A Generalized Blind Adaptive Multi-User Detection Algorithm for Multipath Rayleigh Fading Channel Employed in a MIMO System

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Abstract: **In this paper, a generalized blind adaptive algorithm is introduced for multi-user detection of direct sequence code division multiple access (DS-CDMA) wireless communication systems. The main property of the proposed algorithm is its ability to resolve the multipath fading channel resulting in inter symbol interference (ISI) as well as multiple access interference (MAI). Other remarkable properties are its low complexity and mitigation to the near-far problem as well as its insensitivity to asynchronous transmission. The proposed system is based on the minimization of the output energy and convergence to the minimum mean square error (MMSE) detector. It is blind in the sense that it needs no knowledge of the other users' signatures, only the intended user signature and timing are required. Furthermore, the convergence of the minimum output energy (MOE) detector to the MMSE detector is analytically proven in case of M-ary PSK. Depicted results show that the performance of the generalized system dominates those previously considered. Further improvements are obtained when multiple input multiple output (MIMO) technique is employed.**

Index Terms: **Blind adaptive techniques, multipath Rayleigh fading channel, multiple input multiple output (MIMO), multi-user detection.**

I. INTRODUCTION

In recent years, code division multiple access (CDMA) providing potential increase of system capacity, has received a great amount of interest among other multiple access techniques. In particular, direct sequence CDMA (DS-CDMA) by offering capacity increase, satisfies the rising demand for higher data rate transfer for multimedia services and raises as the main candidate for future multi-user wireless communication systems. By selecting mutually orthogonal signatures for all active users in a DS-CDMA system, multiple access interference (MAI) does not occur. However, it is not possible to ensure orthogonality among received signatures, the MAI increases and the system is interference limited.

In [1], the optimum multiuser detector for asynchronous multiple access Gaussian channel has been obtained and overcome the presence of other interfering users by a complex receiver. Its complexity is exponentially related to the number of users. It also requires the knowledge of the other interfering users' signatures, timing, and complex amplitudes.

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The focus has turned to sub-optimal receivers based on the minimization of mean square error (MMSE) between the output and the data [2] and to the decorrelating detector [3], [4]. Although the adaptive MMSE exhibits good near-far resistance, it substitutes the need to know the other users signature waveform by the need of training data sequences for every active user which strongly reduces the system efficiency.

In order to avoid the need of training sequences, Honig *et al.* [5], have proposed an adaptive receiver, for multi-user CDMA systems, based on the minimization of the mean output energy. This minimization is done subject to certain constraint to guarantee no cancellation of the desired signal. They proved that their minimum mean output energy multi-user detector (MOE-MUD) receiver is equivalent to a MMSE receiver for the case of AWGN and binary transmission. The algorithm applies a steepest stochastic descent technique to minimize the effect of interfering signals.

On the other hand, high data rate communications are limited not only by noise or MAI but sometimes more significantly by the inter symbol interference (ISI) effect produced due to the delay spread resulting from multipath propagation especially in case of bad urban channels where the multipath problem is dominating.

Notable work has been presented in [6] and [7] where four suboptimum detection techniques based on zero forcing (ZF) and MMSE equalization with and without decision feedback (DF) are presented and compared. They combat both ISI and MAI. The main drawback is again the need for all users' waveform signatures to be known.

In [8], the authors have presented a modification to [5] to resolve the multipath by using a MOE-MUD for each path with preselected constraints and then combining the resulting outputs according to some criteria such as maximum ratio combining. The structure is similar to a Rake receiver that employs MOE-MUD receiver at each finger. The same structure has been studied in many publications such as [9], where the constrained MMSE receiver of [10] replaces the MOE-MUD at each finger.

Another structure has been recently proposed in [11] to overcome the multipath fading channel. The time alignment and channel compensation are done prior to a MOE-MUD that uses a modified adaptive formula. A windowing technique for the time varying channel was also provided.

However, the pre-selection of constraints does not grant optimality to the receiver. Multipath components need to be optimally combined to yield satisfactory detection performance [12]. This problem has been tackled in [13], which parameterizes the constraints and performs further optimization of

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constraints. It has been shown that the method not only provides a multi-user receiver but a blind channel estimator in the meantime. However, the receiver considered in [13] is not adaptive.

In the current work, the blind adaptive algorithm first presented in [5] is generalized to be used for MAI and the ISI resulting from multipath Rayleigh fading channel. The general case of transmitting M-ary PSK symbol is considered instead of the simple case of transmitting BPSK previously considered in [5], [8], and [11].

A final contribution is the consideration of multi input multi output (MIMO) system where N transmitting antennas are used by each user and the receiver has M antennas.

The organization of this paper is as follows: First, the mathematical presentation of the system model is given in Section II. In Section III, the generalized algorithm is derived and the equivalence to the MMSE receiver is proved in Section IV. The formula governing the steepest stochastic descent adaptation rule is then derived in Section V. Computer simulations given in Section VI show the performance of the proposed system compared to those previously considered. Results are depicted in terms of the average bit error rate versus the average SNR per bit for different cases including the asynchronous transmission and the near-far problem. As the MIMO-CDMA system is of great interest for the future communication systems, this case is also considered and simulations are given for a system with two transmitting and two receiving antennas. Section VII concludes the paper. Through the text, vectors are represented by small letters while matrices are represented by capital letters.

II. SYSTEM MODEL

Consider a K user communication system that employs N antennas at the transmitter of each user and M antennas at the receiver. The F information bits for the k-th user, $1 \leq k \leq K$, can be written in vector form as

$$\mathbf{x}^{(k)} = \left[x_1^{(k)} x_2^{(k)} \cdots x_F^{(k)}\right]^T \tag{1}$$

where $[\cdot]^T$ designates the transposition. The information bits are then mapped to a particular signal constellation where all the symbols have the same average power (i.e., M-ary PSK) and are equally probable. This mapping results in P symbols at each of the N transmitting antennas. This can be viewed as N vectors of length P each, where for user k and antenna n, $1 \leq n \leq N$, this vector of complex symbols can be expressed as

$$\mathbf{d}^{(k,n)} = \left[d_1^{(k,n)} d_2^{(k,n)} \cdots d_p^{(k,n)} \cdots d_P^{(k,n)}\right]^T, \ 1 \leq p \leq P \tag{2}$$

Each of these symbols is spread using a CDMA code (spreading sequence) defined as

$$\mathbf{c}^{(k,n)} = \left[c_1^{(k,n)} c_2^{(k,n)} \cdots c_q^{(k,n)} \cdots c_Q^{(k,n)}\right]^T, \ 1 \leq q \leq Q \tag{3}$$

with a processing gain (spreading factor) $Q = T_s/T_c$ where T_s is the symbol duration and T_c is the chip duration. Therefore, the transmitted symbols from antenna n of user k are given by

$$s_{(p-1)Q+q}^{(k,n)} = d_p^{(k,n)} c_q^{(k,n)}, \ 1 \leq p \leq P, \ 1 \leq q \leq Q \tag{4}$$

yielding the transmission vector

$$\mathbf{s}^{(k,n)} = \left[s_1^{(k,n)} s_2^{(k,n)} \cdots s_{PQ}^{(k,n)}\right]^T. \tag{5}$$

Signals from different antennas are transmitted simultaneously and they all have the same transmission period T_c.

Assume a MIMO multipath channel where the transmitted signals are added. This model can be fitted to a mobile radio channel in the up or down link. Define the discrete channel response of user k, $1 \leq k \leq K$, from transmitting antenna n, $1 \leq n \leq N$, to receiving antenna m, $1 \leq m \leq M$, as

$$\mathbf{h}^{(k,n,m)} = \left[h_1^{(k,n,m)} h_2^{(k,n,m)} \cdots h_w^{(k,n,m)} \cdots h_W^{(k,n,m)}\right]^T \quad 1 \leq w \leq W \tag{6}$$

where W is the channel response length. The channel low pass impulse response for the signal of the path w from the n-th transmitting antenna of the k-th user to the m-th receiving antenna can be expressed as a complex variable with a Rayleigh distributed attenuation factor and a corresponding phase uniformly distributed in the interval 0 to 2π. The received signal at the receiving antenna m will be

$$\mathbf{r}^{(m)} = \left[r_1^{(m)} r_2^{(m)} \cdots r_j^{(m)} \cdots r_{PQ+W-1}^{(m)}\right]^T \quad 1 \leq j \leq PQ + W - 1 \tag{7}$$

with elements $r_j^{(m)}$ given by

$$r_j^{(m)} = \sum_{k=1}^{K} \sum_{n=1}^{N} \left(\sum_{w=1}^{W} s_{j-w+1}^{(k,n)} h_w^{(k,n,m)} \right) + n_j^{(m)} \tag{8}$$

where the noise samples $n_j^{(m)}$ are modeled as independent samples of a zero mean complex Gaussian random variable with variance $N_0/2$ per dimension. Now, let us define

$$b_{j-(p-1)Q}^{(k,n,m)} = \sum_{q=1}^{Q} c_q^{(k,n)} h_{j-(p-1)Q-q+1}^{(k,n,m)} \tag{9}$$

and using (4) and (9) into (8), we obtain

$$r_j^{(m)} = \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{p=1}^{P} d_p^{(k,n)} b_{j-(p-1)Q}^{(k,n,m)} + n_j^{(m)}. \tag{10}$$

In the following derivation, and without loss of generality, we assume that the intended symbol is the i-th symbol transmitted by the first user on the first transmitter, that is $d_i(1,1)$. To simplify the notation, we define a vector of length $M(Q + W - 1)$ which groups together in one entity $\mathbf{z}(i)$ all received signals that are related to replicas of the intended symbol (i).

$$\mathbf{z}(i) = \left[\mathbf{z}^{(1)}(i)^T \mathbf{z}^{(2)}(i)^T \cdots \mathbf{z}^{(m)}(i)^T \cdots \mathbf{z}^{(M)}(i)^T\right]^T \tag{11}$$

where each of the vectors associated with a receiving antenna is given by

$$\mathbf{z}^{(m)}(i) = \left[z_1^{(m)}(i) z_2^{(m)}(i) \cdots z_l^{(m)}(i) \cdots z_{Q+W-1}^{(m)}(i)\right]^T \quad 1 \leq l \leq Q + W - 1 \tag{12}$$

and the elements are given by

$$z_l^{(m)}(i) = r_{l+(i-1)Q}^{(m)} = \sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{p=1}^{P} d_p^{(k,n)} b_{l+(i-p)Q}^{(k,n,m)} + n_{l+(i-1)Q}^{(m)} \quad (13)$$

which can be rewritten as

$$z_l^{(m)}(i) = \sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{u=-U}^{U} d_{i-u}^{(k,n)} b_{l+uQ}^{(k,n,m)} + n_{l+(i-1)Q}^{(m)} \quad (14)$$

where $-U$ to $+U$, $U = \text{INT}[(Q+W-2)/Q]$, is the range of indices covering the desired and interfering signals with $(u = 0, k = 1, n = 1)$ corresponding to the desired signal. Equation (14) can be rewritten as

$$\begin{aligned} z_l^{(m)}(i) = \; & d_i^{(1,1)} b_l^{(1,1,m)} && \text{required signal} \quad (15)\\ & + \textstyle\sum_{u=-U, u\neq 0}^{U} d_{i-u}^{(1,1)} b_{l+uQ}^{(1,1,m)} && \text{ISI from same antenna}\\ & + \textstyle\sum_{n=2}^{N}\sum_{u=-U}^{U} d_{i-u}^{(1,n)} b_{l+uQ}^{(1,n,m)} && \text{ISI from other antennas of user 1}\\ & + \textstyle\sum_{k=2}^{K}\sum_{n=2}^{N}\sum_{u=-U}^{U} d_{i-u}^{(k,n)} b_{l+uQ}^{(k,n,m)} && \text{MAI from other users}\\ & + n_{l+(i-1)Q}^{(m)} && \text{added white Gaussian noise} \end{aligned}$$

or in a more compact form

$$\mathbf{z}^{(m)}(i) = \mathbf{d}_i^{(1,1)} \mathbf{b}^{(1,1,m)} + \mathbf{n}''^{(m)}(i) \quad (16)$$

where $\mathbf{n}''^{(m)}(i)$ represents ISI, MAI, and the noise terms. Equation (16) is used in (12) and (11) with the concatenation of the vectors $\mathbf{b}^{(1,1,m)}$ and $\mathbf{n}''^{(m)}$ for all receiving antennas in one vector each, to give

$$\mathbf{z}(i) = \mathbf{d}_i^{(1,1)}\mathbf{b} + \mathbf{n}''(i). \quad (17)$$

In this final form, we recognize $\mathbf{n}''(i)$ as the equivalent noise plus interference vector.

III. GENERALIZED BLIND ADAPTIVE MULTIUSER DETECTOR

At the receiver, perfect channel estimation for the intended user is assumed. Treating each transmitting antenna as a virtual user, we therefore have KN virtual users in the system.

The practical implementation of the Generalized MOE (GMOE) detector is as shown in Fig. 1. The received signals are passed through a time alignment that groups together in one vector $\mathbf{z}(i)$ all received signals related to replicas of the specific transmitted symbol (i). This set of signals is then fed to two orthogonal filters. The first filter is matched to the combined spreading code and the channel response vector, $\mathbf{b}$, of the desired user while the other, $\mathbf{x}(i)$, is an adaptive filter that limits the effect of interference and noise. This latter filter is controlled by a steepest descent adaptation rule based on the minimum output energy principle to get the value of $\mathbf{x}(i)$ from the previous value $\mathbf{x}(i-1)$ and the current value of $\mathbf{z}(i)$.

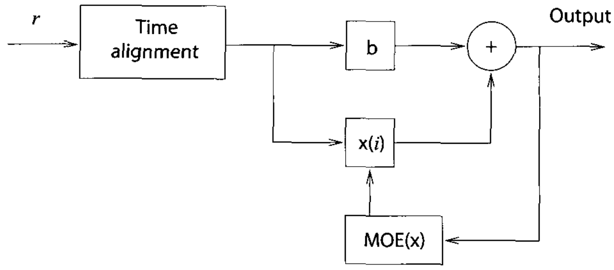

Fig. 1. The GMOE-MUD block diagram.

When the input to the equalizer is given by (17), and assuming orthogonality of the two filters $\mathbf{b}$ and $\mathbf{x}(i)$, the estimated output value is given by

$$[\mathbf{b} + \mathbf{x}(i)]^{*T} \mathbf{z}(i) = d_i^{(1,1)} \mathbf{b}^{*T}\mathbf{b} + [\mathbf{b} + \mathbf{x}(i)]^{*T} \mathbf{n}''(i). \quad (18)$$

IV. EQUIVALENCE OF MOE AND MMSE FOR M-ARY PSK SIGNALS

The equivalence of MOE and MMSE for binary transmission was derived in [5]. For complex M-ary signals, this equivalence does not hold any more with QAM modulation as the MOE is not the right algorithm when using symbols with different energy. However, for M-ary PSK modulation where the symbols still have the same energy the algorithm is valid.

For simplicity, in the following, indices and superscripts appearing in (17) are dropped whenever no confusion arises.

Let us consider the linear detector $(\mathbf{b}+\mathbf{x})$ that minimizes the mean output energy (MOE)

$$MOE(\mathbf{x}) = E\left[\|(\mathbf{b}+\mathbf{x})^{*T}\mathbf{z}\|^2\right] \quad (19)$$

when the input to the equalizer is given by

$$\mathbf{z} = \mathbf{d}\mathbf{b} + \mathbf{n}''. \quad (20)$$

It is intended to find the necessary and sufficient conditions on the vector $\mathbf{x}$ to make the minimization with respect to $\mathbf{x}$ of MOE equivalent to the minimization of the mean square error (MSE) given by

$$MSE(\mathbf{x}) = E\left[\|(\mathbf{b}+\mathbf{x})^{*T}(\mathbf{z}-\mathbf{b}\mathbf{d})\|^2\right]. \quad (21)$$

Expanding the terms in (21) we obtain

$$\begin{aligned} MSE(\mathbf{x}) &= E\left[\left((\mathbf{b}+\mathbf{x})^{*T}(\mathbf{z}-\mathbf{b}\mathbf{d})\right)\left((\mathbf{b}+\mathbf{x})^{*T}(\mathbf{z}-\mathbf{b}\mathbf{d})\right)^*\right]\\ &= E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{z}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{z}\right)^*\right]\\ &\quad + E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\mathbf{d}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\mathbf{d}\right)^*\right]\\ &\quad - E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\mathbf{d}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{z}\right)^*\right]\\ &\quad - E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{z}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\mathbf{d}\right)^*\right]. \end{aligned} \quad (22)$$

The first term is the MOE. Replacing $\mathbf{z}$ by $\mathbf{b}\mathbf{d}+\mathbf{n}''$ in the last two terms, expanding and grouping, we obtain

$$MSE(\mathbf{x}) = MOE(\mathbf{x})$$

$$- E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\right)^{*}\mathbf{d}\mathbf{d}^{*}\right]$$
$$- E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{n}''\right)^{*}\mathbf{d}\right]$$
$$- E\left[\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{n}''\right)\left((\mathbf{b}+\mathbf{x})^{*T}\mathbf{b}\right)^{*}\mathbf{d}^{*}\right]. \quad (23)$$

Using the facts that $E(\mathbf{d}^*\mathbf{d}) = A^2$ where A is the amplitude of the intended user symbols, and that $E(\mathbf{d}) = 0$, (23) is finally modified to

$$\begin{aligned} MSE(\mathbf{x}) =& MOE(\mathbf{x}) \\ & - A^2\left[\left(\mathbf{b}^{*T}\mathbf{b}+\mathbf{x}^{*T}\mathbf{b}\right)\left(\mathbf{b}^{*T}\mathbf{b}+\mathbf{x}^{*T}\mathbf{b}\right)^{*}\right] \\ =& MOE(\mathbf{x}) \\ & - A^2\left[\|\mathbf{b}^{*T}\mathbf{b}\|^2 + \|\mathbf{x}^{*T}\mathbf{b}\|^2 + 2\mathbf{b}^{*T}\mathbf{b}\Re\left(\mathbf{x}^{*T}\mathbf{b}\right)^{*}\right] \end{aligned} \quad (24)$$

which shows that it is necessary and sufficient condition to have both the real and imaginary parts of $(\mathbf{x}^{*T}\mathbf{b})$ equal to zero to set the equivalence between minimizing MOE and MSE with respect to $\mathbf{x}$ since in this case we have

$$MSE(\mathbf{x}) = MOE(\mathbf{x}) - A^2\|\mathbf{b}^{*T}\mathbf{b}\|^2. \quad (25)$$

This is the same (21) of [5] with the exception of the replacement of b with the spreading sequence when there is no channel spreading. To simplify the required condition without any performance loss, we may restrict vector $\mathbf{x}$ to be real and orthogonal to both the real and imaginary vectors forming the complex vector $\mathbf{b}$, that is

$$\begin{aligned} \mathbf{x}^T\Re(\mathbf{b}) &= \mathbf{x}^T\Im(\mathbf{b}) = 0, \text{ or} \\ \mathbf{x}^T\mathbf{b} &= \mathbf{x}^T\mathbf{b}^* = 0. \end{aligned} \quad (26)$$

V. STOCHASTIC STEEPEST DESCENT ADAPTIVE ALGORITHM

The stochastic steepest descent technique consists in searching for the real vector $\mathbf{x}$ orthogonal to both the real and imaginary vectors forming the complex vector $\mathbf{b}$ such as to minimize the effect of interfering signals.

Pre-multiplying (20) by $(\mathbf{b}^* + \mathbf{x})^T$, we obtain

$$(\mathbf{b}^* + \mathbf{x})^T\mathbf{z} = \mathbf{b}^{*T}\mathbf{b}\mathbf{d} + (\mathbf{b}^* + \mathbf{x})^T\mathbf{n}''. \quad (27)$$

The objective now is the search for the vector $\mathbf{x}$ that satisfies the constraints in (26), and that minimizes the energy of the interference and noise components in the detected signal as given by the left hand side of (27). This is equivalent to the minimization of the total output energy as defined by the cost function

$$f = \left[(\mathbf{b}^* + \mathbf{x})^T\mathbf{z}\right]\left[(\mathbf{b}^* + \mathbf{x})^T\mathbf{z}\right]^* + \lambda_1\mathbf{x}^T\mathbf{b} + \lambda_2\mathbf{x}^T\mathbf{b}^* \quad (28)$$

where λ_1 and λ_2 are the Lagrangian multipliers to ensure the constraints given by (26). Differentiating (28) with respect to the elements of the vector $\mathbf{x}$, we obtain

$$\begin{aligned} \mathbf{grad}(f) =& \left[(\mathbf{b}^* + \mathbf{x})^T\mathbf{z}\right]\mathbf{z}^* + \left[(\mathbf{b}^* + \mathbf{x})^T\mathbf{z}\right]^*\mathbf{z} \\ & + \lambda_1\mathbf{b} + \lambda_2\mathbf{b}^*. \end{aligned} \quad (29)$$

The steepest stochastic descent adaptation rule is given by

$$\mathbf{x}(i) = \mathbf{x}(i-1) - \mu\mathbf{grad}(f)$$

where μ is a step control multiplier to be selected, and $\mathbf{x}(0)$ is an initial value of the vector $\mathbf{x}$. Take into consideration the fact that $ab^* + a^*b = 2\Re(ab^*)$, the adaptation rule can then be re-written as

$$\begin{aligned} \mathbf{x}(i) =& \mathbf{x}(i-1) - \mu\left[2\Re\left(\left[(\mathbf{b}^* + \mathbf{x}(i-1))^T\mathbf{z}(i)\right]^*\mathbf{z}(i)\right)\right. \\ & \left. + \lambda_1\mathbf{b} + \lambda_2\mathbf{b}^*\right] \end{aligned} \quad (30)$$

or more compactly

$$\mathbf{x}(i) = \mathbf{x}(i-1) - \mu\left[\Psi + \lambda_1\mathbf{b} + \lambda_2\mathbf{b}^*\right]. \quad (31)$$

Selecting $\mathbf{x}(0) = 0$, the Lagrangian multipliers can be found by pre-multiplying (31) once by $\mathbf{b}^T$ and another time by $\mathbf{b}^{*T}$ and applying the constraints (26) giving

$$\begin{aligned} \mathbf{b}^T\Psi + \lambda_1\mathbf{b}^T\mathbf{b} + \lambda_2\mathbf{b}^T\mathbf{b}^* &= 0 \text{ and} \\ \mathbf{b}^{*T}\Psi + \lambda_1\mathbf{b}^{*T}\mathbf{b} + \lambda_2\mathbf{b}^{*T}\mathbf{b}^* &= 0 \end{aligned} \quad (32)$$

solving for λ_1 and λ_2, we obtain

$$\begin{aligned} \lambda_1 &= \frac{\left(\mathbf{b}^{*T}\mathbf{b}^*\mathbf{b}^T - \mathbf{b}^T\mathbf{b}^*\mathbf{b}^{*T}\right)\Psi}{\left(\mathbf{b}^{*T}\mathbf{b}\right)^2 - \|\mathbf{b}^T\mathbf{b}\|^2} \text{ and} \\ \lambda_2 &= \frac{\left(\mathbf{b}^T\mathbf{b}\mathbf{b}^{*T} - \mathbf{b}^{*T}\mathbf{b}\mathbf{b}^T\right)\Psi}{\left(\mathbf{b}^{*T}\mathbf{b}\right)^2 - \|\mathbf{b}^T\mathbf{b}\|^2}. \end{aligned} \quad (33)$$

Noting that λ_1 and λ_2 are complex conjugates and upon substitution in (30), grouping and rearranging terms we obtain

$$\begin{aligned} \mathbf{x}(i) =& \mathbf{x}(i-1) \\ & - 2\mu\Re\left(\left[(\mathbf{b}^* + \mathbf{x}(i-1))^T\mathbf{z}(i)\right]^*\right. \\ & \left.\left[\mathbf{z}(i) + \mathbf{b}\alpha^T\mathbf{z}(i) + \mathbf{b}^*\alpha^{*T}\mathbf{z}(i)\right]\right) \end{aligned} \quad (34)$$

where

$$\alpha^T = \frac{\left(\mathbf{b}^{*T}\mathbf{b}^*\mathbf{b}^T - \mathbf{b}^T\mathbf{b}^*\mathbf{b}^{*T}\right)}{\left(\mathbf{b}^{*T}\mathbf{b}\right)^2 - \|\mathbf{b}^T\mathbf{b}\|^2}. \quad (35)$$

Several suggestions for the selection of the step control multiplier μ appear in different references using the MOE technique with binary data. These suggestions only give trends and bounds on the selection. During the current work, the most suitable values were determined experimentally and were found to be given by $\mu = \mu_0/(\mathbf{z}^{*T}\mathbf{z})$ where μ_0 varies in the simulations between 0.03 and 0.1 depending on the number of users and the frame length. These values of μ_0 are chosen by using ad hoc optimization.

VI. SIMULATION RESULTS

In this section, the performance of the proposed blind adaptive algorithm based on the MOE rule and referred to as generalized minimum output energy multi-user detector (GMOE-MUD), is simulated for different cases and compared with the conventional rake receiver to show its effect on MAI rejection as well as its effect on ISI rejection.

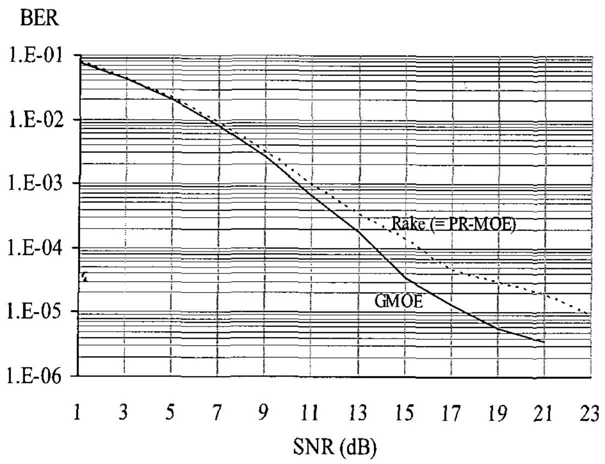

Fig. 2. BER performance for the single user case showing the equalization effect of the GMOE-MUD.

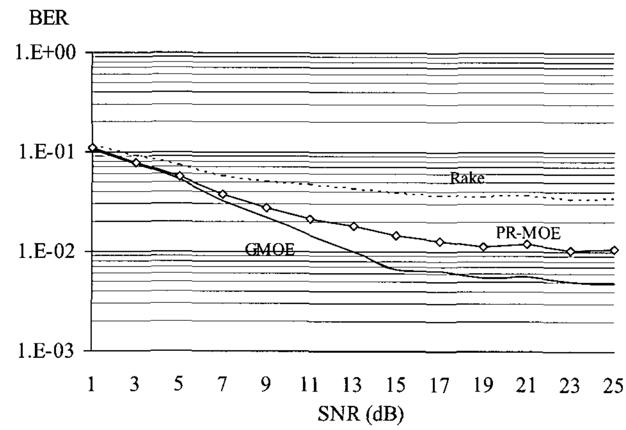

Fig. 3. BER performance for four active users with perfect power control.

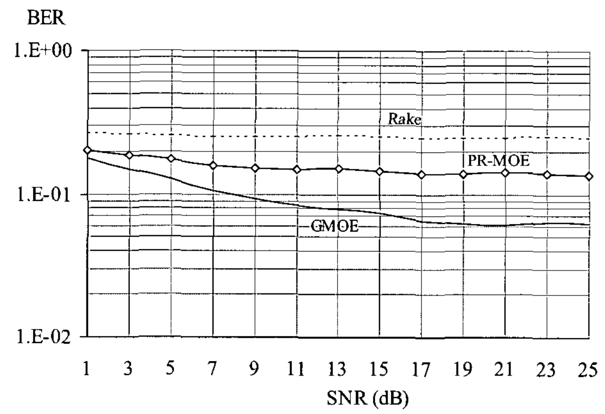

Fig. 4. BER performance for four active users with 10 dB power unbalance.

In the following simulations, the information bits are modulated using a QPSK modulation scheme. Each symbol is then spread using a randomly generated binary signature sequence where the number of chips per data symbol Q is 14 unless otherwise mentioned and the chip duration T_c is equal to $0.5\mu s$.

The channel impulse responses of the K users are different and independent. They are derived from the COST207 [14]. The COST207 channel models are based on the discrete time Gaussian wide scheme stationary uncorrelated scattering (GWSSUS) model. They are seen as being time invariant during the transmission of the data block. Furthermore, for the different data blocks they are independent. The statistics of the GWSSUS channel model are completely given by the power delay profile. The bad urban area channel case with maximum delay time spread equal to $10\mu s$ is considered. This implies a channel response length W equal to 21. At the receiver side the GMOE-MUD is used to combat both MAI and ISI.

In the following results, the GMOE-MUD is first compared with the conventional rake CDMA receiver and with the precombining rake MOE (PR-MOE) of [11]. The parameters of the PRE-MOE are the same as mentioned above in this section. Then the near-far problem is investigated. Next, the asynchronous transmission effect is shown. The frame length affecting the algorithm performance is also studied. Finally, the case of MIMO system is considered for two different cases.

A. Simple Case

First, consider the case of single user to show the performance of GMOE-MUD as an ISI rejection adaptive algorithm. In Fig. 2, the BER versus the signal to noise ratio per information bit is plotted for the proposed algorithm and the conventional rake receiver that spans all the interfering symbols of the intended symbol. The figure shows that the GMOE can combat ISI as well as the rake receiver, it even contributes a gain more than one dB at higher SNR where the noise effect is negligible and the ISI problem is dominating. The PR-MOE performance is the same as the rake receiver.

Next, Fig. 3 considers a communication system where four users are active. The GMOE-MUD is compared with the rake receiver and with the PR-MOE of [11]. Considerable gains are obtained over the rake receiver and the PR-MOE-MUD. All of the three algorithms exhibit steady state performance at high SNR.

B. Near-Far Problem

In Fig. 4, we consider a power unbalance between different users. The three interfering users are each 10 dB higher than the intended user. The gain for the GMOE-MUD over the rake receiver is even higher than the balanced case. The GMOE-MUD compared with the PR-MOE gives better improvement relative to the balanced situation.

C. Asynchronous Transmission and Spreading Sequence Length

Fig. 5 shows that the effect of Asynchronous transmission is insignificant. Only small fluctuations can be seen. This can mainly be explained by the fact that the total number of interfering symbols is not much affected by the asynchronous transmission, due to the presence of ISI. Actually the main parameter affecting the performance is not to be synchronous or asynchronous. It is more about the relation of the spreading sequence (Q) and the channel spreading (W) giving the total number of interfering symbols.

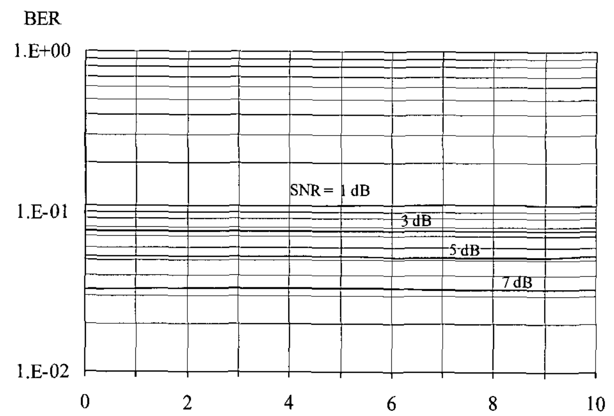

Fig. 5. Effect of asynchronous delay at different signal to noise ratios. Users are randomly delayed by τT_c, normally distributed in $(0, 2\tau_{av} T_c)$

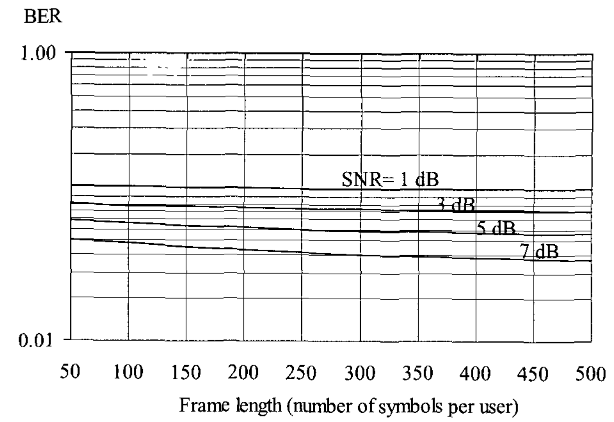

Fig. 6. Effect of frame length at different signal to noise ratios.

D. *Effect of Frame Length*

Fig. 6 is a plot of the BER with different signal to noise ratios versus the frame length. It clearly shows that the BER decreases with larger frame lengths. This is expected as the preliminary adaptation phase, i.e., the convergence to the right value of x becomes smaller with respect to the frame size. Note that we assumed the channel to be constant over the frame transmission and that the counting of the error bits starts from the beginning of the frame and assume no training phase.

E. *MIMO System*

In Fig. 7, the performance comparison for different number of transmitting and receiving antennas are shown for the case of four balanced users. Curves are labeled (N, M) where N is the number of transmitting antennas and M the number of receiving antennas. The dotted curves refer to the conventional rake receiver. When using two transmitting antennas the same information symbol is sent on both but with different spreading sequences. More than 8 dB gain is depicted at 10^{-2} BER when using two receiving antennas. Further improvement, around one dB, results from transmitting diversity. Finally, lower BER can be obtained if higher processing gain and coding are employed.

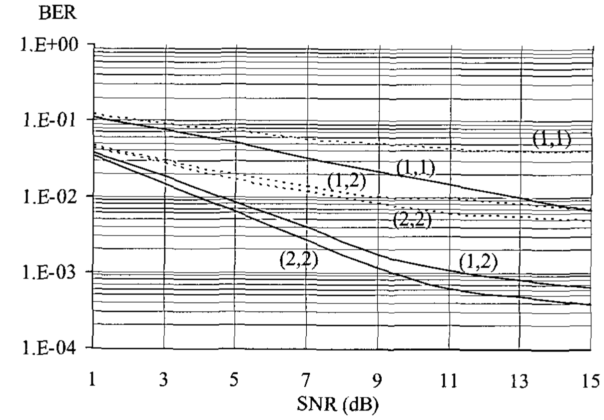

Fig. 7. Performance of four users in MIMO system using the GMOE-MUD, dotted lines refer to the conventional rake receiver.

VII. CONCLUSIONS

In the present article, a generalized blind adaptive multi-user detector is proposed. The main contribution lies in its ability to resolve both the MAI and the ISI resulting from a multipath channel with a low complexity. The GMOE-MUD does not need the other users signatures, timing or complex amplitudes. Depicted simulation results show that this algorithm is robust for the near-far problem. Synchronous as well as asynchronous transmissions have been considered, showing the algorithm capabilities to maintain almost the same performance for both situations. Furthermore, simulations were conducted for MIMO systems yielding appreciable performance improvements. Correlation effect among branches can be considered in a future work.

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