem very complex. Consequently, researchers also started using some of the nature-inspired, nonconvex, and nonderivative-based optimization techniques for the design purpose. Evolutionary algorithms (EAs) have a long history of successfully solving optimization problems regardless of whether or not they have nice mathematical properties. A genetic algorithm (GA) usually discovers the promising regions of search space very quickly; however, it often has two drawbacks: premature convergence and lack of good local search ability [18-19].

The EAs family contains a wide range of algorithms that have been used to solve optimization problems, such as the genetic algorithm (GA) [18-20], differential evolution (DE) [21], evolution strategies (ES) [22], evolutionary programming (EP) [23], and particle swarm optimizer (PSO) [24]. A comparative study among some of these EAs is found in [25]. In this research, we consider DE for solving optimization problems, because DE usually converges quickly, it incorporates a relatively simple and self-adapting mutation, and the same settings can be used for many different problems [21]. DE has shown its superiority over many other EAs for continuous optimization over a decade or so. Many new and improved DE operators were proposed during that period [25]–[28].

In order to overcome these problems, in this paper, an absolutely control parameter-free DE, the novel optimisation algorithm and a novel fitness function are employed to determine the optimal values of the filter coefficients for the MUD. In this paper, we analyze the DE based on CMA to MAI suppression. The emphasis is on the capture analysis of CMA. That is, we investigate conditions under which CMA locks on the desired signal and when it captures the interference. Simulations are performed with the IEEE 802.15a channel models, and severe ISI and MAI are assumed for the evaluation of the proposed scheme against existing techniques. The rest of this paper is structured as follows. Section II presents the DS-UWB system model. The design of the linearly constrained constant modulus algorithm, seeker optimization algorithm and the LCCMA blind receiver are described in Sections III. Then the performance evaluation of the investigated scheme is carried out via the simulation in section IV. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL

We consider a K-users DS-UWB system over the UWB indoor multipath fading channels, where each user employs unique DS spreading code. The transmitted signal $q_k(t)$ for the kth user is obtained by spreading a set of binary phase-shift keying (BPSK) data symbol $\{b_k[i]\}$ onto a spreading waveform $s_k(t)$, which is written as follows:

$$q_k(t) = \sqrt{E_k}\sum_{i=1}^{P} b_k[i]s_k(t-iT_b), \tag{1}$$

where E_k is the symbol energy of the kth user, P is the packet size, $b_k[i]\in\{\pm 1\}$ is the ith data symbol of the kth user, and T_b is the symbol interval duration. The spreading waveform $s_k(t)$ is also written as follows:

$$s_k(t) = \frac{1}{\sqrt{G}}\sum_{n=0}^{N_c-1} c_{k,n} w(t-nT_c), \tag{2}$$

where $G=\sum_{n=1}^{N_c} c_{k,n}^2$, k=1,2,…,K, $c_{k,n}\in\{\pm 1\}$ is the nth chip of the kth user, N_c is the chip numbers, T_c is the chip interval duration, and $w(t)$ is the chip waveform of duration $T_c = T_b / N_c$.

The UWB indoor channel model is based on the Saleh-Valenzuela (S-V) approach [15] where the impulse response is composed of the exponential decay clusters to model the dense multipath components. For the UWB indoor transmission environment, the channel impulse response of UWB indoor channel model is formulated as follows:

$$h_k(t) = \sum_{l=1}^{L_k}\alpha_{k,l}\delta(t-\tau_{k,l}) = \sum_{l=1}^{L_k}\alpha_{k,l}\delta\left(t-(l-1)T_c\right), \tag{3}$$

where L_k denotes the total number of propagation paths of the kth user, $\alpha_{k,l}$ is the channel coefficient of the lth path of the kth user and $\tau_{k,l}$ is the multipath delay of the lth path of the kth user. In this paper, we suppose that the multipath delay $\tau_{k,l}$ is an integral multiple of T_c, $L_1 = L_2 = \cdots = L_K = L$, and the system is assumed to be synchronous.

When passing the signal through the indoor environment, the obstacles in the transmitted path will cause the multipath transmission. Therefore, the total received signal can be formulated as follows:

$$r(t) = \sum_{k=1}^{K} q_k(t)\otimes h_k(t) + n(t) = \sum_{k=1}^{K}\left[\sqrt{E_k}\sum_{i=1}^{P} b_k[i]s_k(t-iT_b)\right]\otimes h_k(t) + n(t)$$

$$= \sum_{k=1}^{K} \sqrt{E_k} \sum_{i=1}^{P} b_k[i] v_k(t - iT_b) + n(t), \tag{4}$$

where $\otimes$ is linear convolution, $n(t)$ is zero-mean additive white Gaussian noise and $v_k(t) = s_k(t) \otimes h_k(t)$ is defined as template signal of the kth user, which is a convolution between the kth user's spreading code and channel coefficient.

The template signal $v_k(t)$ that is transmitted over a channel is corrupted by channel noise. Hence, the function of the receiver must detect the template signal $v_k(t)$ for each user. According to [13], we note that a filter which is matched to a template signal $v_k(t)$ of duration $(N_c+L-1)T_c$ is characterized by an impulse response. The channel response for kth user can be written as follows:

$$h_{opt,k}(t) = v_k^*(-t). \tag{5}$$

So, the output of the filter which is matched to a template signal $v_k(t)$ can be written as follows:

$$y_k(t) = r(t) \otimes h_{opt,k}(t) = r(t) \otimes v_k^*(-t)$$

$$= \sum_{m=1}^{K} \sqrt{E_m} \sum_{i=1}^{P} b_m[i] v_m(t - iT_b) \otimes v_k^*(-t) + n(t) \otimes v_k^*(-t), \tag{6}$$

and the discrete-time impulse response sampling at $t = iT_b$ is represented as follows:

$$y_k[i] = y_k(iT_b). \tag{7}$$

Then the discrete-time received signal after sampling (iT_b) is written as follows:

$$\begin{aligned} y_k[i] &= \sum_{m=1}^{K} \sqrt{E_m} \sum_{j=1}^{P} b_m[j] v_m[i-j] \otimes v_k^*[-i] + n[i] \otimes v_k^*[-i] \\ &= \sum_{m=1}^{K} \sqrt{E_m} \sum_{j=1}^{P} b_m[j] R_{m,k}[i,j] + \tilde{n}_k[i] \\ &= \underbrace{\sqrt{E_k} b_k[i] R_{k,k}[i,i]}_{\text{desired signal}} + \underbrace{\sqrt{E_k} \sum_{\substack{j=1 \\ j\neq i}}^{P} b_k[i] R_{k,k}[i,j]}_{\text{ISI}} \\ &\quad + \underbrace{\sum_{\substack{m=1 \\ m\neq k}}^{K} \sqrt{E_m} \sum_{j=1}^{P} b_m[j] R_{m,k}[i,j]}_{\text{MAI}} + \tilde{n}_k[i], \end{aligned} \tag{8}$$

where

$$R_{m,k}[i,j] = v_m[i-j] \otimes v_k^*[-i],$$

$$\tilde{n}_k[i] = n[i] \otimes v_k^*[-i].$$

Hence, the signal that received by a CD can be detected:

$$\hat{b}_k^{CD}[i] = \operatorname{sgn}\left\{ y_k[i] \right\}, \tag{9}$$

Each filter is matched to one of the signature waveform. In a DS spread spectrum system where all users employ the same chip waveform, the continuous-time-to-discrete-time conversion of the bank of K matched filters can be implemented by a single chip-matched filter. In our DS-UWB systems, we give two restrictions; for example, the system is synchronous, all users adopt the same packet length and chip waveform. Hence, the output vector of the bank of K matched filter outputs [5] [10] can be written as follows:

$$\mathbf{y} = \mathbf{RAb} + \tilde{\mathbf{n}}, \tag{10}$$

where $\mathbf{y}$ is the received signal vector, $\mathbf{R}$ is the cross-correlation matrix which is $KP\times KP$ dimensional matrix, $\mathbf{A}$ is the transmitted amplitude matrix with $KP\times KP$ dimension, $\mathbf{b}$ is transmitted bit vector with $KP\times 1$ dimension and $\tilde{\mathbf{n}}$ is a Gaussian random variable vector with zero-mean and covariance matrix $\sigma^2\mathrm{R}$. Their expressions are formulated as follows:

$$\mathbf{A} = diag\left\{ \sqrt{E_1}, \cdots, \sqrt{E_K}, \sqrt{E_1}, \cdots, \sqrt{E_K}, \cdots, \sqrt{E_1}, \cdots, \sqrt{E_K} \right\},$$

$$\mathbf{y} = \left[y_1[1],\ y_2[1],\ \cdots,\ y_K[1],\ y_1[2],\ y_2[2],\ \cdots,\ y_{K-1}[P],\ y_K[P] \right]^T,$$

$$\mathbf{b} = \left[b_1[1],\ b_2[1],\ \cdots,\ b_K[1],\ b_1[2],\ b_2[2],\ \cdots,\ b_{K-1}[P],\ b_K[P] \right]^T,$$

$$\tilde{\mathbf{n}} = \left[\tilde{n}_1[1],\ \tilde{n}_2[1],\ \cdots,\ \tilde{n}_K[1],\ \tilde{n}_1[2],\ \tilde{n}_2[2],\ \cdots,\ \tilde{n}_{K-1}[P],\ \tilde{n}_K[P] \right]^T,$$

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}[1,1] & \mathbf{R}[1,2] & \cdots & \mathbf{R}[1,P] \\ \mathbf{R}[2,1] & \mathbf{R}[2,2] & \cdots & \mathbf{R}[2,P] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{R}[P,1] & \mathbf{R}[P,2] & \cdots & \mathbf{R}[P,P] \end{bmatrix},$$

and

$$\mathbf{R}[i,j] = \begin{bmatrix} R_{1,1}[i,j] & R_{1,2}[i,j] & \cdots & R_{1,K}[i,j] \\ R_{2,1}[i,j] & R_{2,2}[i,j] & \cdots & R_{2,K}[i,j] \\ \vdots & \vdots & \ddots & \vdots \\ R_{K,1}[i,j] & R_{K,2}[i,j] & \cdots & R_{K,K}[i,j] \end{bmatrix},$$

where $\mathbf{R}[i,j]$ is a $K\times K$ dimensional matrix.

Let user 1 be the desired user and s_1 denote its normalized signature sequence. The typical LMS-type algorithm is the MOE detector attempting to minimize the mean output energy. It is expressed as [13-15]

$$E(y^2) = E\left\{ (w^T r)^2 \right\} \quad \text{subject to} \quad w^T s_1 = 1 \tag{11}$$

where the detector can be expressed as $w = s_1 + x$. A linear detector can be decomposed into two orthogonal components; a fixed component s_1 with tap weights equal to the spreading sequence of the desired user and an adaptive component x. By minimising the minimum output energy (MOE) cost function subject to the orthogonal constraint, i.e. $s_1^T(n) = 0$, the adaptive algorithm can be represented as

$$x(n+1) = x(n) - \mu y(n)\left[r(n) - y_{CD}(n) s_1 \right] \tag{12}$$

where $r(n)$, $y_{CD}(n) = s_1^t r(n)$ and $y(n) = w^T r(n)$ denote the received signal, matched filter and detector output, respectively. Let us first review some commonly used adaptive algorithms for blind multiuser detection. Then the modified algorithm known as LCCMA will be presented. The CMA is an LMS-type algorithm of blind multiuser detection for CDMA systems [17]. The constant modulus algorithm (CMA) error criterion is given by

$$J_{CMA}=\frac{1}{4}E(y^2(n)-\delta) \qquad (13)$$

where $y(n)=w^T r$ is the output of the receiver. The dispersion constant δ is equal to unity for binary phase shift keying (BPSK) signals. By minimizing the CMA cost function with respect to *w* at step size m and taking the instantaneous gradient, the weight update equation is given by

$$w(n+1)=w(n)-u\varepsilon(n)(y^2(n)-1)r(n) \qquad (14)$$

When the filter is initialized to the spreading code of the desired user, capture of the desired user can be guaranteed only when it is the strongest. However, it is not guaranteed that the process always locks to the same signal. Linear constraints may be used to overcome this problem. The linearly constrained constant modulus algorithm (LCCMA) is based on the generalized side-lobe canceller (GSC) for adaptive array systems by making use of a priori information about the user's signal. The linear constraint helps to capture the signal of interest rather than one of the interfering users. The filter coefficients *w*, used for the linearly constrained CMA receiver, are selected according to the optimisation problem subject to

$$J(w)=E\left[(y^2(n)-1)^2\right] \text{ subject to } w^T s_1=1 \qquad (15)$$

where s_1 is the constraint vector with elements equal to the spreading code coefficients of the desired user. The constraints ensures that the weight vector *w* maintains a unity correlation with the desired user's spreading code while adapting to the minimum error criterion. According to the GSC structure, the LCCMA is expressed as [13-15] which is similar to (12) of the MOE algorithm but has an additional CMA factor $(y^2(n)-1)$ in the update term of the LCCMA. It can be seen that the CMA factor approaches zero if the algorithm is used for a sufficient period of time. For convenience, we assume user 1 to be the desired user whose signature code and power are known. LCCMA criterion is used for updating w as following optimization problem:

$$w_{opt}=\min_w J(w)=\min_w\{E[y^2-\alpha^2]^2\} \text{ subject to } w^T s_1=1 \qquad (16)$$

III. Differential evolution ALGORITHM

DE [24-28] is a simple and yet powerful heuristic method for solving non-linear, non-differentiable and multimodal optimisation problems. Like other Eas, DE starts with an initial random population and searches towards the global optimum by some iteration operations including mutation, crossover and selection. The main idea behind DE is a scheme for producing trial vectors according to the manipulation of the target vector and difference vector. If the problem is the minimisation problem, the trail vector competes with the current population vector and the better one is selected to enter the next generation. Different kinds of strategies of DE have been proposed based on the target vector selected, and the number of different vectors used. In this paper, we use the strategy, DE/rand/1/bin, described as follows:

For each target vector $x_i(t)$ (i.e., LCCMA criterion is used for updating w as following optimization equation (16)), trail vector $v_i(t)$, $i=1,2,\ldots,NP,$ let D be the dimension of the target vector, and G be the G generation. The mutant vectors are generated in these DE/rand/1/bin [20][25-26]strategies respectively.
For DE/rand/1/bin

$$v_{i,G}=x_{a,G}+F(x_{b,G}-x_{c,G}) \qquad (17)$$

where $a,b,c,d\in[1,2,\cdots,NP]$ are randomly chosen as integers, and $a\neq b\neq c\neq d\neq i$. F is the scaling factor controlling the amplification of the DE. Following the mutation phase, the crossover operator is applied to the population. The crossover operator, implements a recombination of the trial vector and the parent vector to produce the offspring. This operator is calculated as

$$u_{j,i,G}=\begin{cases} v_{j,i,G}, & (rand_j[0,1]\leq CR) \quad or \quad (j=j_{rand}) \\ x_{j,i,G}, & \text{otherwise} \end{cases} \qquad (18)$$

where $j=[1,2,\cdots,D]$, $j_{rand}=[1,2,\cdots,D]$, $rand_j\in[0,1]$ is the randomly chosen index, *CR* is the DE control parameter that is called the crossover rate and is a user-defined parameter within the range [0, 1]. $v_{j,i,G}$ is the differential vector of the *j*th particle in the *i*th dimension at the *G*th iteration, and $u_{j,i,G}$ denotes the trail vector of the *j*th particle in the *i*th dimension at the *G*th iteration. The selection operator is used to choose the next population between the trail population and the target population

$$x_{i,G+1}=\begin{cases} u_{i,G}, & f(u_{i,G})<f(x_{i,G}) \\ x_{i,G}, & \text{otherwise} \end{cases} \qquad (19)$$

The proposed DE algorithm is carried out in the following steps.1).Run the MRC detector. 2).Initialization: It is known that the conventional detector (i.e., matched filter) is not a good choice for initialization [28]. A bad initial guess for the GA-based MUD can result in poor performance because the BER could be saturated before convergence. As such, a good initial guess (e.g., MRC detector output) is needed for initialization to obtain superior performance for the evolutionary computation technique of GA-based MUD [28]. By the same token, we utilize the output of the MRC detector to provide a good initialization to the DE evolutionary algorithm-based MUD. The standard DE algorithm can be described as Fig1.

Step 1 Randomly generate *NP* number of initial trial solutions.
Step 2 For *i* = 1 to *NP*

Produce an offspring u_i using the standard DE.

Calculate the Euclidean distance of u_i to the other individuals in the DE population.

Compare the fitness of u_i with the most similar individual and replace it if the u_i has a better fitness value.

End for

Step 3 Stop if a termination criterion is satisfied. Otherwise go to Step 2.

Fig. 1 Procedure algorithm description of DE algorithm

IV. SIMULATION STUDY

In this section, simulation results are presented in order to investigate the performance of various receiver structures as a function of the signal-to-noise ratio (SNR). The UWB indoor channel model reported by the IEEE 802.15.3a task group is used for generating UWB multipath channels, and theuplink of a synchronous DS-UWB system with $N_f = 10$, $N_c = 250$, and a bandwidth of 0.5 GHz is considered.Fig.2 illustrate the SINR performance of the detectors versus number of iterations for MAI=10 dB. It shows the convergence rate of DE-LCCMA is very slow so it is unsuitable for real-time system. The DE-LCCMA has a fast convergence rate and high stable SINR. Moreover, the DE-LCCMA decreases computational complexity and is more suitable for adaptive environment. In Figure 3, bit error rates (BERs) of various receivers are plotted as functions of the SNR using 100 realizations of CM-1. There are 5 users in the environment ($K = 5$), where the first user is assumed to be the user of interest. Each interfering user is modeled to have 10 dB more power than the user of interest so that an MAI-limited scenario can be investigated. Note that the benefits of iterative multiuser detectors become more obvious in the MAI-limited regime. From the figure, it is observed that the BERs of the proposed detectors are considerably lower than those of the CD and MRC Rake. In addition, the performance of the proposed receivers gets very close to that of a single user system. Finally, the low complexity implementation based on the DE-LCCMA out-performs the low complexity implementation based on LMS-CMA and CSG-CMA, which is a price paid for the lower complexity of the latter algorithm. Finally, the performance of the receivers that are sampling only the first 5 multipath components is investigated. In this case, it is observed from Figure 4 that the proposed receivers can still perform very closely to the single-user bound, whereas the MRC-Rake receiver experiences a serious error floor.

V. CONCLUSIONS

In this paper, we present a performance analysis of the blind adaptive multiuser detector proposed, which is based on LCCMA. A seeker optimization algorithm tuning unit is designed to adjust the step size of the LCCMA, and the potential benefits of using this adaptive step size approach are investigated. Its performance is studies and compared to that of the CMA receiver in a door channel with a large number of users. The DE based LCCMA is shown to perform better than the constant step size CMA to converge in this environment. Accordingly, we believe that is will make a good candidate for multiuser DS-UWB systems.

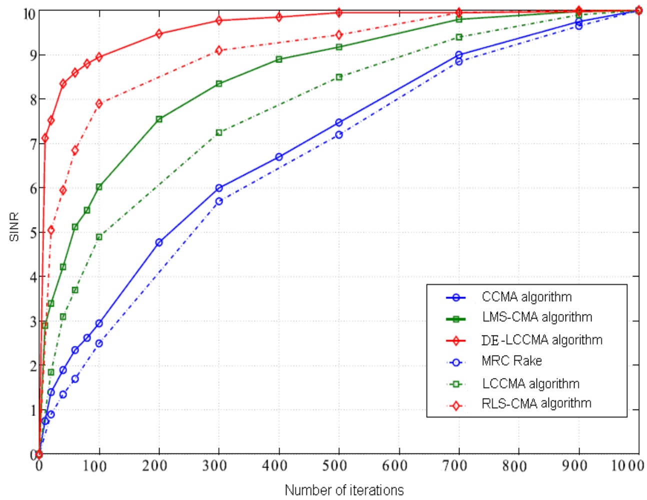

Fig.2 SINR versus number of iterations

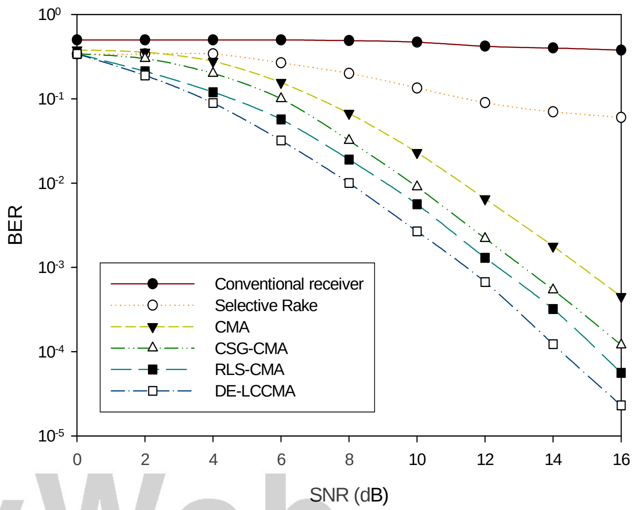

Fig. 3. BER as a function of the SNR for various receivers in CM1.

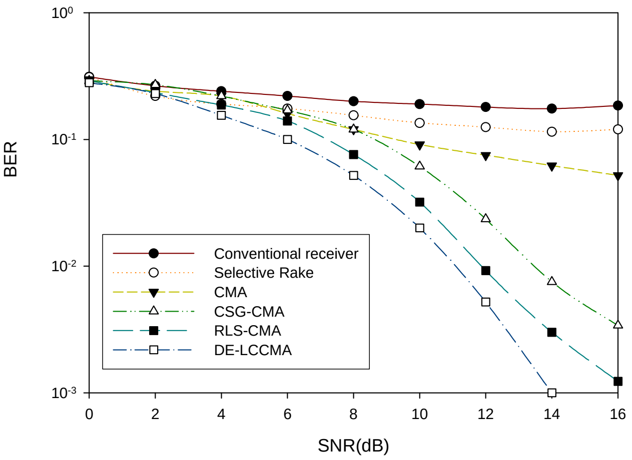

Fig. 4. BER as a function of the SNR for various receivers in CM4.

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